A NOVEL METHODOLOGY FOR MEDIUM AND LONG-TERM ELECTRICITY MARKET MODELING

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ABSTRACT

A NOVEL METHODOLOGY FOR MEDIUM AND LONG-TERM ELECTRICITY MARKET MODELING

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In the electricity market, there is a considerable degree of uncertainty in electricity demand, supply, and price due to the uncertainty in parameters such as economic growth, weather conditions, fuel prices, and timing of new investments, etc. These factors in return affect the predictability of the electricity market. This thesis aims to increase the predictability and observability of the electricity market by means of a suitable and validated electricity market modeling methodology designed for medium and long-term horizon. The proposed methodology consists of electricity demand, supply, and price modeling parts for the medium-term horizon and reveals the possible range of electricity prices considering the uncertainties in demand and supply. This methodology is upgraded with two new features for the utilization in the long-term horizon in the changing market environment. The first one of these features is a generator maintenance scheduling model which enables more realistic electricity supply modeling. The second one is a realistic electricity generation expansion planning model which determines the future electricity generation fleet. Based on these modifications and the previously established electricity price model used for the medium-term horizon, this methodology can reveal how electricity market conditions can evolve for a selected year in the long-term horizon. Thanks to its dynamic structure and ability to yield results on hourly basis, the central planner can benefit from this modeling methodology in policy making.

Keywords: Electricity Market Model, Electricity Price Forecasting, Generation Expansion Planning, Electricity Demand Forecasting, Generator Maintenance Scheduling

ÖZ

ORTA VE UZUN DÖNEMLİ ELEKTRİK PİYASA MODELLEMESİ İÇİN YENİ BİR METODOLOJİ

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Elektrik piyasasında ekonomik büyüme, hava koşulları, yakıt fiyatları ve yeni yatırımların zamanlaması vb. parametrelerindeki belirsizlik nedeniyle elektrik talebi, arzı ve fiyatında önemli derecede belirsizlik bulunmaktadır. Bunun karşılığında söz konusu faktörler elektrik piyasasının öngörülebilirliğini etkilemektedir. Bu tez çalışması, orta ve uzun vadeli ufuk için tasarlanmış uygun ve doğrulanmış bir elektrik piyasası modelleme metodolojisi ile elektrik piyasasının öngörülebilirliğinin ve gözlemlenebilirliğinin artırılmasını amaçlamaktadır. Önerilen metodoloji, orta vadeli ufka yönelik olarak elektrik talebi, arzı ve fiyatı modelleme bölümlerinden oluşmaktadır, ve talep ve arzdaki belirsizlikleri göz önünde bulundurarak elektrik fiyatının oluşması muhtemel aralığı ortaya koymaktadır. Bu metodoloji, değişen piyasa ortamında uzun vadeli ufukta kullanım için iki yeni özellik ile geliştirilmiştir. Bu özelliklerden ilki, daha gerçekçi elektrik arz modellemesi yapılabilmesine imkan veren bir jeneratör bakım planlama modelidir. İkincisi, gelecekteki elektrik üretim portföyünü belirleyen gerçekçi bir elektrik üretim genişleme planlama modelidir. Bu modifikasyonlara ve orta vadeli ufuk için daha önce kurulmuş olan elektrik fiyat modeline dayanarak, bu metodoloji elektrik piyasası koşullarının uzun vadeli ufukta seçilen bir yıl için nasıl gelişebileceğini ortaya çıkarabilmektedir. Dinamik yapısı ve saatlik bazda sonuç verebilme kabiliyeti sayesinde, merkezi planlamacı politika yapımında bu metodolojiden yararlanabilir.

Anahtar Kelimeler: Elektrik Piyasa Modeli, Elektrik Fiyat Tahmini, Üretim Genişleme Planlaması, Elektrik Talep Tahmini, Jeneratör Bakım Planlaması

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LIST OF ABBREVIATIONS

ABBREVIATIONS

ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
APE	Absolute percentage error
AR	Autoregressive
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
ARX	Autoregressive with exogenous input
BIC	Bayesian information criterion
BO	Build-operate
BOT	Build-operate-transfer
CDD	Cooling degree day
CO_2	Carbon dioxide
CV	Cross-validation
EDUD	Expected duration of unmet demand
EENS	Expected value of energy not served
EFOM	Energy Flow Optimization Model
EMRA	Energy Market Regulatory Authority
ERCOT	Electric Reliability Council of Texas
EST	Energy System Model for Turkey
EU	European Union
EXIST	Energy Exchange Istanbul
FOR	Forced outage rate
GAM	Generalized additive model
GARCH	Generalized autoregressive conditional heteroscedasticity
GCV	Generalized cross-validation
GDP	Gross domestic product

GEP	Generation expansion planning
GMS	Generator maintenance scheduling
GRSq	Generalized R-squared
GTEP	Generation and transmission expansion planning
GW	Gigawatt
GWh	Gigawatt-hour
HDD	Heating degree day
IEEE	Institute of Electrical and Electronics Engineers
IET	Institute of Engineering and Technology
IPI	Industrial production index
ISGT	Innovative Smart Grid Technologies
KKT	Karush-Kuhn-Tucker
kWh	Kilowatt-hour
LOLE	Loss of load expectation
LOLP	Loss of load probability
LTLF	Long-term load forecasting
MAPE	Mean absolute percentage error
MARKAL	Market Allocation Model
MARS	Multivariate adaptive regression splines
MCP	Market clearing price
MENR	Ministry of Energy and Natural Resources
MIBLP	Mixed integer bilevel linear programming
MLR	Multiple linear regression
MSE	Mean squared error
MTLF	Medium-term load forecasting
MW	Megawatt
MWh	Megawatt-hour
O&M	Operation and maintenance
RBF-NN	Radial basis function neural network
RES	Renewable energy sources

RMSE	Root mean square error
SARIMA	Seasonal autoregressive integrated moving average
SDDP	Stochastic dual dynamic programming
Sm^3	Standard cubic meter
STLF	Short-term load forecasting
SVM	Support vector machine
TEİAŞ	Turkish Electricity Transmission Company
TEP	Transmission expansion planning
TIMES	The Integrated MARKAL-EFOM System
TOOR	Transfer of operation rights
TWh	Terawatt-hour
UC	Unit commitment
USD	United States Dollar
VSTLF	Very short-term load forecasting
WASP	Wien Automatic System Planning
WNN	Weighted nearest neighbor

LIST OF SYMBOLS

SYMBOLS

DECISION VARIABLES

$ic_{a,t}$	Installed capacity of facility a that exists at year t, in MW
$iu_{g,t}^{C}$	Number of commissioned units of plant g at year t
$m_{a,t}^{S}$	Support/incentive needed for facility a at year t, in 10^6 \$
$m_{a,t}^{R}$	Revenue of facility a at year t, in 10^6 \$
$m_{g,t}^{C}$	Fixed and variable costs of facility a at year t, in 10^6 \$
$m_{g,t}^{P}$	Profit of facility a at year t, in 10^6 \$
$mcp_{o,t}$	Price in day-ahead market at hour o & year t, in \$/MWh
$ou_{g,o,t}$	Number of operating units of plant g at hour o & year t
$p_{g,t}^{C}$	Commissioned capacity of plant g at year t, in MW
$p_{g,t}^{C,all}$	Cumulative commissioned capacity of plant g until year t, in MW
$p_{s,t}^{C}$	Commissioned capacity of storage facility s at year t, in MW
$p_{g,o,t}^{G}$	Generation of plant g at hour o & year t, in MW
$p_{o,t}^{LS}$	Load shedding at hour o & year t, in MW
$p_{g,o,t}^{RES}$	Renewable energy curtailment of plant g at hour o & year t, in MW
$p_{o,t}^{RS}$	Reserve deficiency at hour o & year t, in MW
$sd_{g,o,t}$	Number of shut down units of plant g at hour o & year t
$st_{s,o,t}^{C}$	Charging of storage facility s at hour o & year t, in MW
$st_{s,o,t}^{D}$	Discharging of storage facility s at hour o & year t, in MW
$su_{g,o,t}$	Number of started up units of plant g at hour o & year t

u_w^{hs}	Average storage hydropower plant capacity factor at week w, for hydro scenario hs
v	Maximum of weekly average storage hydropower plant reserve in the forecast horizon
$x_{w,g}$	Maintenance state (0-1) at week w for generator unit g
$y_{w,g}$	Change of maintenance state at week w for generator unit g
z	Maximum of weekly net reserve capacity in the forecast horizon, in MW

PARAMETERS

$AF_{g,o,t}$	Availability factor of plant g at hour o & year t, in %
B	Parameter between 0 and 1, used in the update procedure of MCP following the run of Model II-B
B^{ul}	Parameter used in the update procedure of investment capacity for candidate plants with unit size limitation, used following the run of Model II-A. Typically selected as 1
B^{ull}	Parameter used in the update procedure of investment capacity for candidate plants without unit size limitation and storage facilities, used following the run of Model II-A
$C_{a,t}^{AC}$	Annualized capital cost of facility a at year t, in $/MW
$C_{a,t}^{INV}$	Investment cost of facility a at year t, in $/MW
$C_{o,t}^{LS}$	Load shedding cost at hour o & year t, in $/MWh
$C_{a,t}^{OMF}$	Fixed operation and maintenance cost of facility a at year t, in $/MW
$C_{g,t}^{RES}$	Renewable energy curtailment cost of plant g at year t in $/MWh, typically selected as 50 $/MWh
$C_{o,t}^{RS}$	Reserve deficiency cost at hour o & year t, in $/MWh
$C_{a,t}^{TV}$	Total variable cost of facility a at year t, in $/MWh

$CF_{\overline{h},r}^{rs,hs}$	Capacity factor at hour $\overline{h}$, for resource r, random scenario rs, hydro scenario hs
$diff_t^{MCP}$	Differences among MCPs for iterations i and $i-1$ at year t, in \$/MWh
$diff^{ofv}$	Differences among objective function values for iterations i and $i-1$, in 10^6 \$
$E_{a,t}^{OPH}$	Expected operating hours of facility a at year t
$E_{a,d,t}^{OPH}$	Expected operating hours of facility a at day d & year t
$E_{a,t}^{MCP}$	Expected MCP for facility a at year t, in \$/MWh
$E_{s,t}^{MCPC}$	Expected MCP for charging hours of storage facility s at year t, in \$/MWh
Eff_a	Efficiency of facility a, in %
$F_{d,t}$	Frequency of representative day d at year t
$F_{o,t}$	Frequency of representative hour o at year t
$FNR_{w,rg}^{as,hs}$	Filtered net reserve at week w, for region rg, availability scenario as, hydro scenario hs, in MW
Γ	Discount rate, in %
$HTR_{s,t}$	Heat rate of storage facility s at year t
H_s^{max}	Maximum number of hours that storage facility s can continuously charge or discharge at rated capacity
i	Iteration number
i^{max}	Maximum number of iterations
$I_{a,t}$	Parameter that takes value 1 if facility a has investment cost repayment at year t
IC_g	Installed capacity for generator unit g, in MW
$IC_{a,t}^{max}$	Maximum capacity that can be commissioned for facility a at year t, in MW

IC_g^{max}	Maximum capacity of an existing plant g without unit size limitation, in MW. For existing and candidate plant g with unit size limitation, it corresponds to unit capacity, in MW.
$IC_{\overline{h},r}$	Installed capacity at hour $\overline{h}$, for resource r, in MW
K	Profit margin of plants, in %
$\Lambda_{a,t}$	Parameter that takes value 1 if facility a exists at year t
$MC_{w,rg}^{max}$	Maximum maintenance capacity at week w, for region rg, in MW
MFS	Median filter step
$MRG_{\overline{h},rg}^{as,hs}$	Must run generation at hour $\overline{h}$, for region rg, availability scenario as, hydro scenario hs, in MWh
$MSGR_g$	Minimum stable generation ratio of power plant g, in %
N	Offset parameter for storage hydropower plant capacity factor
NM_g	Number of weeks in maintenance for generator unit g
$NR_{\overline{h},rg}^{as,hs}$	Net reserve at hour $\overline{h}$, for region rg, availability scenario as, hydro scenario hs, in MW
ofv	Objective function value, in 10^6 \$
Ω	Auxiliary parameter that can take values -1, 0 and 1; used in the update procedure following the run of Model II-A
$P_{\overline{h}}^D$	Demand at hour $\overline{h}$, in MW
$P_{o,t}^D$	Demand at representative hour o & year t, in MW
$SH_{o,t}^R$	Minimum level of hourly reserve at hour o & year t, in %
$T0$	Base year. In this study, it corresponds to the year 2015
$T_{0,a}$	Commissioning year of facility a
$T_{1,a}$	Decommissioning year of facility a
T_g^{up}	Minimum number of hours that power plant g must stay online after started up
T_g^{down}	Minimum number of hours that power plant g must stay offline after shut down

Θ	Weight parameter for the lower-priority objective function shown in Model I-S
U_g^{max}	Number of units of an existing power plant g
$U_{g,t}^{max}$	Maximum number of units that can be commissioned for a candidate power plant g at year t
$WCF_w^{ave,hs}$	Weekly average storage hydropower plant capacity factor at week w, for hydro scenario hs
$WCF_w^{max,hs}$	Weekly maximum storage hydropower plant capacity factor at week w, for hydro scenario hs
$WCF_w^{min,hs}$	Weekly minimum storage hydropower plant capacity factor at week w, for hydro scenario hs

SETS

$a(A)$	Set of all facilities including existing, candidate generators and storage facilities; an element is a
$as(AS)$	Availability scenario set, an element is as
$d(D)$	Representative day set for any year t, an element is d
$g(G)$	Plant set including all existing and candidate ones, an element is g
$g(G^C)$	Candidate plant set, an element is g
$g(G^M)$	Generator unit set to be in maintenance, an element is g
$g(G^{re})$	Renewable plant set including existing and candidate generators, an element is g
$g(G^{ul})$	Plant set with unit size limitation, an element is g
$g(G^{ull})$	Plant set without unit size limitation, an element is g
$\underline{h}(\underline{H})$	Hours of day, an element is $\underline{h}$
$\overline{h}(\overline{H})$	Hours of year, an element is $\overline{h}$
$HCF_{\underline{h},w,m,y,r}$	Historical capacity factor set at hour $\underline{h}$, week w, month m, year y for resource r

$hs(HS)$	Hydro scenario set, an element is hs
$m(M)$	Months of year, an element is m
$o(O)$	Representative hour set for any year t, an element is o
$r(STO)$	Set of all storage hydropower plants, an element is r
$r(INT)$	Set of all intermittent renewable power plants, an element is r
$r(ROR)$	Set of all run-of-river hydropower plants, an element is r
$r(SOL)$	Set of all solar power plants, an element is r
$r(THR)$	Set of all thermal power plants, an element is r
$r(WND)$	Set of all wind power plants, an element is r
$rg(RG)$	Set of all transmission regions, an element is rg
$rs(RS)$	Random scenario set, an element is rs
$s(S)$	Candidate storage facility set, an element is s
$t(T)$	Year set in the forecasting horizon, an element is t
$w(W)$	Weeks of year, an element is w
$y(Y)$	Historical years, an element is y

FUNCTIONS

ave	Average function
qnt	Quantile function
smp	Sampling function
$\alpha(hs)$	Function that defines quantile region for hydro scenario hs. Takes values 0-0.25 for low, 0.25-0.75 for reference and 0.75-1 for high scenarios
$\beta(w)$	Function that calculates storage hydropower plant generation base effect at week w. Takes values 0, 0.25 and 0.50 for low, medium and high-water inflow seasons
$\delta(hs, HCF)$	Function that adds standard deviation of historical capacity factor set for high scenario, subtracts for low scenario and does nothing for reference

$\theta_{rs}(as)$	Function that operates as minimum, average and maximum for availability scenarios low, reference and high over random scenarios rs
$\phi(r, rg)$	Function that calculates the installed capacity share of resource r in region rg
$\psi(rg)$	Function that calculates the demand share of region rg

MAPPINGS

$hs \rightarrow y$	Mapping from hydro scenario hs to elements of set of years y
$rg \rightarrow g$	Mapping from region rg to elements of set of generator units g
$w \rightarrow \overline{h}$	Mapping from week w to elements of set of hours of year $\overline{h}$
$w \rightarrow \underline{h}$	Mapping from week w to elements of set of hours of day $\underline{h}$

CHAPTER 1

INTRODUCTION

Turkey has unique electricity generation and demand characteristics. The storage hydropower capacity has an important role in electricity generation and the changes in hydro conditions across years significantly affect the conditions in the electricity market. The electricity generation fleet is rapidly evolving with the addition of renewable energy resources. Also, the electricity demand in Turkey has not been saturated yet. According to the official demand forecasts [1], it is expected to double in the next 20 years and reach to an extent that is around today's level of electricity consumption in Germany. Based on electricity demand growth expectations as well as its high wind and solar potential thanks to the advantages brought by its geographical position, the electricity demand and generation characteristics of Turkey as of today will likely to evolve further in the coming years. This requires the analysis of future market conditions with great care.

The electricity market is liberalized in Turkey, similar to the trends in the developing and developed counties. The reference price for electricity, which is the most important signal for all market participants, is determined on hourly basis in the day-ahead market according to supply and demand dynamics. Despite its unique electricity generation and demand characteristics, the way that the electricity market operates makes the proposed models and approaches in this thesis applicable to other electricity markets in different counties.

This thesis presentes a novel methodology for electricity market modeling to be utilized in medium and long-term planning and forecasting targeting electricity sector. The methodology is designed based on the characteristics of Turkey. However, with proper modifications, it can be utilized for any electricity market.

1.1 Motivation and Problem Definition

The subject of the thesis is the design of a novel electricity market modeling methodology which can perform electricity price forecasting and can concurrently calculate the corresponding electricity generation by fuel and supply-demand balance, i.e. system reserve, for each time step of the forecast horizon. The general purpose of this methodology is to increase the predictability and observability of the electricity market, and ultimately help the central planner take necessary actions.

The central planner can be thought as the main decision maker who has all the means to influence and direct other decision makers in electricity sector. Here, the term "central planner" can correspond to the ministry, regulator or electricity system operator depending on the legislations in a territory. Likewise, the term "central planning" is used for the cooperative decision and behavior of these bodies.

The planning activity in this thesis is assumed to be fulfilled with some basic assumptions such as;

- Electricity industry is deregulated,
- Reference price for electricity and supply-demand schedules for the next day are determined in the day-ahead market operating on hourly basis, which corresponds to the marginal cost of the most expensive operating plant for the respective hour,
- Electricity demand is inelastic,
- Market participants bid their marginal costs to the market, and they cannot influence the market price by their own decisions,
- New investors take investment decisions fully in line with the targets that the central planner announces.

Based on its needs from various fields, the central planner can use various models and methodologies independent from each other. The electricity market modeling methodology in the thesis can be utilized to address the following questions with an integrated modeling approach:

- Main question 1: What will be the range of electricity market price in medium term? What will be the level of electricity market price in long term?
    - According to various cases and corresponding results, the central planner can investigate whether it will be sufficiently low from consumer point of view, and whether the corresponding level of electricity generation and the resulting revenue will be enough for the continuity of operation of each power producer based on a reasonable profit margin.
- Main question 2: What will be the range of reserve capacity in medium and long term?
    - According to various cases and corresponding results, the central planner can analyze whether there will be sufficient reserve in order to maintain uninterruptible power supply.
- Main question 3: From both electricity price and reserve point of view, what should be the level of electricity generation capacity in long term?
    - According to various cases and corresponding results, the central planner can observe whether there will be a need for additional action after checking detailed operational results and determine the relevant actions accordingly.

Not limited to the questions above, with the utilization of the proposed modeling methodology, the central planner can have insight on various topics with hourly details such as;

- Electricity generation by fuel,
- Amount of fuel that will be consumed for electricity generation and the resulting import bill,
- Self-sufficiency and import dependency in electricity generation,
- CO_2 emissions from electricity generation activity,
- Evolution of hourly electricity prices and their pattern,
- How to design future renewable energy support schemes,

- Feasibility of various power plant and storage projects.

In both regulated and deregulated electricity markets, the central planner has the responsibility for monitoring the conditions in electricity sector taking into account the necessity for providing sufficient, good quality, uninterrupted, low cost, and environment-friendly electrical energy to end consumers. However, the capability of tools and measures over which the central planner has control are effective mostly in medium and long-term planning horizons. In shorter term, the decisions are related to day-to-day operations, and in case there are persisting problems having arisen in short term, these can be solved by developing various measures which are expected to take effect beyond short term. Considering that the modeling methodology in this thesis is designed for the central planner and the impact of the decisions taken by the central planner have a lag time, the modeling methodology addresses the questions in medium and long-term horizons. It is assumed that throughout the thesis the medium-term horizon typically corresponds to 1 year and can have a range from 1 year to 5 years. Also, the long-term horizon is considered to be over 5 years.

Among the previous main questions, the first and second ones deal with both medium and long-term horizons whereas the third one is applicable only for long term. The variation of the first two questions is based on the fact that one of the goals in utilizing medium-term horizon is to reveal the risks associated with the fundamental parameters such as economic growth, climate and hydro inflow conditions over the scenarios derived. Therefore, the area of interest is the "range" of results, rather than "point forecast". For the long-term horizon, the main problem is to find a proper generation expansion plan and to put it to further examination in detail for selected years in order to evaluate the future system conditions. Given that the fundamental parameters are fixed due to increasing uncertainty over medium term; "point forecast" is applicable for the long-term horizon.

The time step in the modeling methodology is 1 hour. It means that the electricity market model operates on hourly basis and produces hourly results in a similar way that day-ahead markets operate in liberalized electricity markets. The consolidation of hourly outputs yields monthly and yearly results in aggregated terms. This manner of operation is fully compatible with the de facto situation in the electricity market, at the same time providing complete transparency on results, at the expense of increased complexity. The central planner can perform detailed analysis and examine the root cause of possible future problems, if there will be any, or create justifications for its future decisions.

1.2 Proposed Methods and Contributions

1.2.1 Proposed Methods

The purpose of each model is stated in Table 1.1. In addition, the behavior of each model varies according to planning horizon as summarized as in Table 1.2.

Table 1.1 Purpose of Each Model in the Modeling Methodology

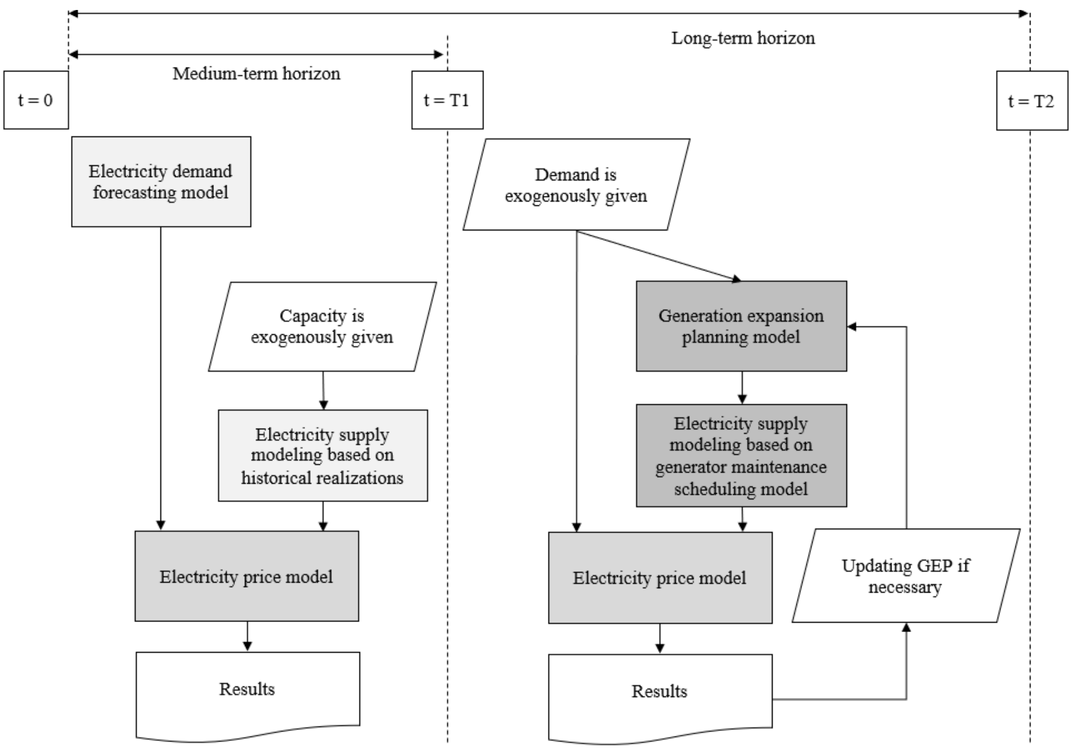
Modeling	*Purpose*
Electricity demand modeling	To obtain hourly electricity demand forecast series to be used in the electricity price model
Electricity supply modeling	To obtain hourly available electricity generation capacity by market participant to be used in the electricity price model
Electricity price modeling	To calculate hourly electricity price based on the results from electricity demand and electricity supply modeling parts considering the specific characteristics of power plants
Generation expansion planning	To decide on the size and fuel type of new generation capacities

Table 1.2 Behavior of Each Model in the Modeling Methodology

Modeling	*Medium-Term*	*Long-Term*
Electricity demand modeling	Electricity demand is forecasted on daily or monthly terms based on economic and climate variables, then disaggregated into hourly terms using the demand profiles calculated according to historical realizations	Electricity demand is exogenously given based on the results from the officially announced electricity demand projection studies
Electricity supply modeling	Hourly available generation capacity is determined based on historical realizations	Hourly available generation capacity is calculated according to a generator maintenance scheduling model which reflects the long-term effect of changing electricity generation mix on maintenance periods in a year, and thereof on availability factors
Electricity price modeling	The operation of electricity price model, i.e. the determination of electricity price, in medium and long term is the same	
Generation expansion planning	Capacity expansion is exogenously given based on the progress level of existing power plants under construction	Capacity expansion is decided by a generation expansion planning model from medium to long-term planning horizon

Day-ahead market is an essential part of organized wholesale electricity markets, in which the reference price for electricity is determined based on supply and demand dynamics. In this respect, a methodology targeting hourly electricity price forecast and the resulting hourly generation should put specific emphasis on demand and supply modeling parts so that the fundamentals of electricity market can precisely be reflected without missing critical details. Accordingly, the modeling structure of the proposed electricity market modeling methodology is built on the parts such as "electricity demand modeling", "electricity supply modeling", "electricity price modeling", and "generation expansion planning".

The distinction among medium and long-term planning horizons is illustrated in Figure 1.1. In this figure, the minimum and maximum values of 'T1' are 1 year and 5 years, respectively. Likewise, the minimum value of 'T2' is 5 years whereas the maximum value of it can cover the period from 5 years up to 10, 20, or 50 years, i.e. whatever is required by the central planner.



(a) Medium-term horizon (b) Long-term horizon

Figure 1.1. Stages of the electricity market modeling methodology

There are four main stages of the proposed modeling methodology which are related to electricity demand, generation capacity, electricity supply, and electricity price, respectively. The proposed modeling approach can be summarized as follows:

To begin with the medium-term horizon, the modeling activity starts with electricity demand forecasting with the utilization of a proper model considering the factors influencing demand. Here, the ultimate goal of demand forecasting model is to obtain an hourly electricity demand series to be used in subsequent modeling stages. Since trying to forecast electricity demand on hourly basis over 1-year period is unrealistic and not reasonable, it is firstly forecasted on daily or monthly basis and then disaggregated into hourly time interval resolution. A daily electricity demand forecasting model with a GAM (generalized additive model) is proposed for the utilization of the methodology up to 1 year, and monthly modeling with a MARS (multivariate adaptive regression splines) model is proposed for the utilization over 1 year and up to 5 years. Both of these models include economic, climate, and calendar variables.

In the second stage of the medium-term horizon, the capacities with respect to fuel type should be determined for future years. In the medium-term horizon, a separate modeling approach for capacity expansion is not needed given that new power plants that will be commissioned in this horizon will be among the ones having already been decided for investment or under construction. This piece of information is expected to be available to the central planner, without resorting to any specialized model dedicated for this task.

In the third stage of the medium-term horizon, the modeling activity continues with electricity supply modeling. Here, the purpose is to obtain hourly available generation capacity for each market participant, which is calculated based on historical data. Available generation capacity corresponds to the expected electricity generation for the ones of which output cannot be controlled. This group includes renewable energy resources such as wind, solar, biomass, geothermal, and run-of-river type hydropower. For the other group, of which output is controllable, available generation capacity corresponds to the maximum possible electricity output for the relevant hour. This group is composed of thermal resources such as gas and coal.

In the last stage of the medium-term horizon, the modeling activity is concluded by running the electricity price model and obtaining the relevant results. The electricity price model operates on daily basis and calculates hourly electricity prices based on the hourly information provided by electricity demand and supply modeling. The calculation of electricity price considers the technical capability of thermal power plants, which is represented by the block order structure in day-ahead markets. In the previous paragraph, the only type of capacity that has not been mentioned in supply modeling is storage hydropower. Considering that the storage hydropower capacity has the ability to store energy and generate electricity according to MCP (market clearing price), an iterative scheme is designed in order to find the reasonable level of electricity generation from storage hydropower plants and MCP.

For the long-term horizon, the above stages involve different modeling approaches. In the first stage, the utilization of the medium-term electricity demand forecasting model operating on daily or monthly basis will be misleading considering that climate variables in the long-term modeling approach will unnecessarily complicate the model. Therefore, unlike the medium-term horizon, the electricity demand is exogenously given based on the results from the officially announced electricity demand projection studies which have full information on the most critical variable, i.e. economic growth. Likewise, another option for electricity demand forecasting can be based on energy sector modeling tools which can model all types of energy resources and sectors in a combined manner using a bottom up approach. However, this is beyond the scope of the thesis.

In the second stage of the long-term horizon, there is a need to determine the future electricity generation capacity by a specialized model, called generation capacity expansion. Here, the future electricity generation capacity by fuel and vintage is decided. The generation capacity expansion problem is nonlinear and requires significant amount of simplification in representing the market participants and horizon. In order to reduce the size of problem, the power plants showing similar characteristics are grouped, modeling horizon is represented by 5-year intervals, and each time step is represented by a representative day instead of modeling all 8760 hours of a year. Since it is not feasible to consider all hours of the long-term modeling horizon in the generation expansion planning (GEP) model, the expansion plan is tested at the last stage in the electricity price model, and following the analysis of details on hourly basis it can be updated if necessary.

In the third stage of the long-term horizon, the electricity supply modeling approach of the medium-term horizon is still valid except for thermal power plants. Here, electricity supply modeling is incorporated by a generator maintenance scheduling model which determines the most plausible maintenance schedule plan for thermal power plants. In principle, the central planner arranges maintenance schedules in such a way that the average reserve capacity in the system is targeted to be evenly distributed throughout a year, if possible. In today's system conditions, firstly spring secondly autumn seasons are mostly preferred for generator maintenance due to relatively lower electricity demand in those seasons and increased availability of hydropower resources in spring season, which is implicitly reflected on available generation capacity forecasts in the medium-term horizon. However, in longer terms, with the evolution of electricity generation fleet and electricity demand, relying on a static maintenance schedule plan can be misleading depending on the degree of evolution, hence a generator maintenance scheduling model is integrated into the modeling methodology in order to enable a dynamic electricity supply modeling.

The last stage of the long-term horizon is similar to that of medium-term. The only difference is that following the run of electricity price model and obtaining the results, in order to fully comply with the predetermined requirements of the central planner, the detailed analysis over all 8760 hours of the selected year may signify to take additional actions over the expansion plan that the generation expansion planning model has previously yielded. In this case, following the amendment of expansion plan, the electricity supply and electricity price models are proposed to be rerun until the requirements are fully satisfied.

1.2.2 Contributions

The general concepts related to the parts of the modeling methodology in this thesis have already been studied individually and discussed in the literature for a very long time. There are numerous works in the literature regarding electricity demand and price forecasting, generator maintenance scheduling, and generation expansion planning. This thesis focuses on a couple of points that have not been addressed in the literature. The uniqueness of the proposed structure and contributions can be summarized as follows:

- Significant accuracy improvements are achieved for electricity demand forecasting which is modeled on daily and monthly basis with the utilization of GAM and MARS models. For demand forecasting, the attention has been given to the short-term horizon in the literature so far. Based on the needs in this thesis, GAM and MARS model are studied in the medium-term forecasting horizon.
- The electricity supply modeling part of market models has not been stressed in the literature with its details. In this thesis, a new hourly availability factor calculation methodology based on historical data is proposed to be used in the price forecasting stage.
- An electricity price forecasting methodology is proposed based on day-ahead market operation. For electricity price forecasting, attention has been given to short-term horizon and artificial intelligence-based models in the literature so far. Due to data requirements, fundamental market models have not been frequently studied. In this thesis, considering the bidirectional relation between storage hydropower generation and electricity market price, a unique iterative scheme is proposed to reach a solution. It is shown that the proposed methodology operating based on the fundamentals of electricity market is able to forecast electricity price with satisfactory accuracy. According to various demand and supply scenarios, the possible range of electricity prices is revealed. It is shown that the yearly average

price in Turkey for the medium-term horizon can be realized in a wide range, corresponding to nearly half of the actual price.

- For the utilization of the electricity market modeling methodology in the long-term horizon, electricity supply modeling is improved with the inclusion of a GMS model in order to use more realistic availability factors for market participants and obtain more reasonable price forecasts. The dynamics of storage hydropower generation capability is also reflected inside the GMS model. In the literature, GMS studies have not been considered together with energy sector planning and forecasting studies so far whereas a novel connection between GMS and long-term studies are established in this thesis. The proposed GMS model is tested with the data belonging to the year 2018, and it yields a reasonable GMS pattern that is similar to the realization. With further analysis, it is revealed that the GMS plan and profile may significantly change based on hydropower and renewable generation expectations, which signify the importance of utilizing such a GMS algorithm in the long-term horizon.
- Another improvement of the electricity market modeling methodology for the long-term utilization is the inclusion of a GEP model. GEP is a subject that has widely been studied in the literature. Therefore, in this thesis, GEP is approached through various cases and from a different point of view such as the missing money problem, which is a widespread phenomenon in today's electricity market. The research direction is unique given that the missing money problem has not yet been addressed together with GEP problems in this context in the literature. A conventional GEP model, a price-based GEP model and a reformulation of conventional GEP model is comparatively used to investigate whether the missing money problem should be taken into consideration in long-term planning studies. Analyses show that any attempt to mitigate the missing money problem in long-term planning would yield higher operation costs, higher market clearing prices, and higher combined costs of generators and consumers. In addition, an

alternative price-based GEP approach is employed based on a dynamic procedure for the determination of market clearing prices. With this model, it can be directly identified which candidate facilities are profitable for investment, instead of the pure cost minimization view in the conventional approach.

- The electricity market modeling methodology is used to analyze the market conditions of 20 years later based on various cases. The most outstanding results from this analysis are such that with electricity demand and intermittent renewable capacity reaching the levels of Germany as of today;
    - The average electricity price significantly decrease by one-fourth compared to the prices of 2019,
    - The electricity price pattern remarkably changes such that zero electricity prices are observed in daytime and nearly in all months,
    - There is a need to curtail electricity from renewable energy resources in nearly one-fourth of the hours in a year,
    - At the same time, there can be instances of unmet demand when wind and solar capacity factors are low which is accompanied by significantly low yearly average utilization rates of thermal power plants.

  Although this is one of the examples for the ways to benefit from such a modeling methodology, the observations made for Turkey is unique. With this methodology, the central planner can explore opportunities to increase the system flexibility with new emerging technologies, or alternatively in its long-term plans it can determine more conservative targets that are more appropriate considering the market conditions.

1.3 Outline of the Thesis

This thesis is composed of six chapters including the introduction and conclusion parts.

Chapter 2 aims to facilitate the understanding for the rest of the thesis. It is dedicated to introduce the background information regarding the characteristics of the electricity sector in Turkey such as electricity demand, generation fleet, generation, supply and demand balance, electricity market, price, medium and long-term planning studies.

Chapter 3 presents the literature review on electricity demand forecasting, electricity price forecasting, generator maintenance scheduling, and generation expansion planning.

Chapter 4 and 5 are the main blocks that represent the structure of the electricity market modeling methodology for medium and long term in detail. In fact, these chapters are comparatively long, and several sections can be a separate chapter in any study. These chapters are intentionally kept long and integrated in order to demonstrate the necessary and connected steps in reaching realistic and reasonable electricity market modeling in medium and long-term horizons, respectively.

Chapter 4 goes into details of the electricity demand, supply, and price modeling parts for the medium-term horizon. In Chapter 5, the electricity supply modeling with the inclusion of generator maintenance scheduling as well as the details and discussions over generation expansion planning from the view of missing money problem are given.

In the last chapter, all the findings are summarized along with possible improvements to be performed in the future.

CHAPTER 2

BACKGROUND INFORMATION

In this chapter, the background information about various topics such as electricity demand, generation fleet, generation, supply and demand balance, electricity market, medium and long-term planning studies in Turkey are presented. Additionally, the simplified market modeling approach that is utilized throughout the thesis is introduced. At the end of the chapter, the key findings are summarized. Since the aim of this chapter is to help the reader to become familiarized with the concepts mentioned in the thesis, the fundamental characteristics of the Turkish electricity sector are focused.

2.1 Electricity Demand

As of the end of 2019, the electricity demand in Turkey is about 304000 GWh which is 56% higher compared to 10 years ago [2]. The electricity demand evolution and year-over-year change in the last 20 years is drawn in Figure 2.1.

The evolution of electricity demand is closely associated with economic activity. As shown in Figure 2.2, there is a directly proportional relationship between GDP (gross domestic product) and electricity demand [2], [3]. At times when GDP shrinks, electricity demand reduces compared to the previous year, and vice versa, when GDP rises, electricity demand increases. Starting from the year 2013, the yearly change in electricity demand has stayed below its 5% long-term average, with the exception of the years 2016 and 2017.

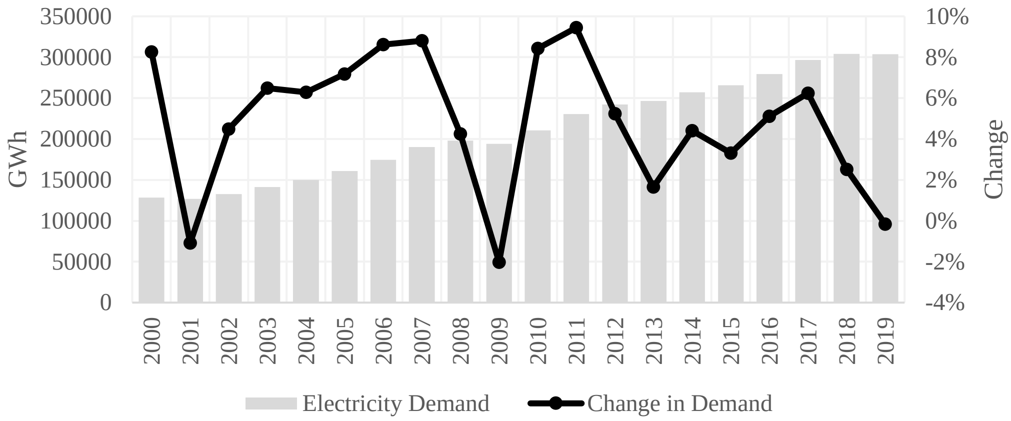


Figure 2.1. Electricity demand evolution

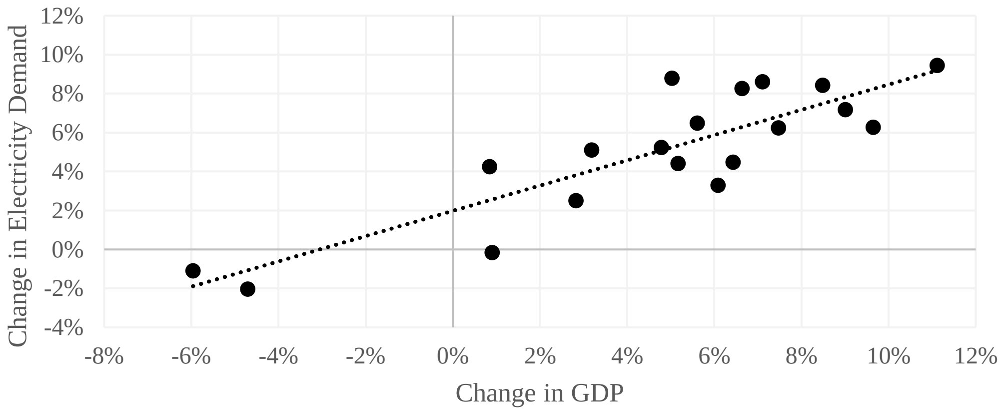


Figure 2.2. Relation between GDP and electricity demand

Despite the fact that the electricity demand growth in Turkey has slowed down in recent years, the demand is expected to increase significantly in long term. According to the reference scenario of the official demand projection study [1], it is expected to reach over 600 TWh around the year 2040. With the improvement of the economy in the future and considering that the electricity consumption per capita, which is an indicator for the development level of a country, is now around 3650 kWh that is well below its counterparts and EU average, over 600 TWh electricity demand is a reasonable level for Turkey. Electrification trends around the world, including the transformation in transport sector with electric vehicles can possibly further increase the existing expectations for electricity demand.

On seasonal basis, the electricity demand in Turkey is higher in summer and winter, and lower in spring and autumn seasons. Temperature is a major factor affecting electricity demand through cooling and heating needs. The pattern of electricity demand is exemplified in Figure 2.3 on hourly basis for the year 2018 [4]. The peak demand including unlicensed generation is around 50000 MW in mid-summer, as well as the winter peak approaches to 45000 MW. The periods coinciding feasts are accompanied by exceptionally low electricity demand, near 20000 MW. It is not possible to attribute this effect to summer season since they are moving 10 days earlier every year due to calendar effect.

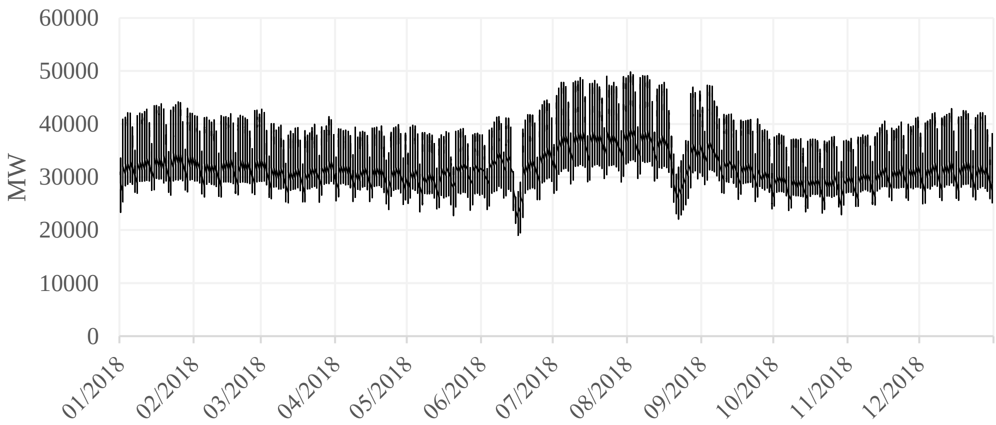


Figure 2.3. Hourly electricity demand in 2018

The pattern of electricity demand throughout a day in various seasons is shown in Figure 2.4. In all seasons, there is a valley in early hours of a day, followed by a sharp increase in the morning. The high-demand period continues within the day until the evening. On average, the electricity demand fluctuates in a 10000-15000 MW range, corresponding to over 30% of the average demand. This characteristic of electricity demand requires the efficient utilization of flexible resources in the electricity generation fleet. Considering the load pattern of similar countries that Turkey is expected to reach in terms of total electricity demand like Germany, the range in which the demand is fluctuating will likely expand, and in this case the importance of flexible resources will increase even more.

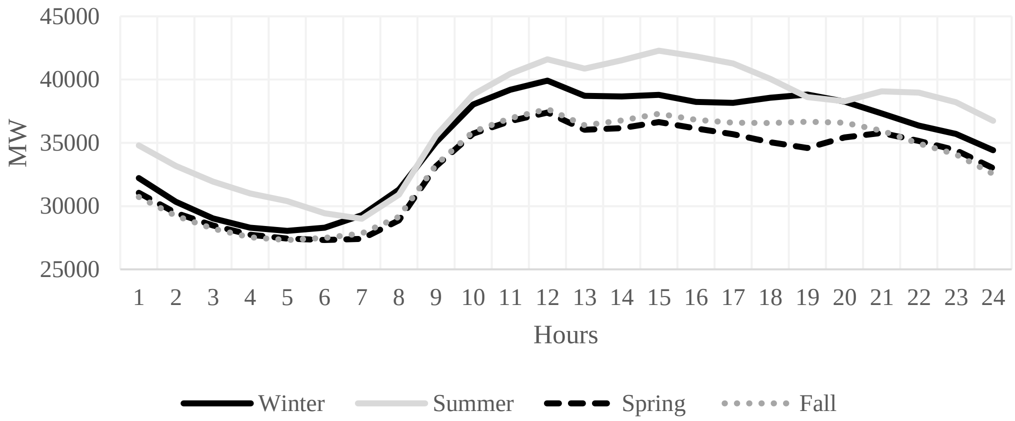


Figure 2.4. Average hourly electricity demand in various seasons

2.2 Electricity Generation Fleet

As of the end of 2019, the total electricity generation capacity in Turkey surpassed 91000 MW, doubled in a 10-year period of time [2]. The fuel with the highest share is hydropower with 29000 MW installed power. Then, in the second and third place, there are natural gas with 26000 MW and coal with 20000 MW. The amount of renewable capacity excluding hydropower exceeded 16000 MW. The overview of installed capacity is shown in Figure 2.5.

With policies prioritizing renewable and domestic energy resources, the share of renewable capacity reaches 49%, up from 35% 10 years ago. That corresponds to 29000 GW capacity increase out of 46500 MW in total. In the last decade, 63% of capacity increase has come from renewable energy resources.

