ISTANBUL TECHNICAL UNIVERSITY ★ ENERGY INSTITUTE

FORECASTING FOR BIOETHANOL PRODUCTION IN TURKEY

Ph.D. THESIS

Ezgi BAYRAKDAR ATEŞ

Energy Science and Technology Division

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ ENERJİ ENSTİTÜSÜ

TÜRKİYE'DE BİYOETANOL ÜRETİMİ İÇİN ÖNGÖRÜ

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To my family and my precious husband,

FOREWORD

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TABLE OF CONTENTS

Page

ABBREVIATIONS

ACVF	: Autocovariance function
AEZs	: Agro-Ecological Zones
AGMEMOD	: Agriculture Member States Modelling
AIC	: Akaike Information Criteria
ANN	: Artificial Neural Network
APSIM	: Agricultural Production Systems sIMulator
AR	: Auto-Regressive
ARIMA	: Auto-Regressive Integrated Moving Average
ARIMAX	: Auto-Regressive Integrated Moving Average eXogenous
ARMA	: Auto-Regressive Moving Average
ARMAX	: Auto-Regressive Moving Average Exogeneous
ARX	: Auto-Regressive Exogeneous
ART	: Self-Adaptive Resonance Theory
BAM	: Bilateral Associative Memory
B.C.	: British Columbia
BP	: Back Propagation
CERES	: Crop Environment Resource Synthesis
CGE	: Computable General Equilibrium
C_2H_5OH	: Ethanol
CO_2	: Carbon dioxide
corr	: Correction Term
cov	: covariance
DMO	: Direct Model Output
DSP	: Digital Signal Processing
E20	: the fuel including 20% alcohol and 80% gasoline
E25	: the fuel including 25% alcohol and 75% gasoline
E85	: the fuel including 85% alcohol and 15% gasoline
E-Diesel	: diesel including maximum 15% alcohol
EAO	: Environmental Assessment Office
EIA	: Environmental Impact Assessment
EMRA	: Energy Market Regulatory Authority
EPA	: Environmental Protection Agency
EPIC	: Environmental Policy Integrated Climate
ePURE	: European Renewable Ethanol Association
EU	: European Union
EtOH	: Ethanol
FAME	: Fatty Acid Methyl Ester
FAO	: Food and Agriculture Organization of the United Nations
FAPRI	: Food and Agricultural Policy Institute
FIR	: Finite Impuls Response
FPE	: Final Prediction Error
FFVs	: Flexible-Fuel Vehicles

g : gram
GE : General Equilibrium
GHG : Greenhouse Gas
GLOBE : Global Legislators Organization for a Balanced Environment
GM : Grey Model
GP : Genetic Programming
GTAP : Global Trade Analysis Project
GTAP-E : Global Trade Analysis Project An Energy-Environmental Version
HVO : Hydrotreated Vegetable Oil
IFPRI : International Food Policy Research Institute
IEA : International Energy Agency
IGC : International Grain Council
IIR : Infinite Impuls Response
IPCC : Intergovernmental Panel on Climate Change
ISO : International Organization for Standardization
kcal : kilocalories
kg : kilograms
LAI : Leaf Area Index
LCA : Life Cycle Assessment
LEITAP : Landbouw Economisch Instituut Trade Analysis Project
LPG : Liquid Petroleum Gas
l : liter
logsig : logarithmic sigmoid
MA : Moving Average
MAPE : Mean Average Percentage Error
MARKAL : Market Allocation
MTBE : Methyl Tertiary Butyl
MFN : Most Favoured Nation
MLR : Multiple Linear Models
mmHg : milimeter of mercury
mol : mole
MON : Motor Octane Number (MON)
MT : Million Tonnes
OECD : Organisation for Economic Co-Operation Development
OFID : OPEC Fund for International Development
OPEC : Organization of the Petroleum Exporting Countries
PE : Partial Equilibrium
PEATSim : Partial Equilibrium Agricultural Trade Simulation
PM : Particulate Matter
PPO : Pure Plant Oil
R&D : Research and Devlopment
RFA : Renewable Fuel Association
RFS : Renewable Fuel Standard
RON : Research Octane Number (RON)
RMS : Root Mean Square
PETDER : Turkish Oil Industry Association
SEA : Strategic Environmental Assessment
SIC : Schwarz Information Criteria
SOM : Self-Organization Mapping
tansig : tangent sigmoid

TAMRA	: Tobacco and Alcohol Market Regulatory Authority
TARKIM	: Agricultural Chemical Technologies Incorporated Company
THC	: Total Hydrocarbons
TSE	: Turkish Standards Institution
UNICA	: Brazilian Sugarcane Industry Association
US	: United States
US EPA	: United States Environmental Production Agency
USAGE	: United States of America General Equilibrium
USDA	**:** US Department of Agriculture
USH	: Ultrasonic Sward Height
VAR	: Vector Autoregression
VBETC	: Volumetric Biodiesel Excise Tax Credit
VEETC	: Volumetric Ethanol Excise Tax Credit
VOC	: Volatile Organic Compounds
WEC	: World Energy Council

SYMBOLS

α : is the lag delay between input and output
a_i : the contribution coefficient of an i-step past value of the objectivevariable in ARX model
α_i : vector
a_p : autoregression coefficient
B : is backshift operator
b_{jg} : model coefficient in ARX model
b_{jg} : the contribution coefficient of the j-step past value of an exogenous input variable in ARX model
b_k : the coefficient in Wold Theorem for ARMA Model
b_k : bias
c : constant in ARMA
C : Carbon
°C : Degree Celsius
D : DMO issuing time
$D+1$: The issuing time of this forecast
E : Expected value
e_t : prediction error term in AR model
e_t : white noise process in ARMA model
H : Hydrogen
k : node number in ANN
k_g : the time lag of the propagation delay of the exogenous input variable in ARX model
n : model order
N : data length
O : Oxygen
OH : Hydroxide
p : the order of the filter
p : the model order parameter in ARX model
P : previous observation in AR model
q_g : the model order parameter in ARX model
R^2 : Correlation Coefficient
s : current time step in ARX model
t : time
$u[t]$: Input signal
u_t : Indeterministic component
w : weight
w_{kj} : is synaptic weights
w/w : weight/weight
X : External input variable
$\overline{x}$: mean value
x_j : is system output

$x[t]$	: output signal
x_s	: predicted value in ARX model
x_t	: predicted value
x_t	: sequence in Wold Theorem
x_{t-a}	: external input variable in ARMAX model
y_g	: exogenous input variable in ARX model
y_k	: output
y_t	: is response (output variable) in ARMAX model
$y(t)$	: random signal
z_t	: Linear deterministic component
$Ø$	: Constant in ARMA model
$Ø_{nØ}$	: Coefficient in ARMAX model
$\sum$	: summing function
β_0	: regression coefficient (or model parameter)
β_1	: regression coefficient (or model parameter)
β_i	: coefficients vector
γ	: Autocovariance function
ε	: error term
ε_t	: white noise in ARMAX model
θ	: Constant in ARMA model
$\theta_{n\theta}$	: Coefficient in ARMAX model
μ	: Mean function
$\xi_{n\xi}$	: Coefficient in ARMAX model
σ_e^2	: Variance
σ_x^2	: Variance of forecasting error
χ^2	: Chi-Square
$\varphi(.)$	: activation function

LIST OF TABLES

Page

LIST OF FIGURES

Page

FORECASTING FOR BIOETHANOL PRODUCTION IN TURKEY

SUMMARY

Biofuels, as a clean alternative to the fossil fuels, are of wide interest according to the raising global energy demand and high prices for fossil based fuels. Today, within the scope of renewable energy technologies research and development studies on biofuels are gradually increasing locally and globally. As a result of biorefinery technologies, biofuels are foreseen to take place in our lifes. Presently, first generation biofuels, which are biodiesel and bioethanol, have been used commercially. In this thesis, forecasting study aims the bioethanol production in Turkey. By appraising the future and potential amounts of the feedstocks which are used for bioethanol production and which are also possible to be used, the forecasting of the bioethanol production in Turkey will to be put forward. Addition to bioethanol production and its feedstocks supply forecasting, gasoline consumption forecasting was also carried out. With this, it has been estimated that the forecasted bioethanol production provides how much of the bioethanol demand for the forecasted gasoline consumption. Then, emissions based on forecasted gasoline consumption were estimated according to several blend mandates in the perspective of environmental assessment. In this study, based on three issues, energy, agriculture and low carbon economy, a roadmap was adviced for bioethanol production and assessment policy.

Biofuel technology is one of the driving powers of sustainable energy production and green growth for today and future. Sustainability of biofuel production process depends on available resource management and continuity of feedstock supply. Thus, an appropriate tool for forecasting agricultural feedstock supply and potential of bioethanol production are so significant for policy making. It was seen that higher potential of bioethanol production and the possible use of main agricultural products as the most suitable feedstock show the importance of bioethanol production and its forecasting in Turkey. As an alternative to fosil based fuels, there are also many advantages of bioethanol production and use such as domestic resources use in energy production, energy and agricultural economics, environmental benefits and energy supply security.

In the first part of thesis, linear and non-linear model approaches are presented to forecast annual potential of the feedstock supply as wheat, corn, barley and sugar beet that could be used to product first generation bioethanol. The linear model as Auto-Regressive (AR) Model and non-linear models as Auto-Regressive eXogeneous (ARX), Auto-Regressive Moving Average eXogeneous (ARMAX) and Artificial Neural Networks (ANN) were performed. Recursive method was also used to improve only the model performances belong to all selected models even if recursive method could not be used to forecast. Firstly, model order determination and modelling of feedstock production were studied. The model orders belonging to wheat and barley production data were 2, while those belonging to corn and sugar

beet were 1 according to major model order selection criterias; Akaike Information Criteria (AIC) and Final Prediction Error (FPE) in AR model. The same model orders were also used in ARX model to compare, while model orders were selected due to model performances in ARMAX model. For recursive model applications; model orders were used according to which model's performance is improved. On the other side, the numbers of nodes in input layer (k) were selected as 1, 2, 3, 4 to examine the effects of numbers changes in input layer and neurons in the hidden layer for ANN correlated to model orders in AR model. Second, model performance tests were performed with Root Mean Square (RMS), R^2 and Chi-Square (χ^2) in optimum model orders for each serie. R^2 was found mainly near to 1, while χ^2 and RMS results were within the acceptable limits in all models. Then, forecasts were estimated for each of feedstocks and it was found that forecasts decreased due to declines in model performances for several prediction horizon values (1, 5, 10, 15 and 20 years). Because selected models were generally used to estimate the next value in time series. The variations have a great effect on Turkey's supply of feedstock and potential amount of bioethanol that can be produced. In ANN, forecast changings were not the same as in other models. Feedstock forecasts were determined to be quantitatively consistent for each model and with legal authority predictions. There were negligible small differences ranging from 0.8% to 2%. Besides, the forecasting study on gasoline consumption in per year was also given to calculate the amount of required bioethanol blending taking into account today's legal obligation and possible alternatives to have the bioethanol blending values per liter of consumed fuel. As in feedstock predictions, the same linear model and non-linear models were performed to forecast annual gasoline consumption of Turkey. Model order is estimated as 8 according to major model order selection criterias; Akaike Information Criteria (AIC) and Final Prediction Error (FPE) in AR model and also used in other models considering model performances, while nod number was 4 in ANN. Then, model performance tests were performed with Root Mean Square (RMS), R^2 and Chi-Square (χ^2) in optimum model order. Performance tests results showed that the models are available for determining on gasoline consumption forecasting for fifteen years (prediction horizon is twenty years in feedstock forecasting) although fuel consumption data set was too short to be modelled. In following step, considering the bioethanol feedstocks production values, how many liters of bioethanol could be produced per ton of selected feedstocks were also determined using references. On the other side, bioethanol demands were estimated for several blend mandates values of forecasted gasoline consumption values. Forecasted bioethanol productions per tonne of selected feedstocks' predictions were compared whether supply with or not bioethanol productions are required for the forecasted gasoline consumptions according to the different bioethanol blend mandates. According to those; Turkey's total feedstock production could be used to produce bioethanol is sufficient to demands of bioethanol blend ratios such as 1%, 2%, 3%, 5%, 10%. Barley and especially wheat potentials could be seperated for bioethanol production also seem as preferable because their potentials are enough for bioethanol production demand. However sugar beet and corn are mainly used to produce bioethanol. Finally, CO_2 emissions were calculated as environmental assessment study to put forward that environmental impacts of forecasted gasoline consumptions and the emission decreases from bioethanol blended-gasoline consumption (in several ratios 1%, 2%, 3%, 5%, 10%). Declines in emissions were increased with incremental bioethanol blend ratios. In the perspective of green economy, sustainability and energy production; Turkey has a significant potential to produce bioethanol without affecting their uses in main areas as food, feed and export and decreases in emissions resulted from gasoline consumption could be provided through this environmentally-friendly fuel use as fuel additive. Namely, sustainability could be provided in the perspective of both energy source production and low-carbon economy. The consistency of the forecastings has been made supports the sustainability of bioethanol production and resource management.

TÜRKİYE'DE BİYOETANOL ÜRETİMİ İÇİN ÖNGÖRÜ

ÖZET

Biyoyakıtlar, fosil yakıtlara alternatif olarak artan enerji ihtiyacını karşılamak ve yüksek fosil yakıt fiyatlarına alternatif olarak, giderek artan oranlarda kullanılmaktadır. Günümüzde yenilenebilir enerji teknolojileri kapsamında hem ülkemiz hem de dünyada biyoyakıtlar üzerine yapılan araştırma ve geliştirme çalışmaları giderek artmaktadır. Biyorafineri teknolojilerinin bir sonucu olarak biyoyakıtların hayatımızda artarak yer alacağı öngörülmektedir. Biyorafineriler petrol rafinerilerinden farklı olarak biyoyakıtlar üretmekte ve hammadde olarak petrol yerine biyokütle kullanmaktadır. Biyorafineri ve biyoyakıt teknolojileri sürdürülebilirlik ve yeşil ekonomi açısından değerlendirildiğinde bu alanda gerçekleştirilecek öngörü ve çevresel değerlendirme çalışmaları büyük önem arz etmektedir.

Biyoyakıtlar üretim şekli ve hammadde türüne göre birinci, ikinci, üçüncü ve dördüncü kuşak biyoyakıt olarak sınıflandırılmaktadır. Günümüzde halen birinci kuşak motor biyoyakıtları olan biyodizel ve biyoetanol ticari olarak kullanılmaktadır. İçten yanmalı motorlarda tasarımda değişikliğe gerek duyulmadan kullanılabilecek yağ asidi metil esteri olarak tanımlanan biyodizel ile şekerli ve nişastalı kaynaklardan üretilen biyoetanol birinci nesil biyoyakıtlar içerisinde yer almaktadır.

Biyoyakıtların önemli bir türü olan biyoetanol şekerli ve nişastalı bikilerin fermantasyonu veya selülozik kaynakların asidik hidrolizi ile üretilebilen bir yakıttır. Antitoksik özelliğe sahip olan ve önemli bir alternatif motor yakıtı olan biyoetanol benzinin yerine geçerek doğrudan yakıt olarak kullanıldığı gibi yakıt katkısı olarak da kullanılabilmektedir. Biyoetanol, konvansiyonel benzinin oktan sayısını artırmada ve bununla birlikte yapısında bulunan oksijen ile benzinin daha verimli ve temiz yanmasına yardımcı olması nedeniyle sıklıkla tercih edilmektedir. İthal edilen petrole önemli bir yerel alternatif olan yakıt etanolü petrol kökenli ürünlere olan bağımlılığı büyük ölçüde azaltarak ekonomik, politik, çevresel ve bilimsel alanlarda önemli konuma gelmektedir. Biyoetanolün yenilenebilir hammadde kaynaklarından elde edilmesi ve bu kaynakların da sürdürülebilirliğinin sağlanması etanol üretiminin sürdürülebilir olarak gerçekleştirilmesini sağlayacaktır.

Dünya ve Türkiye'de biyoetanol kullanımına dair yürürlüğe konulan yasal düzenlemeler ile biyoetanol kullanımının yaygınlaşması ve biyorafineri üretim kapasitelerinin artması beklenmektedir. Biyorafinerilerin artan üretim miktarlarıyla doğru orantılı olarak artış gösteren hammadde gereksinimleri ve üretim proseslerinin iyileştirilmesi teknik, ekonomik, tarımsal ve enerji açısından büyük bir önem taşımaktadır. Tarımsal kökenli hammadde kullanılarak üretilen biyoetanolün yakıt alternatifi ve katkı şeklinde artan kullanımının sonucu olarak tarım sektöründeki etkisi son yıllarda dikkat çekici boyuta ulaşmıştır. Hem kaynaklar hem de üretilen etanol açısından sürdürülebilirlik politikaları göz önüne alındığında hammadde üretim ve kullanım süreci ile etanol üretim süreci üzerinde teknik ve ekonomik

öngörüler ile çevresel değerlendirmelerin doğru ve etkin bir şekilde yapılması gerekmektedir. Bu aşamada kaynak yönetimi kavramı ön plana çıkmaktadır. Hammadde aşamasından biyoetanolün kullanımının son aşamasına kadar olan süreçteki tüm üretim ve tüketim aşamaları başta kaynak yönetimi olmak üzere yeşil ekonomi, tarımsal ekonomi ve enerji ekonomisi açısından değerlendirilmelidir. Özellikle tarımsal ekonomi ve kaynak yönetimi alanında biyoetanol ile ilgili gerçekleştirilen tüm öngörü, modelleme ve optimizasyon çalışmaları ülkelerin ve kurumların yakıt etanolü ile ilgili gelecek stratejilerini belirlemede büyük rol oynamaktadır. Biyoetanol sektöründeki gelişme ve ilerlemeler başta tarım ve enerji sektörlerini de içine alarak etanolün uzun dönemli sosyo ekonomik ve diğer ekonomik etkileri üzerine yapılan çalışmaların artmasına neden olmaktadır. Biyoetanol ile ilgili yapılan birçok ekonomik temelli çalışma, giderek genişleyen biyoetanol endüstrisinin makro ekonomik performans üzerindeki global ve ulusal etkilerinin kısmi ve genel denge modelleri gibi ekonomik teoriler, tarımsal ekonomik modeller ya da simulasyon yöntemleri kullanılarak tespit edilmesi üzerine olmaktadır. Bunun yanısıra önemli bir ekonomik girdi olan ve biyoetanolün üretim süreci ve sonrasındaki tüm ekonomik sonuçları etkileyen hammadde miktarının belirlenmesi ve bununla ilgili yapılan tüm öngörü çalışmaları için farklı öngörü yöntemleri kullanılmıştır. Kaynak yönetiminin başarılı bir şekilde gerçekleşmesi ve biyoetanol üretim sürecinin sürdürülebilir olarak yapılabilmesi için öngörü çalışmaları ve modelleri büyük bir önem taşımaktadır. Gerçekleştirilen öngörü çalışmaları ile yalnızca hammadde miktarının belirlenmesi değil, kaynak kullanımının tarım ve enerji sektörü ile diğer ilişkili olduğu tüm sektörlerdeki etkileri de yorumlanabilmektedir. Öngörü için kullanılan yöntemlerin her biri öngörünün doğruluk derecesine göre farklı avantaj ve dezavantajlara sahip olsa da hammadde ve gıda arzını düzenlemek ile enerji üretim planlamalarını gerçekleştirmek için kullanılmaktadırlar. Bu amaçla, öz bağlanımlı model, öz bağlanımlı hareketli model ortalama hareketli model, yapay sinir ağları, tarımsal kaynaklı hammadde üretimi öngörüsü ile enerji kaynaklarının üretimi öngörüsü için kullanılabilir. Bu modellerin bir kısmı tek başına, farklı model ya da ilavelerle yeniden düzenlenerek biyoetanol ile ilgili farklı çalışmalar için uygun olacaktır.

Bu tez çalışması kapsamında biyoyakıtların önemli bir türü olan birinci nesil biyoetanolün Türkiye'deki üretimi için öngörü çalışması yapılması amaçlanmaktadır. Mevcut biyoetanol üretiminde kullanılan ve olası yeni kaynakların tarımsal üretim potansiyelleri ve gelecekteki durumu değerlendirilerek, birinci nesil biyoetanol üretimi Türkiye öngörüsü ortaya konulmuştur. Hammadde üretim değerleri üzerinde yapılan öngörünün yanısıra Türkiye yıllık benzin tüketim değerleri üzerinde de tahmin yapılarak mevcut yasal düzenlemeler ve alternatif katkı yüzdeleri doğrultusunda gerekli olabilecek biyoetanol miktarı öngörülmüştür. Çalışmada tarım, enerji teknolojileri ve düşük karbon ekonomisi üçgeninde, yapılan öngörü çalışmalarının biyoetanol üretimi politikası için yol haritası olması hedeflenmiştir. Hammadde ve biyoetanol üretimi ile ilgili yapılan öngörülerin sonuçları incelendiğinde Türkiye'nin sürdürülebilirlik politikaları açısından tarım ülkesi olmasının da bir sonucu olarak önemli avantajlara sahip olduğu ve kaynaktan tüketimin son aşamasına kadar doğru bir biyoetanol üretim politikası ile bu kazanımların daha da artacağı görülmektedir.

Bu tez çalışmasının ilk aşamasında birinci nesil biyoetanol üretiminde kullanılan hammaddeler, buğday, mısır, arpa ve şeker pancarı için lineer ve lineer olmayan modellerle yıllık potansiyel üretim arzı öngörülmüştür. Lineer model olarak öz bağlanımlı (Auto-Regressive: AR) model kullanılırken, lineer olmayan model olarak öz bağlanımlı ekzojen (Auto-Regressive eXogeneous: ARX) model, öz bağlanımlı ortalama hareketli ekzojen (Auto-Regressive Moving Average eXogeneous: ARMAX) model, özyinelemeli method (Recursive Method) ve yapay sinir ağları (Artificial Neural Networks: ANN) kullanılmıştır. Bu modeller arasından özyinelemeli model öngörü yapmak için değil yalnızca model başarımlarını iyileştirmek için kullanılmıştır. Öngörünün ilk aşamasında model mertebesi belirlenmiş ve bu model mertebesi değerleri ile her bir hammadde üretim arzına ait zaman serileri modellenmiştir. Güvenilir, doğru sonuçlar veren bir model oluşturabilmek için model mertebesinin doğru tespit edilmesi gerekmektedir. Model mertebesi belirleme öz bağlanımlı model başta olmak üzere tüm modeller için en önemli aşamadır. Literatürde öz bağlanımlı modeller için olan bu tür model seçim kriterlerinin en yaygın kullanılanları ″Akaike Bilgi Kriteri″ (Akaike Information Criteria: AIC), ″Schwarz Bilgi Kriteri″ (Schwarz Information Criteria: SIC) ve ″Son Öngörü Hatası″'dır (Final Prediction Error: FPE). Tez çalışmasında AIC ve FPE kullanılarak en uygun model mertebeleri tespit edilmiştir. Öz bağlanımlı modelde buğday ve arpa yıllık üretim miktarı verileri için model mertebeleri 2 iken, mısır ve şeker pancarı için 1 olarak tespit edilmiştir. Aynı model mertebeleri karşılaştırma yapabilmek ve diğer modellerde de kullanıldığında kabul edilebilir sınırlar dahilinde modelleme sonuçları iyi olması nedenleriyle öz bağlanımlı model için bulunan model mertebeleri öz bağlanımlı ekzojen modelle öngörü yapılırken de kullanılmıştır. Öz bağlanımlı ortalama hareketli ekzojen model için ise model performansları göz önüne alınarak en uygun model mertebeleri seçilmiştir. Öz bağlanımlı ortalama hareketli ekzojen modelde buğday ve arpa için model mertebeleri {6,5} iken, mısır için {4,3} ve şeker pancarı için {3,2} olarak bulunmuştur. Öz bağlanımlı model, öz bağlanımlı ortalama hareketli ekzojen model ve öz bağlanımlı ekzojen model için belirlenen model parametreleri bu modeller özyinelemeli modelle kullanılırken de aynı değerleriyle kullanılmıştır. Yalnızca ARMAX model için özyinelemeli model kullanılırken modelin performansına göre model mertebesi kullanılmıştır. Yapay sinir ağlarında da ilk aşamada giriş tabakası nod sayısı belirlenmeye çalışılmıştır. Her hammadde değeri için diğer modellerle özellikle öz bağlanımlı modelle uyumlu olacak şekilde aynı mertebe seçilmiş ve buna ek olarak farklı nod sayıları da denenmiştir. Belirlenen model mertebeleri ve nod sayıları ile her hammaddeye ait veri serisi için modeller çalıştırılmış ve farklı öngörü ufku değerleri için (1, 5, 10, 15, 20 yıl gibi) performans testleri yapılmıştır. Model performanslarını değerlendirmek için en çok bilinen başarım kriterleri olan Kare kök ortalama (Root Mean Square: RMS), R-Kare (R^2) ve Ki-Kare (Chi-Square: χ^2) kullanılmıştır. R^2 sonuçları yaklaşık olarak 1'e yakın olmuş, RMS ve χ^2 ise kabul edilebilir sınırlar dahilindedir. Model performanslarının değerlendirilmesi aşamasında veri serisi ve model üzerinde etkili olan faktörler açıklanmıştır. Veri serisi kısa olduğunda bile uygulanan modelin başarımının yüksek olması bu modellerin kullanılan veri serileri için uygun olduğunu göstermektedir. Tez kapsamında kullanılan modellerde özyinelemeli model ise öngörü yapmak yerine, diğer modeller ile tahmin edilen sonuçlarıyla oluşturulan serilerin düzeltme terimleriyle düzeltilmesini gerçekleştirmektedir. Oluşturulan yeni serilerle model başarımlarını incelenmiş ve eğer başarımda küçük de olsa bir artış var ise özyinelemeli modelin kullanılmasının uygun olduğu belirtilmiştir. Özyinelemeli model öngördüğümüz dataları gerçeğe daha yakınlaştırmak için kullanılmıştır. Bu çalışmada elde edilen sonuçlarda öz bağlanımlı modelde tüm data serilerinde özyinelemeli model uygulanabilirken, mısır dataları için ki-kare ile özyinelemeli ortalama hareketli ekzojen modelin başarımı değerlendirildiğinde ve şeker pancarı dataları için R-kare ile özyinelemeli modelin başarımı değerlendirildiğinde beklenen artışlar sağlanamamıştır. Bu bölüm içerisinde model başarım hesaplamalarını takiben her veri serisi için farklı öngörü ufku değerleri ile öngörü yapılmış ve Türkiye'nin biyoetanol hammadde üretim değerleri ile ilgili olarak gelecekteki durumu ortaya konulmuştur. Sonuçlar incelendiğinde öngörü ufku değeri arttıkça model başarımlarında olan düşüşe bağlı olarak ve modelin karakteristiği nedeniyle hammadde üretim değerleri tahminlerinde azalma görülmüştür. Bunun nedeni kullanılan modellerin bir adım sonrasını öngörmek için oluşturulan modeller olması ve daha uzun süreli öngörülerde başarımda azalma olmasıdır. Yapay sinir ağları sonuçlarındaki azalmanın daha düşük olduğu gözlenmemiştir. Hammadde üretim arzı ile ilgili yapılan çalışmaların aynıları Türkiye yıllık benzin tüketimi için de gerçekleştirilmiştir. Özbağlanımlı ve özbağlanımlı ekzojen model için model mertebesi 8 olarak belirlenirken, yapay sinir ağları için giriş tabakası nod sayısı 4 olarak tespit edilmiştir. Ayrıca yapay sinir ağlarıyla seçilen nod sayısı değerinde bulunan öngörü sonuçlarının değişen öngörü ufku değerlerine rağmen yakın olduğu tespit edilmiştir. Model mertebesini takiben her bir model için model performansları değerlendirilmiş ve benzin datalarının uzunluğu kısa olmasına rağmen iyi bir başarımla seçilen modellerin bu datalara uygulanabildiği tespit edilmiştir. Bunlardan sonra üretilmesi öngörülen hammadde miktarlarına bağlı olarak ton başına üretilebilecek biyoetanol miktarları hesaplanmıştır.

Diğer taraftan tüketilmesi öngörülen benzin miktarı hesaplanarak bugün yasal olarak benzine katılması zorunlu olan biyoetanol yüzdesi ve diğer etanol harmanlama yüzdeleri üzerinden hesaplama yapılarak farklı öngörü ufku değerleri için gerekli olabilecek biyoetanol miktarları tespit edilmiştir. Bu iki sonuç karşılaştırılarak öngörülen biyoetanol arzının öngörülen biyoetanol gereksinimini karşılayabildiği ortaya konmuştur. Bu karşılaştırma yapılırken, her hammadde için iki farklı durum dikkate alınabileceği öngörülerek her ikisi için de hesaplama yapılmıştır. İlk durumda seçilen her hammaddenin gıda, yemlik ve tohum olarak kullanma gibi öncelikli kullanım alanları dışındaki öngörülen miktarları üzerinden ton başına kaç litre biyoetanol üretilebileceği belirlenmiştir. İkinci durumda ise ilk durumdaki öncelikli alanlara ilave olarak ihracat değerleri de hesaba katılmadan üretilebilecek biyoetanol miktarları belirlenmiştir. Her model için (AR, ARX ve ANN) ayrı ayrı belirlenen bu değerler incelendiğinde benzin tüketimine bağlı olarak %1, %2, %3, %5, %10 biyoetanol harmanlaması durumundaki biyoetanol talebinin farklı öngörü ufku değerleri için (1, 5, 10, 15 yıl) karşılanabildiği görülmüştür. Öz bağlanımlı ortalama hareketli ekzojen model benzin tüketimi öngörüsü için sürdürülebilir sonuçlar vermediğinden bu model sonuçları için gerekecek biyoetanol miktarı verilmemiştir. Yapay sinir ağları kullanıldığında mısır ve şeker pancarı için iki farklı durumun yanı sıra iki farklı giriş tabakası nod sayısı değeri için ayrı ayrı hesaplama yapılmıştır. Ayrıca; yapay sinir ağlarıyla hesaplanan her hammaddeden elde edilebilecek biyoetanolün toplam arzdaki payının değişimi lineer olmamıştır. Türkiye'de biyoetanol üretimi ağırlıklı olarak şeker pancarı ve sonrasında mısırdan gerçekleştiriliyor olmasına karşın, biyoetanol arz grafikleri incelendiğinde buğdayın ve arpanın en büyük paylara sahip olabileceği tespit edilmiştir. Buğday için öngörülen biyoetanol arzındaki payının %70'lere kadar çıktığı tespit edilmiştir. Her iki durum için de elde edilen tüm model sonuçlarına göre gıda, tohumluk ve yem sektörlerindeki kullanımını etkilemeden, Türkiye'de üretimi yüksek seviyelerde olan bu iki hammaddenin de biyoetanol talebini karşılamada önemli bir paya sahip olacak olması ülkemiz açısından önemli bir avantajdır.

Çalışmanın son bölümünde öngörü yöntemleriyle belirlenen gelecekteki potansiyeli göz önüne alınarak biyoetanolün farklı harmanlama oranları ile (%1, %2, %3, %5, %10) benzine katkılandığında benzin tüketimine bağlı CO_2 emisyonu değerleri hesaplanmıştır. Bu emisyon değerlerinin hesaplanması için üç farklı yaklaşım dikkate alınarak yakıt başına (L) yandığında oluşabilecek CO_2 emisyonu değeri hesaplanmıştır. Artan biyoetanol kullanımı ve Türkiye'nin gelecekte de önemli bir biyoetanol üreticisi olacağının öngörüldüğü bu çalışmada çevreci bir yakıt olan biyoetanolün kullanımının motor yakıtı kaynaklı emisyon değerlerinde düşüş sağlayacağı öngörülmektedir. Emisyon hesaplamaları çevresel değerlendirme açısından; çalışmanın da amacı olan biyoetanol öngörüsü doğrultusunda, enerji kaynak üretimi ve düşük karbon ekonomisi perspektifinden ülkemiz için sürdürülebilir ve çevre dostu bir yakıt olduğunu göstermektedir. Öngörülerin tutarlılığı ve öngörülen arz potansiyelinin biyoetanol ihtiyacını karşılayabildiğinin ortaya konması biyoetanol üretiminin Türkiye açısından sürdürülebilir olduğunu göstermektedir.

1. INTRODUCTION

Energy, which is necessary for economical and social development, improves the conditions of life in all countries. Energy is used in different forms to meet the demand coming from various areas. In today and future; the relation and correlation among economic activities, sustainable production policies and development of countries have a significant role to obtain energy supply. All over the world, most prefered energy sources for this energy supply could be classified as different types considering material state, renewability, availability, storage and conversion types. Energy sources are classified as renewable energy resources (geothermal energy, stream energy, solar, wind, hydro energy, biomass, tidal energy and wave energy) and nonrenewable energy sources (oil, coal and natural gas).

Globally, the most commonly preferred energy resource is fossil based sources. Fossil resources, which are defined as nonrenewable energy sources, are limited in resource availability. Due to population growth and industrial improvements in the world, energy demand has globally increased, fossil resource capacities declined and their prices have been increased (IEA, 2006). It is expected that total energy consumption will increase to 629 and 674 quadrillion Btu by the year 2020 and 2025, respectively (EIA, 2016). As a result, alternative energy sources have been regarded as attractive to meet the demand. Thus, there is also a need for an investigation on alternative energy sources (IEA, 2006). Hence, it is more focused on renewable energy sources and alternative fuels, which could reduce climate change effects and minimize the dependency on fossil based sources (Balat, 2011; Fargione et al, 2008; Mizsey and Racz, 2010). Today, renewables are also accepted as tools to satisfy many other critical needs such as advancing the energy security, decreasing the environmental effects, advancing and supporting educational chances, creating job opportunities, lowering poverty (REN,2014). The International Energy Agency (IEA) and Organisation for Economic Co-operation and Development (OECD) are actively supporting the transition to Green Growth Strategy to obtain improving renewable energy technologies. Green growth is a comparatively new concept targeting on awareness for sustainable development via efficient use of environmental sources without decreasing economic growth (Bouzaher et al, 2015).

Biobased energy technologies, one of the renewable energy technologies, have being become an important energy resources (IEA, 2013; OECD, 2012). Biofuels and other industrial output generated from agricultural based biomass have increasingly been the focus of the scientific researches. These reasearches are various investigation perspectives such as process design and technics, environmental effects, system characteristics and the amount of biomass capacity have been investigated (Altmann et al, 2015). Biomass based energy technologies include energy in biomass and convert it appropriate in advantageous different types (Isler and Karaosmanoglu, 2010). Ethanol produced by using biomass, a major type of biomass based energy, has the significant capacity being a sustainable engine fuel. Besides, a fuel oxygenate which could substitute gasoline (Fischer et al, 2010; Kim and Dale, 2004). The leading engine biofuel is one of the key actors of carbon management in the growth process of countries, with the economical impact that is created from the source until expiration (IEA, 2013).

Fuel ethanol production has been carried out commercially in several countries for more than two decades as an alternative engine fuel. Commonly commercialized biofuels are first-generation biofuels (IEA, 2008; Viikari et al, 2012) whose feedstocks are also basic food crops (Serra and Zilberman, 2013; An et al., 2011; Hassouneh et al., 2012). The importance of starches and sugars (e.g. sugar beet/cane, corn and cereal grains) will be continuous although non-food sources use increased in production of fuel alcohol. These sugar crops have a high yield of sugar per acre, low conversion costs and seasonal feasibility (Naik et al, 2010). Bioethanol production increased with a huge rate contrast to biodiesel production year by year. Many countries, mainly in US and EU, targets and legal regulations have been put to increase production and utilization of engine biofuel production year by year (Junginger et al, 2011).

Modelling and forecasting studies with computer programme applications in energy forecasting constitute a very active research and developing area to explain economics of biofuels as investigated in today's studies for biofuels. All forecasting studies containing use of time series are generally described as a time-oriented of observations for related variable. Statistical models are oftenly preferred for analysis and forecasting of time series data. Generally, a model is determined on the basis of a selection criteria to use forecasting future values (Zou and Yang, 2004). Basic models; AR (Yule, 1927) and ARMA (Box et al., 2008; Wold, 1954) are used to forecast on linear systems while ARX (Chen and Tsay, 1993), ARMAX (Box et al., 2008) and ANN (Sharda, 1994; Brown, 1962; Allende et al, 2002) predicting non-linear systems. These models are methodologically straightforward approaches to predict about production, feedstocks and economics of biofuels. AR model or ARMAX derivatives could be developed as alternatives, although literature has widely focused on partial equilibrium (PE) and general equilibrium (GE) models to examine the economic behaviours and impacts of biofuels. Also, Muhammad et al (1992) has shown that forecasts have traditionally used structural econometric models.

Several studies report current and future biofuels production capacities and their feedstocks to estimate at regional and national scales. In literature; forecasting practices by using agricultural data (could be used as biomass feedstock) are generally carried out by Organisation for Economic Co-Operation Development (OECD), International Energy Agency (IEA), US Department of Agriculture (USDA), Food and Agriculture Organization of the United Nations (FAO) and International Grain Council (IGC). There are several approaches on agricultural based forecasting mainly on food supply and energy production planning (Lambert and Cho, 2008), such as trend analysis, moving average, time series, neural networks, grey forecasting and exponential smoothing (Jutras et al, 2009; Agrawal, 2003; Allen, 1994; Ehret et al, 2008; Yang et al, 2009; Kirshen and Flitcroft, 2000; Smith et al, 2009; Gupta, 2003; Uno et al, 2005; Zhao et al, 2009; Higgins et al, 2010). While forecasts could be useful in the perspectives of the policy makers to predict the future demands of grain, import or export and take available measures in terms of resource management (Muhammad et al. 1992), forecasting indicators also direct legal authorities to make critical decision taking into consideration on possible supply and demand gap on production to preserve price balances for the market (Adil et al. 2012). Each method has its own advantages and disadvantages, which could guide to several different results in precision of forecasting. Reddersen et al. (2014), emphasized that significant execution policies or approaches need economical estimations in the basis of appropriate forecasting of biomass type products.

Therefore, it is expected that biomass forecastings on the larger commercial scale be more accurate. Besides, Mansouri et al. (2013), implied that some dynamic nonlinear crop model approaches as Environmental Policy Integrated Climate (EPIC) (Williams et al, 1989)) World Food Studies (WOFOST) (van Diepen et al, 1989), DAISY (Hansen et al, 1990), Simulateur multidisciplinaire pour les Cultures Standards (STICS) (Brisson et al, 1998) and System Approach to Land Use Sustainability (SALUS) (Basso and Ritchie, 2005) have been studied to forecast agricultural output. Crop models have been used to investigate the climate changes effects for the agricultural production (Mansouri et al, 2013). In the last decades, several agricultural economists have started to combine various methods for methods. The annual agricultural production data related to the climate change effects, domestic economical tendencies (Ou, 2012) and energy trends have resulted in increased volatility. Therefore, it is seen to be important that forecasting is based on the agricultural data characteristics and advantage of the selected model. As mentioned in Ilyas and Mirza's (1990) study, when the prediction is accurate, the selected model could be appropriate to aid in resource management. Addition to agricultural feedstock forecasting studies, forecasting approaches of bioethanol production and other subjects have been performed by using various modelling and forecasting studies. The results of all types of forecasting and modelling studies give a direction to energy economics and production, agricultural policies, food security, environment strategies of countries in both national and global scale.

1.1 Purpose of Thesis

Turkey has been a significant producer and exporter for agricultural based products in global markets and has been determined to be the 7th-largest agricultural producer globally by year of 2011 (OECD, 2011). Agricultural production, particularly crop production as wheat, barley, sugar beet (OECD, 2011) and corn (International Grain Council Statistics, 2014) has grown rapidly as the population increases. This increase is seen as a crucial biomass potential to produce first generation bioethanol. It is seen that the estimation of agricultural outputs is significant for biofuel production and resource management. In this thesis, by appraising future conditions and agriculture potential of bioethanol feedstocks, a forecasting study is to be made the production capacities of feedstocks and to determine the bioethanol supply considering these forecasts in Turkey. In the last part of the study, environmental assessment based on CO_2 emissions are calculated showing decreases due to bioethanol blends with the different ratios.

This study is based on the two dimensions; bioethanol feedstocks and bioethanol production forecasting, this study has been intended to be a resource and roadmap for future studies on bioethanol production. In this regard, it is estimated that how much bioethanol (L) could be produced per forecasted bioethanol feedstock production data (ton). The obtained results were seen as economical inputs that effect bioethanol economy and also, these results have critical role in providing direction for both agriculture and bioethanol policies for energy in Turkey. It has been aimed to point out that the impact of biofuel policy on the interdependency between the energy, biomass energy technologies and agricultural markets by estimating feedstock supply of bioethanol production with linear and nonlinear models. Determining an appropriate, technical and functional feedstock forecasting method could ease the government to organize agricultural, energy and economical improvement policies and strategies. Therefore, this study aimed to use basic forecasting models to predict feedstock supply for bioethanol production. It is determined that the results obtained by selected models in optimal model orders and prediction horizons could provide feedstock to meet a significant part of Turkey's legal regulations for gasoline-bioethanol blending requirements. The forecasting results from out-of-sample every data can show us how well our proposed forecasting model according to goodness of fit criterias. Concerning the energy economics and sustainable biofuel production, the goal of the study to describe the most appropriate forecasting approaches for presenting the potential supply of selected feedstocks and bioethanol production from these feedstocks in Turkey between 2014-2033. Monitoring the environmental, economic, and other implications of bioethanol might be possible determining the amount of economic inputs such as both bioethanol and its feedstock supply.

1.2 Literature Review

Reliable and available feedstock forecasting is necessary for resource management and biofuel production planning. Forecasting model types and their predictions are also significant to provide sustainable energy, agriculture and environment strategies and policies. Forecasting and modelling studies regarding bioethanol, biofuels, their feedstocks and related issues are given considering model types, agricultural production, economics and environmental policies. In this part; both forecasting and agricultural model or other crop model studies are mentioned since this thesis is a hybrid study which consists of forecasting methods and forecasting of agricultural based bioethanol feedstocks. Although various studies and different approaches are given in other parts of thesis, selected studies are presented to give a perspective about forecasting and agricultural models.

In forecasting studies, generally time series are prefered. The history of studies about time series had been started on the 19th century and time series have been characterized as an idea of deterministic approach in general (De Gooijer and Hyndman, 2006). Time series considerations began in 1807, after the French mathematician Fourier identified that any series might be approximated as the sum of sine and cosine terms. This fact was evaluated and used by Schuster (1906) who used Fourier expansion to determine the hidden periodicity lengths and who mainly prefered periodogram analysis for his own study. The new period on time series had began in 1927 by Yule (1927). It was the most important benefit made by Yule (1927) which lead to include stochasticity term for time series by assuming that each time series can be considered as the realisation of a stochastic process. Depending on that basic idea, a number of time series approaches have been developed. Researchers named as Slutsky, Walker, Yaglom, and Yule had firstly generated the autoregressive (AR) and moving average (MA) model approach concepts (De Gooijer and Hyndmann, 2006). Following the studies of Yule, Wold (1954) developed a comprehensive theory of Autoregressive/Moving Averages (ARMA). Around 1940, when Wiener and Kolmogoroff (1941) solved the determination problem based on continuous and discrete filters properly (Makridakis, 1976). In the process beginning with improving the radar systems, the most common‟Forecasting Problem˝, that resulted when second world war began, solved by N. Wiener (Wiener, 1944) in US. A. N. Kolmogoroff (Kolmogoroff, 1944) in Russia not being aware of each other during the war. Wiener, showed the mathematical fundamentals of smoothing and mathematical theory that is so significant for especially communication technics. Wold's decomposition theorem led to formulation and solution of the linear forecasting problem of Kolmogoroff (1941) (Bir, 1975). In the scientific world, many extensions and generalizations followed Wiener's basic work and also the extended theories, that involve those studies. Zadeh and Ragazzini (1950) solved the finite-memory case. Concurrently and independently, they also gave a simplified method (Zadeh and Ragazzini, 1950) of solution (Bode and Shannon, 1950). The first generalizations in prediction theory started with the limited memory concept when the article Zadeh and Ragazzini article in 1950. Apart from this, H. W. Bode and C. E. Shannon have been very helpful in terms of understanding and applying the fundamentals of this theory, hence, simplified it for further comprehension (Bode and Shannon, 1950). As an alternative, Booton (1952) discussed the nonstationary Wiener-Hopf equation. Results of these studies are taken into standard texts (Laning and Battin, 1956; Davenport and Root, 1958; Wiener, 1948; Kalman, 1960). At the beginning of the 60's, Kalman (1960) and Kalman and Bucy (1961) have improved Wiener and Kolmogoroff's determination methods for non-stationary series containing systems on the time zone (Makridakis, 1976). Kalman and Bucy used time-domain methods, and obtained major improvements and generalizations of the conventional Wiener theory. Their methods are applied without modification to multivariate problems. When the classical Wiener theory was completely developed and the required mathematical methods were matured, Kalman (1960) presented a new approach to the standard filtering and prediction problem (Kalman and Bucy, 1961). A huge amount of literature seemed to grow for the time series studies, interesting for determination of parameter, identification, checking or accuracy of model, and forecasting (De Gooijer and Hyndmann, 2006).

Forecasting is a developing research subject in various scientific and technical areas for different main topics in today and future. Forecasting studies consist of the utilization of time series data. Different methods generally are developed and used in time series forecasting. The most common and well known statistical approaches preferred on time series forecasting are Box-Jenkins models. Since the late 1959, artificial neural networks (ANN) have been carried out for time series forecasting (Hamzacebi et al, 2009). Through the perspective of bioethanol production; forecasting is significant for policy makers, farm managers and government for better decisions on bioethanol production, its feedstocks and environmental effects. Therefore, overview of forecasting bioethanol production and utilization processes using different crop models, simulation models or other methods is a need. To help the forecasting studies; various bioethanol and biobased energy studies, that could be a support helped for forecasting, were given in this section.

As a result of the sharp decrease on reserves of crude oil and increase in Greenhouse Gas (GHG) emissions in transportation, bioethanol usage as fuel or blend has been promoted in many countries. Taking into consideration the environmental effects of both producing energy feedstocks and bioethanol production in large scale (Carvalho Lopes and Steidle Neto, 2011). They emphasized that production should be taken with care for the effects on agricultural factors (products, biodiversity and land-scape affects, substructure and others), soil quality and improvement (such as erosion, nutrient content and others), emissions (especially affect air) and food security. They reviewed models applied for production of biodiesel, drawing attention to the generally preferred practices and improvements for special products and targets. It is pointed that crop simulation models have been generally helpful for agricultural production to offer avant-garde product management systems, for the climate change effects for products, to understand the risks related to several management strategies and to take decisions. Carvalho Lopes and Steidle Neto (2011) summarized crop simulation models as CROPGRO, Crop Environment Resource Synthesis (CERES), Agricultural Production Systems sIMulator (APSIM), OILCROP-SUN, Cotton Models, SUCROS, Environmental Policy Integrated Climate (EPIC) and also statistical and empirical models. CROPGRO model, is extensively used to determine crop productibility, which is crop growth model capable of imitating basic biological processes to various species in order to forecast growing crop in various conditions (Tsuji et al, 1998). CERES model (Crop Environment Resource Synthesis) has been successfully designed, extensively preferred and well accepted for wheat, maize, barley, sorghum, millet, rice. That model has been described as a comprehensive modelling of plant processes for the root-based-soil system (Lenz-Wiedemann et al, 2010; Singh et al, 2008). Another model APSIM involves a module system to simulate growth, improvement and productivity of several outputs and relation between the products and soil (Keating et al, 2003). OILCROP-SUN could be defined as a version of CERES. It can be a successful approach to compare the scenarios of agricultural management such as water use policies, observing seasonal conditions and taking into account changes in cost (Rinaldi et al, 2003). EPIC is a kind of the major crop approaches which have been oftenly used to integrate analysis and conformate investigations in a regional and global basis. The simulation has been done to estimate crop amount, water use for crop harvesting, and the connections between the two. Carvalho Lopes and Steidle Neto (2011) also gave information on simulation models (statistical models, empirical models, ANN, policy analysis) improved and preferred on specifical uses. They emphasized that statistical and empirical models have been improved for defining the factors which affect crop changes, forecasting future crop models with sensitivity of upon changes in leading effects as located in different scenarios. It is pointed out that multiple linear regression model approaches have been oftenl used to achieve that objective. Almost all methods have been used to include deterministic or stochastic, mechanistic or functional models. The use of different methods allows simulation of several agricultural applications and environmental properties with minimal prices or time based demands. That is the major advantage to make critical investment plans and promote the extension in biofuel based production.

Resop et al (2012) studied the crop model as in Carvalho Lopes and Steidle Neto, (2011). They designed geospatial crop model interface to answer the variability in input data for multiple categories including regional or country based field. That method has showed proof for whatever kind of differences for product amount in the country scale. The interface is planned to be flexible and simple to perform the practices as assessing crop yield and answer in different conditions. Crop based model approaches forecast yield and resource demands as well as to assess varied climate or management policies.

Thelen et al (2012) improved a spreadsheet based model approach whereby students compose financial budgets, carbon budgets and energy budgets on different biobased energy cropping to assess the economical and environmental sustainability by biobased energy cropping. It has been stated that this model assists students to estimate the approximate bioenergy feedstocks value and both the carbon and energy footprint related to the different cropping systems.

Reddersen et al (2014) carried out a multi-sensor approach to forecast biomass of widely managed grassland in the perspective biomass (or feedstock) prediction and compared the model accuracies. Because it is pointed out that effective application practices demand economical estimations in the basis of available judgement of forecasted biomass outputs (Searle and Malins, 2014). They compared the performances and capabilities belong to all of the combinations of three non-destructive sensor approaches to estimate biomass in widely cut grassland in a complex vegetation structure. It was shown that the combination of multiple sensors could sharply increase the forecasting trueness for biomass. The combination of USH with Leaf Area Index (LAI) could enhance the forecasting trueness and decrease the forecasting error by the ratio of 30%.

Considering biomass production variability to design more sustainable systems; Lurette et al (2013) pointed out that it is significant to assess this property to compare the relevancy of different parts of the system. For this, it has been needed to investigate the characteristics or orientations of several systems, containing new systems, for various climatic conditions. In Lurette et al (2013)'s study, the simulator that is easy or basic enough for estimating the improved dairy system's sensibility and encouraging the conflicts about the results. The model has been developed with Scilab software for numerical computation. From the simulation on the biomass production, the forage stocks have been estimated yearly.

Uno et al (2005) brought a new view to forecast corn production data from Compact Airbone Spectrographic Imager data by using ANN. ANN can be a significant tool to make forecasting in biofuel production process when investigated the literature. They used ANN to promote and improve seasonal yield mapping and making forecast. Statistical and ANN approaches with together various vegetation indices have been preferred to develop product forecasting models. Increasing forecasting performance has been provided by an ANN model approach compared to the three conventional empirical methods which are generated based on normalized difference vegetation index, simple ratio, or photochemical reflectance index. There is a sharp difference has not been determined between ANN approach and multiple linear regression model approaches.

Põldaru and Roots's (2014) prefered a basic nonlinear stochastic mathematical model approach to programme the silage maize harvest for farms in Estonian. Various model indications have been used. A computer application has been improved the relationship and interaction between investigators and silage maize farmers in Estonia. The model performance has been determined stating the harvesting date, the production capacity of harvesting machines and the various density functions belong to time. Their results point that the harvest date is a necessary basic determinant for the maize silage total production capacity. It could be thought that this kind of approaches can help the forecasting studies of feedstock production, biofuel production processes and their environmental effects. Increase on discussing and examining of the harvesting process modelling for various areas by several authors bring in a different view to mainly feedstock supply and then biofuel production processes. In this context, the mixed integer linear programming model (Ferrer et al, 2008), large-scale integer programming model (Higgins et al, 1998; Higgins et al, 2004; Higgins and Muchow, 2003) and general agricultural planning models (Tan and Ēömden, 2012; Ahumada et al, 2012; Yu and Leung, 2009; Martin et al, 2012; Ahumada and Villalobos, 2009) were developed for optimization the harvest date, rendement and net income. The results and performances of these models could be evaluated because bioethanol or other biofuels are sourced from agricultural crops and so their harvesting.

Considering these aims from the perspective of agricultural production and resource management, Ou (2012)'s study attracts attention for this thesis study and it has been remarked that agriculture has being the basis of the national economy. Therefore, it is defended that an available approach to predict agricultural or crop yield is so significant in terms of improving policies. In first generation bioethanol production; bioenergy policy makers has given the importance to results and effects of agricultural production forecasts. Agricultural products could be defined as economical parameters or products of agricultural economics. Thus, as emphasized in Ou (2012)'s study, agricultural economics predictions have a significant share to give direction about agricultural sector projection, policy making in agriculture and safetly operated national economy. These kinds of predictions ease countries for making better decisions. Moreover, a logical prediction model could decrease carelessness and develop scientific decision making. For this reason, raising the trueness of forecasts on agricultural output has been a significant matter. With Ou (2012), Lambert and Cho (2008) also pointed out that there are several methods examined and used for agricultural forecasting in literature. Ou (2012) also emphasized that each of those models or approaches could have opportunities, that could display several changes in the accuracy of forecasting. In Ou's study, the grey forecasting model (GM(1,1)) has been performed to predict agricultural output depend on the characteristic of agricultural product data and grey model advantages.

The agricultural product in Taiwan had been selected as the investigation field to prove the practices of different grey prediction approaches. In this study, GM(1,1) model approach has been combined with two types of developed methods to estimate the best parameters. For that aim; GAIGM(1,1) model, which has been performed to predict the Taiwan's agriculture products, was constituted. The MAPE and RMSPE were prefered to estimate the forecasting model performances. They examined the the prediction performances and accuracy of three models.

Agrawal (2003) was examined on different forecasting techniques in crops. It has been mentioned that prediction of crop yields are necessary for different policy makings correlation to storage, costing, marketing, export, import and others. In Agrawal's (2003) study; forecasting studies have been grouped as yield forecast using weather parameters, yield forecast based on plant characters, forecast using spectral data, forecast using farmers appraisal, and an integrated approach. For yield forecast using weather parameters; Fisher (1924) technique, that has required lower numbers of parameters to be determined while handling of weather changes for harvest time, and Hendricks and Scholl's (1943) technique which has been the modified Fisher's technique has been given. Also, Baier (1977)'s study has been referred as significant contribution and crop-weather models classified into three basic types according to this study. These were crop growth simulation model approaches, crop-weather analysis models, empirical statistical models. The most widely preferred models for crop forecastinghave been empirical statistical models. Yield forecast based on plant characters contains two approaches as between year model (Linear regression models and the probability model) and within year model.

Ramasubramanian (2012) studied forecasting techniques in agriculture and divided into different classes. Forecasting model approaches for agriculture contain prediction of crops production capacity and field have been represented in their study. As in pointed out above, it has been emphasized that crop yield forecasts are so useful in formulation of policies regarding stocks, distribution and supply of agricultural production to different areas in the country. According to Ramasubramanian (2012), statistical techniques employed should be able to provide objective crop forecasts with reasonable precisions. These statistical techniques have been examined to discuss their applications in forecasting agricultural systems and classified into three classes as regression models (Multiple Linear Models-(MLR), weather indices based MLR based, logistic regression models), time series models (exponential smoothing models, auto-regressive integrated moving average models-(ARIMA)), probabilistic models (Markov chain models).

Allen (1994) studied and reviewed economic forecasting of agricultural forecasting. In Allen's study, it has been emphasized that agricultural production and costs prediction are aimed to be benefical for people in agriculture, legal authorities and agricultural based industries. Government needs internal predictions to carry out strategies that give scientific and economical support to agribased sectors. Allen's study has monitored the importance of methodological contributions and changes. Allen represented that economical based prediction for agriculture shows several general properties with business based prediction and macroeconomic based prediction. The main target of this review has been to give an information belongs to basic methods prefered by agricultural predictors, with assessing the opportunities from each of approaches. Showing the historical development period of agricultural forecasting, this study has set light to understand better agricultural forecasting and economics period in today. Subsequently, multiequation, multisectoral econometric based approaches have been developed. Although trend extrapolation models have been commonly preferred for commodity researches, modern time series methods's agricultural practices couldn't emerged up to the beginning of 1970s. More advanced researches have been developed by agricultural economists, those researches changing resulting from different types of constitution predictions to vector autoregression (VAR) and state space approaches. Producers and users of agricultural forecasts have been defined and given information about them. Additionally; short term production forecasting has been investigated; major causal model approach was described, econometric models and programming approaches are investigated as sectoral models, aggregate and large scale econometric models have been examined, time series models have been also given in this review in details.

In the leading countries on biofuels, four basic approaches have been used to analyze studies which done for biofuel policy application targets and fuel mixture of mainly biofuel effects in the global, national and regional levels. These are defined as cost approach, partial equilibrium models (they include agricultural sector models), computable equilibrium models, and other time series models and full econometric models (Rajagopol and Zilberman, 2007). In many of the studies about partial and general equilibrium model approaches have been methodologically used to examine the economical effects of biofuels (Beckman et al, 2011). Structural model approaches have had significant interest for examining the economical effects of biofuels due to studies in related subject (Kretschmer and Peterson, 2010; Rajagopal and Zilberman, 2007). There have been a number of studies on modelling for evaluating whole supply chains for biobased products (Stephen et al, 2010; Kim et al, 2011), biorefinery concepts (Fernando et al, 2006; Clark, 2007; Francesco, 2010), relations between related crops and biofuels in the perspective of food crisis (Kristoufek et al, 2012), examination on the impact of biofuel growth on agriculture and energy sectors (especially fossil fuels) (Zhang et al, 2009), biofuel-related price transmission (Serra and Zilberman, 2013), biofuel production costs for different biofuels (Festel et al, 2014) or the biofuel existing production capacities for each of countries (Martinsen et al, 2010). The results of whole basic approaches could be used to help analysing or planning on the forecasting process of biofuels as long as these results could be reviewed and commented in a good way. In the same way, modelling studies and their results are critical point to represent the forecasting and future position of each country which produces biofuel. Therefore; selected modelling studies have been given here as mentioned above.

Partial equilibrium models investigate what the effects or reaction of agricultural sector will be to applied policies at regional or global level. The answers of this are directly related with the forecasting process. In both two of contexts; what the impacts of blend mandates, pollution taxes and trade regulations will be at sector are determined. The interaction between food and fuel markets has been examined due to the supply and demand of sector (Rajagopol ve Zilberman, 2007). Food and Agricultural Policy Institute (FAPRI) (2005), has determined the results of additional bioethanol production capacity for US agricultural market by using partial equilibrium model that is multi-product and multi-country. Obtained results helped to comment about selected crop export, input consumption and stocks to forecast bioethanol position and related sectors. Von Ledebur et al (2008) used AGMEMOD (Agriculture Member States Modelling) (dynamic, multi-product partial equilibrium model) model to be able to forecast the crops and rape production in Germany and France when blend targets applied. In Binfield et al (2008) study, the impacts of the increasing biofuel demand due to biofuel directives on EU agricultural market was determined with FAPRI-GOLD partial equilibrium model. Due to this model; the equations, which predict gasoline cost, diesel cost, total energy consumption on transportation sector, the share of diesel in total fuel consumption, could be formed. At the end of this modelling, bioethanol and biodiesel production and consumption volumes were forecasted. Also, the costs, export and import positions of feedstocks for these fuels were predicted. Another study, which was carried out on the effects of bioethanol production in a multidirectional way such as harvest land, product costs, livestock sector, food costs, was analysed with FAPRI partial equilibrium model by Tokgöz et al (2008). This model, that is multi-commaditied and multi-country, was used to determine the effects under high petroleum costs and blend mandates scenarios.

Treguer and Souri (2006), studied on OSCAR partial equilibrium model to monitor the impacts of EU targets of biofuels on agricultural economics in France. This model might help for analysis in the perspective of the forecasting but mainly it has results for agricultural job opportunities and agricultural revenue.

Elobeid and Tokgöz (2006), simulated to see the impacts of trade tariffs and federal taxes advantages on trade, production and consumption in U.S. establishing multi-commoditied international model for bioethanol. When the model and its results investigated, bioethanol costs could increase such as bioethanol demand for after removing the trade barriers and absolutely bioethanol import would be rised. It has been forecasted that more sugar cane will be used to produce bioethanol and the cost of this feedstock will increase directly. Therefore, it could be easily resulted that the demand of biorefineries will decrease and then import and bioethanol costs will decrease. The net comment on the model effect, the import and bioethanol costs could be rise. The study on this model has presented advantages on examining and commenting the feedstock potential at the end of removing the trade barriers. Elobeid et al (2013) also expanded their researches with other approaches. They represented a model approach correlated with agricultural and energy markets that could be improved by the way of the extension in production of biofuel. They used two models and these are CARD and Market Allocation (MARKAL). Markal model was a mixed-integer linear programming model that has been given primary energy resources. CARD market model has already been accepted as a member of a wide modeling approach for the global agricultural economics consisting of USA and global multimarket, non-spatial simulation model and partial-equilibrium approaches. That integrated model approach between energy and agricultural areas has been expected to be absolutely helpful in examining the policies or studies regarding the role of biobased feedstocks sourced from agricultural market. Tokgoz et al (2008), also projected US ethanol production and its effect on harvested area, product costs, production in livestock and commerce in other study. The conclusions were made by a multicommodity, multicountry and partial equilibrium model.

Modelling study on biofuel expansion was examined by Peters et al (2009). Their study show that the effect of decreasing energy costs for the production and consumption of biofuels and also their inferences to agricultural based commodity areas. This examination has been performed by using Partial Equilibrium Agricultural Trade Simulation (PEATSim) that is a dynamic partial equilibrium, globally trade method for the agriculture area to examine the interactivity among biofuel, product and livestock areas. They implied that capability of countries for achieving their energy targets could be effected from the changes in petroleum prices. According to their analysis; it has been predicted that 50% decrease for fossil based prices will result a sharp decrease in global biofuel utilization, and so it is expected that there will be decrease for feedstock and biofuel cost.

Zhang et al (2009) examined on the effect of biofuel production expansion on agriculture. Their study has prepared as a detail investigation study to show the effects of biofuels in the perspectives of agricultural commodities, and that contained on either general-equilibrium or partial-equilibrium model approaches. Zhang et al (2009) reviewed the results of these approaches for long and medium-term projections. It could be said that the results of this study are suitable for the forecasting study of agricultural feedstocks.

Martinez-Gonzalez et al (2007) show that evaluated the impact of distortions on U.S. imports of ethanol from Brazil. For this aim; they prefer two-stage least squares to estimate a partial equilibrium trade model based on annual data from 1975 to 2006. This study can help to give a lead for predicting on especially import of ethanol and effects of this situation. The main result of this study is given as removing interventions on external trade in the US ethanol market obtains gains the US and Brazil.

Zhang et al (2013) wrote a review for investigating on Partial Equilibrium Model and General Equilibrium Model to compromise the systematical changes on the determined effects of biofuel production extension on the forward prices and production of three significant feedstock crops as corn, sugar cane and oilseeds. This study has quantified the impacts of biofuels on agricultural commodities and modeling approaches. The changes in the PE models were principally depend on variations on the preparations of strategies, the situation of biofuel commerce. These variations have been likely to be driven by model assumptions on agricultural land supply, the inclusion of the byproducts, and assumptions on crude oil prices and the elasticity of substitution between petroleum and biofuels. These changes were likely influenced by method assumptions about the supply of agricultural land, the addition of by-products and assumptions for petroleum prices and the flexibility of replacement between oil and biofuels. Some assessments could be taken to forecast the impacts of biofuel production on feedstocks.

Hoefnagels et al (2013) presented a examining of the economical effects on value added, employment proportions and the commerce balance as well as demanded biomass and explained primary energy and greenhouse gases correlated to huge amount of biomass deployment on a country level (the Netherlands) for various future projections to 2030. They have used the macro based economic computable general equilibrium (CGE) model, Landbouw Economisch Instituut Trade Analysis Project (LEITAP), that is ability of determining all impacts of a bioeconomy related to direct on technological circumstances.

Farm sector and biofuel productions have direct correlation. EU, one of the main biofuel producers, should support EU agricultural sector for being a provider of bio-fuel feedstocks. Effects of the European bio-fuel strategy for the agricultural field aimed to suggest a quantitative assessment of existing profit by using a farm-based computable general equilibrium model approach.

Furthermore, Birur et al (2008) analyzed the inferences of biofuel production in a CGE approach, by using an adapted version of the Global Trade Analysis Project (An Energy-Environmental Version (GTAP-E)). They also included Agro-Ecological Zones (AEZs) in each one of the land utilising fields. Depending on these model approaches, GTAP-E model with biofuels and AEZs, helpful structure to show the extensive significance of biofuels for globally variations in crop production, usage, crop prices, factor utilization, commerce, land utilization variation and others. Utilizing this recorded reenactment, they align and evaluate the key flexibilities of vitality substitution amongst biofuels and oil based commodities in every district. For the three noteworthy biofuel delivering areas (US, EU and Brazil), GTAP-E anticipated the offer of feedstock in biofuels and related segment utilizing the verifiable confirmation.

Banse et al (2008a), forecasted that there will be significant globally results of EU blend targets in EU or outside of EU by using the calculable multi-regional general equilibrium model. One of the critical result of their study is that biofuel demand will reverse the long-term decreasing in agricultural commodity prices. In this study, they prefered GTAP (Version 6) multi-sector, multi-regional computable general equilibrium model and this model gives a permission to interactions among countries. Being multi-country is a good alternative to establish the correlation between energy, transportation and agricultural markets. According to this model results, it was forecasted agricultural products prices will increase.

Dixon and Rimmer (2007), used the United States of America General Equilibrium (USAGE), is a CGE model, to determine the effects of biomass on the policy of decreasing oil dependence. USAGE is a general balance model to detail the energy sector more. Obtaining the energy data from the department of energy, the program was worked with inputs to determine the effects on output, employment, capital and industry investment, consumption, export and import. It could be said that the results of those model's details will help forecasting studies belong to biomass. Gohin (2008), also established CGE model to estimate the results of legal blend mandates on production capacity in EU and to determine whether or not the potential effects on livestock sector. Prices and productions of vegetable oil and its seeds will increase.

Gay et al (2008), used Global Legislators Organization for a Balanced Environment (GLOBE) (Global General Balance Model) to investigate the relations between EU 2010 and 2020 targets and EU's basic trade partners in the context of oilseeds and to search the production potentials in these partner countries. GTAP (Version 6 database) is used for trade analysis of policy scenarios. Banse et al (2008b), forecasted the strong effects of increasing biofuel demand will be in the levels of global and EU by using GTAP model. It is pointed out that biofuel policies will have addition in rising for food prices.

Other model studies correlated to forecasting or other analysis are also carried out for several aims with different programmes. Ubilava and Holt (2010) established that consideration of vitality costs in the model does not enhance corn value conjectures, considering and utilizing week after week midpoints of US fates costs for the period October 2006-June 2009 and non-straight time series model for corn.

Another essential examination was made by Vacha et al (2013) who investigated time and recurrence subordinate connections between's biofuels, agricultural items and non-renewable energy sources. The outcomes has predicted that the cost of creation factors lead the cost of biofuels, yet not the other way around.

Zhang et al (2010) utilize month to month value information for corn, rice, soybeans, sugar, wheat, ethanol, gas and oil from March 1989 through July 2008 to predict and estimate short and long-run effects of fuels on agrarian items for the US. This study could be a guide to monitor the situations of agricultural feedstocks in the perspective of forecasting.

Kristoufek et al (2012) explored the connections between the month to month costs of biodiesel, bioethanol and related fuels and agrarian products. Their examination's outcomes accentuated that in the short and medium term the cost of corn Granger-causes the cost of ethanol, however that there is no causality running the other way.

In Turkey, forecasting studies on energy have short-term background, however there hasn’t been different studies which investigate the relation between agriculture sector and biobased energy sector as economics in empirical base. Agricultural Economics and Policy Improvement Institute, Cagatay et al (2012) examined on biofuels and agricultural policy. In Turkey, although forecasting studies have been generally done for common energy demand and electricity consumption, forecasting studies on biobased energy technologies have been increased day by day. Melikoglu (2014) forecasted the demand for petro-based transportation fuels and biofuels by considering Vision 2023 goals and impending EU regulations. Gaussian, modified Gaussian, and Lorentzian semi-empirical models have been used to forecast gasoline demand in Turkey; exponential semi-empirical models have been preferred to forecast adjusted gasoline consumption in Turkey; linear, quadratic and exponential semi-empirical models have been used to forecast diesel demand in Turkey; linear, quadratic and exponential semi-empirical models have been used for predicting LPG demand in this study. According to this study, it has been clearly showed that gradual implementation of biofuels into the market would indeed decrease Turkey's dependence on petro-based fuels.

2. THEORETICAL STUDY

In this chapter, the theoretical framework is presented to explain the basics of bioethanol production and its environmental issues, the relation among agricultural economics, bioethanol and resource management, forecasting proces and its methods. For this purpose, theoretical researches about these subjects are elaborated following subjects, respectively:

- Biorefineries
- Bioethanol production basics
- Bioethanol targets, mandates and policies in the World and Turkey
- Environmental assessment
- Agricultural economics and resource management
- Forecasting process and methods

2.1 Biorefineries

In the 21st century the bioeconomy has been extended and it is forecasted that biobased items and biofuels will be brought into the center of life at an increasing share. Biorefineries, which are used to produce biofuels are similar to crude oil refineries except they use biomass as feedstock instead of crude oil. A significant research subject as a substantial part of a sustainable economy is biorefinery. Presently a adaptable outcome mixture that contains biochemicals, biomaterials, and biofuels, as well as the production of heat, cold, and electricity could be provided with various conversion processes for biorefineries (Isler and Karaosmanoglu, 2010). The target of a biorefinery is to improve the utilization of feedstocks and decrease wastes, in this way increasing advantages and productivity (WEF, 2010). A biorefinery utilizes different types of biomass, for instance, agricultural crops, wood, forest residues, algae, sea weeds and organic residues. Biorefinery process provides various advantages such as supplying of a subset of existing fuels and chemical building blocks, providing of novel chemical building blocks and of authentic materials with authentic attributes, the administration of some crucial problems or risks related to the deterioration of the petrochemical supply amount, providing of jobs in rural regions that suggest available logistics, decreasing the global-warming problems, and the utilization of wastes consist of agricultural and certain parts of both urban and industrial waste. Particularly, biorefineries could always manage cheap biomass is appropriate, and that changeability provides an opportunity about creating their own domestic energy sources to countries instead of petroleum based sources (Vertès, 2014).

