Modeling Battery Sizing Optimization Algorithms for Various Use Cases

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Modeling Battery Sizing Optimization Algorithms for Various Use Cases

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To my iron will.....

ABSTRACT

Battery energy storage systems (BESS) increase energy controllability and grid flexibility. One of the most important issues in BESS investments is optimal BESS sizing for various needs. In this thesis, it is aimed to develop an optimal battery sizing methodology for the consumer, producer and prosumer. By using Mixed-Integer Linear Programming and Mixed-Integer Quadratic Programming methods, optimal battery sizing algorithms that can be used by all end-user types for different purposes were developed. The advantage of this mathematical modeling is that it can be adapted for different scenario constraints with minor modifications. Various estimation algorithms were used to get more realistic results from the optimization algorithms for the future. Artificial neural network (ANN), deep neural network (DNN), and Long-Short Term Memory models were used to predict generation, consumption, and electricity market data. The importance of estimation algorithms in the smart grid ecosystem was emphasized and it was aimed to predict the needs for the future. Prediction methods and optimization algorithms were developed in the Python environment. Pandas, numpy, sklearn, keras, cvxpy libraries were actively used. It is hoped that it will be beneficial for the investments to be made within the scope of the smart grid concept.

ÖZETÇE

Batarya enerji depolama sistemleri (BESS), enerjinin kontrol edilebilirliğini ve şebeke esnekliğini arttırmaktadır. BESS yatırımlarındaki en önemli konulardan bir tanesi çeşitli ihtiyaçlara yönelik olarak optimal BESS boyutlandırmasıdır. Bu tezde tüketici, üretici ve üreten-tüketici (prosumer) için optimal batarya boyutlandırma metodolojisi geliştirmek hedeflenmiştir. Karmaşık Tamsayılı Lineer Programlama ve Karmaşık Tamsayılı Kuadratik Programlama yöntemleri kullanılarak tüm son kullanıcı tiplerinin farklı amaçlar ile kullanabileceği optimal batarya boyutlandırma algoritmaları geliştirilmiştir. Bu matematiksel modellemenin avantajı küçük değişiklikler ile farklı senaryo kısıtları için uyarlanabilmesidir. Optimizasyon algoritmalarından geleceğe yönelik daha gerçekçi sonuçlar alabilmek için çeşitli tahmin algoritmaları kullanılmıştır. Üretim, tüketim, ve elektrik market verilerini tahmin edebilmek için yapay sinir ağları (ANN), derin sinir ağları (DNN), ve Uzun-Kısa Süreli Bellek modelleri kullanıldı. Tahminleme algoritmaları ile hem akıllı şebeke ekosisteminde tahminleme algoritmalarının önemi vurgulanmış hem de geleceğe yönelik ihtiyaçların tahmin edilebilmesi hedeflenmiştir. Tahminleme yöntemleri ve optimizasyon algoritmaları Python ortamında geliştirilmiştir. Pandas, numpy, sklearn, keras, cvxpy kütüphaneleri aktif olarak kullanılmıştır. Akıllı şebeke konsepti kapsamında yapılacak yatırımlar için faydalı bir çalışma olması umulmaktadır.

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CHAPTER I

INTRODUCTION

The world continues to talk about concepts such as industry 4.0, web 3.0, humanoid robots, and the metaverse. While developing technologies continue to bring unprecedented habits into our lives, they also increase energy consumption. Issues such as the indispensability of electrical energy and the internet and the importance of the continuity of databases have made the security of supply in electrical energy even more important. In this context, the increasing importance of grid-size batteries has been a source of motivation for this study. In this section, the increasing importance of grid-size batteries, the contribution of the thesis to the literature in battery sizing and the scope of the thesis are explained in detail.

1.1 Motivation

When the global climate crisis emerged with the increasing energy demand, renewable energy systems (RESs) came to the fore. The increase in production facilities originating from RES has caused us to encounter the negative aspects of RESs. Unlike conventional electricity generation facilities, RESs has a nature-based intermittent generation profile. In networks where RESs production increases, production cannot be increased by central control as soon as demand increases. Energy storage systems (ESSs) are the only way to flexibly steer RESs to meet demand.

Buying incentive mechanisms have been established in many countries of the world for RESs investors. Incentives are valid until a certain date. In the post-incentive process, generation facility investors will start to sell their RES-sourced generation as part of the electricity market. At this point, there are opportunities to respond to the competition in the electricity market with ESS. Along with the climate crisis, political crises have also led to the discussion of the sources of electrical energy to a large extent. Boycotts or rising prices for energy force countries to establish self-sufficient systems. Likewise, each consumer is individually affected by increasing energy prices. In this respect, consumers as well as producers need smart energy management systems. Intelligent energy management systems can provide bill management sensitive to time-of-use tariffs. Consumers' orientation to the establishment of distributed energy sources (DERs) again with incentives and motivations for self-sufficiency brings us the concept of prosumer. Prosumers also need ESS in order to use their RES resources in the most efficient way. ESSs, which are used for different purposes by both production and consumption and operators, also contribute to grid resiliency.

While the importance and investments of battery energy storage systems (BESSs) have increased, optimal sizing has become one of the most important issues. Although BESSs investment costs are on a downward trend over time, they still have high investment costs. The biggest factor affecting the cost of BESS investment is of course the size of BESS. Basically, sizing is aimed both to meet the needs of the user and not to cause economic waste. In this study, it was aimed to develop optimization algorithms that enable the recommendation of adequate BESS dimensions within the specified use-cases. However, contributions to investment regulations will be proposed to prevent wasteful investments.

1.2 Contributions of Thesis

The contributions of this thesis to the literature can be listed as follows.

i) Historical data is generally used to implement the sizing and power dispatch optimization models. Realizing the forward estimations of production, consumption and electricity market price with NN algorithms allows this study to try a more realistic approach.

ii) Battery sizing optimization algorithms were combined in a single framework. An easy-to-modify algorithm was created that can be used on the consumer, producer, and prosumer sides.

iii) A total of 7 different sizing use-cases was created for the different needs of the consumer, producer and prosumer, where sometimes the objective function changes and sometimes the constraints change.

iv) The maximum size of the battery required for the investment is found with the developed algorithms. Optimally sized battery investment is recommended that maximizes revenue.

1.3 Scope

Within the scope of the thesis, first of all, the smart grid concept will be explained in Chapter II. The roles of consumer, prosumer, producer and grid-size batteries, which are the components of the smart grid concept, and their relations with the grid will be examined in detail.

In Chapter III, machine learning methods to be used for prediction studies will be introduced. These methods include artificial neural networks (ANN), deep neural networks (DNN), and Long Short-Term Memory (LSTM).

Prediction algorithms developed using neural network (NN) models introduced in Chapter III will be explained in Chapter IV. In the subsections divided as consumer, producer, prosumer and electric market, the dataset used for train will be introduced, model parameters will be explained and model results will be displayed. The results of these estimation modules will be used as inputs to battery sizing optimization models.

Mathematical programming methods used for battery sizing optimization algorithms will be introduced in Chapter V. Chapter V will include linear programming, quadratic programming, mixed-integer programming.

Chapter VI includes battery sizing algorithms, model inputs and use-case studies for consumer, producer and prosumer. Modified algorithms will be shown for 7 different use-cases designed for different needs of end-users. The results of use-case studies will be evaluated as a result of these algorithms working with the inputs from the estimation modules.

Finally, the contribution of the battery sizing methodology developed for different end-users investments will be discussed for battery integrations in Chapter VII.

CHAPTER II

SMART GRID CONCEPT

With the developing technology and increasing industrial need, electricity supply is becoming a critical issue. Electrical energy production is in a radical change within the scope of precautionary decisions taken by states and regions with global warming [18, 19]. Renewable Energy Systems (RESs) play an important role in this change. Suppression of treaties and laws increases the demand for RESs, however, RES installation costs are getting cheaper year by year [20]. According to IRENA RES reports [1–3], the increase in RESs worldwide by years is shown in Figure 1. Along with historical data, future prediction of RES installations are also seen. In the light of these data, it is expected that the global installed RES power, which is 2802 GW in 2020, will be 6293 GW in 2030.

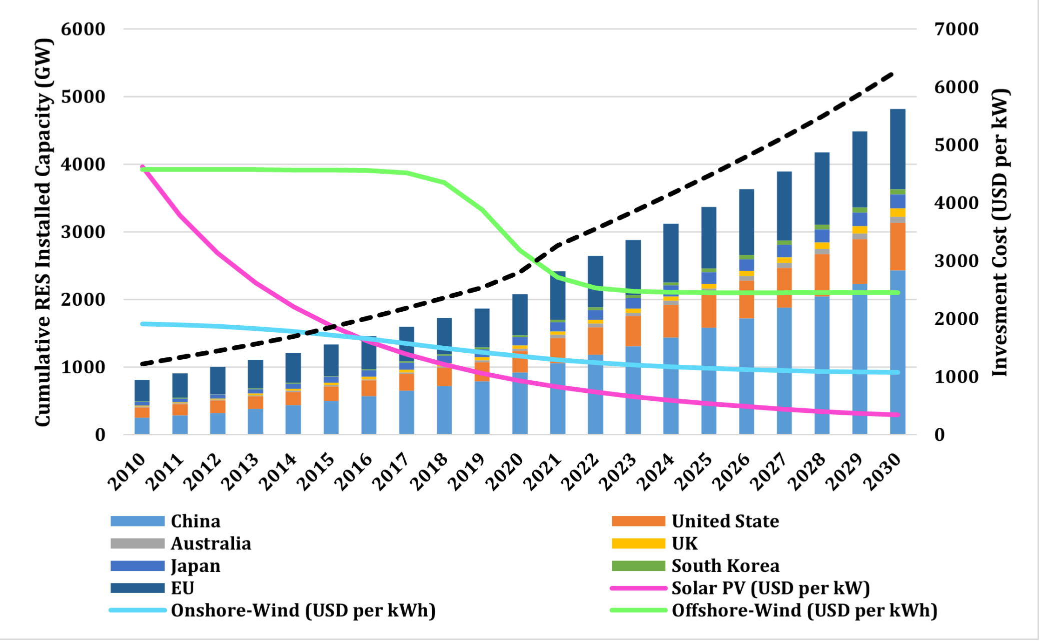

Figure 1: RES Installed Capacities vs RES Installation Costs [1–3]

There are challenges that these expected radical RES increases will create in the grid [21]. In particular, the uncertain generation structure of RESs creates a serious electricity supply challenge [22]. This challenge increases the importance of energy storage systems (ESSs) and estimation algorithms. A rapid increase is expected in the grid integration of elements such as ESSs [23] and decision support mechanisms [24].

In addition to the increase in the installed capacity of RES, there are different factors that will negatively affect the electricity supply. Increasing natural disasters with global warming [25] and the aging structure of grids [26] have also caused significant blackouts and brownouts recently [27]. These cuts cause huge financial losses [28]. All this increasing need for grid resiliency [29] and reliability [30] in the developing world creates a necessity for conventional grids to change [31].

With the help of communication technologies, which have made important developments in recent years, the concept of smart grid has started to be discussed [32]. The general structure of the smart grid is visualized in Figure 2 [4]. According to this structure, one of the most important components is the communication infrastructure. The communication infrastructure connects all the players in the electricity supply. The data obtained from smart meters and sensors [33], the status of production facilities [34], operational processes in transmission [35] and distribution [36], and the electricity market participation [37] can be monitored [38] and managed [39] from an operation center with this connection. The problems caused by the uncertainty in consumption [40] and RES-based distributed generation resources (DERs) [41] are minimized by monitoring and forecasting methods. This infrastructure, which is established for demand-supply balance and includes intelligent decision support mechanisms, increases grid efficiency [42] as well as grid resiliency [43] and reliability [44]. Due to the importance given to DERs [45] and fast frequency regulating systems [46], grid losses can be reduced considerably.

Another important issue in the smart grid is the grid infrastructure that allows bidirectional power flow [47]. It is expected that a new concept will emerge in the distribution system with the increase of DERs [48] and ESSs [49] at the consumer level with the incentive mechanisms developed by the states. For now,

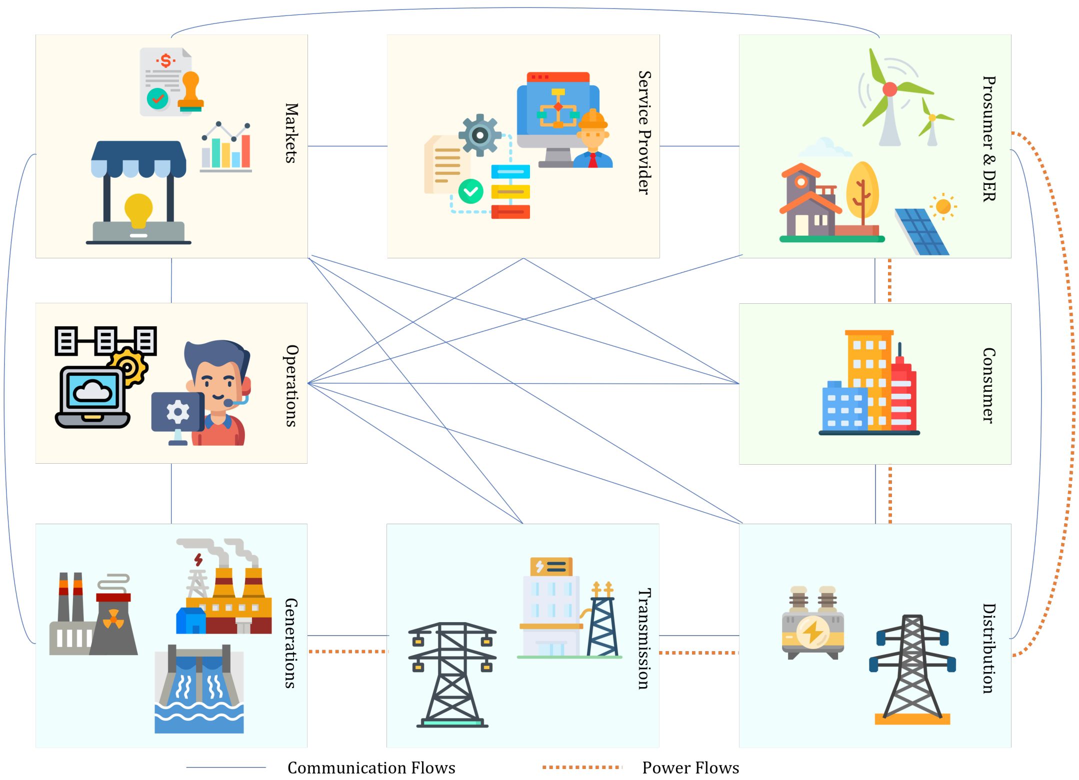

Figure 2: Smart Grid General Concept (adopted from [4])

there is no structure in Turkey and in many parts of the world that allows the end-user to recharge electricity to the grid. However, increasing consumer-based roof top solar systems [50], ESSs [51], and electric vehicle (EV)/mobile power sources [52–54] potential is expected to cause the grid to change its structure bidirectionally. This structure also paves the way for current discussions such as demand side management (DSM) [55], the vehicle to grid concept of EVs [56], electricity cooperatives [57], local electricity markets [58], and peer to peer (P2P) electricity sales [59].

In the continuation of this section, the relationship of consumer, producer, and prosumer components with the grid will be discussed in more detail within the scope of the smart grid concept. In addition, the increasing role and demand of battery ESSs (BESSs) in the grid, their usage areas, BESS and grid integration concepts will be mentioned.

2.1 Consumer

Consumers are the basic element that creates demand in electricity supply. In other words, the main purpose of electricity supply is to meet the electricity needs of consumers spread from cities to rural areas. Consumers are generally divided into 3 categories. These categories are domestic, commercial and industrial consumers. The domestic consumer may be the house type or the apartment type. It usually represents the electrical load of 1 family. Commercial consumers consist of buildings consisting of commercial inns or offices. However, industrial consumers are factory-type intensive production facilities.

Consumers are an uncontrollable and unpredictable structure in the conventional grid system [60]. According to this network structure, the end-user consumes independently from the network and the network is responsible for feeding this demand. This uncertainty and uncontrollability creates a serious challenge in maintaining the production-consumption balance in electricity [61]. This challenge threatens the network frequency [62] and security of supply [63].

