ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

# A DOUBLE-AUCTION MICROGRID MARKET DESIGN AND ITS APPLICATION WITH AGENT-BASED SIMULATION

M.Sc. THESIS

Efe BAŞLAR

Department of Industrial Engineering

Industrial Engineering Programme

JANUARY 2020

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**Thesis Advisor: Dr. Cafer Erhan BOZDAĞ**

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**İSTANBUL TEKNİK ÜNİVERSİTESİ★ FEN BİLİMLERİ ENSTİTÜSÜ**

# MİKRO ŞEBEKELER İÇİN BİR PİYASA ÖNERİSİ VE AJAN TEMELLİ BENZETİM İLE BİR UYGULAMASI

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***For my present and the future family,***

## FOREWORD

What started as an ambitious attempt at an academic pursuit has actually turned bitter thanks to many challenges I’ve faced throughout the Master’s that is concluded by this study. Instead of marking a hopeful kickstart to my career, it seems it is merely the start of the voyage to the unknown. I hope I never rue the day I’ve taken the decision to start studying in this Master’s.

I must thank my advisor Cafer Erhan Bozdağ for his invaluable support and all those anonymous commenters in stackoverflow.com for helping me code the simulation model to the fullness, which actually comprised more than half of all the work I’ve done for this thesis. I also thank my dear Nisa Kömürcü for being there for me, all the time.

November 2019 Efe BAŞLAR

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## ABBREVIATIONS

**CO2**: Carbon dioxide

**EU**: European Union

**US**: The United States of America

**Hz**: Hertz

**DG**: Distributed Generation

**AC**: Alternating Current

**PV**: Photovoltaic

**VPP**: Virtual Power Plant

**P2P**: Peer-to-Peer

**MAPE**: Mean Absolute Percentage Error

**CHP**: Combined Heat and Power

**UK**: The United Kingdom

**ToU**: Time-of-Use Pricing

**kWh**: Kilowatts hour

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**A DOUBLE-AUCTION MICROGRID MARKET DESIGN AND ITS APPLICATION WITH AGENT-BASED SIMULATION**


## SUMMARY

The study aims at illustrating the feasibility of an islanded microgrid system the ability of the microgrids to supply cleaner and cheaper electricity to its stakeholders. The motivation arises from the changing energy visions of the developed world. The Earth can no longer afford being polluted by the rampant burning of the fossil fuel resources to supply energy. The electricity grid that envelops human civilization has changed very little and it is heavily reliant on the fossil fuel resources. To realize the vision of clean energy, the grid must first undergo a structural change and the microgrid might be a stepping stone in this regard. Microgrids are technologically feasible and there are several applications around the world. Before becoming widespread in use, however, the problem of unpredictability and erraticism in renewable generation poses a formidable obstacle for microgrids. To address this problem, new grid paradigms are facilitated, namely, distributed generation, that is electricity generation at the site of consumption, peer-to-peer electricity trading and energy storage. With these possibilities becoming cheaper than ever and continuing to become cheaper, it will not be long before microgrids are regarded as viable alternative in localized generation of electricity. To that end, this study proposes a means to regulate the peer-to-peer trading among the microgrid to alleviate the negative effects of the variability in renewable energy generation. One of the cornerstones of any market structure is the pricing mechanism and it is the part where the dynamics of the market manifests itself. There are no examples literature that integrates the nature of the renewable generation in the market structure in microgrids, that is why this study aims at producing such an effort. To integrate the variability in renewable generation, the idea of coherent arbitrariness is presented as a viable approach. The bid and ask prices in double-auctions are modified with the average forecasting errors to account for the risk in uncertain output from the renewable generation units. For the simulation of the proposed market structure an agent-based model is built with their capability to learn emulated by simple reinforcement learning approach. A simple ARIMA model is used as a placeholder to provide forecast values and their errors in the form MAPE. The simulation is run with real world data from the Low Carbon London project and various meteorological data from the UK Met Office and experimentation of numerous model parameters are carried out and their results are reported. The results of the study indicate that the islanded microgrid can in fact supply cheaper and cleaner electricity yet the high setup costs and how they should be covered, make it rather difficult to implement. Due to these estimated high costs, the grid-connected mode of operation is proposed to be a transitionary period until the islanded form microgrid until renewable generation units and electricity storage becomes cheap enough to make the islanded microgrid a beneficial investment.

# MİKRO ŞEBEKELER İÇİN BİR PİYASA ÖNERİSİ VE AJAN TEMELLİ BENZETİM İLE BİR UYGULAMASI

## ÖZET

Bu çalışma değişen ve gelişen elektrik üretim şekillerinin, özellikle de yenilenebilir enerji kaynakları ile elektrik üretiminin yarattığı çeşitli sorunları göz önünde bulundurarak ve ortaya koyabileceği çeşitli olumlu özelliklerden de yararlanarak, mevcut elektrik şebekesine eklemlenmesine katkıda bulunabilecek microgrid'ler (mikro şebekeler) için bir piyasa tasarımını içermektedir. Bu katkı temel olarak elektriğin şebekeden bağımsız olarak tüketim noktalarında temiz, tüketiciler için karşılanabilir ve üreticiler için de kazanç sağlayabilecek maliyetler ile üretilmesini sağlamaya çalışmaktır. Mikro şebekeler hatırı sayılır bir süredir elektrik şebekeleri literatüründe bulunsa da, hem yenilenebilir enerji kaynaklarının hem de elektrik pillerinin yüksek maliyetleri bu tür uygulamaların önüne geçmekteydi. Bu birimlerin fiyatlarının son yıllarda düşmeye başlaması ve üretimlerinin daha kolay hale gelmesi ile, mikro şebekelerin teknik olurluluğunun yanında yatırımsal olarak da olurluluklarının ihtimali ortaya çıkmıştır. Mikro şebekeler temiz ve ucuz elektrik üretebilme ihtimallerinin yanında, dünya çapındaki çevre örgütlerinin ve bazı gelişmiş ülkelerin ortaya koyduğu karbon salınımı azaltma yönündeki hedeflerin gerçekleşmesi için gerekli olan, enerjinin fosil yakıtlar yerine rüzgar ve Güneş gibi yenilenebilir enerji kaynakları ile üretilmesinin yaygınlaşmasında da bir aracı olarak düşünülebilir. Fosil yakıtların aksine bu yenilenebilir enerji kaynaklarının davranışlarının isabetli şekilde tahmin edilmesi oldukça zordur, bu yüzden de fosil yakıtlara dayalı çalışan alışılagelmiş elektrik şebekesi, yenilenebilir enerji kaynaklarının sisteme dahil olma oranı arttıkça çeşitli sorunlar yaşamaktadır. Bunlardan en önemlisi, elektrik şebekesinde arz ve talebin sistem çalıştığı her an eşitlenmesi gerekliliğidir. Yenilenebilir enerji kaynaklarının davranışlarının tahmin edilmesinde yaşanılan güçlükler de bu dengenin kurulmasını zorlaştırmaktadır. Bu denge bozulduğunda sistemin çalışma frekansında değişmeler yaşanmakta, bu da sağlanan elektriğin kalitesini kötü etkileyip elektrik üreten ve elektrik tüketen aygıtları tehlikeye sokmaktadır. Ancak, bu sorunun da çözümü teknolojinin gelişmesi ile kolaylaşacak gibi görünmektedir. Elektrik pillerinin ucuzlayıp yaygınlaşmaya başlamasıyla yenilenebilir enerji kaynakları beklenenden veya gereğinden fazla üreitim yaptığında bu enerji depolanabilecek, tersi durum olduğunda da gereken enerji depolanmış enerjiden sağlanabilecektir. Tesla gibi firmalar bu konuda çeşitli girişimler yapmış olup, evsel kullanıcı için çeşitli depolama seçenekleri yaratan piller satmaya başlamıştır. Elbette tüm bu bahsedilen gelişmeler çeşitli hukuki ve ekonomik sorunlar da yaratmaktadır. Elektrik şebekesi için elektrik üretenler çoğunlukla elektrik santrali sahibi büyük firmalardır. Elektrik üretimi yöntemleri çoğalıp boyutları küçüldükçe, bunların evsel kullanıcılar tarafından edinilmesinin de yolu açılmıştır. Gelişen elektrik dağıtım teknolojileri ile beraber şebeke dağıtım unsurlarında olabilecek sıkışmaların da çözümlerinin bulunmasıyla evinde yenilenebilir enerji kaynakları ile elektrik üreten kullanıcıların ürettiği elektriği şebekeye veya diğer kullanıcılara satabilmesinin de önü

açılmıştır. İşte önerilen piyasa tasarımı da kullanıcılara elektrik ticareti yapabilme imkanı vermektedir. Literatürde ise bu konuda araştırma sayısı çok fazla olmadığından, gelecekteki elektrik şebekesinin de adım adım daha yerel parçalara bölünebileceği düşünüldüğünden, bu konunun çalışılmasının yararlı olduğu görülmüştür.

Tasarımı yapılan bu piyasa düzeninin en önemli özelliği ise fiyatlandırmada yüksek oranda belirsizlik içeren bu yenilenebilir enerji kaynaklarının davranışlarını da göz önüne almasıdır. Ekonomi literatüründeki bazı çalışmalara göre satıcıların ve alıcıların bir mal için akıllarında noktasal bir değer yoktur ve mallara biçilen değer çeşitli dışsal faktörlerden etkilenebilmektedir. Özellikle elektrik üretiminin yenilenebilir enerji ile yapıldığı bir ortamda elektrik arzının değişkenliği ve dolaylı olarak da değeri oldukça değişken bir halde olacaktır. Coherent arbitrariness (Tutarlı keyfilik) olarak adlandırılan bu durum, piyasa içinde kullanılan çift taraflı açık artırma yönteminde fiyatın tekliflerinin değerlendirilmesi için kullanılmıştır. Elektrik üretimi ile kaynakların ve elektrik tüketiminin tahmini de iç içe olduğundan bu piyasa düzeninin de elektrik tahminine ihtiyacı olacağı düşünülüp, bu tahminlerde oluşan tahmin hatalarının fiyatlara yansıtılması elektrik değerindeki dalgalanmaları hesaba katacağı düşünülmüştür. Bahsi geçen bu çift taraflı açık artırma yöntemi de mikro şebekelerde elektrik ticareti için çeşitli çalışmaların sonuçlarına göre uygun olarak kabul görmüştür. İşte tüm bu bilgileri hesaba katarak, çalışmanın amacını da göz önünde bulundurarak bu piyasa tasarımının nasıl performans gösterdiğini görebilmek adına bu çalışma için bir ajan-temelli benzetim modeli kurulmuştur. Bu model de Londra için yapılan bir projede bulunan, akıllı elektrik ölçer (smart grid) bulunduran evlerin bir yıl boyunca yarım saatlik elektrik tüketimleri verisini, Londra için rüzgar hızı ve güneş enerjisi verisini kullanmıştır. Modelde piyasanın çalışmasını sağlan bir yönetici ajan ve piyasa içinde bulunan ev halklarını temsil eden 13 adet evsel ajan bulunmaktadır. Modelde çeşitliliği sağlamak adına bazı evlerde üretim araçları bulunmakta, bazılarında bulunmamaktadır. Bu ajanlar yönetici ajanın yönettiği açık artırma sisteminde birbirleri ile elektrik alış-verişi yapıp birbirlerine bunun için ücretler öderler. Yönetici ajan sistemde arz ve talebin sürekli eşitlenmesinden, tahminlerin yapılmasından ve bir sonraki aralıkta, mikro şebekeye eklenmiş olan, yakıt hücresinin çalışıp çalışmayacağının kararını vermektedir. Evsel ajanlar ise Pekiştirmeli Öğrenme yöntemlerinden biri olan Q-Learning'i kullanarak açık artırmalarda alış ve satış için hangi teklifleri vermeleri gerektiğini belirlemektedirler. Model ise piyasanın performansını görmek için üretildiği için ve mikro şebekelerin ucuz ve güvenli enerji sağlayabileceği iddia edildiği için, modelin en önemli çıktıları ise modellenen piyasada bulunan hanehalklarının ne kadar elektrik faturası ödediği, mikro şebekenin elektrik arzını sağlamakta ne kadar başarılı olduğu ve ne kadar elektrik ticareti yapıldığı gibi ölçütlerdir. Bu ölçütlerden, özellikle, hanelerin ödediği elektrik faturaları oldukça önemli olup, bu hanelerin mevcut elektrik şebekesine bağlı oldukları takdirde aynı tüketim ile ne kadar elektrik faturası ödeyecekleri değerleri ile karşılaştırılmıştır. Kurulan benzetim modeli çalışıtırılmış ve kurulan mikro şebekenin tüm kullanıcılar için daha ucuz elektrik sağlayabileceği görülmüştür. Ancak, modelin bazı girdilerinin değişkenliği de bu elektrik faturalarını ve kurulan mikro şebekenin elektrik arzını sağlayabilme yetisini etkileyebilmektedir. Bu girdiler için çeşitli deneyler yapılmış olup, hanelerin elektrik faturaları ve mikro şebekenin çeşitli performans göstergeleri karşılaştırılmıştır. Bunun sonucunda mikro şebekenin elektrik sağlamakta ve haneler arası elektrik alış-verişini düzenlemekte oldukça başarılı olduğu görülmüştür. Bu yapılan deneylerin yanısıra, hem düzgün açık-artırmada hem de teklifin ödendiği açık artırma yöntemleri de bu piyasa düzeni için denenmiştir. Mikro şebekelerin özelliklerinden biri olan hem kendi başına izole bir şekilde çalışabilme özelliği hem de ana elektrik şebekesine bağlı olarak çalışabilme özelliği de bu açık artırma yöntemleri ile beraber performanslarının görülebilmesi adına benzetim deneylerine katılmıştır. Fakat, bilinmektedir ki, mikro şebekelerin de maliyeti tüm ucuzlamalara rağmen halen oldukça yüksektir. Bunun için de yatırım analizi yapılmış olup, elektrik faturaları ile sağlanan tasarrufun yapılan yatırımı kaç sene içinde amorti edeceği araştırılmıştır. Tüm bunlar sonucunda, mikro şebekenin tamamen izole şekilde çalışmasının elektrik pillerinin maliyetlerinin devletsel bir otorite tarafından karşılanması halinde bile halen kârlı olmadığı, ancak ana şebekeye bağlanabilen bir mikro şebekenin maliyetini ekipmanların tahmini hayat süresi içerisinde çıkarabildiği görülmüştür. Sonuç olarak, izole mikro şebekelerin daha yaygın hale gelebilmesi için özellikle elektrik pillerinin ucuzlama trendini devam ettirmesi gerekmekte, bu gerçekleşinceye kadar da daha yüksek yenilenebilir enerji üretimi oranlarına ulaşılabilmesi için de ana şebekeye bağlanabilen mikro şebekenin geçiş süreci için kurulabilmesi önerilmiştir.

# 1. INTRODUCTION

Electricity as a power source is arguably humanity's ultimate creation, almost every aspect of what has come to be the "civilization" has either come to being as a result of electricity's inception or has been *empowered* and has been serving humanity ever since. Not much, however, has changed in the way electricity is generated, distributed and consumed. Electricity grid is one giant machine that spans entire countries and even continents. With a flip of a switch, one might tap into the power that has been generated hundreds of kilometres away. It is impossible not to marvel at the perfection of a machine with such simplicity and proportion, however, a portion of grid's weaknesses and related challenges in the years to come, stems from this very attribute of the electricity grid.

Electricity is not a natural resource and therefore it requires to be produced at some form of a facility, at the expense of other resources. Fossil fuels are one type of these resources used for electricity generation, and the primary suspect for the increasing greenhouse gas (mainly $CO_2$) levels in the atmosphere, regarded to be a prime cause for the dreaded global warming. Some developed countries have reached consensus to reduce the greenhouse gas emissions to alleviate the effects of global warming. By 2030, the members of the European Union have agreed to cut the greenhouse gas emissions by 40% according to 1990 levels and to increase the share of renewable energy sources to at least 27% [1]. The United States, on the other hand, seeks to reduce the greenhouse gas emissions by 80% before 2050 [2]. Such vision requires each stakeholder to cooperate towards fulfilment. This need has become even more pressing with the increasing $CO_2$ emissions worldwide, as reported in the 2018 Global Carbon Budget Report [3], the year 2018 saw an increase in worldwide $CO_2$ emissions by burning fossil fuels by 2.7% compared to a 1.6% increase in 2017. Dreadfully, the demand for $CO_2$ emitting energy sources is projected to increase in the coming decades. The ascent can be observed in Figure 1.1.

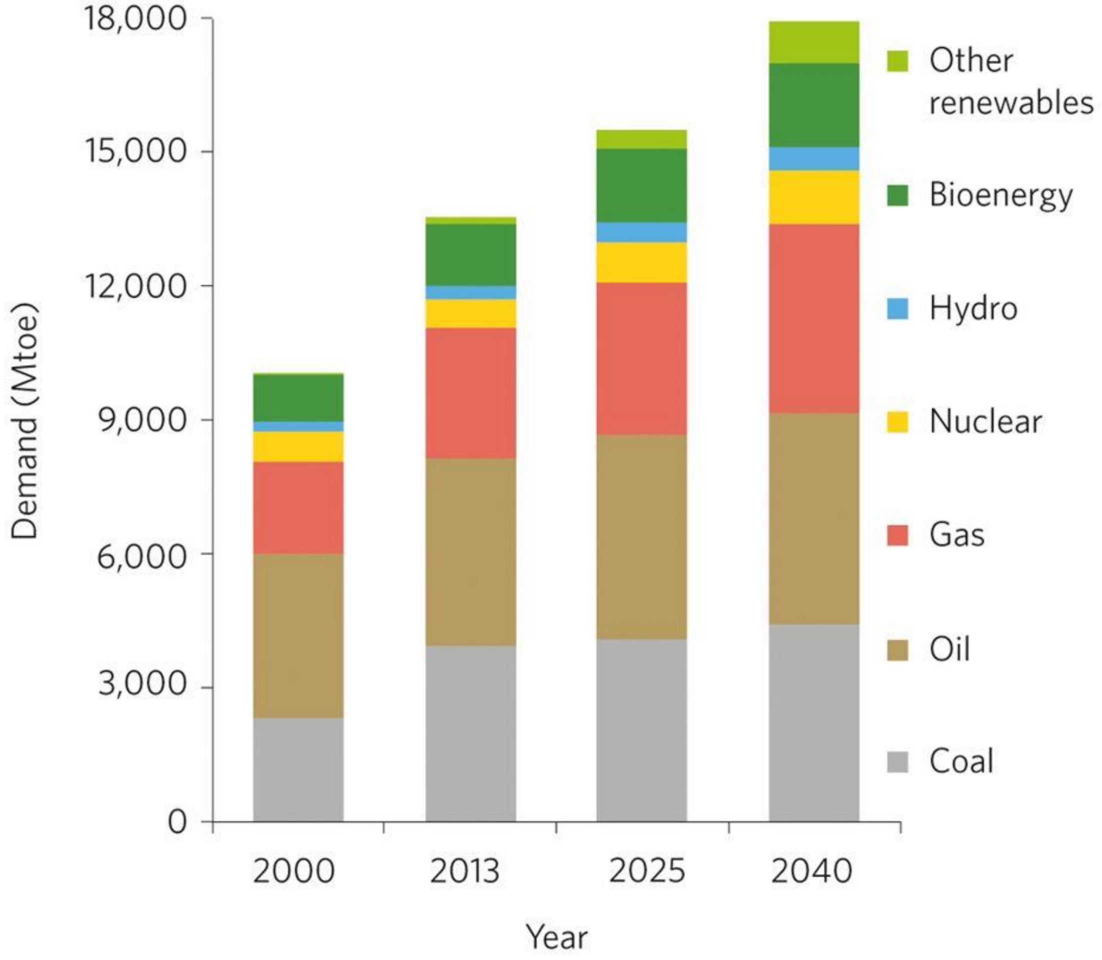


**Figure 1.1** Energy demand for non-renewable resources is expected to grow [4].

The desire to transition from a century-long tradition of fossil-fuel driven electricity generation has expectedly induced its own woes. other non-fossil-fuel electricity generation methods (e.g. Nuclear, Hydroelectric, Geothermal) that can be regarded as clean energy sources have been found to have colossal environmental impacts. Therefore, to achieve the vision of lower $CO_2$ emissions, it is of utmost necessity to effectively utilize solar and wind power which come into play with their own problems and challenges.

Electricity is not a commodity that can be stored conventionally, at least, not without incurring costs detrimental to the profitable operation of electricity providing services. The nature of electricity as a commodity, then, dictates that supply (generation) and demand (load) must always be equal so long as the grid is functional. When the balance shifts in favour of any side, the frequency of the grid steers away from the desired 50 Hz (60 Hz in some regions), causing power overloads or power outages. Because each generator must be generating at the same frequency the grid is on, at that moment. The urgency of the supply-demand balance becomes exacerbated even further with the integration of renewable energy sources that generally behave erratically.

The liberalization of the global economy also happens to be a driving force in the transition and evolution of electricity systems. Contrary to traditional electricity market structure where regulation is a ubiquitous feature of the market, the future electricity grid is thought to be a medium that enables the actors to participate in the market in the presence of minimal number of barriers and minimal amount of regulation.

The advent of new technologies and the change of the economic and financial practices in the global marketplace enabled to progress from century old grid paradigms to new possibilities that can assist the integration of clean energy sources and provide reliable energy to the consumers. It is however, much harder than it sounds. The gargantuan proportions of the electricity grid and the interconnections it encompasses make the transition into a more intelligent electricity grid a formidable challenge. The ever-increasing energy demand coupled with the mentioned issues is driving the policy makers, electricity generators and all stakeholders to seek more reliable, resilient and clean energy technologies.

The answer may just lie in two words: “smart grid”. As defined by the EU Commission Task Force for Smart Grids,

> “A Smart Grid is an electricity network that can cost efficiently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both – in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety.” [5].

The integration of use behaviour has not been possible in the conventional grid framework since it has required constant (mostly automated) communication between the actors in real time. After the introduction of smart meters and energy management systems with proficient artificial intelligence components, it has been made possible, at least in theory, to convert the current grid systems to a “smart grid”. Along with the advantages a smart grid system might bring, the transformation is necessary for alleviating the detrimental effects of the unpredictable nature of renewables via better predictions, reduced transmission losses and more efficient use of the electricity in general. The smart grid might be the only solution to achieve higher penetration of renewable energy sources.

Conventional grid works with centralized generation of resources where the generation of electricity traditionally takes place at remote dedicated power plants. With smart grid, this can finally change because electricity can then be generated at consumption points using renewable energy resources. The practice is known as distributed generation (DG) and is central to this work. DG is defined to be an electric power source that generates power directly in the distribution side of the grid or at the customer site, by Ackermann et al. [6].

A distinction regarding this definition is that of between transmission and distribution. Traditional grid consists of three major elements; generation, transmission and distribution. Generation is self-explanatory, and transmission defines the process of using high-voltage alternating current (AC) lines to transfer electricity through long distances. Distribution, on the other hand, encompasses the delivery of low-voltage electricity to doorsteps of the consumers, usually in residential, commercial or industrial areas. Distributed generation therefore by-passes the transmission phase of electricity production, avoiding the losses that come with it.

Energy storage can be the key to effectively integrate DG within the grid framework, the energy storage costs have traditionally not been very affordable, but this is changing for the better, rapidly. Energy storage units using differing technologies were subjected to an analysis by Schmidt et al. [7] and were projected to decrease in lowest lifetime costs by 36% (2030) and 53% (2050).

The traditional grid is suffering from resiliency and reliability issues. As mentioned above, the grid is a giant machine. Incidents even in the fringes of the grid may meddle with the intricate balances and cascade into a major grid-wide black-out, causing severe pecuniary and non- pecuniary damage. Furthermore, in the case of a natural disaster or a cyber-attack, the grid should stand resilient to mitigate the damage. It is also very difficult to run this huge machine reliably under constantly increasing levels of demand with the current infrastructure.

To remedy these problems, utilizing the idea of DG, a solution was proposed: *microgrid*s. However, for the better part of last twenty years, grid-wide applications of the microgrid idea have remained stagnant due to the profitability and feasibility concerns regarding renewable energy systems and energy storage. The term *microgrid* has several definitions, one of the most prominent is the one given by the Microgrid Exchange Group, an ad hoc group of researchers, and is as follows:

> "…a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island mode." [8]

An important aspect to note regarding this definition is that microgrids are to operate within clearly defined boundaries. This expression should be interpreted as the following: microgrids can be deployed in small communities, creating self-sufficient nexuses of clean energy generating and consuming societies. This idea is the primal purpose of transitioning into a smart grid, signalling that microgrid is the major building block of the future electricity grid. Moreover, one of the most promising features of the microgrid concept is its ability to connect to or disconnect from the grid at will. Grid-disconnected operation is referred as "island" or "islanded" mode, and with the help of this feature, the microgrid can avoid problems caused by the grid by phasing into the self-sufficient islanded operation mode. In the future, the grid may transform into a system of systems, an agglomeration of microgrids.

A microgrid representation showing the connections between the prosumers and the diversification of electricity generation can be observed in Figure 1.2. It is worth noting that setups for microgrids can be very different. The flexibility of the system allows it to adapt to almost any environment.