A biorefinery process comprises basically of framework parts for the pre-treatment and biomass preparation, and additionally for the separation of biomass components named as primary refining and secondary refining (Biorefineries Roadmap, 2012). The primary refining step includes the conversion of biomass constituents into intermediates such as cellulose, starch, sugar, lignin etc. The pretreatment and conditioning of biomass is as well carried out in primary refining. Secondary refining involves the conversion and processing of these intermediates to many finished or semi-finished products (Borand, 2011; Committee on biobased industrial products, 2000). Considering the secondary refining type, biorefineries are classified as sugar biorefinery and starch biorefinery, vegetable oil biorefinery, algal lipid biorefinery, lignocellulosic biorefinery, biogas refinery. Biorefinery process is given in (Figure 2.1).

In biorefinery technology, existent production technologies are also applied to provide new and feasible solutions for the provision, conditioning and conversion of biomass. Generally, biomass characteristics have significant effects on these technologies.

Biorefineries provide high economic and environmental benefits for agriculture or chemical industry and apply hybrid technologies compared to both biorefineries and other concepts for biomass utilization. The combination of processes benefits the waste and water management and the utilization of energy and heat. This technology could reduce the costs, so that it could be an alternative and compete with petroleum-based products. Both oil refineries and biorefineries use the similar processes, however biorafineries could manufacture many other products that oil refineries could not, such as foods, feeds, and biochemicals. The other dissimilarities between oil refineries and biorefineries defined as raw materials type, the composition of raw materials, the refining steps and principles, and the production of food and feedstuffs. The main challenge is the seasonal supply of raw materials.

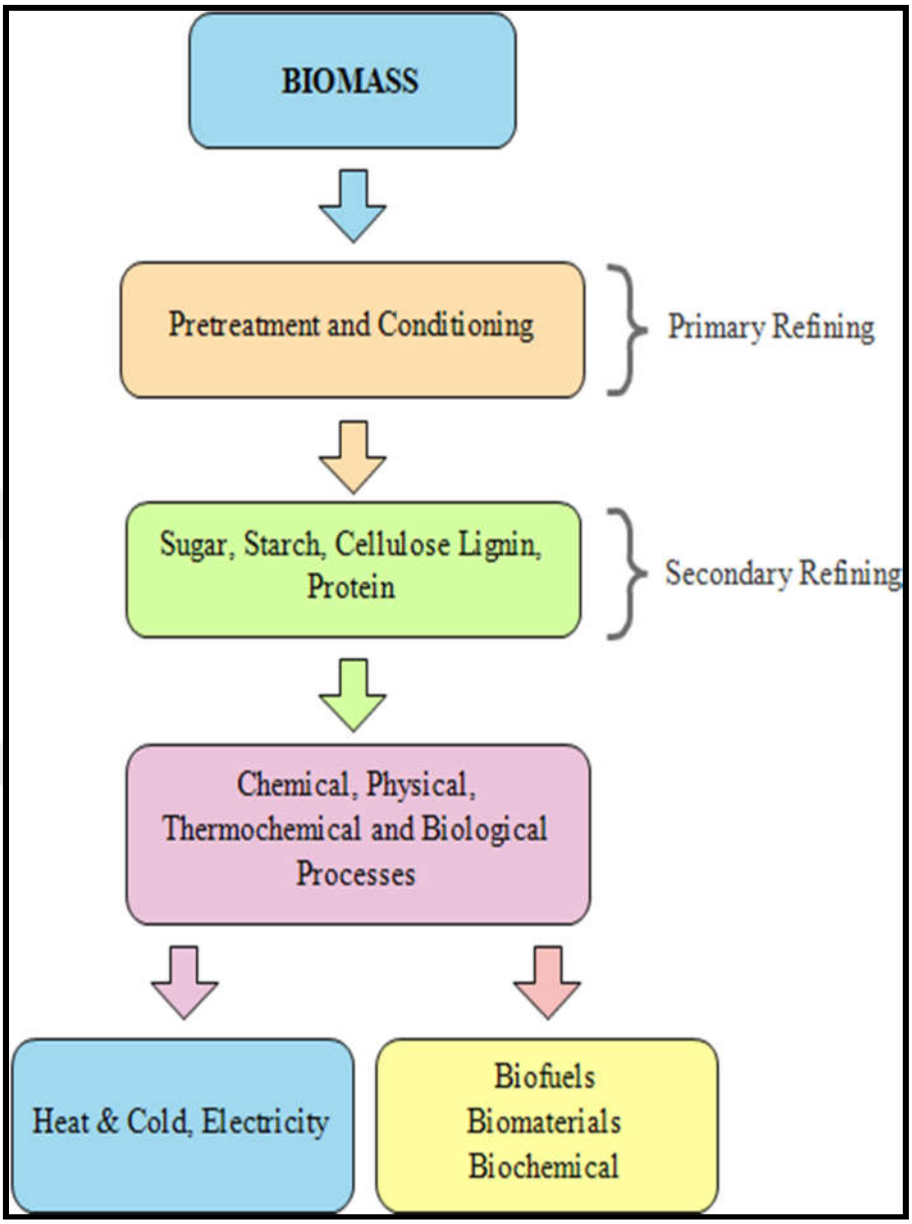

Figure 2.1 : Biorefinery Technology.

Advancement and high effectiveness are the keys to make biorafineries sustainable and feasible (Kamm and M. Kamm, 2004; Kamm et al, 2006). Optimization could be obtained by future advancement in key zones and the proficient utilization of chemical energy in biomass. These key points are defined as technology, exploitation, logistics, economics, sustainability, respectively. Improvements in conversion technologies will give a direction to more of the plant being used to produce a wider, more flexible range of products in addition to biofuels, thereby environmental and economic performance of the production processes. As a result of developments in biorefinery technology and increasing in efficiency of biorefinery process, economics and sustainability of biorefineries could be developed by the advancement of the asset. In the perspective of economics, a proficient biorefinery will guarantee decreasing in cost and a cost advantageous outcomes. The ideal biorefinery process should be good at using biomass that could supply the process energy demands as long as possible (WEF, 2010).

2.2 Biofuels

Bioenergy could be accepted as the biggest renewable energy sreource by 14% out of 18% renewables for energy supply and providing 10% of worldwide energy supply (WEC, 2016). Biofuel, which is an alternative to fossil fuels, has several economical and environmental advantages (Cherubini, 2010). Biofuel production and consumption in transportation have a notable increase and it has been forecasted to proceed in future. Besides, biofuel production and utilization offer employement opportunities mainly in rural areas. Especially, biofuel could contribute to the local economy of the countries and obtain sustainability (Vertès et al, 2010; Isler and Karaosmanoglu, 2010; Naik et al, 2010). Biofuels have considerably remarked as a critical solution for reducing reliance on fossil fuels and decreasing the high-levels GHG emissions for the last decades. In some of national contexts biofuels have been viewed as up and coming, could be successful in becoming a sustainable resource of fuel which could be domestic solution. Besides; biofuels could also provide various benefits on carbon emissions, socio-economic development, poverty alleviation- the rise in the level of prosperity (Gasparatos et al. 2015), reducing dependency on external (if sources are national), energy security, more easier-energy accessibility. As an advantage for the important share of the people in lowest-economy regions, biomass based energy technologies will be the primary and accessibility source of energy in next years.

Biomass sources could be classified as wood (energy forest, cellulosic wastes), oilseed crops (sunflower, safflower, rape, cotton, soy), carbohydrate plants (wheat, corn, sugar beet, sugar cane, potato), fiber plants (linen, kenaf, sorghum, hemp), herbal wastes (branch, handle, hay, root, shell), urban and industrial wastes, algas (Ayas et al, 2009). Today, biomass is drawn attention as one of the major feedstocks of energy production for both developed and developing countries. Various agricultural, forest, and waste based resources could be supplied to the bioeconomy and create new economic opportunities for rural areas in Asian and European countries (Raychaudhuri and Ghosh, 2016). Although traditional biomass has been still widely preferred for direct combustion; solid, liquid, and gaseous biofuels can also be produced from biomass feedstocks as alternative fuel candidates or fuel additives via chemical, physical, thermochemical and biological processes in biorefineries. Gas biofuels are biogas, biohydrogen, biosyngas; solid biofuels are biobriquette, biopellets, wood coal, biocoal; liquid biofuels are biodiesel, biomethanol, bioethanol, biodimethylether, bioethyl tertiary butyl ether, vegetable oils.

Biofuels are classified into first generation biofuels and advanced generation biofuels based on their production methods and feedstock. First generation biofuels (2000-2010) are produced by using conventional technologies and could be utilized as engine biofuel with no adjustment. Biodiesel (fatty acid methyl ester), bioethanol (sugar and starch based), bioethyl tertiary buthyl ether (used as fuel additive) and biogas are in that class. Agricultural outcomes that are significant inputs of food sector are used as feedstock in production of biodiesel and bioethanol, agricultural wastes are prefered to product biogas (Isler, 2012; Naik et al, 2010). Vegetable oil, biodiesel that could be generated from fatty acid ethyl ester, bioethanol that could be generated from lignocellulosic feedstocks, biomethanol, biobuthanol, bioethyl tertiary buthy ether, bio-methyl tertiary buthyl ether, bio-dimethyl ether, biomethane and biohydrogen which could be generated from biomass based production processes outcomes as Fischer-Tropsch Diesel and Fischer-Tropsch Gasoline are included in second generation biofuels (Borand, 2012; IEA, 2008). Those fuels are generated from non-food based lignocellulosic feedstocks. Considering the first generation biofuels, it is estimated that the manufacturing process and utilization cost of second generation biofuels are higher. Nowadays, the cost of second generation biofuels are higher than oil based fuels and traditional biofuels and, furthermore technological competence has not been provided. Innovative technological advancements need for fermentation, several pretreatment processes and chemicals that make the second generation biofuels more costly than oil based fuels and commercial biofuels. In the commercial perspective, new ground works should be for easy and fast transportation, available storage and refining (Ar et al, 2010; Ben-Iwo et al, 2016; IEA, 2008). In second generation biofuels, there is a transition from cellulosic feedstocks to lignocellulosic feedstocks, which aims to use non-food feedstocks. The targets of second generation biofuels production are more carbon dioxide storage in biomass (carbon intensive photosynthesis), higher yields per production area, success in input-output production balance (Isler and Karaosmanoglu, 2010; Schenk et al, 2008).

Third generation biofuels involves genetically modified plants and algae contains high percentage of oil and cellulose. Third generation of biofuels could be produced by unified biorefining processes. According to the IEA Energy Technology Perspectives (2008), third-generation biofuels are defined as biofuels sourced from aquatic feedstock (generally algae). Third generation biofuel contains of two main phases; the first one is the natural growth or aquatic biomass cultivation, and the second one comprises whole process beginning from feedstock cultvation to production of biofuels. The single-output process applied to produce third-generation biofuel is mainly based on multiple targets (Saladini et al, 2016).

Fourth generation biofuels can be produced from consummated genetics feedstocks. This type of biofuels sourced from petroleum-like hydroprocessing, oxy-fuel combustion or thermochemical processes and originated from genetically re-organized feedstocks adapted through both capturing and storing carbon beginning from feedstock stage to the whole process (Lü et al, 2011; Cuellar-Bermudez et al, 2015). In fourth generation biofuels group, the feedstock is adapted to promote the processing proficiency and designed to capture more carbon dioxide than normal. As a result of this, it is expected that fourth generation biofuels will be the best to decrease greenhouse gas emissions compared other types biofuels (Isler and Karaosmanoglu, 2010; Joshi and Nookaraju, 2012). Those fourth generation fuels biomass consists of high biomass crops such, trees with high carbon content and other specifical types (Joshi and Nookaraju, 2012).

In a region-based approach; especially the regions of lowest-economy countries, the share of biofuels has been increasing in the last years (WEC 2016). Biofuels production distribution by selected region are given in (Table 2.1).

Table 2.1 : Biofuels production distribution by selected region (World Energy Sources; 2016).

Region	1993	2003	2013	2014	2015
Asia Pacific	-	3.3%	9.5%	10.5%	10.8%
Africa	-	-	-	1.0%	0.01%*
Europe & Eurasia	1.1%	11.1%	17.1%	16.5%	18.3%
S. & Cent. America	71.4%	49.2%	28.5%	28.7%	27.9%
North America	27.4%	36.4%	44.8%	44.1%	42.9%

For the year 2015, 74% of the biofuel production was dedicated to bioethanol, while 22%was for biodiesel and the rest was for hydrotreated vegetable oil. Environmental, economical and socially sustainable advantages accelerate the rate of biofuel usage in some regions. In the same year, biofuels scaled-up with the ratio of 3% compared in 2014, increasing 133 billion liters in the numerous countries and regions as United States (46%), Brazil (24%), EU(15%), Rest of World (15%) (countries from lowest-economy regions are in this part) (REN 2016). Still United States and Brazil are the leaders of liquid biofuels industry; but new developments have been carried out by the improving markets in Asia and Africa regions. Biodiesel consumption has expanded in European Union (EU) (Bomb et al, 2007; Dautzenberg and Hantl, 2008), despite, only first generation biofuels are produced in larger scales (Festel et al, 2014). Furthermore, another major area to produce and consume bioethanol is North America (REN, 2014), followed by Latin America. In 2016; corn and soybean is used for biofuel production in North America (corn and wheat are for bioethanol while soybean is for biodiesel), while corn and sugar cane are most prefered ones in South America (sunflower is for biodiesel). According to REN report 2016; the world's largest biofuel producer is North America for 2015; maize and rose are major feedstocks in bioethanol while biodiesel is based on soya oil. For EU, potato, wheat and sugar beet are the most preferred feedstocks for producing ethanol. While ethanol have less important share, the share of biodiesel has major share in biofuel production of Europe. Biodiesel in EU produced by using rapeseed oil (around 70%), the other major resource is soybean oil by 17%, sunflower and palm oil are other feedstocks in biofuels production (USDA FAS, 2008). In 2016; canola, soybean and barley are major biodiesel feedstocks in Europe; while wheat, sugar cane, sugar beet are major bioethanol feedstocks for leader producers that are France and Germany. Second larger biofuel producer is Brazil uses sugarcane as a feedstock of bioethanol production (REN Report, 2016).

Encouraging factors, obligations, tax advantages, aids and technical factors applied by many countries have been the main precursors of biofuels expansion as blend into gasoline and diesel, or directly fuel type (Chang et al, 2011). Although economic development is the main driver of biofuel production and its expansion, nowadays energy security has taken the role. Due to geopolitical uncertainties, using local resources is the best option to supply the growing energy demand in particularly lowest-economy countries. Gasparatos et al. (2015) also emphasized that developing regions are being responded for biofuel expanding since biofuels are international commodity. Apart from being a commodity, biofuel is a fuel that requires biomass resource, which in turn requires land (soil) and water (Doku and Falco, 2012). In recent years, numerous biofuel producers and investors have directed their investigation to diversify the biomass feedstock (Arndt et al, 2009). They also pointed out that biobased technologies could require significant amounts of land. If a country has government biofuel support policies and economic considerations with sufficient quantity of arable lands; biofuel production could draw attention for this country. Moreover, manpower in the developing countries is more available and affordable than developed countries which is a big advantage for biofuel producers. Human resource or manpower is a significant factor in poverty reduction, but it should include the employment of poor. Surely, rural development is another biofuel production driver in particularly lowest-economy countries. Doku and Falco (2012) believed that biofuel technology has great ability to provide a rise in employment by creating new sectors, variable jobs, and eventually increase rural income. They also pointed out that providing rural agricultural employment is a key factor to prefer biofuels by refering international authorities as IEA. Consuming domestic resources for national energy production to ensure energy security and rural development; requires protectionism. Avinash et al. (2014) drew attention that developing non Organization of the Petroleum Exporting Countries (OPEC) members with little or no fossil reserves could implement to use existing and unutilized land resources. Especially, various researches have been carried out on biofuel production improvements in lowest-economy developing countries have a potential of producing biofuels to meet demands of local and international markets (Tatsidjodoung et al, 2012; Duku et al, 2011; Mohammed et al, 2013; Amigun et al, 2011). Due to feedstock variability and high rate of human resources, major biofuel producers in European Union (EU) are focusing on biofuel production, which bases in Africa (Gasparatos et al, 2012; von Maltitz et al, 2009). European community exhibit a major role in supporting lowest economies such as West-African countries by providing funds to support biotechnology studies, and also by improving partnerships with local organizations (Black et al, 2011).

2.3 Bioethanol

Three forms of biofuels have a significant share all over the world, all including in the so-called ‘‘first generation’’ fuels: ethanol, fatty acid methyl ester (FAME or biodiesel), and pure plant oil (PPO) (Havlík et al, 2011). All of them have exhibited a significant condition for production and could be commercially obtained (Bringezu et al, 2007). Globally well-known of biofuel production is ethanol (Nigam and Singh, 2011; USDA FAS, 2008), which is mainly generated in the USA and Brazil by using corn or sugarcane (Nigam and Singh, 2011). Bioethanol, one of the leader engine biofuels, has a extensive utilization area in the world. The background for bioethanol is based on the history of the internal combustion engine. In 1860, N.A. Otto had preferred ethanol for own engine research. In the early 1900’s, Henry Ford has investigated the combustion of alcohol in himself design works and defined that the gasoline-alcohol blend as a fuel of the future. Since 1970’s, the relevance to bioethanol has increased as a result of oil embargoes and high oil prices (Luque et al, 2011; CFDC, 2007). Today, bioethanol industry attracts more attention and developes by growing importance of environmental impacts.

Bioethanol, that could be produced by acidic fermentation of sugary and starchy plants or hydrolysis of cellulosic feedstocks, is an engine biofuel. Ethanol (EtOH), also known as "Ethyl alcohol", "Grade alcohol" and "Fuel alcohol" and it's chemical notation as C_2H_5OH (Rutz and Janssen, 2008). Furthermore, bioethanol is also called as depend on its feedstock; for instance, cellulosic bioethanol is sourced based on cellulosic biomass; lignocellulosic bioethanol is generated by using lignocellulosic biomass (Isler and Karaosmanoglu, 2010). Sugar beet, sugar cane, corn, wheat, potato; woody plants such as shell, straw; agricultural wastes and molasses by-product of sugar production are generally used as bioethanol feedstocks (Balat et al, 2008; Luque et al, 2011). Starchy and sugar based bioethanol (first generation bioethanol) is still commercially produced and used. Currently, only small amounts of second generation biofuel could be produced in a few numbers of demo plants around the world that are managed industrially, however are not yet commercial level (Lennartsson et al, 2014; Kaltschmitt, 2001), thereby several pilot plants are in USA. Considering technological status, research opportunities, resource potential; production and government's targets/mandates of biofuels will be primarily continued as first generation biofuels up to carrying out development and commercialization of second generation biofuel in global.

Physical, chemical and thermal properties of bioethanol is shown in (Table 2.2). According to (Table 2.2), bioethanol has been accepted as a significant choice to oil based engine fuel (Pandey et al, 2011). Bioethanol can not be used directly in engines with no alteration, also it could be blended into fuel.

Table 2.2 : Properties of bioethanol (Rutz and Janssen, 2008; IEA-AMF data, 2017).

Properties	Values
Formula	C_2H_5OH
Molecular Weight (g/mol)	46.1
Carbon (w/w, %)	52.1
Hydrogen (w/w, %)	13.1
Oxygen (w/w, %)	34.7
C/H ratio (wt)	4
Specific Weight (kg/L)	0.79
Vapor Pressure (at 38˚C) (mmHg)	50
Boiling Temperature (˚C)	78.5
Solubility in Water	∞
Stoichiometric (air/EtOH)	9
Lower Heating Value (kcal/kg)	6400
Ignition Temperature (˚C)	35
Specific Heat (kcal/kg˚C)	0.6
Melting Point (˚C)	-115
Heat of vaporization (kcal/kg)	839; 923
Cetane Number	2-12
Research Octane Number (RON)	120-135
Motor Octane Number (MON)	100-106

Bioethanol, which has several advantages over fossil based fuels in terms of environmental effects and sustainability, may find many application areas other than being a fuel additive.

Bioethanol advantages could be defined as (Luque et al, 2011):

- Obtaining from renewable raw materials
- Decreasing dependence to petroleum based products
- Reducing emissiond on a large scale
- Increasing the octane number of gasoline
- Helping more efficient and cleaner combustion as a result of oxygen in its structure
- Being biodegradability and having antitoxic property

Bioethanol can find itself a place as fuel, blend for fuel, fuel of fuel cells and raw material to produce biodiesel and bioethyl tertiary buthly ether (Borand, 2012). Currently, bioethanol is utilized in different ways as a fuel additive into gasoline and diesel (Isler and Karaosmanoglu, 2007; Isler and Karaosmanoglu, 2010), which are named as:

- E-Gasoline : gasoline including a maximum of 5% alcohol
- Gasohol : the fuel including 10% alcohol and 90% gasoline
- E20 : the fuel including 20% alcohol and 80% gasoline
- E25 : the fuel including 25% alcohol and 75% gasoline
- E85 : the fuel including 85% alcohol and 15% gasoline
- E-Diesel (Oxydiesel): diesel including maximum 15% alcohol

Bioethanol production process vary due to the type of used feedstocks. Bioethanol production is carried out using three main types of feedstocks: sugar-based and starch-based feedstocks for first generation bioethanol; and also lignocellulose-based feedstocks for second generation bioethanol. Bioethanol production processes in both first generation bioethanol and second generation bioethanol are shown in (Figure 2.2).

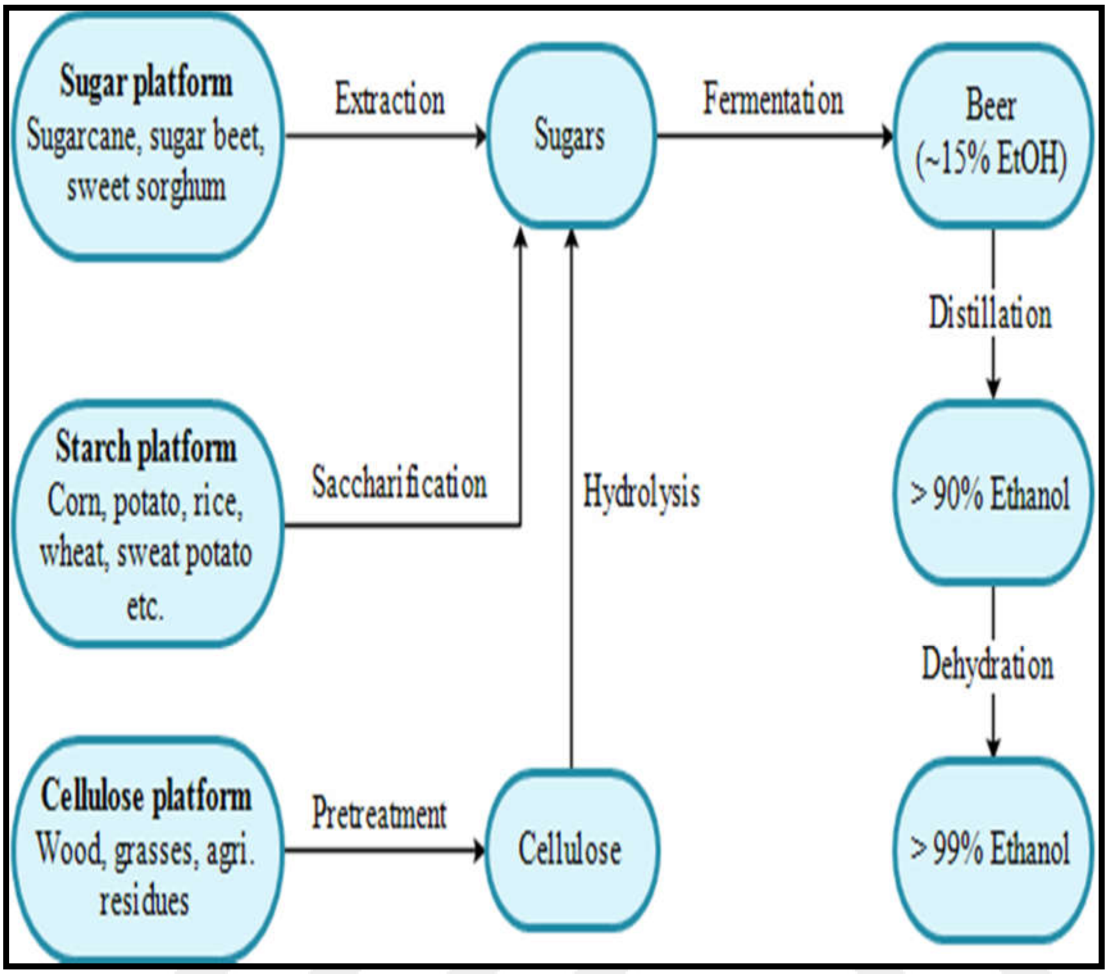

Figure 2.2 : Bioethanol production processes, adapted from (Cheng, 2010).

Production methods of first generation bioethanol is determined whether the feedstock is starch-based or sugar-based. Ethanol production is commonly carried out into the major three steps: (1) to get the mixture including fermentable sugars, (2) occuring ethanol with fermentation and (3) ethanol seperation and remove impurities. In fermentation process; sugar-free part could be used to produce ethanol (Lin and Tanaka, 2006; Cheng, 2010). Sugar based production steps are extraction, fermentation, distillation and dehydration, while starch-based production applied in the same steps except first one. Starch-based production requires primarily the saccharification of starch as an additional step to obtain fermantable sugars. Saccharification contains enzymatic reactions catalyzed by amylases (Kumar et al, 2010). An example diagram (Figure 2.3) of production process of bioethanol from grains and sugar syrups adapted from CropEnergies AG Mannheim (2017).

Ethanolic fermentation, which is the main step of sugar-based and starch-based production, can be carried out by batch, semicontinuous and continuous fermentation. These fermentation types prosecuted in the same temperature and pH conditions. The major differences are their volumetric ethanol productivity or ethanol yield. (Wyman, 2004). In ethanol production, to obtain a product with high ethanol content, distillation (90% ethanol) and dehydration (99% ethanol) should be prefered (Cardona and Sanchez, 2007; Cheng, 2010; Wyman, 2004; Gnansounou, 2009). Ethanol could be produced from corn as well as other starchy crops either by the dry grind or wet milling processes to produce ethanol (Bothast and Schlicher, 2005).

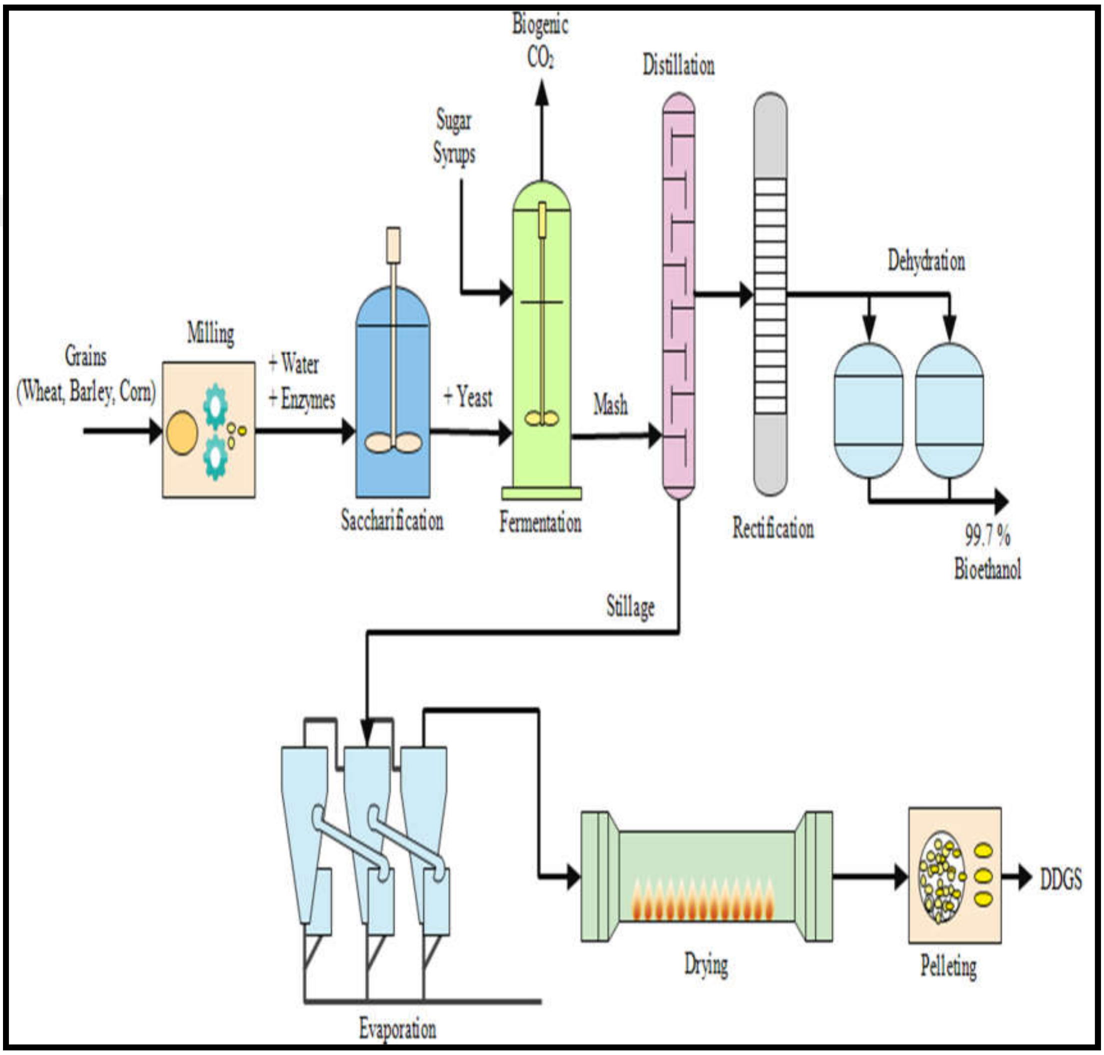

Figure 2.3 : Bioethanol production process from grains and sugar syrups, adapted from (CropEnergies AG Mannheim, 2017).

The difference between dry and wet milling processes is the use of all of ground grains, while various constituents are firstly extricated from feedstocks and only starch is used in the wet milling process (Figure 2.4). Although both dry and wet milling methods are preferred for ethanol production, dry-grind method is used in many of commercial plants.

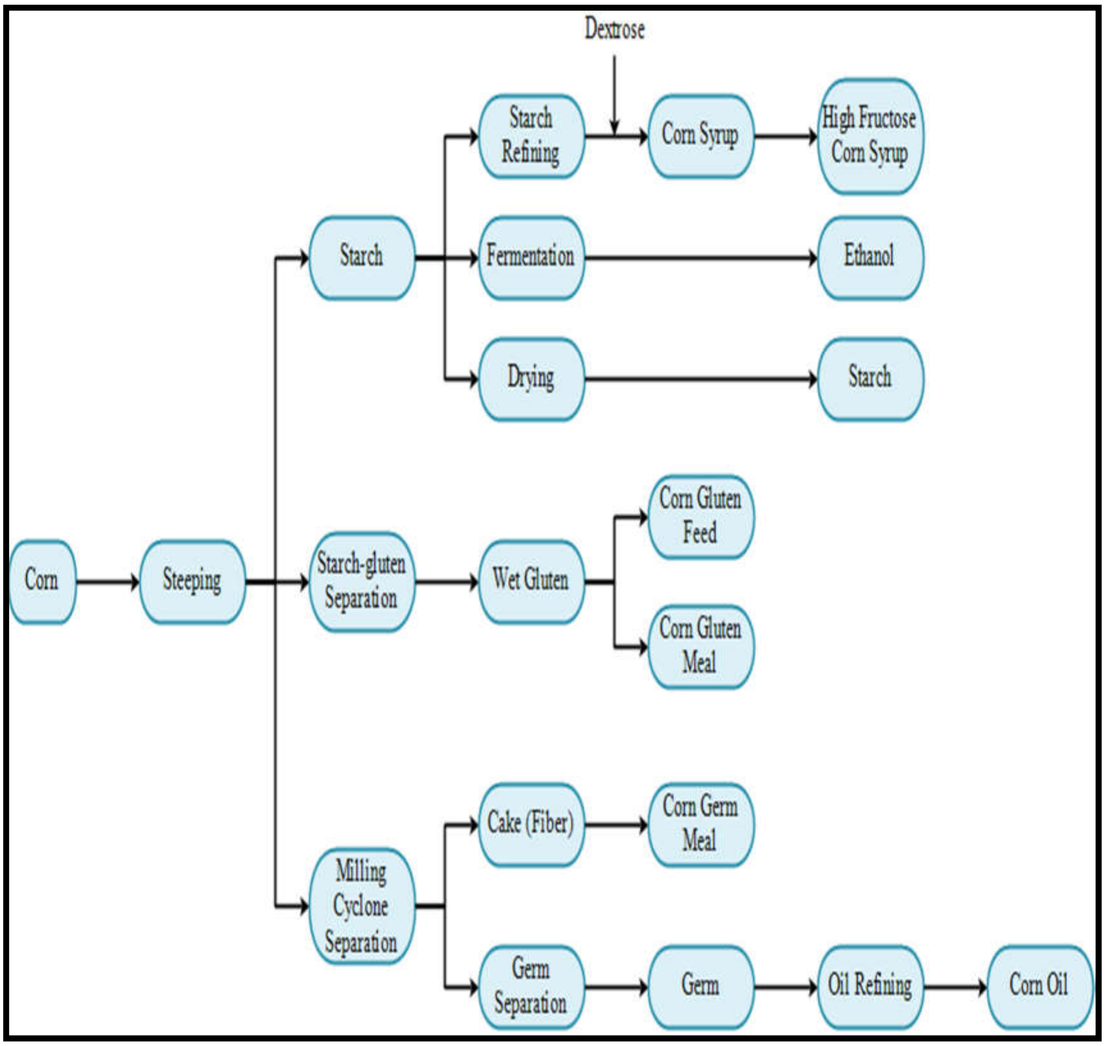

Figure 2.4 : Wet milling process to produce bioethanol from starch, adapted from (Erickson et al, 2005).

Bioethanol has been also generated by using lignocellulosic materials, which have been widely known as second generation bioethanol (Cheng and Timilsina, 2011). At present, several technologies and methods are performed to convert cellulosic feedstocks into ethanol. These methods classified into two extensive types, which could be mentioned as the sugar based class (Biochemical conversion) and the syngas based class (Thermochemical conversion) (Mabee et al, 2011; Vohra et al, 2013). Process parts of thermochemical method are pretreatment, gasification, cleanup, generating synthesis gas (a gas mixture of CO, H_2, CH_3OH and C_2H_5OH (Mabee et al, 2011). In bioconversion method, lignocellulosic biomass is made ready to hydrolyze by using pretreatment operations. Hydrolyzation is carried out using enzyme and acid. Then, sugar solution is obtained. Sugar solution is fermentated to become bioethanol. This ethanol should be distilled to raise density of bioethanol.

Finally distilled ethanol becomes 90-95 % (w/w) and after dehydration, bioethanol can be obtained (Borand, 2012).

Although there are several differences; fermentation, distillation and dehydration steps are carried out for all three of them as seen from flow diagrams of production processes.

2.3.1 Bioethanol in World

In the perspective of global biofuel production derived from different biomass sources; biofuel production has been growing steadily over by government strategies that aim various targets and topics like national energy security, supporting economic development, preventing GHG effects and decreasing oil based fuels cost for the last ten years. In this context, commonly commercially produced biofuels are first-generation biofuels (bioethanol, biodiesel and biogas) based on food crops (Serra and Zilberman, 2013) as mentioned before.

World fuel ethanol volumes had increased by the ratio of 5% to 87.2 billion liters in 2013 (REN, 2014), 20,490 millions of gallons in 2014 (RFA, 2015). Global production of fuel ethanol increased with the ratio of 4% from 2014 to 2015, reaching to 98.3 billion liters. The leader countries, United States and Brazil, had supplied 86% of total ethanol production of world in 2015. China, Canada and Thailand followed them and become the other significant producers (REN, 2016). When the 2022 world bioethanol projection are investigated, their amounts are forecasted to reach up to 167.391 billion liters. Between the years of 2013-2022, the percentage of total bioethanol production growth estimated as 4.10 (least-squares growth rate) (OECD–FAO, 2013). This shows that many factors such as crude oil prices, the changes in the policies and macroeconomic phenomenon have significant impact on bioethanol production and marketing. Therefore, almost all countries, which try to improve bioethanol sector, are concentrating their research and studies to increase the domestic feedstock (OECD-FAO, 2008). Most of the countries all over the world, mainly US and EU countries put legal regulations and targets to support different types of bioethanol production and use, and bioethanol production has been increasing year by year (REN, 2013). Global bioethanol productions of top 5 countries plus EU-27 from 2013 to 2016 are presented as million of gallons in (Table 2.3).

Table 2.3 : Global bioethanol production (millions of gallons) from 2013 to 2016 (REN, 2014; RFA-Industry Statistics, 2017; REN, 2016).

Country	2013	2014	2015	2016
United States	13,300	14,300	14,820	15,330
Brazil	6,267	6,190	7,925	7,295
Europe	1,371	1,445	1,083	1,377
China	696	635	739.7	845
Canada	523	510	449.1	436
India	545	155	317	225

In 2016, the world bioethanol production nearly remained at the 2015's level of 26,584 millions of gallons. The fuel sector still continued to account for 84% of bioethanol. While world leader bioethanol producer, US has the production capacity with 15,330 millions of gallons, followed by second leader country, Brazil by the ratio of 7,295 millions of gallons in 2016. The total production of the EU was estimated as 1,377 millions of gallons in 2016 (RFA-Industry Statistics, 2017).

The United States is the leader ethanol supplier and consumer of the last years. In the case of being dependent on petroleum products, it is forecasted that dependent on external energy sources will be 30% and greenhouse gas emissions will increase with the rate of 40% as a result of having too much fuel consumptions in US. Therefore, bioethanol sector has an important role in US energy policy (Isler, 2012). National need has been supplied with the US Environmental Production Agency's (US EPA) final Renewable Fuel Standard (RFS2) shares to meet annual volume requirements (REN, 2016). In US, ethanol biorefineries are located in 29 states with the production of 14.7 millions of gallons of high-octane bioethanol and some 40 million metric tons of feed in 2015 (RFA, 2016). Brazil is the other important bioethanol producer in the world; depend on a successful agrarian and legal authorities strategies that have affected concentration on bioethanol market (REN, 2016). In Brazil, sugarcane is mostly used as feedstock for bioethanol production and bioethanol is preferred for around 80% of transports. The reason of prefering sugarcane as feedstock could be explained with its major accordance to climatic and geographical properties of Brazilian. Nearly one million workers are employed in bioethanol market for Brazil. There are more 300 bioethanol production plants and it means that over 180 billion dollars is saved. According to Brazilian Sugarcane Industry Association (UNICA), it is forecasted that numbers of bioethanol production plants will scale up to 409 and bioethanol production will be 35.7 billion liters (Pandey et al, 2011; Ar, 2011). The target of the Brazilian government is to increase ethanol production 37.7 million tonnes by 2016 (Timilsina and Shrestha, 2010). Bioethanol is significant for EU to guarantee assuring of energy supply, obtaining agricultural improvement and controlling GHG emissions decrease. It is intended that bioethanol production will increase in 2020 (Ar, 2011); although EU is the world's leader regional biodiesel producer and maintaining this position for many years (Flach et al, 2011). EU leader countries are France, Germany, Belgium and United Kingdom. EU ethanol generation has been declined with nearly 7% for 2015, mainly due to decreased production in the United Kingdom (REN, 2016). It is expected that imports also increase and scale up above 40% of EU utilization for the near future. By 2020, ethanol energy would meet 9.2% of EU gasoline utilization (REN, 2014). Total bioethanol consumption in EU was given as 5.47 billion liters by the year of 2015 according to European Renewable Ethanol Association (ePURE) data (2017). Also, it is given that mainly corn and wheat are used as feedstock to produce bioethanol while other cereals, starch rich crops and lignocellulosic based feedstocks are also utilized by the lower ratio. This ratios (especially low lignocellulosic based feedstocks consumption) show that first generation bioethanol production has a significant commercial share compared to second generation bioethanol production. Besides; US has a high bioethanol production potential by using corn and Brazil is second bioethanol producer by using sugar cane. As in EU; first generation bioethanol production has extended with a significant commercial potential in US and Brazil as a result of selected feedstocks and production systems. Bioethanol production, consumption, imports, exports and installed capacities of biorefineries are given by (Table2.4) for EU, Brazil, China, Canada and India in 2016 (USDA US Bioenergy Statistics, 2017; USDA Gain Reports, 2016 (Canada, India, EU, Brazil); USDA Gain Report for China, 2017).

China, one of the largest ethanol producers, has a production capacity about 2.8 billion liters with a decrease of 14% in 2015. In the same year, ethanol imports has increased in China without establishment of new production capacity. In Asia; another bioethanol production leader, Thailand, has a rising bioethanol production nearly 1.2 billion liters in 2015 compared to production in 2014 (REN, 2016). Although biofuel production in Africa is still very limited compared with others, production of ethanol continued to increase rapidly in Asia (REN, 2014).

Table 2.4 : Statistical data of bioethanol production (million liters) for selected countries in 2016 (USDA US Bioenergy Statistics, 2017; USDA Gain Reports, 2016 (Canada, India, EU, Brazil); USDA Gain Report for China, 2017).

Country	Number of Refineries	Nameplate Capacity of Refineries	Production	Consumption	Import	Export
United States	213	56,413.81	58,026.84	58,474.23	137.046	3,960.36
Brazil	383	39,650	28,02	25,723	530	750
Europe	71	8,480	5,050	5,170	150	150
China	9	3,600	3,155	4,007	853	1
Canada	14	1,775	1,750	2,750	1,000	0
India	162	2,050	2,085	600	450	140

New developments occurred new biofuel sectors in Asia and Africa. In Nigeria, a global supported corporation has been established with cassava producers association for bioethanol production (REN, 2016). In Asia countries aimed to improve biofuels as a solution to enhance energy security. The crucial statistics put forward that the Asia-Pacific region accounts for around 25% of world bioethanol production (Lichts, 2006). Total global bioethanol production by 2015 is given to clearly show the bioethanol production capacities of countries in (Figure 2.5).

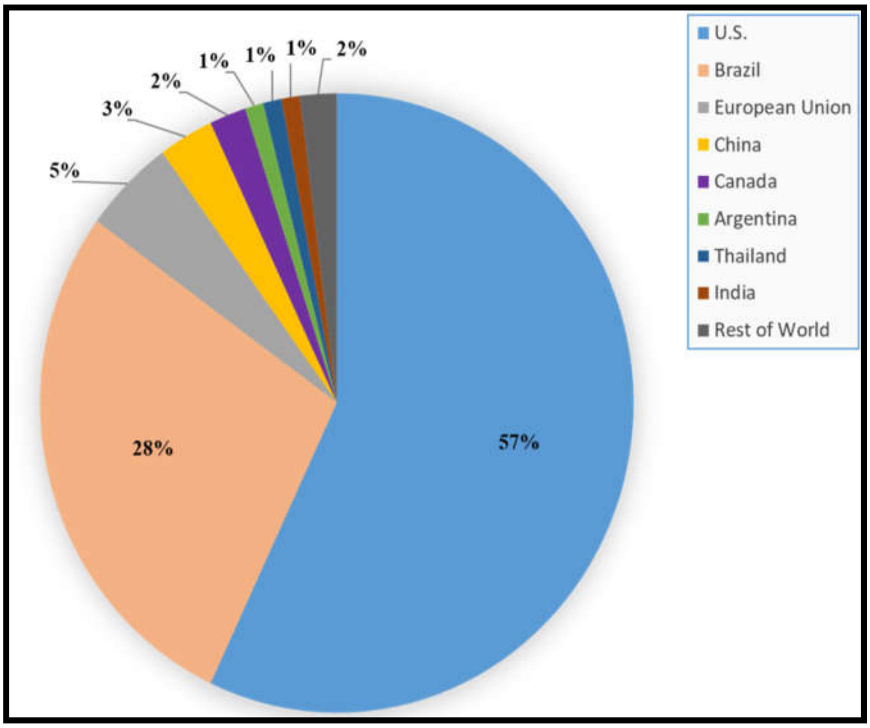

Figure 2.5 : Global bioethanol production in world by the year of 2015, adapted from (RFA-Industry Statistics, 2017).

Increasing of national consumption through utilization obligations or government encouragement, domestic production using production mandates, investment support for production plants, exhibition projects, research and development; raw material supply support are targeted to increase the biofuel (bioethanol and biodiesel) utilization (Lamers, 2013; Junginger et al, 2011).

Many countries in the world, mainly US and EU countries, investigate on different forms of bioethanol production and therefore targets and legal regulations has been constituted to increase production, promotion, or use year by year (Junginger et al, 2011). The US and EU biofuel obligations will affect the situation of world bioethanol markets and its related areas for developed and developing regions (REN, 2014). They could either push (for example blend obligations) or pull (for example taxes) bioethanol into the market (Junginger et al, 2011).

In 2013, strategies continued to be reorganized by many countries that prefer a combination of economical supports and obligations. Generally prefered policies involve biofuel production supports, biofuel blend regulations, and tax advantages.

In the beginning of 2014, 33 countries had constituted blend obligations, by 31 national obligations and 26 additional obligations in the country level (REN, 2014). Bioethanol targets and mandates of several countries are shown in (Table 2.5). Bioethanol or other biofuels production has expanded for the last years and the sharp increase has been encouraged by the gainfulness for production, which is relatively correlated to the petroleum and raw materials cost, but widely with legal authorities strategies and mandates as seen in (Table 2.5) (Steenblik, 2007; FAO, 2008).

The US biofuel improvement strategies are complex (as in the EU) as the result of varying the application of mandates and strategies for each region or country. The United States, the leader ethanol supplier, gave a start its development strategies and plans for ethanol production with the Energy Tax Act of 1978 and these policies are as complex as EU policies. According to this policy, biofuel producers were allowed full exclusion of the legal gasoline excise tax when they generated gasoline blended by the ratio of 10% ethanol resulting in an affective subvention nearly US 40 cents per gallon of ethanol (UN, 2006).

Table 2.5 : Primary energy targets and obligations for bioethanol in selected countries (REN, 2016).

Country	Percentage of Primary Energy based on Renewable Resources - Targets	Percentage of Final Energy based on Renewable Resources - Targets	Transportation Energy Shares (2014) From Renewable Targets	Transport obligation/mandate for bioethanol
Brazil	Existing National	45% by 2030		E27.5
Canada	Existing National	Existing National		E5
China	Existing National	20% by 2030 [11.4% by 2015; 13% by 2017]		E10 in nine provinces
Germany	Existing National	18% by 2020 30% by 2030 45% by 2040 60% by 2050	20% by 2020	
Indonesia	25% by 2025	Existing National	10.2% biofuel share of primary energy by 2025	E3
Thailand	Existing National	30% by 2036 25% by 2021	9 million liters/day ethanol consumption by 2022	E5
Turkey	Existing National	Existing National		E2, E3
United Kingdom	Existing National	15% by 2020	5% by 2014; 10.3% by 2020	
US	Existing National	Existing National		E10 in Hawaii; E20 in Minnesota; E10 in Missouri and Montana; E2 in Washington.

In 1980, extending of subvention had been applied as another mandates like E85. Obligations for biofuel consumption had been constituted under the *Energy Policy Act of 2005* for the federative state that involved a *Renewable Fuels Standard (RFS1)*, although mandates in biofuel consumption are in the state level. This 2005 Act aimed to reach of purchasing 4 billion gallons of biofuels in 2006 and 7.5 billion gallons in 2012. For 2007, the *"Energy Independence and Security Act"* put into action changed the rotation of US policy and mandates came into prominence (Dimaranan and Laborde, 2012). The growth and developments in US ethanol production had been encouraged by the *1990 Clean Air Act* that brought obligation about existing least proportion of oxygen for gasoline. At first, although that rule had been provided with the blended of methyl tertiary butyl ether (MTBE) to gasoline. MTBE had environmental problems when it was blended to fuel. Therefore, it had forbidden in US and so changed with ethanol (Huang et al, 2012, Bradley et al, 2009). In US cars, mostly used blend in E10. After 1988, whole of vehicle engines were generated to use with E10 and for many situations up to E20. By the year 2011, minimum 7 million transports had engines that could utilize an 85% ethanol blend for US (Pandey et al, 2011). In 2014, approximately 25% of new cars released on the market in US could be flexible-fuel vehicles (FFVs) talented of running to E85 (RFA, 2015). Due to *"Development of Biofuel Marketing Draft Law",* 2011 January, aim is 50 % of vehicle which would be designed as flexible-fuel vehicles in 2015 and 90 % of vehicles that would be designed for 2016 could use by E85 (Ar, 2011). This situation caused an increase in ethanol demand and directly affected the ethanol prices. Comparing with increasing gasoline costs, present subvention grades, increase in environmental awareness and low feedstock costs, the gainfulness on ethanol production facilitate the fast established of corn-based ethanol facilities (Pandey et al, 2011) in the US during the mid-2000s (Huang et al, 2012). As a result of developments in bioethanol market, 53.6 billion dollars added-value and 36 billion dollars income increasing were gained for only 2010. Furthermore, employment was provided for 400,677 people at the same time. In the other side, 445 million barrels of petroleum import decreasing had been occured and this means 34 billion dollars savingness (Ar, 2011). For 2014, 14.3 billion gallons of ethanol had been carried out, thereby supported 83,949 employment for the renewable fuel and agriculture markets in U.S. Furthermore, 295,265 undirect and encouraged jobs had been supported (Urbanchuk, 2015).

For 2006, August 3, 250 Million $ budget had been obtained to *Research and Development (R&D) projects*. Due to *"New Energy Law*", 2006, aim was described as 7.5 million gallons of biofuel use for 2012 and US achieved their aims for 2008. Latest aim is reaching 130 billion liter/year of biofuels utilization with 2017 (Ar, 2011). When investigated important production targets; it is seen that US's biofuel generation of 15.2 billion gallons for 2012, 30 billion gallons for 2020 and 36 billion gallons for 2022 introduced with Renewable Fuel Standards (RFSs). These volumetric mandates have been divided depend on source (conventional, cellulosic, and other) with the aim in corn-based (first generation bioethanol) ethanol set at 15 billion gallons. Although subventions and financial support put into legislation into the improvement of second-generation biofuels, the RFS has bias against corn ethanol (Tyner, 2010). The current general biofuel strategies or plans for US contain three major tools: outcome-correlated precautions, promote income factors and utilization subventions. Taxes and obligations preferred by biofuels producers with price encouragement. In the perspective of bioethanol economy, taxes on ethanol (24% in equivalent ad valorem) are superior compared to biodiesel (1% in equivalent ad valorem) which restrict imports particularly from Brazil (one of the largest bioethanol producers). Moreover, producers directly use tax credited-biofuels for mixing to fuels. The *Volumetric Ethanol Excise Tax Credit (VEETC)* and the *Volumetric Biodiesel Excise Tax Credit (VBETC)* provide the single largest subsidies to biofuels, although there are supplemental subventions linked to biofuel outputs (Dimaranan and Laborde, 2012).

Brazil is the second leader supplier of ethanol for global production in 2014 according to RFA 2015 analysis. In this country, ethanol produced mainly from sugar cane via using energy-efficient process. The growth of bioethanol utilization was the result of the government policies and incentives to use biofuels as a fuel substitute. Bioethanol had been firstly utilized like a fuel additive (5%) in 1931. Legal obligation had been prepared for bioethanol in 1938. For 1970s, the government of Brazil put a *National Fuel Ethanol Program* to carry out ethanol policies and extensive the proportion of national generated biofuel utilized for transportation and so ethanol use is up to 20-25% for gasoline (Dimaranan and Laborde, 2012; Nass et al, 2007). In 1990s, ethanol prices were liberalised, but the legal authority targeted and organized some changes on bioethanol policy. For this purpose, government put a legal regulation on ethanol blending proportion to gasoline, taking a lower consumption tariff of ethanol compared to gasoline, and applying an ad-valorem duty for imported ethanol (Pousa et al, 2007). Blend ratio for bioethanol was raised to 22% for 1993 (Pandey et al, 2011). These changes and regulations contained improving the presence of ethanol at gasoline stations and obligated the design of flexible fuel vehicles talented of utilizing pure gasoline, E25 or pure bio-ethanol. That ethanol could have provided 20% of Brazil's total transport-fuel need in 2007 (Nass et al, 2007; Dimaranan and Laborde, 2012). In 2011s late, blend ratio changed between 20 – 26% depending on bioethanol price. The success of the Brazilian government policies are to carry out ethanol production reach 11.5 billion gallons by 2016 (37.7 million tons) (Timilsina and Shrestha, 2010).

The European Union's studies regarding bioethanol goes back to 1900s. The regulation of targets for the use of biofuels to be an alternative fuel or additive in road transportation is a significant process of the European Union's answer to meeting and carrying out own Kyoto aims of GHG emissions (Dimaranan and Laborde, 2012). Due to "Green Paper" (2000), "Biofuel Encouragement Directive" (2003), "Kyoto Protocol" (2005), "Biofuel Strategy Paper" (2006), significant strategies had been improved on biofuel generation and utilization. Therefore, biofuel utilization has been mandated in many of EUcountries (Ar, 2011). EU is the another major producer for bioethanol after US and Brazil, although biodiesel based on rapeseed is produced more than bioethanol (REN, 2014). Particularly sugar beet cultivation for bioethanol production is supported by the European Commission (Ar et al, 2010). which was released in 2003 Biofuels Directive (2003/30/EC) with transport sector, the rate of in 2010 biofuel use is intended (Directive 2003/30/EC).

In the mid-2000s, it is begun to motive EU's Member States to put into essential legislation to guarantee convenience to product and utilize biofuel. Tax prerogatives in the extend of biofuel utilization have been also permitted (Steenblik, 2007). In transportation sector, 2% biofuel utilization for 2005 and 5.75% biofuel use for 2010 were forecasted releasing Biofuels Directive (2003/30/EC) in 2003. The share of renewable energy use (6%) is targeted to be 12% in 2010 by The "*White Paper Declaration*" issued in 1997 (Directive 2003/30/EC). In 2005, with the share of biofuels use at 1.4% in 2005, *Biomass Action Report* (COM(2005)628) was published in 2005; then *Biofuels EU Strategy* (COM(2006)34) was prepared in 2006 to incentive biofuels more (Communication from the Commission: COM(2006)34; Communication from the Commission: (COM(2005)628). EU directive in 23 April 2009 agreed and supported more than before and therefore expanded the obligatory aims in 2010. According to this; 20% of energy must be from renewable resources by 10% dedicated to engine biofuels (Tyner, 2010). The other major regulations affecting the EU biofuel market were Fuel Quality Directive (2009/30/EC) and the European Union Energy and Climate Change package (Flach et al, 2011; Directive 2009/30/EC). Fuel Quality Directive targeted to all the fuel supplier decrease GHGs with the proportion of 6% in 2020, therefore it has take forefront the use of biofuels. European Union Energy and Climate Change package was accepted in 2009 and includes "*20-20-20*" targets.

According to "*20-20-20*" targets, three basic aims have been expected that for 2020:

- A 20% decrease for EU GHG emissions from 1990 stages;
- Increasing the proportion of EU energy utilization generated by using renewable sources to 20% and it has been expected that utilization of biofuels for transportion sector with the proportion of 10%;
- A 20% advancement for the EU's energy proficiency.

Although there are different targets and mandates for each countries were defined to meet the targets of renewable energy use in transportation, however 10% target has been mandated for all members of EU (Directive 2009/28/EC). The sustainability criterias, to achieve 10% target, are stated in Renewable Energy Directive (this directive was adapted for national legislations in each of EU member states) as follows:

- Biofuels, decrease GHG emissions due to fossil fuels, must be certified at least 35%. After 2017, this value will be 50%, for new plants, which began to production then 2017, must be 60%. Greenhouse gas emissions will be determined by life cycle assessment methods. Environmental factors as soil, water and air quality as well as ensuring food security and conservation of biodiversity are among the sustainability criterias.

- Second-generation biofuels (especially lignocellulosic, non-food, cellulosic wastes and residues) will be considered twice the value on the basis of energy to calculate amount of biofuel consumption.
- Bioelectric used by car will be counted as twice the value to calculate amount of biofuel consumption (Flach et al, 2011; Directive 2009/28/EC).

Since 2010, second generation of biofuels have been commercialised and biorefining will be carried out in 2020. For 2013; new blend mandates were introduced and applied in Europe (REN, 2014). By the year of 2015; it was forecasted that 5 million tonnes liquid biofuels (biodiesel and bioethanol) will be utilized in EU due to "*White Paper*". Furthermore, it is defined that 25% biofuels will be consumed for 2030 in "*Vision 2030 Paper*" that has organized by Comission of EU. In 2020, the target is that 20% of energy utilization will be provided via using renewable sources and 10% of biofuel will be consumed as mentioned above (Ar, 2011).

2.3.2 Bioethanol in Turkey

The liquid fuels subject and the significance of consumption alcohols as engine fuel choices to decrease the utilization and depending on imported oil were first came to the fore at a National Agriculture Conference in 1931 (Ültanır, 1985). In the II. Five Year Development Plan, that had been organized by the suggestion of Mustafa Kemal Atatürk, founder of the Turkish Republic, all part had been seperated to provide the production non-oil-based engine fuels from national sources (Tekeli, 1940). In 1942; a 20% ethanol-gasoline blend fuel had been utilized by the military for the first time (Demirliçakmak & Çakmak, 1983). After oil crises; state-owned Turkish Sugar Factories Inc. targeted an important enterprise for fuel alcohol studies compatibly to research & investigation projects in all over the world. Various ethanol-production plants were constructed to upgrade all existing plants (Karaosmanoglu et al, 1998). Although fuel alcohols have been located in nearly all state development plans, fuel alcohols have been investigated in scientific researches up to 2000s.

The activities related to biofuels has begun in Turkey since 2000. According to 2010-2014 Strategic Plan, organized by the Ministry of Energy and Natural Resources, the proportion of renewable energy for electricity production was aimed to be increased to 30% in 2023. Although there are different targets on hydroelectric, wind and geothermal energy, there is no specified target, plan or a road map for biofuels in the Strategic Plan (MENR, 2010). However, recent mandates were introduced for the use of bioethanol and biodiesel with the legal legislations made in Energy Marketing Regulatory (EMRA) Authority on September 2011. Energy agriculture mentioned in 2008-2012 Agricultural Vision that was announced in 2008 by Ministry of Food, Agriculture and Livestock, and also it was decided Black Sea Agricultural Research Institute to specialize in energy agriculture to develop the domestic agriculture which has a very important place in the production of biofuel.

Bioethanol has been described in Act 5015 as a petroleum product blend component. EMRA is the authority for regulating bioethanol and “Tobacco and Alcohol Market Regulatory Authority” (TAPDK) regulates the bioethanol sector. Firstly, bioethanol took place in 5015 – Petroleum Marketing Law as “Blending production with Gasoline” in 2003 and could be used as fuel additive due to TSE EN 228 that is standard belongs to vehicle gasoline. Due to “Technical Regulation Paper” which is prepared by EMRA in September 2011, it was compulsory to use 2% ethanol blends (2 percent ethanol 98 percent petroleum) without special consumption tax for Turkey in 2013 and this ratio was increased to 3% in 2014. Addition to these, Turkey should take into account Directive 2003/30/CE of Promotion and Use of Biofuels that was admitted by the European Parliament (EP) and the European Council (EC) because of it aims to be a member of EU. According to the execution of the Directive to domestic legislation, each Member State must follow Union targets, that need that by December 31, 2005, 2 percent of fuel marketed for transportation be biofuels, step by step raising to 6.76 percent by December 31, 2010. Therefore; considering these directives, application of biofuel mandates and arranging the legal regulations are significant steps in the being a member of EU for Turkey.

Bioethanol is used in Turkey by the legal regulations and some petroleum firms have just started using ethanol as anti-knock. On the other side; gasoline prices are really high in Turkey because of taxes, almost the highest price in the world. Therefore, bioethanol utilization should be considered as a fuel additive into gasoline to overcome high gasoline prices and decrease carbon emissions caused from gasoline.

Turkey has a wide potential for bioethanol production. Sugar beet is the major resource for bioethanol production in Turkey, followed by corn and wheat (USDA Turkey Annual Sugar Beet Report, 2016). Sugar beet is an important feedstock for the bioethanol production in Turkey. Because sugar beet is the most efficient feedstock to produce bioethanol among other sugar-based and starch-based feedstocks. Particularly, sugar beet cultivation is one of the most important sectors that provide employment to the farmers with high income opportunities. Isler and Karaosmanoglu (2010) mentioned that sugar beet is cultivated on about 32 million decares of land in Turkey. Only 20 to 25 percent of this area can be used with rotation planting. According to the new sugar system quotas, sugar beet may only be grown on about 3.5 million decares. As a result of this, the remaining land, an area about 4.5 million decares, can be used for energy agriculture in order to produce bioethanol. In 2015/2016; sugar beet is cultivated on 2.88 million decares except energy agriculture with the production of 16,632,000 tonnes according to USDA Turkey Annual Sugar Beet Report (2016). According to Republic of Turkey Ministry of Food Agriculture and Live Stock data; sugar beet is one of the products in which turkey is the leader in globally agricultural production. Turkey's sugar beet share is 6% in world's sugar beet production.

In bioethanol production extra sugar beets are not harvested for bioethanol production because bioethanol is derived by using molasses, that is a by-product of sugar production process from sugar beets. Firstly the sugar is extracted from beets, then the alcohol is remained in the molasses could be converted into ethanol. The molasses is also utilized as feed and as feedstock in the pharmaceutical industry, cosmetics, construction, alcoholic beverages and yeast. In other side, sugar beet pulp could be directly used or as a mixture with molasses for the feed sector. These by-products production increase correlated to beets production amount Annual molasses production amount generally does not change on a yearly basis and is determined as nearly 670,000 MT (USDA Turkey Annual Sugar Beet Report, 2016).

In 2006, bioethanol production was 1.4 million tonnes. Consequently, Turkey had a production potential of 2-2.5 million tonnes of bioethanol from sugar beet. (Isler and Karaosmanoglu, 2010). This production has raised to nearly 52 million liters with an sharp increase between 2012 and 2013. Total fuel bioethanol productions between 2011 and 2016 are given in (Table 2.6) according to Tobacco and Alcohol Market Regulatory Authority (TAMRA) as below.

Table 2.6 : Fuel bioethanol production statistics in Turkey (TAMRA, 2017).

Years	Fuel Bioethanol Production (liter)
2011	10,959,891
2012	11,062,518
2013	52,739,172
2014	78,025,859
2015	85,173,494
2016	91,799,547

Presently, there are three plants to produce fuel additive-purpose bioethanol with an established total bioethanol production amount of 92.42 million liters (EMRA, 2017 TAMRA, 2017). Çumra sugar and ethanol factory (Konya Sugar Incorporated Company), TARKIM (Agricultural Chemical Technologies Incorporated Company) and TEZKIM (Tezkim Incorporated Company) are still fuel bioethanol producers in Turkey. Fuel bioethanol production capacities for 2016 and feedstocks are shown in (Table 2.7).

Tarkim, which is the first E2 (2 percent ethanol and 98 percent petroleum) supplier in the liquid fuel sector (Isler and Karaosmanoglu, 2010). Tarkim and Tezkim have severally 63,1 million liters of annual bioethanol production capacity in 2016. Cumra annually supplys 29,05 million liters fuel bioethanol in 2016, which is 31.43% of the fuel bioethanol production in Turkey (EMRA, 2017).

Table 2.7 : Fuel bioethanol potentials for Turkey (EMRA, 2017; USDA Turkey Biofuels Report, 2009).

Bioethanol Plants	Establishment Year	Production Capacity (Million liters/year)	Feedstock	Production in 2016 (Million liters/year)
Cumra Bioethanol Production Plant	2007	84,000,000	Sugar Beet and Molasses	29,05
TARKIM	2004	40,000,000	Wheat and corn	34,82
TEZKIM	2007	40,000,000	Wheat and corn	28,30

Apart from other two plants; Pankobirlik is planning to build a new factory for producing fuel ethanol by using corn to meet the raising bioethanol demand in 2017 (USDA Turkey Annual Sugar Beet Report, 2016). Bioethanol production should be carried out due to ASTM D 4806 and Turkish Standards Institution (TSE) (Isler and Karaosmanoglu, 2010). Bioethanol producers has been contiuning activities under the umbrella of Bioethanol Manufacturers Association which was founded in 2006.

The agricultural products are sufficient to supply the necessary amount of bioethanol production for bioethanol blends. In addition, it is well known that the technology, capacity, and quality levels of bioethanol production plants could meet the demand (PETDER, 2012). Gasoline consumption is less than diesel consumption for the last years and hence, there is not expected to be any problems that ethanol blending to gasoline (PETDER, 2013). After these decisions on blending mandates which commercialize the bioethanol, bioethanol production and marketing sectors have been opened. EMRA has done its part with these regulations on blend mandates and has opened a new horizon in front of the agricultural industry and Turkey's agricultural sector. Besides, second and third generation biofuels researches would be able to begun to investigate and develop in our country.

2.4 Environmental Assessment

Environmental assessment is a significant proses that shows the environmental inferences of judgements that are considered before the judgements are made (IEA, 2015). Environmental assessment could be quite complex, especially when applied to broad policies, targets and large sector programmes. Where important existing negative effects are foreseen, a more exhaustive Environmental Impact Assessment (EIA) is needed to organize, containing full technical results and legal exposure (FAO, 2012). " Environmental assessment could be applied for each of projects, such as a dam, motorway, airport or factory, on the basis of Directive 2011/92/EU (known as 'Environmental Impact Assessment' – EIA Directive) or for public plans or programmes on the basis of Directive 2001/42/EC (known as 'Strategic Environmental Assessment' – SEA Directive)." All over the world, the most known rule of both two Directives is to obtain that strategies, programmes, targets, researches and projects likely to show important impacts for environment are made issue to an environmental assessment, before approve. Counsel with the people is a key property of environmental assessment processes. As stated in IEA reports; plans, programmes, strategies and targets which are organized for agriculture, forestry, fisheries, energy, industry, transport, waste/ water management, telecommunications, tourism, town & country planning or land use in the sense of the SEA Directive have to be supported, arranged and applied by an legal authority like as domestic, areal or national stage and be required by legislative, regulatory or administrative provisions and rules. Environmental assessment is mandatory for sustainability especially environmental sustainability as a necessity of satisfying clean production and consumption for all fields in worldwide. According to FAO, UN and IEA or other authorities; sustainability, energy and environment should be investigated under the same headline to contribute the increasing demand for studies in energy and sustainability areas although environmental assessment is critical and mandatory in many different areas. Therefore; environmental assessment studies, that are performed in area of energy, has been gaining importance day by day.

According to British Columbia (B.C.)'s Environmental Assessment Office (EAO) (2017); environmental assessment presents a complex procedur to identify and evaluate the crucial contrary environmental, economical, social, heredity and healthiness impacts of a targeted reviewable work. In this context; reviewable projects are defined as industrial based works, energy works, water administration projects, waste usage projects, mine projects, food processing projects, transportation projects. The assessment process concentrates to investigate significant projects for possibly contrary environmental, economic, social, heredity and healthiness impacts that could take place while the life cycle of those projects is applied.

Addition to definition and process steps of environmental assessment; determining GHG emissions draw attention as a significant step to make environmental assessment for selected processes such as mainly energy production and use, transportation and others when carrying out of environmental assessment is examined. Because today; global warming, is one of the most important environmental issues, that have a significant effect on energy policies and targeted-energy studies. Therefore, taking into global warming; the success of decreasing GHG emissions is one of the major drivers in energy technologies improvement. The bad impacts of GHG emissions on climate change have been recognized and investigated to make solutions for many a long day. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2007) pointed out that GHG emissions require to be decrease with 50-85% by 2050 to balance the amount of GHGs in the atmosphere. Given that non-renewable fuels utilized in transportation and heating and cooling systems are the major auxiliary to global warming (nearly 75% of total CO_2 emissions), one of the main significant aims will be to decrease emissions for that field (Elbehri et al, 2013).

There is a raising mindfulness that climate change is caused with anthropogenic emissions of GHGs that principally derive from the utilization non-renewable fuels. As mentioned before, transportation and fuel combustion has more share in GHGs due to increasing numbers of vehicles and consumptions of growing population. In the EU member points out as well as for another regions of the world, energy studies, strategies and targets are being improved that try to differentiate non-renewable fuels and/or ensure promoting the utilization of renewable energy resources. In many environmental and energy directives and legislations that target to increase the utilization of renewable energy resources and addition to other things promote to decreasing climate change and a sustainable improvement (Markevičius et al, 2010). As given in the previous sections, the directives or legal legislations in EU, US or another country has aimed to expand the proportion of renewable energy resources for energy utilization and specifically increasing constructive targets for biofuels in transportation from year to year. In the literatur, it has been also emphasized that the utilization of fossil based fuels effect the environment, particularly GHG emissions through the atmosphere, that leads to the greenhouse impact and temperature rising in many regions of world. Therefore, most of the countries, with a full concentration to investigate and develop renewable based fuels to decrease fossil fuel utilization. As a result of examining on renewable energy sources, especially there is an increasing biofuels demand for many areas of the world day by day. Besides, they also mentioned that international standards have been put to provide sustainable biofuel production and utilization considering environmental effects. Today, components that are the parts of sustainable bioenergy production processes should be investigated, analyzed and generated; even there is a growing biomass capacity based on forestry and agriculture for biofuel production on the other side. It is respect to great importance that managing the production and consumption processes of both biofuels and their feedstocks to ensure a sustainable supply in an environmental way considering environmental effects. Biofuel technology is viewed as one of the improving powers of sustainable energy production and green growth for today and future. They are new concepts aimed at focusing attention on sustainable development through the efficient use of environmental assets without decreasing economic growth. Sustainability of biofuel production process for low-carbon targets depends on continuity of feedstock supply without damaging environmental factors.

