ISTANBUL TECHNICAL UNIVERSITY ★ ENERGY INSTITUTE

PREDICTION OF THE HEATING SEASON INDOOR THERMAL DATA BASED ON SHORT-TERM MEASUREMENT

M.Sc. THESIS

Sami SHAMS ALDIN

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ ENERJİ ENSTİTÜSÜ

KISA SÜRELİ İÇ ORTAM ÖLÇÜM VERİSİNE DAYALI ISITMA SEZONU TAHMİNİ

YÜKSEK LİSANS TEZİ

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Enerji Bilim ve Teknoloji Anabilim Dalı

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Sami SHAMS ALDIN, a M.Sc. student of ITU Institute of Energy student ID 301161028, successfully defended the thesis entitled "PREDICTION OF THE HEATING SEASON INDOOR THERMAL DATA BASED ON SHORT-TERM MEASUREMENT" which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family and friends,

FOREWORD

I would like to extend my thanks and gratitude to my supervisor Assoc. Prof. Dr. Hatice SÖZER who directed and influenced the thesis work to be improved.
I would also like to extend my sincere thanks to my dear parents, Eng. Ahmad and Nahia SHAMS ALDIN for their continued support at every step, and to my brother Yamen and sister Rand for their beautiful presence on my side.
I will never forget to thanks all my dear friends who made my trip easy and happy.
And before that all praise be to Allah the Lord of the worlds.

June 2019 Sami SHAMS ALDIN
(Civil Engineer)

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ABBREVIATIONS

ANFIS	**:** Adaptive Neuro-Fuzzy Inference System
ANN	**:** Artificial Neural Network
BPS	**:** Back Propagation System
HDD	**:** Heating Degree Days
HVAC	**:** Heating Ventilating and Air Conditioning
RMSE	**:** Root Mean Squared Error

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PREDICTION OF THE HEATING SEASON INDOOR THERMAL DATA BASED ON SHORT-TERM MEASUREMENT

SUMMARY

This thesis aims to predict the heating season indoor thermal comfort data in the Kartal elderly home, which is 8 stories building with 18,108 m2 conditioned floor area in Istanbul, Turkey. The aim of this prediction is providing full heating season's thermal comfort dataset by using short-term measured data while the heating system is performing. The heating season of the building was evaluated by defining a critical monthly heating consumption, which was 250 MWh per month, and select the period when the building monthly consumption exceeds this value to be the heating season. Based on it the heating season was evaluated to be between November 15th and March 21st.

The prediction work was done using two machine learning based models. The targeted dependent variables of the model were the indoor temperature and relative humidity. The independent input variables of the prediction were selected to be the outside dry-bulb temperature, outside dew-point temperature, wind speed, wind direction, atmospheric pressure, and solar azimuth, which obtained from the weather data, in addition to the simulation resulted in heating consumption.

The dependent variables data was obtained by real measurements into the Kartal building. The measurements were done using 4 sensing devices implemented in four points inside the building. The first device was implemented in a basement room, the second in the 3rd floor room, the third in the 1st-floor level lobby and the last one was implemented in the ground floor lobby. The measurement process had been done during one year started by February 22nd, 2018. Short -term measured data had been collected since the measured started until the first heating season ended, these short-term data had been used in the prediction models training phase. The measured data of the second heating season which started on November 15th, 2018 had been compared with prediction results to decide the validity of the prediction models in term of accuracy.

The first prediction approach was the feed forward Artificial Neural Network (ANN) with Back Propagation learning System (BPS). The ANN model was used to perform the prediction and it was structured by an input layer, output layer, and one hidden layer. Four ANN model was performed, each model used to predict the temperature and humidity of one of the four points in the building.

The second prediction approach was the Adaptive Neuro-Fuzzy Inference System (ANFIS). The Sugeno ANFIS method was utilized in this prediction work. The ANFIS model was structured by 6 layers. Eight ANFIS models were performed to achieve the prediction, each model used to predict one of the targeted variables in one of the four selected points.

The prediction results were compared with the measured data of the second heating season. The comparison showed that the ANFIS model was more efficient in this prediction work since it achieved 85% accuracy rate for indoor temperature and 81%

for humidity prediction. While the ANN prediction accuracy was 81%, 80% relatively for the temperature and humidity.
Then the comparison was scaled by selecting the most ordinary period in the measured data to be the data sample which will be used the comparison. The second comparison showed again that ANFIS model was a better fit than ANN model in this prediction work since the ANFIS prediction accuracy became 88% for temperature and 90% for humidity, while the ANN prediction accuracy became 83% for temperature and 87% for humidity.
However, the stochasticity of the measured data which caused by the bad performance of the heating system in some periods, influenced the accuracy rates of the models since it was calculated by comparing the prediction results to the measured data. Hence, according to the achieved accuracy rates, both of the ANFIS and ANN approaches are highly validated in this type of prediction work.

KISA SÜRELİ İÇ ORTAM ÖLÇÜM VERİSİNE DAYALI ISITMA SEZONU TAHMİNİ

ÖZET

Termal çevre, binanın konfor seviyesini iyileştirmek için en önemli faktör olduğundan binanın enerji performansının ve verimliliğinin ana endeksidir ve herhangi bir binada uygulanan sistemlerin çoğunun temel görevi, konforlu bir iç ortam sağlamaktır. Bu nedenle, binanın enerji tüketiminin çoğu ısıtma veya soğutma içindir. Bu sebeple, iç ortam konfor seviyesini yönetmek ve sürdürmek için sıcaklık ve nem gibi bazı konfor koşullarını yönetmek gerekir.

Termal konfor koşullarının ölçülmesi ve doğrulanması ve normal şartlar altında enerji tüketimi üzerindeki etkisi, tüm ısıtma ve soğutma mevsimleri için yaklaşık 1-2 yıl sürer. Saatlik, günlük, aylık ve mevsimsel verilere dayanarak iç mekan termal ortamının dikkatlice tanımlanmasını gerektirir. Bu uzun süre ısıtma ve soğutma sistemlerinin performansını vermez kılan ölçüm ve doğrulama işlemlerini yapar. Her ne kadar ısıtma ve soğutma sistemleri kullanımdayken binanın ısıl çevresini incelemek, düşük sistem performansına neden olabilecek herhangi bir sorunu rapor etme ve çözme imkanı sağlar.

Kısa vadeli ölçülen verileri kullanarak bir binanın iç mekan termal koşullarını tahmin etmek, ölçümler bina içindeki sistemler gerçekleştirilirken belli bir sürede yapıldıysa, binanın termal ortamını incelemek ve anlamak için etkili bir yol olabilir. Bu öngörülen veriler binadaki enerji yönetimini desteklemek için yararlı bir araç olabilir.

Bu tezin amacı koşullandırılmış alanı 18,108 m2 olan İstanbul, Türkiye'de bulunan Kartal yaşlı bakım evinde ısıtma sezonu için iç ortam termal konfor verilerini tahmin etmektir. Bu tahminin amacı ise ısıtma sistemi çalışırken elde edilen kısa vadeli ölçüm verilerini kullanarak tüm ısıtma sezonu için termal konfor veri setini sağlamaktır. Binanın ısıtma sezonu 250 MWh olan bir aylık ısıtma tüketimi tanımlanarak değerlendirilmiş ve binanın aylık ısıtma tüketiminin bu değeri aştığı dönem ısıtma sezonu olacak şekilde seçilmiştir. Buna dayanarak, ısıtma mevsimi 15 Kasım ile 21 Mart arasında olduğu belirlenmiştir.

Tahmin çalışması iki farklı makine öğrenmesi yaklaşımı kullanılarak yapılmıştır. Tahmin çalışmasında kullanılan yaklaşımların hedeflenen bağımlı değişkenleri iç ortam sıcaklığı ve bağıl nemdir. Tahminin bağımsız girdi değişkenleri ise dış ortam kuru ampul sıcaklığı, dış ortam çiğlenme noktası sıcaklığı, rüzgar hızı, rüzgar yönü, atmosferik basınç, hava durumu verilerinden elde edilen solar azimut, ve ayrıca simülasyon sonuçlu ısıtma tüketimi olarak seçilmiştir.

Bağımlı değişken verileri Kartal binasında gerçek ölçümler sonucu elde edilmiştir. Ölçümler, binanın içinde dört farklı noktaya yerleştirilen dört ölçüm cihazı kullanılarak yapılmıştır. Ölçüm cihazlarının ilki bodrum katına, ikincisi üçüncü katta bulunan bir odaya, üçüncüsü birinci katta bulunan lobiye, sonuncusu ise zemin katta bulunan lobiye yerleştirilmiştir. Ölçüm süreci, 22 Şubat 2018'de başlamış ve bir yıl boyunca yapılmıştır. İlk ısıtma sezonu sonlanana kadar ölçümler başladığı için kısa süreli veriler toplanmıştır. Bu kısa süreli veriler tahmin modellerinin eğitim aşamalarında kullanılmıştır. 15 Kasım 2018'de başlayan ikinci ısıtma sezonunun ölçüm verileri, tahmin modellerinin doğruluğu açısından geçerliliğine karar vermek için tahmin sonuçlarıyla karşılaştırılmıştır.

İlk tahmin yaklaşımı, Back Propagation Öğrenme Sistemine (BPS) sahip ileri besleme Artificial Neural Network (ANN) idi. ANN modeli kullanılmış ayrıca bir giriş katmanı, bir çıkış katmanı ve bir gizli katman tarafından yapılandırılmıştır. Dört ANN modeli oluşturulmuştur, her bir model binadaki dört noktadan birinin sıcaklığını ve nemini tahmin etmek için kullanıldı.

Kullanılan ikinci tahmin yaklaşımı ise Adaptive Neuro-Fuzzy Inference System. Tahmin için Sugeno ANFIS yöntemi kullanılmıştır. ANFIS modeli 6 katman ile yapılandırılmıştır. Tahmini gerçekleştirmek için sekiz ANFIS modeli gerçekleştirilmiştir ve her bir model seçilen dört noktadan birinde hedeflenen değişkenlerden birini öngörmek için kullanılmıştır.

ANFIS'i kullanmanın temel nedeni, ısıtma sistemi stokastik performansı nedeniyle açıkça ortaya çıkan ölçülen verilerin belirsizliğinden kaçınmaktı. Verilerin, ANN tahmininde, ölçülen verilerdeki sesleri azaltmak için kullanılmak üzere filtrelenmesine rağmen, ısıtma sistemi performansının stokastikliğinin, ANN tahmininde sakınılması zordu.

Tahmin sonuçları, ikinci ısıtma mevsiminin ölçülen verileri ile karşılaştırılmıştır. Sıcaklık için ANN tahmin hataları, dört noktadaki nem için 1.5 ila 5.2 arasında ve 6.8 ila 10.5 arasında değişmiştir. ANFIS tahmin hataları, sıcaklık tahmin hataları 14 ile 4 arasında olduğundan ve nem için tahmin hataları 5.8 ile 10.4 arasında olduğu için farklılıkları da tanıdı. Bu sonuçlar, ANN ve ANFIS modellerinin, ölçülen verilerin daha az değişiklikle daha stabil olduğu noktada minimum hata oranıyla en iyi tahminde bulunduğunu göstermiştir.

Karşılaştırma, ANFIS modelinin bu tahmin çalışması için daha verimli olduğunu göstermiştir, çünkü ortam sıcaklığı ve nem tahmininde %85 ve %81 oranında doğruluk ANFIS modeli ile elde edilmiştir. ANN yaklaşımıyla sıcaklık tahminin doğruluk oranı 81% iken, nem tahmini doğruluk oranı %80'dır.

Stokastiklik, ölçülen ve öngörülen veriler arasındaki karşılaştırmayı ve hem ANFIS hem de ANN modellerinin tahmin doğruluğunu etkiledi. Bu etkiden kaçınmak için, öngörülen verilerle karşılaştırılacak bir örnek olarak ölçülen verinin en sıradan süresi seçilerek ve ardından seçilen örneğe dayanan doğruluk sağlayarak karşılaştırma ölçeklendirildi.

İkinci karşılaştırma, ANFIS modelinin, bu tahmin çalışmasında ANN modeline göre daha uygun olduğunu, çünkü ANFİS tahmin doğruluğunun sıcaklık için %88 ve nem için %90, ANN tahmin doğruluğunun sıcaklık için %83 ve nem için %87 olduğunu göstermiştir.

Isıtma sisteminin bazı periyotlarda kötü performans göstermesinden kaynaklanan ölçüm verilerinin stokastikliği göz önünde bulundurulmuştur. Tahmin sonuçları ölçülen verilerle karşılaştırılarak hesaplandığı için ölçüm verilerinin stokastikliği modellerin doğruluk oranlarını etkilemiştir. Bu nedenle, elde edilen doğruluk oranlarına göre, hem ANFIS hem de ANN yaklaşımlarının her ikisi de bu tür bir tahmin çalışmasında oldukça geçerli olmaktadır.

Bu çalışma sonuçları ileriki çalışmalar için farklı yönlere gitme fırsatı sunmaktadır. Sonuçlar, gerçek zamanlı kalibrasyon yapmak ve beklenmeyen sonuçları bildirmek için bina içinde uygulanan izleme sistemini destekleyebilir, bu rapor binanın içindeki konfor seviyesinin iyileştirilmesine yardımcı olabilir. Tahmini sonuçlar ayrıca, belirlenmiş noktaları iyileştirerek binanın enerji performans simülasyonunun doğruluğunu kalibre etmek ve geliştirmek için bir endeks olarak da kullanılabilir.

1. INTRODUCTION

Thermal comfort conditions are the most important indicator of energy consumption in the residential, commercial and industrial buildings because the main mission of most of the applied systems in any building is providing a comfortable indoor environment, therefore the cooling and heating consumption represents 50% of the energy consumption inside the buildings [1]. Because of that most of the energy efficiency studies had been done based on the inside thermal conditions to improve the energy performance of the buildings and minimize CO2 emissions.

In addition to its relation with energy efficiency, the thermal environment quality is highly related to the human health and productivity since it has a direct effect on the physical and psychological health of the human [2]. Hence, Measurement and verification of the building's indoor thermal conditions such as the temperature and humidity had been investigated significantly in the last decades, according to its importance to sustain the quality of the indoor environment.

Measurement and verification of the thermal comfort conditions and its effect on the energy consumption under the normal circumstances take a long time approximately 1-2 years for whole heating and cooling seasons. It requires careful identification of the indoor thermal environment based on hourly, daily, monthly and seasonal data. This long time makes the measurement and verification process considering the heating and cooling systems performance inefficient. Although, examining the thermal environment of the building while the heating and cooling systems are in-use provides the opportunity to report and fix any problem may cause poor system performance.

Predicting the indoor thermal conditions of a building using short-term measured data can be an efficient way to study and understand the building's thermal environment if the measurements were done in a period when the systems inside the building are performing. This predicted data can be a useful tool to support energy management in the building.

The Artificial intelligence-based algorithms had been utilized widely in the prediction works and studies. Machine learning is cost effective since it doesn't need special infrastructures to be performed.

Artificial Neural Network algorithm (ANN) is one of the most used machine learning algorithms. ANN mimic the human brain process to convert the information and experiences into decisions, it had been utilized in widely in both classification and prediction studies because of its highly accurate results and its ability to correlate the non-linearity between the variables.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is an algorithm which combines the Fuzzy approach and the ANN algorithm in order to perform better accurate results. The ANFIS approach like the ANN had been used in both of the classification and prediction studies.

In this case, the focus will remain on the heating season by using the short-term measurements to predict the rest of the heating season's thermal data inside a big-scale residential building. The thermal parameters that will be studied are the inside temperature and humidity. The prediction will be performed by the application of both of the Back-Propagation Artificial Neural Network referred as ANN and Adaptive Neuro-Fuzzy Inference System approaches.

The ANFIS model will be implemented in this study to avoid the uncertainty of the temperature and humidity data. Basically, the uncertainty produced by the performance of the heating system inside the building which caused noises to the measurements. The uncertainty of the measured data affects the efficiency of the prediction. Using ANFIS will reflect the uncertainty in the membership, hence it is expected to provide better prediction accuracy.

