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Sustainable Distribution Network Planning Considering Multi-Energy Systems and Plug-In Electric Vehicles Parking Lots

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(3^{rd} cycle of studies)

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Resumo

Entre todos os recursos associados à evolução das redes elétricas para o conceito de smart grid, os sistemas de multi-energia e os veículos eléctricos do tipo plug-in (PEV) são dois dos principais tópicos de investigação hoje em dia. Embora estes recursos possam acarretar uma maior incerteza para o sistema de energia, as suas capacidades de demanda/armazenamento flexível de energia podem melhorar a operacionalidade do sistema como um todo. Quando o conceito de sistemas de multi-energia e os parques de estacionamento com estações de carregamento para os PEVs são combinados no sistema de distribuição, a demanda pode variar significativamente. Sendo a demanda de energia uma importante informação no processo de planeamento, é essencial estimar de precisa essa demanda. Deste modo, três níveis padrão de carga podem ser extraídos tendo em conta a substituição da procura entre carriers de energia, a demanda associada ao carregamento dos PEVs, e presença de parques de estacionamento com estações de carregamento no sistema. A presença de PEVs num sistema multi-energia obriga a outros requisitos (por exemplo, um sistema de alimentação) que devem ser fornecidos pelo sistema, incluindo as estações de carregamento.

A componente elétrica dos PEVs dificulta a tarefa ao operador do sistema na tentativa de encontrar a melhor solução para fornecer os serviços necessários e utilizar o potencial dos PEVs num sistema multi-energia. Contudo, o comportamento sociotécnico dos utilizadores de PEVs torna difícil ao operador do sistema a potencial gestão das fontes de energia associada às baterias. Desta forma, este estudo visa providenciar uma solução para os novos problemas que irão ocorrer no planeamento do sistema. Nesta tese, vários aspetos da integração de PEVs num sistema multi-energia são estudados. Primeiro, um programa de resposta à demanda é proposto para o sistema multi-energia com tecnologias do lado da procura que possibilitem alternar entre fornecedores de serviços. Em seguida, é realizado um estudo abrangente sobre as questões relativas à modelação dos PEVs no sistema, incluindo a modelação das incertezas, as preferências dos proprietários dos veículos, o nível de carregamento dos PEV e a sua interação com a rede. Posteriormente é proposta a melhor estratégia para a participação no mercado de energia e reserva. A alocação na rede e os possíveis efeitos subjacentes são também estudados nesta tese, incluindo o modelo dos PEVs e dos parques de estacionamento com estações de carregamento nesse sistema de multi-energia.

Palavras-chave

Estações de carregamento, carga flexível, sistemas de multi-energia, demanda multi-energia, programação matemática com restrições de equilíbrio, programação linear inteira mista, planeamento da rede, parques de estacionamento, veículos elétricos

Abstract

Among all resources introduced by the evolution of smart grid, multi-energy systems and plug-in electric vehicles are the two main challenges in research topics. Although, these resources bring new levels of uncertainties to the system, their capabilities as flexible demand or stochastic generation can enhance the operability of system. When the concept of multi-energy systems and plug-in electric vehicles (PEV) parking lots are merged in a distribution system, the demand estimation may vary significantly. As the main feed of planning process, it is critical to estimate the most accurate amount of required demand. Therefore, three stages of load pattern should be extracted taking into account the demand substitution between energy carriers, demand affected by home-charging PEVs, and parking lot presence in system.

The presence of PEVs in a multi-energy system oblige other requirements (i.e. fueling system) that should be provided in the system, including charging stations. However, the electric base of PEVs adds to the responsibilities of the system operator to think about the best solution to provide the required services for PEVs and utilize their potentials in a multi-energy concept. However, the socio-technical behavior of PEV users makes it difficult for the system operator to be able to manage the potential sources of PEV batteries. As a result, this study tries to raise the solution to new problems that will occur for the system planners and operators by the future components of the system.

In this thesis, various aspects of integrating PEVs in a multi-energy system is studied.Firstly, a carrier-based demand response program is proposed for the multi-energy system with the technologies on the demand side to switch between the carriers for providing their services. Then, a comprehensive study on the issues regarding the modeling of the PEVs in the system are conducted including modeling their uncertain traffic behavior, modeling the preferences of vehicle owners on the required charging, modeling the PEV parking lot behavior and its interactions with the network. After that the best strategy and framework for participating the PEVs energy in the energy and reserve market is proposed. The allocation of the parking lot in the network and the possible effects it will have on the network constraints is studied. Finally, the derived model of the PEVs and the parking lot is added to the multi-energy system model with multi-energy demand.

Keywords

Charging stations, flexible load, multi-energy systems,multi-energy demand, mathematical programming with equilibrium constraints, mixed integer linear programming, network planning, parking lots, plug-in electric vehicles.

Contents

List of Figures

List of Tables

List of Acronyms

AB	Auxiliary boiler
Agg	Aggregator
BEV	Battery-exchange Electric Vehicles
CBDR	Carrier-Based Demand Response
CHP	Combined Heat and Power
ChS	Charging Stations for PEVs
CS	Carrier Share
DER	Distributed Energy Resource
DG	Distributed Generation
DMG	Distributed Multi-energy Generation
DR	Demand Response
DSO	Distribution System Operator
ED	External Dependency
EENS	Expected Energy Not Served
EEq	Energy Equilibrium point
EM	Electricity Market
EV	Electric Vehicle
FOR	Forced Outage Rate
G2V	Grid to Vehicle
HC	Home-Charging vehicles
HS	Heat Storage
IL	Interruptible Load
KKT	Karush-Kuhn-Tucker
LL	Lower Level
MED	Multi Energy Demand
MES	Multi Energy System
MPEC	Mathematical Programming with Equilibrium Constraints
MILP	Mixed Integer Linear Programming
PDF	Probability density function
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PL	Parking Lot
PV	Photo Voltaic
RER	Renewable Energy Resources
REq	Reserve Equilibrium point
RM	Reserve Market
RWM	Roulette Wheel Mechanism
SOC	State of Charge
TM	Trade with Market
TPL	Trade with PL
TDG	Trade with DG
TDemand	Trade with Demand
UL	Upper Level
V2G	Vehicle to Grid

Nomenclature

The main notations used in this thesis is presented below separately for each chapter. It should be noted that some of the notations are used in different chapters; however, for the sake of consistency they are repeated in each chapter that they are being used.

Chapter 3

Sets and Indices

$a,\ b,\ z$	Index (set) of generic energy carriers.
e	Index of electric energy carrier.
DO	Index of dependent output.
g	Index of gas energy carrier.
h	Index of heat energy carrier.
IO	Index of independent output.
t	Index (set) of Time interval.
ω	Index (set) of uncertainty scenarios.

Parameters

$\overline{G}_{\omega,t}$	Maximum gas input to micro-MES.
$\overline{H}^{AB}$	Maximum heat output of AB unit.
$\underline{H}^{AB}$	Minimum heat output of AB unit.
$\overline{H}^{CHP}$	Maximum heat output of CHP unit.
$\underline{H}^{CHP}$	Minimum heat output of CHP unit.
$\overline{H}^{HS}$	Maximum heat output of HS unit.
$\underline{H}^{HS}$	Minimum heat output of HS unit.
$L_{e,t}$	Electric demand.
$L_{g,t}$	Gas demand.
$L_{h,t}$	Heat demand.
$L_{eg,t}$	Total dependent demand between gas and electricity energy carriers.
$\overline{W}_{\omega,t}$	Maximum electricity input to micro-MES
$\overline{W}^{CHP}$	Maximum electricity output of CHP unit.
$\underline{W}^{CHP}$	Minimum electricity output of CHP unit.
Γ^{HS}	Charge/discharge rate of HS.
η_e^{CHP}	Efficiency of CHP unit in producing electricity.
η_h^{CHP}	Efficiency of CHP unit in producing heat.
η_h^{AB}	Efficiency of AB in producing heat.
η_h^{HS}	Efficiency of HS in providing heat.
$\Pi_{e,t}$	Price of electricity energy carrier.
$\Pi_{g,t}$	Price of gas energy carrier.

$\overline{\Psi}^{CHP}$ Maximum heat to power of CHP unit.

$\underline{\Psi}^{CHP}$ Minimum heat to power of CHP unit.

Variables

$g^{in}_{\omega,t}$ Hourly gas energy carrier input to the micro-MES in different scenarios.

$h^{CHP}_{\omega,t}$ Hourly heat produced by the CHP unit in different scenarios.

$h^{HS}_{\omega,t}$ Hourly heat produced by the HS unit in different scenarios.

$\dot{h}^{HS}_{\omega,t}$ The difference in heat stored in the HS in two consecutive time intervals for each scenario.

$l^{CB}_{eg,\omega,t}$ The hourly amount of DD that will participate in CBDR program in each scenario.

$l^{CB}_{e,\omega,t}$ The hourly amount of electricity from total DD that will participate in CBDR program in each scenario.

$l^{CB}_{g,\omega,t}$ The hourly amount of gas from total DD that will participate in CBDR program in each scenario.

$l^{CS}_{e,\omega,t}$ The hourly amount of electricity from total DD that will behave based on CS in each scenario.

$l^{CS}_{g,\omega,t}$ The hourly amount of gas from total DD that will will behave based on CS in each scenario.

$v^{AB}_{g,\omega,t}$ Decision variable for determining the share of AB unit in consumption of total input gas in different scenarios.

$v^{CB}_{\omega,t}$ Decision variable for determining the hourly share of CBDR program from total DD in different scenarios.

$v^{CHP}_{g,\omega,t}$ Decision variable for determining the share of CHP unit in consumption of total input gas in different scenarios.

$v^{CS}_{e,\omega,t}$ Decision variable for determining the share of DD that will behave based on CS and choose to use electricity in each scenario.

$v^{CS}_{g,\omega,t}$ Decision variable for determining the share of DD that will behave based on CS and choose to use gas in each scenario.

$v^{dd}_{e,\omega,t}$ Decision variable for determining the hourly share of electricity of DD from total input electricity in different scenarios.

$v^{dd}_{g,\omega,t}$ Decision variable for determining the hourly share of gas of DD from total input electricity in different scenarios.

$v^{out}_{e,\omega,t}$ Decision variable for determining the hourly electricity output of micro-MES from total input electricity in different scenarios.

$v^{out}_{g,\omega,t}$ Decision variable for determining the hourly gas output of micro-MES from total input gas in different scenarios.

$w^{in}_{\omega,t}$ Hourly electricity energy carrier input to the micro-MES in different scenarios.

$w^{CHP}_{\omega,t}$ Hourly electricity produced by the CHP unit in different scenarios.

$\psi^{CHP}_{\omega,t}$ Hourly heat to power ratio for CHP unit in each scenario.

Chapter 4

Sets and Indices

$i,\ j$	Indices (sets) indicating the number of urban zones.
$t,\ k$	Indices (sets) indicating the time intervals.
ω	Index (set) of uncertainty scenarios.

Parameters

$C_{i,\omega,t}^{in,Env}$	Hourly PEV capacity entered from environment to zone i in different scenarios.
$C_{j,i,\omega,t}^{in,Zone}$	Hourly PEV capacity entered to zone i from zone j in different scenarios.
$C_{i,j,\omega,t}^{out,Zone}$	Hourly PEV capacity departed from zone j to zone i in different scenarios.
$Dist_{i,j}$	The distance traveled by PEVs from zone i to zone j.
$N_{i,\omega,t=1}^{PL}$	Number of PEVs in PL in zone i in $t = 1$.
$N_{i,\omega,t=1}^{Urban}$	Number of PEVs in urban in zone i in $t = 1$.
$N_{i,\omega,t}^{in,Env}$	Hourly number of PEVs entering from environment to zone i in different scenarios.
$N_{i,\omega,t}^{out,Env}$	Hourly number of PEVs going out zone i to environment in different scenarios.
$N_{j,i,\omega,t}^{in,Zone}$	Hourly number of PEVs entered to zone i from zone j in different scenarios.
$N_{i,j,\omega,t}^{out,Zone}$	Hourly number of PEVs departed from zone j to zone i in different scenarios.
NS_i^{PL}	Number of stations in PL in zone i.
NS_i^{ChS}	Number of individual charging stations in zone i.
$P_{i,j}^{Fuel}$	The amount of power consumed for traveling between zones i and j.
$Sp_{i,j}$	The speed of PEVs while traveling betwenn zones i and j.
β_i^{Urban}	Coefficient determining the share of each PEV category from hourly vehicle departure from charging stations in urban in zone i.
β_i^{PL}	Coefficient determining the share of each PEV category from hourly vehicle departure from PL in zone i.
Γ_i^{ChS}	The Charging/Discharging rate of individual charging stations in zone i.
Γ_i^{PL}	The Charging/Discharging rate of PL in zone i.
$\eta_i^{cha,PL}$	The Charging efficiency of stations in PL in zone i.
$\eta_i^{dcha,PL}$	The discharging efficiency of stations in PL in zone i.
κ_i^{PL}	PEVs participation ration in reserve market.
ϕ_i^{Urban}	Coefficient determining the minimum departure SOC requirement of each PEV category from charging stations in urban in zone i.
ϕ_i^{PL}	Coefficient determining the minimum departure SOC requirement of each PEV category from PL in zone i.
χ^{PEV}	SOC to capacity ratio for each PEV.

Variables

$c_{i,\omega,t}^{ar,PL}$	Hourly PEV capacity arrived to PL in zone i in different scenarios.
$c_{i,\omega,t}^{ar,Urban}$	Hourly PEV capacity arrived to urban area zone i from zone j in different scenarios.
$c_{i,\omega,t}^{Urban}$	The capacity of PEVs in urban area in each hour in zone i in different scenarios.
$C_{i,j,\omega,t}^{out,Zone}$	Hourly PEV capacity departed from zone j to zone i in different scenarios.
$c_{i,\omega,t}^{PL}$	Capacity of PEVs in the PL in each hour in zone i in different scenarios.
$n_{i,\omega,t}^{PL}$	Number of PEVs in the PL in each hour in zone i in different scenarios.
$n_{i,\omega,t}^{Urban}$	Number of PEVs in the urban area in each hour in zone i in different scenarios.
$n_{i,\omega,t}^{ar,PL}$	The number of PEVs arrived to PL in each hour in zone i in different scenarios.
$n_{i,\omega,t}^{dep,PL}$	The number of PEVs departed from PL in each hour from zone i in different scenarios.
$n_{i,\omega,t}^{ar,Urban}$	The number of PEVs arrived to urban area in each hour in zone i in different scenarios.
$n_{i,\omega,t}^{vac,PL}$	The number of vacant stations in PL in zone i in each hour in different scenarios.
$p_{i,\omega,t}^{inj,Urban}$	The injected power to the charging stations in urban area in each hour in zone i in different scenarios.
$p_{i,\omega,t}^{in,PL}$	The injected power to the PL in each hour in zone i in different scenarios.
$p_{i,\omega,t}^{out,PL}$	The power injected from the PL to the grid in each hour in zone i in different scenarios.
$r_{i,\omega,t}^{out,PL}$	The amount of reserve provided by the PL to the grid in each hour in zone i in different scenarios.
$soc_{i,\omega,t}^{PL}$	Hourly SOC of PL in zone i in different scenarios.
$soc_{i,\omega,t}^{Urban}$	Hourly SOC of PEVs in urban area in zone i in different scenarios.
$soc_{i,\omega,t}^{in,Env}$	SOC of the PEVs entering to zone i from environment in different scenarios at time interval t.
$soc_{j,i,\omega,t}^{in,Zone}$	SOC of the PEVs entering to zone j from zone i in different scenarios at time interval t.
$soc_{j,i,\omega,t}^{out,Zone}$	SOC of the PEVs going out from zone j to zone i in different scenarios at time interval t.
$soc_{i,\omega,t}^{ar,Zone}$	SOC of PEVs arrived to zone i in different scenarios scenarios at time interval t.
$soc_{i,\omega,t}^{out,Env}$	SOC of the PEVs going out from zone i to environment in different scenarios at time interval t.
$soc_{i,\omega,t}^{ar,PL}$	SOC of PEVs arrived to PL in each hour in zone i in different scenarios.
$soc_{i,\omega,t}^{ar,Urban}$	SOC of PEVs arrived to urban area in each hour in zone i in different scenarios.

$soc_{i,\omega,t}^{dep,Urban}$	SOC of PEVs departed from urban area in zone i in different scenarios scenarios at time interval t.
$soc_{i,\omega,t}^{dep,PL}$	SOC of PEVs departed from PL in zone i in different scenarios scenarios at time interval t.
$soc_{i,\omega,t}^{dep,Zone}$	SOC of PEVs departed from zone i in different scenarios scenarios at time interval t.

Chapter 5

Sets and Indices

b	Indices (sets) indicating the distribution network branches.
j, k	Indices (sets) indicating the distribution network nodes.
m	Indices (sets) indicating the number of DGs.
t	Indices (sets) indicating the time intervals.
ω	Index (set) of uncertainty scenarios.

Parameters

Cd^{PL}	Cost of equipment degradation in PL.
FOR^{Agg}	Forced outage rate of the aggregator.
FOR^{PL}	Forced Outage Rate of the PL.
$I_{j,k}$	Current of line between nodes j and k.
$N_{\omega,t}^{PL}$	Number of PEVs in PL.
$R_{j,k}$	Resistance of line between nodes j and k.
$SOC_{\omega,t}^{dep,fix1,Sc}$	The SOC of departing PEVs in category fix1 based on the commute scenarios in scenario ω at time interval t.
$SOC_{\omega,t}^{dep,fix2,Sc}$	The SOC of departing PEVs in category fix2 based on the commute scenarios in scenario ω at time interval t.
$SOC_{\omega,t}^{dep,flex1,Sc}$	The SOC of departing PEVs in category flex1 based on the commute scenarios in scenario ω at time interval t.
$SOC_{\omega,t}^{dep,flex2,Sc}$	The SOC of departing PEVs in category flex2 based on the commute scenarios in scenario ω at time interval t.
$X_{j,k}$	Reactance of line between nodes j and k.
V_j	Voltage of node j.
η^{Trans}	Efficiency of the transformer.
$\eta^{cha,PL}$	The Charging efficiency of stations in PL.
$\eta^{dcha,PL}$	The discharging efficiency of stations in PL.
$\beta_{\omega,t}^{fix1}$	Coefficient determining the share of PEV category fix1 from hourly departing vehicle at time interval t.
$\beta_{\omega,t}^{fix2}$	Coefficient determining the share of PEV category fix2 from hourly departing vehicle at time interval t.

Γ_i^{PL}	The Charging/Discharging rate of PL.
$\theta_{\omega,t}^{PL}$	Coefficient determining the share of PEVs in different mode from total PEVs in the PL for different scenarios at time interval t.
Π_t^{G2V1}	The price of purchasing energy by PEV category fix1.
Π_t^{G2V2}	The price of purchasing energy by PEV category flex1.
Π_t^{G2V3}	The price of purchasing energy by PEV category fix2.
Π_t^{V2G}	The price of purchasing energy from PEV category flex2.
Π^{Extra}	The incentive paid to PEVs that agree to participate in V2G mode.
Π_t^{ToU}	The Time of Use tariff paid by loads to the aggregator.
$\Pi_t^{Incentive}$	The incentive paid to the loads participating in the IL program by the aggregator.
Π_t^{Loss}	The price paid for loss in the network.
$\phi_{\omega,t}^{fix1}$	Coefficient determining the minimum departure SOC requirement of PEV category fix1 at time interval t.
$\phi_{\omega,t}^{fix2}$	Coefficient determining the minimum departure SOC requirement of PEV category fix2 at time interval t.
$\phi_{\omega,t}^{flex1}$	Coefficient determining the minimum departure SOC requirement of PEV category flex1 at time interval t.
$\phi_{\omega,t}^{flex2}$	Coefficient determining the minimum departure SOC requirement of PEV category flex2 at time interval t.
χ^{PEV}	SOC to capacity ratio for each PEV.

Variables

$i_{j,k,t}$	The current flowing from node j to node k at time interval t.
$profit^{Agg}$	Total profit of the aggregator.
$profit^{TM}$	Profit of the aggregator through market transactions.
$profit^{TPL}$	Profit of the aggregator through transactions with PL.
$profit^{TDG}$	Profit of the aggregator through transactions with DG.
$profit^{TD}$	Profit of the aggregator through transactions with demand.
$profit^{PL-Agg}$	Profit of the PL operator through transactions with the aggregator.
$profit^{PL-PEV}$	Profit of the PL operator through transactions with PEV owners.
$profit^{DG-Agg}$	Profit of the DG operator through transactions with the aggregator.
$profit^{D-Agg}$	Profit of the load retailer through transactions with the aggregator.
p_t^{Agg}	Amount of energy purchased by the aggregator from the energy market at time interval t.
$\hat{p}_t^{in,PL}$	The expected value of the power injected to the PL from different scenarios at time interval t.
$\hat{p}_t^{out,PL}$	The expected value of the power injected from the PL to the grid from different scenarios at time interval t.
$p_{m,t}^{DG}$	The amount of energy purchased from mth DG at time interval t.

p_t^{D} The amount of energy provided for the demand after possible IL by the aggregator at time interval t.

$p_t^{D,total}$ The amount of energy provided for the total demand by the aggregator at time interval t.

$\hat{p}_t^{in,PL}$ The expected value of PL's input energy at time interval t.

$p_{\omega,t}^{in,PL}$ The hourly amount of PL's input energy for different scenarios.

$\hat{p}_t^{out,PL}$ The expected value of PL's output energy at time interval t.

$p_{\omega,t}^{out,PL}$ The hourly amount of PL's output energy for different scenarios.

$p_{j,t}^{D}$ The amount of energy provided for the demand at node j by the aggregator at time interval t.

$p_{j,t}^{\prime in,PL}$ The hourly amount of power injected to PL on node j.

$p_{j,t}^{\prime out,PL}$ The hourly amount of output power from PL on node j.

$p_{j,t}^{\prime DG}$ The hourly amount of power injected from DG on node j to the grid.

$p_t^{in,DSO}$ The hourly amount of input active power to the grid provided by the DSO for different scenarios.

$p_t^{out,DSO}$ The hourly amount of output active power from the grid to the upstream network for the DSO for different scenarios.

$p_{k,j,t}^{Line}$ The hourly amount of active power going through branch from node k to node$j$.

$p_{\omega,t}^{out,V2G}$ The hourly output power from PL's V2G mode in different scenarios.

$p_{\omega,t}^{in,V2G}$ The hourly input power for charging the PEVs who participate in V2G mode in different scenarios.

$p_{\omega,t}^{in,G2V}$ The hourly input power for charging the PEVs who participate in G2V mode in different scenarios.

$p_{m,t}^{DG}$ The amount of energy produced by the mth DG at time interval t.

p_t^{IL} The amount of IL at time interval t.

$q_t^{in,DSO}$ The hourly amount of input reactive power to the grid provided by the DSO for different scenarios.

$q_t^{out,DSO}$ The hourly amount of output reactive power from the grid to the upstream network for the DSO for different scenarios.

$q_{k,j,t}^{Line}$ The hourly amount of reactive power going through branch from node k to node$j$.

$\hat{r}_t^{PL}$ The expected value of PL's reserve at time interval t.

$r_{\omega,t}^{PL}$ The hourly amount of PL's reserve for different scenarios.

r_t^{Agg} Amount of reserve provided by the aggregator for the energy market at time interval t.

Si^{PL} Binary variable for determining the location of PL in grid nodes.

$soc_{\omega,t}^{dep,flex1}$ The hourly departure SOC of PEVs in category flex1 in different scenarios.

$soc_{\omega,t}^{dep,flex2}$ The hourly departure SOC of PEVs in category flex2 in different scenarios.

$soc_{\omega,t}^{PL,G2V}$ The hourly SOC of PEVs in G2V mode staying in the PL in different scenarios.

$soc_{\omega,t}^{ar,G2V}$	The hourly arrival SOC of PEVs who only participate in G2V mode to the PL in different scenarios.
$soc_{\omega,t}^{dep,G2V}$	The hourly departure SOC of PEVs who only participate in G2V mode from the PL in different scenarios.
$soc_{\omega,t}^{PL,V2G}$	The hourly SOC of PEVs in V2G mode staying in the PL in different scenarios.
$soc_{\omega,t}^{ar,V2G}$	The hourly arrival SOC of PEVs who only participate in V2G mode to the PL in different scenarios.
$soc_{\omega,t}^{dep,V2G}$	The hourly departure SOC of PEVs who only participate in V2G mode from the PL in different scenarios.
$v_{j,t}$	The voltage of node j at time interval t.
$Z_{\omega,t}^{PL}$	The variable defined for linearization of power flow equations.
ε_t^D	The share of IL from total demand at time interval t.
π_t^D	The equilibrium price of demand at time interval t.
π_t^{DG}	The equilibrium price of purchasing energy from DG by the aggregator at time interval t.
$\pi_t^{in,PL}$	The equilibrium price of PL's energy purchase from the aggregator at time interval t.
$\pi_t^{out,PL}$	The equilibrium price of PL's energy sell to the aggregator at time interval t.
$\pi_t^{Re,PL}$	The equilibrium price of PL's reserve provision for the aggregator at time interval t.
ρ_ω	The probability of each scenario.
ρ_t^{del}	The probability of reserve call from the reserve market at time interval t.

Chapter 6

Sets and Indices

b	Indices (sets) indicating the distribution network branches.
$j,\ k$	Indices (sets) indicating the distribution network nodes.
$t,\ h$	Indices (sets) indicating the time intervals.
ω	Index of uncertainty scenarios.
Ω_{PL}	Set of uncertainty scenarios for PL behavior.
Ω_{Pr}	Set of uncertainty scenarios for price.
Ω_{PLA}	Set of uncertainty scenarios for PL behavior in allocation problem.
Ω_{PV}	Set of uncertainty scenarios for PV generation.
Ω_{Wind}	Set of uncertainty scenarios for wind generation.

Parameters

Cd^{PL}	The battery degradation price paid to PEV owners for participating in V2G mode.
CDC	Customer Damage Cost.
$C_{\omega,t}^{PL,Sc}$	The hourly capacity of PL in different scenarios.
FOR^{PL}	Forced Outage Rate of the PL.
$\overline{I_{j,k}}$	The maximum amount of branch current.
$\underline{I_{j,k}}$	The minimum amount of branch current.
NS^{PL}	The total number of stations in the PL.
$N^{PL,Sc}$	The total number of PEVs in the PL in different scenarios.
$NS_{\omega}^{PL,Sc}$	The total number of stations in the PL based on different scenarios.
$p_{j,\omega,t}^{PV,Sc}$	The hourly output power from PV arrays on node j in each scenario.
$P_{j,\omega,t}^{W,Sc}$	The hourly output power from wind turbines on node j in each scenario.
$R_{j,k}$	The resistance of the network branch between nodes j and k.
$SOC_{\omega,t}^{PL,Sc}$	The hourly SOC of PL in different scenarios.
$\overline{V_{j,k}}$	The maximum amount of node voltage.
$\underline{V_{j,k}}$	The minimum amount of node voltage.
$X_{j,k}$	The reactance of the network branch between nodes j and k.
$Z_{j,k}$	The impedance of the network branch between nodes j and k.
$\Gamma^{cha,PL}\eta^{PL}$	The charging rate of charging facilities in the PL.
$\Gamma^{dcha,PL}\eta^{PL}$	The discharging rate of charging facilities in the PL.
$\eta^{PL,cha}$	The charging efficiency of the infrastructure in the PL.
$\eta^{PL,dcha}$	The discharging efficiency of the infrastructure in the PL.
λ_b	Failure rate on branch b.
$\mu_t^{PL,Con}$	The probability of contingency.
Π^{loss}	The price of loss in the system.

Variables

$c_{\omega,t}^{PL}$	The hourly capacity of PL in different scenarios.
$Cost^{Sys}$	Total cost of the system.
$cost_{\omega}^{Ins}$	Installation cost in each scenario.
$cost_{\omega}^{Reli}$	Reliability cost in each scenario.
$cost_{\omega}^{VD}$	Voltage Deviation cost in each scenario.
$cost_{\omega}^{loss}$	Cost of energy loss in each scenario.
$cost_{j}^{PLA,fix}$	Fixed cost of PL allocation in each node.
$cost_{j}^{PLA,var}$	Variable cost of PL allocation in each node.
$cost^{Cap,fix}$	Fixed cost of capacitor installation.
$cost^{Cap,var}$	Variable cost of capacitor installation.
$EENS_{\omega}$	The expected energy not served in each scenario.
$n_{\omega,t}^{PL}$	The hourly number of PEVs in the PL in each scenario.

$ns_{j,\omega}^{PLA}$	The number of charging stations in the PL in each node in the allocation problem.
$i_{j,k,\omega,t}$	The hourly branch current from node j to node k in each scenario.
$profit^{PL}$	Total profit of the PL.
$profit^{EMI}$	Total profit of the PL from interactions with energy market.
$profit^{RMI}$	Total profit of the PL from interactions with reserve market.
$profit^{POI}$	Total profit of the PL from interactions with PEV Owners.
$p_{\omega,t}^{out,PL}$	The hourly output of PL in each scenario.
$p_{\omega,t}^{in,PL}$	The hourly input to PL in each scenario.
$p_{j,\omega,t}^{Sys,in}$	The hourly input active power to the system from node j in each scenario.
$p_{j,\omega,t}^{W}$	The hourly output power from wind turbines on node j in each scenario.
$p_{j,\omega,t}^{PV}$	The hourly output power from PV arrays on node j in each scenario.
$p_{j,\omega,t}^{PLA,in}$	The hourly input power to the PL on node j in each scenario in the allocation problem.
$p_{j,\omega,t}^{PLA,out}$	The hourly output power to the PL on node j in each scenario in the allocation problem.
$p_{j,\omega,t}^{inj,PLA}$	The hourly input power to the PL on node j in each scenario in the reliability problem.
$p^{L}ine_{j,k,\omega,t}$	The hourly line active power from node j to node k in each scenario.
$p_{j,t}^{D}$	The hourly active demand on node j.
$p_{b,\omega,t}^{inj,Res}$	The injected power from the resources in the network.
$p_{b,\omega,t}^{aff,D}$	The affected demand after the contingency on branch b.
$p_{b,\omega,t}^{Shed}$	The total shed load due to contingency on branch b.
$q_{j,t}^{D}$	The hourly reactive demand on node j.
$q_{j,\omega,t}^{Sys,in}$	The hourly input reactive power to the system from node j in each scenario.
$q^{L}ine_{j,k,\omega,t}$	The hourly line reactive power from node j to node k in each scenario.
$r_{\omega,t}^{PL}$	The hourly amount of reserve provided by the PL in each scenario.
$soc_{\omega,t}^{PL}$	The total PL's SOC for different scenarios at time interval t.
$soc_{\omega,t}^{PL,up}$	The hourly amount of increase in the PL's SOC for different scenarios.
$soc_{\omega,t}^{PL,down}$	The hourly amount of decrease in the PL's SOC for different scenarios.
$soc_{\omega,t}^{PL,ar}$	The hourly amount of SOC of the PEVs arriving in the PL in different scenarios.
$soc_{\omega,t}^{PL,dep}$	The hourly amount of SOC of the PEVs departing from the PL in different scenarios.
$soc_{j,\omega,t}^{PLA}$	The hourly SOC of PL for different scenarios at node j in allocation problem.
$v_{j,\omega,t}$	The hourly nodal voltage in each scenario.
$\pi_{\Omega_{Pr},t}^{E}$	The hourly price of energy for different price scenarios.
$\pi^{R}e_{\Omega_{Pr},t}$	The hourly price of reserve for different price scenarios.
π_{t}^{outage}	The hourly penalty price of not being ready for reserve call.
π_{t}^{G2V}	The price paid by the vehicles for G2V charging at time interval t.

π^{Tariff}	The tariff paid by the vehicles for entering the PL.
π_t^{V2G}	The price paid to the vehicles for V2G participation at time interval t.
ρ_t^{del}	The probability of reserve call for reserve execution at time interval t.
ρ_ω	Probability of each scenario.
ϕ_t^{PL}	The aggregated percentage of minimum departure SOC requirement of PEVs in the PL at time interval t.