Biofuels, environmentally friendly fuels, are commonly referred to as liquid and gaseous fuels in transportation sector mainly produced from biomass (Lang et al, 2001). Within bioethanol and biodiesel are the dominant liquid biofuels for transport worldwide (Yan, 2012), bioethanol production has been carried out commercially in several countries for more than two decades as an alternative engine fuel or blend. Bioethanol production is carried out by using biomass is a solution to decrease both the dependence on petroleum and environmental contamination to attain low-carbon targets of countries. In the next decades, the proportion of bioethanol in the vehicle fuel market will extensive increasingly as the most prefered renewable alternative engine fuel due to significant benefits on environment such as increasing greenhouse gas emissions and air pollution, biodegradability, representing a carbon dioxide-cycle in combustion, higher combustion efficiency, low-carbon emissions and less unfavorable impacts on water and soil compared to other fossil fuels. Bioethanol is generally conceived preferable to non-renewable alternatives depend on their renewable structure; however, the environmental side of a outcome could be more complicated than that, and therefore a life cycle approach or any different approaches should be used to estimate existing profits (Miller et al, 2007). The environmental situation of bioethanol requires to be determined regarding a life cycle approach or a similar approach to show a total situation of existing advances and interchanges due to bioethanol is often considered sustainable since its renewable nature (Muñoz et al, 2014). Hence, environmental aspects of bioethanol should be investigated in detail to determine GHG emissions.

There are significant concerns regarding environmental assessment for bioethanol sustainability in many improved regions and cities. Results from IEA, WEC or other international organizations reports represent that bioethanol can suggest a sustainable and low-carbon choice to fossil resources, obtained that environmental safety and resource management guards are activated. All bioethanol technologies trade give a permission to rural development, providing additional income and employment advantages in developing regions, obtaining to the continuity of national sources and bioethanol, unionizing with GHGs emission and environmental aspects decreasing in a cheap and technical way and varying the world's energy demands. Concerning the climate change and decreasing GHG emissions are the main aims of bioethanol policy. It could be identified that the bioethanol industry should show the effect of lower GHGs. While plants get inside CO_2 from atmosphere for photosynthesis, which could correspond the CO_2 occured when fuel is combusted, CO_2 is also given into the atmosphere during the bioethanol production process. GHG emission assessments mainly consists of CO_2, methane (CH_4), nitrous oxide (N_2O) and halocarbons. All those gases are given into atmosphere during the whole-product life-cycle of the bioethanol beginning from the agricultural implementation (containing fertilizer utilization, insecticides, agrarian and others), the production and distribution process of bioethanol, and the last utilization and usage of by-products. For estimating GHG emissions reduction in utilization of bioethanol system, Life Cycle Assessment (LCA) is generally prefered. According to ISO 14040, an LCA is a "compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle." Other whole environmental aspects also could be estimated by using different approaches. LCA of bioethanol and sustainability of bioethanol production have an important relation to provide resource management, directing green-growth strategies and low carbon targets. In a LCA, whole input and outcome data for all levels of the bioproduct's life cycle consisting of biomass generation, feedstock storage, feedstock shipping, biofuel production, biofuel transportation and last utilization are needed. All of these steps directly effect the land, water and air pollution from the environmental perspective. Elbehri et al. (2013) emphasized that LCAs of the environmental effects of biofuel production and usage have had a extensive differences for results, besides existing of unintended bad environmental effects, due to the type of feedstock preferred and how it could be produced. LCA processes are defier because they need extensive information about whole process. Addition to LCA analysis, various empirical formulates or approaches have been also developed to estimate the GHG emissions or pollutants in the literature. Environmental aspects are evaluated and commented in the perspective of air pollution, water pollution and soil pollution according to quantity of pollutants are given out, such as CO, CO_2, particulate matter (PM), total hydrocarbons (THC), volatile organic compounds (VOC), sulphur compounds and dioxins. In LCA or other approaches to calculate GHG emissions or pollutants; there are different parameters that could differ the conclusions. There is a fine detail and changeability of GHG balances depend on the confusion or type of biomass energy systems and the sensibility of a extensive range of parameters. Important methodological topics are defined in Greenhouse Gas Calculation Methods Workshop Sustainability certification prepared for biofuels and bio-energy (2009); such as reference land use, indirect land-use, allocation, data input, time scale issues and uncertains in methodology, are used to estimate GHG balance.

As mentioned before; the most important GHGs are water vapor (H_2O), carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), due to the Environmental Protection Agency (EPA), 2017. Among from those; carbon dioxide has a crucial effect on increasing GHG emissions since it is widely GHG emission through atmosphere. EPA pointed out that nearly 82% of GHG emissions are sourced from CO_2 in US by 2015. One of the main CO_2 emission sources is transportation (second largest source) by the ratio of 32% in US total emissions and 26% in US GHG emissions. Increases or decreases in CO_2 emissions resulted from fossil fuel consumption are directly effected from various factors, containing population growth, economic development, fluctuations in energy prices, improvements on different technological tool, and seasonal situations. From 1990 to 2015, the rising in CO_2 emissions corresponded with expanded energy consumption for a developing economy, growing population and increased demand for travel. Also, transport and fossil fuel consumption based GHG emissions have been increased with a huge rate and CO_2 emissions have a large share among all GHG emissions according to IPCC (2007) Climate Change Report. CO_2 emissions sourced from fossil fuel combustion and industrial processes are nearly equal to 78% of the GHGs with an rising rate beginning from 1970 to 2010. Therefore, CO_2 emissions based on gasoline consumption and CO_2 emission decreases due to bioethanol utilization should be estimated to make the environmental assessment of bioethanol. In the terms of environmental assessment, CO_2 emissions are estimated for forecasted both gasoline consumption and bioethanol blended gasoline in this thesis.

2.5 Agricultural Economics and Resource Management

The agricultural economy and bioethanol economy have been grown rapidly during the last decades in a direct correlation. The first generation bioethanol economy, and its associated agricultural production, will be developed by many of the same factors over the past century. As a result of environmental advantages of bioethanol, it is expected that the share of bioethanol as fuel or blend in transportation market will expand rapidly in the next years. There are also several reasons for bioethanol to be considered as relevant technologies by both developing and industrialized countries.

There are a several researches for determining of existing effects belong to bioethanol improvement on agricultural economy in different cities or regions. International Food Policy Research Institute (IFPRI) (2006) pointed out that when the world leader biofuel producers widen own biofuel production depending on their existing "first-generation biothanol technologies" and aims, it will importantly scale up global costs of feedstock crops and other agricultural products. Biofuel or bioethanol improvement could also show important effects for the structure and distribution of agricultural production and commerce, poorness, and the prosperity of people (Brown Lester, 2007). Therefore farmes' income is expected to raise as a result of increasing for agricultural production and cost. In the utilization part, consumers of agricultural products can be exposed to the increases in food costs (Huang et al, 2004).

Agriculture and first generation bioethanol production have direct relation because of its feedstocks generally sourced from agricultural products. If feedstocks utilization to produce bioethanol is carried out in an uncontrolled way, food crisis, environmental issues or another problems could be occured. In bioethanol - agriculture relation, food crisis is seen as one of the biggest main problem. However (Zilbermann et al, 2012), the concern increased by the world food crisis for 2007/2008 and uncertainty belongs to environmental effect of bioethanol cause legal authorities to rethink their ideas and assessments correlated with bioethanol. They estimated and presented that complication of econometric calculation that generally comes at the cost of several assumptions in the processes underlying the interplay amongst the costs of engine biofuels (bioethanol) and correlated products. They analyzed connections between bioethanol and other biofuels and related commodities (agriculture and energy) with use of emprical methods. When the right connection is presented use of special models for bioethanol technology, there will be good strategic plans and right oriention in crisis period and other situations. Therefore, agricultural policies and agricultural economics strategies should be put into order to obtain sustainable feedstock supply considering human health, environmental issues and agricultural products. In this situation, resource management comes into the prominence to prevent environmental factors and agricultural outputs. The sustainable and commercialisation of bioethanol production depend on available correlation agricultural economics and resource management. Although government policies, target and mandates, and issues are necessary for energy security, environmental and socio-economic effects in expansion of bioethanol production; several challenges such as delays in biofuel strategy, feedstock choice, obligation on organising a strategy for the available management of by-products, some inadequacies and difficulties in technological part and its investment of bioethanol production, food and fuel conflicts, access to land, land use effects, water availability and quality, biodiversity loss are considered to plan agricultural economics strategies (Pradhan and Mbohwa, 2014). In this point, resource management in the terms of selecting proper feedstock and its utilization for bioethanol production will prevent the challenges in mainly lowest-economy-agriculture countries and other regions. Particularly; the most crucial challenge, food-fuel debate, could be prevented with applying resource management as long as first generation bioethanol production continues to be leader commercially.

Resource management in biofuel production can be defined as producing required amount of biofuels considering food demand, environmental effects, land productivity, water scarcity. In other words, resource management in biomass and agriculture is utilization of a country's natural resources by the most efficient and effective way.

Even as land expansion in production of biofuel resources is probably to have a crucial position for meeting raising demand in the last years, the intensification of land use should have to support with developed technological studies and management operations to provide sustainable production in the long term. Crop yield increases with existing land use have mostly been more critical and attractive in high-population-density economies in mainly Sub-Saharan Africa, Asia and Latin America (Hazell and Wood 2008; Cassman et al, 2005) where contain lowest-economy countries and other regions in world. Therefore, management operations are becoming more important and essential to provide meeting the demands on food and biofuel feedstocks and allocation in equitable way considering land use potential. The existing potentials of farm land production capacity are comparatively lower in most of the developing economies (Tilman et al, 2002) and although important amounts of yield in crop harvest globally and these outputs unfortunately could be lower in undeveloped and developing regions. This allocation also should be applied in developed countries to prevent food versus fuel debate or other potential problems.

Current output yields are still lower than their existing capacity for most areas (FAO, 2008) and these cultivable croplands could be seen as an advantage to meet increasing production demand on existing cropland. Implementation of other yield-upgrading applications or additives, such integrated food subtance (nutrient) and struggle with pests (or pest management), conservation tillage and irrigation, have not been succeed in crop production for developing countries (Evenson and Gollin 2003; FAO, 2008). Those auxiliary technologies could increase land productibility capacities and provide the products to be able to make available for other utilizations as biofuels. This kind of productivity expandings could also have advantages in the terms of preventing areas from deforestation, other ecological based destroyer economic utilizations (Prabhakar and Elder 2009), biodiversity and water sources. According to literature, it has been pointed out that heavy demand in biofuels supply causes both direct and indirect effects for land utilization. While the direct effects are changes in yields of biofuel raw material production, indirect effects are the yields of other crops production in the case of available investments to develop required infrastructure and technology, facilitate information access, increase experience and growth markets. The results of both direct and indirect effects on yields are directly related to distribution and management of resource or feedstock in biofuel production.

Resource management could be thought as sharing of sources among different areas (energy, food, etc.) coequally. However; not only land availability, also other factors such as food security or versus fuel, economic growth, water quantity and quality, biodiversity changes, GHG emissions, social impacts, national and local energy security and policies should be taken into account for resource management. It could be expressed that resource management is required to administrate the processes or challenges in these factors since these factors could be directly affected by the results of resource management.

Considering the foremost both social and technical impacts, food security receives the highest attention. In several countries food security problems could showed up even there are high-level agricultural production potentials (FAO, 2008). Even biofuels' impact on food security is seen as a significant problem defined by food and fuel dispute (Rosillo-Calle and Johnson 2010) major issue is not being enough crop production by lagging far below the actual agricultural production potential since insufficient inputs, technologies, investments and a support on small-scale cultivation (von Maltitz et al. 2009). This case points out that resource management is necessary for both production inputs and distribution of producted resources to prevent food crisis or food prices expansions. Although there are some examples about food prices, which increases due to biofuel expansion; it has been suggested that biofuels could not cause to food prices to rise in lowest-economy countries (Sapp, 2013). However, OFID (2009) stated that only new and additional land could not be enough to scale up the agricultural production and achieve the biofuel targets for developing regions. Surplus production is usable for biofuels production (particularly first generation biofuel) without harming the availability and changes in food prices. Resource management is again required to seperate the shares of surplus production and food necessity without effecting economic, social and energy balances of a country. At the same time, resource management could be utilized whether surplus production and agricultural investments or not. Even non-food based sources can be seen as alternatives due to food security, environmental advantages and other opportunities, however Gasparatos et al. (2015) discussed that both non-food sources and food based sources indirectly could be in a competition in the terms of cultivation area, water and other agrarian inputs utilization. Therefore, resource management planning should be carried out how sources are primary shared for food production or biofuel production or other uses. To reveal what the details and necessities of biofuels feedstock management and relations with food security; it should be considered that cultivation is carried out in poor rural-tried to developed-regions and thus, the household and domestic agricultural production characteristics and their dynamics should be examined. As mentioned by Sekoai and Yoro (2016); mainly lowest-economy countries and developing regions in world have considerable amount of regions that are primarily dependent on agriculture to sustain their lifes. This case makes land use more crucial for rural regions' livelihood and thus, it could be succeeded in food security and povery alleviation if the land is primarily utilized for people's food and other demands before use in biofuel expansion concentrating resource management. Escobar et al. (2009) put forward that the squares of agrarian area in global and thus, biomass production area should be seperately defined. It is thought that national or domestic food access and security are not effected in lowest-economies countries by biofuels expansion since biofuel feedstocks are competitor to export rather than domestic food consumption (Arndt et al, 2009). It could be expressed that resource management occurs by itself. Mohammed (2007) pointed out that production of biomass should not directly effect food security. In this context; increases in biofuel feedstock production cultivation should encourage and expand food crops harvesting. These kinds of effects of any resource on other one could be defined as a part of resource management. However, Woods (2006) thought that a great extent, mechansied generation of energy crops could not be suitable in several developing economies as a result of food security. High-quality-soils are particularly prefered for energy crop cultivation and not appropriate to produce food. Unfortunately, fine line seperating energy and agriculture from eachother in some African countries is still not clear. European firms have a debate on farmland to cultivate energy crops for different areas of the African countries. Initiatives from private companies are harvesting now, and these entrepreneurial investments are expected to continue for the next years (Amigun et al, 2011). Thus, resource management policies primarily are regulated and applied for developing-limited-resources regions in lowest-economy countries.

Nigam and Singh (2011) also emphasized that biofuels could just be advantageous when these are produced with a sustainable manner considering biological diversity and the dispute between food and fuel. Sustainability is one of the existing points in resource management. According to Bruinsma (2003), crop production will increase due to expansion of the arable lands, which in turn guides to an expansion in cultivated area and yield increase. It is clear that crop production could be carried out in a sustainable way due to arable land expansion in developing regions, who have arable land expansion much less than they have in the past.

With the optimum states; conservation tillage, crop conversions and another developed management applications could help to reduce adverse effects and eliminate environmental bad effects with increased biofuel feedstock production. It means that available agricultural policies-the first stage of resource management-will take away the unfavorableness in food and biomass production. Further, the feedstock production process requires water. During the planning of resource management, water consumption should be considered, and potential effects on water resources should be included. Many sugar production areas of southern and eastern Africa are trying to operate around hydrological limits of the river potential. Major key factors for increasing biofuel feedstocks production are the access to water sources and land-tenure systems conforming with commercialized production systems (FAO, 2008). Due to data in FAO report (FAO, 2008); Near East and North Africa is reaching their potential. On the other side, South Asia and East and Southeast Asia are rich in terms of water sources, even their irrigated harvesting lands are so little for extra irrigated cultivation. Furthermore; although Latin America and Sub-Saharan Africa have suitable area for irrigation, the limited share of their potentials are still using. In the book edited by Bruinsma (2003); when investigated projections include some expansion about informal irrigation which is crucial in Sub-Saharan Africa. Addition to changes in irrigated lands; increases in biofuel crops production will directly effects both water quality and quantity. Water sources are so crucial and limited factor in lowest-economy countries. Thus, water use efficiency should be considered and coordinated evaluating or calculating these transition countries' water supply since resource use efficiency and its management are correlated to water abundance and irrigated agricultural lands. Addition to food security, water supply and land use; biodiversity should be examined. Several agricultural resource management researches for feedstock production could exhibit different effects on biodiversity.

For resource management, also social impacts should be taken attention in the term of particularly rural development and poverty alleviation. Biofuels could potentially give advantages for rural development and poverty reduction by bring in money with employment or selling of feedstock from smallholders (Gasparatos et al, 2012). Production capabilities and capacities of lands could determine the resource supply of regions or countries through give benefits for rural development and urbanization. For the best management in resource supply and distribution, rural development and their demands can not been ignored. Rural development and poverty alleviation have been also preserved and supported with national and domestic policies and targets. Amigun et al. (2011) stated that in order for biofuel plans to be appropriate and applicable, the rural living conditions should be taken into account. Feedstock supply could increase due to blends/ mandates/policies or targets of countries and; while expanded resource production is bringing economical and social simplicities, the welfare level is growing up. Resource management supports and require well-organized feedstock supply and thus, expanded feedstock production could give advantages in the terms of employment and personel income to domestic rural households. Correlated to rural and country development, resource management is also necessary in order to preserve domestic resources and increase their potential in the context of national and local energy security. Utilization of existing national resources and increasing their capacities could provide opportunities on national energy security. In terms of national energy supply and its security, forecasting of feedstock supply is one of the main keys of resource management in particularly lowest economy countries. In order to plan the land use and its efficiency through providing food security, the productivity capacities of countries should be known and predicted in a feasible way. Therefore, forecasting studies and selected models are so significant and necessary for feedstock production planning and resource management process to provide sustainable both food and biofuel supply. A number of developing economy countries are trying to reach high-levels of biofuel production and available feedstock suppliers. For this, proper resource management process is determined and applied to allocate the resources in a best way.

2.6 Forecasting

Forecasting is a process of making statements on future events using historical data. Forecasting is an important subject for scientific research which contains business and industry, government, economics, environmental sciences, medicine, social science, politics, and finance (Montgomery et al, 2008). The increasing worldwide demand for energy requires development of skillful forecasting methods and algorithms. Today, forecasting and energy modeling on different areas such as biobased energy technologies are very common research area among engineers and scientists concerning the energy production, consumption and problems. Forecasting reserch and development studies in biofuel production help to understand the capacity of a country or an area, so preparing policy makers for possible future outcomes and opportunities, such as the financing, resources, use of new production technologies or environmental effects. However, if the information level is insufficient, a forecasting couldn’t be strong enough; also, the information must be suitable and useful to make modeling without trouble.

2.6.1 The structure of forecasting

Forecasting requirements of today's organizations are categorised into short-term, medium-term and long-term, although there are many different areas requiring forecasts (Makridakis et al,1998). Short-term forecasting approaches contain predicting events only a few time periods like days, weeks, months for future. Medium-term forecastings expand from one to two years into the future. Long-term forecasting approaches could extend for years. Short- and medium-term predictions are generally prefered on situations which range from operation administration to budgeting and election innovative research and improvement designments. Long-term forecastings have an important effect on strategical projections. The base of short- and medium-term forecasting is identifying, modeling, and extrapolating the patterns found in historical data (Montgomery et al, 2008). Econometric modeling and forecasting approaches could be investigated into four classes with another categorization:

- Models utilized for estimating connection amongst illustrative and dependent variables for a certain period of time, associating economical processes;
- Models that point out correlations amongst the past and current values, and predict future events depending on only historical results;
- Cross sectional methods which resolve correlations amongst different variables for any point in time for various units;
- The last one that regard relations amongst dependent and independent variance in various units in progress of time (Verbeek , 2004).

Forecasting studies include the use of time series data. Time series defined as a time-oriented of observings for a interested variable. Several business implementations of forecasting use daily, weekly, monthly, quarterly, or annual data, but any reporting time can be utilized (Montgomery et al, 2008).

There are different kinds of prediction models but the most mainly prefered are regression models, smoothing models, and general time series models (Montgomery et al, 2008). The relations between related variable and one or more determinative variables are utilized when regression method is used for forecasting (Birkes and Dodge, 1993). In smoothing methods present a basic function of previous observations to make a forecast of the interested variable (Montgomery et al, 2008). In general; time series models are prefered to specify a formal model using the statistical properties of the historical data and also calculate the unknown parameters of this model by least squares (Montgomery et al, 2008; Fox, 1997).

2.6.1.1 Forecasting process

A process is a series of interrelated activities that transform one or more inputs to one or more outcomes. Whole activities are carried out in process, and prediction is no exemption. The steps of forecasting process are given in (Figure 2.6).

Problem definition contains development understanding of how the forecast could be used according to user of the forecast. This is the most difficult aspect of the forecaster's task. A predictor has a major agreement of study to availably describe the forecasting problem, before any answers could be obtained (Makridakis et al, 1998). *Data supply and collection* (*or gathering step*) step includes of providing the related background for the variable(s) that will forecast, containing historical knowledge on existing predictor variables (Montgomery et al, 2008).

Data analysis, another significant preliminary step, is the determination of the prediction model which is to be utilized. In this step, time series plots of the data have to be schemed and controlled for cognizable patterns, such as trends and seasonal or other cyclical constituents. Determining or selecting one or more prediction model and best-fitting the approach to the data carried out in model selection and fitting step. Variables of model are determined in determining variables of method step. Examining of the forecasting method for showing and determining how it is likely to perform in the targeted implementation carried out in method validation step. Following validation step, forecasting model deployment step contains taking the model and the conclusing forecasts in use by the customer. The last step, determining forecasting model performance should be an undergoing process later the model has been deployed to guarantee that it is still performing perfectly (Montgomery et al, 2008). The performance of the method could only be availably assessed later data for the prediction period have become favorable (Makridakis et al, 1998).

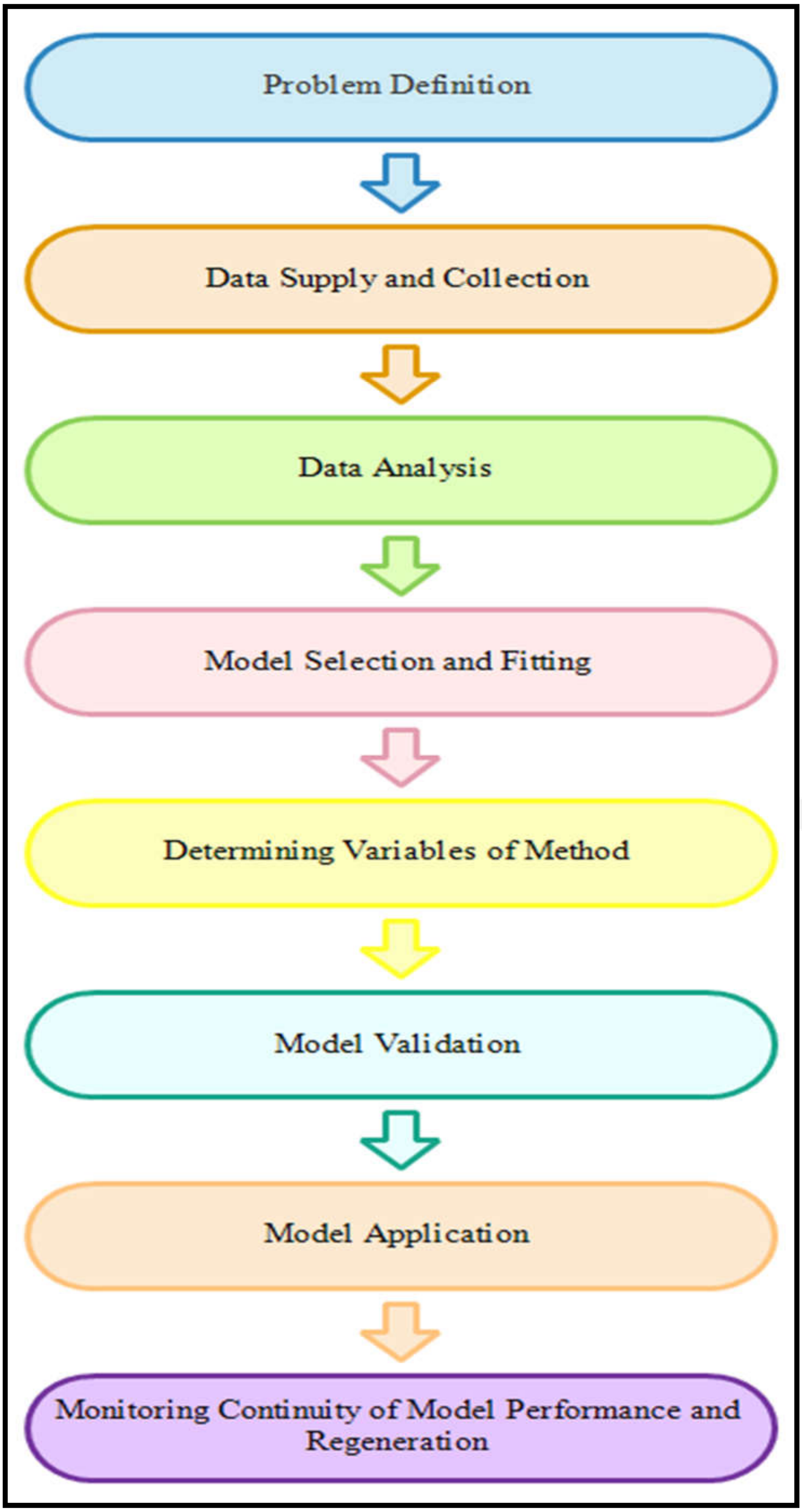

Figure 2.6 : Forecasting Process, adapted from (Montgomery et al, 2008).

2.6.1.2 General approach to time series modeling and forecasting

Modeling and forecasting of the time series performed according to the basic rules. Knowing those basic rules provides the better understanding of forecasting and modeling. The basic steps of time series modeling and forecasting are presented in (Figure 2.7) (Montgomery et al, 2008). The main target of the time-series approach is to seperate the noise from the pattern of a real process. This is carried out in two phases. First phase is called *'time-series analysis'* whose aim is to find the properties of the real process production the series. This is performed by the usage of either autocorrelation or spectral approaches. The second phase contains various classes of models that could be categorized into autoregressive/moving average, transfer function, filtering, exponential smoothing and decomposition (Makridakis, 1976).

In ideal prediction, the output $\big(y(t)\big)$ is becoming $x(t+\tau)$ that is the value of input τ times after, while the input of system is $\big(x(t)\big)$. According this, conversion rule relating to ideal prediction expressed as in equation 2.1 (Bir, 1975):

$$y(t) = x(x+\tau) \tag{2.1}$$

An ideal predictor is a linear, time invariant and a stable system system but it is not causal thus ideal prediction is impossible.

In modeling and forecasting, time series should be stationary. Judging from theoretical perspective, development of stationary and stochastic or namely random time series will be more easier because of computing of stationary models requiring less effort compared to others. This situation could be explained with first 2 moments of time series not changing within time. The most important property of stationary time series is that probability distribution is time-independent. Mean value and variance don't change in stationary time series which has no trend and seasonal effects. However some stationary time series include long-term trend. Generally; in time-series analysis, the series is accepted as stationary although they are quasi-stationary. Therefore, non-stationary time series should be transformed to stationary time series and then should be modeled using various models. It is impossible to carry out an exact forecasting because to be contrary to the principle of causality.

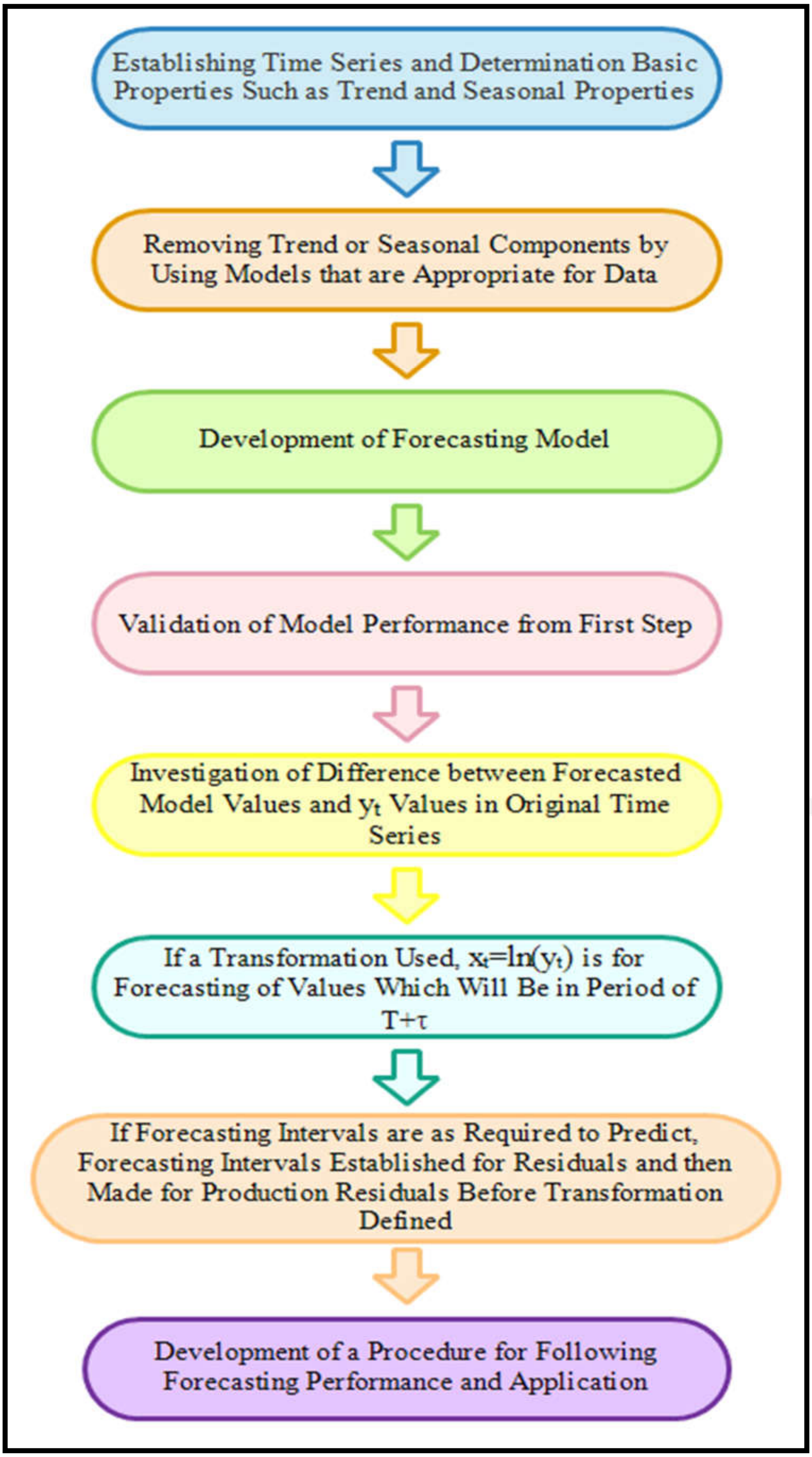

Figure 2.7 : Modelling and forecasting process of time series, adapted from (Montgomery et al, 2008).

2.6.2 Forecasting with linear models

According the Wold Decomposition Theorem; any stationary process can be modelled as an ARMA model. It is considered that the problem of forecasting the values $X_{n+h}, h > 0,$ of a stationary time series with known mean (μ) and autocovariance function (γ) in perspectives of the values $\{X_n, \dots, X_1\}$, up to time (n). The purpose of prediction in linear systems is to determine the linear integration of 1, $X_n, X_{n-1}, \dots, X_1$, which prediction X_{n+h} with minimum mean squared error. The optimal linear forecaster in terms of 1, $X_n, X_{n-1}, \dots, X_1$ will be identified by $P_n X_{n+h}$ and frankly has the style as in 2.2 (Brockwell and Davis, 2002):

$$P_n X_{n+h} = a_0 + a_1 X_n + \cdots + a_n X_1 \tag{2.2}$$

In this equation; n is time, P is the process that will be predicted, a_1, a_2, ..., a_n points the autoregression coefficients, X_{n+h} is predicted value.

P process, that will be forecasted, can have a linear internal dynamics. Linear systems are matter of *Digital Signal Processing* (DSP) theory. *DSP* could carry out linear and time-variant operations on the signal and also perform these by using filters. Therefore; filter design and analysis are the basic subjects of DSP. Filters divided as two major classes as Finite Impuls Response (FIR) filters and Infinite Impuls Response (IIR) Filters. FIR filters take convolution of input signal with coefficients vector $\{\beta i\}$ that belongs to filter. Filter answer is barely different from zero for $q+1$ steps, when impuls signal applied to filters. Therefore this, these filters called as FIR filters and characterized numbers of $q+1$ coefficients. For IIR filters, input signal (*u[t]*) effecting output signal (*x[t]*) directly at any t time. On the other hand, *x[t]* is directly connected to weighted sum of previous values. Although impuls function and $\{\alpha_i\}$ vector have values different from zero, filter answer could be different from zero forever. So; these filters are defined as IIR filters.

Digital Signal Process uses three basic models :

- Auto-Regressive (AR) Model
- Moving Average (MA) Model
- Auto-Regressive Moving Average (ARMA) Model

Regression analysis is another important method to make forecasting in linear systems. In this statistical based method, forecasting is carried out by mathematical modeling of relation between predictor variable and output variable of regression analysis. Although the forecasting studies had been carried out using regression analysis up to 1927; then improvement methods has been emerged. Heuristic methods are used in this thesis study.

Forecasting models like AR Model, MA Model and ARMA Model, that are performed as linear forecasting model approaches, are given begining from regression analysis in detail below.

2.6.2.1 Forecasting and regression analysis

Regression analysis is a statistical based method which is used to determine correlation between two or more variables and to make predictions about that subject using this correlation. In regression solution, mathematical model created to explain the relation between two or more variables and then this mathematical model is defined as regression model (Birkes & Dodge, 1993). Basic regression model has one predictor variable and written as in equation 2.3:

$$y = \beta_0 + \beta_1 x + \varepsilon \qquad (2.3)$$

In this model, x and y showing predictor variable and answer of model respectively, pointing unknown parameters, ε is a symbol of error term. β_0 ve β_1, called as regression coefficients or model parameters, have physical meaning. β_1 measuring change that will occur in variable (y) which is the answer of change in predictor variable (x) (Montgomery et al, 2008).

Regression models generally include one or more predictor variables. Multiple linear regression models for numbers of k predictors implied as in equation 2.4:

$$y = \beta_0 \,.\, \beta_1 x + \beta_2 x_2 + \cdots + \varepsilon \qquad (2.4)$$

Regression models are used for two different situations in the subject of making forecasting or prediction. First is the sum of all data on y and then all answers are in one-time period. Data is summed in determined working time and these data don’t change. That kind of regression data are named as cross-section data. Second one is situation that regression model has time series data (Montgomery et al, 2008; Alma and Vupa, 2008).

Unknown parameters $(\beta_0, \beta_1, \beta_2, \ldots, \beta_k)$ in linear regression model are estimated by using least squares method. In addition to this; least squares method is used to remove trend and seasonal effects in model adjustment step (Alma and Vupa, 2008).

2.6.2.2 Auto-Regressive (AR) model

Auto-Regressive (AR) model is a simple approach that prefered on the strength of effective algorithms for determining model parameters (Cohen, 1986). It is the first time that AR model formulized by G.U. Yule (1927). Until today, lots of preliminary studies in time series area are estimation of parameter, control of model accuracy and also forecasting (Newbold and Bos, 1983). An extremely useful and intuitively appealing extension of regression involves a group of models called as the AR models. Generally it is prefered that most stationary time series approximated as either a moving average or an autoregressive model (Gottman, 1981).

Any observation at time (t) is predictable (to within an un-autocorrelated residual with zero mean and fixed variance) from a weighted sum of the previous observations (p) [called an AR (p) process]. In other words, the series is predictable from its immediate past:

$$(x_t - \bar{x}) = a_1(x_{t-1} - \bar{x}) + a_2(x_{t-2} - \bar{x}) + \cdots + a_p(x_{t-p} - \bar{x}) + e_t \tag{2.5}$$

In this equation 2.5; t is time, p is the order of the filter, a_1, a_2, ..., a_p points the autoregression coefficients, e_t is prediction error term, x_t is predicted value, $\bar{x}$ is mean value.

Where e_t has a variance σ_e^2, has zero mean, is uncorrelated with e_t, for $t' \neq t$, as a consequence, is more generally uncorrelated with the past; that is, $cov[x_{t-1}, e_t]$ is zero for all $k > 0$. In AR process, a random signal $(y(t))$ is stated as a integration of predecessor variables before time t and white noise does not have any correlation with signal but noise of the signal which has a constant spectral power density. The autoregressive model above is generally formulized with the deviations from the mean, $\bar{x}$ assumed as in equation 2.6:

$$x_t = \sum_{i=1}^{p} a_i x_{t-i} + e_t \tag{2.6}$$

In this equation, a_i is the autoregression coefficient, x_t is the series under investigation (or current value of an objective variable), and p is the order (length) of the filter which is generally very much less than the length of the series. Coefficients a_i in equation are computed by using Yule-Walker Method. n called as model order. (Gottman, 1981; Thie, 1981).

As in the finite order MA processes, an approach to modelling that time series is to accept that the additives of the disturbances that are method in the past should be little contrasted to the new disturbances that the process has tried. Because of the disturbances are independently and identically distributed random variables, it could be basicly assumed that a set of infinitely many weights in declining magnitudes representing the decreasing values of additives of the disturbances in the previous (Montgomery et al, 2008).

The first-order autoregressive process is shown as in equation 2.7:

$$x_t = a_1 x_{t-1} + e_t \tag{2.7}$$

Autocorrelation coefficient calculated by multiplying this equation by x_{t-k} and then taken expected values of both sides of the resulting equation as in 2.8 and 2.9:

$$x_{t-k} x_t = a_i x_{t-k} x_{t-1} + e_t x_{t-k} \tag{2.8}$$

then;

$$\operatorname{cov}(x_t x_{t-k}) = a_1 \operatorname{cov}(x_{t-k}, x_{t-1}) + \operatorname{cov}(x_{t-k}, e_t) \tag{2.9}$$

The covariance between e_t and $x_{t-k}$is zero because x_{t-k}depends on only on e_{t-k}, e_{t-k-1},…, which are not correlated with e_t as long as $k > 0$. Therefore, it is taken:

as in equation 2.10:

$$\gamma_k = a_1 \cdot \gamma_{k-1} \tag{2.10}$$

Dividing through equation by γ_0 and moving from the definition of autocorrelation in equation 2.11;

$$\rho_k = \gamma_k / \gamma_0 \tag{2.11}$$

gives the result as in equation 2.12:

$$\rho_k = a_1 \,.\, \rho_{k-1} \tag{2.12}$$

For $k = 1$ this reduces to and shown as in equation 2.13:

$$\rho_1 = a_1 \,.\, \rho_0 = a_1 \tag{2.13}$$

since $\rho_0 = 1$ and then for $k = 2$ as in equation 2.14;

$$\rho_2 = a_1 \,.\, \rho_1 = a_1(a_1) = a_1^2 \tag{2.14}$$

For $k = 3$ as given in equation 2.15;

$$\rho_3 = a_1 \,.\, \rho_2 = a_1(a_3^2) = a_1^3 \tag{2.15}$$

And in general as in equation 2.16;

$$\rho_k = a_1^k \tag{2.16}$$

This means that the autocorrelation function of an AR(1) process does not truncate as was the case for an MA(1) process.

The significant fact on AR models is that it is possible to provide a simple set of linear equations that expresses the parameters of the model in the perspective of the autocorrelations and variance of the data. These linear equations defined as Yule-Walker equations.

The derivative or development of these important equations is done easily. In the first step, write the general AR (p) model as in equation 2.17:

$$x_t = a_i(x_{t-1}) + a_2(x_{t-2}) + \cdots + a_p(x_{t-p}) + e_t \tag{2.17}$$

where once again it is assumed that x_t is a zero-mean process (or that the mean has been subtracted) and that e_t is a white-noise process and that $\mathrm{E}(x_{t-k}) = 0$ for k>0. Once again, compute $\gamma_k$as in equation 2.18:

$$\gamma_k = E(x_t \cdot x_{t-k}) \tag{2.18}$$

This time a different trick is used; it is susbstituted that only the expression in equation (2.18) for x_t and leave x_{t-k} alone in equation 2.19:

$$\gamma_k = E(x_t x_{t-k}) = E\left[\left(a_1(x_{t-1}) + a_2(x_{t-2}) + \cdots + a_p(x_{t-p}) + e_t\right)x_{t-k}\right] \tag{2.19}$$

it is reorganized and shown as in equation 2.20;

$$\gamma_k = a_1 E(x_{t-1}x_{t-k}) + a_2 E(x_{t-2}x_{t-k}) + \cdots + a_p E(x_{t-p}x_{t-k}) + E(e_t x_{t-k}) \tag{2.20}$$

Let us consider equation (2.20) carefully. From the definition of the autocovariance γ_k of a stationary process, it is a function only of the lag between observations, not their starting point. Thus,

$$\gamma_k = E(x_t x_{t-k}) = E(x_{t+s} x_{t+s-k}) \tag{2.21}$$

For any value s, since $(t + s - k) = k.$ We can use this fact to simplify equation (2.21) to obtain :

$$\gamma_k = a_1(\gamma_{t-1}) + a_2(\gamma_{t-2}) + \cdots + a_p(\gamma_{t-p}) + E(e_t x_{t-k}) \tag{2.22}$$

For $k > 0$ it is known that the last term is zero. Therefore, for $k > 0$ it becomes as in equation 2.23:

$$\gamma_k = a_1(\gamma_{k-1}) + a_2(\gamma_{k-2}) + \cdots + a_p(\gamma_{k-p}) \tag{2.23}$$

If it is divided by the variance of the series $\gamma_0 = \sigma_x^2$ and recall the definition of the autocorrelation $\rho_k = {}^{\gamma_k}/_{\gamma_0}$, Yule-Walker Equations can be obtained as in equation 2.24:

$$\rho_k = a_1(\rho_{k-1}) + a_2(\rho_{k-2}) + \cdots + a_p(\rho_{k-p}) \tag{2.24}$$

Second order autoregressive process is expert of representing processes whose spectral density function has one peak. This process explained as a simple extension of autoregressive models to the case where the form of the autoregression extends back two points in time rather than just one. AR (2) processes investigated dividing into four types. That four types are distingusihed by different forms of the autocorrelation function.

This process is presented as in equation 2.25;

$$x_t = a_1(x_{t-1}) + a_2(x_{t-2}) + e_t \tag{2.25}$$

where once again, the x_t are deviations from the mean or are a zero-mean process, the e_t involve an innovation process uncorrelated with observations previous to x_t, and the e_t are independently distributed with constant variance σ_e^2.

The Yule-Walker equations for the AR(2) could be shown as in equation 2.26 and 2.27:

$$\rho_1 = a_1 + a_2\rho_1 \tag{2.26}$$

and;

$$\rho_2 = a_1\rho_1 + a_2 \tag{2.27}$$

However, statistical problem occurs in estimating model order namely determining delay numbers of variables in AR model. Forecasting isn't consistent when model order selected smaller than need to be, and in contrast to this, variance of parameter forecasting is high in the situation of selecting higher model order than need to be. Results obtained from model aren't reliable both in two cases. Delay numbers of model variables should be determined in a flawless manner to generate model that giving reliable and right results (Shibata, 1976). The most likelihood method, that used in model order selection, always determining the greatest possible degree for model. Therefore, dimension choosing with this method causing incorrect results. Generally forecasting error decrease with increasing model orders monotously. Therefore, optimal model order selection is a problem. An extension of the maximum likelihood principle is suggested by H. Akaike (1974) for the slightly more general problem of choosing among different numbers of order. According to this method, choosing realized among different models with the different numbers of parameters. This method estimates the likelihood function of every model and chooses the model, which likelihood function value is maximum, as the most appropriate model (Schwarz, 1978). The common used of this kind of model order selection criterias are '*Akaike Information Criteria*' (AIC), '*Schwarz Information Criteria*' (SIC), and '*Final Prediction Error*' (FPE). In this study; two of them used and first one, FPE, showed as for an autoregressive model as in equation 2.28:

$$FPE_n = \sigma_x^2 \left(\frac{N+n-1}{N-n-1} \right) \tag{2.28}$$

In these equation, N points the data length, n is the order of auto-regressive model and σ_x^2 is variance of forecasting error. Second, AIC shown as in equation 2.29:

$$AIC = \ln\left(\hat{\sigma}_x^2\right) + \left(\frac{2n}{N} \right) \tag{2.29}$$

The second term of this equation causing AIC to expand, otherwise first term is decreasing monotously (Mitra and Kaiser, 1993). The other model order selection criterias are classified as Hannan-Quinn Criterion, Schwarz Information Criterion and Bayesian Information Criterion.

2.6.2.3 Moving Average (MA) model

Moving Average (MA) models that generate new serie by calculating moving average of original serie. They prefered for the purpose of removing white noise from time series and clarifying trend. The new serie is a smoothed version of original time serie. Generally, MA model used with AR model, called as ARMA, instead of using stand-alone.

One way to alter the effect of previous data for the mean as a prediction is to indicate in the beginning only how many old investigations will be included in a mean. The word or term, moving average, is defining that process by reason of every new observation becomes proper, a new mean could be calculated with dropping the primordial observation and containing the newest one. That moving average will then be the prediction in future (Makridakis et al, 1998).

Compared with the simple mean, the moving average of order (k) has the following properties (Makridakis et al, 1998):

- It deals only with the latest k periods of known data,
- The number of data points for each window are not changing with time.

But moving average also has the following defects:

- Moving averages need storage as the result of all of the $k$latest observations must be stored, not just the average,
- It has no ability to manage trend or seasonality successfully, however it could perform compared to the total mean.

In the situation of the data series have trend and seasonability, neither the mean as a forecast nor an MA forecast is appropriate.

MA model expressed as in equation 2.30 (n is model order) :

$$y(t) = \sum_{i=1}^{n} b_i e(t - i\Delta t) + e(t) \tag{2.30}$$

Moving average model is a kind of Finite Impulse Response (FIR) filter.

Moving average obtains a basic model to smooth the *"past history"* data. It considered that various straight forward moving average methods, cantaining basic moving averages, double moving averages, and weighted moving averages. For whole cases the main propose is smoothing past data to compute the trend-cycle component. The term, moving average, is utilized because each average is estimated by throwing away the earliest observation and containing the future observation. The averaging moves through the time series until the trend-cycle is computed at each observation for which all elements of the average are available. The number of data points in every average is constant and is centered on the observation for which the trend-cycle determination is calculated. Smoothness of resulting estimate is directly effected from the number of points included in a moving average. Also; determining the appropriate length of a moving average is an significant process. Generally it is accepted that a larger number of terms in the moving average raises the probability that randomness will be sifted (Makridakis et al, 1998).

A first-order moving-average process, written as MA(1), has the general equation as in equation 2.31:

$$x_t = e(t) + be_{t-1} \tag{2.31}$$

Where e_t is a white-noise series distributed with constant variance σ_e^2. b is parameter in this equation.

A moving average is a weighted sum, with any set of weights choosen; they need not add to unity. MA(1) process has only one zero autocovariance, the one at lag 1, which can be shown to be in equation 2.32:

$$\gamma_1 = b\sigma_e^2 \tag{2.32}$$

A second-order moving-average process, MA (2) process shown as in equation 2.33;

$$x_t = e(t) + be_{t-1} + be_{t-2} \tag{2.33}$$

e_t is showing white noise and using these basic equations for autocovariance function γ_k, truncates after lag q in the q th-order MA process as shown in equation 2.34 and 2.35 (Gottman, 1981):

$$\sigma_x^2 = \left(1 + b_1^2 + b_2^2 + b_3^2 + \cdots + b_q^2\right)\sigma_e^2 \tag{2.34}$$

and;

$$\gamma_k = \sigma_e^2 \sum_{s=0}^{q} b_s b_{s-k} \tag{2.35}$$

2.6.2.4 Auto-Regressive Moving Average (ARMA) model

AR models could be effectively combined with moving average (MA) models to generate a common and appropriate or beneficial type of time series models named as autoregressive moving average (ARMA) models. This method could be used in the situation of datas are stationary (Makridakis, 1998). As the result of a large class of autocovariance functions ($\gamma_x(\cdot)$); it is possible to find an ARMA process $\{X_t\}$ with ACVF $\gamma_x(\cdot)$. Especially; for any positive integer K, there could be an ARMA process $\{X_t\}$ such that $\gamma_x(h) = \gamma_h$ for $h = 0,1,2,\ldots,K$. According to this (and other) reasons, the concept of ARMA processes have an important impact in the modeling of time series data (Brockwell and Davis, 2002).

Yule (1927), Walker (1931) and Slutsky (1937) introduced the concept of autoregressive/moving averages schemes. Yule done an approach, then Walker expanded this approach and produced general autoregressive model. After these works, Slutsky put forth moving average model equation. Wold's work proved the theoretical validity of the method and devised general representation for time series.

Wold's contribution and approach in this field is the most important and he should be thought the establisher or founder of ARMA models. On the estimation side, Wold did not have much contribution, but Kolmogoroff (1941) suggested general solutions to the smoothing and prediction problem. Whittle (1953) extended the concept of ARMA models to cover multiple time series, while Durbin (1959; 1960), devised efficient methods of computing the AR and MA parameters. Durbin and Levinson improved Durbin-Levinson algorithm to compute coefficients recursively using algorithm equations in the situation of predicting a stationary series with nonzero mean (Brockwell and Davis, 2002). Then, Walker (1962) extended the result to mixed ARMA schemes.

Jenkins and Watts (1968) and Box and Jenkins (1970) proposed models which have ability to deal with seasonal series, devised efficient computational formula for digital computers and provided procedures to deal with any kind of series, whether stationary or not. Box and Jenkins have important influence to improve ARMA models other than scientists. Depend on this reason, together with the purely theoretical contributions, has resulted in their name being used synonymous with autoregressive and moving-average models. However, Box and Jenkins have been neither the originators nor the most important contributors in this area. Box and Jenkins method or procedure carried out in two stages by utilizing autoregressive/moving-average schemes. The first stage includes a general class of model named as integrated autoregressive moving-average schemes. The models easily applied to any seasonal or non-seasonal data as well as stationary or non-stationary series. The second step is to use for identfying an adequate model to be fitted into the series by using an autocorrelation and partial-correlation functions (Makridakis, 1976).

ARMA model with higher-order terms is shown as in equation 2.36;

$$Y_t = c + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \tag{2.36}$$

In this equation, Y_t depends on previous Y_{t-1} value and one previous error term e_{t-1}. Also; $c, \emptyset$ and θ are constants, while e_t is white noise process. The series has been accepted stationary for the mean and variance. The same parameter limitations apply here as for pure AR and pure MA models (Makridakis, 1998).

The most of the time series include both AR process and MA process. Model showed as ARMA (p, q) model that has p is theorder of autoregressive part and q is the order of moving average part. ARMA including the AR (p) process which implies the relation of p-th delay of time series with itself, and also MA (q) process is one of the smoothing methods of error terms and showing the relation between previous and current value of error terms.

Wold decomposition theorem used in ARMA model. According to this theorem, linear or non-linear time series, whose mean value is zero, could be decomposed into deterministic and non-deterministic as shown in equation 2.37.

$$x_t = z_t + u_t \tag{2.37}$$

Linear deterministic component (z_t) is modeled with linear relations among past values. Indeterministic component (u_t) could be modeled with moving average of white noise as in equation 2.38 and 2.39.

$$z_t = \sum_{i=1}^{\infty} a_i z_{t-i} \tag{2.38}$$

and;

$$u_t = \sum_{i=1}^{\infty} \beta_i e_{t-i} \tag{2.39}$$

In Wold decomposition theorem, every stationary process could be modeled as auto-regressive moving average model. Firstly, that is considered that special case $(M[|y_t|^2] = d^2 = 0)$ that is the same as $\lim_{n\to\infty}\left(\dots, y_{t-1}^{(n,0)}, y_t^{(n,0)}, \dots\right) = (\dots, 0, 0, \dots)$.

In this theorem, the sequence $\{x_t\}$ is deterministic, the interpretation of this term being as follows: Given the sequence $\{x_t\}$ for all time points up to and including $t - 1$, we may, by the use of a finite number of the given values, predict x_{t+k} with any accuracy; i.e., with a residual error of arbitrarily small variance. This situation could be shown by induction. In fact, it is supposed that it is possible to predict each of $x_t, \dots, x_{t+k-1}$ in such a way that the prediction error has a variance $< \epsilon$, where ϵ arbitrarily prescribed. When letting $\delta > 0$ be arbitrary, it could be a formula of type which predicts x_{t+k} in terms of the exact values x_{t+k-1}, x_{t+k-2},… and which gives a residual variance $\delta/(k + 1)$. Replacing here x_{t+k-1},…,x_t by values so predicted that the residual variances are less than $\delta/(k+1)\left|a_1^{(n,0)}\right|, \ldots, \delta/(k+1)\left|a_k^{(n,0)}\right|$, it is seen that the total error of will have a variance $< \delta$.

We keep on the general case, $d^2 \geq 0$. According to the above analysis, y_t is that part of x_t which cannot be linearly predicted from the previous observations $x_{t-1}, x_{t-2}, \ldots.$. Namely, eachtime point *t* brings in an unpredictable, random-like element y_t in the series $\{x_t\}$. Now while from ($M[y_t\bar{x}_{t-k}] = 0, k = 1,2, \ldots \ldots$) y_t is uncorrelated with the previous observations $x_{t-1}, x_{t-2}, \ldots.$. Therefore, the unpredictable element y_t may be regarded as effecting $x_{t+1}, x_{t+2}, \ldots.$ of the series $\{x_t\}$. To understand and investigate this effect it is proceeded as follows.

It is approximated x_t linearly in terms of $y_t, y_{t-1}, y_{t-2}, \ldots., y_{t-n}$, writing as in equation 2.40:

$$x_t = b_0 y_t + b_1 y_{t-1} + \cdots + b_1 y_{t-n} + u_t^{(n)} = z_t^{(n)} + u_t^{(n)} \tag{2.40}$$

Computing the coefficients b_k by minimizing as in equation 2.41;

$$M\left[\left|x_t - z_t^{(n)}\right|^2\right]; \tag{2.41}$$

the coefficients will be independent of *n* according to equations [($M[y_t\bar{x}_{t-k}] = 0, k = 1,2, \ldots \ldots$) and ($M[y_t\bar{y}_{t-k}] = 0, k = \pm 1,2, \ldots$)].

It is obtained as in equation 2.42;

$$b_0 = 1; b_k = M\left[x_t . \bar{y}_{t-k}\right] / d^2, k = 1,2, \ldots; \tag{2.42}$$

The sequence $\left\{z_t^{(n)}\right\}$ thus being determined for every n, it is further easily shown that $\left\{z_t^{(n)}\right\}$ converges in the mean, say to z_t as in equation 2.43;

$$\lim_{n\to\infty}\left(\cdots, z_{t-1}^{(n)}, z_t^{(n)}, \cdots\right) = \left(\cdots, z_{t-1}, z_t, \cdots\right); \tag{2.43}$$

It may be written as in equation 2.44;

$$z_t = y_t + b_1 y_{t-1} + b_2 y_{t-2} + \cdots, \tag{2.44}$$

Where the sun converges in the mean. Finally, it is written as in equation 2.45 ;

$$x_t = z_t + u_t \tag{2.45}$$

That giving a decomposition of the series $\{x_t\}$ into two components $\{z_t\}$ and $\{u_t\}$ (Wold, 1954).

2.6.3 Forecasting with non-linear models

Nonlinear time series analysis is quite common in science (Kock and Teräsvirta, 2010) and so has drawn attention for the last decades, primarily depending on the reality that linear time series models have met several restrictions for real utilizations and modern computers have obtained improved computational strength that performs probable the nonlinear analysis. Besides, the improvement in nonparametric regression has constituted a solid foundation for nonlinear time series analysis (Chen and Tsay, 1993). The most popular nonlinear forecasting models in these areas are complex dynamic systems based on the concept of chaos, and various neural network models (Kock and Teräsvirta, 2010). Second, if the time series is Gaussian (i.e., normally distributed) then the best linear forecast is in fact the best of all possible forecasts: No nonlinear forecast can do better in terms of mean squared prediction error. Thus, as long as the series is Gaussian, we need look no further than the linear methods (e.g., ARMA forecasting) already presented. If the series is nonlinear, however, then nonlinear forecasting methods may work better than linear ones.

In this study, different non-linear models such as ARX, ARMAX, recursive method and artificial neural networks were applied to data. Further; information regarding the methods is given below.

2.6.3.1 Auto-Regressive eXogenous (ARX) model

One of representer and numerical dynamics modeling approaches which have been mostly utilized in time series analysis is Auto-Regressive eXogenous input (ARX) modeling (Ljung, 1999). An Auto-Regressive eXogenous input (ARX) model has been extensively preferred in engineering fields to model dynamic response of a system to exogenous factors. ARX models are a special type of more general ARIMAX models. Contrast to regression models, ARX total describes the dynamic nature of process. The model parameters could be determined in a recursive way which is ideal for online implementation (Fukata et al, 2006). ARX model structure obtains a more easier determination problem of multivariable system than ARMAX model (Lee et al, 1996). Zhu (1998) and Hjalmarsson (2003) implied high order ARX models that are reduced before used in control design. ARX models constitute the simplest way of providing a dynamic process driven by an input in presence of uncertainties. In fact, these models describe the observed output of process as the sum of a regression on previous input and output observations and of a white noise that describes equation error (Ljung, 1999; Guidorzi, 2003; Söderström, 2007). This stochastic context, as well as that of all other equation error models, does not make explicit assumptions on the origin of the misfit between the observations and the process output (Diversi et al., 2010).

An Auto-Regressive eXogenous input (ARX) model defined as a linear repetition equation to associate the current value of an objective variable $x(s)$ with its past finite time series and the past finite time series of the other exogenous input variables y_g $(g = 1, \ldots, h)$ as in equation 2.46;

$$x(s) = \sum_{i=1}^{p} a_i x(s-i) + \sum_{j_1=1}^{q_1} b_{j_1} y_1(s - j_1 - k_1) + \cdots + \sum_{j_h=1}^{q_h} b_{j_h} y_1(s - j_h - k_h) + e(s) \quad (2.46)$$

where s is a current time step, a_i the contribution coefficient of an i-step past value of the objective variable to its current value, b_{jg} the contribution coefficient of the j-step past value of an exogenous input variable y_g, k_g the time lag of the propagation delay of the exogenous input variable, and p, q_g $(g = 1, \ldots, h)$ the model order parameters which define the finite and maximum time steps of the contributions from the objective and the exogenous variables. Moreover, $x(s)$ is the prediction and $e(s) = x(s) - \hat{x}(s)$ defines their prediction error. The model coefficients a_i $(i = 1, \ldots, p)$ and $b_{jg}(j_g = 1, \ldots, q_g,\ g = 1, \ldots, h)$ could be calculated by the least square principle on the variance of the prediction error $e(s)$ over a given time series data. The combination of the time lags $k_g(g = 1, \ldots, h)$ which are integers is determined by a greedy method to investigate the combination which presents less least square prediction error on the combination lattice. The model orders, the parameter values of $p, q_g(g = 1, \ldots, h)$ are conventionally estimated using AIC index (Fukata et al, 2006).

The ARX models generate a better fit with more statistically important coefficients compared to linear regression equivalents. This could be analyzed by making compare the coefficient of estimation (R^2) and AIC values. The out of sample prediction evaluated and seen that its performance is so excellent according to performance criteria, a Root-Mean-Square (RMS) (Yan et al, 2014).

2.6.3.2 Auto-Regressive Moving Average eXogenous (ARMAX) model

Autoregressive (AR) models could be efficiently coupled with moving average (MA) models to generate a common and appropriate or suitable type of time series models named as autoregressive moving average (ARMA) models. This method, that is one of the static time series models, could be used if data are stationary (Makridakis et al, 1998; Falk and Roy, 2005; Lima et al, 2014). ARMA model is preferable for the time series without trend and seasonality that show time homogeneity. This kind of models such as ARMAX, named as transfer function. Transfer function means explanatory time series filter as a form of dynamic regression model (Ljung, 1999). The ARMAX model is a form of ARMA model which is talented of containing an external, (X), input variable (Chen et al, 2004; Weron, 2014). Identification of ARMAX process plays an important role in modeling many dynamical systems. The form of the ARMAX model given as in equation 2.47 (Chen et al, 2004) :

$$\Phi(B)y_t = \Xi(B)x_{t-a} + \Theta(B)\varepsilon_t , \qquad (2.47)$$

In here, where $x_{t-\alpha}$ is an external input variable, y_t is response (output variable), ε_t is white noise, α is the lag delay between input and output, and B is backshift operator. The polynomials in backshift operator $\Theta, \Xi, and\ \Phi$ are represented as in equations 2.48, 2.49 and 2.50 (Chen et al, 2004):

$$\Phi(B) = 1 + \phi_1(B) + \phi_2(B)^2 + \cdots + \phi_{n\phi}B^{m_\phi} \qquad (2.48)$$

and for Ξ;

$$\Xi(B) = 1 + \xi_1(B) + \xi_2(B)^2 + \cdots + \xi_{n\xi}B^{m_\xi} \qquad (2.49)$$

and for Θ;

$$\Theta(B)=1+\theta_1(B)+\theta_2(B)^2+\cdots+\theta_{n\theta}B^{m_\theta} \quad (2.50)$$

In these equations; $\emptyset_{n\emptyset}$, $\xi_{n\xi}$ and $\theta_{n\theta}$ are coefficients, B is backshift operator, $n\emptyset, n\xi, n\theta$ are the orders. ARMAX and its derivatives has been used for different studies in literature studies (Peng et al., 2001). Mahmoud (1984) proposed that ARMAX and derivatives is better than regression method.

2.6.3.3 Recursive method

Recursive method is used to bring closer the predicted value and actual value to eachother. It is used to correct the future, namely forecasted value. The forecasted value is determined by using equation 2.51 (Boi, 2004):

$$X_{\min_{(i)}}(+n)=X_{DMO_{(i)}}+corr_i \quad (2.51)$$

The first term on the right-hand side is the Xm DMO (Direct Model Output) at forecast time $D + n$ days, with $n = time$. The second term is the correction term, which is updated recursively depend on time (the index i in *corr* indicates the i_{th} iteration or, equivalently, the i_{th} forecast issued). The implicit hypothesis is that the correction calculated on time $D + 1$ is valid also on time $D + n$. The correction term could be calculated as in equation 2.52 (Boi, 2004):

$$corr_i=\frac{1}{2}\left[T_{\min_{OBS}}-T_{\min_{DMO}}(+1)+corr_{i-1}\right] \quad (2.52)$$

The first term in the square bracket is the minimum value on the time "D + 1", the second term is the DMO at forecast time D + 1. The D + 1 is the issuing time of this forecast, while the DMO issuing time is D. The third term in the square bracket is the correction term calculated the time before the time i, corresponding to the previous forecast. The starting value of the correction term is zero ($corr_0 = 0$). The factor (1/2) in means that half the contribution to the correction term is given by the past corrections.

The initial value of the additional correction $corr$ is 0 and it is updated depend on time with each new model and new measurements. In other words, the correction $corr$ at the i_{th} forecast or iteration is a sum as in equation 2.53 (Boi, 2004):

$$corr_i = \sum_{j=0}^{i-1} \frac{1}{2^{j+1}} \left[T_{\min_{OBS_{i-j}}} - T_{\min_{DMO_{i-j}}} (+1) \right] \quad (2.53)$$

The correction thus includes the past relationship between the model and the measurements, but the weighting of $1/2^{j+1}$ biases it towards the last few days, as the first terms of this series are largest.

The advantages of recursive method are given as below:

- There is no necessity to stock up a great number of measurements and great amounts of method predict data;
- The correction terms are readily adjusted to new meteorological states, particularly to seasonal difference;
- The procedure is clear to getting up to date of the model;
- Only one predictor is adequate
- The procedure is easier to apply in operational way, with a short computing time.

The advantage of this method is that, after a few days of iteration, the initial and erroneous value of zero contributes a negligible amount to the correction term. Another advantage is that, unlike the Perfect Prognostic or Model Output Statistics, we do not need a long series of model and measurement data. The third advantage is that the correction term is updated every time the model is reissued and new measurements received (operationally every day); which allows the correction values to be easily adapted to new meteorological conditions, in particular to seasonal variations (Boi, 2004).

2.6.3.4 Artificial neural networks

Artificial neural networks (ANN) are multiple network and nonlinear mapping systems whose structure is loosely based on principles observed in the nervous systems of human and animal brains (Reed and Marks, 1999). In the 1950s, Artificial Neural Networks (ANN) have been improved as a method to simulate the thinking processes of the human brain (Yang et al, 2009). Common definitions of ANN modelling could be made by Lawrence (1993), Smith (1993), Elizondo et al, (1994) and Kohzadi et al, (1995). Artificial neural networks are nonlinear models, that consist of artificial neurons connected to each other, which contain an input set and an output set (Sahin, 2014). There are many cells and numerous synaptic links between inputs and outputs in ANN. ANN can be divided into sub-clusters and these are called as layers. An artificial neural network is formed by connecting these layers in a hierarchical manner (Eker et al, 2012). ANN aims to show brain functions by imitation using computers, by renewing learning mechanism based on human brain. For this reason, ANN could find out the relation between input and outcome based on training data, while it can work as a black box model that does not need detailed knowledge on the system or equipment (Mohanraj et al, 2012). The structure of nonlinear neuron model is given as in (Figure 2.8). In this figure; x_j is system output or data coming from other nodes, while w_{kj} is synaptic weights and $\varphi(.)$ is differentiable nonlinear function called as activation function. Also, $\sum$ is summing function, b_k is bias and y_k is defined as output. If the process of this neuron model is defined, it is multiplying the system inputs by the corresponding weights, passing the result through the $\varphi(.)$ function and obtaining the scalar result. Artificial neural networks could be as desired structure, but layered architects are taking attention in today. In this type of structure; the units are built in layers and the layer, where entry signs are in, is called as the entrance layer; while the layer, where exit signs are in, is called as the exit layer. All layers except the entrance and exit layers are called as hidden layers (Reed and Marks, 1999). One of the first things to think about in the design of an artificial neural network is how many layers it should have.

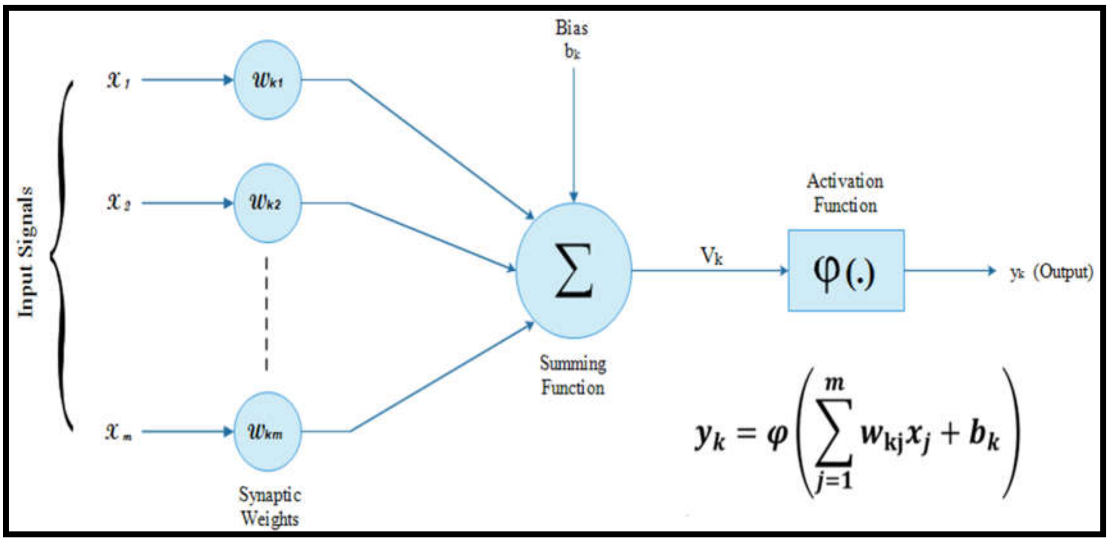

Figure 2.8 : The structure of nonlinear neuron model.

In artificial neural networks, the processing units can be named as neurons. The main components of a neuron contain an arborescent texture that get in touch with and gathers signals from anothers, a cell body which unifies the signals and composes a response, and a branching neurite which delivers the output to other neurons. The reaction of every neuron is a nonlinear capacity of its data sources and inner state. It is believed to be to a great extent controlled by the input connection qualities Every unit gets inputs from numerous different nodes and creates a solitary scalar output which hinges just on locally accessible data either put away inside or arriving by means of the weighted associations (Reed and Marks, 1999). The data going between the units imitates the elements of a man brain neural networks; elements for instance learning, remembering, educing and commenting, etc (Yang et al, 2009).