Nearly 21000 MW of total hydropower capacity is of storage hydropower type, and the remaining 8000 MW being run-of-river. High storage hydropower capacity bringing both flexibility and uncertainty is one of the most prominent features that describe the electricity generation fleet in Turkey. At the beginning of 2000s, Turkey had already owned 11000 MW storage hydropower capacity with big projects such as 2400 MW Atatürk Dam, 1800 MW Karakaya Dam and 1330 MW Keban Dam. In late 2000s and then early 2010s, thanks to profitability of investments with moderately high electricity market prices in USD terms and the implementation of the renewable energy support mechanism ensuring certain level of revenue stream for a 10-year period of time after commissioning provided pace for hydropower investments, especially for the small scale run-of-river type.

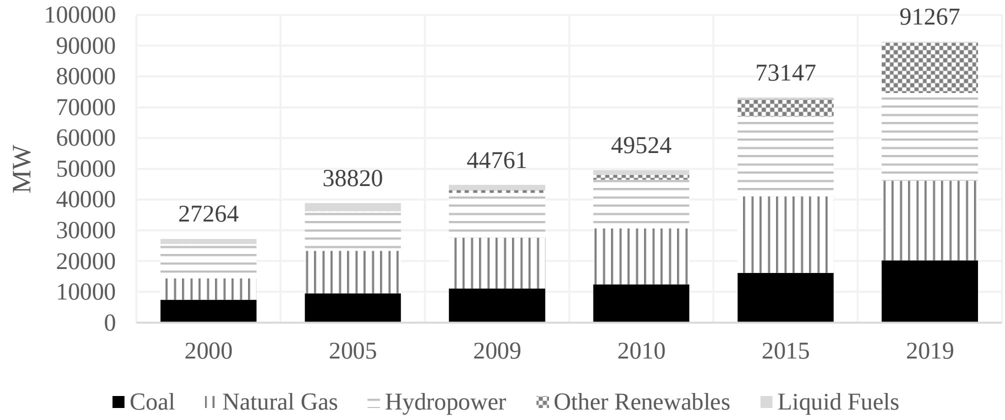


Figure 2.5. Installed capacity development

Out of 26000 MW natural gas power plant capacity, nearly 90% is above 100 MW, and these are predominantly natural gas combined cycle power plants. The first significant rise in natural gas installed capacity occurred in early 2000s, with the construction of power plants with the build-operate (BO) and build-operate-transfer (BOT) models, which were contracted in late 1990s due to increasing electricity demand and tightening reserve margin. The second significant rise occurred in early 2010s with private sector investments without any purchase guarantee. The constitution of free electricity market accompanied by satisfactory profit margins and expectations for electricity demand growth were the main promoters of private sector investments.

The same motivation also helped coal capacity to increase in the same period. Turkey had already owned 7500 MW coal power plants in early 2000s, nearly all of which operated with domestically produced lignite. The investments gained pace with a pattern similar to natural gas. The majority of these new investments use hard coal as fuel which is imported. Both lignite and hard coal capacity play a major role in the generation fleet as they serve as base load power plants and make a reliable contribution in meeting the surging electricity demand.

The installed capacity of other renewable energy resources such as wind, solar, geothermal and biomass increased from 1000 MW in 2009 to over 16000 MW in 2019. Wind and solar are the main contributers with nearly 14000 MW combined. Similar to the trends in emerging and developed countries, Turkey has achieved remarkable success in commissioning renewable energy investments mainly thanks to the successful implementation of the renewable energy support mechanism accompanied by reducing capital costs. The existing mechanism provides support for a 10-year period of time after commissioning with feed-in-tariffs 73 $/MWh for wind and run-of-river hydro, 105 $/MWh for geothermal, 133 $/MWh for solar and biomass. As of September 2020, it is valid for power plants to be commissioned until the end of June 2021, but it will be revised according to decreasing cost trends around the world.

In terms of renewable energy potential, Turkey can be said to be rich in resources. The estimated wind capacity potential is 48000 MW according the wind energy potential atlas [5] prepared in the second half of 2000s and the average annual solar radiation is 1527 $kWh/m^2 \cdot year$ [6]. The realization of wind and solar projects requires acquiring the right in the beginning to build capacity based on a competition procedure. The degree of utilizing wind and solar potential will surely depend on the level of electricity demand and the flexibility of the system to manage the intermittency problem posed by these resources. The potential for hydropower is estimated to be around 35000 MW [7]. The potential for geothermal is estimated to be between 2000 and 4000 MW depending on the viability of the projects awaiting announcement for the revision of the renewable energy support scheme.

One of the mains pillar of the existing electricity policy in Turkey is the promotion of domestic and renewable energy resources [8]. Based on that policy, Turkey is expected to take as much renewable capacity as possible without incurring any significant cost on electricity consumers, but at the same time as the complement of renewables it aims to meet its surging base load need from coal power plants to be built near unexploited domestical lignite fields. Furthermore, as a diversification and strategic step, Turkey is now constructing its first nuclear power plant in Akkuyu, which is expected to be commissioned in the period of 2023-2026. The studies for additional new nuclear power plants are still ongoing on various sites.

2.3 Electricity Generation

As of the end of 2019, the electricity generation in Turkey is around 304000 GWh [2]. In the presence of limited electricity transactions with its neighbours, the electricity generation in Turkey follows the pattern of electricity demand.

The share of resources in total electricity generation is shown in Figure 2.6. For many years, natural gas has the largest share, and with 99% of natural gas being imported, it has raised concerns for import dependency. The trends in electricity generation have started to change profoundly from the year 2015, with the increase in renewable generation capacity and below-expected sluggish electricity demand growth.

As hydropower has the largest share in the electricity generation fleet, it brings unique characteristics to the electricity generation in Turkey. With hydropower being the most dominant energy resource, the meteorological conditions in Turkey make a significant impact on the electricity sector. Depending on the amount of water inflow, in wet seasons excessive hydro generation displaces thermal capacity with which deficient hydro generation in dry seasons is compensated. From year to year, the average capacity factor of hydropower plants can range roughly from 20% to 40%. That is a 50 TWh spread for a 29000 GW hydro fleet, corresponding to a huge 17% of the total electricity generation. The level of uncertainty in the electricity generation fleet requires painstaking planning in medium and long-term horizons and ensuring adequate reserve capacity amidst moderate electricity demand expectations.

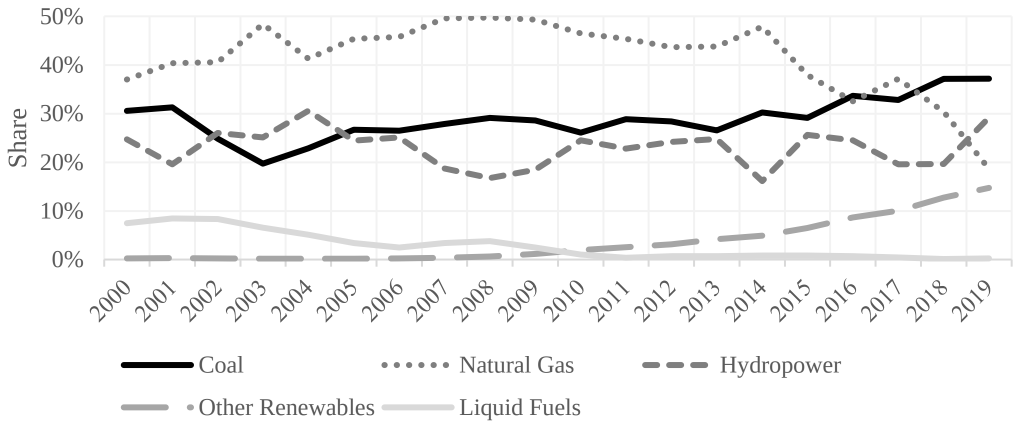


Figure 2.6. Shares of resources in electricity generation

The uncertainties in both electricity generation and demand are managed by natural gas power plants which have the highest marginal cost in the generation fleet except oil power plants, but at the same time have moderate amount of flexibility. After hitting an all-time high in terms of the amount of electricity generation with over 120000 GWh in 2014 which is a remarkably dry year, its generation shrinks to 57000 GWh in 2019, a wet year. Thereby, the share of gas in electricity generation plummets from 48% to an unexpected 19%.

In the reduction of the share of natural gas, firstly electricity demand and secondly renewable energy investments has played a major role. If Turkey had succeeded in growing its electricity demand at the same level, which is 5%, occurred in the period of 2000-2015, the electricity generation would have reached 340000 GWh. It means that around 40000 GWh higher electricity demand would have been compensated by natural gas, and its share would have been significantly higher. The share of renewable energy resources excluding hydropower increases from 1% in 2009 to 15% in 2019. If over 16000 MW renewable energy investments had not been achieved, the electricity generation from natural gas would have been 45000 GWh more. Furthermore, the share of intermittent resources in electricity generation, including wind, solar and run-of-river hydropower reaches a remarkable 15% in 2019. There are not any significant adverse effects reported so far due to intermittency. However, the lack of flexible generation capacity like pumped hydropower and battery energy storage facilities as well as the limited electricity trade opportunities considering the comparatively low level of electricity consumption in the neighbouring countries require carefully assessing the impacts of intermittent renewables on the grid and measuring the maximum possible level of intermittent resources in electricity generation.

2.4 Supply and Demand Balance

One of the most important indicators of security in an electricity system is reserve capacity. Reserve capacity represents the supply and demand balance in a system, and has two components such as total available electricity generation capacity and total electricity demand. The difference among these two components defines the reserve capacity.

For a secure operation of electricity system, there is always a need to keep certain amount of reserve capacity depending on the characteristics of generation resources. From the point of view of electricity system operator, it is more preferable to have a balanced reserve capacity throughout a year. It can also be translated as excessively high or low reserve capacity is undesirable.

As mentioned previously, the electricity demand in Turkey is significantly higher in summer and winter months compared to other seasons of a year. Therefore, the pattern of electricity demand realizes in such a way that it influences the reserve capacity in the decreasing direction in summer and winter months, and vice versa in the increasing direction in spring and autumn seasons.

As the share of renewable energy resources increases, their capacity factors become more influential on the reserve capacity. The capacity factors of the most dominant renewable energy resources in the Turkish electricity generation fleet, including storage hydropower are calculated based on [4] and shown in Figure 2.7, for a 4-year period from 2015 to 2018. Wind has a generation pattern that is higher in summer and winter, and lower in other seasons of the year, which perfectly matches the pattern of electricity demand. Solar capacity factor is highest in summer season; however, it has a pattern that is above its yearly average in spring and autumn seasons and below its yearly average in winter season. This feature of solar generation is incompatible with electricity demand, hence careful analysis should be made upon possibly high amount of solar capacity commissioning in the future. As for run-of-river type hydropower, it has a negative correlation with electricity demand given nearly the half of its yearly generation occurs in spring season. Storage hydropower generation is more stabilized throughout a year. It has above-average generation pattern in summer and winter seasons, which indicates that its flexibility is utilized when needed in those months while concurrently water inflow is lower. However, its summer-like capacity factor in April signifies its flexibility has a degree up to a certain extent, and its generation has to increase even when electricity demand is low.

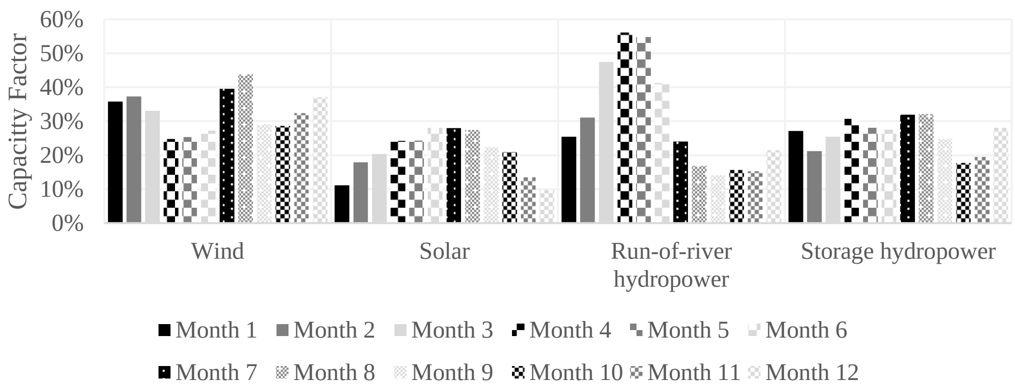


Figure 2.7. Capacity factor of renewable energy resources by months

In a similar fashion, the capacity factors of fossil fuel generation capacity including hard coal, lignite and natural gas are calculated based on [4] and shown in Figure 2.8, for a 4-year period from 2015 to 2018. All of these resources have something in common, that is, their capacity factors are lowest in spring season and highest in summer season. This generation pattern occurs as a result of electricity demand and high amount of electricity generation from hydropower in spring season.

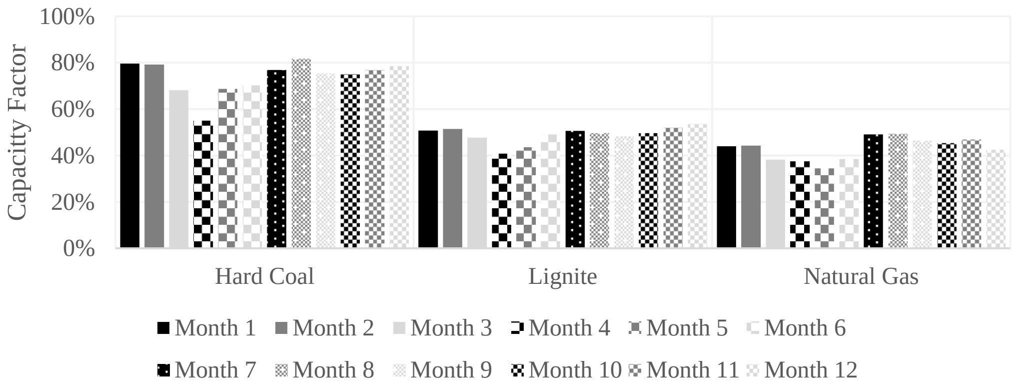


Figure 2.8. Capacity factor of fossil fuel resources by months

As a consequence of supply and demand balance, a certain amount of fossil fuel generation capacity becomes idle in spring season which is mostly preferred for planned generator maintenance. This can be followed from Figure 2.9, calculated based on [4]. Generator maintenance schedules are proposed by generation companies and approved by the system operator. The system operator has the right to disapprove the proposed maintenance plan of a company and reschedule it. The motivation of the system operator is to maintain the secure operation of power system with adequate amount of reserve capacity.

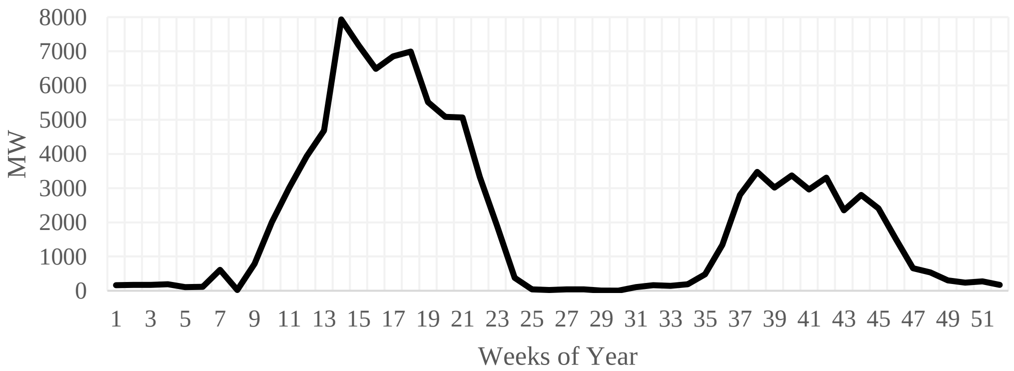


Figure 2.9. Weekly average fossil fuel capacity in maintenance in 2018

As the future electricity generation fleet of Turkey is expected to evolve based on renewable energy resources, and considering the inversely proportional relation between electricity demand and electricity generation from solar, except summer season, it is essential to predict the effect of capacity evolution on the existing generation maintenance schedules, and regarding it as an important parameter in medium and long-term planning horizons.

2.5 Electricity Market

The electricity sector in Turkey has experienced major changes since early 2000s. The restructuring process was stirred by the unbundling of vertically integrated Turkish Electricity Company into Turkish Electricity Generation & Transmission Company and Turkish Electricity Distribution Company in 1993. The attempts to attact private sector investment were not successful amidst surging electricity demand in the second half of 1990s, and thereby new power plant projects would be constructed by the BO and BOT models with 20-year purchase guarantee agreements to be signed in order not to have supply shortage in 2000s. During the financial crisis in 2001, it had already been understood that this mechanism was not sustainable, and private sector investments would be crucial for new generation capacity requirement. In this regard, the restructuring process gained pace as an electricity market law was enacted which unbundled generation, transmission and distribution activities and established Energy Market Regulatory Authority (EMRA), an independent body for the supervision of electricity sector. With all these attempts, the basic idea is to create a free market environment and attact private sector investments in order to sufficiently meet electricity demand. These are followed by the establishment of the organized electricity market in 2006, which is proceeded by the opening of the day-ahead planning with hourly settlement in 2009, and as the final point, the day-ahead market mechanism started in late 2011.

The electricity market structure can be broadly classifed according to the delivery of electricity, such as physical and financial. As of the end of 2019, the financial market has yet to started its operation by Borsa Istanbul. The physical market, which requires physical delivery, can be categorized into three parts such as bilateral contracts, spot market and real time market. The bilateral contracts among market participants are realized individually or via over-the-counter (OTC) platforms, but the trade volumes in these environments are low. The spot market is composed of day-ahead and intraday markets operated by the market operator, EXIST. The real time market is composed of balancing power market and ancillary services market operated by the electricity system operator, TEİAŞ.

Among all of these market environments, the one that defines the reference price for electricity is the day-ahead market. In the day ahead market, the offers of market participants are submitted and the market is cleared one day before the delivery. In liberalized markets, day-ahead is a crucial point of time for market participants to cover their positions [9].

Although in EU there are examples for smaller time frames such as 15-minute, the day-ahead market in Turkey operates on hourly basis, and the reference price for electricity, named as market clearing price (MCP), is determined at the level where supply and demand curves intersect for each hour [10]. The day-ahead market operates on portfolio basis, not on plant basis, indicating that if its sell offer is accepted, a market participant has the option to satisfy the need for electricity generation from any plant in its portfolio.

The offers in the day-ahead market can be categorized as hourly, block and flexible. The most preferred types of offers are hourly and block. Hourly offers contain information regarding quantity and price for the respective hour whereas block offers include quantity and price information along with the time period encompassed. Block offers are either fully accepted or fully rejected, and they are preferrable by market participants having power plants with lower flexibility. More details on the bid types and market clearing algorithm are broadly given in [10].

2.6 Electricity Price

Since the MCP determined in the day-ahead market is the representative price for electricity sector, it has a crucial role in defining how much generators earn and how much consumers pay. The level of MCP in both Turkish Lira and USD terms is shown on yearly basis as in Figure 2.10, from the year 2012 to 2019 [4]. Electricity price is an indicator of supply and demand balance. Therefore, it is expected to evolve in an inversely proportional relation with reserve capacity. However, since the reserve capacity is not the only influential parameter, commenting on the trend of electricity price requires examining in a broader perspective.

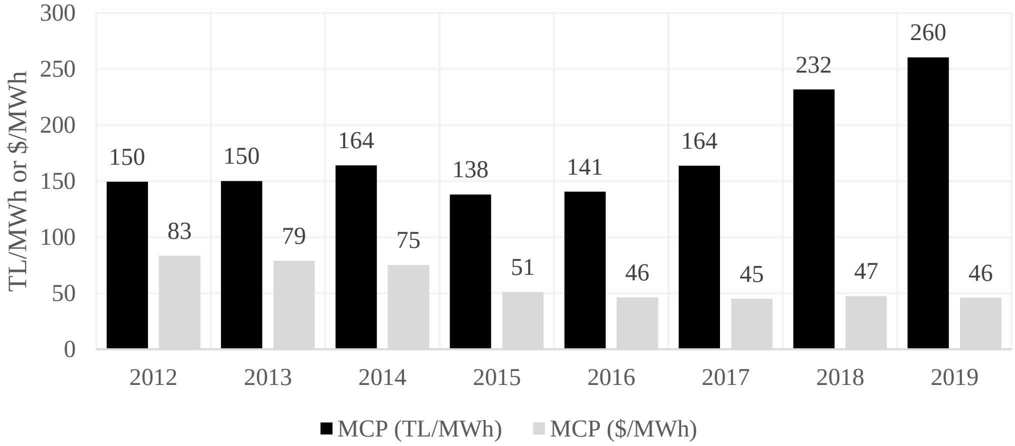


Figure 2.10. MCP in Turkish Lira and USD terms

In USD terms, the MCP in Turkey has a declining trend. The main reason behind the corresponding decline is the fall of oil prices after the year 2014, which influenced oil-indexed natural gas prices starting from the year 2015. Considering that the market participants submit their true marginal costs for electricity generation, the accepted offer with the highest price in the day-ahead market determines the MCP for the whole system, and natural gas has an important share in the electricity generation fleet; natural gas power plants become the marginal ones at most of the hours in a year, which makes MCP to be closely related to natural gas price. It should be noted that oil price has only slightly recovered from its fall in 2015. The second important aspect of the decrease in MCP is the effect of depreciated Turkish Lira against other currencies. Lastly, the third critical aspect can be counted as the slowdown of high electricity demand growth, which improves average reserve capacity. All of these factors can be said to play important roles on the trend of MCP in recent years. Despite the fact that the years 2014 and 2018 coincide with dry seasons, the MCP in 2014 is lower than the previous year, and the MCP in 2018 is around the similar level of the year 2017. This is an indication of that the aforementioned three factors conceal the effect of hydropower availability on the MCP in USD terms.

In Turkish Lira terms, the trend of MCP is almost stable from the year 2012 to 2017. The effect of depreciated currency is reflected on MCP starting from mid-2018 with increased natural gas prices for power plants. The effect of dry and wet seasons can be followed more clearly from Figure 2.10. The MCP in 2014 gained nearly 10% compared to the year 2013 due to dry season, which is then followed by a sharp decrease on the next year. However, caution is always needed due to the mixed effect of various factors while commenting on MCP.

The inversely proportional relationship between daily average reserve capacity and MCP can be followed from Figure 2.11. As reserve capacity becomes tighter, more expensive units must be operated, and thus MCP increases as expected. Therefore, availability calculations can be said to have crucial importance in order to properly represent supply and price dynamics. Likewise, this relation can also be interpreted with the trend of monthly average MCP as shown in Figure 2.12. In Turkish Lira terms, the sharp valleys in spring seasons of the years 2012, 2015, 2016 and lastly 2019 are originated from increasing hydropower generation accompanied by increasing reserve capacity. The effect of natural gas shortages on MCP can be seen on February 2012, December 2013 and December 2016. Those are the times when MCP either hits the price cap of 2000 TL/MWh or approaches this cap. The effect of doubling natural gas price on MCP can also be noticed, which is later stabilized on the following year.

The hourly pattern of MCP on monthly basis for the year 2019 is shown in Figure 2.13 based on [4]. This figure would have been drawn in terms of USD; however, the effect of currency rate fluctuation might have been misleading. The year 2019 coincides to a wet season, and the characteristics of a wet season can be followed especially from May. In early hours of May, the average MCP approaches 0. The similar effect can also be noticed in June and even in January in which unexpectedly high amount of water inflow and rainfall occurred, respectively.

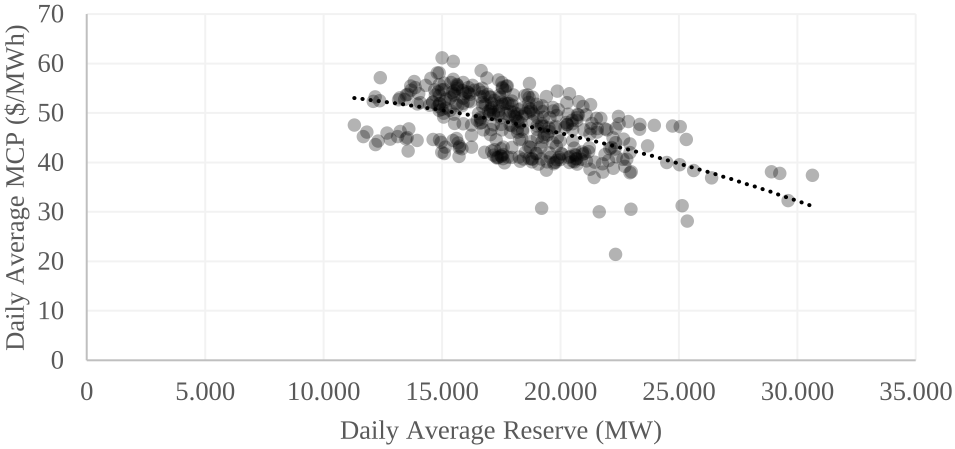


Figure 2.11. Daily average reserve and the corresponding MCP for the year 2018

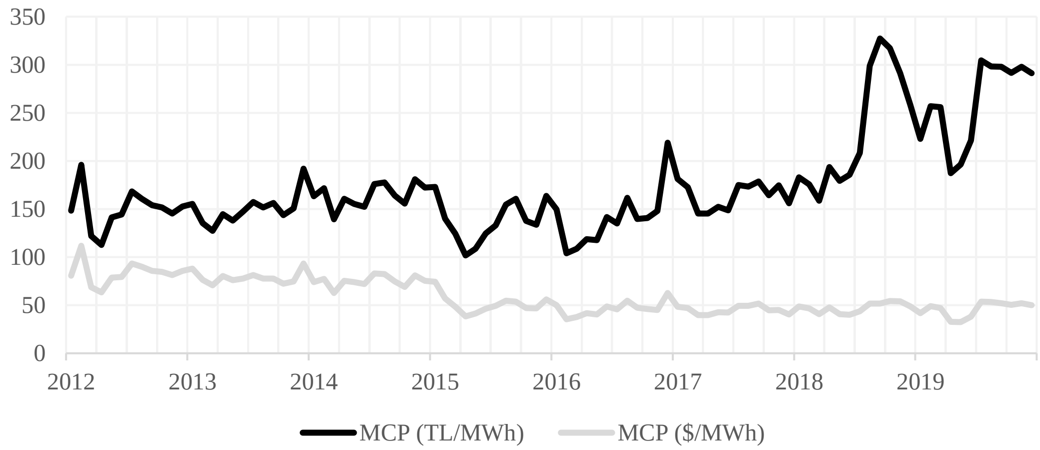


Figure 2.12. Monthly average MCP in Turkish Lira and USD terms

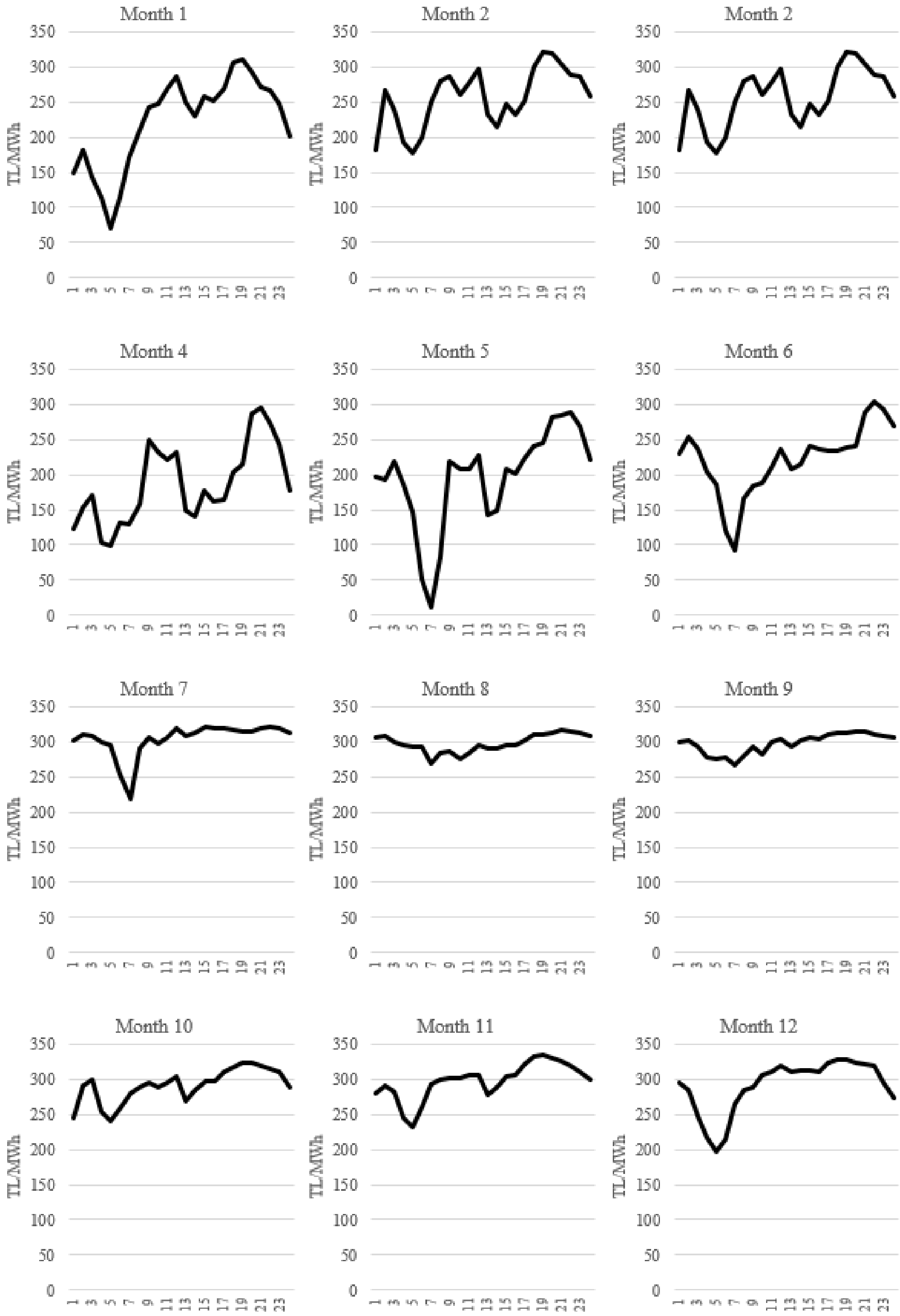


Figure 2.13. Hourly average MCP by month

Many further elaborations can be made on Figure 2.13. Probably one of the most remarkable ones, when compared to the pattern of electricity demand on hourly basis, is that the highest price within a day occurs late in the afternoon and in the evening, which is slightly different than the pattern of demand. This is a crucial finding showing the impact of reserve capacity on MCP through the availability of resources. Among them, even with 6000 MW installed capacity, solar generation notably affects the MCP in the decreasing direction especially at noon. This can be observed in nearly all months except summer and December.

2.7 Medium and Long-Term Planning Studies

The planning studies on electricity sector, in a way, regards electricity security of supply, and those are defined in the electricity market law in Turkey. The responsibility for monitoring electricity security of supply and taking necessary measures is given to the ministry (MENR).

The first study in this context is the electricity demand projection study covering the next 20 years, and it is published biennially. The report consists of the methodology and the results with three scenarios [1].

The electricity demand projection study is the reference point for the electricity system operator, TEİAŞ, to prepare the long-term electricity generation plan for the next 20 years and the generation capacity projection for the next 5 years. The latter one is published annually; however, to the best of its knowledge, the first study is not publicly available. The generation capacity projection report considers generation investments under construction and calculates reserve capacity as well as electricity generation potential according to various scenarios. In [11], this report is described as having a practical and empirical approach, and not based on a modeling. It rather focuses on a medium-term horizon to check whether the planned projects will suffice to meet the future electricity demand. In the past, for supply modeling

WASP model was used by TEİAŞ in order to determine the future electricity mix, dispatch and capacity planning on yearly basis having 12 time steps [11].

Taking into account the aforementioned studies, as well as the electricity market development report of the regulator, EMRA, the ministry is responsible for preparing the electricity security of supply report on annual basis. According to the law, the supply and demand balance, diversification of resources, findings on security of supply and operation of electricity market are taken into consideration. Similar to the long-term electricity generation plan, the electricity security of supply report is not publicly available.

Given that two of the aforementioned studies are not available for the readers, it is not possible to comprehensively comment on neither those studies themselves nor the methodologies that they utilize. However, for the generation capacity projection report, the expected electricity generation by fuel that will meet the future electricity demand is not presented. In this context, the indicators related to electricity generation cannot be calculated. Furthermore, the results are provided on annual terms, and monthly details do not exist. As for electricity demand, two of the three scenarios from the official demand projection study are used in the generation capacity projection report. In such a medium-term study, the consideration of the possible range for electricity demand including economic and weather factors, and presenting results on monthly even daily basis at least for the following year can be a great contribution, which would increase the observability of electricity sector. In [11], the planning activities within the ministry and its relevant bodies are described to be based on ad-hoc projects, and the studies on demand forecasting, capacity planning and greenhouse gas emissions forecasting are performed separately.

Further studies performed within the ministry and its relevant bodies are discussed in [12], mostly in terms energy demand modeling. Electricity demand forecasting studies are performed by the ministry for short-term, i.e. 45-day horizon, and long-term, i.e. 20-year horizon. For various horizons, various studies are also performed or consolidated by EMRA and TEİAŞ. Based on the electricity market law and related regulations, distribution companies submit their 10-year demand forecasts for their regions in the context of network development planning. These forecasts are said to be generally relying on statistical or econometric modeling such as ARIMA, EViews, etc. Moreover, short-term electricity demand and supply forecasting are performed by TEİAŞ, and these studies are said to be not relying on specific models [12].

As for electricity price forecasting, there are not any responsibilities or activities defined by the law for short, medium or long-term. This type of studies is possibly be prepared by the relevant bodies associated with the ministry and utilized when needed.

2.8 Simplified Electricity Market Model

The consideration of the effect of day-ahead market in medium and long-term planning studies requires the utilization of a simplified market model that can operate efficiently.

From modeling perspective, the market clearing problem even for one day is exceptionally complex. However, in the changing market environment, electricity generation is shaped by day-ahead market. Therefore, in order to reflect the effect of day-ahead market and calculate an indicative electricity price more properly in planning activities, some critical assumptions have to be used regarding the rules of the market, number of market participants, elasticity of electricity demand, etc. These are preferred in order to simulate the electricity market in a realistic way and obtain solution in a reasonable amount of time.

The famous supply curve, or also known as the merit-order curve, as well as demand curves at various time points and the corresponding levels of MCP are exemplified in Figure 2.14. The x-axis corresponds to the quantity of electrical energy, and the y-axis corresponds to the marginal cost for the respective supply source.

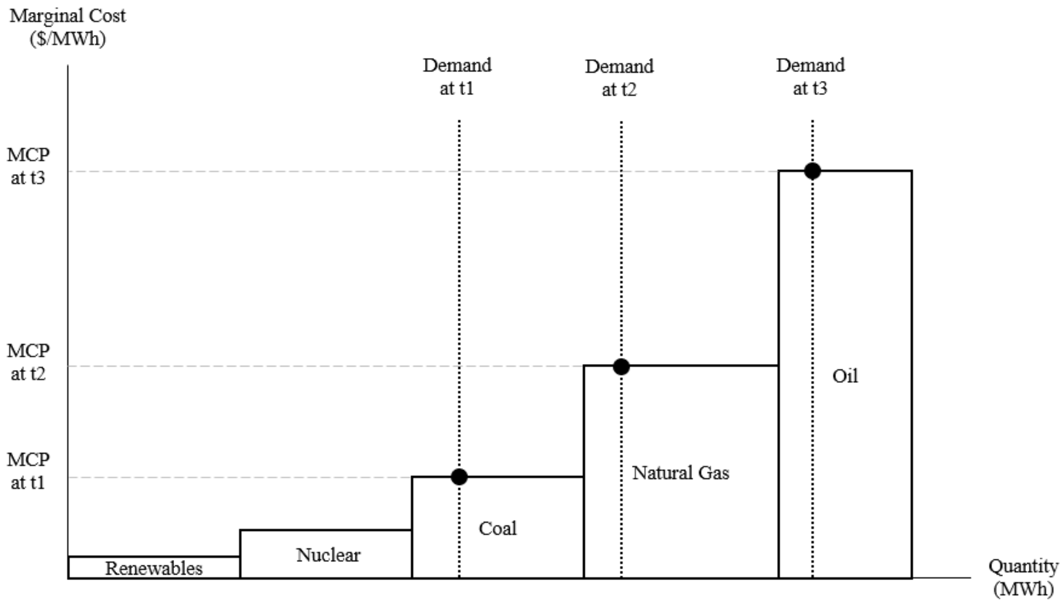


Figure 2.14. A representation of merit-order curve

The merit-order curve, formed by the concetenation of the upper lines of each supply block, is ordered according to the available supply from the lowest marginal cost to the highest one. Typically, since renewable resources have nearly zero marginal cost, they are placed at the bottom of the merit-order curve. Then, there comes nuclear, coal and natural gas power plants ranked majorly according to fuel cost for unit electricity generation. The last part of the supply curve is composed of oil power plants with considerably higher unit electricity generation cost. The intersection point of the merit-order curve and demand at the relevant hour determines MCP. If supply is considered to be fixed, with the increasing or decreasing demand, MCP is also expected to increase or decrease, respectively. Considering that there can be significant marginal cost differences among supply opportunuties, forecasting electricity supply as well as electricity demand is of vital importance in electricity price forecasting studies. The price forecasting activity in this thesis is fulfilled based on hourly merit order curves, and based on the assumption that each power plant and the group of power plants showing similar characteristics are the market participants that submit orders on hourly and block basis. Additionally, the demand is assumed to be inelastic in order to keep the problem linear and be able to obtain the MCP forecast for long-term horizons without computational difficulty.

In the day-ahead market, MCP is determined according to the hourly orders regardless of block orders. Market clearing prodecures and acceptance criteria for block orders can vary across countries. When a block order is accepted, it is assumed to be an offer regardless of the resulting MCP and placed at the bottom of the merit-order curve with 0 marginal cost. The acceptance of a block order mean it will earn at least at the submitted offer price, and it is possible to earn according to MCP if the submitted offer price is lower. This approach is utilized in the thesis.

The fuel cost of each power plant to generate 1 MWh electrical energy can be calculated according to the fuel sales price, excise tax, grid/transportation cost for the delivery of the fuel and efficiency of the power plant. The fuel cost is supplemented by the variable operation and maintenance costs and variable component of the electricity grid tariff. The summation of all of these components yields the marginal cost for a power plant. Thanks to the competitive environment in the electricity market, market participants have the motivation to submit their true marginal costs in order to obtain revenue. The fixed costs such as the investment costs, fixed operation and maintenance cost and fixed part of the electricity grid tariff are not taken into consideration while calculating the marginal cost, as they are to be paid regardless of whether they operate or not. This is the prevalent approach of submitting offers in the Turkish day-ahead market, and the same logic is also utilized in this thesis.

2.9 Summary

According to the information given in this chapter, the main features of the electricity sector in Turkey can be summarized as follows:

- The electricity demand in Turkey is closely related to economic activity. The variations of demand across seasons and hours are significant. The electricity demand is expected to double and surpass 600 TWh in 20 years.
- Turkey has a balanced electricity generation fleet with the contribution of hydropower, natural gas, coal and other renewables. Similar to the trends around the world, the share of renewable energy resources has been steadily rising. Turkey has a rich potential of wind and solar, and thanks to this property, it is highly possible that the amount of intermittent generation can increase tremendously in long term.
- From year to year, according to hydro inflow conditions, hydropower generation dramatically affects the generation level of natural gas power plants. The uncertainties both in demand and supply sides are mostly undertaken by those facilities.
- Seasonal variations among the generation capability of resources are significant. The wind generation pattern is perfectly compatible with electricity demand. For solar, the generation is compatible with the summer demand; however, for other seasons of the year, solar generation characteristics have a mismatch with electricity demand. The run-of-river type hydropower plant generation is again incompatible with electricity demand, having the highest amount of generation in spring season. The storage hydropower generation contributes to the system in terms of flexibility, but moderately high amount of generation in spring season indicates that its flexibility has a limited extent. The availabilities of thermal power plants are influenced by their maintenance periods, and they are determined based on the motivation to keep the reserve capacity in the system stable within a year.
- The electricity sector in Turkey has undergone major changes since 2000s. There is an electricity market structure aiming to attract private sector investments. The reference price for electricity, called as the MCP, is

determined in the day-ahead market, similar to the practices in EU and other liberalized electricity markets around the world.

- The level of MCP is influenced by the variable cost of natural gas power plants which are marginal at most times. The seasonal pattern of MCP reflects the conditions in supply and demand balance. Even with comparatively low solar capacity of 6000 MW, the MCPs at noon and afternoon are affected in the decreasing direction when the availability of solar power plants hits the maximum.
- Medium and long-term studies in Turkey are defined in the electricity market law. The studies regarding supply side are either not published or prepared based on a practical approach, not modeling. It cannot be said that the planning activities regarding different levels and horizons are in harmony. In those studies, there is no evidence that the operation logic of day-ahead market is reflected, nor are there any studies published regarding electricity price forecasting on various horizons.
- The utilization of a simplified electricity market model is needed in order to fulfil the planning and forecasting activity on hourly basis and in longer horizons. In the simplified electricity market modeling approach, the day-ahead market operation can be emulated through the formation of merit-order curves including the reflection of hourly and block orders.

CHAPTER 3

LITERATURE REVIEW

In this chapter, the literature review on the components of the proposed electricity market modeling methodology such as electricity demand forecasting, electricity price forecasting, generator maintenance scheduling (GMS), and generation expansion planning (GEP) is presented.

In the first and second parts, the classifications regarding time horizon and forecasting techniques are given for electricity demand and price forecasting, respectively. In the third part, the literature review is presented on the basis of GMS problem and how GMS is approached in long-term planning studies. In the last part, the literature is reviewed based on the structure of GEP problem, and bilevel models and solutions.

3.1 Electricity Demand Forecasting

Traditionally, electricity demand forecasting studies are critical for planning and operational decisions [13]. With the deregulation of electricity sector and technological progress, they become more important for both grid operators and market participants as well as regulators and ministries; and due to the stochastic and uncertain characteristics, accurate forecasting of electricity demand is still a challenging problem [14].

Demand forecasting studies can be classified according to time horizon. They can roughly be separated into two classes such as short-term load forecasting (STLF) and long-term load forecasting (LTLF) [15]. Typically, they are classified into three categories such as STLF, medium-term or mid-term load forecasting (MTLF), and

LTLF [13], [14], [16]. There are a couple of studies that introduce very short-term load forecasting (VSTLF) as an additional class [17], [18]. Although there is not an exact consensus on the cut-off time horizons i.e. the forecast ranges, they are generally stated as from 1 hour to 1 day for VSTLF, 1-2 weeks for STLF, 1-3 years for MTLF, and 10-20 years for LTLF [17], [13] - [18].

In the literature, it is frequently stated that STLF studies are more prevalent than other classes since STLF is related to the daily operation of generation, and the studies for MTLF as well as LTLF are said to be few in number [17], [14], [18] - [19]. It can be alleged that there are a growing number of studies covering short term with both statistical and artificial intelligence techniques. The main purpose of STLF is to obtain information for economic and secure operation of power system while LTLF is employed for investment planning and decisions [20]. MTLF studies should not be underestimated considering their contribution on outage & maintenance scheduling, meeting load requirements, coordination of load dispatch and price settlement, economic operation of power system, hydro-thermal coordination, hydro resource management, cost efficient fuel purchasing strategies, and better contract negotiations in electricity trading [17], [16], [20] - [21], many of which do not fall into interest of short and long time horizons [22].

With regard to forecasting techniques, demand forecasting studies are classified into two main groups such as statistical techniques and artificial intelligence techniques [17], [13] - [14]. Statistical techniques include multiple linear regression (MLR) models, semi-parametric additive models like generalized additive model (GAM), time series approaches including ARMA, ARIMA, SARIMA, etc. models, exponential smoothing models and similar-day approaches. Artificial intelligence techniques contain artificial neural network (ANN), fuzzy logic, support vector machines (SVM), and other methods such as genetic algorithm, expert systems, adaptive neuro-fuzzy inference system (ANFIS), and hybrid approaches. High adaptability to solve problems with nonlinear relations is stated as there is growing interest for intelligent techniques while statistical techniques are preferred for better interpretation and lack of explanatory variables [21], [23].

For MTLF, the literature is highly concentrated on artificial intelligence-based models, mostly ANN. Statistical techniques can be used separately or in comparison with ANN models. There is not any consensus on the best model for MTLF, and the results vary across cases or countries and can put forward different methods. For example, in [24], optimal network is found for ANN, and it is used to forecast the weekly electricity peak load of the next 52 weeks. [25] compares the results of ANN and MLR models, and ANN is found to be more reasonable and satisfactory. In [16], ANN and SVM are chosen to be applied to forecast the medium-term load, and it is concluded that although both ANN and SVM models successfully solves the problem of forecasting the electricity load for a period from a day to a year, using SVM to do load forecasting is faster as well as much more stable and reliable. [18] considers a variety of methods including exponential smoothing, SARIMA, ARIMA, ANN and ANFIS. Satisfactory results are claimed by ANFIS and ARIMA based various approaches. In [26], ANN is applied along with exponential smoothing and ARIMA, with ANN presenting better forecasting accuracy.

As for GAM, there are only a couple of demand forecasting studies in the literature. In [27], GAM is used in a short-term demand forecasting study in order to forecast uncertainty in electricity demand, and the focus is given to probabilistic forecasting. In [28], GAM is again used for short-term demand forecasting, serving for modeling implicit nonlinear relations between response and explanatory variables. A semi-parametric additive model is used in [29] for long-term peak electricity demand forecasting, and proposed in [30] for both short-term and long-term demand forecasting.