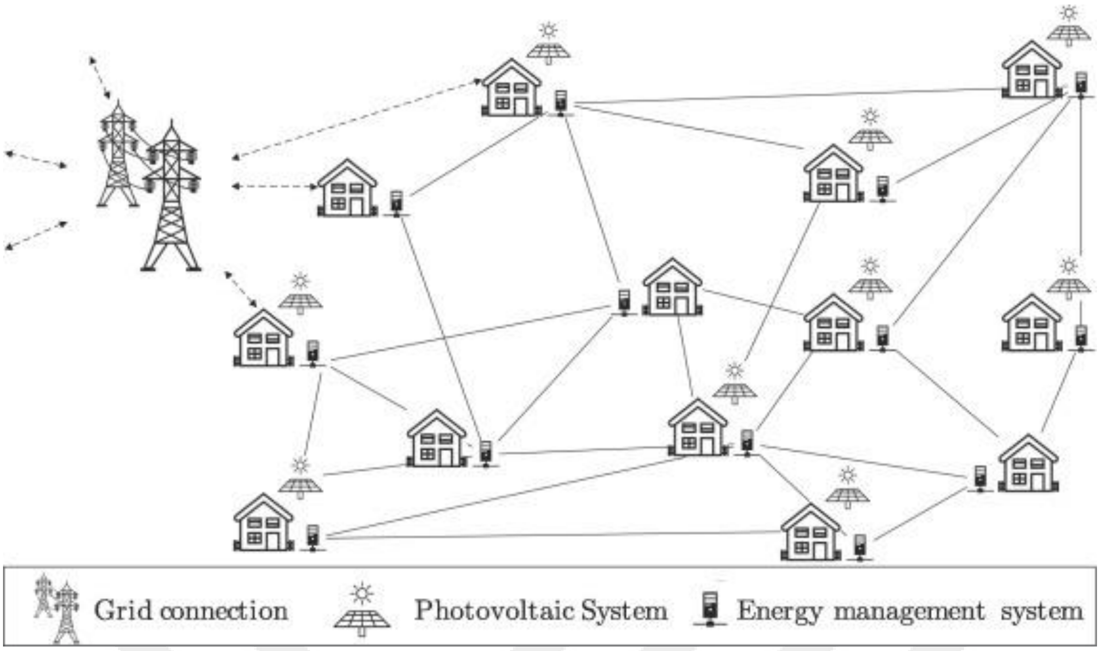


**Figure 1.2** A representative microgrid system, from the study by Mengelkamp et al. [9]

Another idea in the smart grid framework is the *prosumer* actor. In the current grid structure, consumers are merely passive receiver actors. With the integration of distributed generation of electricity and cheaper energy storage systems, consumers have the opportunity to produce and store their own electricity and consume right away or at a later time, hence the name *prosumer*. But this is not all a prosumer can do. In a non-regulated microgrid or a smart grid market, prosumers can sell or buy electricity to or from their peers or the grid. However, prosumers in the current market structure are still governed by the central market entity and priced with a top-to-bottom understanding [10]. With a proper introduction of a decentralized market structure, the potential of liberalized prosumer integration can finally be realized. Before the dawn of the microgrid era, however, there are numerous obstacles that must be overcome.

## 1.1 Renewable Energy Integration Challenges

Renewable energy is clean, but it is not *dispatchable* in the sense that fossil, nuclear and hydro plants are. Dispatch is the practice of assigning electricity generators for generation to specific time windows usually according to a reliable demand forecast.

The non-renewable sources can provide constant levels of power since the power they can generate with respect to the operational parameters, is known. Therefore, they can be assigned to generate a certain portion of their capacity for a certain amount of time, in other words, can be dispatched. Renewable energy sources, on the other hand, generate intermittent and mostly unpredictable power depending on the weather conditions, like, wind speed and direction for wind turbines and solar irradiation for photovoltaic (PV) panels [11]. Which means, renewable energy sources cannot be dispatched, in the traditional sense.

Due to the inability to reliably dispatch renewable energy generators, balancing the supply and the demand at all times, is a daunting task. The variability of the renewables affects the power quality and increase the likelihood of service loss. As the penetration levels of the renewable energy sources increase, the current market structure becomes obsolete.  In microgrids, this problem becomes even more crucial. Microgrids are desired to be self-sufficient when operating in islanded mode.

Thankfully, there are several technologies and methods that can work to alleviate the effects of this problem. Energy storage and *demand response* are examples of these possible solutions.  Large scale energy storage is inevitably going to be a vital part of the future electricity systems [12].  Being able to store electricity when generation from renewables are high and when there is a lack of supply, to consume the stored electricity is surely a gamechanger in dealing with the intermittency issue of renewables. Demand response, on the other hand, is the practice of encouraging the consumers by giving them certain forms of financial compensation to reduce or shift their electricity demand during peak hours [13]. Demand response, with the help of advanced communication technologies and smart meters, can be used in real time. However, the  effectiveness of the methods for incentivization of demand response for the consumers are questionable at best, since some consumers tend to think that the outcome from participating in demand response might now outweigh the investment costs [14]. Microgrids are capable of utilizing both energy storage and demand response.

A concept to note here is the idea of Virtual Power Plants (VPP). Although frequently used interchangeably with microgrids, VPPs incorporate software systems to automatically handle the dispatch and optimization procedures of generation, demand side management and storage resources, providing value to the stakeholders via the utilization of software innovations. Yet, unlike a microgrid, a virtual power plant will always be grid connected. [15]. VPPs can be used to aggregate supply from varying sources and to provide demand response service to the grid.

Renewable energy is cheap, with zero marginal costs, yet, it has the power to take a heavy toll on the electricity market by harshly reducing the market price of electricity, in what is called the *merit-order effect*. As the amount generated by renewables with zero or low marginal costs increase, the market price of electricity tends to dip, in the presence of the price inelasticity of the electricity demand. If left unchecked, this phenomenon might prove to be a deterrent for some investors [16], [17]. Microgrids can offer better local prices to each stakeholder's benefit by integrating prosumers to engage in peer-to-peer trade, using market principles to determine electricity prices.

Several other issues regarding the renewable integration policy covered by Byrnes et al. in the Australian market can be summarized under following points; grid connection costs where a generator must pay a certain amount to connect to the grid, the instability of regulation and policy causing insufficient financial incentives, lack of social/institutional acceptance and issues relating to remote grid disconnected communities [18]. Microgrid deployment in the presence of liberalized policies might prove to be the answer to these hindrances.

## 1.2 Prosumer Integration Challenges and Energy Storage

Prosumer integration is one of the cornerstones of a successful microgrid operation. Active participation from a considerable number of prosumers is necessary to provide continuous and quality power to the stakeholders in microgrids. To achieve the vision of a decentralized, clean and accessible energy, prosumers must effectively be integrated into the grid of the future. For a successful integration of presuming actors, a strategic utilization of the energy storage technologies and techniques is necessary.

Prosumers, in the absence of prohibiting laws and rules, can choose to trade electricity among peers or with the grid itself. This is beneficial for achieving the ever crucial supply-demand balance[19], diversification of generation, the financial outlook of the prosumer actor [20] and higher penetration of renewables [4].

However, several challenges lie ahead before a large-scale adoption of prosumers by the electricity grid. A number of these challenges were shown by Sousa et al. [10] and some of these are as follows; legal and regulatory obstacles, possible energy poverty for some consumers, human involvement in prosumer engagement, technology dependency and being negotiation heavy. But when considered against the achievement of possible improvements after establishing a well-functioning prosumer-based electricity market, the problems start to become only transitionary.

While the prosumer number sees a stable increase [20], energy storage is getting cheaper and becoming a viable solution option for the traditional problems with the unpredictability of the renewable energy sources [21]. As can observed by looking at Figure 1.3, Lithium-Ion storage prices are forecast to drop below 100$/kWh by 2020. From the same figure, solar and wind system prices may be discerned to be following a similar trend. There are several technologies utilizing different methods that can be used for energy storage, a summary of the function of the possible energy storage systems is given by Mariam et al. [22]. According to their work, energy storage should maintain the balance of supply and demand in a microgrid in the presence of load fluctuations, enable the DG units to function as dispatchable power sources and provide the initial energy requirement for transitions between islanded and grid-connected phases of the microgrid.

There are four prominent energy storage technologies that are compatible with microgrid operations, Battery stores the energy in chemical form and when connected to a load discharges the storage as electricity. It is the most popular energy storage choice for microgrids because it can reserve the energy for future demand and it is relatively cheaper than the other options. Flywheel stores kinetic energy, but it is mainly used for power quality improvements and there are only several cases in which it is deployed in a microgrid environment. Super-capacitors store high-cost and limited capacity storage units that store energy in electrostatic fields. They involve no moving parts and no chemical reactions while also being quite efficient. Lastly, fuel cells store fuel energy and convert it to electrical energy at activation.

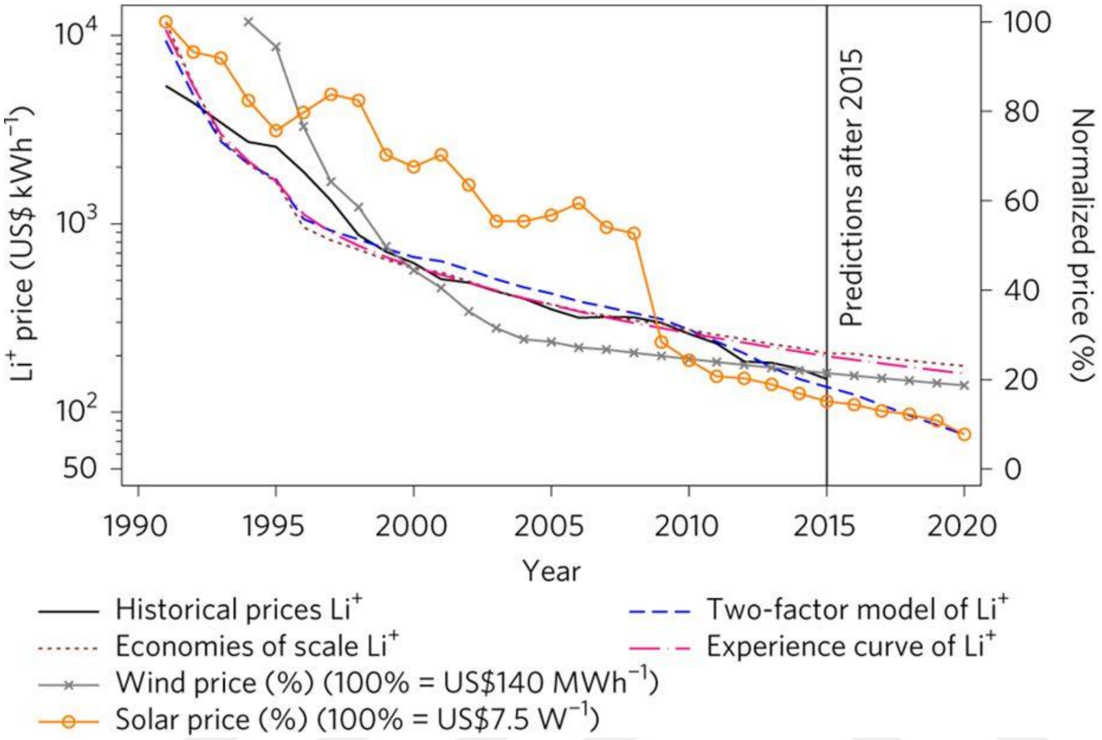


**Figure 1.3** The fare of Lithium-Ion battery prices [21]

The smart grid and energy storage benefit each other. Energy storage helps by providing peak shaving (the practice of reducing the peak load of consumers) and by increasing the dispatchability of renewables. The smart grid, on the other hand, helps by supplying information for more strategic loading and discharging of energy stores. However, in concordance with other smart grid paradigms and innovative energy technologies, several hurdles stand before a high penetration of energy storage utilities including delayed development due to profitability and feasibility concerns and high capital costs of energy storage installations. Also, when deployed as an actor in the traditional grid, energy storage provides no more than peak shaving and load balancing, resulting in limiting its value to energy arbitrage (buying for less, selling for more). With the rise of deregulated markets, energy storage options can provide voltage support and frequency regulation services, emphasizing the need for a comprehensive deregulation policy [23].

The current state of affairs regarding the renewable integration can be summarized in the following manner; higher penetration renewables require widespread adoption of smart energy systems, smart energy systems require microgrids to be effective, microgrids require active prosumers and efficient energy storage, coupled with a capable market structure to envelop all the elements required for a smoothly operating, reliable, resilient and clean electricity grid.

### 1.3 The Purpose of the Study

The current and the future state of affairs, as laid out in the previous sections, requires the employment of the more modern ideas in electricity generation. A localized energy system freed from the confines of the traditional grid might just provide the clean and cheaper energy that will ever be required.  It is worth noting that a localized system does not need to be isolated from the main grid at all times.

In this study, a market structure is developed and tested using real data. The ways which the proposed market structure can help the operation of a resilient localized electricity grid and the ways which it can help the generation of affordable, clean and accessible electricity are investigated.

The main goal of this study is to provide a feasible market structure that fits the nature and the innate problems of localized electricity generation. The structure is expected to contribute to the global energy generation goals described in the previous sections. The primary question of interest whether this market structure is feasible in a microgrid setting. If it is, the secondary questions of interest are, the ability of the structure to deliver cheaper electricity, and the extent to which it can contribute to the future vision of a resilient, clean and affordable electricity grid. The ability of the modern decentralized means of renewable electricity generation to compete with and to replace the traditional grid is vital to its future tenure as a viable alternative.

## 1.4 Microgrid in Literature

Since the conception of the microgrid paradigm, microgrids saw an extensive conduction of research varying from its architecture to its policy implications. Although a rather general review is given here, the main focus and the purpose of this review is to cover the related parts of the literature. Reader must note that technical implementation or similar concerns are not within the scope of this work. It is rather fitting to start from microgrid's role and position in current and future electricity markets.

### 1.4.1 The state of microgrids in current and future electricity markets

As microgrids become technologically feasible, the propensity to deploy microgrid markets and to probe into possible market structures grows rapidly. The integration of distributed generation, storage and prosumers require revisions of current electricity market policies to introduce a more liberalized market structure. Three possible market designs are stated to exist by Parag and Sovacool [20], which are evolving peer-to-peer designs, prosumer-to-interconnected or island mode microgrids; and organized prosumer groups (or community-based groups). As demonstrated by Sousa et al. in their review of peer-to-peer and community-based markets, the distinction between these two regimes are as follows; Peer-to-peer (P2P) defines a market structure in which the actors collaborate with what they have to offer for a commons-based production, trade or distribution of some form of goods or services. In P2P markets there is no central authority that oversees the transactions between the peers. In community-based markets, however, a central authority or a community manager is present to manage trading activities and to intermediate between the community and the rest of the system [10].

The number of works depicting, simulating or designing a P2P market structure started to rise only recently; among them are the study by Zhang et al. [19], in which a trading platform called Elecbay that allows P2P trading in microgrids was proposed. Elecbay, then was simulated and tested using game theory in a low-voltage grid-connected microgrid environment. The simulation results demonstrated the capability of P2P trading to reduce the dependency of the microgrid to the utility grid, balance the local demand and supply and integrate a higher penetration of renewables into the system. All of which are articles of primary motivation behind implementation of microgrids.

The authors conclude with a remark that with the diversification of the actors, microgrids can further the benefits of P2P energy trading.

The scintillating case of Brooklyn microgrid [24] resonated among the microgrid researchers, in a study by Mengelkamp et al. [9], the researchers propose a microgrid market framework based on blockchain technology, seven components that are required for a sustainable microgrid operation and evaluate the Brooklyn case with respect to the derived seven components. These are

a) Microgrid setup: the requirement of a clear definition of the objective, participants and the commodity.
b) Grid connection: at least one point of common coupling must be present to maintain the balance of demand and supply. Also, to enable the construction of a grid of microgrids.
c) Information system: A cutting edge information system must be present to facilitate the information flow among the market participants, provide a market platform and access to it.
d) Market mechanism: To enforce payment rules and to provide a suitable bidding language in a clear bidding format, a mechanism must be well-defined. It should be able to allocate the traded energy by ensuring the coupling of buy and sell orders of the actors within the market.
e) Pricing mechanism: For the efficient allocation of supply and demand, a pricing mechanism must be present. Usually, uniform or pay-as-bid auctions perform this role. Traditionally, a large part of the energy price consists of taxes and other charges, in a microgrid, however, this might be subject to change.
f) Energy management trading system: A system that employs a bidding strategy to automatically maintain energy supply for the market participant that it is subject to. It should require access to the real time data of the participant to forecast its consumption and generation, with the aim of providing sound strategies.
g) Regulation: Microgrids require a legislative framework to be integrated into the energy policies that are in place.

Among others, Lüth et al. [25] develop a linear programming based P2P trading model to evaluate the advantages of two separate market designs and DG setups focused on the battery storage flexibility. The first design is based on a decentralized storage whereas the other is based on a centralized storage. Decentralized storage signifies the distributed storage, privately owned by the prosumers; centralized storage, on the other hand, denotes a storage entity owned by the community. In both cases the price is determined dynamically.

The model minimizes electricity costs of a small locality subject to the usual requisites of an electricity grid operation. The findings of the study assert that both options are viable and provide electricity bill reductions. It is worth noting that the authors state that the future research on this subject should focus on the integration of local energy markets into the intra-day and day-ahead market regime.

Following their own advice, the same group of researchers, Zepter et al. [26], provide another work on the subject, specifically on the prosumer integration in wholesale electricity markets. Using a two-stage stochastic model and their proposed interface STEP (smart electricity exchange platform), the researchers test the value of P2P trade in the context of prosumer integration into the intra-day and day-ahead markets.

Moreover, Morstyn et al. [27] discuss the possibility of bilateral contract networks for a new scalable peer-to-peer market design in which they investigate real-time and forward markets incorporating contracts between generators, suppliers and consumers. The authors find some preferences that maximize the utility of each actor to establish a stable network of contracts with energy trading. Paudel and Peng [28] propose a hierarchical peer-to-peer framework for future networks of microgrid distribution. They show the capability of their proposed framework by an application in a small-scale distribution system, with results indicating that the proposed hierarchical peer-to-peer framework provides better cost reduction than a regular P2P scheme. They note that, with the addition of demand response and energy storage, the work can be extended. Zhou et al. evaluated three different P2P mechanisms, namely, supply-demand ratio, mid-market rate and bill sharing using a multi-agent simulation framework, with a result in which supply-demand ratio outperforms the other methods [29]. El-Baz et al.[30] studied the synthesis of electricity markets and microgrids, proposing a double-sided auction model that considers the limitations of the devices that are bidding. The model works discretely in near-real time and forward markets.

The results show that, while cutting the prosumer costs by around 23%, the proposed model increases the self-sufficiency of the microgrid.

Furthermore, Moret et al. [31] investigate the computational properties of negotiation algorithms for peer-to-peer electricity markets and find that without hybrid approaches or simplification of the negotiation procedures, challenges are likely to arise in the presence of a high number of market participants. It should be noted that some of the works listed here concern the microgrids, others, on the other hand, concern the entirety of the electricity grid. Some of the works can be specialized for the microgrid case. For a review of existing peer-to-peer energy trading projects in or among microgrids, the reader can refer to the work of Zhang et al. [32].

Community based microgrids has also seen the body of research governing the related topic grow. Ma et al. [33] provided a generic framework for a community-based microgrid with wind turbines, PVs and combined heat and power generations, as a result of their simulations, the technological feasibility of the proposed system was demonstrated. An investigation into the feasibility of reducing energy costs via the employment of P2P trading in community microgrids was conducted by Long et al. Three market structures much like the work by Zhou et al. [29]; bill sharing, mid-market rate and an auction-based pricing strategy, were subjected to analysis by the authors in a community microgrid with PV systems, validating the effectiveness of the proposed mechanisms[34]. A book chapter by Bird et al. investigates the resilience of community microgrids and analyses the case of the Potsdam microgrid, emphasizing the need to engineer an electricity grid that could withstand large-scale catastrophes [35]. A double phase aggregated battery control to facilitate peer-to-peer energy trading in community microgrids was proposed by Long et al. [36], in which individual prosumers use a third party entity to regulate their generation. In the first stage of the proposed system a constrained non-linear programming optimization minimizes the costs, then, in the second stage a rule-based control considers some real-time input to control set points. In the end, the proposed method was able to reduce the community energy costs by around 30%.

Overall, it is possible to observe, that the body of research continues to grow with an expedition. Currently, only several works are present within the topic of microgrid markets. The number can be expected to increase as the newfound feasibility of microgrids necessitate sound market structures to accompany the technological research on microgrids.

### 1.4.2 Simulation of electricity markets

Before proceeding to microgrid simulations, it is useful to infer some insights from the existing simulation practices on the electricity market. To that end, a brief review of the works pertaining to this subject is going to presented. There are several approaches to electricity market simulations and chief among them is the agent-based simulation approach.

Before moving further on, it is necessary to provide the fundamentals regarding agent-based simulation.

#### *1.4.2.1 Agent-Based Simulation*

To understand what agent-based simulation models are, it is necessary to understand what complex systems are. Perhaps what Aristotle had the say on the subject still has some degree of validity, as he said, “The whole is more than sum of its parts.”. Indeed, complex systems are more than the congregation of their elements. Complex systems are systems that are unpredictable in which their behaviour is unlikely to be reminiscent of the properties of the elements that comprise the system. Complexity should not be confused with complicatedness. Complicated systems are usually accompanied by sheer size and not as hard to analytically solve or behaviourally predict as complex systems. Examples to complex systems come in many varieties since almost every system that involves human factors can be considered complex systems. The electricity market, without a doubt, falls under the complex system denominator.

A fitting method to grasp the intricacies of complex systems can be found in Agent-Based Modelling (ABM). ABM is an approach that aims define and incorporate the behaviour of the elements (or agents) in the system and build the system with a bottom-up approach. The agents can be anything that is integral in understanding or reconstructing the overall behaviour of the system. Agents tend to communicate with other agents, and react to changes in the environment and to the actions of other agents. Most of the time, complex systems are composed of parts that behave pre-emptively. To capture that behaviour, agents in the Agent-Based Models are required to have some degree of learning capacity. The global behaviour of the system, then, emerges from all the micro interactions that occur within the model.

Usually, the Agent-Based Modelling approach is used in Agent-Based Simulation models. In the electricity market modelling literature, the use of agent-based simulation is heavily favoured by researchers since it is one of the better methods in trying to capture the supposedly rational behaviour of the actors. In 2014, Ringler et al. [37] provided a major review of the works concerning the simulation of electricity markets and in particular, smart grids. It is not surprising that the locus of the research is around the more modern grid paradigms, namely demand response and distributed generation. Further, it is worth noting that, by 2014, not much tangible research was available on possible markets to govern microgrids. As noted by the authors, studying smart grid and its paradigms with Agent Based Modelling and Simulation is still a young and a limited research area and further research should take an even more pronounced approach on the analysis of local trading and local storage systems, which is exactly what this certain piece of research is attempting. In an earlier review of the subject of agent-based simulation of electricity markets, Sensfuß et al. [38] indicates that agent-based modelling is a capable means to produce insightful analyses into market design of electricity systems, further justifying the choice of agent-based simulation approach for this study. The remaining cutting-edge research, as narrated by the authors, is centred around the simulation of the idea that agent-based energy management systems could be used to help control the future electricity grid. Guerci et al. [39] introduced agent-based modelling approach -or agent-based computational economics (ACE) from the vantage point of economists- as a suitable method to study various issues in the electricity market. They further indicate that Erev-Roth and Q-Learning algorithms are quite useful for simulating the learning processes of the agents in agent-based models.

Among the more prominent research in the field is the work of Zhou et al. [40] on analysing the benefits of a demand response program with an agent-based simulation model. The focus of the study is the commercial buildings since a considerable amount of avoidable electricity consumption is situated at such buildings. A building profile set that comprises more than 80% of all electricity consumption by all commercial buildings is picked and simulated with proper generating agents under different market structures with varying levels of competition. The findings indicate that employing demand response could provide peak shaving and reduce electricity prices in the market. In the work by Kahrobaee et al. [41], an agent based modelling approach is adopted to test whether various demand side management methods, including electricity trading among neighbourhoods, are useful to decrease peak loads and electricity prices. It turns out customers can save as much as 40% if they participate in the neighbourhood trading programme. With load shifting utilizing electricity storage, a considerable degree of demand flattening, making renewable integration to the system much easier. Vasiljevska et al. [42] investigate the effects of different contracts adopted by customers, that enables the use of different services made possible by installing smart meters. The main performance variables for the analysis are, monetary savings, change in comfort defined by temperature change, CO2 emissions savings and security of electricity supply. However, the customers seemed to remain with more conservative contracts rather than the more technologically advanced, environment friendly contracts. In the study by Zhou et al. [29], three different peer to peer electricity sharing mechanisms are subjected to juxtaposition. Aliabadei et al. provided two works on the field, in of the studies [43] the authors test the feasibility of several classic and hybrid pricing mechanisms under a bidding procedure with learning agents. After simulating detailed learning sessions, interesting result here is that, at the market clearing price, a policy that assigns the remaining demand randomly to the electricity generators seem to be the better choice in providing more affordable electricity. In the other study conducted by the same group of researchers [44], they build another agent-based simulation model to analyse the effects of Q-Learning parameters on decision making under risk and uncertainty. The authors conclude that, following an acceptable level of risk averting policy can increase the profits of a market participant.

For the other not directly electricity market related works, Hansen et al. [45] provide a literature review on the use of agent-based modelling as a tool to assess the benefits of a possible transition, change or an upgrade on a present electricity system. Energy transition as a definition could also include the installation of microgrids. The authors recommend an interdisciplinary approach to aid the policy making procedures with agent-based models, since they must also incorporate the social aspects of the issues at hand. Chappin et al. [46] provide an agent-based simulation framework to monitor and adapt to the climate change and its policy implications for energy systems.

Overall, it can be observed that agent-based simulation is a well-established tool for studying the electricity grid. When supplemented with learning methods or other advanced statistical methods, agents can quickly approximate to the real-world behaviour of the stakeholders in systems.

#### *1.4.2.2 Agent-based simulation of microgrids*

The difficulties surrounding the real-life applications of microgrids due to practicality concerns engendered the various approaches for microgrid modelling to take the spotlight. This has led to a great amount of research to be produced in modelling of microgrids. For the evaluation of microgrids, simulation seems to be the go-to choice for the practitioners. In an attempt to solidify agent-based simulation as a form of good practice, Kremers et al. [47] argue that conducting the agent-based microgrid simulations with a double-layered approach should cover both technical and systemic issues. A simple model is built on the AnyLogic software with six agents but the study seems to be focused more on the technical implementation of microgrids. Peer-to-peer or other smart grid paradigms are not included in the model. It is, however, a noteworthy study in the field due to I ts nature as a pioneer. Many studies seem to have used the double-layered framework laid out by this study. Alzahrani et al. [48] choose to define microgrids as *systems of systems,* the conglomeration of numerous likely autonomous systems cooperating for a purpose. The definition is quite fitting and its accuracy can be discerned just by glancing at the framework of microgrids. The authors present the technical feasibility of a microgrid using a real-world example in the US. However, the study focuses solely on the technical aspects not on the market implications. The findings of study indicate that similar microgrids could be installed with proper controlling measures.