ANN is qualified by alteration of the synaptic significances because of the intended values in entry and outlet, on account of the capability of artificial neural networks to understand from illustrations. The automatically learning ability from examples of ANN is considered as one of the most critical properties which emphasize them. In order for the learning process to take place; the model, which is fully representing the problem and could work in ANN, should be designed. At the next stage, determination of learning algorithm which is used to update weights is required (Rustemoglu, 2010). By taking random weight values at the first stage of the learning process; the output value of the network is determined and examined for the sample whose iteration result is shown to the neural network. Output is contrasted with the goal and afterward; weights must be restored by utilizing the response or forward feed approaches subjected to failure especially if the result is proper or not. In second stage; weights are changed by showing various samples to ANN since the determination of the best weight value is required to obtain true output (Oztemel, 2012). At the end of the weight renewing process; network training is continued or completed according to error value. Input and related output vector are used to train network. Using appropriate algorithm is necessary while learning process is carried out and, the most common used is back propagation algorithm (Yang et al, 2009). After the weights which give the best output value are determined; neural network learning status is required and this process called as network testing. In learning stage; ANN is qualified with the early observed cases and an output is created by the finest importance values which are set in teaching step. While output value is putting forth the learning process of neural network; the more successful the result, the training performance of the network will be better. The teaching procedure is concluded automatically when the flaw drops below a specified value or the peak time is surpassed (Kalogirou, 2000; Kalogirou, 2001). Following the training process, the network can "recognize" and "recall" the raw data. When the network is induced by activities like those learnt in advance its outcome part can present equivalent conclusions. Exclusively the ANN has this exceptional capability of treaning, storage, and ability to distinguish (Yang et al, 2009).

The required data for ANN's training are error term which is related with input data and output data generated thanks to these input data. Error term is described as the difference between the outcome information driven by network and outcome data should be in actual. If there are to be done to create ANN (Rustemoglu, 2010);

- By introducing input data; it is provided that ANN generates the output data;
- Error is estimated by comparing the required output data and the data given by the network;
- Derivative is calculated according to weight values of error ;
- Weight values are adjusted to reduce the error to smaller values,
- This process is continued until the error value can be reduced within acceptable limits or until the timeout.

ANN could be used to predict the next step in a time serie. When the more distant is desired to forecast namely for the prediction horizon is $s > 1$; $\{x[t], x[t-1], x[t-2], \dots\}$ is trained to forecast $\hat{x}[(t+s)]$. For $1 \geq i \geq s$, it is required that all $x[t+i]$ values have to be trained (it is successful for only small 's' values) or it is iterated to $x[t+s]$ for any 's ' value by training the forecast of $x[t+1]$ value.

Today, there are in excess of forty forms of network types in ANN. Common types are Back Propagation (BP) network, Madaline model, Bilateral Associative Memory (BAM), Self-adaptive resonance theory (ART), Hopfield network, Machine perception and Self-Organization Mapping (SOM) (Yazdan et al, 2008). Another classification, the ANN are classified into two types as feed- forward supply network and back-forward supply network according to structures of networks. When the ANN are classified due to learning types, these are consultant learning, non-consultant learning and strengthening learning. ANN learning algorithms are classified as BP, Newtonian algorithms, Quasi-Newtonian algorithm etc.

Among the network models, the Back Propagation (BP) network is the most commonly used. Its transfer functions are non-linear, and the most well-known functions are the logarithmic sigmoid form (logsig) function and the hyperbolic tangent sigmoid form (tansig) function. In a BP network, connections between neurons is a front feedback neural network; the training approach pertains to supervision survey (Yang et al, 2009). A back propagating neural network shows certain superiorities essentially precision, convergency speed, financial and recorded information need for learning. The huge advantage of this calculation over back propagation algorithm is with regards to progress in “mean average percentage error” (MAPE) (Baliyan et al, 2015).

ANN have been utilized as a part of nonlinear modeling and prediction (Azadeh et al, 2008). An ANN is a non-linear design method which provides patterns in sample information sets. Entries along with common outputs are showed on an according to circumstance basis to the ANN program that arranges importance elements implemented to every entry by trial and error just before forecastings comply with the common outputs (Ehret et al, 2008). Generally, Box–Jenkins models, regression models, econometric models, and neural networks are very popular methods in energy prediction investigations to forecast energy utilization, feedstock supply or different matters on energy. Nevertheless, the significance and benefit of the ANN method, besides decreasing the time needed, is that it is feasible to make energy operations more reasonable and therefore more conspicuous to possible consumers, like energy engineers. In addition, this method has the benefits of calculation speed, convenience, economic feasibility, and simplicity of design by users with limited technical practice. For this reason, the utilization of ANN for modeling and forecasting functions has evolved into an progressively well-known trend in the last twenty years. This is primarily since ANN shows great approximation skills and suggests extra benefits, described as short improvement and rapid operating times. ANN have an ability in forecasting problems where mathematical notation and primary knowledge on the connection between entries and outcomes are unknown. ANN surpasses the restrictions of classical methods by gathering the necessary data using learning information, that has not needed any certain analytical formulations.

ANN model could be easily used to forecast the preferred result of the system by qualified training information (Mellit and Kalogirou, 2008; Kalogirou, 2003; Sozen and Arcaklioglu, 2007; Murat and Ceylan, 2006; Sozen et al, 2005; Mohanraj et al, 2012;). Besides prediction, ANN have been employed in different applications to solve different problems such as signal processing, pharma, pattern identification, robotics, control, speech production, speech recognition, business, manufacturing, power systems and also in the renewable energy field. ANNs present alternative approaches to address complex problems as a calculation and learning approach (Mellit and Kalogirou, 2008; Kalogirou, 2003).

In artificial neural networks surveys; it is seen that the latent layers in ANN are complicated to express, and the connection between entry and outcome factors in ANN is not simple to represent as a precise prediction equation. In order to overcome this issue and compare the prediction accuracy with ANN, several surveys have implemented genetic programming (GP) to supply a explicit forecasting formula and compared the prediction accuracy with different forms (Lee and Tong, 2011).

3. METHODOLOGY AND DATA

3.1 Methods of Application

In this thesis for all data; modelling and forecasting studies started with determination of optimal model orders for AR, ARX and ARMAX model and number of nodes in input layer of ANN, second is the comparison of model performances and last one is forecasting which was performed by using selected linear (AR Model) and non-linear models (ARX, ARMAX Models, ANN). Recursive model is also used to improve the AR, ARX and ARMAX models performances. The same procedure is also applied for gasoline consumption. A brief information about the data and model's applications, assessment of model performances, prediction of datas and performing the environmental assessment (estimating CO_2 emissions) are presented on following subjects, respectively:

- Information about the bioethanol feedstocks (wheat, barley, corn and sugar beet) data and gasoline consumption data,
- Model order determination for AR, ARX and ARMAX Model; while number of nodes in input layer of ANNs is determined,
- Model performances on feedstocks and gasoline consumption data,
- Performing recursive method to better model performances (for AR, ARX and ARMAX model),
- Forecasting on bioethanol feedstocks data and gasoline consumption data,
- Forecasting on bioethanol production in Turkey based on model results forecasting,
- Determining decrease in CO_2 emissions for bioethanol blended gasoline as environmental assessment

In this study, wheat, corn, barley and sugar beet are selected. In this thesis study, by appraising agricultural potential of bioethanol feedstocks, a forecasting study to be made is taken as an aim to estimate the production (or producible) capacities of bioethanol and its feedstocks in Turkey with all that predicting gasoline consumption. In this way, it could be determined that how much of the Turkey's bioethanol need could be met depend on forecasted gasoline consumption. Finally, CO_2 emissions were calculated for bioethanol blended-forecasted gasoline consumption as environmental assessment. Feedstock production, bioethanol production and consumption values, as well as gasoline demand and consumption values are considered as economical inputs. Therefore, forecasting study on all about of them could be seen as a part of bioethanol economy and economics forecasting. Whole data series have significant economical meanings in the perspective of bioeconomy and agricultural economy.

We focused on the linear model (AR) and non-linear models (ARX), (ARMAX) and (ANN) to estimate yield (tonne) of those feedstocks in different prediction horizons (1, 5, 10, 15 and 20 years). First of all; model orders belong to feedstock data series were determined by using AIC and FPE for AR model. AIC, which is a combined measure of model accuracy and model complexity, could be also used to evaluate model predictability, not only to choose model order. Model performance results were taken into consideration depend on lack of model order selection criterion for ARX and ARMAX models. Optimal model orders estimated for AR model have been adapted for ARX model to compare model performances and prediction results in all feedstock data. In ARMAX model; even if more greater or lower model order values could be used. Furthermore, we aimed to analyze the behavior of models to see whether the characteristics of data impact results with the type of model or not. Therefore; most common preferred performance criterias in modelling studies such as RMS, R^2 and χ^2 were used at optimal model order for each data serie in order to evaluate the model performances. On the other hand, gasoline consumption data were collected and the same process was carried out for them as in feedstock data. In prediction studies; considering the forecasting results, we were interested to estimate the production amounts of feedstock by these linear and nonlinear forecasting approaches for bioethanol demand in future (nearly from 1 to 20 years). Based on the two issues; bioethanol feedstocks and their forecasting, this study has been intended to be a resource and roadmap for the studies on bioethanol production. Therefore, the forecasted feedstock data have been used to estimate the producable bioethanol capacities by using ethanol yield (L) from these feedstocks (per tonne). Following the forecasting studies on bioethanol feedstocks and bioethanol production, gasoline consumptions have been forecasted to find out the required amount of bioethanol that should be added to gasoline. Finally, environmental assessment in terms of CO_2 emissions have been estimated according to bioethanol added-gasoline.

3.2 Application Data

The yearly production of wheat, corn, barley and sugar beet data were provided from statiscs of Turkish Grain Board and Turkish Sugar Authority, which are the two of the most authoritative public sources on agricultural researches in Turkey. The whole data for each of feedstocks obtained by authorities were used for the prediction models without any modification in this study. Wheat, corn and barley production data (ton) per year were gathered from Turkish Grain Board (TGB, 2013) and shown in (Figure 3.1, 3.2, 3.3), respectively.

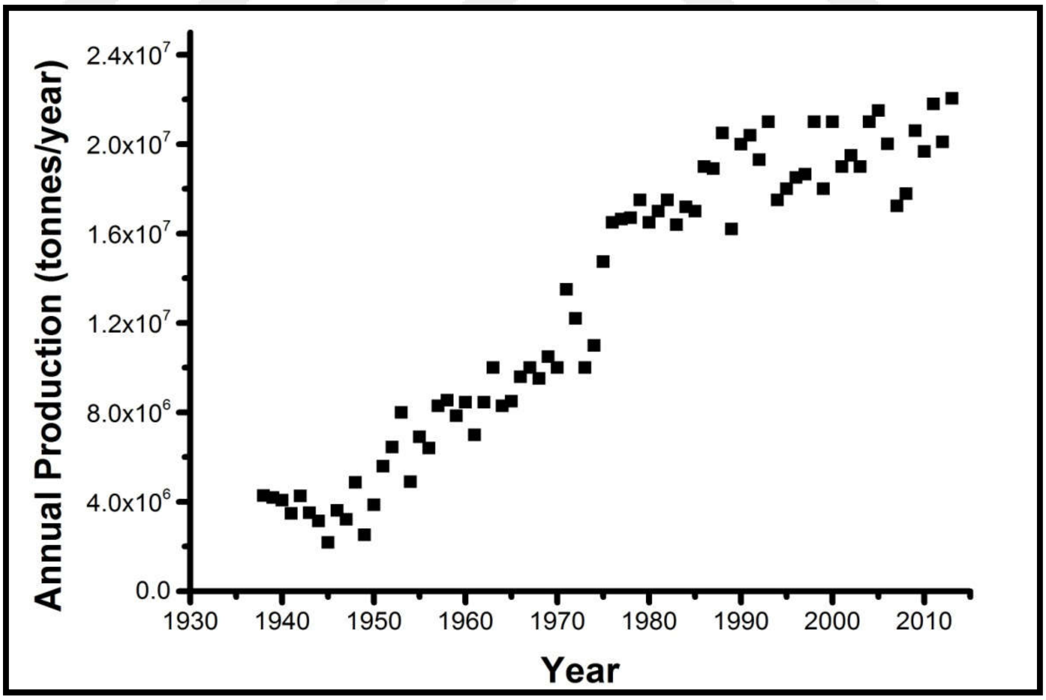

Figure 3.1 : Annual wheat production (tonnes/year) in Turkey.

Wheat and barley production data length is 76 years as seen in (Figure 3.1) and (Figure 3.3), while corn data length is 43 years as in (Figure 3.2).

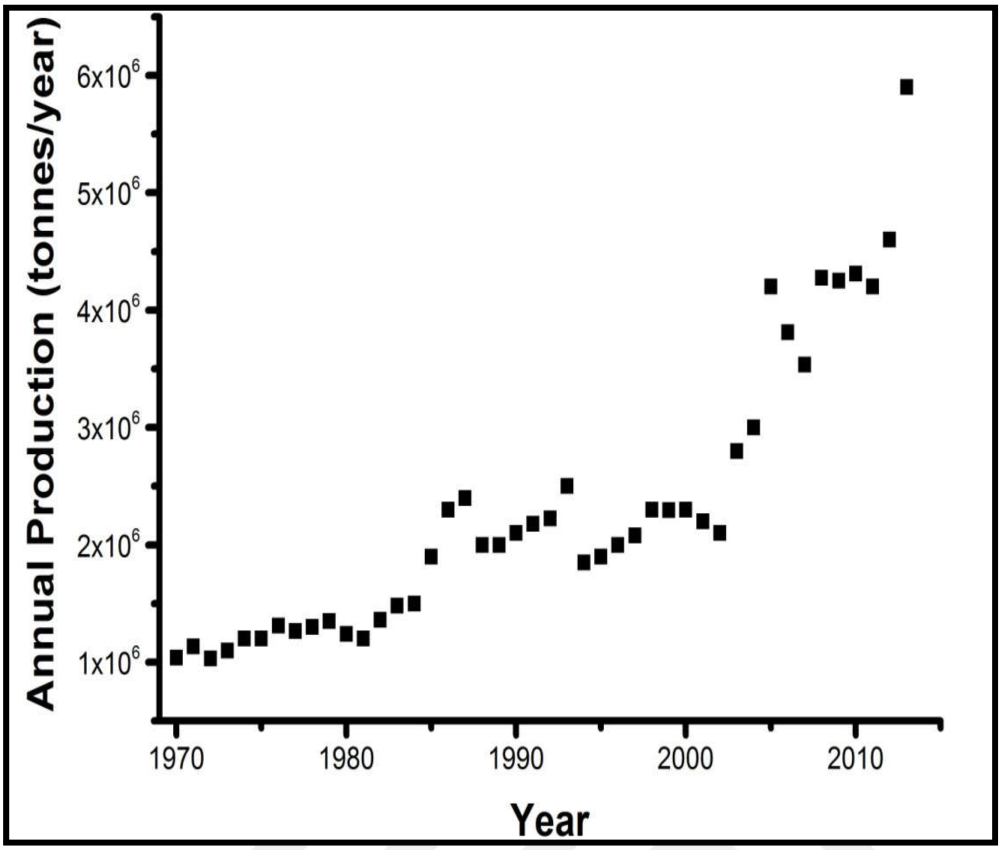

Figure 3.2 : Annual corn production (tonnes/year) in Turkey.

Barley production data have the similar production curve as in wheat production as seen in (Figure 3.3). Wheat and barley production has shown a significant increase from the beginning of 1980 in Turkey. However, corn production has increased with 2000's in our country due to agricultural production policies. Improved agricultural technologies, increasing demand depends on population growth, public strategies and government supports, the importance of agricultural outputs as biomass sources have affected the increases in annual productions. However, declines for some years are sourced from climatic factors, changes in government supports or strategies, harvest conditions, quotas and other agricultural reasons. In general, it is clearly concluded that those important four agricultural products as bioethanol feedstock had been produced at an increasing proportion for many years. Different from others, sugar beet data length is 26 years. Sugar beet is one of the crucial agricultural products in Turkey to provide the sugar demand and other uses in industry. With these; sugar beet and generally its molasses are the most preferred feedstock in Turkey to produce bioethanol. Although sugar beet production capacity mostly meets the demand in Turkey, there is a fluctuation in sugar beet production in Turkey as seen in (Figure 3.4).

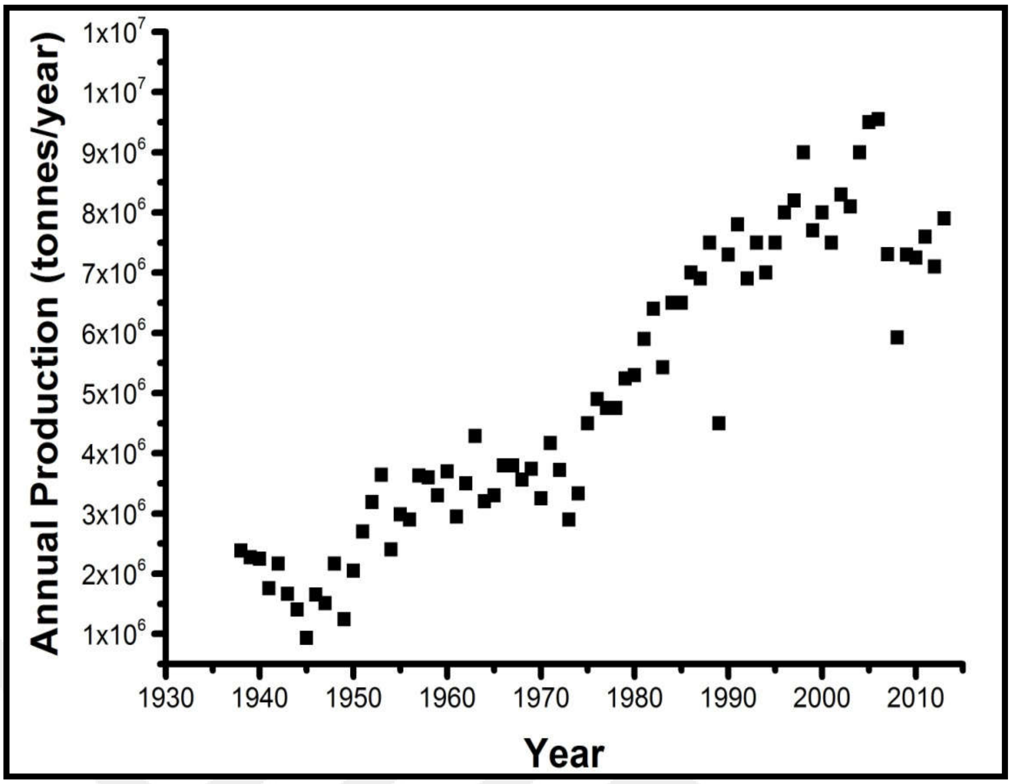

Figure 3.3 : Annual barley production (tonnes/year) in Turkey.

Sugar beet production data from Turkish Sugar Authority (Turkish Sugar Authority, 2014; Turkish Statistical Institute Statistics, 2013) given as in (Figure 3.4).

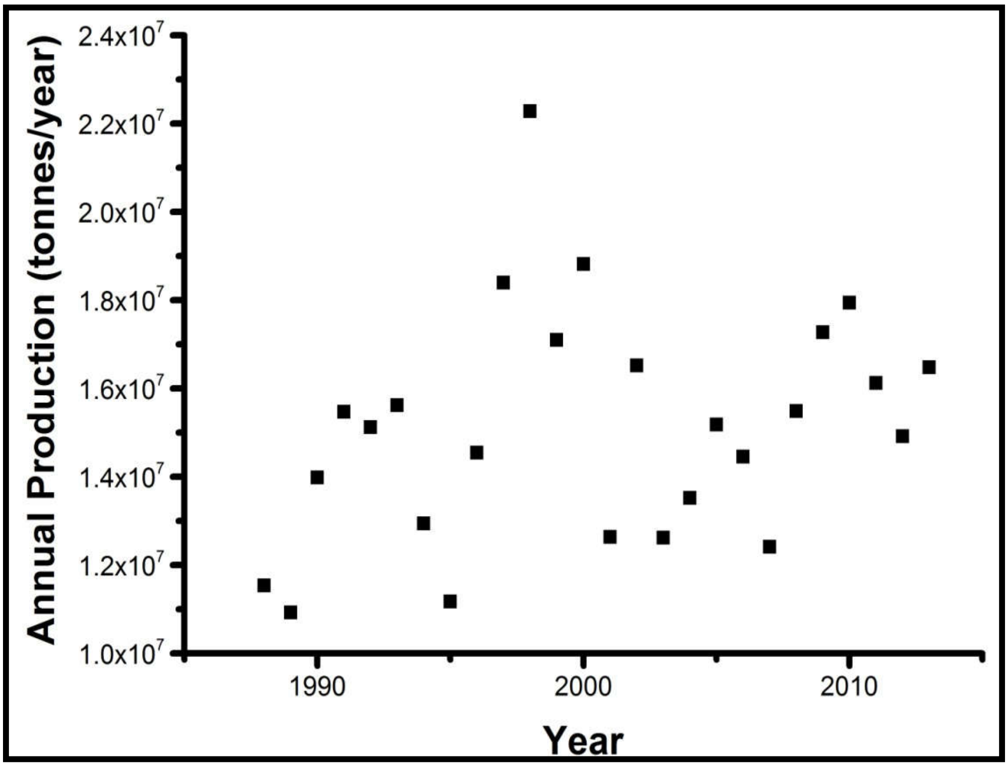

Figure 3.4 : Annual sugar beet production (tonnes/year) in Turkey.

Addition to feedstock data; gasoline consumption data were provided from statistics of EMRA, one of the most authoritative public sources on gasoline consumption in Turkey. The whole data obtained from this authority were used in the forecasting models without any modification as in feedstock data. Gasoline consumption data are given in (Figure 3.5). According to EMRA data, gasoline consumption has decreased from the beginning of 2000's depending on increase in diesel and Liquid Petroleum Gas (LPG) use. But it is still a significantly being consumpted petroleum product.

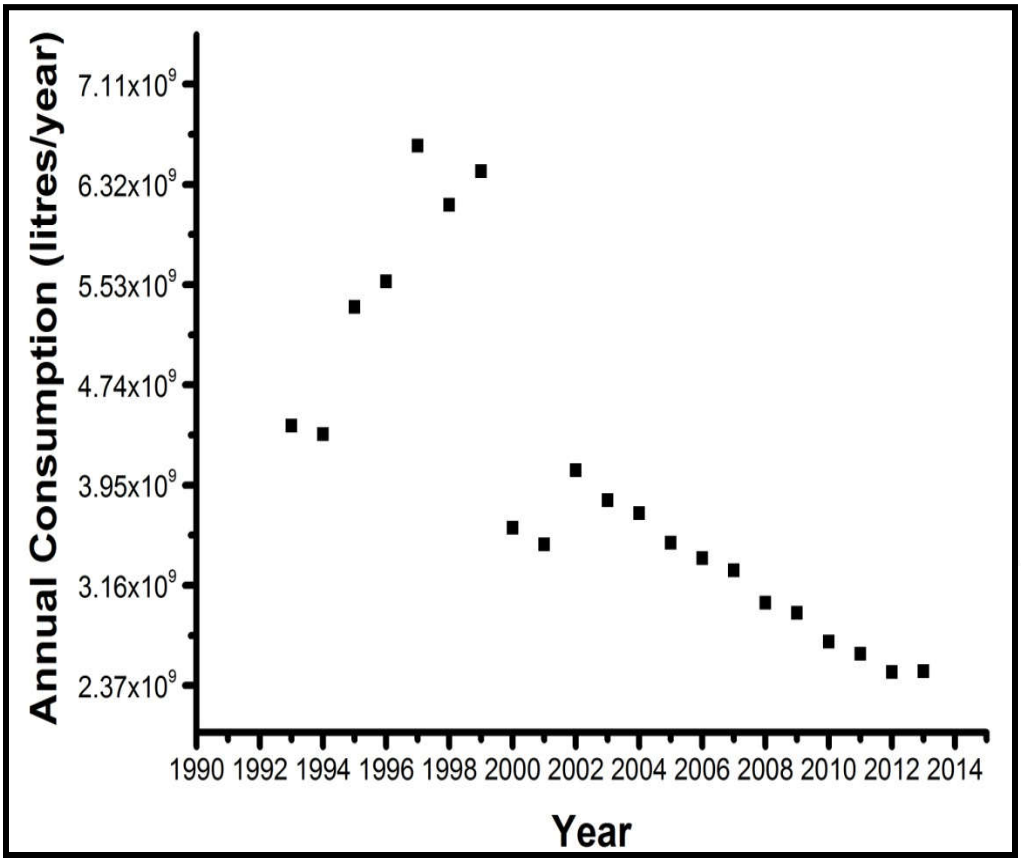

Figure 3.5 : Annual gasoline consumption in Turkey.

4. APPLICATION

In this chapter; the results, belong to the applications of the forecasting methods for selected data mentioned in the previous section, are presented step by step. Addition to forecasting studies, CO_2 emissions calculations are given as environmental assessment of blending bioethanol into gasoline.

4.1 Model Orders Determination

Modelling and forecasting studies for all data have been started with determination of optimal model orders for AR, ARX and ARMAX models. Most appropriate model orders of feedstock production data and gasoline consumption data are individually given in this section.

4.1.1 Model order determination for bioethanol feedstock data

The most appropriate order for each model was identified using the annual production data of 1938-2013. However, corn data dated from 1970 and those of sugar beet's from 1988. Model orders were found to be 2 using both of these criteria for wheat and barley. The model orders of corn and sugar beet were estimated at 1 within the acceptable limits in the AR model (Table 4.1). Estimated model orders for all models are listed in that table.

Table 4.1 : Estimated model orders for bioethanol feedstocks.

Models	Wheat	Corn	Barley	Sugar Beet
AR Model				
- AIC	2	1	2	1
- FPE	2	1	2	1
ARX Model	2	1	2	1
ARMAX Model	{6,5}	{4,3}	{6,5}	{3,2}

Model performance results were considered because of a lack of model order selection criteria in the ARX and ARMAX models. Optimal model order estimated by the AR model was adapted to ARX model to compare model performances and prediction results for all feedstock data. In the ARMAX model, even if larger or smaller model order values could be used, the model orders were determined by choosing the lowest model order values that can be applied to the AR and MA parts considering model performances. Optimal model order was accepted as {6,5} for wheat and barley. Here, 6 pertains to the AR model part and 5 to the MA model part, owing to data length and model performance. Model orders of sugar beet and corn data were determined as {4,3} and {3,2}, respectively. AIC and FPE values estimated for model orders from 1 to 20 (only model orders from 1 to 14 are estimated for sugar beet) over all data in each crop were shown in (Figure 4.1 and Figure 4.2).

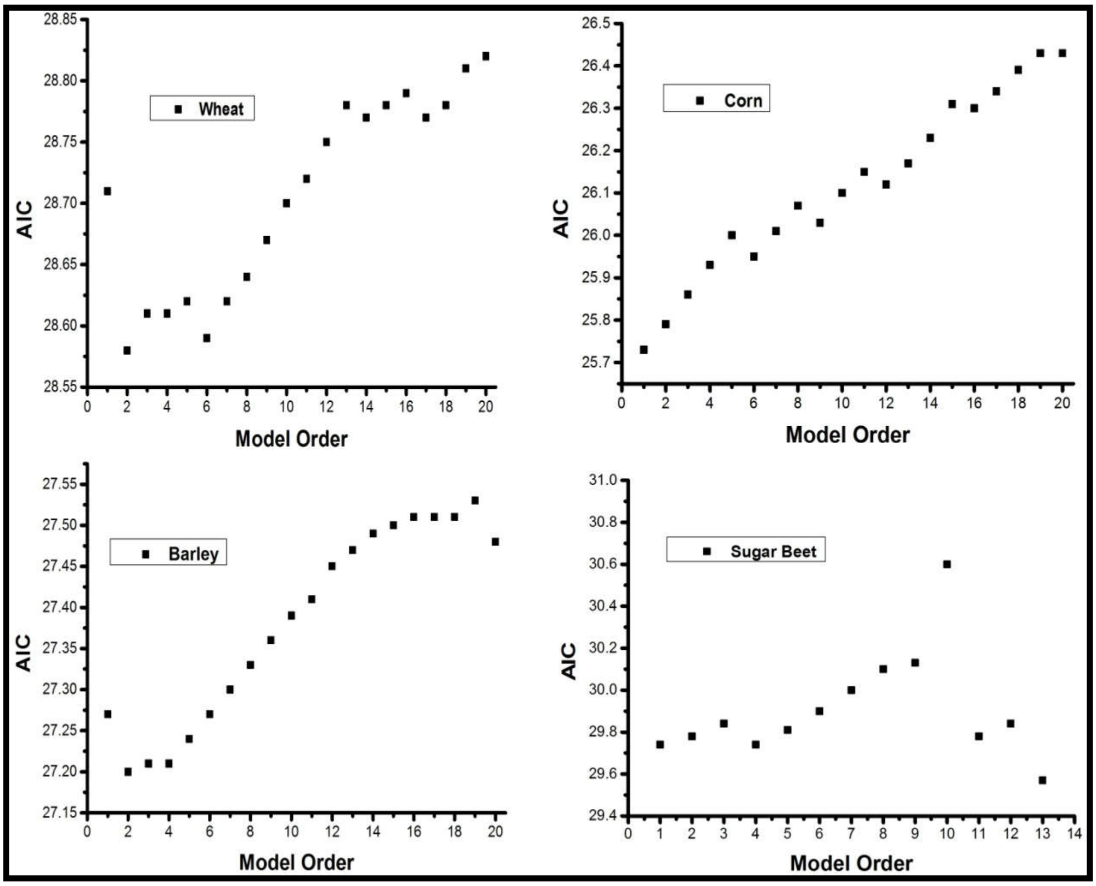

Figure 4.1 : AIC values in model orders for bioethanol feedstocks production data.

These two kinds of figures (belong to AIC and FPE) show similar characteristics and tendency for each one of the bioethanol feedstocks. It has been tried to choose the most-possible-smallest model order value where the curve is the lowest according to both criterias. Although there are more than values where the curve is the lowest for sugar beet data, the smallest one among them was selected for each criterion.

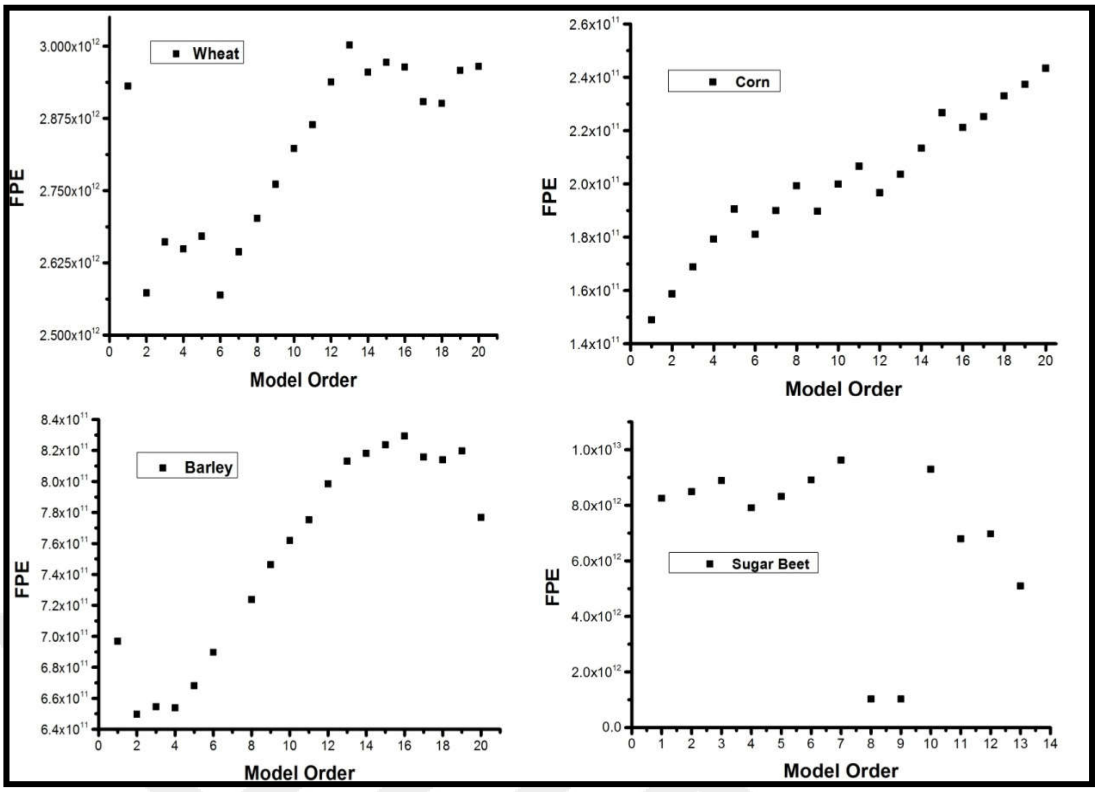

Figure 4.2 : FPE values in model orders for bioethanol feedstocks production data.

4.1.2 Model order determination for gasoline consumption data

The most appropriate model order for each model was identified by using the annual gasoline consumption data between the years of 1993-2013. In AR model; AIC and FPE performed, and model orders have been found as 8 with both of these criterias for gasoline consumption datas as shown in (Table 4.2).

Table 4.2 : Estimated model orders for bioethanol feedstocks.

Models	Gasoline Consumption Data
AR Model	
- AIC	8
- FPE	8
ARX Model	8
ARMAX Model	{3,2}

Model performance results were taken consideration due to lack of model order selection criteria in ARX and ARMAX models. Optimal model order estimated for AR model has been adapted for ARX model to compare model performances and prediction results for gasoline consumption data as in all feedstock data. In ARMAX model; even if greater or lower model order values could be used, optimal model order was accepted as {3,2} for gasoline consumption data, which 3 belongs to AR model part while 2 is for MA model part, due to data length and model performance. AIC and FPE values estimated for model orders from 1 to 12 over all data in gasoline consumption data were shown in (Figure 4.3).

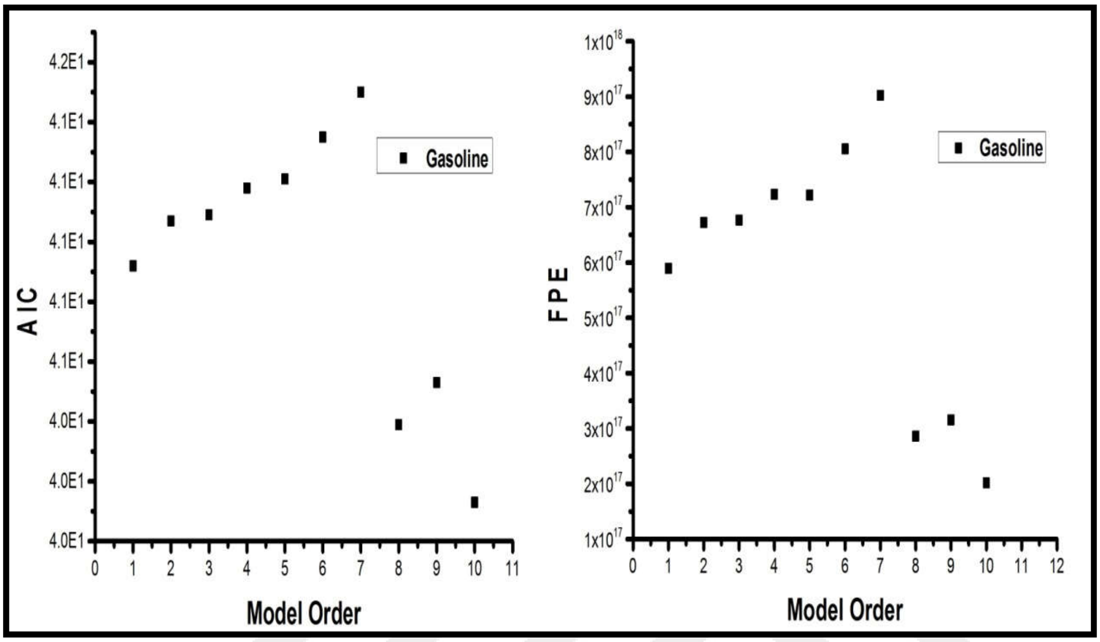

Figure 4.3 : AIC and FPE values in model orders for gasoline consumption data.

These two kinds of figures (belong to AIC and FPE) show similar characteristics and tendency for gasoline consumption data as in each one of bioethanol feedstocks production data. It has to be chosen the model order as order of smallest information criteria value. Although the determined model order (where the curve is the lowest) is higher feedstock's model orders, the smallest one (8) among model orders where the curve is the lowest was selected for two of criterias.

4.2 Model Performances

Model performance is based on similarity between the time series to be desired to modeled and the time series obtained at the end of modeling on the same graphic. The degree of conformity among real data after model analysis was estimated using RMS, R^2 and χ^2 in all models. Goodness-of-fit was measured via the estimation coefficient of determination R^2. R^2 is closer to 1 for a good fit. The accuracy of forecasts was evaluated based on error estimation, so the smaller the values of RMS (Emang et al, 2010), χ^2 and AIC, the better the forecast. As will be seen, all results, both linear (AR model) and non-linear models (ARX, ARMAX models, Recursive method and ANN) examined in this study are in a good fitting with the bioethanol feedstock production and gasoline consumption data.

4.2.1 Model performances with AR, ARX and ARMAX model for bioethanol feedstock production data

RMS, R^2 and χ^2 results associated for selected feedstocks with the AR, ARX and ARMAX models are presented with figure 4.4, 4.6, 4.8 and 4.10 to compare the model performances.

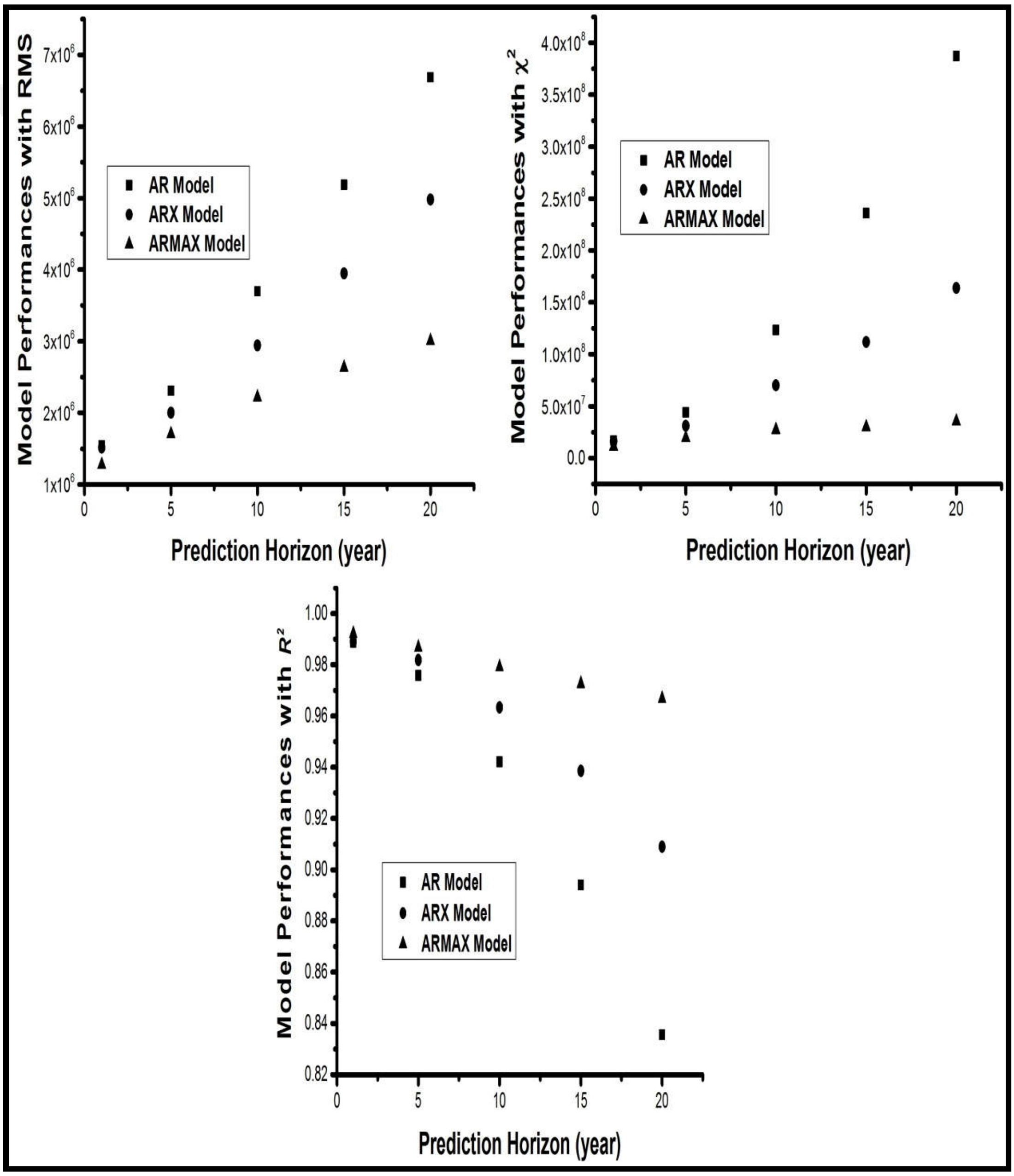

Figure 4.4 : Model performances from RMS, χ^2 and R^2 for wheat.

Forecasted data, real data and absolute error estimated for wheat production data are given to show absolute error and model performances in (Figure 4.5).

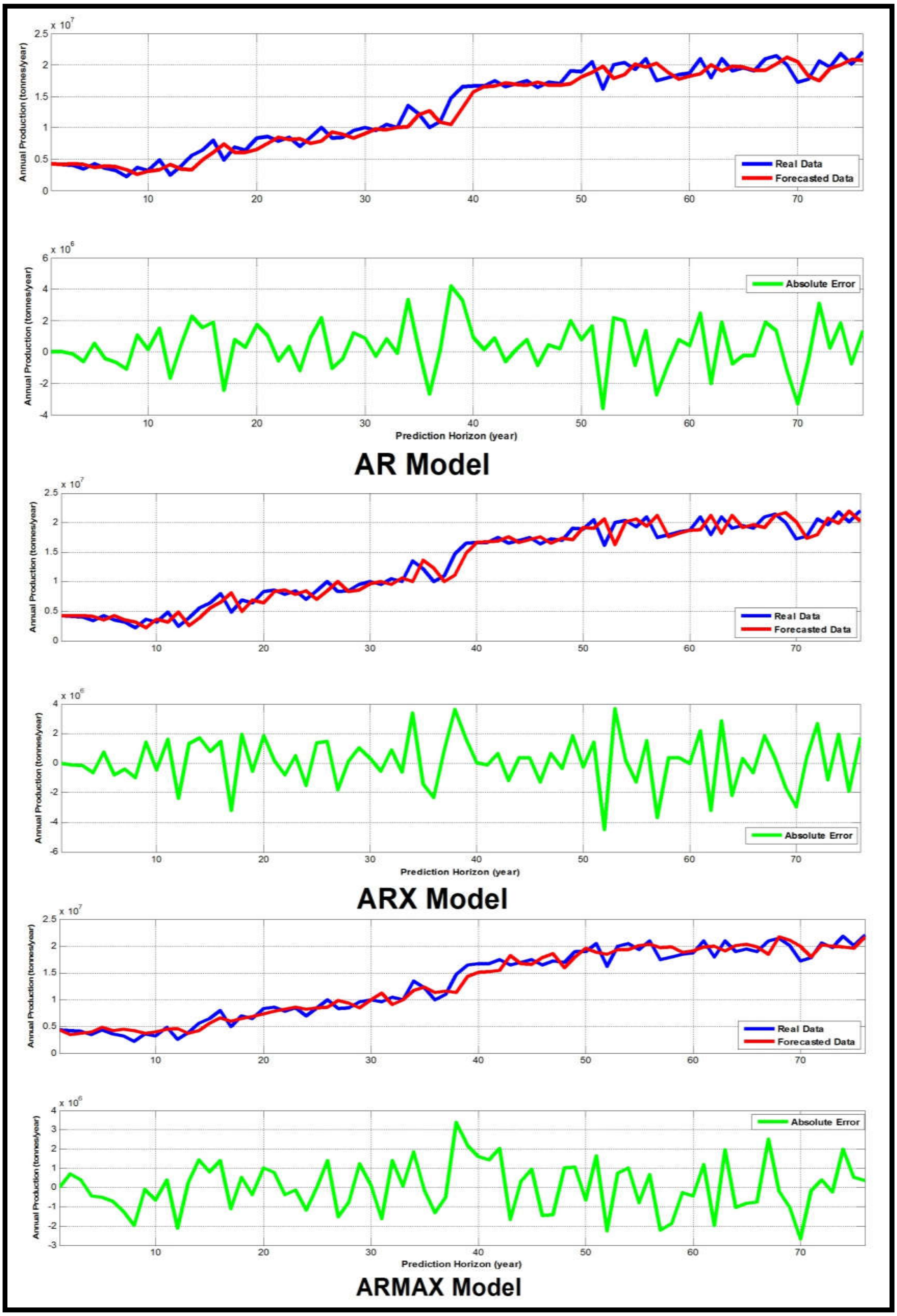

Figure 4.5 : Wheat production data and forecasting serie obtained with AR, ARX and ARMAX model.

It is analyzed that AR model also has shown good performance especially for the first 10 years. ARX model has better performance than AR model at the same conditions for each serie. As shown in graphics drawn for R^2 results; performances for near future of between 1 and 5 years are higher, even if it has been pointed out that AR, ARX and ARMAX could be applied for twenty years. As can be seen, all results, both linear (AR model) and non-linear models (ARX and ARMAX models) examined in this study were in a good fitting with the production data of selected feedstocks. Model performances, determined for wheat production data in Turkey, are given in (Figure 4.4). Although R^2 values are mostly above 90% for all three models used to predict wheat production, it is seen that the highest model performance is achieved by the ARMAX model. The highest model performance could be obtained by using AR model is 98.87%, while it is 98.90% and 99.22% with ARX and ARMAX models, respectively. For all models; model performances indicators are decreasing (in small quantities) with increasing prediction horizon values (from 1 to 20 years). Although the same trends for the curves in the three of models are observed, AR and ARX models give the more close results and have more similar "absolute error" curves with each other in (Figure 4.5).

Model performances, determined for corn production data in Turkey, are given in (Figure 4.6). Although R^2 values are mostly above 90% for all three models used to predict corn production, it is seen that the highest model performance is achieved when the ARMAX model used. The highest model performance could be obtained by using AR model is 97.94%, while it is 98.31% and 98.6% with ARX and ARMAX models, respectively. Particularly, there is a decline in AR model performance due to corn data's characteristic and length. In all models; model performances indicators are decreasing (in small quantities) with increasing prediction horizons (from 1 to 20 years). Forecasted data, real data and absolute error was determined with AR, ARX and ARMAX models for corn production data are shown to clarify absolute error and model performances in (Figure 4.7). Although corn data length is shorter than wheat and barley data lengths, the same trends are observed for the curves in the three of models. There is a negligible fluctuation on "Absolute Error" curve for the increasing prediction horizon values in all models. According to (Figure 4.7), there is a good correlation between forecasted value and real data for the first fifteenth year.

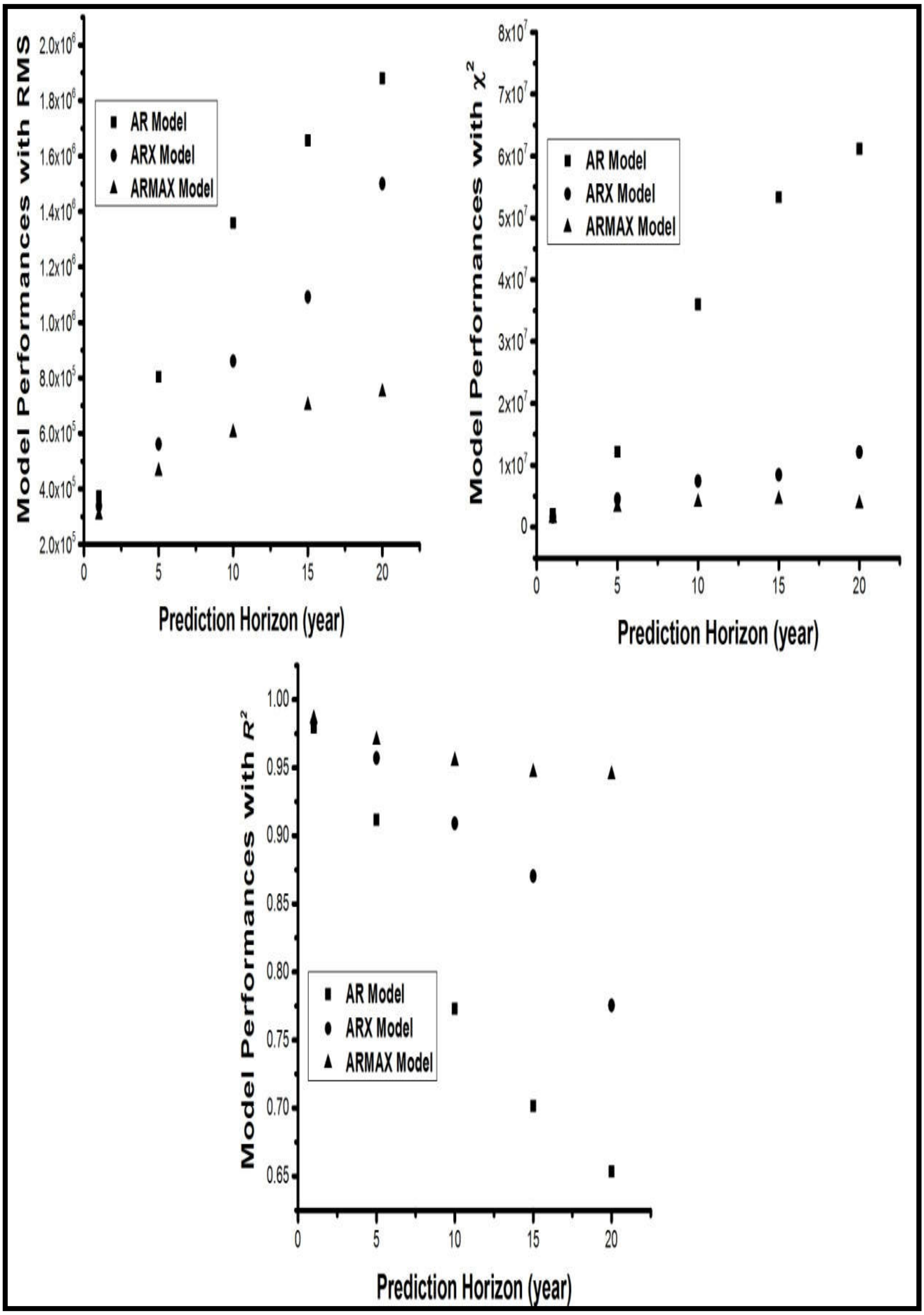

Figure 4.6 : Model performances from RMS, χ^2 and R^2 for corn.

Forecasted data, real data and absolute error estimated for wheat production data are given to show absolute error and model performances in (Figure 4.7) for shorter prediction horizon compared to barley and wheat production data. This situation is resulted from corn data length.

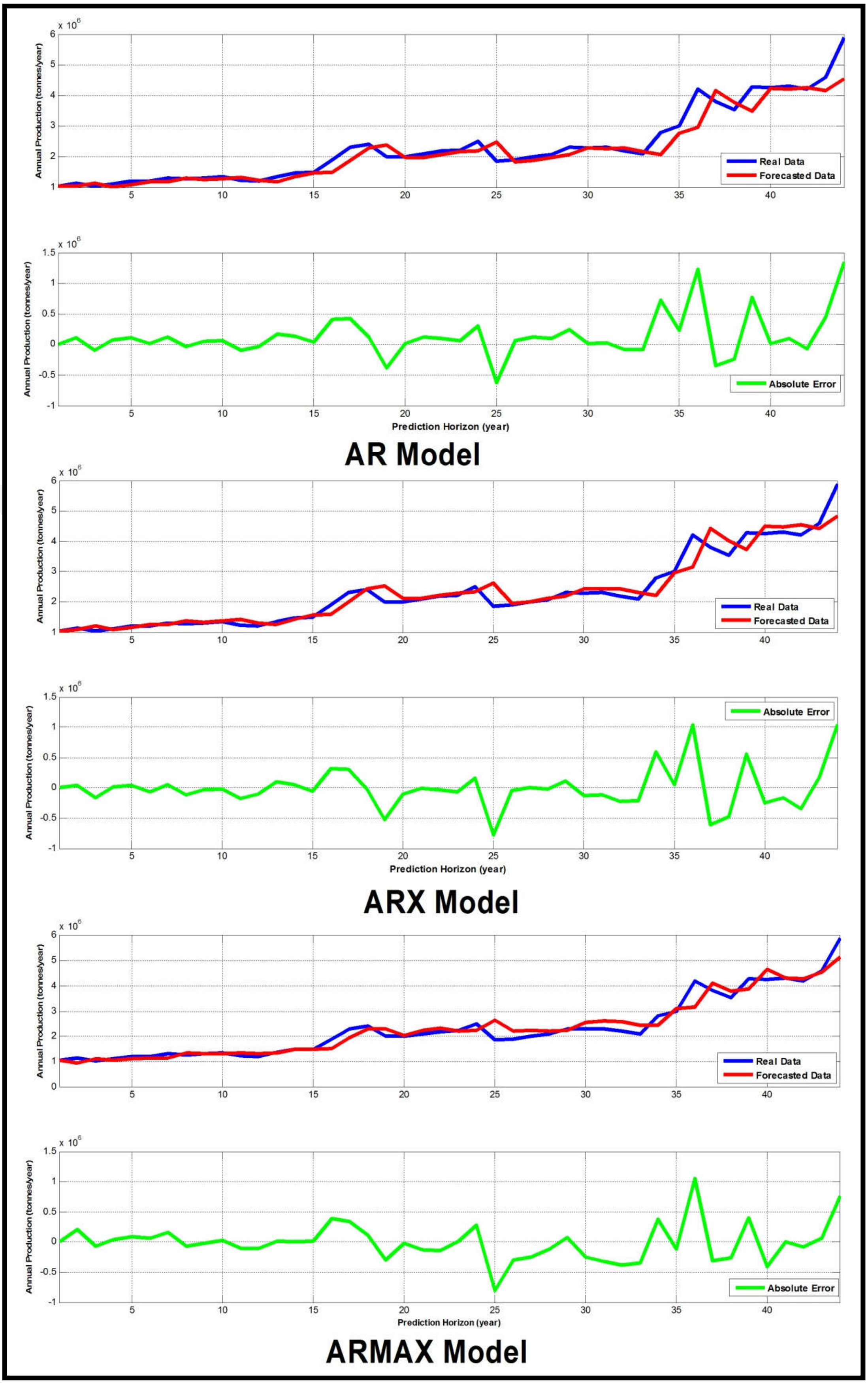

Figure 4.7 : Corn production data and forecasting serie obtained with AR, ARX and ARMAX model.

Model performances estimation for barley production data in Turkey, are shown in (Figure 4.8). Although R^2 values are mostly above 90% for all three models used to forecast barley production. It is seen that the highest model performance is achieved when the ARX model is used for all prediction horizon values, although ARMAX has also high performance values. The highest model performance could be obtained by using AR model is 98.02%, while it is 98.05% and 98.55% with ARX and ARMAX model, respectively.

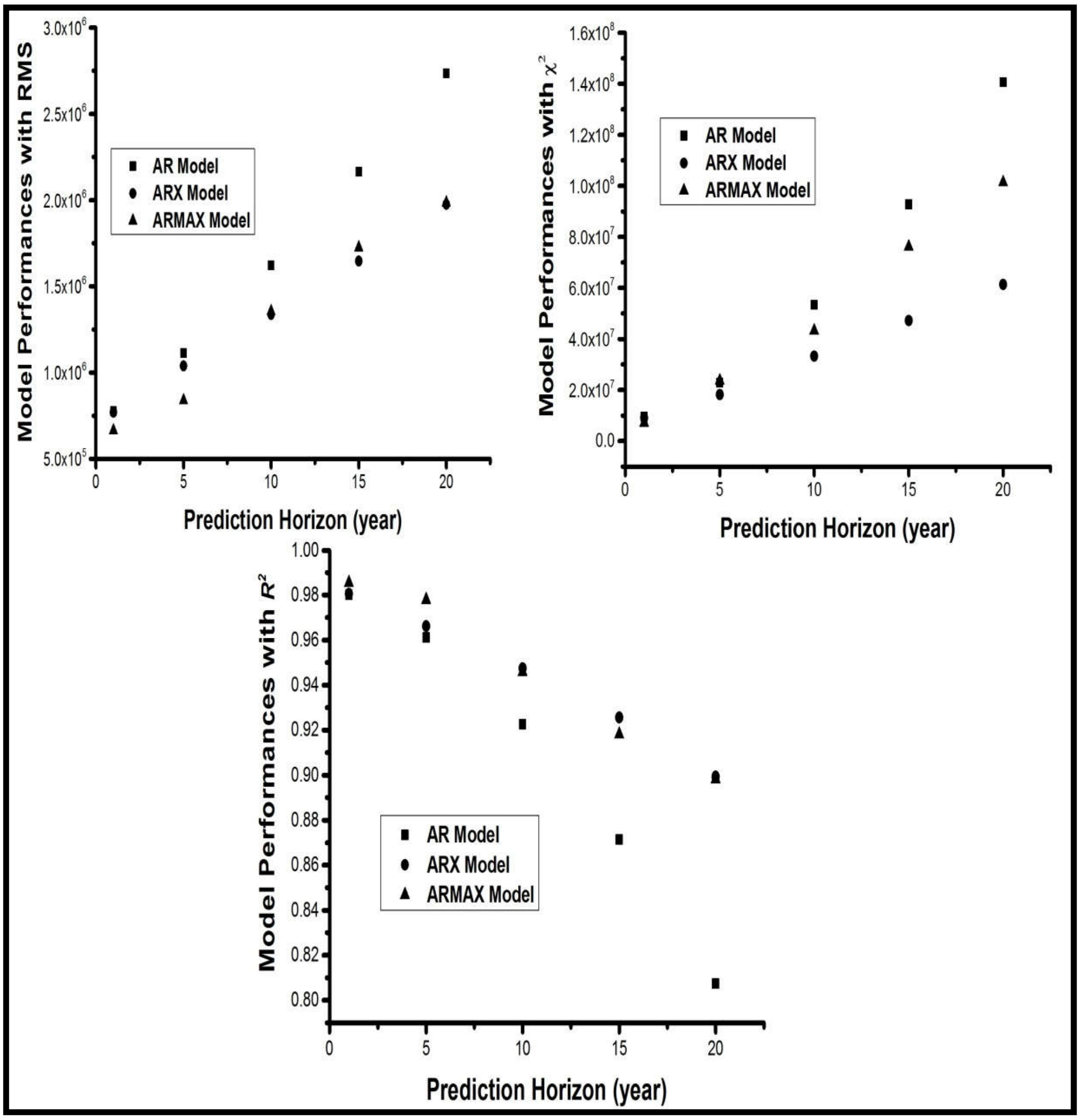

Figure 4.8 : Model performances from RMS, χ^2 and R^2 for barley.

Forecasted data, real data and absolute error determined with AR, ARX and ARMAX models for barley production data are given to show absolute error and model performances in (Figure 4.9). AR and ARX models give the more close results and have more similar "absolute error" curves with each other.

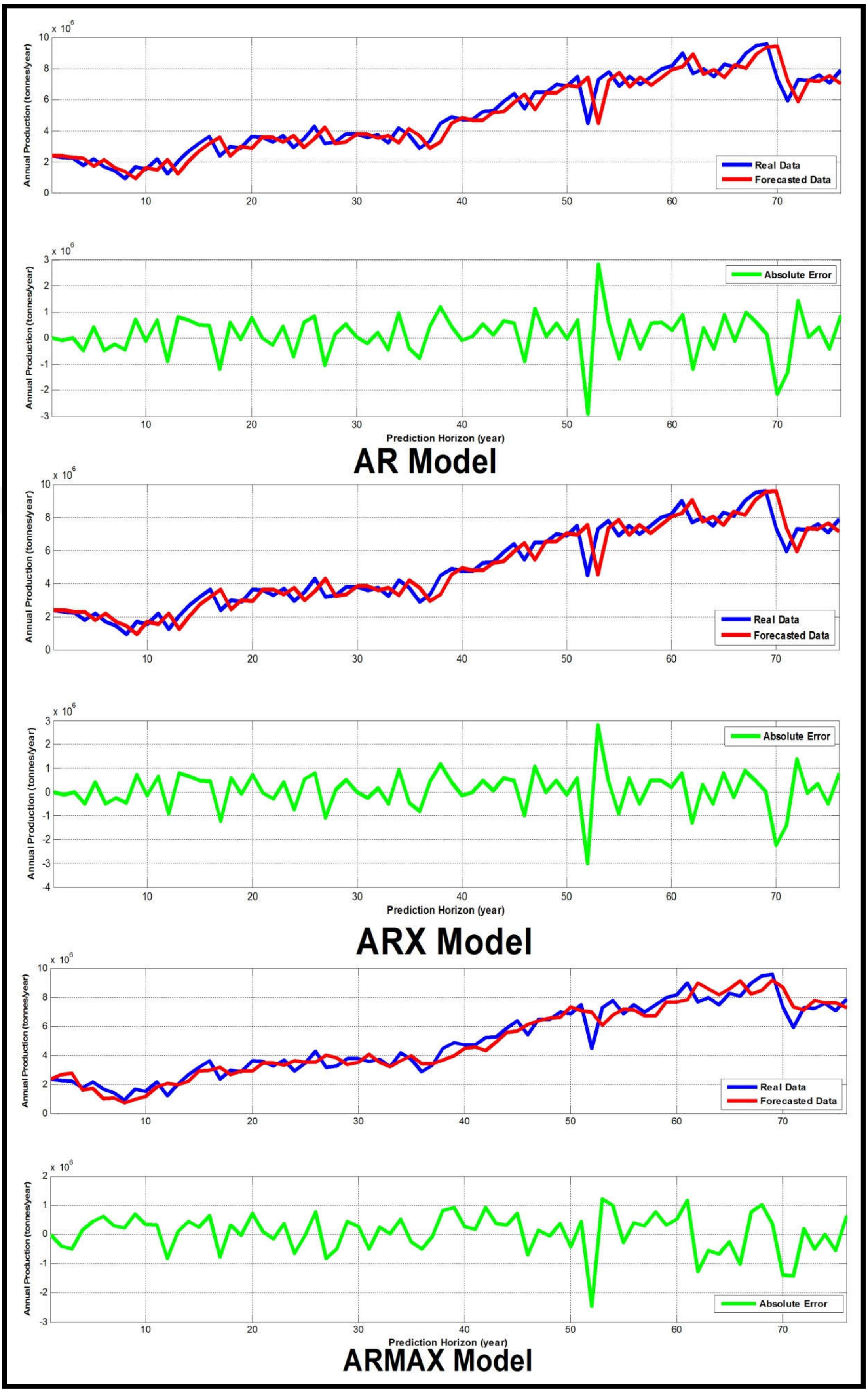

Figure 4.9 : Barley production data and forecasting serie obtained with AR, ARX and ARMAX model.

Model performances estimation for sugar beet production data in Turkey, are shown in (Figure 4.10). Although sugar beet data length is fairly shorter than other data length, R^2 values are mostly above 90% for all three models used to forecast sugar beet production. It is seen that the highest model performance is achieved when the ARMAX model is used for all prediction horizon values. The highest model performance could be obtained by using AR model is 96.87%, while it is 96.89% and 98.9% with ARX and ARMAX model, respectively.

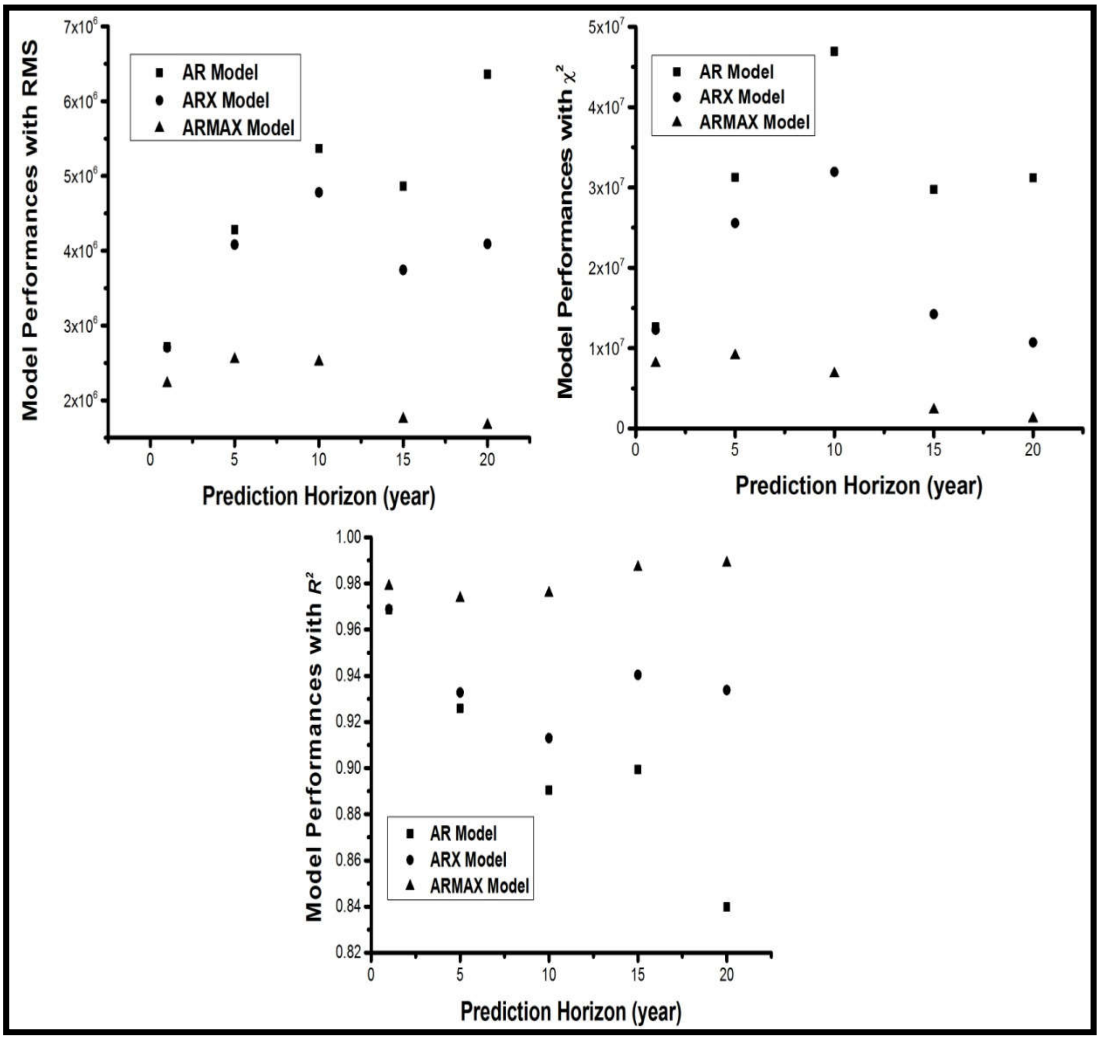

Figure 4.10 : Model performances from RMS, χ^2 and R^2 for sugar beet.

Forecasted data, real data and absolute error determined with AR, ARX and ARMAX model for sugar beet production data are presented to show absolute error and model performances in (Figure 4.11). Although sugar beet data length is shortest among all of feedstocks, the same trends are observed for the curves in the three of models. ARMAX model's "Absolute Error" curve is quite different from the tenth-year-forecasting horizon.

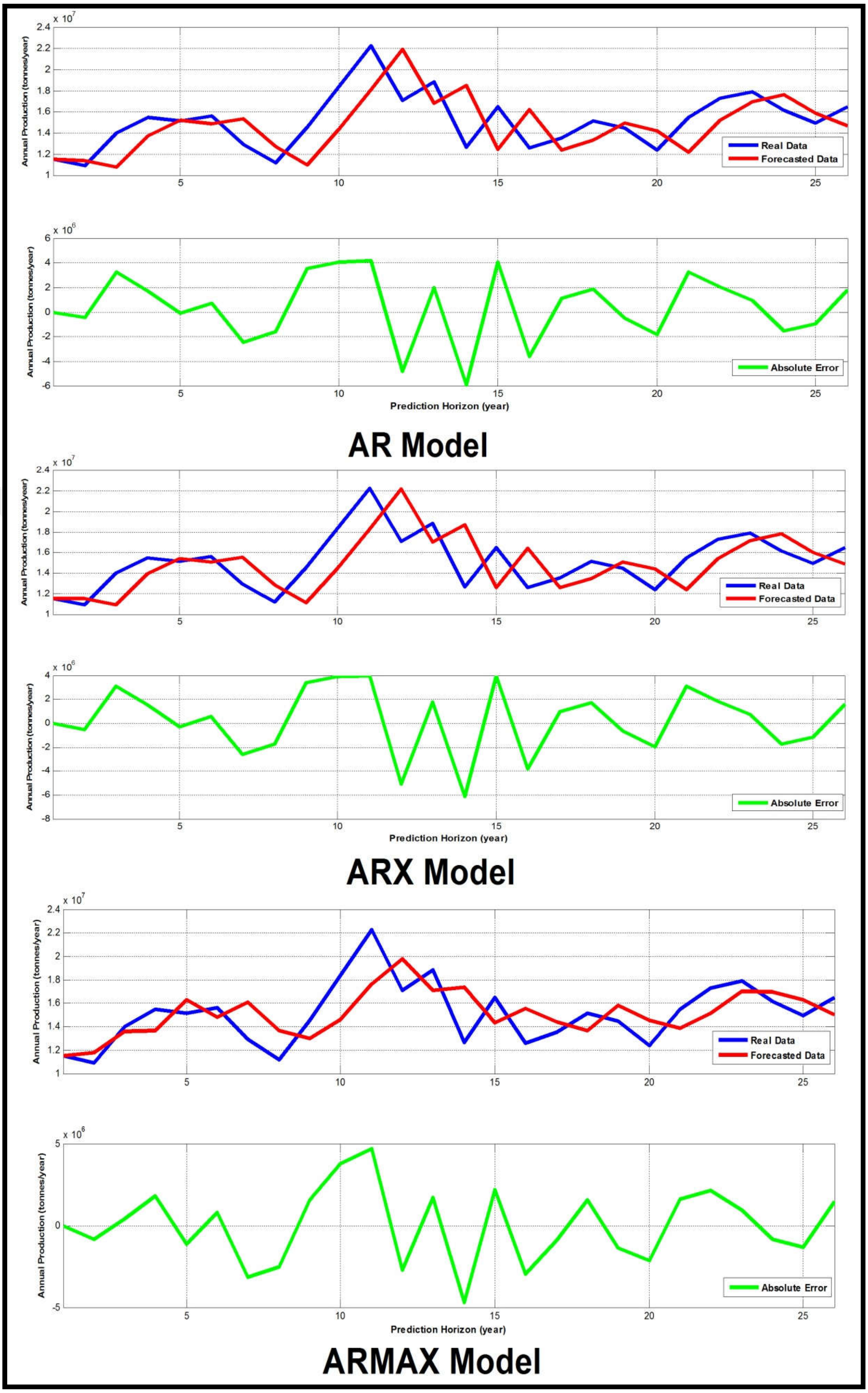

Figure 4.11 : Sugar beet production data and forecasting serie obtained with AR, ARX and ARMAX model.