As a non-parametric regression technique, multivariate adaptive regression splines (MARS) and its application for prediction purposes have increased recently, but so far, its usage in electricity sector has been mainly for price forecasting purposes [31], [32]. MARS can be seen as a method for flexible regression modeling of high dimensional data, and it uses piecewise basis functions to define relationships between a response variable and predictor variables [33], [34]. It enables fitting interaction among variables, but interactions are specified locally rather than globally [34]. It emerges as a successful tool to model nonlinearities like ANN, but while doing so it conserves the property of interpretability.

In this thesis, based on the literature review and objectives of the thesis, a proper electricity demand forecasting technique is searched for the medium-term forecasting horizon. Firstly, medium-term demand forecasting is performed on daily basis by utilizing two types of models based on statistical techniques such as MLR and GAM, and the improved performance of GAM is revealed. Secondly, medium-term demand forecasting is performed on monthly basis by utilizing four models, from the classes of statistical and artificial intelligence techniques, such as MLR, GAM, MARS and ANN. In the end, it is found out that MARS model has superior performance among its counterparts while GAM and ANN show similar and satisfactory performances, as alternatives to MARS. Further details and discussion are presented in Section 4.1.

3.2 Electricity Price Forecasting

Similar to electricity demand forecasting, electricity price forecasting studies can be classified according to forecast period and modeling approach.

As for modeling approach, various classifications can be claimed. In [35], price forecasting models are divided into three categories such as financial models, production cost models and market simulation models. Financial models benefit from time series methods, and they are based on the analysis of historical data. This method is only advised for the short-term horizon. Production cost models operate based on the principle to meet the electricity demand with minimum cost. They are said to capture the points that econometric models ignore. They are criticized for not being able to reflect the changing market conditions. Unlike production cost models, market simulation models can take into account the strategic decisions of market participants, and they are generally based on game theoretic approaches. Since the behavior of market participants needs to be modeled, this type of modeling requires extensive data on purchase and sale bids which are not publicly available.

One of the limited number of books on price forecasting [36] makes a classification such as production cost models, equilibrium models, fundamental models, quantitative models, statistical models, and artificial intelligence-based models. Production cost models are said to determine the market price based on supply and demand curves, and they are criticized for not being able to model market power. Equilibrium models employ game theoretic approach, but they include complex optimization procedures and require significant running time. Fundamental models are again based on supply and demand curves, with special attention to the parameters affecting electricity price such as temperature, precipitation, water inflow, snow cover, etc. The motivation of these models is to enable the user to be able to explain the fundamental changes in price. Quantitative models are known as stochastic, econometric and reduced-form models. They aim to predict the prices in derivatives market and use the statistical properties of electricity prices in forecasting. Statistical models employ similar day methods, exponential smoothing, regression, AR, ARMA, ARIMA and GARCH methods. They highly rely on historical data. Artificial intelligence-based models are attributed to be flexible, good at modeling nonlinearities. Similar to demand forecasting, ANN models are mostly used for price forecasting in the short-term forecast horizon.

Based on the range of forecast period, price forecasting models can be divided into three categories. Long-term price forecast typically covers a period of a couple of years or longer, which has an objective of supporting strategic decisions. Medium-term price forecast typically covers a period up to a couple of years and is used for risk management, resource allocation, bilateral contracting, hedging strategies, and budgeting. Short-term price forecast typically covers a period up to a couple of weeks and is related to portfolio management and maximizing profit [37], [38].

There are a large number of studies for short-term electricity price forecasting, but medium-term and long-term studies are few in number. Some of the medium-term studies focus SVM in [39] and [40]; SVM, radial basis function neural network (RBF-NN) and weighted nearest neighbor (WNN) in [41], autoregressive modeling in [42], market equilibrium model with Monte Carlo simulation and spatial interpolation techniques in [43].

In [39], a SVM model is developed and tested by New England ISO data in United States, with data concerning average fuel price, demand, weather, calendar days, import/export power while economic and demographical factors are not included. Data preprocessing, feature selection and model selection processes are applied. It is found out that by normalizing the input data, forecasting accuracy can be enhanced with the use of SVM. Similarly, in [40], multiple SVM models are developed and tested at this time by the PJM data in United States, in order to forecast hourly electricity prices of six months ahead. A data classification module is designed before the price forecasting module in order to preprocess the input. In [41], various forecasting models and inputs are compared for Nord Pool in Europe and Ontario in Canada. Data preprocessing, feature selection and model selection processes are applied. WNN method relying on finding similarities in time series yields the best results for less volatile Nord Pool, whereas the most accurate predictions are obtained by the SVM model for Ontario which has highly dynamic price trends. In [42], two regression based linear forecasting models are developed to predict monthly average electricity prices for a full year forecast horizon of 12 months ahead, and they are tested with the data of Nord Pool. First lagged historical price is chosen to improve the accuracy of the results based on the finding that there is a large correlation between the electricity prices of consecutive months. In [43], a probabilistic hourly electricity price forecasting is performed for the Spanish market. The proposed approach consists of nested combination of several modeling stages such as generating multiple scenarios of uncertain variables, designing a fundamental market equilibrium model incorporating Monte Carlo simulation, reducing the number of scenarios and utilization of spatial interpolation techniques to estimate feasible realizations of electricity prices.

Recently, there is an increasing trend in the literature towards probabilistic forecasting of electricity prices. This is performed by various techniques such as a hybrid forecasting method by recalibrating a fundamental model with quantile regression in [44], quantile regression analysis in [45], generalized extreme machine learning in [46], a two-stage method based on extreme machine learning and maximum likelihood method in [47], a multiparametric linear programming technique in [48].

The literature on electricity price forecasting for the Turkish case is limited to a number of studies. These studies are concentrated on short-term price forecasting and methods such as time series models like ARIMA, SARIMA, etc. as in [49], [50], and artificial intelligence techniques like ANN as in [51], [52]. The aim of those studies is to obtain point forecasts rather than obtaining price ranges in the short-term horizon.

In [49], the dynamics of electricity prices observed in Turkish day-ahead market and their relationship with temperature are explored. AR and ARX models are compared, and it is concluded that there is little relation between price and temperature fluctuations. In [50], a combination of SARIMA and ANN model with back propagation learning is proposed. The trend component of price is forecasted by SARIMA whereas ANN forecasts the nonlinear residuals. Almost 4% of reduction of forecast errors is said to be achieved. In [51], an ANN model is created, and its performance is compared with a model built via ARIMA approach. Several types of inputs such as historical prices of similar hours of n days and m weeks before, weighted average temperature of the biggest three cities, electricity demand forecast, estimated volume of bilateral contracts, total available capacity and dummy variables indicating the respective day are utilized. It is found out that ANN model shows slightly better performance for the test period. In [52], the performances of an ANN and MLR model are compared. Historical price and load variables are claimed to be sufficient for accurate day-ahead price forecasting. It is concluded that MAPE for the test period is below 10%, hence the proposed model is said to produce reasonable accuracy for price forecasting.

The literature review process has shown that electricity price forecasting studies concentrate just on the price itself, not on other types of outputs such as generation by fuel, reserve capacity, etc. This aspect is more of a concern in medium and long-term planning models included in commercial software dedicated for energy sector planning. Also, the general preference in the literature is to utilize statistical and artificial intelligence-based models rather than fundamental models. In this thesis, the electricity price forecasting approach belongs to the classification of fundamental models, which reflects the supply and demand dynamics of the market on hourly basis. This is necessary in order to establish a reasonable and transparent connection between electricity price and the influential factors mainly demand and supply. By doing so, it is possible to explicitly investigate the effects of parameters such as economic and climate conditions on electricity price through their effects on electricity demand and supply.

Unlike electricity demand modeling, a literature review section is not dedicated for electricity supply modeling since there is not a specific discussion on how to determine the availability factors of power plants. These factors are calculated and utilized based on the statistical analysis of historical realizations, as presented in Section 4.2.

In this thesis, the strategy is determined based on firstly proving the effectiveness of the proposed electricity price modeling approach in the medium-term forecasting horizon, as discussed in Section 4.3. Then, the utilization of this approach is extended to the long-term horizon, as presented in Chapter 5, considering the objectives of the thesis. The long-term utilization of this approach requires two modifications in electricity supply modeling. The first one is the inclusion of generator maintenance scheduling for thermal power plants in order to obtain a dynamic electricity supply modeling strategy in the long-term horizon. The second one is the inclusion of generation expansion planning in order to determine a reasonable electricity generation fleet for a future year. The following two sections present the literature review on those two topics.

3.3 Generator Maintenance Scheduling

In this thesis, the role of generator maintenance scheduling is to enable a dynamic electricity supply modeling beyond the medium-term horizon. Therefore, emphasis is given to obtaining proper maintenance schedules for thermal power plants, calculating the availability factors accordingly, and then utilizing them in price modeling. Considering this framework, in this section, the literature is reviewed firstly according to the GMS problem itself, then long-term planning studies are examined from the GMS point of view. These are summarized under the next two titles.

3.3.1 GMS Problem

The GMS problem has been widely studied in the past. By its nature, the GMS problem is a nonlinear, nonconvex and complex combinatorial optimization problem, hence it is a difficult problem to solve [53], [54]. The GMS problem have an impact on both short and long-term decisions such as unit commitment, storage hydropower plant operation, fuel scheduling, reliability calculations, generation costs, and system design [55]. Therefore, it can be alleged that GMS strongly affects MCP and the corresponding supply composition in electricity markets.

There are two maintenance categories for power plants, such as corrective and preventive. Corrective maintenance is performed after breakdown occurs, and in the modeling procedure this affect is generally represented by a forced outage rate (FOR) by power plant. Preventive maintenance is performed in order to reduce the probability of failure and occurs at predetermined time intervals [56]. The GMS problem is concerned with the preventive maintenance.

GMS studies can be evaluated in terms of solution methods, objective functions, constraints, time horizon, unit of time period, and targeted plant type.

Solution methods proposed in the literature can be broadly grouped under mathematical programming approaches, heuristics and metaheuristics, constraint programming, and game theory [56]. Under the group of mathematical programming, integer programming (it can be in the form of both mixed integer linear programming and integer linear programming) and dynamic programming can be counted. Heuristics and metaheuristics include genetic algorithm techniques, particle swarm optimization, simulated annealing, tabu search, knowledge-based models, etc. [53], [55] - [57]. Those techniques can be coupled with each other in search of yielding improved results. Constraint programming and game theory studies are few in number.

Objective functions for the GMS problem can be categorized as reliability-based and cost-based or combination of both. From generator point of view, it is required to minimize the generation and operational costs or increase the revenues based on MCP, whereas from the perspective of system operator, it is required to operate the system by maintaining reliability [55]. Possible objective functions for the GMS problem are regarded as maximizing the minimum reserve (also known as "leveling of reserves"), maximizing the minimum of supply reserve rate (defined as the ratio of reserve and peak demand) by time interval, minimization of standard deviation in supply reserve rate, minimizing the maximum of some reliability indices by time interval such as loss of load expectation or probability (LOLE or LOLP), expected duration of unmet demand (EDUD), expected value of energy not served (EENS). Reliability indicators can also be expected unsupplied energy, expected lack of reserve, expected lack of peak net reserve, etc. From cost point of view, the objective functions can be minimizing the total generation cost, minimizing the sum of the overall fuel cost and the overall maintenance cost. Those can include some types of functions such as inclusion of multi-criteria like CO_2 minimization or minimizing the amount of schedule change compared to the existing schedule [53] - [55], [58], [59]. As in [60], the focus can be a GMS coordination mechanism between the system operator and generation companies in restructured electricity markets. The coordination mechanism possibly requires complex iterative negotiations between counterparts. Here, the objective is to maintain the operational reliability for the system operator and to maximize the maintenance preference for generators at the same time.

There can be various constraints for the GMS problem. For each time interval, those can be as follows [53], [55], [56]:

- Supply-demand balance: Total output of all generators must be equal to demand.
- Reserve constraint: Total reserve capacity must not be less than the summation of demand and required reserve.
- Duration constraint: Once the maintenance of a unit starts, this unit must be in the maintenance state for a predetermined number of contiguous periods.
- Sequence constraint: A unit can be taken out at least a predetermined number of weeks after another unit comes back online.
- Exclusion constraint: No more than one of units can be in maintenance state simultaneously.
- Generating unit constraint: The highest and lowest generation levels with ramp-up and ramp-down rates can be defined for each unit.

The constraints can also include material and manpower, maintenance priority, maintenance exclusion, separation between consecutive maintenance outages, overlap in maintenance, electricity network, etc. [56], [61].

Time horizon in GMS studies can be short-term and long-term. The general preference is long-term with a time horizon of 1 year. The unit of time period is subperiods of equal length, which is generally one week. Higher time resolution, e.g. days, is not preferred to prevent possible high computational burden.

In the vast majority of GMS studies, the scheduling problem concerns only thermal generators. However, there are a couple of examples dealing with the maintenance schedule optimization of only hydropower plants. In [62], a mixed-integer programming model considering time windows of maintenance activities and nonlinearities of hydropower plant generation functions is proposed for a real hydropower system in Canada. The study focuses on decreasing the computational time by applying various approaches. In [63], an ant colony optimization formulation is proposed as an alternative, and test is applied on a hydropower system composing of five stations in Australia with various water inflow conditions.

The effect of hydropower plant generation together with thermal power plants is only considered in a limited number of studies. In hydrothermal systems, there are difficulties arising from the dynamics of reservoir systems and uncertainty due to water inflow as well as their ability to meet peak loads and cover outages of thermal units [59]. In [59], the proposed method is based on transforming the load curve into a thermal load curve, enabling to separate completely the hydrothermal system thereby facilitating both the reliability evaluations and the maintenance scheduling via a heuristic algorithm assessing the reliability in terms of LOLE indicator, and seeking to level the risk in different periods. However, the fact that the hydro energy and capacity are fixed for each period can be regarded as a disadvantage. In [64], the proposed model is a medium-term production cost model formulated as a large-scale mixed integer optimization problem subject to operation and maintenance constraints, and the optimization is performed in two stages with cost and reliability criteria. However, the uncertainty in hydropower plant generation is treated under the assumption of average hydrology, and hydro constraints do not reflect the economic value of the water reserve. In [65], the approach is similar to [59] and the aim is to determine the optimal hydro energy production for a subperiod, in this case one month, over a one-year time span so that the annual hydraulic constraints are satisfied as well as the reliability of the system is leveled over all months. The proposed method is based on the approximation of the functions relating the LOLE of months with the hydro energy allotted to it. A test is performed on the Spanish power system in three steps: Firstly, the hydro energy is allocated according to initial hydro energy utilization selected by the user. Secondly, using this allocation, a maintenance scheduling program of the thermal units is established using a heuristic algorithm. Lastly, ten equally spaced hydro levels are selected, and LOLE is calculated for each one of them. It is not possible to comment on the resulting GMS program since it is not presented, but with this approach it is considered that there is the risk of utilizing hydro resources in place of the thermal capacity in maintenance, and the hydro potential may be unduly spent in lower water inflow periods.

In this thesis, the GMS methodology uses integer linear programming as a solution method, with the objective function of leveling reserve margins, on weekly basis for 1-year horizon. The fundamental constraints in the literature are taken into account. The targeted plant types are thermal power plants considering that hydropower plants typically have maintenance when water inflow is lowest throughout a year, thus this does not have a significant impact on their available generation in the case of Turkey. As a secondary objective function, the criterion of minimizing the maximum of weekly storage hydropower plant reserves is included in order to utilize them reasonably and prevent the irrational utilization of the resource in place of the maintenance capacity.

3.3.2 GMS in Long-Term Forecasting and Planning Studies

Long-term forecasting and planning tools generally utilize block methodology for load profiles and establish supply and demand balance in each load profile. This representation is used to address the trade-off between accuracy and computation time. The time frame is mostly monthly or yearly, and daily or weekly results are out of consideration.

In long-term studies, there are various approaches for GMS. In [66], a long-term power generation expansion planning model with a more than 20-year planning horizon capability as well as an hourly representation of day-ahead electricity markets are presented, and it is assumed that the scheduled maintenance occurs in low-demand months, i.e. from March to May and from September to November in ERCOT region. The disadvantage is to assume that low-demand months are fixed throughout the study period, which indeed should be expected to be influenced by the evolution of electricity generation capacity and different characteristics of future resources.

In [67], a generation expansion planning including the effects of variable renewables generation on thermal plants efficiency is presented with the integration of an hourly unit commitment problem for a 10-year planning period. It is stated that despite not frequent, plant outages with different causes such as breakdown and stoppages for maintenance must be considered, and this is reflected in the model with only a fixed reliability factor which is not influenced by total system reserve.

In [68], a long-term simulation-based market model with system dynamics is of consideration, focusing on long-term prices and long-term supply reliability. The dynamics of the market is represented by nonlinear differential equations taking into account system feedbacks, delays, flow structures and nonlinearities. In this model with an integration step of 1/16 month to solve the delay-differential equations, a FOR is assumed for all generating units; however, to keep the model simple preventive maintenance is not considered.

In [69] TIMES model and in [70] an extension of TIMES energy planning tool for investment decisions in electricity generation with consideration of seasonal, daily and hourly supply and demand dynamics are presented for Portugal, but they do not take into account generator maintenance.

Also, similar studies are performed with a variety of focus such as;

- Long-term potential supply scenarios and associated impacts on the marginal cost, global warming potential, etc. are studied in [71], [72], [73],
- Influence of environmental variables in power system expansion and the resulting financial costs are focused in [74],
- Several generation agents maximizing their profits are used in a system dynamics and genetic algorithm model in order to characterize the evolution of electricity price and demand, and solving individual optimization problems for agents as in [75],

- Different modeling methodologies for balancing electricity supply resources composed of intermittent renewable resources and demand are considered in [76], and it is concluded that choosing high time resolution reveals the overestimation of renewable share and underestimation of the amount of emissions in lower time resolution studies,
- An improved version of MARKAL model that takes into account flexibility feature in electricity sector is developed in [77], in order to achieve more reliable results for supply figures and emissions.

As a result of literature review process, it is concluded that in long-term forecasting and planning studies, the general tendency is to neglect the effect of GMS or to make simplifications to represent the effect of GMS by some fixed factors. Also, while the latest studies on GMS aim to improve the existing approaches and consider various new obstacles, the methodology in this thesis is rather dedicated to establishing a novel connection between the GMS study field and power sector forecasting & planning studies. For an evolving electricity generation fleet in which wind and solar resources are expected to dominate, the potential benefits of such a methodology are investigated in Section 5.1, and then it is used in various case studies as in Section 5.3.

3.4 Generation Expansion Planning

In this thesis, the electricity market modeling methodology needs future electricity generation fleet data for long-term utilization. Future electricity generation capacity is forecasted by GEP models. In search of a reasonable generation fleet of the future, instead of directly utilizing a standard GEP model in the literature, special emphasis is given to the investigation of the missing money problem, which is a widespread phenomenon in today's liberalized electricity markets as well as a popular topic. The mitigation of the missing money problem in GEP studies requires paying attention to both GEP problem itself and the bilevel modeling structure. Therefore, in this section, the literature review is presented in terms of firstly the definition and structure of GEP problem, and then bilevel models and the solution for mixed integer bilevel linear programming (MIBLP) problem.

3.4.1 Definition and Structure of GEP Problem

The GEP problem has been addressed in the literature since 1950s, but it is still taking attention of the researchers [78]. GEP studies mainly deal with determining the type, size and timing of generation technologies to be added to the system over a medium to long-term planning horizon while ensuring several constraints related to supply-demand balance, ancillary services requirements, policies as well as other technical constraints including investment, plant-related characteristics, fuel consumption and resource availability [79]. The GEP problem can be investigated from different aspects such as solving method, reliability, electricity market, uncertainty, time horizon, end effect, size reduction, recent developments, and coordination with transmission expansion planning (TEP) studies [80], [81], [82].

- Solving methods: They can be divided into two parts such as mathematical and heuristic optimization methods. The former one includes linear programming, mixed integer programming, iterative algorithm, bender's decomposition, decision tree, dynamic programming, etc. whereas the latter one comprises of evolutionary programming, ant colony optimization, tabu search, genetic algorithms, expert system, etc. [80].
- Reliability: The issue of reliability can be included as a constraint in the optimization problem or it can directly be a part of objective function. The most commonly used metrics are LOLE, EENS, LOLP, etc. [80].
- Electricity market: From electricity market point of view, while in regulated systems the planning aims at minimizing total system costs, with the liberalization of electricity sector each market agent tries to maximize its own profit in deregulated systems [80].
- Uncertainty: Some generic uncertainties can be counted related to load, price, availability of system components, regulation, fuel availability, fuel cost,

new technologies and policies. The commonly used methods to deal with uncertainty are probabilistic methods, stochastic programming and robust optimization [80], [81].

- Time horizon: GEP studies can be classified as static and dynamic. In static GEP, the optimal expansion plan is formed for a single year at the end of the horizon, whereas in dynamic GEP, the years of the horizon are separately studied [80].
- End effect: The value of investments can be distorted by the fact that the planning horizon in GEP models is lower than the lifetime of power plants. There are a couple of methods that can alleviate this problem such as adding recovery values for the assets at the end of the horizon, running an extended simulation and annualizing the value of investments, the last of which is the most prevalent among others [81].
- Size reduction: For GEP models, there is the tradeoff for the detail of representation among short-term operational constraints and long-term investment decisions. If the GEP problem deals with the optimal site of investments, then network representation can be reduced. Also, time steps can be reduced by forming load levels by grouping similar ones and utilizing representative days [81]. Furthermore, in order to make the model with short-term operational constraints more tractable, many types of power plants can be successfully grouped into categories by similar characteristics such as technology and fuel, which in turn results in dramatic space requirement reduction [83].
- Recent developments: Energy storage systems, demand response, integration of electric vehicles, evaluation of power and natural gas systems independence are becoming more critical as the integration level of renewables in the system as well as the effect of intermittency increases, and technological advancement in certain technologies are intensified [82].
- Coordination with TEP studies: With the development of computational capability, there has been a growing interest towards coordinated generation

and transmission expansion planning (GTEP) studies which co-optimize both problems and search for lower system costs compared to separate optimization approaches [80], [81].

In this thesis, the candidate GEP models utilize mixed integer programming among mathematical optimization methods. The criterion of reserve margin is adopted as a reliability metric. The size of the problem is reduced by grouping plants showing similar characteristics, without taking into account uncertainty and transmission network. In terms of time horizon, the dynamic GEP approach is used for a 20-year horizon with 5-year time steps. Among recent developments, energy storage systems are included in candidate facilities. Depending on the model type, the approaches of minimizing total costs and maximizing profit are utilized. In addition, considering the specific needs in this thesis, the minimization of total costs including the support need of existing plants is used, which ideally requires the utilization of the bilevel model structure as discussed in the next part.

3.4.2 Bilevel Models and Solution for MIBLP

Since in this thesis the focus is given to generators' profit and decreasing the support need, the level of resulting MCP based on supply and demand dynamics in electricity markets is critical as it defines how much plants are utilized and how much they earn. The market clearing problem is itself an optimization problem. However, long-term planning models have other types objective functions such as maximization of profit and determining the corresponding optimal investment mix. This is within the concept of multilevel programming, and the structure with multiple decision makers and stages cannot be formulated as a single-level model. Instead, it is more suitable to use bilevel models with nested optimization problems [84], [85], [86].

Bilevel optimization problem has a market clearing problem at the lower-level, and the investment decisions are taken at the upper-level [84]. This problem can be formulized as in (3.1):

$$\begin{aligned}
&\max f_1(x, y^*, \lambda^*) \\
&\text{s.t.} \quad g_1(x, y^*) \leq 0 \\
&\qquad\; h_1(x, y^*) = 0 \\
&\qquad\; y^* \in argmin\, f_2(x, y) \\
&\qquad\; \text{s.t.} \quad g_2(x, y) \leq 0 \\
&\qquad\qquad\; h_2(x, y) = 0 \\
&\qquad\qquad\; h_{2-SD}(x, y) = 0 \,:\, \lambda
\end{aligned} \tag{3.1}$$

The above formulation aims to maximize the profit of each candidate plant shown with function f_1. The functions g and h represent the inequality and equality constraints related to investment and operation. The variable x represents the investment decisions, y represents the operation decisions, and λ represents the MCP for each operating condition. The upper-level constraints are related to investment decisions, and the optimal solution of the lower-level problem is utilized as shown by asterisk sign. The lower-level problem aims to minimize the operation cost for each operating condition as denoted by the function f_2, and it treats the upper-level problem variables, x, as parameters. The optimal solution of the lower level problem is denoted by y^*, and the dual variable of supply-demand balance constraint is λ.

Including lower-level dual solutions, such as the amount of generation, MCP, etc. in the upper-level brings a couple of complications, especially when these are represented as a bilinear term in order to calculate the revenue of participants. Under some assumptions, the bilinear term can be linearized with the utilization of KKT conditions and the property of strong duality for the lower-level problem [84].

Most of the solution methods are based on reformulating this problem as mathematical program with complementarity conditions in which lower-level problem is replaced by its necessary and sufficient optimality conditions [84]. However, in reality the lower-level market clearing problem has integer variables representing the operating, startup and shutdown states of plants with unit limitation. Those states should not be underestimated or omitted in order not to lose accuracy in the solutions of GEP problem given that the traditional supply composition has been significantly changing, and new technologies are rapidly emerging. This problem structure is called as a MIBLP. Since KKT conditions aren't applicable to mixed-integer programs, some other methods are used to handle this problem.

As a general tendency in the literature, no integer decisions are taken in the lower-level problem. Studies on MIBLP [87], [88], [89], [90] are few in number as mentioned in [85], [91]. The algorithms developed for this problem either heavily depend on branch-and-bound strategies based on weak relaxation or involve problem specific and challenging operations [91]. In [92], the computational challenges are counted as nonconvexity of feasible region, possible inaccessibility of optimal value, detecting unboundedness, and possible failure of relaxation to serve as an upper bound.

In [89], the solution of MIBLP containing integers in both upper and lower level is called to be very difficult. The proposed method is based on the application of a reformulation and linearization scheme resulting in the convex hull representation of inner problems. However, large number of equations obtained as the number of integer variables exponentially increasing is reported as a major drawback.

Based on the results on convex hull representation first stated in [93], the representation of operational flexibility in the GEP problem is studied in [94], through the convex relaxation of unit commitment (UC). The feasible set of each generating unit is replaced by its convex hull so that binary variables can be modeled as continuous and cost function of each unit is replaced by its convex envelope which in turn leads to a convex relaxation as tight as Lagrangian relaxation, and thus the resulting single-level problem can be integrated into the GEP problem as the operational model. The proposed method in [94] yields successful results and keeps tractability; however, the convex hull representation is valid only for the proposed problem, and it does not directly allow the integration of additional constraints unless rigorous proof of convex hull representation including those constraints is provided, but this is hard to achieve.

Due to the limitations counted previously, in this thesis, instead of formulating the problem as a MIBLP and putting significant effort to try to solve it with a novel approach, the problem is reformulated and solved by the standard GEP model having the objective function of minimizing the total costs, through an iterative process. Further details both on this topic and other GEP models along with discussions are presented in Section 5.2.

CHAPTER 4

MEDIUM-TERM MODELING OF ELECTRICITY MARKET

In this chapter, electricity market is modeled for the medium-term forecasing horizon. The main idea of the medium-term electricity market model is to increase the observability for the decision maker in terms of market conditions such as demand, supply, and price. The primary aim is to obtain electricity price forecasts which reflect the conditions in demand and supply. Also, obtaining electricity generation by fuel concurrently with electricity price forecasting is crucial to interpret the resulting price forecasts. One-hour time step is used in order to maintain the accountability of results. The model utilizes various scenarios on multiple parameters such as economic growth, temperature and hydro inflow; and then calculates the corresponding electricity price forecasts. In the end, the decision maker can recognize the possible ranges of electricity price for the period taken into consideration. In terms of time, the forecast range is typically 1 year; however, it is possible to extend this period up to several years.

The chapter is organized according to the parts of the medium-term electricity market model. The modeling activity starts with electricity demand forecasting as presented in the first section. Medium-term electricity demand forecasting is studied with various approaches based on time horizon such as on daily and monthly level. In the second section, electricity supply modeling approach is described. In the third section, electricity price forecasting activity is fulfilled. The proposed methodology for electricity price forecasting is presented along with a special module dedicated for realistic utilization of storage hydropower plants. The chapter is concluded by the findings obtained as a result of electricty market modeling activity in medium term.

This chapter is prepared based on the author's works [95], [22] and [96], which are published as a journal paper in IEEE Transactions on Power Systems in 2018, and as conference papers in 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe) and 2019 IEEE Milan PowerTech, respectively.

4.1 Electricity Demand Modeling

This section describes how electricity demand is modeled and forecasted to be used in other parts of the electricity market modeling methodology. Hourly electricity demand forecasting series are needed to provide input for electricity price forecasting model which would match supply and demand on hourly basis. Due to its direct effect on reserve capacity, electricity demand forecasting studies are closely linked with electricity price forecasting studies [97]. In this section, electricity demand forecasting is performed on both daily and monthly basis, which is to be split into hourly resolution by a profiling method.

The section is composed of five parts. In the first part, the candidate explanatory variables are introduced from both daily and monthly time steps. The second part gives information about the candidate models which are multiple linear regression (MLR), generalized additive model (GAM), multivariate adaptive regression splines (MARS) and artificial neural networks (ANN). In the third part, daily electricity demand forecasting model is selected among the candidate models of MLR and GAM based on various performance metrics. In the fourth part, monthly electricity demand forecasting modeling process is introduced, and the final model is decided among the alternatives of MLR, GAM, MARS and ANN, again based on performance of each model. The last part discusses the studies on electricity demand modeling and summarizes the key findings.

4.1.1 Candidate Explanatory Variables

In this part, the most frequently utilized explanatory variables are introduced and discussed from both daily and monthly time steps.

According to [98], there are six main factors influencing electricity demand. These are related to economy, time, climate, randomness, price and geography. In the literature, for MTLF studies, the utilization of historical load data, gross domestic product (GDP), weather information and indicator variables representing time factors are common as presented in [13], [14], [16], [20] - [21], [25], [99].

In the process of searching for a proper demand forecasting model, it is found that in short term, weather conditions have the highest impact on results, while economic parameters are more effective in long term. Some of the most commonly used variables in demand forecasting studies are calendar variables such as month of year, day of week, hour of day and other categorical variables indicating holidays and daylight saving time; historical load, historical temperature and humidity, GDP and trend [27], [100], [17], [101].

Various climate variables can be used in order of decreasing importance starting from temperature, humidity, wind and precipitation being the last on the list [14]. Climate condition is one of the main determinants of electricity demand due to fluctuating heating and cooling needs across seasons as in the case of Turkey, situated in the northern hemisphere between latitudes 36-42° that corresponds to the middle climate zone. Considering this zone and the characteristic geographical position of Turkey, the continental climate is widely dominant, i.e. summers are generally dry and hot; winters are generally cold and snowy. Spring and fall seasons are generally neither hot nor cold with precipitation in varying amount depending on the region. In short, heating and cooling needs are lowest in spring and fall seasons, and highest in summer and winter seasons. This statement can be verified with Figure 4.1, the scatter plot of daily mean temperature in Istanbul, versus the daily electricity demand of Turkey in the period of 2012-2015. It appears that throughout the year the lowest demand occurs at temperatures around 18-20°C, where cooling and heating needs are at minimum.

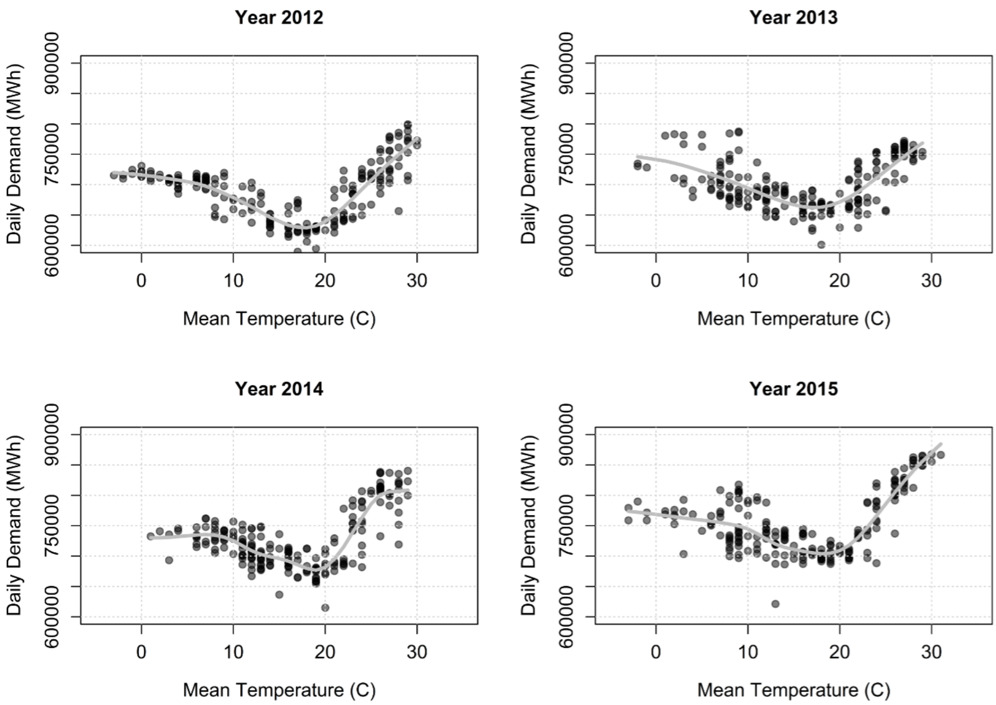


Figure 4.1. Relation between daily mean temperature in Istanbul and daily electricity demand in Turkey from 2012 to 2015

As they are related to temperature, heating degree days (HDD) and cooling degree days (CDD) are the measures of the severity and duration of cold/hot weather, which quantify the heating/cooling requirement [99]. In addition to those variables, the usage of snow presence and cloud coverage in [102] for MTLF studies, and composite weather variables measuring discomfort such as temperature-humidity index and wind chill index in [13] for STLF studies, are reported.

The time factors, as stated in [13], include month of year, day of week, and hour of day considering that there can be significant differences in consumption at various times of a year. Electricity demand is known to be strongly related to life activities. Electricity demand in weekdays are significantly higher than weekends, also difference among Saturdays and Sundays is remarkable. The effect of days of week as well as seasons of year are together represented by Figure 4.2.

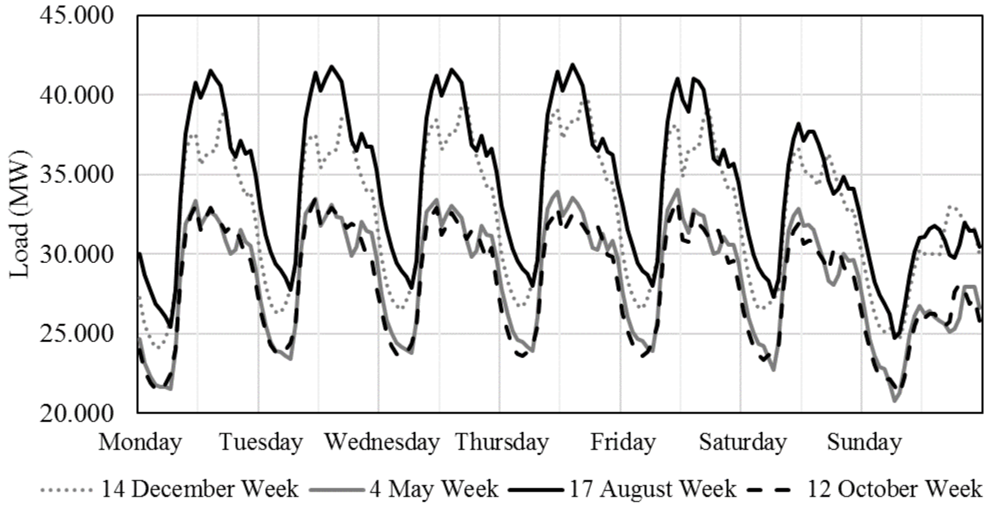


Figure 4.2. Hourly electricity demand for four different weeks of four different seasons in 2015

The candidate explanatory variables in this study do not contain any lagged values of dependent or independent variables, which helps maintaining interpretability of results and utilization of models in a longer time horizon.

4.1.1.1 Candidate Explanatory Variables for Daily Electricity Demand Forecasting

The proposed candidate explanatory variables for daily electricity demand forecasting are grouped under three categories as follows:

- Category 1 – Economy: Industrial production index (IPI)
- Category 2 – Weather: HDD of the country, CDD of the country
- Category 3 – Time: Calendar variables, Holiday variables

Category 1 – Economy: As mentioned previously, economy is the main determinant of electricity demand in long term. However, there is not any variable representing economy for a daily forecasting study. There are two candidates: One is GDP published on quarterly basis, and the other one is IPI published on monthly basis. The analysis for the quarterly GDP and 3-month averaged IPI shows that 1% change in the GDP is related to 0.99% change in the IPI. Therefore, it is concluded that the IPI can represent the economy in this study and is preferable due to its monthly publication frequency.

Category 2 – Weather: The data corresponding to five big cities (Istanbul, Ankara, Izmir, Antalya and Diyarbakir) in Turkey from five different climate regions are chosen. As proposed in [27], a different variable representing the HDD for Turkey (HDD_{Turkey}) is derived from the HDD data of these cities in such a way that the contribution of each city is related to the amount of consumption of that city in winter season as shown in (4.1) - (4.2). In the first equation, HDD_i and c_i represent the HDD value and the coefficient for the city i. The second equation corresponds to the ratio of electricity consumption of city i (P_i) to the sum of electricity consumption of those cities in winter season. The c_i values are found to be 0.45 (Istanbul), 0.11 (Ankara), 0.18 (Izmir), 0.07 (Antalya) and 0.19 (Diyarbakir).

$$HDD_{Turkey} = \sum_{i=1}^{5} c_i \; x \; HDD_i \tag{4.1}$$

$$c_i = \frac{P_i}{\sum P_i} \tag{4.2}$$

For CDD, the method is similar to the HDD case. The coefficients are determined as 0.41 (Istanbul), 0.13 (Ankara), 0.19 (Izmir), 0.08 (Antalya) and 0.19 (Diyarbakir) based on the amount of consumption in summer.

Category 3 – Time: The calendar variables are indicator variables representing days of week and seasons of year. As for holiday variables, in a calendar year, there are special days in which electricity consumption differs significantly owing to change in activity. These days can be counted as national and religious holidays. National holidays occur on the same day of every year, but the days differ for religious ones due to calendar effect.

In addition to those variables, a trend variable and the interaction terms between the IPI and calendar variables are added to the variable pool since the effect of industry on the electricity demand cannot be same across the days of the week. In the end, there are, in total, 23 variables in the variable pool.

4.1.1.2 Candidate Explanatory Variables for Monthly Electricity Demand Forecasting

For monthly electricity demand forecasting, 46 candidate variables are employed, which are divided into four categories as listed below:

- Category 1 – Economy: Industrial Production Index – Overall (IPI_{Total}), Industrial Production Index – Manufacturing (IPI_{Manu})
- Category 2 – Weather: HDD of a city, CDD of a city
- Category 3 – Time: Adjusted number of working days in a month (Wday), Month of year
- Category 4 – Demographics: Population (Pop), Number of households (NoH)

Category 1 – Economy: There are two variables in this category, such as industrial production index (IPI_{Total}) and industrial production index – manufacturing (IPI_{Manu}), as obtained from [3]. Since time factor will be represented by variables in another category, both are seasonally and calendar adjusted industrial production indices; the first one represents the total index, and the second one represents the manufacturing sector which comprises mainly of energy-intense industries.

Category 2 – Weather: HDD and CDD values are again considered as the representatives of the weather category. These values for each city are published by [103]. Differently from the daily model, instead of deriving a single indicator representing for the whole country, these values are treated separately for each city. However, since there are 81 cities in Turkey, there would be 81 variables for HDD and CDD values each, and this number is considerably high compared to the other class of variables. Therefore, some of the cities are eliminated based on population.

According to [3], there are 20 cities over 1 million population. The HDD and CDD values for these cities with population threshold of 1 million are taken into consideration.

Category 3 – Time: There are two variables in this category, such as month index and adjusted number of working days in a month called Wday. Wday variable represents the calendar effect in each year and month. The number of weekdays, Saturdays and Sundays in a month changes from year to year. This is valid for national and religious holidays. Both of the holidays coincide with different days of a week in every year. Religious holidays have a special case, and they occur at different dates in different years, resulting in a potentially troubling situation that must be considered in a medium-term study.

In order to obtain a single variable that represents the effect of time on the electricity demand for each month, days other than weekdays must be adjusted and expressed in terms of a weekday. In this study, the adjustment coefficients are found to be as in Table 4.1. For example, in the row of Saturdays, the value is 0.96, indicating that the electricity demand on Saturdays realizes at a level that corresponds to 96% of the demand that occurs in a weekday, on average throughout the year. The remaining of the table can be interpreted similarly. Thanks to these coefficients, the adjusted number of working days can be calculated for each month.

Table 4.1 Adjustment Coefficients for the Calculation of Wday

Type of Day	*Coefficient*	Type of Day	*Coefficient*
Weekdays	1.00	National holidays	0.88
Saturdays	0.96	New Year’s day	0.81
Sundays	0.87	Religious holidays	0.69

Category 4 – Population: In this category, there are two variables such as population and number of households as obtained from [3]. Population corresponds to the total number of people living in Turkey. The number of households corresponds to the total number of houses. They are yearly indices and are not announced monthly. Since a monthly electricity demand forecasting study is of consideration, there is a need for monthly data. The monthly data, for past and future values, is generated by interpolating the values between two consecutive years.

4.1.2 Candidate Models

In this study, there are two candidate models for daily electricity demand forecasting, and four candidate models for monthly electricity demand forecasting. These are MLR and GAM for the daily model; MLR, GAM, MARS and ANN for the monthly model, as introduced below:

Multiple Linear Regression (MLR): MLR model assumes that the output is linear in inputs. It is viewed as simple and has interpretability advantage while explaining how inputs affect output [104]. An MLR model has the form as shown in (4.3).

$$f(X) = \beta_0 + \sum_{j=1}^{p} X_j \beta_j \tag{4.3}$$

In this equation, X_j's are inputs, p represents the dimension and β_j's are unknown coefficients which are generally estimated by least squares method.

Generalized Additive Model (GAM): GAM provides an extension of linear models and makes them more flexible by allowing non-linear functions of each of the variables while maintaining additivity and retaining much of their interpretability [104], [105]. A GAM has the form as shown in (4.4).

$$Y = \alpha + \sum_{j=1}^{p} f_j(X_j) \tag{4.4}$$

In this equation, Y represents the response variable, α represents the bias, X_j's represent the predictors and f_j's are unspecified smooth functions.

Multivariate Adaptive Regression Splines (MARS): MARS, which is viewed as well suited to high-dimensional problems with large number of inputs, is an adaptive procedure for regression and uses expansions in piecewise linear basis functions [104]. A MARS model has the form as shown in (4.5).

$$f(X) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(X) \tag{4.5}$$

In this equation, f(X) represents the model, β_0 represents the intercept or bias, $h_m(X)$ is a basis function or product of two or more basis functions, M is the effective number of parameters in the model, and β_m represents coefficients of the corresponding basis functions. Coefficients are estimated by minimizing the residual sum-of-squares.

Artificial Neural Network (ANN): It is a nonlinear black box process that is used to model the relationship among inputs and output by using an approach similar to how a biological brain responds. A simple NN model has the form shown in (4.6).

$$Y = f\left(\sum_{i=1}^{n} w_i x_i\right) \tag{4.6}$$

In this equation, n is the number of inputs, w's are the weights, f is the activation function, and Y is the output. There are several types of neural networks that can be characterized by activation function, network topology and training algorithm. Activation function is generally in the form of logistic sigmoid whereas linear, saturated linear, hyperbolic tangent and gaussian functions are the other alternatives. Network topology is about the number of layers, the number of nodes within each layer of network and the travel direction of information. In terms of training algorithm, the most widely used one is backpropagation, which adjusts the connection weights by following a strategy of back-propagating errors [106].

4.1.3 Daily Electricity Demand Forecasting

The schematic view of the daily electricity demand forecasting model with inputs and output is shown in Figure 4.3. Since the available daily average temperature data is more reliable than the hourly ones, instead of building up 24 different models for each hour of a day, a single daily demand forecasting model is preferred. The data used in this study belong to the period of 2007–2015.

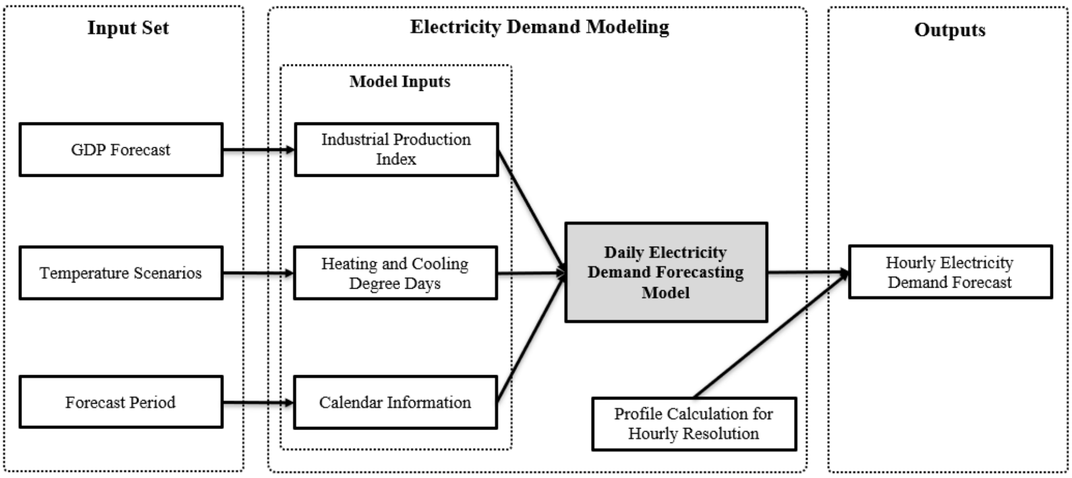


Figure 4.3. Daily electricity demand forecasting model with inputs and outputs

In this study, only two of the non-black box, interpretable models that provide insights into the relationship between the demand and the corresponding driving factors [17] are considered such as MLR and GAM. Linear models are attributed as easy to define and interpret compared to the other types of models, but they have limitations in terms of forecasting accuracy [107]. Besides, they are criticized for not being able to explain the complex relations between the explanatory variables and the dependent variable [108]. In [107], it is stated that relaxing the linear assumption while preserving the interpretation ability is possible with a couple of approaches such as polynomial regression, step functions, spline fit, local regression and GAMs.