The ANN and ANFIS models' predicted data will be validated by comparing it with the measured datasets. Then, define the best effective model in term of prediction accuracy rate.

2. LITERATURE REVIEW

There is a considerable amount of research on prediction around the world in many fields and many objectives like weather data forecasting, energy consumption, economic and currencies changes and as many other fields. Machine learning and deep learning approaches are the state of the art of the prediction and forecasting work. Artificial Neural Network approach is one of the most common machine learning algorithms because of its ability to produce cost-effective accurate predictions.

For indoor conditions prediction, some studies accomplished around the world in the last few years. In 2017, Afroz, Shafiullah, Urmee, and Higgins [1] used Artificial Neural Network to predict the indoor space temperature of an institutional building in Australia. They collected data about 25 related parameters, then used neural fitting tool to sort out the most relevant parameters based on network performance. They selected 8 variables to be prediction inputs (Indoor temperature set point, outdoor temperature, wind speed, wind direction, dew point temperature, barometric pressure, relative humidity, and solar radiation), as each parameter of these 8 has its effect on the prediction which cannot be ignored. They used 3 different algorithms for training the network and then comparing the results, they also applied their methodology in two different buildings and they found out that Lovenberg-Marquardt is the best-suited training algorithm to predict the indoor space temperature in terms of prediction accuracy, generalization capability and iteration time to train the algorithm. In 2017, Buratti, Palladino, and Moretti [2] used computational fluid dynamics (CFD) simulation tool and experimental data to predict indoor conditions and thermal comfort for a classroom in Perugia University. They took the data in April where the HVAC system turned off. Outdoor air temperature, solar radiation and the thermal characteristics of the external walls used as inputs while other indoor and outdoor parameters collected for validating the model. They found that solar radiation has the most effect, on the thermal sensation and when there is no solar radiation the thermal data take a uniform aspect. In 2017, Djamila [3] worked on predictions of the indoor thermal comfort in of determined locations by Meta-analysis of the ASHRAE RPA-

884 database. This study suggested a new classification for indoor temperature and relative humidity and by more than one case proved that a huge amount of data is not an indicator for the prediction accuracy. In 2008, Tao Lu and Martti Viljanen [4] used four Artificial Neural networks to predict indoor Temperature and relative humidity inside a test house. They implemented a weather station inside the house and on its roof to make the measurements for data inside and outside the building to use in their study and selected 5 parameters of their measured data (time, outdoor temperature, indoor temperature, outdoor relative humidity and indoor relative humidity) to be used as inputs and outputs in the prediction model. They employed Nonlinear AutoRegressive with eXternal input (NNARX) model and genetic algorithm to establish their networks. By comparing the prediction results with the real measurements, they found out that temperature predictions had a good accuracy but relative humidity results need to be improved. In 2015, Zhang and You [5] predicted the indoor environment in an MD-82 aircraft cabin a test place based on computational fluid dynamics (CFD) using Artificial Neural Network. 5 parameters used as inputs of the prediction model: inlet velocity, inlet temperature, inlet angle, the location of inlet and the location of the outlet. They studied training and normalization methods to evaluate the ANN. They concluded that using the local logarithm normalization instead of local linear normalization improved the ANN accuracy. In 2016, L. Mba et al, [6] performed an ANN model to predict the indoor temperature and relative humidity for a modern building in a humid climate. They found that there is a recognizable relation between the number of input variables and the model performance and they approached that ANN has highly effective prediction model for the indoor thermal parameters. In 2018, Z. Afroz et al, [7] developed a non-linear autoregressive network with exogenous inputs-based system identification method to predict indoor temperature. The aim of their study was to raise the energy efficiency of a commercial building by using the predicted temperature to reset the air set-points, which provides advanced energy management. They found that evaluating the context of the model and the network's size provide well optimized model, and approached that using the prediction model to support the energy management system into the commercial building for a long time will achieve high energy savings, and will improve the thermal environment and comfort level into the building. In 2012, S. Pandey et al, [8] used three different experimental data generated by three passive cooling techniques to develop an Artificial Neural Network model. The model

developed to predict the indoor temperature of the room when applying each of the three passive cooling methods aiming to find the best comfort conditions can be achieved. They used the outside temperature, relative humidity, solar intensity and wind speed as independent variables of the models, and concluded their study by satisfying results which can lead to extended further work. In 2017, S. Magalhães et al, [9] aimed to figure out the relationship between the indoor temperature, heating energy consumption and typical heating energy demand which obtained by the available rating systems in residential buildings. The correlation considered different types of occupant behavior, and it has been done using an Artificial Neural Network model. The model was performed based on data offered by dynamic thermal simulations of varied types of buildings. The ANN model achieved a satisfied accurate prediction with a square mean error less than 0.93 to estimate both of the heating energy consumption and the indoor temperature. In 2016 S. Magalhães et al, [10] developed a linear regression model with panel connected standard errors model to predict the indoor temperature of the bathrooms and living rooms for 141 households in the north of Portugal. The model used the winter season measured data to train the model. The study figured out the correlation between the building characteristics and the indoor temperature. In 2019, C. Xu et al, [11] developed a novel Long Short-term memory model to predict the indoor temperature in public buildings. The study aimed to compare the established novel LSTM model performance with the ordinary LSTM model and the used machine learning tools' performance to predict the indoor temperature. The results of the study showed that the approached novel LSTM model prediction performance was slightly better than other machine learning tools. The difference was in term of the accuracy of the directional predictions and the variation trends predictions. In 2009, when H. Alasha'ary et al, utilized the Sugeno-type of the ANFIS model in order to predict the indoor temperature of a residential building's room in Australia. The climatic data were used as input data. The datasets were distributed in for dataset types 1-day per month dataset, 1-week per month, 2-week per month and 3- week per month datasets for the measured year based on the input/output pattern of the ANFIS model. The measurement was done every 10 minutes in 3 height levels representing the floors of the building. The prediction outcome data has been validated and the average error was estimated to be 4% which far less than 10% (the maximum error). Depending on these results the ANFIS model can be a very effective approach for indoor thermal prediction [12]

ANN is one of the most used tools in prediction and forecasting studies in various fields around the world because of its accuracy and low costs. In 2017, Ümmühan Başaran Filik and Tansu Filik [13] used ANN to predict the wind speed in Eskisehir based on multiple local measurements. In 2018, Guillermo R. Chantre, Mario R. Vigna, Juan P. Renzi, and Aníbal M. Blanco [14] put a flexible and practical approach for real-time weed emergence prediction based on Artificial Neural Networks. In 2018, A. Tebabal, S.M. Radicella, M. Nigussie, B. Damtie, and B. Nava, E. Yizengaw [15] used ANN for Local TEC modeling and forecasting. In 2016, Xueqian Fu, Shangyuan Huang, Rui Li, and Qinglai Guo [16] considered solar radiation and weather to predict the thermal load using ANN. In 2018, Ali Taheer Hammid, Mohd Herwan Bin Sulaiman, and Ahmed N. Abdalla [17] Predicted of small hydropower plant power production in Himreen Lake dam (HLD) using an artificial neural network. In 2018, Wei Sun and Yuwei Wang [18] forecasted Short-term wind speed based on fast ensemble empirical mode decomposition, phase space reconstruction, sample entropy, and improved back-propagation neural network. In 2016, Shuangyin Liu, LongqinXu, and Daoliang Li [19] performed multi-scale prediction of water temperature using empirical mode decomposition with back-propagation neural networks. In 2018, K.Muralitharan, R.Sakthivel, and R.Vishnuvarthan [20] used ANN to perform an optimization approach for energy demand prediction in a smart grid. In 2018, A.M. Durán-Rosal, J.C. Fernández, C. Casanova-Mateo, S. Salcedo-Sanz, and C. Hervás Martínez [21] predicted an efficient fog with multi-objective evolutionary neural networks. In 2018, Madasthu Santhosh, Chintham Venkaiah, and D.M.Vinod Kumar [22] performed an ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction. In 2018, Yi FeiLi and Han Cao [23] predicted tourism flow based on LSTM neural network. In 2015, Radiša Ž.Jovanovid, Ale ksandra A.Sretenovid, and Branislav D.Živkovid [24] used an ensemble of various neural networks for prediction of heating energy consumption. In 2018, Abir Jaafar Hussain, Panos Liatsis, Mohammed Khalaf, Hissam Tawfik, and Haya Al-Asker [25] structured a dynamic neural network with immunology inspired optimization for weather data forecasting. In 2018, Zheng Liu and Clair J.Sullivan [26] predicted weather induced background radiation fluctuation with recurrent neural networks. In 2010, Murat Kankal, Adem Akpınar, Murat İhsan Kömürcü, and Talat Şükrü Özşahin [27] used ANN for modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables. In 2010, Mehmet Bilgili, Besir Sahin, Abdulkadir Yasar, and Erdogan Simsek [28] used ANN to forecast the electric energy demands of Turkey in residential and industrial sectors. It is impossible to mention each study had been done by ANN because of its huge literature.

Fuzzy modeling is a branch of system identification which deals with the construction of a fuzzy inference system or fuzzy model that can predict and explain the behavior of an unknown system described by a set of sample data. Adaptive neuro-fuzzy inference system (ANFIS) is an efficient approximation model that combines neuro-fuzzy systems and the other machine learning techniques. The ANFIS's map is significantly different from that of the ANN. It goes from input characteristics to input membership functions, from rules to a set of output characteristics, then to output membership functions, to a single-valued output, or to a decision associated with the output [29].

Since the ANFIS algorithm can be used for classification and prediction work, the researchers used for many purposes. The predictive ANFIS model had been utilized in varied fields and studies. In 2015 A. Abdulshahed et al, employed ANFIS to design two models to predict the thermal effect on CNC machines [30]. In 2009, Y. Vural et al, established a predictive ANFIS model which trained and compared with independent experimental model and trained again in order to predict the exchange fuel cell of the proton [31]. In 2017, E. Yadegaridehkordi and M. Nilashi, applied the Adaptive Neuro-FIS prediction model aiming to define the most important successful parameters of a hotel's successful development [32]. In 2008, H. Esen et al, used a pre-processing based ANFIS model to predict the performance of a heat pump system and compare its results with a proposed ANFIS prediction model [33]. In 2010, M. Acar and D. Avci, The study aimed to observe the ability of the ANFIS model to forecast accurately the return of the stock market, they tested the model on the Istanbul stock market and they could produce a prediction with 98.3% accuracy rate [34].

ANFIS also has been used in some energy performance prediction researches. In 2019, W. Gao et al, predicted the energetic performance of a thermal photovoltaic heating system into a building using three artificial intelligence-based algorithms, Artificial Neural Network, Genetic programming, and Adaptive Neuro Fuzzy Inference system in order to compare the prediction accuracy of the algorithms. They found out that the Genetic Programming is the best algorithm in their case [35]. In 2011, B.Bektas Ekici and U. Aksoy, used the Adaptive Network Fuzzy Inference system to forecast the energy load of a building in Elaziğ region. They approached the ANFIS is one of the best tools for energy consumption prediction in the pre-designed phase [36]. In 2010, K. Li and H. Su, predicted over than three months consumption of a hotel's daily air conditioning using the ANFIS approach, and they found that its prediction accuracy is better than the Neural Network's prediction accuracy in that case [37]. In 2011, K. Li et al, used the Neural Networks and the adaptive network-based inference system to predict a building's energy performance, then by comparing the results they observed that the ANFIS model's results better than the NN's results in term of prediction accuracy [38]. In 2018, J. Woo et al, established a rule-based algorithm, fuzzy logic algorithm, ANN, and ANFIS in order to test the openings and cooling system of a double skin envelope the building. They found that the Fuzzy Logic algorithm was the best fit with an accuracy rate of 99.98% [39].

In this case, Artificial Neural Network and Adaptive Neuro-Fuzzy Inference system had been utilized to predict the indoor comfort conditions for a big-scale residential building which hosted to elderly people in Istanbul, Turkey. A monitoring system has been implemented in selected rooms of the building to conduct real-time measurements. The indoor humidity and temperature were foremost measured parameters. The prediction has been done depending on short-term measurements in purpose to use the results in the building thermal comfort calibration. About 31.5 days measured data used to predict the rest of the heating season which was defined as 137 days, which saves 77% of the measurement time, which provides the possibility of examining the thermal environment and the heating system's performance before occupying the building, as well as the possibility to start real-time calibration simultaneously with the occupation phase. Since the heating system is running during the measurement period, therefore minimizing the measurement period saves energy and cost. The importance of this study comes from the ability of predicting the whole heating season's data with the short term monitored data to be used in a real-time calibration process. The real-time calibration is a potential opportunity to improve the indoor thermal comfort by reporting any unexpected measured data immediately, which may also help to avoid some losses of thermal performance. Correspondingly, the building energy model was developed and simulated to analyze its energy performance. The results of the prediction can be used as feedback data to improve simulation accuracy.

3. METHODOLOGY

The methodology to develop the indoor thermal environment predictor models is explained in this chapter. Firstly, to be able to develop the structure of each ANN and ANFIS model, the available data sources and its intervals must be defined. Since both of the algorithms are supervised machine learning algorithms, that's made enough amount of historical data for the targeted variables is required. At the time, evaluating the heating season period is a must in order to prepare the required data to run the prediction models. Figure 3.1 shows the methodology's followed steps.

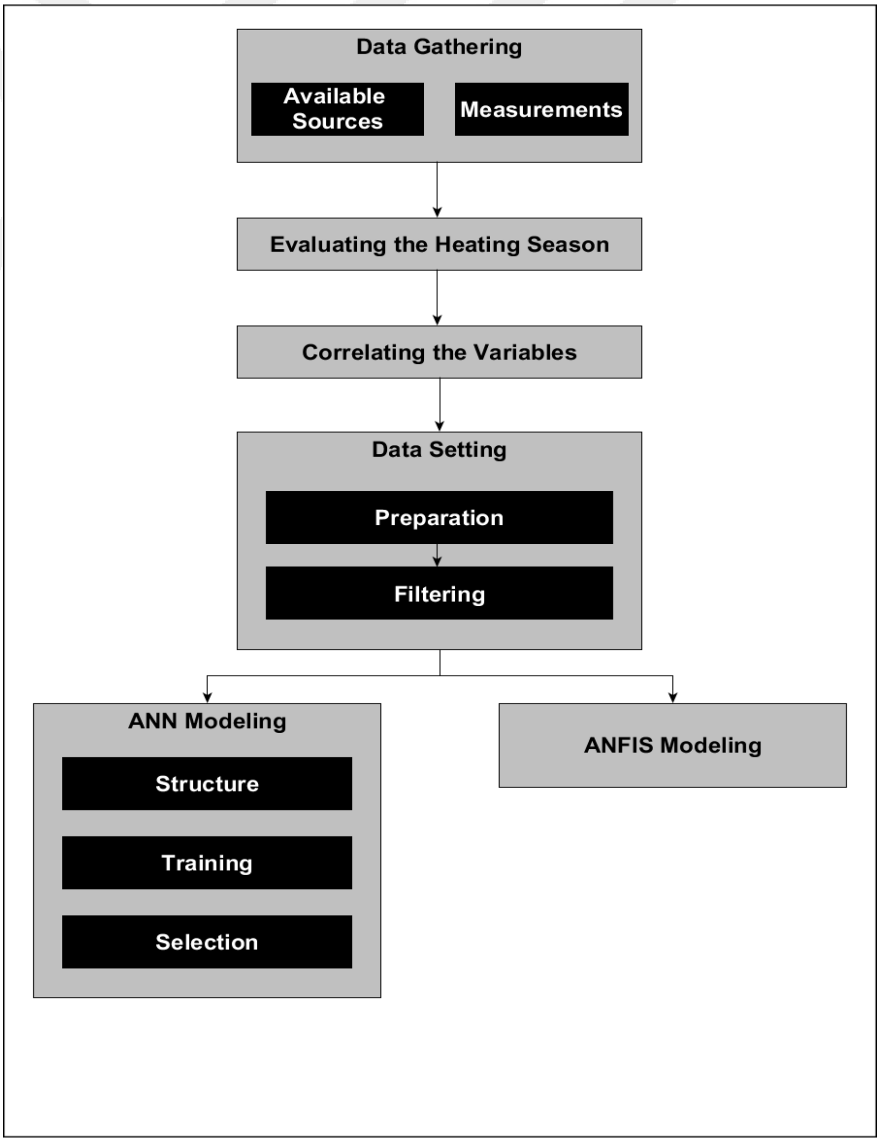

Figure 3.1: Methodology flowchart.