Chapter 1

Introduction

1.1 Background and Motivation

Emerging technologies and changes in decision making structure have altered the planning issues in distribution systems. The interest in Distributed Energy Resources (DER) as a tool for meeting distribution system requirements has been intensified by recent DER technological improvements, improved technical understanding and capabilities in the areas of interconnection and controls, as well as regulatory attention on the potential benefits of DERs [1]. In this new environment, the impact of new resources and their behavioral uncertainties along with taking their advantages should be considered [2]. Among all resources introduced by evolution of smart grid, multi-energy system (MES) and plug-in electric vehicles (PEVs) are the two main challenges in research topics. Although, these resources bring new levels of uncertainties to the system, their capabilities as flexible demand or stochastic generation can enhance the operability of system [3].

When the concept of multi-energy systems and PEV parking lots are merged in a distribution system, the demand estimation may vary significantly. As the main feed of planning process, it is critical to estimate the most accurate amount of required demand. Therefore, three stages of load pattern should be extracted taking into account the demand substitution between energy carriers, demand affected by home-charging PEVs, and parking lot presence in system [4].

The main goal of this research is to provide a sustainable network planning framework for future distribution systems that benefit from various smart technologies. This study tries to raise the solution to new problems that will occur in front of distribution system planners by the future components of the system. One of these problems is efficient allocation of DERs throughout the distribution network. On the other hand, optimum utilization of facilities brought by these resources will be a tool to solve the occurred problems. Therefore, DERs (in this project's case PEV parking lots) should be considered as new elements (tools) of the planning procedure. This obliges the future distribution planner to propel towards revising the conventional solutions tending to consider more smart resources. On this basis, each step of the planning have to be taken with regard to new elements imposed into the system. After recognizing the impact of these technologies on demand estimation, it is necessary to plan the network in a way to be properly configured. The following steps are intended to take place in the planning phase:

Multi-energy systems provide the opportunity of various energy carriers which could serve the corresponding demand and have the ability of the substitution through energy converters in the system. This matter necessitates the availability of certain technology on demand-side that can provide the same service through multi carriers. The possibility of such devices has been increasing by the vast penetration of MES programs and planning. As a result, the situation will cause a dependency on the demand side. This dependency is due to the fact that the estimation of the demand and the required input resource will be dependent to the customer's choice of carrier. As this dependency occurs on demand-side, it is different from those dependencies that are within the local network system due to its internal converters such as CHP units and results in the dependent demand. For the first step of thesis, the dependency occurred on the demand side is modeled and is employed in the operation of the system through a carrier based demand response program.

Forthcoming urban systems will be equipped with high-tech infrastructures that could make difficult to deal with both operational and planning aspects. The PEVs offer a vast spectrum of possibilities for future systems. As well as enhancing system's efficiency and operational conditions, other issues such as greenhouse gas emissions and fossil fuel shortages will be met if higher penetration of PEVs in both transportation and electrical systems is encouraged. The presence of PEVs in a system oblige other requirements (i.e. fueling system) that should be provided in the system, including charging stations. However, the electric base of PEVs adds to the responsibilities of the DSO to think about the best solution to provide the required services for PEVs and utilize the potentials of PEVs as well. However, the socio-technical behavior of PEV users makes it difficult for the DSO to be able to manage the potential sources of PEV batteries. On the other hand, the distance that the PEVs travel is another factor affecting the amount of energy that PEVs lose during their travels and is changed by the topographical characteristics of the environment under study.

In this regard, confronting with the PEVs management in the system requires the clarifications of the inter-relations between various components of the system with PEVs through determining their possible behavior. As a result, for the next step, a model to describe the traffic pattern behavior of PEVs that can be added as a sub-module in any other studies (e.g. operation and planning) for decision makers in an urban environment with high penetration of PEVs.

On the next step, this traffic pattern is employed to derive the possible operational behavior of the PL and its market participation. The PLs provide a medium for the PEVs to charge their batteries also an aggregated version of PEVs to act as storage. PLs equipped with enough facilities can deliver grid to vehicle (G2V) and vehicle to grid (V2G) opportunities of the PEVs at the same time. Operation of PL in both G2V and V2G modes affects the operation of the system. Therefore, in this step the market participation of PEVs through the PL is investigated. This situation will cause a bilevel problem in which the PL has interactions with the market in one hand and with the PEVs constrained by their preferences on the other hand. This bilevel decision making problem is modeled mathematically and converted into a single level problem using mathematical programming with equilibrium constraints (MPEC) approach.

Managing the power needed for charging vehicles in a parking lot and the potential of PEVs to inject power into the grid is a challenging issue that may have conflicting impacts on the network. As a result, the DSO has to study the effects of PL network integration while considering the use of PL as a network resource in the most efficient way. This can be achieved through the optimal allocation of PLs in the system. Usually, PLs are connected to distribution networks, thus, the responsibility of the DSO is to investigate possible effects of this integration. High penetration of storage devices such as PEVs can have adverse impacts on the grid because of their randomly located charging loads or unmanaged additions. On the contrary, the optimal allocation of PLs can provide benefits both to its owner and the DSO. To achieve all the advantages of PLs, both the optimal sizes and sites are needed. Therefore, the optimal allocation of PLs is one of the most important issues to be considered while trying to minimize undesirable effects on the distribution system. In this regard, the next step in this project is going to be the allocation of the PEVs' PL in a distribution network considering the presence of renewable energy resources (RERs) in the system.

Although the PEVs' demand is only electrical, while being included in the multi-energy systems, the charging of the PEVs should be scheduled compatible to the prospects of the MES approach. Moreover, the cross impact of PEVs and other resources cannot be neglected. The operation of the resources such as combined heat and power (CHP) units will change due to the extra load imposed to the system by PEVs. The PEVs batteries as a potential storage in the system imposes certain changes in the modeling of a micro-MES. On the other hand, the dynamic nature of the PEVs makes them different from the regular electric loads. The uncertain behavior of the PEV owners in using the PEVs will cause an uncertain state of charge (SOC) in the system which should be fulfilled by the MES operator. As a result, in the final step of the study, the PEV parking lots as well as the charging stations are included as modules in the multi-energy system models. In this case, the PL and charging stations act as the energy converters who accepts PEVs and electricity as the inputs.

1.2 Research Questions and Contribution of the Thesis

This thesis aims to model the integration of the PEVs in the multi-energy systems. This integration can be through the infrastructure needed for the PEVs interconnection to the grid such as PEV charging stations whether in the form of PEV PL or individual stations. It is intended to find the optimized system operation with the potentials that the PEVs can bring in a multi-energy system.

In particular, the following research questions will be addressed:

- How a multi-energy environment can provide the scheme for the multi-energy demand to use the demand side facilities and contribute in the system operation strategies?
- What are the uncertainties imposed by the vehicle owners' behavior to the PEVs' potential? How the preferences of the owners can be included in the mathematical model?
- How the market strategies can be designed with the availability of the PEVs in the system? What is a better choice in case of PEVs for participating in electricity market?
- What are the roles that can be assigned to the PEVs in a multi-energy system?
- What are the solutions for the system operator to take benefit from the opportunities of the multi-energy system equipped with various resources as well as PEVs?

The main contributions of this thesis can be identified as follows:

- To represent customer's choice in the multi-energy system model to increase flexibility, by extending the matrix model of the multi-energy system to incorporate the effects of dependent demand though introducing the Carrier Based Demand Response program.
- To propose a model to impose the preferences of the PEVs who use the PL based on their choice of G2V/V2G mode, time of stay and their requirement of SOC on departure time.
- To model the integrated behavior of PLs through PEVs' arrivals and departures and also PLs interaction with energy and reserve markets.

- To investigate the effects of PEV preferences on equilibrium point of PL and aggregator for the energy and reserve interaction.
- To propose a two-stage model that determines the optimal behavior of PLs at the first stage. Then, this behavior is subject to network-constrained objectives in order to allocate PLs at the second stage.
- To propose the matrix modeling for the micro MES with PL and HC elements.
- To model the inter-relation of PEVs PL and Chs within the energy hub concept.
- To consider the PEVs traffic pattern as the inputs of the energy hub.

1.3 Outline of the Thesis

This thesis is divided into the following Chapters and Appendices as follows:

Chapter 2 provides a comprehensive survey on the literature regarding the main subjects of this thesis which are the PEVs and MES. Different aspects of PEVs including their modeling in G2V and V2G modes, market participation, network integration, and different aggregation forms are investigated. On the other hand, the MES concept and the approaches for modeling the future MES systems with various components are presented. Finally, the merging of PEVs in MES as a new component is investigated in the previous studies.

Chapter 3 introduces the new dependencies that are occurring in the MES due to the new technologies on the demand side. These dependencies between various energy carriers which affect the total provision of the MES are modeled and added to the conversion matrix of the MES. Using the stochastic modeling, the uncertain nature of these dependencies are also considered in the model as they are dependent to the behavior of the end-users. A Local multi-energy system with dependent demand of hot water is undertaken as the illustrative example.

Chapter 4 gives the various models that are needed for PEV PL's integration in the system including the PEV PL traffic pattern, the PEV owner preferences on using the PEV PL, and the PEVs commute pattern within an urban zone. Firstly, based on the historical data from the surveys a stochastic model for the PL's traffic pattern is derived which contains the scenarios for PEVs arrival, departure, duration of stay, and the hourly capacity and SOC of the PEVs in the PL based on the average battery capacity and travel distances. After that and based on the real data surveys, the preferences of the PEV owners while using the PEV PL is modeled with different coefficients. This is used to limit the operation of the PL based on the owners' needs and requirements in the system. Moreover, the traffic commute in an urban area and the division of the PEVs between PEV PL and individual charging stations in the urban area is modeled considering various constraints of the PL, zone, and charging stations.

Chapter 5 models the operational behavior of the PEV PL in the market place. Considering the PL to be able to operate in both G2V and V2G modes, a problem is designed to model the inter-relations of PEV-PL-Market. A bilevel model is encountered because of the contradictory objectives of PEV owners, PL operator and the market interface agent. Other resources such as DG and IL are also considered to be available for the market interface agent. To keep up with the MILP solving procedure of the whole thesis, an MPEC approach is implemented to the bilevel model to convert it into a single level linear model, then to be solved by MILP. The PEV owners preferences derived in Chapter 4 are employed in this chapter. Various analysis on the PL tariffs,the equilibrium prices, and the behavior of each component of the system is explained in the case studies section.

Chapter 6 covers the network integration concerns of the PEV PL deployment. In this chapter, the allocation of the PEV PL in a renewable-based network with wind turbines and PV arrays is studied. In this chapter, the PL's behavior which has been comprehensively discussed in Chapter 5, is considered in a simplified manner as the input of the network planning problem. The case studies show the allocation of the PL and the optimum number of stations in each installed PL considering different network-constrained objectives. The interaction of the PL's behavior with the RERs in the system and the inter-relation of their locations are investigated through the case-studies.

Chapter 7 is the core of the study and integrates all the outcomes from the previous chapters. It illustrated the integration of electric mobility in the MES concept. Numerous case studies are discussed in this chapter considering different models of PEV charging possibilities. The dependency of the demand in the MES in Chapter 3 is employed in this chapter through modeling of the PEVs home charging station on the MED and adding the PL as a module to the MES. The traffic pattern and the commute pattern derived in Chapter 4 is applied in the case studies of this chapter. The market behavior of the PL from Chapter 5 is also considered as the behavior of the PL. Moreover, the intermittent mitigation of the PV is also included in the cases defined in this chapter.

Chapter 8 concludes the thesis findings and gives the outcomes of the possible future works. The publications based on the works of this study is also provided in this chapter.

Appendix A shows the detailed mathematical equations for the MPEC approach.

Appendix B gives the schematic of the test system employed in Chapter 5 and the related data.

Chapter 2

Literature Review

2.1 PEVs State Description in Energy Systems

Electrified transportation has been one of the most recent approaches arising in nowadays energy systems. This issue has contributed for improving many environmental and energy concerns. Besides to the environmental concerns that have been a major apprehension during previous years, other usages of electrified transportation can hedge the problems of energy resource shortages. Many researchers have identified the advantages that electric vehicles can bring into play [5].

As firstly proposed by Kempton in [6], electric drive vehicles can be potential resources in the electric systems and their manipulation and public trend will increase within the forthcoming decades. The interpretation of Kempton had came true and nowadays the tendency towards PEVs is emerging both from the manufacturers side and the consumers side. As a result, various new aspects regarding deployment of PEVs has risen in the studies. The general view on the role of electric vehicles in the smart grids is presented in [7]. A case-study for the peak power purchase from the PEVs in Japan has been implemented in [8].

There are two main aspects of the PEVs in the system. First, is the provision of electricity for their required charging schedule. The second issue regarding the PEVs is their potential in V2G mode operation. Both of these issues are better addressed in the system while the PEVs are treated aggregatedly. As a result, in this chapter a comprehensive review on modeling the charging scheduling of the PEVs is going to be conducted. Then, different views for aggregating the PEVs with aggregator agent or PEV parking lots are going to be presented. The market participation of the aggregated PEVs are going to be investigated. Besides, the network impact of the PEVs aggregation and the network planning issues are going to be surveyed.

From another point of view, the vast penetration of technology in everyday life, has grown the interrelation of different energy resources leading to the inevitable prospect of multi-energy systems for the future. The multi-energy systems (MES) contain key resources driving the evolution of the future systems. However, making MES consistent with all the possible components of the future systems is a challenging problem. The intent of this thesis is to integrate the optimum deployment of PEVs in a MES considering the various issues regarding the PEVs including the PEV owners, the PEV traffic pattern, different charging places, PEVs' aggregation, etc. As a result, the MES concept is also surveyed in the content of this thesis.

2.2 Potential PEV Modes in the system

When connected to the grid, PEVs can be utilized in different manners. In the literature, these different utilization modes have been referred as uncontrolled/controlled charging status or providing the V2G services. By V2G mode, it is meant that the PEVs not only requires the charging energy for their batteries but they also have the possibility to be discharged which enables them to be considered as a resource in the system. The state of being resource for the PEVs in V2G mode can be either to act as a storage or deliver the energy There have been many studies on both aggregated/managed and completely uncontrolled PEVs. The studies are mainly about aggregated/managed PEV due to the disadvantages of the uncontrolled PEV scenario.

2.2.1 Uncontrolled/Controlled Charging mode

In [9], different studies are presented for different charging scenarios, which include uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging and uncontrolled public charging throughout the day. The worst case scenario was the uncontrolled domestic charging where all vehicles are charged at the same time. In this case, the charging affects the local distribution in terms of capacity limit. In the second scenario, uncontrolled off-peak domestic charging improves the results because the charging does not occur during off-peak hours. In the third scenario, smart domestic charging, the charging is controlled to optimize according to the needs of filling the load curve, it improves the sales and does not overload the system. The last scenario presented uncontrolled public charging throughout the day, which can be divided into three categories: industrial, where people charge while at work, commercial charging, and residential charging at night. In the latter case, there would be a peak while people are at work. In this scenario, the industrial and commercial loads cannot absorb PEV charging load without exceeding the natural peak load if all PEVs start charging at the same time.

In [10], the effects of uncontrolled charging on distribution equipment is presented. Uncontrolled charging for a PEV with 50% penetration, the transformer life is reduced by 200–300%. Comparing the scenarios of uncontrolled and smart or controlled charging, the controlled charging increases the life expectancy of the transformers by 100–200%.

In [11], uncontrolled and controlled charging of PEVs is investigated with different penetration levels to show their impacts on the grid. One of the cases is studied on the modified IEEE 23 kV distribution system, where it is observed that high (63%) or low (16%) penetration of the PEVs with the uncontrolled charging results in severe voltage deviations of up to 0.83 p.u., high power losses and higher costs in generation.

In [12], an uncontrolled PEV load modeling is presented. In this study it is suggested that when users randomly plug-in their vehicles, they must choose the type of charging adequate to their needs and their car. Forecasting tools are used to predict the charging levels. It is also stated that unregulated charging can cause power spikes and safety margins in the power grid. The use of charging incentives for specific times or locations is suggested in order to regulate the power. An aggregated/managed charging is recommended, which can be uncontrolled by giving incentive to people to charge in a certain pattern. The customers do not use this charging method if it is inconvenient for them to go to the charging locations, when in an emergency and they need to have enough charge immediately, or they do not need an incentive. Therefore, in such cases it would seem a slight contradiction to call it uncontrolled charging when it is being managed by giving incentives.

Therefore, taking into consideration all the cases presented above, the uncontrolled scenario has many disadvantages in comparison with the controlled PEV charging scenario. In most reports, it is concluded that aggregated/managed charging brings many benefits not only to the user but also to the distributor. Some new strategies are reported to address the issues regarding the coordination of PEVs' charging load in the future smart grid. On this basis, two major charging strategies including multiple tariff policies and centralized controlled charging are investigated in [13], which explores the impacts of these strategies on the distribution network. The charging of the PEV can be controlled by the operator, who can manage it according to needs using smart charge like functions to maximize.

In [14], an aggregator based market is presented. It is shown how the market works and the roles of each individual entity, aggregator and user. From the operator point of view, it will be a minimization of cost problem; to even the load curve, there is a need to turn on power plants or purchase electricity from other countries or entities. By using the V2G concept they reduce the costs of these problems; in this study a minimization solution from the operator point of view is presented, and monetary rewards are given to the aggregators so that they can negotiate on their behalf. As mentioned before, home users cannot interact with the operator, and they need to enroll on a DR program, which is provided by the aggregator. The aggregator's role is to provide DR services to the operator and to guarantee a reduced electricity bill to the users. It presents a profit maximization solution for the aggregators. Finally, they consider the problem from the point of view of users, who receive monetary rewards for consuming off-peak and their objective is either a reduced electricity bill or monetary pay. The study presents the equations to maximise the net payoff to the user.

Based on the above discussion, the intention is to present the aggregator scheme and how it works. There might be some variations in the equations used, but the idea behind it is the same. Taking into consideration both scenarios, the uncontrolled and the aggregated, the differences as well as the advantages and disadvantages of both can be seen. Starting with the aggregated scenario, there is no overload of the system because it is controlled by the operator, the end user has the advantage of monetary rewards and the operator saves on the operational costs of power plants and other power sources. The uncontrolled scenario has many disadvantages, primarily, the degradation of the PEVs, which is severely increased, the peak problems and a worst efficiency. On this basis, the aggregation/management of the PEVs yields better results than the uncontrolled PEVs.

2.2.2 V2G mode

The V2G mode of the PEVs was firstly introduced by Kempton and Letendre in [6]. It is shown that with the appropriate charging facility the PEVs have the potential to inject power stored in their batteries while they are parked. This concept changed the former paradigm where the vehicles were only loads added to the system [15]. There are different definitions for the concept of PEVs' V2G, however, the concept which is employed in this thesis is based on what Quinn has proposed in [16] where the V2G mode is regarded when the PEVs has the ability to inject electricity to the network and the G2V mode is when the grid provides electricity to the PEV. Many references such as [17], [18–20] also added the V2G mode as well as the G2V considerations to their models. Although these references may have different approaches regarding market participation and battery degradation, the inclusion of this technology is present in all of them.

These references showed that the V2G mode of PEVs can have several benefits such as enabling the PEVs to take part in the ancillary services and act as a resource in the system. For instance, [17] presents a strategy for peak reduction in urban regions in Brazil in a smart grid environment. For this, they develop a model taking into consideration V2G and G2V. As another example, in [18] an algorithm is developed for integration of the V2G in the current market, which studies its potentialities, grid penetration and introduction into the ancillary service market. However, as suggested by Kempton in [6] a considerable number of PEV batteries should be present in the system that can have significant effect on the system. As a result, treating the PEVs in the aggregated manner will be more beneficial for the system. Moreover, leaving the numerous PEV owners to interact with the grid on their own will confront the grid operator with a horrendous amount of uncertainty that will be almost impossible to deal with. In this regard, this study undertakes the aggregated form of the PEVs in the system rather than the individual operation.

2.3 Aggregated Operation of PEVs in the Electric System

A study on integration of PEVs in the system by ISO/RTO [21] defines the responsibility of the PEV aggregator as: "aggregator will coordinate the application of multiple PEVs to meet product or service commitments to the ISO/RTO while also achieving targeted charge levels per commitments to the vehicles".

In literature, the preliminary impressions of agents for PEVs were brought by Kempton [22] indicating that the presence of an agent is necessary for the operation of PEVs in the system; Lopes [23] encouraging the aggregation of the PEVs in order to have a considerable effect on the system is inevitable; Guille [24] that proposed the aggregator as a critical entity to enable the V2G operation of EVs. A comprehensive survey on EV aggregation can be found in [25]. The real-time regulation allocation on EV aggregators is presented in [26] with welfare-maximization objective. Jin et al. in [27] reported an optimized EV charging schedule through an aggregator while considering the aggregator's revenue and the EVs' charging demand. In [28], the scheduling of EVs by aggregators to take part in V2G regulation is studied where the forecast of schedules based on the uncertainties of EVs is performed by multi-level aggregators.

2.3.1 Charging Scheduling of PEV Aggregator

The energy which is required to be provided for the PEVs in the system is the main challenge in integration of PEVs in the system. As a result, the charging schedule of the PEVs is the first issue to deal with. As previously described, different modes of controlled or uncontrolled charging of the PEVs will have different impacts on the grid as well as the entity who is responsible for providing the required energy. Some of the references in the literature are dedicated to this problem.

In [29] a microgrid network is considered with PHEVs and the possibility of smoothing out the load variance for the residential consumption by regulating the charging patterns of family PHEVs is investigated. Moreover, the effects of PEV charging on residential distributions and the possible effects on the transformer life has been studied in [30]. It shows that different levels of PEV penetration will have different effects on the transformer insulation life aspect. However, it determines that the impacts of uncoordinated charging of the PEVs will be more severe in the system.

The EV charging profiles will change the conventional load profile of the network which they are added to. As mentioned before, the most effective factor in this regard is controlled or uncontrolled charging of the PEVs. The study in [31] has considered the large aggregated datasets of transportation data to compare the controlled and uncontrolled charging scenarios.

2.3.2 Market Participation of PEV Aggregator

A considerable number of available studies have dedicated the focus of their study to the integration of EVs into marketplace through aggregators. Bessa et al. in [32] introduce an EV aggregation agent and propose an optimization approach for the agent to bid and participate in day-ahead and reserve markets. However, it considers individual EVs plugged to the grid from charging stations and the aggregator controls the EV charging for specific time duration based on the contract between each EV and the aggregator. The authors also investigated the model for hour-ahead market in [33] as well as the manual reserve, not considering the V2G mode though. In [34] a coordination approach between EV aggregator and system operator is presented in both electricity market and ancillary services.

The authors in [35] developed a model for charging the EVs while the aggregator trades with energy and reserve markets. In [35], it is considered that the charging of EVs is optimized with the presence of electric storage. However, it does not consider the V2G mode of the EV operation. Similarly, in [36] a bidding strategy for stochastic behavior of EV aggregator is acquired to participate in energy and regulation markets. Reference [36] also considers the EVs to be operated in G2V mode only and the aggregated EV potential is deployed as regulation up/down. Li et al. in [37] used an EV aggregator model in their locational marginal pricing method to alleviate the congestion caused by EVs' load. Although most of the studies have only considered the G2V mode of the EVs to participate in the electricity market, there are some studies that consider the V2G mode. Sortomme and El-Sharkawi in [28] and [38] developed a V2G algorithm for an EV aggregator to participate in both energy and ancillary service markets.

In [39] a price-responsive strategy for a market using the V2G concept is presented. The market considered in the study is Singapore. They begin by describing the base, central and peak load of the market. It is stated that 96% of the electricity generation is provided by gas and oil power plants, and that with flexibility the previously stated three types of loads can be covered. As a result, there is only one entity to regulate the market. As these sources are highly reliable with low fluctuations, and the electricity market is easy to predict, it is an efficient method to use. Because of their efficiency and low cost, it is not a viable market for the use of V2G concept.

Another kind of service provided is the ancillary service, which can be divided into six main categories: (1) active power control reserve, (2) voltage support, (3) compensation of active power losses, (4) black start and island operation regulation, (5) system coordination and (6) operational measurement [40]. The active power control reserve compensates the fluctuations and it consists of primary, secondary and tertiary controls, depending on the durations of time that they are providing the ancillary service. In a normal market, compensation would be given to providers of these kinds of services, or if there is too much power for holding the power generation which is good for cars with V2G and G2V implementation. The Singapore market is different because these kinds of compensations do not exist.

In [41] it is stated that with the development of smart grids and V2G technology, it is easy for people who own PEVs to inject power into the grid and to receive power at all times. Power can be injected at peak times to obtain maximum revenue and charge at off-peak times when the price is at a minimum. V2G networks are an important part of smart grids because they can provide better ancillary services than traditional approaches. The biggest challenge of the V2G in the power system is giving ability to control it.

In [42] the author examines PEVs with V2G implementation. This cannot be considered a power source; the V2G is a form of storing and then releasing energy. That said, PEVs cannot produce new electricity for the system; the only applicable function of PEVs is for storing energy, off peak, unwanted renewable energy and base-load energy. Then, after storing the electricity, they can resupply using the V2G whenever necessary. The authors suggest supplying the system at peak periods so it would not be necessary to peak fossil fuel plants.

Taking into consideration the discussed papers, the PEVs are good for ancillary services, with V2G and G2V technology, because of their fast charging and discharging, ability to store power and provide power when needed. Additionally, selling at peak power is where maximum profits can accrue; obviously, they would not provide the entire peak, just a part of it, with the base load power, but this can only happen in markets where compensation is given for selling and buying power, which does not happen in Singapore. There are also further studies regarding other countries including Germany in [43]. The base load because of their low prices of production would obviously be kept as it is provided by power plants.

There have been several studies regarding different types of markets that do not apply to real life markets. However, only as an overall study, there are many markets to which this kind of idea can be applied. For example, regarding spinning and non-spinning reserves, there are some reports, such as [11] and [44], which take these kinds of markets into consideration. Regulation markets are presented in [42] and [45].

2.3.3 Network Impacts and Planning Concerns of PEV Aggregator

Literature on the subject is limited. Among the related studies, a comprehensive overview of the inclusion of PHEVs has been provided in [46]. In [47], the optimal sites for PEV charging stations are identified through a two-step screening method. However, the study has only considered charging stations focusing on the battery package effect and environmental issues affecting site selection. In [48], the optimal sizing and siting of EV charging stations is studied in distribution networks. Then, again in [48], charging stations are allocated instead of using a PL. Besides, charging stations are only considered as loads.

The authors in [49] have considered network topology and traffic constraints simultaneously for optimal planning of charging stations. However, like previously mentioned studies, the authors in [49] have only considered the charging stations and the grid to vehicle (G2V) mode. Moreover, the only discharge of PEV batteries is due to consumption on road travel, not through a network interface. Different concepts of central charging stations to accommodate EV charging in low voltage networks are proposed in [50] where the location and size for such infrastructures are identified for two grids with different capacity.

The technical and economical feasibility of of improving the utilization of the electric grid during off-peak hours and an optimization model for planning the transition to these types of vehicles is presented in [51]. Monte Carlo simulations are used to to determine the impact of estimation errors on the parameters of the planning model.

Regarding the network integration impact, few attempts have been made to investigate its effects. In [52], the impact of various penetration levels of PEVs on distribution networks has been assessed. However, [52] only considers PEV integration adding loads to the grid. Although [53] studies two states of coordinated and uncoordinated charging of PEVs in a radial distribution network and reports the possible effects, the authors are mainly focused on charging stations and their effects on power quality. The impact of PEV fleet in the voltage unbalance of a distribution network is presented in [54].

Although in [55] a reliability cost evaluation model is proposed for a distribution system with both wind generation and PEVs, it does not consider the V2G mode of PEVs in the reliability study. Reference [56] has studied the real-time coordinated operation of PEVs in order to minimize distribution network effects, including voltage and loss. However, the study in [56] is more concentrated on the load management aspect of the coordinated charging of PEVS. As a result, this approach is mostly used by the PEV aggregator.

In [57], both V2G and G2V modes of PEVs are studied at different penetration levels to reach acceptable bus voltages and power loss in the grid. The study in [57] has introduced a stochastic model for PEV behavior. In the present study not only the PEV's stochastic behavior is modeled, but also PL behavior is derived from market interactions considering a profit maximization objective. This approach may fulfill some of the PL owner's investment concerns. Moreover, in [57], simultaneous V2G and G2V states are not considered, whilst both states are simultaneously considered in the present study.

The optimal planning of EV charging stations is a significant problem affecting the network. inappropriate siting and sizing of EV charging stations could have negative effects on the development of EVs, the layout of the traffic network in a city concerned, and the convenience of EV drivers. It could also lead to an increase in network losses and degradation in voltage profiles at some nodes. In this regard, [47] tried to systematically address all the important factors having impacts on the candidate sites of EV charging stations, such as the distribution features of the charging demands, the performance of battery packs, and the possible effects of the power system concerned.

On the other hand, the uncertainties caused by the stochastic behavior of the PEVs owners on their charging and discharging schedule will cause the risks of system planning with the integration of PEVs. This uncertainty is magnified when other uncertain resources such as wind generation or PV arrays are existing in the system. The study in [58] concentrates on the optimal siting and sizing of DGs in a distribution network with penetration of PEVs.

2.4 The PL as a New Mode of PEV Aggregation

The introduction of EV PLs has changed the features of PEV penetration studies. As firstly proposed by [6], the utilization of EVs' V2G mode can be facilitated by deployment of PLs as an aggregated source of PEVs. However, the PL as the aggregation of the PEVs is different from a PEV aggregator because in the PL all the PEVs' location is fixed; hence, the vision of its market participation should be treated differently from an aggregator. On the other hand, as the PL has a limited capacity due to restricted number of PEV stations, it may not be able to participate individually in the market and should be examined in a mixed resource environment.

All the concerns regarding the operation of PEV aggregators are valid while studying the effect of PEV PL in the system. The V2G mode operation has more dominant role in case of PEV PL rather than the aggregator agent. The reason is that the PL has a specific location and more authority over the PEV's SOC while they are parked inside the PL. The PL has the opportunity to employ the SOC of the PEVs with less uncertain behavior comparing to the aggregator agent. As a result, some of the studies are dedicated to the V2G mode of the PL.

A scheme for effective operation of PEVs in the system is proposed in [59] through PEV parking lot and PV roof. Several aspects of the PEV involvement in the system including the inverter state of efficiency as well as the grid capacity is investigated. The results show that matching the PV roof with the PEV PL can reduce the burden caused by the extra loads of PEVs on the grid. Moreover, better supply of power to grid can be achieved when excess power is generated by PV.

Treating the charging/discharging of PEVs in a PL can have different aspects comparing to the PEV aggregator due to different strategy and schedules that the operators may employ. The study in [60] considered the real-time managing of charging schedule of PEVs in a PL taking into account the arrival pattern of PEVs to the PL.

Other than the problem of allocating PLs in the system [16], [17], the effects caused by the procedure of charging/discharging in the PL have been the matter of interest in the literature. The reason is that, Further studies such as [19] - [21] addressed the V2G mode of PL. However, the study on the simultaneous charging/discharging of the PL is still very limited. Some studies such as [22] and [23] have studied the management of the PL's interaction,

2.5 Integration of PEVs in the MES concept

Recent trends in smart system studies made the plug-in electric vehicles (PEVs) inevitable components of the future systems. Modeling the future energy systems without considering various energy carriers of the system, leads to a non-realistic view. Therefore, it is necessary to have a comprehensive model to integrate all components of the future system in an inclusive model [61].

Various researches have been conducted about modeling and studying multi-energy networks. Geidl et al. [62] proposed an integrated model for this kind of networks as an energy hub. Following this model, further studies and model developments have been surveyed, some of which have been summarized in Table 2.1 [62–91].

As shown in Table 2.1, the references proposing energy hub models consider the partitioning of the multi-energy system into two parts: 1) energy hubs; and 2) inter-connectors. In these studies, the input and output energy carriers are considered individually.

Regarding the modeling of the system, two main approaches have been previously adopted for comparing the solutions in multi-energy networks. The first group of researchers does not consider the demand side energy converters and models the network just before end use [62], [92]. The second group [75] models networks with energy converters at the end service level with high resolution, but in a very limited area such as a household.