Mengelkamp et al. [49] investigate the efficiency of different electricity storage approaches under a peer-to-peer market structure. Agents in the simulation continuously solve linear programming models. This study is one of the few that features a focus on the market structure rather than the technical plausibility of microgrids. The authors state that without an installed energy storage system, only around 26% of total the electricity demand would be covered, thus justifying the vitality of storage systems in microgrids. The simulated microgrid uses a community energy storage system, which all the qualified prosumers in the microgrid are allowed to make storage operations with. The authors assert that, with further studies on intelligent automated bidding strategies (they employed only zero intelligence agents for the bidding task), enveloping legislative framework  and fitting market structures microgrids could prove to be an alternative to the possibilities for localized generation of electricity , Li et al. [50] propose a reinforcement learning based control system for grid connected microgrids, they compare several state-of-the-art reinforcement learning methods for the task. Their study features no peer-to-peer trading but the prosumers can feed-in their excess generation to the grid, if the grid buying price is desirable for such occasions. The study by Sanseverino et al. [51] is an another attempt to assess the technical feasibility in microgrids but their work is focused on island mode of microgrids. In the study, agent-based simulation is used to solve the optimal-flow problem, which is a prominent issue in the field of electricity grid research. Agents communicate with each other to direct the flows through the more efficient buses.  He and Sharma [52] build an agent-based simulation model, abiding by the double-layered simulation framework, with the ability to expand the generation capabilities, the agents employ the Erev-Roth reinforcement learning algorithm. Finally, Prinsloo et al. [53] build an agent-based simulation approach to ascertain the capabilities of microgrids to bring affordable electricity to remote rural localities.

Considering the lack of quantity in the agent-based simulation of microgrid market structures and the relative youth of this particular branch of research, therefore the topic of choice for this study seems justified and appropriate.

# 2. PROPOSED MARKET STRUCTURE

## 2.1 Coherent Arbitrariness

As evinced by the work of Mengelkamp et al.[9], one of the pillars of a functioning microgrid is the existence of a market structure and a pricing mechanism. Previously in this study, the erratic behaviour of the renewable generation sources and the necessity to incorporate energy storage systems was discussed. The nature of renewable generation creates an uncertainty regarding the true value of the supplied commodity, in a small microgrid, the number of generators to be aggregated also tends to be small and this number might not be enough to form a predictable supply curve. Under uncertainty, as shown by the work of Ariely et al., [54], buyers tend to have difficulties in pinpointing the value of a commodity. The phenomenon that even ostensibly or inherently irrelevant factors can affect the valuation process of a commodity for market participants is named to be *coherent arbitrariness.* The findings of the study by Ariely et al. were corroborated by Hanley et. al [55], in a study where they found that participants are willing to report their valuations as intervals and the size of the intervals are affected significantly by the experience participants have on the subject.

The malleability of the reported prices by the market participants show that, they, instead of having point valuations for commodities, rather have an interval that represents their valuations. Furthermore, even with enough experience, the valuations are shown to be still somewhat arbitrary. Experience is demonstrated to create, however, an anchor that the participants can base their prices on. Assuming that, the volatility of supply and demand levels in the microgrid affects the inherent value of the electricity as a commodity, then the assumption that even automated buyers and sellers could have problems in constructing accurate approximations for the true value of the supply of electricity at a given time, automatically follows.

Since forecasting for the dispatch of dispatchable elements in the microgrid to maintain the supply-demand balance is very crucial, it is useful to record the past forecast errors in some form and to discern a possible pattern among the errors. One of the propositions of this work is to use forecast errors to account for the unpredictability of the electricity supply and demand in a microgrid. The *coherent arbitrariness* phenomenon, on the other hand, is proposed to be the basis for constructing bidding intervals for the double-auction market mechanism.

## 2.2 Double-Auction Market Mechanism with Forecast Error Adjustment

The focus of this study is on the real-time microgrid markets that encourage P2P electricity trade. P2P Electricity trade has its own challenges; as discussed previously. Without a market mechanism in place, the microgrid not only loses one of its major highlights, but also its ability to reliably balance consumption and generation.

An auction is defined to be a construct that conveys price and quantity information from and to sellers and buyers. If this exchange is a one-way procedure, then the auction is a *single auction*, if both parties actively participate in the market, then it arranges the *bids* of buyers and the *ask*s of sellers and this form of auctions is known to be the *double-auction* [56].

Double auction mechanism for P2P trading is proposed to be a valid market mechanism in the foregoing work by Mengelkamp et al. [9]. Other studies have shown the viability of different forms of double auctions for energy trading in microgrids, including the work of Faqiry and Das [57], in which they propose a double auction algorithm that incorporates proportionally fair allocation of energy. Another algorithm by Majumder et al., [58] continuously solves optimization problems to maximize the social welfare of the participants . A work by Guerci et al.[59] facilitates two different reinforcement learning algorithms, one of which being the Q-learning algorithm, to approximate different behaviour of buying and selling agents under two double-auction settings. Rosen and Madlener [60] develop an understandable auction mechanism aimed at the prosumers in local electricity markets, because the ones who are trading energy are not seasoned traders and therefore must be tailored to their needs and information level. Their findings indicate that, in a competitive market, the price convergence is achieved rather quickly

The study by Block et al. [61] also offers a double-auction mechanism that takes into consideration the requests of the interested parties, these request may vary from price restrictions to capacity restrictions. They provide a mixed integer problem to model the microgrid market with combined heat and power (CHP).

Interval bidding utilizes the idea of *coherent arbitrariness*. Banerjee and Shogren [62] studied the behavioural difference between point and interval approaches on valuation and bidding procedures in different auction settings. Their findings partially support the findings of Ariely et al. [54] and support the finding that that people are willing to bid with intervals as stated by Hanley et. al [55]. One of the combinations they experimented with is the coincidence of point valuation and interval bidding. This study makes use of the same approach to construct bidding intervals.  A study by Mahieu et al. [63] investigates interval bidding to elicit the preferences of the participants as probability distributions. A simpler approach but a different take to approximate valuations of the participants is adopted in this work.  Because, in microgrids, lingering inaccuracies of demand and supply forecasts causes the uncertainty of the valuations of the participants to exacerbate. Even the best forecast methods tend to have abysmal forecast errors and it is necessary to anticipate such occurrences. Therefore, in this work, a double auction mechanism that allows the participants to place their bids by constructing bidding intervals using the hourly average percentage forecast errors is proposed.

The forecasting error metric of choice for this study is the Mean Absolute Percentage Error (MAPE). The formula is given below (2.1):

$$\boldsymbol{MAPE}(\%) = \frac{\mathbf{100}}{\boldsymbol{n}}\ \mathbf{x} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \frac{|\hat{\boldsymbol{y}}_{\boldsymbol{i}} - \boldsymbol{y}_{\boldsymbol{i}}|}{\boldsymbol{y}_{\boldsymbol{i}}} \tag{2.1}$$

Where $n$ is the total number of observations in the forecasting period, $\hat{y}_i$ is the forecast for period $i$ and $y_i$ is the true value for the observation.

In the double auction procedure, the buyers bid their maximum affordable prices and the sellers ask for a minimum desirable sale price for the commodity to be traded. However, considering the uncertain outlook of supply-demand balance and *coherent arbitrariness,* the prices offered by the participants might not converge to the true value of the commodity, resulting in an inefficient market clearing price and a suboptimal social welfare.

Below, assuming the demand for buyers and the supply for sellers equal to 1, in Table 2.1: Regular double-auction , $s_i$ denotes the minimum price seller $i$ is asking for the commodity and $b_j$ denotes the maximum price the buyer $j$ is willing to pay. In the representation below, $s_i$ are sorted into an ascending order and $b_j$ into a descending order. Given that $s_1 \leq b_1$ and $s_4 > b_4$, the conventional incomplete information double auction procedure (the participants only have the information of their own valuations, not of their peers) is as follows;

**Table 2.1**: Regular double-auction setup

| Sellers | Buyers |
|---|---|
| $s_1$ | $b_1$ |
| $s_2$ | $b_2$ |
| $s_3$ | $b_3$ |
| $s_4$ | $b_4$ |
| $s_5$ | $b_5$ |

Starting from the lowest seller and the highest bidder, the participants are matched as long as $s_i < b_j$.

The **market** is said to be *clear* when all potential buyers and sellers are matched. The market clearing price $p_c$, according to example above, is between $s_3$ and $b_3$. In some forms of double auctions $p_c$ is calculated by the equation shown in (2.2) [64].

**Table 2.2** shows the cleared market and matched participants.

The market is said to be *clear* when all potential buyers and sellers are matched. The market clearing price $p_c$, according to example above, is between $s_3$ and $b_3$. In some forms of double auctions $p_c$ is calculated by the equation shown in (2.2) [64].

**Table 2.2**: Market clearance with double-auction

| Sellers | | Buyers |
|---|---|---|
| $s_1$ | $\Rightarrow$ | $b_1$ |
| $s_2$ | $\Rightarrow$ | $b_2$ |
| $s_3$ | $\Rightarrow$ | $b_3$ |
| $s_4$ | ✗ | $b_4$ |
| $s_5$ | ✗ | $b_5$ |

$$\boldsymbol{p_c = \delta * s_k + (1 - \delta) * b_k} \tag{2.2}$$

Where $\delta$ is a real number in [0,1] and $k$ is the index that belongs to the participants that coincide with the market clearing point. It is worth noting that, $p_c$ can sometimes refer to prices higher than the market clearing price if the auction is not a uniform auction. In the uniform auction, all the matched participants trade via the market clearing price, in non-uniform auctions the price could be decided as discussed above.

In the context of electricity markets, the definition of double-auctions is not enough due to the nature of electricity having very little tolerance for supply-demand imbalances. The interval bidding approach helps in this department by allowing the participants to bid in a more flexible manner. Having calculated the MAPE of the forecast for the difference between supply and demand for a specific hour $t$, the bidding approach in the real time market for the buyers can be expressed as in (2.3):

$$B_{k_t} = b_{k_t} * (1 + \mathrm{MAPE_t}) \tag{2.3}$$

And for the sellers:

$$S_{k_t} = s_{k_t} * (1 - \mathrm{MAPE_t}) \tag{2.4}$$

The expressions above imply that buyers bid their maximum affordable price with the interval $[b_{k_t}, B_{k_t}]$ and sellers ask a value in the interval $[S_{k_t}, s_{k_t}]$. By increasing the maximum affordable prices and decreasing the minimum allowable prices help the system to, in case of unexpected supply-demand difference surges in either direction, adapt to the changes and set the market clearing prices accordingly.

There is one final matter on this subject, that is, the distinction between uniform auctions and pay-as-bid (or discriminatory auctions). In uniform auctions, the transactions are realized using the market clearing price while in pay-as-bid auctions each transaction takes place with the corresponding negotiation price. Both these types of auctions are compared in this study.

## 2.3 Features of the Proposed Market Design

The primary goal of the proposed market, as in any electricity market, is to provide reliable and resilient service to the consumers. In a microgrid, however, this is not a simple task. To maintain the supply-demand balance, the market requires much more than traditional dispatch mechanisms. Thankfully, with the advent of battery storage technologies, there are several methods to maintain the microgrid operations.

Without a considerable battery capacity, it is impossible to integrate high penetrations of renewable generation. Because of that, battery storage takes a central stage in the daily operations of a microgrid. In the proposed market, prosumers can…

- buy excess electricity generation of other prosumers for immediate consumption to cover their own lack of supply.
- buy excess electricity generation of other prosumers for later consumption, in other words, to store in their own storage system.
- buy electricity from the stores of other prosumers for immediate consumption.
- sell their excess electricity to other prosumers for their immediate consumption.

- sell their excess electricity to other prosumers to be stored in their storage systems.
- sell certain amounts of their own storage to satiate the supply needs of other prosumers.
- feed their excess generation to the grid if the microgrid is running on the islanded mode.
- choose their own price for selling and buying electricity, however, they can be penalized for damaging the welfare of other market participants.
- install additional wind and solar generation systems after consulting with the microgrid operator.
- cover the lack of supply from the grid if the microgrid is not running on the islanded mode.

As for the role of the entity, henceforth named the system operator, the microgrid system operator may choose to install and dispatch additional generation units that may or may not be renewable sources. A microgrid consisting of 100% renewable generation might not be possible for most of the regions around the world.

The system operator is responsible for making hourly forecasts for renewable generation and electricity consumption. With the forecasts in hand, the operator can schedule dispatchable generation units if there is any. The operator is also responsible for conveying the average and real time hourly forecast errors to all the participants in the system that require forecast information. Furthermore, it is the operator's task to determine tariffs for the prices of additional generation units if the outlook of the microgrid might necessitate the installation of such units.

If the market chooses to employ balancing techniques including demand response or peak shaving, the operator is the natural entity with the power and knowledge to take these actions. The operator must record the electricity trades that took place between prosumers and the prices the parties involved in the trade negotiated to. If the pricing mechanism involves a modified version of the double-auction method, then the system operator must determine the inputs to maintain the satisfaction of the prosumers as close as possible to the optimal welfare of the market. If a market mechanism necessitates the system operator to pay the market participants some subsidies or premiums, then the operator must be willing to undergo these operations for the sustainable operation of the microgrid and for supplying uninterrupted, quality power to the market participants.

Incorporating the features and functionalities briefly mentioned above, the proposed market design is expected to provide reliable, resilient and clean power to the market participants while also offering better prices that allows the sellers to stay profitable. With better prices and energy generation capabilities, the electricity bills of the prosumers are expected to drop.

# 3. SIMULATION

To test whether the market design proposed in this work fulfils the expectations, an agent-based simulation model is built with real-world data. As discussed in previous sections, simulation techniques and agent-based simulation approaches are particularly well-suited for the simulation of electricity markets and especially microgrids that house peer-to-peer energy trading prosumers. To provide a setting that is as real as possible, real-life energy consumption and weather data is used to create a data-driven agent-based simulation model of the proposed interval bidding based double-auction microgrid market.

## 3.1 Description of the Data: London

Data transparency policies of energy institutions around the world engenders tremendous opportunities to retrieve, use and analyse large, sophisticated data. The United Kingdom (UK) having such policies and a will to transform its electricity grid in line with the European renewable energy vision, has created a great source of energy consumption data collected from smart meter user households. Between November 2011 and February 2014, electricity consumption data of 5567 London households are systematically collected and publicized via the Low Carbon London project by the UK Power Network [65]. This study makes use of this dataset and in this subsection some facts about the selected portions of the dataset are presented.

The high number of households participating in the data collection period is no mere coincidence. UK has engaged in a program to install smart meters by 2020 called the Smart Meter Rollout.

The Low Carbon London project was not only about collecting consumption data but also the project experimented with dynamic time-of-use (ToU) electricity prices. In 1122 of all households participating the project, dynamic prices were used. The project determined three pricing tariffs, first being the “low” tariff in which customers paid 0.039 Pounds per kWh of energy consumed, second, the 0.1176 Pounds/kWh costing “default” tariff and third, the costly “high” tariff at 0.672 Pounds/kWh [65]. For the other households that did not take part in the dynamic pricing experiments, a flat tariff was put in place at 0.14228 Pounds/kWh These prices will be treated as one of the benchmarks for this simulation study. The dataset is accessible via the London Datastore website [66].


**Figure 3.1** Average Hourly Consumption Values of Each Household

To simulate a microgrid to test the proposed market design, 13 Households were randomly selected among the households participating in the dynamic pricing project. 2013 was chosen as the year for simulation and all the relevant data pertaining to 2013 were collected. The dataset for each household contains 17520 (the number of half-hours in a year) entries that correspond to the energy consumed in that half-hourly period. However, for simplicity purposes and to avoid high consumption of computational resources, the datasets are combined into hourly datasets. Below, hourly annual average consumption data for the households are plotted. The horizontal axis represents the hours of the day, the vertical axis represents the average electricity consumption.

As seen in the figure above, Household 1 engages in a very light consumption behaviour whereas Household 2 is a moderate consumer. Household 3, shown in, displays the characteristics of what is called “the Duck Curve”. This household houses very heavy consumers.  Further, one of the high-volume consumers, Household 4, shows an interesting peak around the midday.

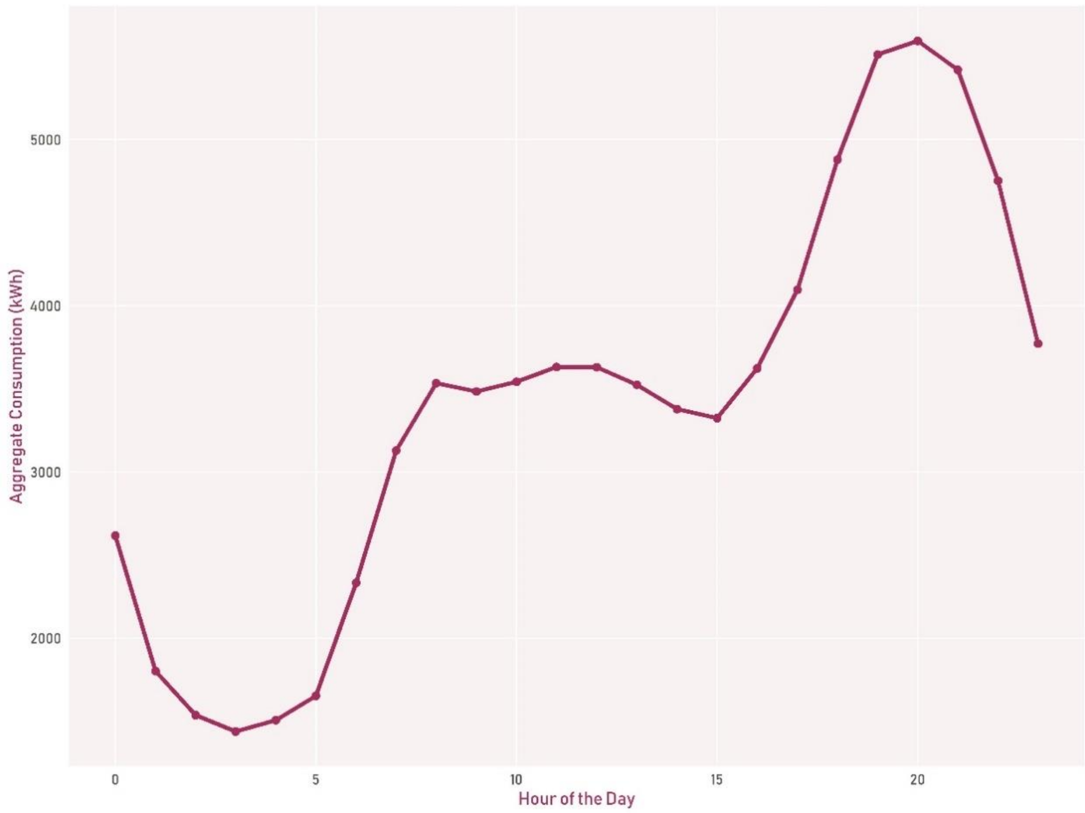


**Figure 3.2** Aggregated Hourly Load

Household 5 displays a light behaviour with what may be called a “pressed duck curve”. Household 6 displays a similar behaviour to Household 5. It is important to notice the discrepancy between heavy consumers and light consumers. When the consumption values of all the household over a course of a year are aggregated, the system displays the behaviour shown in Figure 3.2.  The load profile, known as “the duck curve” is even easier to discern from the plot. There are no unusual load patterns and there is an expected peak around 8 PM. After midnight, the consumption levels dip to daily lows and in the morning climb to a plateau. From Figure 3.3 the monthly trends in electricity consumption can be observed. High consumption in winter can mostly be attributed to heating requirements. The part above summarizes the load profile of the randomly selected households from the dataset. What’s integral to the simulation is, however, the wind and solar energy potential of the chosen location. London is not known for its sunny outlook, yet, considerable amount of electricity especially during the summer could be generated in London.

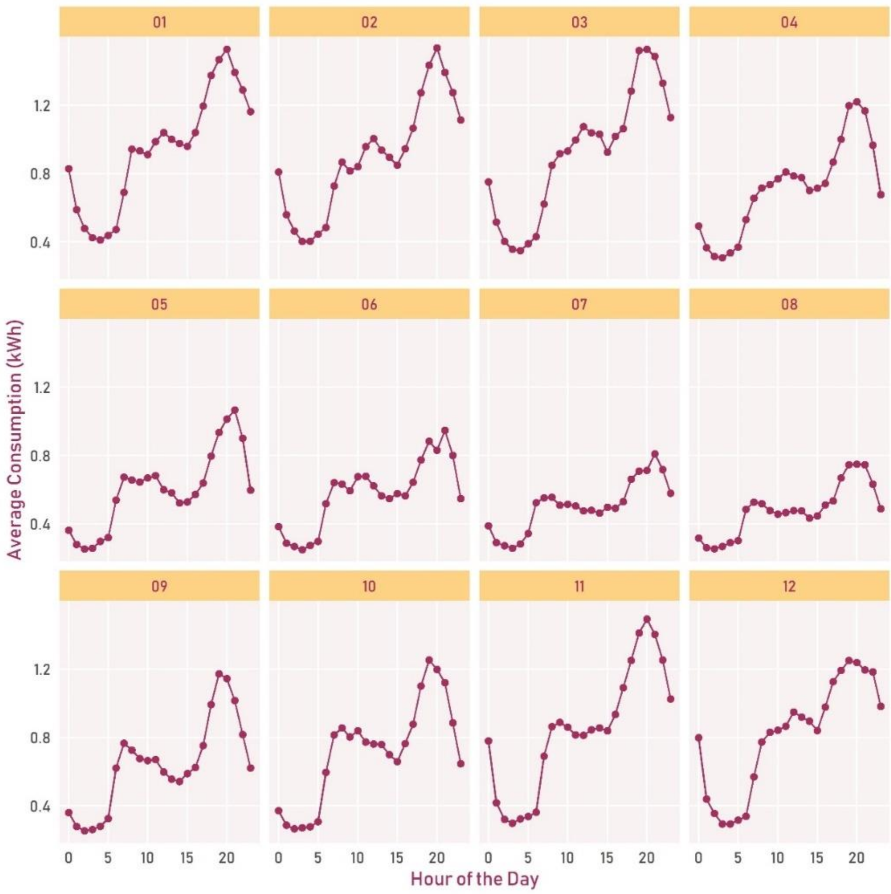


**Figure 3.3** Monthly Consumption Summary

Thanks to numerous databases, data containing hourly entries both for solar irradiation and average wind speeds are publicly available. This study makes use of such databases. The MIDAS project by the UK Met Office [67] features records of mean hourly windspeed data dating back to as early as 1950s taken from the vast number of stations around the UK. Similar to the handling of the load data, the dataset from the year 2013 was taken. Heathrow station was chosen since the airport located there is not obstructed by any buildings and could provide a better approximation for the widespread wind energy tendencies in the vicinity. The measurements were taken at a height of 25 meters which is an acceptable height for the installation of residential wind turbines. Due to the nature of wind, the wind displays an erratic behaviour that could partially be attributed to the distance from the ground level [68]. Therefore, the measurements at 25 meters should provide a rather accurate estimate for the wind energy potential in the area.

The more elusive and trickier is finding a reliable solar irradiation database. There are many methods to measure solar irradiation and many do not account for all the necessary factors. Solar irradiation a location receives could be estimated by the longitude and latitude of that location, because any point on Earth is periodically bathed in solar energy from distinct angles along the course of distinct durations. However, such methods do not stem from localized observations and are usually inaccurate mostly because their lack of consideration for numerous obstructing factors. The Photovoltaic Geographical Information System (PVGIS) has been developed as an initiative of the European Commission and provides reliable solar irradiation data based on observations, for most of Europe and its surrounding regions [69]. The interface with which the users can communicate also recommends installation angles for photovoltaic cells. This study assumed that the photovoltaic cells in the simulation are installed in lieu of the recommended optimal angles by the PVGIS interface. The values found both in the wind data and the solar irradiation data are properly converted to their metric system counterparts.

The histogram of mean hourly wind speed data is shown below in Figure 3.4. Hourly wind speed values generally tend to follow the Weibull distribution [70]. This seems to be the case for the dataset retrieved from the MIDAS project. It is therefore possible to infer that there is not much complication with the wind speed data and it is authentic.

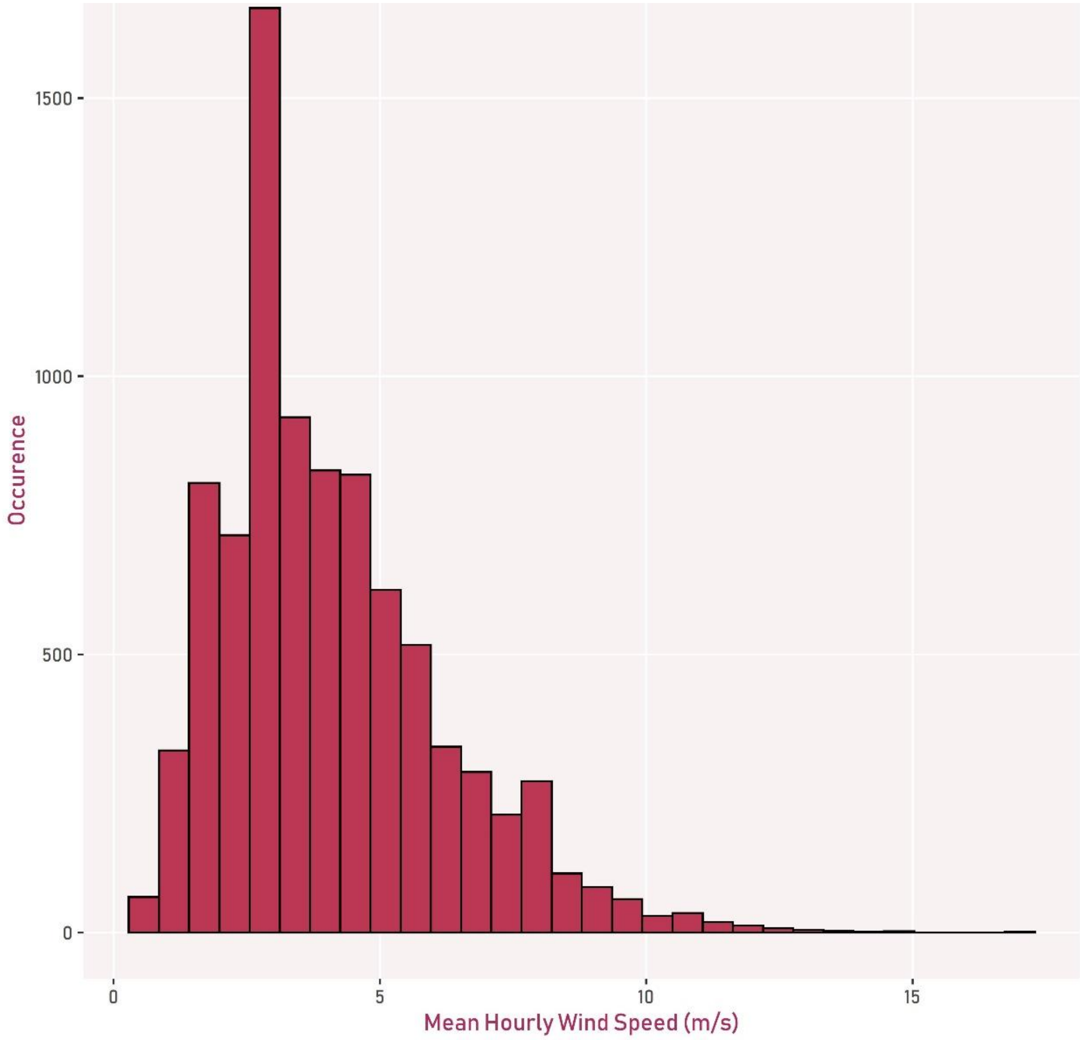


**Figure 3.4** Mean Hourly Wind Speed Values Histogram

The distribution of average hourly solar irradiation values throughout the months could be observed in Figure 3.5. Unsurprisingly, the solar irradiation values are higher in summer days and dramatically lower in winter. Combined with the increased need during winter nights to engage in heating activities that require a large amount of electricity, the task to provide reliable simultaneous electricity becomes even more pressing.