3.1 Data Gathering

The quantity and quality of available data play a key role in the formation and accuracy of the predictive model. Therefore, data gathering is a systematic process to collect and measure the desired information of the dependent and independent variables to be used in the prediction model. For the supervised machine learning tools as ANN and ANFIS there must be available two kinds of data, the historical dependent data, and the independent data. The historical dependent data is the index of the predictive model since it must be measured data for the prediction targeted outputs, and the accuracy of the prediction results is proportional to the quantity and distribution of this data. The independent variables are the variables that non-linearly correlated with the output targeted variables, the quality and variety of these data is affecting directly the prediction results since it is the inputs of the model and it must be available for the historical period and for the period to be predicted.

3.2 Evaluating the Heating Season

Developing supervised machine learning models is highly dependent on the valid ranges of the collected data, whether input or output data. This thesis is totally focusing on thermal environment prediction for the heating season; therefore, the valid collected data must be in the range of heating season period. Hence, evaluating the heating season period is necessary to form a clear understanding of what data is available, and how it will be organized in the prediction model.

The heating period is different for each building based on the location, weather data, level, occupancy, and many other factors. That means evaluating and defining the heating period must be the first step in the prediction work. The heating degree day is the most relevant parameter to identify the heating period. The heating degree days had used in the simulation of the building, which means that using the heating consumption results data as the main factor for the period evaluation will be more customized to the case study.

The changes in the heating consumption data must be observed to define the most dramatic change from relatively low to high consumption. Based on this change a value must be set, the period which its heating consumption exceeds the set value defined as the heating period of the building.

3.3 Correlating the Variables

Data correlation is the process to figure out the linear relationship between the input and targeted variables. In the correlation analysis, the changes of each input variable correlated to the changes of each targeted variable. This correlation produces a coefficient to express the dependency between those two variables. The coefficient value is between 1 and -1. The proportion of the variables is direct when the coefficient value is 1, and it is reverse when the coefficient value -1, and there is no relation when the coefficient value is 0. Since all of the gathered data are continuous the linear correlation coefficient formula will be used in the correlation process.

$$r(xy) = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}\sqrt{n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}} \tag{3.1}$$

Where: x is the input variable, y is the output variable, n is the total number of datasets, and i is the dataset's order.

3.4 Data Setting

The prediction stage is mainly about data management. The more organized, clear and relevant data would be performed with a more accurate prediction. For this reason, the data must be obtained and prepared before starting any step of the prediction model. The data-setting phase must go through the following steps:

3.4.1 Preparation

The obtained data need to be prepared to implement in the prediction model. The different variables data collected with different frequencies and initial time sometimes could be in different units and structure. These data must be organized and unified within their parameters.

3.4.2 Filtering

The filtering process is to avoid or reduce the noises of the measured data. The filtering is the process of removing or un-using the measured data instances which have unexpected or out of the normal range values. There are several methods to filter the data, mostly it was performed by setting maximum and minimum values for the measured data. Any instance has measured value out of the range between the minimum and maximum values, should be un-used in the prediction. The minimum and maximum values for each variable defined by the following equations:

$$Max = \mu + 1.5 * \sigma \quad (3.2)$$

$$Min = \mu - 1.5 * \sigma \quad (3.3)$$

Where: μ: the mean – σ: the standard deviation.

3.5 ANN Modeling

ANN is a successfully applied method in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, and neurology, therefore this approach used to correlate data and variables that do not have a clear algorithm to solve, or link to each other to predict their outputs. The ANN model has many types, the most used are the linear multi perceptron. The most introduced model in the prediction work is the feed forward ANN with the BPS model.

3.5.1 Structure

The structure of the ANN is obtained by defining the number of the hidden layers and the number of the neurons in the hidden layers. Then defining the ANN model and the loss index error method in addition to the training algorithm which is totally optional based on different training trials by considering the quality of the prediction results. Additionally, the data must be distributed for training and selection phases.

3.5.2 Training

Training and running the ANN by setting the number of the iterations and defining the activation function between the layers which defines the numerical calculations between the neurons of the network. The network calculations will depend on the sigmoid (logistic) activation function to avoid the non-linearity between the variables. Sigmoid activation function can be expressed by the following equations:

$$\mathrm{sigmoid(x)\ or\ sig(x)} = 1/(1 + \mathrm{e}\hat{}(-\mathrm{x})) \quad (3.4)$$

$$\mathrm{Zj} = \mathrm{sig}(\textstyle\sum(\mathrm{xi} \times \mathrm{wij}) - \theta) \quad (3.5)$$

Where: Zj is the set that received by the artificial neuron, xi the input value, wij is the weight and θ is the use of a threshold.

3.5.3 Selection

The selection is the process of measuring the features and performance of the model. By a defined number of iterations, the ANN compares the selection data prediction results with its actual targeted data and calculates the losses of the model, then it improves the parameters of the model until it reaches the minimum losses. When based on the minimum losses the final structure of the model will be defined, then the last training performs. The selection loop is shown in Figure 3.2.

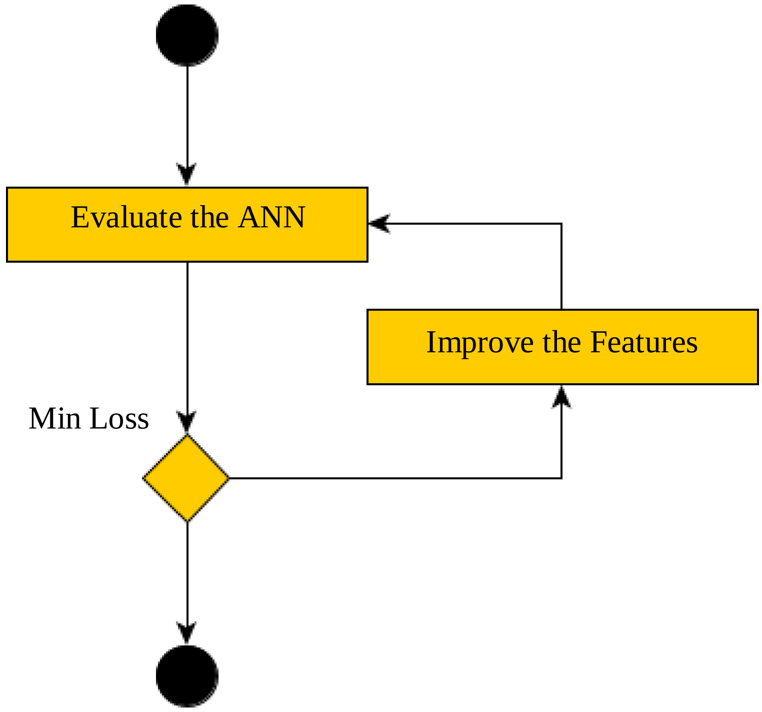

Figure 3.2: Selection model.

3.6 ANFIS Modeling

Adaptive Neuro-Fuzzy Inference System modeling can be performed in two methods. The first method is the Mamdani fuzzy inference and the second one is the Sugeno fuzzy inference, both of them are similar to each other in fuzzing the inputs and applying the fuzzy operator. But the Sugeno method's output membership functions are either linear or constant.

The Sugeno method was used in this study because it is a more compact and computationally efficient than a Mamdani method. The Sugeno system is suited for modeling nonlinear systems by interpolating between multiple linear models, and it uses adaptive techniques for constructing fuzzy models which can be used to customize the membership functions so that the fuzzy system best performs data modeling.

ANFIS is a class of adaptive, multi-layer feedforward networks, which is comprised of input and output variables and fuzzy rule base of Takagi-Sugeno fuzzy if-then rules for a first-order Sugeno fuzzy model. A two rule-based ANFIS model with x and y inputs and f output is expressed in equations.

Rule (1): If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$ (3.6)

Rule (2): If x is A_2 then y is B_2 then $f_2 = p_2x + q_2y + r_2$ (3.7)

Where A_1 and A_2 are the input membership functions for the input layer, B_1 and B_2 are the input membership functions of y. The output function parameters are p_1, q_1, r_1, p_2, q_2, and r_2. The framework of ANFIS consists of five layers, which are described below:

Layer 1: This layer is responsible for the production of the input variable membership grades in each node. The values of membership functions for each $i\ th$ nodes are defined in this layer:

$$Qi^1 = \mu Ai\ (x) = \frac{1}{1+\left[\left(\frac{x-Ci}{ai}\right)^2\right]^{bi}} \quad (3.8)$$

Where x is the input to node i and Ai if the linguistic label associated with this node function, ai,bi,ci is the parameter set that changes the shapes of the membership function.

Layer 2: In this layer, each node multiplies by the incoming signals, as shown by the equation:

$$Qi^2 = wi = \mu Ai\,(x)\ \mu Ai\ (x) \times \mu Bi\ (y),\ I = 1, 2\ \ldots. \quad (3.9)$$

Layer 3: This layer is responsible for the normalized firing strength for the membership values in node $i\ th$ by the equation:

$$Qi^3 = wi = \frac{w1}{(w1+w2)} \quad i = 1, 2\ldots. \tag{3.10}$$

Layer 4: In this layer, the relationship between the input and output value can be established by the equation:

$$Qi^4 = wi\,(pi\;x + qi\;y + ri) \tag{3.11}$$

Where wi is the output from layer 3 and pi, qi, and ri are the parameters. Parameters in this layer will be referred to as ‘consequent parameters.

Layer 5: This layer includes only one node and it makes a summation of all the output results which comes from the previous node and gives the output in a single node by the equation:

$$Qi^5 = \frac{\sum iwi\;fi}{\sum iwi} \tag{3.12}$$

The learning rule of ANFIS is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks. The optimization parameters are ai ,bi ,ci which are the premise parameters, while pi ,qi ,ri are the consequent parameters. A hybrid-learning rule was employed in this research, which involves gathering the gradient descent and the least-squares method in order to find the appropriate set of preceding and consequent parameters [40]. The advantage of using a hybrid-learning rule was that it also seemed to be significantly faster than the classical back-propagation method [29]. Figure 3.3 shows the structure of ANFIS.

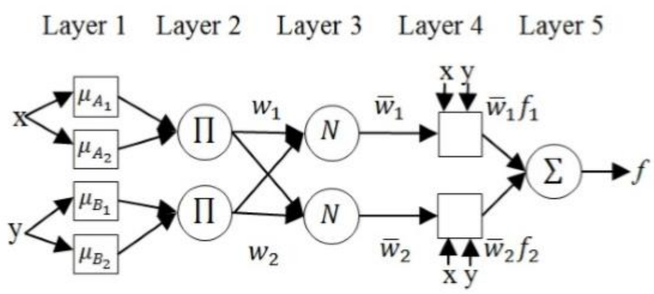

Figure 3.3: Structure of ANFIS. [41]

The hybrid-learning procedure includes two passes, namely the forward pass and the backward pass. In the forward pass, the functional signals will go forward till layer 4 and the least-squares technique will identify the consequent parameters. In the backward pass, the error rates transmit backward and the gradient descent will update the premise parameters. While the values of the premise parameters are fixed, it’s possible to express the overall output as a linear combination of the consequent parameters [42]

4. CASE STUDY

The thermal comfort conditions were studied in an 8 stories elderly home building with 18,108 m^2 conditioned floor area in Kartal, Istanbul during the heating season, where the heating system was running but the building wasn't fully occupied. Figure 4.1 demonstrates the image of the building.

Figure 4.1: Kartal elderly home.

4.1 **Data Gathering:**

The prediction models highly dependent on the quality and quantity of the available data, so the first step in this process was defining the available data sources.

4.1.1 Measurements

The most important source of the data was the measurements. The temperature and relative humidity had been measured in four different points into the building. The measurements into the building had been done during one year starting from 2018 February 22 until 2019 February 29.

The measurements were done by four Testo devices distributed into the selected four points. The first point was in the room 4 in the basement, the second point was selected to be in the room 16 in the third floor and the rest two points were in the lobby but one of them was in the ground floor level and the another was in the first-floor level. This distribution of the sensors was done considering the big-scale of the building in order to make the measurements in different places and locations in the building. The measurements were taken in 15 minutes interval. The selected four points are demonstrated in Figures 4.2, 4.3 and 4.4.

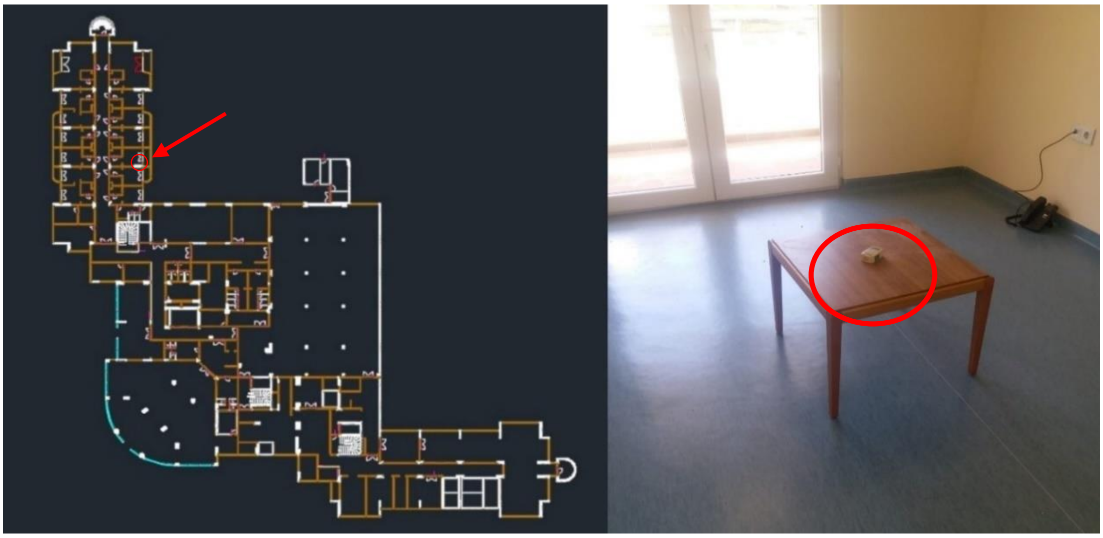

Figure 4.2: Basement (room 4) point.

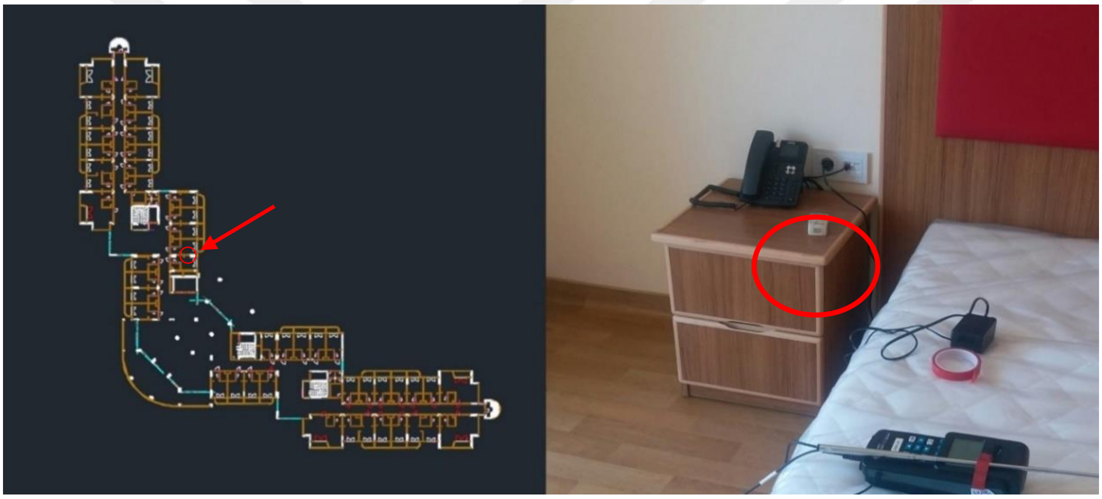

Figure 4.3: 3rd floor (room 16) point.