In the smart grid concept, consumers have an active communication with the grid and an important role in the supply-demand balance [64]. This role first appears when the consumer regulates consumption in multi-time [65] or dynamic network pricing [66]. The purpose of multi-time tariffs or dynamic grid pricing is to increase demand control over the consumer. It is expected that consumers will naturally tend to shift their consumption to periods when prices are cheaper. While grid pricing creates expectations about the consumer's trend, it still does not provide complete control over consumption. However, if the consumer wants to do bill management, end-user can follow the grid pricing periods manually and regulate her consumption. As the next step, it can consume the stored electricity when the electricity price is expensive, by using batteries to store when the electricity price is cheap [qatar paper].

The smart home structure, in which consumption can be monitored and controlled by the end-user, continues to be discussed with different approaches. Sensors come to the fore in the smart home concept [67]. Especially the automatic control of heating and hot water systems with sensors [68] and smart decision support mechanisms [69] has a serious effect on electricity demand. In addition, systems that provide control by monitoring consumption, such as smart lighting [70], also provide convenience in electricity management. In addition to the concept of smart home, terms such as smart building and smart industry continue to be reflected in life. There are smart building applications such as smart security systems [71] and space planning [72], and smart industry applications such as production [73] and maintenance planning [74].

Consumers, who manage their electricity demand by optimizing their energy management, form a new consumer structure. As the last step, the establishment of the communication infrastructure of the smart consumers with the grid comes [75]. This communication infrastructure enables demand-side management applications [R] that consider both consumer and grid needs. The key components of smart consumer buildings with the potential to increase efficiency [76], sustainability [77] and two-way gain with grid [78] are given in Figure 3.

2.2 Producer

The facilities where electricity generation takes place are known as producer. Fossil fuels such as wood and coal, fission elements such as uranium and thorium, and streams are used as sources in conventional production facilities. These production facilities have features such as adjusting the generation level, providing continuous generation and not requiring storage. However, the structure and features of production facilities will be changed in the smart grid concept.

Renewable energy systems such as wind and solar are rapidly being included in production facilities with private and state initiatives. The biggest positive feature of these production facilities is that they are an important step towards reducing

Figure 3: Residendital-Commercial-Industrial Smart Consumer Concepts

carbon emissions. However, the biggest negative aspect is that they have a nature-dependent discontinuous production profile. It is expected that this discontinuous structure will create various problems in the network with the increase of RES penetration.

Despite some negative effects, the energy independence of countries and the nature-based and free RES resources increase the importance of RES installation. Especially with the recent political problems such as the Russia-Ukraine war in the world, it has been seen that the electricity potential of the countries that they produce with the raw materials they import from abroad can be endangered. However, as seen in the recent examples of Texas and Isparta, the effects of natural disasters and major problems in domestic electricity supply systems have seriously brought security of supply back to the agenda and reminded the importance of distributed generation systems (DGS).

Although DGSs are an alternative source for security of supply, they are accepted as the new model of production facilities in the smart grid concept. DGSs are small in scale compared to traditional large power plants. As part of the energy transition, they were generally not included in grid planning studies, considering that DGS's assets would have little impact on a large electricity grid. In the current order, it is aimed to increase the number of mechanisms, also called unlicensed generation. As a successful result of the incentive mechanisms, DGS has emerged as solar power plants or rooftop photovoltaic (PV) panels where the sun is abundant, and as small-scale wind turbines where the wind is high. The number of DGSs, which are located at the points desired by the investor, by following a resource-based approach, is increasing. With the increase in the installed capacity of DGS, operational difficulties have arisen for the electricity grid, whose management uses traditional methods. One of the important factors causing these difficulties is that there is no information flow from the DGS to the central operator. Therefore the central operator has to make predictions about the instant situations of the DGS while establishing the generation-consumption balance. The high margin of error in the forecasts forces operators to manage networks more sparingly in order to take less risk, which leads to a serious decrease in energy efficiency.

About 15% of the installed power in Turkey is provided by solar and wind energy systems, which are mostly preferred as DGS [79]. According to the data shared by the Ministry of Energy, Turkey's wind energy potential is estimated at 48,000 MW (51.6% of the current installed power) [80]. However, according to [81], 2.583 MW unlicensed solar power distributed generation units were established in 2017 and 1.578 MW in 2018. As a result of the global problems brought by carbon emissions, it is known that renewable energy systems related to the decisions taken worldwide and the targets of achieving zero emissions are increasing rapidly. Although the increase in renewable electricity capacities around the world has been interrupted by the 2020 pandemic process, it is seen that it has increased over the years, and it is estimated that the increase will continue in the coming years [82].

In addition to the role of environmentally friendly generation on sustainability, it has been demonstrated by many studies that DGS has a reducing effect on system losses if it is built geographically close to the consumer and at the distribution level [83–85]. Inverter-based DGSs provide grid balance very quickly by changing the inverter current and active/reactive power generation when extreme situations such as sudden voltage drops occur [86].

One of the most important terms in the smart grid concept is flexibility. DGS's installed inverter has control potential to provide more flexible operation in the grid. In order to keep the voltage in the network between operational limits, reactive power control can be achieved with many methods and devices. Within the scope of the smart grid, the potential of DGSs to participate in control, flexibility, and investment planning mechanisms in the grid can be listed as follows.

- Development of a distributed reactive power control method for the distribution grid [87]
- Developing an approach that coordinates active and reactive power to be provided from DGS and capacitor units [88]
- Developing algorithms to increase DGS density by regulating the power factors of DGSs and reducing their negative effects on transmission and distribution networks [89]
- The use of inverters in DGS facilities for flexible voltage intervention in response to sudden voltage drops [90]
- The use of local reactive power control capacities of PV inverters in order to increase the PV generation density at low voltage level [91]

Optimal power flow (OPF) serves the smart grid concept in order to obtain optimum solutions [92] for grid planning, production control and grid management. OPF has an important place in examining the effects of generation units on the grid. Some studies using OPF are as follows;

- Combined optimization of power flows in a system where different energy sources are connected [93]
- Positioning and sizing of DGS plants to reduce power losses [94–96]
- Investigation of the effects of DGSs on reactive power and voltage control [97]
- Evaluation of grid capacity for DGS connection [98]
- Energy management of grid-connected PV and battery systems [99]

One of the most important issues with power systems optimization approaches in smart grids is generation estimation. Power estimation of a PV system as a short-term estimation [100] and estimation of hourly solar radiation from the day ahead [101] are possible with artificial intelligence algorithms. Many studies on the estimation of solar [102–105] and wind [106–109] productions can be reviewed for detailed information.

2.3 Prosumer

The word prosumer is derived from the combination of the words producer and consumer. It emerges as a new role in the transformation of energy systems. As this role name includes, it represents the end user who has both production and consumption actions. The most common version is created by end users who integrate roof top solar energy systems at their consumption points.

Being a prosumer provides the advantage for end users to make their own production and reduce electricity purchase from the grid. Thus, this production system investment has an effect on reducing invoices. The spread of distributed generation on the consumer side and the increase in self-sufficiency actually have a positive effect on electricity supply. Because network investments and losses decrease. Therefore, on-site production investments are supported in Turkey and around the world with various government incentives [110–117].

Prosumers represent the holistic and active end user with the production unit, controllable loads, electric vehicle, battery and its own energy management system within the smart grid concept. It brings up the terms self-consumption and self-sufficiency with a structure that can be called a nanogrid. A lot of work has been done to optimize the energy management of such smart home or smart buildings [118–122]. It is important for prosumer's energy management systems to reduce the electricity bill, to sell electricity to the grid, and to have controllable loads that can respond to demand-side management applications.

Of course, DGSs being uncontrollable poses a problem for the consumption balance of prosumers. These problems are tried to be solved with energy storage systems.

2.4 The Role of Batteries in the Grid

In this section, the role of batteries in the smart grid concept will be explained. Within the scope of the chapter, the usage areas of grid-size battery systems, the increase in battery demand over the years, optimization approaches used in battery integrations, and battery sizing applications will be discussed in detail.

2.4.1 Battery Services

Grid-size batteries have started to be used for different purposes in the grid. These purposes can be listed as frequency control, voltage control and reactive power supply, virtual inertia support, renewable firming with storage ramping, bill management etc. The usage areas that will be exemplified in this Subsection are expected to solve many problems in conventional grid systems.

2.4.1.1 Frequency Control

In electrical power systems, supply and demand balance should be provided instantly. This balance directly affects the system frequency, which determines power quality and reliability. Various applications are carried out by a transmission system operator (TSO) to maintain the balance between production and consumption and to keep the frequency stable. Frequency control is performed at 3 levels [123]. Primary frequency control (PFC) responds to frequency disturbances within a few seconds. Traditionally the only way was to use the thermal generators that are already online and actively producing energy to provide such service. While thermal generators are used as spinning reserves for PFC on the production side, there are studies to provide the frequency control service at the consumption side [124–126]. Since Battery Energy Storage Systems (BESS) can ramp up and down very fast, they can be robust equipment in frequency control [127, 128]. However, current studies continue [129–131].

2.4.1.2 Voltage Control and Reactive Power Supply

Voltage, along with frequency, is another factor that determines power quality in power systems. Thanks to the inverter connection, BESSs can provide reactive power as well as active power to the grid. The possibility of reactive power contribution makes BESSs advantageous in voltage control. Modeling studies are carried out with various methods to use BESSs in reactive power support and voltage control [132]. However, BESS allocation has also become an important issue [133].

2.4.1.3 Virtual Inertia Support

Renewable energy penetration is expected to increase rapidly soon as a result of the targets set by countries and regions to reduce carbon emissions. With the intermittent nature of renewable resources and the increase in penetration, the share of synchronous generation in the generation mix will keep decreasing. Renewable sources, especially photovoltaics, are expected to cause low system inertia as the challenge power systems will face [134]. Various studies have been carried out to solve the inertia problem in power systems by using the BESS's fast frequency response feature [135–137].

2.4.1.4 Renewable Firming with Storage Ramping

Fluctuations in output power are another challenge that renewables bring to the power system. Solar PV and wind energy generation, whose power output depends on the weather, may increase or decrease at high ramp rates. They can force the ramp-up and ramp-down constraints of the grid. Various applications have shown that BESS can be used to firm the renewable's output power [138–140]. The energy and power capacity of BESS has also become important in hybrid systems for renewable firming service [141, 142].

2.4.2 Increase in Battery Demand

In Figure 4, the past installed power and future outlooks of grid-size ESSs are compiled from various reports [5–15]. As a result of the targets and forecast reports announced by the countries, a significant increase is expected in ESS investments. However, cell prices of Li-on batteries have decreased from \$750/kWh in 2010 to \$100/kWh in 2020. With the increase in investments, further reductions in ESS investments are expected in the coming years.

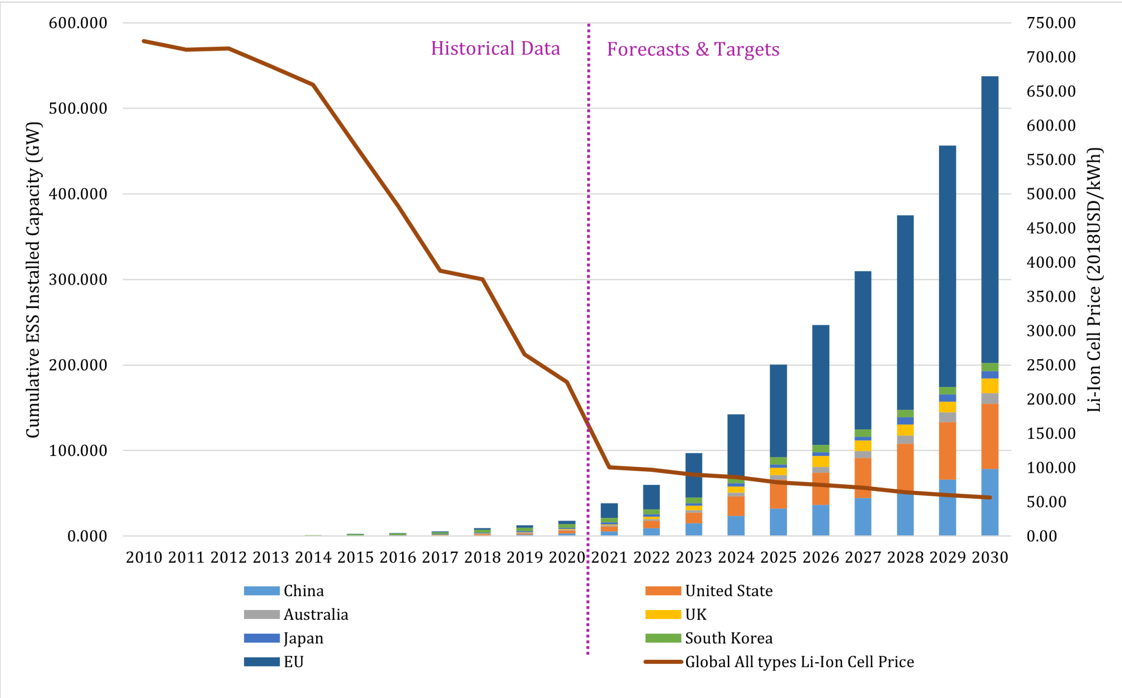

Figure 4: ESS Installed Capacities vs ESS Installation Costs [5–15]

2.4.3 Battery Sizing Applications

Battery storage investments are increasing within the scope of increasing energy storage need. One of the most important issues in battery investments is the sizing of the ESS. ESS sizing directly affects both the investment costs and the operating efficiency at the point of use.

Studies for sizing the ESS installation are generally carried out for the needs of the end user. In the literature, it has been seen that ESS sizing algorithms can be grouped in 3 categories under the titles of producer, prosumer and consumer.

The main purpose of sizing algorithms in Producer-integrated ESS installations can be summarized as absorbing intermittent generation, increasing generation efficiency and maximizing revenue due to grid purchase pricing. However, the most important agenda item when sizing the battery for the prosumer is self-sufficiency. Consumers, on the other hand, need battery sizes where they can bill management within the scope of TOU with their current load profiles. The scope and objectives of battery sizing approaches in the literature are summarized in Table 1.

In this study, in addition to those in the literature, an algorithm that can make battery sizing for all end users with simple modifications will be presented. These modifications were designed to suit the different needs of end users. Within the scope of this thesis, an algorithm has been developed that will enable consumers to make bill management connected to TOU and minimize transformer losses of end-users with transformers. The algorithms have been developed for producers according to scenarios with limited network purchase contract and hourly power purchase contract. Sizing for the production facility that will make sales sensitive to the electricity market price has also been added to the producer use-case studies. For prosumers, prosumer agreements that can and cannot sell to the grid are evaluated separately.

Table 1: Battery sizing literature review.

	end-user type	usage area	purpose	year	ref
Literature	Producer	PV	conventional operation strategy, the dynamic price load shifting strategy, and the hybrid operation strategy	2017	[143]
		Wind	wind curtailment, network ageing and reliability	2020	[144]
		Wind	minimise the difference squared between wind output and desired output for a wind generator	2013	[145]
		Wind	accommodating the spilled wind and minimising the annual cost	2010	[146]
		PV	minimise the total cost of the storage system and energy supply	2016	[147]
		Wind	minimising the penalty cost from forecast errors and the cost of the ESS	2014	[148]

Table 1: Continuing

	end-user type	usage area	purpose	year	ref
Literature	Producer	Wind	minimising the capital cost of the BESS and maintaining the constant wind production	2008	[149]
		Wind	maximise the expected operation benefit	2003	[150]
	Prosumer	Residential-PV	economic assessment	2014	[151]
		Residential-PV	maximizing home economy, while satisfying home power demand	2017	[152]
		Residential-PV	most cost effective battery size	2012	[153]
		Residential-PV, Commercial-PV	minimising the electricity cost and the cost of battery capacity loss	2013	[154]
		Residential-DGS	levelising power consumption	2012	[155]
		Residential-PV	cost-optimal sizing of the battery and power electronics	2017	[156]
		Building-PV	comply with the definition of zero energy building concept of the European Union	2020	[157]

Table 1: Continuing

	end-user type	usage area	purpose	year	ref
Literature	Prosumer	Residential-PV	achieve satisfactory battery sizing results with a limited amount of net meter electricity data	2019	[158]
		Building-PV	demand shift at peak electricity cost times and outage protection	2010	[159]
		Residential-PV	minimize the total annual cost of electricity	2019	[160]
		Residential-PV	minimize the total annual cost including both energy and battery degradation-based costs	2020	[161]
	Consumer	Industrial	peak load shaving	2007	[162]
		Industrial	peak shaving applications	2018	[163]
		Industrial	minimize electricity bills	2019	[164]

Table 1: Continuing

	end-user type	usage area	purpose	year	ref
This Paper	Producer	PV	LPA		
			PPA		
			EMP		
	Prosumer	commercial-PV	with power sale to the grid		
			without power sale to the grid		
	Consumer	commercial	TOU		
			TOU, tr loss		

CHAPTER III

MACHINE LEARNING AS A FORECASTING METHOD

Estimation algorithms have an important place in the smart grid concept. First of all, the uncertainty in the generation profile of RESs poses a threat to the supply-demand balance in the grid. The most appropriate way to overcome this challenge is to plan the grid supply by accurately predicting the future generation from RES with machine learning algorithms [165–168]. Likewise, the estimation of consumption on the end-user side also contributes to the supply-demand balance, unlike conventional grid models [169–172].