The main challenge of supplying the increased consumption levels in winter months by diminished renewable supplies during those times, could only be overcome by rigorous utilization of energy storage units when the microgrid is operating in the islanded mode.

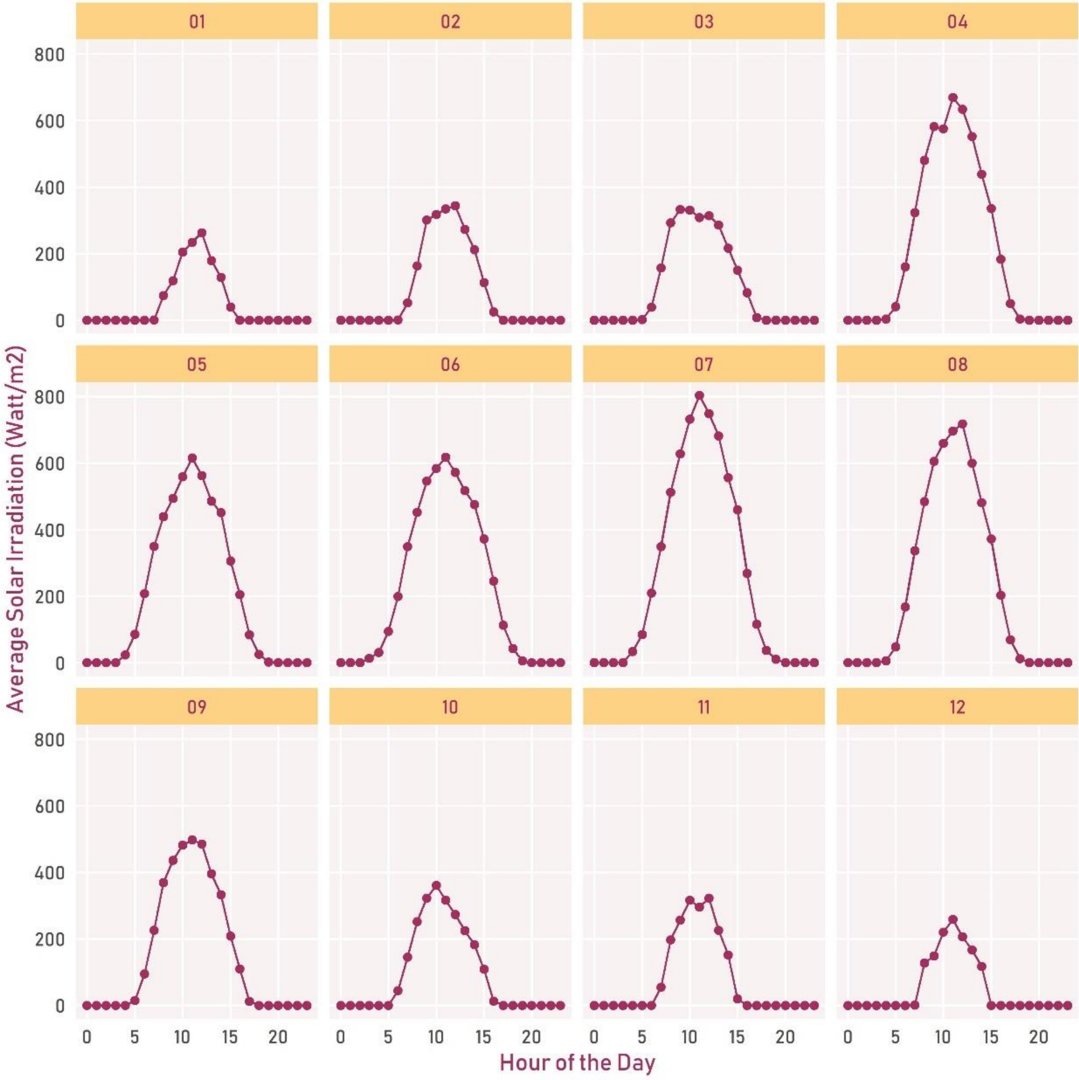


**Figure 3.5** Average Solar Irradiation

The data fed to the simulation is summarized above, there seems to be no obstacles in furthering this study with the data available.

## 3.2 Highlights of the Simulation

The simulation of the proposed microgrid intra-day market structure is aimed to be comprehensive. Using the aforementioned principles and utilizing the summarized data, an agent-based simulation model is built on the *AnyLogic* simulation software using the Java language. Preliminary analysis, data preparation, forecasting, and post-analysis were carried out using the R programming language and several related packages. A Java library for maintaining an interface between Java and R named "RCaller" is used [71]. The interface is used to provide the simulation with on-demand hourly forecasts for load and renewable generation. The forecasts are vital because the proposed market structure featuring forecast error-adjusted bids necessitate the retrieval of forecast errors to function as intended.

There are numerous highlights of the simulation model that are developed to make the simulation as close to the reality as possible. The first and the most important step was the integration of real-world data into the model.

### 3.2.1 Learning agents

One of the more contemporary research topics in agent-based simulation is about making agents decide more intelligently and learn from their previous experiences. Among the algorithms that strive to achieve this goal, the Q Learning [72] and Roth-Erev [73] algorithms are fairly prominent and proficient. Variants of these algorithms have been used in this study to induce learning in agents.

These algorithms qualify as simple reinforcement learning algorithms. Reinforcement learning is defined by Sutton and Barto [74] as "learning what to do". If an agent is learning with reinforcement, then the agent does not know which actions to take at first, but rather learns about the relative benefits of each possible actions by trial and error. This process is known as discovery. After accumulating enough experience, or having spent enough time discovering the environment, agent may be dictated to cease learning and use the experience in choosing further actions.

Q learning is defined as follows:

$$Q(s_t, d_t) \leftarrow (1-\alpha)\; x\; Q(s_t, d_t) + \; \alpha\; x \left[R(s_t, d_t) + \; \gamma\; x\; \max_{d} Q(s_{t+1}, d)\right] \tag{3.1}$$

In the equation above, there are two parameters related to the intensity of learning. The index t represents The parameter $\alpha$ is a real value in [0,1] and it is called the "learning rate". Higher $\alpha$ values induce a more forgetful learning process, in which the recent experiences have more weight in defining the Q values, meaning that the agent is more open to newer experiences and more "eager" to learn.

The other parameter $\gamma$ is called the "discounting rate" and it is also a real valued scalar and an element of [0,1]. This parameter sets the rate at which the immediate and future rewards affect the experiences of the agent. In the auction model, however, $\gamma$ is always 0, because there is no one specific goal at the end of the year, or the learning period. The auctions are run on an hourly basis and each hour is independent of the other.

$Q(s_t, d_t)$ defines the Q value of a possible action $d_t$ at time t and at state $s_t$. Q values represent the value of the potential reward that can be achieved by making the specific decision corresponding to the explicit combination of the given action, state and time.

The essence of the Q-Learning algorithm is that, these Q values are not static. They get updated with the tested reward values according to the pre-determined parameters as long as the learning session is live. $R(s_t, d_t)$ represents the value of the reward received for taking the action $(s_t, d_t)$. It must be noted that the reward must not always be positive. If the action results in an undesirable outcome, then the reward will have to signal that. Further, Q-Learning may or may not include delayed rewards, the possible future rewards are considered using the best Q values for future actions. The algorithm just assumes that, after taking the action, the agent will continue taking the best action rationally.

All the Q values that are constantly updated for every combination for the state-action space exist only for a single purpose: being a guide for making the best decision based on experience and discovery. Before making each decision, all the Q values available for each available action are compared and the action corresponding to the highest Q values is chosen for that specific state and period.

As stated earlier, the learning procedure in Q-Learning could be deactivated, or could be set to occur sporadically. The so-called discovery parameter, ε is a real value representing the probability that the next action taken will be decided not by the highest Q value but randomly among all possible actions.

Roth-Erev algorithm on the other hand is slightly different than the Q-Learning algorithm. The update rule for the classic Roth-Erev algorithm is defined in (3.2) and (3.3). The main difference between two algorithms is, in Q-Learning -unless it is dictated by the ε value- the action is chosen deterministically looking at the highest Q value. However, in Roth-Erev algorithm the actions for each state have their own probabilities. These probabilities are set by the propensity values which are calculated and updated in similar fashion to the Q values. In the equation below, k and j are elements of the decision set, $j, k \in \{1,2, \ldots N\}$

$$q_j(t+1) \leftarrow (1-r) * q_j(t) + \pi_k * (1-e) \qquad if\ j = k \quad (3.2)$$

$$q_j(t+1) \leftarrow (1-r) * q_j(t) + \pi_k * e/(1-N) \qquad if\ j \neq k \quad (3.3)$$

$\pi_k$ represents the reward for the chosen action $k$ at time $t$. The update rules for the chosen action and the rest of the action space are slightly different. The updated values are "propensities": the tendency to take an action. Here, $e$ represents the exploration or experimentation parameter. It is a real value in [0,1], similar to Q-Learning's learning parameter, it dictates the rate at which the algorithm learns. Higher $e$ values make $\pi_k$ less important in updating the propensities. The update of the rest of the actions take place inversely proportioned to the number of actions $N$ available. The recency parameter $r$ affects the rate at which the algorithm forgets previous experiences. Higher $r$ means, less weight given to previous experiences. Initial propensities $q_j(0)$ are input parameters and might have effects on the learning process to an extent.

The expressions given above are only for updating the propensities, Roth-Erev algorithm functions with probabilities. The means to transition from propensities to probabilities is given below in (3.4).

$$p_j(t) = \frac{q_j(t)}{\sum_{i=0}^{N-1} q_i(t)} \quad (3.4)$$

It can easily be inferred from the above equation that probabilities for taking any action is just the reflection of their propensities.

For auctions, however, a variant of the Roth-Erev algorithm could be used. The reason for this is that, the derivation method for probabilities of the classic Roth-Erev algorithm given in (3.4) cannot properly account for negative rewards and propensities. In this study, agents have to overcome negative rewards after they fail to win in auctions.

The variant Roth-Erev algorithm proposed by Sun and Tesfatsion [75] makes necessary adjustments for the integration of negative propensities into the algorithm. The authors used this algorithm specifically for electricity market auctions, making it a viable option for further studies which aim to do the same. The update rules and probability calculations are given below in (3.5) and (3.6).

$$q_j(t+1) \leftarrow (1-r) * q_j(t) + \pi_k * (1-e) \qquad if\ j = k \quad (3.5)$$

$$q_j(t+1) \leftarrow (1-r) * q_j(t) + q_j * e/(1-N) \qquad if\ j \neq k \quad (3.6)$$

The update rules for propensities are the same with a single exception. Instead of updating using the reward value $\pi_k$, the propensities corresponding to the rest of the action space decay according to the experimentation parameter $e$. This is perhaps more suitable for an environment in which the rewards are more volatile, like that of in the auction setting. The calculation of probabilities take place as follows:

$$p_j(t) = \frac{exp^{\frac{q_j(t)}{T}}}{\sum_{i=0}^{N-1} exp^{\frac{q_i(t)}{T}}} \quad (3.7)$$

As seen in (3.7), using the Euler number e solves the negativity problem since any exponent of the number e is nonnegative.

Both of the algorithms are suited to the needs of this particular study. The setting necessitates the utilization of opportunity costs so that the agents could tailor their bids and asks to more appropriate values to their advantage.

### 3.2.2 Renewable generation and energy storage

As stated earlier, one of the major goals of installing microgrid systems is to be able to incorporate distributed generation of clean electricity. The most prominent opportunities for this are installing solar panels and residential wind turbines. Electricity power generation from these sources could be estimated by formulae given in (3.8) and (3.9)

$$Power_{wind} = \frac{1}{2} * C_p * \rho * \pi * r^2 * V_{wind}^3 \tag{3.8}$$

The power generated by the wind depends on the wind speed elevated to the power of three ($V_{wind}^3$), the area swept by the blades (with the radius of $r$) of the wind turbine ($\pi * r^2$), the air density $\rho$ and the power coefficient $C_p$. Air density is estimated to be 1.225 kg/$m^3$ by the International Standard Atmosphere [76]. The power coefficient, on the other hand is a measure of the efficiency of the wind turbine. The theoretical maximum for this value is found to be 0.593 according to Betz's Law. A study by Dai et al. [77] showed that a reliable estimate for this value is 0.397.

The solar power, on the other hand is estimated by the following expression:

$$Power_{solar} = A * r * G * PR \tag{3.9}$$

Where, $A$ is the total area of solar panels installed in $m^2$. the yield of the solar panel denoted by $r$ is defined by the power of a single solar panel divided by the area of that specific solar panel. $G$ is the solar irradiation (Watt/$m^2$) and $PR$ is the performance ratio of the solar panel. According to a report from the WISE-PV Stakeholder

Workshop [78], the average performance ratio for solar panels in UK is 0.84. This value is used throughout the study.

For the modelling of energy storage devices in this study, Tesla Powerwall 2 [79] is used as the storage device of choice. Depending on how heavy the households consume electricity, different number of storage devices are installed for those households. A single unit of Tesla Powerwall 2 can store up to 13.5 KWh of electricity to be used on demand.

The proposed setup of the microgrid is as follows. The number of storage units and solar panels are decided according to the consumption profiles of the households. A standard residential turbine with a blade length (radius) of 2 meters and a standard residential solar panel with a peak power capability of 250W is used in the study.

### 3.2.3 Forecasting

The necessity of forecasts for the proposed market structure were discussed in previous sections. Forecasting various parameters of interest in the electricity markets is a thoroughly studied field. Therefore, many viable forecasting methods have been made available by researchers. For its simplicity and somewhat gentle handling of the computational resources compared to more modern methods featuring neural networks, Autoregressive Integrated Moving Average (ARIMA) models have been chosen as the forecasting method for this study. Providing accurate forecasts is not one of the aims of the study, thus, no further discussion takes place on forecasting. ARIMA models however, are regarded as one of many methods to be relied on for both load and renewable energy generation forecasting, the reader could refer to various reviews on load [80], wind [81] and solar [82] generation forecasting

The ARMA (without integration) models are defined as follows:

$$X_t - a_1 X_{t-1} - \cdots - a_p X_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \qquad (3.10)$$

$X_t$ is the observation of the time series at time $t$. The term $\varepsilon_t$ is the residual of the model at the same time period, while $a_p$ denotes the level of association between the lagged terms of the time series and the current observation. The integer $p$ is therefore the order of the Autoregressive part. Likewise, $\theta_q$ shows the association between the current and lagged error terms, assuming that error terms are somehow correlated with each other. The order of the Moving Average part is signified by $q$. The integration, however, necessitates the use of the lag parameter, with

**Table 3.1** The Microgrid Setup

| Household | Wind Turbine Blade Length (m) | Solar Panel Count | Energy Storage (kWh) |
|---|---|---|---|
| Household 1 | 0 | 0 | 13.5 |
| Household 2 | 2 | 0 | 13.5 |
| Household 3 | 2 | 30 | 67.5 |
| Household 4 | 2 | 20 | 54 |
| Household 5 | 0 | 0 | 13.5 |
| Household 6 | 0 | 0 | 13.5 |
| Household 7 | 2 | 0 | 13.5 |
| Household 8 | 2 | 10 | 40.5 |
| Household 9 | 2 | 0 | 27 |
| Household 10 | 0 | 0 | 13.5 |
| Household 11 | 0 | 0 | 13.5 |
| Household 12 | 2 | 0 | 13.5 |
| Household 13 | 2 | 20 | 40.5 |

the inclusion of integration the model becomes the expression below (3.11).

$$\left(1-\sum_{i=1}^{p}\varphi_i * L^i\right) * (1-L)^d * X_t = \delta + \left(1+\sum_{i=1}^{q}\theta_i * L^i\right) * \varepsilon_t \tag{3.11}$$

$L^i$ represents the lag parameter. The multiplication of the lag parameter by the actual observation $X_t$ gives itself minus its $i$'th lag. The value $\delta/(1-\sum_{i=1}^{p} L^i)$ is known to be the *drift* of the ARIMA model.

The values that need to be forecast are load and the combined generation of wind and solar units. The forecast values are used not only for generating the bidding intervals but for the activation in backup generation units in the islanded mode or the activation of the grid connection in the grid-connectable mode. If the forecast difference between the load and the renewable generation is less than backup generation capabilities and if the current levels of storage is considered not to be able compensate for the lack of supply, then the backup generation is scheduled an hour-ahead to provide electricity. A similar directive is employed for grid connection, basically, if the microgrid cannot sustain itself and it is not operating with the island-only approach, then it can connect to the grid to cover for the deficient supply.

That being said, the necessity arises for the determination of ARIMA parameters.

#### *3.2.3.1 Load Forecasting*

As seen from the summaries of the data, load profiles change drastically from season to season. It is, therefore, highly likely that the behaviour of the data generation process behind the values of interest changes from season to season. The difference in monthly consumption shows that the months could be grouped in three. For the heavy consumption from January to March, Figure 3.6 shows the stationarised time series with the autocorrelation and partial autocorrelation functions.

After first differentiation, the series seem to display, as expected from an hourly time series, a seasonal behaviour at around Lag 24. On the other hand, the autoregressive components of both the regular and the seasonal part of the time series seem to display the behaviour of orders 1 to 2, as evidences by the spikes on the partial autocorrelation function at their respective observations. The autocorrelation function, on the other hand shows that a seasonal first differencing and a first order of moving average might be necessary. After consideration of various combinations, the diagnosis of an ARIMA(1,1,1)x(1,1,1) model, which found to be the best according to the Bayesian Information Criterion (BIC), is shown below.

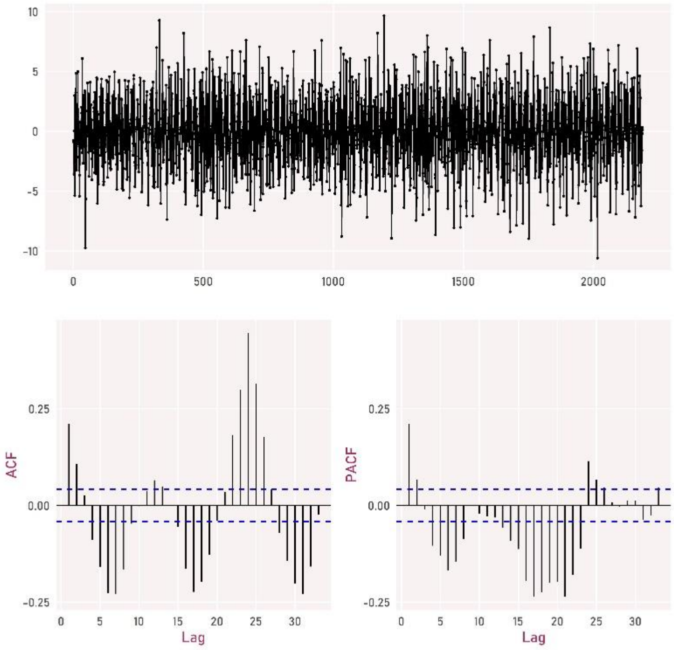


**Figure 3.6** January-March Load Time Series

The residuals seem to display a white noise behaviour and to be almost normally distributed, indicating that the model could be used for forecasting load data. The Ljung-Box statistic fails to reject the null hypothesis that the residuals come from a white noise process (Q* = 2.5788, P= 0.8595).

For from April to August, the same procedure is followed. Below, the pre-analysis and the diagnosis of the first differenced time series can be found.

The following months, as observed on the figure 3.8, display a similar but a subtle behaviour. The same parameters ARIMA(1,1,1)x(1,1,1) is found to the best and the most fitting alternative among possible combinations. The diagnosis of the time series can be found in Figure 3.9. This time, the Ljung-Box statistic (Q*=12.703, P=0.04799) barely fails to reject the null hypothesis. This might be due to the downwards trend in consumption from April to August, while the first three months display a more static behaviour.

The same procedure for the remaining four months yields the following results that can be observed from Figure 3.10 and 3.11. Again, similar patterns can be read from the pre-analysis of the time series in Figure 3.10.

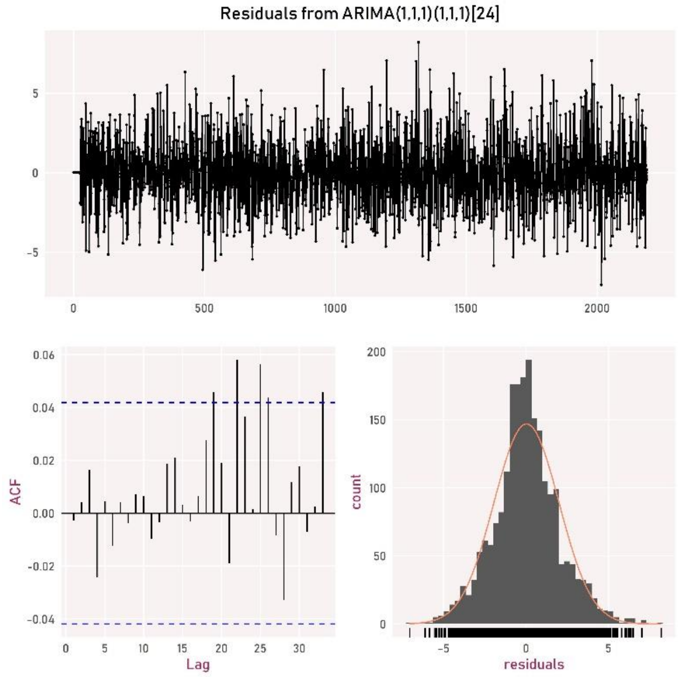


**Figure 3.7** January-March Diagnosis

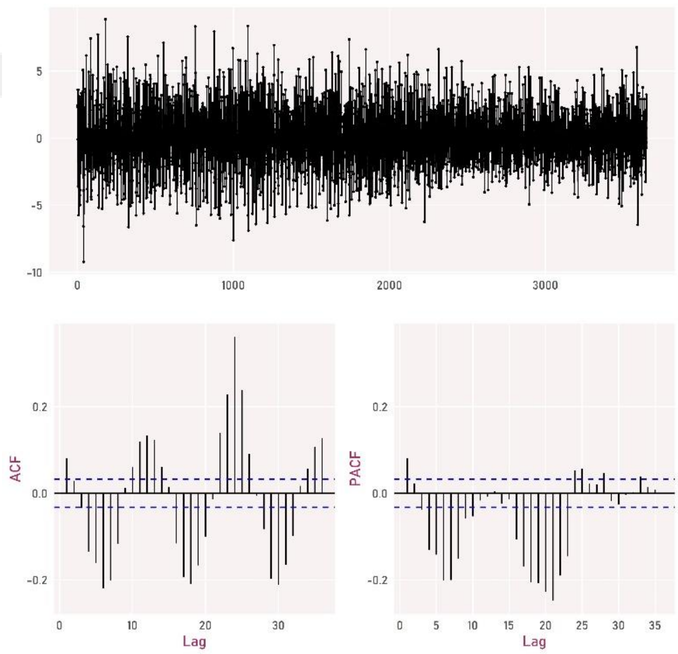


**Figure 3.8** April-August Load Time Series

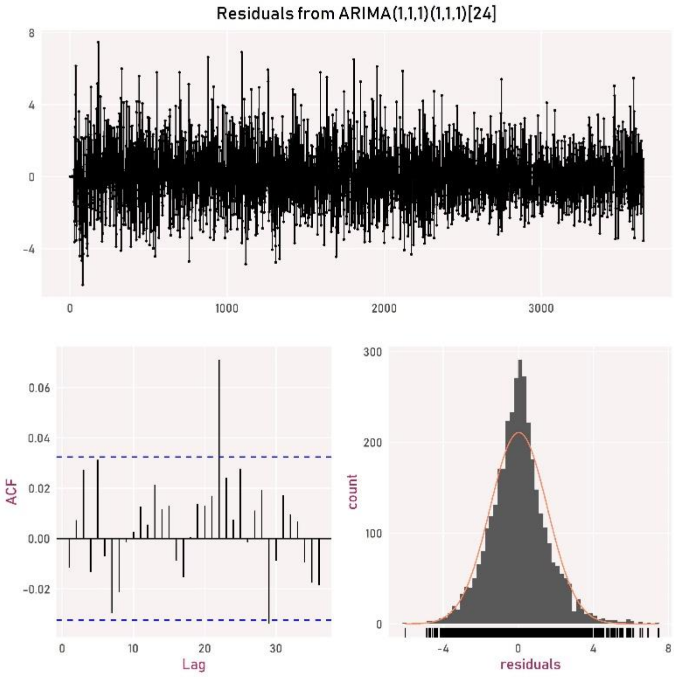


**Figure 3.9** April-August Diagnosis

Therefore, the same actions are taken to ascertain the parameters of this portion of the time series. This time, the hypothesis that the residuals come from the white noise process is rejected but the best alternative in terms of Ljung-Box statistic (Q*=24.171, P=0.00048) is ARIMA(1,1,1)x(1,3,1).

The forecasting during the simulation takes place every hour, using the past 144 observations. This number is a compromise between accuracy, computational resource and recency of the observations, 144 hours equalling to 6 days is tried and found to be good figure for more than 15000 forecasts required in a year. For the first 143 hours, simple mean of the previous observations is taken to provide the forecast.

### *3.2.3.2 Renewable generation forecasting*

The same approach is taken to forecast the electricity generation with renewable resources. While the load is relatively less cumbersome to forecast, the erraticism of renewable generation becomes highly apparent after recurrent attempts at forecasting the fare of renewables.