GAMs allow the use of the aforementioned methods in an additive manner, which enable using every explanatory variable with nonlinear fit and catching the points that the linear regression misses [107]. As it has advantages over linear regression, GAM is found superior as presented below, hence it is finally chosen for daily electricity demand forecasting.

In order to make a selection among candidate explanatory variables, the best-subset selection algorithm in [109] is used to obtain the variables and corresponding coefficients for the MLR model with smallest in-sample prediction error. With the same class of variables, a GAM is created, and the performances of these two models are compared.

For training, the data between the years of 2007–2014; for testing, the data for the year 2015 are used. For the linear model, the Adjusted R^2, Mallows' Cp and BIC (Bayesian Information Criterion) are determined in order to detect the optimal number of variables in the model. The Adjusted R^2 and Mallows' Cp criteria indicate a 16-variable model and the BIC criterion indicates a 12-variable model is the best one to choose. Since the Adjusted R^2 and Mallows' Cp criteria agree, the 16-variable model is selected. The same variables are utilized to form the GAM. The MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Square Error) and yearly APE (Absolute Percentage Error) criteria are used to evaluate the model performance as shown in Table 4.2. In terms of all criteria, the GAM provides improvement.

Table 4.2 Comparison of Linear Model and GAM

Model	*MAPE*	*RMSE*	*APE*
MLR	2.88%	25378	0.94%
GAM	2.63%	23018	0.69%

The resulting model equation and explanations of the variables that are found significant are shown in (4.7) and Table 4.3. In the equation, "s" represents the smoothing term, "I" represents the indicator variable.

$$
\begin{aligned}
daily_{demand} = {} & intercept + s(IPI) + s(IPI_{v1}) + s(IPI_{v2}) \\
& + s(IPI_{v3}) + s\left(HDD_{Turkey}\right) + s\left(CDD_{Turkey}\right) \\
& + I(Holiday_{v1}) + I(Holiday_{v2}) + I(Holiday_{v3}) \\
& + I(Holiday_{v4}) + I(Workday_{v1}) + I(Workday_{v2}) \\
& + I(Season_{v1}) + I(Season_{v2}) + I(Season_{v3})
\end{aligned} \tag{4.7}
$$

Table 4.3 Variables Used in GAM

Abbreviation	*Explanation*
IPI	Industrial Production Index
$IPI_{v1}, IPI_{v2}, IPI_{v3}$	Interaction of IPI with indicator variables such as Monday (v1), national holiday (v2), religious holiday (v3)
$CDD_{Turkey}, HDD_{Turkey}$	Cooling degree days and Heating degree days representing Turkey
$Holiday_{v1}, Holiday_{v2}, Holiday_{v3}, Holiday_{v4}$	Indicator variables for holidays such as eve (v1), feast day (v2), Saturday (v3), Sunday (v4)
$Workday_{v1}, Workday_{v2}$	Indicator variables for workdays such as Monday (v1), Tuesday (v2)
$Season_{v1}, Season_{v2}, Season_{v3}$	Indicator variables for seasons such as winter (v1), spring (v2), summer (v3)

To derive multiple scenarios to address the uncertainty in demand, five different levels of GDP growth from 1% to 5%, and nine different temperature levels from the year 2007 to 2015 are utilized and there are, in total, 45 different demand forecast scenarios. The yearly results for the year 2016 are shown in Figure 4.4. Based on the model assumption, the electricity demand is expected to be between 269.5 and 284.1 TWh, and the uncertainty is nearly 14.5 TWh. Nearly 3.0 TWh of this uncertainty is found to be related to the temperature scenarios and nearly 11.5 TWh of it is related to the GDP growth scenarios. The electricity demand in 2016 is realized at around 279 TWh [110], which is within the forecast range of the proposed method.

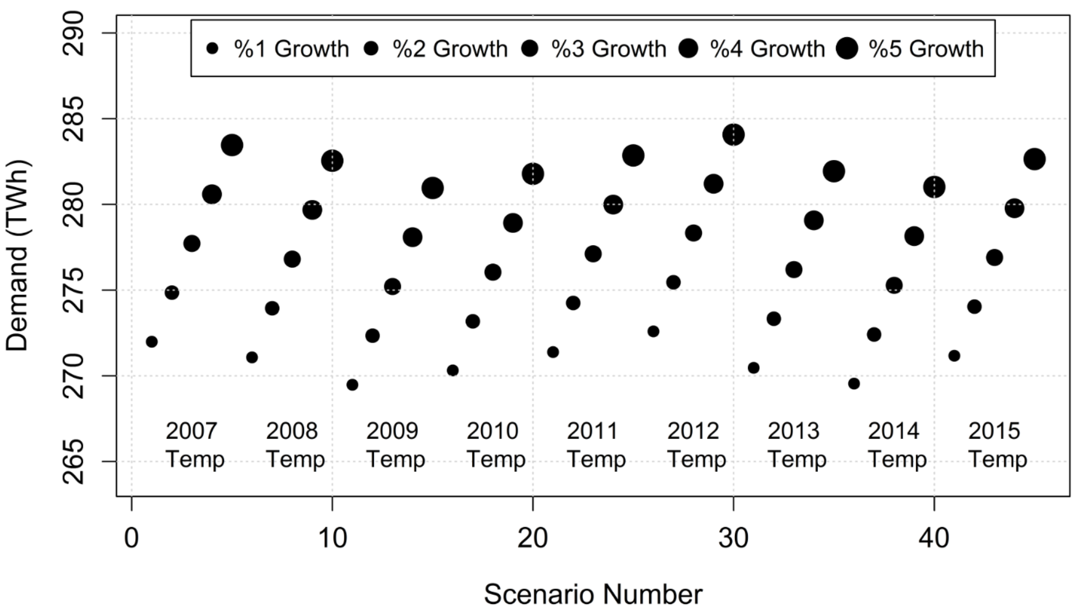


Figure 4.4. Different scenarios for electricity demand for the year 2016

The need for hourly resolution for the electricity demand is realized by the profiling method that splits daily demand into hourly demand. The process is represented in (4.8).

$$coef_{m,d,h} = ave\left(demand_{y,m,d,h}/demand_{y,m,d}\right)$$
$$for\ y = 2012, \dots, 2015;\ m = 1,\dots,12;\ d = 1,\dots,7;\ h = 1,\dots,24 \qquad (4.8)$$

In (4.8), $demand_{y,m,d,h}$ represents hourly electricity demand values for year "y", month "m", day "d" and hour "h"; $demand_{y,m,d}$ represents daily electricity demand values for year "y", month "m" and day "d". The coefficient shown as $coef_{m,d,h}$ corresponds to the averages of the ratios between the hourly electricity demand values and the corresponding daily electricity demand values, which will be used to obtain the future values of hourly electricity demand for the month m, day d and hour h. Considering that there are 12 different months in a year, 7 different days in a week and 24 different hours in a day, there are in total 2016 hours showing different pattern. This profile, which is represented in Figure 4.5, is applied to all 45 daily demand scenarios to obtain hourly demand series. The range of the resulting demand forecast series are exemplified in Figure 4.6, for only the first Monday of the forecast period, in order to show how much they differ.

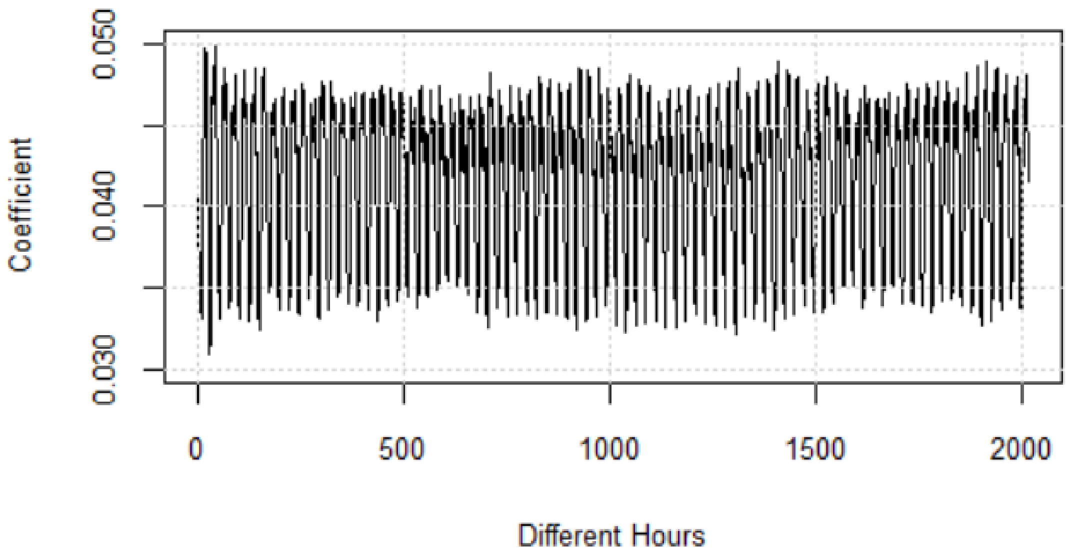


Figure 4.5. Coefficients for calculating hourly electricity demand

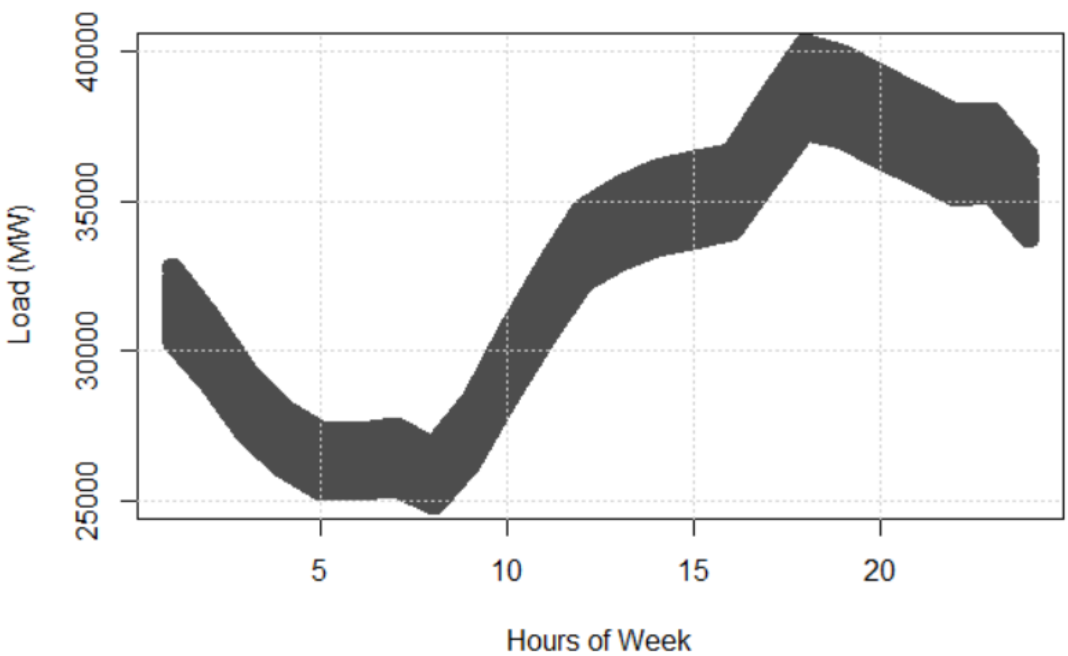


Figure 4.6. Demand forecast range for a selected day of the year 2016

4.1.4 Monthly Electricity Demand Forecasting

This part of the section focuses on MTLF with special attention to monthly electricity demand forecasts over 1-year forecast horizon. It differs from LTLF studies in terms of monthly precision, taking into account that LTLF generally provides results in yearly precision. The structure is shown in Figure 4.7. The data used in the monthly electricity demand forecasting study belong to the period of 2007–2016.

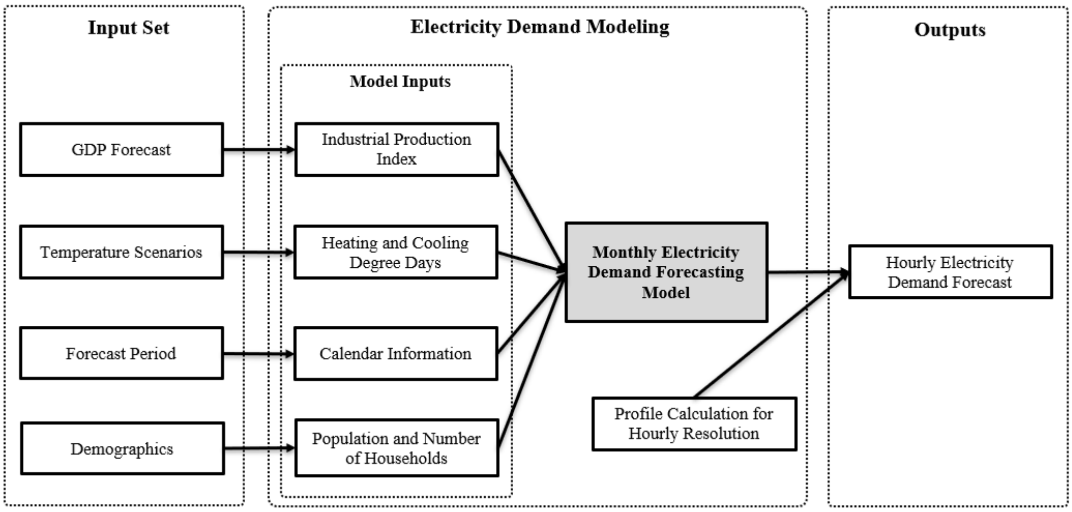


Figure 4.7. Monthly electricity demand forecasting model with inputs and output

As it has advantages over MLR, ANN and even GAM, a MARS model is found superior as presented below, and hence it is finally chosen for monthly electricity demand forecasting.

The candidate models that are studied can be introduced as follows:

Model 1 – Multivariate Adaptive Regression Splines (MARS): For MARS, the “earth” package in R is employed [111], which is used to fit the model to data. A good feature of “earth” package is that it automatically performs cross-validation and selects the best model among other possibilities. There are two different cases of the proposed MARS model. In Case 1, the degree is unspecified, i.e. the default value is 1; and in Case 2, the degree is set to 2, i.e. the interaction terms are allowed. That logic is preferred in order to see the effect of interaction terms on the performance more clearly. The number of terms and the number of predictor variables are selected based on GRSq (generalized R-squared) criterion which is an estimate of the predictive power of the model. The highest values for GRSq are obtained with 8-predictor and 12-term model for Case 1, and 7-predictor and 12-term model for Case 2.

The resulting MARS models for Cases 1 and 2 are shown in (4.9) and (4.10), in which $\text{CityName}_{\text{HDD}}$ corresponds to the HDD and $\text{CityName}_{\text{CDD}}$ corresponds to the CDD of the specified city. Here, each function is piecewise linear with different knot values. Since MARS models for Cases 1 and 2 are in the same model family, the GCV (generalized cross-validation) criterion [33] can be used to compare the performance of these models. The GCV value for Case 1 is 120123, and that of Case 2 is 90732. Therefore, it is concluded that the MARS model for Case 2 provides considerable improvement to the MARS model for Case 1, with the inclusion of the interaction term.

$$\begin{aligned}
demand &= \beta_0 + \beta_1 \times h(112.12 - IPI_{Total}) + \beta_2 \times h(IPI_{Total} - 112.12) \\
&+ \beta_3 \times h(29.00 - Wday) + \beta_4 \times h(Wday - 29.00) \\
&+ \beta_5 \times h(7.23\times 10^7 - Population) + \beta_6 \times h(Population - 7.23\times 10^7) \\
&+ \beta_7 \times h(207 - Hatay_{HDD}) + \beta_8 \times h(Manisa_{HDD} - 260) \\
&+ \beta_9 \times h(Antalya_{CDD} - 31) + \beta_{10} \times h(Is\tan bul_{CDD} - 4) \\
&+ \beta_{11} \times h(Izmir_{CDD} - 188)
\end{aligned} \tag{4.9}$$

$$\begin{aligned}
demand &= \beta_0 + \beta_1 \times h(112.12 - IPI_{Total}) + \beta_2 \times h(IPI_{Total} - 112.12) \\
&+ \beta_3 \times h(29.00 - Wday) + \beta_4 \times h(Wday - 29.00) \\
&+ \beta_5 \times h(7.23\times 10^7 - Population) + \beta_6 \times h(Population - 7.23\times 10^7) \\
&+ \beta_7 \times h(207 - Hatay_{HDD}) + \beta_8 \times h(Manisa_{HDD} - 260) \\
&+ \beta_9 \times h(Antalya_{CDD} - 31) + \beta_{10} \times h(\text{Istanbul}_{CDD} - 4) \\
&+ \beta_{11} \times h(Population - 7.23\times 10^7) \times Ankara_{CDD}
\end{aligned} \tag{4.10}$$

Model 2 – Multiple Linear Regression (MLR): For MLR, the “leaps” package in R is utilized for MLR analysis [109]. MLR enables to select the best linear models for the given number of variables. The overall aim for using this package is to decide the number of variables in the linear regression model. In this process, k-fold cross-validation approach is used.

Reserving the data belonging to the year 2016 as test set, the remaining 108 observations are used for k-fold cross-validation. For k-fold cross-validation, the data is partitioned into k different groups, and at each step, one selected group becomes the validation set whereas the remaining groups form the training set. At each of these steps, the training set is used to build the model, and the validation set is used to measure how well the model fits to unseen data. After k-steps, the overall value corresponding to cross-validation process is calculated, and the decision for the number of variables in the linear model is made based on cross-validation error.

In order to have equal number of observations in each group, k value is selected as 12, i.e. 12-fold cross-validation is applied. The elements are randomly partitioned into the folds. They are not recursive such that each observation is assigned to just one-fold, and the number of observations in each fold is equal. The same folds are also used for the cross-validation process for the selection of a GAM that will be introduced in the next title.

Having the mean squared error (MSE) as the cross-validation error, the lowest amount of error occurs for an 8-variable model as seen in Figure 4.8.

In the last step of the linear model selection, the best 8-variable model is searched with all the data excluding the test set. The resulting MLR model is represented in (4.11).

$$\begin{aligned} demand &= \beta_0 + \beta_1 xIPI_{Total} + \beta_2 xIPI_{Manu} + \beta_3 xWday + \\ &\beta_4 xPopulation + \beta_5 xAydin_{HDD} + \beta_6 xHatay_{CDD} + \\ &\beta_7 xIstanbul_{CDD} + \beta_8 xVan_{CDD} \end{aligned} \tag{4.11}$$

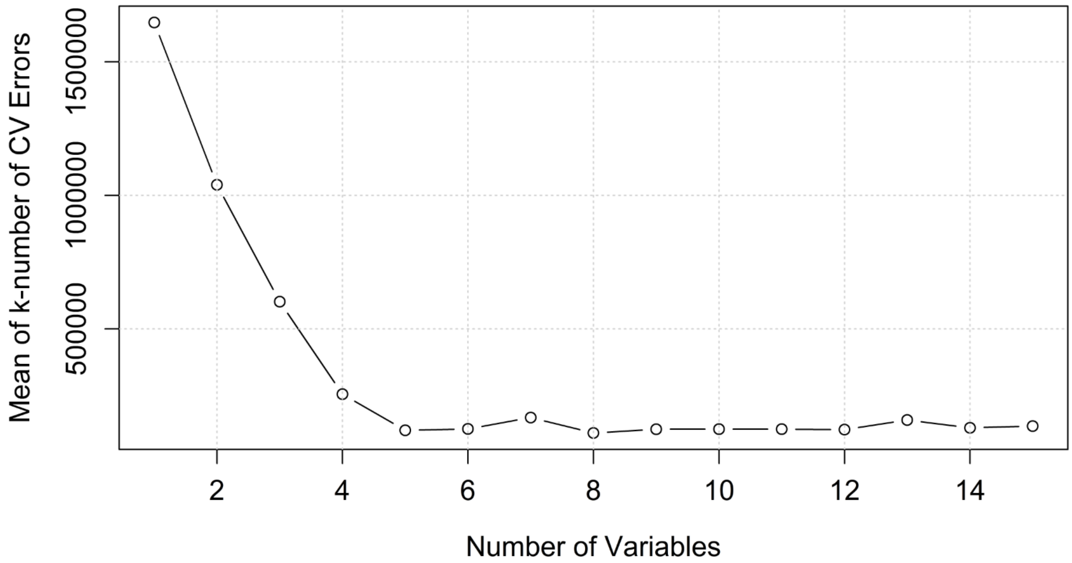


Figure 4.8. Mean of k-fold cross-validation errors for the number of variables in MLR

Model 3 – Generalized Additive Model (GAM): For GAM, the “mgcv” package in R is used for GAM analysis [112]. The main function used from this package is the “gam” which is used to fit a generalized additive model to the data. The process of the search for the best GAM is complicated. Here, a more basic approach is applied. The cross-validation errors are checked, and the lowest error is for the models having 5 to 10 variables. The idea is that the variables found from the best subsets for the linear regression in the previous step can be utilized to form GAMs. The variables obtained from 5 to 10 variable best subsets are used to form 6 different GAMs. Each predictor variable is selected to be inside the smoothing terms with unspecified degrees of freedom. The selection for the degrees of freedom is defined by the gam function inside the “mgcv” package.

As in the case of linear regression model, k-fold cross-validation process is applied in order to be able to choose the best model among 6-variable ones. Here, k is selected as 12, and the same partitioned sets are used as in the previous section. Among the mean of k-fold cross-validation errors, that of a 6-variable model is the lowest as shown in Figure 4.9. The resulting GAM is shown in (4.12) in terms of smooth functions (s) and their estimated degree of smoothness.

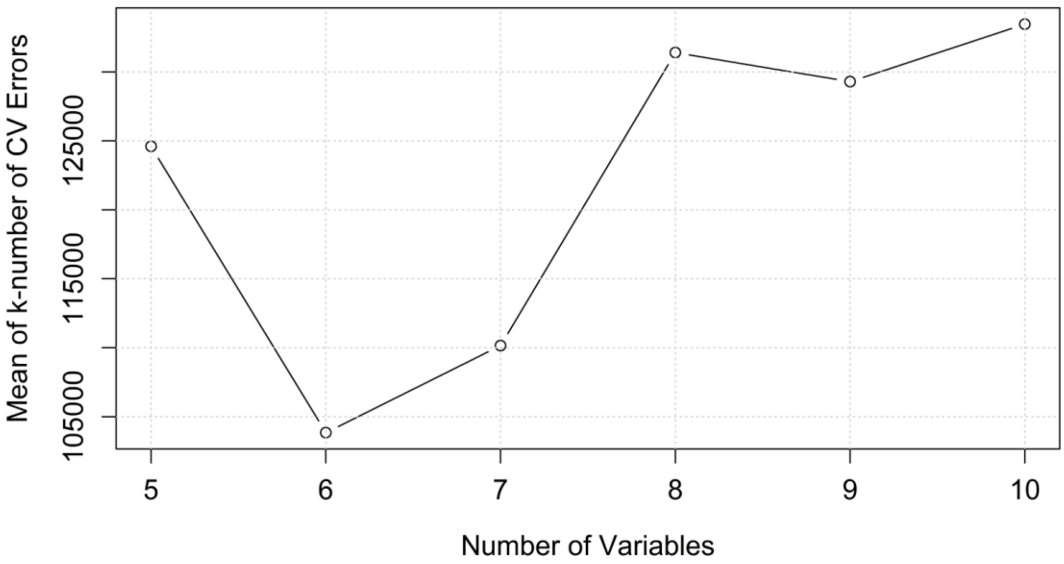


Figure 4.9. Mean of k-fold cross-validation errors for the number of variables in GAM

$$\begin{aligned}&demand = s(IPI_{Total},1) + s(IPI_{Manu},1) + s(Wday,1) + \\ &s(Population,1) + s(Aydin_{HDD},1) + s(Gaziantep_{CDD},4.15)\end{aligned} \tag{4.12}$$

Model 4 – Artificial Neural Network (ANN): For ANN, the neural network toolbox in MATLAB is used and 15 different training algorithms available in this toolbox are considered. Also, different numbers of neurons from 5 to 20 are studied. The network performances are measured by the MSE metric. The algorithm based on Bayesian regularization with 16 neurons yields the lowest error, with a MSE of 19706. Therefore, it is employed in the model assessment.

The performance of the selected models from the MLR, GAM, MARS and ANN model families are tested with the test set which belongs to the year 2016, which is separated from the main data set at the beginning of the study.

The overall test errors in terms of the MSE and MAPE are presented in Table 4.4. The GAM, MARS and ANN models provide improvements to the selected linear model. However, the improvement that the MARS model has provided is remarkable.

Table 4.4 Comparison of Test Errors

Model	*MSE*	*MAPE*
MLR	196978	1.25%
GAM	131349	1.13%
MARS	45288	0.84%
ANN	127808	1.09%

The monthly absolute percentage errors are shown in Figure 4.10. Here, it seems that the errors for the MARS model are mostly within 1%, with the exception of December which had been one of the coldest Decembers of all times in Turkey. For the other months, the significant improvement of the MARS model for months March, July and August can again be seen. It is concluded that the MARS model is able to capture some important points that the other considered models may overlook. Therefore, for medium-term forecasting of electricity demand on monthly basis, the MARS model can be selected.

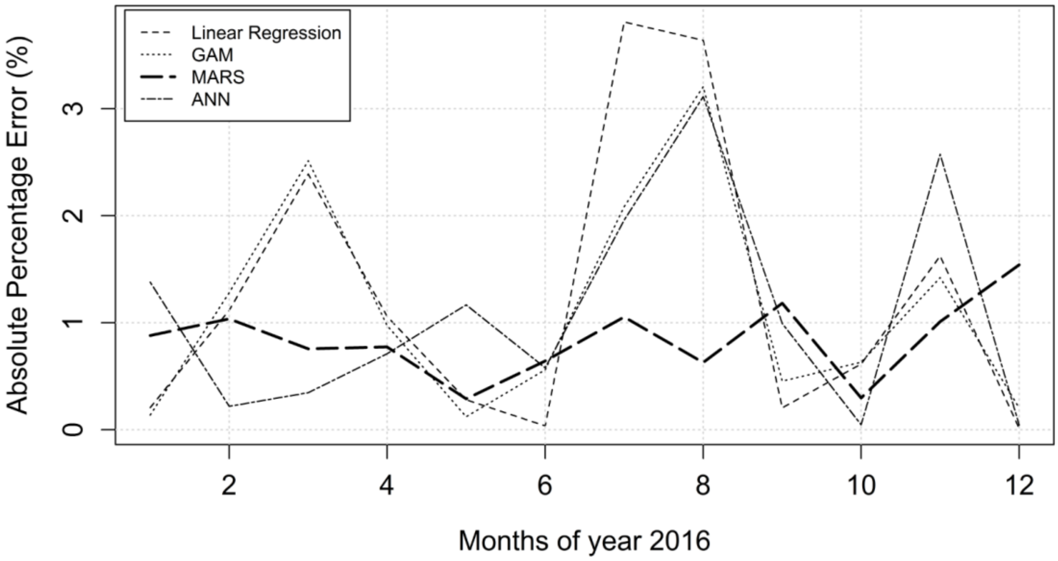


Figure 4.10. Monthly absolute percent errors by models

The results of monthly electricity demand forecasting can further be disaggregated into hourly time frame with the utilization of a similar profiling method described in the previous section.

4.1.5 Discussion

As for electricity demand modeling, two different time frames, such as daily and monthly, are considered in order to perform MTLF. Firstly, the daily electricity demand forecasting model has been studied with MLR and GAM, and it has been shown that GAM has superior performance as it is more capable of modeling the nonlinearities in electricity demand. Secondly, the monthly electricity demand forecasting model has been studied with an extended set of models such MARS, MLR, GAM and ANN, and it has been found out that the proposed MARS model outperforms its counterparts. The basis functions used in MARS, which can be in the form of a constant, multiple hinge functions as well as the multiplication of two hinge functions that enables interaction terms, seem to capture the nonlinearities, some of which may be missed by GAM and ANN.

Even if the best linear regression model is selected, it may fail to make predictions as accurate as nonlinear methods. It is obvious that the variables that affect electricity demand have rather a nonlinear relationship with the response variable, and this prevents a linear model from performing well. However, the advantages of linear models should not be underestimated in that they are comparatively fast and easy to interpret in terms of the relation among the response variable and predictor variables.

With the utilization of the GAM, it is experienced that more accurate electricity demand forecasting is possible. In this type of model, the effect of predictor variables is nonlinear, but the effect of each one is still in an additive fashion. Since the GAM is found to be superior to the linear model in terms of test error, the results are interpreted such that the effect of predictor variables on the response variable is quite likely to be nonlinear.

The ANN model provides slight improvement over MLR and GAM thanks to its advantages for modeling nonlinear relationships, but still its performance remains below MARS for the case of Turkey.

Further improvements can be achieved by working more on details as presented in [96]. Considering that there can be numerous explanatory variables, there will be a need for dimension reduction techniques, such as feature selection, to be able to extract useful information from data. Whether any feature selection methods can reduce the number of features in the dataset and improve forecasting accuracy, as well as which feature selection method and forecasting algorithm pair yields the best performance for MTLF are investigated in [96]. It is shown that demand forecasting studies are still open for further improvement. With the utilization of proper feature selection methods, even an MLR model can yield performance similar to nonlinear models.

Nevertheless, the improvements that have been shown in this thesis so far are found to be sufficient to move to the other parts of the electricity market modeling methodology, as a reasonable electricity demand forecast series can be obtained with the proposed daily and monthly models.

4.2 Electricity Supply Modeling

The aim of electricity supply modeling is to provide the necessary information for the formation of supply curves for each hour of the year. This information consists of availability factors of each market participant on hourly basis. Since this is a medium-term study reaching one year ahead, the supply side of electricity market is modeled based on scenarios, instead of directly forecasting hourly availability factors. The schematic view of electricity supply modeling used in this section is shown in Figure 4.11.

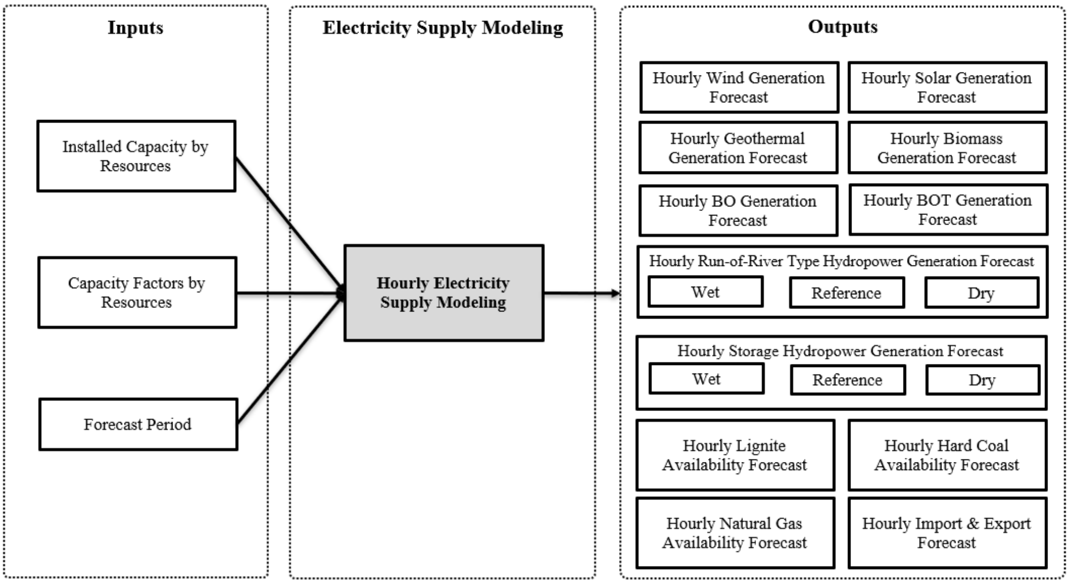


Figure 4.11. Electricity supply modeling with inputs and outputs

In the day-ahead market, generation is offered on portfolio basis rather than power plant basis, i.e. if a market participant has several types of power plants in its portfolio, the combined generation of the portfolio is offered. However, since the amount of generation and generation cost are of critical importance, modeling supply on power plant basis is a reasonable option.

As of the year 2016, there are 132 power plants over 100 MW, constituting 77% of the installed capacity in Turkey. These facilities can be evaluated separately, but forming the supply curve for each hour of the year by using information from those 132 power plants prolongs the amount of time for the calculation of price forecast series. Therefore, without any loss of critical information, the number of market participants is limited as much as possible to keep the running time within reasonable margins, which enables studying numerous scenarios. In order to do so, 41 different market participants are defined based on fuel type and ownership, as shown in Table 4.5. Renewable generation such as wind, solar, geothermal, biomass, run-of-river hydropower, as well as storage hydropower is modeled with respect to fuel type. Natural gas and hard coal power plants of private sector, with installed capacity over 500 MW, are modeled based on both fuel type and ownership.

Table 4.5 List of Market Participants

Resource Type	*Number of Market Participants*
Natural Gas (State, Private, Purchase-Guaranteed)	17
Hard Coal-Asphaltite (Private)	8
Lignite (State, Private, Purchase-Guaranteed)	5
Wind, Geothermal, Biomass, Solar	4
Peaker (Fuel-Oil, Diesel)	3
Import, Export	2
Run-of-River Type Hydropower	1
Storage Hydropower	1

The methodology for the calculation of hourly availability factors determined based on historical data are represented in Table 4.6. Each group except solar and peaker has different number of power plants sampled based on the availability of the data from the year 2007 to 2015. The weighted average availability factor for each hour within each group is calculated from the data grouped by similar 15-day periods. With this approach, the events affecting availability such as failure, maintenance, etc. are implicitly taken into consideration at calendar level. The expression "hourly" corresponds that the availability factor calculation considers hour of day, and the expression "daily" corresponds that it considers day of week. The expression "expected value" is used to underline that hourly availability factor for a participant is calculated by taking the mean of the data grouped by similar 15-day periods, hour of day and day of week. This process is equal to forming the probability density function of availability factors based on the historical data, and assuming that it is normally distributed, the expectation operation corresponds to getting the value at which the density function reaches its maximum. In order to create more scenarios, instead of taking the expected value, the first quartile and the third quartile values of the probability density functions or other values based on various logic can be proposed. However, keeping the number of scenarios at a reasonable level requires this study to focus only on hydro inflow condition which is one of the biggest sources of uncertainty in the electricity supply side of Turkey.

Table 4.6 Hourly Availability Factor Calculation Methodology

Resource Type	*Methodology*
Wind	Hourly average of the last 4 years
Solar	15-day, hourly, theoretical approach
Geothermal	15-day, daily, hourly, expected value
Biomass	15-day, daily, hourly, expected value
BO-BOT-TOOR	15-day, daily, hourly, expected value
Run-of-River Type Hydropower	15-day, daily, hourly (3 Scenarios)
Lignite-State	15-day, daily, hourly, expected value
Lignite-Private	15-day, daily, hourly, expected value
Hard Coal	15-day, daily, hourly, expected value
Natural Gas-High Efficiency	15-day, maximum capacity factor
Natural Gas-Other	15-day, maximum capacity factor
Peaker	90% availability factor at all times
Import and Export	15-day, daily, hourly, expected value

For solar, theoretical availability factors are created based on the monthly solar radiation and the time between sunrise and sunset. For natural gas power plants, the maximum, not the expected values of availability factors are taken since they are not baseload power plants, and averaging operation can be misleading. The term “high efficiency” represents the power plants started in operation after the year 2009 and having an installed capacity over 500 MW. Since peaker power plants operate only in a small portion of the year, 90% availability is assumed to provide them the opportunity for operation whenever it is possible.

In Turkey, hydro inflow condition is volatile, i.e. the standard deviation from the long-term averages is fairly high. Therefore, this condition is handled by forming three scenarios for run-of-river hydro power plant availability factors, named as reference, wet (high) and dry (low). The methodology for determining the availability factors is represented in Figure 4.12. Within similar periods, the probability density functions in hourly resolution are calculated, and the availability factors that will make the value of the cumulative distribution function 0.2, 0.5 and 0.8 are chosen as scenario values. A separate methodology is employed in order to determine the availability factors of storage hydropower plants as mentioned in the next section.

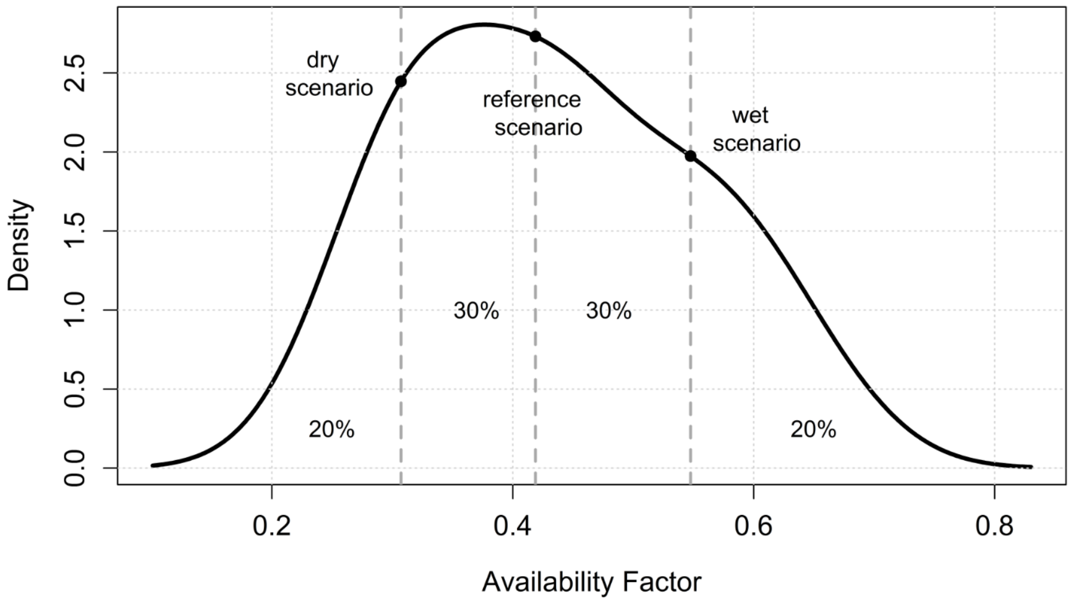


Figure 4.12. Probability density function and three scenarios for 2nd half of December, Tuesday and hour 17

The patterns of availability factors calculated for a lignite and a natural gas market participant are exemplified in Figure 4.13. For lignite, there are two valleys corresponding to spring and fall seasons. For natural gas, the valley occurs in spring season. These time periods include the effect of generator maintenance implicitly. Since the calculations are performed based on historical data, the utilization of this methodology for future years requires caution considering the evolution of electricity generation capacity.

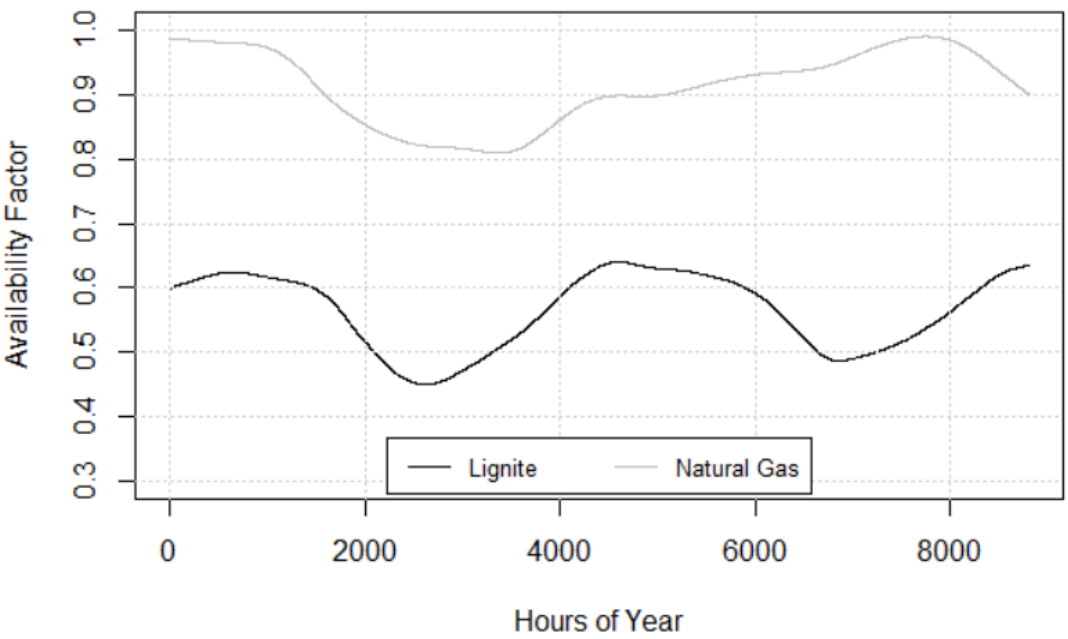


Figure 4.13. Pattern of availability factors for selected market participants from lignite and natural gas

4.3 Electricity Price Modeling

This section describes how electricity price is modeled and forecasted in the medium-term horizon. Hourly electricity demand forecasts and hourly availability of market participants have been obtained in the previous sections. These are needed as input for the electricity price forecasting model which would match the supply and demand on hourly basis. The modeling activity is performed based on the data of the year 2016, and the results are also compared with the realizations for the years 2014 and 2015.

The section is composed of three parts. In the first part, the price forecasting methodology is proposed. The second part mentions the details of a module for the realistic utilization of storage hydropower plant generation. In the last part of this section, the results are presented according to various scenarios on demand and supply.

4.3.1 Proposed Methodology

With the proposed methodology, the aim is to obtain electricity price forecast series and determine the possible ranges of electricity price in medium-term, rather than a single forecast. It is formed with a theoretical approach considering the uncertainties in demand and supply.

The electricity price modeling in medium term depends on the intersection of the supply and demand curves at each hour of the forecast period. The demand is assumed to be inelastic, and the results of the demand forecasting model are to be directly used. The electricity supply obtained for each hour of the forecast period is ordered according to the corresponding generation cost of electricity and is assumed to be submitted as supply bids to the day-ahead market. In order not to violate the operation principles of thermal power plants, block bid option containing all 24 hours in a day is created for hard coal and natural gas fired power plants.

Unit generation cost of electricity is calculated with fuel price and efficiency information. The sales price of national natural gas company to eligible customers is taken as the natural gas price for power plants [113]. For hard coal power plants, international prices [114] are taken as reference. For O&M costs per MW, the average values of Europe and China are taken as reference [115] and distributed per MWh using the expected operating hours of these power plants. Plant efficiencies are estimated depending on the entry year of each facility.

The generation of renewable energy sources, as well as that of purchase-guaranteed power plants such as BO, BOT and TOOR, is assumed be offered regardless of the market price, i.e. 0 $/MWh. Similarly, the generation of lignite power plants is assumed to be offered at a price of 0 $/MWh based on the price behavior of those power plants in the period of 2012-2015. Therefore, the generation cost of lignite power plants is irrelevant for this part of the study. The price floor is 0 $/MWh, and the price cap is chosen as the maximum hourly price between the years 2013 and 2015, which is approximately 225 $/MWh.

Hourly electricity price forecasts are determined at the point at which supply and demand curves intersect as represented in Figure 4.14. This process is applied for all hours of the forecast period. The supply curve, or also known as the merit order curve, has the available generation information, sorted from the lowest to the highest bidding price and consists of 41 different step functions representing the price behavior of each market participant. A large amount of supply is offered to the market regardless of the market price, i.e. at 0 $/MWh, due to the considerable share of renewables, purchase-guaranteed and lignite power plants. Demand curve is assumed to be inelastic, and its value should be determined based on the electricity demand forecasting model results.

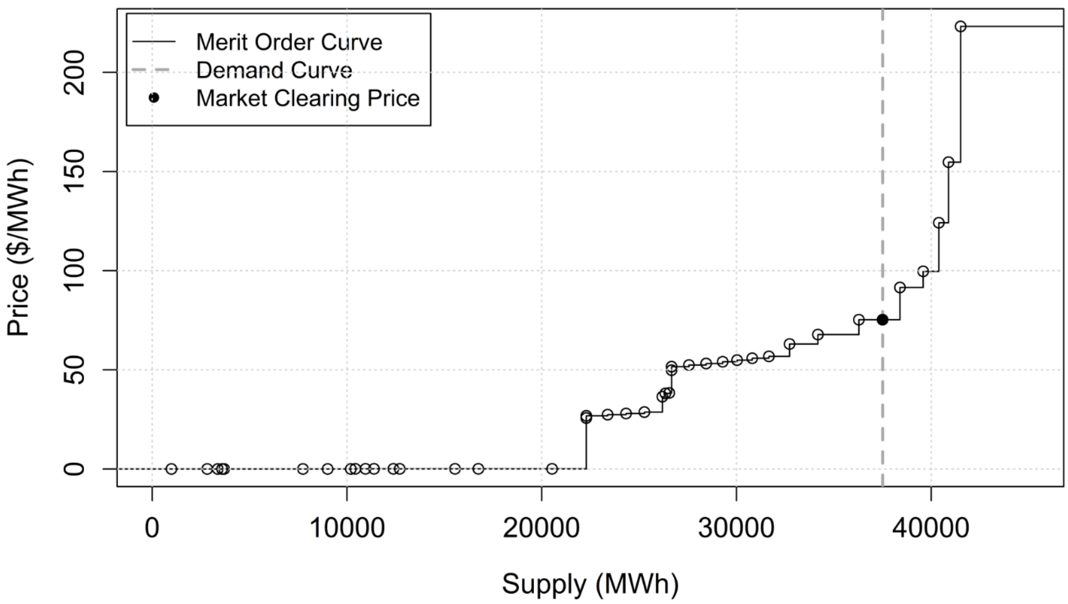


Figure 4.14. Illustration of market clearing price formation for a particular hour

In the above representation, the merit order curve has a dynamic behavior for storage hydropower plants, which is to be explained in detail in the next section. Also, the dynamic behavior is applicable to hard coal and natural gas fired power plant generation which are submitted in block format, but the latter type of power plants has the ability to submit hourly bids at the same time thanks to their flexibility. The acceptance criteria for a block bid depends on the comparison of bid price and daily average price, hence this process requires a multiple-step operation. In the first step, only hourly bids of market participants are utilized to meet the forecasted demand for 24 hours of a day. If the price of the lowest block bid is lower than the daily average calculated price, the corresponding block bid is accepted, and new hourly prices are calculated based on the newly accepted block bid. In the next step, the same procedure is applied to the second lowest block bid. If any block bid is rejected, this procedure is terminated regardless of the remaining orders. Although this is not the exact way for the acceptance of the block bids in the Turkish case, this procedure is applied in the Nordic power market and preferred in this study due to its easier implementation.