3.1 Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) emerged on the basis of mimicking biological neural networks [173]. Similar to biological neural networks, artificial neural networks are made up of nodes and layers. Each of the nodes represents a neuron. Layers, on the other hand, contain multiple nodes. In artificial neural network applications, it is basically aimed to solve the relationship between the information introduced as input and output data and to generalize the models [174]. After the input and output information is taught to the model, the model is expected to calculate the weights that the layers will affect on the output. The general structure of neural networks consisting of nodes, layers, and connections is shown in Figure 5 [16].

ANN, which is constantly developing and providing successful results in forecasting, natural language processes, and decision support applications, also comes to the fore in meeting the generation and consumption forecasting needs of smart grids. Zhang et al. [175] evaluated ANNs while using different algorithms for load

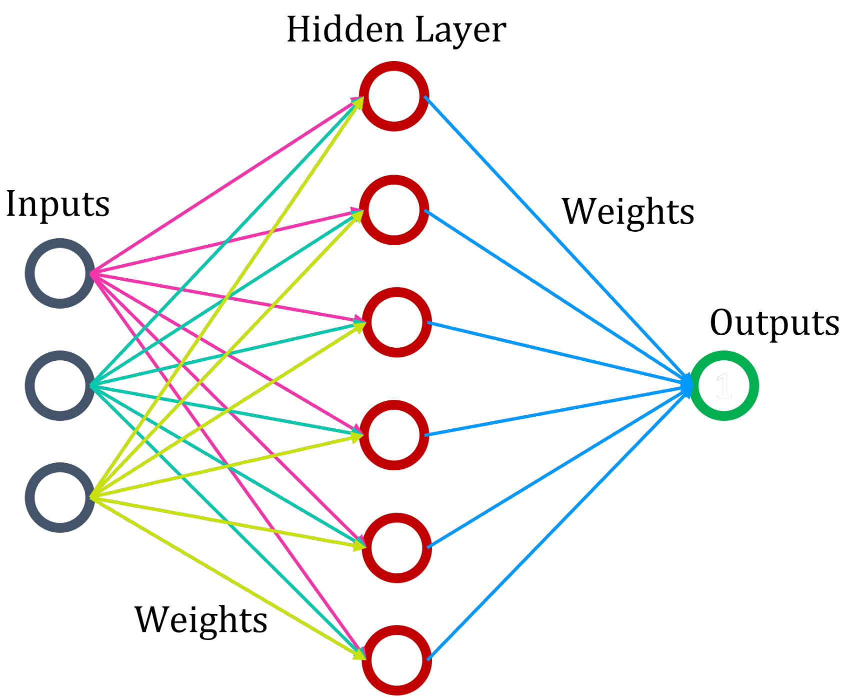

Figure 5: Neural Networks structure (adopted from [16])

estimation in smart grids. Additionally, in [176] was studied that the utility can use it for demand side management by estimating load profiles with ANN.

On the generation side, it is seen that ANN models are used for wind generation forecasting [177], solar generation forecasting [178], and optimal fuel cell operation [179]. Detailed reviews of studies using ANN for wind and solar can be found in [180] and [181].

3.2 Deep Neural Networks (DNN)

Deep neural networks represent multiple layers of ANN models. As in the ANN model, it consists of node and layer units. Unlike the ANN model, it contains more than one layer. Layers can consist of many nodes, as well as weights occur between layers. There are weights from each node in the layers to each node in the next layer. Thus, the neural network is established. In addition to the ANN hyperparameters, how many layers to build a model with becomes an engineering problem. The basic DNN model consisting of 3 hidden layers is visualized in Figure 6.

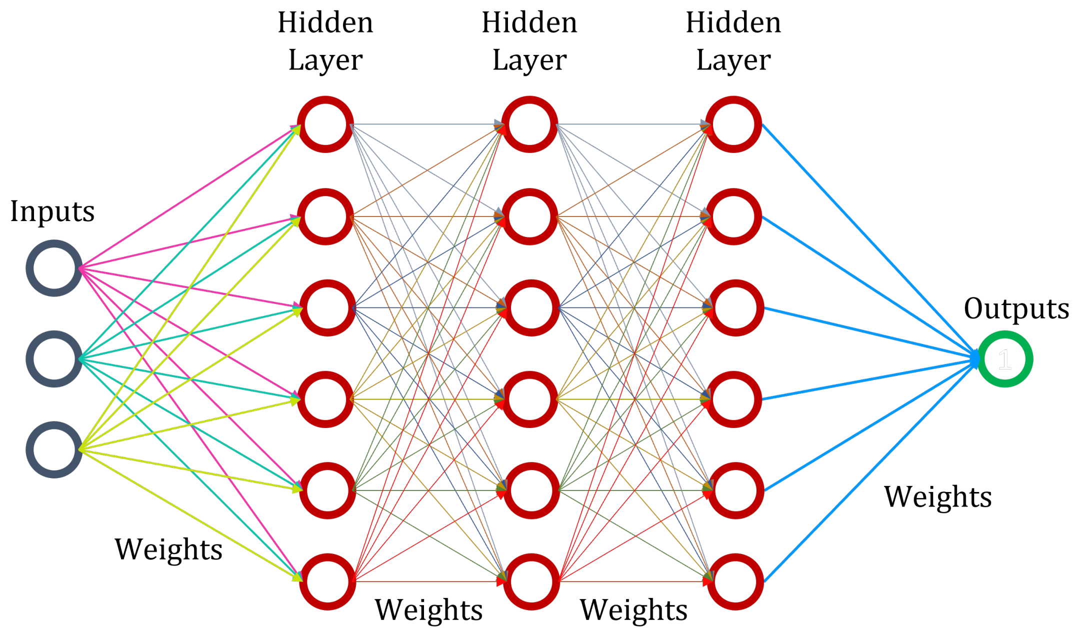

Figure 6: Deep Neural Network Structure

DNN models can be used for many applications within the scope of the smart grid concept. Hossen et al [182] used DNN model for short-term load forecasting. Likewise, load prediction [183] has been studied with DNN based on smart meter data. The use of DNN in estimating the energy load is seen in [184] and [185]. In addition, DNN models can be used for the detection and prediction of cyber [186, 187] and physical [188] problems. MehdipourPicha et al. [189], on the other hand, used DNN for error estimation of power transformers. In this study, the DNN model will be used to predict electricity market pricing.

3.3 Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) is part of recurrent neural networks. Unlike feed-forward neural networks, they have the ability to keep the results from previous neural networks in their memory and previous iteration results affect subsequent iterations. LSTM general structure is shown in Figure 7 [17]. This feature provides an advantage in using LSTM in sequential [190] and time-dependent [191] estimation processes.

Since LSTM is time and period sensitive, it can be used in power systems,

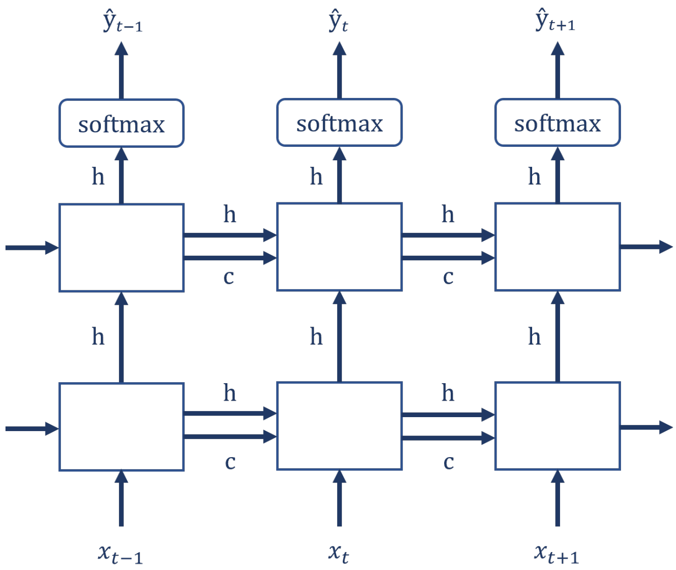

Figure 7: LSTM structure (adopted from [17])

especially for estimating the electricity demand of buildings [192] or regions [193]. In addition, applications such as estimating electricity market prices, which are important for smart grids, are also suitable for the use of LSTM [194].

CHAPTER IV

CREATING INPUTS BY MACHINE LEARNING

In this chapter, input data will be created to be used in battery sizing algorithms. Input data includes future forecasted demand, PV generation, and electricity market prices from outdated datasets. LSTM models will be used to predict demand, ANN to predict PV generation, and DNN models to predict market clearing price (MCP). Details of historical data sets, hyperparameters of constructed models and estimation results will be explained in detail.

4.1 Demand

For use in demand profiles, 1-year and 15-minute consumption data of a real commercial building is used. The consumption profile seen in Figure 8 belongs to this commercial building. The base load of this commercial building is approximately 50 kW. However, the annual maximum power consumption is 292 kW. Consumption data is obtained from meter records and the start date is ”20.09.2020” and the ending date is ”19.09.2021”. The data consists of 34987 periods in total.

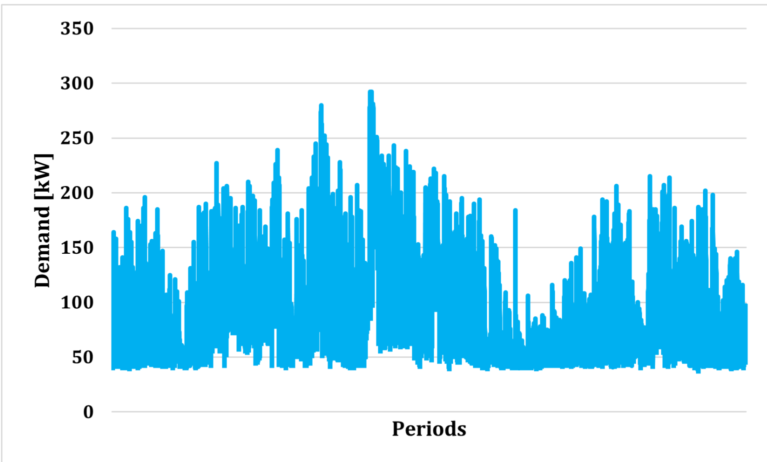

Figure 8: 1-year 15-minute demand profile.

By using this 1-year demand profile, the next 1-month demand profile is estimated. While estimating, the LSTM method mentioned in Subseciton 3.3 was used. The LSTM method is implemented in Python with the "keras" library. The hyperparameters of the LSTM model, which is built as a 1-layer in demand estimation, are given in Table 2.

Table 2: LSTM model hyperparameters.

units	*loss*	*optimizer*	*epochs*	*batch − size*
100	mae	adam	300	100

The hyperparameters given in Table 1 affect the estimation result. These hyperparameters are tuned to improve the results. "units" consists of positive integers and returns the number of nodes in the layer [195]. "loss" represents the error measuring method of the model. In this LSTM model, the mean absolute error method is used. "mae" performs an error measurement by taking the absolute value of the difference between the actual data and the model results [196].

With the "optimizer" parameter, the method to find the solution is selected. Adam optimizer is used in this LSTM model. The "adam" optimizer is a stochastic gradient descent method that evaluates first-order and second-order moments [197]. Kingma et al [198] states *"computationally efficient, has little memory requirement, invariant to diagonal rescaling of gradients, and is well suited for problems that are large in terms of data/parameters"*.

"epoch" means that the whole train set is passed once while performing the regression. In other words, the eores are evaluated as much as the number of epochs and the teaching is performed by passing over the train set [199]. "batch" refers to the set of N dataset elements. These clusters are processed independently of each other. The size of the number assigned to the "batch-size" generally improves the results, but also slows down the processing speed of the model [199].

As a result of demand estimation using LSTM with the above parameters, a 1-month demand profile was obtained. This profile, seen in Figure 9, will be used in the next sections for battery sizing. The purpose of this estimation process is to develop a model that can predict future needs, not based on past demand data.

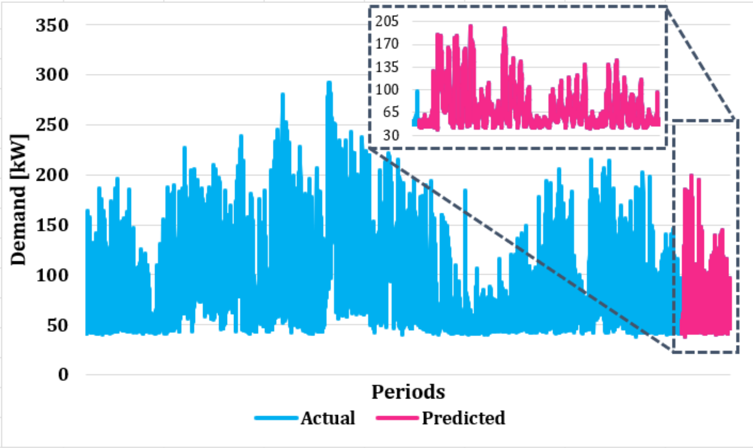

Figure 9: 1-year 15-minute demand profile & 1-month 15-minute prediction profile.

4.2 PV Generation

The real 1-year 1-hour production data of a solar generation facility with an installed power of 25 kWp is used as the solar generation profile. This production profile is seen in Figure 10. According to this production profile, which includes the dates between "01.01.2020" and "31.12.2020", the maximum production period was realized at 1 pm on "20.03.2020" with 4.96 kW. The generation profile includes 8760 periods in total. In Figure 11, 1-week generation profiles from each season are visualized in order to show the generation profile more clearly.

Using 1-hour 2020 generation data, the solar generation profile for January 2021 is estimated. The ANN model, whose working principle is described in Section 3.1, is used for production estimation. The ANN model is built in Python with the "keras" library. The hyperparameters used for the ANN model consisting of 1 hidden layer are given in Table 3. While installing ANN, 100 nodes were used in the hidden layer. "mae" is defined as the error measuring method and "adam" as the optimizer. While the "epoch" number is kept as 300, the "batch-size" value is 1500.

As a result of the solar production estimation made with the ANN model, the

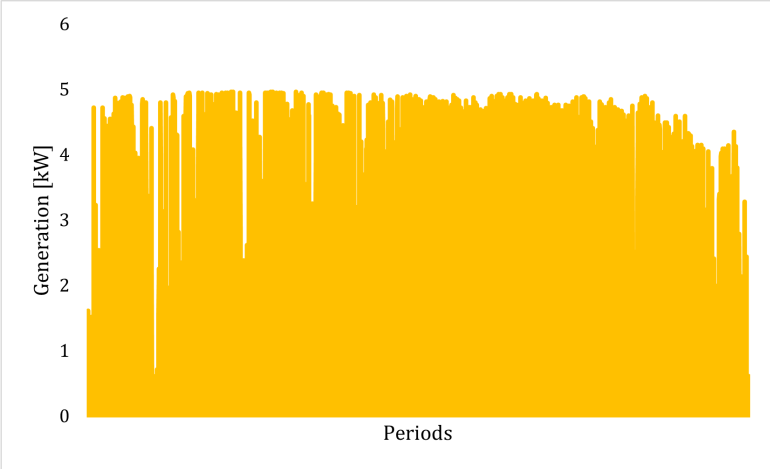

Figure 10: 1-year 1-hour generation profile.

Table 3: ANN model hyperparameters.

units	*loss*	*optimizer*	*epochs*	$batch - size$
100	mae	adam	300	1500

production profile for January 2021 was obtained. Figure 11 shows the generated and predicted solar profiles. However, 1 week of the estimated production profile is visualized in Figure 12 to better illustrate the produced profile. This estimated production data will be used in battery sizing optimization for the Producer.