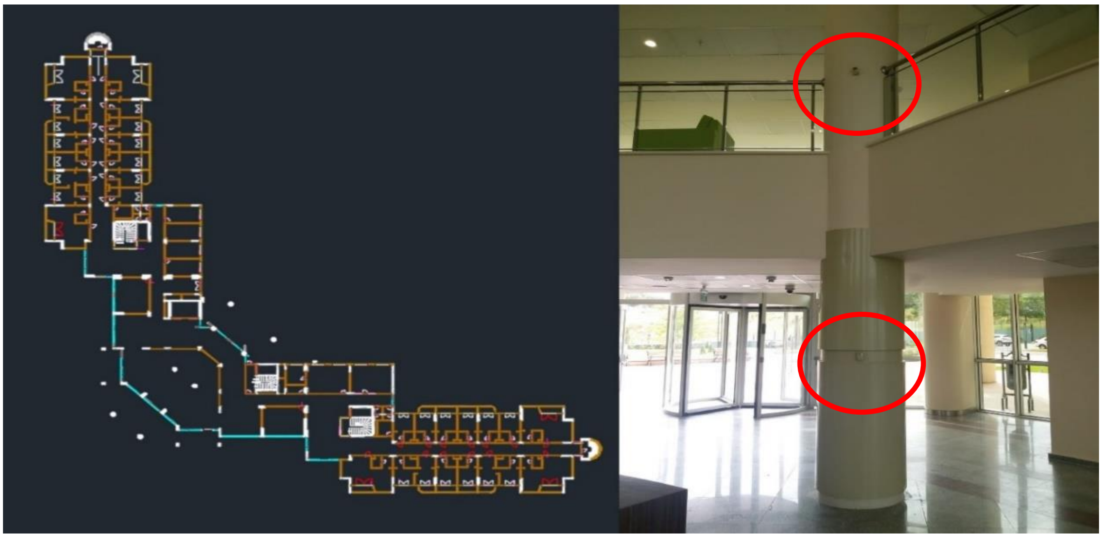

Figure 4.4: Lobby points.

4.1.2 Weather data

The temperature and humidity data were collected as the targeted dependent variables of the prediction models, but the models need to input independent variables. The independent variables are available data which are non-linearly correlated with dependent variables and available for the whole period to be predicted. The outside weather data are the most important variables that have a high impact on the indoor thermal environment. In the time, weather data can be obtained from different sources. In this thesis, the weather data was obtained from the used weather data in the DesignBuilder simulation software. The obtained variables from the weather data were the outside dry-bulb temperature, outside dew-point temperature, wind speed, wind direction, atmospheric pressure and, solar azimuth.

4.1.3 Energy performance simulation

Since the heating system was active during the measured period, a heating consumption related data source was needed to be involved in the prediction model in order to provide a balance in the input datasets with the real case and to achieve better prediction in term of accuracy. The building has an energy performance simulation model which has been done by the DesignBuilder software. The simulation provides many types of predicted results, one of these types is the hourly heating consumption which can be used as an independent variable in the prediction model.

4.2 Evaluating the Heating Season

The scope of the prediction work in this thesis is the indoor thermal data of the heating season, but the heating season is different for each region and also for each building. The heating degree days is a very important tool to define the heating season. But since the heating consumption data is available from the simulation result so the heating season can be defined using this data. By observing the heating consumption data, it is recognized that a dramatical change in the heating consumption is happening directly before reaching the 250 MWh per month as heating consumption, which makes this point able to be as the heating season's set-point. Based on this the heating season of the Kartal building as the period where the monthly heating consumption exceeds 250 MWh, which is roughly the period between November 15th and March 31st (137 days per year), as represented in Figure 4.5.

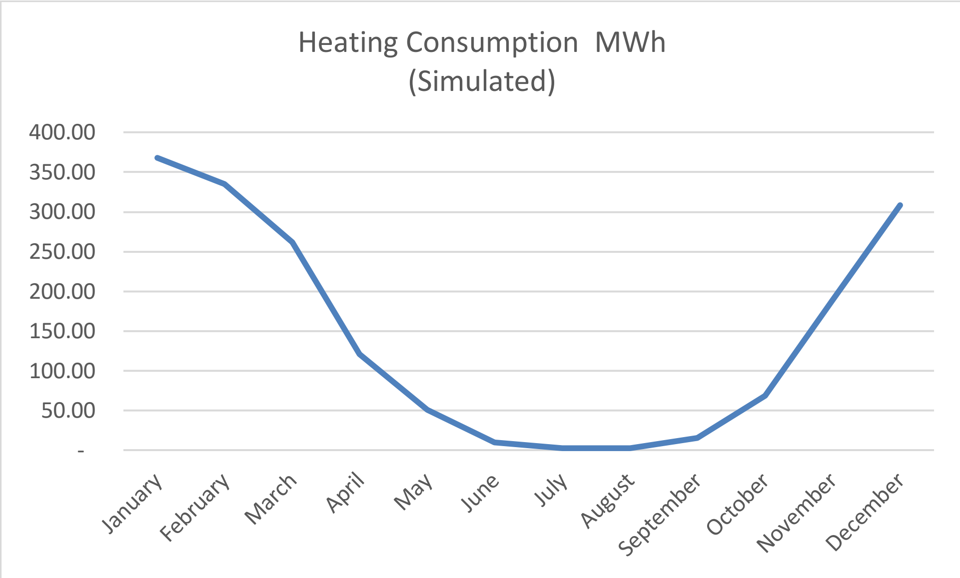

Figure 4.5: Monthly heating consumption graph from the building energy model.

4.3 Data Setting

4.3.1 Data preparation

The gathered data were collected with different structures and frequencies. In this part, the datasets had been unified in term of frequency and prepared to be distributed in one datasheet in an appropriate form to be imported to the prediction models.

4.3.2 Data correlation

After collecting the available data and prepare it to be usable and comparable, the independent variables and dependent correlation must be analyzed to figure out if any of the independent variables has no numerical impact on the dependent outputs so it can be eliminated from the model. The Table shows the correlation factor of each of the independent variables with each of the dependent variables, the results of the correlation analysis showed that each of the selected variables was correlated to the dependent variables with different effect as shown in Table 4.1.

4.3.3 Data filtering

In the measured data there is some pick points which make noise for the model that was filtered respectively, 68 data sets in the basement's point, 88 data sets in the upper room, 138 data sets in the upper lobby, and 178 data sets in the ground lobby, which reduced the data sets and increased the accuracy.

Table 4.1: Input – output variables correlation

Intput \ Output	Basement room		Upper room		Upper Lobby		Ground Lobby	
	Inside Humidity Rate	Inside Temperature	Inside Humidity Rate	Inside Temperature	Inside Humidity Rate	Inside Temperature	Inside Humidity Rate	Inside Temperature
Outside Dry-Bulb Temperature	0.057	0.0925	0.151	0.205	0.385	0.428	0.29	0.392
Outside Dew-Point Temperature	0.239	0.251	0.437	0.456	0.461	0.542	0.416	0.57
Wind Speed	0.0969	0.272	0.084	0.134	0.368	0.135	0.272	0.0419
Wind Direction	0.0216	0.0469	0.0686	0.116	0.039	0.115	0.00865	0.0896
Atmospheric Pressure	0.464	0.367	0.392	0.375	0.0288	0.0324	0.203	0.246
Solar Azimuth	0.0265	0.0294	0.0252	0.039	0.00152	0.0377	0.0571	0.0916
Heating (Gas)	0.0224	0.000904	0.00826	0.0189	0.0195	0.0506	0.006	0.0515

4.4 ANN Modeling

4.4.1 ANN structure

Four Artificial Neural Networks used to predict thermal comfort data. Each network represents one of the four points (Basement, Upper room, Upper lobby, and Ground lobby). Each network concludes three layers, the first layer is the input layer, which contains 7 neurons represent the independent variables. The second layer is the hidden layer, which contains 3 neurons. The third layer is the output layers, which is 2 neurons represent the targeted data (Temperature and Relative humidity) for each point. Structure of ANN was represented in Figure 8.

4.4.2 Training the artificial neural network

Firstly, the measured data was organized and sorted in an hourly data format to match with the hourly weather and heating consumption data. This process was also minimized the amount of data to be trained. That’s mean only 753 measured datasets for each point in the heating season is able to be trained. Later the data were scaled by using the Minimum-Maximum method to be used into the activation function. Based on the short-term measured data, 85% of the datasets were used for the training phase, which used Quasi-Newton algorithm and sigmoid activation function to go from the input to the hidden layer and linear function to move to the input layer with 0.3 learning rate. Python code was used to perform the ANN model.

4.4.3 Selection

After training the ANN, 15% of the data was used into the selection method of 10 iterations to test the performance of the model and the parameters. The selection phase has changed the structure of the Network by increasing the hidden nodes to be 8 nodes and minimized the losses of the model. By using the selection phase' results, the model was trained again to achieve the minimum losses as shown in Table 4.2. The final structure of the ANN model was shown in Figure 4.6.

Table 4.2: Final losses.

	Basement room	Upper room	Upper Lobby	Ground Lobby
Final Losses	0.295	0.369	0.38	0.56

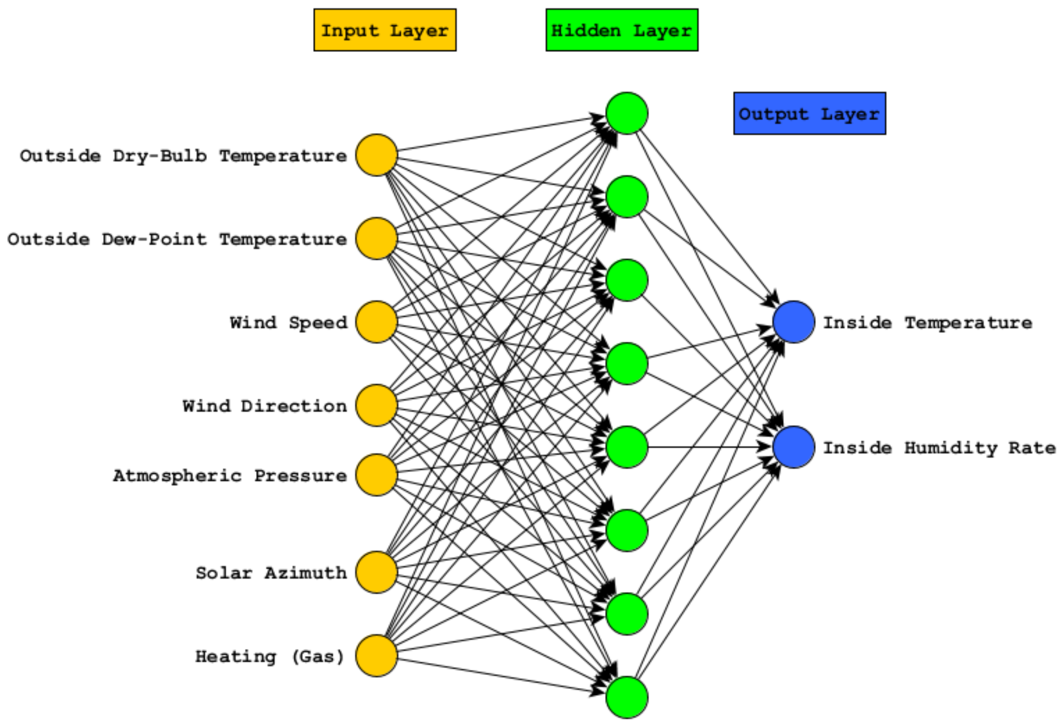

Figure 4.6: ANN final structure.

The performed ANN showed that filtering the data reduced the confused results of the model and improved the accuracy. In addition, the number of hidden layers, which changed through the selection analysis, had a significant effect on the final losses. The major effect of those phases made them the most critical parts of this prediction work.

4.5 ANFIS Modeling

4.5.1 ANFIS structure

Eight adaptive neuro-fuzzy inference system models had been developed to predict the indoor temperature and the relative humidity of the building. Each model used to predict one of the targeted parameters in one of the four points. Each of the utilized models structured by six layers, the first layer is the input layer which it is include 7 nodes each node represents one of the independent variables. The second layer is the input membership function layer, this layer contains 14 adaptive nodes, each pair of adaptive nodes receives the value of one of the independent variables to use it as input in its function. The third layer includes fixed nodes which receive signals from the input layer, the output of this layer is the product of the received signals and it's called the firing strength of the rules. The fourth layer is the normalization layer, in the nodes of this layer the ratio of each rule's firing strength has been calculated. The layer 5 is the output membership function layer, and the last layer is the single output layer which is the temperature or relative humidity for each point. The ANFIS final structure is shown in Figure 4.7.

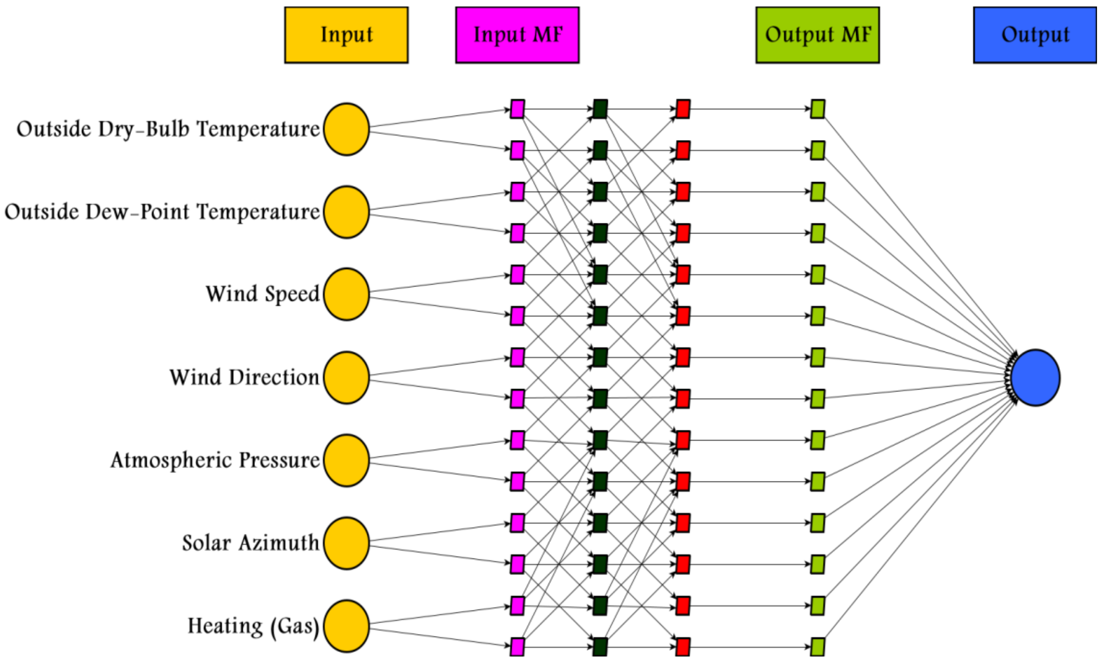

Figure 4.7: ANFIS final structure.

4.5.2 Training the adaptive neuro-fuzzy inference system

The data set of the ANFIS is the same in the ANN model, which means that the available datasets to be trained are 753 hourly datasets for the heating season. The ANFIS model utilized the Sugeno method and its output membership functions. The hybrid-learning algorithm's feedforward backpropagation procedures had been used as the learning algorithm for the 20 iterations ANFIS model. The number of iterations was defined by the testing phase since the datasets were distributed in 85% for the training phase and 15% for the testing phase. Matlab's ANFIS tool was used to perform the model.

5. RESULTS AND DISCUSSION

5.1 ANN Results

5.1.1 Basement

The prediction results of the Artificial Neural Network models are slightly different in term of being in the comfort level for each point and parameter. The predicted temperature data in the basement room, in general, seems to be close to the temperature comfort level in the heating season which is in the range 22-24°C, and the average of the ANN predicted temperature in the basement 21.7°C. In the same time, the hourly data is significantly varying, it reached 27.1°C as the maximum value and 15.1°C as it is shown in Figure 5.1 and Table 5.1.