The electricity price forecasting model methodology can be summarized as in Figure 4.15. The modeling part consists of three main functions. The main task of it is to determine which of the block bids are to be accepted on daily basis. This is returned by the daily block bid selection function, in which the block bid price of a market participant is compared to the daily average market price. Daily mean price is calculated by the daily mean price calculator function that calls the hourly price calculator function. As this is a multiple-step operation, in the first step no block bids are considered, i.e. hourly and daily prices are calculated based on only hourly bids. In further steps, the daily block bid selection function checks the feasibility of the lowest block bid price and continue operation until a bid is unfeasible or all bids are accepted. After the acceptance of block bids is specified for a particular day, it is trivial to calculate the hourly electricity price forecast and electricity generation forecast by market participant.

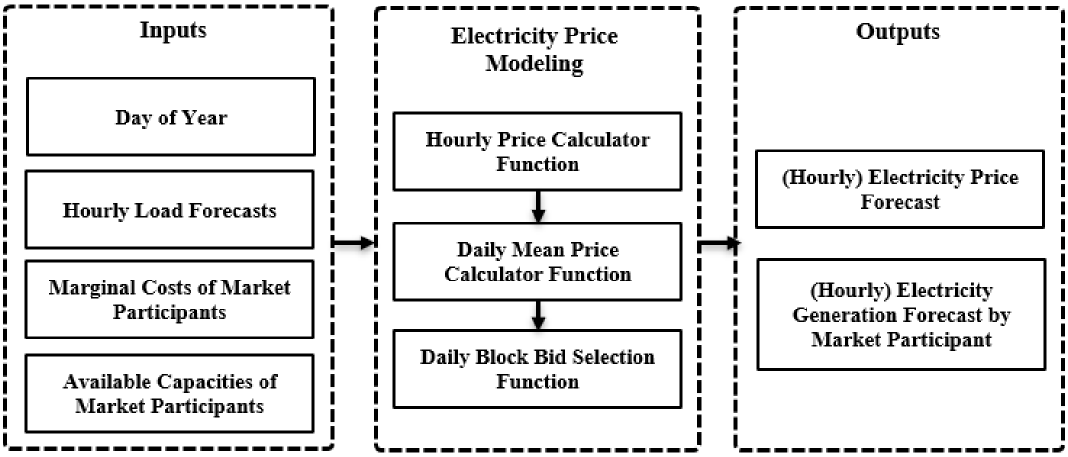


Figure 4.15. Electricity price forecasting model with inputs and outputs

4.3.2 Realistic Utilization of Storage Hydropower Plants

The proposed electricity price forecasting model tries to perform hourly forecasting of yearly electricity prices. The critical point is that it tries to optimize the generation of storage hydropower plants with an optimization procedure based on linear programming in order to reflect the bidirectional relationship between the market price and generation of those facilities.

Based on the fact that storage hydropower plants have flexibility in operation to a certain degree, there is a nonlinear relation between the MCP and the amount of generation from storage hydropower plants. This flexibility must be considered to reflect more reasonable market prices. Since there are over 110 storage hydropower plants in Turkey for the year 2016, and each one has different characteristics in terms of water inflow, reservoir and operation; the optimization process proceeds for the cumulative amount of storage hydropower plant generation for simplicity.

In order to solve this problem, the objective function is defined as in (4.13),

$$max \sum_{i=1}^{N} MCP_i \; x \; CF_i \qquad (4.13)$$

where N represents the total number of hours in a year, MCP_i represents the calculated market price at hour i and CF_i represents the capacity factor for cumulative storage hydropower plant generation at hour i. For the first iteration, the hourly market prices for the previous year are selected as initial values as a reasonable starting point.

The constraints can be grouped by monthly, daily and hourly basis. They are deterministic and derived from the historical cumulative hourly storage hydropower plant capacity factors which are expected to represent the generation behavior.

The monthly constraints are defined as shown in (4.14),

$$\frac{1}{N_m}\sum_{i=1}^{N_m} CF_{m,i} \leq HMCF_{m,s}, for\ m = 1,2,\dots,M \tag{4.14}$$

where M represents the total number of months in a year, m represents the month of the year, N_m represents the total number of hours in the corresponding month, $CF_{m,i}$ represents the capacity factor for cumulative storage hydropower plant generation at month m and hour i, and $HMCF_{m,s}$ represents the historical monthly average capacity factor for month m and scenario s. For the calculation of these averages, firstly, monthly average capacity factors are calculated, then monthly historical maximum and minimum values are discarded. For the remaining series the mean of the monthly averages is taken as the reference scenario, whereas two standard deviations from the mean are taken as wet and dry scenarios, based on the assumption that the aforementioned capacity factor series is normally distributed, and two standard deviations represent 95% confidence interval that is used to define the values for wet and dry scenarios.

The daily constraints are defined as shown in (4.15) and (4.16),

$$\frac{1}{24}\sum_{i=1}^{24} CF_{d,i} \leq HDCF_{m,1-d}, for\ d = 1,2,\dots,D \tag{4.15}$$

$$\frac{1}{24}\sum_{i=1}^{24}\left(CF_{d,i} + CF_{d+1,i}\right) \leq HDCF_{m,2-d}, for\ d = 1,2, \dots, D-1 \tag{4.16}$$

where D represents the total number of days in a year, d represents the day of the year, $CF_{d,i}$ represents the capacity factor for cumulative storage hydropower plant generation at day d and hour i, $HDCF_{m,1-d}$ represents the historical maximum daily capacity factor for month m and $HDCF_{m,2-d}$ represents the historical maximum capacity factor for successive 2 days for month m.

The hourly constraints can be classified into two. One is the minimum hourly operation requirement and the maximum reachable hourly capacity factor. The other one depends on differences in capacity factors for the successive 1, 2, and 3 hours. Hourly constraints of the first classification can be defined as shown in (4.17) and (4.18),

$$CF_{m,i} \geq HHCF_{min,m,s}, for\ i = 1,2, \dots N_m;\ m = 1,2, \dots, M \tag{4.17}$$

$$CF_{m,i} \leq HHCF_{max,m,s}, for\ i = 1,2, \dots N_m;\ m = 1,2, \dots, M \tag{4.18}$$

where $HHCF_{min,m,s}$ and $HHCF_{max,m,s}$ represents the historical hourly minimum and maximum capacity factors for month m and scenario s. For the calculation of these capacity factors, the historical hourly capacity factors for each month are sorted, and then for the minimum case the capacity factors that correspond to the lowest 5%, 10% and 15% are selected for dry, reference and wet scenario, whereas, for the maximum case, the capacity factors that correspond to the highest 5%, 10% and 15% are selected for wet, reference and dry scenarios, respectively.

The hourly constraints of the second classification are defined as in (4.19) - (4.24),

$$|\ CF_{i+1} - CF_i| \leq CFD_{inc,1-h}, for\ \ CF_{i+1} \geq CF_i\ \&\ i = 1, \dots, N-1 \tag{4.19}$$

$$|\ CF_{i+1} - CF_i| \leq CFD_{dec,1-h}, for\ \ CF_{i+1} < CF_i\ \&\ i = 1, \dots, N-1 \tag{4.20}$$

$$|\ CF_{i+2} - CF_i| \leq CFD_{inc,2-h}, for\ \ CF_{i+2} \geq CF_i\ \&\ i = 1, \dots, N-2 \tag{4.21}$$

$$| CF_{i+2} - CF_i | \leq CFD_{dec,2-h}, for\ CF_{i+2} < CF_i \ \&\ i = 1, \dots, N-2 \tag{4.22}$$

$$| CF_{i+3} - CF_i | \leq CFD_{inc,3-h}, for\ CF_{i+3} \geq CF_i \ \&\ i = 1, \dots, N-3 \tag{4.23}$$

$$| CF_{i+3} - CF_i | \leq CFD_{dec,3-h}, for\ CF_{i+3} < CF_i \ \&\ i = 1, \dots, N-3 \tag{4.24}$$

where $CFD_{inc,t-h}$ and $CFD_{dec,t-h}$ for $t = 1,2,3$ represents the maximum capacity factor deviation for the successive t hours. For the calculation of t-hour deviations, both in the increment and decrement direction, the values are sorted, and then the value that corresponds to the highest 10% is selected.

The methodology for the optimization procedure of storage hydropower plants is summarized below:

- Step 1: An initial price vector is chosen with a length of Nx1. Hourly prices of the previous year can be chosen as a reasonable initial point.
- Step 2: The price vector defined in Step 1 is used for optimizing the revenue of storage hydropower plants within a 1-year period. The optimized generation values are stored in a vector with a length of Nx1.
- Step 3: Based on the optimized generation values in Step 2, the price forecasting model is run, and a new hourly price series is obtained.
- Step 4: The hourly average value of prices obtained in the previous iterations from the price forecasting model is used to optimize the revenue of storage hydropower plants.
- Step 5: Step 3 and Step 4 are repeated until a certain criterion such as the objective function value in successive iterations is below a threshold level.

The iterations in the optimization process are summarized in Table 4.7. The amount of change in the yearly average price is high in three iterations, but starting from the 4th iteration it is fairly limited and the yearly price oscillates between 45.9 and 47.0 \$/MWh, implying that it stays within certain ranges. The same comments are applicable to the objective function value. The proportional change is below 1% after the 5th iteration and below 0.05% after the 10th iteration.

Although both yearly price and objective value stay within certain limits, the monthly average price and hourly price show different patterns. As the number of iteration increases, prices can still be volatile, especially for the spring months in which hydro potential is high, as shown in Table 4.8. This implies that the solution for the problem is not unique and changes in each iteration, but the impact on the monthly and yearly average prices are limited as the iteration proceeds.

Table 4.7 Summary of the Optimization Process

Iteration	*MCP ($/MWh)*	*Change*	*Obj. Func. Val. ($/MW)*	*Change*
1	43.55		-174952	
2	42.60	-2.20%	-155266	-11.25%
3	46.54	9.26%	-140089	-9.77%
4	46.40	-0.30%	-137013	-2.20%
5	45.94	-0.99%	-135915	-0.80%
6	46.26	0.70%	-135102	-0.60%
7	46.77	1.09%	-134864	-0.18%
8	46.10	-1.42%	-134943	0.06%
9	46.38	0.60%	-134758	-0.14%
10	46.86	1.03%	-134667	-0.07%
11	46.83	-0.06%	-134737	0.05%
12	46.82	-0.02%	-134780	0.03%
13	46.36	-0.98%	-134752	-0.02%
14	46.67	0.67%	-134679	-0.05%
15	47.01	0.73%	-134687	0.01%
16	46.49	-1.10%	-134712	0.02%
17	46.76	0.58%	-134676	-0.03%
18	46.55	-0.44%	-134697	0.02%
19	46.76	0.44%	-134660	-0.03%
20	46.88	0.27%	-134692	0.02%

Table 4.8 Maximum Absolute Monthly Average Price Deviation with respect to the Previous Iteration

Iteration	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Jan	-4.6%	8.4%	0.8%	-0.9%	-2.4%	4.1%	-5.7%	2.4%	0.0%	-0.2%
Feb	7.9%	8.7%	-0.5%	-0.8%	-0.2%	3.5%	-3.7%	0.5%	0.5%	1.8%
Mar	3.3%	13.7%	2.3%	-0.6%	1.6%	-0.9%	2.0%	-2.4%	1.1%	-0.1%
Apr	-1.5%	16.9%	-4.4%	-5.6%	4.9%	2.4%	-3.1%	3.4%	1.4%	1.4%
May	-5.5%	16.3%	-6.7%	0.5%	5.4%	2.3%	-3.2%	2.4%	2.7%	1.1%
Jun	-3.3%	12.3%	0.2%	-1.8%	-0.3%	3.1%	-0.1%	-2.5%	2.6%	-1.7%
Jul	-1.6%	8.3%	1.7%	0.5%	-2.9%	1.2%	-0.5%	1.2%	0.5%	0.5%
Aug	-5.9%	12.0%	3.8%	1.4%	-2.9%	0.1%	0.7%	-0.8%	1.7%	-0.3%
Sep	0.3%	3.1%	0.2%	-1.3%	0.3%	0.9%	-0.8%	-1.7%	3.5%	-0.9%
Oct	-3.6%	1.1%	-3.4%	-0.2%	2.2%	-2.3%	2.0%	-1.4%	1.7%	-2.1%
Nov	-2.6%	6.1%	0.9%	-3.6%	4.0%	-1.7%	-3.4%	4.9%	-1.4%	-1.2%
Dec	-6.5%	9.1%	0.5%	-0.2%	0.6%	1.3%	-1.5%	2.2%	-1.3%	1.3%
Avg.	3.9%	9.7%	2.1%	1.4%	2.3%	2.0%	2.2%	2.1%	1.5%	1.0%
Iteration	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	
Jan	2.0%	0.7%	-0.5%	1.3%	-1.9%	-0.4%	-0.4%	-0.5%	-0.2%	
Feb	-3.8%	1.1%	-0.5%	2.7%	-1.1%	2.0%	0.5%	-3.9%	4.1%	
Mar	0.7%	-1.8%	1.1%	-0.7%	-1.6%	2.3%	-1.4%	-0.8%	2.5%	
Apr	-2.8%	-0.3%	-0.9%	5.0%	-2.1%	-0.6%	-2.6%	4.3%	-0.4%	
May	-2.4%	-0.4%	0.3%	-1.6%	-0.3%	-0.6%	-0.6%	4.0%	1.0%	
Jun	0.7%	-2.6%	1.9%	0.7%	0.0%	-1.7%	2.1%	-1.6%	1.7%	
Jul	0.1%	-5.1%	4.0%	2.4%	-1.1%	0.7%	-2.1%	3.4%	-3.0%	
Aug	0.0%	1.3%	-2.0%	0.2%	0.4%	0.0%	-2.1%	2.2%	0.3%	
Sep	0.4%	-1.4%	1.2%	-0.4%	-2.5%	2.6%	-0.8%	0.5%	-0.8%	
Oct	1.9%	-0.4%	1.6%	-0.9%	-2.3%	1.5%	1.4%	1.3%	-3.1%	
Nov	3.2%	-2.9%	3.0%	0.6%	-0.7%	-0.2%	1.2%	-2.0%	1.2%	
Dec	-1.2%	-0.1%	-0.8%	0.3%	-0.1%	1.3%	-1.0%	-0.1%	0.4%	
Avg.	1.6%	1.5%	1.5%	1.4%	1.2%	1.2%	1.3%	2.1%	1.6%	

4.3.3 Medium-Term Price Forecasting Results and Evaluation

The proposed model is run with the demands realized for the years 2014, 2015 and 2016. The results with respect to the hydro inflow conditions and realizations are shown in Figure 4.16. It should be noted that in terms of hydropower generation, the years 2014 and 2015 are close to the dry and reference scenario, respectively, and the year 2016 is close to the reference scenario. The yearly average prices in 2014 and 2015 are 77 and 52 $/MWh, respectively, and it is 46 $/MWh in 2016. When the simulation results and yearly realized prices are compared, the yearly absolute percentage errors are found to be below 3% as shown in Table 4.9.

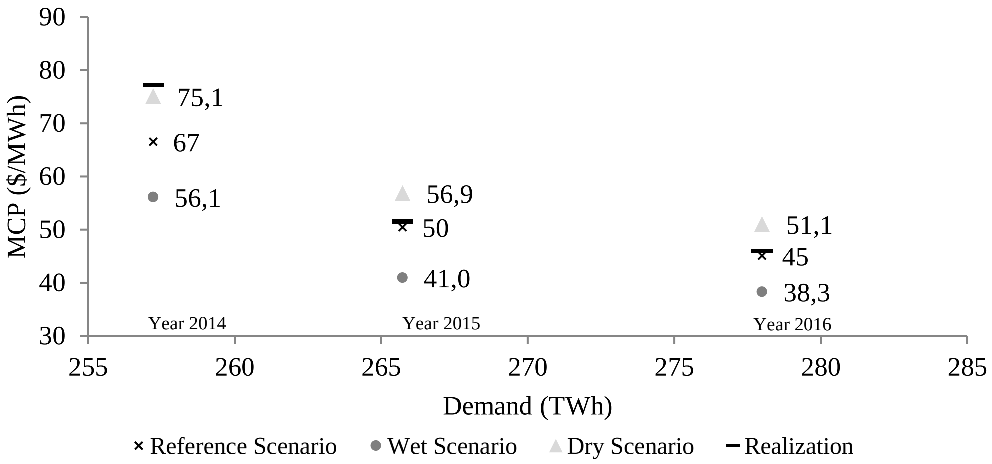


Figure 4.16. Simulation results for years 2014-2016

Table 4.9 Price Forecasting Errors

Year	*Yearly Absolute Percentage Error (APE)*
2014	2.8%
2015	2.4%
2016	1.9%

The differences can be explained by the deviations in supply scenarios from the realizations including the natural gas supply shortages which had occurred a couple of times in a year, affecting primarily natural gas fired power plants and causing the market prices to jump for a week or two. This is a situation that is not modeled in this study since it is considered as outlier but must be considered while evaluating the model accuracy. Another fact that should be considered is that there are only three scenarios for hydropower generation in this study, but this is just an approximation, and in reality, infinitely many scenarios can be generated. Also, the difference in the acceptance criteria for block bids can play a role. Last but not least, the hydro optimization procedure has the assumption that the cumulative amount of generation from storage hydropower is submitted based on the forecasted electricity prices and this approach includes the optimal behavior, but, in reality, hydropower plants are operated by different market participants, and their behaviors can be sub-optimal at various times of the year. These factors together can surely have impact on the yearly average electricity price. However, in this study, their effect is found to be limited in overall.

In Figure 4.16, only one demand forecast scenario is used for the year 2016. In order to reflect the impact of demand and hydro generation on yearly average price, 45 demand scenarios and 3 hydro inflow scenarios are used, and the results are shown in Figure 4.17. The expected price range for reference, wet and dry scenarios are found to be between 41-46, 31-39 and 48-54 \$/MWh, respectively, i.e. the overall range is 31-54 \$/MWh, which corresponds to nearly 23 \$/MWh uncertainty considering all scenarios. The level of 23 \$/MWh uncertainty is nearly half of the realized electricity price in 2016. The 1% change in electricity demand corresponds to changes 2.2%, 4.2%, 2.3%; and 1 TWh change in electricity demand corresponds to changes 0.35, 0.53, 0.43 \$/MWh in reference, wet and dry scenarios, respectively. These numbers can be interpreted as the impact of demand is highest in wet scenario and lowest in reference scenario. It should be noted that these consequences are valid only for the year 2016, and the same analysis should be performed for each year that is to be analyzed.

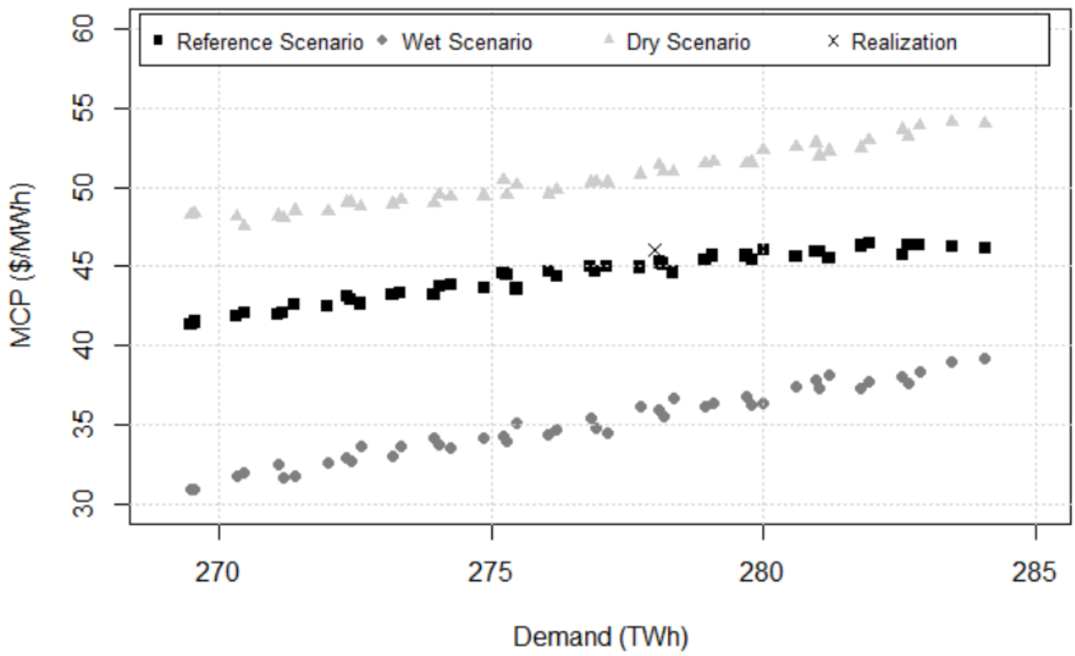


Figure 4.17. Yearly average price forecasts for the year 2016

4.4 Conclusion for Medium-Term Modeling of Electricity Market

In this chapter, an electricity market model considering supply and demand dynamics, and representing the Turkish electricity market under specific conditions is formed for medium-term forecasting activities. Hourly price forecasting for yearly price averages is performed, and scenarios for supply and demand sides are included such that price ranges are obtained rather than single point forecasts.

For this purpose, three main components such as electricity demand modeling, electricity supply modeling and electricity price modeling including a special module to simulate the realistic utilization of storage hydropower generation are developed. This approach has a unique structure considering that it uses all of these models for the same purpose.

The main findings from this chapter can be summarized as follows:

- In order to improve the accuracy of the electricity demand forecasts in the medium-term horizon up to 1 year and on daily basis, GAM is found to have superior performance compared to linear models as it has the improved capability to model the nonlinearities in demand.
- In case of a need for the electricity demand forecasts over 1 year, it has been shown that the utilization of MARS model for monthly electricity demand forecasting has even more improved accuracy and yields a more stable performance.
- An hourly availability factor calculation methodology based on historical data is proposed as a contribution to the existing literature which lacks of detailed representation.
- Based on the proposed modeling approach for electricity price forecasting including a unique methodology that considers the realistic utilization of storage hydropower plants, it has been found that the average electricity price on yearly basis can be modeled with satisfactory accuracy.
- Considering all the uncertainties affecting both supply and demand, electricity prices are formed in a wide range, corresponding to nearly half of the actual price.

In the end, there is still room for improvement for the proposed approach. One of the improvements can be on the availability factors of thermal capacity. The availability factors obtained in the electricity supply modeling section imply that the maintenance schedule for thermal power plants is static, i.e. it does not depend on electricity price or reserve capacity in the system. A more dynamic maintenance plan structure is necessary in order to more realistically reflect the market conditions in the changing market environment and to obtain more realistic price forecasts. Also, the number of market participants can be increased such that the new structure better reflects the market conditions closer to the real operation.

CHAPTER 5

LONG-TERM MODELING OF ELECTRICITY MARKET

In this chapter, the previously proposed electricity market model structure for medium term is improved in order to perform modeling for the long-term horizon. The improvements include two new features such as generator maintenance scheduling (GMS) and generation expansion planning (GEP). Similar to the previous one, the main idea of the long-term electricity market model is to increase the observability for the decision maker in terms of the market conditions such as price, supply, and reserve capacity. The primary aim is to gain insight about the future electricity prices, their patterns, as well as to get prepared and take necessary measures by analyzing the results in detail. Also, in the improved structure, the electricity market clearing mechanism of the previous one remains unchanged, so that electricity generation by fuel is obtained concurrently with the electricity price forecasts, and 1-hour time step is preserved in order to maintain the accountability of results. The possible ways to benefit from the proposed modeling structure is exemplified over various cases for 20 years later from now. The analysis is performed only for the end year, which is 2040. However, the system conditions for any year can be simulated. In the end, the decision maker can rely on a reasonable modeling methodology to recognize how the electricity price can evolve based on a GEP scenario, what the degree of imbalances among supply and demand can be, and to what extent flexibility is needed in the changing market environment.

This chapter is organized according to the parts of the long-term electricity market model. Since electricity demand is assumed to be exogenously given in the long-term horizon, a separate section is not dedicated for electricity demand modeling. Instead, the chapter starts with the improvement provided by a GMS algorithm in the first section. The details of the proposed GMS model structure are given, along with comparisons with the realization and elaborations for future. In the second section, a proper GEP model is searched in line with one of the most prevalent market problems such as the missing money problem. Three distinct modeling approach is presented, and their results are compared. In the third section, the electricity price forecasting activity for the long-term horizon is fulfilled. Since the same modeling routine is used as in medium term, instead of literature review or model description, the possible ways to utilize the proposed modeling approach over four cases based on the improvements achieved in the first and second sections are focused. The chapter is concluded by the findings obtained as a result of the electricity market modeling activity in long term.

This chapter is prepared based on the author's work [116] and [117], the first of which is published as a journal article in IET Generation, Transmission & Distribution in 2020, and the latter one is sent to Applied Energy in 2020.

5.1 Extension of Medium-Term Electricity Supply Modeling to Long-Term by Incorporating Generator Maintenance Scheduling

The objective of this section is to propose a dynamic GMS algorithm for long-term power sector forecasting and planning studies in which electricity price and the resulting supply composition are determined based on merit-order dispatch. The principle idea is to improve the static elecricity supply modeling of thermal power plants presented in the previous chapter and reflect the effect of a reasonable GMS plan which can help obtaining more realistic forecasts in longer horizons. The idea can also be stated as determining the most likely maintenance schedule considering the dynamics of the market, to be applied in future studies for long-term electricity price forecasting and supply planning in order to improve forecasting accuracy. The study addresses the needs of the central planner, not just the system operator, which deals with long-term planning studies.

Thorough availability calculations require the consideration of generator outages which can be in the forms of forced outages or planned maintenance. The forced outage term is considered as random and generally represented by a fixed parameter throughout the planning horizon. On the other hand, the unavailability period of a generator due to planned maintenance is a complex parameter. It is determined with the consensus of the system operator and market participants, which have completely distinct objectives, such that the former considers reliability while the latter considers profit or revenue. The determination of generator maintenance programs in a certain timeframe is generally referred as “generator maintenance scheduling” in the literature.

The supply side of the system is more uncertain than ever due to increasing penetration of intermittent renewable resources, primarily wind, solar and run-of-river type hydropower. Especially for countries in which renewable capacity has yet to saturated, the degree of uncertainty for the supply side will be even higher in the next 5 to 10-year period of time. This aspect makes planning and forecasting studies more challenging.

This section consists of three main parts. The first part presents the proposed GMS methodology, the second part shows the results, and the findings of this section are summarized in the last part. The nomenclature can be followed from the “List of Symbols” part.

5.1.1 Proposed Methodology

This part presents the general concept regarding the GMS algorithm with an emphasis on the calculation of reserve capacity, definition of the scenarios for storage hydropower generation and formulation of the problem along with the constraints. While preparing the methodology, the fundamental concepts accepted by the majority of the literature are predicated.

It is expected that electricity supply modeling will be improved with the inclusion of a proper and basic GMS algorithm. Therefore, it is important to underline that the aim is not to utilize the best GMS algorithm and obtain the optimal result but to reflect the fundamental effects of GMS on available capacity calculation and solve the problem with an acceptable quality of solution in reasonable amount of time.

The properties of the GMS algorithm are represented in Table 5.1.

Table 5.1 Evaluation Criteria for the Proposed GMS Algorithm

Evaluation Criterion	*Proposed GMS Algorithm*
Solution method	Mathematical programming – Integer linear programming
Objective function	Leveling reserve margins (minimizing the maximum of reserves)
Constraints	Fundamental constraints such as supply and demand balance, reserve, duration. However, these are formulated on regional basis and with the inclusion storage hydropower plant flexibility.
Time horizon	Long-term (1 year)
Unit of time period	Weekly (52 decision variables)
Targeted plant type	Only thermal power plants

The leveling reserve margins criterion is said to yield always less riskier solutions than those obtained by the optimization under other reliability criteria [64]. Therefore, this criterion is preferred in the GMS algorithm, with the objective function of minimizing the maximum of reserves in a 52-week horizon, i.e. utilizing integer linear programming technique. While the main objective is the leveling of reserves, in this case net reserve is implied, which is defined as the maximal power that can be generated with the available generating units minus the estimated demand [56].

Minimizing the total cost is not an explicit objective of the GMS algorithm. However, it is included by implication since trying to level reliability tends to yield low generation costs and vice versa [55], [65].

The GMS algorithm presented in this work is performed on weekly basis for 1 year. It means that there are 52 decision variables indicating the maintenance state of a power plant, such as on and off. As such, in long-term forecasting and planning studies, this algorithm can be utilized on weekly basis for each of the years in the planning horizon, but each 52-week period is solved separately to decrease the computational burden. It is possible that the granularity of the existing time resolution, which is 1 week, can be extended to 1 month and narrowed down to 1 day, depending on the user preferences and needs.

Although the existence of hydropower plants is considered in the proposed GMS, only thermal power plant maintenances are scheduled. This can be evidenced from the fact that there is a particular hydro inflow pattern within a year, and low water inflow seasons are generally preferred for maintenance which in turn affect the daily average availability of those power plants only slightly.

Differently from the existing literature, the proposed GMS approaches and models storage hydropower plants in two parts such as must-run generation and price or reserve-dependent generation based on scenarios derived according to historical data. A user-defined parameter is introduced as proposed in [64], but at this time to make a compromise between reliability and hydropower utilization. The structure of the GMS algorithm prevents the utilization of hydropower resources in place of deficient thermal capacity in maintenance. By compromising on hydro calculations by plant; hydropower plants are grouped as a single unit by an equivalent capacity, a certain amount of available energy and with generalized constraints to increase computational efficiency as proposed in [59], [65].

5.1.1.1 Must-Run Renewable Electricity Generation Modeling and Calculation of Reserve Capacity

The methodology for must-run electricity generation modeling and calculation of reserve capacity is represented in Figure 5.1.

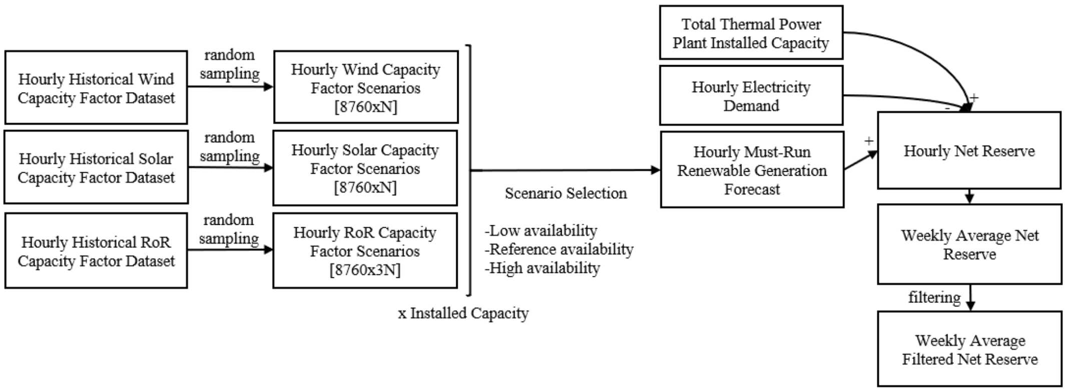


Figure 5.1. Summary of must-run renewable electricity generation modeling and calculation of weekly average reserve capacity

Since intermittent renewable electricity generation is independent from MCP or system reserve, it can be modeled separately while calculating reserve capacity. For wind, solar and run-of-river type hydropower plants, hourly capacity factors for 8760 hours in a year are modeled according to (5.1) - (5.3). The logic is based on random sampling from historical capacity factor set HCF of resource r, with an attempt to take into account the uncertainty by generating a specified number of scenarios, e.g. the number of elements in random scenario set RS is chosen as 100 for this case. No correlation is assumed between run-of-river type hydropower and wind or solar, hence hydro scenario hs – which are selected as low (referring to dry season), reference and high (referring to wet season) based on hydropower plant generation capability as proposed in [95] – does not affect wind and solar generation. The calculation of run-of-river hydropower plant generation differs in terms of the function α via which the sampling region is specified according to the hydro scenario selection. The values that α gives with respect to hs are selected based on the cumulative distribution function of the historical data in the period of 2008-2018, such that random selection on hourly basis is performed from the 1st quartile for low, from the interquartile range for reference and the 3rd quartile for high hs.

$$CF_{\overline{h},r}^{rs,hs} = smp\left(HCF_{\underline{h},w,r}\right), \forall\overline{h}, \underline{h}, w, r \in WND \tag{5.1}$$

$$CF_{\overline{h},r}^{rs,hs} = smp\left(HCF_{\underline{h},m,r}\right), \forall\overline{h}, \underline{h}, m, r \in SOL \tag{5.2}$$

$$CF_{\overline{h},r}^{rs,hs} = smp\left(qnt\left(HCF_{\underline{h},w,r}, \alpha(hs)\right)\right), \forall\overline{h}, \underline{h}, w, r \in ROR \tag{5.3}$$

The must-run renewable generation MRG is calculated for the intermittent generation for all hours of a year according to (5.4). It is on regional basis in order to force the constraints regarding regional supply and demand balance. The regional generation is computed with the multiplication of the capacity factor, installed power and the value of the function ϕ which yields the capacity share of resource r in region rg. The capacity factors by regions are assumed to be constant. Availability scenario as, which can be labeled as low, reference or high, is used to determine how the must-run generation by random scenarios is to be behaved such that the function θ operates as the minimum, average and maximum function, respectively.

$$MRG_{\overline{h},rg}^{as,hs} = \theta_{rs}(as)\left(\sum_{r\in INT} CF_{\overline{h},r}^{rs,hs} * IC_{\overline{h},r} * \phi(r, rg)\right), \forall\overline{h}, rg \tag{5.4}$$

The reserve capacity, or net reserve, by region and scenario is calculated, as stated in (5.5), at hourly time intervals by the subtraction of the thermal installed capacity from the residual demand which is stated as the demand P^D minus the must run renewable generation MRG. Here, as in the case of the installed capacity, the overall demand is allocated to regions by the function ψ, the values of which represent the share of each region, and are determined according to the previous year's realization.

Only one scenario is assumed for the demand, but possibly it can also take values according to various demand scenarios, which would result in increasing the number of scenario outputs.

$$NR_{\bar{h},rg}^{as,hs} = \sum_{r \in THR} IC_{\bar{h},r} * \phi(r,rg) - \left[P_{\bar{h}}^{D} * \psi(rg) - MRG_{\bar{h},rg}^{as,hs}\right], \forall \bar{h}, rg \tag{5.5}$$

The reserve capacity is filtered by a median filter with a step number MFS, which is useful to eliminate spikes due to significantly lower demand behavior at national holiday seasons. The filtered net reserve FNR is calculated as in (5.6) on weekly and regional basis by availability and hydro scenarios. The choice of MFS should be an odd number, and it is selected as low as possible, e.g. 3 in this thesis, to prevent the reserve capacity not to be unduly flattened.

$$FNR_{w,rg}^{as,hs} = med\left(ave_{w \to \bar{h}}\left(NR_{\bar{h},rg}^{as,hs}\right), MFS\right), \forall w, \bar{h}, rg \tag{5.6}$$

The comparison of the overall weekly average NR and FNR is represented by Figure 5.2.

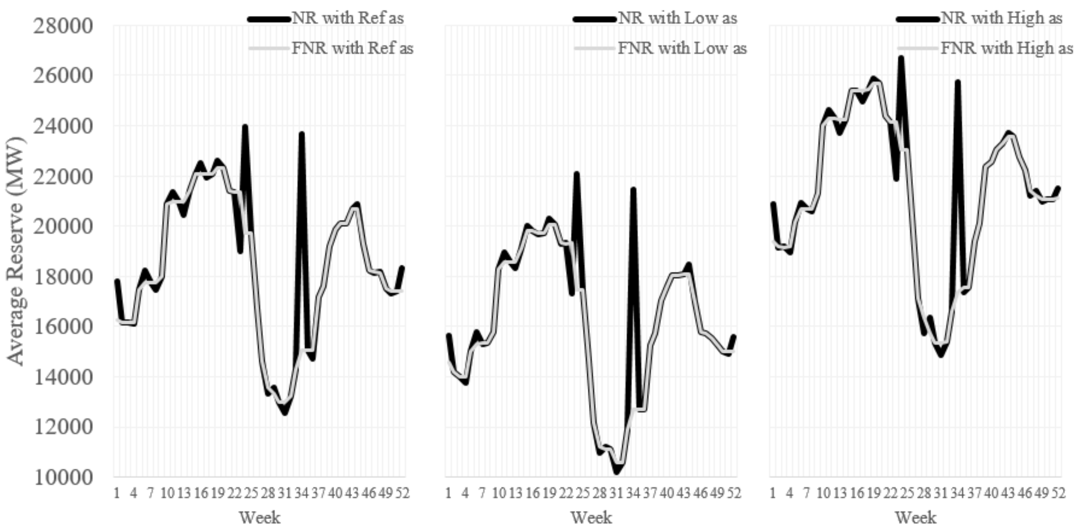


Figure 5.2. Weekly average and filtered net reserve by availability scenarios such as reference (left), low (middle) and high (right)

If FNR weren't calculated and used as the reserve parameter, the selected GMS algorithm, which tries to level average weekly reserves across the forecast horizon, would select peak reserve weeks as the best available places for maintenance, which would be misleading. FNR does not include the availability of storage hydropower plants due to the complexity such that their ability to generate electricity is limited and subject to specific constraints unlike thermal resources.

5.1.1.2 Definition of Capacity Factor Levels and Scenarios for Storage Hydropower Generation

The methodology for the definition of capacity factor levels and scenarios for storage hydropower generation is represented in Figure 5.3.

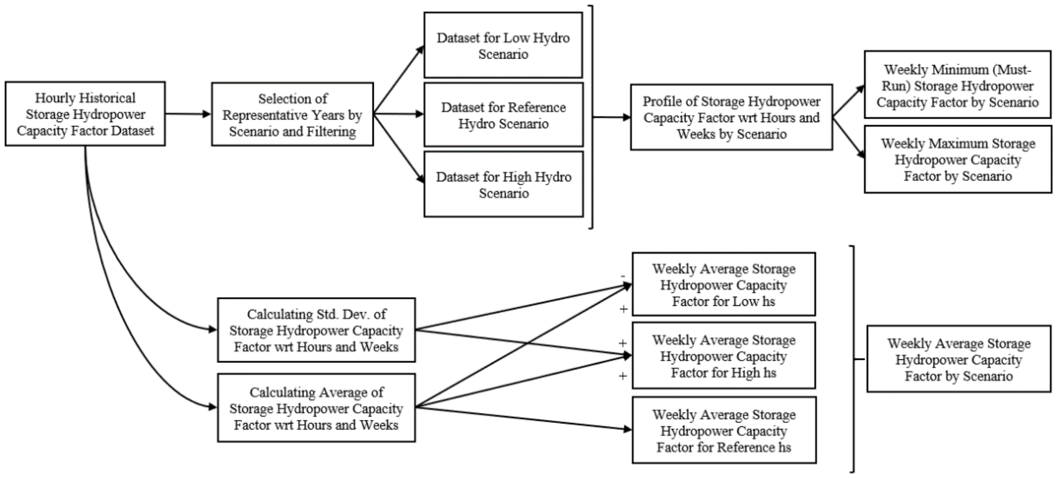


Figure 5.3. Summary of definition of capacity factor levels and scenarios for storage hydropower plant generation

As mentioned previously, instead of performing calculations for every storage hydropower plant, these units are grouped as a single one by an equivalent capacity, a certain amount of available energy and with generalized constraints to increase computational efficiency as proposed in [59], [65], [95]. For these type of power plants, there are applications of SDDP (stochastic dual dynamic programming) [118], which is widely utilized in the literature. With SDDP, each power plant can be modeled individually with stochastic inflow modeling. However, in a long-term study aiming hourly time resolution, using SDDP would be inappropriate in terms of highly increased complexity and computation time, hence a simpler model for storage hydropower plant generation is preferred, and the scenarios for these are defined based on hourly historical capacity factor data.

As compatible with the scenarios for run-of-river type hydropower, hydro scenarios for storage hydropower are determined as low, reference and high, based on the hourly capacity factor data in the period of 2008-2018. The same notation is used similar to run-of-river type hydropower in order to limit the number of scenarios as much as possible without loss of any valuable information and to represent the most probable scenario with reference as well as drawing a frame at the lower and upper boundaries based on historical instances of data as mentioned in [95]. In order to be able to represent the contribution of storage hydropower resources on reserve levels, three conditions are determined as to become constraints in the GMS problem later. These are weekly average, minimum and maximum capacity factor levels as represented in (5.7) - (5.9). (5.7) calculates the weekly average capacity factor by scenario. The first part of the equation calculates weekly averages from hourly historical data, and in the latter part the function δ calculates the standard deviation of the first part and operates according to the designated hs. If hs is low or high, the second part is subtracted or added to the first term accordingly, and no operation is performed in case of reference hs.

$$WCF_{w}^{ave,hs} = ave_{w \to \underline{h}}\left(HCF_{\underline{h},w,r}\right) + \delta\left(hs, HCF_{\underline{h},w,r}\right), \forall w, \underline{h}, r \in STO \qquad (5.7)$$

(5.8) defines the minimum or must-run generation level for storage hydropower plant generation, and it has two parts. In the first part, for each week w, the minimum of hourly average capacity factors for the relevant hs is calculated. The mapping from hydro scenarios to years means that only data of corresponding low, reference and high water-inflow years are to be used for the respective hs. The second part of the equation yields how much additional generation can be considered in the must-run category. Firstly, the difference of average and minimum hourly capacity factors is computed on weekly basis, and the resulting levels are multiplied by the function β, which determines the additional storage hydropower plant generation base effect. This function takes values 0, 0.25 and 0.50 for low, medium and high-water inflow seasons in a year.

$$\begin{aligned} WCF_w^{min,hs} &= min_w\left(ave_{hs\to y,w,\underline{h}}\left(HCF_{\underline{h},w,y,r}\right)\right) \\ &+ \left[ave_w\left(ave_{hs\to y,w,\underline{h}}\left(HCF_{\underline{h},w,y,r}\right)\right)\right. \\ &- \left.min_w\left(ave_{hs\to y,w,\underline{h}}\left(HCF_{\underline{h},w,y,r}\right)\right)\right] \\ &* \ \beta(w), \forall w, \underline{h}, y, r \in STO \end{aligned} \tag{5.8}$$

(5.9) determines the maximum level that weekly capacity factor can reach by hs. It is specified by an offset parameter N upon the minimum level, which is calculated according to (5.10). This parameter is fixed for all possible hs.

$$WCF_w^{max,hs} = WCF_w^{min,hs} + N, \forall w, r \in STO \tag{5.9}$$

$$\begin{aligned} N = ave &\left[max_w\left(ave_{w,\underline{h}}\left(HCF_{\underline{h},w,r}\right)\right)\right. \\ &- \left.min_w\left(ave_{w,\underline{h}}\left(HCF_{\underline{h},w,r}\right)\right)\right], \forall w, \underline{h}, r \in STO \end{aligned} \tag{5.10}$$

The resulting weekly average, minimum and maximum capacity factor series by hydro scenarios reference, low and high are shown in Figure 5.4. In this figure, the straight lines are the expected capacity factor values while the dotted lines are the must-run levels and the dashed lines are the maximum levels that can be achieved in weekly terms, i.e. 168-hour averages. That is, the utilization of storage hydropower plants can be anywhere between minimum and maximum levels. However, as described in the next part, since this capacity should not be unduly used, e.g. excessive levels of capacity factors should not be reached in order to compansate the capacity in maintenance, especially in winter and summer seasons when load is high, storage hydropower plant utilization becomes part of the objective function.