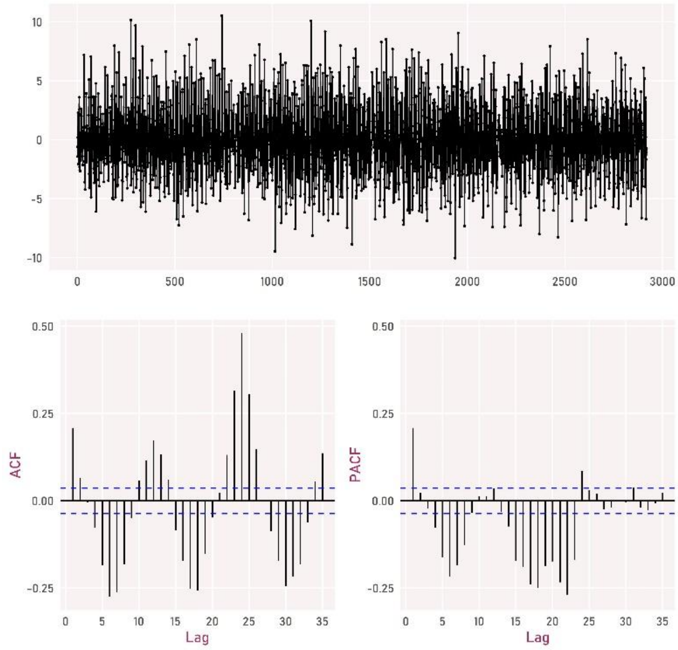


**Figure 3.10** September-December Load Time Series

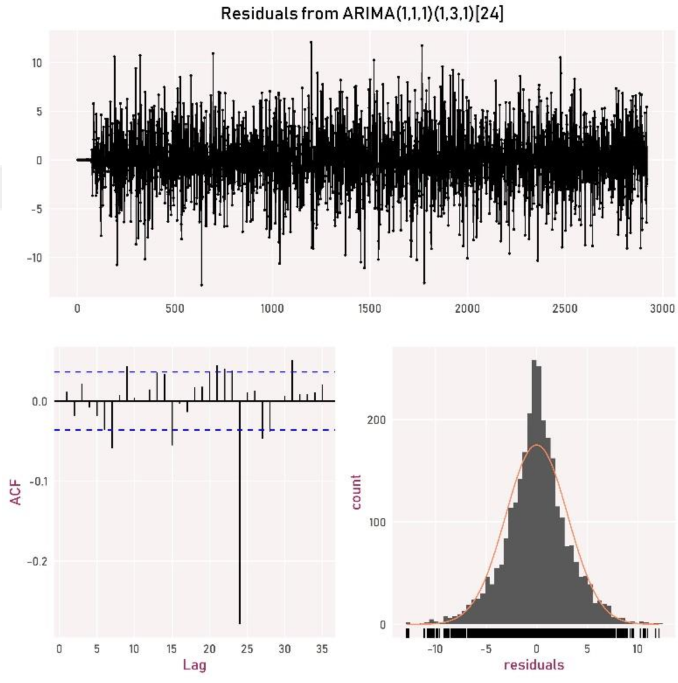


**Figure 3.11** September-December Diagnosis

While rather convincing patterns could be found for load forecasting, the same is not particularly valid for the forecasting the generation with renewables.  The best fit using ARIMA family of models is found to be a non-seasonal ARIMA (1,1,0) process with unconvincing performance in post-analysis.

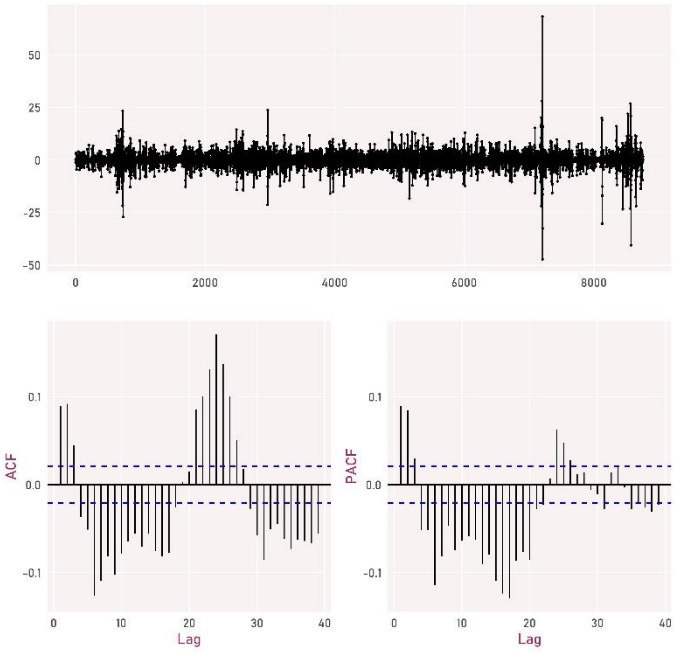


**Figure 3.12** Generation Time Series

Renewable generation values are generated using the microgrid setup given in Table 3.1, and the renewable generation formulae given in (3.8) and (3.9).  The forecast values are aggregated energy values generated by solar and wind power.

Shown in Figure 3.12 is the first differenced time series of renewable generation estimates, from which not much could be inferred. Both Autoregressive and Moving Average components seem to display the behaviour of orders of 0 to 2. After trials, as stated previously the best fit is found to be the ARIMA(1,1,0) model. The distribution of residuals shows a tendency to high kurtosis values while the Ljung-Box statistic rejects the null hypothesis that the residuals come from a white noise process.

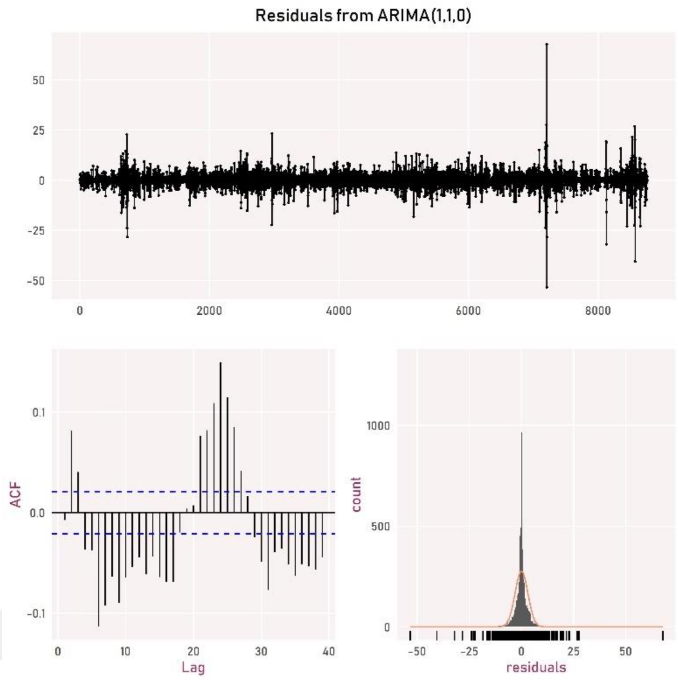


**Figure 3.13** Generation Diagnosis

### 3.2.4 Implications of integrating P2P trading to double-auctions

An elaboration as to how auctions with learning agents work is necessary at this stage of the study. Details regarding various update rules and reward-punishment relations of the learning algorithms are given here. In addition, a further inquiry into how pay-as-bid and uniform auctions relate to the given study is presented.

The double-auction mechanism had previously been summarized in earlier sections. There is, however, an issue that arises from the nature of the islanded operation of microgrids. That being, the double-auction mechanism does not, by definition, allow trades beyond the market clearance line. This proves to be a problem in the islanded operation setting of the microgrids. Since the microgrid is designed to be self-sufficient, unmatched demand or excess supply poses an obstacle to the perpetuation of the microgrid system. If some of the buyers and sellers are not matched during the double-auction process, it is just fine in the grid-connected operation of the microgrid. The sellers that were not able to sell their excess electricity could just feed the excess electricity to the grid and get paid for it while the buyers can just satiate their demand from the grid, paying the grid price per kilo-watt hours of energy.

However, in the islanded mode, without any interference to the double-auction process instabilities in the microgrid are bound to occur due to the void of a mechanism that compensates for the unmatched buyers and sellers. The problem actually arises from the buyers trying to bid an undesirable price and sellers trying to ask a too expensive price for that specific iteration of the double-auction process. This could be dealt with by introducing penalties to low bidding or high asking agents. The pecuniary penalties would then manifest themselves on the electricity bills of the prosumers. A simple approach would be, having the buyers paying the actual or the average market clearing price (or a fixed penalty) but having the sellers receive none of the paid amount.

There is another implication of the islanded operation of the microgrid. The excess generation should be directed either to consumers whose demand is not satiated, or to consumers who can store electricity in their storage devices. For the islanded operation this is not an option but a necessity. Along with the implication discussed in the previous paragraph, this second implication necessitate special measures to be taken for the islanded operation of the microgrid.

There is a logical precedence order between three types of trades that can take place in this microgrid. Actions 1 and 2 could fall under the umbrella of ancillary markets which is not the scope of this study. There is not really any competition in the markets that are created by these actions, especially when the microgrid is functioning in the islanded mode. The main market structure, on the other hand, is mostly maintained by action 3.

1. <u>Excess generation to immediate consumption</u>: If a consumer cannot satiate their demand either by self-generation, self-storage or by other microgrid measures and if the prosumer cannot store the excess generation in batteries, this portion excess generation must be consumed by those with uncovered demand. Pricing could be a pre-set value or the average market clearing price for that window of time.
2. <u>Excess generation to storage</u>: For the sustainable operation of the microgrid and for keeping the system frequency at acceptable levels, excess generation must be directed elsewhere. After covering the unmet demand, the remaining excess generation should be stored in batteries. To reiterate a vital point again, these operations are necessary and out of the scope the main market structure.

Pricing could be a pre-set value or the average market clearing price for that window of time. During the operation of the grid-connected mode, excess generation can be sold to the grid instead of storing the electricity inside the batteries.

3. Storage to consumption: After the allocation of excess generation, the less volatile type of trades can take place. The consumers that still need their demand met by external sources, can compete to buy the electricity from the batteries of others or the prosumers can compete to sell electricity from their stores. If the microgrid is on the grid-connected mode, then the competition is more meaningful. The grid competes on both sides of the market and participants can choose to buy from or sell to the grid according to the market prices.

## 3.3 The Logical Flow of the Simulation

The agent-based simulation model consists of two types of agents, the "residential" agent simulating the prosumers and consumers and the "operator" agent fulfilling the regulator role for the market. Laying out the actions of these agents summarizes the main flow of the simulation at each iteration. The simulation depicts every hour in a day and runs for a year, totalling in 8760 hours. In each of these 8760 hours, the simulation tries to balance the consumption with generation while regulating the trades between the prosumer agents, making forecasts, calculating forecasting errors and recording the variables that give insight to the process that is being simulated.

### 3.3.1 The Agent "Residential"

The residential agent represents the prosumers. Each instance of the agent has its own learning procedure that is set according to either one of Roth-Erev or Q-Learning algorithms and data storing capabilities to calculate the performance variables like amount of electricity bought from other customers or the total electricity bill.

The agents use these learning procedures to set their bidding and asking prices. There are five options each representing the level of prices from "very low" to very high. After determining the level with which the agent wants to bid or ask, average forecasting errors and the pricing function is used to determine the final bid. The pricing is based on the real-time pricing policy of the Low Carbon London project. The details of the project were given in the beginning of this section. To reiterate, consumers paid 0.039 Pounds/kWh with the "low" tariff, 0.1176 Pounds/kWh with the "default" , and 0.672 Pounds/kWh with the "high" tariff. The function for determining the price values is shown below in (3.12), the function is taken from a polynomial regression fit to the values given above:

$$price(x) = 0.074525 * x - 0.0474 * x^{2} + 0.011875 * x^{3} \tag{3.12}$$

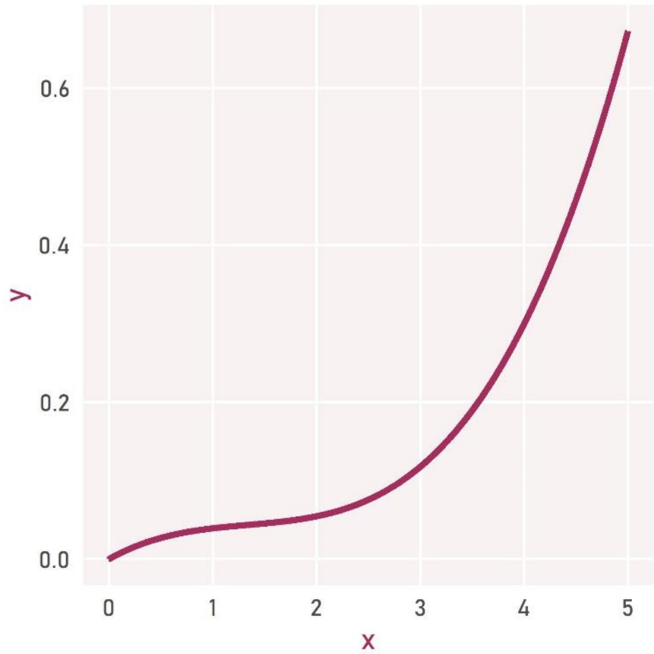


**Figure 3.14** Price determination function

The x variable represents the choice of prosumer residential agent after the adjustment as shown in (2.1) for buyers and (2.2) for sellers. Therefore, before being transformed to the monetary value by (3.12). Then the bidding (3.13) and asking (3.14) intervals are constructed using the expressions below:

$$B_t = (price(b_t), price(b_t * (1 + \mathrm{MAPE_t})) \tag{3.13}$$

$$S_t = (price(s_t * (1 - \mathrm{MAPE_t})), price(s_t)) \tag{3.14}$$

The intervals are in fact the relaxation of the lower bound for asking prices and of the upper bound for bidding prices. Making the acceptable intervals for bids or asks a little longer. Therefore, depending on the realized demand and supply values, the participants have better chances of getting matched in auction process. This is beneficial both for the participants and for the microgrid. It prevents likely losses from inaccurately evaluated values of supply and demand (this confusion directly affects the asking and bidding prices, damaging the social welfare in the microgrid electricity market).

In Q-Learning and Roth-Erev algorithms, agents learn with rewards. Accurate determination of these rewards plays a large role in this microgrid market simulation. The determination of rewards and punishments simply follow the idea of opportunity cost.

What the buyer prosumers want to achieve, rationally, is buying the electricity at cheapest prices possible. Yet, at the time of bidding, the agent does not know whether their bid is overpriced or not. The agent can only understand the true position of their bidding, after learning about the market clearing price. The market clearing price is a good indicator as to what the true value of a commodity is in that given transaction period. The determination of the reward for buying customers is as follows, the reward for a successful bid is set to the actual amount paid per the unit of energy, to . Since the goal of the buyers is to minimize expenditure, it is rational to assume that the buyers would be more willing to decrease their bids after a successful bid for not paying more than the market value of the commodity and to increase their bids after a failed bid for being able to buy the commodity.

$$\pi_{tk}(B_j) = \begin{cases} 0, & B_j < B_i \text{ and } B_i \text{ won} \\ 0, & B_j > B_i \text{and } B_i \text{ lost} \\ -prices(B_j), & B_j = B_i \text{ and } B_i \text{ won} \\ -1, & B_j = B_i \text{and } B_i \text{ lost} \end{cases} \tag{3.15}$$

Above in (3.15) $B_i$ represents the bid price, $B_j$ represents the price whose Q or propensity value is being updated and $p_c$ shows the market clearing price, finally $\pi_{tk}$ represents agent $k$'s reward at period $t$ . The reward for buying is nonpositive and the rewards are used to update Q values and Roth-Erev propensities. The price choice with less negative Q or Roth-Erev value is more likely to be bid in the coming auction window. For each agent there are 24 sets of Q-Learning or Roth-Erev algorithms and accompanying data pertaining to the 24 hours in a day. Each set is used exclusively for the hour it belongs to. The underlying logic for the update rule laid out in (3.15) could be summarized as following: since buyers would like the minimize their expenses, after winning a bid, their tendency to bid lower increase. Same is valid for the bids that do not win in the latest iteration of the double-auction. The buyer, after failing to win, would be more willing to increase their bids. After the undergoing a standardization process, they could be assigned as rewards in either one of Q-Learning or Roth-Erev algorithms.

For sellers a similar path is taken. If an agent's ask is accepted, the agent becomes more willing to increase the value of the ask. Likewise, if the agent were not able to sell, the agent becomes more willing to make discounts in the ask price.

For both the buyers and the sellers, the tendencies elaborated above could be explained by the opportunity cost phenomenon. If the agents "feel" as if they are missing out or as if they are being "abused" by very low ask/very high bid prices, it is rational to assume that they would like to change their behaviour. The reward functions that are set considering opportunity costs of these actions are reflected below in (3.16).

The difference in the seller reward function (3.16) is the ease of integrating opportunity cost, if the ask is successful, the reward is simply the market clearing price $p_c$ since it signifies the market value of the commodity, in this case the price per power. If the ask is not successful, on the other hand, the agent misses the opportunity to sell electricity valued at the market clearing price, and should therefore be penalized. The general workflow of the residential agent is shown below in Figure 3.15.

$$\pi_{tk}(S_j) = \begin{cases} -prices(S_j) + p_c + 1, & S_j > S_i \text{ and } S_i \text{ won} \\ prices(S_j) - p_c + 1, & S_j < S_i \text{and } S_i \text{ lost} \\ 1 + prices(S_j)\,, & S_j = S_i \text{ and } S_i \text{ won} \\ -1, & S_j = S_i \text{and } S_i \text{ lost} \end{cases} \qquad (3.16)$$

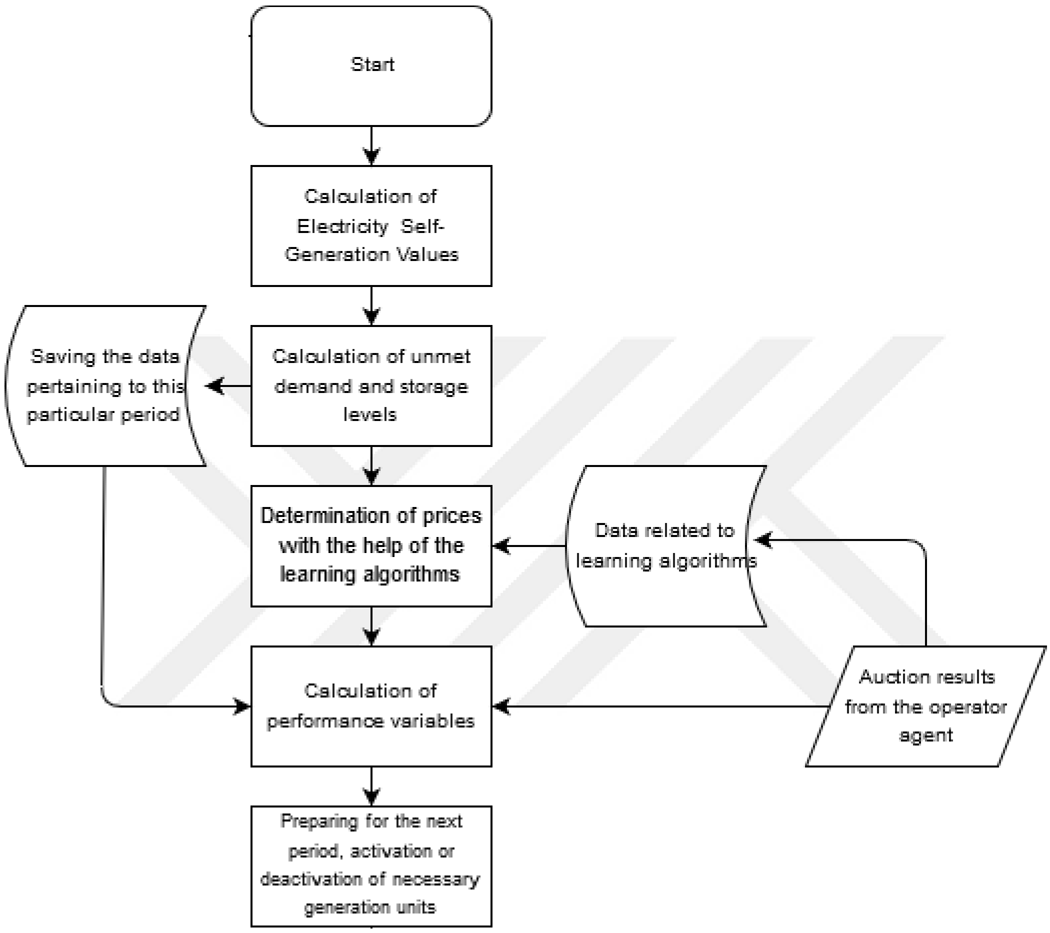


**Figure 3.15** The workflow of the residential agent

There are several variables of interest belonging to both agent types available in the model. For the residential agent, the most prominent of these variables are:

- Generated Electricity (Solar, Wind)
- Stored Electricity
- Bought Electricity (from Prosumers, Grid or other generators)

- Sold Electricity (to consumers, grid)
- Electricity Bill

Several others are used to assess whether the simulation is running as intended or not.

The electricity bill parameter is particularly important since it is a major variable of interest for this study. One of the aims of the study is to show that with microgrids, cheaper electricity could be provided for the end users.

The residential agents must report their excessive or deficient demand so that the operator knows which agents are willing to participate in the next iteration of the auction. The residential agents send their bids or asks, and the operator responds whether they have won or not. According to the resulting auction, the electricity trades and payments take place, the operator makes a final check and each participant gets ready for the next period. On extreme occasions or in the case of a predicted system overload, the operator may order the users to deactivate their distributed generation units to protect the system integrity.

### 3.3.2 The Agent "Operator"

The operator entity is responsible for the sustenance of the microgrid system. The forecasts, the auctions, deactivation orders and grid connection decisions are all maintained and ordered by the operator. The manner with which the forecasts are governed were laid out previously along with the general auction process. The general workflow of the operator agent is shown below in Figure 3.16.

The operator agent is the omniscient agent in the simulation. It collects generation, consumption and storage level data to make forecasts, oversee auctions and calculate the related variables of interest, including the electricity bills. Some of the variables calculated by the operator agent are as follows:

- Total demand
- Total supply
- Total unmet demand
- Total excess generation
- Total amount of electricity stored, used and sold from storage.

- Total amount of electricity trade broken down to subtypes
- The amount of electricity sold to or bought from the grid

The operator also supplies backup electricity in the islanded mode by employing fuel cells. Fuel cells were chosen to be a clean alternative but cheaper diesel generator could be used for the same purpose. The integration of fuel cells due to their dispatchable nature necessitates making activation and deactivation decisions beforehand. The dispatch of the fuel cell requires forecasts for the next period and it is decided according to the following expression. The activation rule utilizes the safety stock idea. The critical level, or the reorder level, is a parameter that should be optimized. If the conditions given in (3.17) and (3.18) are together satisfied or the condition in (3.19) is satisfied, then the fuel cell unit (or the grid connection) is scheduled to be active for the next hour.

$$forecast_{diff} * \left(1 + error_{diff,t}\right) \leq \varphi \tag{3.17}$$

$$\sigma_t + \varphi + forecast_{diff} * \left(1 + error_{diff,t}\right) \leq \sigma_{system} * \rho_{critical} \tag{3.18}$$

$$\sigma_t \leq \sigma_{system} * \rho_{critical} \tag{3.19}$$

$\varphi$ represents the power of the fuel cell unit in kilowatts or 0 if the system is able to connect to the grid. $forecast_{diff}$ is the forecast difference between the renewable generation and the system load. $error_{diff,t}$is the average of MAPE's for that specific period for the difference between renewable generation and system load. The variables related to storage $\sigma_t$ and $\sigma_{system}$ represent the current level of system-wide storage in kWh and the total system-wide storage available in kWh. $\rho_{critical}$ on the other hand, is the critical level of storage, a real value in [0,1]. (3.17) and (3.18) together imply that, if the storage level is forecast to decrease to a critical level then the backup measures (fuel cell) should be activated. (3.19) implies that if the storage level is already critical, then the backup measures should be activated.

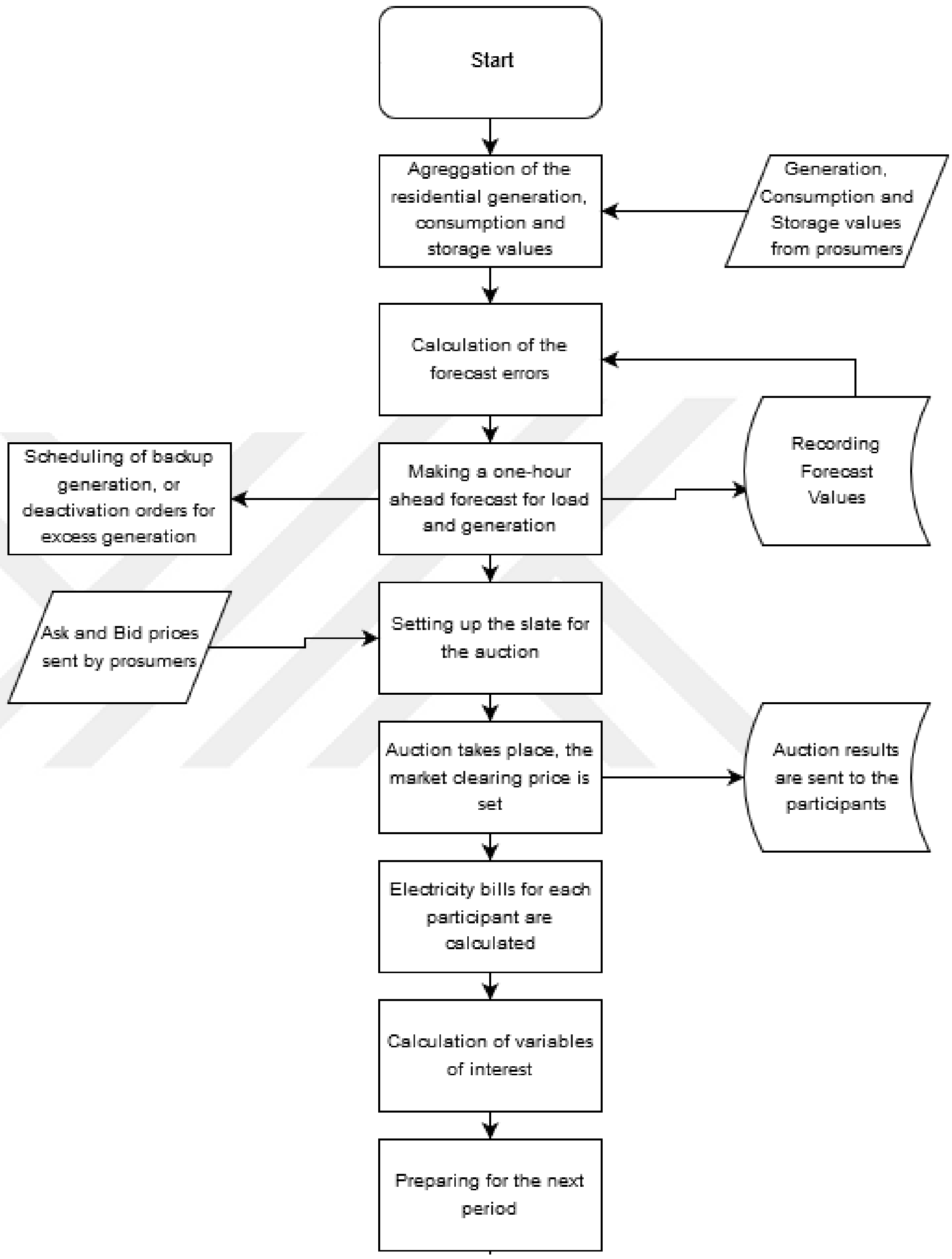


**Figure 3.16** The workflow of the operator agent

## 3.4 Simulation with Default Parameters

The generation and storage capabilities were listed in Table 3.1. The remaining default parameters are given below in Table 3.2. Q-Learning is assumed to be the default learning algorithm of choice and the microgrid is assumed to be islanded.