4.3 Electricity Market Price

For electricity market prices, the 2-year 1-hour market clearing price (MCP) data set covering 2017 and 2018, taken from the EPDK transparency platform, is used. EUR/MWh prices are taken as basis to avoid the effect of exchange rate difference. The 2-year MCP profile is shown in Figure 14. The data set consists of a total of 17520 market prices.

Using the MCP profile containing 2-year 2017 and 2018 data, January 2019 MCP values are estimated. The DNN model, the structure of which is described in Section 3.2, is used for market price estimation. The parameters of the DNN model constructed with 3 neural network layer are given in Table 4. While constructing the DNN model, 100 nodes were created in each of the 3 hidden layers. ”mae”

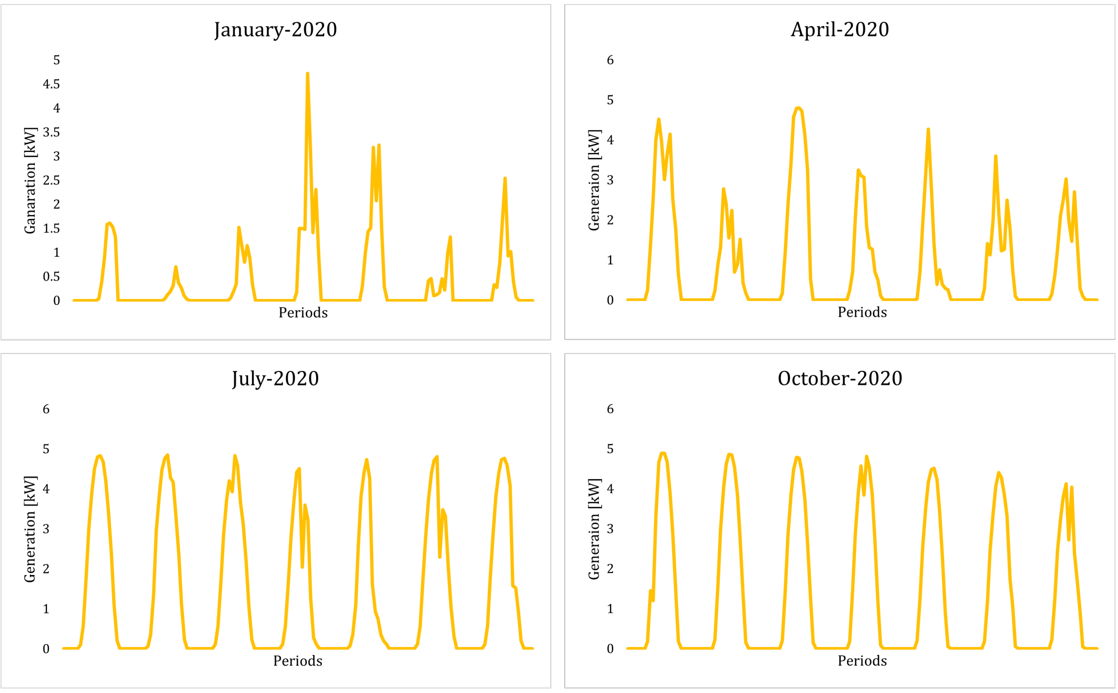

Figure 11: 1-week 1-hour seasonal generation profile.

is used for error measurement. "mae" was used as the optimizer. The "epoch" number was set to 300 and the "batch-size" was taken as 1500.

Table 4: DNN model hyperparameters.

units	*loss*	*optimizer*	*epochs*	*batch − size*
100	mae	adam	300	1500

January 2019 MCP values were estimated by MCP estimation with the DNN model. In Figure 15, 2-year train set and estimated 1-month data are visualized. However, in order to show the estimated values in more detail, the last 1 week of the train set and the estimated 1 month data set are given in Figure 16. Estimated MCP values will be used for battery sizing in the producer scenario that will offer a selling price to the market.

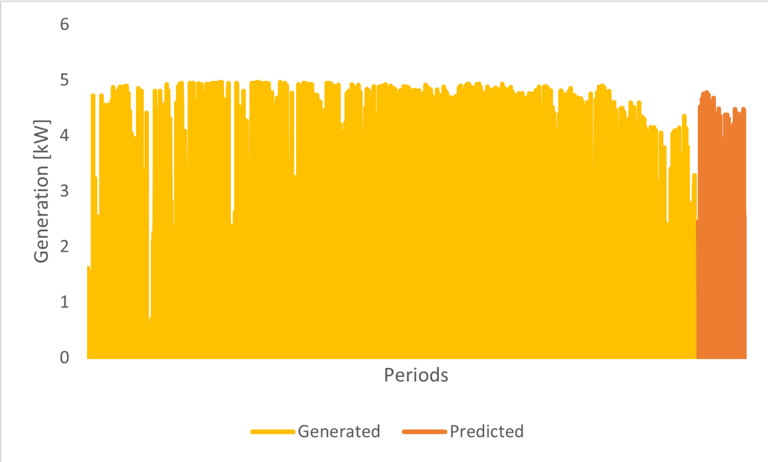

Figure 12: 1-year 1-hour generation profile.

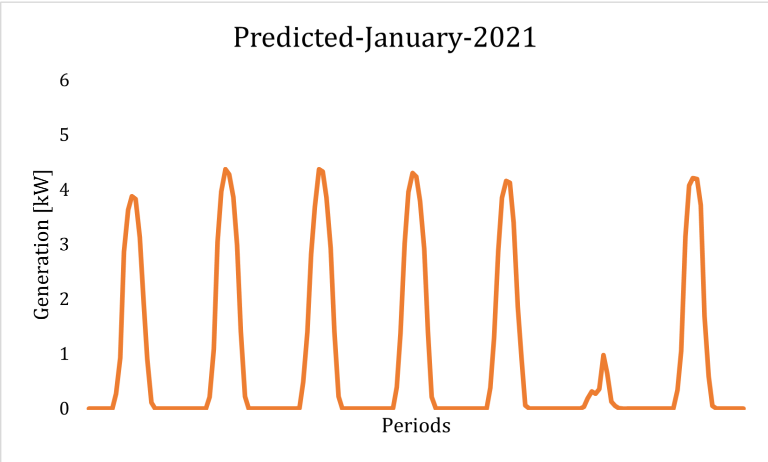

Figure 13: 1-week 1-hour generation profile.

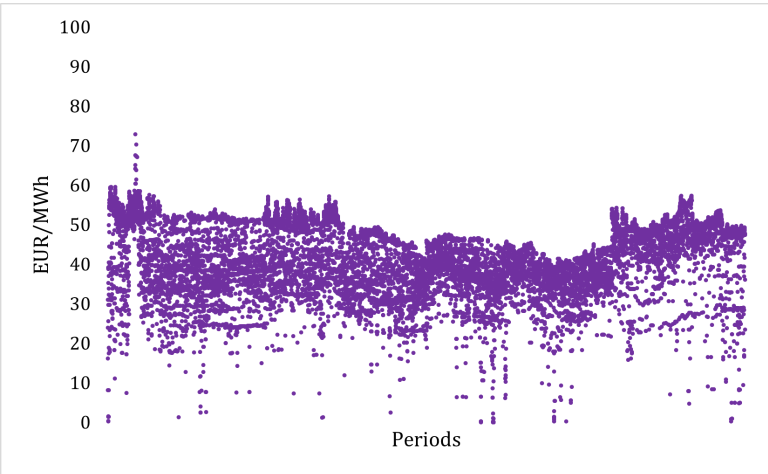

Figure 14: 2-year 1-hour MCP profile.

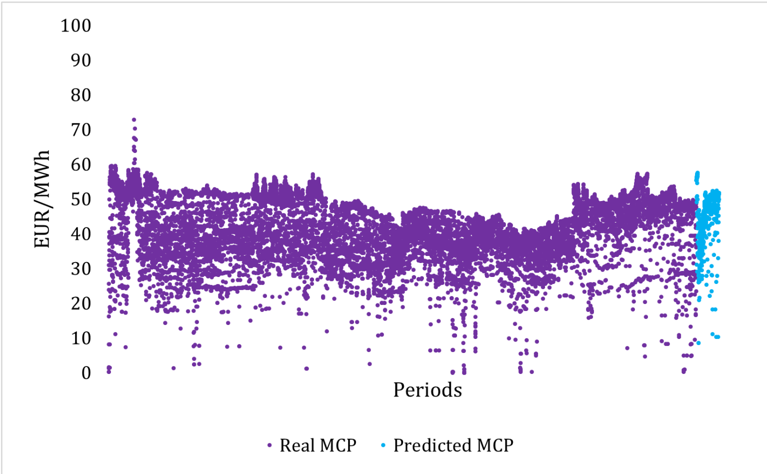

Figure 15: 2-year 1-hour real & predicted MCP profile.

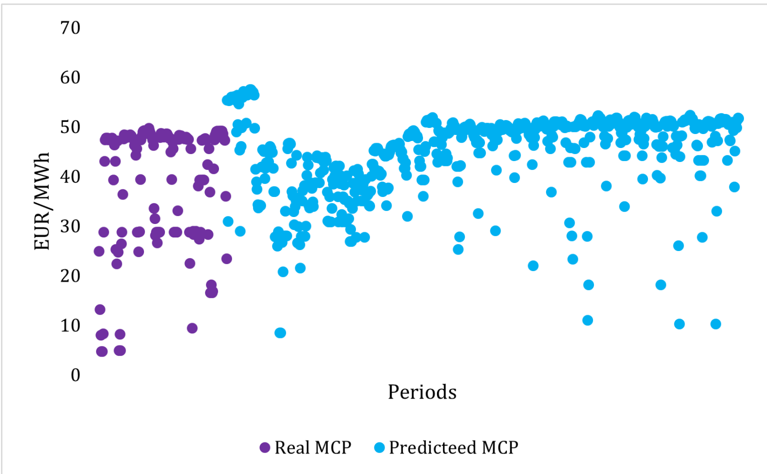

Figure 16: 1-month 1-hour predicted MCP profile.

CHAPTER V

OPERATIONS RESEARCH IN POWER SYSTEMS

Battery sizing algorithms will be established with various optimization models. The mathematical infrastructure of these optimization models is explained in this chapter. In this context, linear programming, quadratic programming, integer programming and multi-objective subsections were created. In the subsections, the mathematical infrastructures of the algorithms and their usage areas were explained in detail.

5.1 Linear Programming

Linear programming is defined as *"The process of minimizing a linear objective function subject to a finite number of linear equality and inequality constraints."* [200]. It is used to model equation systems with thousands of variables and constraints in many areas such as production and logistics. The standard notation [201] in linear programming is as in Equation 1.

$$minimize\ \left\{c^T.x\right\} \tag{1}$$

$$subject\ to$$

$$A.x \leq b$$

Automated systems gained importance thanks to optimization within the scope of smart grid applications. Since linear programming is very advantageous in terms of solution speed, it is widely used in many smart grid concepts.

The main area of use of linear programming has been energy management systems. Tan et al. have proposed a model that can manage both the supply and demand sides and provides flexibility in energy management [202]. In this model, it is aimed to minimize the energy cost in demand-side planning and to maximize the load factor in supply-side planning. However, linear programming technique can also be used in grid planning and investment to calculate the optimum placement of grid units [203] and the most efficient routing of energy supply lines [204].

The hourly peak load shaving model was developed with a linear programming approach so that smart homes, which are an important unit in smart grids, can participate in grid flexibility [205]. On the other hand, Kim et al. suggested the optimal power flow and energy dispatch model for smart buildings with their own production and storage units [206].

5.2 Quadratic Programming

Quadratic programming has a quadratic objective function and a set of linear constraints. They can be found in convex and non-convex structures. Non-convex quadratic optimization problems are more difficult to solve because there may be more than one local minima point. The standard notation [207] for Quadratic programming is as in Equation 2.

$$minimize \left\{ q(x) = \frac{1}{2}.x_T.G.x + x_T.c \right\} \tag{2}$$

$$subject\ to$$

$$a_T.x = b$$

$$a_T.x \leq d$$

Quadratic programming is more complex than linear programming and may be more difficult to solve. However, since the power transmitted in electrical grids consist of active and reactive components, quadratic programming provides a more realistic approach to modeling power systems.

von Berg et al. proposed quadratic programming algorithms that can provide real-time operation for optimal reactive power flow in networks with distributed generator systems [208]. There are also studies that model both AC [209] and DC [210] optimal power flow approach for smart grids.

Integration and power exchange of electric vehicles, whose usage is increasing, has also become a challenge especially for distribution networks. Quadratic programming has taken place in the modeling of electrical and mechanical systems within electric vehicles [211] and in the participation of electric vehicles in power systems, both singular and aggregator-wide [212, 213].

5.3 Integer Programming

It is formed by entering integer coefficients in the integer programming optimization algorithm. It is a version of mixed-integer programming (MIP) used with linear or quadratic programming. However, since it introduces a discrete structure to the linear solution set, it has a more complex and difficult solution than linear programming [214]. Mixed-integer programming general problem structure is as in Equation 3 [215].

$$\begin{gathered} maximize \ \{c.x + h.y\} \\ subject\ to \\ A.x + G.y \leq b \\ x \geq 0 \ and\ integer, \ y \geq 0 \end{gathered} \tag{3}$$

Optimization algorithms such as mixed-integer linear programming (MILP) or mixed-integer quadratic programming (MIQP) are often used for intelligent solutions in power systems. This method is used especially when unidirectional power flow modeling is required. Algorithms designed to ensure that the mains and the prosumer receive power at the same time [216] or [217] to prevent the battery from charging and discharging at the same time are examples of this.

CHAPTER VI

BATTERY SIZING ALGORITHMS

In this chapter, different models were established for consumer, producer and prosumer and use-cases were examined. These different use-cases, which are determined according to the needs of the end-user, consist of 2 different models for the consumer, 3 different models for the producer, and 2 different models for the prosumer. First of all, the general structure of all models, then the mathematical algorithm, and finally the use-cases created for different end-users will be examined.

6.1 Consumer

Two different battery sizing models have been developed for the consumer. These models are "Time-of-Use Oriented Battery Installation" and "Time-of-Use & Transformer Loss Oriented Battery Installation".

6.1.1 Time-of-Use Oriented Battery Installation

This algorithm has been developed for all end-user profiles. The purpose of the model is to provide bill management by making appropriate battery operation in multi-time tariff systems. The MILP method is used in this model.

The basic structure of the consumer model with battery sizing optimization is visualized in Figure 17. According to this structure, commercial, residential or industrial end-users can perform battery charge-discharge operation according to the TOU tariff. In this model, the consumer is not allowed to sell electricity to the grid.