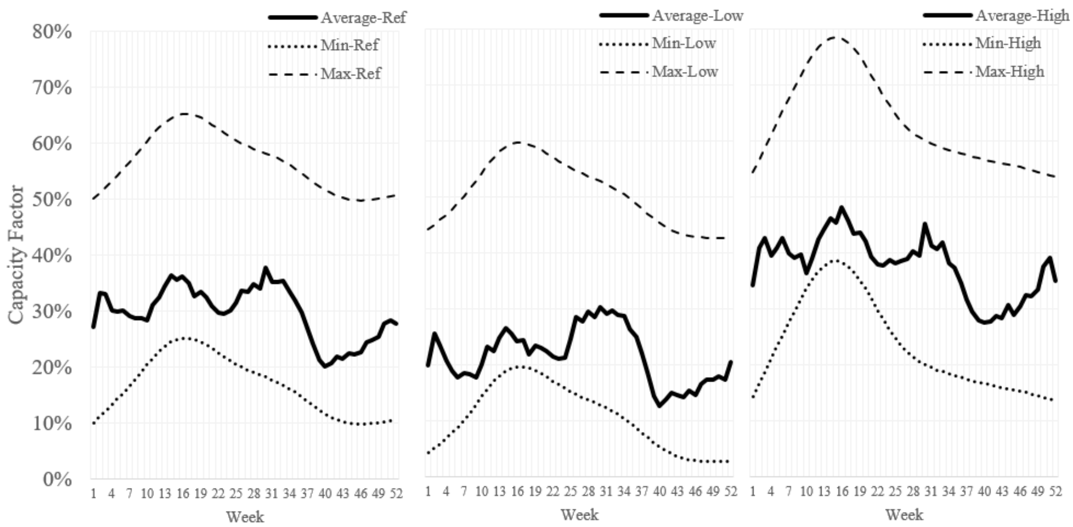


Figure 5.4. Weekly average (straight), minimum (dotted) and maximum (dashed) capacity factor levels by storage hydropower plant generation scenarios such as reference (left), low (middle) and high (right)

5.1.1.3 GMS Problem Formulation

The GMS problem is formulated as a multi-objective optimization problem shown in (5.11).

$$min \begin{Bmatrix} z \\ v \end{Bmatrix} \tag{5.11}$$

The primary objective is defined as the leveling of the weekly average reserve capacity by minimizing the variable z, the maximum of weekly reserves. The second objective is minimizing the variable v, the maximum of weekly storage hydropower plant reserves. These two objectives together try the utilization of water resources in compatible with must-run generation level as much as possible through a parameter which is the amount that allows second objective function to degrade the first one.

The weighted sum method is applied as a part of multi-objective optimization problem. Here, since this is an integer problem, there is the risk for the solutions to be Pareto-dominated and not belonging to the optimal Pareto set [119], [120]. Nevertheless, considering that the aim in this thesis is not to find the best GMS result but to obtain a reasonable solution to be used in later stages, finding a solution that is close to optimality is evaluated to be acceptable.

The constraints are defined through (5.12) - (5.21). (5.12) frames the initial and end point conditions for maintenance decision. (5.13) is the duration constraint, (5.14) guarantees the contiguity of maintenance states, and (5.15) relates the previous two constraints. (5.16) is the reformulation of the reserve capacity with the subtraction of the capacity decided to be in maintenance and addition of expected storage hydropower plant generation. (5.17) - (5.19) put minimum, maximum and yearly average capacity factor constraints for storage hydropower plant generation. (5.20) calculates the weekly average storage hydropower plant reserves. (5.21) forces the weekly capacity in maintenance by region, to be within predetermined safety margins, which are specified according to regional supply and demand balance.

$$x_{w,g} = 0, \forall w \in \{0,53\}, g \tag{5.12}$$

$$\sum_{w} x_{w,g} = NM_g, \forall w, g \tag{5.13}$$

$$\sum_{w} y_{w,g} = 1, \forall w, g \tag{5.14}$$

$$x_{w,g} - x_{w-1,g} + y_{w,g} \geq 0, \forall w \in \{W, 53\}, g \tag{5.15}$$

$$z \geq \sum_{rg} FNR_{w,rg}^{as,hs} - \sum_{g} IC_g * x_{w,g} + \sum_{w} ave_{w\to\overline{h}}\left(IC_{\overline{h},r}\right) * u_w^{hs}\ , \forall rg, w, g, \overline{h}, r \in STO \quad (5.16)$$

$$u_w^{hs} \geq WCF_w^{min,hs}, \forall w \quad (5.17)$$

$$u_w^{hs} \leq WCF_w^{max,hs}, \forall w \quad (5.18)$$

$$\sum_{w} u_w^{hs} = \sum_{w} WCF_w^{ave,hs} \quad (5.19)$$

$$v \geq WCF_w^{max,hs} - u_w^{hs}, \forall w \quad (5.20)$$

$$\sum_{rg\to g} x_{w,g} * IC_g \leq MC_{w,rg}^{max}, \forall rg, w, g \quad (5.21)$$

5.1.2 Results

The presented algorithm is tested with the real data of the Turkish system. The year 2018 is selected as the base year, and the future calculations are performed for the year 2028 in order to detect whether the expected average capacity to be maintenance by weeks changes considerably. The total installed capacity is 88.6 GW as of the end of 2018, with shares of 29% natural gas, 12% lignite and 10% hard coal. 32% of the capacity is hydropower of which 23% is storage and 9% is run-of-river hydropower. The remaining 17% belongs to the other types of renewable resources such as mostly wind and solar.

For simplification, the minimum capacity limit for thermal capacity to be in maintenance is determined as 10 MW. That is, the facilities under 10 MW are neglected. The amount of total maintenance capacity is 30 GW and 160 units in 2018, and with the addition of new thermal power plants according to the capacity projection, it would increase to 44 GW and 184 units. In terms of renewable resources, 10 GW wind and 20 GW solar capacity additions are assumed. The total electricity demand is fixed for all random scenarios, and it is around 304 TWh in 2018. A demand increase of 3% per year is assumed until 2028, in line with the official electricity demand projections.

The study is performed in R using Gurobi as solver with a PC of 2.60 GHz processor and 16 GB RAM. The number of decision variables and constraints is 17174 and 9797, respectively, for the year 2018. The execution time, corresponding duality gap and mean absolute differences among resulting weekly average reserve capacity compared to the best available solution (Case III) are reported in Table 5.2. In 18 seconds, the duality gap reduces to 0.50%. Considering that zero duality gap couldn't be reached in 48 hours, the duality gap of 0.30% is selected as a threshold to terminate the execution and save the results with 0.76% difference compared to Case III which is the best among other cases.

Table 5.2 Comparison of Results in terms of Time, Duality Gap and Mean Absolute Differences

Cases	*Time*	*Duality Gap (%)*	*Mean Abs. Diff (%)*
I	18 sec	0.50	1.37
II	3 min	0.30	0.76
III	6 hours	0.14	-

The results are presented in terms of comparison with the realization and the effects of hydro scenarios, capacity evolution and hydro optimization on maintenance schedules. The comparison of GMS results by availability scenarios with the realization is shown in Figure 5.5.

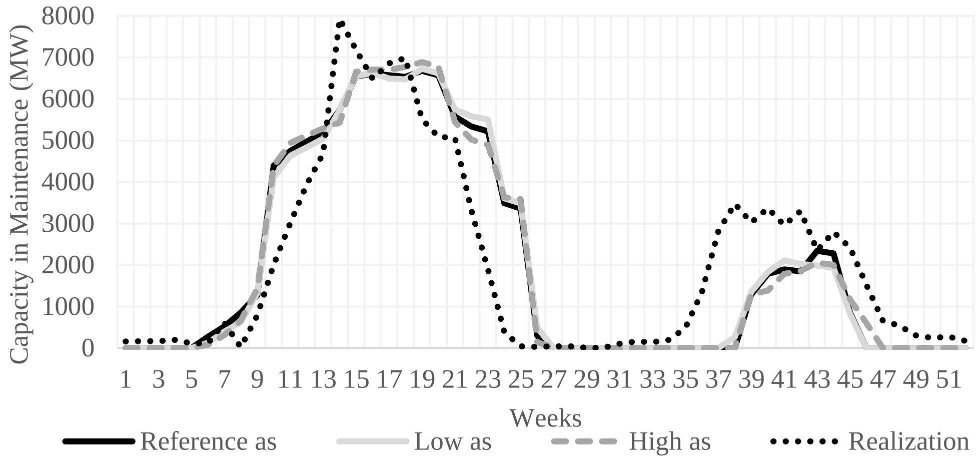


Figure 5.5. Weekly average capacity in maintenance by availability scenarios and realization in 2018

The hydro scenario is assumed to be reference case and fixed. The differentiation across the availability scenarios seems to be limited, hence it is concluded that assuming the worst and best cases of availability for all weeks do not have a significant impact on the resulting weekly average capacity to be in maintenance. The general profiles of the GMS results and realization match each other, i.e. the majority of the maintenance occurs in spring season with additional considerable amounts in fall season, as well as approximately no maintenance in winter and summer seasons. Since this is a simplification of reality and does not include all information of the system and constraints, there can be differences such as;

- in reality the rise and fall of maintenance capacity occurs later and earlier in spring season, respectively,
- and the amount of maintenance capacity is higher in fall season.

The first distinction can be improved by considering also various demand scenarios instead of assuming a fixed demand since the demand uncertainty is significant especially during season changes, i.e. from winter to spring and from spring to summer. As such, taking into account demand scenarios that include winter-like weather conditions in early spring and summer-like weather conditions in late spring would surely increase the expected demand for those weeks, thereby would reduce the reserve capacity, the amount of capacity to be in maintenance and better approximate the conditions in reality. The second distinction can be corrected with the inclusion several constraints such as manpower and some unit specific ones.

The effect of hydro scenarios on the GMS results is presented in Figure 5.6. In this case, the availability scenario is assumed to be reference case and fixed. The pattern of schedules does not change. However, across hydro scenarios, over 2000 MW capacity may need to be relocated for maintenance in order to sustain optimality. Therefore, reliable hydropower availability forecasts to define appropriate hydro scenarios can increase the reliability of the system. This is a more valuable evaluation from the view of system operator for medium-term planning. As soon as the newest information regarding the hydropower availability is obtained by the system operator, and it contradicts with the previous one, the system operator should make necessary adjustments in terms of the amount of capacity to be taken offline by cooperating with generator companies. Also, from the long-term planning perspective, it is possible to gain insight about at what level the margins for the amount of maintenance capacity by weeks, months and seasons will be.

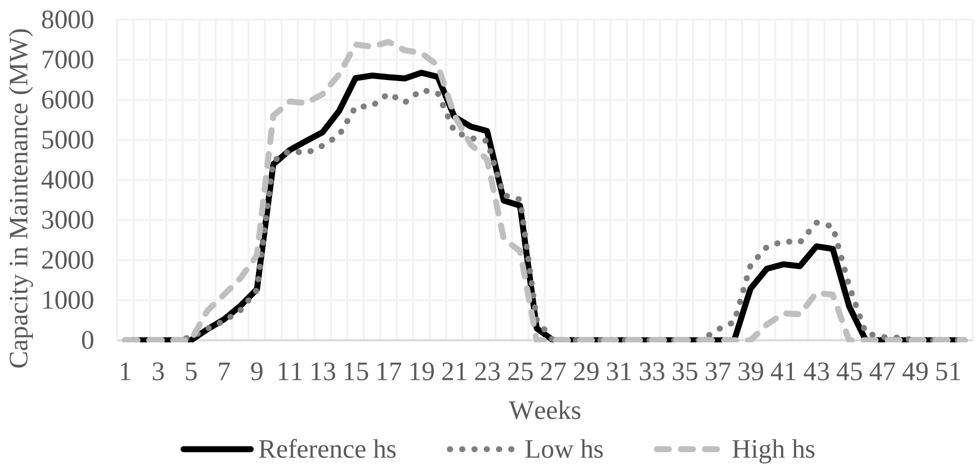


Figure 5.6. Weekly average capacity in maintenance by hydro scenarios in 2018

The effect of the capacity evolution from 2018 to 2028 is shown in Figure 5.7. The pattern of the maintenance schedules fairly changes although the majority of the capacity is taken offline in spring season. There are hardly any changes for winter season, but the most prominent difference is the maintenance capacity in summer season. The amount of that capacity can further increase with the evolution of demand such that the amount of demand growth across all seasons gets closer implying higher demand growth rates in spring. This is a finding supporting the inclusion of the generation maintenance effect in forecasting and planning studies.

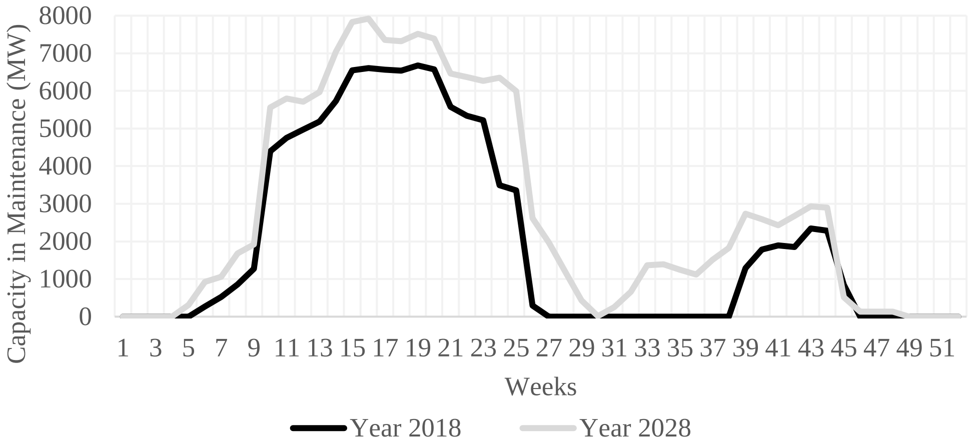


Figure 5.7. Comparison of weekly average maintenance capacity for reference hydro scenario in 2018 and 2028

The effect of the hydro optimization procedure on the resulting maintenance schedules can be evaluated with Figure 5.8 - Figure 5.9. This procedure seems not to have a significant impact for the year 2018. However, the future electricity supply composition can change the issue such that without an optimization procedure, the capacity can be taken into maintenance in winter season with the additional utilization of storage hydropower plants, as can be seen in Figure 5.9, from week 45 to 52 and from week 1 to 5. That means risking the water resources at winter season with the lowest expectation of water inflow throughout a year by utilizing storage hydropower plants more for compensating additional maintenance capacity, which is highly undesirable in terms of reliability point of view. In longer periods of time horizon such as 20-year and 50-year, this finding can help better description of future system conditions while performing long-term forecasting and planning studies.

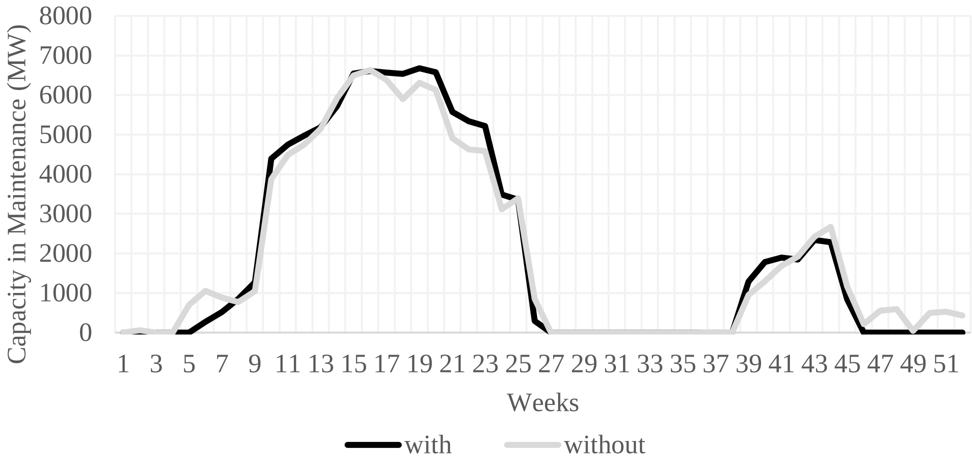


Figure 5.8. Comparison of GMS results with and without utilization of hydro optimization procedure in 2018

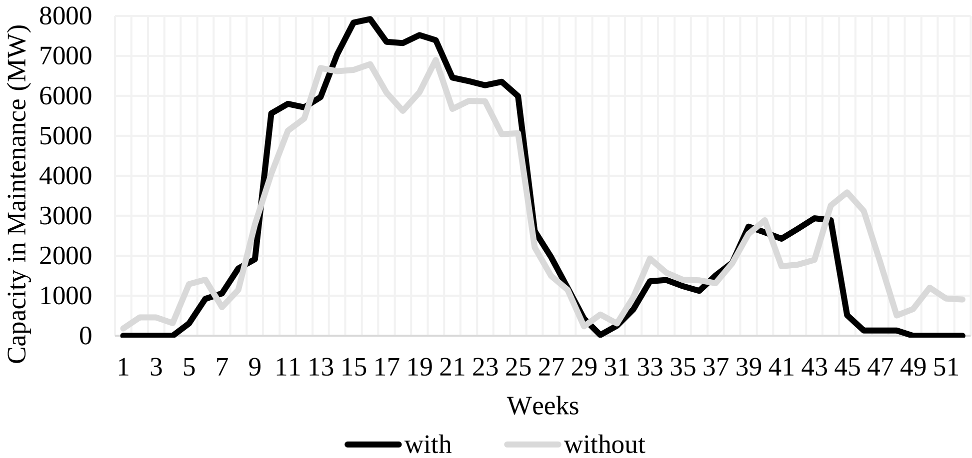


Figure 5.9. Comparison of GMS results with and without utilization of hydro optimization procedure in 2028

The weekly average reserve capacity forecasts with and without GMS algorithm is shown in Figure 5.10. If the GMS algorithm is not used, and maintenance in 2028 is static, i.e. determined according to the maintenance calendar in 2018, the lowest reserve weeks coincide with spring and autumn in which demand is lowest. This can also be followed from Figure 5.11.

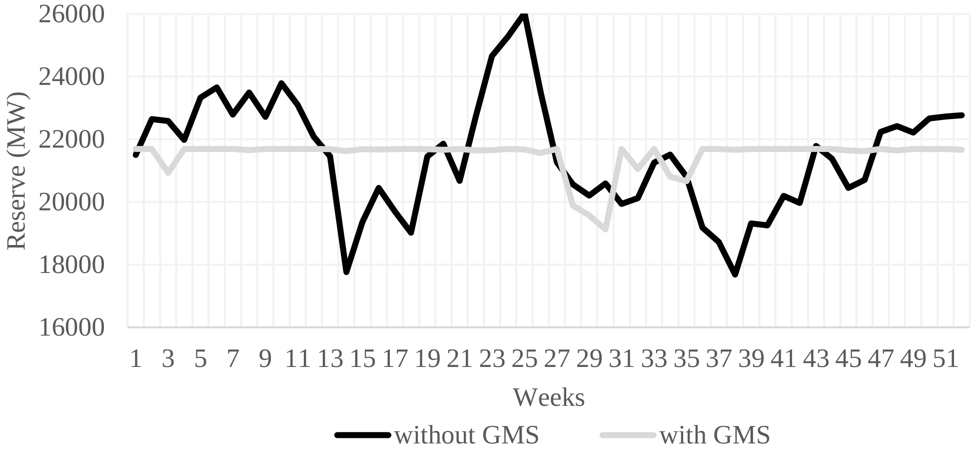


Figure 5.10. Weekly average reserve capacity forecasts with and without GMS algorithm in 2028

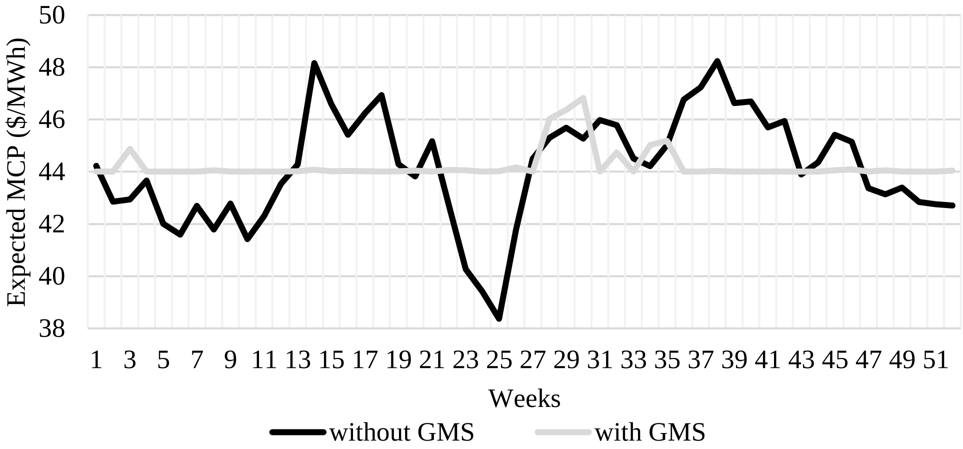


Figure 5.11. Weekly average expected MCP with and without GMS algorithm in 2028

Figure 5.11 represents the weekly average expected MCP calculated according to the reserve-MCP relation given in Figure 2.11. Without GMS, the highest expected MCPs occur in spring and fall and the lowest ones occur in summer and winter. This is on the contrary of what happens in 2018 and quite unlikely given that the demand is higher in summer and winter. Thanks to the GMS algorithm, the resulting dynamic GMS yields more evenly distribution of reserves as well as expected MCPs, in parallel with the assumption that the system operator and generators will logically follow their own objectives.

5.1.3 Discussion

In this section, a reasonable GMS algorithm is proposed for long-term power sector forecasting and planning studies to be utilized in the stage of available capacity calculation. It can also be used for the medium-term time horizon having at least 1-year forecast period. Storage hydropower plants are modeled as must-run and price-dependent generation in order to reflect their effect on GMS more realistically.

The main contributions and revelations of this section are listed as follows:

- For long-term forecasting and power sector planning studies that simulate the electricity market and yield detailed results in hourly resolution such as the electricity generation, price, supply and demand balance, etc., a reasonable GMS algorithm is designed to be taken into consideration while calculating available capacity by power plant, which is critical for the merit-order dispatch.
- For storage hydropower plant-dominant power systems, the dynamics of storage hydropower plant generation capability, which can adjust its generation level according to MCP and also to reserve capacity, is included in the GMS algorithm, along with the inclusion of regional constraints on maintenance considering regional supply and demand balance. Storage hydropower plants are modeled as must-run and price-dependent generation, differently from the existing literature, in order to reflect their effect on GMS more realistically.
- In long term, e.g. a 10-year period, the results indicate that the future expected profile of maintenance schedules is significantly different from that

of today. Therefore, it is advisable that the utilization of the proposed GMS method can provide a more qualified modeling structure and yield improved results in long-term power sector forecasting and planning studies, instead of neglecting or reflecting the maintenance effect through just a fixed maintenance parameter.

- Three different hydropower capacity factor scenarios are determined according to water inflow characteristics that can vary across years. These are labelled as low, reference and high. The effect of those scenarios on maintenance scheduling is demonstrated. The variation among capacities to be taken into maintenance is significant, hence for medium-term operation, the most recent information regarding water inflow should be considered. This type of utilization of the GMS algorithm can also be beneficial to the system operator during or prior to the negotiation process for maintenance planning with generator companies.

5.2 Generation Expansion Planning Considering Missing Money Problem

The objective of this section is to find and apply a proper methodology for installed capacity forecasts to be utilized in the long-term utilization of the electricity market modeling methodology proposed in the thesis. While searching for a reasonable generation fleet of the future, this section investigates whether the missing money problem, which is a widespread phenomenon in today's liberalized electricity markets, can be mitigated in GEP studies, and whether the conventional approach to GEP problem should be updated.

Most of the electricity sector investments is in the field of power supply [121]. However, in mature wholesale electricity markets, the problem that thermal plant generators exposed to MCPs are getting less profitable or even unprofitable is becoming serious. With policies encouraging liberalization of electricity markets, renewable energy integration and competition, considerable amount of investments were realized which resulted in weakened price signals based on short-term marginal cost pricing and reduced profitability of existing generators [122].

This problem in wholesale markets is in parallel with what has been called as the "revenue adequacy" or "missing money" problem which is of growing concern [123]. The missing money problem arises when price caps in wholesale markets is too low which results in prices below market clearing levels in scarcity conditions; or ancillary services like flexibility, ramp rates, frequency response etc. and balancing services are inadequately remunerated; or energy prices are inefficiently low which have been depressed by the expansion of subsidized intermittent generation and other subsidized investments [123], [124]. As a result, some of the plant investors are unable to recuperate their investment and other fixed costs. Recently, low energy prices are prevalent across many liberalized markets in both developing and developed countries thanks to decreasing hydrocarbon prices, massive amount of RES integration and stagnant demand [125], [126], [4].

In such an environment where the majority of plants without guarantees are struggling, and there is need for reliable system operation with adequate supply, this study investigates whether it is possible to mitigate the missing money problem in GEP to find balance from both investor's and central planner's view by reconsidering the GEP problem. To do so, firstly based on the central planner's way of thinking, the standard GEP problem with 'minimization of total system costs including investment and operation costs', secondly the GEP problem with 'maximization of generators' profit' as objective functions are presented and solved. Then, a third problem is created aiming to minimize the generator cost including both investment & operation cost and the support needed by existing plants to cover their investment and fixed costs at least in the debt repayment period while preserving a targeted level of reserve. Utilizing three different approaches, the following questions are addressed:

- How much investment decisions differ across various objective functions such as minimization of investment & operation cost, maximization of generators' profit and minimization of generators' cost including total support needed by existing plants?

- Is it possible to fully eliminate the missing money in a GEP study?
- Considering that there is significant interest for investing in renewable energy capacity, hence this new capacity is auctioned by the central planner, how much renewable capacity should be auctioned to mitigate the missing money problem?
- Is it reasonable to expect the mitigation of the missing money problem in a GEP study?

This section consists of three main parts. The first part is devoted to the description of models based on various objective functions and the description of technical data. The second part presents the results for all cases created based on profit margin of plants, age of generation fleet and demand forecast. In the last part, the findings of this section are summarized. The nomenclature can be followed from the "List of Symbols" part.

5.2.1 Proposed Models and Assumptions

Following the literature review process in Chapter 3, it is concluded that to address the specific needs in this study and answer the questions based on profitability and support need, an iterative procedure can be proposed considering the need for simplification as the previously mentioned MIBLP structure in Chapter 3 has its own limitations. This procedure aims to find a solution having an acceptable quality. In this respect, the models are introduced as follows:

- Standard GEP model with UC constraints (Model I): It runs a GEP algorithm in line with the constraints used in a standard GEP study. The UC constraints are considered. It is analogous with central planners' approach to minimize total investment and operation costs. The GEP approach in EST (Energy System Model for Turkey) [127], which is based on the mathematical formulation of PRIMES model [79] is a good example and used as basis for Model I. Model I can also be called as the conventional GEP model.

- GEP model aiming generators' profit maximization (Model II): It tries to maximize the profit of each candidate generator so that the feasible units are commissioned. An investment is realized if found feasible according to the MCPs in the operation period. This is analogous with investors' approach. The investment (Model II-A) and operation (Model II-B) problems are decomposed and solved in an iterative process. Model II is used to validate Model I and reveal the possible differences among the results of those two models. Model II can also be called as a price-based GEP model.
- GEP model aiming generators' total cost minimization including support need (Model I-S): It tries to minimize the support needed by existing plants and investment & operation costs. Here, the term 'support' is used as synonymous to 'incentive' required for those unable to recuperate the capital cost of investments and aim to return at least the capital cost in payback period. It is analogous with central planners' behavior aiming to prevent the decommissioning of young plants having already been in debt repayment period in the presence of moderate amount of demand growth and the approach to keep a reasonable amount of reserve for system safety.

5.2.1.1 Formulation of Model I

The objective function is the minimization of all investment and operation costs as in (5.22). The investment cost is represented by annualized capital cost. The operation costs include variable generation cost, fixed operation & maintenance cost, start-up cost, renewable energy curtailment cost, load shedding and reserve deficiency cost. All costs are discounted and expressed in base year monetary terms.

$$
min \sum_{t} (1+\Gamma)^{T0-t} * \left\{ \begin{array}{c} \sum_{o} F_{o,t} * \left[\begin{array}{c} \sum_{g} \left(p^{G}_{g,o,t} * C^{TV}_{g,t}\right) + \sum_{g \in G^{ul}} su_{g,o,t} * C^{SU}_{g,t} + \\ \sum_{g \in G^{re}} p^{RES}_{g,o,t} * C^{RES}_{g,t} + \\ \sum_{s} \left(\left(st^{C}_{s,o,t} + st^{D}_{s,o,t}\right) * C^{TV}_{s,t} \right) + p^{LS}_{o,t} * C^{LS}_{o,t} + \\ p^{RS}_{o,t} * C^{RS}_{o,t} + \end{array} \right] + \\ \left[\sum_{a \in G \cup S} \left(ic_{a,t} * \left(C^{AC}_{a,t} * I_{a,t} + C^{OMF}_{a,t} * \Lambda_{a,t} \right) \right) \right] \end{array} \right\} \tag{5.22}
$$

The constraints of Model I are represented in Appendix A through (A.1) - (A.35). They are related to supply-demand balance, load shedding limit, capacity limit by fuels as well as generation limit, minimum stable generation limit, start up & shut down conditions, minimum uptime & downtime for power plants, and operational constraints of storage facilities.

5.2.1.2 Formulation of Model II

Model II has two components such as Model II-A (investment model) and Model II-B (operation model). Model II-A takes investment decisions based on profit maximization of candidate plants and storage facilities as in (5.23).

$$
max \sum_{t} (1+\Gamma)^{T0-t} * \left(\sum_{g \in G^{C}} m^{P}_{g,t} + \sum_{s} m^{P}_{s,t} \right) \tag{5.23}
$$

The definition of profit, revenue and cost are presented in (5.24) - (5.27). (5.24) shows the relation among profit, revenue and cost. Revenues for any facility depend on the expected MCP, expected operating hours and installed capacity (5.25). Costs for generators and storage facilities are differentiated by (5.26) and (5.27), the latter of which includes the MCP for charging hours as additional cost.

$$m_{a,t}^{P} = m_{a,t}^{R} - m_{a,t}^{C}, \forall a, t \tag{5.24}$$

$$m_{a,t}^{R} = E_{a,t}^{MCP} * E_{a,t}^{OPH} * ic_{a,t}, \forall a, t \tag{5.25}$$

$$m_{g,t}^{C} = \left(C_{g,t}^{AC} + C_{g,t}^{OMF} + C_{g,t}^{TV} * E_{g,t}^{OPH}\right) * ic_{g,t}, \forall g, t \tag{5.26}$$

$$m_{s,t}^{C} = \left[C_{s,t}^{AC} + C_{s,t}^{OMF} + \left(C_{s,t}^{TV} + E_{s,t}^{MCPC}\right) * E_{s,t}^{OPH}\right] * ic_{s,t}, \forall s, t \tag{5.27}$$

The constraints related to investment such as (A.1) - (A.4), (A.23) and (A.25) - (A.35) are taken from Model I and inserted into Model II-A.

At each iteration, Model II-A is updated based on the rules in (5.28) - (5.31). In order to limit possible oscillations between Model II-A and II-B, the change across iterations, i and $i-1$, in terms of both the amount of capacity to be commissioned for plants without unit size limitation and storage facilities (5.28) and the number of units to be commissioned (5.29) are restricted. (5.30) tells that the change in the amount of capacity in (5.28) for the consecutive iterations is limited by the parameter B^{ull}. Similarly, the change in the number of units is limited to 1 (5.31).

$$p_{g/s,t}^{C\,(i)} = \begin{Bmatrix} p_{g,t}^{C\,(i-1)} + \Omega * B^{ull}, \forall g \in G^{C,ull}, t \\ p_{s,t}^{C\,(i-1)} + \Omega * B^{ull}, \forall s, t \end{Bmatrix} \tag{5.28}$$

$$iu_{g,t}^{C\,(i)} = iu_{g,t}^{C\,(i-1)} + \Omega * B^{ul}, \forall g \in G^{C,ul}, t \tag{5.29}$$

$$\text{where } \Omega = \begin{Bmatrix} 1, if\ p_{g,t}^{C} > p_{g,t}^{C\,(i-1)} \\ -1, if\ p_{g,t}^{C} < p_{g,t}^{C\,(i-1)} \\ 0, otherwise \end{Bmatrix} \tag{5.30}$$

$$\text{and } \Omega = \begin{Bmatrix} 1, if\ iu_{g,t}^{C} > iu_{g,t}^{C\,(i-1)} \\ -1, if\ iu_{g,t}^{C} < iu_{g,t}^{C\,(i-1)} \\ 0, otherwise \end{Bmatrix} \tag{5.31}$$

In Model II-B, operational decisions are determined for all facilities based on minimization of total operation costs (5.32). These costs are variable cost, start up cost, renewable energy and load shedding costs.

$$min \sum_t (1+\Gamma)^{T0-t} * \left\{ \sum_o F_{o,t} * \left[\begin{array}{c} \sum_g \left(p^G_{g,o,t} * C^{TV}_{g,t}\right) + \\ \sum_{g \in G^{ul}} su_{g,o,t} * C^{SU}_{g,t} + \\ \sum_{g \in G^{re}} \left(p^{RES}_{g,o,t} * C^{RES}_{g,t}\right) + \\ \sum_s \left(\left(st^C_{s,o,t} + st^D_{s,o,t}\right) * C^{TV}_{s,t}\right) + \\ p^{LS}_{o,t} * C^{LS}_{o,t} \end{array} \right] \right\} \tag{5.32}$$

The operational constraints such as (A.5) - (A.22) are taken from Model I and inserted into Model II-B.

After Model II-B runs, the model is updated at each iteration based on the rules in (5.33) - (5.36). In (5.33), the MCPs calculated in Model II-B are represented by $mcp_{o,t}$. In order to limit the amount of oscillations between consecutive iterations i and $i-1$, the recently calculated MCP is weighted by the parameter B, and the remaining part is weighted by the previously fed MCP's to Model II-A. The expected MCPs for generation and discharging activities are calculated based on the generation and discharging pattern obtained from Model II-B (5.34). Similarly, the expected MCP for charging activity is calculated separately (5.35). The expected number of operating hours in a year is calculated in (5.36).

$$mcp^{(i)}_{o,t} = mcp^{(i-1)}_{o,t} * (1-B) + mcp_{o,t} * B, \forall o,t \tag{5.33}$$

$$E^{MCP\,(i)}_{g/s,t} = \left\{ \begin{array}{l} \dfrac{\sum_o p^G_{g,o,t} * F_{o,t} * mcp^{(i)}_{o,t}}{\sum_o p^G_{g,o,t} * F_{o,t}}, \forall g,t \\ \dfrac{\sum_o st^D_{s,o,t} * F_{o,t} * mcp^{(i)}_{o,t}}{\sum_o st^D_{s,o,t} * F_{o,t}}, \forall s,t \end{array} \right\} \tag{5.34}$$

$$E^{MCPC\,(i)}_{s,t} = \frac{\sum_o st^C_{s,o,t} * F_{o,t} * mcp^{(i)}_{o,t}}{\sum_o st^C_{s,o,t} * F_{o,t}}, \forall s,t \tag{5.35}$$

$$E_{g/s,t}^{OPH\,(i)} = \begin{Bmatrix} \dfrac{\sum_o p_{g,o,t}^{G} * F_{o,t}}{ic_{g,t} * 8760}, \forall g \in G, t \\ \dfrac{\sum_o st_{s,o,t}^{D} * F_{o,t}}{p_{s,t}^{C,all} * 8760}, \forall s, t \end{Bmatrix} \quad (5.36)$$

If no investment decision is taken for any candidate plant or storage facility, the update of (5.34) - (5.35) is performed as shown in (5.37) - (5.39). In this case, the initially estimated expected operating hours are used instead of (5.36). The MCPs for generating and discharging hours are calculated based on the maximum of n hours (5.37), and those for charging are calculated based on the minimum of n hours (5.38) in terms of the ranking of MCPs from highest to lowest at the iteration i. (5.39) would be used to determine the expected operating hours in a representative day if the respective capacity were required to operate.

$$E_{a,t}^{MCP\,(i)} = \frac{\sum_d max_{E_{a,d,t}^{OPH}}\left(mcp_{o,t}^{(i)}\right) * F_{d,t}}{\sum_d F_{d,t}}, \forall a \in G^C \cup S, t \quad (5.37)$$

$$E_{s,t}^{MCPC\,(i)} = \frac{\sum_d min_{E_{a,d,t}^{OPH}}\left(mcp_{o,t}^{(i)}\right) * F_{d,t}}{\sum_d F_{d,t}}, \forall s, t \quad (5.38)$$

$$\text{where } E_{a,d,t}^{OPH} = \begin{Bmatrix} \frac{E_{a,t}^{OPH}}{8760} * 24, if a \notin G^{C,re} or\ a \in S \\ 24, if\ a \in G^{C,re} \end{Bmatrix} \quad (5.39)$$

To summarize all critical points of Model II, the schematic view is presented in Figure 5.12.

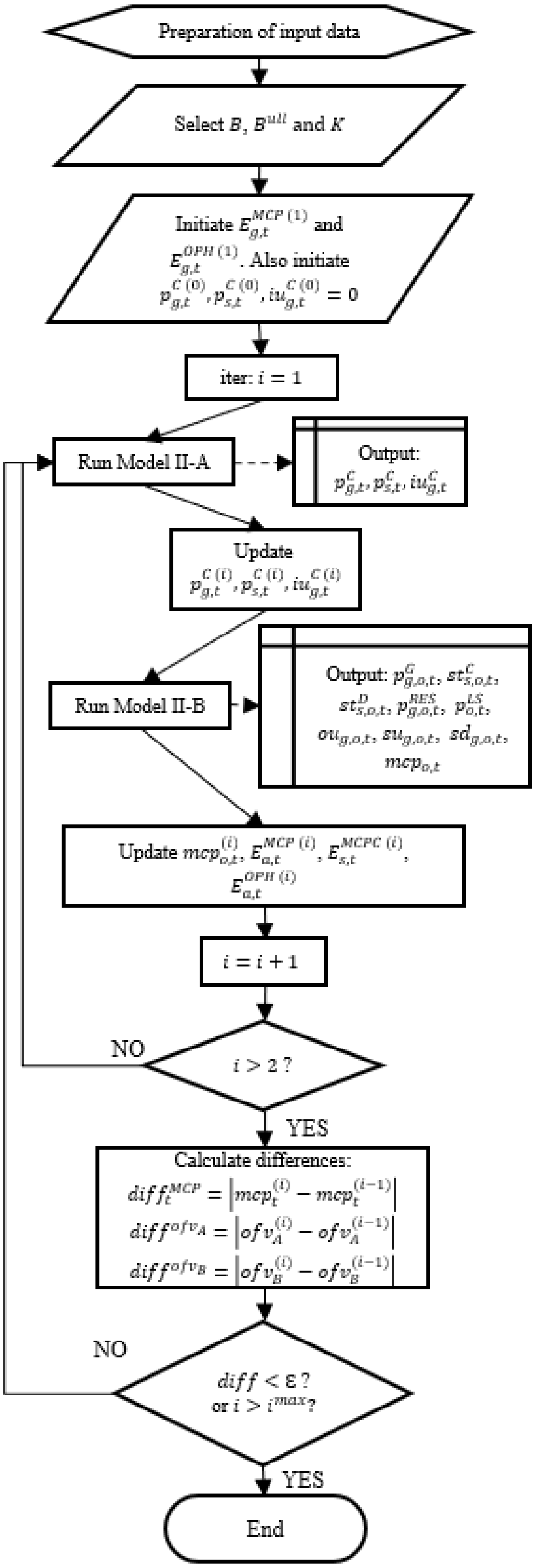


Figure 5.12. Schematic view of Model II

5.2.1.3 Formulation of Model I-S

Ideally, the third model in this study should be designed to minimize the support needed by all existing and candidate facilities by utilizing the similar iterative structure of Model II. The objective function is shown in (5.40). In case there will be no support need for candidate power plants and storage facilities, and there is need for new capacity investment in order to comply with the reserve margin, the most profitable ones are prioritized with the inclusion of profit variable multiplied by a small weight parameter Θ, which makes it a multi-objective optimization problem. Support is defined as in (5.41) in which revenue and support need should be at least equal to total costs in debt repayment period which is characterized by the parameter $I_{a,t}$. However, with this structure, it is not possible to commission new investments unless the reserve margin reduces below a threshold level. Also, the connection between the support need and total operation & investment cost will be completely lost which is not sensible from overall system planning point of view.

$$min \sum_{t} (1+\Gamma)^{T0-t} * \left[\left(\sum_{g} m_{g,t}^{S} + \sum_{s} m_{s,t}^{S} \right) - \left(\sum_{g} m_{g,t}^{P} + \sum_{s} m_{s,t}^{P} \right) * \Theta \right] \tag{5.40}$$

$$\sum_{t} (1+\Gamma)^{T0-t} * \left(m_{a,t}^{S} + m_{a,t}^{R} - m_{a,t}^{C} \right) * I_{a,t} \geq 0, \forall a \tag{5.41}$$

Obviously, the above model should be formulated in a MIBLP model structure. However, due to the difficulties to solve a MIBLP having integer variables in the lower-level problem as in this case, as a third model (Model I-S), Model I is modified to be iterated through a series of predefined total capacity which is inserted as constraint in Model I. At each iteration, for the respective total capacity constraint, optimal decisions are taken based on the minimization of total investment & operation cost. Also, the support needed by existing facilities is calculated and saved.

In the end, generators' total costs can be found including the total investment & operation cost and support needed. The lowest of these is the optimal one, taken as the result of Model I-S. The support need for candidate facilities are not included as their costs have already been considered in the objective function, hence the inclusion of this term would result in double counting and would be misleading. The schematic view of Model I-S is presented in Figure 5.13.

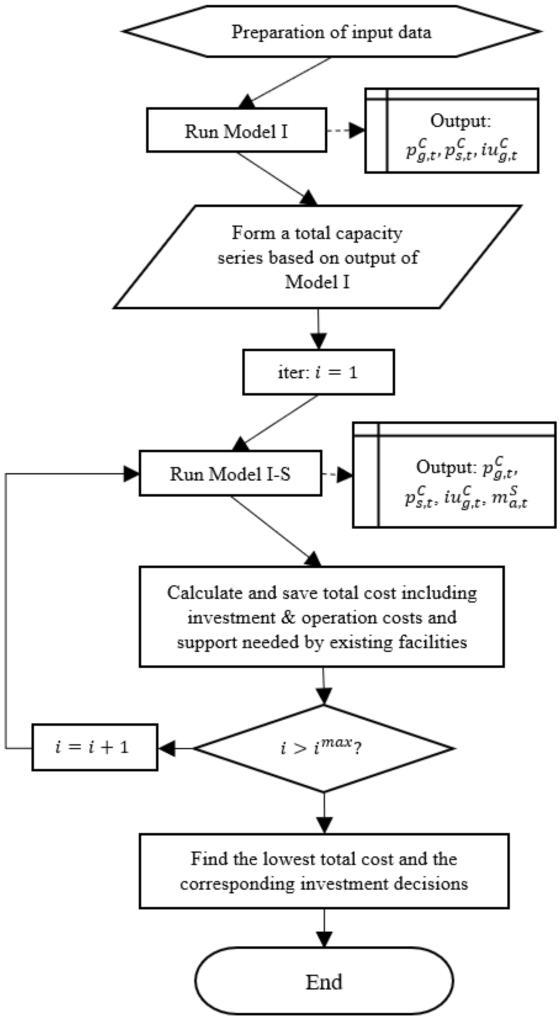


Figure 5.13. Schematic view of Model I-S

5.2.1.4 General Assumptions and Technical Data

The assumptions are taken based on instances in the literature and expert view as follows:

- Electricity demand is inelastic, i.e. consumers do not change their consumption level with respect to price [84], [128].
- Plants showing similar characteristics are grouped in order to reduce the problem size [83].
- Cost of generation is linear [84].
- Market participants bid their marginal cost to the market.
- Plants are dispatched starting from lowest generation costs to highest.
- There is perfect competition. All participants are price-takers. They do not affect the price by changing generation [84], [128].
- MCP is calculated according to UC and economic dispatch decisions in each model. The marginal cost (in some cases plus a reasonable profit margin K) of the most expensive operating plant is the MCP for the corresponding hour.
- For the operation of thermal plants due to operational constraints, which is also related to the objective of minimization of total operation costs, for hours at which the MCP is lower than the marginal cost of the thermal plants, those are assumed to be remunerated by their own marginal price (in some cases plus a reasonable profit margin K) as this logic tries to imitate the block bid behavior in day-ahead markets.

The technical data used in this study are summarized in Table 5.3. They are prepared based on IEA data and a survey filled by expert view based on the power sector investments in Turkey.

The line 9 represents the nuclear plant under construction that is expected to be in operation starting from the 3rd time period.

The lines 10-26 and 27-30 represent the candidate plants and storage facilities that can be commissioned at the corresponding time T_0. The step size of time periods is 5 years, meaning that the 5th time period represents the year 2040. The columns T_0 and T_1 represent the commissioning and decommissioning time of facilities according to technical lifetime as shown in the column $\Lambda_{a,t}$.

The column $I_{a,t}$ is the time period that a facility is to recuperate its investment cost (debt repayment period). It is also used to annualize the investment cost $C_{a,t}^{INV}$ to obtain yearly payments with 5% discount rate. The investment costs are based on estimation for Turkey. The reduction in costs is reflected on future technologies.

The column $IC_g^{max}/IC_{a,t}^{max}$ represents either the overall capacity of plants for the ones without unit limitation or the unit capacity for the ones with unit limitation. The number of units is shown in the column $U_g^{max}/U_{g,t}^{max}$. For existing plants, those represent the numbers in operation, and for candidate ones they indicate the maximum possible number. The amount of unit capacity is squeezed to 50 MW per unit in order to limit the amount of possible oscillations in Model II.

The expected operating hours $E_{a,t}^{OPH}$ show how many hours a facility is expected to operate in a year at full capacity equivalent.

The minimum stable generation ratios for thermal plants and efficiencies are shown in the columns $MSGR_g$ and EFF_a.

The total variable cost $C_{a,t}^{TV}$ of a plant is calculated according to fuel cost, efficiency and other variable costs. The fuel costs are assumed in line with the fuel prices in Turkey as of 2019, and they are assumed to be fixed in the forecast horizon. Those are 30 \$/ton for lignite (having 2000 kcal/kg calorific value), 270 \$/1000Sm^3 for natural gas, 1.3 \$c/kWh for nuclear. The load shedding cost and reserve deficiency cost are assumed to be 20000 and 10000 \$/MWh, respectively.

The total coal capacity that can be commissioned is limited to 10000 MW. For other resources, the maximum capacity is limited by the column based on either capacity (9th column) or unit (10th column) for candidate facilities.