4.2.2 Model performances with recursive method for bioethanol feedstock production data

RMS, R^2 and χ^2 results associated for selected feedstocks with the recursive method are presented with figure 4.12, 4.13, 4.14 and 4.15 to compare recursive method's effect on model performances. It is analyzed that recursive method exhibits different effects on model performances due to data lengths and characteristics. Model performances, determined for wheat production data in Turkey by using recursive method, are given in (Figure 4.12).

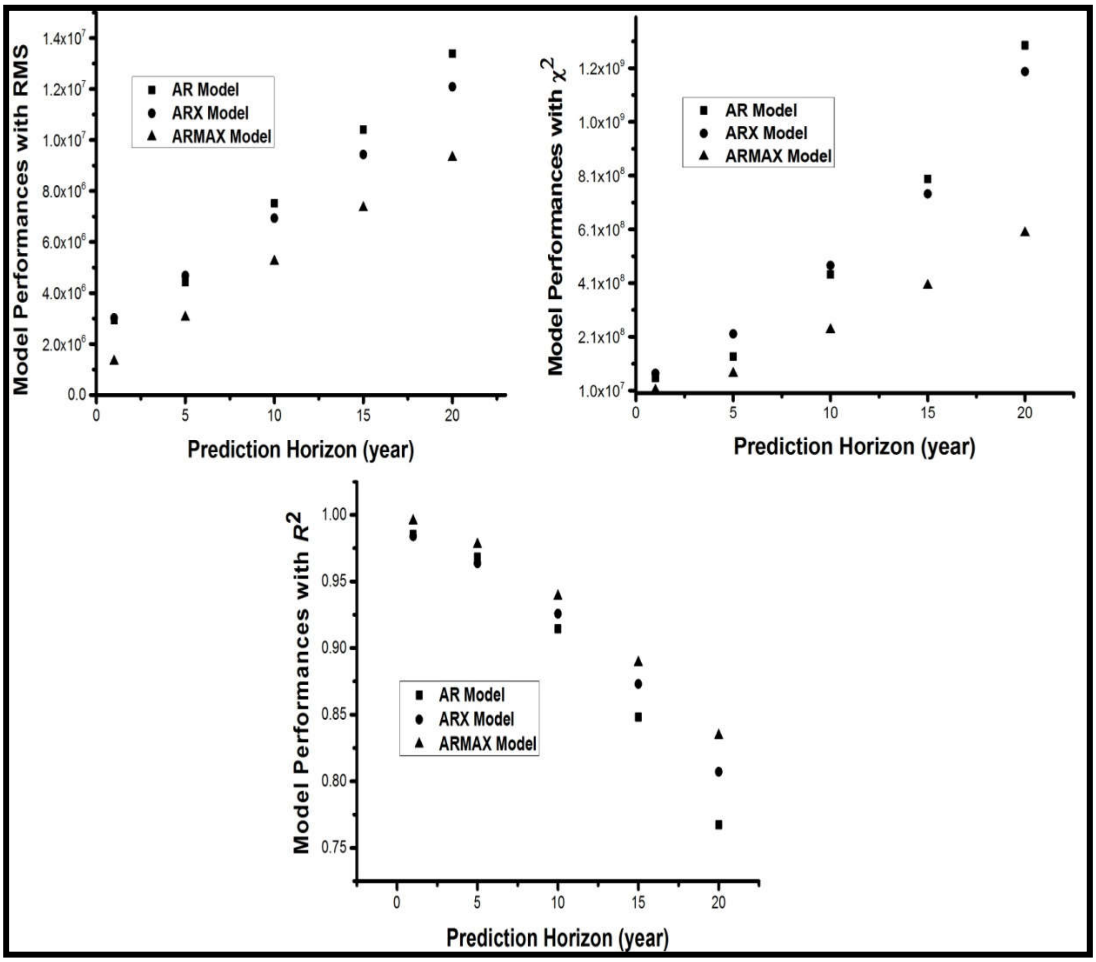

Figure 4.12 : Model performances from RMS, R^2 and χ^2 for wheat by using recursive method.

Although R^2 values are partly increased for all three models when improvement is carried out by using recursive method, expected model performance improvement is achieved in ARMAX model for increasing prediction horizons (1 to 20 years). When recursive method applied, the highest model performance could be obtained by using AR model is 98.53%, while it is 98.4% and 99.56% with ARX and ARMAX model, respectively. For all models; model performances indicators are decreasing (in small quantities) with increasing prediction horizons (from 1 to 20 years). However, this decline has been more pronounced in AR model by comparison to other two models.

Model performances, determined for corn production data in Turkey by using recursive method, are given in (Figure 4.13). It is determined that recursive method has not been able to achieve the expected improvement in model performances for each of three selected models. When recursive method applied, the highest model performance could be obtained by using AR model is 97.86%, while it is 95.7% and 98.4% with ARX and ARMAX model according to R^2 values, respectively. While it is observed that firstly a decline and then a sharp increase in ARX model whose prediction horizon is 20 years according to R^2, not expected increase in ARMAX models's performances results are observed with χ^2. Therefore; ARMAX model's performances estimated with χ^2 are not given in below figure.

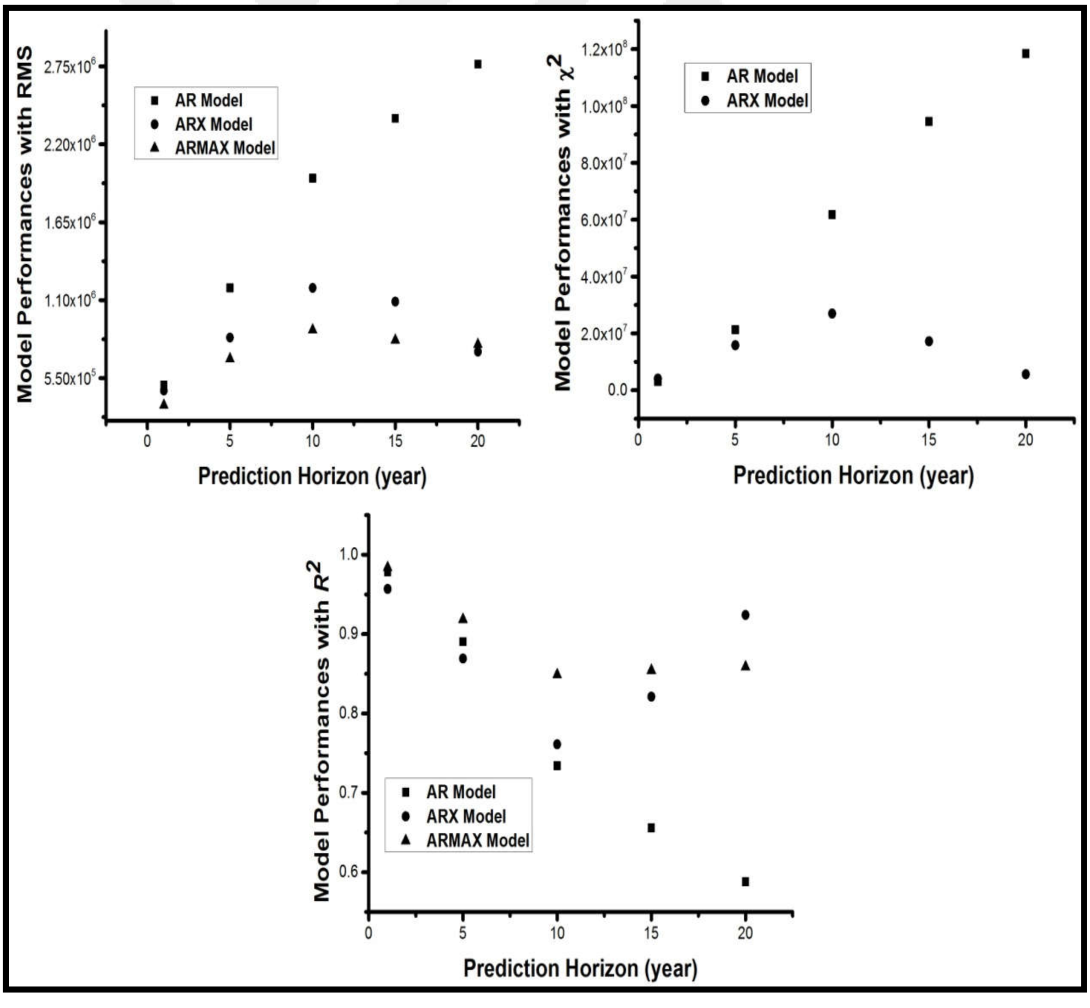

Figure 4.13 : Model performances from RMS, R^2 and χ^2 for corn by using recursive method.

Model performances, determined for barley production data in Turkey by using recursive method, are given in (Figure 4.14). Although R^2 values are partly increased for all three models when improvement is carried out by using recursive method, it is seen that improvements for model performance are achieved in AR and ARMAX model for increasing prediction horizon values (1 to 20 years). Instead of expected increases, it is observed that declines in ARX model according to R^2.

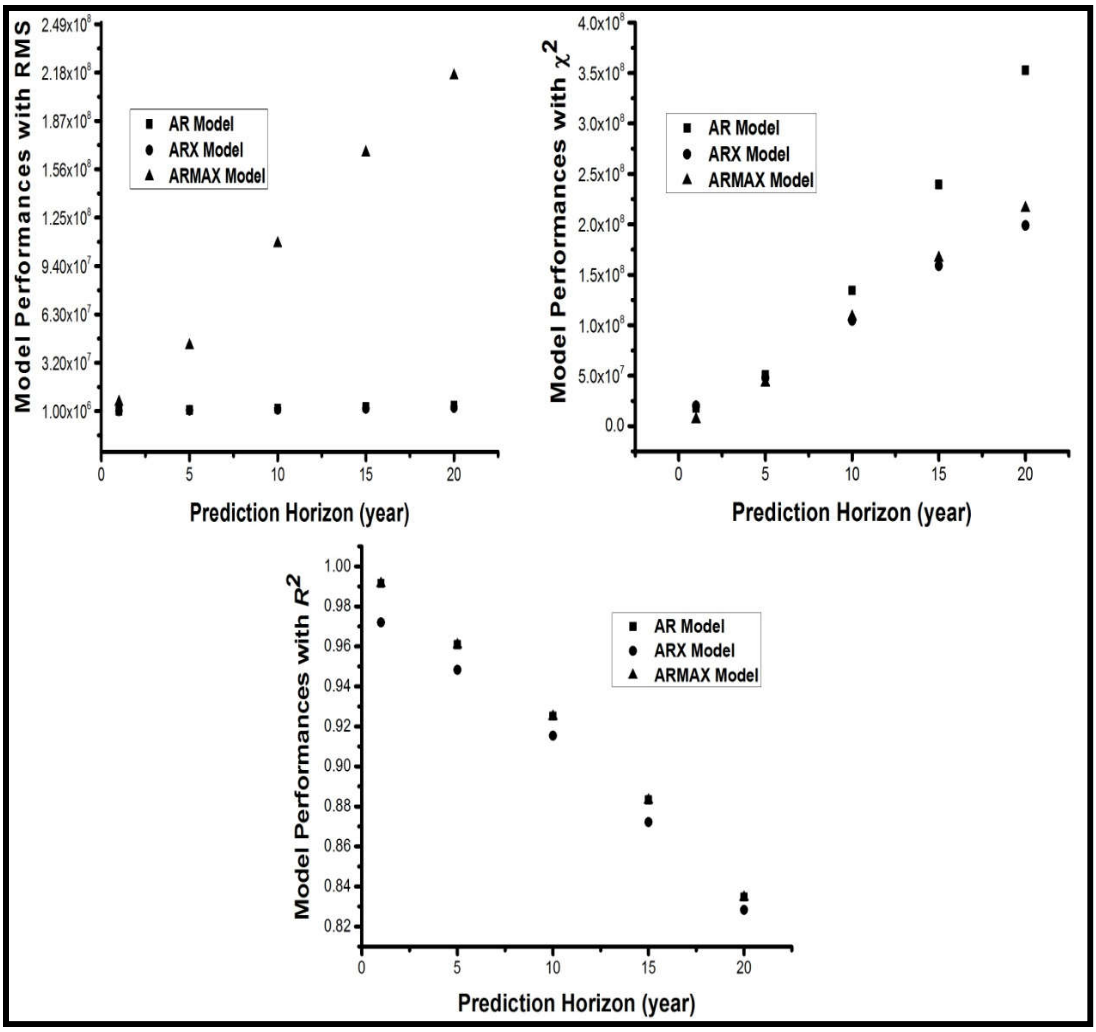

Figure 4.14 : Model performances from RMS, R^2 and χ^2 for barley by using recursive method.

When recursive method applied, the highest model performance could be obtained by using AR model is 0.9915, while it is 0.972 and 0.9915 with ARX and ARMAX model according to R^2 values, respectively. According to RMS; model performances results are very similar in AR and ARX models for the whole selected prediction horizon. Compared to corn and sugar beet production data, recursive method could be applicable to make better model performances for wheat and barley production data since data lengths and characteristics of these.

Model performances, determined for sugar beet production data in Turkey by using recursive method, are given in (Figure 4.15).

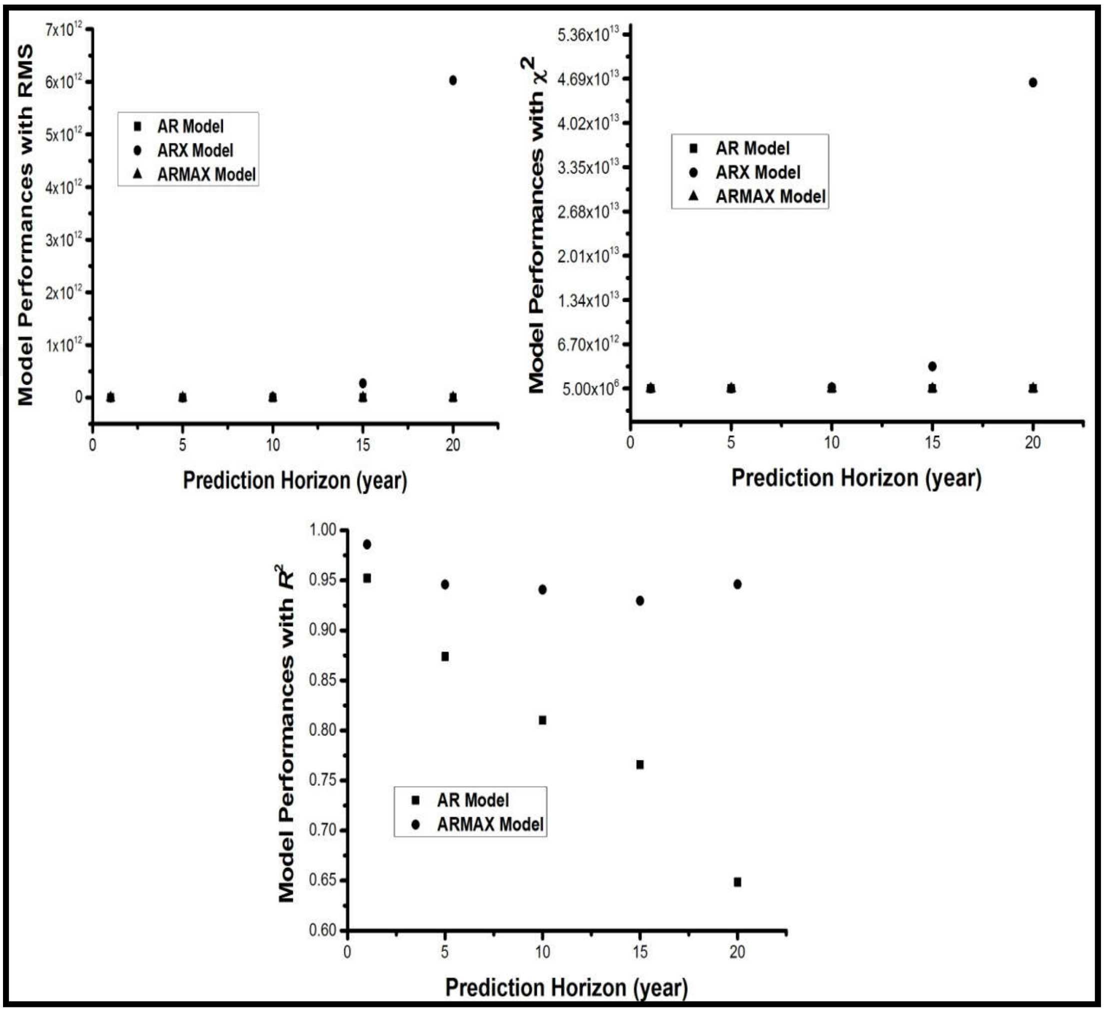

Figure 4.15 : Model performances from RMS, R^2 and χ^2 for sugar beet by using recursive method.

Although sugar beet data length is fairly shorter than other data lengths, R^2 values are mostly above 90% for AR and ARMAX models used to forecast sugar beet production. When improvement is carried out by using recursive method, it is determined that improvements for model performance are not achieved in AR and ARMAX models for increasing prediction horizon values (1 to 20 years) as expected. Instead of expected increases, it is observed that declines in ARX model according to R^2. Therefore, only AR and ARMAX models performances are given for R^2 results. When recursive method applied, the highest model performances could be obtained by using ARX and ARMAX models are 95.23% and 98.6% according to R^2 values, respectively. According to RMS and χ^2; model performances results are very similar in each of three models for the fifteen-year prediction horizon. Compared to barley and wheat production data, recursive method are not needed to apply better model performances for sugar beet production data since its data lengths and characteristics.

4.2.3 Model performances with ANN for bioethanol feedstock production data

In order to compare with the AR, ARX and ARMAX models, a model with ANN was performed in this thesis study. ANN, used in this study, are feed-forward and has single hidden layer. Number of nodes in input layer of ANN was considered due to determined model orders in AR and ARX models for each of bioethanol feedstock production data. However, different numbers of nodes have been performed in accordance with AR or ARX model orders and, model performances have been estimated for each selected number. The numbers of nodes in input layer were selected as 1, 2, 3, 4 to examine the effects of numbers changes in input layer and neurons in hidden layer. The number of neurons in hidden layer was estimated as " (number of nodes+1) / 2 " since the selected geometry was triangular, hidden layer was decreasing against output layer. On the other hand, there is one neuron in output layer. The training algorithm used in the study is Levenberg-Marquardt Method that has a common use. Although Levenberg-Marquardt algorithm reaches to the minimum value and error term will not decrease after this, ANN has been trained in 500 iterations by using Levenberg-Marquardt Algorithm to give a chance to all tests. RMS, R^2 and χ^2 results associated for selected feedstocks with ANN are given with figure 4.16, 4.18, 4.20 and 4.22 to evaluate the ANN performance. It has been concluded that ANN have shown more better performance especially for the first 5 or 10 years. The forecasting performance of ANN has been more directly affected from the data lengths and their characteristics. ANN's performance has been decreased or showed fluctuations in different predicton horizons for especially corn and sugar beet data. As shown in graphics drawn for R^2 results; performances for near future of between 1 and 5 years were higher as in AR model types (AR, ARX and ARMAX), even if ANN could be applied for twenty-years-prediction horizon. As can be seen, all results, ANN for this study were in a good fitting with the cereal production data (mainly wheat and then barley). ANN performance, determined for wheat production data by using in Turkey, are given in (Figure 4.16).

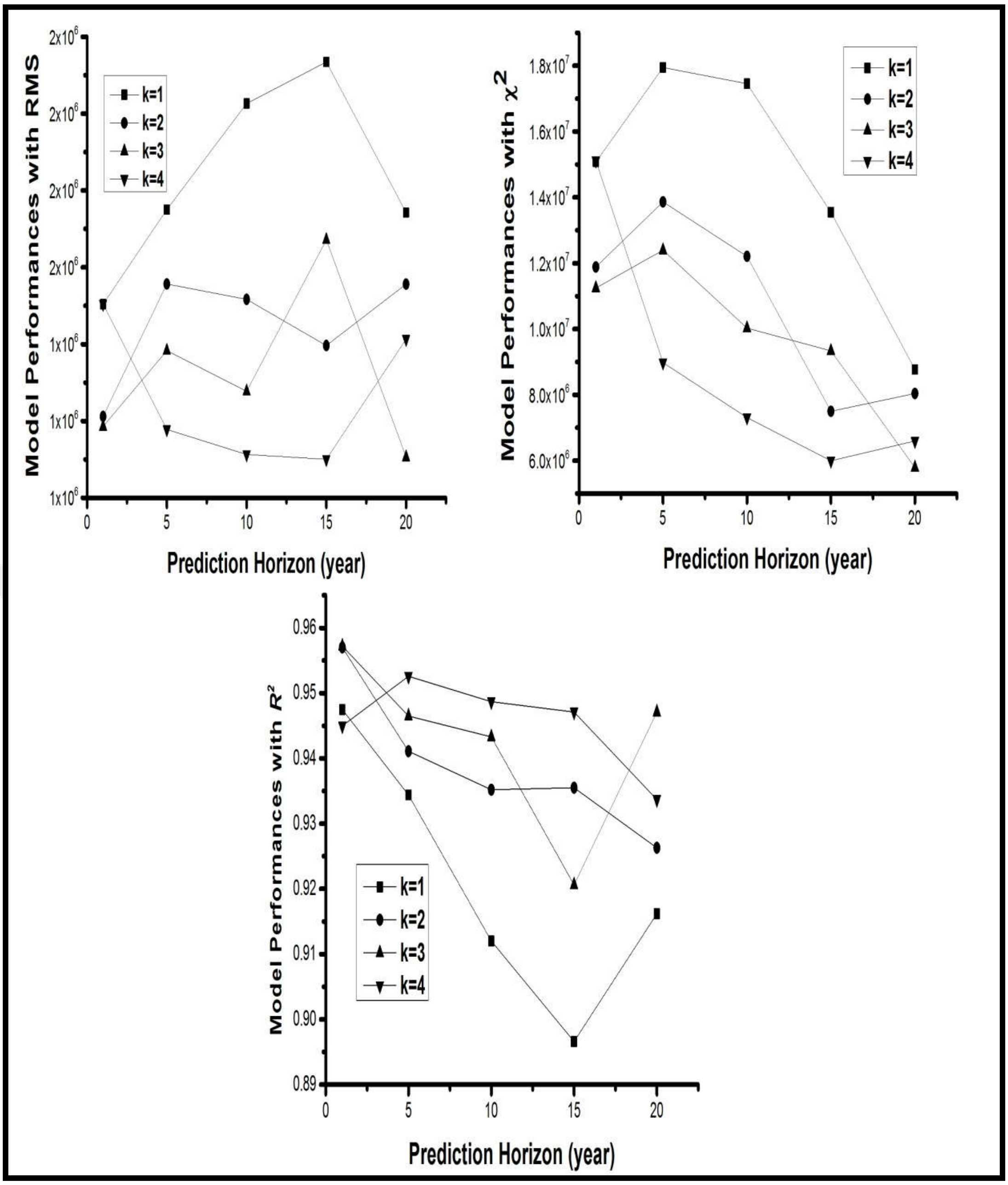

Figure 4.16 : ANN performances with RMS, χ^2, and R^2 for wheat production data.

Although R^2 values are mostly above 90% for all numbers of nodes in input layer used to run ANN for wheat production forecasting, it is seen that the highest model performance is achieved when the numbers of nodes in input layer is 3. The highest ANN performances without fluctuation could be obtained for wheat production data.

RMS, R^2 and χ^2 results associated for selected feedstocks with the recursive method are also presented to compare recursive method's effect on model performances as in auto-regressive-type models. It has been analyzed that recursive method exhibits different effects on model performances due to data lengths and characteristics.

Model performances, determined for wheat production data in Turkey by using recursive method, are given in (Figure 4.17).

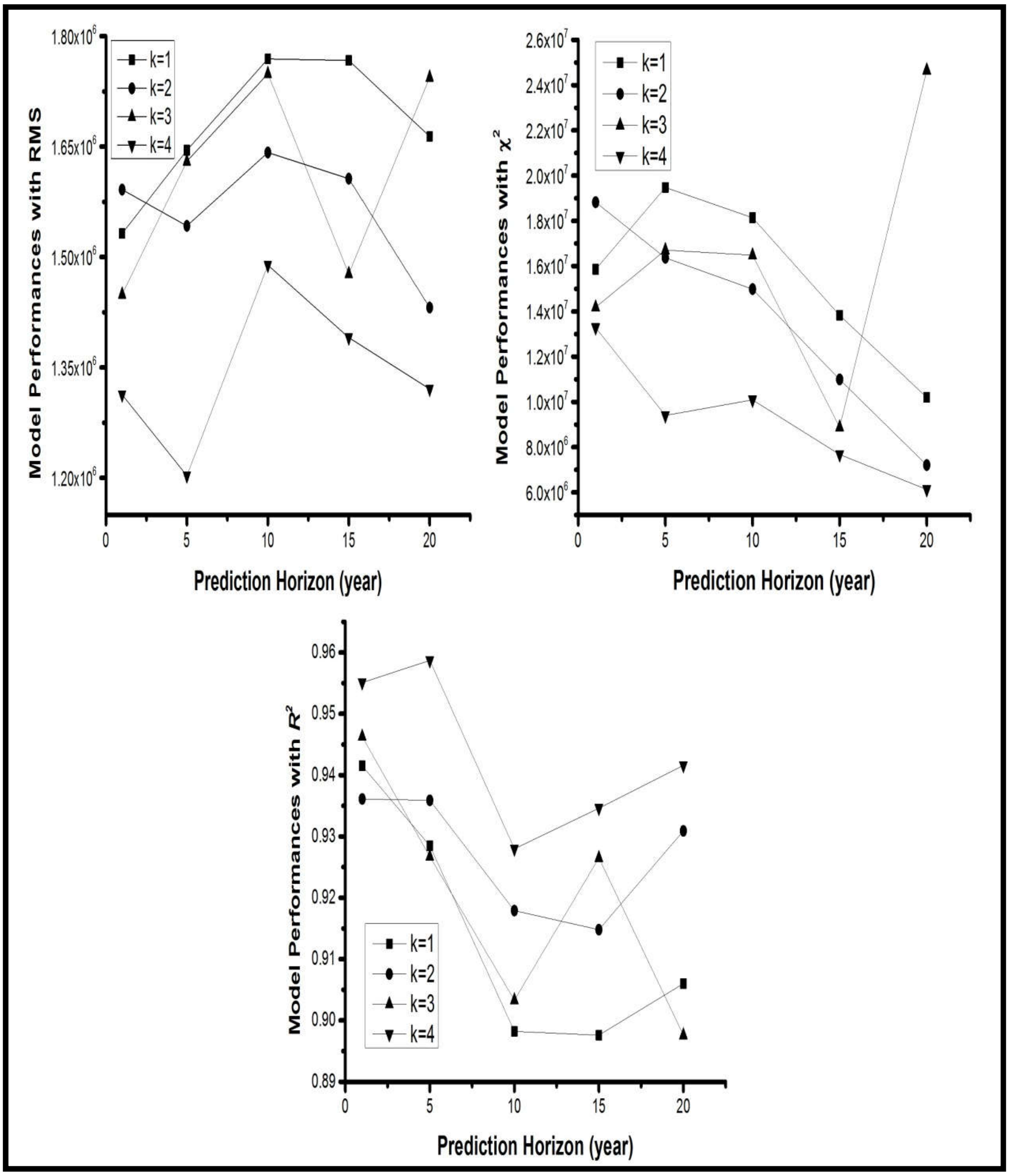

Figure 4.17 : ANN performances from RMS, R^2 and χ^2 for wheat by using recursive method.

When recursive method applied, the highest model performance could be obtained by ANN is 95.87% for k is 4 and prediction horizon is 5. While k is 3, highest model performance has been estimated as 94.63%. For all node numbers; model performances indicators are decreasing (in negligible quantities) for some of the prediction horizon values (from 1 to 20 years).

ANN performance, determined for corn production data by using in Turkey, are given in (Figure 4.18). Although R^2 values are mostly above 90% for all numbers of nodes in input layer used to run ANN for corn production forecasting, it is seen that the highest model performance is achieved when the numbers of nodes in input layer is 3. ANN's performance is decreased and shows fluctuations in different prediction horizons (from 5 to 15 years) when numbers of nodes input layer are 1 or 4. However, R^2 values in these two conditions are respectively reached to 97.1% and 98.94% after these fluctuations.

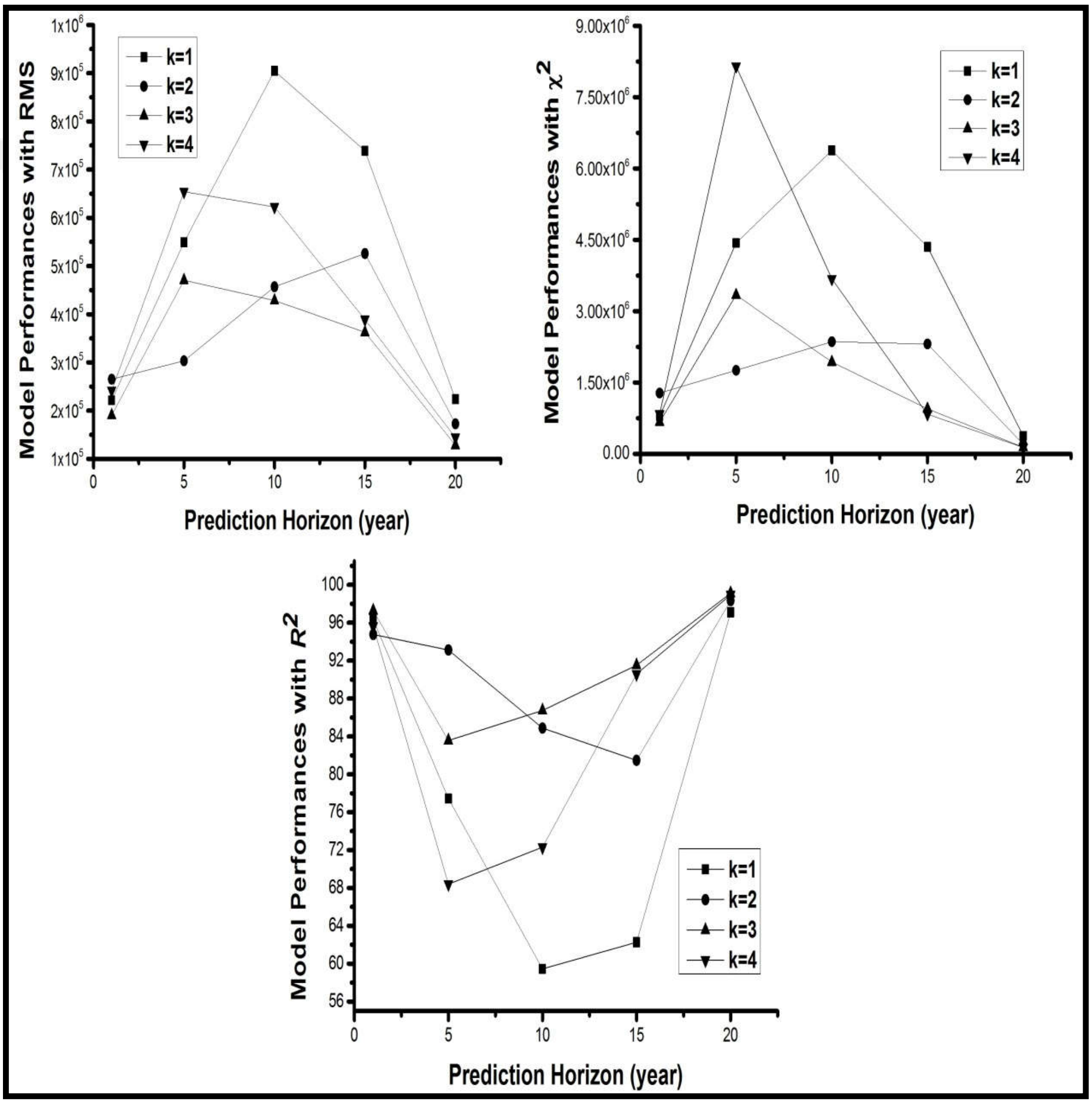

Figure 4.18 : ANN performances with RMS, χ^2, and R^2 for corn production data.

Model performances, determined for corn production data in Turkey by using recursive method, are given in (Figure 4.19). It is determined that recursive method has not been able to achieve the expected improvement in model performances for each of selected node numbers. When recursive method applied, the highest model performance could be obtained by ANN is 95.87% for k is 4 and prediction horizon is 20 according to R^2 values. It has been observed that firstly a decline and then a sharp increase according to R^2 when k was 1 and prediction horizon is 15, not expected increase and sustainable results could not be obtained when k is 3. Therefore; ANN performances estimated with this node number are not given in below figure.

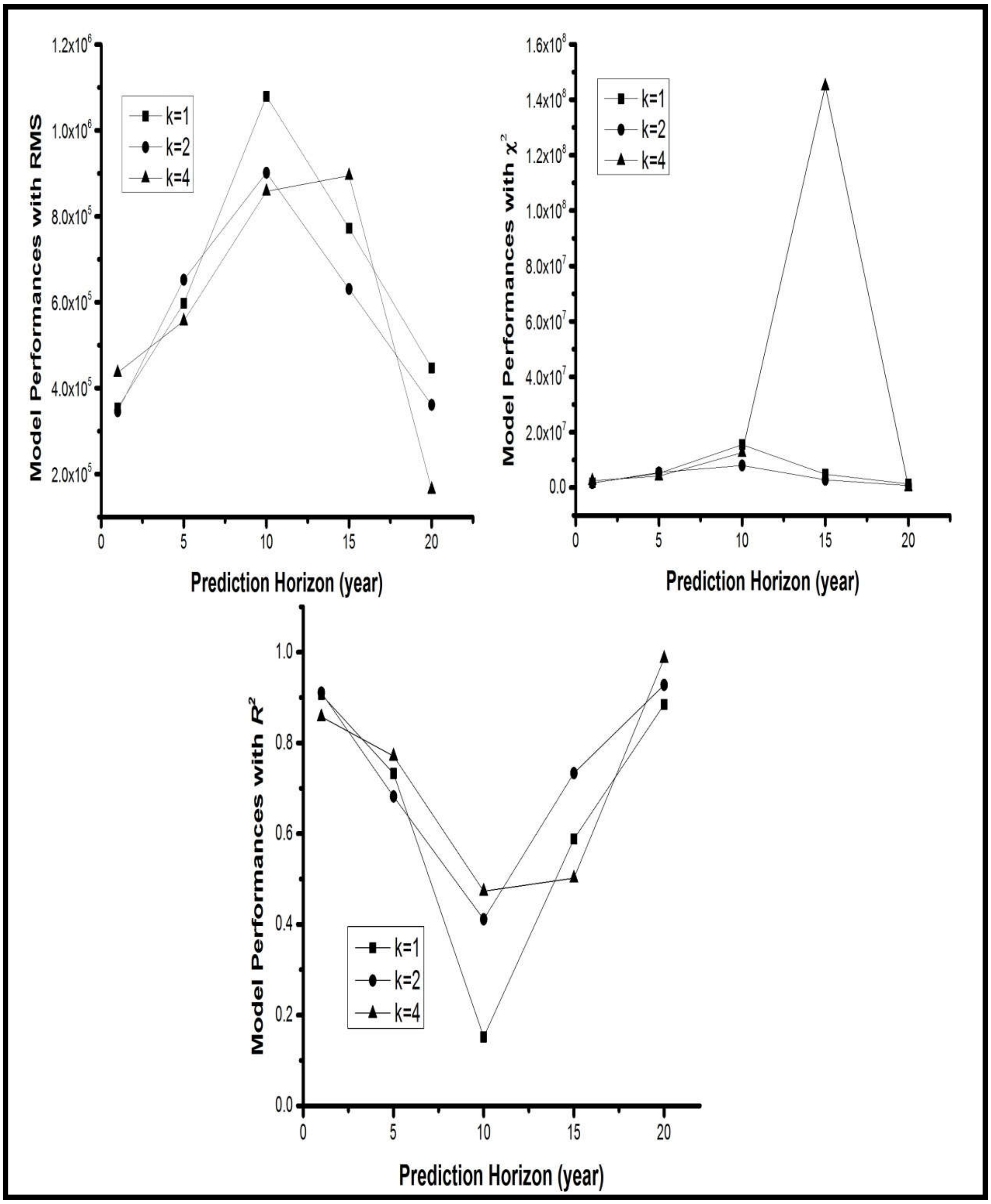

Figure 4.19 : ANN performances from RMS, R^2 and χ^2 for corn by using recursive method.

ANN performance, determined for barley production data by using in Turkey, are given in (Figure 4.20). Although R^2 values are mostly above 90% for all numbers of nodes in input layer used to run ANN for barley production forecasting, it is seen that the highest model performance is achieved when the numbers of nodes in input layer is 2. When this becomes 1 or 4; the model performances decrease especially for fifteenth and twentieth year. The highest ANN performances without fluctuation could be obtained for wheat production data as in wheat production data.

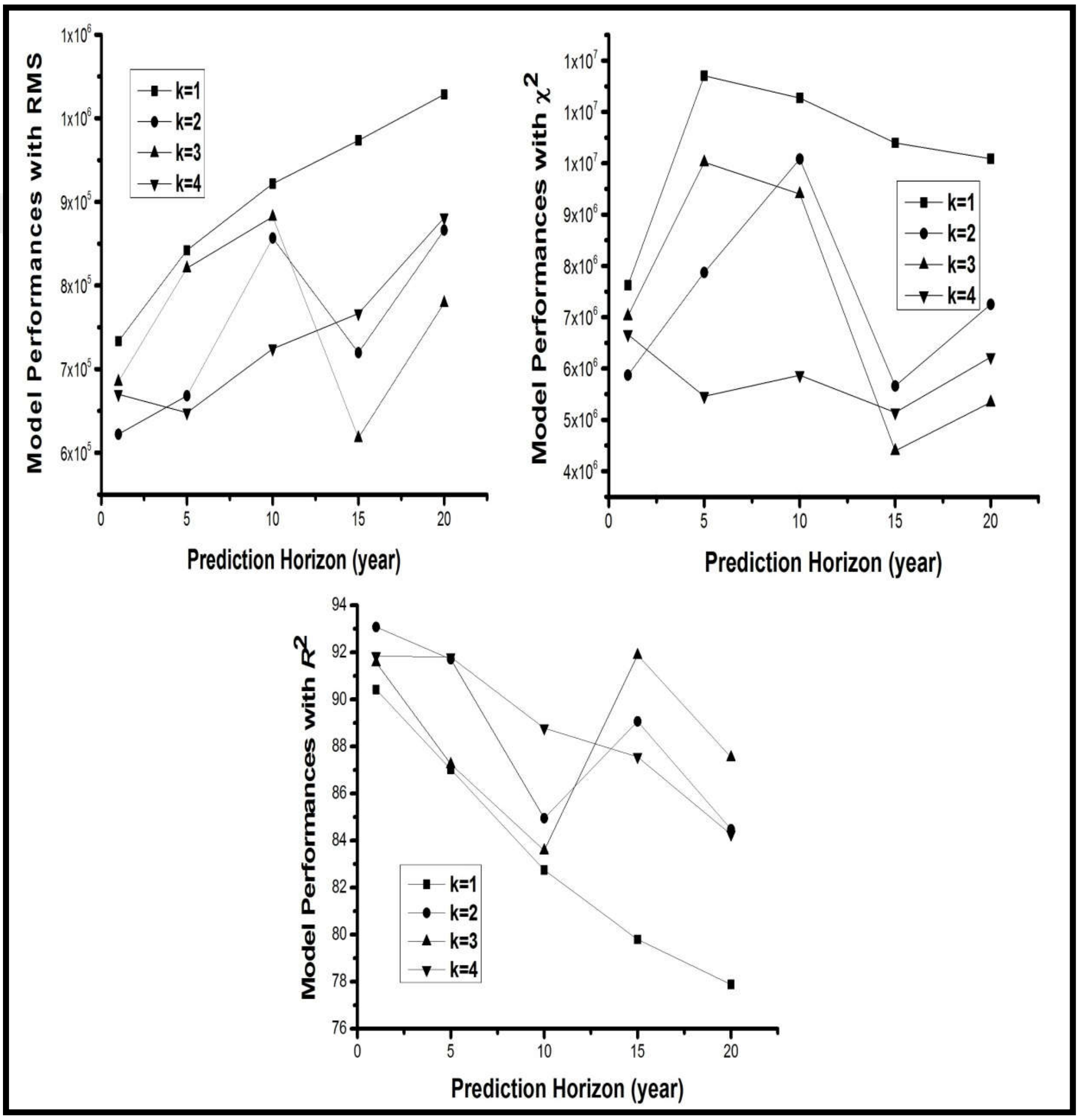

Figure 4.20 : ANN performances with RMS, χ^2, and R^2 for barley production data.

When recursive method applied, the highest model performance could be obtained by ANN is 91.04% for k is 3 and prediction horizon is 1 in (Figure 4.21). While k is 2, highest model performance has been estimated as 89.94%. For all node numbers; model performances indicators are decreasing (in negligible quantities) for some of the prediction horizon values (from 1 to 20 years). While k is 1, model performances have been decreased to 78.56% and 76.41% for the fifteenth and twentieth year, respectively.

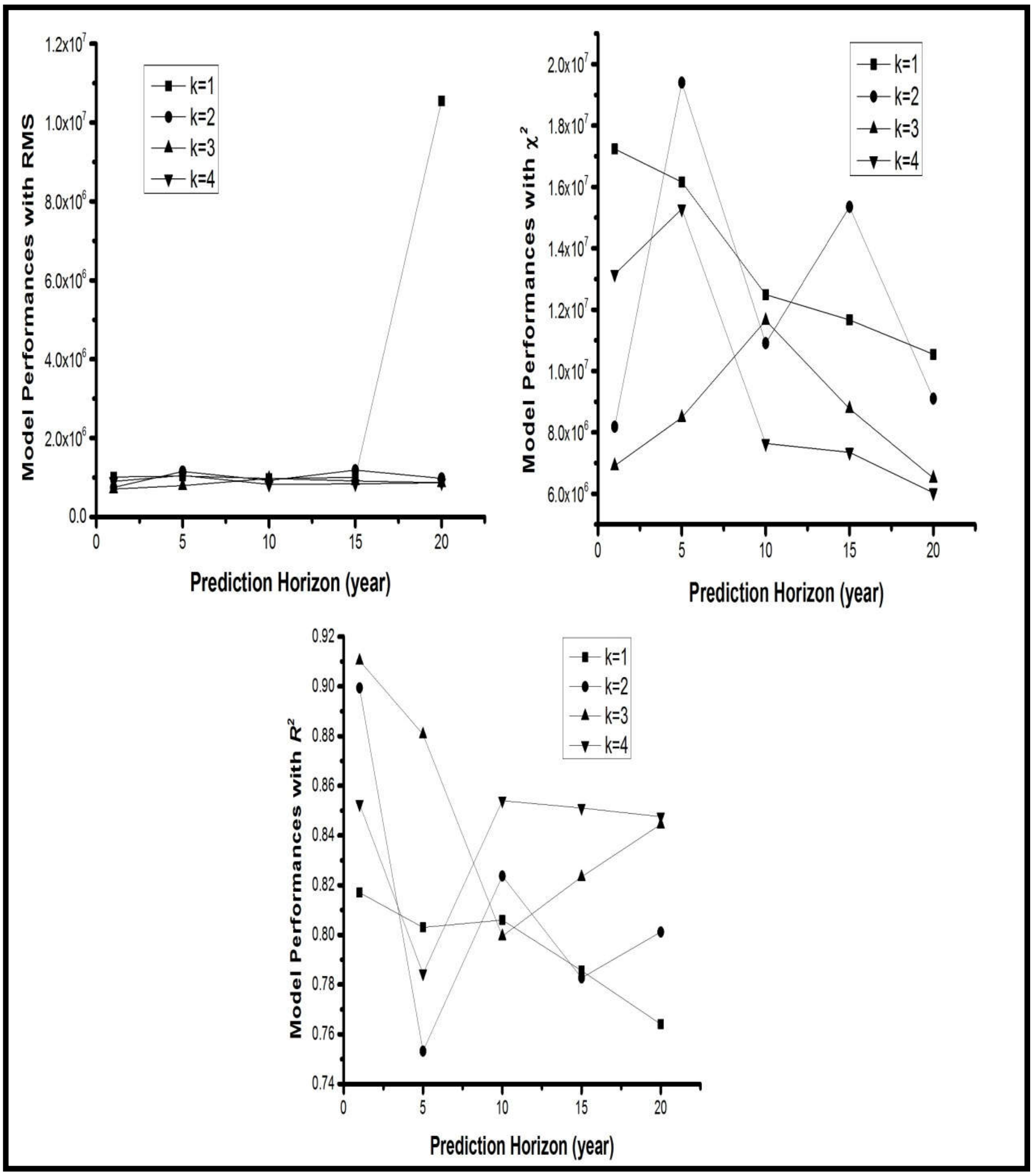

Figure 4.21 : ANN performances from RMS, R^2 and χ^2 for barley by using recursive method.

ANN performance, determined for sugar beet production data by using in Turkey, are given in (Figure 4.22). It could not be concluded that R^2 values are mostly above 90% for all numbers of nodes in input layer used to run ANN for sugar beet production forecasting as in other feedstocks. ANN's performances are decreased and show fluctuations in different prediction horizons (from 5 to 15 years) when numbers of nodes input layer are 1, 2 or 3. The cause of all them thought as data length is too short compared with other feedstocks data. It is seen that the highest model performance is achieved when the numbers of nodes in input layer is 4. In this point; a fluctuation are also observed between fifth and fifteenth years. However, R^2 values in here is reached to 100% after these fluctuations, while χ^2 and RMS results are found as " 0 " in twentieth year. It means that this result is "best fit" for this forecasting.

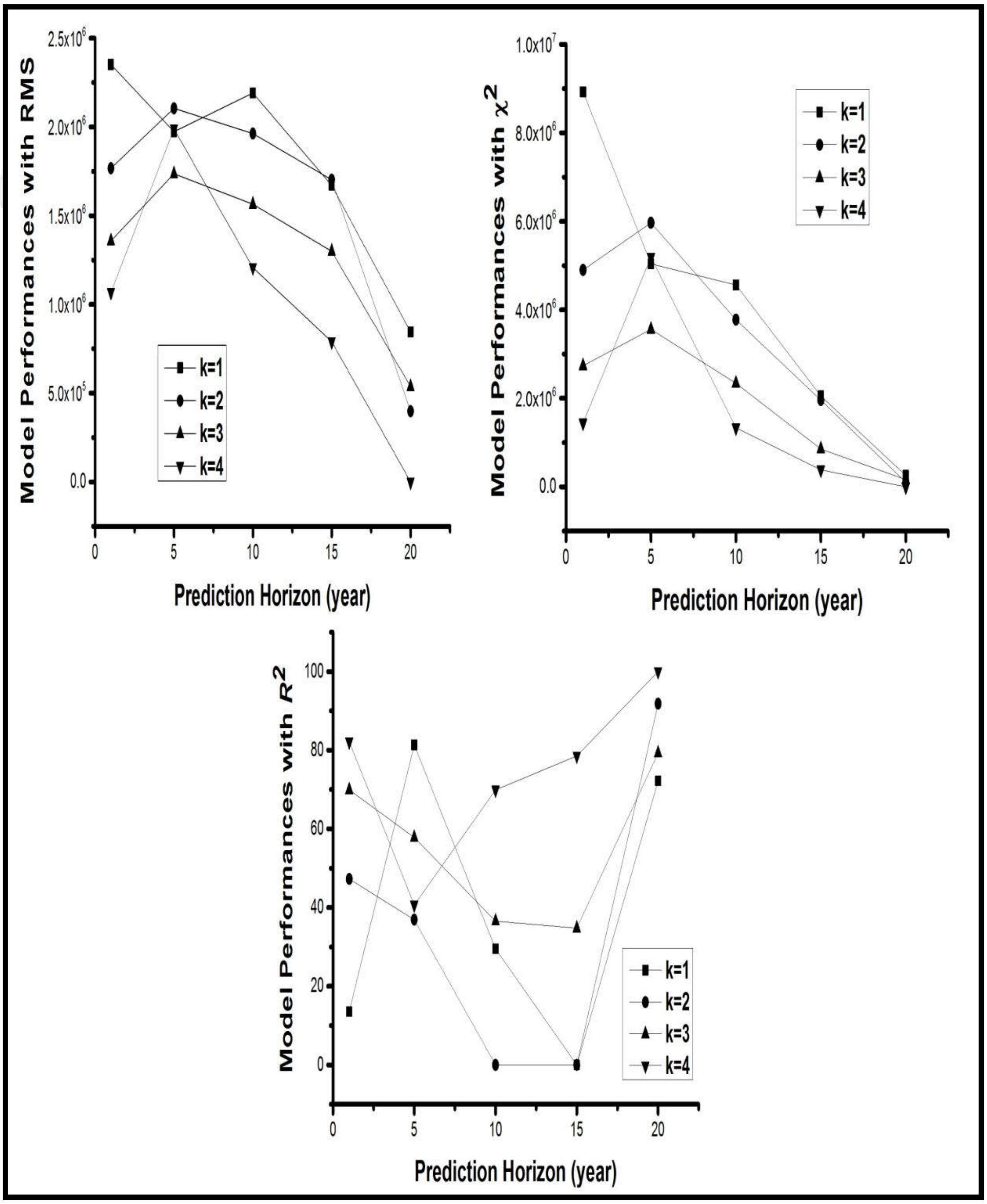

Figure 4.22 : ANN performances with RMS, χ^2, and R^2 for sugar beet production data.

When improvement is carried out by using recursive method, it is determined that improvements for model performance are not achieved as expected. Instead of expected increases when k are 1, 2 and 3, it is observed that declines estimated and sustainable results could not be obtained by using recursive method in ANN. Therefore, results belong to k is 4 are only given in (Figure 4.23). When recursive method applied, the highest model performances could be obtained 80.39% according to R^2 values. Compared to barley and wheat production data, recursive method are not needed to apply better model performances for sugar beet production data since its data lengths and characteristics as in auto-regressive-type models.

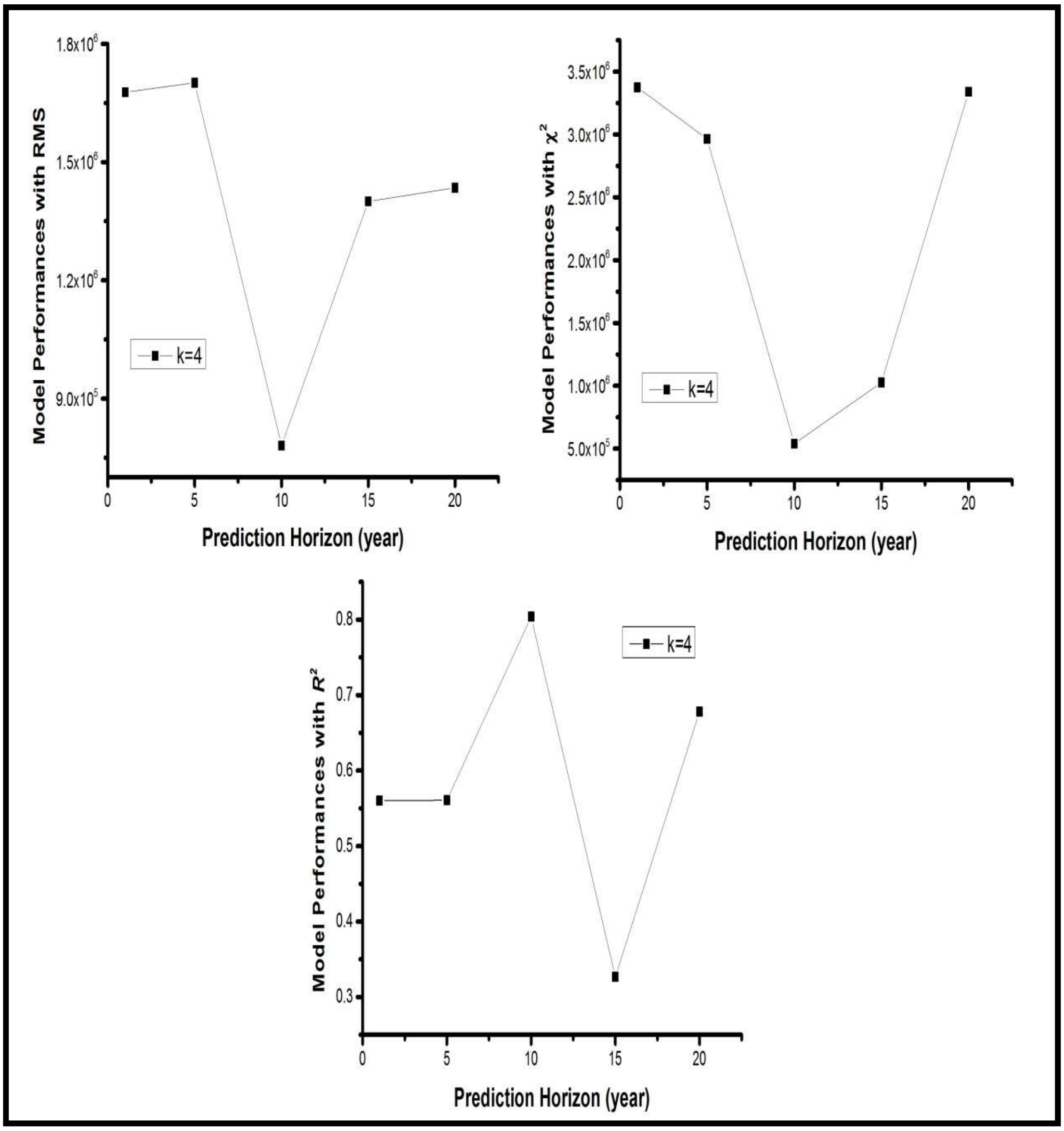

Figure 4.23 : ANN performances from RMS, R^2 and χ^2 for barley by using recursive method.

4.2.4 Model performances with AR, ARX and ARMAX model and Recursive method for gasoline consumption data

RMS, R^2 and χ^2 results associated for gasoline consumption with the AR, ARX and ARMAX models are presented with (Figure 4.24) to compare the model performances. All selected models could be applied in a sustainable and reliable way for fifteen years not twenty years as in bioethanol feedstocks data. It is analyzed that ARX model has shown the best performances (99.99%) especially for the first 15 years. Also; AR and ARMAX models have performances by above 90-95% as in ARX model at the same conditions for each serie.

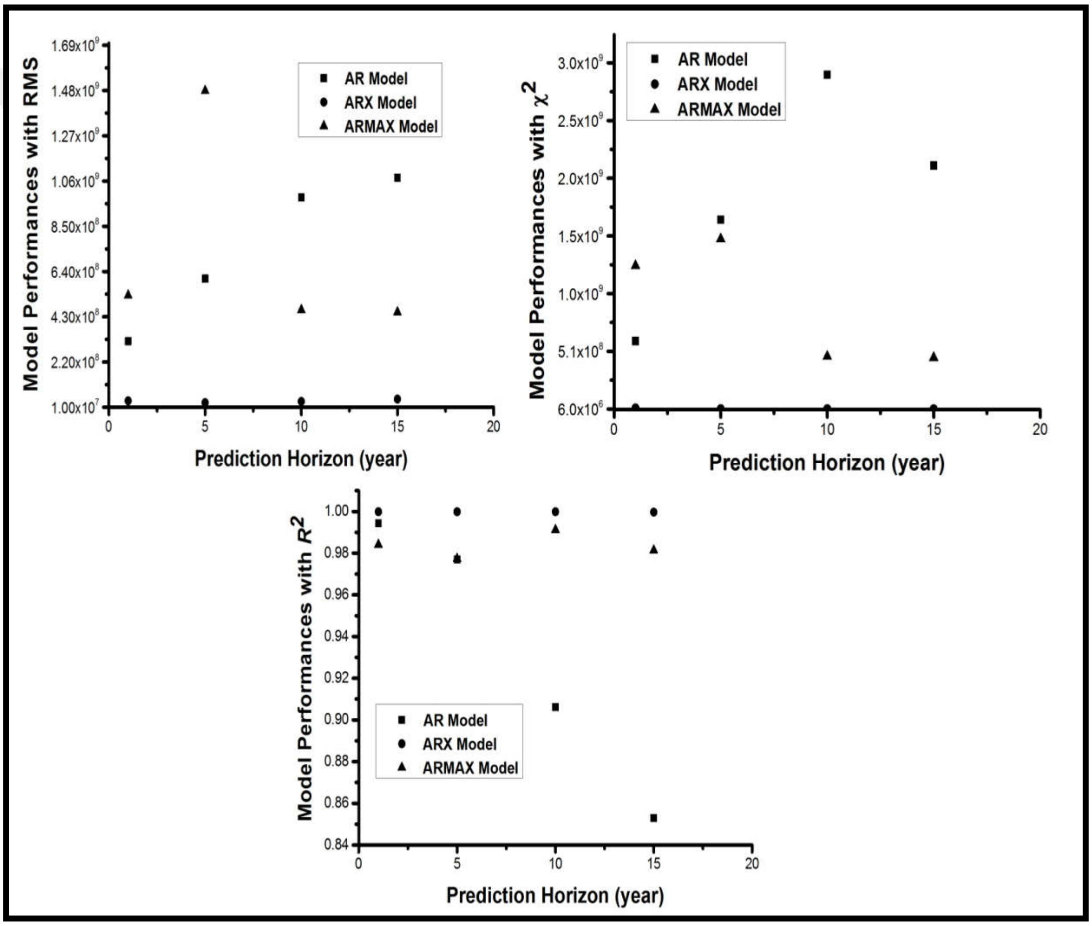

Figure 4.24 : Model performances from RMS, χ^2, and R^2 for gasoline consumption data.

As can be seen, all results, both linear (AR model) and non-linear models (ARX and ARMAX models) examined in this study were in a good fitting with the gasoline consumption data. The highest model performance could be obtained by using ARX model is 99.99% by R^2, while it is 99.43% and 99.12% (by R^2) with AR and ARMAX model, respectively.

Forecasted data, real data and absolute error determined with AR, ARX and ARMAX model for gasoline data are given in (Figure 4.25).

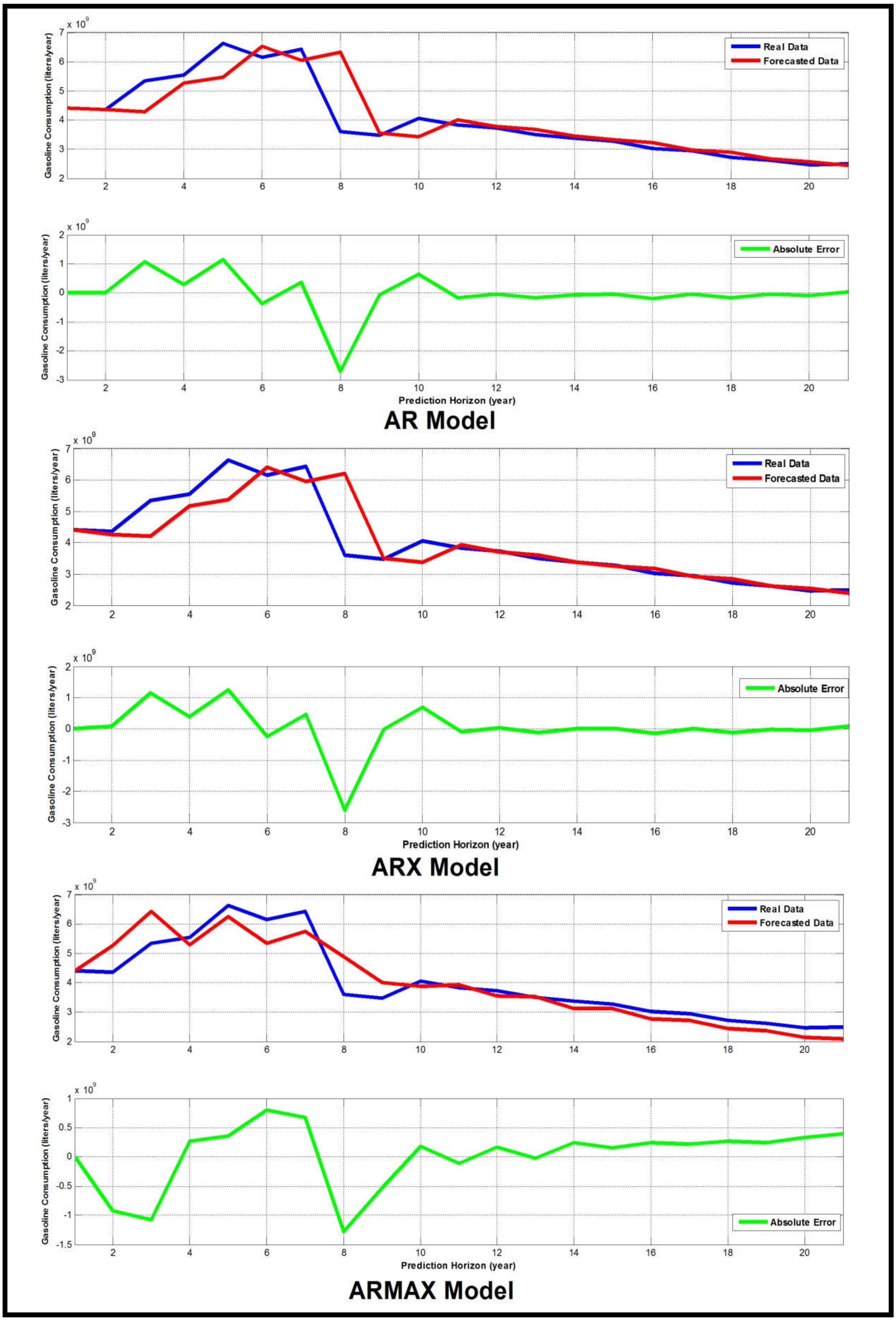

Figure 4.25 : Gasoline consumption data and forecasting serie obtained with AR, ARX and ARMAX model.

Although gasoline consumption data length is a little short to be able to make forecast, the same trends are observed for the curves in the three of models. But, there is a different view of "Absolute Error" curve for the increasing prediction horizon values in all models compared to feedstock curves. ARMAX model's "Absolute Error" curve is quite different from other two models beginning from the fourth-year-forecasting horizon. It is concluded that the length of data serie is so crucial for model performance whichever kind of model is used. Fluctuations on increase "Absolute Error" curve as the length of the data serie becomes shorter.

RMS, R^2 and χ^2 results associated for gasoline consumption data with the recursive method are presented with (Figure 4.26) to determine recursive method's effect on model performances.

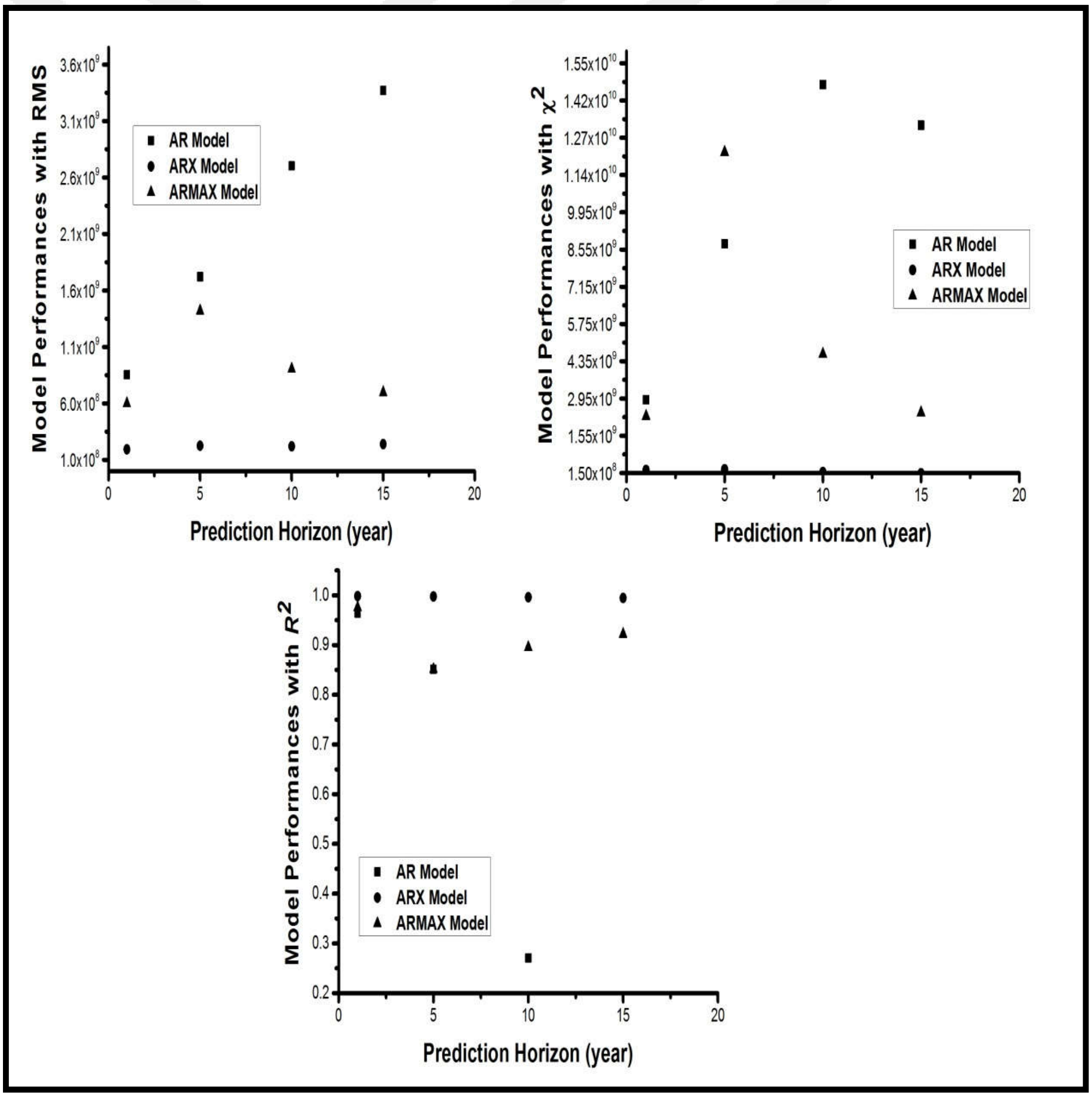

Figure 4.26 : AR, ARX and ARMAX performances from RMS, R^2 and χ^2 for gasoline consumption by using recursive method.

It is analyzed that recursive method exhibits different effects on model performances due to gasoline consumption data length and characteristics. As shown in graphics drawn for R^2 results; application of recursive method for ARX and ARMAX model will be better to obtain higher model performances. The expected performance improvement could not be achieved by recursive method in AR model especially after the tenth year. Therefore; R^2 results, belong to only the first ten years, are given in (Figure 4.26). Although R^2 values are partly increased for ARX and ARMAX models when improvement is carried out by using recursive method, it is seen that the highest improvement for model performance is achieved in ARX model for increasing prediction horizon values (1 to 15 years). When recursive method applied, the highest model performance could be obtained by using AR model is 96.43%, while it is 99.83% and 97.58% with ARX and ARMAX model, respectively. Model performances indicators are decreasing with increasing prediction horizon values (from 1 to 15 years) in AR model by comparison to other two models. According to R^2; model performances results are very similar in ARX model for the selected prediction horizon. Besides, both RMS and χ^2 curves (each in its own right) for ARX model show similar trends as seen from (Figure 4.26).

4.2.5 Model performances with ANN for gasoline consumption data

In order to compare with the AR, ARX and ARMAX models, a model with ANNs is performed for gasoline consumption data as in feedstocks data. ANN, used in this study, is forward-feed and has single hidden layer. Although number of nodes in input layer of ANNs is considered due to determined model orders in AR and ARX models for gasoline consumption data, the same numbers selected as in feedstocks data (such as 1, 2, 3, 4) and model performances has been estimated for each selected number. The numbers of nodes in input layer (k) are selected as 1, 2, 3, 4 to examine the effects of numbers changes in input layer and neurons in hidden layer. The number of neurons in hidden layer is estimated as " (number of nodes+1) / 2 " since the selected geometry of hidden layer is decreasing to forward. On the other hand, there is a one neuron in output layer. The training algorithm used in the study is Levenberg-Marquard Method that has a common use. ANN is trained in 500 iterations by using Levenberg-Marquard Algorithm as in bioethanol feedstocks data ANNs applications. RMS, R^2 and χ^2 results associated for gasoline consumption data with ANN are given with (Figure 4.27) to evaluate the ANN performance. It is analyzed that ANN have shown different performances with the numbers of nodes in input layer. ANN's performances are not decreased or shows fluctuations in different predicton horizons for gasoline consumption data for these numbers. As shown in graphic drawn for R^2 results; ANN could be applied for fifteen-years-prediction horizon. As can be seen, all results, ANN for this study were in a good fitting with the gasoline consumption data. ANN performance, determined for gasoline consumption data in Turkey, are given in (Figure 4.27).