In [92], a matrix model is proposed considering the same input and output vectors, showing how the models of the individual components can be aggregated to obtain the matrix model of the

Table 2.1: Research Domains in Energy Hub System Studies

Research Domain	References	Description
Modeling and Optimal Energy Flow	[62–69]	Multi energy system is decomposed into two parts, energy hubs and interconnectors. The energy flow is investigated in both parts and integrated system.
Operation	[70–75]	Energy hub system operation considering energy carriers price and operation objectives is surveyed.
Planning and Investment Portfolio	[76–81]	Future energy system characteristics are determined and the planning procedure is designed.
Reliability and Security Studies	[82–86]	Reliability analysis and security assessment (cascading failure case) are investigated in various operation conditions and the impact of storages is considered.
Modeling of DER Technologies in Energy Hub System	[81], [87–91]	The role of PHEVs, DRs and wind turbines are modeled in energy hub system studies.

overall energy system. However, as the penetration of smart technologies grows in the system, the input and output vectors of the multi-energy system will no longer be only composed of individual components [93]. In fact, various devices that can use different sources of energy for producing the same output service are employed by the end users. Then, the output of the multi-energy system will depend on these devices and the consumers' behavior on utilizing them. As a result, the effects of the consumers' behavior and the randomness associated to it have to be considered.

One of these elements and the main content of this thesis is the PEVs. Although the PEVs' demand is only electrical, while being included in the MES, the charging of the PEVs should be scheduled compatible to the prospects of the MES approach [94]. The cross impact of PEVs and other resources cannot be neglected. The operation of the resources such as CHP units will change due to the extra load imposed to the system by PEVs [95]. However, the dynamic nature of the PEVs makes them different from the regular electric loads. The uncertain behavior of the PEV owners in using the PEVs will cause an uncertain SOC in the system which should be fulfilled by the MES operator. The different charging possibility (i.e., home charging stations, parking lots, urban charging stations) adds to the complexity of the incorporating PEVs in MES model.

Integration of the PEVs in the multi energy systems has been the interest of some previous studies. Authors in [87] have modeled the plug-in hybrid electric vehicles (PHEVs) as an energy hub considering the driving behavior of the PHEVs. Continuing this work, they integrated the PHEV as a component in the matrix modeling of the energy systems in [91]. In [96], the electrical load added due to the PHEVs are served through an energy hub and the management of their demand in the energy hub context is discussed. Charging of PHEV in a residential area in a multi-carrier household is the content of study in [97]. These studies have added the extra load due to the electric vehicles to the total load of the multi energy system and served this load through an energy hub model.

From another point of view, the PEVs batteries as a potential storage in the system imposes certain changes in the modeling of a micro-MES [98]. The V2G mode of the PEVs whether in PL or home ChS can act as a resource; hence, change the conversion matrix of the MES. Including the PEVs traffic to the MES as a new input to the MES changes the conventional view to the input/outputs of the system. In addition, the PEVs' SOC will change during their travels which causes a new series of dependencies in the MES which has not been addressed before in the literature.

With the above premises, this thesis intends to fill the gaps remaining in the literature of PEV studies. It addresses various aspects of the PEVs' aggregation in PL and their integration in the MES. In the meantime, other aspects of PEVs' deployment in the system such as the owenrs preferences, the G2V/V2G tariffs, traffic pattern, and different charging possibilities are included in the model.

Chapter 3

Modeling the Demand Dependency in Multi-Energy Systems

3.1 Introduction

The introduction of distributed energy resources is taking a significant part in forwarding the sustainable development and hedging the problems occurring to future energy portfolios [99]. Being co-related to both loads and energy supply system, DERs can increase the opportunities to enhance the services offered to loads as well as taking more benefits of loss reduction by changing the way of power transfer. As the penetration of technology grows among the devices that are used by end users, the demand side will be more capable and eager to participate in advancing the sustainable development. This process does not only help the progress of sustainable development, but also will bring more technical and economic advantages to end users.

However, utilization of these resources for achieving the sustainable development objectives necessitates the employment of smart grids in order to convert this potential possibility into actual solutions [100]. Facilitating the bi-directional relation between the user and the system operator makes it possible to utilize and operate DERs at different levels [101]. In this regard, the technological development and commercialization is increasing the availability of technologies such as small-scale CHP units and energy storage systems, which are introduced in distributed multigeneration systems [102] to enhance the flexibility of serving a multienergy demand.

This chapter addresses the presence of the demand that can be supplied by various types of carriers, its effects on multi-energy system modeling, and the exploitation of this type of demand within DR programs.

3.2 Carrier-Based Demand Response Concept Description

The basic concept considered in this chapter is the one of dependent demand, that is, the demand referring to a specific service that can be covered by producing the related energy from different energy carriers. Examples of dependent demand can be indicated for energy systems of different size. In a simple case, the required heat of a typical house can be provided both by electrical and gas-fired heaters. The amount of gas or electricity required for the system depends on the user's choice of the energy carrier in providing its dependent demand. Similar situations may occur in larger buildings where more persons are living or operating, by considering the possibility of obtaining services such as water heating, cooking, and air conditioning (with multiple points in which these services can be provided) from multiple energy carriers, leaving the end user the possibility of choosing the energy carrier to supply the dependent demand.

The possibility of providing services from various energy carriers is linked to the availability of different energy supply systems in the same area. This may seem impractical. However, there are situations in which this kind of solutions are present or expected in real-life situations. The most remarkable situation is the one in which the trend of energy supply in the region in which the demand is located is changing, for instance because the energy mix in that region has been varied by the availability of new energy sources (e.g., from renewable generation) or by obsolescence of the existing power plants that are replaced with new technologies using different energy carriers. This situation includes for example either change from power to gas (leading to “less-electric” demand, or from gas to power (leading to “more electric” demand) [103]. In these cases, the end users can be induced to change the technologies they are using. However, the end users could decide to keep the previously used technology and integrate them with a new one, with the prospect of possible usage of both technologies depending on their convenience, e.g., to manage the case of shortage of energy supply for one energy carrier or large price fluctuations for the energy carriers that can be used to provide the same service. The demand side can change the source of providing the same service based on each energy carrier’s price, availability of technologies, or only its preference. In the presence of multiple end users acting on the same system, the customer choices can be applied in a random way, so that the dependent demand becomes stochastic.

The system operator can set up DR programs aimed at taking benefits from this flexibility to manage the dispatch of the energy carriers within the multi-energy system. In [104], it is shown how DR can be activated to promote changes in the demand behavior in response to changes occurred as exogenous stimuli (supply carriers’ price variations, or specific incentives), defining a procedure according to which no customer suffers from these changes. In [105], it is indicated how DMG can be exploited to reduce the electricity input from the upstream network. This possibility is discussed on the basis of the concept of electricity shifting potential in the prospect of using DMG to provide real-time DR. In [106], an electric heat pump is used to provide heating and cooling to a multi-energy system, switching the heating/cooling from electric heat pump to another equipment as a DR program.

The dependent demand can be totally or partially made available by the end user to participate in specific DR programs. For this purpose, the following possibilities are defined for the dependent demand usage.

- *Carrier Share (CS)*: The user decides which energy carrier is used for the part of dependent demand that does not participate in DR programs.
- *Carrier-Based DR (CBDR)*: The user decides which energy carrier is used for the part of dependent demand that participates in DR programs. This means that, if needed, the system operator can send a signal to the customer so that the energy carrier for providing a specific service will be shifted to another one, instead of just shedding the service.

CBDR is applied to change the type of energy supply from different sources (including energy storage) in such a way that the service is provided, and hence the level of comfort and customers’ satisfaction remain unchanged. It is assumed that on the demand side the technology of having dependent demand does exist. If the end user agrees to participate in the CBDR program, whenever the operator needs less/more usage on one energy carrier, it sends a signal to the end users to change the source of energy carrier (from one type to another) by an amount that does not affect the service provided. In practice, the network operator can communicate with the consumers to motivate them for changing their consumption pattern during time. Facilitating this communication also makes an opportunity for implementing various DR programs. Relating to the incentives and affected satisfaction of consumers in the DR process, the consumers' response to these programs can be different. One-way communication and sending signals for encouraging the participation of consumers in DR programs is already achievable [106–108].

The CBDR program is supposed to be the change in the conversion pattern of energy with the purpose of keeping the customers' level of satisfaction in a constant state. This program is provided by the MES operator for those end-use customers that have the technology of choosing between the carriers for providing the required demand. The operator offers the CBDR and if the end-use approves to participate in the program it should change, while the ultimate service will remain unaffected.

The previously known procedure of DR programs was that the network operator communicates with the consumers and motivates them for changing their consumption pattern in time. Although the process of implementing a CBDR program is also through communicating with the consumers, what is changed by the customer is the conversion pattern instead of consumption. If an upstream constraint signal such as price that is received by the local network operator determines a surge of price, the operator will communicate with the CBDR participants asking them to exchange their input energy carrier to another one (which is adaptable to their technology for providing the service) with lower price.

The same approach can be used in other circumstances, such as shortage of resources or peak demand duration for a specific carrier. Hence, when the required service is shifted from one carrier to another, the total expenses of the operator will be managed to be reduced. As this way of communication and sending signals to customers for encouraging their participation in DR programs is already achieved [68, 69], developing the proposed program on this basis will be also practical.

3.3 Internal and External dependencies

In a multi-energy system, the dependencies can be divided in two main categories: 1) internal dependencies; and 2) external dependencies.

The internal dependencies refer to the relations between input and output energy carriers due to the presence of energy converters existing in the multi-energy system and controlled by the system operator (for example, deciding the energy flows among multiple equipment belonging to a multigeneration system, on the basis of a specified control strategy or optimization objective [70], [92]).

Conversely, the EDs are mainly due to actions not depending on the network operator, which may have effects on the way the multi-energy demand is served. These actions generally depend on the user's preferences triggered by DR programs and incentives established by the regulator.

The considerations of the EDs also depend on the penetration level of the distributed energy converters located at the user's side and directly activated by the customers for changing the energy supply (e.g., electrical and gas boilers for hot water production, and local management of storage).

In a typical multi-energy system, various components of distributed energy resources such as Distributed Generation (DG), Distributed Storages (DS) and conventional DR programs may exist. Assume that in such system the multi-energy demand is enriched with the technologies that can have various energy carriers as an input and convert them to required services. These converters are located on demand side and are apart from those internal converters that MES may contain. For better comprehension, assume that MES covers a residential urban area. In this case, some DGs such as diesel engines, Combined Heat and Power (CHP) units and storage units exist in the local network. However, on the demand-side there exist devices that benefit from the multi-carrier input technology. Therefore, this technology will bring the opportunity for both demand-side and system operator to take benefit from it. In this situation, whenever one carrier has higher price compared to another one, the consumer may have the choice to select between two or more carriers to use as an input. On the other hand, the system operator will also be able to choose between various sources for supplying one certain service, which is beneficial during system emergencies or resource shortages, as well as high price intervals. Therefore the situation will cause a dependency on demand side. This dependency is due to the fact that the estimation of the demand and the required input resource will be dependent to the customer's choice of carrier. As this dependency occurs on demand-side, it is different from those dependencies that are within the local network system due to its internal converters such as CHP units. As a result it is called external dependency.

All components of a local energy network in MES, as well as the dependencies occurred in the system (both internal and external), can be considered as DERs that can be employed by the MES operator in its operation or planning schedules for providing the customers need of energy. The framework representing the relations of various elements in the multi-energy system and the position of internal dependencies/EDs is shown in figure 3.1.

Based on the definitions, DR is the change in electric usage by end-use customers from their normal consumption patterns in response to various changes such as price, incentive payments, etc. Regarding this definition, the external dependency in this study is considered as a DR resource. The details of this DR program are explained in the following subsection.

As the dependent demand causes an ED in the system, it will affect the conventional models used for the multi-energy systems. Two main references that have focused on modeling the dependencies are [62] and [109]. In these references, the dependency between carriers is considered through the coupling matrix.

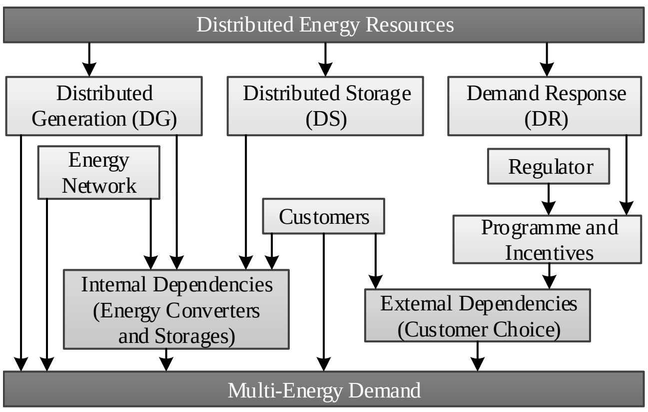

Figure 3.1: Structure of DER supply and related dependencies in serving multi-energy demand

Furthermore, Kienzle et al. [81] addressed the model of the external time dependency arising by modeling the stored heat demand as DR in a residential area. However, the survey of the literature approaches shows that a structured view of the dependencies among the energy carriers, taking into account the role of the user and the related preferences, has not been provided yet. Hence, the ED on the demand side is modeled as a specific module in the multi-energy system, which has not been tested in previous studies, posing a new contribution. In addition, the stochastic nature of consumer preferences is addressed. This will bring higher levels of flexibility to the energy usage in the network, while reducing operation costs.

3.4 Comprehensive Energy System Model

Energy systems have a multilayer nature. A possible representation with three main layers is indicated in figure 3.2, namely, macro-multi-energy system (referring to external energy systems and networks), micro-multi-energy system (i.e., the local system under analysis), and multi-energy demand.

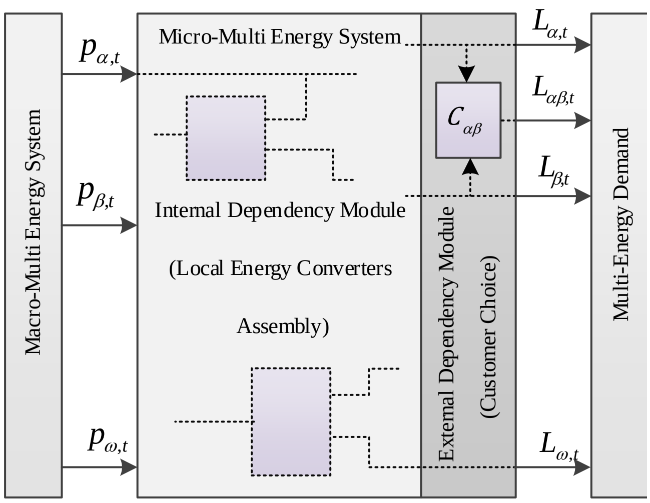

Figure 3.2: Energy system comprehensive module considering internal and external dependencies.

The energy system analysis is carried out by assuming that the services requested by the user and the associated multi-energy demands are known. Looking at the multi-energy system equipment, two main elements exist in the energy system model: 1) energy converters; and 2) energy storages. In this section, the matrix model for these elements is presented, highlighting the effects of the possible interdependencies among the energy carriers. The time scale used for the representation depends on the averaging time interval with which the data are available. Without loss of generality, the subscript t is used here to scan the time intervals.

Thereby, this model is efficient both on the operation timescale, provided that appropriate control or DR signals are available in a relatively short term (from minutes to hours) to change the equipment set point (thus affecting the internal dependencies) or to induce changes in the customers' preferences as EDs, and in long-term planning of local energy networks.

3.4.1 Energy Converter Model

In the classical energy hub model, the overall system is represented by a coupling matrix $\mathbf{C}$ that converts the input energy carriers, vector $\mathbf{p}$, e.g., natural gas, electricity, and district heating, into output energy services, vector λ , like electricity, cooling and heating, and mechanical power.

$$\Big[\mathbf{L}\Big] = \Big[\mathbf{C}\Big]\Big[\mathbf{p}\Big] \tag{3.1}$$

Based on figure 3.2, the expansion of equation (3.1) showing the relation between input and output carriers is modeled as:

$$\begin{bmatrix} L_{at} \\ L_{bt} \\ \vdots \\ L_{\omega t} \end{bmatrix} = \begin{bmatrix} C_{aa} & \dots & C_{az} \\ C_{ba} & \dots & C_{bz} \\ \vdots & \ddots & \vdots \\ C_{za} & \dots & C_{zz} \end{bmatrix} \begin{bmatrix} p_{at} \\ p_{bt} \\ \vdots \\ p_{zt} \end{bmatrix} \tag{3.2}$$

Each element of the matrix $\mathbf{C}$ denotes the conversion of one carrier into another and is composed of two categories of parameters: the first category includes coefficients depending on physical characteristics of the system and of the energy converters, such as the efficiencies (η_a).

The second category includes the decision variables, here denoted as weighted energy contribution variables ($v_{a,t}$), which indicate the energy distribution among the energy converters in 3.3. In fact, these are continuous variables that determine the share of each energy carrier in the total energy demand. Only in very simple cases the decision variable can be considered as binary, representing a switch between two possible alternatives to supply the demand needed for a given service by using two energy carriers. Hence, the entries of the matrix $\mathbf{C}$ can be expressed as:

$$C_{ab} = f(v, \eta) \tag{3.3}$$

The classical model encompasses the presence of the internal dependencies referring to the energy CS among different equipment, in which the decision variables (e.g., the dispatch factors indicated in [6]), represent degrees of freedom to determine the energy flows in the multi-energy system and can be set up as a result of optimization procedures run by considering specific objective functions [6], [38]. However, this model formulation does not include the representation of the customer choice affecting the energy carriers' usage. This representation is incorporated here in the ED module highlighted previously in figure 3.2.

The proposed extension of the model shows that, besides consuming a certain amount of each energy carrier at each time interval (L_{at}, L_{bt}, etc.), the multi-energy demand has the ability to receive a defined amount of energy (L_{abt}) from different carriers to supply the required service. The weighted energy contributions depending on the customer preferences in the ED module are equivalent to the dispatch factors considered in the model representing the internal dependencies.

Dependency between outputs is added to the demand vector through one or more additional entries, which increase the number of rows of the coupling matrix (3.4). It should be noted that these added lines do not represent actual outputs, but virtually illustrate the dependency in output.

$$\begin{bmatrix} L_{at} \\ L_{bt} \\ \vdots \\ L_{zt} \\ L_{abt} \end{bmatrix} = \begin{bmatrix} C_{aa} & \dots & C_{az} \\ C_{bb} & \dots & C_{bz} \\ \vdots & \ddots & \vdots \\ C_{za} & \dots & C_{zz} \\ C_{aba} & \dots & C_{abz} \end{bmatrix} \begin{bmatrix} p_{at} \\ p_{bt} \\ \vdots \\ p_{zt} \end{bmatrix} \tag{3.4}$$

Hence, the output vector $\mathbf{L}$ in the proposed model (column vector containing the terms L_{at}, L_{bt}, etc.) can be divided into two sections as in equation (3.5), with rows indicating independent output carriers ($\mathbf{L_I}$) and rows introducing dependency in the output ($\mathbf{L_D}$). The same approach can be performed on the coupling matrix. Therefore, the matrix model will have new rows that make it different with respect to the one used in [63] and [83].

$$\begin{bmatrix} \mathbf{L_D} \end{bmatrix} = \begin{bmatrix} \mathbf{L_I} \\ \mathbf{L_D} \end{bmatrix} = \begin{bmatrix} \mathbf{C_I} \\ \mathbf{C_D} \end{bmatrix} \begin{bmatrix} \mathbf{p} \end{bmatrix} \tag{3.5}$$

where

$\mathbf{C_I}$	traditional coupling matrix that states the conversion of independent inputs into independent outputs;
$\mathbf{C_D}$	matrix showing the share of the independent inputs in providing dependent demand;
$\mathbf{p}$	column vector containing the input variables.

3.4.2 Energy Storage Model

As Arnold and Andersson [65] and Kienzle and Andersson [78] have explained, the role of energy storages can be modeled through some changes in the coupling matrix and the input energy vector. Regarding the EDs, the fact that the user can resort to individual storages causes the definition of an extended input vector ($\mathbf{p_n}$) with respect to the input vector $\mathbf{p}$ used in the case where no storage exists.

On the one hand, the amount of energy consumed from storages (vector $\dot{\mathbf{es}}$) is added to the input vector. On the other hand, the coupling matrix of the storage ($\mathbf{S}$), which represents how changes in the amount of energy stored will affect the system output, is added to the total system coupling matrix. Hence, the combined model is shown as:

$$\begin{bmatrix} \mathbf{L} \end{bmatrix} = \begin{bmatrix} \mathbf{C} & -\mathbf{S} \end{bmatrix} = \begin{bmatrix} \mathbf{p_n} \\ \dot{\mathbf{es}} \end{bmatrix} \tag{3.6}$$

In the modified model, $\dot{ES}$ is the change in the stored energy and can be computed from equation (3.7) and (3.8) by considering the charge/standby conditions or the discharge conditions.

$$\dot{es}_{a,t} = es_{a,t} - es_{a,t-1} \tag{3.7}$$

$$\eta_a^r = \begin{cases} \eta_a^{r(+)} & if\ \dot{ES}_{a,t} \geq 0\ (Charge/Standby) \\ 1/\eta_a^{r(-)} & if\ \dot{ES}_{a,t} < 0\ (Discharge) \end{cases} \tag{3.8}$$

By decomposing the storage coupling matrix $\mathbf{S}$ into its components $\mathbf{S_I}$, showing changes of independent output versus changes in the stored energy, and $\mathbf{S_D}$, showing changes of dependent output versus changes in the stored energy, the matrix formulation becomes as:

$$\begin{bmatrix} \mathbf{L_I} \\ \mathbf{L_D} \end{bmatrix} = \begin{bmatrix} \mathbf{C_I} & \mathbf{S_I} \\ \mathbf{C_D} & \mathbf{S_D} \end{bmatrix} \begin{bmatrix} \mathbf{p_n} \\ \dot{\mathbf{e}}_\mathbf{s} \end{bmatrix} \tag{3.9}$$

3.5 Local Energy System Stochastic Operational Model

In order to show an application of the proposed model, a typical local network model is shown in figure 3.3, with CHP unit, AB, and HS.

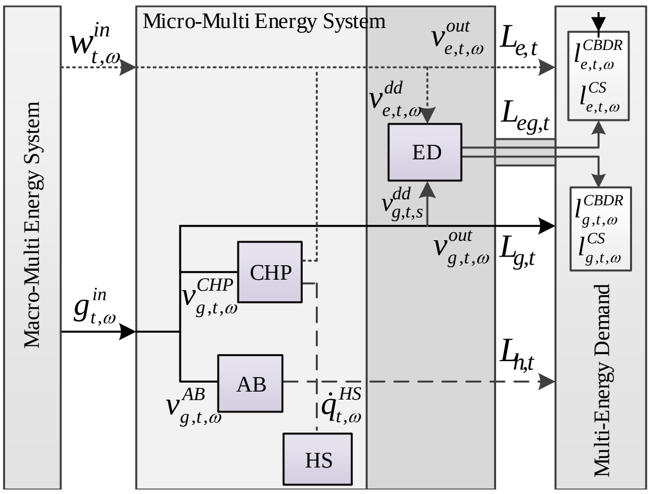

Figure 3.3: A typical local energy network model considering the energy carriers dependency.

The input carriers of the system are electricity and gas, while the output carriers are electricity, gas, and heat. The ED between gas and electricity carriers in this network is considered through the demand dependency module ED in the output (with output variable $L_{eg,t}$). The EDs due to the behavior of the consumers are not deterministic; therefore, the related uncertain variables are considered in a scenario-based stochastic model, in which the subscript s represents the scenarios. The typical scenarios considered are the CS indicated in Section 3.2 when no DR program is defined, and the CBDR scenarios considering the shifting between energy carriers in order to maintain the customers' satisfaction through the definition of DR programs. It is assumed that some customers agree that their demand would be participating in this type of DR.

CS is based on the user's decision on which multi-energy carrier has to be used for the part of dependent demand that does not participate in CBDR programs, while the remaining part of the dependent demand is available to contribute to CBDR.

The considerations on uncertainty and the details of the scenarios are described in Section 3.6. The energy dispatch between the various elements is described by using the weighted energy contribution variables v, for both internal dependencies and EDs. The links among the weighted energy contribution variables are indicated hereafter.

Based on the proposed model in the previous section, the mathematical model of this network is:

$$\begin{bmatrix} v_{e,\omega,t}^{out} & v_{g,\omega,t}^{CHP}\eta_e^{CHP}v_{e,\omega,t}^{out} & 0 \\ 0 & v_{g,\omega,t}^{CHP}\eta_h^{CHP} + v_{g,\omega,t}^{AB}\eta_h^{AB} & 1/\eta^H S_h \\ 0 & v_{g,\omega,t}^{out} & 0 \\ v_{e,\omega,t}^{dd} & v_{g,\omega,t}^{dd} + v_{e,\omega,t}^{dd}v_{g,\omega,t}^{CHP}\eta_e^{CHP} & 0 \end{bmatrix} \begin{bmatrix} w_{\omega,t}^{in} \\ g_{\omega,t}^{in} \\ \dot{es}_{h,\omega,t}^{HS} \end{bmatrix} = \begin{bmatrix} L_{e,t} \\ L_{h,t} \\ L_{g,t} \\ L_{eg,t} \end{bmatrix} \tag{3.10}$$

It should be noted that the model is studied in steady state, namely, the time step of analysis is considered to be sufficiently long to assume that all the equipment (also the slower thermal elements on the demand side) have concluded their transient period and have reached their steady state. As a result, the dynamics on the demand side can be neglected.

The local energy network is assumed to consist of small residential smart buildings, in which indicatively the minimum time step for analyzing successive steady-state conditions can be of the order of minutes. In any case, the time step used for the calculations is longer (hours), so the representation of the equipment dynamics is not needed.

3.5.1 Objective Function

The objective function in operating this system is to minimize the costs of providing the required amount of gas energy input $g_{\omega,t}$ and electrical energy input $w_{\omega,t}$, taking into account the costs per unit of energy $\Pi_{e,t}$ and $\Pi_{g,t}$ for electricity and gas, respectively.

This model has been formulated to obtain the total expected cost for various scenarios of dependency in the system.

$$Minimize\left\{ f(x) = \sum_{\omega} \rho_{\omega} \sum_{a} \sum_{t} \left[w_{\omega,t}^{in}\Pi_{e,t} + g_{\omega,t}^{in}\Pi_{g,t} \right] \right\} \tag{3.11}$$

with

$$\rho_{\omega} = \{\rho_{\omega}^{CB}, \rho_{\omega}^{CS}\} \tag{3.12}$$

where ρ_s^{CB} and ρ_s^{CS} are respectively the probabilities of being in the CBDR or in the CS scenarios. The details of the scenarios are explained in Section 3.6.

3.5.2 Operational Constraints

The constraints are generally expressed in terms of capacity. As such, in order to check the constraints it is needed to express the average power values in the relevant time subinterval. Let us consider for each hour the number n_τ of uniformly spaced time subintervals (e.g., $n_t = 4$ for 15 min subintervals) [84]. Hence, the energy input corresponds to the average power as in equation (3.13).

The same relation holds between any average power and energy quantities. The constraints for system operation are formulated as follows

$$w_{\omega,t} = w_{\omega,t} \big/ n_t \tag{3.13}$$

$$g_{\omega,t} = g_{\omega,t} \big/ n_t \tag{3.14}$$

Input Carriers Constraints: Each energy carrier has a supply limit that may be due to the power amount from the supply source or power transmission limits.

$$0 \le w_{\omega,t}^{in} \le \overline{w}_{\omega,t}^{in} \tag{3.15}$$

$$0 \le g_{\omega,t}^{in} \le \overline{G}_{\omega,t}^{in} \tag{3.16}$$

Operational Constraints of the CHP Unit: Regarding manufacturing characteristics of the CHP unit, they face limits in the amount of electrical power output $w_{\omega,t}^{CHP}$ or heat power output $q_{\omega,t}^{CHP}$. Furthermore, the CHP unit should be operated in the allowed heat to power ratio zone.

$$\underline{W}^{CHP} \le w_{\omega,t}^{CHP} \le \overline{W}^{CHP} \tag{3.17}$$

$$\underline{Q}^{CHP} \le q_{\omega,t}^{CHP} \le \overline{Q}^{CHP} \tag{3.18}$$

$$\psi_{\omega,t}^{CHP} = q_{\omega,t}^{CHP} \Big/ w_{\omega,t}^{CHP} \tag{3.19}$$

$$\underline{\Psi}^{CHP} \le \psi_{\omega,t}^{CHP} \le \overline{\Psi}^{CHP} \tag{3.20}$$

Operational Constraints of the Auxiliary Boiler: Heat output from the AB has some capacity limits.

$$\underline{Q}^{AB} \le q_{\omega,t}^{AB} \le \overline{Q}^{AB} \tag{3.21}$$

Operational Constraints of Heat Storage:Indicating the limit for storing energy in heat storage

$$\left| \dot{es}_{h,\omega,t}^{HS} \right| \le \Gamma^{CHP} \tag{3.22}$$

$$\underline{Q}^{HS} \le q_{\omega,t}^{HS} \le \overline{Q}^{HS} \tag{3.23}$$

Constraints on the Weighted Energy Contribution Variables: decision-making variables will determine energy dispatch between various elements. These variables are system freedom degrees for optimization of least-cost operation procedure.

$$0 \leq v \leq 1 \quad \text{for all weighted energy contribution variables} \tag{3.24}$$

$$v^{dd}_{e,\omega,t} + v^{out}_{e,\omega,t} = 1 \tag{3.25}$$

$$v^{AB}_{g,\omega,t} + v^{CHP}_{g,\omega,t} + v^{dd}_{g,\omega,t} + v^{out}_{g,\omega,t} = 1 \tag{3.26}$$

3.5.3 Model of External Dependency

As shown in the proposed model, the EDs are modeled in a block added to the rest of the micro-multi-energy system model. In fact, this block is the interface between the micromulti-energy system and the output demand. However, in the proposed model, the dependency that actually happens on the demand side is modeled as a part of the micro-multi-energy system. The block is added as a module in the model (figure 3.3). It should be noted that this module does not give a physical outcome, but it helps the operator of a multi-energy system to have an insight from possible customers' choice of carriers. In a real network, this module can have outputs such as data or information signals that are sent to the operator 24 h before the operation day. Nevertheless, the mathematical model for investigating the compatibility of the model is presented. Based on these explanations, the dependency module demonstrates that part of the multi-energy demand can utilize both electricity and gas carriers to provide the required service. In order to deal with the dependency between the carriers in the system model, two weighted energy contribution variables are used, namely, $v^{dd}_{e,\omega,t}$ and $v^{dd}_{g,\omega,t}$, stating the share of dependent energy demand in the output of each carrier (electricity and gas, respectively).

$$f\left(v^{dd}_{e,\omega,t}, v^{dd}_{g,\omega,t}\right) = L_{eg,t} \tag{3.27}$$

In equation (3.27), it is shown that the output dependent demand is a function of the variables of the two carriers (electricity and gas). The ED variables illustrate the dependent demand's share in usage of each carrier. Thus, it is necessary to balance them with some coefficients and then exploit them in the model.

The following new weighted energy contribution variables in the output show the share of each carrier in demand provision:

$$v^{dd,new}_{e,\omega,t} = \left(\frac{w^{in}_{\omega,t} + g^{in}_{\omega,t} v^{CHP}_{g,\omega,t} \eta^{CHP}_{e}}{L_{eg,t}}\right) v^{dd}_{e,\omega,t} \tag{3.28}$$

$$v^{dd,new}_{g,\omega,t} = \left(\frac{w^{in}_{\omega,t}}{L_{eg,t}}\right) v^{dd}_{g,\omega,t} \tag{3.29}$$

As it is shown, a new variable is defined to determine the share of dependent demand from electricity and gas, respectively. These equations show the share of dependent demand from the total input energy carriers. In other words, $v^{dd,new}_{e,\omega,t}$ shows what amount of dependent demand is served by electricity. The same can be interpreted for $v^{dd,new}_{g,\omega,t}$. Besides, these new variables are used to avoid the multiplication of weighted energy contributions and make the problem linear with respect to the decision variables.

Furthermore, it is clear that there is some equipment that enables the possibility of dependent demand. However, the equipment that has shares on energy contribution of the EDs is not ideal, and may waste some part of energy through the energy conversion process. Therefore, equation (3.30) represents the limit on the amount of weighted energy contribution variables depending on this block. This will ensure that the amount of energy that is assigned to each carrier is obtainable by the related equipment.

$$v_{e,\omega,t}^{dd,new} + v_{g,\omega,t}^{dd,new} \geq 1 \tag{3.30}$$

3.6 Uncertainty Characterization of Internal and External Dependency

One concern on CBDR programs is the way that the customers are going to behave upon being called for participating as a CBDR. It is assumed that the local network operator will send hourly signals to its consumers to inform them of its desirable energy dispatch. The consumers' response to this request will be based on various criteria, such as economic and social behavior. One of the main incentives that can highly motivate consumers to participate in CBDR programs is based price signals. However, even with the best incentives the uncertainty in consumers' behavior will remain. The uncertainty refers to the percentage of consumers who will take part in CBDR. There may be a number of consumers that possess the technology that enables them to participate in CBDR, but not all of them will accept to cooperate in this program.