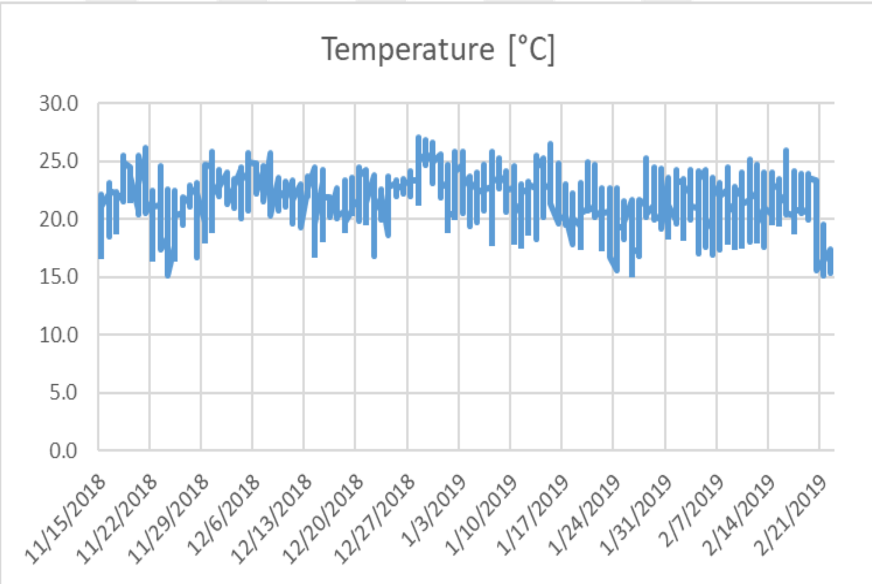

Figure 5.1: Basement - ANN hourly predicted temperature.

The predicted humidity is also in the same situation. It didn't reach the comfort level range which starts with 50% relative humidity, but it still close since the average of the predicted relative humidity is 44.1%. But again, the variation of the result is significant since the maximum value reached 56.7%, whereas the minimum value was 30.1%. The variation of the humidity data is clearly shown in Figure 5.2, and the maximum and minimum values are shown in Table 5.1.

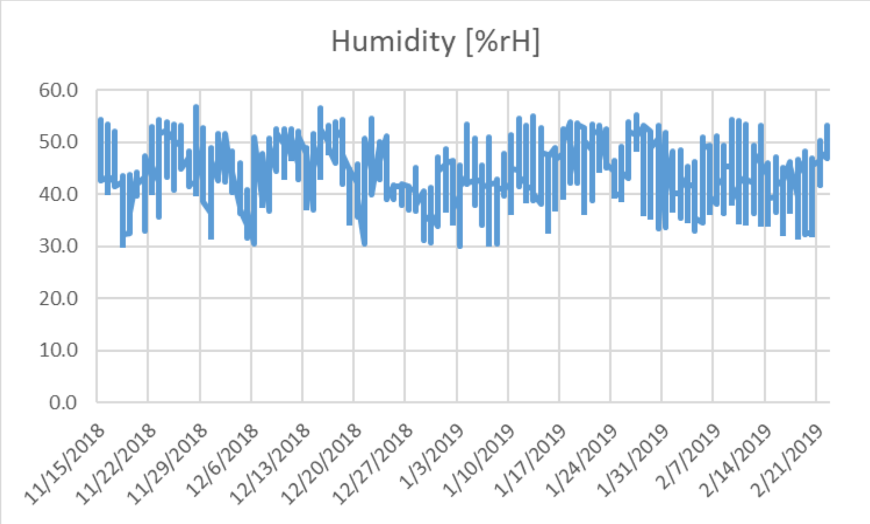

Figure 5.2: Basement - ANN hourly predicted humidity.

Table 5.1: Basement - ANN predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	56.7	27.1
Min	30.1	15.1
Average	44.1	21.7

5.1.2 Upper room

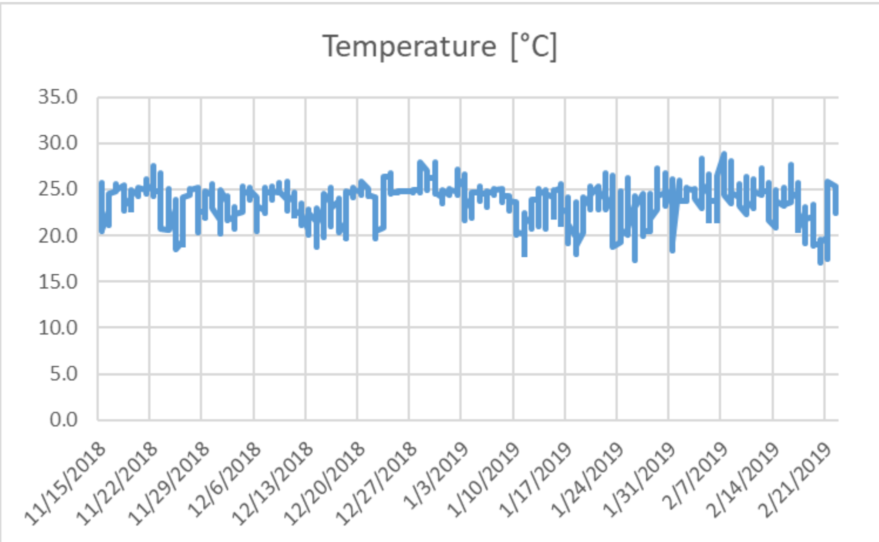

Figure 5.3: Upper Room - ANN hourly predicted temperature.

The prediction results for the upper room is not that much different than the results in the basement, as but the predicted temperature in this poin , in general, reached the comfort level since the average temperature is 23.7°C which is perfect. In the time, the data variation is again significant sine the maximum temperature was around 28.9°C, while the minimum value didn't exceed 17.1°C. The temperature predicted data in the upper room is shown in Figure 5.3 and the predicted parameters are shown in Table 5.2.

The average predicted humidity in the upper room is around 36.5% which is far lower than the comfort level. Although it reached 49.2% this was the maximum value which doesn't represent a considerable time out of the heating season and as shown in Table 5.2 in a peak point the humidity was around 22.1% which is extremely under the comfort level. Figure 5.4 represented the predicted relative humidity in the upper room.

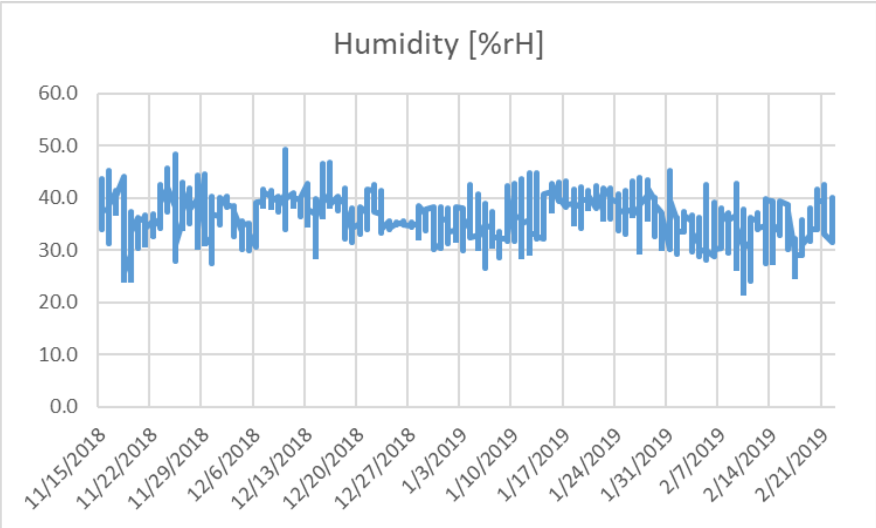

Figure 5.4: Upper Room - ANN hourly predicted humidity.

Table 5.2: Upper Room - ANN predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	49.2	28.9
Min	22.1	17.1
Average	36.5	23.7

5.1.3 Upper lobby

As in the third-floor room, the average of the predicted temperature in the lobby first-floor level is in the comfort level which is around 23.7°C. In addition, the maximum temperature value was around 29.3°C, while the minimum value around 17.7°C as shown in Table 5.3. Figure 5.5 showed the predicted temperature data.

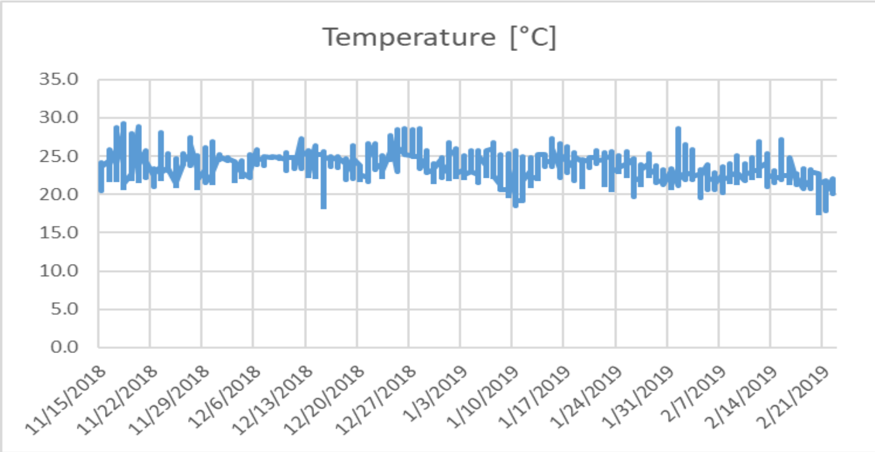

Figure 5.5: Upper Lobby - ANN hourly predicted temperature.

In the same time, the humidity average was better than the 3rd floor room since it reached 41.3%, which is slightly closer to the comfort level. The maximum relative humidity value was around 63.1% and the minimum value was around 22.4%. The predicted humidity data are shown in Figure 5.6.

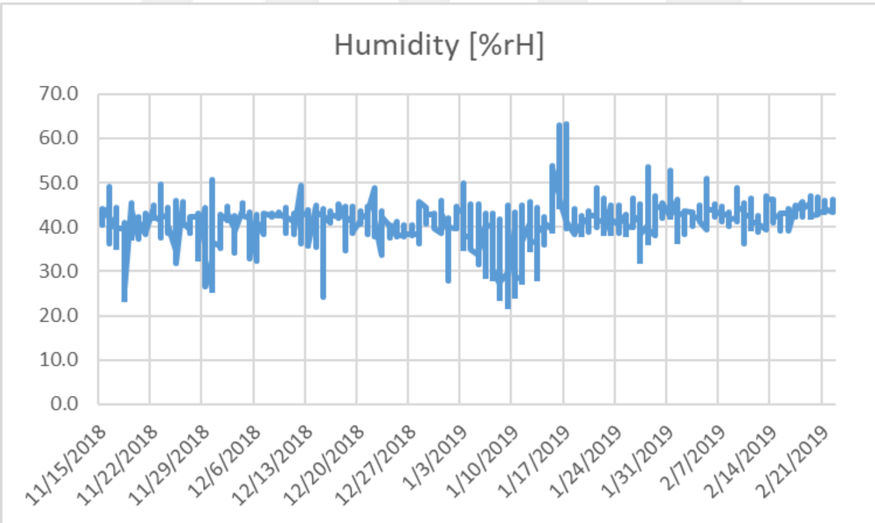

Figure 5.6: Upper Lobby - ANN hourly predicted humidity.

Table 5.3: Upper Lobby - ANN predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	63.1	29.3
Min	22.4	17.7
Average	41.3	23.7

5.1.4 Ground lobby

The temperature in the ground floor lobby was under the comfort level since the average was about 20.7°C. The maximum temperature value reached 24.8°C, while the minimum value 16°C. These results are clearly shown in Figure 5.7 and in Table 5.4.

Table 5.4: Ground Lobby - ANN predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	64.8	24.8
Min	32.2	16.0
Average	43.7	20.7

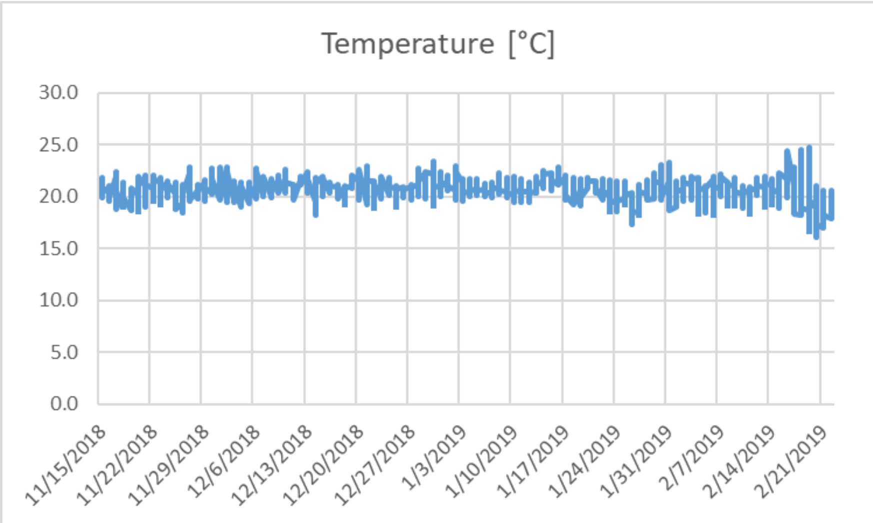

Figure 5.7: Ground Lobby - ANN hourly predicted temperature.

The humidity in this point also reached significant peak points since the maximum relative humidity was 64.8% and the minimum value was 32.2%. But the average humidity was closed to the comfort level as it was estimated to be about 43.7%, as shown in Table 5.4. and Figure 5.8.

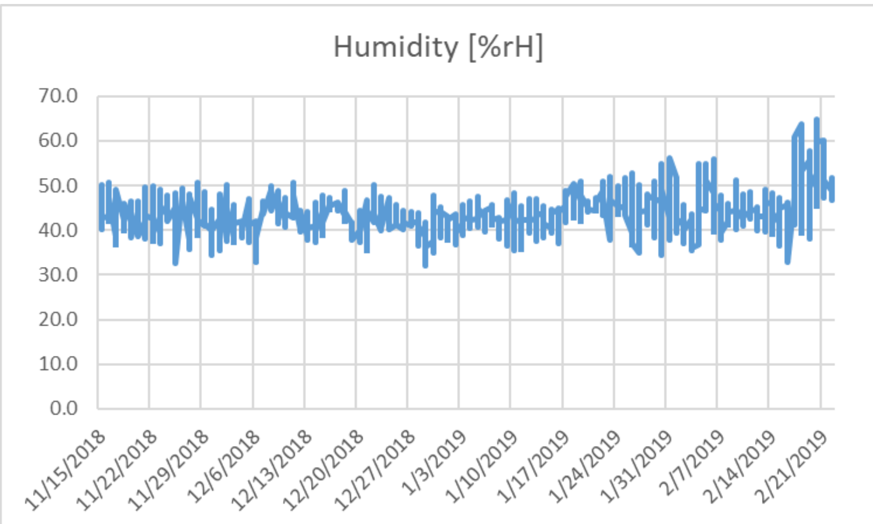

Figure 5.8: Ground Lobby - ANN hourly predicted humidity.

5.2 ANFIS Results

5.2.1 Basement

The results of the Adaptive Neuro-Fuzzy Inference Systems prediction are as expected relatively close to the ANN prediction results. The average of the predicted temperature of the basement room is estimated to be 20.4°C which under the comfort level range. The maximum predicted temperature in the basement was 21.9°C, and the minimum temperature was predicted to be 14.9°C as shown in Table 5.5. Figure 5.9 shows the hourly predicted temperature in the basement.