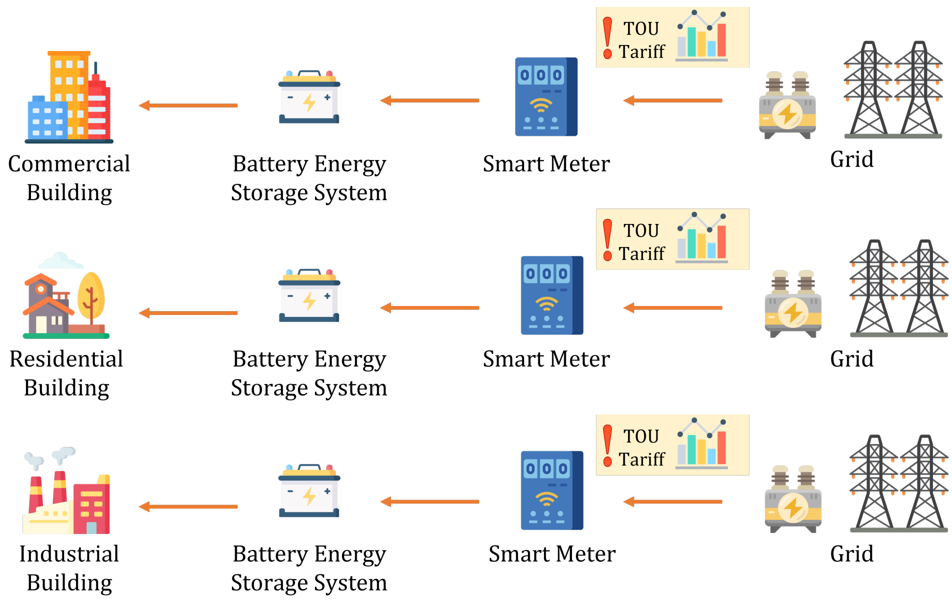

Figure 17: Time-of-Use Oriented Battery Installation General Structure

6.1.1.1 Model

In the sizing of the battery to be used by the consumer for bill management, the objective function consists of the bill related to the energy consumed is tried to be minimized in Equation 4.

$$min\left\{\left(\sum_{t}^{T} g_t.TOU_t.\Delta T\right)\right\} \tag{4}$$

In Equation 5, power balance was created for the end-user bus. In this equation, the power to be purchased from the grid and the discharge power of the battery represent the supply, the demand of the commercial building and the charging power of the battery represent the total demand.

$$g_t + d_t.\eta^{discharge} = D_t + c_t, \forall t \tag{5}$$

Equation 6 ensures that the SOE of the battery is always higher than the depth-of-discharge rate. At the same time, Equation 7 prevents the instantaneous SOE of the battery from exceeding the battery energy capacity.

$$DoD.E \leq e_t, \forall t \tag{6}$$

$$e_t \leq E, \forall t \tag{7}$$

The SOE amount in the first and last periods are fixed in Equation 8 so that the energy exchange analysis can be done correctly with the optimization algorithm. SOE values for all periods except the first and last periods depend on the instantaneous charge and discharge in Equation 9.

$$e_t = DoD.E, \forall t \tag{8}$$

$$e_t = e_{t-1}.\left(c_t.\eta^{charge} - d_t\right).\Delta T, t = \{1, T\} \tag{9}$$

Equation 10 and Equation 11 constraints are used to prevent charge and discharge from taking negative values. However, the battery can be charged as much as the available gap in the energy capacity of the battery in Equation 12.

$$0 \leq c_t, \forall t \tag{10}$$

$$0 \leq d_t, \forall t \tag{11}$$

$$c_t.\eta^{charge}.\Delta T \leq E - e_t, \forall t \tag{12}$$

It cannot be discharged more than the battery's current SOE in Equation 13. However, Equation 14 and Equation 15 limit charge and discharge by the battery's power capacity.

$$d_t.\Delta T \leq e_t, \forall t \tag{13}$$

$$c_t \leq P, \forall t \tag{14}$$

$$d_t \leq P, \forall t \tag{15}$$

Equation 16 and Equation 17 are added to the algorithm with the help of binary variables to avoid simultaneous charge and discharge in the optimization results.

$$d_t \leq G.u_t, \forall t \tag{16}$$

$$c_t \leq G.(1 - u_t), \forall t \tag{17}$$

Finally, physical constraints are added so that the power purchased from the grid is not negative and not higher than the transformer power to which the commercial building is connected in Equation 18 and Equation 19.

$$0 \leq g_t, \forall t \tag{18}$$

$$g_t \leq G, \forall t \tag{19}$$

6.1.1.2 Use-Case Study - 1

For this use-case study, the commercial building demand profile predicted in Subsection 4.1 was used. Data are in 15-minute periods and tariff pricing is based on EPDK 3-time tariff prices for commercial consumer [218]. It is assumed that the commercial building is connected to a 400 kVA transformer with 65 kW agreement power.

The depth-of-discharge of the battery planned to be installed is taken as 0.2. In this case, the battery SOE will not fall below 20%. In the use case, the discharge efficiency of the battery is 0.875 and the charge efficiency is 0.9.

In Figure 18, the state-of-energy (SOE) status of the consumer is shown as 3-day according to the simulations. The maximum SOE value for this consumer was found to be 553 kWh by the developed algorithm. However, the power capacity of the battery was calculated as 61 kW. Figure 18, shows that this battery performs 1 cycle per day. Since the TOU tariff times have a sequential period, the battery performs sequential charging and discharging processes.

The charge-discharge profile of the consumer integrated battery is shown in Figure 19 as 3-day. At night, when the TOU tariff is cheap, the battery is charged. At peak charging times, it discharges and feeds the consumer's demand.

Figure 20 shows the pricing profile of the TOU tariff with black dashes. However, the blue line represents the pre-battery load profile of the building. When the battery is used for charge-discharge operation and bill management within

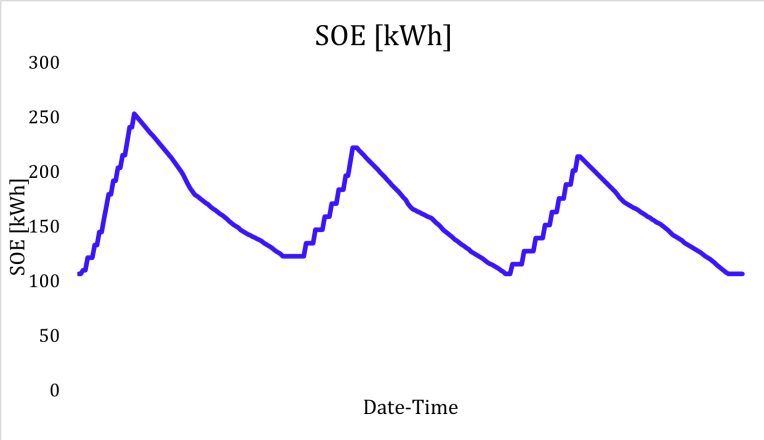

Figure 18: Periodical State-of-Charge

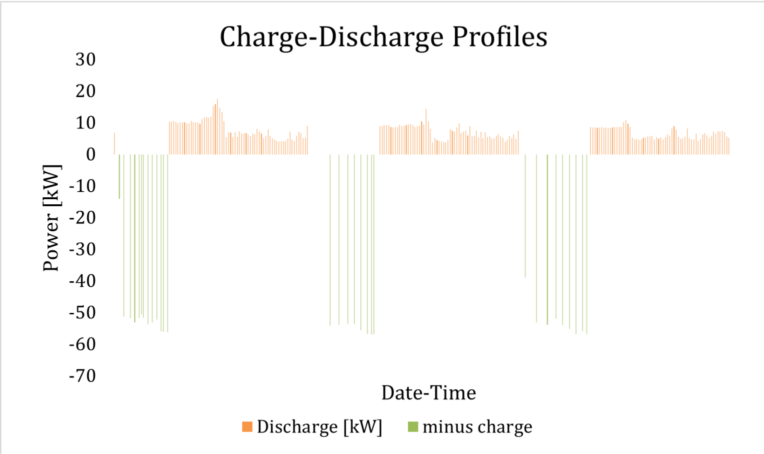

Figure 19: Periodical Charge-Discharge Operations

the scope of TOU tariff, the load profile of the consumer turns into a pink line. According to the post-battery load profile, no power is supplied from the grid in peak tariff pricing. In cheap tariff periods, the load profile rises above the pre-battery load profile. In this way, load shifting is realized thanks to the battery, and electricity is used from the grid during the hours when the electricity price is cheap.

In Table 5, battery sizing optimization results are given according to the 1-month consumption estimate of the consumer with 65 kW contract power. In the table, the battery energy capacity calculated with the proposed model is given in kWh and the battery power capacity is given in kW. According to the TOU tariff pricing, the total bill before the battery is 3,928.55 TL, and the total bill after the battery is 2,378.97 TL. In this case, the integration of the battery with optimum

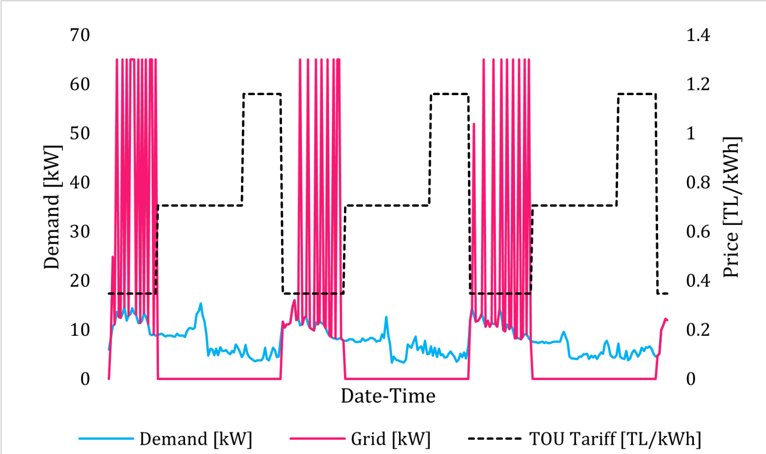

Figure 20: Periodical Demand-Supply Balance

sizing provides a monthly profit of 1,549.58 TL for the consumer.

Table 5: 1-month simulation results of Profile 1.

Profile No.	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)	Total Bill (Before)	Total Bill (After)	Saving (TL)
1	553	61	3,928.55	2,378.97	1,549.58
	Max Demand (kW)	Min Demand (kW)	Mean Demand (kW)	Power Contract (kW)	Total Energy Demand (kWh)
	49.14	2.50	8.17	65	5,883

Table 6 shows the results of TOU oriented battery sizing optimization for different consumers. Battery sizing optimization has been made for 5 different consumer profiles. The maximum power consumptions of these consumers are 49.14 kW, 38.21 kW, 20.67 kW, 199.23 kW, 614.29 kW, respectively. However, grid power purchase contracts have been accepted as 65 kW, 75 kW, 50 kW, 400 kW and 1000 kW, respectively. The monthly total energy consumption is 5,883 kWh, 10,220 kWh, 7,427 kWh, 205,413 kWh, and 1,086,146 kWh. Different sized consumers were selected to further compare the battery sizing optimization results.

The battery energy and power capacity recommendations of the battery sizing algorithm for consumers are shown in Table 6. However, the monthly consumer bill before and after the battery was calculated according to the 3-time TOU tariff and added to the table. The Bill calculated the savings potential of 39%, 38%, 38%, 42% and 28%, respectively. The ratio of the recommended battery energy capacity to the total energy consumption of consumers was determined as 9.1% at the highest and 2.4% at the lowest. However, it was observed that the ratios of the average power demand of consumers to the recommended battery power capacities are in the range of 13.4% - 53.2%. It was determined that the battery power capacities are shaped according to the power constraint in the power purchase agreement. With the various use-cases carried out in this context, the importance of network agreement power for optimal sizing is understood as well as battery sizing.

Within the scope of TOU Oriented battery installation scenario, consumers are considered to be connected to transformers of standard sizes, which will correspond to the smallest power larger than itself, depending on the power contract. In this scenario, losses in the transformer do not affect the consumer bill. However, it was observed that the losses in transformers increase due to battery charge-discharge processes. The algorithm that consumers with transformers can do bill management and is sensitive to transformer losses will be explained in the next subsection.

Table 6: 1-month simulation results of consumers.

Profile No.	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)	Total Bill (Before)	Total Bill (After)	Saving (TL)	Max Demand (kW)	Min Demand (kW)
1	553	61	3,928.55	2,378.97	1,549.58	49.14	2.50
2	407	70	6,659.13	4,098.11	2,561.02	38.21	3.87
3	266	45	4,883.42	3,011.41	1,872.01	20.67	3.11
4	3,034	359	36,978.72	21,452.37	15,526.35	199.23	38.38
5	43,035	760	183,868.95	131,500.12	52,368.83	614.29	231.06
Profile No.	**Mean Demand (kW)**	**Power Contract (kW)**	**Total Energy Demand (kWh)**	**Total Transformer Loss(Before) (kWh)**	**Total Transformer Loss(After) (kWh)**	**Battery Energy Capacity / Total Energy Demand (%)**	**Battery Power Capacity / Mean Power Demand (%)**
1	8.17	65	5,883	1,459	1,532	9.1	13.4
2	14.20	75	10,220	1,493	1,597	4.0	20.3
3	10.31	50	7,427	1,502	1,622	3.6	22.9
4	71.35	400	205,413	1,500	1,602.56	5.9	19.9
5	404.52	1000	1,086,146	1,255.63	1,436.81	2.4	53.2

6.1.2 Time-of-Use & Transformer Loss Oriented Battery Installation

Unlike Subsection 6.1.1, end-user is assumed to have special transformer for this optimization model. The aim of the model is to reduce transformer losses while operating the battery for multi-time tariff. The MIQP method is used in this model.

The basic structure of the consumer model with battery sizing optimization is visualized in Figure 21. According to this structure, commercial, residential and industrial end-users can maximize the efficiency of their transformer while performing bill management according to the TOU tariff. In this model, the consumer is not allowed to sell electricity to the grid.

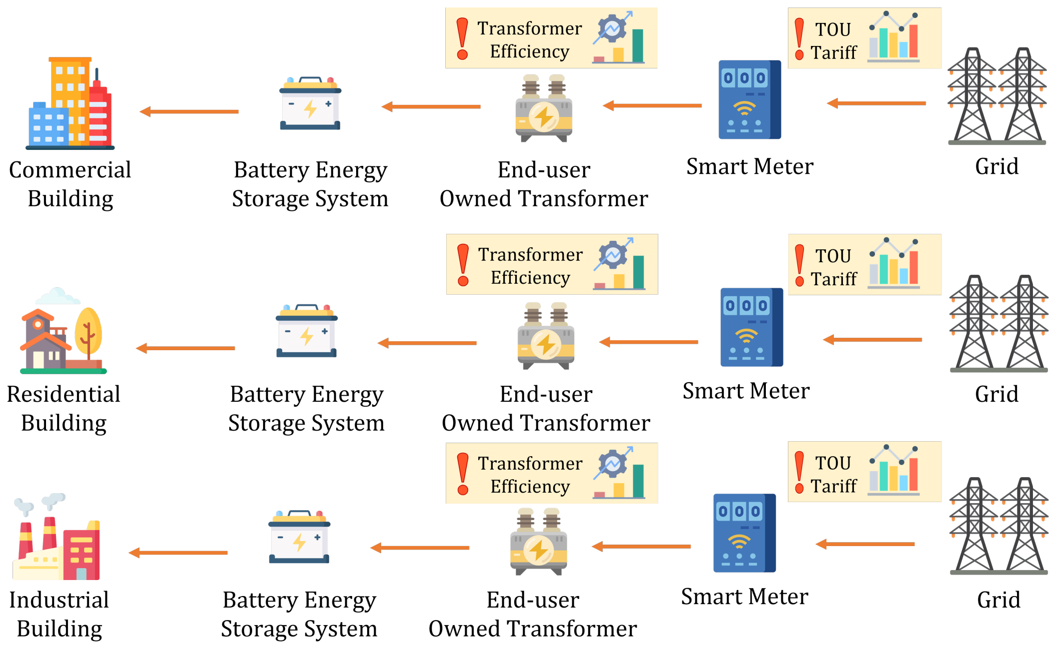

Figure 21: Time-of-Use & Transformer Loss Oriented Battery Installation General Structure

6.1.2.1 Model

While constructing the battery operation for the end-user with a special transformer, the monetary value of the transformer losses due to the instantaneous load has been added to the objective function in the first consumer model.

$$min\left\{\left(\sum_{t}^{T} g_t.TOU_t.\Delta T\right)+\left(P_k.\sum_{t}^{T}\left(\frac{g_t}{G}\right)^2.TOU_t.\Delta T\right)\right\} \tag{20}$$

Idle losses in transformers occur in every period. Copper losses are proportional to the square of the transformer occupancy. Thanks to the objective function in Equation 20, it is ensured that the losses caused by the transformer load are reduced along with the consumer bill. The rest of the model should be set up in the same way as the first consumer model.

6.1.2.2 Use-Case Study - 2

For this use-case study, the commercial building demand profile predicted in Subsection 4.1 (Profile 4) and was used. Data are in 15-minute periods and tariff pricing is based on EPDK 3-time tariff prices for commercial consumer [218]. It is assumed that the commercial building is connected to a 400 kVA transformer. The copper loss coefficient of the transformer was taken as 3.575 in accordance with the TEDAŞ specification [219].

The depth-of-discharge of the battery planned to be installed is taken as 0.2. In this case, the battery SOE will not fall below 20%. In the use case, the discharge efficiency of the battery is 0.875 and the charge efficiency is 0.9.