On the other hand, those consumers that have the possibility of changing carriers but do not participate in CBDR programs may decide to control their demand individually, which will add to the uncertainty. This uncertainty represents the probabilistic nature of consumers' behavior to select the carriers for supplying their own demand. In figure 3.4 it is assumed that the dependency between carriers exist between electricity and gas energy carriers. It shows that of the total demand that can be served with multiple energy carriers (dependent demand), different shares can be appointed to each carrier.

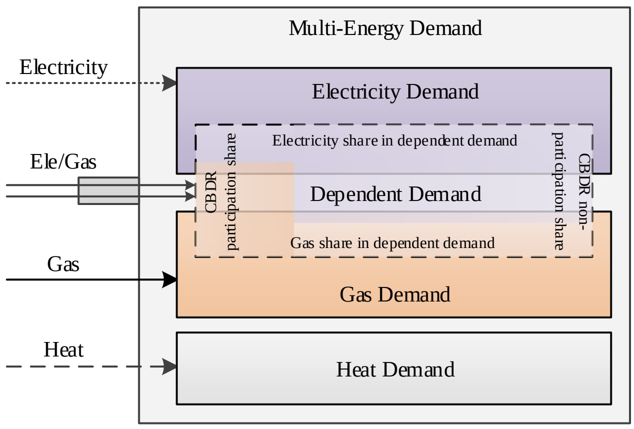

Figure 3.4: Share of demand participation variables in dependent demand.

The consumers' behavior for utilizing the mentioned dependencies is uncertain from the operator's point of view. Therefore, a scenario-based approach is adopted to characterize this behavior. This section describes the model of the uncertainties on CBDR and energy carriers share.

3.6.1 Uncertainty of Carrier-Based Demand Response

Let us assume that the local energy network operator can send signals at each hour to its consumers to inform them on the desirable energy dispatch. The consumers can respond to this request based on economic and social behavior. One of the main stimuli that motivate consumers to participate in CBDR programs is the presence of incentives that can be based on price signals.

Some reports (see [110], [111]) have focused on modeling the customers' response during a DR event and obtaining the DR baseline error/accuracy. Customers' response uncertainty refers to the percentage of consumers who participate in CBDR programs. In other words, consumers' CBDR acceptance is the main source of uncertainty considered in the ED modeling.

In this chapter, a scenario-based approach is utilized to investigate the effect of the customers' response uncertainty on the operator's behavior. Another important uncertainty regards the consumers who do not participate in CBDR programs, thus their demand is individually controlled, contributing to the terms referring to the internal dependency. This uncertainty represents the probabilistic nature of consumers' behavior to select the carriers for supplying their own demand (figure 3.4).Equations (3.31)–(3.36) represent the share of each carrier for providing CBDR and individually controlled demand.

$$l^{CB}_{eg,\omega,t} = L_{eg,t} v^{CB}_{\omega,t} \tag{3.31}$$

where $v^{CB}_{\omega,t}$ represents the variable indicating the customers that agree to participate in CBDR. Hence, $l^{CB}_{eg,\omega,t}$ determines the part of dependent demand that takes part in CBDR. The share of electricity and gas demand from total dependent demand is expressed as:

$$l^{CB}_{eg,\omega,t} v^{dd,new}_{e,\omega,t} = l^{CB}_{e,\omega,t} \tag{3.32}$$

$$l^{CB}_{eg,\omega,t} v^{dd,new}_{g,\omega,t} = l^{CB}_{g,\omega,t} \tag{3.33}$$

The choice of the customers who do not participate in CBDR from electricity and gas (that is, the users with CS dependent demand) is represented in the following equations, the variables $v^{CS}_{e,\omega,t}$ and $v^{CS}_{g,\omega,t}$ represent the share of electricity and gas, respectively.

$$\left(L_{eg,t} - l^{CB}_{eg,\omega,t} v^{CS}_{e,\omega,t}\right) = l^{CS}_{e,\omega,t} \tag{3.34}$$

$$\left(L_{eg,t} - l^{CB}_{eg,\omega,t} v^{CS}_{g,\omega,t}\right) = l^{CS}_{g,\omega,t} \tag{3.35}$$

$$v^{CS}_{e,\omega,t} + v^{CS}_{g,\omega,t} \geq 1 \tag{3.36}$$

In addition, the amount of dependent demand in the study (demand dependency percentage) is calculated through the following equation:

$$dd\% = \frac{L_{eg,t}}{\bar{L}_{eg,t}} \tag{3.37}$$

3.6.2 Modeling the Uncertainties of CBDR and Carrier Share

The model of the local energy system should estimate the uncertain parameters of probabilistic consumers' behavior by past statistics data. To create appropriate scenarios to model the mentioned uncertainties, several methods based on time-series (see [112]), artificial intelligence and evolutionary algorithms (see [113]) can be utilized.

In this thesis, the uncertainties are modeled as multiple different scenarios. Then, a scenario-based stochastic programming approach is employed to handle uncertainties. The scenario-based stochastic programming is an efficient tool to find optimal decisions in problems involving uncertainty. When it comes to make decisions under uncertainty using stochastic programming, the building of scenario sets that properly represent the uncertain input parameters constitutes a preliminary task of utmost importance. In reality, the optimal decisions derived from stochastic programming models may be indeed remarkably sensitive to the scenario characteristics of uncertain data. For this reason, a large number of researches have been accomplished to design efficient scenario generation methods. A brief description of the most relevant methods is presented in [114].

However, the generation of a huge number of scenarios may render the underlying optimization problem intractable. Therefore, it is necessary to consider a limited subset of scenarios without losing the generality of the original set. Scenario reduction techniques can reduce the number of scenarios effectively [115], [116]. The probabilistic behavior of customers has caused the operator to face plenty of uncertainties in order to participate effectively in the market. Each customer behaves differently because of social and economic concerns. Therefore, each individual behavior will be different from others. In this chapter, two sets of uncertainty are considered, regarding the customers' behavior. The first set is the uncertainty of customers' response to participate in a CBDR program, and the second set is the uncertainty of selecting the different carriers by the customers.

In order to generate scenarios with the mentioned uncertain variables, the normal distribution has been utilized, with PDF

$$f(x,\mu,\sigma) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{3.38}$$

where μ and σ represent the mean value and the standard deviation, respectively.

In other words, it is assumed that the uncertain variables have normal deviations around their mean values. On this basis, different realizations of CBDR and CS are independently modeled by employing a scenario generation process based on roulette wheel mechanism [117]. For the sake of fair comparison, it is assumed that μ is equal to its amount in the deterministic case and different values of σ have been considered.

3.7 Case Studies

For assessing the effectiveness of the proposed model, numerical results have been developed. As the internal dependency has been investigated in prior researches (see [75] and [92]), the numerical results presented here focus on the EDs. The nonlinear formulation presented in this chapter has been linearized and modeled in such a way to be solved by using mixed integer linear programming with the CPLEX 12 GAMS solver. The local energy network under study (shown in figure 3.3) consists of CHP unit, AB, and HS. Inputs of this system are gas and electricity carriers, while the outputs are electricity, gas, and heat. Detailed information on these elements is provided in Table 3.1.

Table 3.1: Data of Local Energy Network Elements.

Elements		**p.u.**
CHP	Energy Output (Min-Max)	0 - 5
	η_h^{CHP}	0.35
	η_e^{CHP}	0.45
	$\underline{\Psi}^{CHP}, \overline{\Psi}^{CHP}$	1, 2
AB	Heat Output (Min-Max)	0 - 10
	η_h^{AB}	0.9
HS	Energy Capacity (Min-Max)	0.5 - 3
	η_h^{HS}	0.9

The illustration of the results is organized in two cases. Case I addresses the impact of the dependency existing in the proposed operational model of the multi-energy system. Case II shows and compares the results of stochastic models (representing the uncertainty in customers' choices) and deterministic models. All the studies in this section are first implemented on a base case where the amount of dependent demand is assumed to be zero ($l_{eg,t} = 0$). Then, in each step the level of dependency is increased. However, it is assumed that the total amount of energy that the customers require remains equal in all steps. As a result, the total amount of independent usage of electricity and gas has to be reduced. This reduction is conducted based on the efficiency of electricity and gas production elements in the system.

The information about local energy consumption in the base case and input energy carrier prices is indicated in figures 3.5 and 3.6. The hot water consumption is considered as the ED that can be supplied by both gas-fired and electrical heaters. The numerical amount of dependency is considered like energy and is expressed in per unit (p.u.).

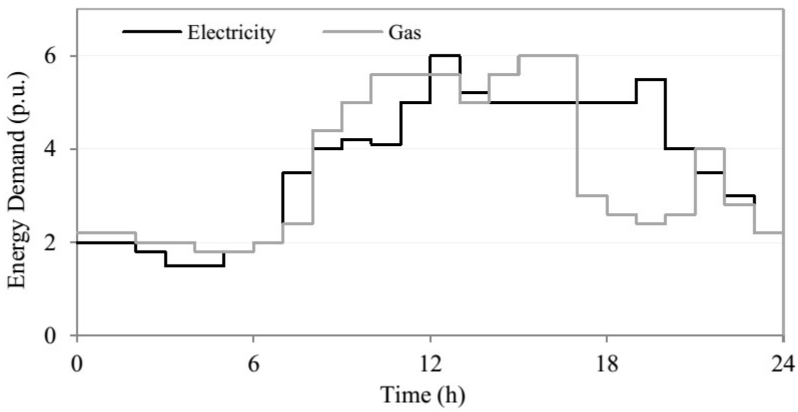

Figure 3.5: Energy carriers demand data in the operation time horizon.

The heat demand data is depicted in figure 3.7. The relation between electricity and gas carrier weighted energy contribution variable in the dependent output of these two carriers is shown in equation (3.39).

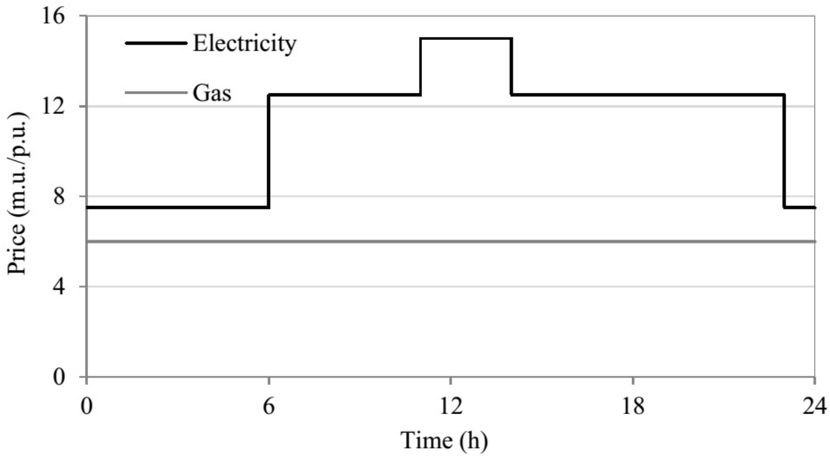

Figure 3.6: Energy carriers price data in the operation time horizon.

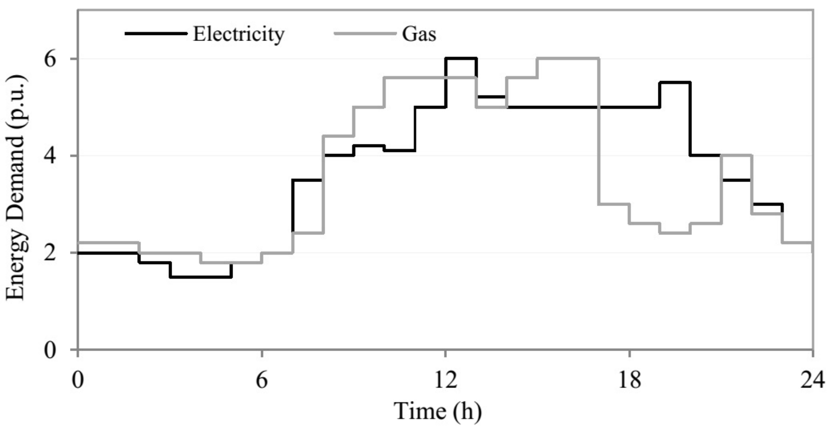

Figure 3.7: Heat demand data in the operation time horizon.

$$\eta_e^{dd} v_{e,\omega,t}^{dd,n} + \eta_g^{dd} v_{g,\omega,t}^{dd,n} = 1 \tag{3.39}$$

where η_e^{dd} and η_g^{dd} are the efficiencies of the electrical and the gas-fired water heaters, respectively. The typical amounts considered for η_e^{dd} and η_g^{dd} are 0.9 and 0.6, respectively, based on [118]. Furthermore, the typical amounts of $v_{e,\omega,t}^{CS}$ and $v_{g,\omega,t}^{CS}$ are 0.26 and 0.74, respectively, based on [119]. In these studies, it is assumed that the system operator enables CBDR by controlling the gas and electricity dependent consumption. This can be achieved by sending one-way communication signals to the multi-energy demand, taking advantage of the flexibility brought through this model.

3.7.1 Case I: The Operational Model Study

The first case study regards the impact of dependency and related CBDR programs in the network. The aim is to investigate how the cost of the system and the energy dispatch between the carriers are affected by the dependency existing in the multi-energy demand. Various levels of hot water usage as dependent power in the output are considered (leg,t varies from 0% up to 100% by intervals of 5%). In addition, five different values for the efficiency η_g^{dd} are assumed, while the efficiency of electricity η_e^{dd} is considered to be fixed. For generating these cases, first, the total amount of the gas and electricity output from the local energy network to the multi-energy demand are set up to specific values.

Then, as it is assumed that the total amount of output does not change, when the level of dependency increases, part of the previous demand of a carrier does not exist anymore and will be replaced by another carrier. The corresponding demand amount is reduced from the original carrier and is added to the so-called dependency. The energy carriers are adjusted on the basis of the typical output share and efficiency of energy converters. For example, the gas and electricity shares are adjusted based on predetermined η_e^{dd} and η_g^{dd}. Furthermore, the total share of ED is considered for the CBDR program ($l_{\omega,t}^{CB} = L_{eg,t}$).

Figure 3.8 shows the total system cost versus gas-fired heater efficiency for various levels of the demand dependency percentage indicated in equation (3.34). When the output dependency increases with the same η_e^{dd}, the operational flexibility increases, resulting in lower system operation cost. Conversely, for the same percentage of dependency when η_e^{dd} changes, the costs reach a maximum amount and then gradually decrease. The reason is that, as the output energy amount of local energy network remains constant, by reducing the gas energy converters' efficiency the system will provide more dependent demand through the electricity carrier. This means that up to a certain point, the operator of the micro-multi-energy system still can manage to keep the balance between the total system cost and gas energy carrier's consumption, but after that it is better for the operator to exchange the carrier to another one, electricity in this case.

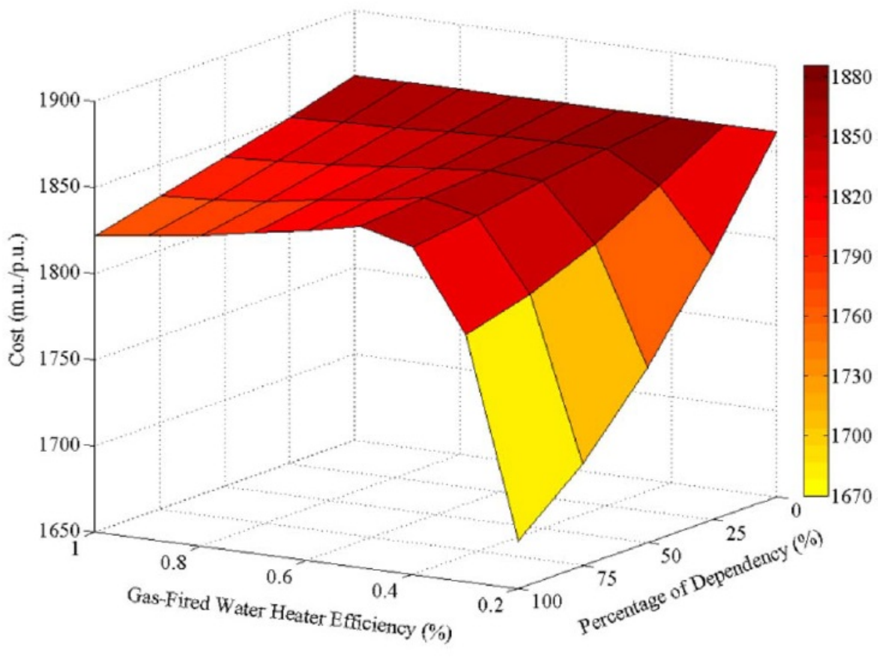

Figure 3.8: System operation cost based on demand dependency percentage for different water heater efficiencies.

With relatively low efficiency of gas energy converters, the demand requirements can be achieved by taking the benefits of using less electricity with higher efficiency than the gas carrier and in a total view reducing the system operation cost. In other words, when the efficiency of an energy carrier converter on the demand side is too low compared to other carriers in the micro-multi-energy system, it is better to change the source of dependent demand to another carrier that produces the required output with higher efficiency.

In general, this case study determines that more proficiency occurs when the micro-multi-energy system and multi-energy demands efficiencies are not close to each other. In this condition, the coordinated decision making between micromulti-energy system and multi-energy demand will decrease the system's operational cost. The proposed ED model enables the quantification of the operational costs in different conditions.

Figures 3.9 and 3.10 depict the amount of input electricity and gas carriers when η_g^{dd}= 0.6 for various levels of dependency. In these figures, the dependency level is shown for 0% and 100%. The density of the colored region appearing between the 0% and 100% limits indicates that the input quantities change when the dependency level varies. The zoomed-in views included in the figures indicate the corresponding type of variation of the input quantities at a specific hour (7 A.M.).

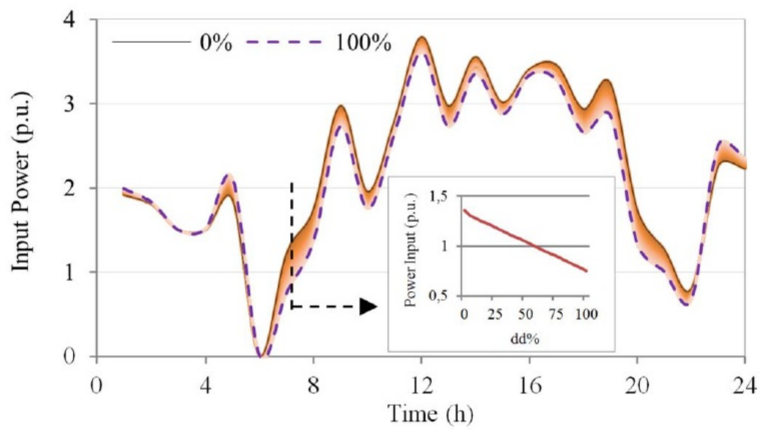

Figure 3.9: Evolution of the electricity input for demand dependency percentage from 0 to 100%, with $\eta_g^{dd} = 0.6$. Internal zoom for hour 7 A.M..

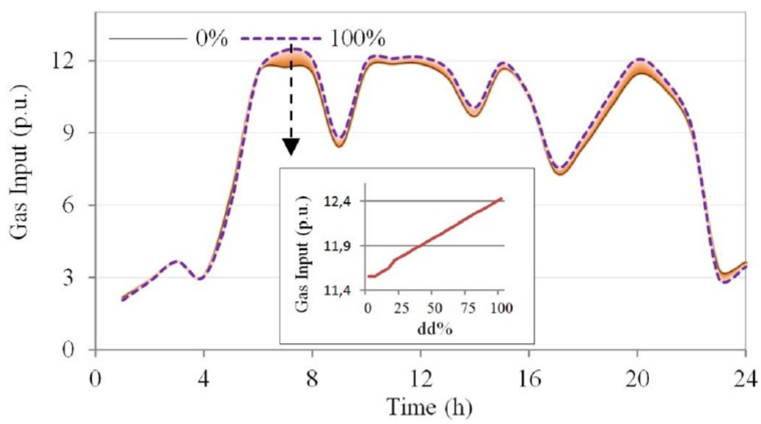

Figure 3.10: Evolution of the gas input for demand dependency percentage from 0 to 100%, with $\eta_g^{dd} = 0.6$. Internal zoom for hour 7 A.M..

As it is shown in figures 3.9 and 3.10 at the specific hour 7 A.M., the variation of power and gas input versus increasing variation of demand dependency follows an opposite manner. With increase in dependency percentage the consumption of electricity decreases while the consumption of gas has an increasing trend. The reason is that during hours 6–22 the average electricity price is high; therefore, the system operator prefers to provide the dependent energy amount through gas carrier rather than electricity, which also results in the reduction of the total operation cost. On the other hand, during hours 1–5, 23, and 24, when electricity price is lower, by increasing the level of dependency the tendency for electricity carrier consumption increases, while gas consumption shall decrease.

3.7.2 Case II: Comparison of Stochastic and Deterministic Results

This case study intends to examine the stochastic modeling of the customers' choice and derive the differences with the deterministic model. Data on dependency scenarios is considered based on the input energy carriers' prices, as presented in Table 3.2. In addition, as shown in equations (3.28)–(3.33) and figure 3.4, part of the hot water consumption is dependent on the CBDR program and the other part can be supplied by gas or electricity according to customer's choice.

Table 3.2: Data on Dependency Scenarios

Time (hours)		**1-5**	**6-10**	**11-13**	**14-22**	**23-24**
CBDR (%)	μ	10	15	20	15	10
	σ	1.66	1.66	1.66	1.66	1.66
Carrier Share (%)	μ	69	74	80	74	69
	σ	5	5	5	5	5

The share of gas and electricity consumption is uncertain because it depends on the consumer's behavior in using electrical and gas-fired water heater and responding to CBDR program. The mentioned uncertainty is considered in the stochastic model. For the sake of a fair comparison, the mean value of the mentioned ratio in the stochastic model is equal to the corresponding amount in the deterministic case. Figures 3.11 and 3.12 compare the share of CBDR and CS from total dependent demand for both gas and electricity carriers of multi-energy demand in stochastic and deterministic situations.

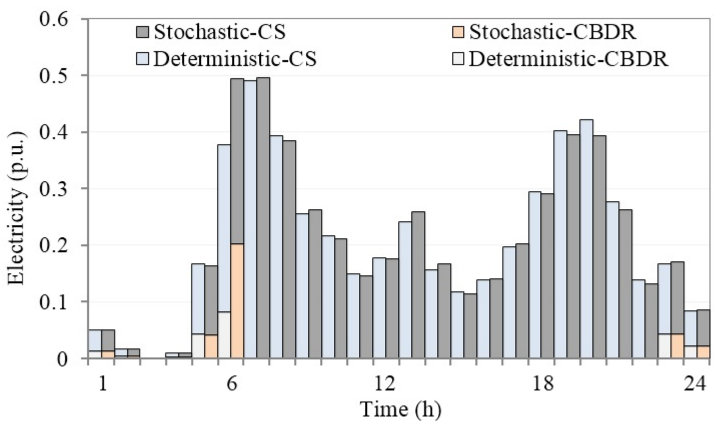

Figure 3.11: Contribution of CBDR and CS to the electricity share of dependent demand for deterministic and stochastic models.

From figure 3.11, most of the consumers tend to have their own choice of the electricity carrier for most of the time, with reduced participation in CBDR in early morning and late night. On the other hand, figure 3.12 shows that the consumers have the tendency to take part in the CBDR program for their gas consumption. This tendency occurs mostly between hours 7–22 where no

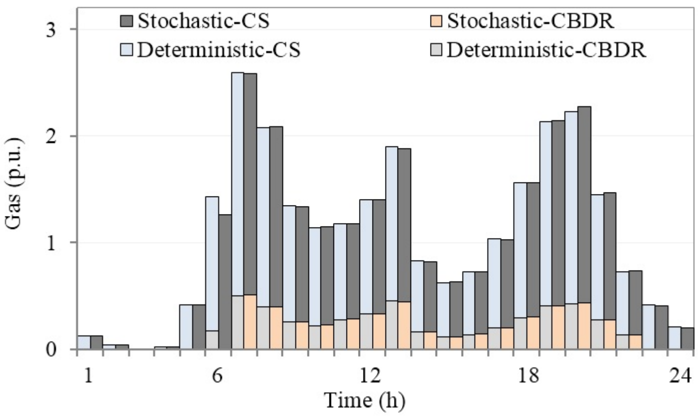

Figure 3.12: Contribution of CBDR and CS to the electricity share of dependent demand for deterministic and stochastic models.

consumer participates in electric CBDR.

From figures 3.11 and 3.12, it can be seen that the results obtained from the deterministic and stochastic models are similar. However, in hour 6 A.M., a significant difference between the results of electricity demand in stochastic and deterministic modeling occurs. The reason is that the assumed system hour 6 A.M. is critical, being the point where the interaction of internal and ED has the highest effect on the operator's decision making. Taking a look at figure 3.6 shows that this hour is the time when the electricity price shows a rise and will have a significant difference from the gas price. Besides, considering figure 3.7, it shows that at the same hour (6 A.M.) the demand for heat has its highest amount. Therefore, the system operator is going to operate the CHP unit in a way to be able to provide the required heat demand. The CHP unit will be producing more electricity; hence, the system operator will decide to reduce the amount of electricity purchased from the upstream network and supply its customers with the electricity produced by the CHP unit. Figure 3.9 proves this and indicates that the amount of electricity purchased at 6 A.M. is zero. The situation shows that, in such hours where high link between internal dependencies and EDs may occur, neglecting the stochastic modeling would affect the results on the balance between power and gas inputs seen by the operator.

Figures 3.13 and 3.14 depict the variations of the input electricity and gas for various scenarios of uncertainty for both CBDR and CS. In these figures, for 900 scenarios, the amount of input energy is illustrated. In these figures, the color code is shown in the figure determining the variation between the lowest (dark blue) and highest (dark red) amount of input energy carrier. The figures are plotted using surfaces with black edges. The black areas in these figures show the density of the scenarios' number that occurred with the same trend. In other words, in those areas, there are more scenarios that have equal amount of input carrier in each hour (or with a very small difference) causing the black edges to overlap and form a black area. It also should be noted that the arrangement of the scenarios are in a way that the scenarios are started from the lowest probability of occurrence, then reach the highest probability and after that the probability decreases again. This means that scenarios with numbers 1–100 and 800–900 have the lowest probability.

In figure 3.13, the black area is concentrated for the scenarios number 200–700. This shows that the scenarios that have higher probability of occurrence tend to follow similar trend, while the other scenarios show high distortion in their results. On the other hand, in figure 3.14, the scenarios do not show a dramatic change in the amount, but overlapping edges show that more probable scenarios exist regarding gas input.

The reason can be found beneath the fact that there are other elements in the multi-energy system that help the system operator to damp the effects of harsh uncertain scenarios regarding the gas input energy. The AB and CHP unit are two elements that help the supply of gas and heat in the system. As a result, in such systems the uncertainty of end users' stochastic behavior can be managed through the internal dependency in the multi-energy system.

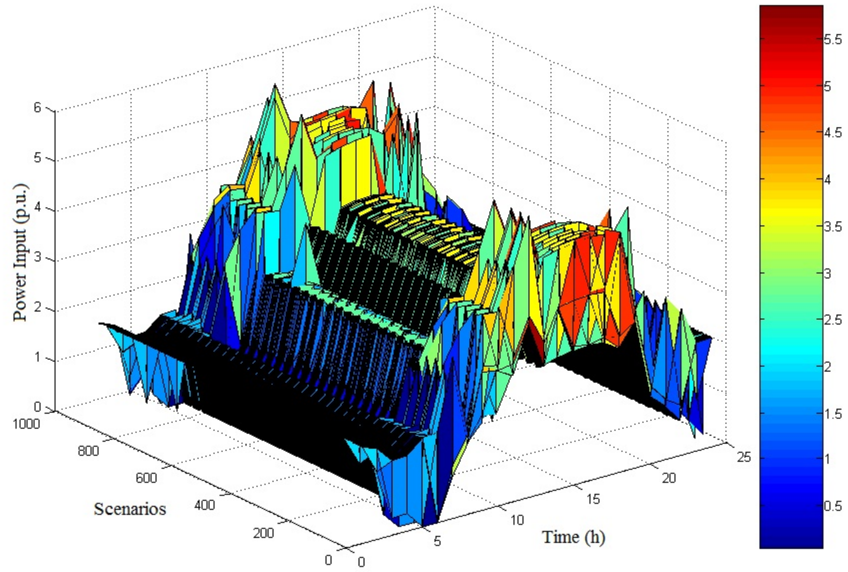

Figure 3.13: Electricity input variation for various stochastic scenarios.

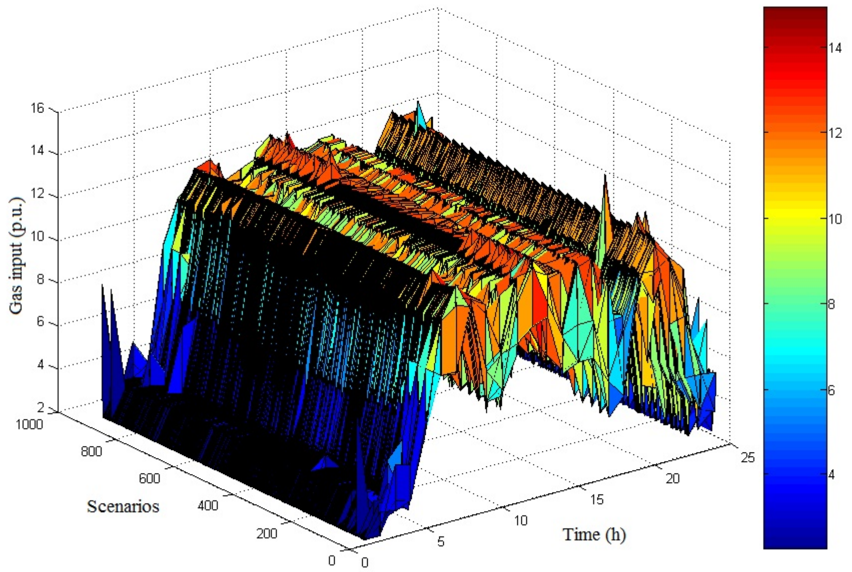

Figure 3.14: Gas input variation for various stochastic scenarios.

The results from the scenarios presented in figures 3.13 and 3.14 are obtained to show the variance of input energy carriers. Figure 3.15 shows that not only the changes in input gas variance are extended to 24 h (while the variance of input power is limited to hours 6–22), but also the amplitude of the variance is higher compared to electricity. The reason is due to various uncertainties that are imposed to the decision making process for the multi-energy system's total gas input.

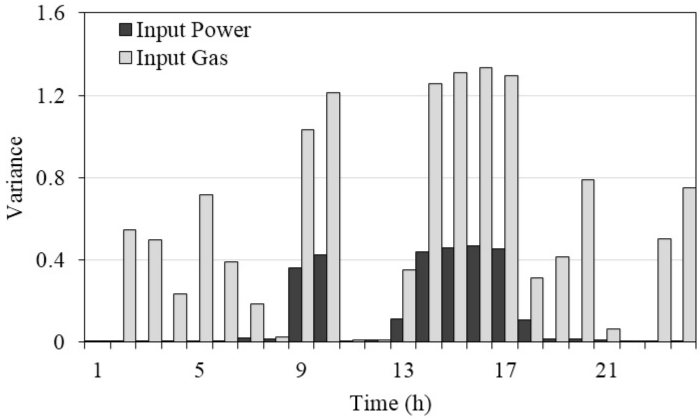

Figure 3.15: Variance of input power and gas.

Regarding the gas energy carrier, not only the dependent demand uncertainty should be considered, but also the effects of HS and CHP unit should not be neglected. As the storage has a time-dependent nature, the variance of gas input is extended to various hours. In addition, the CHP unit's consumption of gas and its conflicts with the independent gas consumption and the dependent demand impose other factors to the decision making problem.

For presenting the mechanics of the stochastic model, figure 3.16 shows the variation of total cost versus the variations in CBDR and CS variance. As it is observed, by increase in the CS variance the total cost increases. On the other hand, the increase in CBDR variance does not impose any significant change in the amount of total cost. The reason is that when the variance of CS is increasing, the uncertainty of customer's choice on different carriers is getting higher. The customer choice referring to CS is not under control by the operator.