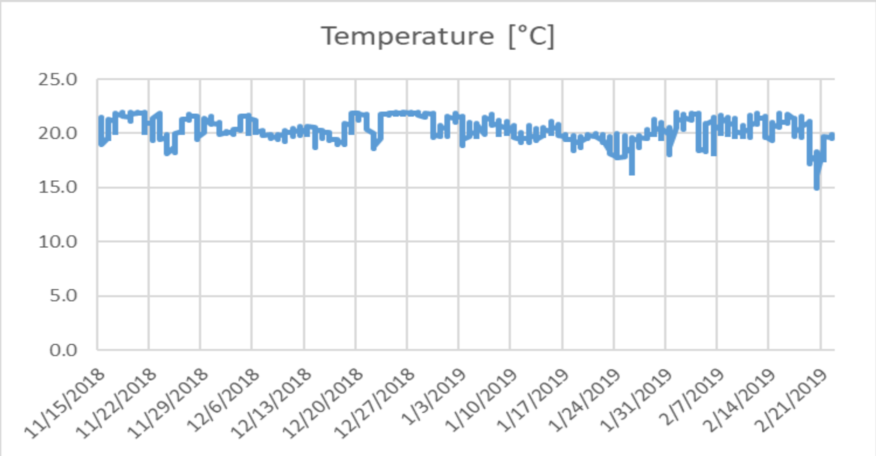

Figure 5.9: Basement - ANFIS hourly predicted temperature.

The predicted humidity in the basement was between 36.9% as a minimum value and 48.2% as a maximum value. The average of the predicted humidity was estimated to be 43.4% which is relatively close to the comfort range but didn't reach it. Figure 5.10 shows the hourly dataset of the humidity predicted by ANFIS for the basement room.

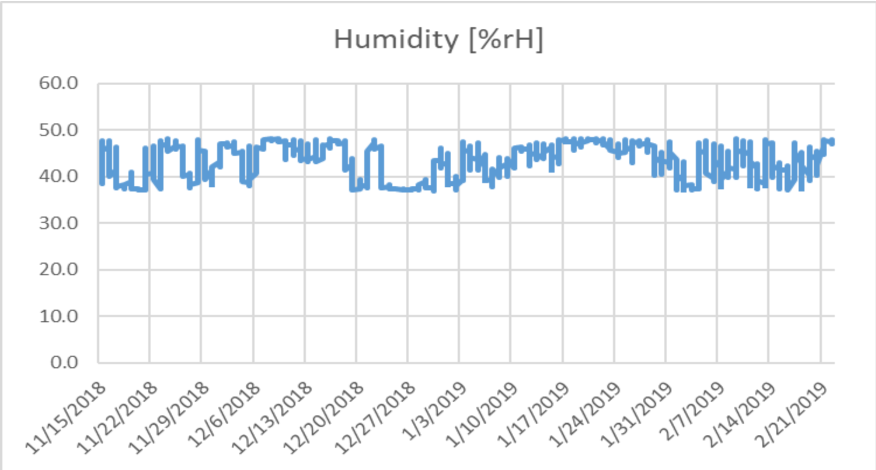

Figure 5.10: Basement - ANFIS hourly predicted humidity.

Table 5.5: Basement - ANFIS predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	48.2	21.9
Min	36.9	14.9
Average	43.4	20.4

5.2.2 Upper room

The predicted average of the temperature in the 3rd floor room was calculated to be 22.8°C which reflects perfect expectation for the heating system performance in this room where the average is in the comfort level, and the peak points are varying far out the thermal comfort range, since the maximum predicted temperature was 24.5°C and the minimum was around 19.4°C. The predicted temperature data is shown in Figure 5.11.

Table 5.6: Upper Room - ANFIS Predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	41.0	24.5
Min	31.9	19.4
Average	36.2	22.8

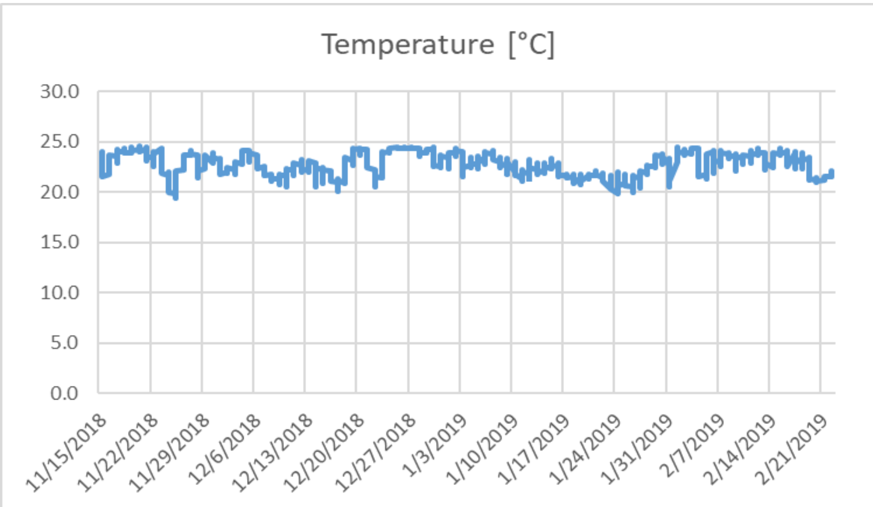

Figure 5.11: Upper Room - ANFIS hourly predicted temperature.

On the other hand, the predicted humidity in this room is far under the humid comfort range, where the average was 36.2%. The minimum humidity value was 31.9% and the maximum value 41%, as shown in Table 5.6. Figure 5.12 shows the hourly humidity dataset.

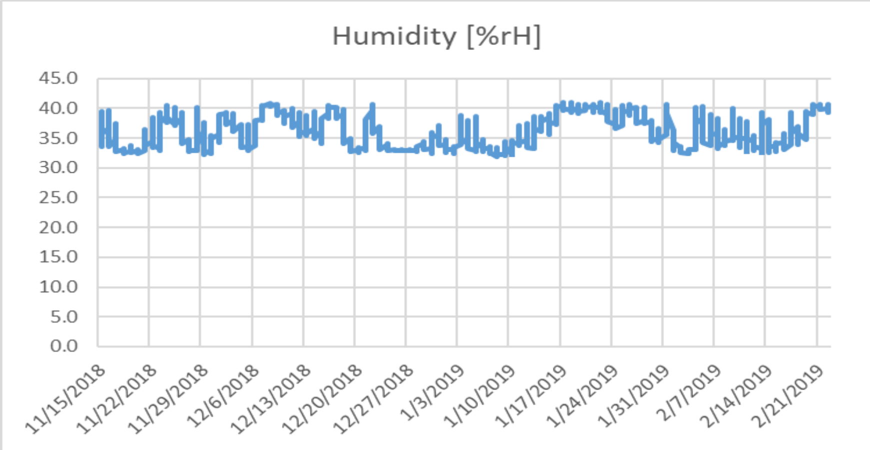

Figure 5.12: Upper Room - ANFIS hourly predicted humidity.

5.2.3 Upper lobby

The 1st floor level lobby predicted temperature results are mostly in the comfort level. The average of the predicted temperature in this point was 22.4°C. The maximum temperature value was 23.4°C and the minimum value was 16.1°C but this minimum value represents very unique peak point as shown in Figure 5.13 while the most of the predicted results are in a reasonable range in term of comfort conditions.

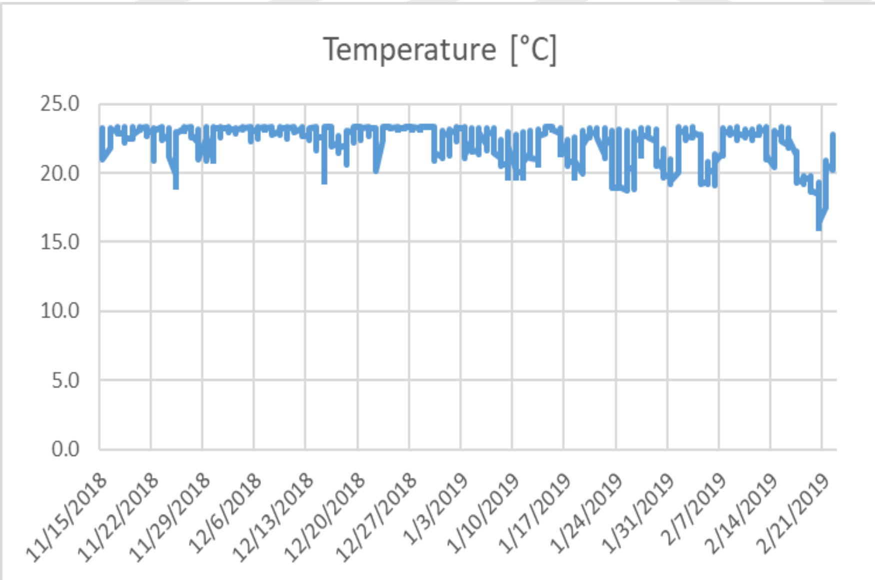

Figure 5.13: Upper Lobby - ANFIS hourly predicted temperature.

Table 5.7: Upper Lobby - ANFIS predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	49.9	23.4
Min	33.5	16.1
Average	42.4	22.4

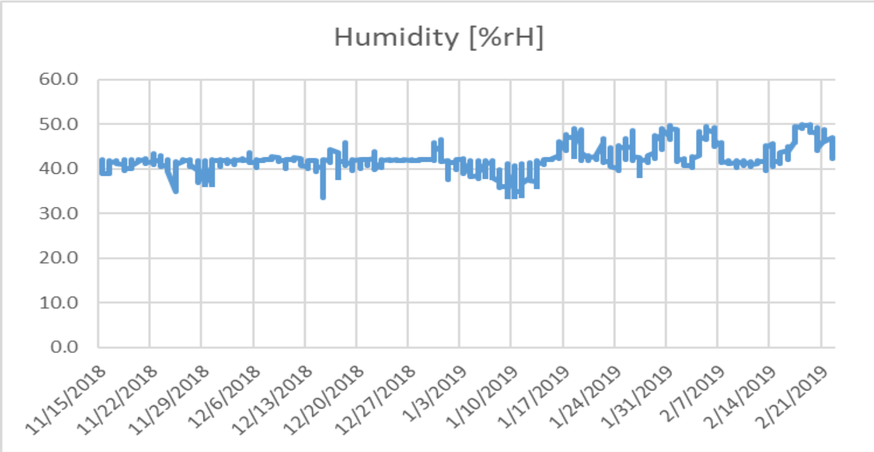

Figure 5.14: Upper Lobby - ANFIS hourly predicted humidity.

The average of the predicted humidity is around 42.4% which is relatively close to the comfort range as shown in Table 5.7. The values of the humidity in this point varies between 49.9% as the maximum value and 33.5% as the minimum value. Figure 5.14 represented the predicted humidity dataset.

5.2.4 Ground lobby

The ANFIS predicted temperature results were mostly varying around 20°C which relatively close to the comfort level. The average of the predicted temperature in the lobby was 20.1°C and the maximum was 20.9°C. In rare peak points, the results went down to be 15.5°C which is the minimum value. These results are clearly shown in Figure 5.15 and Table 5.8.

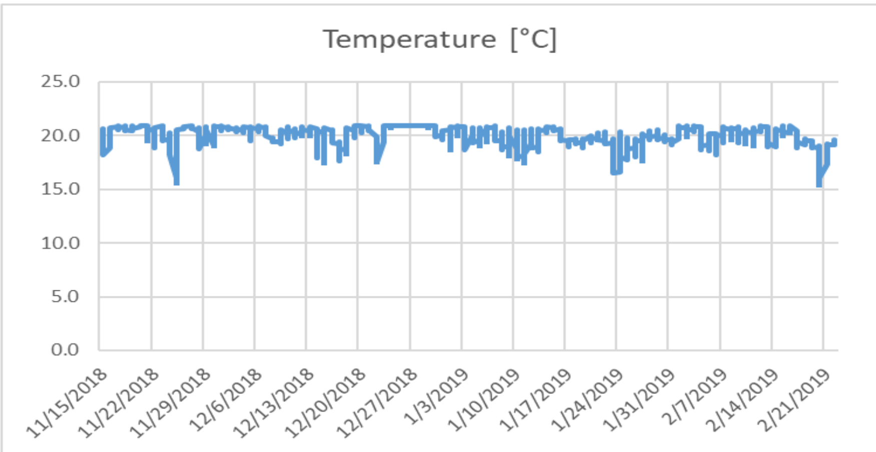

Figure 5.15: Ground Lobby - ANFIS hourly predicted temperature.

The ANFIS predicted humidity for the lobby is under the comfort range. The average of the humidity results was 42.3% in this point which is not far less than 50%. The results varied between 32.9% as the minimum rate and 47.8 as maximum rate. The predicted humidity dataset is represented in Figure 5.16.

Table 5.8: Ground Lobby - ANFIS predicted parameters.

	Humidity [%rH]	Temperature [°C]
Max	47.8	20.9
Min	32.9	15.5
Average	42.3	20.1

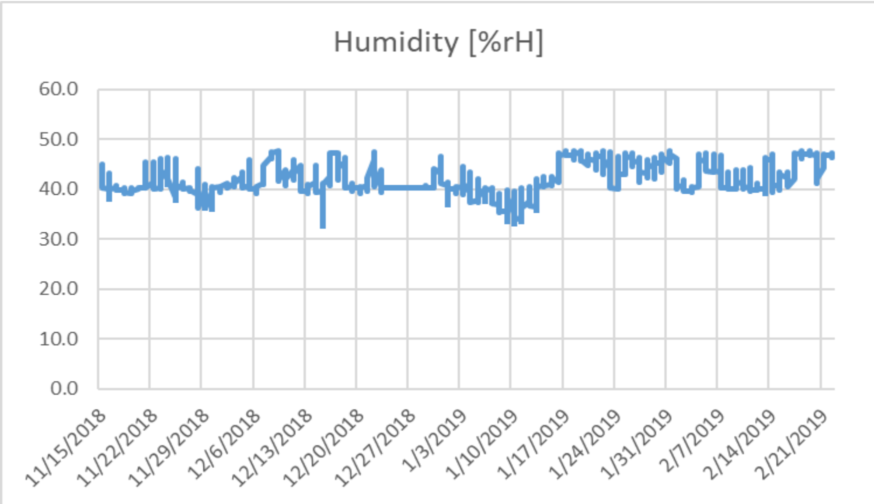

Figure 5.16: Ground Lobby - ANFIS hourly predicted humidity.

5.3 Comparing the Results

In this part, the ANFIS and ANN prediction results will be compared with the second-year heating season measurements. This comparison will show whether the approached are applicable to predict the indoor thermal data, and which one is more appropriate in term of accuracy.

Figures 5.17, 5.18, 5.19, 5.20, 5.21, 5.22, 5.23, and 5.24 show that both of the predicted data of ANN and ANFIS are relatively matching the measured data. For both temperature and humidity, The ANN predicted results' variation seems to be more realistic and closer to the measured data. While the ANFIS results seem to be more stable with fewer variations.

In the Figure 5.17, it is recognized that the period between December 27th and January 1st the measured data seems to be far less than the average, in some points it went down less than 10°C, which shows that the heating system wasn't properly performing. This deviation in some periods may cause mistakes in estimating the errors of the prediction work. It will decrease the accuracy of the prediction models since the errors were calculated by comparing the predicted data with the measured data. Therefore, the prediction model will carry responsibility for the heating system's bad performance.

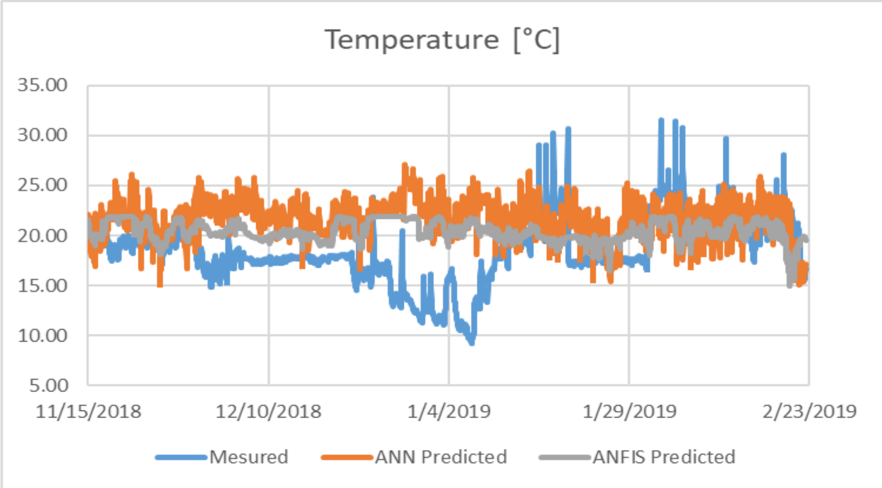

Figure 5.17: Basement - hourly predicted and measured temperature.