For better comparison, along with Profile 4, Profile 5 detailed in Subsection 6.1.1 was also used as consumer for TOU and transformer loss oriented battery installation scenario. The 1-month consumption estimation of Profile 5 was carried out in accordance with the method in Subsection 4.1. In Figure 22 and Figure 23, transformer loss analyzes for Profile 4 and Profile 5 end-users are visualized. When the figures are examined, first of all, attention should be paid to the transformer losses before the battery, which is shown with the red line. Since these transformer losses occur depending on the demand profile before the battery, they show an independent profile from the TOU. The transformer losses for the TOU oriented battery installation scenario are shown with the cream colored line. The main purpose of the TOU oriented battery installation scenario is to buy electricity in cheap periods. With the increase in electricity purchase in cheap periods, the occupancy of the transformer to which the consumer is connected also increases. The increase in occupancy causes an increase in copper losses. Finally, the green dotted line represents transformer losses in the TOU & transformer loss oriented scenario. In this scenario, electricity is purchased in cheap periods. However, the battery does not tend to draw all the power it can draw under the transformer size constraint. Instead, it keeps transformer losses at a lower level by spreading the charging time. Thus, transformer losses to be experienced throughout all periods are minimized.

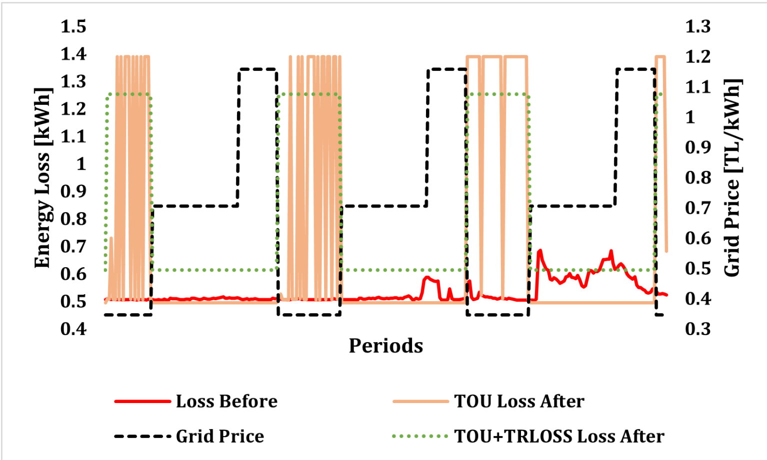

Figure 22: Time-of-Use vs Transformer Loss Oriented Transformer Losses for Profile 4

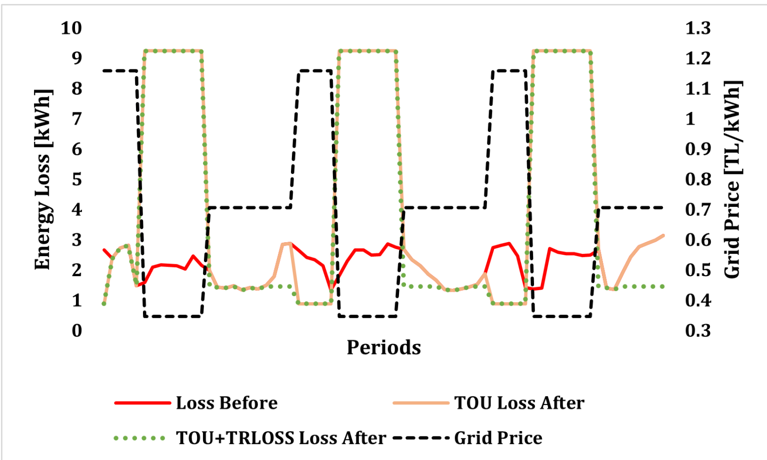

Figure 23: Time-of-Use vs Transformer Loss Oriented Transformer Losses for Profile 5

In Table 7, use-case 1 and use-case 2 scenario results for Profile 4 and Profile 5

Table 7: Time-of-Use vs Transformer Loss Oriented Transformer Losses.

Profile No.	Use Case	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)	Total Transformer Loss (Before) (TL)	Total Transformer Loss (After) (TL)
4	1	3,034	359	1,500.00	1,602.56
4	2	4,196	281	1,500.00	1,553.18
5	1	43,035	760	1,255.63	1,436.81
5	2	9,774	760	1,255.63	1,356.99

are compared. There have been some changes in recommended battery capacities. For use-case 1 and use-case 2 scenarios, it is seen that post-battery transformer losses increase. However, considering the transformer losses after the battery in the use-case 1 and use-case 2 scenarios, it was calculated that the transformer losses increased less. This transformer loss savings also reflects positively on the consumer bill.

6.2 Producer

Optimal battery sizing algorithms for producer were developed for 3 types of producers. These 3 types of producers consist of producers with different needs, with limited power agreement, producers with power purchase agreement, and producers who sell by giving prices to the electricity market.

6.2.1 Limited Purchase Agreement

The basic structure of the producer model with battery sizing optimization is visualized in Figure 24. According to this structure, RES based power generation facilities have a power purchase agreement with the grid. This agreement includes a fixed power purchase price for the instant purchase of the generated power. However, there is a fixed power limit for which the purchase is contracted. In order to meet the agreement limit properly, RES power plants are generally installed with a capacity above this limit. This creates the need for storage for the periods when the production is above the limit.

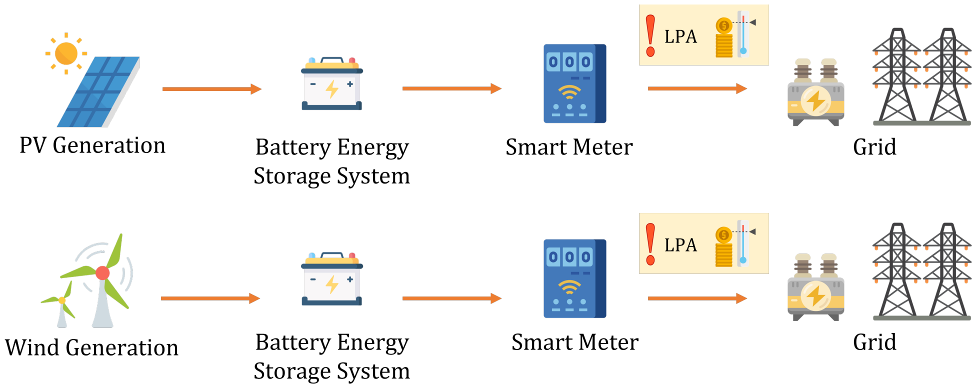

Figure 24: Limited Purchase Agreement Oriented Battery Installation General Structure

6.2.1.1 Model

In the sizing of the battery to be used by the producer for energy selling management, the objective function consists of the energy selling income related to the solar or wind generation is maximized in Equation 21. "-" is used with the minimize objective function because the energy sales revenue is tried to be maximized. The gain in power sales is calculated as the product of the constant C sales price with the instantaneous power supplied to the grid.

$$min\left\{-\left(\sum_{t}^{T} g_t.C.\Delta T\right)\right\} \tag{21}$$

In Equation 22, power balance was created for the producer bus. In this equation, DER generation and battery discharge power are equalized to battery discharge with power supplied to the grid.

$$s_t + d_t.\eta^{discharge} = g_t + c_t, \forall t \tag{22}$$

Equations such as battery SOE, charge-discharge and physical constraints of the grid are the same as in Subsection 6.1.1.1.

6.2.1.2 Use-Case Study - 3

For this use-case study, the solar generation profile predicted in Subsection 4.2 was used. Data are in 60-minute periods. The power level that the producer has agreed with the grid is accepted as 4 MW. According to the agreement, all power produced by the solar-based generator up to 4 MW is purchased by the grid at a fixed price 2 TL/kWh.

The depth-of-discharge of the battery planned to be installed is taken as 0.2. In this case, the battery SOE will not fall below 20%. In the use case, the discharge efficiency of the battery is 0.875 and the charge efficiency is 0.9.

In Table 8, the charge-discharge profiles of the solar integrated battery are shown according to the simulation results performed in accordance with the LPA scenario. Due to the maximum reception capacity of the grid, which is determined as 4 MW in the LPA scenario, generation exceeding 4 MW in the pre-battery situation cannot be sold to the grid. In a battery-free environment, the generation potential of 4 MW and above would be wasted. However, due to battery integration, the entire installed power and generation potential can be efficiently sold to the grid. Since the only constraint in the LPA scenario is the grid purchasing power, the energy stored in the battery can be sold to the grid at a level not exceeding 4 MW in all periods.

Table 8: Charge Discharge Operations for the LPA Oriented Producer.

Date - Time	GES Generation [kW]	Before Battery Sold [kW]	After Battery Sold [kW]	Discharge [kW]	Charge [kW]	SOE [kWh]	Electricity Agreement Price [TL/kWh]	Revenue Before Battery [TL]	Revenue After Battery [TL]
3.01.2021 06:00	0.00	0.00	0.00	0.00	0.00	7382.86	2.00	0.00	0.00
3.01.2021 07:00	0.00	0.00	0.00	0.00	0.00	7382.86	2.00	0.00	0.00
3.01.2021 08:00	32.55	32.55	32.55	0.00	0.00	7382.86	2.00	65.09	65.09
3.01.2021 09:00	662.68	662.68	3122.69	2811.43	0.00	4571.43	2.00	1325.36	6245.37
3.01.2021 10:00	2359.20	2359.20	2359.20	0.00	0.00	4571.43	2.00	4718.40	4718.40
3.01.2021 11:00	3852.13	3852.13	3852.13	0.00	0.00	4571.43	2.00	7704.26	7704.26
3.01.2021 12:00	4559.82	4000.00	4000.00	0.00	559.82	5075.27	2.00	8000.00	8000.00
3.01.2021 13:00	4744.02	4000.00	4000.00	0.00	744.02	5744.88	2.00	8000.00	8000.00
3.01.2021 14:00	4705.24	4000.00	4000.00	0.00	705.24	6379.60	2.00	8000.00	8000.00
3.01.2021 15:00	4336.85	4000.00	4000.00	0.00	336.85	6682.76	2.00	8000.00	8000.00
3.01.2021 16:00	3551.61	3551.61	3551.61	0.00	0.00	6682.76	2.00	7103.21	7103.21
3.01.2021 17:00	2242.86	2242.86	2242.86	0.00	0.00	6682.76	2.00	4485.73	4485.73
3.01.2021 18:00	536.65	536.65	536.65	0.00	0.00	6682.76	2.00	1073.31	1073.31
3.01.2021 19:00	0.00	0.00	0.00	0.00	0.00	6682.76	2.00	0.00	0.00
3.01.2021 20:00	0.00	0.00	0.00	0.00	0.00	6682.76	2.00	0.00	0.00

It was observed on the side of the producer that it was aimed to be less affected by natural conditions by installing above the agreement power in solar production systems. However, the production beyond the power of agreement with this generation will be wasted. Optimal battery sizing results for 5 different production profiles are given in Table 9. These profiles were obtained from the EPIAS transparency platform and Renewable.ninja databases, and 1-month generation estimation was made with the method in Subsection 4.2. Limited power agreement powers were determined according to their maximum power generation capacity. It was seen that the battery size is proportional to the waste potential between maximum generation and limited power agreement. With this result, the importance of determining the power limit in the agreement with the grid is seen. Energy sales increased due to the storage of wasted generation.

Table 9: Producers results of LPA.

Pro. No.	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)	Max Gen. (kW)	Installed Power (kW)	Limited Power Agreement (kW)	Total Energy Sold Before Battery (kWh)	Total Energy Sold After Battery (kWh)
6	22	4	5	10	4	699	722
7	569	113	104	150	100	12,138	12,247
8	1,713	342	343	500	300	39,012	39,647
9	3,714	742	707	1,000	650	80,630	81,551
10	22,857	4,571	4,763	5,000	4,000	693,320	716,151

6.2.2 Power Purchase Agreement

The basic structure of the producer model with battery sizing optimization is visualized in Figure 25. According to this structure, RES based power generation facilities have a power purchase agreement with the grid. This agreement includes a fixed power purchase price for the instant purchase of the generated power. In addition, an agreement has been made with the production facility to purchase different power levels for different periods. In order to meet the power demand by the grid in different periods, storage needs arise when production is high. At the same time, if the agreed power with the grid cannot be supplied, a penalty is paid.

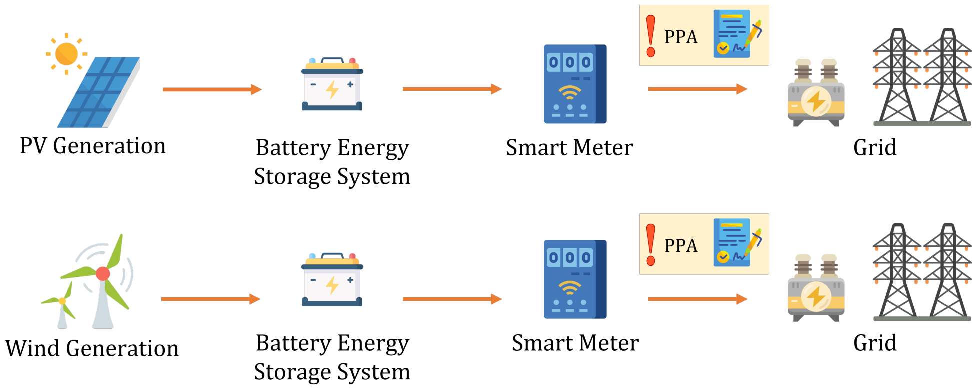

Figure 25: Power Purchase Aggrement Oriented Battery Installation General Structure

6.2.2.1 Model

In the sizing of the battery to be used by the producer for energy selling management, the objective function consists of two parts in which the energy selling income related to the solar or wind generation is maximized and the penalty payout is minimized in Equation 23. "-" is used with the minimize objective function because the energy sales revenue is tried to be maximized. The gain in power sales is calculated as the product of the constant C sales price with the instantaneous power supplied to the grid. Penalty payment is calculated by multiplying the difference between the instantaneous power capacity agreed with the grid and the instantaneous power supplied to the grid by the penalty fee.

$$min \left\{ - \left(\sum_{t}^{T} g_t.C.\Delta T \right) + \left(\sum_{t}^{T} \left(GPA_t - g_t \right).PC.\Delta T \right) \right\} \tag{23}$$

The power balance equation is the same as Subsection 6.2.1.1. Unlike the producer model in Subsection 6.2.1.1, Equation 19 in Subsection 6.1.1.1 should be changed in Equation 24. According to this change, the power supplied to the grid is limited by the power limit agreed with the grid.

$$g_t \leq GPA_t, \forall t \tag{24}$$

Equations such as battery SOE, charge-discharge and physical constraints of the grid are the same as in Subsection 6.1.1.1.

6.2.2.2 Use-Case Study - 4

For this use-case study, the solar generation profile predicted in Subsection 4.2 was used. Data are in 60-minute periods. The agreement of the solar facility with the grid was determined to always supply a minimum of 1000 kW and a maximum of 4000 kW to the grid between 9 AM-7 PM. According to the agreement, all power sold by the solar-based generator is purchased by the grid at a fixed 2 TL/kWh. The penalty of 0.02 TL/kWh was determined for the supply periods under the agreement.

The depth-of-discharge of the battery planned to be installed is taken as 0.2. In this case, the battery SOE will not fall below 20%. In the use case, the discharge efficiency of the battery is 0.875 and the charge efficiency is 0.9. Table 10 shows the battery charge-discharge operations as a result of the battery sizing algorithm of the producer with an installed power of 5 MW. By agreement, the grid demand starts at 9 AM. Generation starting before 9 AM is wasted in the battery-free scenario, while it is stored in the battery integrated scenario. An agreement has been made with the grid that the supply can not fall below 1,000 kW between 9 AM-7PM. However, the generation is 556 kW at 5 PM and 0 in the following periods. In the battery-free scenario, penalty fee is paid for these periods. In the battery integrated scenario, energy is stored in order to meet the low generation periods in the previous periods. Thus, the generation potential is managed according to the contract power and schedule.

Table 10: Charge & Discharge Operations for the PPA Oriented Producer.