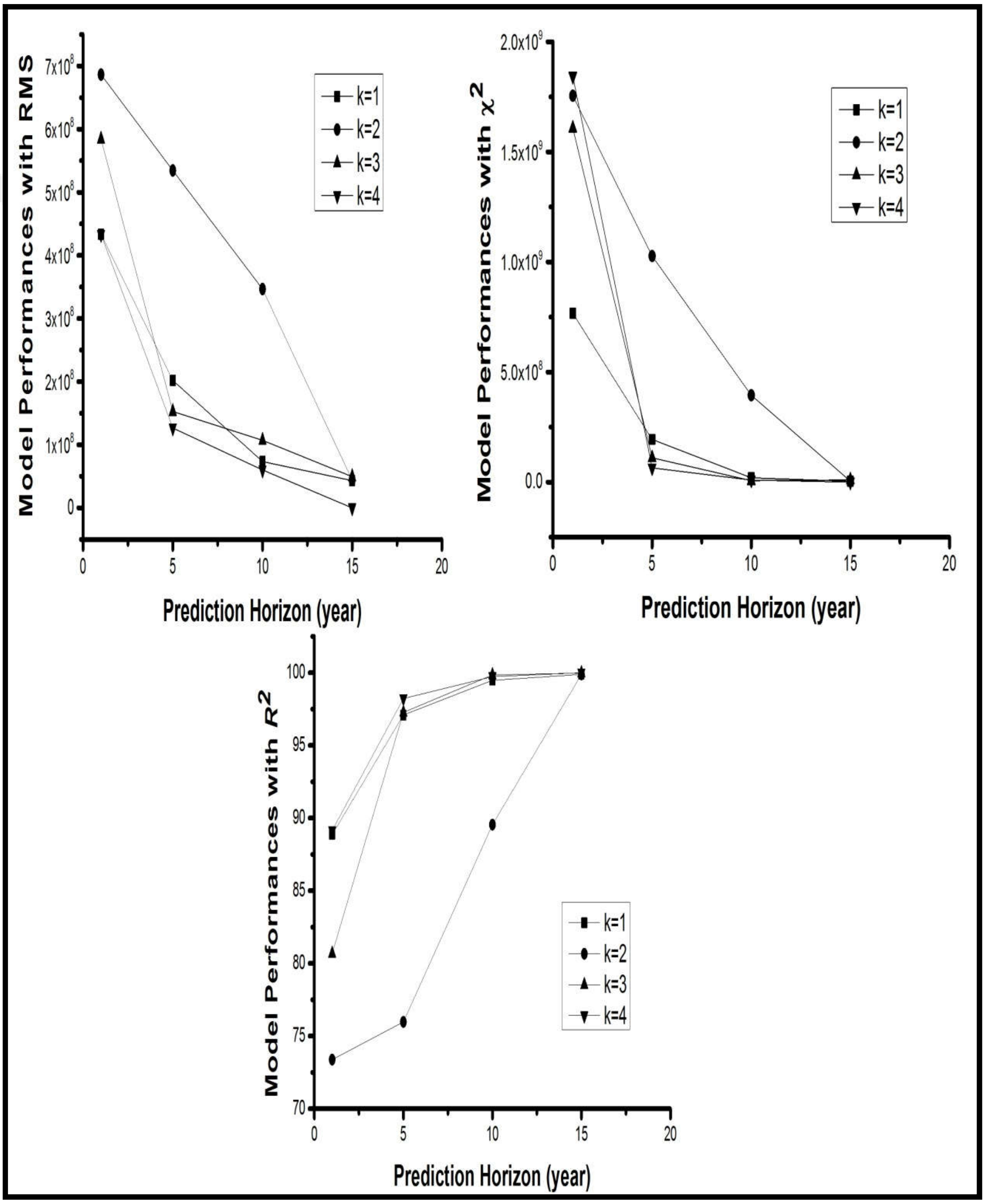

Figure 4.27 : ANN performances from RMS, χ^2, and R^2 for gasoline consumption data.

Although R^2 values are mostly above 90% for all numbers of nodes in input layer used to run ANNs for gasoline consumption forecasting, it is seen that the highest model performance is achieved when the numbers of nodes in input layer is 4. For this number; the highest achievable performance is 100% in twentieth year and it defined as best fit. The highest ANN performances (99.98%) without fluctuation could also be obtained when the numbers of nodes in input layer is 3.

RMS, R^2 and χ^2 results associated for gasoline consumption data with the recursive method are presented with (Figure 4.28) to determine recursive method's effect on ANN performance.

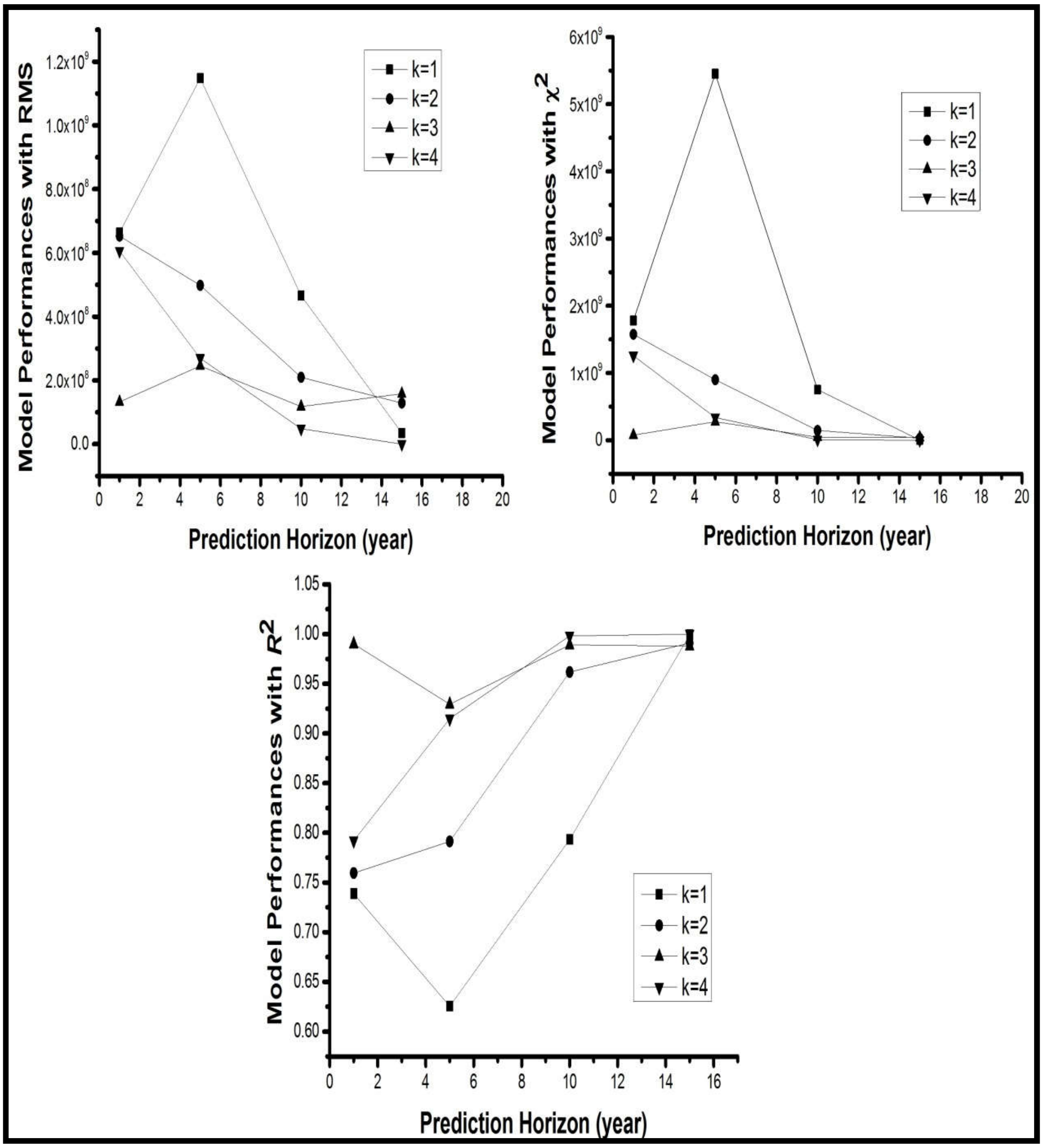

Figure 4.28 : ANN performances from RMS, R^2 and χ^2 for gasoline consumption by using recursive method.

It is seen that the highest improvement for model performance is achieved as 100% when the k is 4 and 15th year ("Best fit"). When recursive method applied, the highest model performances could be obtained for the fifteenth year in all node numbers. According to R^2; when the k are 1 and 2, model performances results have been estimated as 99.92% and 99.1%, respectively.

4.3 Forecasting Results

In this thesis study, forecasting on bioethanol feedstock production data for next twenty years and forecasting on gasoline consumption data for next fifteen years in Turkey have been carried out by using AR, ARX, ARMAX models and ANN considering performance results in earlier stage. Forecasting results are seperately given as "Forecasting of bioethanol feedstock production data" and "Forecasting of gasoline consumption data".

4.3.1 Forecasting of bioethanol feedstock production data

In this study, bioethanol feedstocks production data forecasting in Turkey, for next twenty years between 2014 and 2033 was carried out using AR, ARX and ARMAX models in the same model orders and prediction horizons considering performance results in earlier stage. Prediction results regarding wheat, corn, barley and sugar beet were estimated with AR, ARX and ARMAX models, and represented in (Figure 4.29-4.32), respectively. It is seen that production decrease with increasing the period of prediction horizon due to the decline in model performances in these figures. Also; forecasting results for all of them generally have lower values than original data. It is thought that this situation derived from some decline in model performances and data characteristics.

Compared to studies in literature such as International Grain Council; IGC, (2014) and Food and Agriculture Organization of the United Nations; FAO (2014) reports, there is no longer forecasts on grain which could be used for bioethanol production. According to IGC statistics for 2014, the wheat forecast is 22.1 million tonnes/years. In the present study, forecasted wheat production was 21.32 (AR Model), 21.3 (ARX Model) and 20.95 (ARMAX Model) million tonnes (Figure 4.29). The data in the reports and forecasts are sufficiently similar as to verify consistency of the models.

In 2018, wheat production is forecasted to be 20.08 (AR Model), 20.02 (ARX Model) and 19.8 (ARMAX Model) million tonnes.

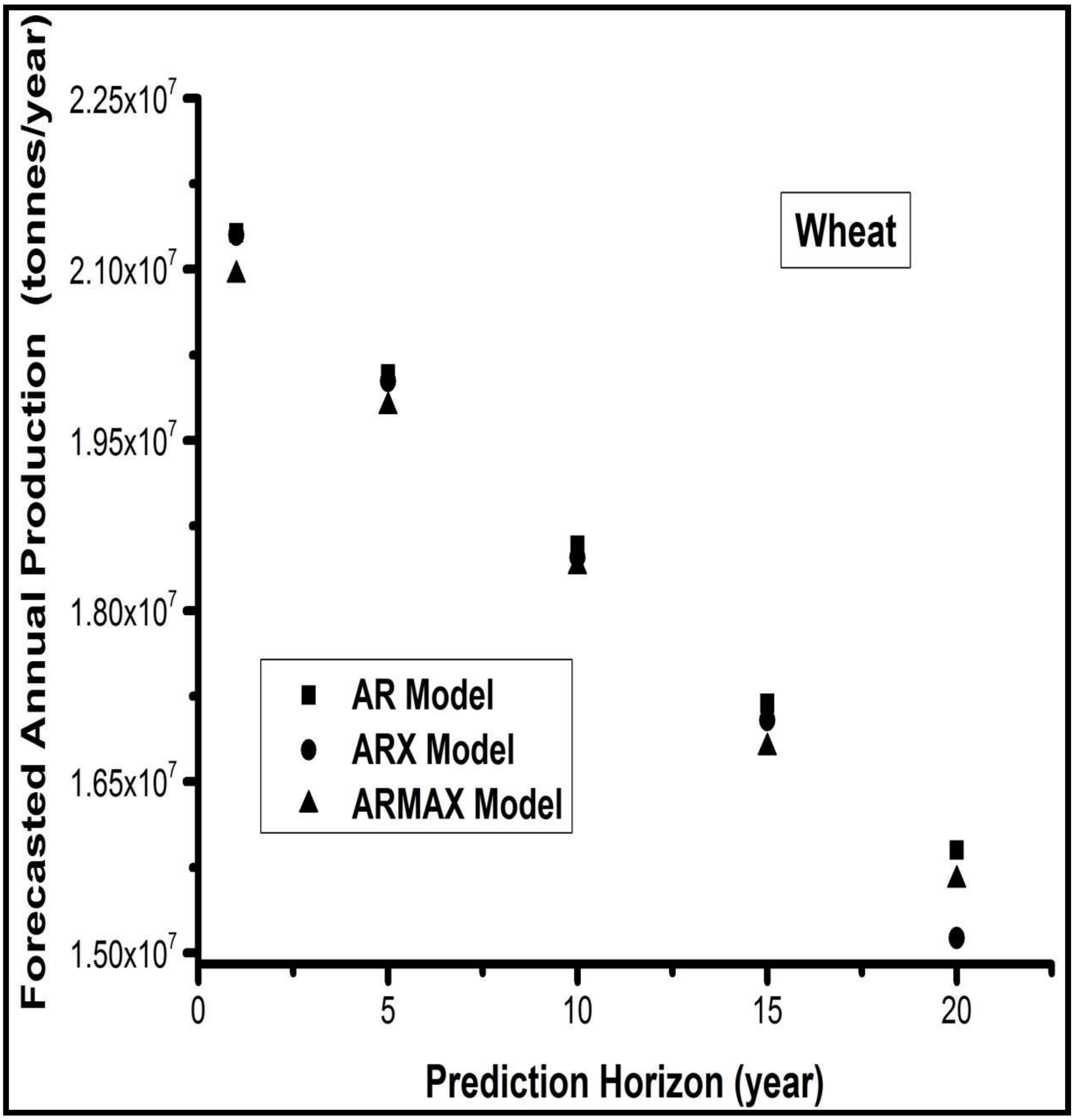

Figure 4.29 : Forecasted annual production of wheat (tonnes/year) for 20-year prediction horizon (2014-2033) in Turkey.

Corn production from IGC data was 5.9 million tonnes for 2014, but the corn forecast was 5.496 (AR Model), 5.486 (ARX Model), 5.3 (ARMAX Model) million tonnes (Figure 4.30). Corresponding for 2018 is forecasted to be 4.138 (AR Model), 4.101 (ARX Model) and 4.35 (ARMAX Model) million tonnes. Although AR and ARX models are similar; if not much, ARMAX model indicators are started to move away them beginning from first ten years when the model results compared to wheat production data forecasting. It is thought that shorter data length and characteristics of corn production are effective in this case.

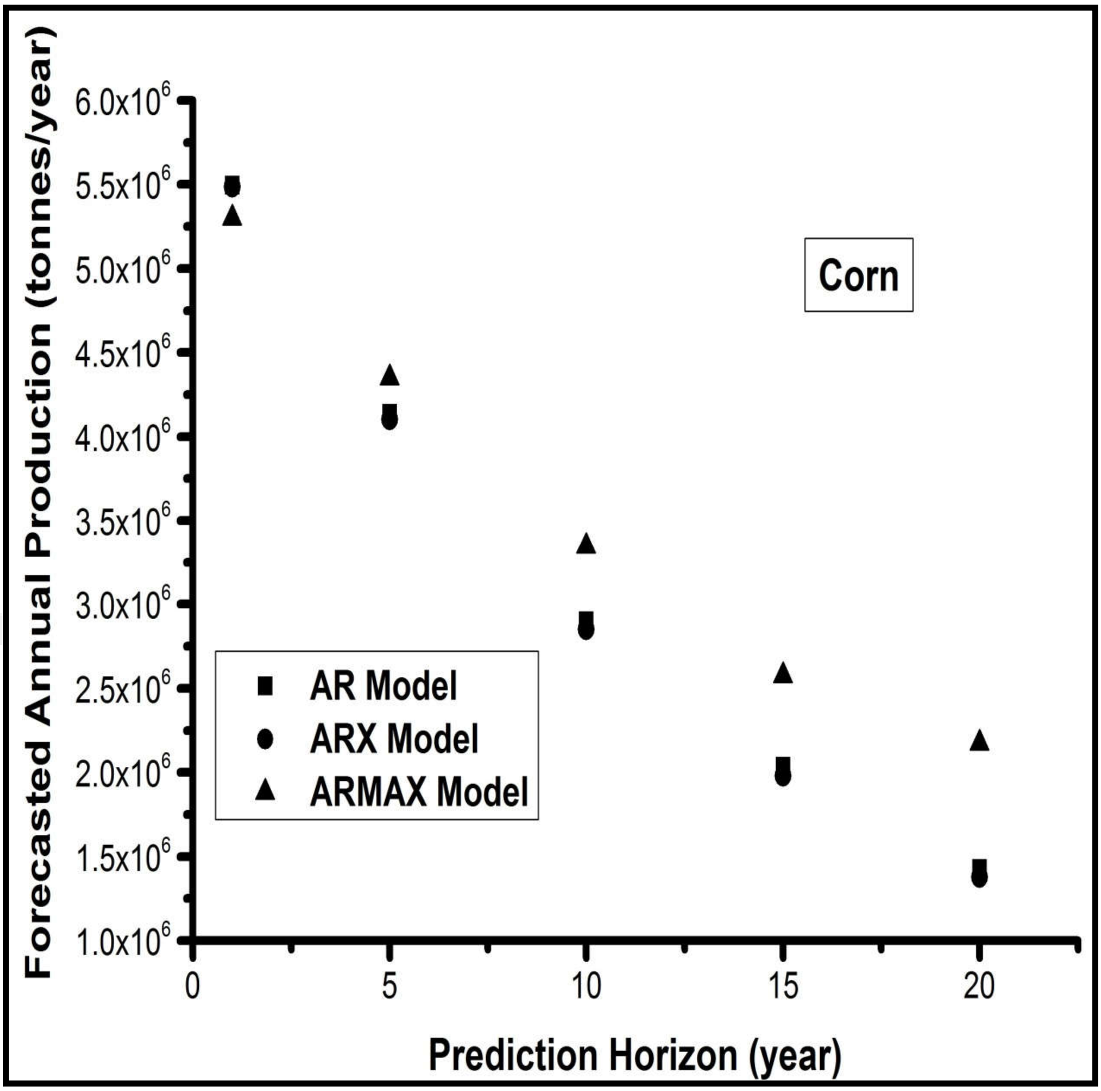

Figure 4.30 : Forecasted annual production of corn (tonnes/year) for 20-year prediction horizon (2014-2033) in Turkey.

Barley production was predicted with AR, ARX and ARMAX model as given in (Figure 4.31). For barley in 2014; production was predicted at 7.9 million tonnes in IGC data, whereas forecasts were 7.591 (AR Model), 7.581 (ARX Model), 7.088 (ARMAX Model) million tonnes. Although AR and ARX models are similar as in corn and wheat data; if not much, ARMAX model indicators are started to move away them beginning from first years when the model results compared to wheat and corn production data forecasting. Also, there is a decline in ARMAX model forecasting for the fifth year, then this is balanced with an increase by the tenth year and after. However, these fluctuations or changes do not conclude significant effects on prediction indicators. The general structure of data causes several changes in forecasting results. In 2018, the barley production is forecasted to be 7.127 (AR Model), 7.083 (ARX Model) and 6.438 (ARMAX Model) million tonnes.

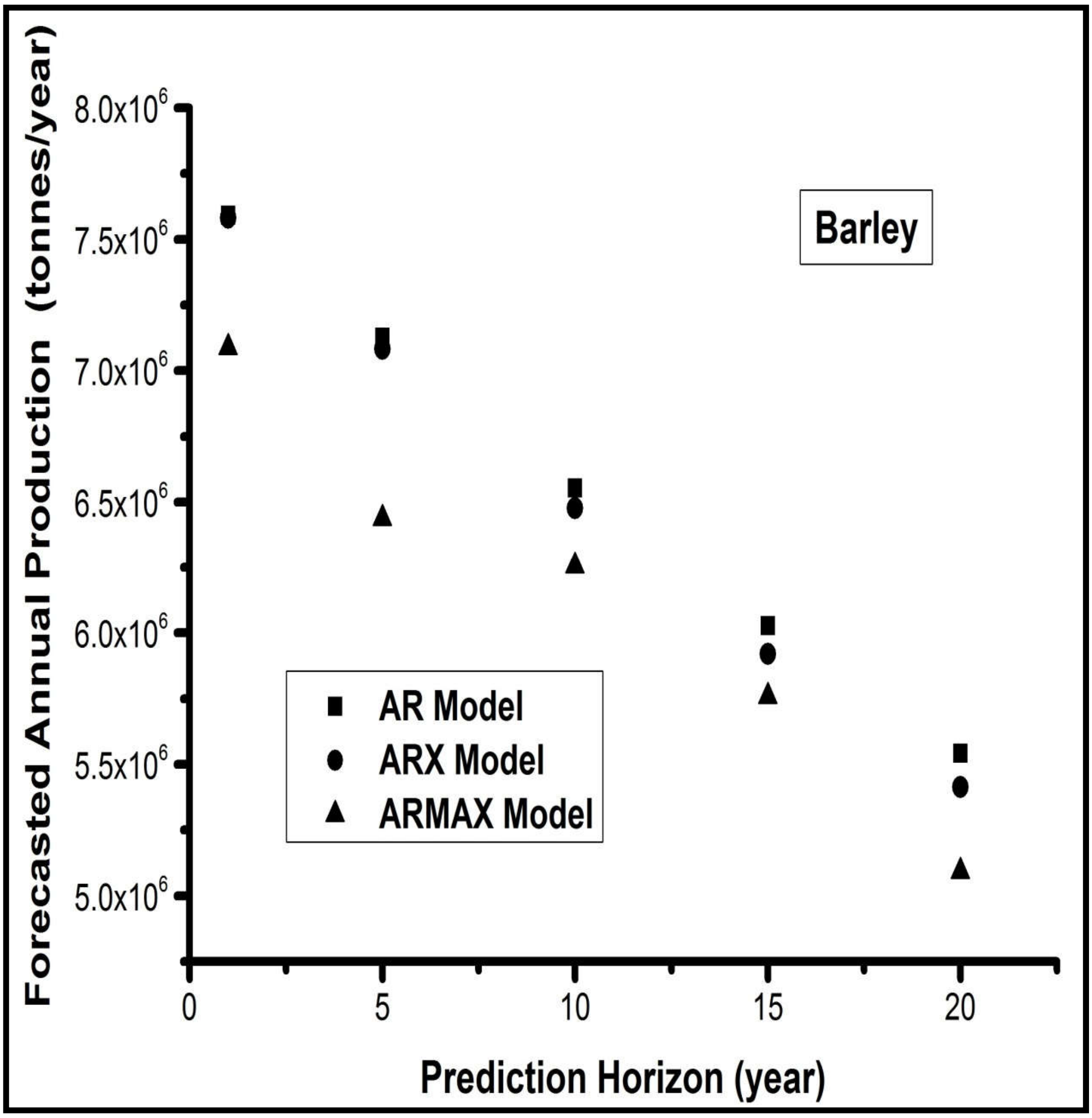

Figure 4.31 : Forecasted annual production of barley (tonnes/year) for 20-year prediction horizon (2014-2033) in Turkey.

Sugar beet production was forecasted with AR, ARX and ARMAX model as given in (Figure 4.32). Sugar beet production in 2014; was forecasted as 16.86 million tonnes by Turkish Statistical Institute statistics, (2013) and Republic of Turkey Ministry of Food, Agriculture and Livestock data, whereas it was estimated as 15.85 (AR Model), 15.68 (ARX Model) and 13.35 (ARMAX Model) million tonnes as shown in (Figure 4.32). Production forecasts for 2018 were 13.57 (AR Model), 12.85 (ARX Model) and 11.18 (ARMAX Model) million tonnes. There is a decline in sugar beet production forecasts. It is thought that this situation is resulted from quotas, production encouragements and policies on sugar beet. Also, decreasing forecast results could depend on forecasting performance for selected prediction horizon values.

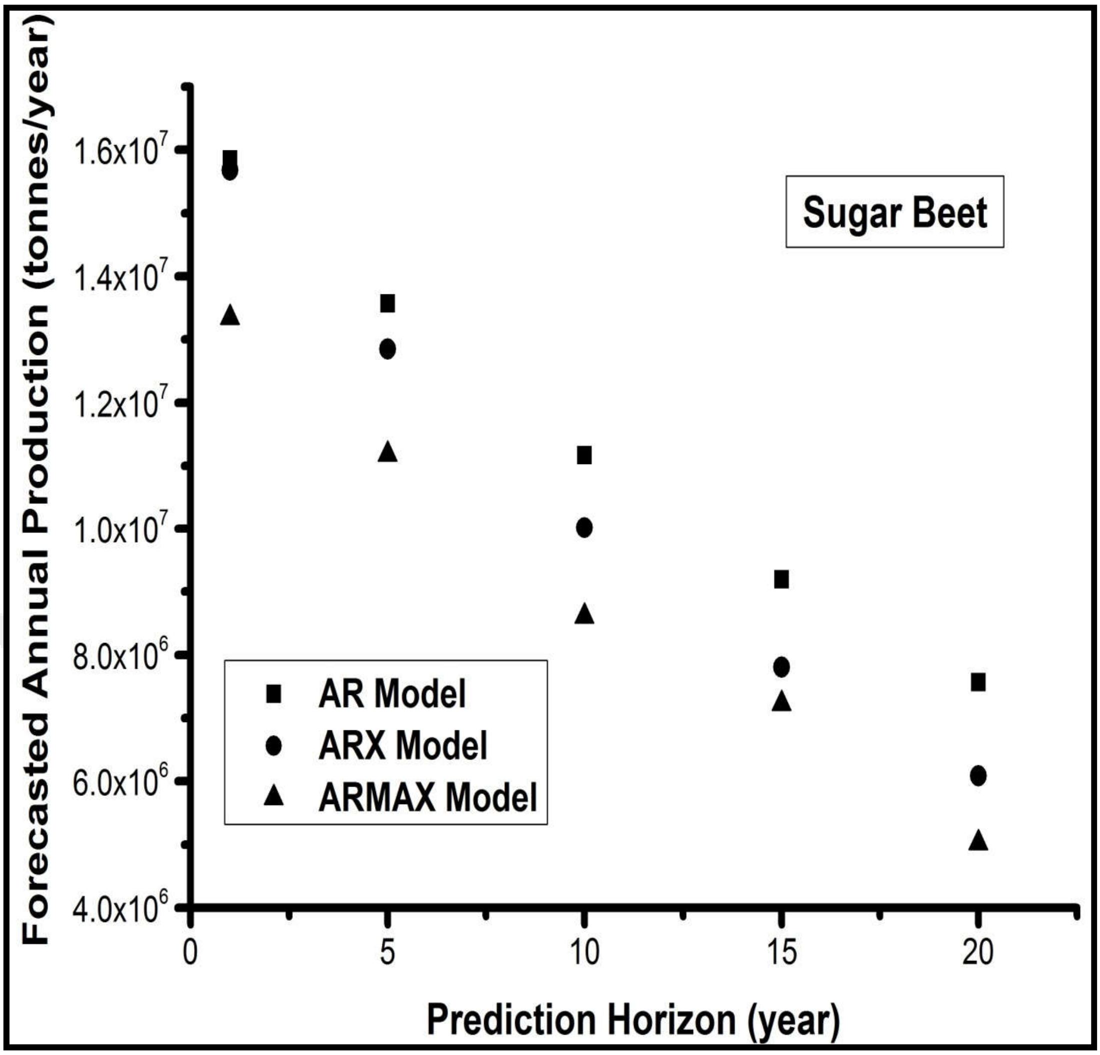

Figure 4.32 : Forecasted annual production of sugar beet (tonnes/year) for 20-year prediction horizon (2014-2033) in Turkey.

Addition to auto-regressive type models; bioethanol feedstock production data forecasting in Turkey, for next twenty years between 2014 and 2033 was also carried out using ANN in the selected numbers of nodes in input layer and prediction horizons considering performance results in earlier stage. Prediction results regarding wheat, corn, barley and sugar beet were estimated with ANN, and represented in (Figure 4.33-4.36), respectively. Although the model performance results were given for four different numbers of nodes in input layer above; the nodes numbers for forecasting studies performed with ANN were selected as the same as other models's (AR and ARX) orders. However, the node number was selected for sugar beet different from model order in AR model since ANN performance results. It is seen that negligible fluctuations were determined for all feedstock production forecastings with increasing the period of prediction horizon due to the changes in model performances and data characteristics production. Wheat production was forecasted by using ANN as given in (Figure 4.33).

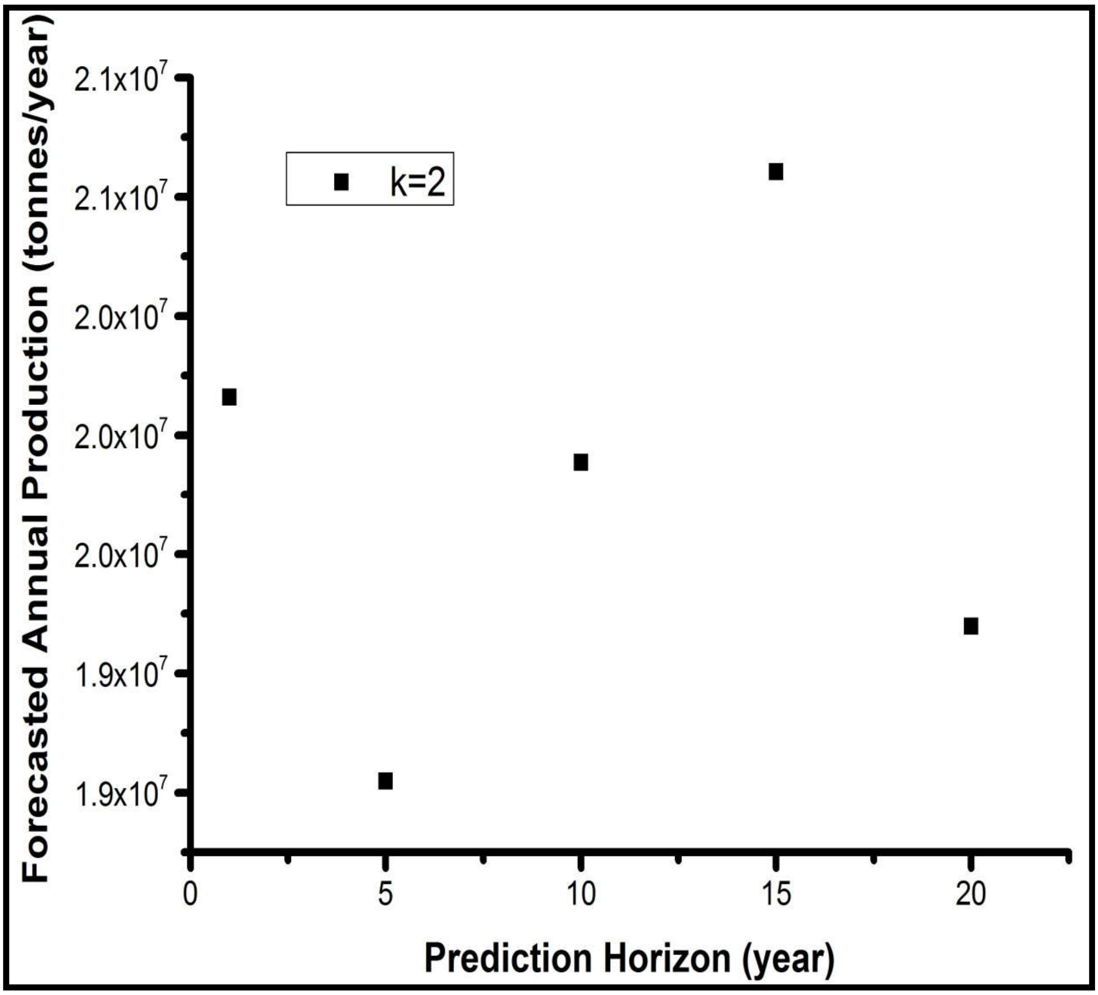

Figure 4.33 : Forecasted annual production of wheat (tonnes/year) for 20-year prediction horizon (2014-2033) with ANN in Turkey.

Although the best model performance is estimated at the node number is 3; the forecasted results are given when node number is 2 in here. It is estimated as 20.16 million tonnes (prediction horizon is 1) by using ANN, while it is 21.32 (AR Model), 21.30 (ARX Model) and 20.95 (ARMAX Model) million tonnes for the same prediction horizon. For 2018, while wheat production has been forecasted as 18 million tonnes in United States Department of Agriculture (USDA) Turkey Grain and Feed Annual Report (2017), it was predicted as 18.5 million tonnes for the same prediction horizon in here.

Corn production was forecasted by using ANN as given in (Figure 4.34). Although the best model performance has been estimated at the node number is 3; the forecasted results have been given when node numbers are 1 and 3 in here. The model order in corn production forecasting was determined as 2 for both AR and ARX model.

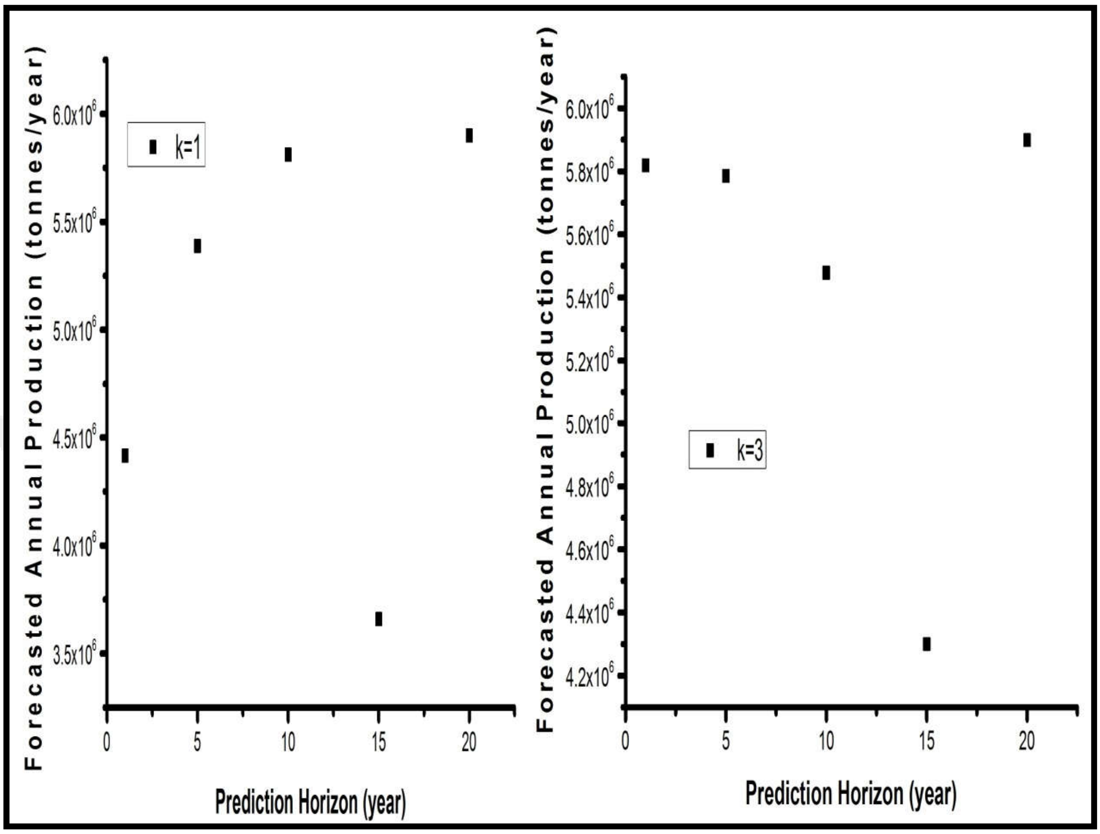

Figure 4.34 : Forecasted annual production of corn (tonnes/year) for 20-year prediction horizon (2014-2033) with ANN in Turkey.

It is estimated as 4.41 million tonnes (when k is 1) and 5.81 million tonnes (when k is 3) by using ANN (prediction horizon is 1), while it is 5.49 (AR Model), 5.48 (ARX Model), 5.3 (ARMAX Model) million tonnes. When compared to literature, corn production was predicted as 5.9 million tonnes for 2014 according to both IGC and Agricultural Economics and Policy Development Institute of Ministry of Food, Agriculture and Livestock data. In 2015, it was forecasted 5.95 million tonnes by Agricultural Economics and Policy Development Institute of Ministry of Food, Agriculture and Livestock data. According to above figure, production forecast is likely to show a similar trend for 2015. When the prediction horizon reaches 5 years, the corn production forecast was estimated as 5.78 million tonnes for 2018 while corn production has been predicted as 5.5 million tonnes for the same horizon by United States Department of Agriculture (USDA) Turkey Grain and Feed Annual Report (2017).

Barley production was predicted by using ANN as given in (Figure 4.35). The best model performance was estimated at the node number is 2 as the same as determined model order in AR and ARX model. Therefore, the forecasted results are given when node numbers are 2 in here.

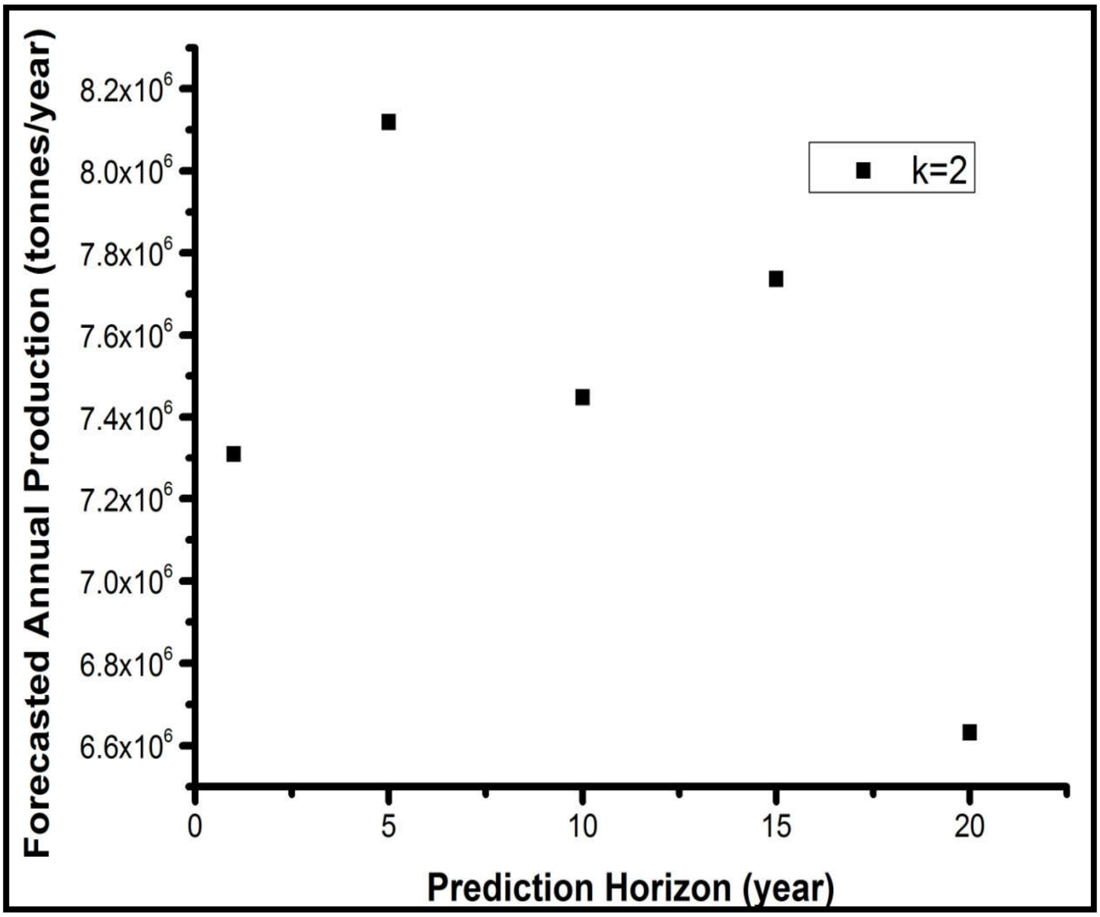

Figure 4.35 : Forecasted annual production of barley (tonnes/year) for 20-year prediction horizon (2014-2033) with ANN in Turkey.

For barley in 2014; the amount of foreacast has been predicted as 7.9 million tonnes in IGC data, on the other side barley production was forecasted as 7.59 (AR Model), 7.58 (ARX Model), 7.088 (ARMAX Model) million tonnes when it was forecasted as 7.30 million tonnes (when k is 2 in ANN). When the prediction horizon reaches to 5 years, the barley production forecast was estimated as 8.11 million tonnes for 2018 while barley production has been predicted as 5.5 million tonnes for the same horizon by United States Department of Agriculture (USDA) Turkey Grain and Feed Annual Report (2017). In 2018, it was given that the barley production is forecasted to be 7.127 (AR Model), 7.083 (ARX Model) and 6.438 (ARMAX Model) million tonnes in previous section, correlated to our ANN result.

Sugar beet production was forecasted by using ANN as given in (Figure 4.36). Although the best model performance is estimated at the node number is 4; the forecasted results are given when node numbers are 1 and 4 in here.

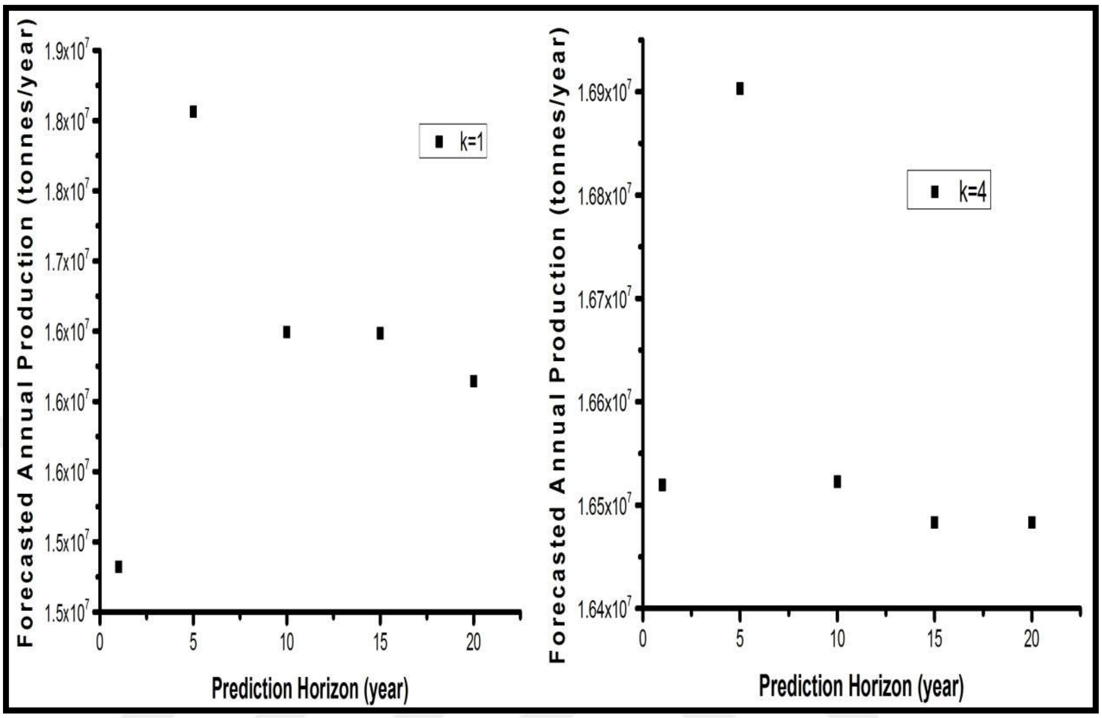

Figure 4.36 : Forecasted annual production of sugar beet (tonnes/year) for 20-year prediction horizon (2014-2033) with ANN in Turkey.

The model order in sugar beet production forecasting was estimated as 1 for AR and ARX model. Sugar beet was estimated as 14.82 million tonnes (when k is 1) and 16.52 million tonnes (when k is 4) by using ANN (prediction horizon is 1), while it was estimated as 15.85 (AR Model), 15.68 (ARX Model) and 13.35 (ARMAX Model) million tonnes. Production forecasts for 2018 were given as 13.57 (AR Model), 12.85 (ARX Model) and 11.18 (ARMAX Model) million tonnes, while it was predicted as 18.06 million tonnes (when k is 1) and 16.90 million tonnes (when k is 4) by using ANN (prediction horizon is 5). Sugar beet production has been predicted as nearly 20 million tonnes for the same horizon by United States Department of Agriculture (USDA) Turkey Annual Sugar Report (2017).

4.3.2 Forecasting of gasoline consumption data

In this section, gasoline consumption data forecasting in Turkey, for next fifteen years (from 2014 to 2028) was carried out using AR, ARX and ARMAX models in the same model orders and prediction horizons considering performance results in earlier stage. Prediction results regarding gasoline consumption data were estimated with AR, ARX and ARMAX models, and represented in (Figure 4.37). However; ARMAX model could not be performed by a sustainable way to predict gasoline consumption beginning from the ten year prediction horizon. It was seen that consumption decrease with increasing prediction horizon due to the decline in model performances as in feedstock data forecastings. Also; forecasting results for all of them generally have lower values than original data. It is thought that all of these derived from some decline in model performances and data characteristics. Gasoline consumption data length is too short to be use in forecasting models. Nevertheless; auto-regressive model types are applied with a successful way to predict gasoline consumption data as shown before.

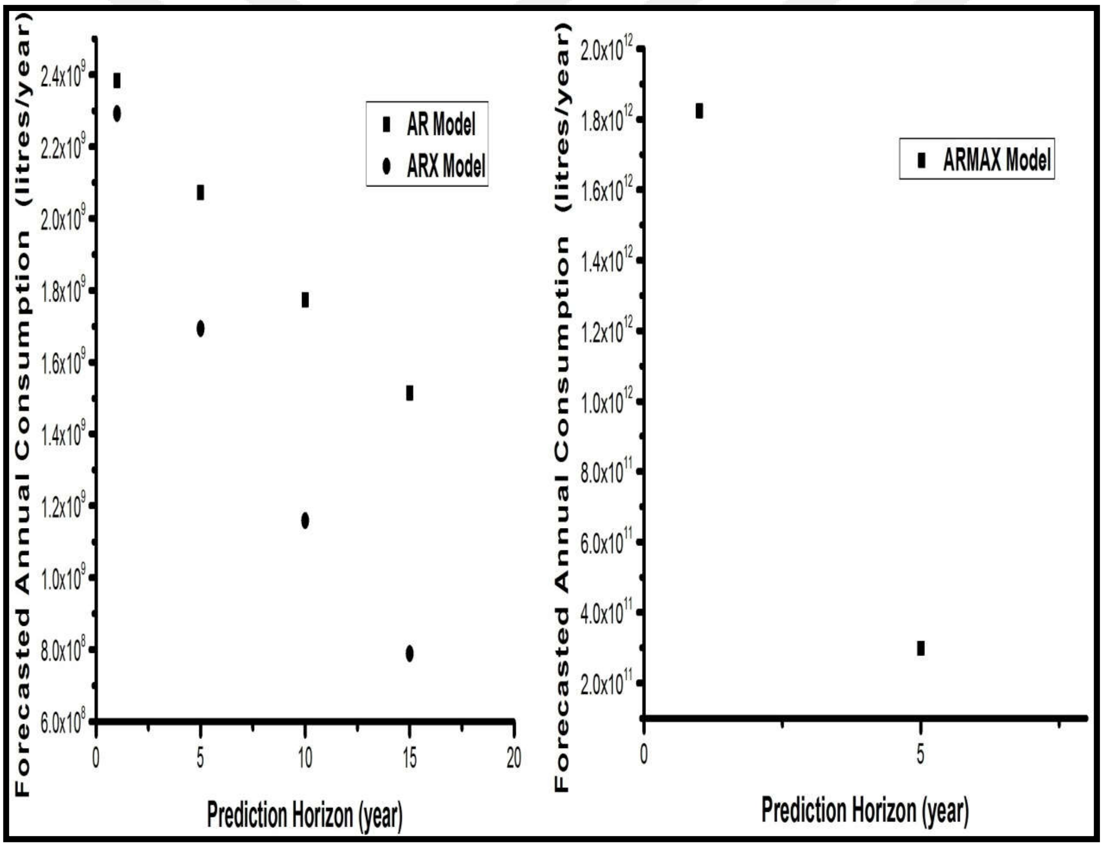

Figure 4.37 : Forecasted gasoline consumption (liters/year) for 15-year prediction horizon (2014-2033) in Turkey.

Addition to AR, ARX and ARMAX models, annual gasoline consumption was also forecasted by using ANN as given in figure 4.38. The best model performance (" best fit ") was estimated at the node number is 4; the forecasted results are given for this node number in here. It was estimated as $2.4*10^9$ liters (when k is 4) by using ANN (prediction horizon is 1), while it was estimated as $2.3*10^9$ (AR Model), $2.2*10^9$ (ARX Model) and $1.82*10^{12}$ (ARMAX Model) liters for the same prediction horizon as given in (Figure 4.37).

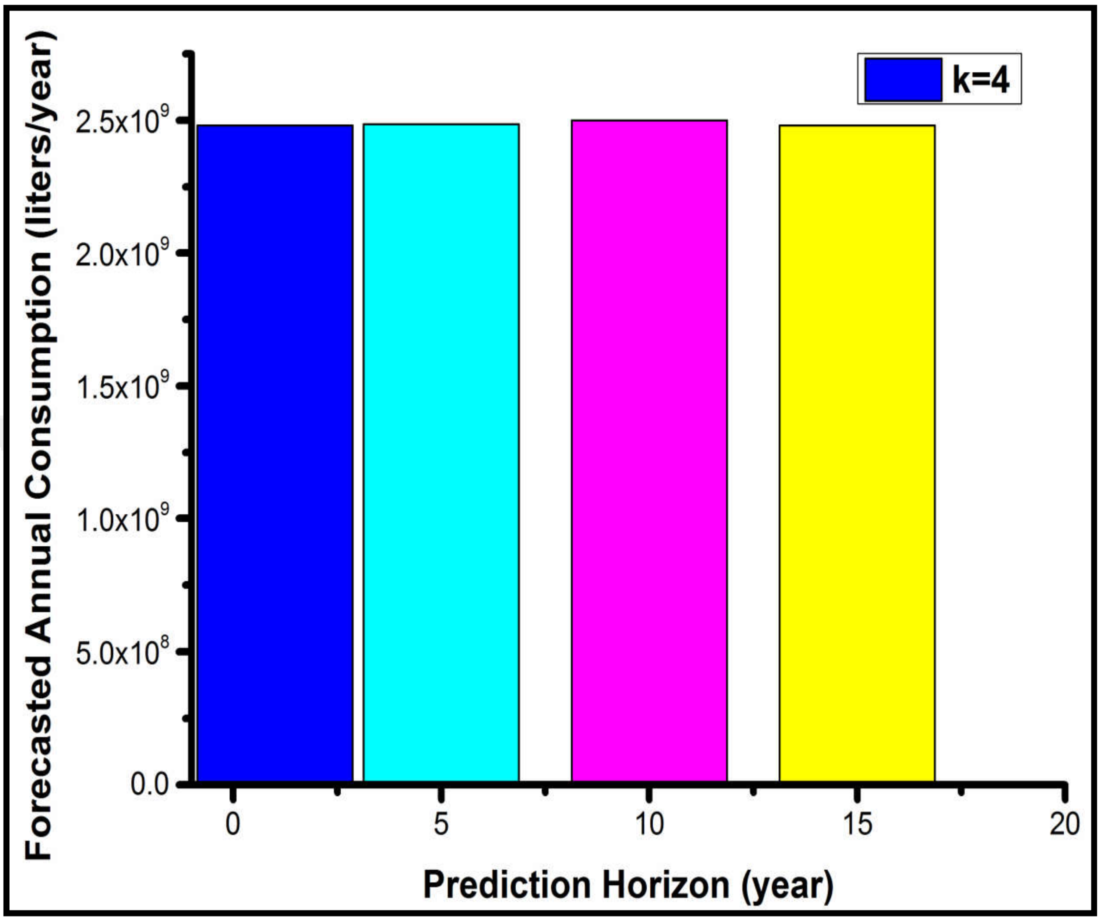

Figure 4.38 : Forecasted gasoline consumption (liters/year) for 15-year prediction horizon (2014-2033) with ANN in Turkey.

4.4 Forecasted Bioethanol Production

Forecasted annual bioethanol production capacity of Turkey was estimated by using forecasted feedstocks data and gasoline consumption data. Our priority in this regard is how much bioethanol could be produced from the forecasted bioethanol feedstock production data. Then; how much bioethanol will be needed for the forecasted gasoline consumption considering blend mandate for gasoline in Turkey. EMRA (Energy Market Regulatory Authority) is the responsible authority for bioethanol and "Tobacco and Alcohol Market Regulatory Authority" regulates the legal obligations in bioethanol sector. According to the declaration of EMRA in official gazette about ethanol blend to gasoline types on 7 July 2012, it is compulsory to use

2% ethanol blends (2 percent ethanol 98 percent petroleum) in 2013 without special consumption tax in Turkey and this ratio will be 3% in 2014. Today, this proportion has been set at 3% from the beginning of 2018. In this study; forecasted bioethanol production will be compared to legal bioethanol blend (3%) demand in forecasted gasoline consumption. Also; bioethanol demands belong to other blend proportions (1%, 2%, 5% and 10%) has been determined and compared with forecasted bioethanol production.

Various feedstocks show different bioethanol production yield capacities depending on agricultural properties and the several conversion efficiencies of the feedstocks. For example, the highest conversion rate is for corn at 400 l/tonne. This is followed by wheat is at 340 l/tonne, and the sugar beet ethanol conversion rate is 110 l/tonne (Rajagopal and Zilberman, 2007; FAO, 2008). Nigam and Agrawal (2004) gave the comparative bioethanol production potential as a corn production rate of 360 l/tonne, wheat at 340 l/tonne; barley and sugar beet at 250 and 110 l/tonne, respectively. Linoj Kumar et al. (2006) referred to that study and its values, and Kocar and Civas (2013) and Bayrakcı and Kocar (2012) referred to Linoj Kumar et al. Bioethanol production potentials of the selected feedstocks are re-organized and presented in (Table 4.3).

Table 4.3 : Bioethanol production capacities (l/tonne) of selected feedstocks (Rajagopal and Zilberman, 2007; FAO, 2008; Nigam and Agrawal, 2004).

Feedstock	Bioethanol production capacities (l/tonne)
Wheat	340
Corn	400
Barley	250
Sugar Beet	110

In this thesis study; bioethanol potentials to be produced are estimated considering the conversion values in Table 4.3 (except sugar beet). According to these; forecasted wheat, corn, barley and sugar beet-derived bioethanol productions were estimated and individually given for different prediction horizons in below. Firstly; the shares of forecasted wheat data (tonne) are used for bioethanol production were shown coming from AR, ARX, ARMAX models and ANN as seen in (Table 4.4) and (Table 4.5). For the first case in wheat; amount of wheat required for bioethanol production was estimated considering production losses, utilization losses and export values except primary utilization areas as food consumption, seed and feed utilization. The share of wheat production could be allocated for bioethanol production is determined as nearly 25.75% due to the allocated average share for this between the years of 2008-2012 according to Turkish Statistical Institute's crop products balance sheets. 25.75% of the feedstock production values predicted for each model in previous section were calculated and presented to show wheat production potential in bioethanol production in (Table 4.4).

Table 4.4 : The amount of forecasted wheat data (million tonnes) for bioethanol production in first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	5.831	5.48	5.39	5.186
5	5.166	5.15	5.094	4.772
10	4.78	4.752	4.731	5.116
15	4.422	4.384	4.322	5.43
20	4.091	3.892	4.024	4.94

Bioethanol production amounts, that could be produced from these shares from each of models, are estimated by using conversion value (340 l bioethanol per tonne of wheat as in Table 4.3) and given in (Table 4.5).

Table 4.5 : Forecasted bioethanol production (million liters) from wheat in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	1982.54	1863.36	1832.74	1763.57
5	1756.63	1751.38	1732.14	1622.73
10	1625.41	1615.792	1608.79	1739.77
15	15038.15	1490.693	1469.69	1846.29
20	1390.96	1323.602	1368.21	1679.47

For the second case in wheat; amount of wheat required for bioethanol production was estimated considering production losses and utilization losses values (similar to first case in wheat but export values is not included in second case) except primary utilization areas as food consumption, seed and feed utilization. The share of wheat production could be allocated for bioethanol production is determined as nearly 7.62% due to the allocated average share for this between the years of 2008-2012 according to Turkish Statistical Institute's crop products balance sheets. 7.62% of the feedstock production values predicted for each model in previous section are calculated and presented to show wheat production potential in bioethanol production in (Table 4.6).

Table 4.6 : The amount of forecasted wheat data (million tonnes) for bioethanol production in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	1.624	1.623	1.596	1.536
5	1.53	1.525	1.508	1.413
10	1.415	1.407	1.401	1.515
15	1.309	1.298	1.28	1.608
20	1.211	1.152	1.191	1.462

Bioethanol production amounts, that could be produced from these shares from each of models, are estimated by using conversion value (340 l bioethanol per tonne of wheat as in Table 4.3) and given in (Table 4.7).

Table 4.7 : Forecasted bioethanol production (million liters) from wheat in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	552.35	551.84	542.77	522.285
5	520.23	518.678	512.98	480.57
10	481.37	478.52	476.448	515.23
15	445.358	441.472	435.25	546.785
20	411.937	391.988	405.201	497.38

In both cases created for wheat production and bioethanol generated based on wheat above; the shares of wheat production could be allocated for bioethanol production and bioethanol production were similar for all models although ANN results exhibit small differences compared to other models. The common point for selected forecasting tools is defined as the amount of wheat could be seperated for bioethanol production and bioethanol production amount are decreased by increasing prediction horizon values. Small decreases in model performances and data or model characteristics have significant effect on predicted bioethanol production values. Besides, the performance of a model is more accurate for near future or short prediction horizon values.

The amounts of forecasted corn data (tonne), which are coming from AR, ARX, ARMAX models and ANN and are used for bioethanol production, are given in (Table 4.8 and Table 4.10). For the first case in corn; amount of corn required for bioethanol production was estimated considering production losses, utilization losses, industrial utilization and export values except primary utilization areas as food consumption, seed and feed utilization. The share of corn production could be allocated for bioethanol production is determined as nearly 14.89% due to the allocated average share for this between the years of 2008-2012 according to Turkish Statistical Institute's crop products balance sheets. This share is lower than wheat's share although corn is a significant feedstock for bioethanol production both Turkey and world. Even so; respectable bioethanol production could be carried out using this potential. 14.89% of the feedstock production values predicted for each model in previous section are calculated and presented to show corn production potential in bioethanol production in (Table 4.8).

Table 4.8 : The amount of forecasted corn data (million tonnes) for bioethanol production in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANNs k=3
1	0.818	0.816	0.789	0.657	0.866
5	0.616	0.610	0.647	0.802	0.861
10	0.432	0.424	0.498	0.865	0.815
15	0.303	0.294	0.383	0.544	0.64
20	0.212	0.205	0.324	0.878	0.878

In Table 4.8; forecasted corn data for bioethanol production is calculated for ANN considering both node number (k) is 1 and 3 due to ANN performance results. Bioethanol production amounts, that could be produced from these shares from each of models, are estimated by using conversion value (400 l bioethanol per tonne of corn as in Table 4.3) and given in (Table 4.9). The highest conversion from per feedstock (tonne) to bioethanol (l) is carried out by using corn among all selected feedstocks.

Table 4.9 : Forecasted bioethanol production (million liters) from corn in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANNs k=3
1	327.34	326.74	315.66	262.988	346.55
5	246.45	244.25	259.08	320.972	344.56
10	172.84	169.74	199.28	346.123	326.29
15	121.26	117.98	153.48	217.89	256.084
20	85.05	82.014	129.60	351.403	351.313

For the second case in corn; amount of corn required for bioethanol production is estimated considering production losses, utilization losses and industrial utilization values (similar to first case in corn but export values is not included in second case) except primary utilization areas as food consumption, seed and feed utilization. The share of corn production could be allocated for bioethanol production is determined as nearly 9.0065% due to the allocated average share for this between the years of 2008-2012 according to Turkish Statistical Institute's crop products balance sheets. 9.0065% of the feedstock production values predicted for each model in previous section are calculated and presented to show corn production potential in bioethanol production in (Table 4.10).

Table 4.10 : The amount of forecasted corn data (million tonnes) for bioethanol production in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANNs k=3
1	0.494	0.494	0.477	0.397	0.524
5	0.372	0.369	0.391	0.485	0.521
10	0.261	0.256	0.301	0.523	0.493
15	0.183	0.178	0.232	0.329	0.387
20	0.128	0.124	0.195	0.531	0.531

Bioethanol production amounts, that could be produced from these shares from each of models, are estimated by using conversion value (400 l bioethanol per tonne of corn as in Table 4.3) as in first case for corn-based bioethanol production and given in (Table 4.11). When k is 3 in ANN, obtained results are more correlated with auto-regressive-model types for the first prediction horizon value.

Table 4.11 : Forecasted bioethanol production (million liters) from corn in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANNs k=3
1	197.998	197.638	190.937	159.073	209.623
5	149.075	147.742	156.713	194.146	208.413
10	104.547	102.674	120.542	209.359	197.362
15	73.348	71.367	92.839	131.79	154.89
20	51.445	49.607	78.392	212.553	212.498

In both cases created for corn production and bioethanol generated based on corn above; the shares of corn production could be allocated for bioethanol production and bioethanol production are similar for all models although ANN results exhibit small differences compared to other models. These differences are especially seen from beginning tenth year. The common point for selected forecasting tools is defined as the amount of corn could be seperated for bioethanol production and bioethanol production amount are decreased by increasing prediction horizon values. It is thought that small decreases in model performances and short data length have directly effect on predicted bioethanol production values. Besides, the performance of a model is more accurate in near future or short prediction horizons for this kind of short-length-time series. Although the highest conversion from per feedstock to bioethanol is carried out by using corn among all selected feedstocks; bioethanol production is lower than wheat based bioethanol capacity.

The amounts of forecasted barley data (tonne), which are coming from AR, ARX, ARMAX models and ANN and are used for bioethanol production, are shown (Table 4.12 and Table 4.14). For the first case in barley; amount of barley required for bioethanol production is estimated considering production losses, utilization losses, industrial utilization and export values except primary utilization areas as food consumption, seed and feed utilization. The share of barley production could be allocated for bioethanol production is determined as nearly 14.92% due to the allocated average share for this between the years of 2008-2012 according to Turkish Statistical Institute's crop products balance sheets as wheat and corn. This share is lower than that of wheat but is almost the same as that ofcorn, although barley is a significant agricultural output with a high production capacity for Turkey. The large amount of barley production is utilized to provide feed demand in livestock sector.

Even so; respectable bioethanol production could be carried out using barley production potential with this allocated share (14.92%). 14.92% of the feedstock production values predicted for each model in previous section are calculated and presented to show barley production potential in bioethanol production in (Table 4.12).

Table 4.12 : The amount of forecasted barley data (million tonnes) for bioethanol production in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	1.132	1.131	1.057	1.09
5	1.063	1.056	0.96	1.211
10	0.977	0.966	0.933	1.11
15	0.899	0.883	0.859	1.154
20	0.827	0.807	0.759	0.989

Bioethanol production amounts, that could be produced from these shares from each of models, are estimated by using conversion value (250 l bioethanol per tonne of barley as in Table 4.3) and given in (Table 4.13).

Table 4.13 : Forecasted bioethanol production (million liters) from barley in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	283.144	282.771	264.382	272.614
5	265.837	264.195	240.137	302.851
10	244.464	241.554	233.386	277.831
15	224.807	220.816	214.810	288.567
20	206.753	201.904	189.968	247.378

For the second case in barley; amount of barley required for bioethanol production is estimated considering production losses, utilization losses and industrial utilization values (similar to first case in barley but export values is not included in second case) except primary utilization areas as food consumption, seed and feed utilization. The share of barley production could be allocated for bioethanol production decreased compared to first case's share and is determined as nearly 11.61% due to the allocated average share for this between the years of 2008-2012 according to Turkish Statistical Institute's crop products balance sheets. 11.61% of the feedstock production values predicted for each model in previous section are calculated and presented to show barley production potential in bioethanol production in (Table 4.14).

Table 4.14 : The amount of forecasted barley data (million tonnes) for bioethanol production in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	0.881	0.88	0.822	0.848
5	0.827	0.822	0.747	0.942
10	0.760	0.751	0.726	0.864
15	0.699	0.687	0.668	0.898
20	0.643	0.628	0.591	0.769

Bioethanol production amounts, that could be produced from these shares from each of models, are estimated by using conversion value (250 l bioethanol per tonnes of barley as in Table 3.3) as in first case for barley-based bioethanol production and given in (Table 4.15).

Table 4.15 : Forecasted bioethanol production (million liters) from barley in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANN
1	220.328	220.038	205.729	212.134
5	206.861	205.584	186.862	235.663
10	190.229	187.965	181.609	216.194
15	174.933	171.828	167.154	224.549
20	160.885	157.112	147.824	192.497

The amounts of molasses produced from forecasted sugar beet data (tonne), which are coming from AR, ARX, ARMAX models and ANN and are used for bioethanol production, are shown in (Table 4.16 and Table 4.18). Forecasted bioethanol amount could be producted from sugar beet was estimated different from other feedstock's cases. For the two of the cases in sugar beet; amounts of sugar beet required for bioethanol production were estimated considering bioethanol is produced from molasses. While it was assumed that whole of molasses is used to produce bioethanol production in the first case, it was estimated considering processed molasses to produce bioethanol (it means that processed molasses is only used for alcohol production in second case). Sugar beet and sugar product report prepared by Agricultural Economics and Policy Development Institute in Republic of Turkey Ministry of Food, Agriculture And Livestock (these data taken from Turkish Sugar Authority and Türkşeker 2015 between from 2006 to 2014) was used to determine the total produced molasses and processed molasses to produce bioethanol. The share of per sugar beet production (tonne) could be converted to molasses was determined as averagely 3.84% between the years of 2006-2014 according to data was mentioned Ministry's above report (This step is applied for two of cases). 3.11% of this molasses were used for ethanol production for the same years (This step is applied for only second case). Besides, it was estimated that 325.357 l ethanol could be produced per molasses (tonnes) in these two cases. Although a conversion share was given in (Table 4.3) for sugar beet; utilization of the conversion rates through molasses in these two cases will be better. Even so; almost whole bioethanol production was carried out using sugar beet as a feedstock with this allocated molasses shares. Sugar beet has been the common feedstock and so nearly all of the bioethanol production is still carried out with sugar beet in Turkey. For the first case; 3.84% of the sugar beet production values predicted for each model in previous section are calculated and presented to show molasses production potential from sugar beet for bioethanol production in (Table 4.16).

Table 4.16 : The amount of forecasted sugar beet molasses data (million tonnes) for bioethanol production in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANN k=4
1	0.608	0.602	0.512	0.569	0.634
5	0.521	0.493	0.429	0.693	0.649
10	0.428	0.384	0.33	0.633	0.634
15	0.353	0.299	0.277	0.633	0.632
20	0.29	0.233	0.193	0.619	0.632

In Table 4.16; forecasted molasses data converted from sugar beet for bioethanol production were calculated for ANN considering both node number (k) is 1 and 4 due to ANN performance results. Also; it was assumed that all amount of molasses will be used to produce bioethanol as mentioned above in the first case. Bioethanol production amounts, that could be produced from these amounts from each of models, are estimated by using conversion value (325.357 l bioethanol per tonne of molasses as mentioned above) and given in (Table 4.17).

Table 4.17 : Forecasted bioethanol production (million liters) from sugar beet molasses in the first case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANN k=4
1	283.14	282.77	264.38	185.188	206.390
5	265.83	264.19	240.13	225.676	211.182
10	244.46	241.55	233.38	206.070	206.429
15	224.8	220.816	214.81	205.961	205.937
20	206.75	201.9	189.96	201.701	205.937

For the second case in sugar beet; addition to first case, 3.11% of molasses was calculated for every models and these results were accepted as bioethanol source amounts for the selected prediction horizon. Firstly, 3.84% of the sugar beet production values predicted for each model in previous section were calculated as in first case and then 3.11% of molasses is estimated as bioethanol production sources. Then, these molasses amounts are presented to show processed molasses production potential for bioethanol production in (Table 4.18).

Table 4.18 : The amount of forecasted sugar beet molasses data (million tonnes) for bioethanol production in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANNs k=4
1	0.0189	0.0187	0.0159	0.0177	0.0197
5	0.0162	0.0153	0.0133	0.0215	0.0201
10	0.0133	0.0119	0.0102	0.0196	0.0197
15	0.0109	0.0932	0.00863	0.0196	0.0196
20	0.0904	0.0726	0.006	0.0192	0.0196

Bioethanol production amounts, that could be produced from these shares from each of models, were estimated by using conversion value (325.357 l bioethanol per tonne of molasses as mentioned above) as in first case for sugar beet-based bioethanol production and given in (Table 4.19). When k is 4 in ANN, the forecasts are very close for each prediction horizon value.

Table 4.19 : Forecasted bioethanol production (million liters) from sugar beet molasses in the second case.