**Table 3.2** Default Parameters

| Parameter | Value |
|---|---|
| $\rho_{critical}$ | 0.19 |
| $\varphi$ | 12 kW |
| $\alpha$ | 0.95 |
| $\varepsilon$ | 0.3 |
| k | 0.65 |
| Fuel Cell price per power | 20 pence/kWh |

With given consumption data and the standard tariff for electricity (14.62 pence/kWh), the electricity bills appear as shown in Table 3.3. All values are given in Pounds. The fuel cell price per power is assumed to be 20 pence/kWh with profit premium added on top, as the cost of fuel cell is estimated to be around 0.14-0.15$/kWh[83].

Table 3.3 Electricity Bills Under the Regular Market Regime

| | | | |
|---|---|---|---|
| Household 1 | Household 2 | Household 3 | Household 4 |
| 257.36 | 646.40 | 1992.88 | 1670.57 |
| Household 5 | Household 6 | Household 7 | Household 8 |
| 384.67 | 271.31 | 801.98 | 1172.83 |
| Household 9 | Household 10 | Household 11 | Household 12 |
| 957.43 | 590.31 | 599.66 | 804.97 |
| Household 13 | | | |
| 1473.79 | | | |

The electricity bills shown in Table 3.3 are the benchmark values for the simulation. Naturally, the bills represent the consumption profile of each household.

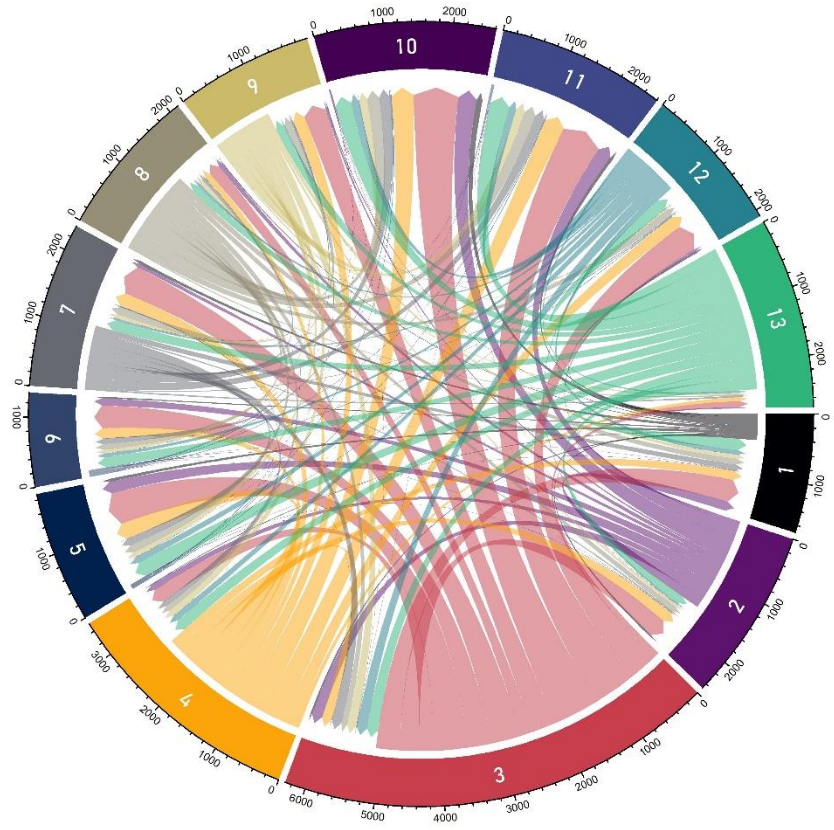


**Figure 3.17** Chord Diagram showing all P2P Trades [84]

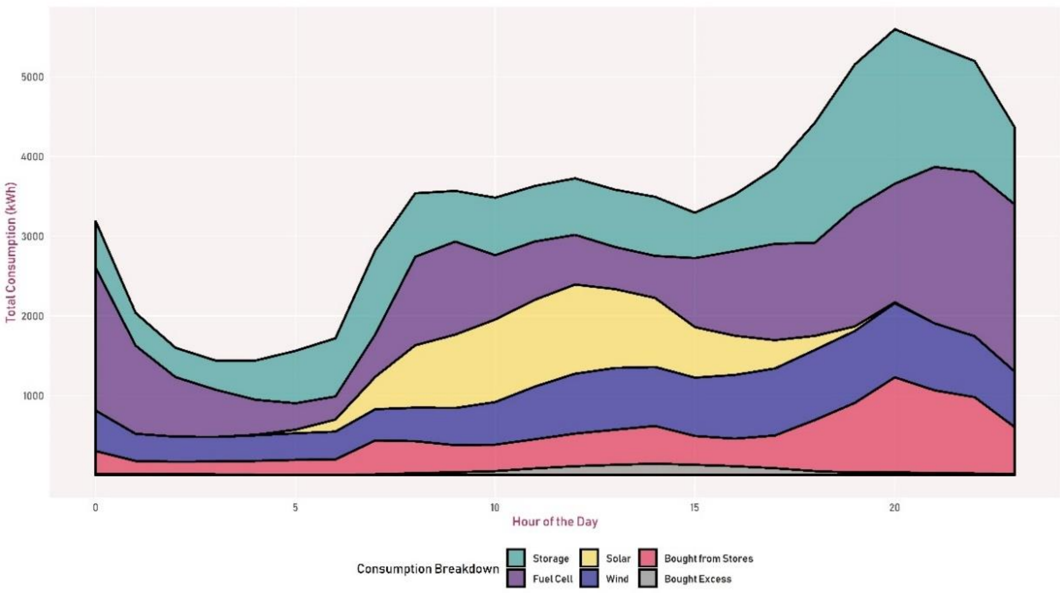


**Figure 3.18** Consumption Source Breakdown

**Table 3.4** Electricity Bills Under the Proposed Market Structure

| | | | |
|---|---|---|---|
| Household 1 | Household 2 | Household 3 | Household 4 |
| 233.4091 | 385.8987 | 1086.6185 | 848.7048 |
| Household 5 | Household 6 | Household 7 | Household 8 |
| 268.6266 | 203.1526 | 465.4144 | 558.7616 |
| Household 9 | Household 10 | Household 11 | Household 12 |
| 722.1396 | 414.6025 | 493.9944 | 484.1165 |
| Household 13 | | | |
| 670.5140 | | | |

The simulation is run 100 times with the default parameters. With learning algorithms carrying over each simulation iteration, agents did not have to start learning anew every time an iteration is run. The results show a clear reduction in the electricity bills. This is expected, since the prosumers do not pay for the electricity that they generate. The households that do not generate electricity, however, have also had their electricity bills decreased by relatively lower percentages. These values are marked with red in Table 3.4. The bills can be seen in Table 3.4 and the percentage changes in the electricity bills can be seen in Table 3.

**Table 3.5** Percentage Change in Electricity Bills

| | | | |
|---|---|---|---|
| Household 1 | Household 2 | Household 3 | Household 4 |
| -9.30% | -40.30% | -45.47% | -49.19% |
| Household 5 | Household 6 | Household 7 | Household 8 |
| -30.16% | -25.12% | -41.96% | -52.35% |
| Household 9 | Household 10 | Household 11 | Household 12 |
| -24.57% | -29.76% | -17.62% | -39.85% |
| Household 13 | | | |
| -54.50% | | | |

The Figure 3.17 shows the chord diagram of the amount of P2P electricity trades between each household in the microgrid. From the figure, it can be inferred that the market is quite competitive. The market shares of each participant are proportional to their generation capability. There are no signs of collusion between participants as well, showing the power of the simple Q-Learning algorithm to emulate the behaviour of market participants under repetitive auction episodes.

Figure 3.18 shows the breakdown of the aggregated electricity consumption of the households to hours of the day and to its components. The figure clearly shows when solar and wind generations take place. As expected, solar energy is only available during the day, peaking around the noon. It is a formidable source of energy when it is available. It can be argued that most the electricity storage is filled during and around the noon using solar energy, due to the plateau in consumption. Wind energy, on the other hand, follows a more consistent pattern with a slight setback during the night. The "bought from stores" part highlights the part of the P2P trade that is facilitated via auctions. P2P trades tend to dip as the morning approaches, this can be attributed to the fact that after a long night with no solar power output, the storage either plunges to very low levels or gets exhausted. After the stores climb back to more safe levels the volume of P2P trade increases back again. This is accompanied by the fact that the demand is significantly lower during the night when most of the residents are sleeping.

The average market clearing prices for each hour of the day is shown in Figure 3.19 with the forecast error adjustments to the prices and Figure 3.20 without the forecast error adjustments. The explanation of these prices is not straightforward and there are many factors involved in the determination process of these prices.

The classical supply and demand relation dictates that, the market price should increase as demand increases and supply decreases, ceteris paribus. But the other variables do not remain constant throughout the operation of the microgrid. Both demand and supply are affected by factors other than those that belong to this isolated auction market. The overall supply depends dramatically on the availability of the fuel cell while the overall demand is affected by the abilities of the prosumers to cover their own unmet demand using their own storage. The most prominent factor driving the pricing patterns is the forecast errors. The supply-demand relation, on the other, can better be observed in Figure 3.20 where the scenario displayed does not feature forecast errors incorporated to the price determination mechanism.

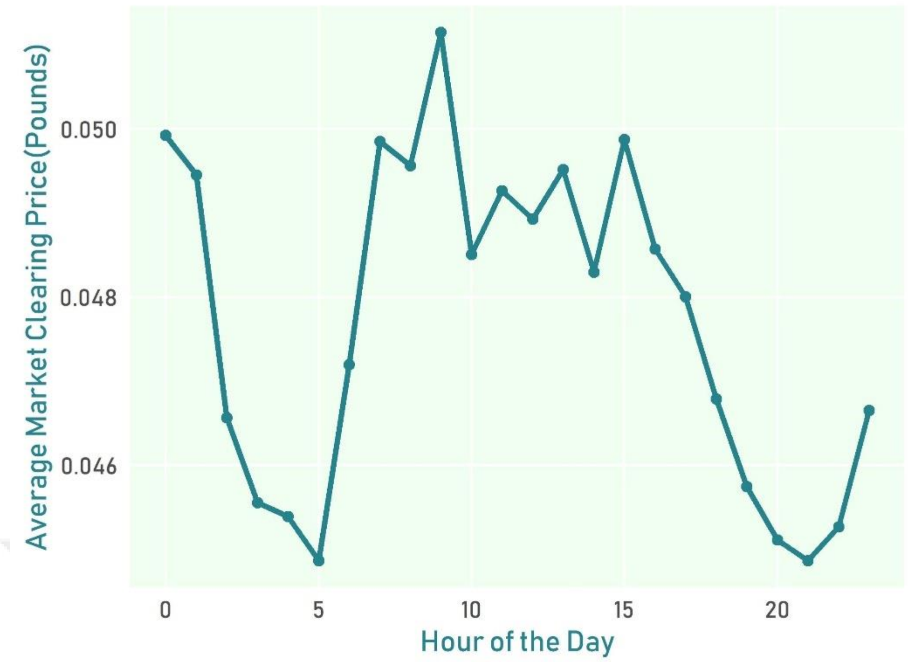


**Figure 3.19** Average Market Clearing Prices with Error Adjustment

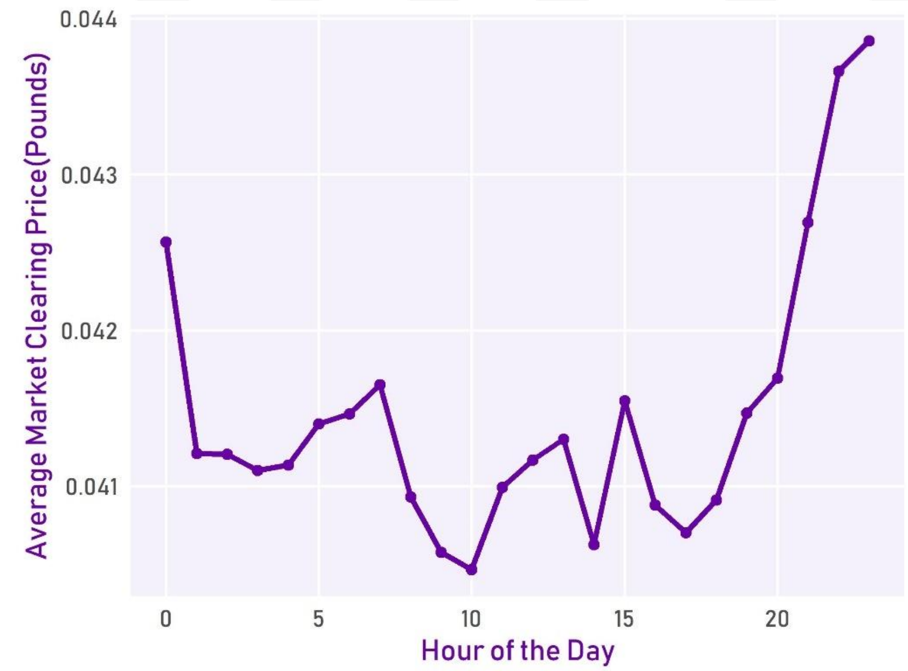


**Figure 3.20** Average Market Clearing Prices without Error Adjustment

The prices reported in Figure 3.19 display the behaviour of the forecast difference errors. The difficulties in forecasting solar and wind power, as laid out in section 3.2.3, emerge as a major factor in the determination of the prices. The behaviour of the market clearing price under the adjustment regime is parallel to the solar power availability. The uncertainty in the availability of solar power makes the market prices climb during the noon. What makes electricity more valuable during these periods is the risk factor. Inaccuracy of the solar irradiation forecast is directly connected to the dispatch/deactivation decision for the fuel cell, the component of the microgrid which supplies more expensive electricity.

It is also possible to observe the underlying dynamics of the islanded microgrid electricity market as a special case. What determines the market clearing price and indirectly the behaviour of the suppliers is mostly the demand level of the system at a given episode. If the system is operating as intended, that is, without a lack of supply, then the competition is quite stiff for the supplier side of the market. The suppliers, in turn, are left with no choice other than to reduce their prices as much as possible to be able to sell anything at all. This is a direct result of the classical supply-demand relation: If the supply in the market exceeds the demand, the prices are expected to drop.

It is possible to iterate that, with the inclusion of the forecast adjustments, it has become more tempting to trade during the day for the suppliers and more affordable during the day for the demand side. The uncertainty in the supply especially during the day and the accompanying risk is compensated to a degree with the adjustment by the forecast errors. Creating a balance between risk and affordability is vital to achieve a higher level of welfare in the market.

The part of the prices that are dictated by the supply-demand relations can be observed in Figure 3.20. The behaviour displayed by the market clearing prices resembles that of the aggregated load profile of the market, shown in Figure 3.2. As the demand increases the market clearing prices also seem to increase. The demand, however, is not the sole factor in this process. The availability of the electricity storage is well effective in the occurrence of these prices. The storage levels tend to be at their maximum right after the sun sets and at their minimum right before the sun rises. Heavy consumption during the evening and stable consumption during the night take their toll on the storage, occasionally pushing the storage to dangerous levels. As a result, the prices are highest around 9 to 11 PM when and lowest after the morning rush. Not much difference actually exists between the prices due to the aforementioned feature of the islanded microgrid market. Suppliers should lower their prices to stay competitive and that most of the time the suppliers choose to stick to the lowest prices. These results and findings indicate that the learning algorithm and the double-auction mechanism perform well and realistically.

The fare of the learning component and how fast it adapts to the given market is given below. As can be observed from the chord diagram in Figure 3.17, Household 3 is the household with the largest sales volume and Household 10 is the household that realized the highest number of procurements. The Q values for all available bid and ask alternatives are given in in Figures 3.21 and 3.22. How Household 3 learned to sell its electricity and how Household 10 learned to buy the most advantageous manner can be seen from the change in their Q values. As one of the busiest hours, 10 PM is chosen to

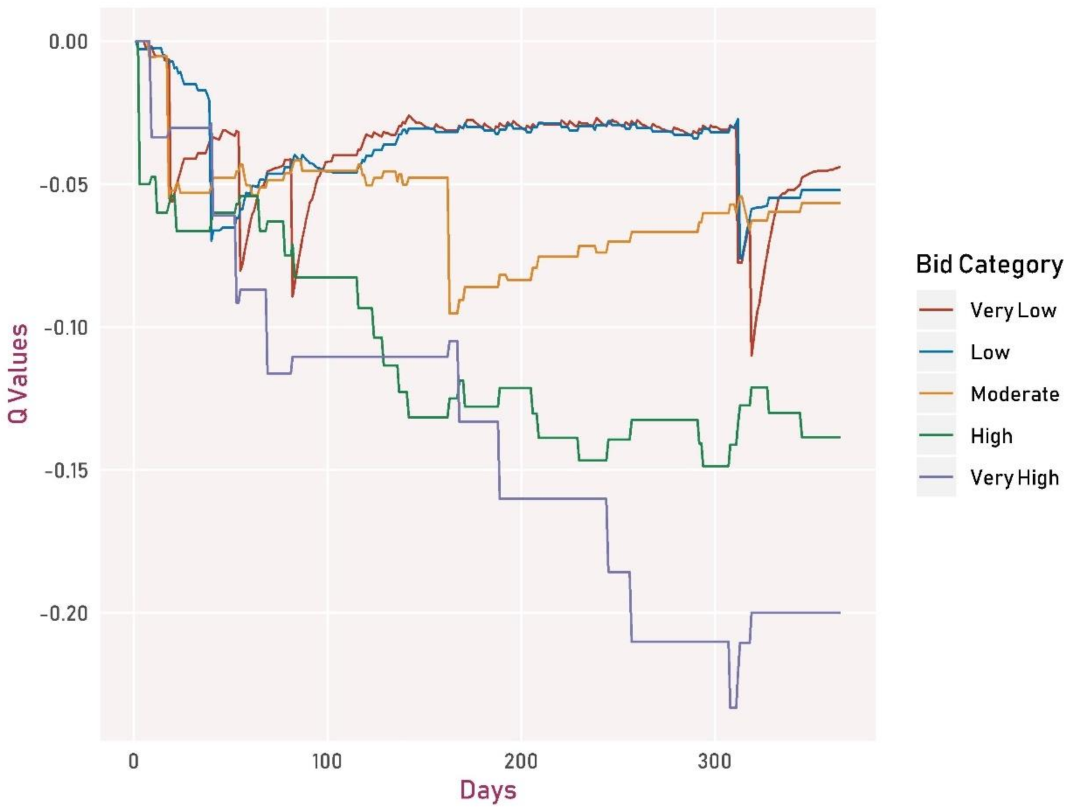


**Figure 3.21** Household 10 – Q-Values for Bids at 10 PM

display the behaviour of the learning algorithm.

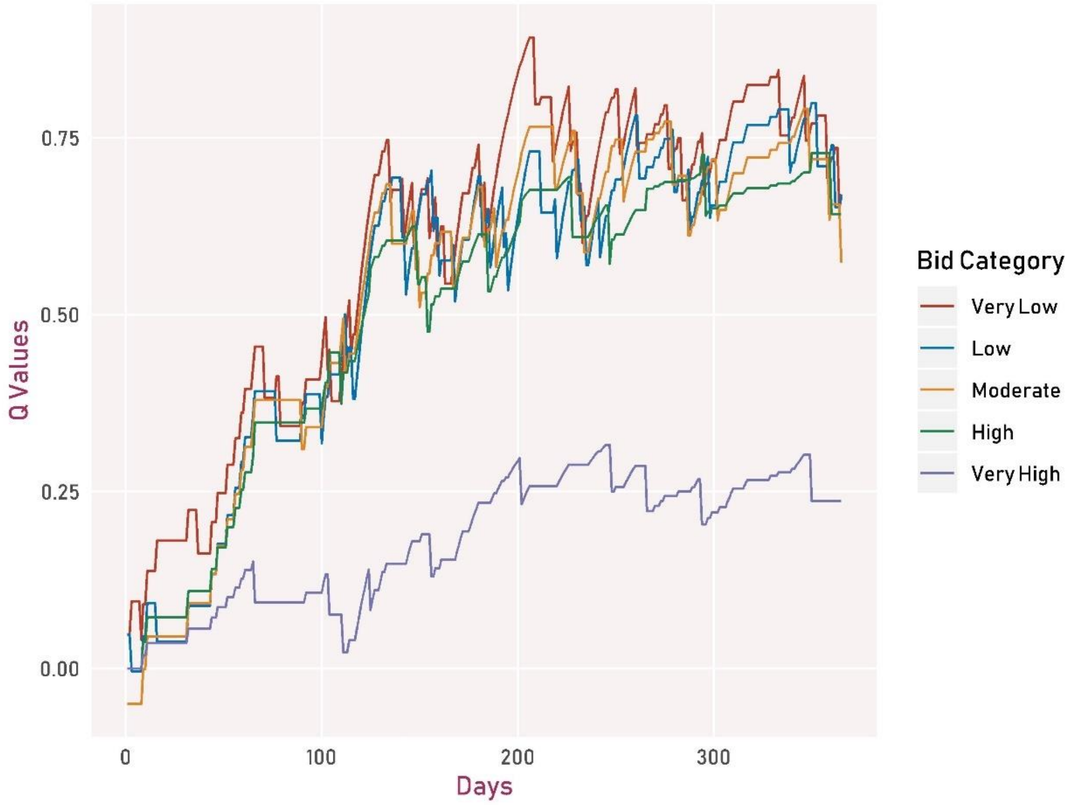


**Figure 3.22** Household 3 – Q-Values for Asks at 10 PM

It is obvious that buying for “high” or “very high” prices are not efficient options for a buyer. This can be explained by the aforementioned feature of this particular market that the supply generally exceeds the demand. This renders bidding high prices a disruptive option both for the sellers and buyers. Winning a round of the auction process with higher ask prices is a distant possibility while winning with a higher bid price is simply paying too much for the round. The most favoured choices both for the seller and the buyer seem to be the “very low” and “low” options, understandably. The nature of this market, without any outside interference, makes the prices converge to these values. Because these prices are all determined as a result of repetitive auctions and with no regulation in the market, they can be regarded as the true indicator of the value of the electricity in this market. It must be noted; however, the installation and maintenance costs of the renewable generation units and the electricity storage units are not considered in the price determination process. How these expenditures are going be covered or whether these are going to be considered as mere infrastructure of the future (thus making this a responsibility of the governing authorities) is surely up for debate.

**Table 3.6** Simulation Results

| Variable of Interest | Value (kWh) |
| --- | --- |
| Total Demand | 81,699.605 |
| Total Supply | 81,272.249 |
| Supply from Wind Generation | 25,440.669 |
| Supply from Solar Generation | 21,877.377 |
| Unmet Demand (Blackout) | 126.744 |
| Sold via Auctions | 11,187.197 |
| Excess Generation Fed to the System | 113.819 |
| Sold Excess Generation | 1,454.837 |
| Sold Excess Generation for Storage | 4,552.792 |
| Total Stored | 31,879.85 |
| Total Used from Storage | 20,993.27 |
| Initial Storage | 337.5 |
| Final Storage | 36.888 |

The values shown in Table 3.6 provide the benchmark for further experiments. Despite all the efforts to balance the supply and the demand, 126.7 kWh of demand could not be covered. Using the typical values, this corresponds to around half a day's electricity consumption. Throughout the year, the total duration of blackouts was around 12 hours. The highlight of these results is the amount of electricity traded between the market participants. 21% of all demand were covered using P2P trades, this ratio could change under different market regimes and different market decisions, one of which being the critical storage level. Storage were also utilized effectively, covering 25,6% of all demand throughout the year. Figure 3.18 shows a detailed breakdown of these values to the hours of the day. Additionally, the difference forecast errors in the form of MAPE, broken down into the hours of the day can be found below in Figure 3.22

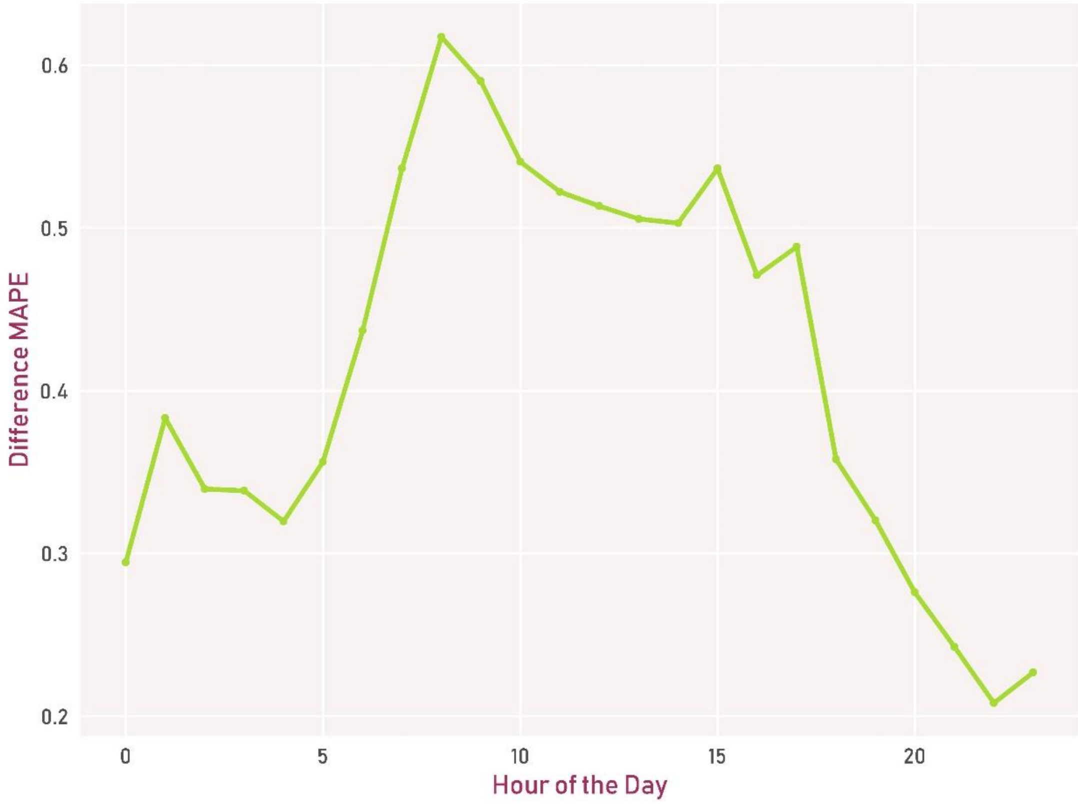


**Figure 3.23** Average Hourly Difference Forecast Errors

The inaccuracy of the forecasts during the noon is largely attributable to the erratic behaviour of solar irradiation. While the load is relatively easier to forecast (18% MAPE on average), the difference forecasting proves to be a challenge (69% MAPE) due to the unpredictability of the renewable generation resources.