Date	GES Generation [kW]	Before Battery Sold [kW]	After Battery Sold [kW]	Discharge [kW]	Charge [kW]	SOE [kWh]	Electricity Agreement Price [TL/kWh]	Revenue Before Battery [TL]	Revenue After Battery [TL]
2.01.2021 06:00	0.00	0.00	0.00	0.00	0.00	55309.37	2.00	0.00	0.00
2.01.2021 07:00	0.00	0.00	0.00	0.00	0.00	55309.37	2.00	0.00	0.00
2.01.2021 08:00	42.24	0.00	0.00	0.00	42.24	55347.38	2.00	0.00	0.00
2.01.2021 09:00	643.29	0.00	0.00	0.00	643.29	55926.35	2.00	0.00	0.00
2.01.2021 10:00	2291.34	1500.00	1500.00	0.00	791.34	56638.55	2.00	3000.00	3000.00
2.01.2021 11:00	3658.24	1500.00	1500.00	0.00	2158.24	58580.97	2.00	3000.00	3000.00
2.01.2021 12:00	4395.02	1500.00	1500.00	0.00	2895.02	61186.49	2.00	3000.00	3000.00
2.01.2021 13:00	4647.07	1500.00	1500.00	0.00	3147.07	64018.85	2.00	3000.00	3000.00
2.01.2021 14:00	4627.68	1500.00	1500.00	0.00	3127.68	66833.77	2.00	3000.00	3000.00
2.01.2021 15:00	4249.60	1500.00	1500.00	0.00	2749.60	69308.41	2.00	3000.00	3000.00
2.01.2021 16:00	3367.41	1500.00	1500.00	0.00	1867.41	70989.08	2.00	3000.00	3000.00
2.01.2021 17:00	2087.76	1500.00	1500.00	0.00	587.76	71518.06	2.00	3000.00	3000.00
2.01.2021 18:00	556.04	556.04	1500.00	1078.81	0.00	70439.25	2.00	923.29	3000.00
2.01.2021 19:00	0.00	0.00	1500.00	1714.29	0.00	68724.96	2.00	-300.00	3000.00
2.01.2021 20:00	0.00	0.00	1500.00	1714.29	0.00	67010.68	2.00	-300.00	3000.00
2.01.2021 21:00	0.00	0.00	0.00	0.00	0.00	67010.68	2.00	0.00	0.00
2.01.2021 22:00	0.00	0.00	0.00	0.00	0.00	67010.68	2.00	0.00	0.00

In order to better compare both battery sizing and differences between scenarios, the same generation profiles as Subsection 6.2.1 were also used for the tests of the PPA algorithm. In order to better understand the battery sizing ratios, the minimum supply power is selected as 20% of the installed power and the maximum supply power is selected as 80% of the installed power for all profiles. In Table 11, the amount of energy sold according to the pre-battery and battery-integrated scenarios is given. In addition, total revenues are calculated with fixed selling price and penalty prices.

Table 11: Producers results for PPA.

Pro. No.	Instal. Power (kW)	Max. Gen. (kW)	9AM-7 PM Min. Power Agree. (kW)	Max. Power Agree. (kW)	Battery Energy Cap. (kWh)
6	10	4.76	2	8	9
7	150	104.08	45	120	434
8	500	342.64	100	400	1,388
9	1,000	707.46	200	800	3,404
10	5,000	4,763.40	1,000	4,000	228,413

Pro. No.	Battery Power Cap. (kW)	Total Revenue (Before)	Total Revenue (After)	Total Energy Sold Before Battery (kWh)	Total Energy Sold After Battery (kWh)
6	3	1,075.90	1,315.31	579.04	687.87
7	59	16,269.56	21,920.71	8,745.25	11,313.96
8	192	53,690.51	71,935.35	28,904.78	37,197.88
9	407	109,924.86	148,042.57	58,965.85	76,292.08
10	3,263	642,907.02	990,000.00	337,230.46	495,000.00

6.2.3 Electricity Market Participating

This algorithm has been developed for all producer profiles. The purpose of this model is to sell energy at the highest prices in the face of variable grid purchase prices. The MILP method is used in this model.

The basic structure of the producer model with battery sizing optimization is visualized in Figure 26. According to this structure, the RES sourced electricity generation facility participates in the electricity market and sells power capacity at the electricity market price.

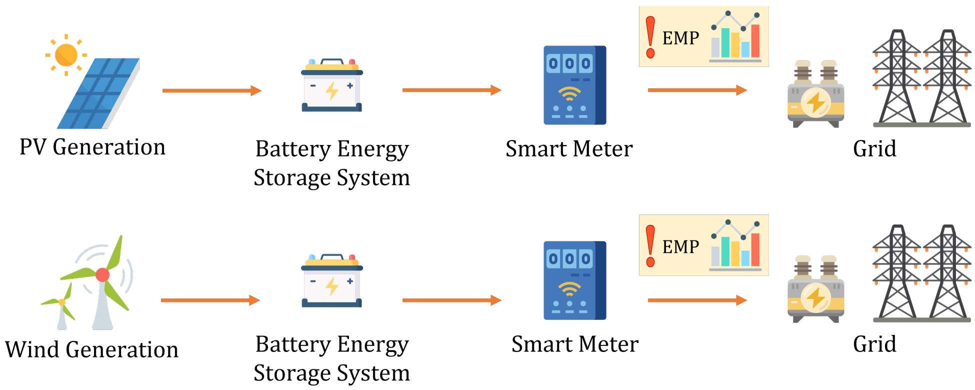

Figure 26: Electricity Market Participating Oriented Battery Installation General Structure

6.2.3.1 Model

In the sizing of the battery to be used by the producer for energy selling management, the objective function consists of the energy selling income related to the solar or wind generation is maximized in Equation 25. "-" is used with the minimize objective function because the energy sales revenue is tried to be maximized.

$$min\left\{-\left(\sum_{t}^{T} g_t.DAM_t.\Delta T\right)\right\} \tag{25}$$

In Equation 26, power balance was created for the producer bus. In this equation, solar generation and battery discharge power are equalized to battery discharge with power supplied to the grid.

$$s_t + d_t.\eta^{discharge} = g_t + c_t, \forall t \tag{26}$$

Equations such as battery SOE, charge-discharge and physical constraints of the grid are the same as in Subsection 6.1.1.1.

6.2.3.2 Use-Case Study - 5

For this use-case study, the solar generation profile predicted in Subsection 4.2 was used. Data are in 60-minute periods and tariff pricing is based on EPIAS day-ahead market prices for generation unit. The electricity market price was estimated using the method in Subsection 4.3 as 1-month 1-hour data. It is assumed that the generation unit is connected to a 6,250 kVA transformer [220].

The depth-of-discharge of the battery planned to be installed is taken as 0.2. In this case, the battery SOE will not fall below 20%. In the use case, the discharge efficiency of the battery is 0.875 and the charge efficiency is 0.9.

In Figure 27, grid supply powers are visualized according to the EMP oriented battery installation scenario. In this scenario, there is no agreement or power limit with the grid. The solar producer wants to make the most profit by selling in the electricity market. While the battery is stored in cheap market times, it is discharged for sale at expensive market times. Since both solar generation and electricity market price are estimated in this scenario, the accuracy of the prediction algorithms will gain importance in the realization of the scenario. According to the estimated data in the figure, the grid supply powers are seen. In the pre-battery scenario, the electricity produced is sold directly. However, in the battery-integrated scenario, the decrease in the market price in the 11th period resulted in battery storage instead of electricity sales. In the 106th period, it is seen that the high market price and the grid supply power are higher than the pre-battery scenario.

While testing the EMP oriented battery sizing algorithm, end-user profiles used in other producer algorithms were used. There is no power limit in the EMP scenario. In this case, the power of the transformer to which the generation facility is connected limits the grid supply power. As seen in Table 12, it was accepted that the installed power of the solar generation facilities depended on the standard transformer power above. It was determined that this algorithm, which is sensitive only to the electricity market price, uses the entire transformer

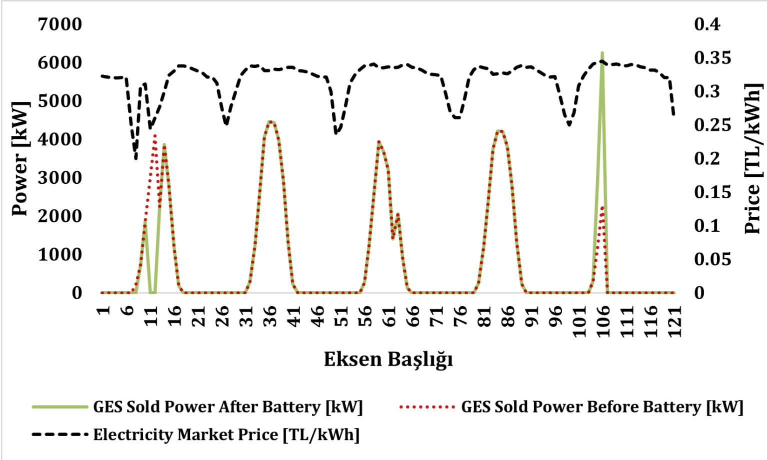

Figure 27: Grid Selling Operations with EMP

capacity in the periods when the electricity market price is high, and the battery power capacities are determined accordingly. Total energies sold decreased. This is because the battery efficiency is not 100%. However, revenues compared to the pre-battery scenario as stored energy was sold in higher priced periods.

6.3 Prosumer

This algorithm has been developed for all prosumer profiles that can have solar or wind systems. The purpose of this model is to perform bill management within the scope of TOU by realizing an optimum energy sharing for the generation unit, battery and grid. The MILP method is used in this model.

6.3.1 Without Contract for Power Sale to the Grid

The basic structure of the prosumer model with battery sizing optimization is visualized in Figure 28. According to this structure, the end-user, which has a RES sourced electricity generation facility, performs bill management according to the TOU tariff. The end-user is not allowed to sell power to the grid, so it can consume the generated power or store it in the battery.

6.3.1.1 Model

In Equation 27, power balance was created for the prosumer bus. In this equation, the unit of generation, battery discharge power and grid as supply; building

Table 12: Producers results for EMP.

Pro. No.	Transformer Cap. (kVA)	Installed Power (kW)	Max. Gen. (kW)	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)
6	50	10	5	250	50
7	160	150	104	800	160
8	630	500	343	3,150	630
9	1,250	1,000	707	6,250	1,250
10	6,250	5,000	4,763	31,250	6,250
Pro. No.	**Total Revenue (Before)**	**Total Revenue (After)**	**Revenue Increase (TL)**	**Total Energy Sold Before Battery (kWh)**	**Total Energy Sold After Battery (kWh)**
6	235.64	235.93	0.29	717	715
7	3,959.53	3,963.75	4.22	12,007	11,970
8	13,003.23	12,993.39	13.62	39,437	39,240
9	26,675.58	26,703.20	27.62	80,973	80,729
10	235,642.46	235,924.88	282.42	717,232	715,045

demand and battery charge power as total demand are added to the algorithm.

$$g_t + s_t + d_t.\eta^{discharge} = D_t + c_t, \forall t \tag{27}$$

Equations such as objective function, battery SOE, charge-discharge and physical constraints of the grid are the same as in Subsection 6.1.1.

6.3.1.2 Use-Case Study - 6

The building demands used for this use-case were estimated by the method described in Subsection 4.1. Data are in 15-minute periods and tariff pricing is based on EPDK 3-time tariff prices for commercial consumer [218]. It is assumed that the commercial building is connected to a 400 kVA transformer. The solar generation datas for The Prosumers were estimated by the method in Subsection 4.2.

The depth-of-discharge of the battery planned to be installed is taken as 0.2. In

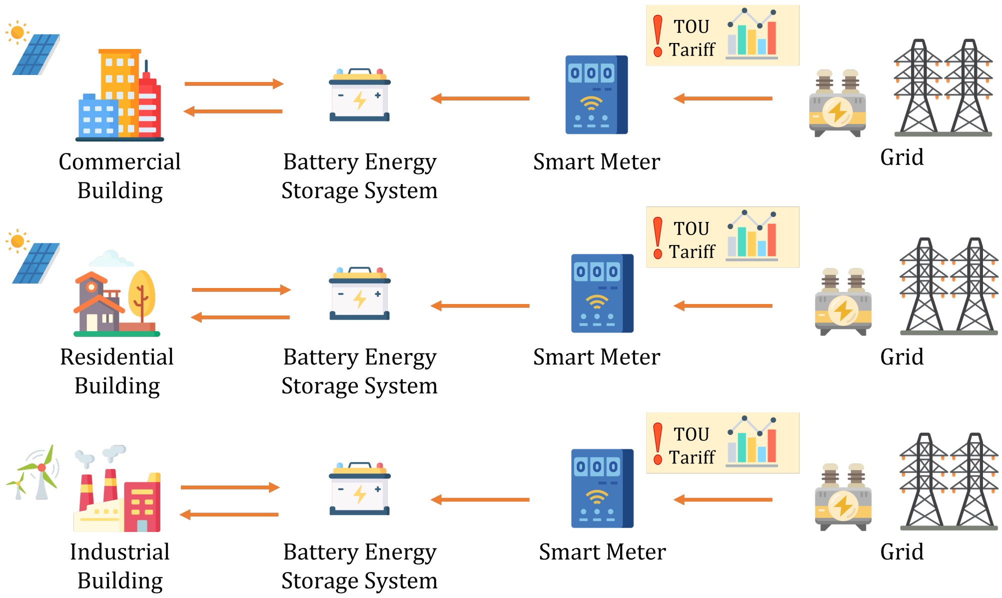

Figure 28: Without Contract for Power Sell Oriented Battery Installation General Structure

this case, the battery SOE will not fall below 20%. In the use case, the discharge efficiency of the battery is 0.875 and the charge efficiency is 0.9.

In Figure 29, the periodic power balance for the prosumer, which has a 400 kW grid power agreement and a 150 kWp solar generation facility, is visualized. In this scenario, since there is no sale to the grid, the demand of the prosumer consists of the consumption of the building and the charge of the battery. Demand is shown on the negative axis of the graph. Meeting the demand is provided from 3 sources. These resources consist of grid, solar generation and battery. As can be seen in the graph, a demand-supply balance is established in the prosumer bus. In the pre-battery scenario, electricity would be taken from the grid until "buying grid = demand - solar generation". In the absence of a battery, there would be no tariff-sensitive structure. And if solar generation is more than demand, it will be wasted. However, with the battery-integrated scenario, power is drawn from the grid only during cheap hours. With the electricity purchased from the grid in cheap hours, the building consumption is met and the battery is charged. During the daytime and peak tariffs when tariff prices are high, the consumption of the building is met from solar generation and battery. Thus, the bill is lowered.

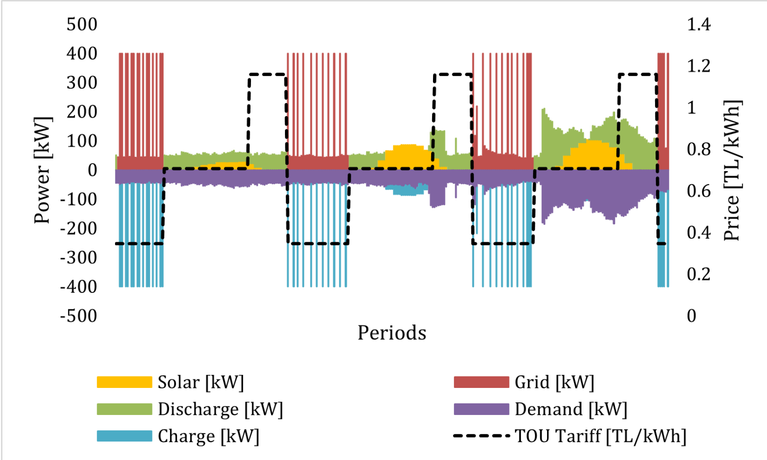

Figure 29: Without Power Selling Prosumer Power Balance.

The prediction methods from Chapter 4 were used to construct the prosumer models. 4 different prosumers with different consumption and generation profiles were modeled. Detailed generation and consumption information of prosumers are given in Table 13. For the pre-battery scenarios, it is seen that the energy purchased from the grid for profile 11, 12 and 13 end-users increases in a 1-month period. This is not an expected result considering that the battery increases the generation usage by storing excess solar generation. Battery efficiency not being 100% increases energy purchase. Despite this, it is seen that the bills of the prosumers decrease. Because the battery, with its energy storage capacity, postpones the electricity purchased from the grid to the periods when the tariff is cheap. In profile 14, the power purchased from the grid decreases. The reason for this is that it has much more solar generation capacity than electricity consumption. The production, which would be wasted in the pre-battery state, becomes usable with the battery. For this reason, the recommended battery energy capacity was much higher than other profiles.