Table 5.3 Technical Data of Facilities

No	*Name*	T_0	T_1	$I_{a,t}$	$\Lambda_{a,t}$	$C_{a,t}^{INV}$ (M$/MW)	$C_{a,t}^{OMF}$ (k$/MW)	$IC_g^{max}/IC_{a,t}^{max}$ (MW)	$U_g^{max}/U_{a,t}^{max}$	$E_{a,t}^{OPH}$ (hours)	$MSGR_g$ (%)	EFF_a (%)	$C_{a,t}^{TV}$ ($/MWh)
1	COAL	-2	5	4	8	1.00	32.5	500	37	6,570	70	33	33.8
2	GAS_CCGT_1	-2	4	3	7	0.70	22.5	400	33	4,380	40	55	53.7
3	GAS_CCGT_2	0	6	3	7	0.70	22.5	400	33	4,380	40	59	50.2
4	GAS_OCGT	-3	2	2	6	0.43	20.0	300	10	438	20	33	87.8
5	HYDRO	-4	10	5	15	1.20	55.0	30,000		2,716			2.5
6	WIND	0	4	3	5	0.80	38.0	7,500		2,917			2.5
7	SOLAR	0	4	3	5	0.70	14.0	6,000		1,752			2.5
8	GEOTHERMAL	0	5	4	6	2.60	52.5	2,500		7,008			2.5
9	NUCLEAR_2030	3	12	6	10	3.80	145.0	1,200	4	8,059	85	33	6.4
10	LIGNITE_2030	3	10	4	8	1.00	32.5	50	80	6,570	60	41	27.7
11	LIGNITE_2035	4	11	4	8	1.00	32.5	50	80	6,570	60	42	27.1
12	LIGNITE_2040	5	12	4	8	1.00	32.5	50	80	6,570	60	42	27.1
13	GAS_CCGT_2030	3	9	3	7	0.63	22.5	50	140	4,818	30	62	47.9
14	GAS_CCGT_2035	4	10	3	7	0.60	22.5	50	140	5,037	30	63	47.2
15	GAS_CCGT_2040	5	11	3	7	0.57	22.5	50	140	5,256	30	64	46.5
16	GAS_OCGT_2040	5	10	2	6	0.35	20.0	50	100	438	20	36	80.7
17	WIND_2025	2	6	3	5	0.76	38.0	10,000		2,917			2.5
18	WIND_2030	3	7	3	5	0.72	38.0	15,000		2,917			2.5
19	WIND_2035	4	8	3	5	0.69	38.0	15,000		2,917			2.5
20	WIND_2040	5	9	3	5	0.65	38.0	15,000		2,917			2.5
21	SOLAR_2025	2	6	3	5	0.67	14.0	10,000		1,752			2.5
22	SOLAR_2030	3	7	3	5	0.63	14.0	15,000		1,752			2.5
23	SOLAR_2035	4	8	3	5	0.60	14.0	15,000		1,752			2.5
24	SOLAR_2040	5	9	3	5	0.57	14.0	15,000		1,752			2.5
25	NUCLEAR_2035	4	13	6	10	3.80	145.0	50	192	8,059	85	33	6.4
26	NUCLEAR_2040	5	14	6	10	3.80	145.0	50	192	8,059	85	33	6.4
27	STORAGE_2025	2	4	1	3	0.93	10.0	10,000		2,190		90	2.5
28	STORAGE_2030	3	5	1	3	0.71	10.0	10,000		2,190		90	2.5
29	STORAGE_2035	4	6	1	3	0.55	10.0	10,000		2,190		90	2.5
30	STORAGE_2040	5	7	1	3	0.42	10.0	10,000		2,190		90	2.5

5.2.2 Results

There are 12 cases studied based on the level of price bids of market participants, maturity of generation fleet and demand forecast. These are represented by the notation 'Case x.y.z' where;

- 'x' can be 'A' or 'B' where 'A' represents the case where market participants submit their exact marginal costs to the market and 'B' represents the case where they submit a price based on their marginal costs and a reasonable profit margin K,
- 'y' can be '1' or '2' where '1' denotes to a young and '2' denotes to a mature generation fleet,
- 'z' can be 'I', 'II' or 'III' by which reference, saturated and lower demand evolution are represented, respectively.

Normally, in a competitive market, all market participants are expected to submit their true marginal costs to the market, and in this case the profit margin is zero. However, since the number of market participants is reduced in order to maintain the tractability of models in a reasonable amount of time, some of the market participants like gas fired plants are always marginal, making impossible to recuperate their costs. Therefore, in addition to Case A, Case B is created and the level of profit margin is selected, without being too high or low, as 10%.

The composition of generation fleet is inspired from that in Turkey. There are two cases envisaged for generation fleet. In the first one, all plants are assumed to be in the first year of their operation, their debt repayment has just been started, and there will be no decommissioning in the forecast horizon. This is a fictitious case in which the aim is to measure the extent of support that can be needed by existing generators. In the second one, the age of plants is assumed to be as given in Table 5.3 as well as the remaining time period of debt repayment.

The demand is represented by three scenarios such as reference, saturated and lower as in Figure 5.14.

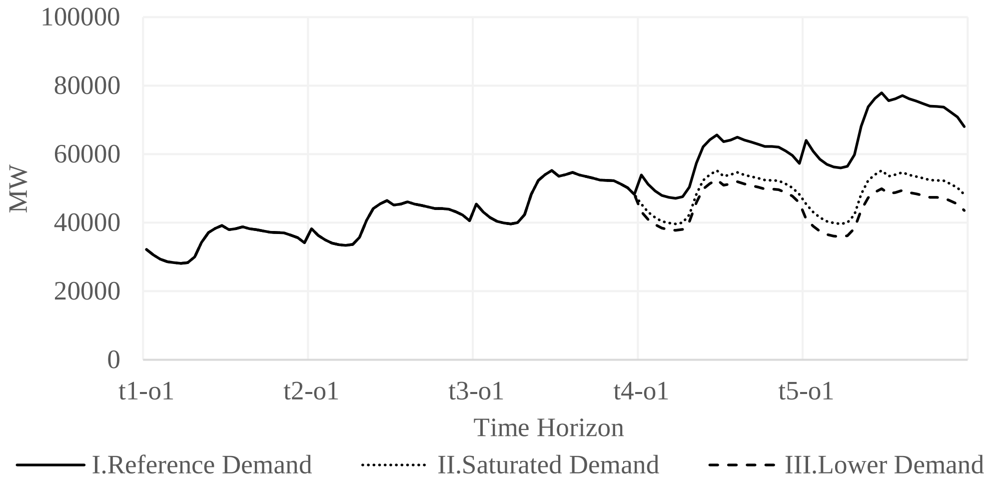


Figure 5.14. Electricity demand evolution by representative hour

In Figure 5.14, ‘t1’ represents the initial year which is the year 2020, and the step size is 5 years, meaning ‘t5’ represents the year 2040. ‘o’ is the representative hour or operating condition in each year, ranging from 1 to 24, implying that only one representative day is considered. The pattern of the load curve belonging to the year 2019 is adjusted according to the demand in 2020. The pattern of the load curve is assumed to be similar for all time periods. The reference is based on the official demand forecast announced for Turkey, corresponding to nearly 3.5% per year increase. The second one assumes that after the time period ‘t3’, the demand will be saturated and will not increase further in future years considering the tendency to use energy more efficiently. In the last one, the assumption in the previous one is extended further with %1/yr demand decrease after the time period ‘t3’.

5.2.2.1 Test Case

This case study is primarily used to test the user-defined parameters in Model II. Model II is studied with 17 scenarios over 500 iterations each, in which the parameters B, B^{ull}, initial MCPs and profit margin K differ. The convergence characteristics of the main scenario (M2-0) are represented in Figure 5.15 to show that main indicators of Model II converge to a solution region, not to an exact solution; however, oscillations are limited. The top-left figure shows the evolution of the objective function values of Model II-A (objval1) and Model II-B (objval2), as well as the amount of support needed by existing plants (SupportE) and candidate plants & storage facilities (SupportC&S). The top-right figure shows the level of new capacity investments by resources. The bottom-left and bottom-right ones show the evolution of minimum hourly reserve and MCP. The iterative nature of Model II prevents reaching an exact solution; however, this is not necessary considering the results of Model II are evaluated to be reliable as will be discussed in the next part, and the main purpose is the mitigation of the missing money problem.

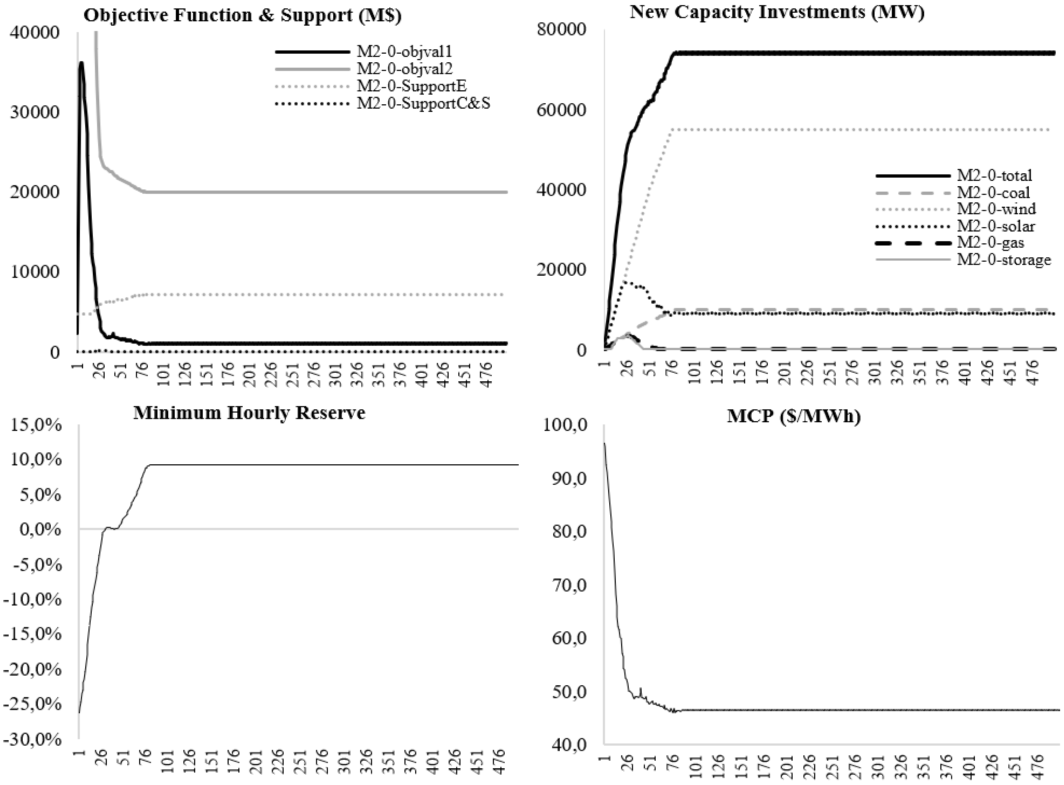


Figure 5.15. Results of Model II with scenario 0 over 500 iterations

The results of each scenario are shown in Table 5.4. The results from M2-0 to M2-12 are similar in terms of investment cost, operation cost, long-term average MCP, minimum reserve margin and capacities to be commissioned. Therefore, it is concluded that the selection of the parameters such as B, B^{ull} and initial MCPs does not have significant impact on the final results. The tests for other cases, which are not represented here in detail as in Table 5.5, also validates this conclusion.

Table 5.4 Results of Model II by Scenarios

					Objective value - model II-A (10^6 $)			*Objective value - model II-B (10^6 $)*			*Long-Term Average MCP ($/MWh)*			*Minimum reserve margin*		
Sce.	B	B^{ull}	*Initial MCP*	K	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*
M2-0	0.50	200	50	0%	89	36	1025	78	14	20008	85	0.2	46.4	81	0.0%	9.2%
M2-1	0.10	200	50	0%	154	10	997	108	42	20015	103	0.4	46.3	92	0.0%	9.2%
M2-2	0.20	200	50	0%	82	41	1006	76	43	20016	79	0.4	46.3	81	0.0%	9.2%
M2-3	0.80	200	50	0%	83	51	1018	79	14	19979	81	0.2	46.3	81	0.0%	9.2%
M2-4	0.90	200	50	0%	87	143	969	78	18	19976	83	0.5	46.2	81	0.0%	9.2%
M2-5	0.50	50	50	0%	321	62	1010	297	7	20012	302	0.3	46.3	300	0.0%	9.2%
M2-6	0.50	100	50	0%	165	49	1004	150	7	20012	153	0.3	46.3	151	0.0%	9.2%
M2-7	0.50	400	50	0%	86	40	938	77	135	20014	80	0.3	46.1	81	0.5%	9.2%
M2-8	0.50	500	50	0%	84	48	987	82	36	20047	82	0.3	46.2	81	0.0%	9.2%
M2-9	0.50	200	40	0%	89	36	1025	78	14	20008	85	0.2	46.4	81	0.0%	9.2%
M2-10	0.50	200	45	0%	89	36	1025	78	14	20008	85	0.2	46.4	81	0.0%	9.2%
M2-11	0.50	200	55	0%	89	36	1025	78	14	20008	85	0.2	46.4	81	0.0%	9.2%
M2-12	0.50	200	60	0%	89	36	1025	78	14	20008	85	0.2	46.4	81	0.0%	9.2%
M2-13	0.50	200	50	5%	92	256	1393	87	57	19987	76	1.1	48.2	81	0.0%	9.2%
M2-14	0.50	200	50	10%	90	175	1798	81	53	19876	83	0.3	50.3	86	0.0%	9.2%
M2-15	0.50	200	50	15%	98	116	1971	92	53	19709	90	1.0	51.9	83	0.1%	9.2%
M2-16	0.50	200	50	20%	82	593	2352	102	96	19702	117	2.1	53.7	106	0.1%	9.2%

					Total capacity investments (MW)			*Coal capacity investments (MW)*			*Wind capacity investments (MW)*			*Solar capacity investments (MW)*		
Sce.	B	B^{ull}	*Initial MCP*	K	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*	*Cnvg. iter*	*Cnvg range*	*Cnvg. mean*
M2-0	0.50	200	50	0%	81	400	74000	81	0	10000	76	0	55000	79	400	9000
M2-1	0.10	200	50	0%	108	1200	73992	81	0	10000	76	0	55000	108	1200	8992
M2-2	0.20	200	50	0%	84	1200	74016	81	0	10000	76	0	55000	84	1200	9016
M2-3	0.80	200	50	0%	81	400	74000	81	0	10000	76	0	55000	78	400	9000
M2-4	0.90	200	50	0%	84	400	74000	83	0	10000	76	0	55000	84	400	9000
M2-5	0.50	50	50	0%	299	200	73900	81	0	10000	301	0	55000	301	200	8900
M2-6	0.50	100	50	0%	152	200	73900	81	0	10000	151	0	55000	152	200	8900
M2-7	0.50	400	50	0%	77	2000	74200	81	0	10000	38	1200	55000	72	800	9200
M2-8	0.50	500	50	0%	82	1000	73500	81	0	10000	31	0	55000	82	1000	8500
M2-9	0.50	200	40	0%	81	400	74000	81	0	10000	76	0	55000	79	400	9000
M2-10	0.50	200	45	0%	81	400	74000	81	0	10000	76	0	55000	79	400	9000
M2-11	0.50	200	55	0%	81	400	74000	81	0	10000	76	0	55000	79	400	9000
M2-12	0.50	200	60	0%	81	400	74000	81	0	10000	76	0	55000	79	400	9000
M2-13	0.50	200	50	5%	87	800	74200	81	0	10000	76	0	55000	87	800	9200
M2-14	0.50	200	50	10%	84	800	76600	81	0	10000	76	0	55000	84	800	11600
M2-15	0.50	200	50	15%	92	850	78625	81	0	10000	76	0	55000	92	800	13600
M2-16	0.50	200	50	20%	124	1600	78988	81	0	10000	76	0	55000	124	1600	13956

For the next part in which the results for all models will be compared, the parameters used for M2-0 such as 0.50 for B, 200 MW for B^{ull}, 50 \$/MWh for initial MCP, are selected as basis for Model II. As the profit margin K increases from M2-13 to M2-16, the long-term average MCP increases as expected, and this makes new investments more profitable, which in turn results in new capacity commissioning and higher investment cost. As mentioned previously, the cases are divided into two groups according to profit margin, which cannot be exactly known, such as 0% and 10%.

As for Model I-S, the only user-defined parameter is the total capacity series. For Case A.1.I, the optimal level of new capacity for Model I slightly over 74000 MW, hence, a series starting from 0 to 74000 MW incremented by 200 MW step size is formed. The lowest cost for generators including the support needed by existing plants is obtained to be 26200 MW as shown in Table 5.5. The costs and amount of support for each 200 MW increment is shown in Figure 5.16.

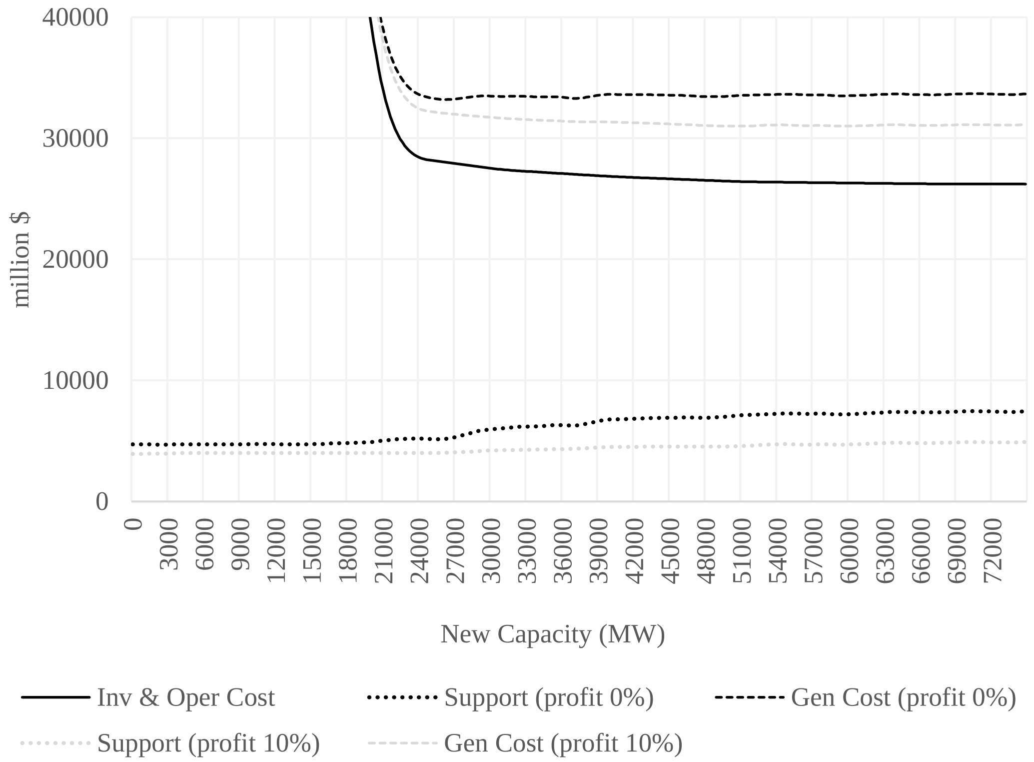


Figure 5.16. Pattern of costs & amount of support for Model I-S, Cases A.1.I & B.1.I

With more capacity, the total investment & operation cost reduces as can be seen from the straight black line. The amount of support needed by existing plants is shown with dotted lines for profit margin 0% and 10%, and with more capacity the amount of support need increases and then stabilizes beyond a certain level. The dashed lines are the summation of investment & operation cost and the amount of support needed for respective scenarios. The lowest point of the generator cost with 0% profit corresponds to the capacity at 26200 MW and that with 10% profit at 61000 MW. It is concluded that the inclusion of support need with various levels of profit margin leads to minimum cost at different levels of new capacity. The amount of support needed by candidate plants and storage facilities is not represented as it is negligibly small compared to that of existing plants.

5.2.2.2 All Cases

All cases are run via Model I, Model II and Model I-S in R using Gurobi as solver. The results are shown in Table 5.5. The light grey background color indicates that the cost given by the respective model is lowest, and the dark grey one indicates that it is highest among the respective cases. As such, the following can be deduced:

Model I with the objective of minimizing investment & operation costs always yields the lowest cost. In all cases except Case A.2.I and Case B.2.I of which belong to mature generation fleet with reference demand evolution, Model II yields similar investment and operation costs to those of Model I, and the differences are below 0.11%. The costs in Model I are always lower than those in Model II, which is expected considering the iterative nature of Model II, and Model II converges to a solution region, not an exact solution. The proximity of solutions among Models I and II in terms of not only total investment and operation cost, but also MCP, minimum reserve margin, new capacity and its distribution with respect to resources indicates that the operation of Model II can be evaluated to be reliable.

The operation costs are more decisive for the total of investment & operation costs such that the results having the least operation costs also have the least total investment & operation cost. For the selected level of 5% discount rate, this finding signifies that investments with lower operation costs are more favorable in such a long-term optimization problem.

The results with the least support for existing facilities also yield the highest operation costs. This is sensible considering that the less the support needed by existing facilities the more they generate electricity and make profit which in turn makes fossil fuel plants operate and in the end increases the operation costs.

The total cost of generators including the total investment & operation cost and support needed by existing facilities is lowest for Model I-S, as expected. The results based on this objective have the downside of higher MCP and consequently higher payments by consumers.

The level of payment by consumers is the main determinant of the total combined cost of generators and consumers. The higher the consumers pay the higher the cost occurs for generators and consumers in total, or vice versa. This finding signifies that total cost is minimized when MCP is minimized. Therefore, the attempts to decrease the support level lead to higher MCP and result in suboptimal solutions.

The support needed by existing facilities cannot be eliminated but for Cases A.1 can be reduced by 30-35% from 7.6-7.9 to 4.9-5.5 billion $. The downside of minimizing the total support is the increasing operation cost by 3.5-5.5 billion $ and MCP with decreased level of new investments. The choice of fuel type for new investments drastically changes for Case A.1.I as ~10 GW nuclear capacity with higher LCOE is invested, and wind investments with lower LCOE fall to ~3 GW for Model I-S which is suboptimal for investors. Besides, beyond 20-year horizon, significantly higher operation costs are not preferable.

Table 5.5 Comparison of Results for All Cases

Case A: MCP Exactly Equal to Marginal Cost of Last Generator in Merit Order

Results	*Case A.1: Young Electricity Generation Fleet*									*Case A.2: Mature Electricity Generation Fleet*								
	Case A.1.I: Reference Demand			*Case A.1.II: Saturated Demand*			*Case A.1.III: Lower Demand*			*Case A.2.I: Reference Demand*			*Case A.2.II: Saturated Demand*			*Case A.2.III: Lower Demand*		
	Model I	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*
Investment and operation cost (10^6 \$)	26218	26234	28044	22718	22733	23482	21954	21979	22676	26834	29717	26878	23040	23064	23045	22258	22282	22322
Investment cost (10^6 \$)	*6443*	*6226*	*2668*	*4625*	*4600*	*1672*	*3997*	*3859*	*1154*	*7245*	*6803*	*7228*	*5121*	*4908*	*4948*	*4393*	*4194*	*3875*
Operation cost (10^6 \$)	*19775*	*20008*	*25375*	*18093*	*18133*	*21809*	*17957*	*18120*	*21521*	*19589*	*22915*	*19650*	*17918*	*18156*	*18098*	*17865*	*18087*	*18447*
Support needed by existing facilities (10^6 \$)	7622	7142	4968	7923	7430	5367	7900	7378	5519	2468	2232	2350	2519	2446	2463	2570	2444	2403
Total cost of generators (10^6 \$)	33840	33377	33011	30642	30163	28848	29854	29357	28195	29302	31950	29229	25558	25510	25509	24828	24725	24725
Payment by consumers (10^6 \$)	46916	48086	52331	42044	42795	47115	41098	42023	45701	45972	49355	47525	41898	42636	42505	40435	41881	42319
Combined cost of generators & consumers (10^6 \$)	**80756**	**81463**	**85342**	**72686**	**72958**	**75963**	**70953**	**71381**	**73895**	**75274**	**81305**	**76754**	**67456**	**68146**	**68014**	**65263**	**66606**	**67044**
Average MCP (\$/MWh)	**45.3**	**46.4**	**50.6**	**43.2**	**44.0**	**49.6**	**42.6**	**43.9**	**48.9**	**44.3**	**47.6**	**45.6**	**42.6**	**43.7**	**43.8**	**41.7**	**43.8**	**44.9**
Minimum hourly reserve margin at 5th period	9.4%	9.2%	3.0%	29.8%	29.0%	10.1%	38.0%	34.9%	8.1%	3.0%	-1.8%	3.0%	10.4%	6.8%	8.0%	12.2%	8.6%	5.4%
Total capacity investments (MW)	**74539**	**74000**	**26200**	**37832**	**39650**	**9800**	**29320**	**28481**	**6600**	**91715**	**88270**	**77000**	**54652**	**50275**	**49000**	**40468**	**36675**	**27000**
Coal (MW)	10000	10000	10000	1850	50	0	1750	117	0	10000	10000	10000	200	75	2150	150	75	3700
Wind (MW)	55000	55000	2805	35765	39600	9796	26946	28364	6600	55000	55000	55000	52680	50200	45837	38949	36600	23265
Solar (MW)	9376	9000	0	0	0	0	0	0	0	14791	15600	688	804	0	627	506	0	35
Gas (MW)	0	0	0	0	0	0	0	0	0	4750	2045	0	0	0	0	0	0	0
Nuclear (MW)	0	0	9600	0	0	0	0	0	0	4800	2645	9300	0	0	0	0	0	0
Storage (MW)	163	0	3795	217	0	4	624	0	0	2374	2980	2012	968	0	386	863	0	0
Expected generation by new investments (TWh/y)	242.6	241.9	151.3	116.5	115.8	28.6	90.1	83.5	19.3	311.5	283.7	302.3	156.4	146.9	148.9	115.5	107.3	92.2

Case B: MCP Equal to Marginal Cost of Last Generator in Merit Order plus a Reasonable Profit

Results	*Case B.1: Young Electricity Generation Fleet*									*Case B.2: Mature Electricity Generation Fleet*								
	Case B.1.I: Reference Demand			*Case B.1.II: Saturated Demand*			*Case B.1.III: Lower Demand*			*Case B.2.I: Reference Demand*			*Case B.2.II: Saturated Demand*			*Case B.2.III: Lower Demand*		
	Model I	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*	*Model I*	*Model II*	*Model I-S*
Investment and operation cost (10^6 \$)	26218	26239	26295	22718	22729	22947	21954	21969	22303	26834	29240	26878	23040	23053	23045	22258	22273	22322
Investment cost (10^6 \$)	*6443*	*6362*	*6001*	*4625*	*4737*	*3400*	*3997*	*4172*	*2087*	*7245*	*7092*	*7228*	*5121*	*5020*	*4948*	*4393*	*4361*	*3875*
Operation cost (10^6 \$)	*19775*	*19876*	*20294*	*18093*	*17992*	*19547*	*17957*	*17798*	*20216*	*19589*	*22149*	*19650*	*17918*	*18033*	*18098*	*17865*	*17912*	*18447*
Support needed by existing facilities (10^6 \$)	5026	4812	4507	5273	5610	4355	5374	5553	4698	1704	1539	1571	1757	1855	1693	1810	1844	1626
Total cost of generators (10^6 \$)	31244	31051	30803	27991	28339	27302	27328	27522	27001	28537	30780	28449	24796	24908	24739	24068	24117	23948
Payment by consumers (10^6 \$)	51608	52187	53058	46249	45319	49609	45208	42026	49050	50570	53136	52278	46087	45312	46756	44479	44616	46551
Combined cost of generators & consumers (10^6 \$)	**82852**	**83238**	**83860**	**74240**	**73657**	**76911**	**72536**	**69548**	**76051**	**79107**	**83916**	**80727**	**70884**	**70220**	**71495**	**68546**	**68733**	**70499**
Average MCP (\$/MWh)	**49.8**	**50.3**	**51.0**	**47.5**	**46.1**	**51.6**	**46.8**	**46.3**	**52.3**	**48.7**	**51.2**	**50.2**	**46.9**	**46.0**	**48.1**	**45.8**	**46.1**	**49.4**
Minimum hourly reserve margin at 5th period	9.4%	9.2%	6.8%	29.8%	31.6%	22.4%	38.0%	39.0%	14.2%	3.0%	-1.6%	3.0%	10.4%	8.7%	8.0%	12.2%	10.5%	5.4%
Total capacity investments (MW)	**74539**	**76600**	**61000**	**37832**	**39425**	**23200**	**29320**	**30910**	**12600**	**91715**	**88065**	**77000**	**54652**	**49025**	**49000**	**40468**	**35690**	**27000**
Coal (MW)	10000	10000	10000	1850	3025	4200	1750	2506	2600	10000	10000	10000	200	3025	2150	150	2642	3700
Wind (MW)	55000	55000	49604	35765	36400	18990	26946	28390	10000	55000	55000	55000	52680	46000	45837	38949	33048	23265
Solar (MW)	9376	11600	1396	0	0	0	0	14	0	14791	14852	688	804	0	627	506	0	35
Gas (MW)	0	0	0	0	0	0	0	0	0	4750	3013	0	0	0	0	0	0	0
Nuclear (MW)	0	0	0	0	0	0	0	0	0	4800	5100	9300	0	0	0	0	0	0
Storage (MW)	163	0	0	217	0	10	624	0	0	2374	100	2012	968	0	386	863	0	0
Expected generation by new investments (TWh/y)	242.6	246.5	212.8	116.5	126.1	83.0	90.1	99.3	46.3	311.5	306.5	302.3	156.4	154.1	148.9	115.5	113.8	92.2

The support needed by existing facilities is reduced by up to 34% from Case A to B as they are making more profit. For Case A.2 and B.2, the reduction in the support needed by existing facilities is quite limited as less investment and higher MCP couldn't affect the level of support as followed from Model I-S. The generators having lower expected operating hours need more profit. However, higher MCP triggers new capacity investments. For the levels of demand and composition of supply in this study, it is not possible to fully eliminate the support needed by existing facilities. Any attempt to decrease this cost by influencing the supply composition and MCP yields significantly higher combined costs of generators and consumers.

The differences among the long-term average MCPs obtained in Model I and II are below 3.4 \$/MWh, with Model II having slightly higher prices and less reserve for Case A. The profit maximization objective of Model II forces new investments to be strictly profitable which in turn rejects a small part of investments found feasible in Model I. For Case B, there are three instances (Case B.1.II, B.1.III and B.2.II) where the total cost and MCP are lowest for Model II. The increased level of MCP thanks to the profit margin of generators attracts more investments for these cases in which the MCP is stabilized at around 46 \$/MWh.

For two instances (Case A.2.I & B.2.I) in which the demand is highest, the reserve margin becomes negative for Model II. This can be explained by the level of MCP which is unable to attract more investments aside from fully utilized wind and coal capacity. However, more investments are commissioned to comply with the 3% minimum reserve margin rule embedded in Model I. It signifies that those additional investments are not profitable, thus may need to be subsidized by special mechanisms. The level of new storage investments is low (below 1000 MW) except for cases with reference demand (Case A.2.I and B.2.I), and they are mostly seen in Model I. Although those investments are not profitable from investor point of view, the total benefit that they provide to the system can be higher than their cost, implying that support mechanisms may be necessary for their promotion depending on the revenues that can be obtained in the ancillary services market. For the cases with reference demand, the amount of storage investments is highest with the total capacity surpassing 2000 MW.

The amount of solar capacity is low except for the cases with reference demand (Case A.2.I and Case B.2.I). Despite having the lowest investment cost, lower utilization factor compared to wind and fossil fuel generation as well as the effect of significant MCP decline due to the operation of those facilities only within daytime seem to limit their capacity. Exposing solar energy to MCP might not be profitable from investor point of view unless the primary purpose of the solar investments is to meet self-consumption, or the commissioning of fossil fuel capacity is restricted due to environmental concerns. Otherwise, they would still be in need of support mechanisms under the assumptions in this study.

The important points from results of the modeling activity presented in this section can be summarized as follows:

- Investment decision characteristics are similar for Model I and Model II. The differences occur especially for storage investments, showing that even in small capacities, storage facilities can provide benefit beyond their cost. However, since they are generally not profitable, they may need subsidy. The results obtained from support minimization-oriented Model I-S are completely different from their counterparts, and in most cases indicate significantly lower amount of capacity expansion. Despite yielding the lowest generation cost, those are unfavorable given that with the inclusion of consumer payment, overall costs are getting much higher with increasing level of MCP.
- The least generation cost obtained by Model I-S can considerably reduce the amount of the support needed by existing facilities. However, even with a mature generation fleet, it is not possible to fully eliminate the support need.
- Since the support minimization-oriented results lead to overall costs at an undesired level, the determination of intermittent renewable capacity should not be based on this motivation. Even with saturated and lower demand

evolution, the optimal level of wind capacity commissioning can be in the range of 30000-40000 MW in the next 20 years. For the cases considered, wind capacity does not need any support mechanism, but the situation is not the same for solar. In short, massive amount of renewable capacity integration is possible from economic point of view. However, additional studies regarding impacts on grid can surely be needed.

5.2.3 Discussion

In this section, in order to utilize a more reasonable GEP model in line with changing market needs, three GEP models are studied, and the research is focused on whether it is needed to change the conventional structure of GEP modeling. It is found out that any attempt to mitigate the missing money problem in a GEP study would yield higher operation costs, MCPs and combined costs of generators and consumers. Therefore, if the services of any facilities, which are unable to recuperate their fixed costs, are needed for the sake of the system, the energy market should not be even indirectly influenced. Instead, special support schemes should be resorted.

The investment decisions of Model I and Model II are similar. The capacity of storage facilities is found to be as one of the major differences among these two models. Based on the results, it can be concluded that either model can be chosen depending on the needs. If all new investments are required to be profitable, Model II can be preferred. If the capacity expansion is studied from the central planner's point of view, Model I is more preferable thanks to its easier implementation. Another option can be a combined utilization such that, given storage investments are not generally preferred in Model II as they are not found to be profitable, Model I can be utilized with storage investment options disabled. This is the preferred option in the next section.

Based on its findings, the contributions of this section are stated as follows:

- The main contribution of this research is on the findings revealed with the combination of models and cases. Many liberalized electricity markets have been facing similar problems. In the end, it is revealed that GEP studies should not try to mitigate the missing money problem, but the plants of which operation is needed for the sake of the system should be supported via specialized mechanisms. The conventional modeling approach with total cost minimization yields sensible results in terms of new investments, but the investment choices proposed by this approach can make the situation financially worse for existing plants. The research direction is unique given that the missing money problem has not yet been addressed together with GEP problems in this context in the literature.
- A new objective function such as the minimization of the support needed by existing plants and new constraints within this context are created. Although those are unable to be utilized successfully in the MIBLP model, Model I-S which is a variation of Model I is used in order to overcome the problems posed by the bilevel model structure.
- An alternative model (Model II) aiming the profit maximization of candidate facilities is developed of which operation is based directly on MCP while a specific module is dedicated for the calculation of market price. In the literature, there are instances in which profit maximization is used as the objective function. However, those do not include a dynamic procedure for the determination of MCP or MCP is proportionately indexed to the difference between electricity demand and installed capacity. In this study, an alternative approach is proposed so as to include MCP in the objective function, and in the end it can directly be identified which candidate facilities are profitable for investment instead of pure cost minimization view. With this model, it is possible to compare the differences of investment decisions between the cost minimization and the profit maximization point of view.

5.3 Long-Term Price Forecasting Results and Evaluation

Following the improvement of supply modeling by a proper generator maintenance scheduling algorithm and the utilization of a proper generation expansion planning model, the next step is to combine these two stages and calculate relevant indicators such as MCP and reserve capacity in the long term. The aim of this section is to exemplify possible ways to utilize the long-term electricity market model based on various cases and to present corresponding results.

The methodology for long-term electricity price forecasting is the same as that of medium-term, as it has already been shown that the modeling approach yields satisfactory results. The forecasting horizon is considered to be 20 years, i.e. from the year 2020 to 2040. The results are only elaborated for the end year of the forecast horizon, i.e. the year 2040, for simplicity.

This part of the thesis is presented over various cases. In total, there are four cases considered according to the capacity decisions and selection of hourly capacity factors for wind power plants. Here, hourly wind capacity factors are given special attention due to high amount of wind capacity commissioning as obtained in the previous section. Another critical point is about the wind capacity factors calculated in the electricity supply modeling in Chapter 4. Those are calculated according to the historical realizations. However, this calculation based on multiple years causes the wind capacity factors to stay at its seasonal averages for all hours of the year. This corresponds to the expected value, but its realization throughout a year would be unrealistic in terms of volatility. This aspect has not been a concern in medium-term modeling given today's wind installed capacity is far below than what is expected in 20-year time. This aspect is illustrated in Figure 5.17. The realization for a selected year frequently diverges from its seasonal averages, which is studied through two cases.

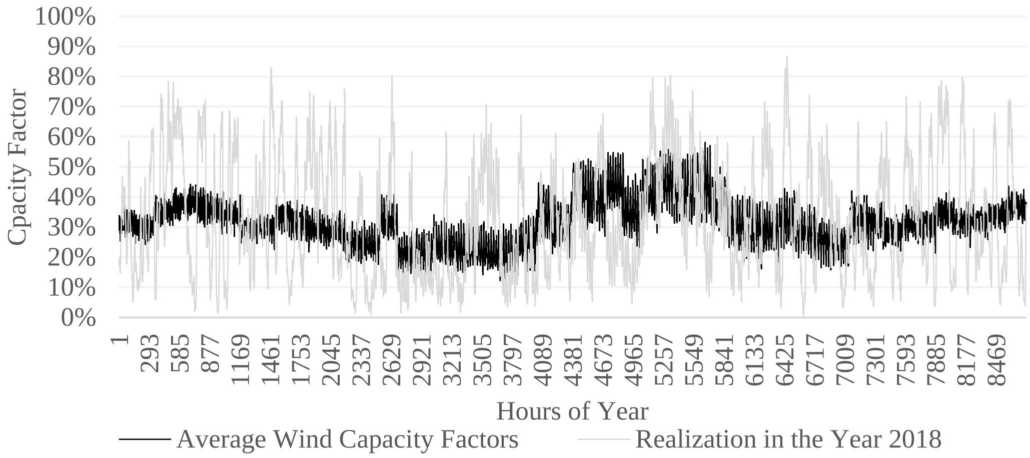


Figure 5.17. Average wind capacity factors and comparison with realization

According to the information above, the cases are defined as shown below. Here, the notations ‘1’ and ‘2’ are used to differentiate between capacity expansion scenarios, whereas the notations ‘A’ and ‘B’ used to show the difference among scenarios for wind capacity factors.

- Case A.1: Capacities calculated based on the GEP model,
- Case A.2: Manually inserted wind and solar capacity targets, and leaving the rest of the capacity decisions to the GEP model,
- Case B.1: Capacities calculated based on the GEP model, and as for hourly wind capacity factors the real data of the year 2018 is preferred,
- Case B.2: Manually inserted wind and solar capacity targets, and leaving the rest of the capacity decisions to the GEP model, and as for hourly wind capacity factors the real data of the year 2018 is preferred.

This section consists of three main parts. In the first part, the capacity decisions and relevant assumptions are given. In the second part, the proposed GMS algorithm is applied for two capacity expansion scenarios. The third part presents the long-term results and touches upon some critical aspects for the future.

5.3.1 Capacity Decisions

In long-term price forecasting, the first step is to decide on what the future capacity by fuel will be. The assumptions presented in Section 5.2.1.4 is still valid including the candidate generation facilities, the amount of capacity to be commissioned by fuel and at least hourly 3% reserve requirement. The electricity generation fleet is assumed to be mature, and facilities are decommissioned after their lifetime expires. The reference demand scenario is taken as reference for electricity demand evolution. The only exception is about storage facilities. The inclusion of a storage facility in the electricity generation fleet requires significant modification in electricity price modeling. A dedicated methodology similar to storage hydropower plant utilization will be necessary. Considering that the amount of capacity decided by the GEP models is limited as shown in Section 5.2, the effect of storage facilities is neglected in this part of the thesis.

The structure of the GEP models used for Cases 1 and 2 is the same. The only difference is that apart from 55000 MW wind capacity, 55000 MW solar capacity is enforced in Case 2 based on the motivation for utilizing renewable energy resources. The level of those capacities is inspired from Germany based on nearly 110000 MW wind and solar installed capacity in Germany as of the year 2020, as well as the electricity demand of Turkey in 2040 is assumed to be around 600 TWh which is similar to the demand level of Germany in the period of 2000-2020. The demand for the year 2040 is disaggregated in hourly terms based on the profile of the year 2018.

The capacities for Cases 1 and 2 are presented in Table 5.6. Despite the fact that the electricity demand is the same for those cases, the difference among total capacity can be evaluated as high. It can be thought that the reason for that difference is due to imposing 55000 MW solar PV capacity. However, in Case 2, around 21000 MW coal and gas capacity combined is decided internally by the GEP model. Another issue that is worth mentioning is that the coal capacity represents the total of hard coal and lignite. No additional hard coal capacity is assumed, that is, the level of hard coal installed capacity is 9100 MW, and the rest of the coal capacity belongs to lignite.

Table 5.6 Capacities by Cases for the Year 2040

Year	*Case 1 (MW)*	*Case 2 (MW)*
Nuclear	6000	4800
Coal	28600	27700
Gas	21900	25200
Hydro	30000	30000
Wind	55000	55000
Solar	21178	55000
Other RES	2500	2500
Total	165178	200200

5.3.2 Maintenance Decisions and Supply Modeling

According to the capacity decisions, the maintenance periods are determined by utilizing the methodology presented in Section 5.1. The pattern of resulting maintenance decisions is presented in Figure 5.18.

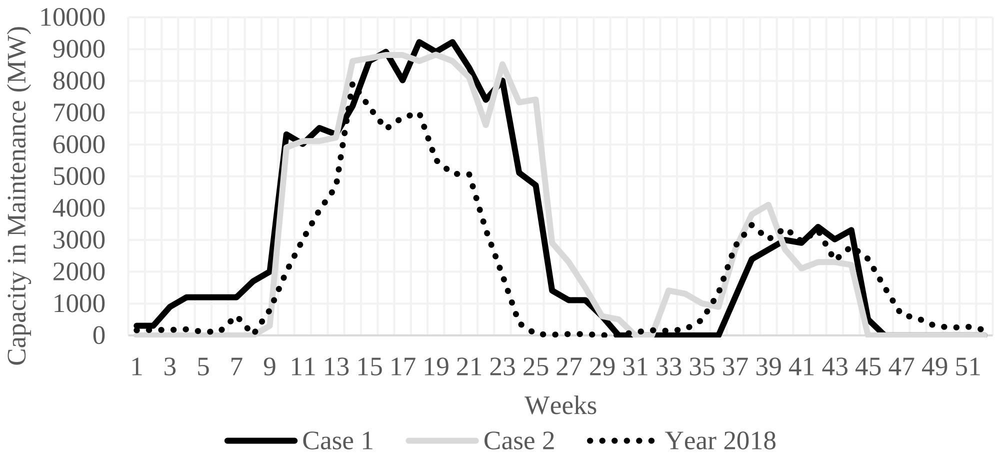


Figure 5.18. Maintenance decisions by cases for 2040 and comparison with 2018

The actual data for the year 2018 is included in this figure for comparison purpose. Despite the fact that the pattern of these schedules is similar, it is important to note that the maintenance plans are spread in a wider range of weeks until the beginning of July.

The size of units with respect to fuel is taken as 1200 MW for nuclear, 500 MW for hard coal, 300 MW for lignite and gas. Since the maintenance scheduling algorithm is applied only on thermal capacity, it means that the algorithm runs for 161 units for Case 1 and 168 units for Case 2. The time limit of 3 minutes is applied in order to reach a reasonable maintenance pattern in a reasonable amount of time, based on the finding in Table 5.2.

As a dynamic maintenance scheduling algorithm is utilized in long term, the approach for supply modeling presented in Section 4.2 is no longer valid for obtaining the available generation capacity of thermal power plants. However, the availabilities of renewable power plants are still defined by the supply modeling as in Section 4.2.

5.3.3 Results

In this part, the results are presented firstly for the cases based on hourly historical wind capacity factors, and secondly for wind capacity factors of the year 2018.

5.3.3.1 Results for Cases A.1 and A.2

The average MCP obtained from the price model and GEP for the year 2040 is shown in Figure 5.19. The forecasts are similar for Case A.1. However, there is a significant 8 \$/MWh difference for Case A.2, with the commissioning of more solar capacity. Considering the price forecasts obtained from GEP are based only on the representative day of the year 2040, the utilization of the price model signifies the requirement and benefits to analyze the results in detail.

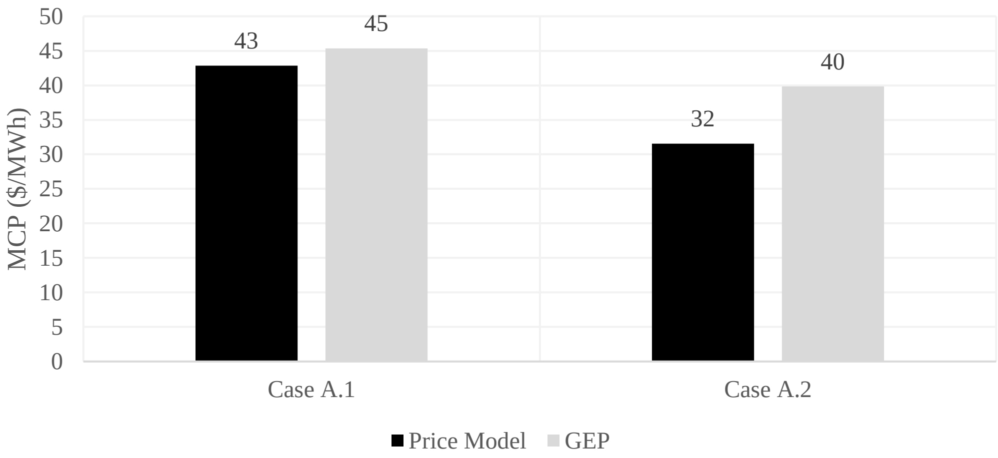


Figure 5.19. Yearly average MCP for Cases A.1 and A.2

The average MCP on hourly basis as calculated from the price model is shown in Figure 5.20. The pattern of average MCP is similar for Case A.1 and the realization in the year 2018. However, the addition of more solar capacity causes daytime prices to fall below 10 $/MWh.