Conversely, CBDR is also driven by the operator's action in promoting the DR program, and when the CBDR variance is increasing the operator can maintain its cost through scheduling the consumption of the dependent demand. Moreover, it shows that in higher variances of CS, as the CBDR variance increases the total cost will be reduced. This also indicates that the CBDR program will help the operator to reduce its operation costs.

In order to indicate the performance of the stochastic model, the stored heat is presented as one of the decision variables of the operator in figure 3.17. As it can be seen, the uncertainty of energy carriers' demand in the stochastic model causes the HS to be operated less compared with the deterministic case. The main reason is that a part of stored heat in each hour is wasted as heat loss. Therefore, with higher amount of stored heat more heat loss will be produced in the system, which during the optimization process leads to less utilization of HS from the operator point of view.

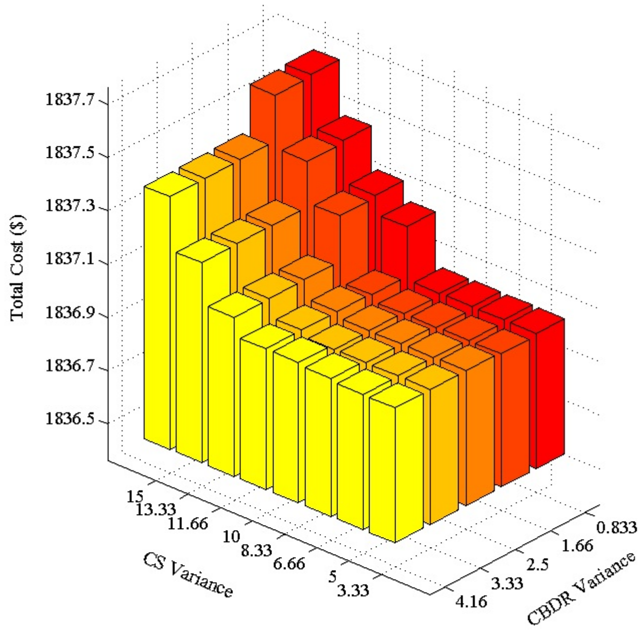

Figure 3.16: Variation of total cost vs. variation in CBDR and CS variance.

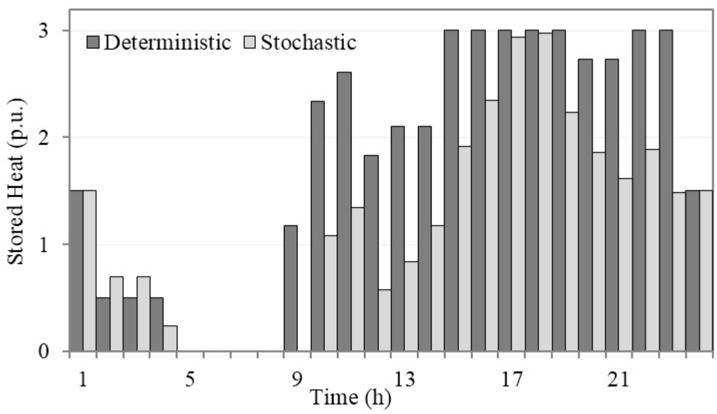

Figure 3.17: Stored heat variation in heat storage for deterministic and stochastic models.

3.8 Chapter Summary

For a local multi-energy system, this chapter has introduced the concepts of dependent demand, referring to a specific service that can be supplied through different energy carriers, internal dependencies (referring to changing the energy source in multi-energy flows under the control of the system operator) and EDs (representing changes in the energy source driven by the customer choice of the end user, also due to possible participation in DR programs). A new stochastic model based on the energy hub approach has been developed to represent the EDs and their uncertainty referring to multi-energy system operation. For assessing the efficiency of the developed model, a local energy system was considered and the uncertain behavior of the consumers was modeled in a stochastic framework.

The uncertainties include the response of the customers participating in a CBDR program, and the selection of different carriers by the customers not participating in the CBDR program, both affecting the energy carriers share. The numerical results obtained on a case study show how an increased share of participation in the CBDR program can reduce the operational costs. Furthermore, in networks with inefficient DERs it will be more significant to manage part of the demand as DR programs. In addition, the proposed approach enables quantifying to what extent the stochastic dependencies impact on the operating conditions of the system and can vary the schedule of the operator because of the more accurate representation of the relevant variables.

Chapter 4

Deriving the PEVs Traffic Pattern Model based on the Socio-Technical Preferences

4.1 Introduction

Various studies have been dedicated to model the PEVs in the system. However, it is necessary to describe the models for the PEVs in a way to be compatible with the urban restrictions. In this regard, there are few studies that have focused on the traffic flow of PEVs in a system from both electric system and urban planning points of view.

Authors in [120] considered various aspects of electric mobility including power system, transport system and the technology of vehicles for efficient controlling of PEVs in the system. The trips traveled by PEVs affect their required energy. The management of this power for hybrid PEVs based on the trips they travel is studied in [121]. On the other hand, when the PEVs are interconnected to the grid, they will add to the total load of the network as they need electricity for their charging. In [9], the energy which is needed for the PEVs is considered as a load and is modeled based on the daily distances that the PEV users travel. As the traffic behavior affects the location of charging stations, in [49] these effects are studied in a planning time horizon. Moreover, the mobility of the PEVs affects the scheduling of the system. Therefore, the authors in [122] studied the locational energy requirement of PEVs due to their random driving pattern. The interrelation of electricity grid and transportation network for the PEVs' case is an important issue. In [123], a model for the PEVs' fleet is proposed to be used in the national energy and transportation planning. Also from the urban planning point of view, the allocation of charging infrastructures considering the traffic ways and congestions is studied in [124]. Although there are many studies that have used the PEVs as their main concern of study, there are few in the literature that have merged the simultaneous concern of PEVs traffic pattern effect on the behavior of power system components. This study intends to address this issue.

In this chapter, the PEV parking lot is considered as the main charging station for the PEVs and the stochastic behavior of the PEVs in using PL is modeled. The PEVs arrival, departure, duration of stay, required departure SOC are derived from the real data and mathematically modeled in this chapter. The outcomes of the studies in this chapter are used in the rest of the thesis as the input of the problem.

4.2 Stochastic Modeling of PEVs' Parking Lot

A stochastic model is developed to quantify behavior patterns of PEVs at a parking lot. The nominal capacity of parking and the sum of SOC of EVs plugged-in at the parking lot in each hour are the outputs of the model. Capacity of parking lot relies on the number and type of PEVs parked at the parking lot. The hourly number of PEVs connected to the grid at the parking lot is a probabilistic variable that is related to behavior of PEV owners. In this chapter, the pattern of available PEVs at the parking lot is extracted from the real data that is obtained from number of vehicles parked at parking lots [125].

The energy storage capacity of each PEV represents the total energy capacity and it is dependent on the PEV class. For example, the energy storage capacity of plug-in hybrid electric vehicles (PHEVs) typically is between 6 kWh and 30 kWh; whereas, the capacity for BEVs varies from 30 to 50 kWh [126]. In [126], twenty four different classes have been considered for PEV batteries. The probability distribution of the battery capacities in each PEV class occurring in a market is illustrated in figure 4.1.

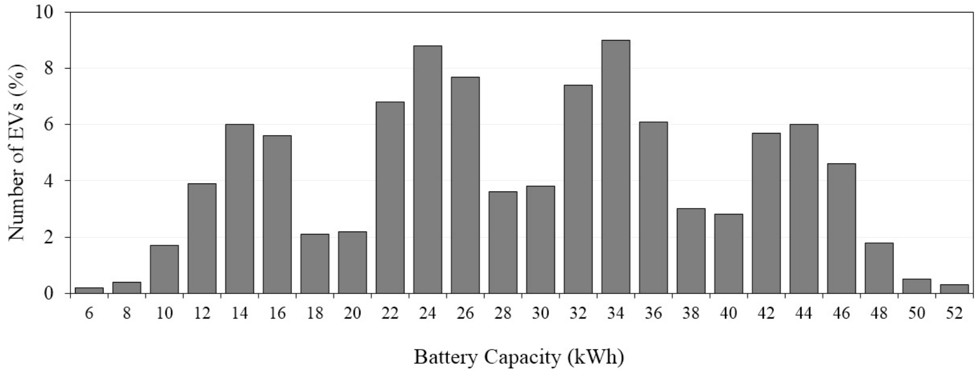

Figure 4.1: Distribution of battery capacity.

In order to consider the market share of each PEV class, the battery capacity of each class is considered. Taking into account the distribution of PEV classes and probability number of PEVs at parking lot, the hourly possibility of parking lot capacity is obtained as figure 4.2.

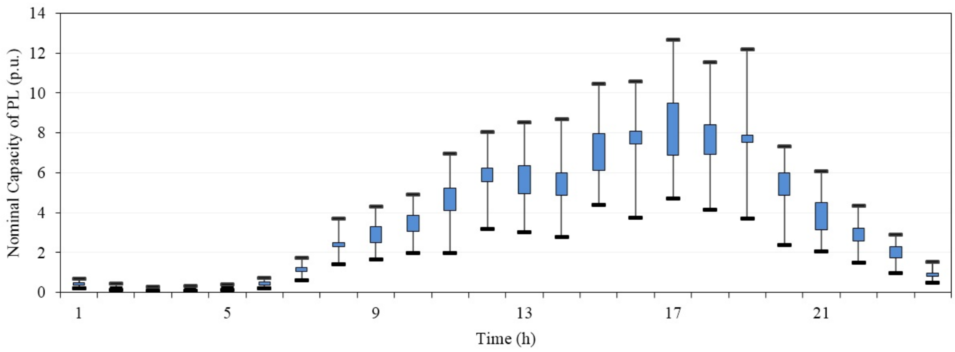

Figure 4.2: The hourly nominal capacity of parking lot.

SOC of Parking lot is dependent on number of PEVs parked at the parking lot, the type of each PEV and the daily driven distance of each PEV. The probabilistic traveled distance is applied as a parameter of calculating the SOC of parking lot. The lognormal distribution function is utilized to generate the probabilistic daily traveled distance [127]. The lognormal random variables are generated using standard normal random variable, N, and are computed using equation (4.1) [128].

$$M_d = exp\left(\mu_m + \sigma_m \cdot N\right) \tag{4.1}$$

where M_d is the daily driven distance. μ_m and σ_m are the lognormal distribution parameters and are calculated from mean and standard variation of M_d based on the historical data, denoted as μ_{md} and σ_{md}, respectively [12]. μ_m and σ_m are calculated based on equations (4.2) and (4.3), respectively.

$$\mu_m = ln\left(\frac{\mu_{md}^2}{\sqrt{\mu_{md}^2 + \sigma_{md}^2}}\right) \tag{4.2}$$

$$\sigma_m = \sqrt{ln\left(1 + \frac{\sigma_{md}^2}{\mu_{md}^2}\right)} \tag{4.3}$$

The vehicles used in [125] made an average of 4.2 trips per day, yielding an average daily distance of 39.5 miles. On the other hand, an electric vehicle takes approximately 0.35 kWh to recharge for each mile traveling [125]. On this basis and according to the mentioned above discussion, the hourly SOC of Parking lot can be obtained as illustrated in figure 4.3.

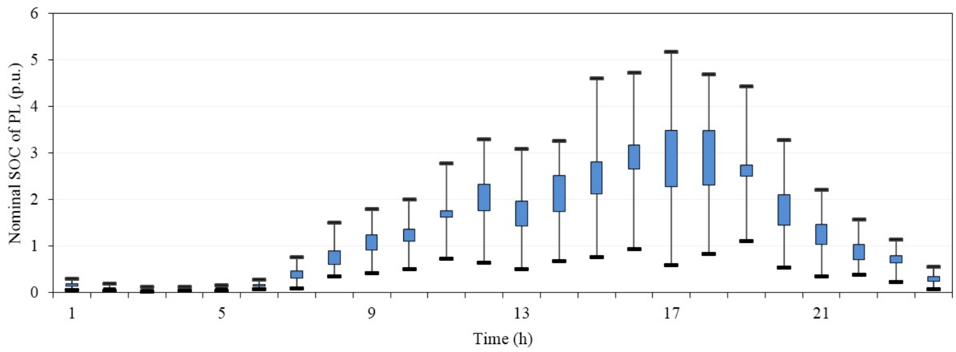

Figure 4.3: The hourly SOC of parking lot.

4.3 PEV Characterization

One of the main issues regarding the manipulation of PEVs in the system as a resource is how to manage the grid's need while maintaining the PEV owners' preferences at their satisfaction level. As a result, in some of the recent studies on this subject, such as [129–131] the behavior of PEVs has been considered pertaining their driven distance and state of charge. However, the owners of these vehicles may also have preferences other than the limitations of PEV. When considering the PL as a place to charge the vehicles, these concerns become more critical. In a charging station, the management of charging can be in owners' hands; however, in a PL, the PEVs are mostly left in the stations for a couple of hours. Therefore, the owners will have the least control on the (dis)charging of their vehicles. This matter in long term may result in fewer tendencies towards using the PL. As a result, a procedure of acquiring owners' preferences and including them in the strategy determination of the PL is necessary.

Hence, in this thesis, it is assumed that the PEVs can submit their preferences when entering the PL. However, they will not be treated the same. The PL, on the other hand, needs to compromise between the encouragement of owners to participate in PL and its own expenses. As a result, it should treat the PEVs with tariffs that are proportional to the opportunities that they give to the PL or the restrictions that they put on it. It is assumed that all the vehicles entering the PL are categorized into four groups:

- G2V mode with fixed departure SOC;
- G2V mode with flexible departure SOC;
- Both G2V, V2G mode with fixed departure SOC;
- Both G2V, V2G mode with flexible departure SOC.

4.3.1 PEV Behavior

The PL has to know how many of the PEVs that enter the PL belongs to each category. In this section, the pre-calculations of the PL for the total number of PEVs in the PL, duration of stay, and PEVs preferences are performed. In this study, a PL with 250 stations in a commercial area is considered. Figures 4.4 and 4.5 depict the arrival and departure scenarios employed in this study. The total number of PEVs in the PL is shown in figure 4.6. The mean values for the scenarios are derived from reports and surveys on European driving pattern presented in [125, 132, 133] and the household travel survey in US. The data presented in these studies are employed to acquire the expected stay duration of PEVs as shown in figure 4.7. As it is assumed that the PL is in a commercial center, the PEVs that enter the PL may stay from 1 to 12 hours in the PL. Therefore, the total PEVs can be classified into different groups based on their stay duration. Figure 4.8 shows the number of PEVs in each class.

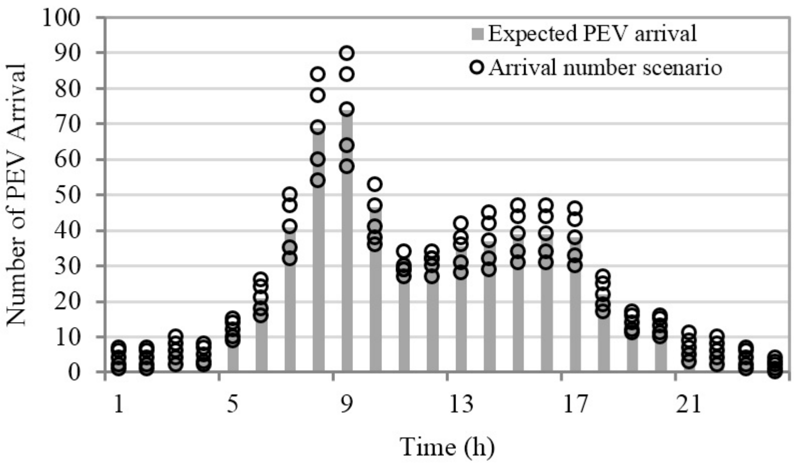

Figure 4.4: Expected value of PEV arrival to PL and its scenarios.

4.3.2 Scenario Generation for PEV Behavior in PL

Considering the real data from the surveys and the stay duration classification in figure 4.8, the scenarios for the arrival of PEVs in the PL is generated using the approach in previous section where a lognormal distribution function is considered. Then the departure scenarios are derived from the arrival scenario and stay duration. However, due to the fixed number of stations in the PL, the scenarios generated for arrival/departure may result in PEVs' number in the PL more than

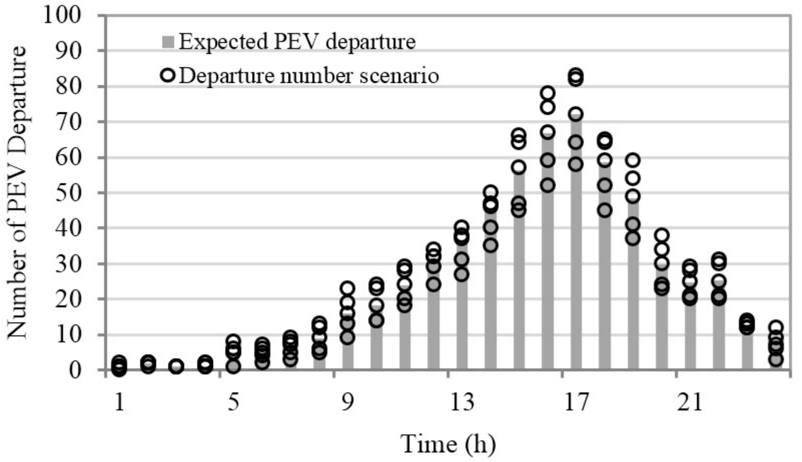

Figure 4.5: Expected value of PEV departure from the PL and its scenarios.

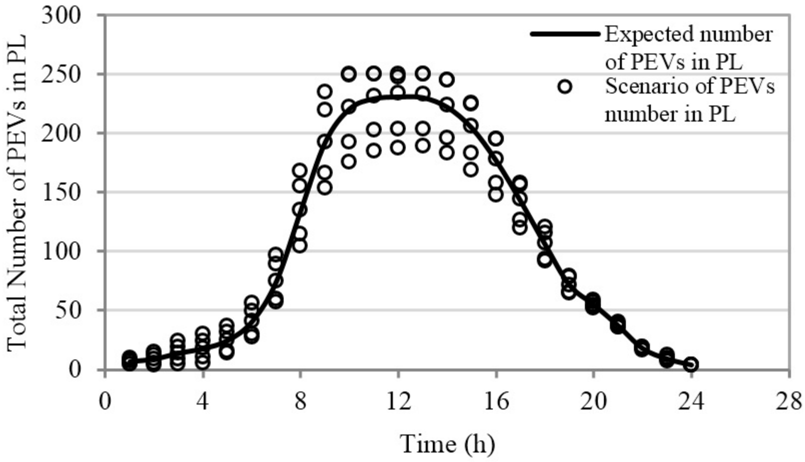

Figure 4.6: Expected value of PEVs' number in the PL and its scenarios.

the PL's station number. To prevent this, a procedure is implemented on the scenario generation as shown in figure 4.9. The scenario of PEV numbers in the PL is generated from the summation of the remainder PEVs in the PL from the previous hour and the arrived PEVs in each hour minus the departed PEV. Whenever the PEV numbers exceed the PL's stations, the number of excess PEVs is reduced from the arrival scenario on that hour.

Now, the arrival scenarios need to be changed which consequently cause the change in the stay duration. Considering the discrete distribution of stay duration pattern (figure 4.8), the new arrival scenario and stay duration scenario is formed. Based on the new arrival and stay duration scenario, the new departure scenario is generated. Once again the number of PEVs in PL is calculated. The procedure is performed until the PL's number scenario does not exceed the total PL's station number (figure 4.9).

4.3.3 Determination of PEV Preference Parameters

As mentioned before, the PL needs to compromise with the preferences of the PEV owners and its own profit. The PEVs should be treated relative to the opportunities or restrictions they bring for the PL. This can be through different tariffs attributed to different preferences. If the PL operator

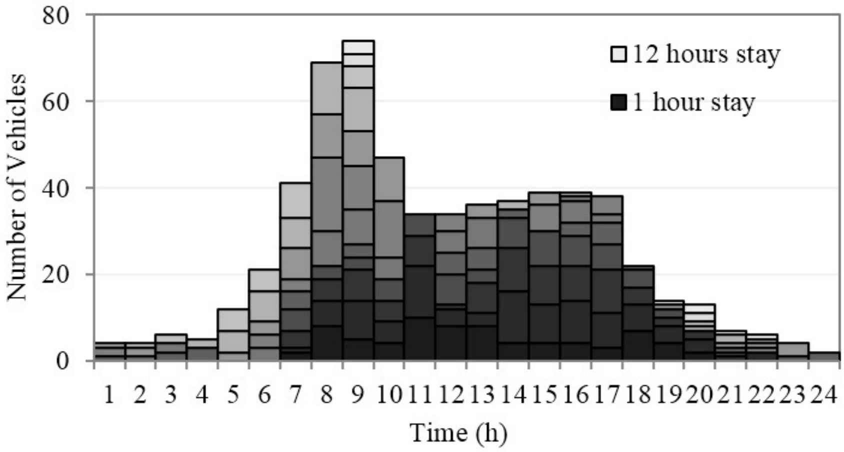

Figure 4.7: Total number of PEVs in the PL in each hour based on their expected stay duration.

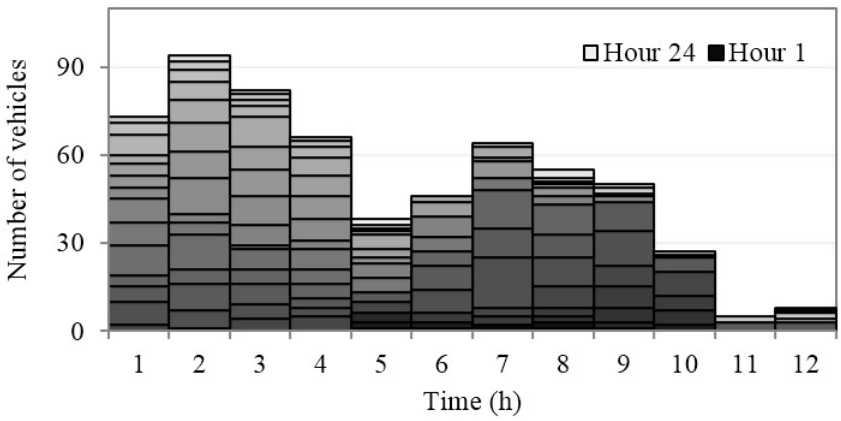

Figure 4.8: Classification of PEVs based on their stay duration.

wants to implement different tariffs to different PEVs, it needs to determine the number of PEVs in each category in each hour of arrival, and when they depart. Formerly, it was assumed that the PEVs' preferences are to have the choice whether to take part in G2V mode only or both G2V and V2G mode. They can also determine their need for fixed or flexible departure SOC.

Besides, it was considered that all PEVs will determine their minimum requirement of SOC when departing the PL. This preference is applied to the objective of the PL through coefficient ϕ which determines the minimum departure SOC requirement of each PEV category. The values for ϕ are shown in Table 4.1.

Table 4.1: Values of ϕ for different PEV categories

Mode	Departure SOC Requirement	Duration of stay (hours)		
		1-3	4-7	9-12
G2V	Fix	0.6	0.8	0.9
	Flex	0.4	0.6	0.6
G2V+V2G	Fix	0.4	0.5	0.6
	Flex	0.3	0.4	0.5

As it is shown, the PEVs are categorized based on their duration of stay into three groups. The estimation of the presumed required departure SOC is from the survey presented in [134]. The

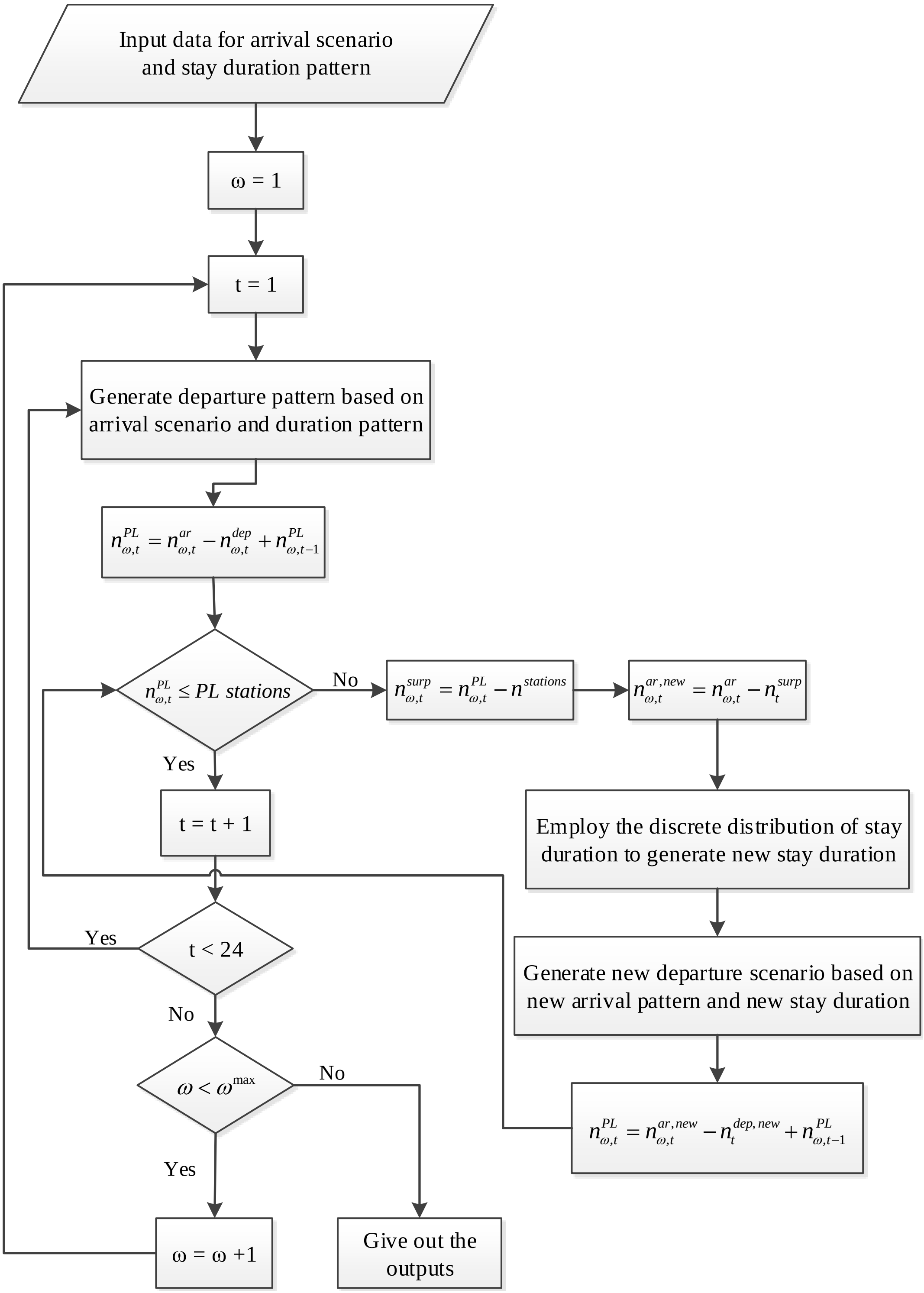

Figure 4.9: Flowchart of generating scenario for PEVs' number in PL.

values to determine the share of each category from the total departed PEVs are presented by coefficient β in Table 4.2. It is necessary to determine the share of each category from departing PEVs, because the amount of trade with each of these PEVs and PL should be calculated for the payments of PEVs on their departure.

From another point of view, the PL should be aware of its capacity to participate in the market. This means that it should have enough information on how many PEVs take part in G2V or V2G

Table 4.2: Values of β for different PEV categories

Mode	Departure SOC Requirement	Duration of stay (hours)		
		1-3	4-7	9-12
G2V	Fix	0.56	0.32	0.08
	Flex	0.14	0.08	0.02
G2V+V2G	Fix	0.06	0.12	0.18
	Flex	0.24	0.48	0.72

mode. For this purpose another coefficient is defined as θ which determines the share of each PEV category from total PEVs in the PL in each hour. The hourly amounts of θ are calculated from the stay duration pattern and β. It should be noted that for each scenario of PL number, a scenario for θ is also generated. The amounts for θ are shown in Table 4.3.

Table 4.3: Values of θ for different PEV categories

hour	θ values in each scenario				
	1	2	3	4	5
1	0.5	0.4	0.4	0.4	0.4
2	0.6	0.5	0.4	0.4	0.4
3	0.5	0.4	0.4	0.4	0.3
4	0.4	0.4	0.3	0.3	0.3
5	0.3	0.3	0.2	0.2	0.2
6	0.3	0.2	0.2	0.2	0.3
7	0.3	0.3	0.3	0.3	0.3
8	0.4	0.4	0.4	0.4	0.4
9	0.4	0.4	0.4	0.4	0.4
10	0.4	0.4	0.4	0.4	0.4
11	0.4	0.4	0.4	0.4	0.4
12	0.4	0.4	0.4	0.4	0.4
13	0.4	0.4	0.4	0.4	0.4
14	0.4	0.4	0.4	0.4	0.4
15	0.4	0.4	0.5	0.4	0.5
16	0.5	0.5	0.5	0.5	0.5
17	0.5	0.5	0.5	0.5	0.6
18	0.6	0.6	0.6	0.6	0.6
19	0.6	0.6	0.6	0.6	0.7
20	0.5	0.5	0.6	0.6	0.6
21	0.5	0.5	0.5	0.5	0.6
22	0.4	0.5	0.5	0.5	0.6
23	0.5	0.5	0.5	0.6	0.6
24	0.5	0.5	0.5	0.5	0.5

4.4 Traffic Pattern Mathematical Model

In the introduced traffic pattern model, in each hour a number of PEVs enter the zone. Some of these PEVs choose the PL installed in that zone for the duration of their stay; some other travel in the urban area of the zone and park in some places other than the PL. Besides, some of the PEVs may travel through a zone, pass this zone and go out to another zone or the neighboring area. The model for the number of PEVs and the probable travel in each zone is shown in figure 4.10. As it is illustrated, vehicles from both neighboring zone and the environment enter a zone, then divided into those who enters the PL ($n^{ar,PL}$) or those who travel in the urban area ($n^{ar,Urban}$). The same procedure happens when the PEVs leave the zone.

On the other hand, the PEVs that enter the zone bring their capacity and SOC with them. However, during their travel they lose some of their SOC, which causes them to need fuel to continue their travel. As a result, the power interaction between PEVs and grid will be through the PL and charging stations in each zone. The amount of energy that is needed for PEVs in a zone depends on their initial SOC and the distance they travel. However, the energy consumption for a vehicle is affected by various factors. The PEV traffic behavior, the area that is assigned to the zone, the distance that PEVs travel to reach the zone and the extent of the zone are some of the factors that change the amount of needed energy for a PEV.

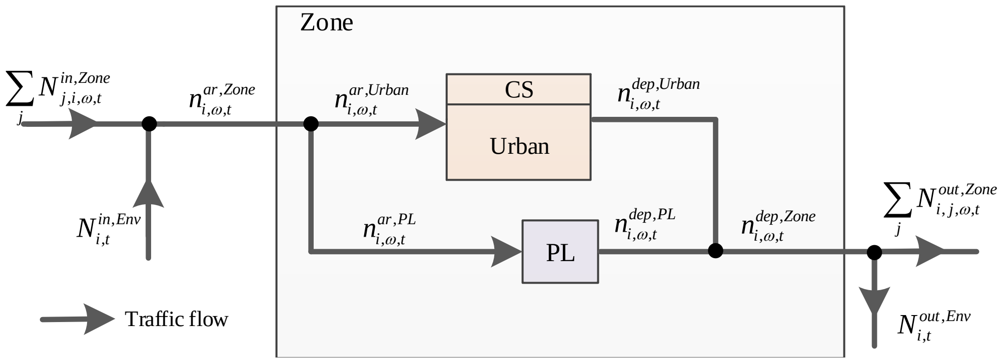

Figure 4.10: The interaction of PEV numbers between environment and zone and inside the zone.

In figure 4.11 the power exchange between zone, PL, urban charging stations and the upstream grid is shown. This power exchange determines the amount of SOC that travels to another zone and the amount of energy that should be purchased and planned by the DSO. It is shown that the PEVs enter the zone with their initial SOCs ($soc^{in,zone}, soc^{in,Env}$) that determines their starting point (neighboring zone or environment). However, some of them arrive at the PL ($soc^{ar,PL}$) while others travel in the urban part of the zone ($soc^{ar,Urban}$). The PL is a point where the power trade is made with the upstream network to charge/discharge the PEVs ($p^{in,PL}, p^{out,PL}$)). As a result, the SOC arrived to the PL will change due to the charging/discharging that occurs in the PL. On the other hand, the SOC that arrives to the urban area also changes firstly because the PEVs drive within the urban area and hence lose some of their charge; second, because they may use the charging stations in the urban. Therefore, the amount of SOC that departs from the PL or urban is different from the arrived one. In this regard, it is important to comprehensively model these interactions.