Next, results of a series of experiments are given.

# 4. EXPERIMENTS

In this section, several experiments are run with the aim of either investigating the effects of the model parameters or testing another method against the already-established methods presented previously in this study. The random seed was kept constant throughout the relevant experiments to follow the principles of experimental design as closely as possible. The set of random seeds allow for reproducible experiment runs and a scientific testbed for the experiments of interest.

## 4.1 Critical Storage Level

The critical storage level is an integral part of the islanded mode of operation of the microgrid system. As the operator agent continuously monitors the level of aggregate storage, the dispatch decisions of the fuel cell are made according to these measurements. Therefore, the critical storage level affects pretty much every aspect of the system, making it one of the most important parameters of interest in the model.

The simulation model is run 10 times per critical storage level increment, totalling to 110 runs. The critical storage level increases by the increments of 0.01 from 0.15 to 0.25. The values of the affected model variables are given below in Figure 4.1 and Figure 4.2.

The most immediate effect of the storage level on the system is the changing values of total unmet demand and the excess electricity generation. The goal of this experiment is to find an acceptable level of critical storage that minimizes both the unmet demand and the excess generation and to investigate the collateral effects of the change in critical storage level. The critical storage level becoming more sensitive (or increasing) means the uptime of the fuel cell increases. It must be noted that, the fuel cell usually provides more costly power than the other means of generation, at least in the present microgrid system.

The rows marked by “Unmet Demand” and “Excess Gen” in Figure 4.1 represent the total unmet demand and the total excess generation that was not utilized by any means.

The unmet demand shows a downward trend as the critical storage level increases. Excess generation, on the other hand follows a more erratic pattern. While low levels of critical storage, thus shorter uptime for the fuel cell, might cause amounts of wasted electricity to decrease, it surely does not provide the means to cover the total demand in the system. The storage level 0.22 seems to present the most improvement in the unmet demand variable and the lowest wasted electricity in the high end of the critical storage level interval. This value is used for further analyses.

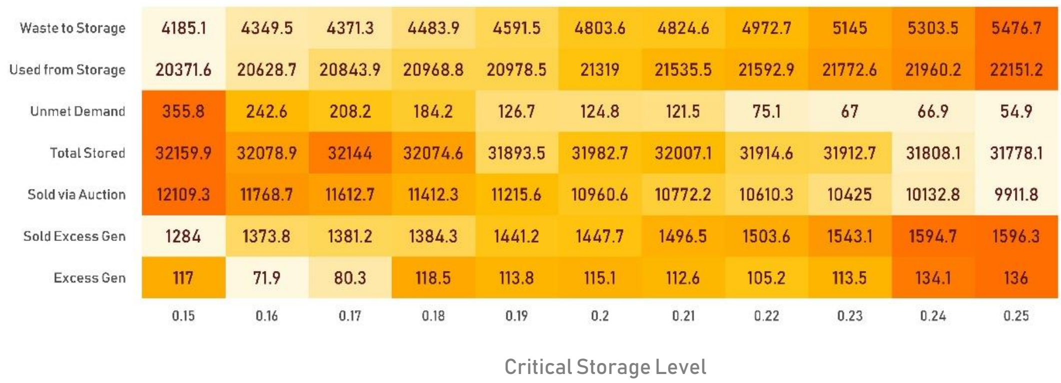


**Figure 4.1** Critical Storage Level Experiment Results

The indirect effects of the critical storage level are as follows. The total stored energy decreases while the total amount of electricity supplied from storage increases. Although this is a rather interesting result, it has a somewhat simple explanation. As the share of the fuel cell in the total generation increases, the number of occasions that feature market participants seeking to cover their electricity via P2P decreases, because the market participants are either using their own stored electricity or the electricity that is provided by the fuel cell directly.  As a result, the users become free of their liability to replace the missing storage that was sold via P2P trades. This could be corroborated by the “Sold via Auction” row shown in Figure 4.1 displaying a steady decline in the amount sold from the stores of the market participants.

The increased fuel cell input in the system causes the manageable excess electricity generated (stored or sent to be directly consumed by other consumers) to increase. This helps the total storage amounts in the system to fare around higher values, making the users more reliant on their own storage units.

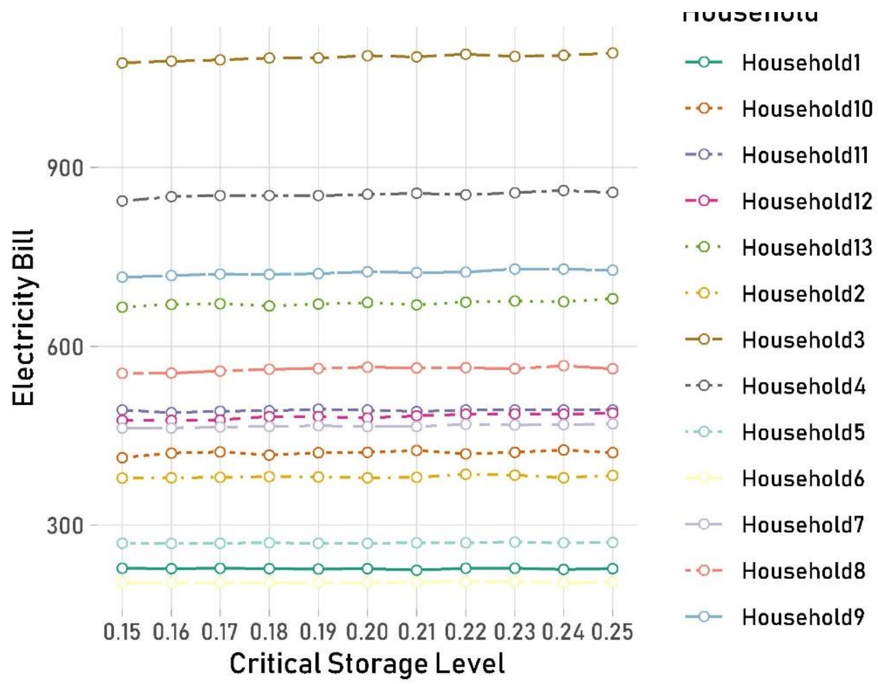


**Figure 4.2** Electricity Bills with respect to the Change in the Critical Storage Level

Figure 2 shows the change in the electricity bill of each market participant with respect to the change in the critical storage level. While it seems that critical storage level may affect the amount of the electricity bill the market participants have to pay, it is more of a mediating effect. The slight increase in the electricity bills can be explained by the increasing amount of overall consumption. More uptime of the fuel cell means larger amounts of electricity being fed into the system, decreasing the unmet demand in the system. Moreover, the fuel cell usually provides more expensive energy to the customers than they themselves produce or procure via P2P trading. It is therefore safe to say that the critical storage level has no significant effect on the electricity bills, but is quite a significant factor that contributes as to how the system operates.

## 4.2 Double-Auction Allocation Coefficient (k)

The allocation coefficient is a value shown in equation 2.2 that helps determine the transaction price for a matched buyer-seller couple. While the proposed market structure with the error adjustments to the bid and ask prices is a much-needed help in this regard, there is still the matter as to how the weights to buyers and sellers are given during the price determination process. It is worth noting that there is no optimal value that is being sought in this experiment. The market participants themselves are the most likely candidates for determining this value, yet the experimentation with the value is necessary to provide support for the decision-making process. 10 replications for each increment in the k value was run, totalling to a 210 simulation runs.

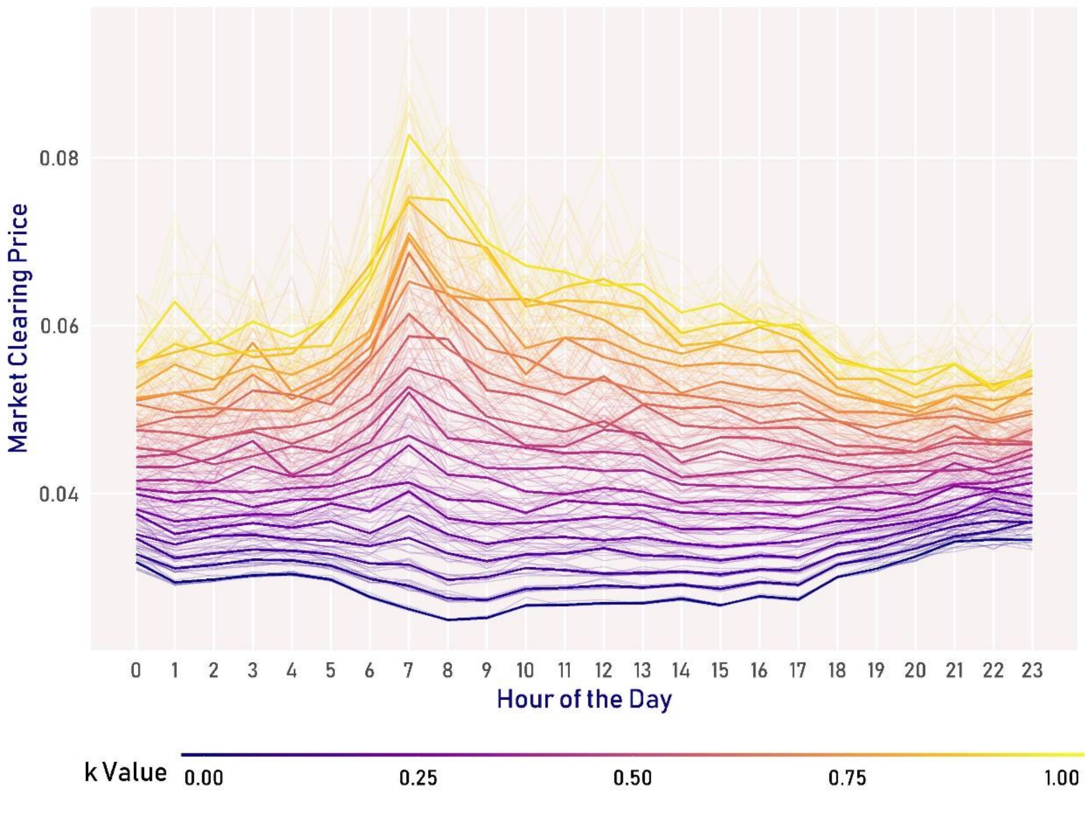


**Figure 4.3** Market Clearing Price and k Value

Figure 4.3 displays the super-positioned average hourly market clearing prices with respect to the k value. Note that the final averages are emphasized with an emboldened line. Low k values give more weight to the seller prices while higher k values give more weight to buyer prices. The results of the simulation with default parameters show that the seller prices converge to low prices very fast but the buyer prices, possibly due to the market penalties, have the tendency to sporadically be bid in higher prices. Accompanied by the occasional power outages, the mostly buyer's market becomes a seller's market affecting the average market clearing prices. These prices are the prices that are adjusted by the forecast errors, so they usually display similar behaviour to that of solar irradiation. The price spike in the morning, however, signifies the point at which the storage levels being driven to low levels by a long night with low wind generation output.

In lieu with the structure of the double-auction market, in which the buyer price must always exceed the seller price, greater weight given to the sellers results in reduced market clearing prices. It must be noted, however, that the market clearing price behaviour with lower k values better represent the overall supply-demand relation in the market. The lower prices that correspond to the lower k values might not always mean reduced electricity bills for each market participant and this can be observed in Figure 4.4.

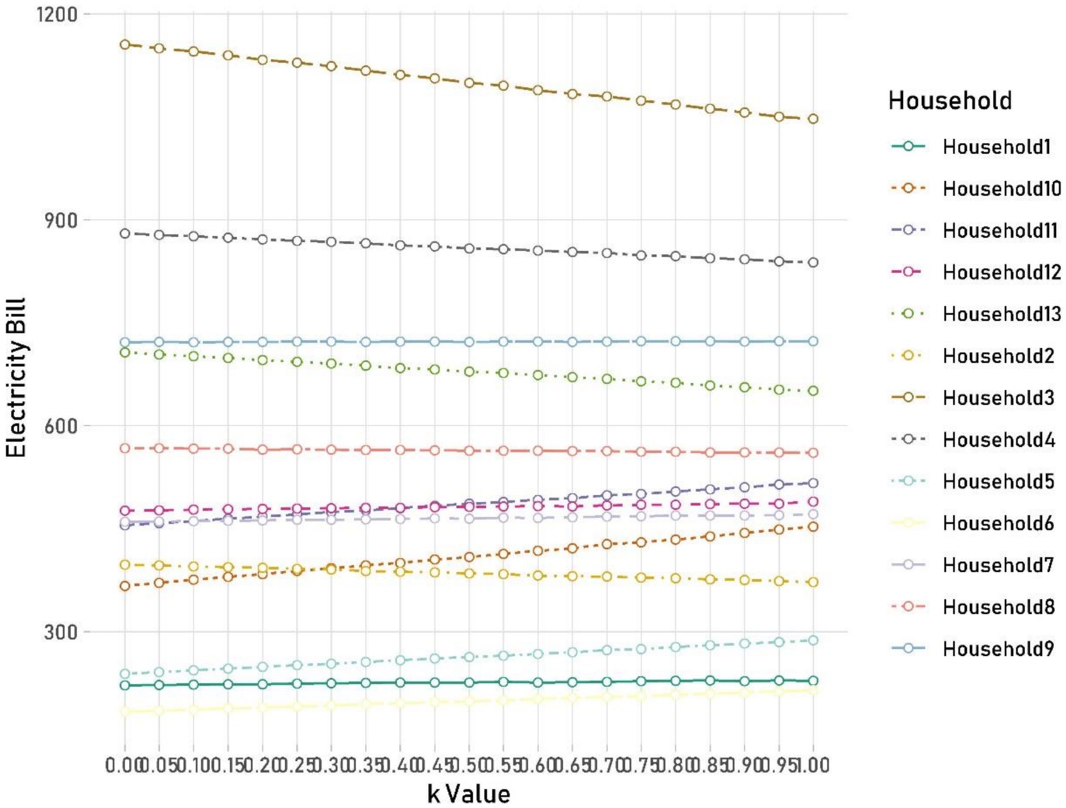


**Figure 4.4** Electricity Bills with respect to the k value

Higher market clearing prices tend to favour the market participants with greater electricity generation capabilities. The market participants with little or no such capabilities tend to suffer from the increased prices in the form of higher incurred electricity bills. The final decision as to which value of k should be used in the simulation could be made after the two-parameter experiment takes place.

Figure 4.5 shows the results of experiments for each combination of critical storage level and the k value. 5 replications for each combination totalling to 605 simulation runs were made with the results below.

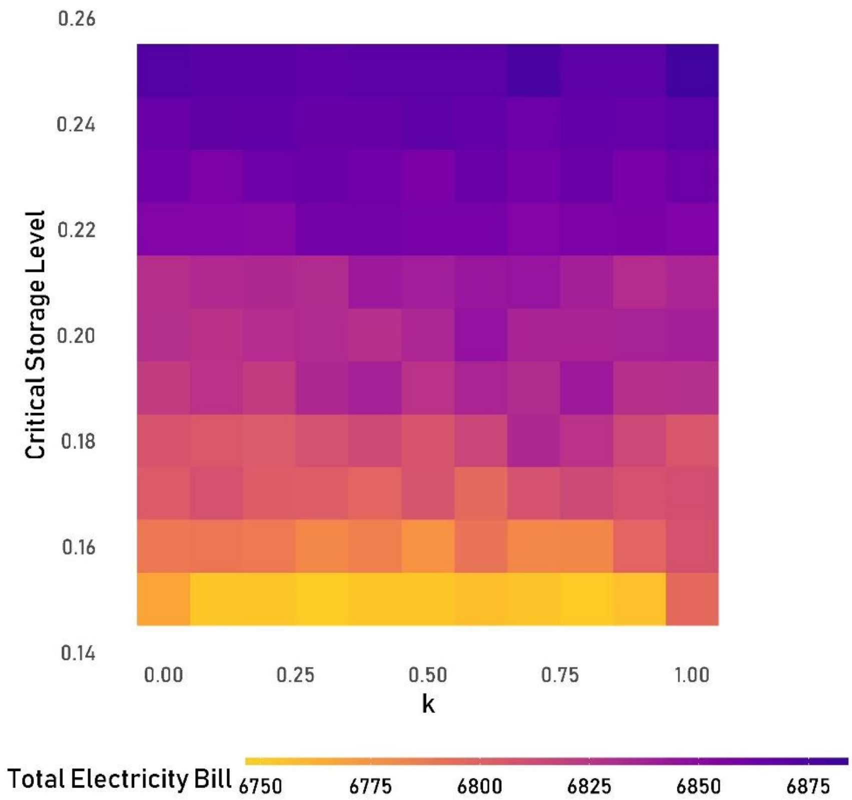


**Figure 4.5** Total Bill Values with respect to the joint change in Critical Storage Level and the k value

The total electricity bills paid by the households seem to increase as both critical storage and k value increases. Given that the critical storage level of 0.22 was found to be a suitable figure for the operation of the microgrid, the accompanying k value could be chosen as 0.5 since it doesn't seem to make a significant difference in the total electricity bill value. The value of 0.5 could be regarded as choice that approaches both the buyer's and the seller's sides equally.

## 4.3 Learning

The Q learning algorithm employed in this study does not actually feature delayed rewards. The rewards are pretty much instant and agents are not compelled to build long term strategies.

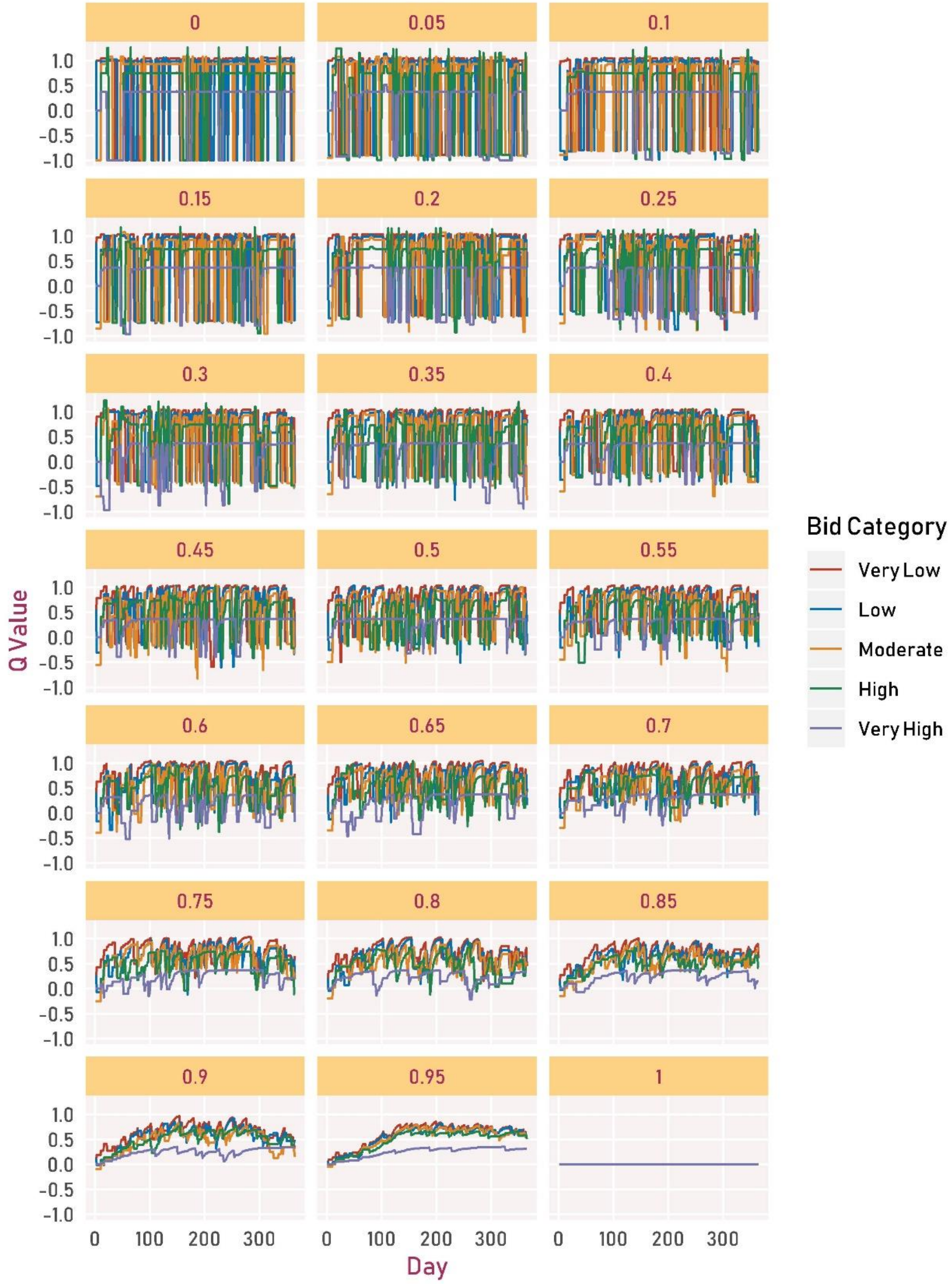


**Figure 4.6** Household 3 – Q-Values for Asks at 10 PM

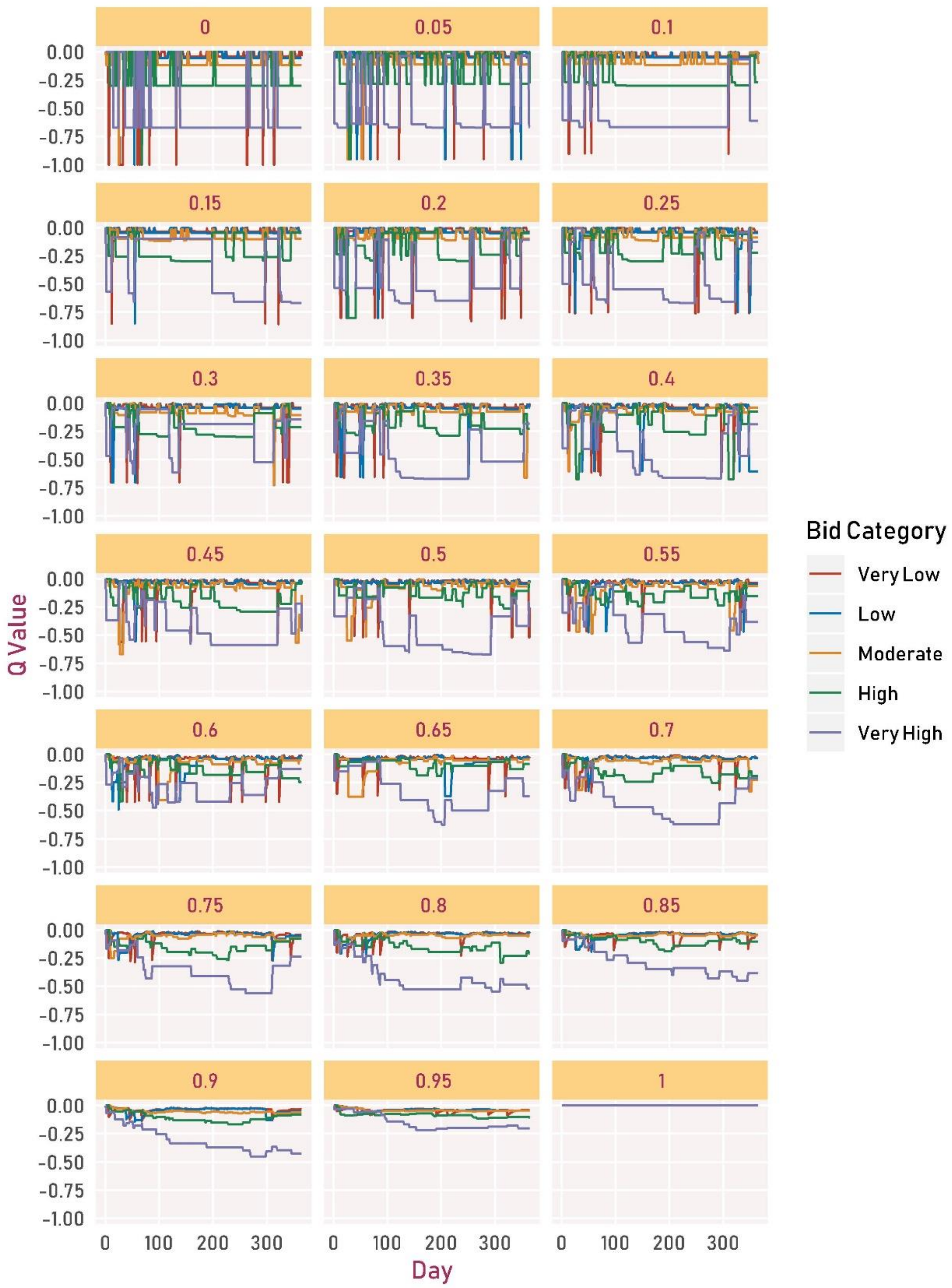


**Figure 4.7** Household 10 – Q-Values for Bids at 10 PM

Figure 4.6 and Figure 4.7 show the learning performance of selected households at selected hours under changing values of the learning parameter $\alpha$.