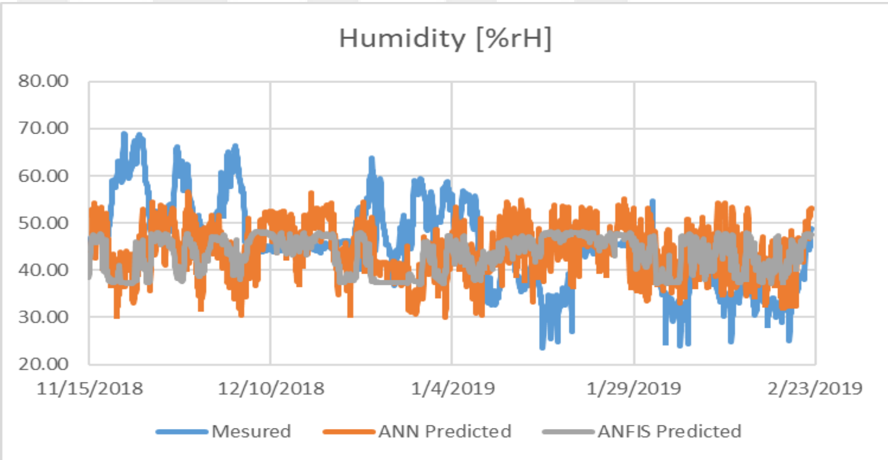

Figure 5.18: Basement - hourly predicted and measured humidity.

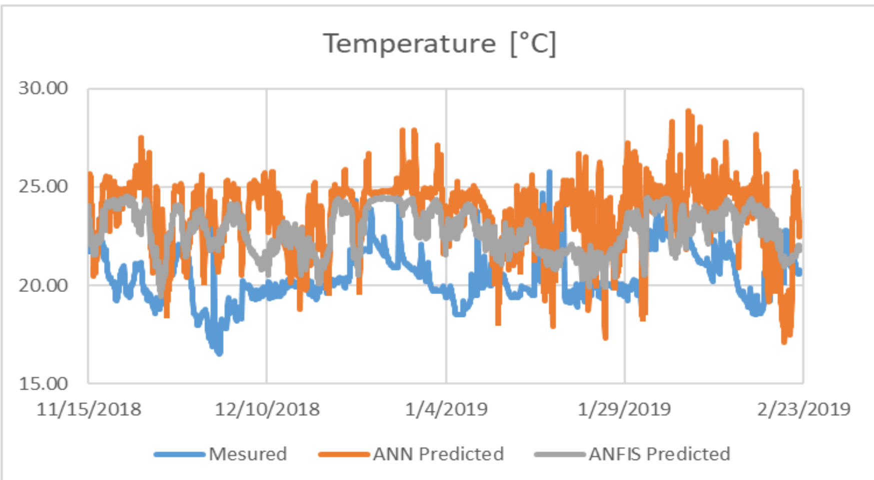

Figure 5.19: Upper Room - hourly predicted and measured temperature.

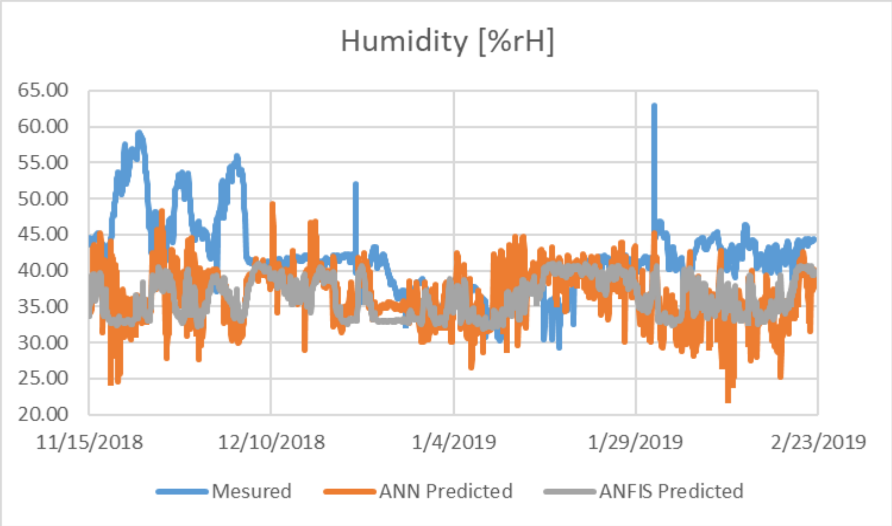

Figure 5.20: Upper Room - hourly predicted and measured humidity.

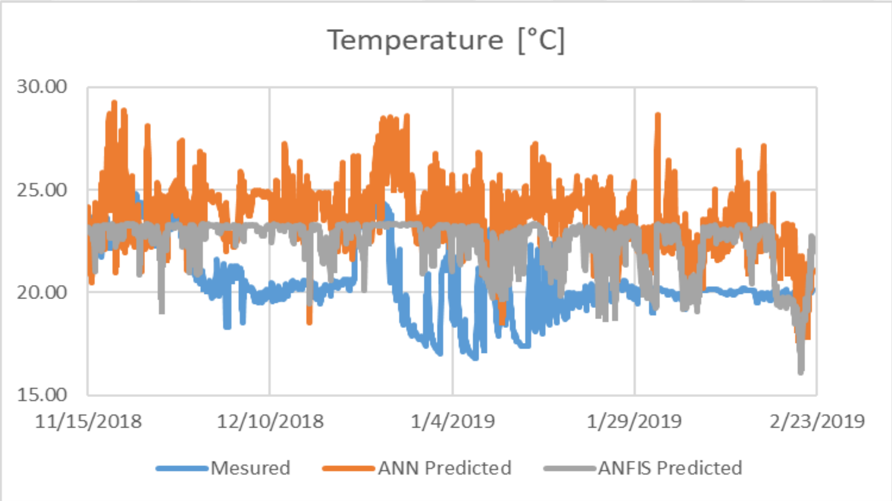

Figure 5.21: Upper Lobby - hourly predicted and measured temperature.

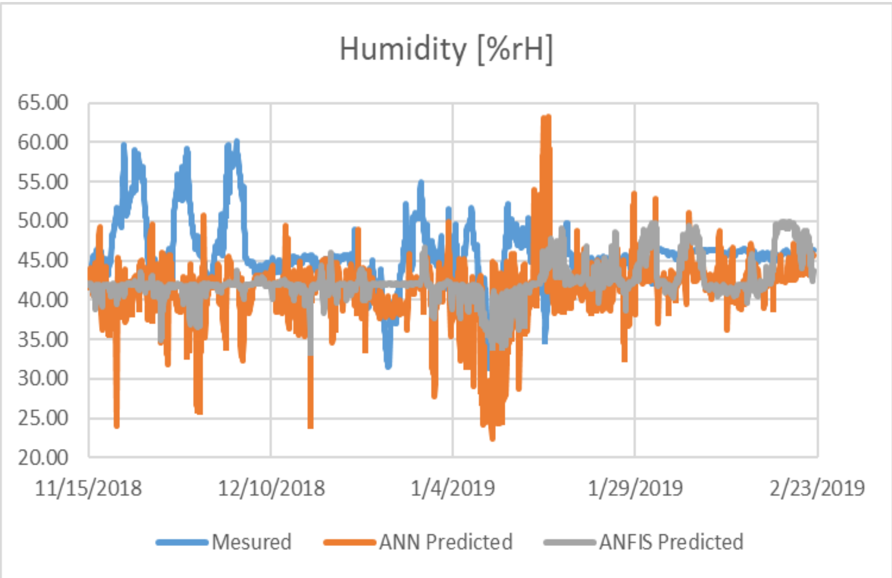

Figure 5.22: Upper Lobby - hourly predicted and measured humidity.

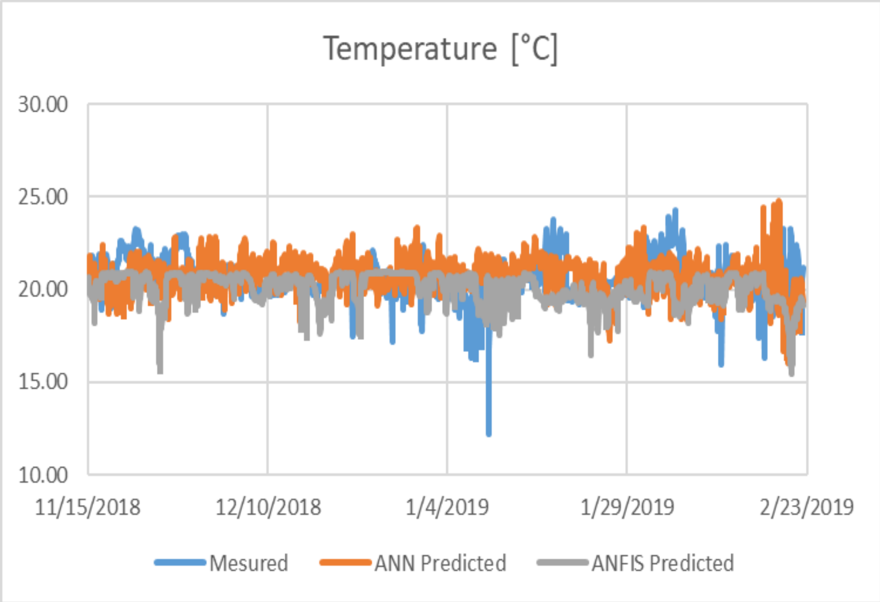

Figure 5.23: Ground Lobby - hourly predicted and measured temperature.

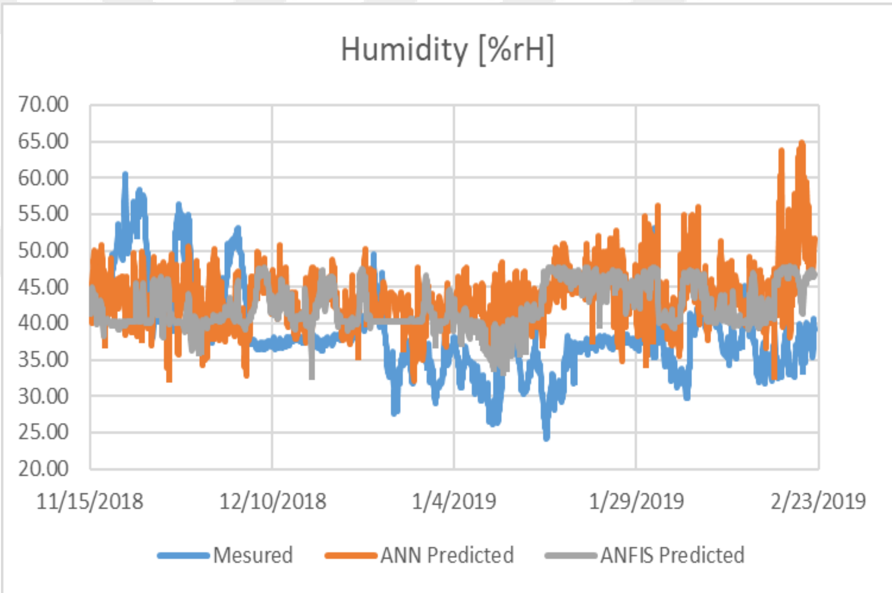

Figure 5.24: Ground Lobby - hourly predicted and measured humidity.

Table 5.9, shows that the ANFIS model prediction of the temperature has less than the ANN model prediction in 3 points out of four. The ANFIS temperature prediction results' RMSEs (Root Mean Square Error) are 4, 2.9, 2.7, and 1.4 respectively in the basement room, upper room, upper lobby, and ground lobby, while in the same order the ANN prediction errors are 5.2, 3.9, 3.8, and 1.5.

It is significant the small error of both of the models in the ground lobby which. This can be explained by observing the measured temperature dataset in Figure 5.23. It is clear that the measured data at this point is more stable with fewer variations compared to other points. Even though the average of the measured temperature which is 20.74°C, which is less than the comfort range, but the stability of the measured data in the point shows that the heating system is performing properly in the lobby. However, these results show that the ANFIS prediction has better accuracy when it is compared with these stochastic measured data of the four points since the overall temperature prediction accuracy of the ANFIS model has been calculated to be 85%, in the other hand the accuracy of the temperature ANN prediction was 81%.

Table 5.9: Predicted and measured temperature parameters.

		Inside Temperature [°C]			
		Basement room	Upper room	Upper Lobby	Ground Lobby
Measured	Average	18.5	20.4	20.6	20.7
ANN Predicted	Average	21.7	23.7	23.7	20.7
	RMSE	5.2	3.9	3.8	1.5
	Final RMSE	3.8			
ANFIS Predicted	Average	20.4	22.8	22.4	20.1
	RMSE	4.0	2.9	2.7	1.4
	Final RMSE	2.9			

According to Table 5.10, both of the ANFIS and ANN predictions' errors are close to each other. The ANFIS humidity prediction results' RMSEs were 10.4, 8.3, 5.8, and 7.9 respectively in the basement room, upper room, upper lobby, and ground lobby, while in the same order the ANN prediction errors were 10.5, 8.5, 6.8, and 9. The ANFIS prediction was better in the four points. However, for overall humidity prediction again the ANFIS model which had 81% accuracy rate was slightly more accurate than the ANN model which had an accuracy rate of 81%.

Table 5.10: Predicted and measured humidity parameters.

		Inside Humidity Rate [%rH]			
		Basement room	Upper room	Upper Lobby	Ground Lobby
Measured	Average	45.4	42.0	45.6	38.6
ANN Predicted	Average	44.1	36.5	41.3	43.7
	RMSE	10.5	8.5	6.8	9.0
	Final RMSE	8.8			
ANFIS Predicted	Average	43.4	36.2	42.4	42.3
	RMSE	10.4	8.3	5.8	7.9
	Final RMSE	8.3			

5.4 Scaling the Comaprison:

The irregular performance of the heating system produced a stochastic measured data in some periods. This stochasticity affected the comparison between measured and predicted data and the prediction accuracy of both of the ANFIS and ANN models. To avoid this effect the comparison will be scaled by selecting the most ordinary period of the measured data as a sample to be compared with the predicted data and then provide the accuracy based on the selected sample.

By observing Figures (5.17, 5.18, 5.19, 5.20, 5.21, 5.22, 5.23, and 5.24), it is recognized that the most stable period for the measured data was the period between 10/12/2018 and 20/12/2018. The data of this period will be the sample which is used for the comparison scaling.

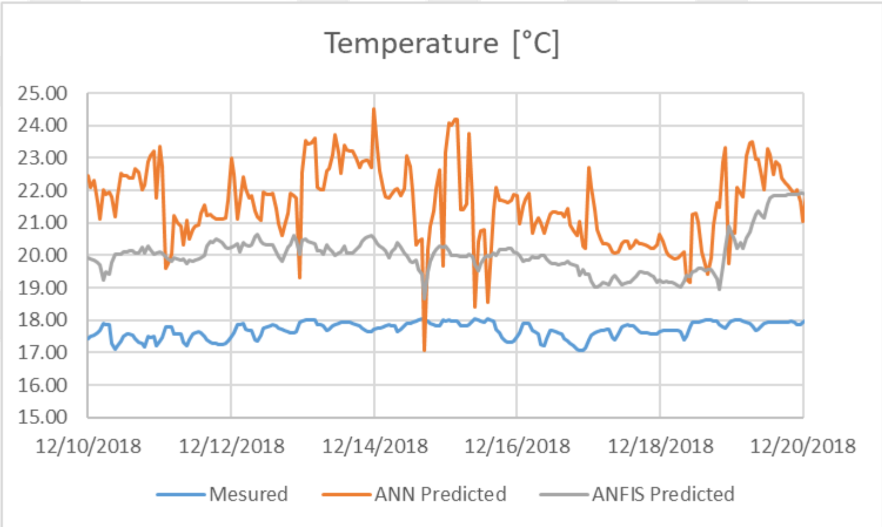

Figure 5.25: Basement temperature data sample.