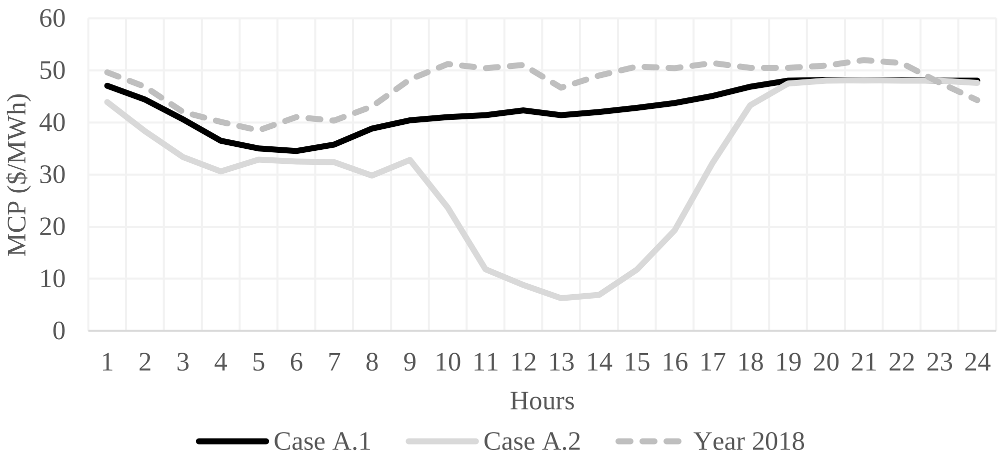


Figure 5.20. Hourly average MCP for Cases A.1 and A.2 and comparison with 2018

Further examination can be performed by analyzing the MCP on monthly and hourly basis. The corresponding representation is shown in Figure 5.21. The lines belonging to Case A.1 is similar to the profile that is experienced in today's electricity market conditions. The lower prices in August is remarkable, but it should be noted that it occurs due to the effect of the long festival period in 2018 as the demand is disaggregated with the load profile of 2018 for the year 2040. As for Case A.2, except January and December, the average prices at noon reduces to 0 $/MWh for every month. The standard deviations of hourly prices are 13 and 20 $/MWh for Cases A.1 and A.2, respectively, stressing the effect of volatility stemming from high solar capacity. The details show that the number of hours with 0 $/MWh MCP is 609 for Case A.1 and 1896 for Case A.2, which corresponds to a remarkable 22% of the hours in whole year.

Since the number of hours with 0 $/MWh prices are significantly high, it implies curtailment from renewable energy resources in order to match electricity demand. The pattern of curtailment from wind and solar on hourly basis in shown in Figure 5.22. Whereas it is only 0.6 TWh for Case A.1, it increases to 8.5 TWh for Case A.2, corresponding to nearly 1.5% of total electricity demand in 2040. On hourly basis, there is a requirement to curtail over 20000 MW generation. The curtailment-duration curve for the worst 3000 hours is plotted as in Figure 5.23. It can be followed that there are 124 hours with over 10000 MW and 661 hours with over 5000 MW wind and solar curtailment.

Moreover, one can calculate electricity generation based on hourly results from the electricity price model as shown in Table 5.7. The increase in solar capacity displaces fossil fuel generation as it reaches nearly 15% in Case A.2 where the intermittent renewable share approaches to 40%. The observations for these cases require either the reconsideration of the solar capacity targeted in Case A.2 or significantly upgrading the flexibility of the system based on developments in storage technologies.

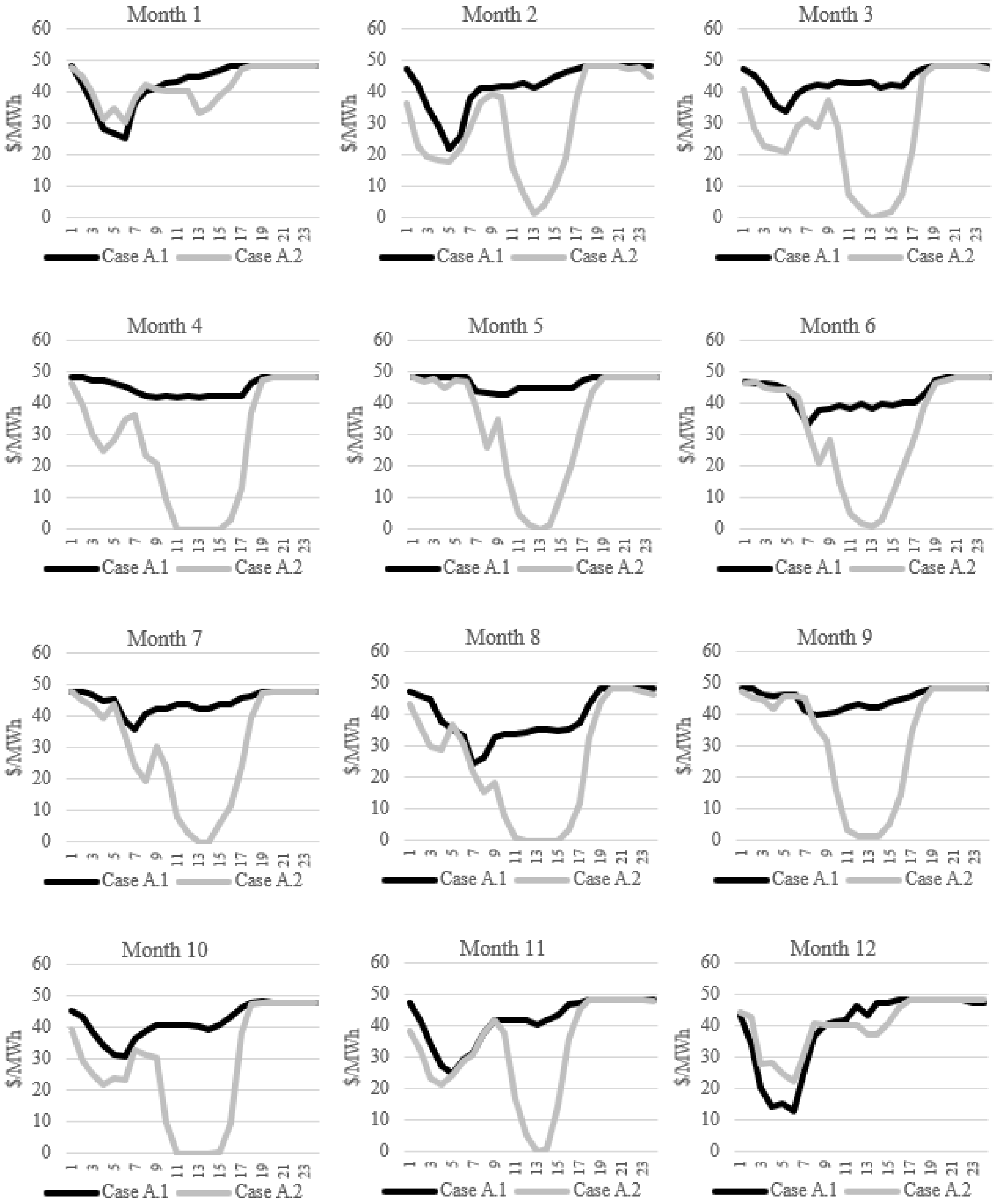


Figure 5.21. Hourly and monthly average MCP for Cases A.1 and A.2

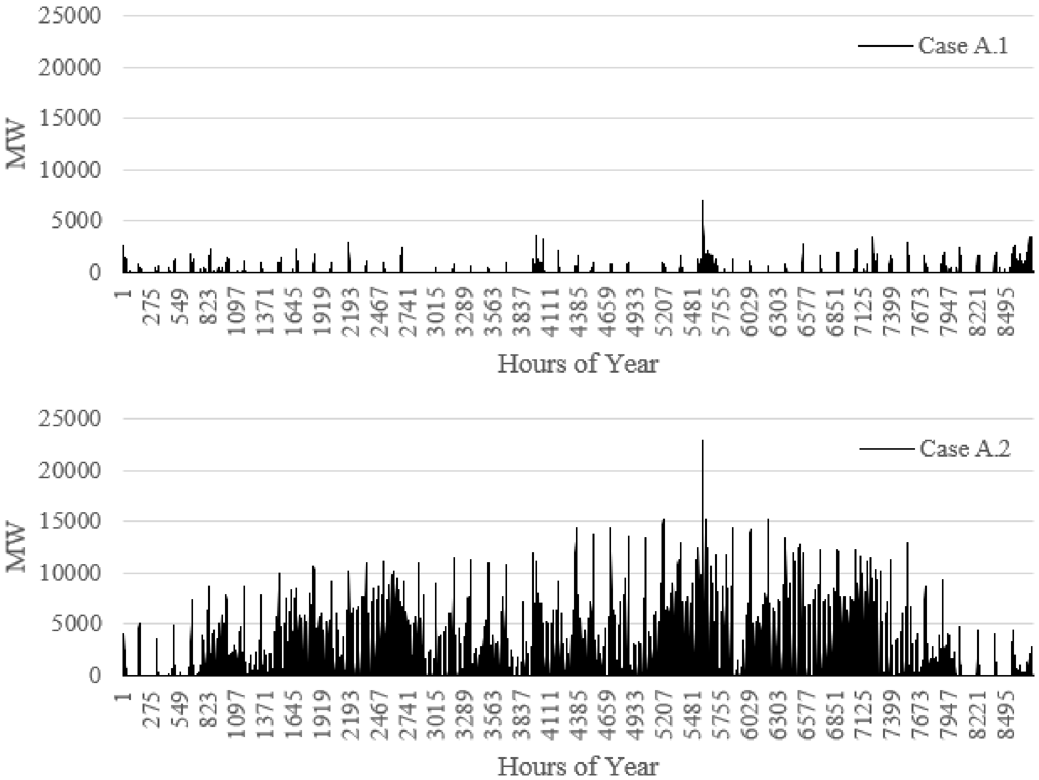


Figure 5.22. Curtailment of wind and solar generation for Cases A.1 and A.2

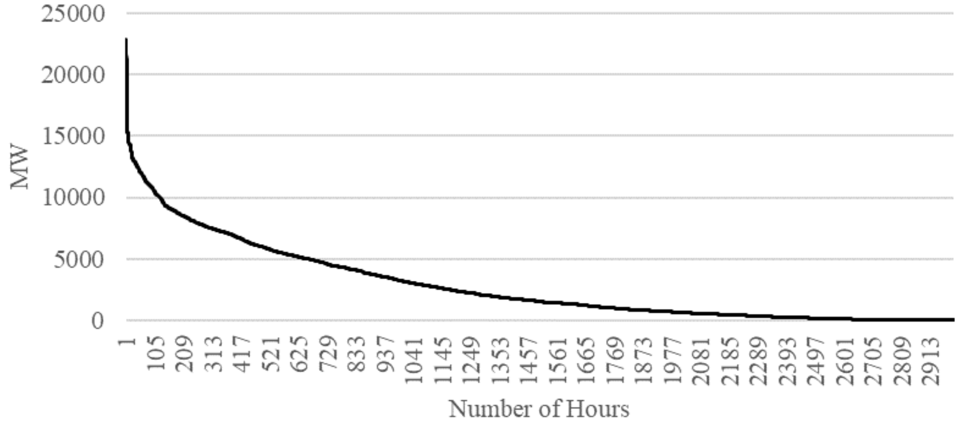


Figure 5.23. Curtailment-duration curve for Case A.2

Table 5.7 Generation by Fuels and Cases for the Year 2040

Fuel	*Case A.1 (TWh)*	*Shares*	*Case A.2 (TWh)*	*Shares*
Fossil Fuels	317.4	52.6%	271.5	45.0%
Hydro	82.9	13.7%	79.7	13.2%
Wind	154.2	25.6%	151.7	25.1%
Solar	35.7	5.9%	87.5	14.5%
Other RES	13.3	2.2%	13.1	2.2%
Total	603.5	100%	603.5	100%

Lastly, hourly minimum and average reserves are investigated with Figure 5.24. The hourly minimum reserve is calculated to be around 3300 MW for both cases, in December for Case A.1 and in June for Case A.2. From the hourly average reserves, it can be claimed that the new investments are not unjustifiable given that the reserve margin is around 4%. The hourly average reserve of 17400 MW for Case A.1 and 24400 MW for Case A.2 both signify the reduced utilization factors for fossil fuel plants.

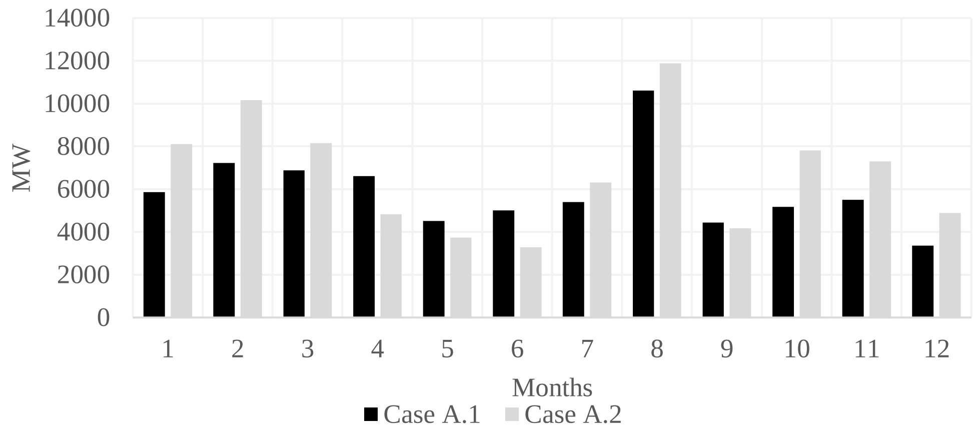


Figure 5.24. Monthly minimum reserve capacity for Cases A.1 and A.2

5.3.3.2 Results for Cases B.1 and B.2

Similar to Figure 5.19, the average MCP is obtained from the price model and GEP for the year 2040 as shown in Figure 5.25. The differences are marginal, i.e. from Case A.1 to Case B.1 it reduces by 2 $/MWh and from Case A.2 to Case B.2 it increases by 2 $/MWh.

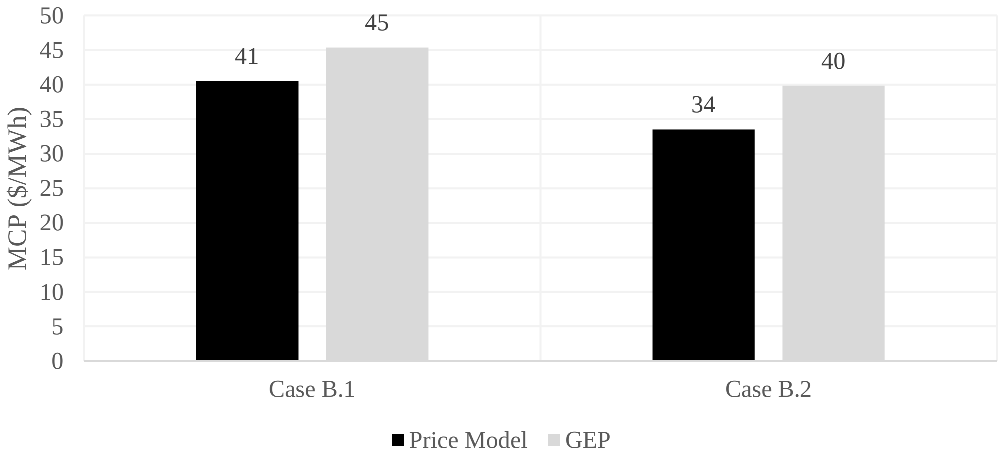


Figure 5.25. Yearly average MCP for Cases B.1 and B.2

Similar to Figure 5.21, the MCP is analyzed on monthly and hourly basis in Figure 5.26. One of the most striking differences among these figures is the price spikes observed in the evenings for several months. The high average prices at those hours imply that the generation is insufficient to meet the demand. The standard deviation of hourly prices are calculated as 26 $/MWh for both cases, indicating that the volatility of prices increases compared 13 and 20 $/MWh deviation in Case A.1 and Case A.2. Also, similar to Case A.2, there are still steep valleys in price patterns of daytime. It signals that there might still be a need for curtailment in daytime. When all hours are examined, it is revealed that the number of hours with 0 $/MWh MCP is 1241 and 2008 for Case B.1 and Case B.2, both up from 690 and 1896 in the previous cases.

Similar to Figure 5.22, the pattern of curtailment from wind and solar on hourly basis is investigated with Figure 5.27. The amount of curtailment from wind and solar reaches 3.0 and 9.5 TWh, both up from 0.6 and 8.5 TWh in previous cases. On hourly basis, there is a requirement to curtail up to 25000 MW generation. The curtailment-duration curve for the worst 1000 hours is plotted for Cases B.2 and A.2 as in Figure 5.28. It can be seen that with the utilization of more volatile wind capacity factors closer to reality, the curtailment requirement becomes slightly intensified.

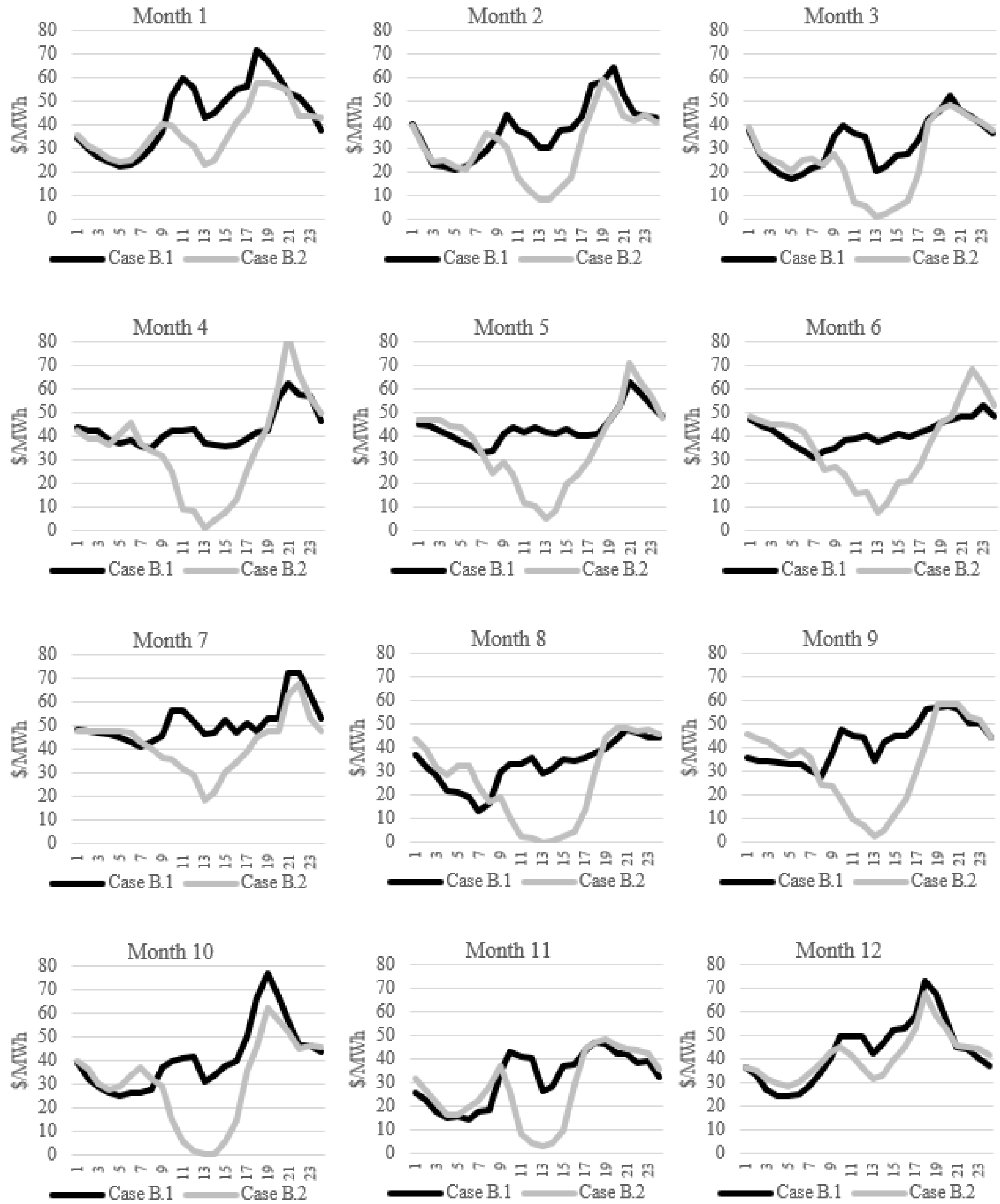


Figure 5.26. Hourly and monthly average MCP for Cases B.1 and B.2

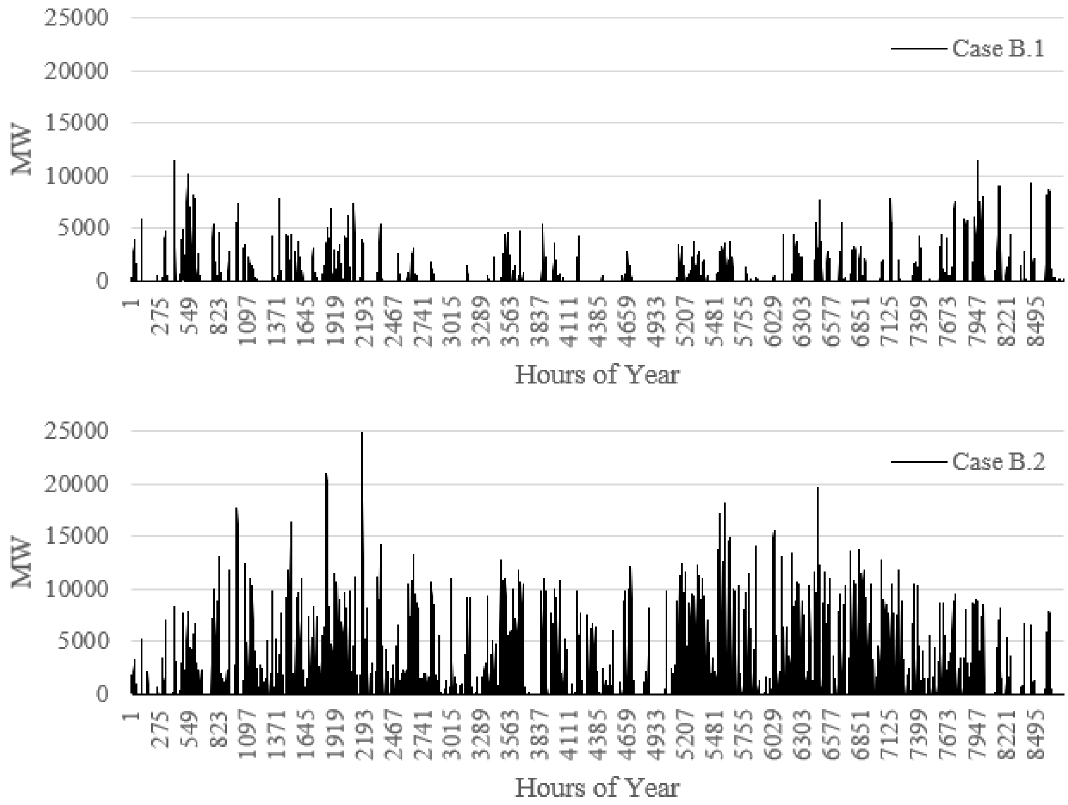


Figure 5.27. Curtailment of wind and solar generation for Cases B.1 and B.2

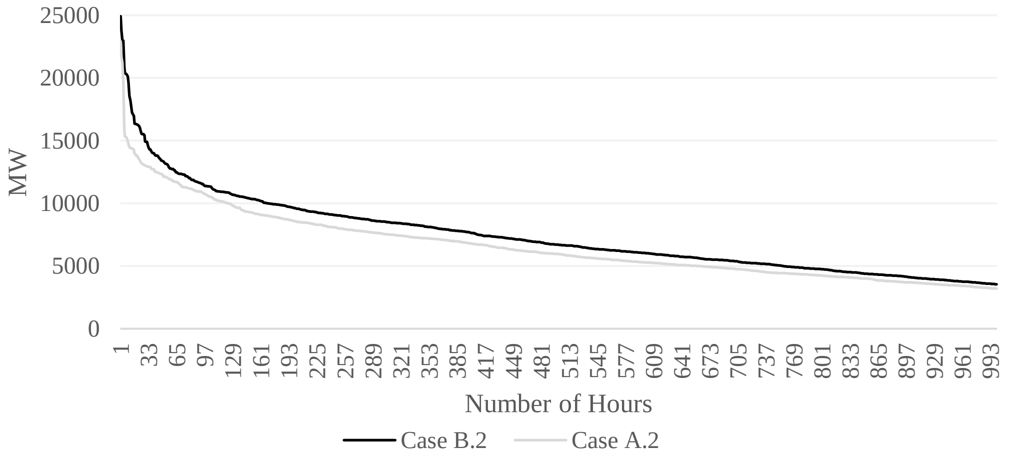


Figure 5.28. Curtailment-duration curve for Cases B.2 and A.2

The share of intermittent resources in total electricity generation for Case B.2 is examined in Figure 5.29. The number of hours with share over 90% reaches 248, up from 101 in Case A.2. Likewise, there are 3690 hours with share over 50%, up from 2727 hours in Case 2. It fluctuates significantly in a wide range from 10% to 90%.

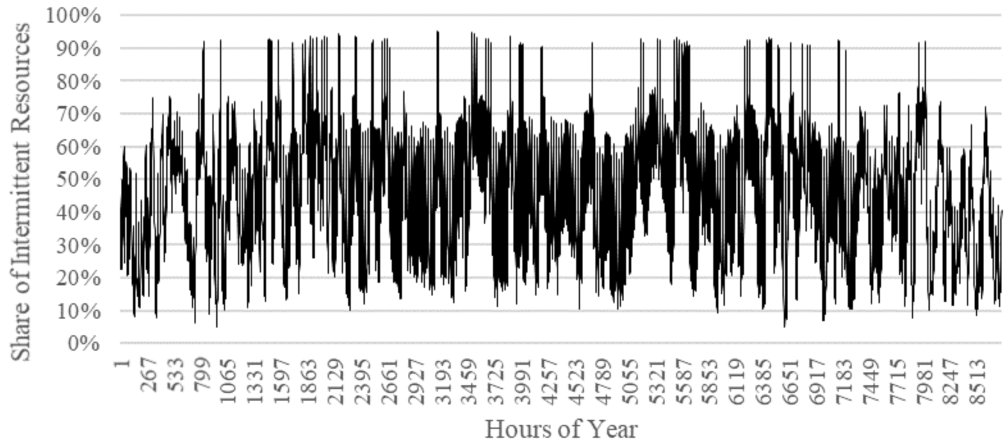


Figure 5.29. Share of intermittent resources for Case B.2

The price spikes observed in the evenings as in Figure 5.26 is further investigated with Figure 5.30, showing the number of hours with MCP hitting the price cap. It is found that there are 131 and 79 hours with maximum MCP for Cases B.1 and B.2, respectively.

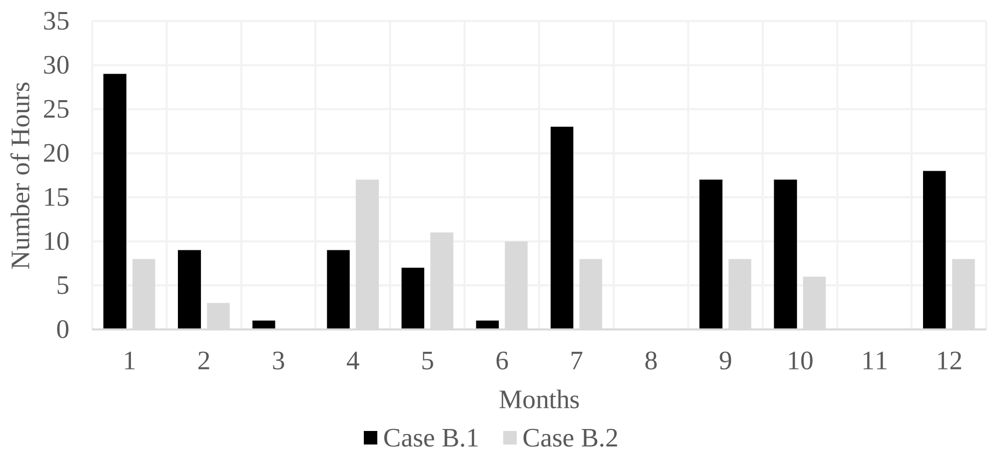


Figure 5.30. Number of hours with MCP hitting the price cap for Cases B.1 and B.2

The previous finding indicates that the number of hours with insufficient reserves is also 131 and 79 hours. In detailed analysis, it is found out that the amount of shortage in generation reaches 7200 and 5200 MW for Cases B.1 and B.2 as shown in Figure 5.31. The average yearly reserve is 18400 and 25300 MW, found to be similar to the previous cases. When electricity generation by power plant is examined for Case B.2, it is revealed that the most efficient natural gas power plant operates at 38% capacity factor whereas the least efficient one operates at just 1%. This observation signifies the importance of resorting to flexibility options in the system instead of new generation capacity considering that some of the power plants have unreasonably low capacity factor.

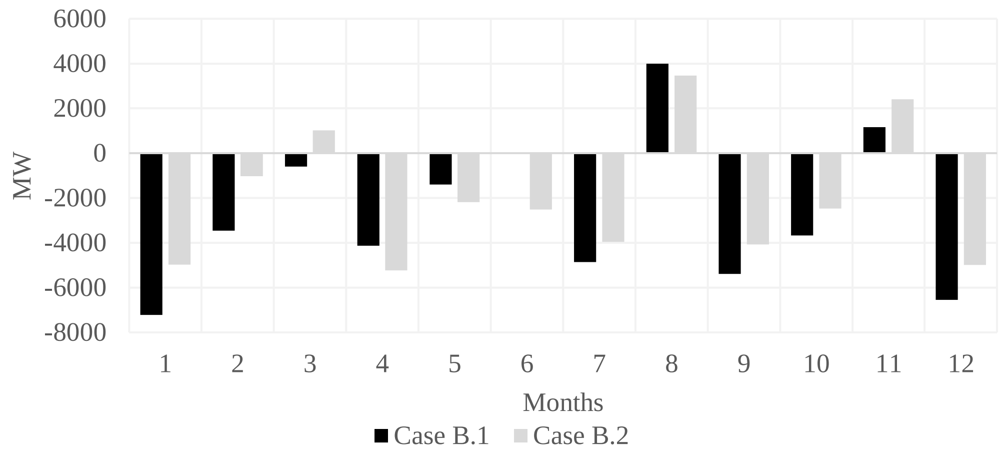


Figure 5.31. Monthly minimum reserve capacity for Cases B.1 and B.2

Instead of averages, the preference of hourly wind capacity factors from a single year such as 2018 has indicated that there are more severe system conditions that needs to be managed in terms of minimum reserve capacity, number of hours hitting price and floor, wind and solar generation curtailment. The proposed long-term electricity market modeling methodology helps to detect these conditions in detail. By changing the input parameters, the models can be rerun, and more desirable system conditions can be searched.

5.4 Conclusion for Long-Term Modeling of Electricity Market

In this chapter, the electricity market is modeled in long term with additions over the previously proposed modeling approach for medium term. The medium-term model is enriched with two additional features such as GMS and GEP, which are necessary to perform a realistic and reasonable modeling in the long-term horizon.

The proposed GMS model is used to obtain more dynamic availability factors for thermal generators considering the evolution of the electricity generation fleet. Similarly, a proper GEP model that is compatible with today's market environment is searched. In the end, depending on the needs, two various GEP models or a combination of both are proposed. With the utilization of the GMS and GEP models, several cases are studied in the long-term horizon, via the price forecasting model. These cases along with the results and emphasized problems are some examples to show how the proposed modeling methodology can be used in long-term forecasting studies.

The main findings from this chapter can be summarized as follows:

- GMS plans can significantly change by hydro scenarios, and the future capacity composition is able to change the pattern of GMS profile.
- The proposed GMS algorithm is an improvement of electricity supply modeling and can be utilized in long-term hourly price forecasting studies. It provides value both from medium to long-term studies that need more precision, at the stage where supply is calculated or various supply scenarios are generated on hourly basis, and in systems which now or in the future are expected to include significant share of storage hydropower or renewable power plants. In overall, dynamic GMS algorithms, in which generator maintenance decisions are influenced by total system reserves, are recommendable instead of static ones that employ fixed parameters for reflecting generator maintenance effect.

- Three various GEP practices and their results indicate that any attempt to mitigate today's missing money problem in a GEP study would yield higher operation costs, MCPs and combined costs of generators and consumers. Therefore, this practice should not be preferred in a long-term modeling horizon.
- The conventional GEP approach is still practical for the central planner. If all investments are needed to be profitable, the conventional and market based GEP approaches can be utilized in a combined manner.
- The proposed market model can be used in various ways for long-term practices. As an example, for Turkey, with an increasing amount of intermittent renewable resources similar to Germany, a significant amount of renewable generation curtailment becomes necessary, as well as the system can experience conditions of huge amount of average reserve capacity and insufficient generation to meet the demand for the same year. The analysis proves that in such a case the central planner should either look for opportunities to increase system flexibility with new emerging technologies or revise its long-term targets.

CHAPTER 6

CONCLUSION

This thesis proposes a novel electricity market modeling methodology for medium and long-term horizon. It is specifically designed for Turkey, but with the proposed structure, it can be used in any liberalized electricity market.

The modeling activity in the medium-term horizon consists of electricity demand, supply and price modeling parts. With electricity demand and supply modeling, hourly electricity demand and availability series with respect to market participants are obtained. Then, electricity price is forecasted on hourly basis for a 1-year horizon. Several scenarios based on the uncertainties affecting demand and supply are run on the model. With relevant inputs, the model is able to simulate the market conditions for any year. After the operability of the model is shown for the medium-term horizon, the modeling approach is improved with two additional features for long term. The first one is the inclusion of a GMS model to make the electricity supply model dynamic and to obtain more realistic supply series in the changing market environment, and the second one is the inclusion of a reasonable GEP algorithm that can define the size and fuel of future generation capacity. Following the addition of those models in the modeling structure, a representative example for a 20-year horizon is studied to show the possible ways to benefit from such a modeling methodology. Thanks to the capability of the methodology to model in hourly time step, results can be obtained in hourly resolution, and detailed analysis can be performed. The main contributions of this thesis can be counted as follows:

- Electricity demand forecasting accuracy is improved with the models based on GAM and MARS which are capable of modeling the nonlinearities in electricity demand.

- A new hourly availability factor calculation methodology is proposed based on historical data, to be utilized in price forecasting.
- A unique iterative scheme between storage hydropower generation and electricity market price is proposed for the price forecasting stage, with test results having satisfactory accuracy. Using various demand and supply scenarios, it is revealed that electricity price can be realized in a wide range, nearly corresponding to the half of the electricity market price.
- A GMS model is included in the electricity market modeling methodology to improve forecasting capability. It is shown that the inclusion of a proper GMS model can be useful for the long-term utilization of the electricity market modeling methodology, given that today's GMS plan can significantly change according to capacity evolution.
- The missing money problem in today's electricity markets is addressed together with the GEP problem. A conventional GEP model, an alternative price-based GEP model, and a reformulation of the conventional GEP model is comparatively used. It is discovered and proposed that the missing money problem should not be tackled in GEP, as otherwise total system costs significantly increase. Two GEP models based on conventional approach and price-based approach or the combination of both are proposed to determine the future electricity generation fleet.
- In the end, the electricity market modeling methodology can be used to analyze future market conditions and unique observations can be made.

In the future, the modeling methodology can be designed in such a way to be able to represent the capability of storage technologies at the price forecasting stage. Considering the electricity generation fleet evolution towards intermittent renewable resources, market conditions will need to be analyzed to enable as much renewable capacity as possible. By properly upgrading this modeling methodology, it can be used to determine the flexibility requirements more accurately.

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APPENDICES

A. Constraints of Model I

In this part, the constraints of Model I described in Section 5.2.1 are given.

The capacity constraints for candidate generators without unit size limitation and storage facilities are shown in (A.1) - (A.4). Since candidate facilities are represented by the possible commissioning year such as "resource_year" as in Table 5.3, they can only be commissioned at the designated year.

$$p_{g,t}^{C} \leq IC_{g,t}^{max}, \forall g \in G^{C,ull}, t \in T_{0,g} \quad \text{(A.1)}$$

$$p_{g,t}^{C} = 0, \forall g \in G^{C,ull}, t \notin T_{0,g} \quad \text{(A.2)}$$

$$p_{s,t}^{C} \leq IC_{s,t}^{max}, \forall s, t \in T_{0,s} \quad \text{(A.3)}$$

$$p_{s,t}^{C} = 0, \forall s, t \notin T_{0,s} \quad \text{(A.4)}$$

The supply-demand balance for each hour of the forecast period is represented in (A.5). The amount of generation and discharging of storage facilities must exactly be equal to the summation of demand, load shedding and charging of storage facilities at each hour.

$$\sum_{g} p_{g,o,t}^{G} + \sum_{s} st_{s,o,t}^{D} = P_{o,t}^{D} + p_{o,t}^{LS} + \sum_{s} st_{s,o,t}^{C}, \forall o, t \quad \text{(A.5)}$$

The generation limit for existing and candidate power plants without unit size limitation is expressed as in (A.6) - (A.9). For a power plant that is not a renewable one, the hourly electricity generation is restricted by the availability factor at the corresponding hour. For a renewable power plant, the expression is amended by the inclusion of possible renewable energy curtailment.

$$p_{g,o,t}^{G} \leq ic_{g,t} * AF_{g,o,t}, \forall g \in G^{E,ull}, g \notin G^{E,re}, o, t \quad \text{(A.6)}$$

$$p_{g,o,t}^{G} \leq ic_{g,t} * AF_{g,o,t}, \forall g \in G^{C,ull}; g \notin G^{C,re}, o, t \tag{A.7}$$

$$p_{g,o,t}^{G} + p_{g,o,t}^{RES} = ic_{g,t} * AF_{g,o,t}, \forall g \in G^{E,re}, o, t \tag{A.8}$$

$$p_{g,o,t}^{G} + p_{g,o,t}^{RES} = ic_{g,t} * AF_{g,o,t}, \forall g \in G^{C,re}, o, t \tag{A.9}$$

The load shedding limit is shown in (A.10). The amount of load shedding cannot surpass the electricity demand at any hour.

$$p_{o,t}^{LS} \leq P_{o,t}^{D}, \forall o, t \tag{A.10}$$

The minimum stable generation limit for existing and candidate power plants with unit size limitation is represented by (A.11). If any unit is operating, it must at least operate at its technically minimum level.

$$p_{g,o,t}^{G} \geq ou_{g,o,t} * IC_{g}^{max} * MSGR_{g} * \Lambda_{g,t}, \forall g \in G^{ul}, o, t \tag{A.11}$$

The generation limit for existing and candidate power plants with unit size limitation is shown in (A.12). This is similar to (A.6) - (A.9) but only expressed in terms of unit characteristics.

$$p_{g,o,t}^{G} \leq ou_{g,o,t} * IC_{g}^{max} * AF_{g,o,t} * \Lambda_{g,t}, \forall g \in G^{ul}, o, t \tag{A.12}$$

The startup condition for existing and candidate power plants with unit size limitation is represented by (A.13). The change in the number of operating units must exactly be equal to the difference between started up and shut down unit at the corresponding hour.

$$ou_{g,o,t} - ou_{g,o,t-1} = su_{g,o,t} - sd_{g,o,t}, \forall g \in G^{ul}, o, t \tag{A.13}$$

The startup and shutdown condition for existing and candidate power plants with unit size limitation expressed as (A.14). The number of start ups and shut downs cannot exceed the number of installed units for any hour.

$$iu_{g,t} \geq su_{g,o,t} + sd_{g,o,t}, \forall g \in G^{ul}, o, t \tag{A.14}$$

The link between operating and installed units of existing and candidate power plants with unit size limitation is shown in (A.15). The number of operating units can at most be equal to that of installed units.

$$iu_{g,t} \geq ou_{g,o,t}, \forall g \in G^{ul}, o, t \tag{A.15}$$

The minimum uptime and downtime limits for existing and candidate power plants with unit size limitation are formulated as in (A.16) - (A.17). They are composed of two parts in order to represent the continuity of a representative day after the last hour.

$$ou_{g,o,t} \geq \sum_{\substack{o' \\ if(o' \leq o) \\ \left(o \leq o' + T_g^{up}\right)}} su_{g,o',t} + \sum_{\substack{o' \\ if(o' > o) \\ \left(24 - o' + o \leq T_g^{up}\right)}} su_{g,o',t}, \forall g \in G^{ul}, o, t \tag{A.16}$$

$$iu_{g,t} - ou_{g,o,t} \geq \sum_{\substack{o' \\ if(o' \leq o) \\ (o \leq o' + T_g^{down})}} sd_{g,o',t} + \sum_{\substack{o' \\ if(o' > o) \\ (24 - o' + o \leq T_g^{down})}} sd_{g,o',t}, \forall g \in G^{ul}, o, t \tag{A.17}$$

The operational constraints related to storage facilities are formulated as in (A.18) - (A.22). The amount of charging is restricted by the installed capacity and heat rate (A.18), and similarly that of discharging is restricted only by the installed capacity (A.19). On daily basis, the amount of charging and discharging must be balanced (A.20). The cumulative amount of discharging in any representative day must be less than or at most equal to that of charging until the corresponding hour (A.21). The ability to store energy is limited by the maximum hours of continuous operation (A.22).

$$st^C_{s,o,t} \leq ic_{s,t} * HTR_{s,t}, \forall s, o, t \tag{A.18}$$

$$st^D_{s,o,t} \leq ic_{s,t}, \forall s, o, t \tag{A.19}$$

$$\sum_o \left(st^D_{s,o,t} * HTR_{s,t}\right) = \sum_o st^C_{s,o,t}, \forall s, t \tag{A.20}$$

$$\sum_{o' \leq o} st^D_{s,o\prime,t} \leq \sum_{o' \leq o} \frac{st^C_{s,o\prime,t}}{HTR_{s,t}}, \forall s, o, t \tag{A.21}$$

$$\sum_{o' \leq o} \left(\frac{st^C_{s,o\prime,t}}{HTR_{s,t}} - st^D_{s,o\prime,t}\right) \leq ic_{s,t} * H^{max}_s, \forall s, o, t \tag{A.22}$$

The capacity limits for each power plant type by resources is represented by (A.23). It is used to limit the amount of coal, nuclear, wind and solar capacity at any year, as permitted by the user.

$$\sum_{g \in G^r} ic_{g,t} \leq IC^{max}_{r,t}, \forall r \in \{coal, nuclear, wind, solar\}, t \tag{A.23}$$

The hourly minimum reserve constraint is shown in (A.24). The difference between available capacity and total electricity generation must be greater than the minimum desired level of reserve. This is formulated as a soft constraint in order to allow for reserve deficiency depending on economics.

$$\sum_g \left(ic_{g,t} * AF_{g,o,t} - p^G_{g,o,t}\right) + p^{RS}_{o,t} \geq P^D_{o,t} * SH^R_{o,t}, \forall o, t \tag{A.24}$$

The auxiliary equalities and inequalities for power plants and storage facilities are expressed by (A.25) - (A.35). (A.25) - (A.26) are similar to (A.1) - (A.4), and they are used to limit the number of units based on what is allowed by the used at the corresponding year. (A.27) is for representing the cumulative number of commissioned units for candidate power plants, and (A.28) is the same one for existing power plants with unit size limitation. (A.29) - (A.30) shows the cumulative amount of capacity for candidate power plants with unit size limitation and storage facilities. (A.31) - (A.35) are presented here in order to express the total installed capacity for all types of facilities, with the same notation in order to simplify the reading of this study.

$$iu_{g,t}^{C} \leq U_{g,t}^{max} * \Lambda_{g,t}, \forall g \in G^{C,ul}, o, t \tag{A.25}$$

$$iu_{g,t}^{C} = 0, \forall g \in G^{C,ul}, o, t \notin T0_{g} \tag{A.26}$$

$$iu_{g,t}^{C,all} = iu_{g,t} = \sum_{t' \leq t} iu_{g,t'} * \Lambda_{g,t}, \forall g \in G^{C,ul}, o, t \tag{A.27}$$

$$iu_{g,t} = U_{g}^{max} * \Lambda_{g,t}, \forall g \in G^{E,ul}, o, t \tag{A.28}$$

$$p_{g,t}^{C,all} = \sum_{t' \leq t} p_{g,t'}^{C} * \Lambda_{g,t}, \forall g \in G^{C,ull}, o, t \tag{A.29}$$

$$p_{s,t}^{C,all} = \sum_{t' \leq t} p_{s,t'}^{C} * \Lambda_{s,t}, \forall s, o, t \tag{A.30}$$

$$ic_{g,t} = IC_{g}^{max} * \Lambda_{g,t}, \forall g \in G^{E,ull}, t \tag{A.31}$$

$$ic_{g,t} = p_{g,t}^{C,all}, \forall g \in G^{C,ull}, t \tag{A.32}$$

$$ic_{g,t} = p_{s,t}^{C,all}, \forall s, t \tag{A.33}$$

$$ic_{g,t} = U_{g}^{max} * IC_{g}^{max} * \Lambda_{g,t}, \forall g \in G^{E,ul}, t \tag{A.34}$$

$$ic_{g,t} = U_{g}^{max} * iu_{g,t}^{C,all}, \forall g \in G^{C,ul}, t \tag{A.35}$$

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