The lower values of $\alpha$ implies a more "forgetful" learning process. If $\alpha$ is equal to 0, that means the agent only considers the latest event while making its decision for the next period. If $\alpha$ is 1, then the agent does not learn anything at all. The Q value doesn't change and all of the decisions become random. The agent that employs such strategy is called a "zero-intelligence" agent.

Both while learning how to sell and buy, the agents seem to eliminate the high values rather quickly, not regarding that as a viable strategy. Due to the nature of the microgrid market, the agents settle on "low" to "average" options. For this type of learning process, where the past experience is quite valuable, forgetful learning seems to create a chaotic learning environment for the agent which makes it harder for the agents to pinpoint the true value of electricity in a given period.

The default value 0.95 of the learning rate parameter seems to be a reasonable choice for this study. The value provides a balance between learning and exploration under the current settings defined by the opportunity cost-fuelled reward.

## 4.4 Grid Connection and Discriminatory Auctions

It is useful to assess the performance of the proposed market structure under the grid-connected mode of operation of the microgrid. The four possible cases are investigated with the aim to observe the electricity bills each household has to pay. Before moving to the juxtaposition of the combinations of the cases, it is necessary to see if previously tested parameters for the uniform auction is also valid for the discriminatory auction.

Figure 4.8 displays the results of the same experiment that is shown in Figure 4.5. The results, other being more homogenous, display a similar result thus implying that same sets of parameters are also viable for the discriminatory auction practice. Other than the pricing mechanism, the operation of the market does not significantly change compared to the uniform auction case. The only difference is the amount of electricity bills each household has to pay. The electricity bills are given along with all the other results of the experiments in Table 4.1. The average price per power under the discriminatory auction setting with and without the forecast error adjustments are given in Figure 4.9 and Figure 4.10 respectively.

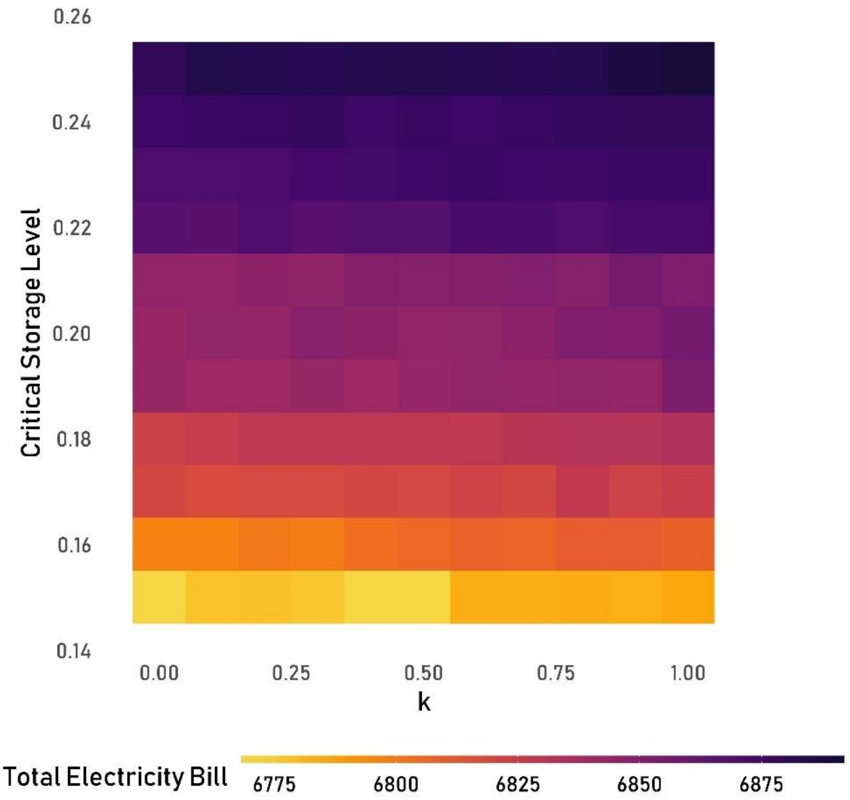


**Figure 4.8** Critical Storage Level and k value for Discriminatory Auctions

Figure 4.9 shows the average price per energy traded via the discriminatory double auction mechanism. It features super-positioned results of the all 100 runs of the simulation. The prices, again roughly display the pattern of the forecast errors. For the supply-demand relation, the reader could observe the Figure 4.10, which shows prices peaking around when the demand is higher and the overall storage level is lower. The difference between the accumulated electricity bills under uniform and discriminatory auctions is along with the cases of the remaining experiments are presented in Table 4.1. From Table 4.1 it could be read that, discriminatory auction and uniform auction result in similar electricity bills for the household, while slightly favouring the producers.

The next is the investigation of the grid connection mode of the microgrid under both the uniform and the discriminatory pricing methods.

The chord diagram showing all P2P trades with the amount of grid feed-ins and regular consumption from the grid is given in Figure 4.11. The high prevalence of the grid as a competitor in these result stems from several causes. First being, the feed-in price.

The feed-in price is assumed to be 0.07 pounds/kWh in lieu with the industry standards [85]. The grid price is the same 0.1442 pounds/kWh as used in the London project. The amount traded is reduced to 10% of its value under the islanded mode of operation. The reason for this drastic decrease is that, in the islanded mode, all the excess generation must be stored in the batteries or else they will destabilize the microgrid while in the grid-connected mode, the prosumers could just feed their excess generation to the grid at the grid feed-in prices set by the managing authority. Rationally, the market participant would not want to sell electricity at prices lower than the grid feed-in price and they would not want to buy electricity at prices higher than the grid electricity price.

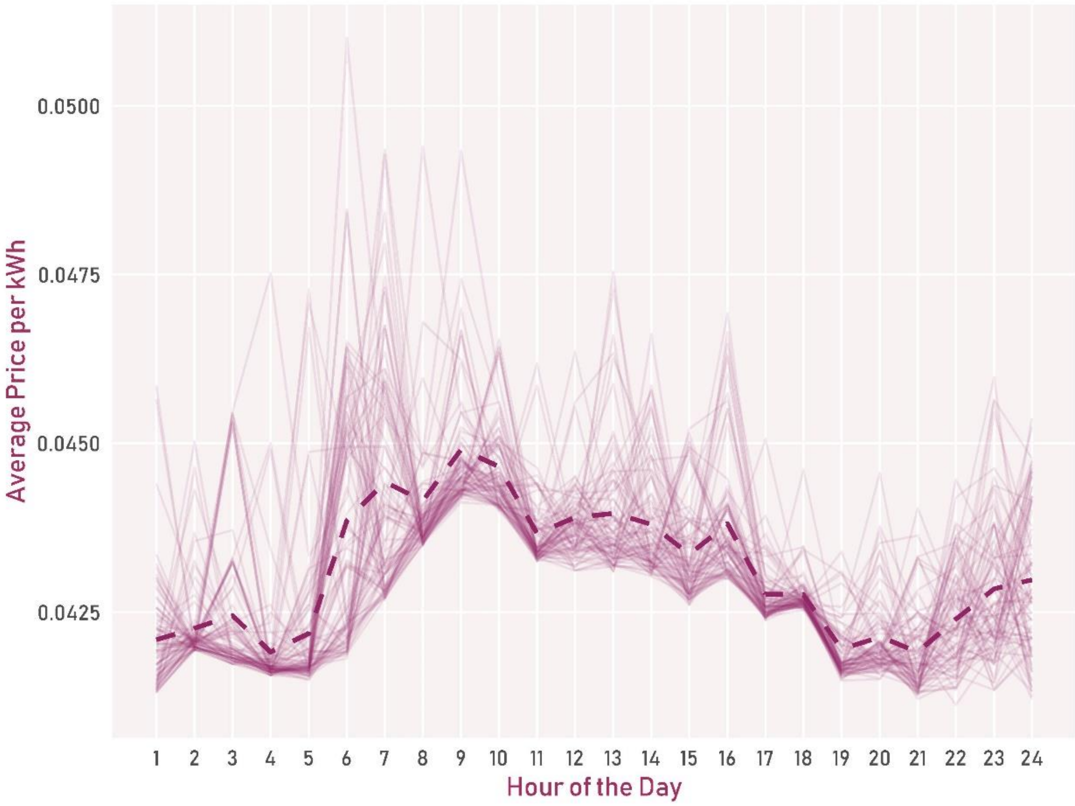


**Figure 4.9** Average Price Per kWh throughout the simulation runs

The storage too is not as effective as it is in the islanded-mode. Most of the storage is not even utilized. Storage is mostly used for storing the excess generation. The user is assumed to keep the energy in storage if the offers for the trade is not tempting to complete the transaction. Which is rational, because the user would like to avoid selling something at half the price at which they have possible bought it. The grid feed-in is approached as a last resort if both the storage is full and if the market does not offer tempting prices.

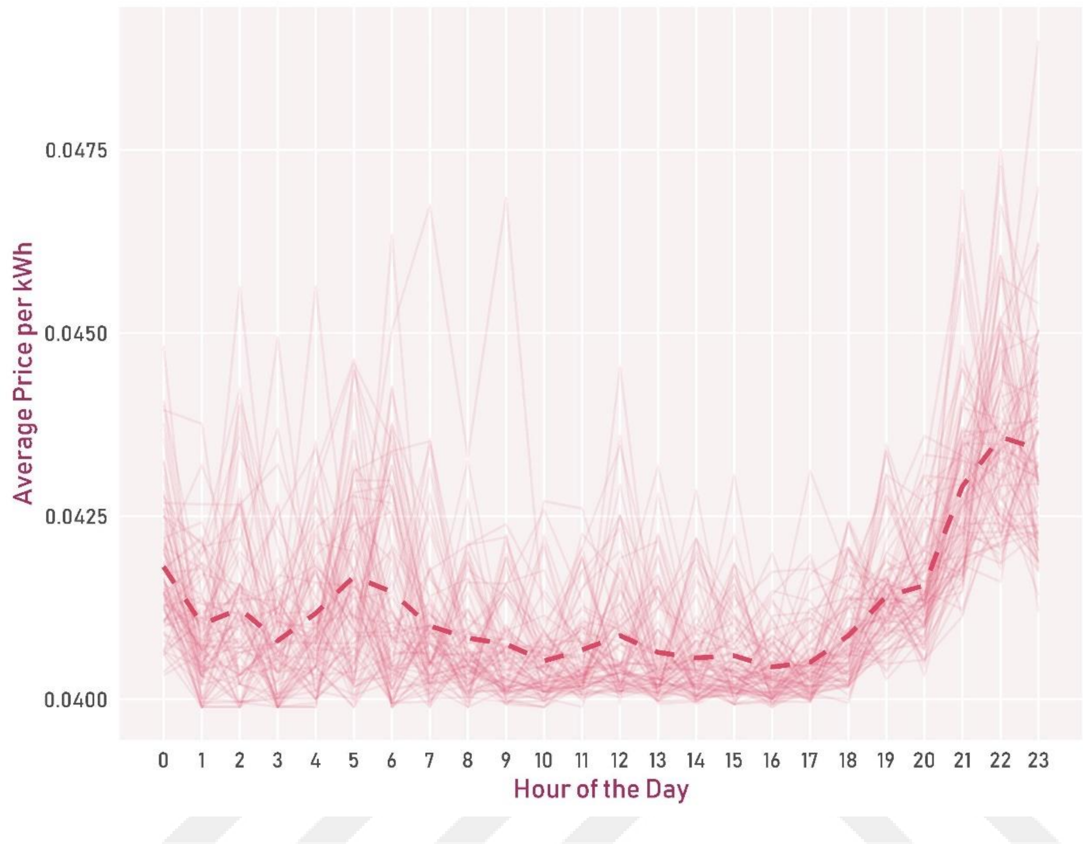


**Figure 4.10** Average Market Clearing Price Throughout the Simulation Runs

Because this study is primarily focused on the islanded mode, the details grid-connected operation of the microgrid is not available in depth. The grid-connected mode is used as a benchmark for the islanded mode for comparison purposes.

For each case, simulation was run 100 times with the same random numbers and the resulting average bills for each household are given in Table 4.1. The total bills shown are, as expected, highest in the islanded operation mode with discriminatory auction, on the other hand the lowest amount of the total bills was achieved by employing the grid-connected mode with both alternatives equalling in the total amount paid. Each household, however, displays a different behaviour that corresponds to its

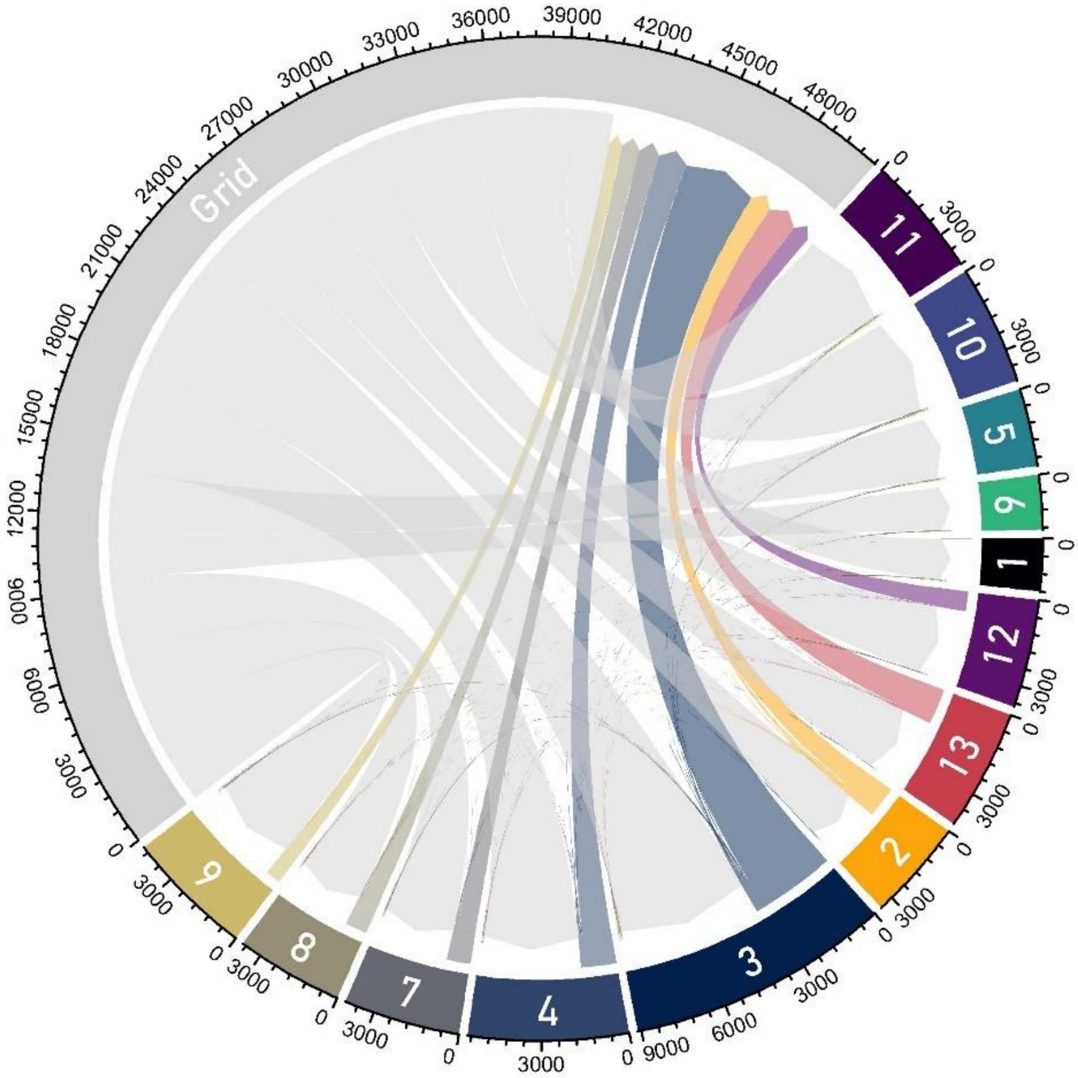


**Figure 4.11** Chord Diagram for the Grid-Connected Setting

characteristics. Households that do not possess any means of electricity generation show little reduction in their electricity bills while those that possess both wind and solar generation units had their electricity bills reduced the most. The somewhat subtler result belongs to those without any means of generation.

While the fuel cell is more expensive than the grid itself, the pricing mechanism makes the P2P electricity cheaper in the islanded operation of the microgrid, because the market is a totally competitive buyer's market. The consumers can get their electricity actually cheaper in the islanded mode, because in the grid-connected mode the grid itself interferes with the free state of the market, installing itself as a supplier with practically infinite amount of supply and a consumer with an infinite amount of demand.

**Table 4.1** Bills in Comparison

| Household | Islanded Uniform | Islanded D'tory | Grid-Connected Uniform | Grid-Connected D'tory | Regular Bills |
|---|---|---|---|---|---|
| Household 1 | 230.58 | 241.76 | 242.89 | 243.70 | 257.36 |
| Household 2 | 393.47 | 380.02 | 284.21 | 282.81 | 646.40 |
| Household 3 | 1105.14 | 1090.65 | 770.97 | 769.02 | 1992.88 |
| Household 4 | 862.20 | 855.51 | 561.80 | 560.61 | 1670.57 |
| Household 5 | 260.13 | 278.27 | 367.94 | 369.28 | 384.67 |
| Household 6 | 198.59 | 210.93 | 262.30 | 263.22 | 271.31 |
| Household 7 | 467.61 | 461.71 | 421.50 | 421.29 | 801.98 |
| Household 8 | 562.69 | 556.60 | 384.11 | 382.89 | 1172.83 |
| Household 9 | 724.21 | 724.91 | 528.88 | 529.28 | 957.43 |
| Household 10 | 400.47 | 416.4129 | 579.74 | 581.75 | 590.31 |
| Household 11 | 481.83 | 490.56 | 592.37 | 594.36 | 599.66 |
| Household 12 | 482.64 | 473.52 | 399.78 | 399.96 | 804.97 |
| Household 13 | 684.72 | 672.75 | 366.18 | 364.52 | 1473.79 |
| Total | 6623.76 | 6853.66 | 5762.72 | 5762.72 | 11624.21 |

The feed-in price at 0.07 pound/kWh makes it impossible to sell to other market participants at rates below this mark. The grid connection mode, for the consumers is still slightly cheaper because they can still get electricity from other prosumers at prices between the feed-in price and the grid price.

**Table 4.2** Variables of Interest in Comparison

| Variable | Islanded Mode | Grid-Connected Mode |
|---|---|---|
| Total Stored | 31952.34 | 14393.45 |
| Used from Storage | 21593.32 | 13646.15 |
| Sold via Auction | 10647.63 | 1065.85 |
| Sold Excess Generation | 1465.91 | 1130.13 |
| Fuel Cell | 34236.00(32.56% uptime) | 0 |
| Bought from the Grid | 0 | 40968.73 |
| Sold to the Grid | 0 | 9606.20 |

In Table 4.2, the storage and trade related variables are shown with respect to the mode of operation.

### 4.5 Breaking Even

Although renewable generation and storage units are getting cheaper than ever, they are still quite expensive. Without incentives and subsidies, a prosumer cannot hope to make a profitable investment within the current state of affairs. As the need to transform the grid into the clean and digital grid of the future, various policy makers are opting in to financially support such enterprises. With sound policy support and a clear vision widespread employment of microgrids can be a reality. This, however, could be a bit difficult considering the costs of installing a microgrid system.

After investigating the industry averages, assuming 2500$ for the 2 meter-blade-length residential wind turbines, 2.99$ per W capacity for solar panels and 6500$ for the total installation price of a single unit of Tesla Powerwall 2. The installation costs in Pounds for each household are given below in Table 4.3. The required breakeven period in years is also given in the table below.

It is obvious that, with solely savings made under the current circumstances, it is not possible to overcome the high installation costs of the systems. In fact, it is quite impossible to make profits with current prices as seen in Table 4.3. Considering that the expected lifetime of these appliances are around 20 years, any breakeven period longer than 20 years means it is not a profitable investment. Even with a state entity covering the installation costs of the storage devices, the breakeven period for all households do not go below 20 years. It is wise to think that, the islanded residential microgrid is still quite a utopic idea without any assistance from politically motivated groups with environmental concerns. Yet, the grid-connected microgrid, only going into the island mode when it is absolutely necessary might prove to be the most suitable transitionary approach to the electricity grid of the future.

Table 4.4 summarizes the case in which the grid-connected uniform auction operation mode is considered for the breakeven analysis. Since energy storage in each household is not necessary, the setup costs could be considered to only consist of the costs of the generation units. Under these assumptions, breakeven periods recede to acceptable levels even without outside financial help.

**Table 4.3** Break-Even Analysis, Islanded Mode

| Household | Total Cost (Pounds) | Only Generation Units (Pounds) | Savings Made (Pounds) | Breakeven Period (Total coverage) | Breakeven Period (Only Gen.) |
|---|---|---|---|---|---|
| Household 1 | 5070 | 0 | 26.78 | 190 | 0 |
| Household 2 | 7020 | 2500 | 252.93 | 28 | 10 |
| Household 3 | 44791.5 | 24925 | 887.74 | 51 | 29 |
| Household 4 | 33891 | 17450 | 808.37 | 42 | 22 |
| Household 5 | 5070 | 0 | 124.54 | 41 | 0 |
| Household 6 | 5070 | 0 | 72.72 | 70 | 0 |
| Household 7 | 7020 | 2500 | 334.37 | 21 | 8 |
| Household 8 | 22990.5 | 9975 | 610.14 | 38 | 17 |
| Household 9 | 12090 | 2500 | 233.22 | 52 | 11 |
| Household 10 | 5070 | 0 | 189.84 | 27 | 0 |
| Household 11 | 5070 | 0 | 117.83 | 44 | 0 |
| Household 12 | 7020 | 2500 | 322.33 | 22 | 8 |
| Household 13 | 28821 | 17450 | 789.07 | 37 | 23 |

**Table 4.4** Break-Even Analysis, Grid-Connected Mode

| Household | Total Cost (Pounds) | Only Generation Units (Pounds) | Savings Made (Pounds) | Breakeven Period (Only Gen.) |
|---|---|---|---|---|
| Household 1 | 5070 | 0 | 14.48 | 0 |
| Household 2 | 7020 | 2500 | 362.2 | 7 |
| Household 3 | 44791.5 | 24925 | 1221.91 | 21 |
| Household 4 | 33891 | 17450 | 1108.78 | 16 |
| Household 5 | 5070 | 0 | 16.74 | 0 |
| Household 6 | 5070 | 0 | 9.01 | 0 |
| Household 7 | 7020 | 2500 | 380.49 | 7 |
| Household 8 | 22990.5 | 9975 | 788.72 | 13 |
| Household 9 | 12090 | 2500 | 428.55 | 6 |
| Household 10 | 5070 | 0 | 10.57 | 0 |
| Household 11 | 5070 | 0 | 7.29 | 0 |
| Household 12 | 7020 | 2500 | 405.19 | 7 |
| Household 13 | 28821 | 17450 | 1107.62 | 16 |

# 5. DISCUSSION AND FUTURE RESEARCH

This study aims to design a feasible microgrid market for future applications of microgrids. One of the greatest obstacles before the higher levels of integration of renewable energy generation is the unpredictability of such energy resources. With that in mind, the market structure is built to envelop forecasts and their unavoidable errors. Because pricing is one of the most important aspects of any market structure, and the auctions are the widely accepted pricing mechanisms in electricity markets. The double-auction mechanism was used to construct the market. The forecast errors were incorporated to the system following the *coherent arbitrariness* idea that is rooted deep in the economics literature.

There are several aspects in the proposed market structure that is quite open to improvements. First, is the forecasting method. The ARIMA method that is employed in this study is merely used as a placeholder. More modern and more accurate methods could be used for the same purpose. Forecasting errors have proven to be quite high in this study, strongly signalling the necessity for a more powerful and robust forecasting method. The second is the learning method. The Q-Learning algorithm that is used to determine the bidding and asking prices of the agents is fairly primitive and simple, while it rather produces acceptable results it is by no means a cutting-edge method to emulate learning in agents.

The results, on the other hand, owing to the fact that the data is real-world data, are quite reliable assuming that the model itself is consistent with the real-world. Low levels of stochasticity in the model helps generate more reliable results. The market structure and bidding processes could be improved as well, coherent arbitrariness is a fine idea that could be implemented in number of areas. This study attempts to incorporate coherent arbitrariness in the agents and emulate the uncertainty encircling the prices during the operation of the microgrid with 100% clean electricity.

The results, however, indicate a mixed outlook for the microgrids. While microgrids can provide cheap, reliable and clean energy, the very high setup costs might prove to be an obstacle for its widespread application. Before the world moves on the islanded, isolated microgrids, it seems, the microgrids will have to pass the grid-connected phase, keeping the islanding ability as a countermeasure for avoiding cascading grid-wide failures, problems or malfunctions. While the financial feasibility of the islanded microgrid could not be found, the grid-connected microgrid seems to be ready to be regarded as a viable alternative.

There are, however, legal obstacles. The electricity grid has not changed much ever since its inception, the legal approach to how electricity is generated, transmitted and distributed is well established. It is a whole different adventure in the world of bureaucracy to accept and adapt to a very radical and challenging idea. The mammoth proportions of the grid and the way it covers every corner of the grid makes the transition to new paradigms a formidable challenge.

The research of the microgrid markets is a very young field. Looking at the findings of this study, it is safe to say that, the most pressing matter in the grid is to find transitionary systems to move towards the grid of the future. Instead of having perfect dreams, what more valuable is, perhaps, the ability to dream imperfectly, to be able to envisage the steps in between.  The changes do not happen overnight, the step-by-step approach is more likely to work under these circumstances. Preparing the grid for the next level, piece by piece, seems to be the better choice.

The microgrid is an exciting utopia of the liberalized electricity market. Currently, it is technologically possible to achieve such systems, however, it might be still early to consider the widespread installation of the microgrids due to financial concerns. The microgrid can provide clean and cheap electricity, as can the electrical vehicles work without rampantly polluting the environment. Both technological marvels will seemingly be keeping the world waiting for a while until they become financially feasible to be considered as viable alternatives.

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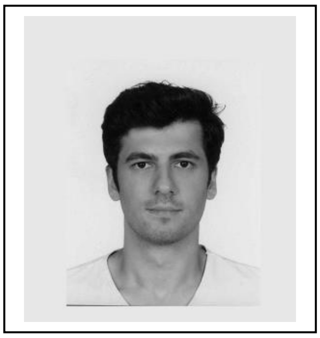
**CURRICULUM VITAE**



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