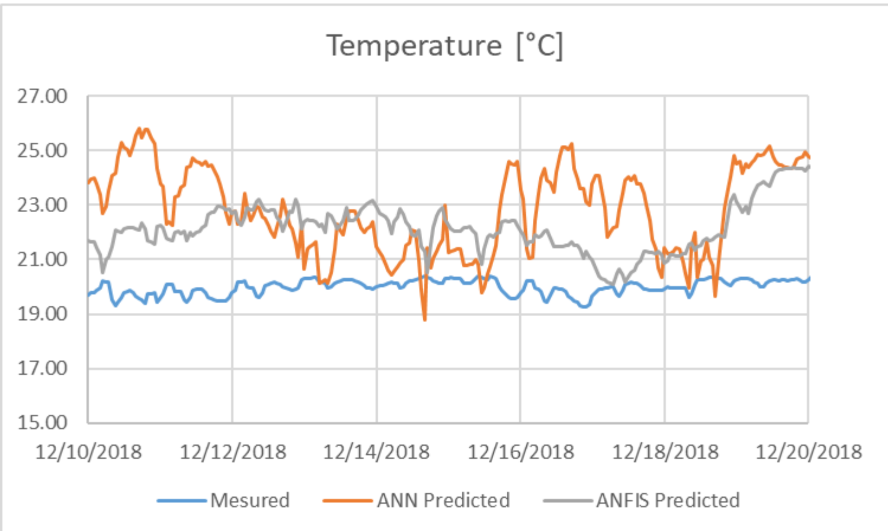

Figure 5.26: Upper room temperature data sample.

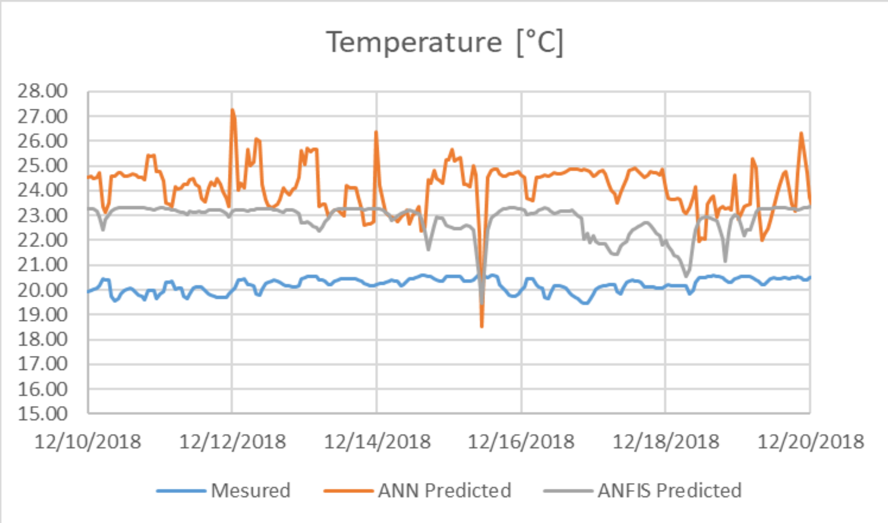

Figure 5.27: Upper lobby temperature data sample.

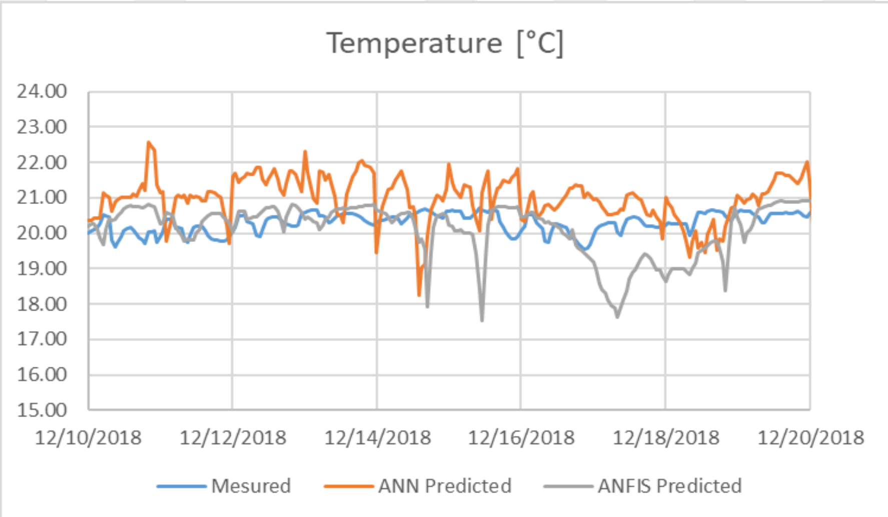

Figure 5.28: Ground lobby temperature data sample.

Table 5.11: Data sample temperature parameters.

		Inside Temperature [°C]			
		Basement room	Upper room	Upper Lobby	Ground Lobby
Measured Average		17.7	20.0	20.2	20.3
ANN Predicted	Average	21.7	23.0	24.0	21.0
	RMSE	4.1	3.4	3.9	1.0
	Final RMSE	3.4			
ANFIS Predicted	Average	20.2	22.3	22.9	20.2
	RMSE	2.6	2.5	2.7	0.8
	Final RMSE	2.3			

Figures 5.25, 5.26, 5.27, 5.28, and Table 5.11 show that the temperature prediction error increased in the most stable sample of the measured data for both ANN and ANFIS prediction models. For ANN the accuracy rate after scaling increased from 81% to 83%, but this increasing rate still affected by the quality of the measured data, because even though the measured data is stable but it doesn't match the expected results especially in the basement where the average of the measured data was less than 18°C, which is far away under the comfort zone. So the more the measured data is closed to the comfort zone, the less prediction error achieved. The ANN maximum RMSE was in the basement around 4.1, while it was minimum in the ground lobby point which is around 1. For ANFIS model the temperature prediction accuracy after scaling was increased by 3%, again the accuracy rate was affected by the heating system performance, and the average error decreased when the measured temperature was closer to the temperature comfort zone. The accuracy of ANFIS prediction became 88% after scaling while the ANN prediction accuracy increased to be 85% which make the ANFIS model more eligible in term of accuracy to perform the kind of prediction work.

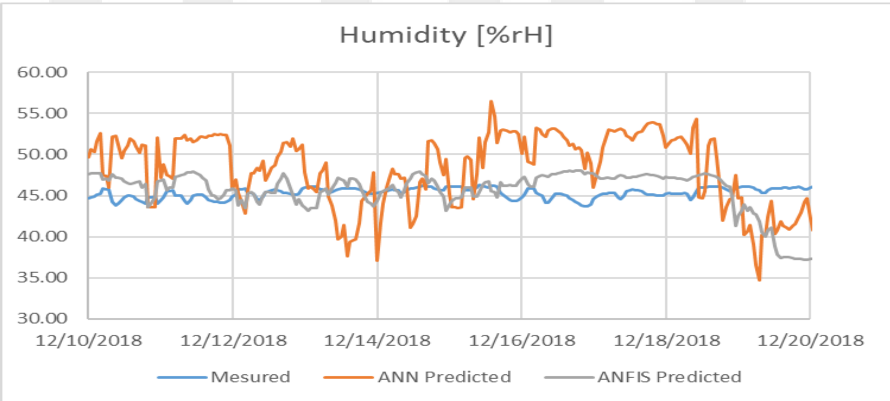

Figure 5.29: Basement humidity data sample.

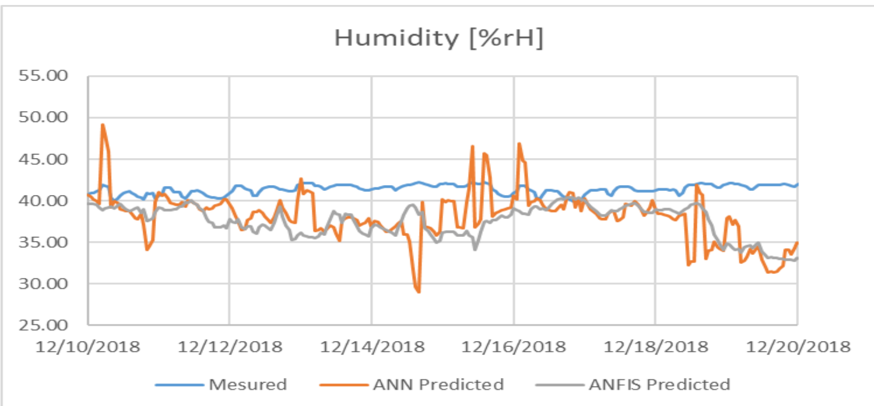

Figure 5.30: Upper room humidity data sample.

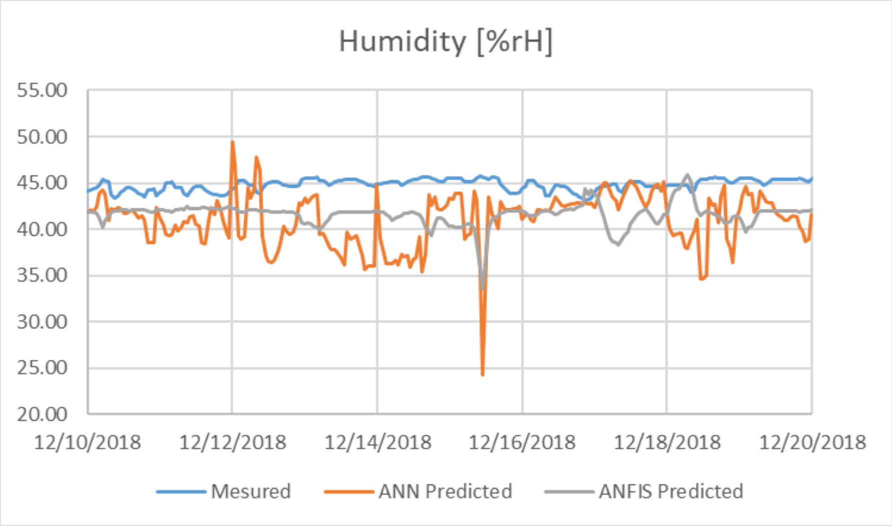

Figure 5.31: Upper lobby humidity hata sample.

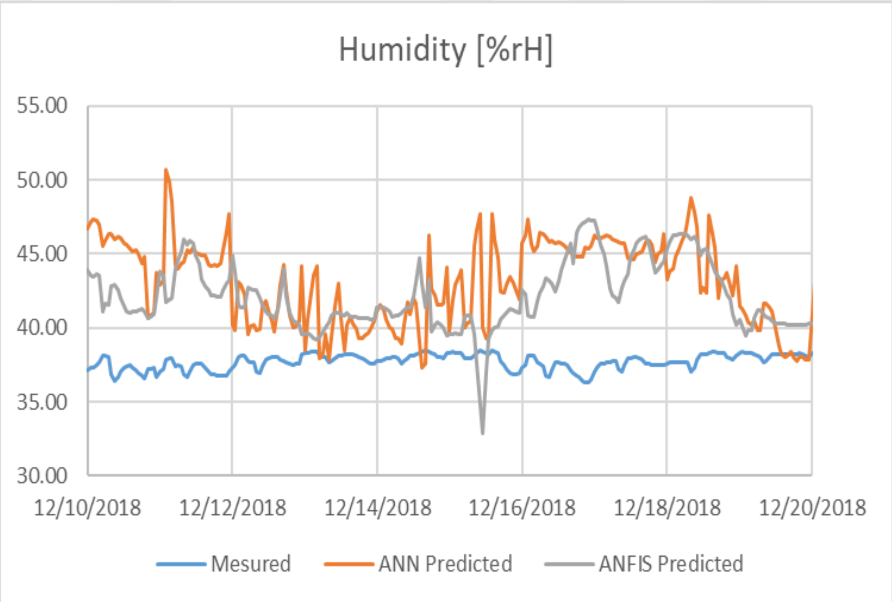

Figure 5.32: Ground lobby humidity data sample.

Table 5.12: Data sample humidity parameters.

		Inside Humidity Rate [%rH]			
		Basement room	Upper room	Upper Lobby	Ground Lobby
Measured Average		45.4	41.4	44.9	37.8
ANN Predicted	Average	47.5	37.9	41.1	42.8
	RMSE	5.7	4.8	4.8	6.0
	Final RMSE	5.3			
ANFIS Predicted	Average	45.0	37.2	41.6	42.0
	RMSE	3.5	5.0	3.6	4.9
	Final RMSE	4.3			

Figures 5.29, 5.30, 5.31, 5.32, and Table 5.12 showed that the prediction accuracy of the humidity was improved after scaling for both ANN and ANFIS prediction models. For ANN results the final prediction accuracy was increased by 6% after scaling. For ANFIS results also the final prediction error was decreased and the accuracy rate increased. The final humidity prediction accuracy of ANN is 87% while it is 90% for ANFIS, which shows that ANFIS model's accuracy is better than the accuracy of the ANN model in the whole cases in this study.

6. CONCLUSION

The thermal environment is the main index of the building energy performance and efficiency, since it is the most important factor to improve the comfort level of the building, and the main mission of most of the applied systems in any building is providing a comfortable indoor environment. Hence, most of the building energy consumption is for heating or cooling. Therefore, it is necessary to manage certain comfort conditions like temperature and humidity in order to manage and sustain the indoor environment comfort level.

This thesis aimed to predict the heating season indoor thermal comfort data in the Kartal elderly home, which is 8 stories building with 18,108 m2 conditioned floor area in Istanbul, Turkey. The aim of this prediction is providing full heating season's thermal comfort dataset by using short-term measured data while the heating system is performing. The heating season of the building was evaluated by defining a critical monthly heating consumption, which was 250 MWh per month, and select the period when the building monthly consumption exceeds this value to be the heating season. Based on it the heating season was evaluated to be between November 15th and March 21st.

The ANFIS and ANN approaches had been used as predictive models. The two approaches were trained based on the measured indoor temperature and relative humidity data. The measurements inside the building were taken for one year which started on the 22nd of February 2018. Therefore, short-term data was collected in the first heating season and these data were used into the models training phase. While the data collected in the second heating season was used in validating the prediction results. In addition, the independent variables were obtained from the weather data and heating consumption simulated data.

The measurement and prediction works were done into four different points inside the building. The prediction results showed that the temperature averages should be in the comfort level for two points out of four, while the measured data showed that the four points are under the comfort condition. This was because of the poor performance of the heating system in some periods. This poor performance cause recognized stochasticity in the measured data which influenced the prediction results validation and affected the prediction accuracy calculations.

The ANN prediction errors for temperature were varied between 1.5 and 5.2, and between 6.8 and 10.5 for humidity in the four points. The ANFIS prediction errors have recognized variations too since the temperature prediction errors were between 14 and 4, and for the humidity, prediction errors were between 5.8 and 10.4. These results showed that the ANN and ANFIS models achieved the best prediction with a minimum error rate in the point where the measured data was more stable with fewer variations.

However, the ANFIS prediction was more accurate in general since its prediction final accuracy rate was 85% for temperature and 81% for humidity, while the ANN prediction final accuracy rates were 81% for temperature and 80% for humidity.

These results were significantly affected by the heating system poor performance, in order to minimize this effect, the comparison was scaled by selecting the best measured period to be the data sample which will be used in the comparison. After scaling, the prediction accuracy was increased for both ANN and ANFIS models, to be 83% and 88%, respectively for temperature prediction. For humidity the accuracy rate of 87% for ANN and 90% for ANFIS. According to the results, the ANFIS model was the best fit for all of this prediction work cases. Considering the measured data stochasticity, both of the ANFIS and ANN approaches are highly validated in this type of prediction work. Since the building is an elderly home, these results can be an indicator to improve the thermal environment inside the building Taking into account its impact on the health and well-being of older persons.

This study results offer the opportunity to go in different directions as further work. The results can support the monitoring system which was implemented inside the building to perform real-time calibration and report the unexpected results, this report can help to improve the comfort level inside the building. The prediction results can also be used as an index to calibrate and develop the accuracy of the energy performance simulation of the building by improving the set points.

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