In the absence of a battery, excess generation is wasted. Therefore, it is meaningless to increase the generation potential without battery integration. The self-consumption value represents how much of the generated energy is consumed in the prosumer. The self-consumption ratios in Table 13 show how much of the installed generation capacity of prosumers are able to use. In this scenario, since there is no electricity sales to the grid, it is ensured that the self-consumption with the battery is 100%. The self-sufficiency value represents how much of the energy consumption is not purchased from the grid. In Profiles 11, 12 and 13, energy purchase from the grid increased due to battery operating efficiency. Likewise, the self-sufficiency rates decrease for these three end-users for use-cases with battery integration. In fact, the self-sufficiency rates for profile 11 and profile 12 drop to negative. The reason for this is that the energy purchased from the grid is more than the prosumer consumption.

Table 13: 1-month simulation results of the Prosumer without power selling.

Pro. No.	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)	Total Bill (Before)	Total Bill (After)	Max Generation (kW)	Installed Power (kW)	Power Contract (kW)	Max Demand (kW)	Min Demand (kW)
11	2,996	359	36,454.51	21,136.19	4.76	10	400	199.23	38.38
12	200	26	4,356.23	2,824.92	4.76	10	30	20.67	3.11
13	2,834	359	28,542.14	16,222.98	104.08	150	400	199.23	38.38
14	4,775	357	21,844.05	6,316.31	342.64	500	400	199.23	38.38

Pro. No.	Mean Demand (kW)	Total Energy Demand (kWh)	Total Energy Generation (kWh)	Total Energy Purchased Before Battery (kWh)	Total Energy Purchased After Battery (kWh)	Self Sufficiency Before Battery (%)	Self Sufficiency After Battery (%)	Self Consumption Before Battery (%)	Self Consumption After Battery (%)
11	71.34	51,364.25	717.23	50,647.02	60,981.50	1.40	-18.72	100	100
12	10.31	7,426.73	717.23	6,711.02	7,647.34	9.64	-2.97	99.8	100
13	71.34	51,364.25	12,007.10	39,953.40	46,806.05	22.22	8.87	95.0	100
14	71.34	51,364.25	39,359.91	31,293.56	18,223.63	39.08	64.52	51.0	100

6.3.2 With Contract for Power Sale to the Grid

The basic structure of the prosumer model with battery sizing optimization is visualized in Figure 30. According to this structure, the end-user, which has a RES sourced electricity generation facility, performs bill management according to the TOU tariff. The end-user is allowed to sell power to the grid, so it can consume the generated power, store it in the battery or sell it to the grid.

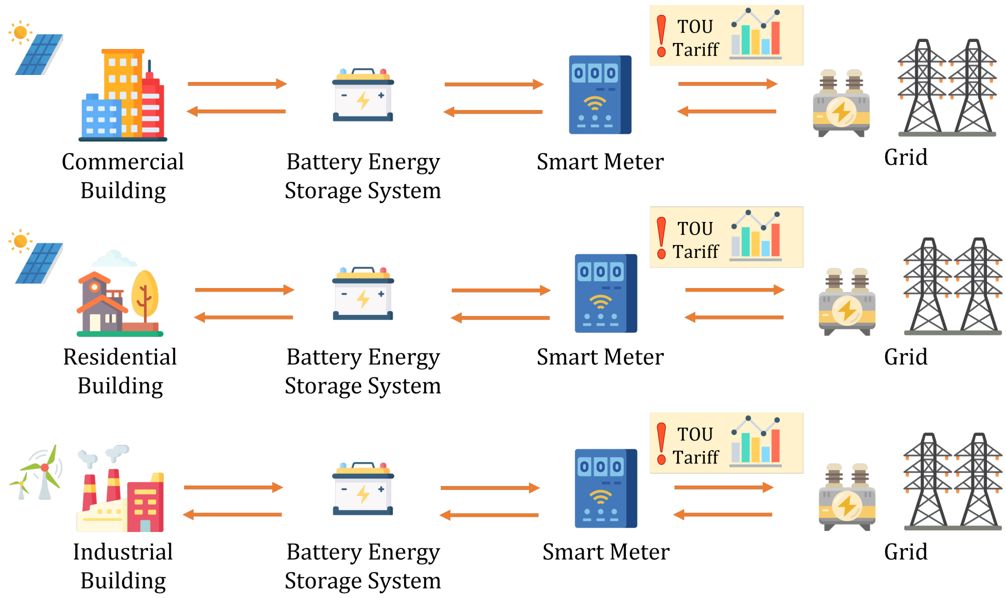

Figure 30: With Contract for Power Sell Oriented Battery Installation General Structure

6.3.2.1 Model

This model is the version of the consumer whose production facility is integrated and can sell electricity to the grid. Therefore, the objective function given in Equation 28 primarily aims to minimize the bill as in consumer models. However, unlike the prosumer model in Suubsection 6.3.1, it is possible to sell electricity to the grid in this prosumer model. In some applications, since bills are paid for prosumer by monthly set-off method, in this model, the buying and selling prices are considered equal. While trying to minimize the electricity purchase from the grid with the relevant TOU tariff period, at the same time, prosumer's electricity sales are maximized within the same TOU tariff.

$$min\left\{\left(\sum_{t}^{T} g_t.TOU_t.\Delta T - \sum_{t}^{T} g_t^{sell}.TOU_t.\Delta T\right)\right\} \tag{28}$$

Unlike all models described so far, in the prosumer model, which can sell to the grid, there is a two-way exchange with the grid in the power balance equation. Equation 29 has electricity sold to the grid along with the building's consumption and battery charging on the demand side. On the supply side, there is solar generation, grid and battery discharge.

$$g_t + s_t + d_t.\eta^{discharge} = D_t + g_t^{sell} + c_t, \forall t \tag{29}$$

Equations such as battery SOE, charge-discharge and physical constraints of the grid are the same as in Subsection 6.1.1.1.

6.3.2.2 Use-Case Study - 7

Prosumer constructs with features in Subsection 6.3.1 were used to test the algorithms of the prosumer model capable of selling to the grid. Prosumers with the same consumption profile and generation potential were modeled. Table 14 shows the generation and consumption details of prosumers. According to the prosumer models in subsection 6.3.1, the bill before the battery differs. Because according to the model in Subsection 6.3.1, the electricity generated more than the demand is wasted. In this model, the excess of the electricity generated is sold to the grid. The TOU tariff in the relevant generation period was determined as the sales price. Due to this selling option, the bill is lowered for the pre-battery scenario compared to the previous prosumer model. Especially for Profile 14, whose installed power is higher than demand, the bill has dropped to 1/3.

In scenarios with battery integration, the self-consumption is 100%. This means that all of the electricity generated was consumed by the building and no sales were made to the grid. In other words, in the 1st prosumer model and the 2nd prosumer model, the bills after the battery were equal to each other. It should be noted that the sell-to-grid strategy will vary with the grid buy-sell pricing. However, the most important output in this model is that the energy stored during the generation is used for the consumption of the building during the peak pricing periods. Although there is no sale to the grid with the battery, the bill decreases. Since the amount of electricity purchased from the grid did not change for the prosumer models, the self-sufficiency rates did not change either.

Table 14: 1-month simulation results of the Prosumer with power selling.

Pro. No.	Battery Energy Capacity (kWh)	Battery Power Capacity (kW)	Total Bill (Before)	Total Bill (After)	Max Generation (kW)	Installed Power (kW)	Power Contract (kW)	Max Demand (kW)	Min Demand (kW)	Mean Demand (kW)
11	2,996	359	36,454.51	21,136.19	4.7634044	10	400	199.23	38.38	71.34
12	200	26	4,355.15	2,824.92	4.7634044	10	30	20.67	3.11	10.31
13	2,836	359	28,120.89	16,222.98	104.08227	150	400	199.23	38.38	71.34
14	4,775	357	7,956.15	6,316.31	342.63513	500	400	199.23	38.38	71.34

Pro. No.	Total Energy Demand (kWh)	Total Energy Generation (kWh)	Total Energy Purchased Before Battery (kWh)	Total Energy Purchased After Battery (kWh)	Total Energy Sold Before Battery (kWh)	Total Energy Sold After Battery (kWh)	Self Suff. Before Battery (%)	Self Suff. After Battery (%)	Self Cons. Before Battery (%)	Self Cons. After Battery (%)
11	51,364.25	717.23	50,647.02	60,981.50	-	0	1.40	-18.72	100	100
12	7,426.73	717.23	6,711.02	7,647.34	1.53	0	9.64	-2.97	99.8	100
13	51,364.25	12,007.10	39,953.40	46,806.05	596.25	0	22.22	8.87	95.0	100
14	51,364.25	39,359.91	31,293.56	18,223.63	19,289.22	0	39.08	64.52	51.0	100

CHAPTER VII

DISCUSSION

Optimal battery sizing is presented for 14 end-users with 7 mathematical models. It was seen that a battery sizing algorithm can be developed for the consumer, producer and prosumer with minor changes in the objective function and power balance equations, along with the limitations of general battery operation.

Two different battery sizing needs were determined for consumers. These needs are bill management and minimization of transformer losses. End-users who want to invest in batteries for bill management can benefit from the developed algorithms. However, if the end-user has its own transformer, they can use the battery sizing algorithm as a decision-support mechanism with the algorithm sensitive to losses that will occur in the transformer. In the modeled use-case scenarios, it was seen that battery energy capacities are recommended in the range of 2.4%-9.1% of monthly energy consumption for consumer bill management. In other words, if a consumer with any size of consumption will invest in batteries for bill management purposes, the optimal battery capacity within the scope of the 3-time tariff is 5% of the monthly consumed energy. It was observed that the power capacity of the battery is directly proportional to the power of the consumer's grid agreement. This is where the value in the consumer's agreement to draw power from the grid comes to the fore. Since this value is used as a constraint in the algorithm, the battery charging power increases depending on the mains power draw. In this study, grid purchasing power was accepted with a cautious margin above the maximum demands. Reducing transformer losses in the second consumer model was also added to the targets. This goal has constrained the battery's radical power draw shifting in times of cheap tariffs. Because the optimal loading of the transformer (depending on the transformer size in the range of 35%-45%) is exceeded by the battery's demand for extreme charging. Thus, it has been calculated that 50% of transformer losses that will increase due to battery operation can be prevented.

Developed 3 different optimal battery sizing models that producers may need. These needs have been compiled according to various procurement strategies applied to RES-sourced generation facilities around the world. In this context, a model was first developed for production facilities with a purchase guarantee up to a certain power limit. This model was tested with use-case scenarios for RES resources of various sizes. It is known that producers with limited power purchase agreements invest in installed power slightly above the power of the agreement in order to be able to evaluate the entire purchase guarantee. However, for generation facilities that do not use batteries, the installed power above the limit power will be wasted if the weather is efficient. A battery is required both in order not to waste the installed power potential and to eliminate the uncertainty of RES sourced generation facilities to some extent. The ratio of recommended battery energy capacities to monthly energy generation is 4% on average. In addition, since some wasted periods can be stored and sold during low generaion hours, monthly energy sales increase with the battery scenario. It was observed that the recommended battery power capacity for some generation facilities is greater than the maximum generation power. The reason for this is that the discharge power is dependent on the grid limit. At the same time, the discharge efficiency also has an impact on the determination of the battery power capacity.

The second model for generation facilities was developed for generation facilities that guarantee sales in a certain power range. In this model, penalty payment to the grid was envisaged if the generation facility did not meet the minimum power limit. The minimum agreement limits were determined as 20% of the installed power and the maximum power sales limit as 80% of the installed power. Penalty cost was determined as 10% of the fixed purchase price. With this model, optimal battery sizing can be made for manufacturers promising a minimum power supply at certain hours. Thus, the control of generation and shifting of generation potential are also ensured. Measures are taken for periodic generation reductions against clouding and adverse weather conditions. Since the minimum power supply agreement is considered proportional to the installed power, it increases as the installed power increases. For this reason, it is seen that the recommended battery energy capacity increases as the installed power increases. It was observed that the monthly energy sales volumes increased in TL terms in the range of 22%-54%. The ratio of the recommended battery power capacities with the minimum power agreement was calculated as 55% on average.

Within the scope of incentives, production facilities other than fixed price purchase agreements participate in the electricity market like conventional generation facilities. Another model was developed for generation facilities that will invest in batteries to plan their operations to join the electricity market. In this model, it is aimed to discharge during the periods when the market price is low and the charge is high. Thus, the revenue to be obtained from the sale of electricity is maximized. Since there is no power supply limit, the power supply to the grid in these use cases is limited by the transformer size. Transformer sizes were chosen as standard transformer sizes above the installed power. Since the discharge power of the battery depends on this limit, all of the transformer power determined as the constraint was suggested by the algorithm as the battery power capacity. However, different measures should be taken for problems that may occur in the use of the entire transformer capacity on the network side. The ratio of the proposed battery energy capacity to the amount of energy sold after the battery was determined as 12% on average. With the battery integration, which is formed according to the estimated values of the electricity market price and the results of the optimization algorithm, the estimated income increase is calculated according to the mobility of the market price. That's why revenue growth may seem small. At this point, the electricity market strategy also gains importance.

2 different use-case scenarios were determined for prosumers. These scenarios are adapted for end-users who have permission to sell electricity to the grid and

who do not have permission to sell electricity to the grid. For prosumers who do not have permission to sell to the grid, batteries allow to consume all of the energy produced. Since the battery charge and discharge efficiencies are taken into account in the algorithms, it was observed that the energy purchased from the grid increased in some scenarios. The greater the installed generation potential, the less energy purchased from the grid. Although the energy purchased from the grid increases, the total bill decreases. Because the produced prosumer battery sizing algorithms ensure that electricity is purchased in the most suitable strategy for the 3-time TOU tariff. Prosumers who have permission to sell electricity to the grid consume some of the energy generated and sell some of it to the grid, according to the scenario without batteries. However, when the battery is included in the system, the optimization model wants to consume all generation since its objective function is bill minimization. Battery sizing is affected by 2 components for prosumers. Both the generation potential and the consumption potential affect the energy capacity of the battery in particular. Here, the correct sizing of the generation facility according to consumption also shows its importance.

Optimal battery sizing algorithms was developed for various end-user profiles. As a data set, there are 1 year generation, consumption and electricity market prices. However, since consumer bills and electricity sales of generation facilities are calculated for 1 month in general, 1-month optimization simulations were set up. Battery sizing based on historical data profiles is an option. However, the future uncertainty of generation and consumption must also be modeled in some way. In this study, generation, consumption and electricity market values were estimated with 3 different neural network models. The estimated data set includes 1-month periodic data sets. In addition to classical methodologies in statistical models, neural network models have become a popular topic recently. The fact that their performance is quite strong will give better answers to the estimation requirements as the strength goes on. Tuning hyper parameters is also becoming a separate field of study. In this study, basic structures of single-layer ANN, multi-layer DNN and LSTM models were used. Both predictions are provided for the periods ahead of the train set, and the uncertainty factor, which strengthens the results of the optimization model, is added instead of using the historical data set.

This thesis provided a useful basis for battery sizing applications. In future studies, it is planned to work on wind production results. However, it is aimed to modify the algorithms in order to calculate the required battery sizes for multi-source microgrid self-sufficiency. Applications developed for parking and charging stations for electric vehicles have become popular recently. It is thought that battery sizing algorithms can be implemented for self-sufficient parking and charging stations. Both the extension of the battery sizing algorithms for the mentioned applications to different areas and the ability to combine all the algorithms with a single objective function will be worked on.

In this study, an optimal battery sizing approach is proposed for battery investments. Models meeting different needs were developed for 14 end-users. In order for these models to fully meet the needs, issues such as budget constraints were not taken into account. It is provided to suggest battery sizes for the estimated future time data using data such as actual generation consumption and market price. In other words, batteries with the optimal sizes required for end-users, given their profiles and agreement or installed power, were proposed. Of course, the budget capacities that come with the investment costs of the batteries may impose restrictions on these sizes during the investment. In the next period, it is planned to be developed by using algorithms in real investment projects. In addition, studies on the effect of estimation algorithms on network investments and operations are aimed.

CHAPTER VIII

CONCLUSION

In this thesis, it was aimed to develop a common methodology that can make battery sizing for consumer, producer, and prosumer. Mathematical models that can be used for the 3 end-user types was developed with minor changes in the objective functions and power balance equations. 7 different mathematical algorithms were tested with 14 different end-user profiles and use-case scenarios. Thanks to these end-user profiles of varying sizes, the algorithms were found to be suitable for end-users of all sizes. At the same time, machine learning-based estimation algorithms were developed for generation, consumption, and electricity market prices, aiming to increase the reality of optimization models. It is hoped that it will be a useful study for future BESS investments.

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