Prediction Horizon (year)	AR Model	ARX Model	ARMAX Model	ANNs k=1	ANNs k=4
1	6.158	6.092	5.187	5.759	6.418
5	5.272	4.992	4.344	7.018	6.567
10	4.340	3.893	3.345	6.408	6.419
15	3.573	3.033	2.808	6.405	6.404
20	2.941	2.365	1.955	6.272	6.404

In both cases examined for molasses production from sugar beet and bioethanol producted based on sugar beet above; the shares of sugar beet production could be allocated for bioethanol production and bioethanol productions were similar for all models although ANN results exhibit small differences compared to other models. These differences were especially seen from beginning fifteenth and tenth years. The results of all models were so close for the first year prediction as in other feedstocks. It was thought that small decreases in model performances and short data length have directly effect on predicted bioethanol production values. In ANN; prediction results of the sugar beet and its molasses production were the same in fifteenth and twentieth years for the two of the cases (when k is 1). Besides, the performance of a model was more accurate in near future or short prediction horizons for this kind of short-length-time series. Because; making forecast is generally carried out in a hard way in the case of short-length-time series. Even so the forecast of sugar beet molasses based bioethanol production could be carried out by using sugar beet molasses although sugar beet based bioethanol production has the lowest data length among feedstocks.

4.5 Forecasted Bioethanol Demand

Forecasted annual bioethanol demand of Turkey was estimated by gasoline consumption data. Our priority in this regard is how much bioethanol will be needed to supply with bioethanol blend due to gasoline consumption forecastings. Then, forecasted bioethanol production has been compared to legal bioethanol blend (3%) demand in forecasted gasoline consumption. It was examined that bioethanol demand could be supplied with whether or not. However; bioethanol demands for gasoline consumptions were estimated for fifteen-years-prediction horizon since gasoline consumption predictions could be made up to fifteen years due to short-data-length of gasoline consumption. Therefore; the bioethanol demands (l) were given for gasoline consumptions (l) forecastings determined by AR, ARX models and ANN in (Table 4.20). The forecasting results belong to gasoline consumption AR, ARX and ANN were given, because the gasoline consumption forecast results from ARMAX were not sustainable and repeatable as mentioned before.

Table 4.20 : Forecasted bioethanol production (million liters) due to forecasted gasoline consumption (for 3% blend mandate).

Prediction Horizon (year)	AR Model	ARX Model	ANN
1	71.52	68.76	74.44
5	62.16	50.82	74.550
10	53.22	34.77	74.982
15	45.45	23.673	74.44

AR and ARX models have the close prediction results from first year to fifth year. However, prediction differences are increasing by long prediction horizon values. Forecasted bioethanol consumption (l) due to forecasted gasoline consumption determined by using ANN are the same in first and fifteenth year-prediction horizon. Besides; all forecast indicators for ANN are so close for each prediction horizon values.

The amounts of bioethanol needed for gasoline consumption according to each of models were also calculated and presented in (Tables 4.21, 4.22, 4.23 and 4.24) when the other possible legal bioethanol blend mandates in world as 1%, 2%, 5% and 10% alternative to 3% blend mandate.

Table 4.21 : Forecasted bioethanol production (million liters) due to forecasted gasoline consumption (for 1% blend mandate).

Prediction Horizon (year)	AR Model	ARX Model	ANN
1	23.840	22.920	24.815
5	20.720	16.940	24.850
10	17.740	11.590	24.994
15	15.150	7.891	24.815

Alternatively; forecasted bioethanol demand (l) was calculated and given in (Table 4.22) when 2% blend mandate was applied.

Table 4.22 : Forecasted bioethanol production (million liters) due to forecasted gasoline consumption (for 2% blend mandate).

Prediction Horizon (year)	AR Model	ARX Model	ANN
1	47.680	45.840	49.631
5	41.440	33.880	49.700
10	35.480	23.180	49.988
15	30.300	15.782	49.631

When blend mandate is up to 5%, forecasted bioethanol demand is compatibly increased. Although this blend mandate (5%) is still not applied in Turkey, the forecasted bioethanol demands due to this blend rate were estimated and presented in (Table 4.23).

Table 4.23 : Forecasted bioethanol production (million liters) due to forecasted gasoline consumption (for 5% blend mandate).

Prediction Horizon (year)	AR Model	ARX Model	ANN
1	119.200	114.600	124.079
5	103.600	84.700	124.250
10	88.700	57.950	124.970
15	75.750	39.455	124.079

In Turkey; 10% blend has not been mandated to gasoline yet while this mandate has being supported as legal regulations or national targets in the world. It is expected that utilization of 10% blend mandate to gasoline will increase bioethanol demand. This demand has been estimated considering gasoline consumption forecastings as in other blend proportions. This blend mandate will be so significant to supply with future enhancing bioethanol demand if bioethanol mandate is supported and its proportion (%) is increased by government. Forecasted bioethanol demands (l) were calculated and given in (Table 4.24) when 10% blend mandate was applied. Due to increasing bioethanol blend ratio (%), it is forecasted that bioethanol demand will increase compared to other blend ratios (%). However, it is forecasted that this demand will decrease in itself due to decreasing gasoline consumptions.

Table 4.24 : Forecasted bioethanol production (million liters) due to forecasted gasoline consumption (for 10% blend mandate).

Prediction Horizon (year)	AR Model	ARX Model	ANN
1	238.400	229.200	248.158
5	207.200	169.400	248.501
10	177.400	115.900	249.940
15	151.500	78.910	248.158

In this study, bioethanol supply potential due to feedstock production forecasting and bioethanol demand due to gasoline consumption for different blend mandate were seperately estimated. According to those; Turkey's bioethanol production potential and it supplies with how much of bioethanol demand are shown with drawn figures below. Only at that time, the bioethanol blend mandate was considered as 3% to determine bioethanol demand for gasoline due to present legal legislations in Turkey. For AR model, the share of forecasting of bioethanol production based on wheat, corn, barley and sugar beet in total bioethanol production (for first case) was given for each prediction horizon values in (Figure 4.39). First and second cases have been defined before.

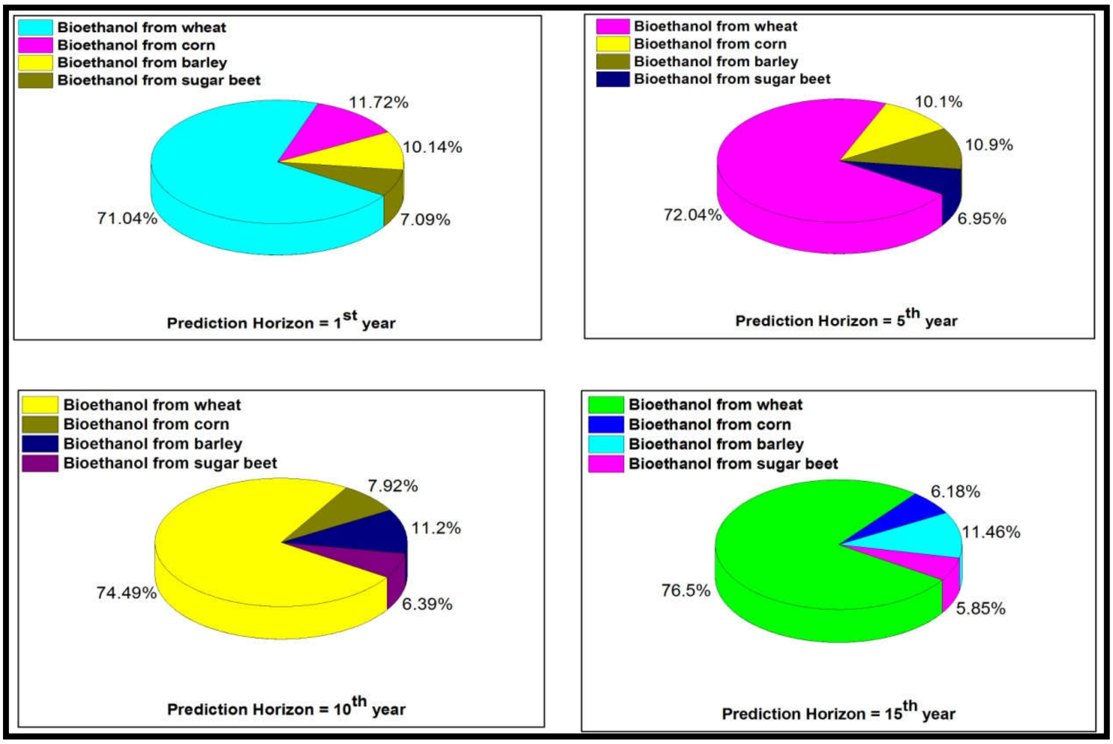

Figure 4.39 : Shares of bioethanol supply forecasting based on each feedstock for the first case (according to AR model).

According to this figure, wheat based bioethanol supply forecasting's share was higher than other feedstocks's at an increasing rate for each prediction horizon value in AR model forecasting results. Barley has followed this share while sugar beet and corn based bioethanol production share were decreasing with increasing prediction horizon. Bioethanol supply forecasting shares for each feedstock depend on data length, data characteristics, volumes of production, present production values and most importantly bioethanol capacity (l) per feedstock production (tonne). Wheat and barley had significant bioethanol production potentials as alternative to sugar beet and corn. Bioethanol production forecastings supply with how much of bioethanol demand in first case for AR model were shown in (Figure 4.40).

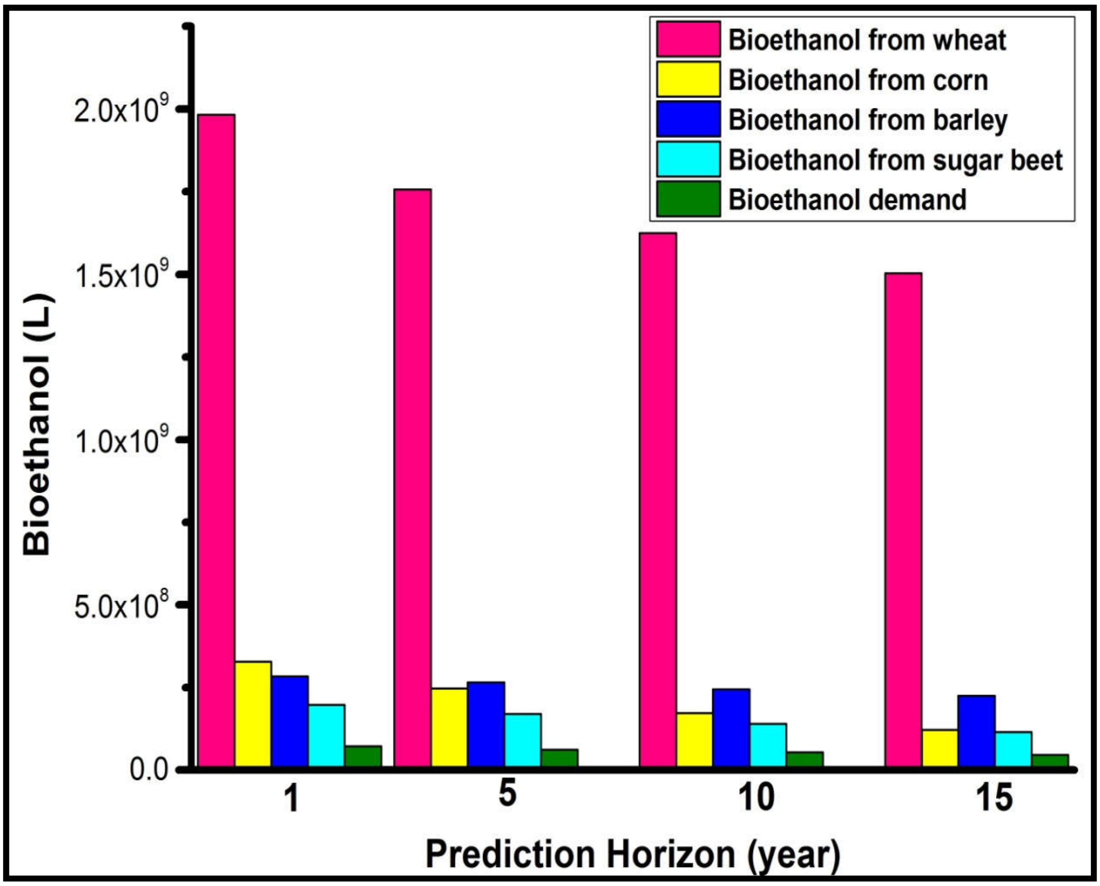

Figure 4.40 : Bioethanol supply forecastings from selected feedstocks and bioethanol demand in the first case for AR model.

According to (Figure 4.40); total bioethanol production forecasting provide bioethanol demand forecastings exceedingly. For AR model, the share of forecasting of bioethanol production based on wheat, corn, barley and sugar beet in total bioethanol production (for second case) was given for each prediction horizon values in (Figure 4.41).

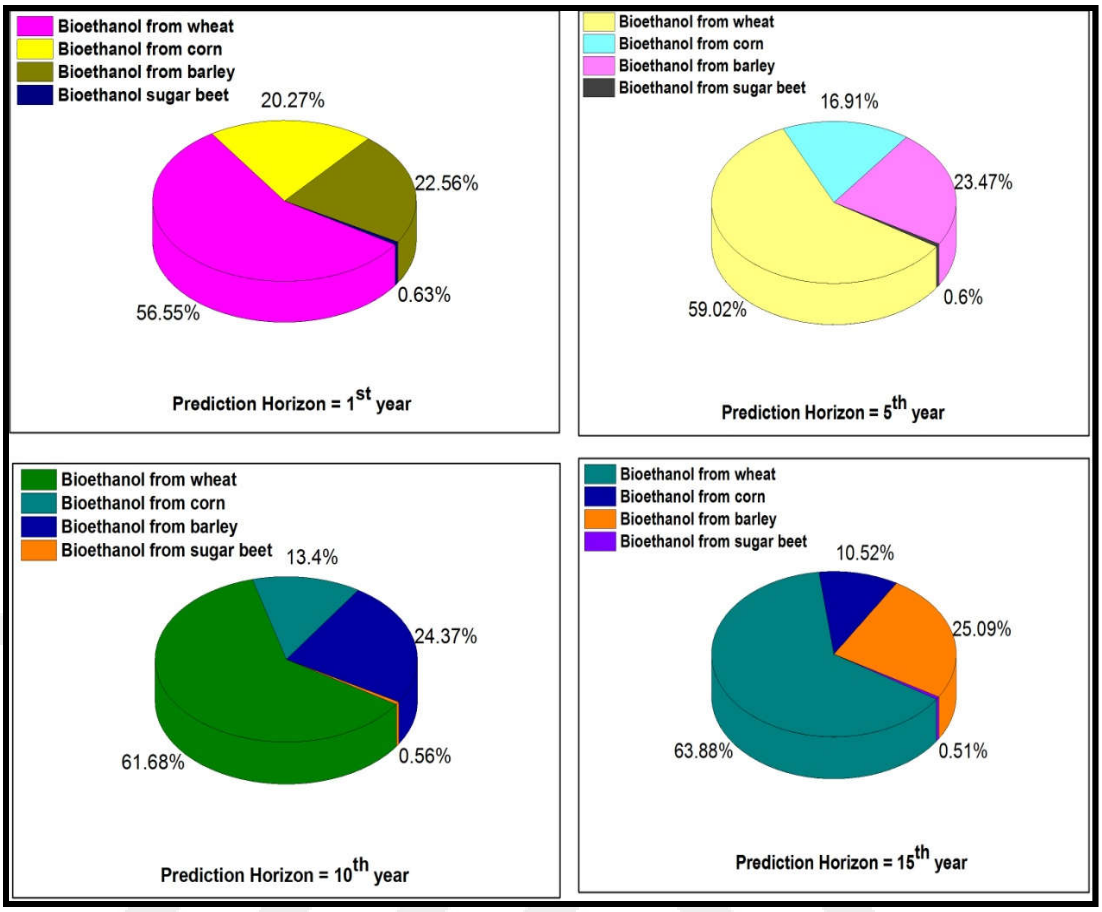

Figure 4.41 : Shares of bioethanol supply forecasting based on each feedstock for the second case (according to AR model).

According to this figure, wheat based bioethanol supply forecasting's share is higher than other feedstocks's at an increasing rate for each prediction horizon value as in first case. Barley is following this share while sugar beet and corn based bioethanol production share were decreasing with increasing prediction horizon. Although wheat and sugar beet based bioethanol shares in second case are lower than first case, barley and corn based bioethanol shares in total bioethanol production are higher in second case. This situation results from that the allocated amounts of wheat and sugar beet production forecastings are lower in second case. With this; although corn and barley shares have increased, their allocated amounts as in wheat and sugar beet's have been decreased in second case. Total bioethanol supply showed a decrease depend on decreasing allocated feedstock productions though bioethanol capacity (L) per feedstock production (tonnes) is constant according to this figure. It was concluded that wheat and barley have significant bioethanol production potentials as alternative to sugar beet and corn as in first case. Bioethanol production forecastings supply with how much of bioethanol demand in second case for AR model were shown in (Figure 4.42). According to (Figure 4.42), total bioethanol production forecasting provide bioethanol demand forecastings exceedingly. However; sugar beet based bioethanol production forecasting is not enough to bioethanol demand forecasting in second case when prediction horizon is 15th year.

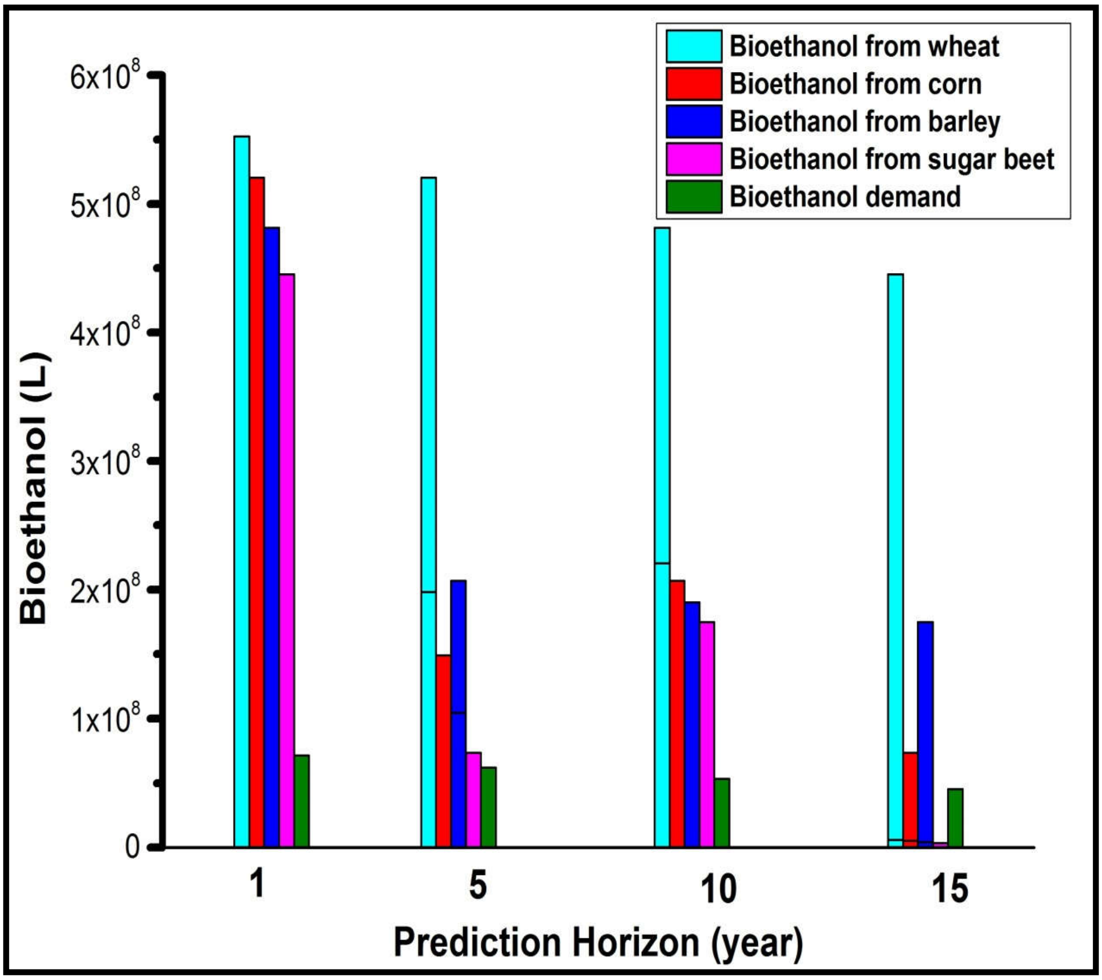

Figure 4.42 : Bioethanol supply forecastings from selected feedstocks and bioethanol demand in the second case for AR model.

For ARX model, the share of forecasting of bioethanol production based on wheat, corn, barley and sugar beet in total bioethanol production (for the first case) was given for each prediction horizon values in (Figure 4.43). According to this figure, wheat based bioethanol supply forecasting's share is higher than other feedstocks's at an increasing rate for each prediction horizon value. Barley is following this share while sugar beet and corn based bioethanol production share are decreasing with increasing prediction horizon. Wheat and barley have significant bioethanol production potentials as alternative to sugar beet and corn although forecasting model changed.

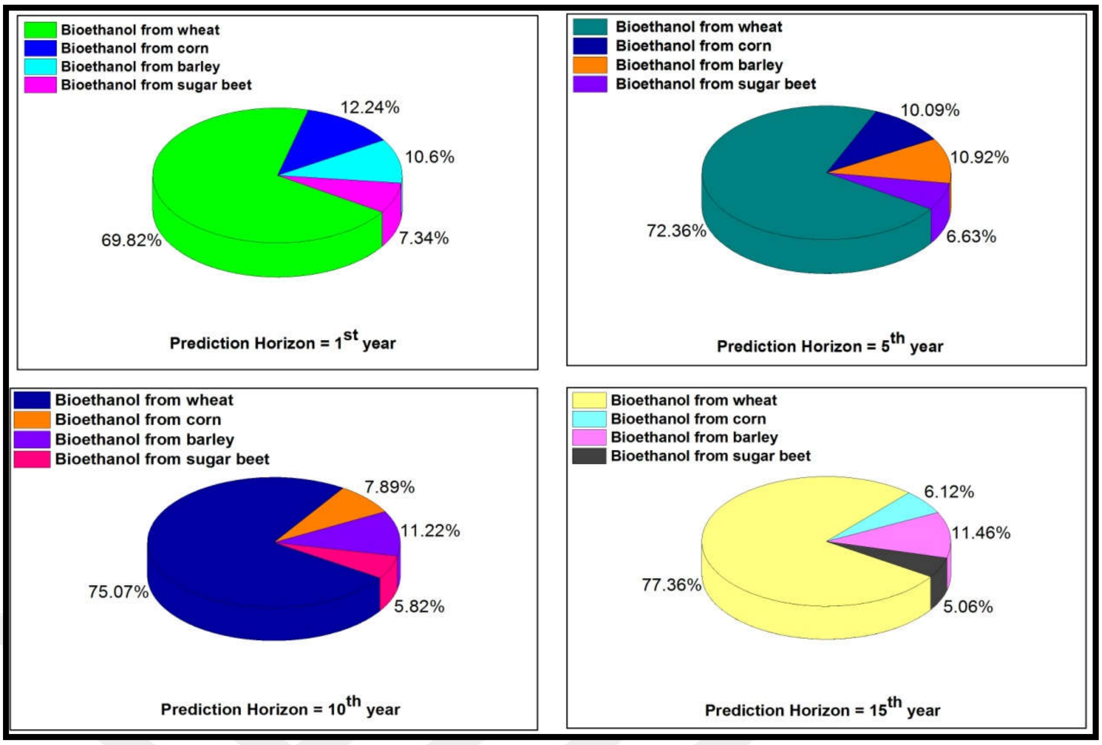

Figure 4.43 : Shares of bioethanol supply forecasting based on each feedstock for the first case (according to ARX model).

Bioethanol production forecastings supply with how much of bioethanol demand in first case for ARX model were shown in (Figure 4.44).

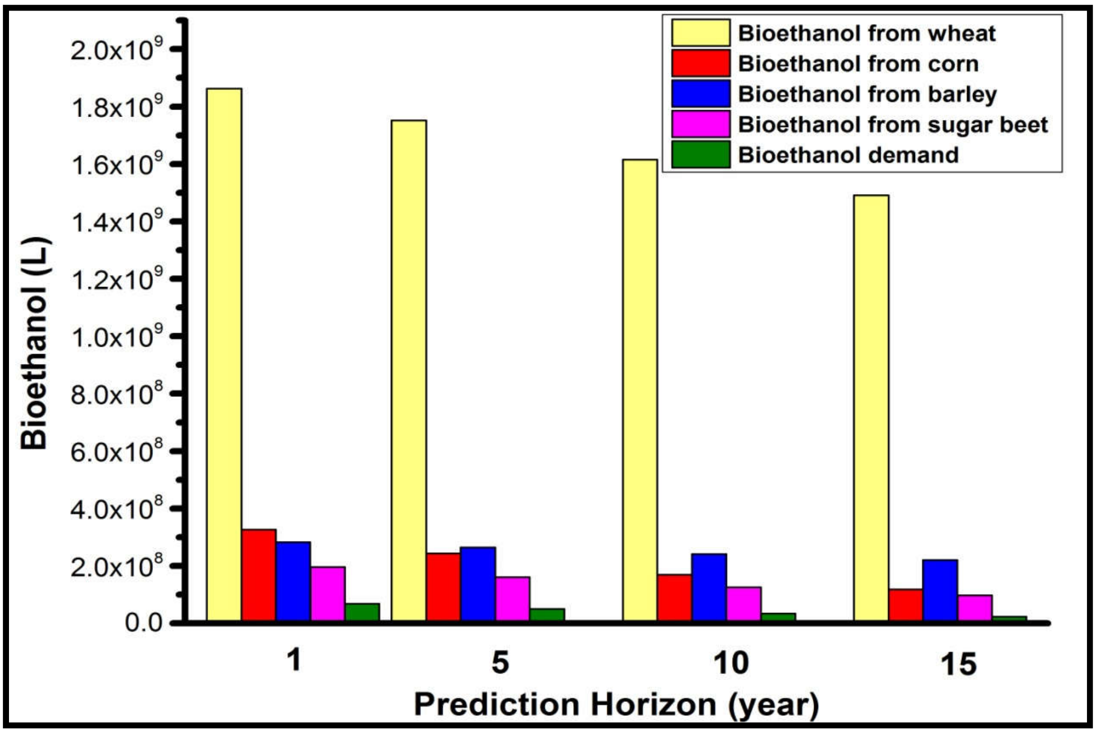

Figure 4.44 : Bioethanol supply forecastings from selected feedstocks and bioethanol demand in the first case for ARX model.

According to (Figure 4.44); total bioethanol production forecasting provide bioethanol demand forecastings exceedingly. For ARX model, the shares of forecasting of bioethanol productions based on wheat, corn, barley and sugar beet in total bioethanol production (for second case) were given for each prediction horizon values in (Figure 4.45).

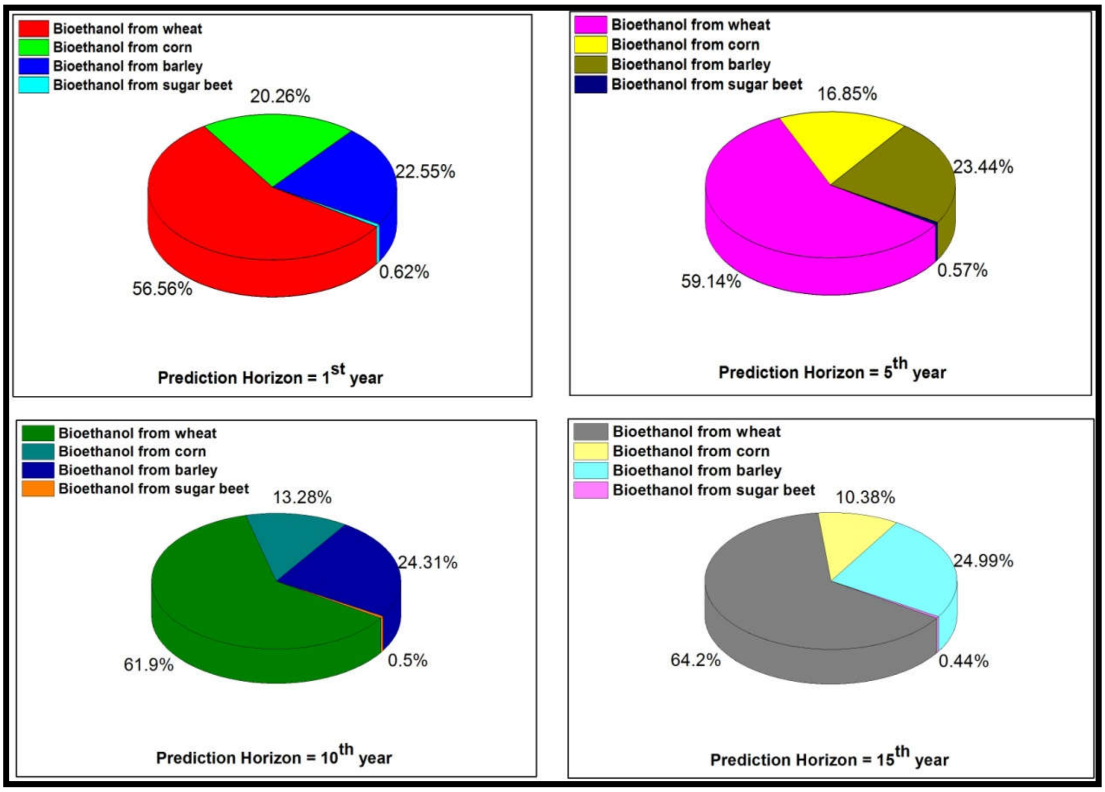

Figure 4.45 : Shares of bioethanol supply forecasting based on each feedstock for the second case (according to ARX model).

According to this figure, wheat based bioethanol supply forecasting's share is higher than other feedstocks's at an increasing rate for each prediction horizon value as in first case. Barley is following this share while sugar beet and corn based bioethanol production share are decreasing with increasing prediction horizon. Although wheat and sugar beet based bioethanol shares in second case are lower than first case, barley and corn based bioethanol shares in total bioethanol production are higher in second case as in AR model. This situation results from that the allocated amounts of wheat and sugar beet production forecastings are lower in second case. With this; although corn and barley shares have increased, their allocated amounts as in wheat and sugar beet's have been decreased in second case. All shares of bioethanol production forecastings for each of feedstocks are close to AR model results. Total bioethanol supply decreases depend on decreasing allocated feedstock productions though bioethanol capacity (l) per feedstock production (tonnes) is constant. Wheat and barley have significant bioethanol production potentials as alternative to sugar beet and corn as in first case and AR model. Bioethanol production forecastings supply with how much of bioethanol demand in second case for ARX model were shown in (Figure 4.46).

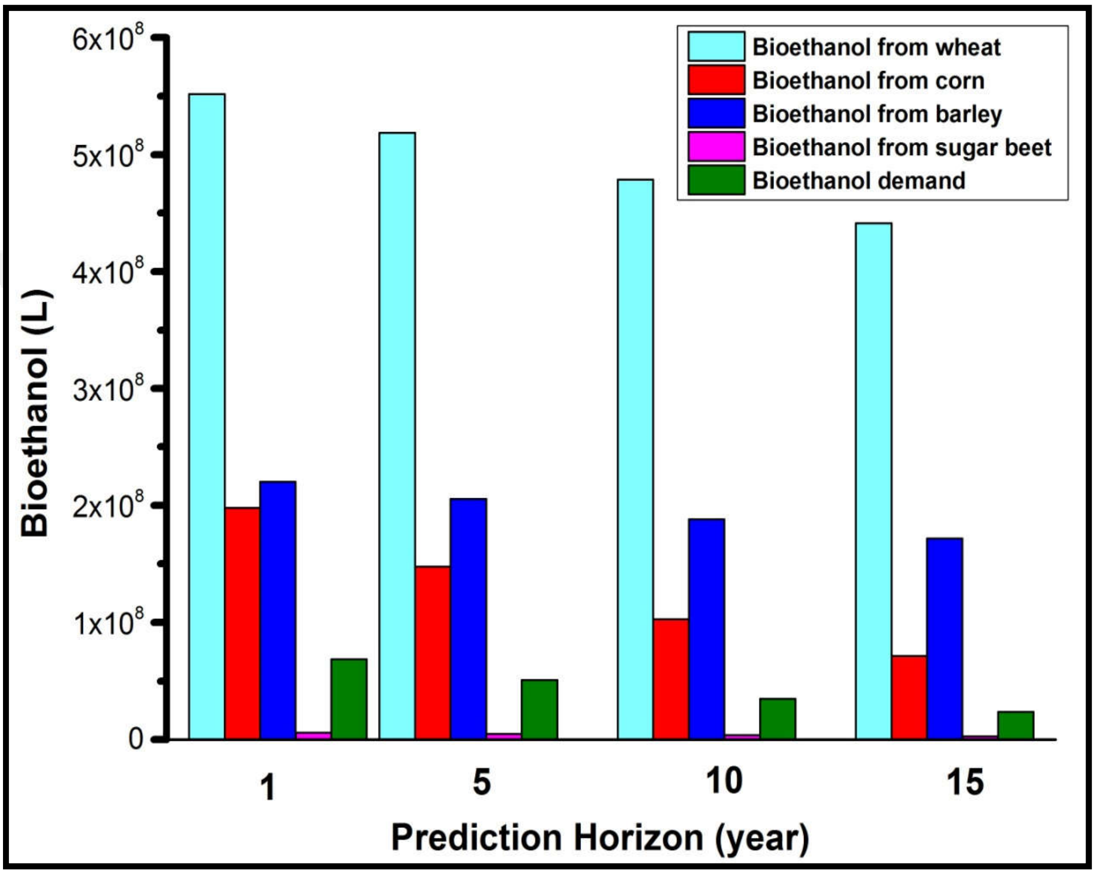

Figure 4.46 : Bioethanol supply forecastings from selected feedstocks and bioethanol demand in the second case for ARX model.

According to (Figure 4.46); total bioethanol production forecasting provide bioethanol demand forecastings exceedingly as in AR model. However; sugar beet based bioethanol production forecasting is not enough to bioethanol demand forecasting for all prediction horizon values while wheat, barley and corn productions are enough to produce bioethanol at each prediction value in second case. That is why that sugar beet and bioethanol based on it productions's prediction according to ARX model is lower than AR model's forecasts. Besides, all of the molasses are not converted into bioethanol in second case as mentioned before.

Therefore; decreasing allocated sugar beet and so molasses amount has a significant effect on decrease in bioethanol supply depend on sugar beet.

For ANN forecasting applications, the share of forecasting of bioethanol production based on wheat, corn, barley and sugar beet in total bioethanol production (for first case) was given for each prediction horizon values in (Figure 4.47).

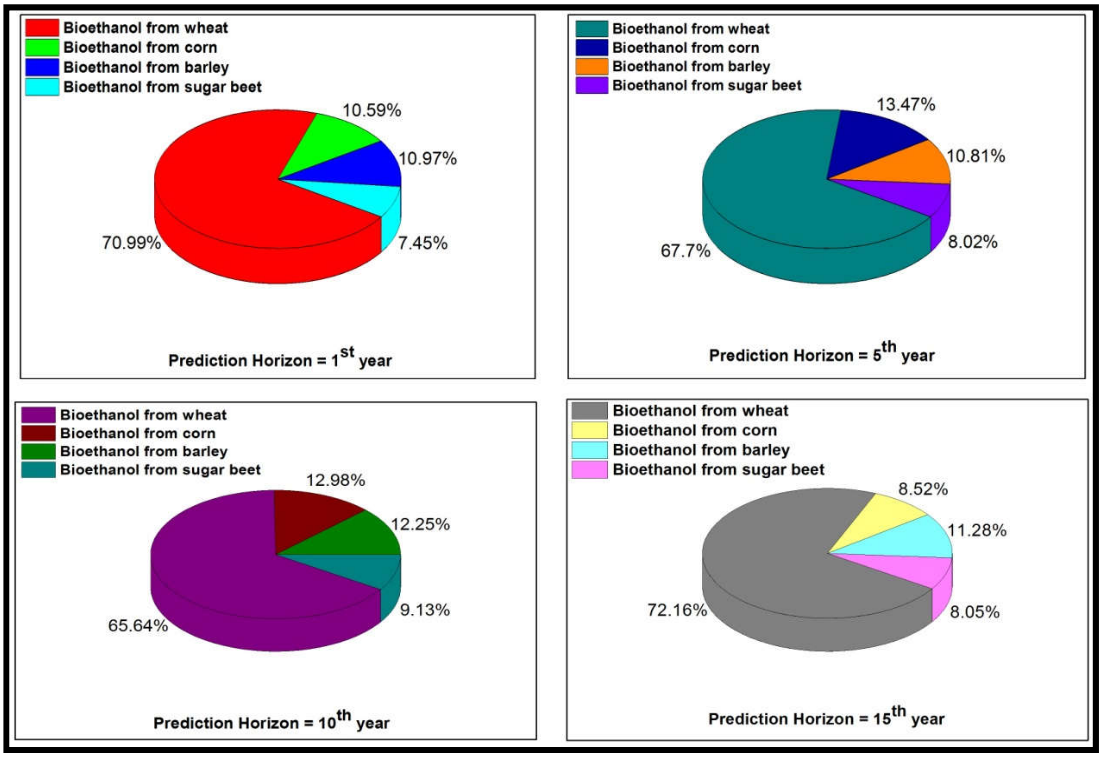

Figure 4.47 : Shares of bioethanol supply forecasting based on each feedstock for the first case (according to ANN).

According to this figure, wheat based bioethanol supply forecasting's share is higher than other feedstocks's at a fluctuation rate for each prediction horizon value. Barley, shares of sugar beet and corn based bioethanol production forecastings are also fluctuated with increasing prediction horizon. Namely; there is no linear increasing on share of bioethanol supply forecasting. Even so; wheat and barley have the highest bioethanol production potentials as alternative to sugar beet and corn as in AR and ARX models. Shares of sugar beet based bioethanol productions are estimated more higher than AR and ARX model results in both first and second cases when especially prediction horizon is 10^{th} and 15^{th}. Fluctuations in shares of bioethanol productions result from data characteristics, model performances and data lengths. Bioethanol production forecastings supply with how much of bioethanol demand in first case for ANN were shown in (Figure 4.48).

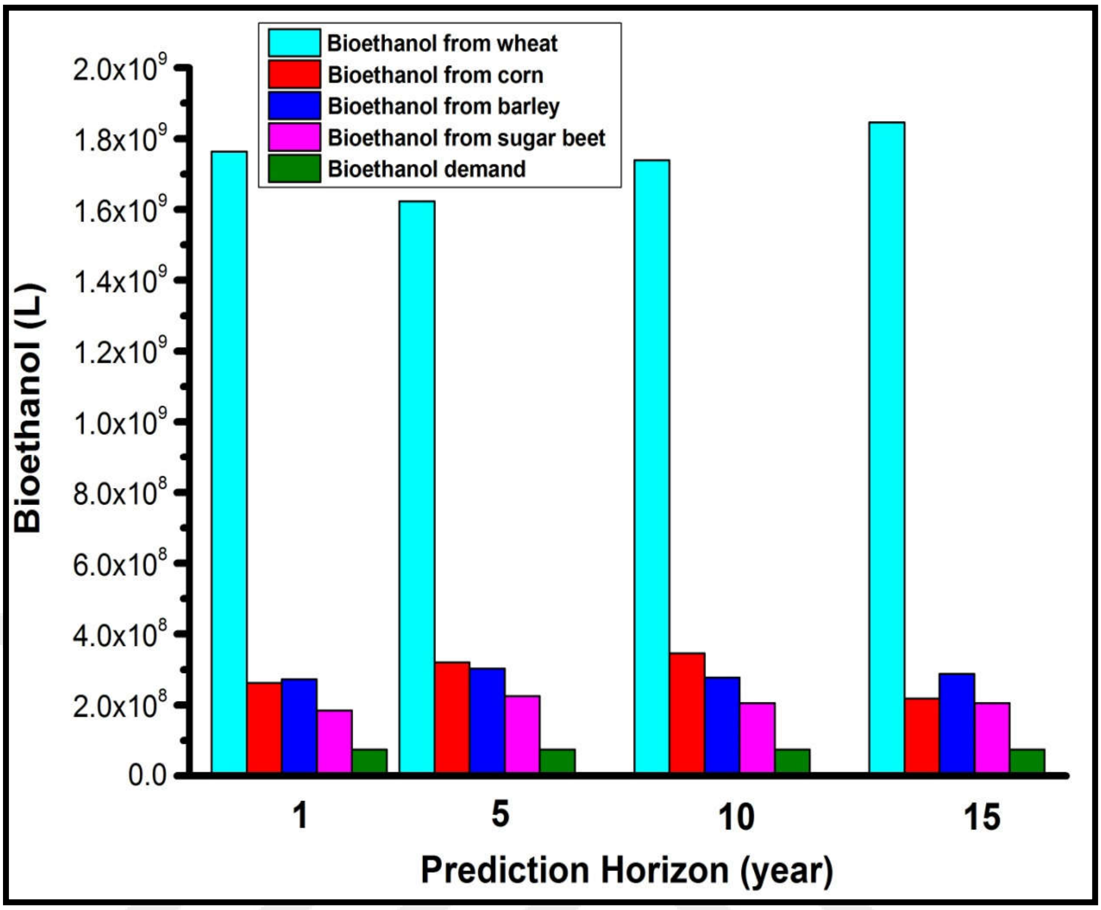

Figure 4.48 : Bioethanol supply forecastings from selected feedstocks and bioethanol demand in the first case for ANN.

According to (Figure 4.48); total bioethanol production forecasting provide bioethanol demand forecastings exceedingly as in AR and ARX models. For ANN model, the shares of forecasting of bioethanol productions based on wheat, corn, barley and sugar beet in total bioethanol production (for second case) were given for each prediction horizon values in (Figure 4.49). According to this figure, wheat based bioethanol supply forecasting's share is higher than other feedstocks's at a fluctuating rate for each prediction horizon value as in first case. Barley based bioethanol is following this share by fluctuating share, corn and sugar beet have lower shares compared to wheat and barley based production with increasing prediction horizon. Barley and corn based bioethanol production have close shares fifth and tenth years-predicion horizons. Although wheat and sugar beet based bioethanol shares in second case were lower than first case, barley and corn based bioethanol shares in total bioethanol production were higher in second case as in AR and ARX model. This situation results from that the allocated amounts of wheat and sugar beet production forecastings were lower in second case. With this; although corn and barley shares have increased, their allocated amounts as in wheat and sugar beet's have been decreased in second case. All shares of bioethanol production forecastings for each of feedstocks are close to AR and ARX model results. Total bioethanol supply decreases depend on decreasing allocated feedstock productions though bioethanol capacity (l) per feedstock production (tonne) is constant. In ANN; there was no explicit decreasing in forecasting results for each of feedstock's bioethanol productions with the increasing prediction horizon values as in AR and ARX models. Wheat and barley have significant bioethanol production potentials as alternative to sugar beet and corn as in first case and AR model types.

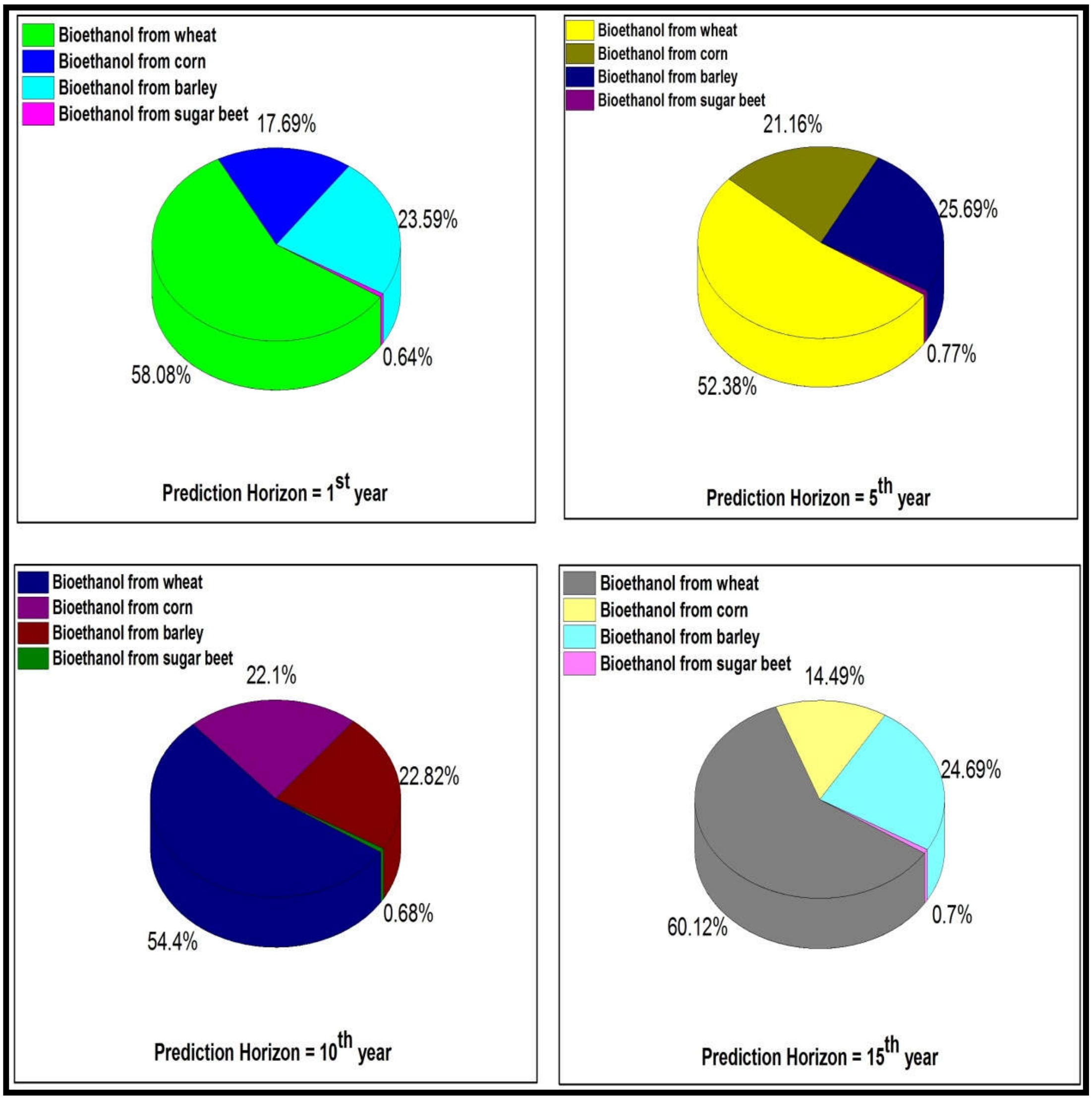

Figure 4.49 : Shares of bioethanol supply forecasting based on each feedstock for the second case (according to ANN).

Bioethanol production forecastings supply with how much of bioethanol demand in second case for ANN model were shown in (Figure 4.50).

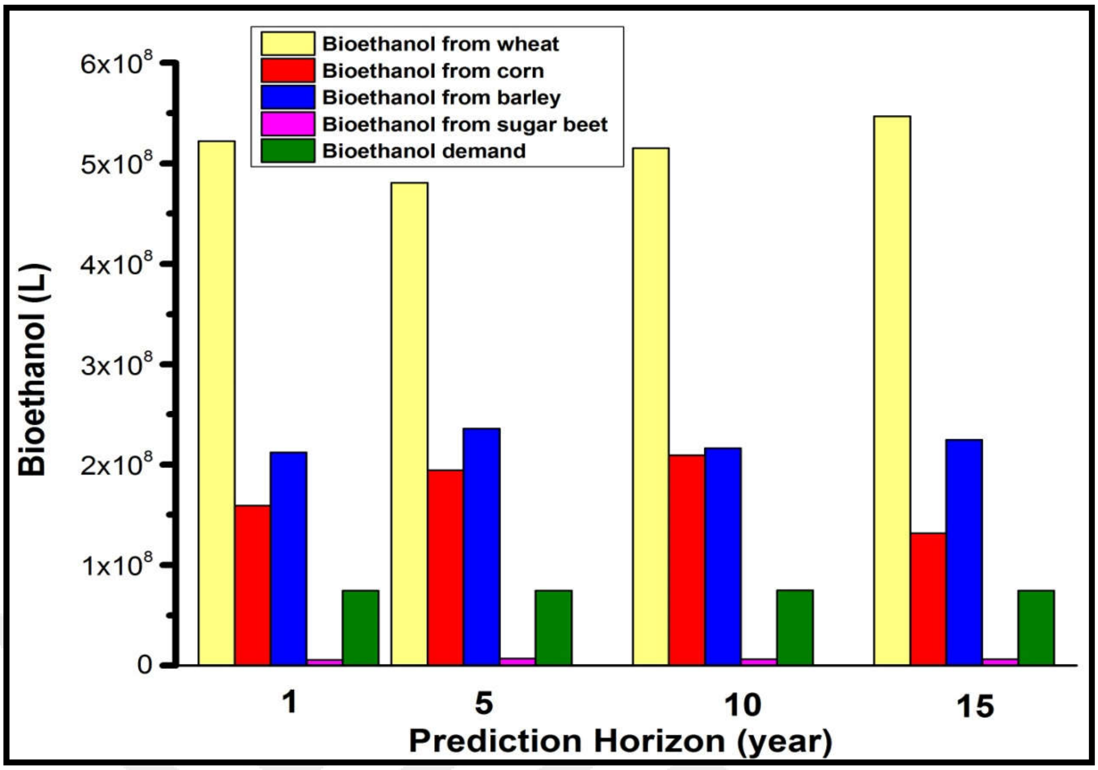

Figure 4.50 : Bioethanol supply forecastings from selected feedstocks and bioethanol demand in the second case for ANN.

According to (Figure 4.50); total bioethanol production forecasting provide bioethanol demand forecastings exceedingly as in AR and ARX model. However; sugar beet based bioethanol production forecasting is not enough to bioethanol demand forecasting for all prediction horizon values while wheat, barley and corn productions are enough to produce bioethanol at each prediction value in second case. That is why that sugar beet and bioethanol based on it productions's prediction according to ANN is lower than AR model's forecasts (In AR model, sugar beet is not only enough for fifteenth year bioethanol demand in second case). Contrary to the first case, all of the molasses are not converted into bioethanol in second case as mentioned before. Therefore; decreasing allocated sugar beet and so molasses amount has a significant effect on decrease in bioethanol supply depend on sugar beet.

In Turkey, the bioethanol blend mandate is 3% and so, all comparisons and estimations in this part were carried out by the ratio of 3%. Even so, bioethanol demand forecastings have been determined by the ratio of 1%, 2%, 5% and 10%. According to results; Turkey's wheat, corn, barley and sugar beet production potential's could be allocated to provide bioethanol demands forecastings were exceedingly enough. Addition to 3% blend mandate; Turkey's bioethanol production forecastings pointed out that 5% blend mandate could be applied in the first and second cases. Especially; wheat and barley shares could be allocated for bioethanol production were so enough to provide this bioethanol demand. Only; sugar beet potential could not be enough when the second case considered. All of the selected forecasting models's indicators supported that total or individual production amounts of wheat, sugar beet, corn and barley could be allocated for bioethanol production are significant and enough in bioethanol supply. Besides; 10% bioethanol blend could be mandated although sugar beet based bioethanol production in second case could be unsufficient to supply with bioethanol demand. Even so; it is expected that total bioethanol supply from the selected four feedstocks is sufficient.

4.6 Environmental Assessment

Environmental effects of bioethanol blended gasoline was examined in this study where bioethanol supply potentials depend on selected feedstocks and comparison these supplies with bioethanol demands were carried out. The amount of CO_2 originated from combustion one gallon of fuel due to the existence of carbon in the fuel. In general, nearly 99% of the carbon in a fuel converted into CO_2 and is emitted into atmosphere when the fuel combusted. (it is generally accepted that fuel combusted with 100% efficiency). Quite small amounts are emitted as hydrocarbons and CO, that could be converted to CO_2 in a quick way in the atmosphere. Therefore, estimating gasoline emissions as CO_2 emissions will be more feasible. CO_2 emissions result from forecasted gasoline consumptions in before section were estimated when the bioethanol blend mandates are 1%, 2%, 3%, 5%, 10%. Firstly; CO_2 emissions, coming from gasoline consumption which bioethanol is not blended, are determined. Then, the CO_2 emissions based on gasoline whose bioethanol demands are 1%, 2%, 3%, 5%, 10% are estimated. For CO_2 emissions estimations, stoichiometric calculation is performed according to combustion of octane which is the major component of gasoline. The combustion reaction of octane is showed as:

$$2C_8H_{18}(l)+25O_2(g)\rightarrow 16CO_2(g)+18H_2O_{(g)} \tag{4.1}$$

1 mole octane weights 114 g and its density is 0.72 g/cm^3 (720 g/l or 720 g/dm^3). It means that 1 l gasoline weights 720 g and from hence its mole number is estimated

as 6.315 mole. According to equation, 8 moles CO_2 is occured when 1 mole octane is combusted. Therefore; 50.52 moles CO_2 is occured as a result of 6.315 moles octane or 1 l gasoline. Namely; the CO_2 emission (kg) per gasoline combustion (l) is stated as 2.2228 kg/l. United States Environmental Protection Agency (EPA) and International Energy Agency (IEA) gave CO_2 emission values based on gasoline consumption. Carbon content could be vary depend on fuel type, and some variations could be seen according to each type of fuel is possible. The EPA and other authorities utilized the following average carbon content values to determine CO_2 emissions. According to EPA, CO_2 emissions from a gallon of gasoline were given as 8887 grams CO_2/gallon. It is equivalent to 2347.7043 g CO_2/l or 2.3477 kg CO_2/l. On the other hand, CO_2 emissions as a result of burning a gallon of gasoline were given as 19.64 pound CO_2/gallon by IEA. It means 2353.3979 g CO_2/l or 2.3533 kg CO_2/l. When three aspects for CO_2 emissions were evaluated and mean emission value approved as 2.30 kg CO_2/l considering them in this study. According to this emission value, CO_2 emission values for combustion of gasoline (not blended with bioethanol) whose consumptions are forecasted by AR, ARX models and ANN were given in (Table 4.25).

Table 4.25 : CO_2 emissions (kg) for gasoline consumption (l) forecasted by AR model, ARX model and ANN.

Prediction Horizon (year)	AR Model	ARX Model	ANN k=4
1	5483200000	5271600000	5707636300
5	4765600000	3896200000	5715537260
10	4080200000	2665700000	5748640240
15	3484500000	1814930000	5707636300

Correlated to gasoline consumption values, CO_2 emissions are so close in ANN for each prediction horizon value. Carbon dioxide emissions is decreased with declines in gasoline consumption forecastings along with increasing prediction horizon values. Bioethanol was mandated as 3% in Turkey to decrease these CO_2 emissions. According to this current blend ratio; CO_2 emission values for combustion of gasoline (blended with 3% bioethanol) whose consumptions are forecasted by AR model, ARX model and ANN were given in (Table 4.26). Correlated to gasoline consumption values, CO_2 emissions are so close in ANN for each prediction horizon value. Carbon dioxide emissions were decreased by 3% compared to consumption of gasoline which is not blended with bioethanol.

Table 4.26 : CO_2 emissions (kg) for 3% bioethanol blended-gasoline consumption (l) forecasted by AR model, ARX model and ANN.

Prediction Horizon (year)	AR Model	ARX Model	ANN k=4
1	5318704000	5113452000	5536407211
5	4622632000	3779314000	5544071142
10	3957794000	2585729000	5576181033
15	3379965000	1760482100	5536407211

Although bioethanol was mandated as 3% in Turkey, CO_2 emission values for combustion of gasoline (blended with 1% bioethanol) whose consumptions are forecasted by AR model, ARX model and ANN were given in (Table 4.27).

Table 4.27 : CO_2 emissions (kg) for 1% bioethanol blended-gasoline consumption (l) forecasted by AR model, ARX model and ANN.

Prediction Horizon (year)	AR Model	ARX Model	ANN k=4
1	5428368000	5218884000	5650559937
5	4717944000	3857238000	5658381887
10	4039398000	2639043000	5691153838
15	3449655000	1796780700	5650559937

Besides, CO_2 emission values for combustion of gasoline (blended with 2% bioethanol) whose consumptions are forecasted by AR model, ARX model and ANN were given in (Table 4.28). As in 1% blend mandate, it could not be observed a significant decrease in CO_2 emissions.

Table 4.28 : CO_2 emissions (kg) for 2% bioethanol blended-gasoline consumption (l) forecasted by AR model, ARX model and ANN.

Prediction Horizon (year)	AR Model	ARX Model	ANNs k=4
1	5373536000	5166168000	5593483574
5	4670288000	3818276000	5601226515
10	3998596000	2612386000	5633667435
15	3414810000	1778631400	5593483574

Although gasoline consumption has not been mandated with 5% bioethanol blend in Turkey yet. CO_2 emission values for combustion of gasoline (5% bioethanol blended) whose consumptions are forecasted by AR model, ARX model and ANNs were given in (Table 4.29).

Table 4.29 : CO_2 emissions (kg) for 5% bioethanol blended-gasoline consumption (l) forecasted by AR model, ARX model and ANN.

Prediction Horizon	AR Model	ARX Model	ANNs k=4
1	5209040000	5008020000	5422254485
5	4527320000	3701390000	5429760397
10	3876190000	2532415000	5461208228
15	3310275000	1724183500	5422254485

Most of the countries has put legislations or targets to mandate bioethanol blend by the ratio of between 5% and 10%. Therefore; CO_2 emission values for combustion of gasoline (5% bioethanol blended) were estimated to show the environmental advantage. Because Turkey's bioethanol production capacity is sufficient to provide 5% bioethanol blend mandate as shown in before. With this, CO_2 emission values for combustion of gasoline (10% bioethanol blended) whose consumptions are forecasted by AR model, ARX model and ANN were given in (Table 4.30).

Table 4.30 : CO_2 emissions (kg) for 10% bioethanol blended-gasoline consumption (l) forecasted by AR model, ARX model and ANN.

Prediction Horizon	AR Model	ARX Model	ANNs k=4
1	4934880000	4744440000	5136872670
5	4289040000	3506580000	5143983534
10	3672180000	2399130000	5018562930
15	3136050000	1633437000	5136872670

In the case of 10% blend is mandated, CO_2 emissions could be changed more than other mandates. When it is considered that Turkey has a sufficient bioethanol supply capacity for this mandate ratio as mentioned above, 10% bioethanol blend mandate could be encouraged by government due to environmental and economic advantages. Decreases in emissions should be evaluated as crucial effects for the future whatever bioethanol blend ratio is.

5. CONCLUSIONS AND RECOMMENDATIONS

Four different models were preferred and compared in the forecasting of wheat, corn, barley and sugar beet amounts for bioethanol feedstock in Turkey. Also, the recursive method was also used to improve three types of auto-regressive models. From the results section, it was concluded that the determination of optimal model order (for auto-regressive type models) and optimal node number (for ANN), and the selection of the most appropriate prediction horizon directly affect the forecasts. The first step in making forecast is estimating the optimal model order for each model. For AR model, model order selection criteria such as the AIC and FPE were preferred, and were therefore applied to each feedstock separately. According to Shibata (1976), there is generally a statistical problem in the estimation of model order, i.e., determining delay numbers of variables in the model, although Cohen (1986) stated that AR model is a basic model that includes effective algorithms for determining model parameters. According to our model results, a lower model order is preferred, if there are both low and high model orders. The AR model may be applied for higher model orders such as 20 (for barley, corn and wheat) and 13 (for sugar beet). However, lower orders were chosen because of the advantages of low-order models such as fewer data required, leading to both fewer operations and generally short operation times. Ljung (2008) recommended starting with a smaller model order and simple model structures, because high model order techniques are not always accurate. Greater model complexity increases uncertainty on model parameters and requires more data. Delay numbers of model variables should be determined flawlessly to generate a model that gives reliable and accurate results. Therefore, our modeling and forecasting began with model order determination for each feedstock. For ARX model, optimal model orders were estimated using the same as in the AR model. There is strong forecast correlation for these two models as an advantage, although ARX model performance was slightly better than that of AR model for the same prediction horizon values. Modeling results and data length were considered to estimate optimal model order, because there is not model order selection criteria for the ARMAX model. Optimal model orders of its AR and MA parts were separately determined but on the condition that MA model order was one less than that of the AR model part, as in Montgomery et al. (2008). Therefore, model orders were selected and arranged according to how model performances and forecast results correlated with those of other models. ARMAX model performance was the best because of compatibility with estimated model orders of ARMAX model. For all models, the selected model order should have strong correlation with model internal dynamics.

According to variations in data length, model order and prediction horizon values, comparisons and validations of model results were conducted using R^2, RMS and χ^2 revealing which model was the most appropriate. From the literature, one of the most preferred goodness-of-fit criteria for model forecast performance is R^2. From R^2, RMS and χ^2, it was seen that model performances, using the same model orders and prediction horizon values had similar variations. This is explained that a signal has a particular character and that data characteristics were settled. This directly enhanced model performances so that they gave accurate results.

Forecasting performance was dependent on the optimal model order selection criteria, forecast periods and horizon, and the time series to be forecast. Prediction error declined with the increasing model order in AR model (Mitra and Kaiser, 1993). Model performance increased with larger model orders for the same prediction horizon in our study. However, there was a decline in performances with extended prediction horizon for a given model order. Because there may be a predictable future within certain limits, the AR model is often used to predict the next value. Nevertheless, forecasting studies for barley and wheat were carried out with strong performance out to 20 years or longer, because there was a good correlation between our data and the models. Forecasting performance for sugar beet data was also good for extended prediction horizon values, but after twenty-years prediction horizon, the prediction studies were more reliable for barley and wheat data because the data series of those were longer than sugar beet data serie. The AR model had good performance for the first 10 years of the time series, confirmed by comparing its results to others. Makridakis and Hibon (1997) supported this, and stated that AR model forecasts were as good as those of ARMAX model and sometimes better. They also emphasized that simple forecast techniques such as AR model yield better forecasts than complex techniques as with ARMAX. We determined ARX model performances to be as good as that of AR, even for extended prediction horizon. Diversi et al. (2010) identified ARX as one of the simplest models within the equation error family, but indicated that it had many practical advantages in both estimation and prediction, because its optimal predictors are often stable. (Fukata et al., 2006).

The best-performing model for each time series was ARMAX, although others had strong performances. In the literature, it is indicated that non-linear or complex associated systems can be modeled and forecasted using ARMAX model. Chen et al. (2004) emphasized that ARMAX models are capable of incorporating external inputs and model feedbacks. However, this model may be suitable for time series that do not include trend or seasonality (Makridakis et al., 1998). Stationarity is defined such that variance and mean are constant over time, and the covariance of variables depends on latency between them but time independence in the case of two-delayed-time intervals (Gujarati, 2003). In the present case, time series of cereals may be seen as stationary because their data are from annual time series although external factors affect the series. As an advantage, the forecasts can be made directly because of a lack of trend in the time series, even if models such as ARMAX are preferred. ARMAX model has advantages owing to its consideration and reduction of external factors in its setup, in contrast with the other two models.

In ANN application for forecasting, although model performances for wheat and barley data were determined as above 90%, a desired increase in model performance depend on ANN use could not be obtained. The highest model performance (99.12%) was achieved when the node number was 3 for corn data, while the highest model performance (100%) was estimated for the node number was 4 for sugar beet data. The proportion "100%" means that this result is "best fit" for this forecasting. Unfortunately, R^2 values for sugar beet data model performances reached to the best fit with fluctuations between fifth and fifteenth years because sugar beet data were too short to be forecasted. Contrary to this, although it could not be reached to expected model performances for model performances in barley and wheat data forecasting performances, any fluctuations were not observed for different prediction horizons as in sugar beet data. Thanks to ANN could learn the characteristic of signal, ANN show higher model performances in forecasting of time series whose statistical structure changes little with time. Therefore, continuous and high model performances are directly correlated with compatibility between data and ANN characteristics. Besides, ANN do not need that their input should be near to white noise and the mean value of signal should be zero. Because they are nor system model such as AR model types. High noise tolerance due to nonlinear structures also provide a great advantage to artificial neural networks. Thus, high model performances as "best fit" or (99.12%) could be achieved despite short data lengths such as in sugar beet (26 years) and corn (43 years).

Investigation and evaluation of forecast results in reports of the IGC, FAO, Turkish authorities and corporations in energy sectors will thus be more accurate. As an example, the Turkish Statistical Institute and Turkish Grain Board stated that production of cereals would decline 8.8% by 2016 in Turkey. Given this, it is predicted that wheat production will decrease at the rate of 9.3% to ~ 20,5 million tonnes, although barley production will decline 15.6% to nearly 6.8 million tonnes. In our study, forecasts for 2016 are consistent with both the expected decline from the Turkish authorities and graphics of forecasted annual production. However, it was forecasted that corn production would have a small increase (6.6%) by 2015, to 6.4 million tonnes (AEPDI, 2017). The most important bioethanol resource in Turkey, sugar beet, has an increasing portion with legislation supporting bioethanol production. It is forecasted that the sugar beet harvest will be affected by quotas, as mentioned in FAO Food Outlook 2014 and a Turkish Sugar Factories Sectoral Report of 2013. This forecast has a strong correlation with the decreasing sugar beet forecasting results in the present study. Our forecasts are also accordance with USDA Turkey Grain and Feed Annual Report (2017) and USDA Turkey Sugar Annual Report (2017) as mentioned in fourth chapter. Furthermore, decreases in biomass resources production are expected to depend on legal authorities in subsequent years, with changes in agricultural policies, climatic factors, economic conditions, growing population. Our forecast decreases confirm a potential decline in production for each feedstock with the extended prediction horizon. Such a decreasing relationship is expected because preferred models are often accurate in predicting subsequent values. Overall, our foreseen yields are consistent with both agricultural economics policies and bioethanol production demand for Turkey.

The most crucial outcomes of that study are that amounts of each feedstock can be separated for bioethanol production and forecasted bioethanol production by increasing prediction horizon values. Small decreases in model performances and data or model characteristics have powerful effects on predicted bioethanol production. Model performance is more accurate for near-future or short prediction horizon values, so it will be common to encounter with these differences. Although the greatest conversion from feedstock to bioethanol among all selected feedstocks was for corn, bioethanol production is less than wheat based bioethanol capacity. For sugar beet, the results of all models are similar for first-year prediction, as with other feedstocks. It is believed that small decreases in model performances and a short data length have direct effects on predicted bioethanol production values. Further, model performance is more accurate for near-future or short prediction horizon values for this type of short duration time series (sugar beet data length is shorter than the others). This is because; forecasting is generally difficult for the short-length-time series. Bioethanol production capacity is realized by using sugar beet molasses although sugar beet-based bioethanol production has the shortest data length among the feedstocks. According to AR model results for the "first case", the wheat-based bioethanol supply forecast share (71%-76%) is larger than those of feedstocks with an increasing rate with prediction horizon value. Barley (10%-11.50) follows that share, whereas sugar beet and corn based bioethanol production shares decrease with the increasing prediction horizon. Wheat and barley have strong bioethanol production potentials as alternatives, although sugar beet and corn are dominant in Turkey. Bioethanol supply forecast shares for each feedstock depend on data length and characteristics, production volumes, present production values and most importantly, bioethanol capacity (L) feedstock production per tonne. According to the ARX model for "the second case", the wheat-based bioethanol supply forecast share (69%-77.50%) is greater than the other feedstocks, with an increasing rate with a prediction horizon value as in the AR model. The barley share (10%-11.50%) follows whereas sugar beet and corn based bioethanol production shares decrease with the increasing prediction horizon. In the ANN model, bioethanol supply percentages for each feedstock are similar to the AR and ARX model results. This indicates that feedstock bioethanol supply proportions of total bioethanol supply are similar, although bioethanol amounts that could be produced show differences with model type. Wheat and barley, the most common products in Turkey, may be seen as supplementary feedstocks to sugar beet and corn. Although present bioethanol production facilities use the latter two, wheat and barley potentials could be tapped to produce bioethanol, without affecting areas primarily using them for feed, food and seed consumption.

General conclusions and recommendations are also summarized and given as below:

- Although it could be reached to high model performances (such as 99.56%) with the recursive method for each data, model performance improvement for AR, ARX and ARMAX model could not be achieved for especially extended prediction horizon values at the desired scale. This could be explained with the changes in data characteristics and data serie lengths, correlation between data and model characteristics, prediction horizon value.

- Linear models are preferred because of their well-known in literature and their simplicities when they are applied for whatever data serie. Linear predictive coding of a random process find outs an approach for the process, named as the AR model. This model is so ideal both adroitly and for approximating the process with a basic model (Vaidyanathan, 2008). In this model, the current value of the process is expressed as a finite, linear aggregate of previous values of the process. AR model is appropriate for the forecasting of zero average-signals because of it has high noise tolerance and also this is linear model which is driven with white noise. Their main disadvantage is that sometimes they can not be good at forecasting of complex systems. Addition to ANN's high performances, it should be preferred instead of linear models due to there is no need to take out the mean value of signal as an advantage. The only problem is that there is no method like AIC or FPE to determine the optimal order of the model to be done with ANN. Depending on those models advantages, both linear model (AR model) and non-linear models (such as ANN) could be applied for our whole data which have only input.

- All peaks belong to forecasted data were accordance with real data when all time series were forecasted with AR, ARX and ARMAX model. Particularly, long time series such as barley and wheat data could generate forecasted data serie which are so close to real data serie compared to sugar beet data serie.

However, all selected models could be applied for forecasting of all selected data serie whatever their lengths. Because of the nonlinear nature of the artificial neural networks, obtained forecasted data series were so close to real data as in auto-regressive type models.