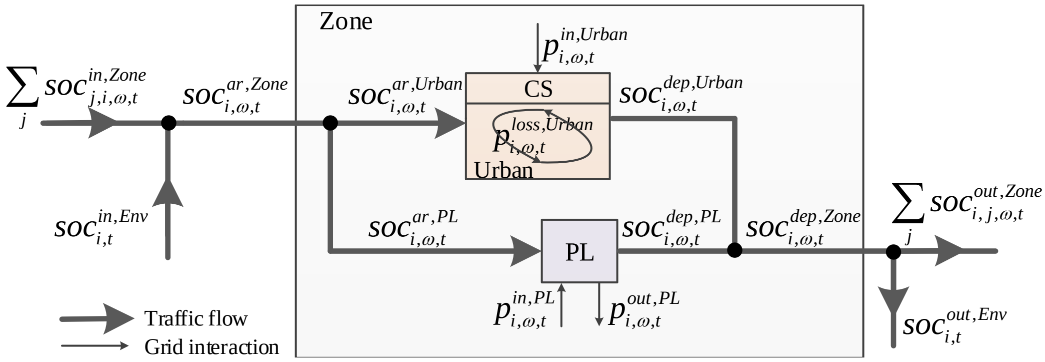

Figure 4.11: The amount of power exchanged between environment and zone (PL and urban area).

In this study it is assumed that from other urban and traffic studies the number of PEVs that enter or exit each zone is specified. In addition, the division of the arrived or departed PEVs to the zone (from/to environment or from/to another zone) is also assumed to be known. However, their SOC as well as their participation in PL or urban within the zone should be calculated.

4.4.1 Traffic Flow Constraints

Regarding the above explanations, the traffic flow should maintain the following constraints. Firstly, the time difference for departing one zone and arriving at another zone should be determined. It is dependent on the distance between zones and the average speed of the PEVs. This time is calculated by equation (4.4). If PEVs depart zone i at time t and reach the neighboring zone j after the time delay calculated by equation 4.4, the amount of SOC that arrives to j is based on equation (4.5), where the SOC departed from zone i minus the amount of energy lost for traveling the distance between the two zones.

$$\alpha_{i,j} = \frac{Dist_{i,j}}{S_{i,j}} \tag{4.4}$$

$$k = t + \alpha_{i,j} \Rightarrow soc^{in,Zone}_{j,i,\omega,k} = soc^{out,Zone}_{j,i,\omega,t} - N^{out,Zone}_{j,i,\omega,t} Dist_{i,j} P^{Fuel}_{i,j} \tag{4.5}$$

Moreover, the SOC that enters or departs a zone should not exceed the amount of arrived or departed PEV capacity as:

$$soc^{in,Zone}_{j,i,\omega,t} \leq C^{in,Zone}_{j,i,\omega,t} \tag{4.6}$$

$$soc^{out,Zone}_{i,j,\omega,t} \leq C^{out,Zone}_{i,j,\omega,t} \tag{4.7}$$

4.4.2 Zone Constraints

After determining the general flow of the PEVs, the arrival and departure pattern of PEVs' number, capacity, and SOC should be determined for each PL, urban area, and zone. The total number of

PEVS in each zone is calculated from:

$$n_{i,\omega,t}^{ar,PL} + n_{i,\omega,t}^{ar,Urban} = N_{i,t}^{in,Env} + \sum_{j} N_{j,i,\omega,t}^{in,Zone} \tag{4.8}$$

Each PEV carries the capacity of battery based on their type and model:

$$c_{i,\omega,t}^{ar,PL} + c_{i,\omega,t}^{ar,Urban} = C_{i,\omega,t}^{in,Env} + \sum_{j} C_{j,i,\omega,t}^{in,Zone} \tag{4.9}$$

It is assumed that the PEVs that arrive at the zone prefer to park in the PL; if the PL does not have enough vacant stations, then they will go to park in the urban. As a result, the number of PEVs arrived to the PL will be considered as:

$$n_{i,\omega,t}^{ar,PL} = \begin{cases} n_{i,\omega,t}^{vac,PL} & \text{if } N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} > n_{i,\omega,t}^{vac,PL}; \\ N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} & \text{if } N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} \leq n_{i,\omega,t}^{vac,PL}. \end{cases} \tag{4.10}$$

The vacant number of PL stations is based on equation (4.11) where it equals the total installed stations in the PL minus the number of available PEVs in the PL.

$$n_{i,\omega,t}^{vac,PL} = NS_{i}^{PL} - n_{i,\omega,t}^{PL} \tag{4.11}$$

Consequently, the capacity that arrives with the PEVs to the PL is calculated from:

$$c_{i,\omega,t}^{ar,PL} = \begin{cases} \left(\frac{n_{i,\omega,t}^{ar,PL}}{N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone}} \right) \sum_j C_{j,i,\omega,t}^{in,Zone} & \text{if } N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} > n_{i,\omega,t}^{vac,PL}; \\ C_{i,\omega,t}^{in,Env} + \sum_j C_{j,i,\omega,t}^{in,Zone} & \text{if } N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} \leq n_{i,\omega,t}^{vac,PL}. \end{cases} \tag{4.12}$$

Like capacity, the total amount of arrival and departure SOC in the zone is calculated from the arrived vehicles both from another zone and environment as in:

$$soc_{i,\omega,t}^{ar,PL} + soc_{i,\omega,t}^{ar,Urban} = soc_{i,\omega,t}^{ar,Zone} = soc_{i,\omega,t}^{in,Env} + \sum_{j} soc_{j,i,\omega,t}^{in,Zone} \tag{4.13}$$

$$soc_{i,\omega,t}^{ar,PL} = \begin{cases} \sum_k \Delta soc_{i,\omega,t,k}^{ar,PL} & \text{if } N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} > n_{i,\omega,t}^{vac,PL}; \\ soc_{i,\omega,t}^{in,Env} + \sum_j soc_{j,i,\omega,t}^{in,Zone} & \text{if } N_{i,\omega,t}^{in,Env} + \sum_j N_{j,i,\omega,t}^{in,Zone} \leq n_{i,\omega,t}^{vac,PL}. \end{cases} \tag{4.14}$$

The same happens for the departure SOC from PL and urban equals the total departed SOC from the zone ($soc^{dep,Zone}$) as well as the summation of the SOC that goes out to environment ($soc^{out,Env}$) and the SOCs that goes out to neighboring zones ($soc^{out,Zone}$) as:

$$soc_{i,\omega,t}^{dep,PL} + soc_{i,\omega,t}^{dep,Urban} = soc_{i,\omega,t}^{dep,Zone} = soc_{i,\omega,t}^{out,Env} + \sum_j soc_{j,i,\omega,t}^{out,Zone} \tag{4.15}$$

$$soc_{i,\omega,t}^{dep,Urban} = \frac{\left(N_{i,\omega,t}^{out,Env} + \sum_j N_{i,j,t}^{out,Zone}\right)}{\sum_h \left(N_{i,h}^{in,Env} + \sum_j N_{i,j,h}^{in,Zone} - N_{i,h}^{out,Env} - \sum_j N_{i,j,h}^{out,Zone}\right) + N_{i,\omega,t=1}^{PL} + N_{i,\omega,t=1}^{Urban}} soc_{i,\omega,t}^{Urban} \tag{4.16}$$

$$soc_{i,\omega,t}^{dep,PL} = \frac{\left(N_{i,\omega,t}^{out,Env} + \sum_j N_{i,j,t}^{out,Zone}\right)}{\sum_h \left(N_{i,h}^{in,Env} + \sum_j N_{i,j,h}^{in,Zone} - N_{i,h}^{out,Env} - \sum_j N_{i,j,h}^{out,Zone}\right) + N_{i,\omega,t=1}^{PL} + N_{i,\omega,t=1}^{Urban}} soc_{i,\omega,t}^{PL} \tag{4.17}$$

In order to compute the SOC that goes out from a zone to go to another zone or to the environment the equations in equations (4.18) and (4.19) is employed. As it can be seen, it is calculated from the predetermined PEVs' number that goes out to environment or another zone.

$$soc_{i,\omega,t}^{out,Env} = \frac{N_{i,\omega,t}^{out,Env}}{N_{i,h}^{out,Env} + \sum_j N_{i,j,h}^{out,Zone}} soc_{i,\omega,t}^{dep,Zone} \tag{4.18}$$

$$soc_{i,\omega,t}^{out,Zone} = \frac{N_{i,\omega,t}^{out,Zone}}{N_{i,h}^{out,Env} + \sum_j N_{i,j,h}^{out,Zone}} soc_{i,\omega,t}^{dep,Zone} \tag{4.19}$$

4.4.3 Urban Constraints

Same as other components of the proposed model, some constraints are put upon urban area. As it was explained before, urban denotes the area within a zone other than the PL. The number of PEVs in the urban in each hour is calculated from the number in urban in previous hour plus the number of arrived PEVs minus the departed PEVs in that hour as in equation(4.20). The capacity of the urban in each hour is calculated same as its number. However, the SOC in each hour of the urban is dependent on the PEVs that charge their batteries in the charging stations in the urban other than the initial SOC that PEVs bring with them to the urban. Therefore, the SOC in urban in each hour is calculated from equation (4.21) where the injected power to the urban through charging stations is also considered. However, it should be noted that the injected power is affected by the efficiency of charging station ($\eta^{cha,Urban}$).

$$n_{i,\omega,t}^{Urban} = N_{i,\omega,t_0}^{Urban}|_{t=1} + n_{i,\omega,t-1}^{Urban}|_{t>1} + n_{i,\omega,t}^{ar,Urban} - n_{i,\omega,t}^{dep,Urban} \tag{4.20}$$

$$soc_{i,\omega,t}^{Urban} = SOC_{i,\omega,t_0}^{Urban}|_{t=1} + soc_{i,\omega,t-1}^{Urban}|_{t>1} + p_{i,\omega,t}^{inj,Urban}\eta_i^{cha,Urban} + soc_{i,\omega,t}^{ar,Urban} - soc_{i,\omega,t}^{dep,Urban} \tag{4.21}$$

In the urban area, it is assumed that in each hour a specific proportion (β^{Urban}) of the existing SOC in the urban is added to the total SOC of the urban (i.e., PEVs in the urban area are charged by that amount). Hence, the total power injected from the upstream network to urban charging stations is limited to this minimum amount. On the other hand, the maximum energy that can be injected to the urban area is limited to the maximum charging capability of each station (Γ^{Urban}) multiplied by the number of PEVs that are charged (16). However, this number is variable in each hour. As a result, in each hour is the number of PEVs is higher than the total number of stations in urban then the total charging PEVs in each hour is equal to the number of stations (NS^{Urban}); otherwise, the number is less than NS^{Urban}. Therefore, the maximum limitation of the injected power is the minimum of these two amounts as in equation (4.22). Moreover, the total SOC in the urban should not exceed its total capacity which is imposed to the model by equation (4.23).

$$0 \leq p_{i,\omega,t}^{inj,Urban} \leq min\{\Gamma_i^{ChS} NS_i^{ChS}, \Gamma_i^{ChS} n_{i,\omega,t}^{Urban}, \left(C_{i,\omega,t}^{Urban} - soc_{i,\omega,t}^{Urban}\right)\beta_{i,t}^{Urban}\} \tag{4.22}$$

$$\underline{\chi}^{PEV} c_{i,\omega,t}^{Urban} \leq soc_{i,\omega,t}^{Urban} \leq \overline{\chi}^{PEV} c_{i,\omega,t}^{Urban} \tag{4.23}$$

4.4.4 PL Constraints

In this study, the PL is introduced as a place where PEVs can be charged and also take benefit of participating in energy and reserve market through V2G mode. The total number of available PEVs in the PL in each hour is based on equation (4.24). Moreover, the total number of available PEVs in the PL should not exceed the number of available PL stations as in equation (4.25).

$$n_{i,\omega,t}^{PL} = N_{i,\omega,t_0}^{PL}|_{t=1} + n_{i,\omega,t-1}^{PL}|_{t>1} + n_{i,\omega,t}^{ar,PL} - n_{i,\omega,t}^{dep,PL} \tag{4.24}$$

$$n_{i,\omega,t}^{PL} \leq NS_i^{PL} \tag{4.25}$$

The SOC in the PL, like urban, is affected by the initial SOC of the arriving and existing PEVs as well as the injected power into the PL. However, for the PL's SOC it should be noticed that in addition to the power injection to the PL, the PEVs are able to inject power to the grid while they are in the V2G mode. As a result, the power delivered to the grid divided by the discharge efficiency is reduced from the SOC in each hour:

$$soc^{PL}_{i,\omega,t} = SOC^{PL}_{i,\omega,t_0}|_{t=1} + soc^{PL}_{i,\omega,t-1}|_{t>1} + p^{in,PL}_{i,\omega,t}\eta^{cha,PL}_i - \frac{p^{out,PL}_{i,\omega,t}}{\eta^{dcha,PL}_i} + soc^{ar,PL}_{i,\omega,t} - soc^{dep,PL}_{i,\omega,t} \tag{4.26}$$

$$\underline{\chi}^{PEV} c^{PL}_{i,\omega,t} \leq soc^{PL}_{i,\omega,t} \leq \overline{\chi}^{PEV} c^{PL}_{i,\omega,t} \tag{4.27}$$

The specifications of the charging facilities that are installed in the PL restrict the total amount of injected power as well as the power that can be delivered to the grid. In equation (4.28) it is shown that the maximum charging capability of each station in the PL multiplied by the number of available PEVs in the PL determines the maximum limit for the power injection into the PL. On the other hand, in equation (4.29) it is shown that the output of the PL which includes the amount of energy and reserve for the energy and reserve market should be less than the minimum amount of possible capacity of PLs due to the available number of PEVs in the PL comparing to the minimum requirement of SOC for PEVs. In this study, it is also assumed that the PEVs that enter the PL agree to take part as V2G mode determine their preferences by imposing the minimum amount of required SOC when they are departing the PL. This preference is imposed to the PL's SOC by factor ϕ^{PL}.

$$p^{in,PL}_{i,\omega,t} \leq \Gamma^{PL}_i n^{PL}_{i,\omega,t} \tag{4.28}$$

$$p^{out,PL}_{i,\omega,t} \leq min\{\Gamma^{PL}_i n^{PL}_{i,\omega,t}, soc^{PL}_{i,\omega,t}\phi^{PL}_i\} \tag{4.29}$$

$$p^{out,PL}_{i,\omega,t} + r^{out,PL}_{i,\omega,t} \leq min\{\Gamma^{PL}_i n^{PL}_{i,\omega,t}, soc^{PL}_{i,\omega,t}\kappa^{PL}_i\} \tag{4.30}$$

4.5 Chapter Summary

In this chapter the stochastic behavior of the PEVs for their usage pattern of PEV PLs are derived from the real data. Moreover a model is proposed for the PEVs interaction between various zones in an area with multiple PLs and charging stations. The model considers the constraints imposed to the model by traffic pattern of the area or zone as well as the components of the power system. The outcomes of this section are very essential for all the studies involving the electric vehicles.

Chapter 5

Modeling the PL's Operational Behavior and Market Participation

5.1 Introduction

Electrification of transportation is an emerging trend in power system studies, traffic planning and urban studies. Penetration of electric vehicles in everyday life has several aspects that should be dealt with. Deployment of PEVs not only affects the operation of the power system, but also imposes some necessary interactions that have not existed in the system before. These interactions regard the technical impacts of PEVs as well as economics, traffic and allocation of PEVs and occur among all the parties that are involved with the PEVs. The parties could be the owners of the PEVs, the operator of the charging stations, the distribution system operator , the urban planner, etc.

Vast penetration of PEVs in the system requires foreseeing of necessary infrastructures. One of the recent solutions to provide the needed platform for better utilization of PEVs is the PEVs' P. PLs provide a medium for the PEVs to charge their batteries and an aggregated version of PEVs to act as storage. PLs equipped with enough facilities can deliver grid to vehicle and vehicle to grid opportunities of the PEVs at the same time. This situation brings the PL the potential of being a resource in the system as well as the flexible load. Therefore, introducing the PL as a new party to the aforementioned interactions of the PEV-involved parties brings more conflicts and challenges to the problem.

On the other hand, the traffic pattern of the area where the PL is installed and the behavior of the PEV owners that use the PL considerably affect the operation of the PL. The arrival and departure pattern of PEVs to the PL and the duration they intend to stay influences the participation of the PL in the market. Besides, their charging requirements impose other restrictions to the PL operation. As a result, modeling the PEVs behavior and their obligations' effects on the PL's behavior is necessary in the study of the transactions of the PL and the market.

Confronting with the above-mentioned challenges, the aim of this chapter is to investigate the interactions of the PL in market place affected by the PEVs' preferences in a mixed resource environment.

5.2 Problem Description

As comprehensively discussed in the literature, numerous interconnections of PEVs should be managed through the new entity of PEV aggregator. Although a PL is an aggregated form of PEV, restrictions of its operation confine the PL to compete independently in the market. However, the potential of the PL as a resource in the system as well as its nature of being a flexible load cannot be disregarded. In fact, the special role of the PL as a prosumer in the system can be best employed along with other available resources in the system. Therefore, aggregating the PL's opportunities with other resources such as DG and DR provides a suitable environment for the aggregator to achieve higher level of flexibility.

On the above premises, this chapter proposes a model in which an aggregator is the interface of local resources with the market. The basic visual of such environment is shown in figure 5.1. In this environment, the PL participates in the market through an aggregator which has to provide the required demand for the load retailer. Another resource (DG) is also present in the system to study the variations of price. The aggregator combines all the resources in the local network to maximize its profit when participating in the upstream energy and reserve markets. However, each of the components that are aggregated by the aggregator has its own objective and restrictions that may have conflict with the objective of the aggregator. Therefore, a bilevel problem is encountered in this situation. In the upper-level (UL) problem, the objective of the aggregator is to maximize its own profit through its interaction with the upstream market on one hand and the energy and reserve trade with the PL, energy purchase from the DG and providing the required demand on the other. On the lower-level (LL), the PL, the DG, and the load retailer are the components who also want to maximize their profit. As a result, an equilibrium point should be found for the operation of such system. The interactions between the two levels of the model are described in follows.

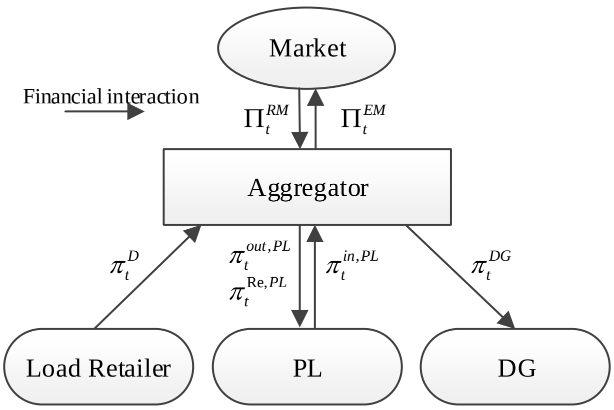

Figure 5.1: Interactions of the components in the environment.

5.2.1 Aggregator-PL-PEV interactions

The PL provides the opportunity for the PEV owners to charge their batteries and take part in the V2G mode if they are willing to. The PL can act more efficiently in the market comparing to charging stations because it enables the simultaneous G2V/V2G mode and it also benefits from the longer stay of the PEVs in the PL. Consequently, it can have the role of storage as well as the flexible load in the system. However, when operating a PL, it is necessary to consider the preferences of the PEV owners. In this study, it is assumed that the PEVs who enter the PL restrict the PL's behavior in the marketplace with their choice on whether taking part as G2V mode or V2G. Note that by V2G mode, we mean that PEVs take both G2V and V2G mode. For the sake of simplification, only the V2G term is used for this type of PEVs. Moreover, it is assumed that all PEVs determine a minimum amount of SOC to remain in their batteries when they are leaving the PL; however, some of the PEVs need a fixed amount of departure SOC while others agree to have a flexible departure SOC and the only limit for them is their minimum SOC. The reason for considering fixed departure SOC is to take into account the possible contracts of PEV owners with other PEV-aggregators which obliges them to keep a specific portion of their capacity empty.

Therefore, four different categories of the PEVs enter the PL: G2V/V2G mode with fix/flexible departure SOC. Each of these categories and their requirements restrict the PL in utilizing the total available capacity in the PL. Due to fixed departure SOC, the PL should consider that it cannot charge the G2V vehicles more than their fixed requirements; hence, it will have less revenue from charging the PEV batteries. In addition, for the V2G mode, fixed departure SOC prevents the PL from offering higher amount of SOC in the energy or reserve markets.

Figure 5.2 shows various interactions that occur from market to PEVs through the aggregator and PL. As it is shown, two main physical and financial interactions exist. The objectives of the PL and the aggregator due to its interactions with PL are based on financial transactions shown in figure 5.2. In each interface (aggregator or PL) different prices are applied to the transactions and are illustrated with different line types. As a result, an equilibrium point should be found between all the objectives.

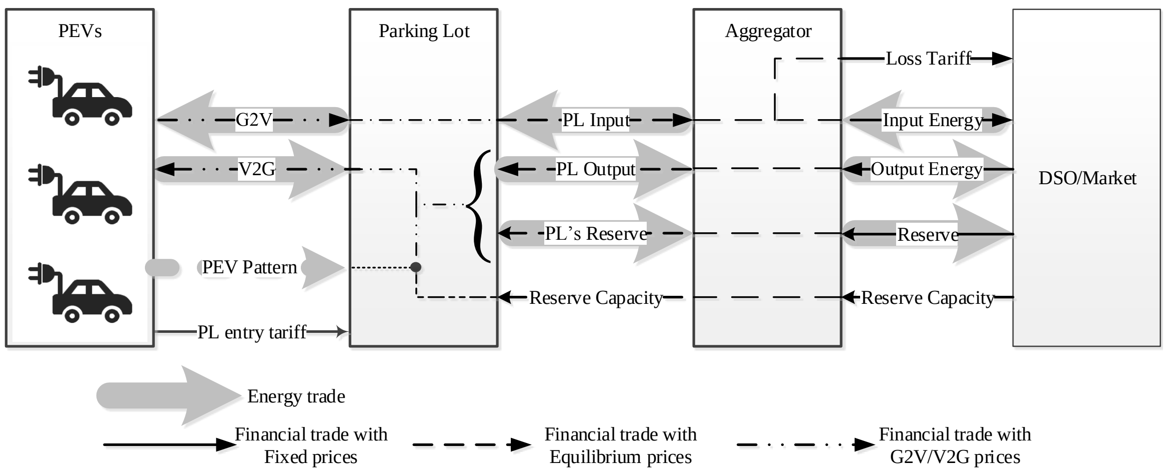

Figure 5.2: The sequence of interactions from PEVs to Market

5.2.2 Aggregator - DG Interaction

As a main feature of the forthcoming power systems and for enabling the aggregator to have access to more resources, DGs are also considered in the system. It is assumed that the DGs offer their price and quantity to the aggregator, but they should reach an equilibrium point in their trade. Hence, the price that the aggregator buys the power from DG is the decision variable for the UL and the amount of power that DG should sell to the aggregator is the decision variable for the LL.

5.2.3 Aggregator – Demand Interaction

All the end-users in the system are served by a load-retailer which purchases the required amount from the aggregator. On the other hand, the load-retailer can play with its capability in providing the DR option. The DR option here is supposed to be as the interruptible load which is a definite percent of the total demand. Therefore, the retailer has the opportunity to reduce its total demand by IL when the aggregator increases the demand price. On the other hand, it should consider paying an incentive to the interrupted loads.

5.3 Approach for solving the problem

Nonlinear complementarity problems arise in many economic applications, most notably in the applied general equilibrium area. The past decade has seen an enormous increase in the ability to solve large scale complementarity problems, due not only to the phenomenal increase in computer speed, but also to advances made in algorithms and software for complementarity problems. One of the solutions for solving optimization problems with complementarity constraints, typically termed Mathematical Programs with Equilibrium Constraints in the literature which is used in this thesis.

The main approach for the solution of optimization problems with complementarity constraints used is a reformulation of the problem as a standard linear program, thus enabling solution using existing linear programming algorithms such as MILP.

The problem discussed in this chapter is a bilevel problem with inter-related objectives. In this model, the UL problem is the aggregator's decision making and the LL problem is the decision making of local resources. As also employed in [135], the decision making conflict between two levels of players is modeled as a bilevel problem and converted to a mathematical programs with equilibrium constraints. This non-linear bilevel problem is converted to a single level mixed-integer linear programming by implementing the duality theorem. The procedure is based on [136] and [137].

For this purpose, the bilevel problem developed in this study is transformed into a single-level problem by replacing the LL problems by their primal-dual optimality conditions through the following steps:

- Formulate the LL problem as a linear and convex problem.
- Consider the decision vector of the UL problem as an input parameter for the LL problem.
- Implement the duality theorem and replace the LL problem with its Karush-Kuhn-Tucker (KKT) optimality conditions.
- Apply strong duality to the LL problem and linearize the non-linear terms of the UL objective function.

Then, the equilibria of the problem is found by formulating and solving an MILP problem whose constraints are the system of equalities and inequalities of the system.

In this Study, the UL and LL are presented with their mathematical models in Sections 7.4 and 7.5, respectively. In order to implement the duality theorem, all the constraints of the LL problem are succeeded by the respective dual variables separated by a colon. They are classified into equality and inequality constraints with the respective dual variables represented by λ and μ, respectively. Finally, the Lagrangian equation for the LL problem is developed.

5.4 Upper Level Mathematical Model

In the UL, the aggregator manages its interactions with the upstream energy and reserve markets and is restricted by the objectives of its components as well as the loss tariff of the distribution network. It is assumed that the aggregator pays the loss tariff to the distribution system operator in response to the energy purchased from the distribution network. Therefore, the objective of the UL problem will be as:

$$Max\{profit^{Agg}\} = Max\{profit^{TM} + profit^{TPL} + profit^{TDG} + profit^{TD}\} \tag{5.1}$$

Each of the components of the objective function is explained below. The aggregator trades energy and reserve with the upstream market based on the market prices, which are treated in the problem as known parameters as in equation (5.2). As it is shown, the aggregator is reimbursed for being ready to deliver reserve (Π^{RM}) and if by the probability of reserve call (ρ_t^{del}) it is summoned to provide the reserve, it will be paid by energy price (Π^{EM}). Otherwise, if the aggregator fails to deliver the amount of reserve due to FOR^{Agg}, it is subject to a penalty based on the hourly energy price. The amount of FOR^{Agg} is dependent on the network and the LL resources' failure rate.

$$profit^{TM} = \sum_t \left(-p_t^{Agg}\Pi_t^{EM} + r_t^{Agg}\Pi_t^{RM} + r_t^{Agg}\rho_t^{del}\Pi_t^{EM} - r_t^{Agg}\rho_t^{del}FOR^{Agg}\Pi_t^{EM}\right) \tag{5.2}$$

The profit of the aggregator from its interaction with the PL is caused by the revenue from selling power to PL for charging its vehicles minus the costs of purchasing energy and reserve from the PL. The PL interacts with the aggregator with the equilibrium prices of energy and reserve ($\pi_t^{in,PL}, \pi_t^{out,PL}, \pi_t^{Re,PL}$). Note that in this study various uncertainty scenarios are considered for arrival, departure and duration of stay in the PL. As a result, the amount of PL's input/output power will be different for each scenario. However, as the PL's internal interactions do not affect the aggregator's decision making it trades with the aggregator with the expected values (i.e., $\hat{p}_t^{in,PL}, \hat{p}_t^{out,PL}, \hat{r}_t^{Re,PL}$).

$$\begin{aligned} profit^{TPL} = \sum_t (&\hat{p}_t^{in,PL}\pi_t^{in,PL} - \hat{p}_t^{out,PL}\pi_t^{in,PL} - \hat{r}_t^{PL}\pi_t^{Re,PL} - \hat{r}_t^{PL}\rho_t^{del}\pi_t^{out,PL} \\ &+\hat{r}_t^{PL}\rho_t^{del}FOR^{Agg}\pi_t^{out,PL}) \end{aligned} \tag{5.3}$$

It is assumed that there can be multiple numbers of DGs in the network and sell their power to the aggregator with equilibrium price of DG (π_t^{DG}) as:

$$profit^{TDG} = \sum_t (-\sum_m p_{m,t}^{DG}\pi_t^{DG}) \tag{5.4}$$

The demand is delivered to the end-users with the hourly equilibrium demand price (π_t^D). It is also assumed that the aggregator has to pay for the network loss:

$$profit^{TD} = \sum_{t}(p_t^D \pi_t^D - \sum_{k}\sum_{j} R_{j,k}(i_{j,k,t})^2 \Pi_t^{Loss}) \tag{5.5}$$

The assumptions and constraints of the above objective are as follows. It is assumed that the only reserve provider in the system is the PL. Hence, the total reserve that the aggregator can present in the market is equal to the expected amount of reserve that the PL can provide:

$$r_t^{Agg} = \hat{r}_t^{PL} \tag{5.6}$$

The expected value for the PL's reserve, input and output power is the summation of their amount in each scenario multiplied by the probability of each scenario. These are shown in (5.7)-(5.9) for the reserve, input and output power, respectively.

$$\hat{r}_t^{PL} = \sum_{\omega} \rho_\omega r_{\omega,t}^{PL} \tag{5.7}$$

$$\hat{p}_t^{in,PL} = \sum_{\omega} \rho_\omega p_{\omega,t}^{in,PL} \tag{5.8}$$

$$\hat{p}_t^{out,PL} = \sum_{\omega} \rho_\omega p_{\omega,t}^{out,PL} \tag{5.9}$$

The total power of the aggregator is equal to the amount of demand in each node, the input power of the PL to the node on which it is installed minus the output power of the PL on that node and the output power of the DG (equation 5.10). In order to identify the node on which the PL is installed the binary variable (Si) is defined as in equations (5.11) and (5.12).

$$p_t^{Agg} = \sum_{j}(p_{j,t}^D + p_{j,t}^{\prime in,PL} - p_{j,t}^{\prime out,PL} - p_{j,t}^{\prime DG}) \tag{5.10}$$

$$p_{j,t}^{\prime in,PL} = Si^{PL} \hat{p}_t^{in,PL} \tag{5.11}$$

$$p_{j,t}^{\prime out,PL} = Si^{PL} \hat{p}_t^{out,PL} \tag{5.12}$$

The load flow equations are presented in equations (5.4) – (5.18). It is assumed the power injected from the upstream network ($p_{j,t}^{in,DSO}$) or delivered to it is affected by the efficiency of the connection transformer. In addition, in order to calculate the share of IL on each node, the assumption of spread share of IL on all loads is used. As a result, the share of the demand after IL (p_t^D) from total demand ($p_t^{D,total}$) is multiplied by the load of each node. Besides, the power factor of IL is considered equal to the power factor of the whole system; hence, the same approach can be used for the reactive power. The approach to perform the load flow of the system is based on [138] and [139] and is linearized in the problem.

$$p_t^{in,DSO}\eta^{Trans} - \frac{p_t^{out,DSO}}{\eta^{Trans}} + \sum_b p_{k,j,t}^{Line} - \sum_b [p_{j,k,t}^{Line} + R_{j,k}(i_{j,k,t})^2] = \frac{p_t^D}{p_t^{D,total}} p_{j,t}^D$$

$$+p_{j,t}^{\prime in,PL} - p_{j,t}^{\prime out,PL} p_{j,t}^{\prime DG} \tag{5.13}$$

$$q_{j,t}^{in,DSO} - q_{j,t}^{out,DSO} \sum_b q_{k,j,t}^{Line} - \sum_b [q_{j,k,t}^{Line} + X_{j,k}(i_{j,k,t})^2] = \frac{p_t^D}{p_t^{D,total}} Q_{j,t}^D \tag{5.14}$$

$$v_{j,t}^2 - 2[R_{j,k}(p_{j,k,t}^{Line} - p_{k,j,t}^{Line}) + X_{j,k}(q_{j,k,t}^{Line} - q_{k,j,t}^{Line})] - Z_{j,k}^2 i_{j,k,t}^2 - v_{k,t}^2 = 0 \tag{5.15}$$

$$v_{j,t}^2 i_{j,k,t}^2 = (p_{j,k,t}^{Line})^2 + (q_{j,k,t}^{Line})^2 \tag{5.16}$$

$$\underline{V}_j \leq v_{j,t} \leq \overline{V}_j \tag{5.17}$$

$$-\underline{I}_{j,k} \leq i_{j,k,t} \leq \overline{I}_{j,k} \tag{5.18}$$

Considering the objective and constraints of the UL problem, the decision vector of the UL for the bilevel model will be as:

$$\mathbf{DV^{UL}} = \left[p_t^{Agg}, r_t^{Agg}, \pi_t^{in,PL}, \pi_t^{out,PL}, \pi_t^{Re,PL}, \pi_t^{DG}, \pi_t^{D}\right] \tag{5.19}$$

5.5 Lower Level Mathematical Model

The objective on the LL problem consists of the objectives of the players on the LL based on their contribution in the equilibrium price. These objectives are for the trades of PL with the aggregator, the interactions of the PL with PEV owners, the trade of DG with the aggregator and the opportunity of IL on behalf of retailer. In this regard, the objective of the LL will be as:

$$Max\{profit^{LL}\} = Max\{profit^{PL-Agg} + profit^{PL-PEV} + profit^{DG-Agg} + profit^{D-Agg}\} \tag{5.20}$$

5.5.1 PL-Aggregator Interaction

The profit gained by the PL owner through its interaction with the aggregator is shown in equation (5.5.1). In this level, the vehicles that participate in both G2V and V2G mode are separated from those who are only operated in G2V mode. It is obvious that the output power of the PL is only due to the opportunity of V2G; however, the input power of the PL is required for both types of vehicles (G2V and V2G). On the other hand, the reserve presented to the market is from the opportunity of V2G, hence is treated with the same price of output power whenever it is called. If the PL fails to deliver the required reserve amount (FOR^{PL}), it will be charged with the output energy rate. It can be observed that in (5.5.1), there are common terms with the UL objective (5.1) that make the equilibrium point with UL.

$$profit^{PL-Agg} = \sum_t \Big(\sum_\omega \Big((p^{out,V2G}_{\omega,t}) \pi^{out,PL}_t - (p^{in,V2G}_{\omega,t} + p^{G2V,in}_{\omega,t}) \pi^{in,PL}_t + r^{PL}_{\omega,t} \pi^{Re,PL}_t$$
$$+ r^{PL}_{\omega,t} \rho^{del}_t \pi^{out,PL}_t - r^{PL}_{\omega,t} \rho^{del}_t FOR^{PL} \pi^{out,PL}_t \Big) \Big) \tag{5.21}$$

The interaction of the PL with the PEV owners that use the PL is modeled with details in equation (5.22). As it was explained before, four different categories of the PL-users are considered in this study. The first two categories involve G2V mode vehicles with fixed/flexible requirement of departure SOC. The next two categories involve those PEVs that agree to participate in V2G mode either with fix or flexible need of departure SOC. For better comprehension the naming and clustering of these categories are shown in Table 5.1.

Table 5.1: PEV Owners Clustering

Mode	Fixed departure SOC requirement			Flexible departure SOC requirement		
	Naming	Price of G2V	Price of V2G	Naming	Price of G2V	Price of V2G
G2V	*fix1*	Π^{G2V1}	-	*flex1*	Π^{G2V2}	-
V2G	*fix2*	Π^{G2V3}	Π^{Extra}	*flex2*	Π^{G2V3}	Π^{Extra}, Π^{V2G}

$$\begin{aligned}
profit^{PL-PEV} = & \\
& \sum_t \Big(\sum_\omega \Big((\phi^{fix1}_{\omega,t} \beta^{fix1}_{\omega,t} C^{dep,PL}_{\omega,t} - SOC^{dep,fix1,Sc}_{\omega,t}) \Pi^{G2V1}_t \\
& + (soc^{dep,flex1}_{\omega,t} - SOC^{dep,flex1,Sc}_{\omega,t}) \Pi^{G2V2}_t \\
& + (\phi^{fix2}_{\omega,t} \beta^{fix2}_{\omega,t} C^{dep,PL}_{\omega,t} - SOC^{dep,fix2,Sc}_{\omega,t}) (\Pi^{G2V1}_t + Cd^{PL}) \\
& - (\beta^{fix2}_{\omega,t} C^{dep,PL}_{\omega,t} - \phi^{fix2}_{\omega,t} \beta^{fix2}_{\omega,t} C^{dep,PL}_{\omega,t}) \Pi^{Extra}_t \\
& + (soc^{dep,flex2}_{\omega,t} - SOC^{dep,flex2,Sc}_{\omega,t}) (\Pi^{G2V3}_t + Cd^{PL})|_{(soc^{dep,flex2}_{\omega,t} \geq SOC^{dep,flex2,Sc}_{\omega,t})} \\
& + (SOC^{dep,flex2,Sc}_{\omega,t} - soc^{dep,flex2}_{\omega,t}) \Pi^{V2G}_t |_{(soc^{dep,flex2}_{\omega,t} < SOC^{dep,flex2,Sc}_{\omega,t})} \\
& - (\beta^{flex2}_{\omega,t} C^{dep,PL}_{\omega,t} - \phi^{flex2}_{\omega,t} \beta^{flex2}_{\omega,t} C^{dep,PL}_{\omega,t}) \Pi^{Extra}_t \\
& - (p^{out,V2G}_{\omega,t} + p^{in,V2G}_{\omega,t} + r^{PL}_{\omega,t} \rho^{del}_t) Cd^{PL} + N^{PL}_{\omega,t} \Pi^{Tariff} - r^{PL}_{\omega,t} \rho^{del}_t) \Pi^{V2G}_t \Big) \Big)
\end{aligned} \tag{5.22}$$

The financial transaction of PL with each group of these vehicles should be different due to different restrictions and opportunities that they put upon the PL; therefore, they should be treated proportionally to the opportunity they bring because they lead to different levels of profit for the PL. In this regard, in each hour and in each scenario, the share of each category should be determined. On the other hand, it should be specified that the amount of departed SOC belong to which category.

The share of each category in the departure SOC is needed for precisely calculating the hourly revenue and costs of PL. For this purpose, two coefficients are defined to impose the preferences of the PEV owners to the objective of the PL. The coefficient β is defined to determine the share of each category from departing vehicles. Another coefficient ϕ is defined to determine the preference of each category for the minimum required SOC at their departure. Besides, the coefficient θ determines the amount of PEVs in G2V or V2G mode in each hour. These coefficients are derived based on the explanation on previous chapter.

In this study, the PEVs that agree to take part in the V2G mode are paid an incentive amount for being ready (as reserve or energy). This amount is calculated through the multiplication of their available capacity by the incentive price (Π^{Extra}). However, when actual energy is purchased from V2G PEVs, they are paid by V2G price (Π^{V2G}) as well as the degradation cost. Moreover, all the PEVs that enter the PL have to pay the usage tariff based on the total hours that they have stayed in the PL multiplied by the PL tariff (Π^{Tariff}). Also in Table 5.1 it is shown that different G2V price are considered for different categories. The reason is that the PL owner encourages the PEVs to participate in flexible modes by selling the energy with lower prices to them ($\Pi^{G2V3} < \Pi^{G2V2} < \Pi^{G2V1}$).

As shown in equations (5.23) and (5.24) the PL's SOC in each hour is separated for G2V and V2G modes. It is assumed that the PL starts with an initial amount of SOC at t=1 and the arrival and departure SOC as well as the power traded with grid form the hourly SOC of the PL. The facilities in the PL restrict the charging/discharging of PL due to their efficiency ($\eta^{cha,PL}, \eta^{dcha,PL}$).

$$\begin{aligned} soc_{\omega,t}^{PL,G2V} &= \\ soc_{\omega,t-1}^{PL,G2V}|_{t>1} &+ SOC_{\omega,t_0}^{PL,G2V}|_{t=1} + soc_{\omega,t}^{ar,G2V} - soc_{\omega,t}^{dep,G2V} + p_{\omega,t}^{in,G2V}\eta^{cha,PL} \quad : \quad \lambda_{\omega,t}^{PL,G2V} \end{aligned} \tag{5.23}$$

$$\begin{aligned} soc_{\omega,t}^{PL,V2G} &= \\ soc_{\omega,t-1}^{PL,V2G}|_{t>1} &+ SOC_{\omega,t_0}^{PL,V2G}|_{t=1} + soc_{\omega,t}^{ar,V2G} - soc_{\omega,t}^{dep,V2G} + p_{\omega,t}^{in,V2G}\eta^{cha,PL} - \frac{p_{\omega,t}^{out,V2G}}{\eta^{dcha,PL}} \\ : \quad \lambda_{\omega,t}^{PL,V2G} \end{aligned} \tag{5.24}$$

The SOC that is departed from the PL in each hour is equal to the minimum requirement of PEVs with fixed departure SOC and those who accept to have flexible departure SOC. This is applicable to both G2V and V2G modes as follows, respectively.

$$soc_{\omega,t}^{dep,G2V} = \phi_{\omega,t}^{fix1}\beta_{\omega,t}^{fix1}C_{\omega,t}^{dep,PL} + soc_{\omega,t}^{dep,flex1} \quad : \quad \lambda_{\omega,t}^{dep,G2V} \tag{5.25}$$

$$soc_{\omega,t}^{dep,V2G} = \phi_{\omega,t}^{fix2}\beta_{\omega,t}^{fix2}C_{\omega,t}^{dep,PL} + soc_{\omega,t}^{dep,flex2} \quad : \quad \lambda_{\omega,t}^{dep,V2G} \tag{5.26}$$

Although some PEVs agree to have a flexible amount of departure SOC, the departure SOC is still limited to their minimum preference and the maximum possible SOC due to the limitation of their capacity. These restrictions on minimum and maximum limitations of departure SOC for two flexible categories are presented in:

$$\phi_{\omega,t}^{flex1}\beta_{\omega,t}^{flex1}C_{\omega,t}^{dep,PL} \leq soc_{\omega,t}^{dep,flex1} \leq \overline{\chi}^{PEV}\beta_{\omega,t}^{flex1}C_{\omega,t}^{dep,PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{dep,flex1}, \overline{\mu}_{\omega,t}^{dep,flex1} \tag{5.27}$$

$$\phi_{\omega,t}^{flex2}\beta_{\omega,t}^{flex2}C_{\omega,t}^{dep,PL} \leq soc_{\omega,t}^{dep,flex2} \leq \overline{\chi}^{PEV}\beta_{\omega,t}^{flex2}C_{\omega,t}^{dep,PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{dep,flex2}, \overline{\mu}_{\omega,t}^{dep,flex2} \tag{5.28}$$

The SOC of PL in the G2V mode should not pass the maximum available capacity of G2V vehicles in the PL multiplied by the maximum possible SOC of each PEV as in equation (5.29). For the V2G vehicles, as the PL has the control to discharge the PEVs' batteries a minimum limit also should be bounded by the SOC of PL in each hour (quation 5.30). Note that as the SOC of the PL is representing an aggregated amount of SOC. Due to variable levels of PL's capacity resulting from PEVs arrival/departure, the hourly SOC of the PL is considered in kWh instead of the ratio of the total capacity.

$$soc_{\omega,t}^{PL,G2V} \leq \theta_{\omega,t}^{PL}C_{\omega,t}^{PL}\overline{\chi}^{PEV} \qquad : \qquad \overline{\mu}_{\omega,t}^{PL,G2V} \tag{5.29}$$

$$\left(1-\theta_{\omega,t}^{PL}\right)C_{\omega,t}^{PL}\underline{\chi}^{PEV} \leq soc_{\omega,t}^{PL,V2G} \leq \left(1-\theta_{\omega,t}^{PL}\right)C_{\omega,t}^{PL}\overline{\chi}^{PEV} \qquad : \qquad \underline{\mu}_{\omega,t}^{PL,V2G}, \overline{\mu}_{\omega,t}^{PL,V2G} \tag{5.30}$$

The facilities in the PL's stations have a charging/discharging rate (Γ^{PL}) that limits the maximum amount of input/output power of the PL:

$$0 \leq p_{\omega,t}^{in,G2V} \leq \Gamma^{PL}\theta_{\omega,t}^{PL}N_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{in,G2V}, \overline{\mu}_{\omega,t}^{in,G2V} \tag{5.31}$$

$$0 \leq p_{\omega,t}^{in,V2G} \leq \Gamma^{PL}\left(1-\theta_{\omega,t}^{PL}\right)N_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{in,V2G}, \overline{\mu}_{\omega,t}^{in,V2G} \tag{5.32}$$

$$0 \leq p_{\omega,t}^{out,V2G} + r_{\omega,t}^{PL} \leq \Gamma^{PL}\left(1-\theta_{\omega,t}^{PL}\right)N_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{in,V2G1}, \overline{\mu}_{\omega,t}^{in,V2G1} \tag{5.33}$$

The maximum amount that PL can offer in the market (including energy and reserve) should not pass the limit of available SOC from V2G vehicles and the minimum SOC that can remain in the PEVs' batteries:

$$0 \leq \frac{(p_{\omega,t}^{out,V2G} + r_{\omega,t}^{PL})}{\eta^{dcha,PL}} \leq soc_{\omega,t}^{PL,V2G} - \underline{\chi}^{PEV}\left(1-\theta_{\omega,t}^{PL}\right)C_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{in,V2G2}, \overline{\mu}_{\omega,t}^{in,V2G2} \tag{5.34}$$

The reserve and energy output of the PL are defined as positive variables:

$$0 \leq r_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{Re,PL} \tag{5.35}$$

$$0 \leq p_{\omega,t}^{out,V2G} \leq \qquad : \qquad \underline{\mu}_{\omega,t}^{out,PL} \tag{5.36}$$

For the purpose of linearization in equation (5.22), a variable ($Z_{\omega,t}^{PL}$) is defined to compare the departed SOC in each hour with the scenario pattern:

$$\begin{aligned}
&(soc_{\omega,t}^{dep,flex2} - SOC_{\omega,t}^{dep,flex2,Sc})(\Pi_t^{G2V3} + Cd^{PL})|_{(soc_{\omega,t}^{dep,flex2} \geq SOC_{\omega,t}^{dep,flex2,Sc})} \\
&+ (SOC_{\omega,t}^{dep,flex2,Sc} - soc_{\omega,t}^{dep,flex2})\Pi_t^{V2G}|_{(soc_{\omega,t}^{dep,flex2} < SOC_{\omega,t}^{dep,flex2,Sc})} = \\
&(soc_{\omega,t}^{dep,flex2} - SOC_{\omega,t}^{dep,flex2,Sc})\Big(\big((\Pi_t^{G2V3} + Cd^{PL}) + \Pi_t^{V2G})\big)/2\Big) \\
&- Z_{\omega,t}^{PL}|\Pi_t^{V2G} - \Big(\big((\Pi_t^{G2V3} + Cd^{PL}) + \Pi_t^{V2G})\big)/2\Big)
\end{aligned} \tag{5.37}$$

$$Min\{Z_{\omega,t}^{PL}\} \tag{5.38}$$

$$(soc_{\omega,t}^{dep,flex2} - SOC_{\omega,t}^{dep,flex2,Sc}) \leq Z_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{Aux,PL1} \tag{5.39}$$

$$(SOC_{\omega,t}^{dep,flex2,Sc} - soc_{\omega,t}^{dep,flex2}) \leq Z_{\omega,t}^{PL} \qquad : \qquad \underline{\mu}_{\omega,t}^{Aux,PL2} \tag{5.40}$$

5.5.2 DG-Agg Interactions

The profit gained by the DG owner from selling energy to the aggregator is shown by:

$$profit^{DG-Agg} = \sum_t \Big(\sum_m (p_{m,t}^{DG} \pi_t^{DG} - A_m^{DG} p_{m,t}^{DG}) \Big) \tag{5.41}$$

where A_m^{DG} is the marginal cost for m^{th} DG.
All the DGs should be limited to their maximum generating power as:

$$0 \leq p_{m,t}^{DG} \leq \overline{P}_m^{DG} \qquad : \qquad \underline{\mu}_{m,t}^{DG}, \overline{\mu}_{m,t}^{DG} \tag{5.42}$$

5.5.3 Demand-Agg Interactions

The loads in the system are supplied by a load retailer who purchases the required amount of energy from the aggregator with equilibrium price (π_t^D) and sell it to the load with the time of use tariff (Π_t^{ToU}). The users who participate as IL are also paid an incentive ($\Pi_t^{Incentive}$).

$$profit^{D-Agg} = \sum_t \Big(p_t^D \left(\Pi_t^{ToU} - \pi_t^D \right) - p_t^{IL} \Pi_t^{Incentive} \Big) \tag{5.43}$$

It is assumed that the amount of demand that is purchased from the aggregator (p_t^D) is after the implementation of IL (equation 5.44). Moreover, the demand after the IL implementation should be limited to the maximum total demand and the minimum of not interruptible load (equation 5.45).

$$p_t^{IL} = p_t^{D,total} - p_t^D \qquad : \qquad \lambda_t^{IL} \tag{5.44}$$

$$(1 - \varepsilon_t^D) p_t^{D,total} \leq p_t^D \leq p_t^{D,total} \qquad : \qquad \underline{\mu}_t^{D,total}, \overline{\mu}_t^{D,total} \tag{5.45}$$

Considering all the equations presented for the LL problem the decision vector for lower level will be as:

$$\mathbf{DV^{LL}} = [p_{\omega,t}^{in,PL}, p_{\omega,t}^{out,PL}, r_{\omega,t}^{PL}, soc_{\omega,t}^{dep,PL}, p_{m,t}^{DG}, p_t^D] \tag{5.46}$$

5.6 MPEC Formulation and Strong Duality

The approach employed for solving the bilevel problem is the implementation of MPEC solution. Firstly, the Lagrangian of the LL problem is developed in equation (5.47). The variables in this equation are the decision variable vectors in LL problem in equation (5.48). The components of the Lagrangian are shown in equations (5.49)-(5.51) which are the LL objective, equality constraints ($\mathbf{E}(\mathbf{X})$) and non-equality constraints ($\mathbf{N}(\mathbf{X})$). The stationary conditions, primal optimality conditions, and complementary conditions for the LL problem are shown in equations (5.52)-(5.54).

$$l \quad = -\mathbf{f}(\mathbf{X}) - \mu \mathbf{N}(\mathbf{X}) + \lambda \mathbf{E}(\mathbf{X}) \tag{5.47}$$

$$\mathbf{X} = \mathbf{DV^{LL}} \tag{5.48}$$

$$\text{f(X)} = \text{e.q. (5.21)} \tag{5.49}$$

$$\mathbf{E}(\mathbf{X}) = \text{e.q. (5.23)-(5.26), (5.44)} \tag{5.50}$$

$$\mathbf{N}(\mathbf{X}) = \text{e.q. (5.27)-(5.40), (5.42), (5.45)} \tag{5.51}$$

$$\frac{\partial l}{\partial \mathbf{X}} = 0 \tag{5.52}$$

$$\frac{\partial l}{\partial \lambda} = \mathbf{E}(\mathbf{X}) = 0 \tag{5.53}$$

$$0 \leq \mu \perp \mathbf{N}(\mathbf{X}) \geq 0 \tag{5.54}$$

For linearization of the non-linear terms in the UL, the strong duality theorem is employed which states that when a problem is convex, the primal and dual objective functions of can be considered equal at the optimum.

The required equations for implementation of MPEC approach including the Largrangian equation, stationary and complimentary conditions, as well as the strong duality equation are presented in Appendix A.

5.7 Case Studies

The model proposed in this chapter is implemented to the PEVs and PL characterized in Chapter 4. The prices for energy and reserve market are from the Spanish electricity market [140] and are adapted to the distribution level based on [141]. In [141] it is mentioned that a surplus should be added to the upstream energy prices when it is implemented to lower voltage levels. This surplus is divided between the aggregator and the lower level components of the problem. In this study the surplus is considered as 5 cents. Therefore, 3 cents is added to the upstream market energy price and then implemented to the energy trades of the aggregator with the upstream network. The remaining 2 cents is added to the LL resources transaction price. Note that the trades between the aggregator and LL resources take place based on the equilibrium prices. In this study, all the stations in the PL are the same and are quick charging stations with a charging rate of 11 kW per hour. Other specifications of the PEVs and tariffs are based on [142].

It is assumed that two approaches for the aggregation of resources on LL (i.e., PL, DG, and load retailer) exist. On the first approach, the individual interaction of each LL resource with the aggregator is examined through the Pay as Bid pricing model. In the second approach, the cross effect of the resources in their market participation is investigated through uniform pricing. These approaches are investigated in two different cases, separately.

The problem is modeled as a mixed integer linear programming problem and implemented in GAMS using CPLEX12 solver.

5.7.1 Case I: Pay as Bid

In this case, the behavior of the aggregator and each of the components are investigated. As the aggregation approach in this case causes a leader/follower framework, in order to bind the profit of the leader, a price cap is put upon the maximum trade price between aggregator and each of the LL components. The cap is 10 cents per kWh.

In figure 5.3 the prices of the upstream energy market (i.e., the amount paid by the aggregator to the upstream market), the PL price (i.e., the price paid by the PL to the aggregator for energy purchase), and the DG price are shown.

As shown, the PL's price reaches the price cap for the whole 24 hours. The variations of prices in

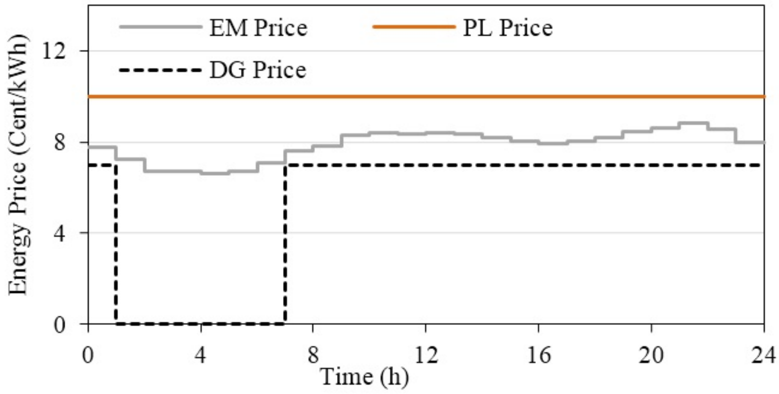

Figure 5.3: Energy prices for aggregator, PL, and DG in Case I.

this case can be evaluated with the energy interaction balance of the system in figure 5.4. It can be seen that the behavior of the aggregator is relatively justifiable to the EM price variations.

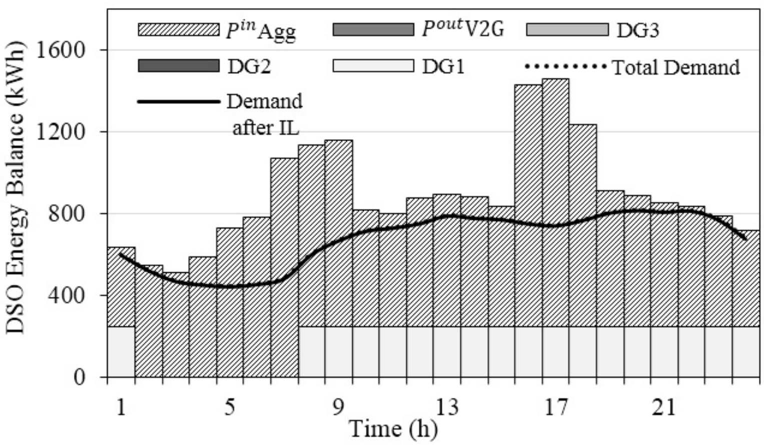

Figure 5.4: Energy balance of system in Case I.

As shown in figure 5.4, during hours 2-7 A.M. when the upstream energy price has the lowest amount, none of the resources in the LL is activated. For the remaining hours, only DG1 is committed to supply energy. Therefore, the PL's power exchange is only for input power as figure 5.5.

The PL can make a profit through its participation in the upstream reserve market. Being the only reserve source of the aggregator, all the possible SOC of PL is presented in the reserve market. Accordingly, the price of the reserve paid to the PL can be a motivating factor to change the PL's behavior. It indicates that considerable higher payment to the PL in order to maintain its SOC for participating in reserve market is profitable in this case. The SOC of the PL for various PEV categories in the PL is shown in figure 5.7.

In this case, the aggregator trades with each component individually. This case validates the accuracy of the model.

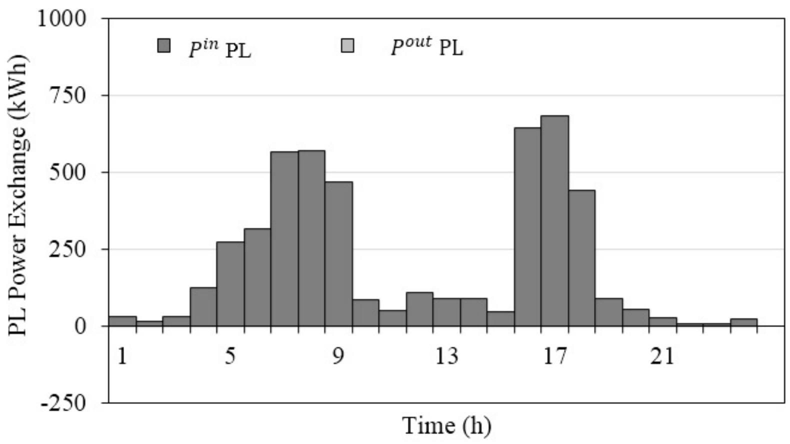

Figure 5.5: PL's power exchange in Case I.

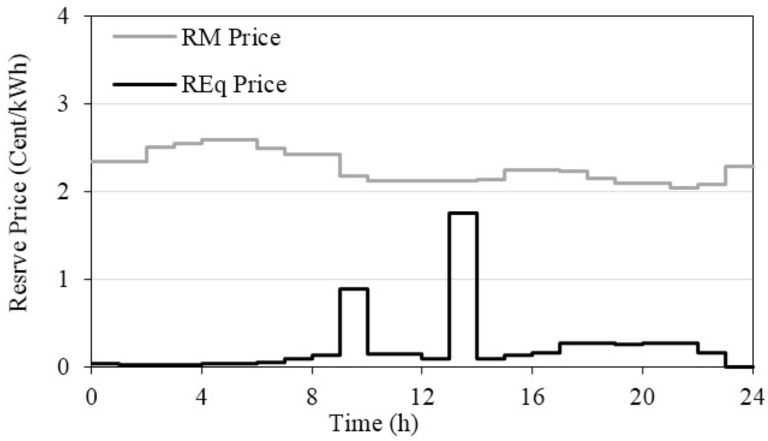

Figure 5.6: Upstream reserve market and LL reserve equilibrium prices in Case I.

5.7.1.1 DG-Aggregator Interaction

As seen in figure 5.4, the aggregator makes a compromise between the price of DG and the upstream energy market price. Whenever it is profitable the aggregator will buy from the DG that is in hour 1 and hours 8 to 24.

5.7.1.2 Retailer-Aggregator Interaction

For the load retailer, it is shown that the aggregator sells the energy at the maximum price. Therefore, it is necessary to put a price cap on the transactions between the aggregator and load retailer. With this price cap, in this case, it is not profitable for the load retailer to activate the IL and thus it provides the total demand from the EM.

5.7.1.3 PL-Aggregator Interaction

The most challenging resource in this model is PL. In this case as shown in figure 5.3, the price for PL's energy trade is a constant value for the whole 24 hours. This price is the equilibrium price derived from the behavior of the PL and the aggregator considering other resources available to

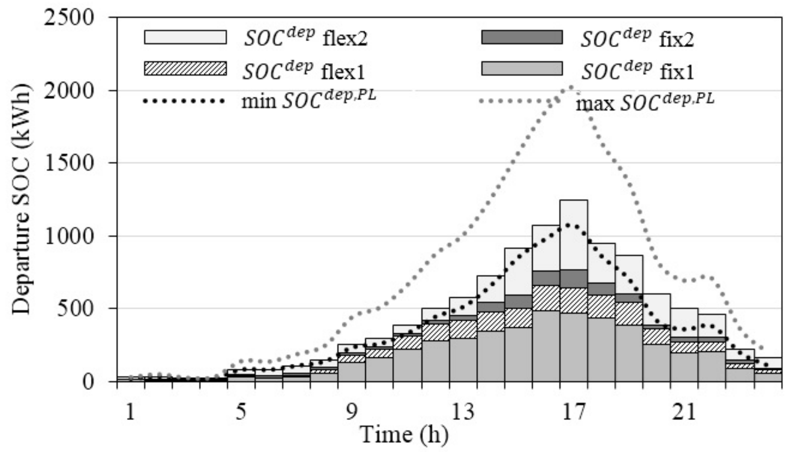

Figure 5.7: PL's state of charge for various categories of PEVs in PL in Case I.

the aggregator. In other words, if the PL changes its behavior, the price will also change.

However, both the PL's behavior and the price are propelled to the equilibrium price as in this price the optimum profit is obtained. During the early hours of the day (hours 1-9) the PL starts to charge the PEVs in the PL because the energy price is low. The PL can make profit from selling energy to the PEVs, however the preferences of PEVs on requiring a fixed amount of departure SOC limits the charging behavior of the PL.

Meanwhile, the aggregator wants to increase its profit from selling energy to the PL; as a result, it will encourage the PL to charge its PEVs by increasing the price of reserve at hours 10 and 14 (see figure 5.6). The price of reserve is increased by the aggregator so that the PL will be motivated for charging; however, the preferences of the PEVs limit the maximum charging of PL.

In fact, noting figure 5.7, it is shown that the PEVs are charged almost the same as their minimum requirement of departure SOC. The reason is that from hour 16, the PEVs departure from the PL increases. As a result, in order to meet the PEV's preferences the charging of PL is limited.

For the reserve provision, except where the reserve price faces a spike at hour 15, in other hours the price is almost equal to the marginal price of PL for providing reserve.

5.7.2 Case II: Uniform Pricing

In this case, all the resources on the LL trade with the aggregator with a uniform price which is the equilibrium price. As a result, the LL resources can have more flexibility on their transactions with the aggregator comparing to Case I.

As can be seen in figure 5.8, the LL energy equilibrium (EEq) price has significant differences from the EM price and the pay as bid case. Moreover, figure 5.9 shows the contribution of all resources in the system. In contrary to Case I, in this case all the resources (i.e., DG, PL's V2G mode, and IL) take part in the schedule. The reason is that one equilibrium price concerning all the constraints and objectives of various components is calculated and hence more flexibility for the aggregator to compromise between the various objectives is provided.

From another point of view, the reserve price in this case in figure 5.10 is higher than the first case

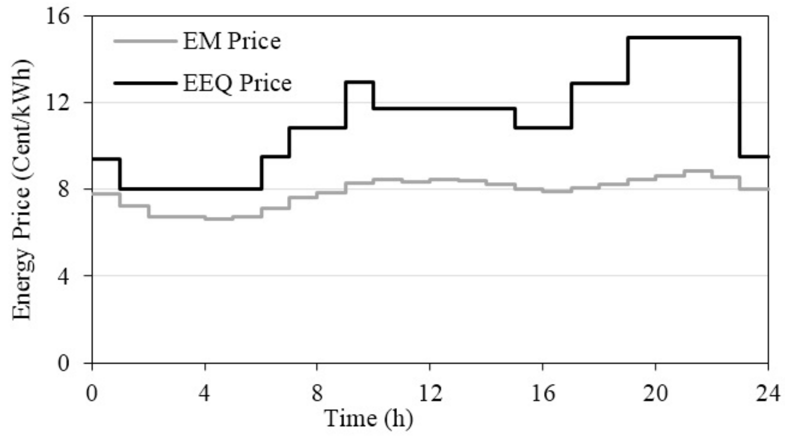

Figure 5.8: Energy Market and Energy Equilibrium prices in Case II.