- With the growing debate over developing biofuels in the transportation sector from first generation biofuels, the utilization of national agricultural products offers substantial potential as a sustainable biofuel feedstock in Turkey. Building an accurate, scientific and operational feedstock forecast model can help the government develop agricultural, energy and economic development strategies. Therefore, the present study used basic forecasting models to predict feedstock supplies and use them to determine bioethanol production capacity. Based on wheat, corn, barley and sugar beet production data for Turkey from the Turkish Sugar Authority and Turkish Grain Board, heuristic models as AR, ARX and ARMAX using optimal model orders and prediction horizon values indicated sufficient feedstock production to meet a substantial part of Turkey´s legal regulations for gasoline-bioethanol blending demands. Forecasting results from every data show the effectiveness of our proposed forecasting model according to goodness-of-fit criteria. ARMAX had the best performance for a 20-year prediction horizon, but AR and ARX were also satisfactory. Optimal model orders and the longest prediction horizon can be changed by the length and characteristics of the time series.

- In this thesis study, single input for each serie was used in the forecasting process. For future prospects, it is aimed that multi inputs for each serie is tried in forecasting process. Mainly targeted points in this thesis were gaining the forecasting concept and the importance of its results to bioethanol economy in Turkey. Also, applying forecasting for resource management in both agriculture and energy sector were carried out for an accurate resource allocation. Because, sustainable bioethanol production depends on continuity of feedstock supply. Thus, an appropriate tool for forecasting agricultural feedstock supply is very important for an available allocation process between bioethanol production and areas of usage. Because the feedstocks of first generation bioethanol directly affect more than one sector such as agriculture, export, import, energy, livestock, economy, environment and others. Therefore it was presented that linear and non-linear models for forecasting on annual potential of feedstock supply as wheat, corn, barley and sugar beet that could be used to product first generation bioethanol in this study. The selection of models that will used for forecasting as far as the forecasting of bioethanol production to be achieved has become very important. For this reason, it has been very focused on comparing model performances and available model orders or node numbers estimations for each data and gasoline consumption. One of the most important reasons of this study is making the positive contribution of available models to Turkey's bioethanol production strategies, as well as forecasting of bioethanol production.

- First generation bioethanol production process has a crucial impact on agricultural economics. Globally, many associations, different research and development studies has considered the relation between bioethanol production and agricultural economics. As mentioned before, commonly commercialized biofuels (both bioethanol and biodiesel) are first generation biofuels whose feedstocks are also basic food crops (Serra and Zilberman, 2013). The importance of starches and sugars (e.g. sugar beet/cane, corn and cereal grains) will continue although non-food source utilization has increased in the production of bioethanol. Thus, forecasted data for each feedstock in here will directly affect the agricultural sector and its economy. Determined declines (for especially extended prediction horizon values) or increases in forecasted feedstock data are directly correlated with agricultural economics. Selected feedstocks could be accepted as economic inputs in agricultural economy and energy area. Therefore, forecastings of their producable capacities and products to be produced by them were examined from the perspective of agricultural economics.

- Each of selected feedstocks have a significant potential for biofuel production as well as their use in food, feed and seed. It is concluded that barley and wheat supplies have significant potentials to produce bioethanol except for their primary uses in food consumption, seed and feed. However, sugar beet and corn are mainly used in fuel bioethanol production plants in Turkey. Also, forecasted bioethanol produced from those feedstocks supplies with how much of bioethanol demand were given with comparative graphics for each models except ARMAX. Because; sustainable results could not be obtained in forecasting of gasoline consumption by ARMAX model, and so bioethanol demand results have been estimated and given for AR, ARX model and ANN. Although forecasted bioethanol production data have been given for four of selected models in tables to show the Turkey bioethanol supply. In extended prediction horizon values, declines have been determined depending on decreases in feedstock supply forecastings. These declines are accordance with literature data as mentioned before. Not only feedstock data, it was expected that declines in gasoline will be occured according to our forecasts by each model. This decline is consistent with the expected decrease in gasoline consumption due to the use of LPG and diesel throughout Turkey as mentioned in various sources.

- According to results, wheat and barley use in bioethanol production should be encouraged to produce bioethanol to meet the expected increase of demand for the next years considering the priority consumption areas. In this case, the facts of resource management and agricultural economy have to be considered for right allocation. That is why forecasting is important and necessary.
- Bioethanol production has been come into prominence in the perspective of clean environment strategies because of it is environmentally friendly. Therefore; carbon dioxide emissions were calculated to show emission decreases in bioethanol blended-gasoline consumption data. Calculations were made on forecasted gasoline consumption data (blended bioethanol in the different proportions).

In conclusion, from the perspective of bioenergy economics and sustainable bioethanol production, the study aim was to find the most available forecasting approaches to determine the selected feedstocks supply and producible bioethanol amount from those feedstocks in Turkey over 2014-2033.

REFERENCES

Adil, S. A., Maqsood, A., Bakhsh, K., and Hassan, S. (2012). Forecasting demand and supply of onion in Pakistani Punjab, *Pak. J. Agri. Sci. 49*, (2): 205-210.

AEPDI*. (2017). Agricultural Economic and Policy Development Institute, Crop Production Statistics. Retrieved June 15, 2017, from http://www.tarim.gov.tr/sgb/Belgeler/SagMenuVeriler/BUGEM.pdf.*

Agrawal, R. (2003). Forecasting Techniques in Agriculture, Indian Agricultural Statistics Research Institute. Retrieved: 20 Eylül 2014, http://www.iasri.res.in/ebook/EB_SMAR/e-book_pdf%20files/Manual%20IV/2-Forecasting%20techniques.pdf.

Ahumada, O., and Villalobos, J. R. (2009). Application of planning models in the agric-food supply chain: a review. *Eur. J. Oper. Res. 195*, 1–20.

Ahumada, O., Villalobos, J. R., and Mason, A. N. (2012). Tactical planning of the production and distribution of fresh agricultural products under uncertainty. *Agric. Syst. 112*, 17–26.

Akaike, H. (1974). A New Look at the Statistical Model Identification, *IEEE Trans. Autom. Control., 19* (6), 716-723.

Allen, P. G. (1994). Economic forecasting in agriculture. *Int. J. Forecasting*. *10* (1), pp.81–135.

Allende, H., Moraga, C., and Salas, R. (2002). Artificial neural networks in time series forecasting: A comparative analysis. *Kybernetika. 38,* 685-707.

Alma, G. O., and Vupa, O. (2008). Regresyon Analizinde Kullanılan En Küçük Kareler Ve En Küçük Medyan Kareler Yöntemlerinin Karşılaştırılması, *SDÜ Fen Edebiyat Fakültesi Fen Dergisi*. *3* (2), 219-229.

Altman, I., Bergtold, J., Sanders, D., and Johnson, T. (2015). Willingness to supply biomass for bioenergy production: A random parameter truncated analysis. *Energ Econ*. *47*, 1-10.

Amigun, B., Musango, J. K., and Stafford, W. (2011). Biofuels and sustainability in Africa. *Renew. Sustain. Energ. Rev. 15* (2)*,* 1360–1372.

Ar, F., Karaosmanoğlu, F., Koç, A., Acaroğlu, M., Mutlu, F., Sarısu, F., Özsöyler, Y., Bölük, G., İşler, A., Aygün, Ö. F. (2010). *Biyoyakıtlar*. Ankara: Dünya Enerji Konseyi Türk Milli Komitesi Biyoyakıtlar raporu.

Ar, F. F. (2011). *VI. Yeni ve Yenilenebilir Enerji Kaynakları Semp. Kitabı: Biyoyakıtlar ve Sektördeki Sorunlar* (No:E/2011/565, pp.31-40). Kayseri: MMO Yayın.

Arndt, C., Benfica, R., Tarp, F., Thurlow, J., and Uaiene, R. (2009). Biofuels, poverty, and growth: a computable general equilibrium analysis of Mozambique. *Environ. Dev. Econ. 15*, 81–105.

Avinash, A., Subramaniam, D., and Murugesan, A. (2014). Biodiesel a global scenario. *Renew. Sustain. Energ. Rev. 29*, 517–527.

Ayas, C., Demirayak, F., Karaosmanoğlu, F., İş, G., Kumbaroğlu, G., Or, İ., Can, O., Yenigün, O. and Arıkan, Y. (2009). *İklim Çözümleri: 2050 Türkiye Vizyonu.* Istanbul: Türkiye Doğal Hayatı Koruma Vakfı raporu.

Azadeh A., Ghaderi S. F., and Sohrabkhani S. A. (2008). Simulated-based neural network algorithm for forecasting electrical energy consumption in Iran. *Energ. Policy. 36*, 2637–2644.

Baier, W. (1977). *Crop weather models and their use in yield assessments.* (Tech. note no. 151). Geneva: World Meteorological Organization (WMO) Technical Note.

Balat, B., Balat, H., and Öz, C. (2008). Progress in bioethanol processing. *Prog. Energ. Combustion Sci. 34*, 551-573.

Balat, M. (2011). Production of bioethanol from lignocellulosic material via the biochemical pathway: a review. *Energ Convers. Manag*. *52*, 858-875.

Baliyan, A., Gaurav, K., and Mishra, S. K. (2015). A review of short term load forecasting using artificial neural network models. *Proce. Comp. Sci. 48,* 121–125.

Banse M., Meijl H. V., Tabeau A., and Woltjer G. (2008a), Impact of EU Biofuel Policies on World Agricultural and Food Markets. In 107 th EAAE Seminar. *Modelling of Agricultural and Rural Development Policies,* Sevilla, Spain, 29 January - 1 February.

Banse M., Van Meijl H., Tabeau A., and Woltjer G. (2008b), Consequences of EU Biofuel Policies onAgricultural Production and Land Use, *Choices*. *23* (3), 22-27.

Basso, B., and Ritchie, J. (2005). Impact of compost, manure and inorganic fertilizer onnitrate leaching and yield for a 6-year maize-alfalfa rotation in Michigan. *Agr. Ecosyst. Environ. 108*, 329–341.

Bayrakcı, A. G., and Kocar G. (2012). Utilization of renewable energies in Turkey's agriculture. *Renew. Sustain. Energ. Rev. 16* (1), 613– 633.

Beckman, J., Hertel, T. and Tyner, W. (2011). Validating energy-oriented CGE models. *Energ. Econ. 33,* 799–806.

Ben-Iwo, J., Manovic, V., and Longhurst, P. (2016). Biomass resources and biofuels potential for the production of transportation fuels in Nigeria. *Renew. Sustain. Energ. Rev. 63,* 172-192.

Binfield J., Westhoff P., and Cadre E. L. (2008). Incorporating Biofuels Into A Partial Equilibrium Model of the Agricultural Sector. In *107 th EAAE Seminar. Modelling of Agricultural and Rural Development Policies*, Sevilla, Spain, 29 January - 1 February.

Bir, A. (1975). *Belirgin ve Olasıl Kontrol Sistemlerinde Prediksiyon*. (Doktora tezi). Istanbul Technical University, Electrical Faculty, Istanbul.

Birkes, D., & Dodge, Y. (1993). *Alternative Methods of Regression*. New York, NY: John Wiley Sons.

Birur, D. K., Hertel, T. W., and Tyner, W. E. (2008). *Impact of Biofuel Production on World Agricultural Markets: A Computable General Equilibrium Analysis* (Report No. 53). Indiana: Department of Agricultural Economics Purdue University GTAP Working Paper.

Black, R., Fava, F. Mattei, N., Robert, V., Seal, S., and Verdier, V. (2011). Case studies on the use of biotechnologies and on biosafety provisions in four African countries. *J Biotechnol. 156*, 370-381.

Bode, H.W., and Shannon, C.E. (1950). A Simplified Derivation of LinearLeast-Squares Smoothing and Prediction Theory. *Proceedings I R.E., 38*, 417-425.

Boi, P. (2004). A statistical method for forecasting extreme daily temperatures using ECMWF 2-m temperatures and ground station measurements. *Meteorol. Appl. 11*, 245–251.

Bomb, C., McCornic, K., Deurwaarder, E., and Kaberger, T. (2007). Biofuels for transport in Europe: lessons from Germany and the U.K. *Energ. Policy. 35,* 2256-2267.

Booton, R. C. (1952). An optimization theory for time-varying linear systems with non-stationary Statistical inputs. *Proceedings L, R.E., 40*, 977-981.

Borand, M. N. E. (2012). *Effects of Pretreatment Methods on Lignocellulosic Bioethanol Production*. (M.Sc. Thesis). Istanbul Technical University, Graduate School Of Science Engineering and Technology, Istanbul.

Bothast, R.J., and Schlicher, M.A. (2005). Biotechnological processes for conversion of corn into ethanol. *Appl. Microbiol. Biotechnol. 67* (1), 19-25.

Box, G. E. P., and Jenkins, J. M. (1976). *Time Series Analysis: Forecasting and Control*. San Francisco, CA.: Holden-Day.

Box, G. P., Jenkins, G. M., and Reinsel, G. C. (2008). *Time series analysis forecasting and control* (4th ed.). New York: John Wiley & Sons, Inc.

Bouzaher, A., Sahin, S., and Yeldan, E., (2015). How to go green: A General Equilibrium Investigation of Environmental Policies for Sustained Growth with an Application to Turkey's Economy. *Lett. Spat. Resour. Sci. 8,* 49-76.

Bradley, K., Sweets, L., Bailey, W., and Wrather, J. (2009). *Missouri pest management guide: corn, grain sorghum, soybean, and winter wheat.* Columbia, Missouri: University of Missouri Extension M171.

Bringezu, S., Ramesohl, S., Arnold, K., Fischedick, M., Geibler, J. von, Liedtke, C., Schutz, H. (2007). *Towards a sustainable biomass strategy. What we know and what we should know. Wuppertal Institute for Climate, Environment and Energy* (Report no. 163). Wuppertal: Report of Wuppertal Institute for Climate, Environment and Energy.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M., Ruget, F., Nicoullaud, B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C., Richard, G., Beaudoin, N., Recous, S., Tayot, X., Plenet, D., Cellier, P., Machet, J. M., Meynard, J. M., Delecolle, R. (1998). STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory, and parameterization applied to wheat and corn. *Agronomie, 18*, 311–346.

British Columbia (B.C.) Environmental Assessment Office (EAO). (2017). Retrieved: May 2, 2017, from http://www.eao.gov.bc.ca.

Brockwell, P. J. and Davis, R. A. (2002). *Introduction to Time Series and Forecasting,* (2nd ed.). New York: Springer Science.

Brown, R. G. (1962). *Smoothing, forecasting and prediction of discrete time series*. New Jersey: Prentice-hall.

Brown Lester R. (2007). *Distillery demand for grain to fuel cars vastly understated: world may be facing highest grain prices in history*. Washington, DC: Report of Earth Policy Institute.

Bruinsma, J. (2003). *World agriculture: towards 2015/2030: An FAO Perspective*. London, UK: Earthscan Publications Ltd.

Cagatay, S., Kıymaz, T., Koç, A., Bölük, G., and Bilgin, D. (2012). *Dünya ve Türkiye Biyo-enerji Piyasalarındaki Gelişmelerin ve Potansiyel Değişikliklerin Türk Tarım ve Hayvancılık Sektörleri Üzerindeki Etkilerinin Modellenmesi ve Türkiye için Biyo-enerji Politika Alternatiflerinin Oluşturulması* (Report No. 204). Ankara: Agricultural Economics and Policy Improvement Institute Working Report.

Cardona, C., and Sanchez, O. (2007). Fuel ethanol production: process design trends and integration opportunities, *Bioresour. Technol. 98,* 2415-2457.

Carvalho Lopes, D. C., and Steidle Neto, A. J. (2011). Simulation models applied to crops with potential for biodiesel production. *Comput. Electron. Agric. 75*, 1-9.

Cassman, K. G., Wood, S., Choo, P. S., Cooper, H. D., Devendra, C., Dixon, J., Gaskell, J., Kahn, S., Lal, R., Lipper, L., Pretty, J., Primavera, J., Ramankutty, N., Viglizzo, E., Wiebe, K. (2005). Millennium Ecosystem Assessment Series. In R. Hassan, R. Scholes and N. Ash (Eds.), *Cultivated systems. In Ecosystems and human well-being: current state and trends* (Vol. 1, pp. 745–794). Washington, DC: Island Press.

CFDC. (2007). *Ethanol Fact Book*. US: Clean Fuels Development Coalition Publications.

Chang, T. H., Su, H. M., and Chiu, C. L. (2011).Value -at-risk estimation with the optimal dynamic biofuel portfolio. *Energ. Econ. 33,* 264-272.

Chen R., and Tsay, R. S. (1993). Nonlinear additive ARX models. *J. Am. Stat. Assoc. 88* (423): 955-967.

Chen, H., Nicolis, O., and Vidakovic, B. 2004. Multiscale Forecasting Method Using ARMAX Models. *Technol. Forecast. Soc. 1*, 34 - 39.

Cheng, J. J. (2010). *Biomass to Renewable Energy Processes*. Boca Raton, Florida, US: CRC Press/Taylor & Francis Group.

Cheng, J. J., and Timilsina, G. R. (2011). Status and barriers of advanced biofuel technologies: a review. *Renew. Energ. 36,* 3541-3549.

Cherubini, F. (2010). The biorefinery concept: using biomass instead of oil for producing energy and chemicals. *Energ. Convers. Manag. 51*, 1412-1421.

Clark, J. H. (2007). Green chemistry for the second generation biorefinery-sustainable chemical manufacturing based on biomass. *J. Chem. Technol. Biotechnol. 82*, 603-609.

Cohen, A. (1986). Biomedical Signal Processing I. Florida: CRC Press Inc.

Committee on biobased industrial products. (2000). *National research council of USA, Biobased Industrial Products: Research and Commercialization Priorities.* Washington, US: The National Academic Press.

Communication from the Commission: COM(2005)628, Biomass action plan, *Official Journal of the European Union*.

Communication from the Commission: COM(2006)34, An EU strategy for biofuels, *Official Journal of the European Union.*

CropEnergies AG Mannheim (2017). Retrieved: May 5, 2017, from http://www.cropenergies.com/en/Bioetha nol/Produk tionsverfahren/.

Cuellar-Bermudez, S. P., Garcia-Perez, J. S., Rittmann, B. E., and Parra-Saldivar, R. (2015). Photosynthetic bioenergy utilizing CO_2: an approach on flue gases utilization for third generation biofuels. *J Clean Prod. 98,* 53–65.

Dautzenberg, K., and Hantl, J. (2008). Biofuel chain development in Germany: organisation, opportunities, and challenges. *Energ. Policy. 36,* 465-489.

Davenport, W. B., and Root, W. L. (1958). *An introduction to the theory of random signals and noise.* New York, US: McGraw-Hill Book Company.

De Gooijer, J. G., and Hyndman, R. J. (2006). 25 years of time series forecasting. *Int J Forecasting. 22*, 443-473.

Deci, E. L., & Ryan, R. M. (1991). An motivational approach to self: Integration in personality. In R. Dienstbier (Ed.), *Perspectives on motivation* (Vol.38, pp. 237-288). Lincoln: University of Nebraska Press.

Demirliçakmak , A., and Çakmak, M. (1983). *Increasing the alcohol production as a precautionary measure to reduce oil consumption* . (No. 283, pp. 11-90). Ankara: National Productivity Centre publication.

Dimaranan, B. V., and Laborde, D. (2012). Ethanol Trade Policy and Global Biofuel Mandates report, Selected Paper prepared for presentation at the *International Association of Agricultural Economists (IAAE) Triennial Conference*, Foz do Iguaçu, Brazil: August 18-24.

Directive 2003/30/EC of the European Parliament and of the Council of 8 May 2003 on the promotion of the use of biofuels or other renewable fuels for transport, *Official Journal of the European Union* L 123/42.

Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC, Official Journal of the European Union L 140/16.

Directive 2009/30/EC of the European Parliament and of the Council of 23 April 2009 amending Directive 98/70/EC as regards the specification of petrol, diesel and gas-oil and introducing a mechanism to monitor and reduce greenhouse gas emissions and amending Council Directive 1999/32/EC as regards the specification of fuel used by inland waterway vessels and repealing Directive 93/12/EC, *Official Journal of the European Union* L 140/88.

Dixon P. B., and Rimmer M. T. (2007). *The Economy-Wide Effects in the United States of Replacing Crude Petroleum with Biomass*. Indiana: Purdue University GTAP Paper.

Diversi, R., Guidorzi, R., and Soverini, U. (2010).Identification of ARX and ARARX models in the presence of input and output noises. *Eur. J. Control. 16* (3), 242–255.

Doku, A., and Falco S. D. (2012). Biofuels in developing countries: Are comparative advantages enough? *Energ. Policy, 44*, 101-117.

Duku, M. H., Gu, S., and Hagan, E. B. (2011). A comprehensive review of biomass resources and biofuels potential in Ghana. *Renew. Sustain. Energ. Rev. 15*, 404–415.

Durbin, J. (1959). Efficient estimation of parameters in moving-average models. *Biometrica. 46*, 306-316.

Durbin, J. (1960). Estimation of parameters in time-series regression models. *J Roy. Stat. Soc. 22*, 139-153.

Ehret, D. L., Hill, B. D., Raworth, D. A., and Estergaard, B., (2008). Artificial neural network modelling to predict cuticle cracking in greenhouse peppers and tomatoes. *Comput. Electron. Agric. 61* (2), 108–116.

EIA, (2016). *International Energy Outlook 2016* (Report no. DOE/EIA-0484(2016)). Washington DC: Report of U.S. Energy Information Administration (EIA).

Eker, A. M., Dikmen, M., Cambazoğlu, S., Düzgün, H. S. B., and Akgün, H. (2012). Application of Artificial Neural Network and Logistic Regression Methods to Landslide Succeptibility Mapping and Comparison of the Results for the Ulus District, Bartın, *J Fac. Eng. Archit. Gaz., 27* (1), 163-173.

Elbehri, A., Segerstedt, A., and Liu, P. (2013). *Biofuels and the sustainability challenge: A global assessment of sustainability issues, trends and policies for biofuels and related feedstocks* (ISBN: 978-92-5-107414-5). Rome: Report of Trade and Markets Division in Food and Agriculture Organization (FAO) of the United Nations.

Elizondo, D. A., McClendon, R. W., and Hoogenboom, G. (1994). Neural network models for predicting flowering and physiological maturity of soybean. *T. ASAE. 37*, 981-988.

Elobeid A. and Tokgoz S. (2006). *Removal of U.S. Ethanol Domestic and Trade Distortions: Impact on U.S. and Brazilian Ethanol Markets* (Paper No. 06-WP 427), Ames, Iowa: Working paper of Center for Agricultual and Rural Developement of Iowa State University.

Elobeid, A., Tokgoz, S., Dodder, R., Johnson, T., Kaplan, O., Kurkalova, L., and Secchi, S. (2013). Integration of agricultural and energy system models for biofuel assessment. *Environ. Modell. Softw. 48,* 1-16.

Emang, D., Shitan, M., Ghani, A. N. A., and Noor, K. M. (2010). Forecasting with Univariate Time Series Models: A Case of Export Demand for Peninsular Malaysia's Moulding and Chipboard. *J Sust. Devel. Can. Cent. Sci Educ. 3* (3), 157-161.

EMRA. (2017). Personal Interview. 02 June, Ankara.

EPA. *(2017). Overview of Greenhouse Gases Statistics from United States Environmental Protection Agency. Retrieved May 31, 2017, from http://www.tarim.gov.tr/sgb/Belgeler/SagMenuVeriler/BUGEM.pdf*

Erickson, G. E., Klopfenstein, T. J., Adams, D. C., and Rasby, R. J. (2005). Corn Processing Co-Products Manual: A Review of Current Research on Distillers Grains and Corn Gluten. *Faculty Papers and Publications of Animal Science in University of Nebraska*. *509*, 2-33..

Escobar, J. C., Lora, E. S., Venturini, O. J., Yanez, E. E., Castillo, E. F., and Almazan O. (2009). Biofuels: environment, technology and food security. *Renew. Sustain. Energ. Rev. 13*, 1275-1287.

Evenson, R. E., and Gollin, D. (2003). Assessing the impact of the green revolution 1960–2000. *Sci. 300* (5620), 758–762.

FAO. (2008). *The State of Food and Agriculture* (ISBN: 978-92-5-105980-7). Rome: Report of Food and Agricultural Organization (FAO).

FAO. (2012). *Environmental Impact Assessment*: *Guidelines for FAO Field Projects* (ISBN: 978-92-5-107276-9). Rome: Report of Food and Agricultural Organization (FAO).

FAO. (2014). *Food Outlook: Biannual Report on Global Food Markets* (ISSN: 0251-1959). Rome: Report of Food and Agriculture Organization (FAO).

FAPRI. (2005). *Implications of Increased Ethanol Production for U.S. Agriculture*, Columbia: FAPRI-UMC Report of Food and Agricultural Policy Research Institute (FAPRI) in College of Agriculture, Food and Natural Resorces.

Fargione, J., Hill, J., Tilman, D., Polasky, S., and Hawthorne, P. (2008). Land clearing and the biofuel carbon debt. *Sci. 319*, 1235-1238.

Fernando, S., Adhikari, S., Chandrapal, C., and Murali, N. (2006). Biorefineries: current status challenges and future direction. *Energ. Fuel. 20*, 1727-1737.

Ferrer, J. C., MacCawley, A., Maturana, S., Toloza, S., and Vera, J. (2008). An optimization approach for scheduling wine grape harvest operations. *Int. J. Prod. Econ. 112* (2), 985–999.

Festel, G., Würmseher, M., Rammer, C, Boles, E., and Bellof, M. (2014). Modelling production cost scenarios for biofuels and fossil fuels in Europe. *J Clean. Prod. 66,* 242-253.

Fischer, G., Prieler, S., Velthuizen, Hv., Berndes, G., Faaij, A., Londo, M., and Wit, Md. (2010). Biofuel production potentials in Europe: Sustainable use of cultivated land and pastures, Part II: Land use scenarios. *Biomass Bioenerg. 34* (2),173-87.

Fisher, R. A. (1924). The influence of rainfall on the yield of wheat at Rothamsted. *Phil. Trans. Ser. B. 213*, 89-142.

Flach, B., Lieberz, S., Bendz, K., and Dahlbacka, B. (2011). EU-*27 Annual Biofuels Report*. Washington DC: USDA Foreign Agricultural Service Publications.

Fox, J. (1997). *Applied Regression Analysis: Linear Models and Related Methods.* US: Sage Publication.

Francesco, C. (2010). The biorefinery concept: using biomass instead of oil for producing energy and chemicals. *Energ. Convers. Manag. 51*, 1412-1421.

Fukata, A. K., Washio, T., Yada, K., and Motoda, H. (2006). *A Method to Search ARX Model Orders and its Application to Sales Dynamics.* Osaka, Japan: Research Study of The Institute of Scientific and Industrial Research in Osaka University.

Gasparatos, A, Lee, L. Y., von Maltitz, G. P., Mathai, M. V, de Oliveira, J. A. P., and Willis, K. J. (2012). *Biofuels in Africa: Impacts on ecosystem services, biodiversity and human well-being* (ISBN: 978-92-808-4537-2). UNU-IAS Policy Report of United Nations University, University of Oxford, and Council for Scientific and Industrial Research (CSIR) South Africa.

Gasparatos A, von Maltitz G.P., Johnson, F.X., Lee, L., Mathai, M., Puppim de Oliveira, J.A., Willis, K.J. (2015). Biofuels in sub-Sahara Africa: Drivers, impacts and priority policy areas. *Renew. Sustain. Energ. Rev. 45*, 879-901.

Gay, S. H., Mueller, M., and Santuccio, F. (2008), Analysing the Implication of the EU 20-10-20 Targets for World Oil Production, *107 th EAAE Seminar "Modelling of Agricultural and Rural Development Policies",* Sevilla, Spain : January 29th-February 1st.

Gnansounou, E. (2009). Fuel ethanol current status and outlook. In: A.Pandey (Ed.), *Handbook of Plant Based Biofuel* (pp. 57-71). Boca Raton: CRC Press Taylor & Francis Group.

Gohin, A. (2008). Impacts of the European Biofuel Policy on the Farm Sector: A General Equilibrium Assessment. *Rev. Agri. Econ. 30*, 1-19.

Gottman, J. M. (1981). *Time Series Analysis a Comprehensive Introduction for Social Scientists*. New York, US: Cambridge University Press.

Greenhouse Gas Calculation Methods Workshop. (2009). Sustainability certification for biofuels and bio-energy. January 29, Jinke van Dam Copernicus Institute - Utrecht University, Brussels.

Gujarati, D. N. (2003). *Basic Econometrics* (2nd ed.). US: McGraw Hill Book Company.

Guidorzi, R. (2003). *Multivariable System Identification: From Observations to Models*. Bologna, Italy: Bononia University Press.

Gupta, S. (2003). *Forecasting of Agricultural Output in India*. New Delhi, India: Saloni Publishing House.

Hamzacebi, C., Akay, D., and Kutay, F. (2009). Comparison of direct and iterative artificial neural network forecast approaches in multi-periodic time series forecasting. *Expert Syst Appl. 36*, 3839-3844.

Hansen, S., Jensen, H., Nielsen, N., and Svendsen, H. (1990). NPo-research, A10: DAISY: soil plant atmosphere system model. Miljøstyrelsen.

Hassouneh, I., Teresa, S., Goodwin, B. K., and Jośe, M. G. (2012). Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships. *Energ Econ. 34*, 1507-1513.

Havlík, P., Schneider, U. A., Schmid, E., Böttcher, H., Fritz, S., Skalsky, R., Aoki, K., Cara, S. D., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., Obersteiner, M. (2011). Global land-use implications of first and second generation biofuel targets. *Energ. Policy. 39,* 5690–5702.

Hazell, P., and Wood, S. (2008). Drivers of change in global agriculture. *Phılos. T. Roy. Soc. B*, *363*, 495-515.

Higgins, A. J., and Muchow, R.C. (2003). Assessing the potential benefits of alternative cane supply arrangements in the Australian sugar industry. *Agric. Syst. 76*, 623–638.

Higgins, A. J., Antony, G., Sandell, G., Davies, I., Prestwidge, D. B., and Andrew, B. (2004). A framework for integrating and optimising a complex harvesting and transport system for sugar production. *Agric. Syst. 82*, 99–115.

Higgins, A. J., Muchow, R. C., Rudd, A., and Ford, A. (1998). Optimising harvest date in sugar production: a case study for the Mossman mill region in Australia I. Development of operations research model and solution. *Field Crop. Res. 57*, 153–160.

Higgins, A., Prestwidge, D., Stirling, D., and Yost, J. (2010). Forecasting maturity of green peas: an application of neural networks. *Comput. Electron. Agric. 70* (1), 151–156.

Hjalmarsson, H. (2003). From experiments to closed loop control, *The 13th IFAC Symposium on System Identification, Conference Center De Doelen*, Rotterdam, Netherlands: August 27–29.

Hoefnagels, R., Banse, M., Dornburg, V., and Faaij, A. (2013). Macro-economic impact of large-scale deployment of biomass resources for energy and materials on a national level - A combined approach for the Netherlands, *Energ Policy. 59,* 727-744.

Huang, J., Rozelle, S., and Chang, M. (2004). Tracking distortions in agriculture: China and its accession to the World Trade Organization. *World Bank Econ. Rev. 18,* 59-84.

Huang, J., Yang, J., Msangi, S., Rozelle, S., and Weersink, A. (2012). Global biofuel production and poverty in China. *Appl. Energ. 98*, 246–255.

IEA. (2006). *World Energy Outlook 2006* (ISBN: 92-64-10989-7 - 2006). Paris: Report of OECD/IEA.

IEA. (2008). *From 1st to 2nd generation biofuel technologies: An overview of current industry and RD & R activities*. Paris: Report of OECD/IEA.

IEA. (2013). *World Energy Outlook 2013* (ISBN: 978-92-64-20130-9). Paris: Report of OECD/IEA.

IEA. (2015). *World Energy Outlook 2015* (ISBN: 978-92-64-24366-8). Paris: Report of OECD/IEA.

IEA-AMF. *(2017). Retrieved May 5, 2017, from http://www.iea-amf.org/content/fuel_information/ethanol/e10/ethanol_properties#octane_numbers*

IFPRI. (2006). *Biofuel production in developing countries.* Washington, DC: Unpublished working paper of International Food Policy Research Institute (IFPRI).

Ilyas, M. and Mirza, Z.I. (1990). Yield prediction of sugarcane (Saccarum Officinarum) as related to evapotranspiration (ET) in Pakistan. *Pak. J. Agri. Sci. 28* (3), 292-297.

International Grains Council Statistics. (2014). Retrieved December 19, 2014, from http://www.igc.int/en/Default .aspx

IPCC. (2007). *Climate Change 2007: Mitigation of Climate Change* (ISBN 978-0-521-88011-4). New York: Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

Isler, A. (2012). *Aspir Yaği Etil Esteri ve Yaşam Döngüsü Değerlendirmesi*. (Ph.D. Thesis), Istanbul Technical University, Graduate School Of Science Engineering and Technology, Istanbul.

Isler, A., and Karaosmanoglu, F. (2007). Yakıt Alkolü: Mevcut Durumu ve Geleceği, *Biyoyakıtlar ve Biyoyakıt Teknolojileri Sempozyumu,* Ankara, Turkey: December 12-13.

Isler, A., and Karaosmanoglu, F. (2010). Chapter 17: Biofuels in Turkey, Rethinking Structural Reform in Turkish Agriculture: *Beyond the World Bank's Strategy -2010,* ed. B. Karapınar, F. Adaman and G. Ozertan, Nova Science Publisher, In Press.

Joshi, C. P., and Nookaraju, A. (2012). New Avenues of Bioenergy Production from Plants: Green Alternatives to Petroleum. *J Pet. Environ. Biotechnol. 3*, 1-5.

Junginger, M., van Dam, J., Zarrilli, S. Z., Mohamed, F. A., Marchal, D., and Faaij, A. (2011). Opportunities and barriers for international bioenergy trade. *Energ Policy. 39,* 2028-2042.

Jutras, P., Prasher, S. O., and Mehuys, G. R. (2009). Prediction of street tree morphological parameters using artificial neural networks. *Comput. Electron. Agric. 67* (1–2), 9–17.

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems, *J Basic Eng-T ASME. 82*, 35-45.

Kalman, R. E. (1960). On the General Theory of Control Systems. *Proceedings First International Conferance on Automatic Control Systems* (vol. 1, pp. 481–492). Moscow, USSR.

Kalman, R. E., and Bucy, R. S. (1961). New Results in Linear Filtering and Prediction Theory. *J Basic Eng-T ASME. 83*, 95-108.

Kalogirou, S. A. (2000). Applications of artificial neural networks for energy systems, *Appl. Energ. 67,* 17-35.

Kalogirou, S. A. (2001). Artificial neural networks in renewable energy systems applications: A review, *Renew. Sustain. Energ. Rev. 5,* 373-401.

Kalogirou, S. A. (2003). Artificial intelligence for the modeling and control of combustion processes: a review. *Prog. Energ. Combust. Sci. 29*, 515–566.

Kamm, B., and M. Kamm. (2004). Principles of biorefineries. *Appl. Microbiol. Biotechnol. 64* (2), 137-145.

Kamm, B., Gruber, P. R., and Kamm, M., (2006). *Biorefineries–Industrial Processes & Products* (Vol. 1, 2). Weinheim, Germany: WILEY-VCH Verlag GmbH & Co. KGaA.

Kalman, R. E. and Bucy, R. S. (1961). New Results in Linear Filtering and Prediction Theory, *J Basic Eng-T ASME. 83*, 95-108.

Kaltschmitt, M. (2001). Grundlagen der Festbrennstoffnutzung-Begriffsdefi nitionen. In M., Kaltschmitt, H., Hartmann, (Eds.), *Energie aus Biomasse-Grundlagen*, *Techniken und Verfahren* (pp. 770). Berlin: Springer.

Karaosmanoglu, F., Isigigur Ergudenler, A., and Aksoy, H. A. (1998). Alcohol Fuel Research in Turkey. *Energ. Source. 20*, 955-960.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. *Eur. J Agron. 18*, 267–288.

Kim S., and Dale, B. E. (2004). Global potential bioethanol production from wasted crops and crop residues. *Biomass Bioenerg. 26*, 361-375.

Kim, J., Realff, M. J., Lee, J. H., Whittaker, C., and Furtner, L. (2011). Design of biomass processing network for biofuel production using an MILP model. *Biomass Bioenerg. 35*, 853-871.

Kirshen, P. H., and Flitcroft, I. D. (2000). Use of seasonal precipitation forecasting to improve agricultural production in the Sudano Sahel: an institutional analysis of Burkina Faso. *Nat. Resour. Forum. 24* (3), 185–195.

Kocar, G., and Civas, N. (2013). An overview of biofuels from energy crops: Current status and future prospects, *Renew. Sustain. Energ. Rev. 28*, 900–916.

Kock, A. B., and Teräsvirta, T. (2010). *Forecasting with nonlinear time series models*. Denmark: *CREATES Research Paper 2010-1* of Aarhus University.

Kohzadi, N., Boyd, M. S., Kaastra, I., Kermanshahi, B. S., and Scuse, D. (1995). Neural networks for forecasting: an introduction. *Can. J. Agric. Econ. 43*, 463-474.

Kolmogoroff, A. (1941). Interpolation und extrapolation von stationären folgen. *Bull. Acad. Sci. USSR, Math. Ser. 5*, 11-14.

Kretschmer, B., and Peterson, S. (2010). Integrating Bioenergy into Computable General Equilibrium Models – A Survey. *Energ. Econ. 32*, 673-686.

Kristoufek, L., Janda, K., and Zilberman, D. (2012). Correlations between bio-fuels and related commodities before and during the food crisis: a taxonomy perspective. *Energ. Econ. 34*, 1380–1391.

Kumar, S., Singh, N., and Prasad, R. (2010). Anhydrous ethanol : a renewable source of energy, *Renew. Sustain. Energ. Rev. 14*, 1830-1844.

Lang, X., Dalai, A. K., Bakhshi, N. N., Reaney, M. J., and Hertz, P. B. (2001). Preparation and characterization of bio-diesels from various bio-oils. *Bioresour. Technol. 80* (1), 53-62.

Laning, J. H., Jr., and Battin, R.H.. (1956). *Random Processes in Automatic Control*. New York, US: McGraw-Hill Book Company.

Lambert, D. M., and Cho, S. (2008). Forecasting input demand shocks on China's gross value of agricultural output. *Rev. Reg. Stud. 38,* 343–359.

Lamers, P. (2013). *Sustainable International Bioenergy Trade.* (Ph.D. Thesis), Utrecht University, Utrecht, Holland.

Lawrence, J. (1993). *Introduction to Neural Networks. Design, Theory and Applications* (5th ed.). Nevada City, CA: California Science Software Press.

Lee, Y. S., and Tong, L. I. (2011). Forecasting time series using a methodology based on autogressive integrated moving average and genetic programming. *Knowl-Based Syst. 24,* 66–72.

Lee, W. Y., Park, C., and Kelly, G. E. (1996). Fault detection in an air handling unit using residual and recursive parameter identification method, *Technical and Symposium Papers of Winter meeting of American*

Society of Heating, Refrigeration and Air Conditioning Engineers. Atlanta, Georgia: February 17–21.

Lennartsson, P. R., Erlandsson, P., and Taherzadeh, M. J. (2014). Integration of the first and second generation bioethanol processes and the importance of by-products. *Bioresour. Technol. 165*, 3–8.

Lenz-Wiedemann, V. I. S., Klar, C. W., and Schneider, K. (2010). Development and test of a crop growth model for application within a Global Change decision support system. *Ecol. Model. 221,* 314-329.

Levenberg, K. (1944). A Method for the Solution of Certain Problem in Least Squares, *Quarterly App. Math. 2*, 164-168.

Linoj Kumar, N. V., Dhavala, P., Goswami, A., and Maithel, S. (2006). Liquid Biofuels in South Asia: Liquid Biofuels in South Asia: Resources and Technologies. *Asian Biotechnol. Dev. Rev. 8* (2), 31–49.

Lin, Y., and Tanaka, S. (2006). Ethanol fermentation from biomass resources: current state and prospects. *Appl. Microbiol. Biotechnol. 69*, 627-642.

Ljung, L. (1999). *System Identification: Theory for the User* (2nd ed.). New Jersey, US: Prentice Hall.

Luque, R., Campelo, J., and Clark, J. H. (2011). *Handbook of biofuels production: Processes and technologies.* Oxford: Woodhead Publishing Limited.

Lurette, A., Aubron, C., and Moulin, C. H. (2013). A simple model to assess the sensitivity of grassland dairy systems to scenarios of seasonal biomass production variability. *Comput. Electron. Agric. 93,* 27-36.

Lü, J., Sheahan, C., and Fu, P. (2011). Metabolic engineering of algae for fourth generation biofuels production. *Energ. Environ. Sci. 4*, 2451–2466.

Mabee, W. E., McFarlane, P. N., and Saddler, J. N. (2011). Biomass Availability for Lignocellulosic Ethanol Production, *Biomass and Bioenerg. 35,* 4519-4529.

Mahmoud, E. (1984). Accuracy in forecasting: A survey. *J Forecasting. 3*, 139–159.

Makridakis, S. (1976). A survey of time series. *Int. Stat. Rev. 44* (1), 29-70.

Makridakis, S., and Hibon, M. (1997). ARMA models and the Box-Jenkins methodology. *J. Forecasting*. *16,* 147–163.

Makridakis, S., Wheelwright, S. C., and Hyndman, R. J. (1998). *Forecasting Methods and Applications* (3rd ed.). US: John Wiley & Sons, Inc.

Mansouri, M., Dumont, B., and Destain, M. F. (2013). Modeling and prediction of nonlinear environmental system using Bayesian methods. *Comput. Electron. Agric. 92,* 16-31.

Markevičius, A., Katinas, V., Perednis, E., and Tamašauskiene, M. (2010). Trends and sustainability criteria of the production and use of liquid biofuels. *Renew. Sustain. Energ. Rev. 14*, 3226–3231.

Marquardt, D. (1963). An Algorithm for Least Squares Estimation of Nonlinear Parameters, *SIAM J. App. Math., 11,* 431-441.

Martin, G., Duru, M., Schellberg, J. and Ewert, F. (2012). Simulations of plant productivity are affected by modelling approaches of farm management. *Agric. Syst. 109*, 25–34.

Martinez-Gonzalez A., Sheldon I. A., and Thompson S. (2007). Estimating the Welfare Effects of U.S. Distortions in the Ethanol Market Using a Partial Equilibrium Trade Model, *J Agri. Food Indst. Org. 5* (2), 2-30.

Martinsen, D., Funk, C., and Linssen, J. (2010). Biomass for transportation fuels e a costeffective option for the German energy supply? *Energ. Policy 38*, 128-140.

Melikoglu, M. (2014). Demand forecast for road transportation fuels including gasoline, diesel, LPG, bioethanol and biodiesel for Turkey between 2013-2023, *Renew. Energ. 64*, 164-171.

Mellit, A., and Kalogirou, S. A. (2008). Artificial intelligence techniques for photovoltaic applications: a review. *Prog. Energ. Combus. Sci. 34,* 574–632.

Menon, V., and Rao, M. (2012). Trends in bioconversion of lignocellulose: Biofuels, platform chemical & biorefinery concept, *Prog. Energ. Combust. Sci, 38*, 522-550.

MENR. (2010). *2010-2014 Strategic Report*. Ankara, Turkey: Minister of Energy and Natural Resources.

Miller, S. A., Landis, A. E., and Theis, T. L. (2007). Environmental trade-offs of biobased production. *Environ. Sci. Technol. 41,* 5176-5182.

Mitra, S. K., and Kaiser, J. F. (1993). *Handbook for Digital Signal Processing*. New York, US: John Wiley & Sons, Inc.

Mizsey, P., and Racz, L. (2010). Cleaner production alternatives: biomass utilization options. *J Clean. Prod. 18,* 767-770.

Mohanraj, M., Jayaraj, S., and Muraleedharan, C. (2012). Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems—A review. *Renew. Sust. Energ. Rev. 16*, 1340-1358.

Mohammed, F. A. (2007). Sustainable biofuels production and use with a focus on Africa. *Eastern and Southern Africa regional workshop on biofuels-UNEP*, Nairobi: June 28–29.

Mohammed Y. S., Mustafa M. W., and Bashir N. (2013). Status of renewable energy consumption and developmental challenges in Sub-Sahara Africa. *Renew. Sust. Energ. Rev. 27*, 453–63.

Montgomery, D. C., Jennings, C. L., and Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting.* New Jersey, US: John Wiley & Sons.

Muhammad, F., Javed, M. S., and Bashlr, M. (1992). Forecasting sugarcane production in Pakistan using arima models. *Pak. J. Agri. Sci. 9* (1): 31-36.

Muñoz, I., Karin, F., Jungbluth, N., Rigarlsford, G., Canals, L. M., and King, H. (2014). Life cycle assessment of bio-based ethanol produced from different agricultural feedstocks. *Int J Life Cycle Assess. Sci. 19* (1), 109–119.

Murat Y. S. and Ceylan H. (2006). Use of artificial neural networks for transport energy demand modeling. *Energ. Policy*. *34*, 3165–3172.

Naik, S. N., Goud, V. V., Rout, P. K., and Dalai, A. K. (2010). Production of first and second generation biofuels: A comprehensive review. *Renew. Sust. Energ. Rev. 14,* 578-597.

Nass, L., Pereira, P., and Ellis, D. (2007). Biofuels in Brazil: An overview. *Crop Sci. 47*, 6, 2228–2237.

Newbold, P., and Bos, T. (1983). ARIMA model building and the time series analysis approach to forecasting. *Int. J. Forecasting. 2,* 23-35.

Nigam, R. B., and Agrawal, P. K. (2004). Ethanol manufacturer from cane juice and molasses: A diversification for sugar industry in India. *The Proceedings of the International Conference on Biofuels: Perspectives & Prospects,* Organized by Winrock International, India: September 16-17.

Nigam, P. S., and Singh, A. (2011). Production of liquid biofuels from renewable resources. *Prog. Energ. Combus. Sci. 37*, 52-68.

OECD. (2011). *Evaluation of Agricultural Policy Reforms in Turkey* (ISBN: 9789264113220) . Paris: OECD Publishing.

OECD. (2012). *Green Growth Indicators 2014*. Paris: OECD Publishing.

OECD-FAO. (2008). *OECD-FAO Agricultural Outlook 2008-2017*. Paris: Report of OECD and FAO.

OECD-FAO. (2013). *OECD-FAO Agricultural Outlook 2013-2022*. Paris: Report of OECD and FAO.

OFID. (2009). *Biofuels and food security.* Vienna, Austria: Opec Fund for International Development (OFID) Study prepared by International Institute for Applied Systems Analysis (IIASA).

Ou, S. L. (2012). Forecasting agricultural output with an improved grey forecasting model based on the genetic algorithm. *Comput. Electron. Agric. 85,* 33-39.

Oztemel, E. (2012). *Yapay Sinir Ağları*. Istanbul: Papatya Yayıncılık.

Pandey, A., Larroche, C., Ricke, S. C., Dussap, C. G., and Gnansounou, E. (2011). *Biofuels: Alternative Feedstocks and Conversion Processes*. US: Elsevier Press.

Peng, H., Ozaki, T., Toyoda, Y., and Oda, K. (2001). Modeling and control of systems with signal dependent nonlinear dynamics. *The proceedings of the 2001 European Control Conference (ECC), Seminario de Vilar*, Porto, Portugal: September 4-7.

Peters M., Somwaru A., Hansen J., Seeley R., and Dirkse S. (2009). Modeling Biofuels Expansion in a Changing Global Environment, *International Association of Agricultural Economics Conference,* Beijing, China: August 16-22.

PETDER, (2012). *Turkish Petroleum Industry Association, Sector Report 2012*. Istanbul: Report of PETDER.

PETDER, (2013). *Turkish Petroleum Industry Association, Sector Report 2012*. Istanbul: Report of PETDER.

PETDER-Statistics, (2013). Retrieved September 21, 2013, from http://www.petder .org.tr/yayinlar/sektorel-veri-ve-istatistikler/

Põldaru, R., and Roots, J. (2014). Using a nonlinear stochastic model to schedule silage maize harvesting on Estonian farms. *Comput. Electron. Agric. 107,* 89-96.

Pousa, P. A. G., Santos, A. L. F., and Suarez, P. A. Z. (2007). History and policy of biodiesel in Brazil. *Energ. Policy*. *35* (11), 5393–5398.

Prabhakar, S. V. R. K., and Elder, M. (2009). Biofuels and resource use efficiency in developing Asia: Back to basics. *Appl. Energ. 86*, 30–36.

Pradhan, A., and Mbohwa, C. (2014). Development of biofuels in South Africa: Challenges and opprtunities. *Renew. Sustain. Energ. Rev. 39*, 1089-1100.

Rajagopal, D. and Zilbermann, D. (2007). *Review of environmental, economic and policy aspects of biofuels.* Washington, DC: Policy Research Working Paper of The World Bank.

Ramasubramanian, V. (2012). *Forecasting Techniques in Agriculture*. New Delhi: The paper of Indian Agricultural Research Institute.

Reddersen, B., Fricke, T., and Wachendorf, M., (2014). A multi-sensor approach for predicting biomass of extensively managed grassland. *Comput. Electron. Agric. 109*, 247-260.

Reed, D. R., and Marks, R. J. (1999). *Neural Smithing Supervised Learning in Feedforward Artificial Neural Networks*. Cambridge, London, England: Massachusetts Institute of Technology Press.

REN. (2013). *Renewables 2013 Global Status Report* (ISBN: 978-3-9815934-0-2). Paris: Report of Renewable Energy Policy Network for the 21st Century.

REN. (2014). *Renewables 2014 Global Status Report* (ISBN: 978-3-9815934-2-6). Paris: Report of Renewable Energy Policy Network for the 21st Century.

REN. (2016). *Renewables 2016 Global Status Report* (ISBN 978-3-9818107-0-7). Paris: Report of Renewable Energy Policy Network for the 21st Century.

Raychaudhuria, A., and Ghosh, S. K. (2016). Biomass Supply Chain in Asian and European Countries. *Proc. Environ. Sci. 35*, 914 – 924.

Resop, J. P., Fleisher, D. H., Wang, Q., Timlin, D. J., and Reddy, V. M. (2012). Combining explanatory crop models with geospatial data for regional analyses of crop yield using field-scale modeling units. *Comput. Electron. Agric. 89,* 51-61.

Rinaldi, M., Losavio, N., and Flagella, Z. (2003). Evaluation and application of the OilCrop-Sun model for sunflower in southern Italy. *Agr. Syst. 78,* 17-30.

Roberts. S., and Jackson, J.A.(1991). Active normal faulting in central Greece: An overview, In A. M. Roberts, G. Yielding, and B. Freeman (Eds.), *The Geometry of Normal Faults,* (Vol. 56, pp. 125-142). Oxford: Geological Society London Special Publications by Blackwell Scientific Publications.

Rosillo-Calle, F., and Johnson, F. X. (2010). *Food versus fuel: an informed introduction to biofuels.* London: Zed Books.

Rustemoglu, S. (2010). *Akış Alan Modellemesi ve İstatistiksel Enerji Öngörüsü: Maslak Örneği*. (M.Sc. Thesis). Istanbul Technical University, Graduate School Of Science Engineering and Technology, Istanbul.

Rutz, D., and Janssen, R. (2008). *Biofuel Technology Handbook* (2nd ed.), München, Germany: WIP Renewable Energies Press.

Sahin, I. (2014). Prediction of Surface Roughness of Al/SiC Composite Material with Artificial Neural Networks. *J Fac. Eng. Archit. Gaz*., *29 (1)*, 209-216.

Saladini, F., Patrizi, N., Pulselli, F. M., Marchettini, N., and Bastianoni, S. (2016). Guidelines for emergy evaluation of first, second and third generation biofuels. *Renew. Sustain. Energ. Rev. 66*, 221-227.

Sapp, M. (2013). Can biofuels really be blamed for food insecurity in Africa. *Biofuel. Bioproduct. Bior. 7,* 482–484.

Schwarz, G. (1978). Estimating the Dimension of a Model. *Ann. of Stat. 6*, 461-46.

Schenk, P., Thomas-Hall, S., Stephens, E., Marx, U., Mussgnug, J., Posten, C., Kruse, O., Hankamer, B. (2008). Second generation biofuels: highefficiency microalgae for biodiesel production. *BioEnerg. Res*. *1,* 20-43.

Schuster, A. (1906). On the periodicities of sunspots. *Philos. T Roy. Soc. A*. 206, 69-100.

Searle, S. Y., and Malins, C. J. (2014). Will energy crop yields meet expectations? *Biomass Bioenerg. 65*, 3–12.

Sekoai, P. T. and Yoro, K. O. (2016). Biofuel Development Initiatives in Sub-Saharan Africa: Opportunities and Challenges. *Climate*, *4*, 33.

Serra, T., and Zilberman, D. (2013). Biofuel-related price transmission literature: A review. *Energ. Econ. 37*, 141-151.

Sharda, R. (1994). Neural networks for the MS/OR analyst: An application bibliography. *Interfaces, 24 (2),* 116–130.

Shibata, R. (1976). Selection of the Order of an Autoregressive Model by Akaike’s Information Criterion, *Biometrika*. *63* (1), 117-126.

Singh, A. K., Tripathy, R., and Chopra, U. K. (2008). Evaluation of CERES-Wheat and Crop-Syst models for water–nitrogen interactions in wheat crop. *Agr. Water Manag. 95*, 776–786.

Slutsky, E. (1937). The summation of random causes as the source of cyclic processes. *Econometrica*. *5*, 105-146.

Smith, M. (1993). *Neural networks for statistical modelling*. New York: Van Nostrand Reinhold.

Smith, B. A., Hoogenboom, G., and McClendon, R. W. (2009). Artificial neural networks for automated year-round temperature prediction. *Comput. Electron. Agric. 68* (1), 52–61.

Sozen, A., Arcaklioglu, E., and Ozkaymak, M. (2005). Modeling of the Turkey's net energy consumption using artificial neural network. *Int. J Comput. Appl. Technol. 22,* 130–136.

Sozen, A., and Arcaklioglu, E. (2007). Prospects for future projections of the basic energy sources in Turkey. *Energ. Sour. B: Econ, Plann, Policy. 2,* 183–201.

Söderström, T. (2007). Errors in variables methods in system identification. *Automatica. 43,* 939–958.

Steenblik, R. (2007). *Biofuels–At What Cost ? Government Support for Ethanol and Biodiesel in Selected OECD Countries*. Genava, Switzerland: Global Subsidies Initiative (GSI) of the International Institute for Sustainable Development (IISD).

Stephen, J. D., Mabee, W. E, and Saddler, J. N. (2010). Biomass logistics as a determinant of second-generation biofuel facility scale, location and technology selection. *Biofuels Bioprod. Biorefin*. *4,* 503-518.

TAMRA. *(2017). Official Statistics for fuel bioethanol in Tobacco and Alcohol Market Regulatory Authority.* Retrieved June 20, 2017, from *http:// www.tapdk.gov.tr/tr/piyasa-duzenlemeleri/alkol-piyasasi/resmi-ista tistikler.aspx*

Tan, B., and Ēömden, N. (2012). Agricultural planning of annual plants under demand, maturation, harvest, and yield risk. *Eur. J. Oper. Res. 220*, 539–549.

Tatsidjodoung, P., Dabat, M. H., and Blin, J. (2012). Insights into biofuel development in Burkina Faso: potential and strategies for sustainable energy policies. *Renew. Sustain. Energ. Rev*. *16*, 5319–5330.

Tekeli, S. T. (1940). *Gasoline-ethanol published by Institute of Agriculture*. Istanbul: Çeltüt Press.

Thelen, K. D., Gao, J., Hoben, J., Qian, L., Saffron, C., and Withers, K. (2012). A spreadsheet-based model for teaching the agronomic, economic, and environmental aspects of bioenergy cropping systems. *Comput. Electron. Agric. 85,* 157-163.

TEPGE. (2012). *Dünya ve Türkiye Biyo-enerji Piyasalarındaki Gelişmelerin ve Potansiyel Değişikliklerin Türk Tarım ve Hayvancılık Sektörleri Üzerindeki Etkilerinin Modellenmesi ve Türkiye için Biyo-enerji Politika Alternatiflerinin Oluşturulması* (Report No. 204, ISBN:978-605-4672-01-1). Ankara: Report of Institute of Agricultural Economics and Policy Development (TEPGE) of Republic of Turkey, Ministry of Food, Agriculture and Livestock.

***TGB**. (2013). Cereal Statistics in Turkish Grain Board. Retrieved September 20, 2013, from http://www.tmo.gov.tr/Main.aspx?ID=40.*

Thie, J.A. (1986). *Power Reactor Noise. Illinois*. US: American Nuclear Society.

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., and Polasky, S. (2002). Agriculture sustainability and intensive production practices. *Nature, 418*, 671–677.

Timilsina, G. R., and Shrestha, A. (2010). *Biofuels: Markets, Targets and Impacts* (Paper No. 5364). Washington DC: Policy Research Working Paper of Environment and Energy, Development Research Group in the World Bank.

Tokgoz S., Elobeid A., Fabiosa J., Hayes D. J., Babcock B. A., Yu T. E., Dong F., and Hart C.H. (2008), Bottlenecks, Drought, and Oil Price Spikes:Impact on U.S. Ethanol and Agricultural Sectors, *Rev. Agr. Econ*. *30*, 1-19.

Treguer D., and Sourie J-C. (2006), The Impact of Biofuel Production on Farms Jobs and Income: The French Case, *96 th EAAE Seminar,* Tänikon, Switzerland: January 10-11 .

Tsuji, G. Y., Hoogenboom, G., and Thornton, P. K. (1998). *Understanding Options for Agricultural Production Understanding Options for Agricultural Production*. Dordrecht, the Netherlands: Kluwer Academic Publishers.

***Turkish Statistical Institute Statics**. (2013). Agricultural Products Statistics. Retrieved February 13, 2014, from http://www.turkstat.gov.tr/Start .do;jsessionid¼9tFFJBDTS7Qd4nXmWnszGPnx6Wpsp6Wy29p2dc2l2 hfs7wR0nwf4!-728548976.*

***Turkish Sugar Authority**. (2014). Feedstock Data. Retrieved February 15, 2014, from http://www.sekerkurumu.gov.tr/hammadde.aspx*

***Turkish Sugar Factories Sectoral Report**. (2013). Sugar beet production and quotas in Turkey. Retrieved January 01, 2015, from http://www.turksek er.gov.tr/FaaliyetRapor/Seker_Fabrikalari_Faaliyet_Raporu_2013.pd f*

Tyner, W. E. (2010). Comparison of the US and EU approaches to simulating biofuels. *Biofuels*. *1*, 19–21.

Ubilava, D., and Holt, M. (2010). Forecasting Corn Prices in the Ethanol Era, mimeo, Department of Agricultural Economics, Purdue University.

Ultanir, M. O. (1985). Developments in synthetic engine fuels that will substitute petroleum derivates . *Electr. Pow. Res. Coun. Bull. 116,* 1-33.

UN. (2006). *The Emerging Biofuel Market: Regulatory, Trade and Development Implications.* New York and Geneva: United Nations Report.

Uno, Y., Prasher, S., Lacroix, R., Goel, P., Karimi, Y., Viau, A., and Patel, R. (2005). Artificial neural networks to predict corn yield from Compact Airborne Spectrographic Imager data. *Comput. Electron. Agric. 47* (2), pp. 149–161.

Urbanchuk, J. M. (2015). *Contribution of The Ethanol Industry to the Economy of The United States in 2014*. US: *LLP Publications*.

USDA FAS. (2008). *EU-25 Biofuels Annual* (Report No. NL7015). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Gain Report for Brazil. (2016). *Brazil: Biofuels Annual Report for 2016* (Report No. BR16009). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Gain Report for Canada. (2016). *Canada: Biofuels Annual Report for 2016* (Report No. CA16038). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Gain Report for China. (2017). *China: Biofuels Annual Report for 2016* (Report No. CH16067). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Gain Report for EU. (2016). *EU: Biofuels Annual Report for 2016* (Report No. NL6021). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Gain Report for India. (2016). *India: Biofuels Annual Report for 2016* (Report No. IN6088). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Gain Report for Turkey. (2017). *Turkey Grain and Feed Annual Report for 2017* (Report No. TR7014). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Turkey Annual Sugar Beet Report. (2016). *Turkey Annual Sugar Report for 2016* (Report No. TR6018). US: GAIN Report of USDA Foreign Agricultural Service.

USDA Turkey Biofuels Report. (2009). *Turkey: Biofuels Annual Report for 2009* (Report No. TU9020). US: GAIN Report of USDA Foreign Agricultural Service.

USDA US Bioenergy Statistics. *(2017). Retrieved May 30, 2017, from https://www.ers.usda.gov/data-products/us-bioenergy-statistics/>*

Walker, A. M. (1931). On the periodicity in series of related terms. *Proceed. Roy. Soc. of London, A. 131*, 518-532.

Walker, A. M. (1962). Large-sample estimation of parameters for autoregressive processes with moving average residuals, Parts I, II. *Biometrika. 49*, 117-131.

WEC. (2016). *World Energy Resources*, London: Report of World Energy Council (WEC).

WEF. (2010). *The Future of Industrial Biorafineries.* Geneva, Switzerland: World Economic Forum Report.

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *Int. J Forecast. 30*, 1030–1081.

Whittle, P. (1953). The analysis of multiple stationary time series. *J. Roy. Stat. Soc. B. 15,* 125-139.

Wiener, N. (1944). *The Interpoaltion, Extrapolation and Smoothing of Stationary Time Series*. New York: John Wiley.

Wiener, N. (1948). *Cybernetics or Control and Communication in the Animaland the Machine*. Cambridge, Massachusetts, US: The Massachusetts Institute of Technology Press.

Williams, J., Jones, C., Kiniry, J., and Spanel, D. (1989). The EPIC crop growth model. *Transactions of* ASAE, *32,* 497–511.

Wold, H. (1954). *A study in the analysis of stationary time series* (1st ed.). Stockholm, Sweeden: Almqrist & Wiksell.

Woods, J. (2006). Science and technology options for harnessing bioenergy's potential - Brief 6 of 12. In: P., Hazell, and Pachauri, R. K. (Eds.), *Bioenergy and Agriculture: Promises and Challenges,* Washington DC: International Food Policy Research Institute.

Wyman, C. E. (2004). Ethanol fuel. In: C. J. Cleveland, R. U. Ayres, R. Costanza, J. Goldemberg, et al.(Eds.), *Encyclopedia of Energy* (Vol.2, pp. 541-555). Amsterdam, Boston: Elsevier Academic Press.

Vacha, L., Janda, K., Kristoufek, L., and Zilberman, D. (2013). Time-frequency dynamics of biofuel-fuel-food system. *Energy Econ. 40,* 233-241.

Vaidyanathan, P. P. (2008). The Theory of Linear Prediction. Morgan & Claypool, San Rafael, CA, USA.

van Diepen, C.A., Wolf, J., Van Keulen, H., and Rappoldt, C. (1989). WOFOST: a simulation model of crop production. *Soil Use Manage. 5*, 16-24.

Verbeek. M. (2004). *A guide to modern econometrics* (2nd ed.). US: John Wiley & Sons.

Vertès, A. A. (2014). Biorefinery Roadmaps. In N. Qureshi, D. Hodge, A. Vertès (Eds.), *Biorefineries* (1st ed.). United Kingdom: Elsevier.

Vertès, A. A., Qureshi, N., Blaschek, H. P., and Yukawa, H. (2010). *Biomass to Biofuels: Strategies for Global Industries.* West Sussex, England: John Wiley & Sons.

Viikari, L., Vehmaanpera, J., and Koivula, A. (2012). Lignocellulosic ethanol: From science to industry. *Biomass Bioenerg. 46*, 13-24.

Vohra, M., Manwar, J., Manmode, R., Padgilwar, S., and Patil, S. (2013). Bioethanol Production: Feedstock and Current Technologies. *J Environ. Chem. Eng. 2,* 573-584.

von Ledebur O., Salaman P., Zimmerman A., Leeuwen M. V., Tabeu A., and Chantreuil F. (2008). Modeling Impacts of Some European Biofuel Measures, *107th EAAE Seminar: Modelling of Agricultural and Rural Development Policies*. Sevilla, Spain: January 29-February 1.

von Maltitz, G., Haywood, L., Mapako, M., and Brent, A. (2009). *Analysis of opportunities for biofuel production in Sub-Saharan Africa*. Bogor, Indonesia: Environmental Services Briefs of Center for International Forestry Research (CIFOR).

Yan, K., Wen, S., Mulumba, T., and Afshari, A. (2014). ARX model based fault detection and diagnosis for chillers using support vector machines. *Energ. Build. 81*, 287–295.

Yan, X. (2012). Bioethanol and Biodiesel as Alternative Transportation Fuels in China: Current Status, Future Potentials, and Life Cycle Analysis. *Energ. Sour. Part A. 34*, 1067–1075.

Yang, L., Peng, L., Zhang, L., and Yang, S. (2009). A prediction model for population occurrence of paddy stem borer (Scirpophaga incertulas), based on back propagation artificial neural network and principal components analysis. *Comput. Electron. Agric. 68* (2), 200–206.

Yazdan, S., Mohsen, H., and Rostam, M. (2008). Numerical solution of the nonlinear Schrödinger equation by feed forward neural networks. *Commun. in Nonlinear Sci. Num. Simul. 13* (10), 2132–2145.

Yu, R., and Leung, P. S. (2009). Optimal harvest time in continuous aquacultural production: the case of non homogeneous production cycles. *Int. J Prod. Econ. 117*, 267–270.

Yule, G. U. (1927). On a method of investigating periodicities in disturbed series, with special reference to Wolfer's sunspot numbers. *Philos T R Soc Lond*, *226*, 267-298.

Zadeh, L. A., and Ragazzini, J. R. (1950). An Extention of Wiener's Theory of Prediction, *J Appl. Sci*. *21*, 645-655.

Zhang, Z., Lohr, L., Escalante, C. and Wetzstein, M. (2009). Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. *Energies*. *2*, 230–339.

Zhang, Z., Lohr, L., Escalante, C., and Wetzstein, M. (2010). Food versus fuel: what do prices tell us? *Energ Policy. 38*, 445-451.

Zhang, W., Yu, E. A., Rozelle, S., Yang, J., and Msangi, S. (2013). The impact of biofuel growth on agriculture: Why is the range of estimates so wide?. *Food Policy. 38,* 227-239.

Zilberman, D., Hochman, G., Rajagopal, D., Sexton, S., and Timilsina, G. (2012). The Impact of Biofuels on Commodity Food Prices: Assessment of Findings. *Am. J. Agric. Econ. 95* (2), 275-281.

Zhao, Z., Chow, T. L., Rees, H. W., Yang, Q., Xing, Z., and Meng, F. R. (2009). Predict soil texture distributions using an artificial neural network model. *Comput. Electron. Agric. 65* (1), 36–48.

Zhu, Y. (1998). Multivariable process identification for MPC: The asymptotic method and its applications. *J. Process Control. 8* (2), 101–115.

Zou, H., and Yang, Y. (2004). Combining time series models for forecasting. *Int. J. Forecasting. 20*, 69-84.

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PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **Bayrakdar, E.**, Işler, A., Kumbaroglu, G. and Karaosmanoglu, F. Phase-In of Engine Biofuels And Uranium Under Rapid Growth of Carbon Emissions in Turkey. 13th European IAEE Conference 2013 Energy Economics of Phasing out Carbon and Uranium, August 18-21, 2013 Dusseldorf, Germany.
- **Bayrakdar Ates, E.**, Barutcu, B. and Karaosmanoglu, F. Comparison of Auto-Regressive Model and Artificial Neural Networks for feedstock supply forecasting in first generation bioethanol production. International Conference on Energy and Thermal Engineering: Istanbul 2017 (ICTE 2017), April 25-28, 2017 Istanbul, Turkey.
- **Bayrakdar Ates**, **E.**, Barutcu, B. and Karaosmanoglu, F. 2017. Forecasting on first generation bioethanol production: A comparison of selected linear and non-linear models, *Journal of Renewable and Sustainable Energy*, 9, 043101, 1-16, DOI number: 10.1063/1.4997058.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Bayrakdar, E.,** Altincekic, T. and Oksuzomer, F. 2013. Effects of PVP on the Preparation of Nanosized Al_2O_3 Supported Ni Catalysts by Polyol Method for Catalytic Partial Oxidation of Methane. *Fuel Processing* Technology, 110 (2013), 167-175.
- **Bayrakdar, E**., Oksuzomer, F. and Altıncekic, T. Synthesis of Nanosized Al_2O_3 Supported Ni Catalysts By Polyol Method For Catalytic Partial Oxidation Of Methane: The Effects of PVP And NaOH. Energy Challenges for Advanced Materials and Process (EnCAMP-2011), May 25-29, 2011 Cappadocia, Turkey.
- Altincekic, T., **Bayrakdar, E**. and Oksuzomer, F. Effects of PVP on the Prepa ration of Nanosized Al_2O_3 Supported Ni Catalysts by Polyol Method for Catalytic Partial Oxidation of Methane. International Conference on Hydrogen Production (ICH2P-2011), June 19-22 2011 Thessaloniki, Greece.
- Oksuzomer, F., **Bayrakdar, E**., Altıncekic, T. Study of Nano Nickel Particles Supported On Alumina By Polyol Method: The Effects Of Support Surface Area. NANOTR-VII, June 27- July 01, 2011 Istanbul, Turkey.
- Altıncekic, T., Oksuzomer, F., and **Bayrakdar, E.** Synthesis of Nano Nickel Particles on Alumina by Surfactant-Assisted Modified Polyol Method. NCC4, 4. National Catalysis Conference, March 21-24, 2012 Kocaeli, Turkey.
- Altıncekic, T., **Bayrakdar, E.,** Oksuzomer, F. and Cınar, T. Synthesis and Characterization of Alumina Supported Nickel Nanoparticle Catalyst by Polyol Method. VIII. Turkey Nanoscience - Nanotechnology Congress, June 25-29, 2012 Ankara, Turkey.
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