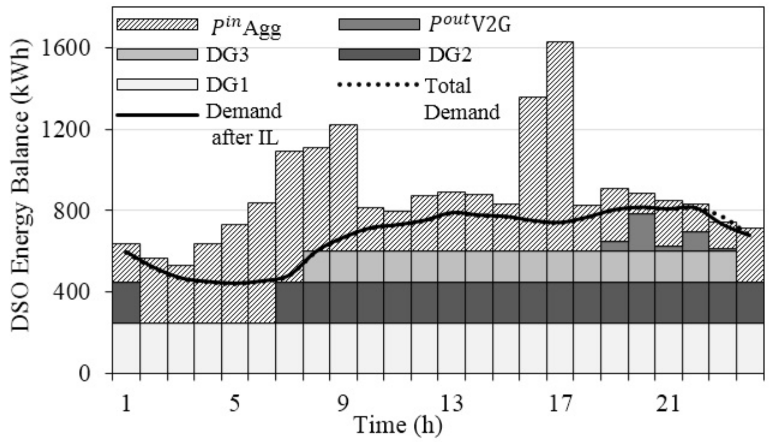

Figure 5.9: Energy balance of system in Case II.

and in some hours the aggregator is persuaded to increase the reserve price up to the upstream reserve market price. As a result, the LL resources will be encouraged to participate more effectively in the market.

In figure 5.10, it is shown that in the reserve price experience a spike from hour 19 to 23. At hours 19 to 23 the aggregator increases the reserve price to encourage the PL to charge its PEVs. In fact, the equilibrium price is a compromise between the lowest amount of EM price and RM prices.

5.7.2.1 DG's behavior

During hours 2 to 6, the EM price is in its lowest amount; however, during those hours DG1 is committed for the energy generation but two of the DGs cannot compete and are not operating. At hour 7, DG2 is committed and after that all DGs are participating in the energy production of the system. This happens because of the EEq price increase on that hour. The reason is that from hour 7 the arrival to the PL is increasing; as a result, the PL will be able to charge the batteries of arriving PEVs, increase its potential of reserve provision and consequently increase its own profit.

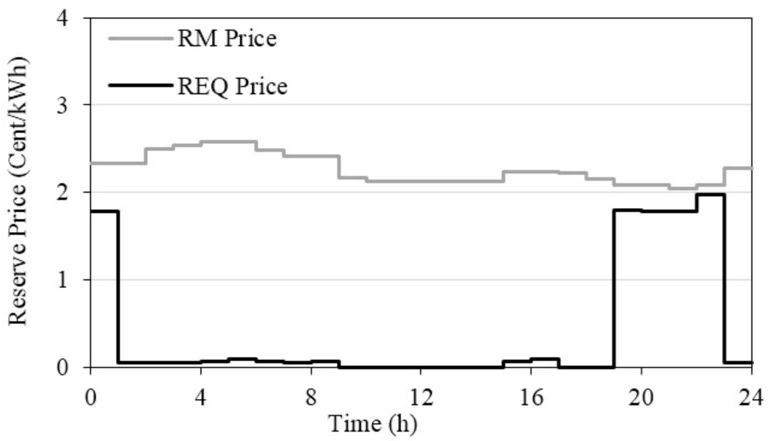

Figure 5.10: Reserve Market and Reserve Equilibrium prices in Case II.

5.7.2.2 Load Retailer's behavior

The aggregator's decision making on operating its resources impose significant changes on the EEq price during 24 hours. However, these changes are not tempting enough for the load retailer to activate its IL until hours 19-23 when the end users' demand is on its peak amount. As a result, the load retailer will use the IL to reduce its costs.

5.7.2.3 PL's behavior

During early hours of the day, the PL is encouraged to charge the PEVs due to low energy prices. After hour 6 up to 9, although the EEq price is increased, it is still maintained in low amount; therefore, the PL keeps charging the batteries. In other words, in these hours the aggregator holds the EEq price relatively low so that the PL continues on its behavior of charging.

In hour 10, the price of the EM increases and consequently the aggregator increases the price to make benefit from selling energy to load retailer and PL.

Referring to figure 5.5, it is observed that from hour 10 most of the PEVs that enter the PL are those who need to stay in the PL for a short stay. As a result, the EEq price is reduced and the energy trade is reduced (figure 5.8 and 5.10). Consequently, from hours 10 to 15, the PL changes its strategy.

Although the EEq price is reduced at hour 11 comparing to hour 10, the PL is not motivated to increase its charging. During this period, the PL will charge mostly the PEVs that only take part as G2V mode. The reason is that the price reduction is up to the G2V2 price considering the efficiency of the station charger. In other words, the Fix2 contracts are the most preferred contracts for both PL and the aggregator, because the aggregator benefits from selling energy to PL and the PL benefits from selling to the PEVs.

After that in hours 16 and 17, the EEq price is decreased. The reason is not only due to the price reduction in the EM, but also due to the fact that from hour 16, the number of PEV departure increases. Hence, the PL needs to charge the batteries, especially the flexible ones, to increase its own profit. As a result, the aggregator decreases the EEq price so that the PL is encouraged to charge the PEVs which are about to depart the PL. This increase in the SOC can be seen in figure

5.12.

Unlike Case I, in this case the V2G power is injected into the grid (see figure 5.11). The reason is that in hours 16 and 17 the PL charges the PEVs but from hour 19, it has to discharge the batteries because it gets near to the ending hours and the PEVs leaves the PL. As a result, in order to meet the requirements imposed to the PL by PEVs' categories, it will inject the excess power to the grid. Consequently, the price of energy spikes in hour 19 and remains high after that, both due to this reason and the fact that the demand peak is also during those hours.

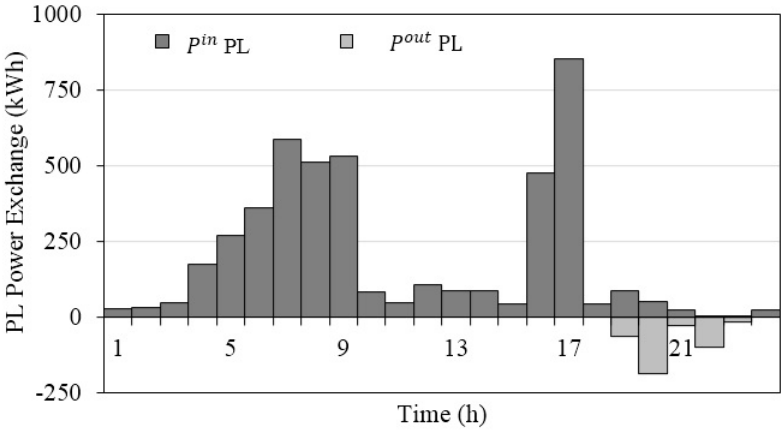

Figure 5.11: PL's power exchange in Case II.

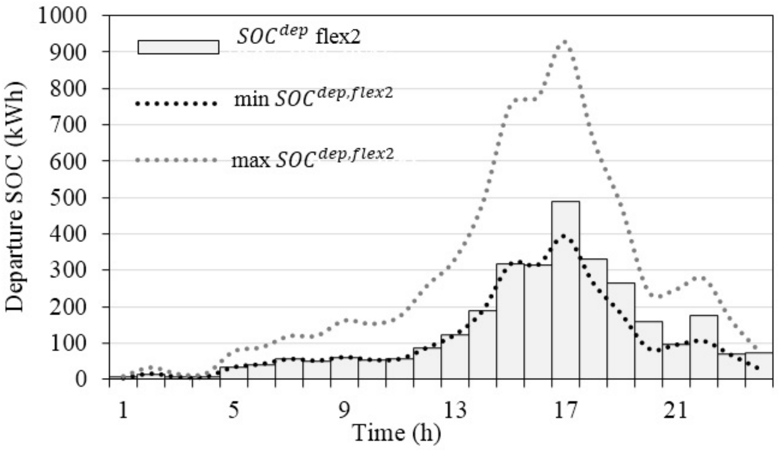

Figure 5.12: The behavior of PL in charging Flex2 contracts in Case II.

Although the strategy of PL from hour 19 to 24 is to discharge most of the energy stored in PEV batteries, the aggregator will equilibrate the situation by increasing the reserve up to the upstream reserve market (see figure 5.10). The total departure SOC of PL for Flex2 contracts in this case is shown in figure 5.12. As shown, the difference of SOC in the PL with the minimum requirement of PEVs' departure SOC is higher in hours 17-22 which is due to higher reserve price encouraged by the aggregator. For other hours the PL tends to keep the PEVs on their minimum requirement. figure 5.13 shows the total PL's SOC and capacity and the reserve provision of the PL.

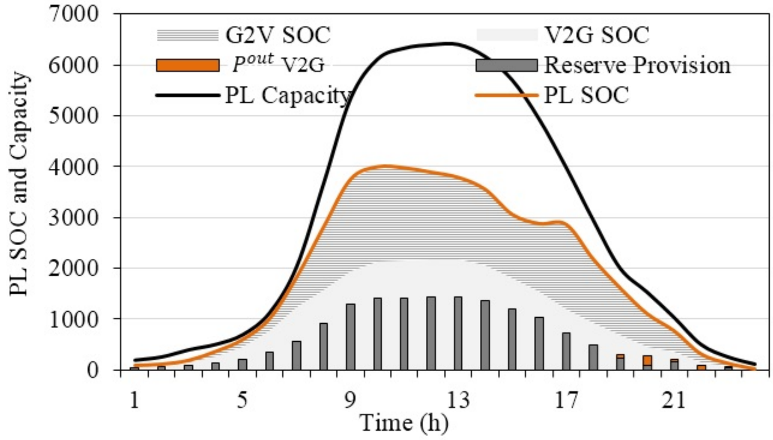

Figure 5.13: Comparison of PL's capacity and SOC divided by G2V and V2G PEVs in Case II.

5.8 The role of PEV preferences on Aggregator Equilibrium

The PL as the main concern of the study changes its behavior based on its trade with the PEV owners and the aggregator. As a result, the tariffs that are implemented to the PEVs can significantly change the strategy of the PL in the market. The variation of the behavior also leads to different levels of profit gain for the PL and aggregator. In this study, PL is a complicate resource in the system which can act as a flexible demand and as a resource as well. Therefore, the aggregator can benefit the most from the PL's potential to act as the flexible load. However, the aggregator needs to manage the market wisely to encourage the PL to show more flexibility.

In this regard, in figure 5.14 and 5.15 the profits of the aggregator and PL for the variation of G2V2 and G2V3 prices in case II are shown, respectively. For the aggregator in figure 19, the total profit is reduced constantly with the reduction of the G2V prices. The reason is that as the prices decreases, the tendency of the PL to charge its PEVs will decrease and consequently the aggregator's profit will decrease.

However, it can be seen that when the G2V2 price goes less than 11 cents, the aggregator's profit decreases drastically. It is due to the fact that G2V2 price is for those PEVs that only participate in G2V mode, but they agree to have flexible departure SOC (i.e., Flex1 contract). In this case, the PL's choice of profit is only through charging these PEVs and no encouragement for charging the PEVs to take benefit from them in the reserve market does not exist. As a result, the PL reduces its flexibility and considerably affects the aggregator's profit.

In figure 5.15, it is observed that the total profit of the PL can have significant changes with the changes in G2V2 and G2V3 prices. These prices are the incentives that the PL determines for its trade with those PEVs that agree to have flexible departure SOC requirements. It should be noted that these tariffs can considerably affect the role of the PL as a flexible load or as a resource. In other words, these two prices can change the marginal price of the PL and change its behavior in contact with the aggregator.

Moreover, the equilibrium prices are investigated for various G2V and V2G tariffs. The variation of the equilibrium energy price for different G2V3 prices is shown in figure 5.16 at a fixed G2V2 equal as 10 cent/kWh (i.e., the minimum amount). As the G2V2 is at its minimum amount the PL cannot make much profit through selling energy to the G2V PEVs. Therefore, it is encouraged

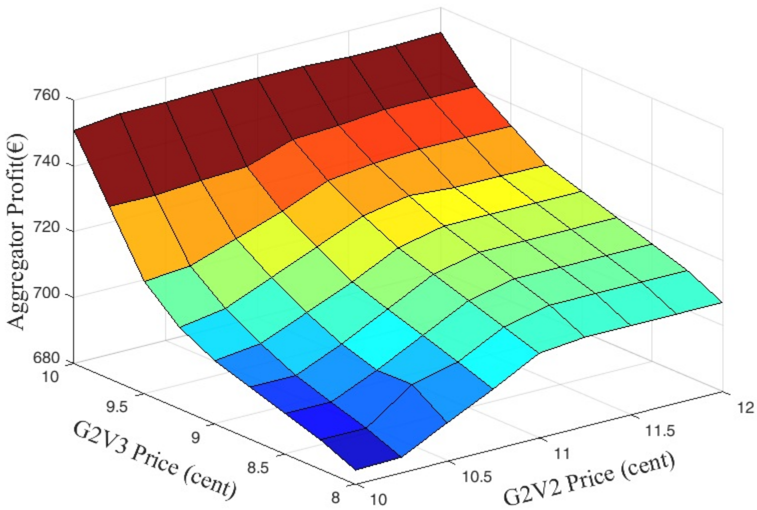

Figure 5.14: Aggregator profit in Case II for various G2V2 and G2V3 prices.

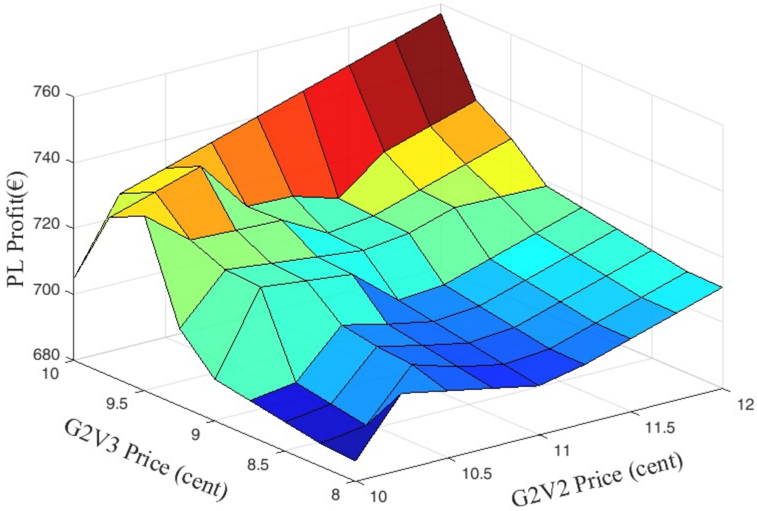

Figure 5.15: PL profit in Case II for various G2V2 and G2V3 prices.

to increase the SOC of the V2G PEVs and make profit through reserve market. The G2V3 is the price with which the PL trades with the flexible V2G PEVs. As a result, it can significantly change the equilibrium price of PL and aggregator as it changes the available PL's SOC. As it can be seen in figure 3 the upstream energy price is around 8 cent/kWh for most of the hours in a day. Therefore, for G2V3 prices less than 9 cent/kWh the equilibrium price is so high that the aggregator can make a profit through selling energy to the PL.

However, the PL may not be intimated by this price to charge the V2G or G2V mode. As a result, the aggregator will make a spike in the reserve price, especially on the hours where the number of PEV departure is high (figure 5.17). With this game, the PL is motivated to charge its PEVs and make profit from reserve declaration. However, when the G2V3 is higher than 9 cents, then even the reserve price spike is not enough to persuade the PL to charge. Hence, the equilibrium price is decreased unless for hour 8, 9, and 10 when the arrival of the PEVs to PL reaches its maximum. Again for the G2V3 higher than 9.75 cent/kWh the equilibrium price is increased and the reserve

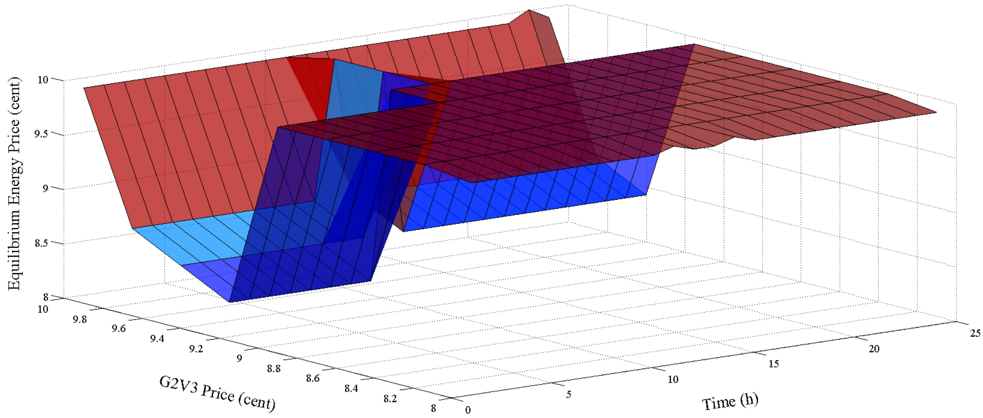

Figure 5.16: Equilibrium energy price for various G2V3.

price spike occurs again.

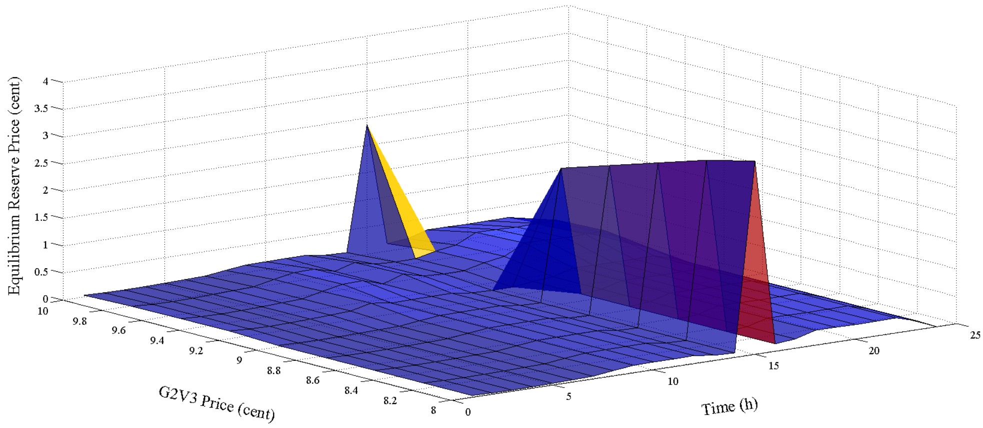

Figure 5.17: Equilibrium reserve price for various G2V3.

In figure 5.18 the variations for the equilibrium reserve price is shown for different values of G2V2. As the main motivation for the PL in V2G mode is making profit through reserve provision, the aggregator imposes variations to the reserve price, particularly during the hours when the PEVs are departing the PL. Although the G2V2 is the price for the G2V mode PEVs but still while this price is low, the reserve spike occurs.

5.9 Chapter Summary

A comprehensive bilevel model to derive the equilibrium price of energy and reserve trade of PL has been proposed considering the preferences of the PEV owners. It is obvious that a critical influence is put on the manipulation of the electric vehicles in future systems by their owners. The behavior of the PEV users can significantly change the process of the system operator. On the other hand, in such environment with various components and complicated interactions, an organized inter-relation should be defined so that all the involved parties in this system could

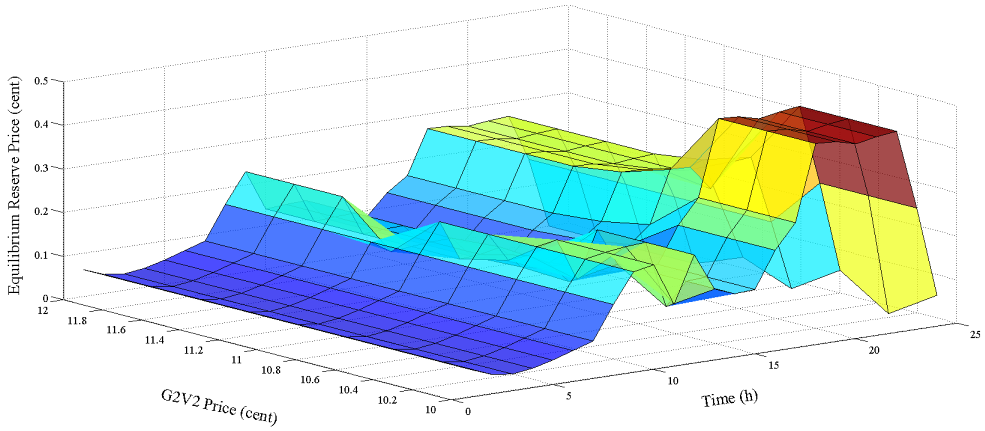

Figure 5.18: Equilibrium reserve price for various G2V2.

assure their own profit. In this regard, it is intended to propose a model for such situation. The main characteristic of this model is that in the upper level the price was specified while the lower level determined the quantity. This was accurately compatible with the reality of PL operation. In fact, the main role of PL as a flexible load is to add the potential of possible load increase or decrease.

Chapter 6

Allocation of the PL in a Renewable-based Distribution Network

6.1 Introduction

Forthcoming urban systems will be equipped with high-tech infrastructures that could make difficult to deal with both operational and planning aspects. Emerging facilities such as Plug-in Electric Vehicles (PEVs) offer a vast spectrum of possibilities for future systems. As well as enhancing system's efficiency and operational conditions, other issues such as greenhouse gas emissions and fossil fuel shortages will be met if higher penetration of PEVs in both transportation and electrical systems is encouraged. On the other hand, Renewable Energy Resources (RERs) are among the most used choices for sustainable development paths.

The presence of these two resources in the system provides the distribution system operator (DSO) with both generating and storage units that can be used profitably. Therefore, the problem of planning the optimal location of PEVs and RERs has to be solved by power system operators like any other resource in the system.

Managing the power needed for charging vehicles in a Parking Lot and the potential of PEVs to inject power into the grid is a challenging issue that may have conflicting impacts on the network. As a result, the DSO has to study the effects of PL network integration while considering the use of PL as a network resource in the most efficient way. This can be achieved through the optimal allocation of PLs in the system. Usually, PLs are connected to distribution networks, thus, the responsibility of the DSO is to investigate possible effects of this integration. High penetration of storage devices such as PEVs can have adverse impacts on the grid because of their randomly located charging loads or unmanaged additions [143]. On the contrary, the optimal allocation of PLs can provide benefits both to its owner and the DSO. To achieve all the advantages of PLs, both the optimal sizes and sites are needed. Therefore, the optimal allocation of PLs is one of the most important issues to be considered while trying to minimize undesirable effects on the distribution system.

This chapter investigates the allocation of PL from both technical and economic points of view. First, the stochastic behavior of PEVs is modeled. Then, based on this behavior in order to achieve PL owner's profit maximization, the optimal PL interaction with the energy and reserve markets is derived. Finally, the allocation of PLs in the distribution network is studied with several objectives: power loss, bus voltages, and network reliability.

6.2 Problem Overview

The growing tendency towards the electrification of transportation has fostered the use of PEVs in the distribution grid. One way to do it is to use PEVs through the installation of PLs in the system.

The DSO should benefit more from PLs if they could be operated in a V2G mode. Consequently, the operational planning of PLs as well as their allocation should be comprehensively analyzed.

6.2.1 Procedure and Assumptions

The main purpose of the current study is to investigate the optimal location of PLs in a distribution network in order to gain the maximum benefit of these resources. It is assumed that urban studies need the installation of PLs in a distribution network. As a result, individual PL operators own and operate PLs in the system. However, the allocation of PLs is assigned to the DSO.

This idea starts from the fact that, in future sustainable distribution networks, the installation of PL stations with high charging requirements of PEVs will be inevitable. As a result, it is assumed that new system agents such as PL owners/operators need to be introduced. Accordingly, a two-stage optimization problem is defined for this purpose. Figure 6.1 shows the procedure that has been adopted to solve the problem.

The flowchart in figure 6.1 showcases the optimization problem procedure, the scenarios assumed, the controlling variables and the input/outputs at each stage. As shown, the uncertain characteristics of the problem (PEVs, RERs, and prices) are solved generating various scenarios at the first stage. These scenarios are the main inputs of the study. More explanations about scenario generation are presented in the following subsection.

The first stage of the problem is dedicated to model PLs' behavior based on the input scenarios given by PL uncertainty characterization. At this stage, based on PL traffic patterns and electricity market price scenarios, PLs' energy trade behavior, including input power to the PLs and the power purchased from PEV batteries as well as the total PLs SOC, is computed. At this step, the PL operator tries to maximize its profit via market interaction along with the revenue from contracts with those PEV owners that use PLs. This means that PLs participate in both energy and reserve markets while demonstrating the best possible behavior through interacting with PEV owners (based on their preferences and requirements). This is an input for the next stage, which is the PL allocation problem.

Managing a PL is a challenging issue due to the uncertain behavior of PEVs. Although it is difficult to derive a pattern for a vehicle's arrival/departure behavior, it is possible to characterize PL behavior. In case of a PEV, it should be noticed that the PEV's batteries have an SOC which is the main source to be utilized by a PL or system operator. Therefore, uncertainty characterization of PLs has been studied for a better illustration of the PL behavior. The second stage is the PL allocation problem that determines the optimum locations for PLs based on network-constrained objective functions. It is executed through the separate minimization of the costs of reliability, power loss, and bus voltage deviation.

The presence of PEVs in PLs brings in both challenges and opportunities to the system. Those PEVs that are parked in a PL not only can be utilized as battery resources but also need to be charged at least up to their minimum required SOCs. Accordingly, PLs are energy resources that may also be considered as controllable loads. By controllable loads, we mean that the PL owner can control the amount of energy that is needed to fuel up the PEV batteries during the period of their stays at the PL. The reason is that this time interval gives the PL the opportunity to see market prices and decide when to charge the batteries and when to sell energy to the grid. This makes PLs different from other distribution resources such as conventional DGs. Consequently, their planning should be performed over a period of time.

Other assumptions are also imposed to examine various cases and to make the problem more compatible with the distribution grid. For example, it is assumed that PEVs that agree to be in a V2G mode sign a contract with the PL and determine a minimum amount of SOC before they leave the PL. Moreover, in this study, PEVs that use PLs do not necessarily have to be part of this network. This means that they can come from neighboring networks. As a result, they will not increase the total load of the system during the hours that they are not at a PL.

As shown in figure 6.1, each stage of the problem is solved in different environments. The first stage is solved in a market environment (energy and reserve) to maximize the PL owner's profit. At the second stage, the problem is solved under network constraints considering the power generated from renewable resources. At the second stage, three network-constrained objective functions are solved, as shown in figure 6.1.

The results indicate the optimum location for installing PLs as well as the number of stations at each bus. The results are obtained by optimizing the cost function for each of the objectives mentioned.

6.2.2 Uncertainty Characterization

The behavior of PEVs, RERs generation and energy market prices are considered to be uncertain. As a result, in order to model the stochastic behavior of these elements, a scenario generation approach has been used.

As already explained in Chapter 4, in order to investigate the uncertain behavior of PEVs, a stochastic model is used to provide the required scenarios for the number, SOCs, and battery capacities of the PEVs in each hour. The total aggregated capacity and SOC for EVs plugged-in at the PL are derived from the model. It should be emphasized that PEV scenarios are generated for the whole network. In other words, it is assumed that the PEVs in a certain geographical area, e.g., a district of a city, follow a certain behavior.

The scenarios for the PEVs that have been employed in this chapter is shown in figure 6.2 and it is based on the computations from Chapter 4. As it can be seen, the expected value of the scenarios is used in the calculations.

In order to characterize the uncertainty of RERs, the same method is utilized for both resources: wind power and photovoltaic (PV). Wind speed distributions are characterized by Weibull distributions [144] and the Probability Distribution Function (PDF) is calculated. Different realizations of wind power generation are modeled through a scenario generation process based on the Roulette Wheel Mechanism (RWM).

First, the distribution function is divided into several class intervals. Hence, each interval is associated with a probability. The Probability Density Function (PDF) of wind speed is represented by equation (6.1), where $m > 0$ and $y > 0$ are referred to as the scale factor and shape factor, respectively.

$$f_u(u) = \frac{y}{m}\big(\frac{u}{m}\big)^{y-1} exp\big[-\big(\frac{u}{m}\big)^{y}\big] \tag{6.1}$$

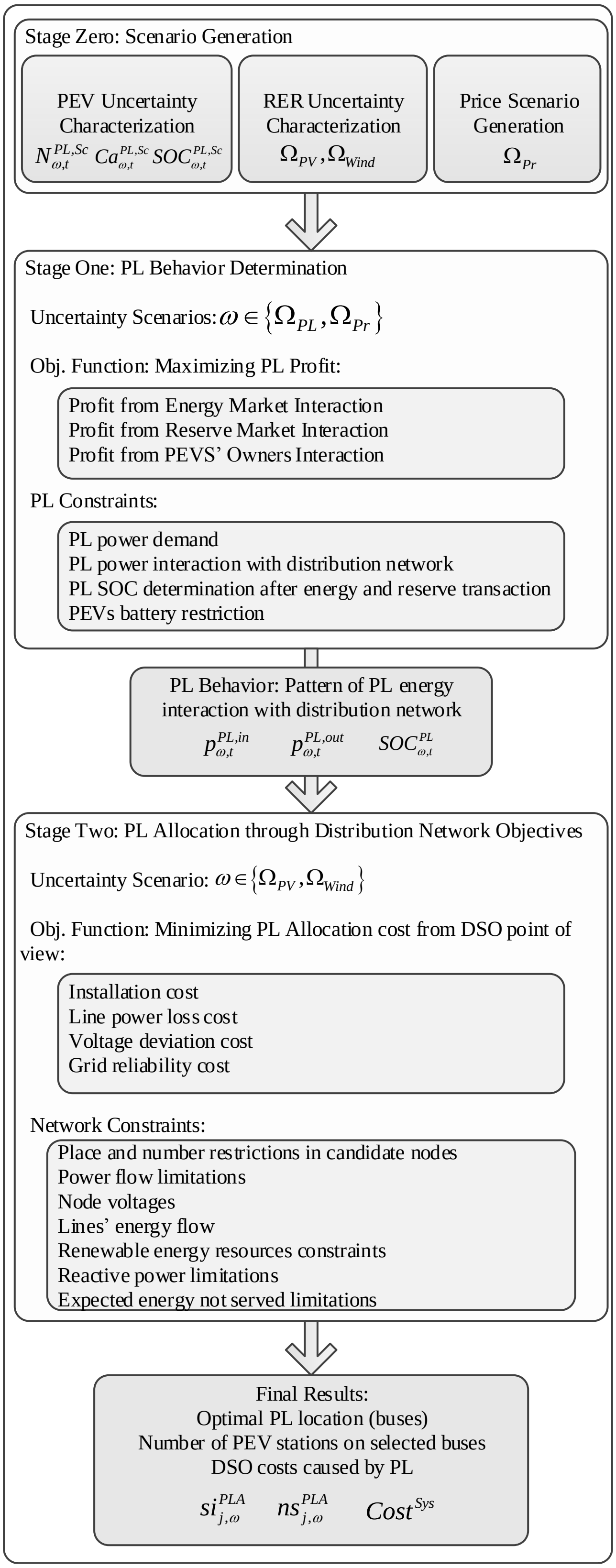

Figure 6.1: Flowchart of the overall algorithm.

The probability distribution function is divided into SN scenarios, and the probability of each step can be calculated as follows:

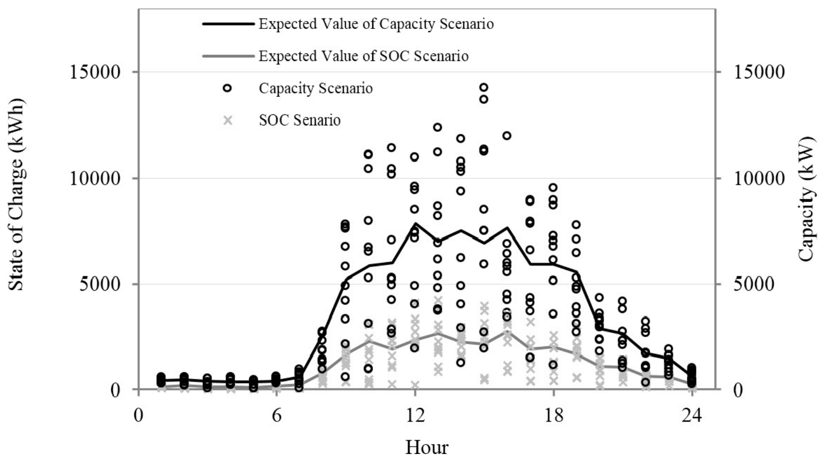

Figure 6.2: Capacity and SOC scenarios of PEVs.

$$prob_\omega = \int_{WS_\omega}^{WS_{\omega+1}} f_u(u)du, \qquad \omega = 1, 2, \cdots, SN \tag{6.2}$$

where WS_ω is the wind speed of the ω^{th} scenario. The power generated, P_ω^W, is correspondent to a specific wind speed, WS_ω , can be obtained from equation (6.3) where a', b' and c' are constants that can be calculated according to [144].

$$P_\omega^W = \begin{cases} 0 & 0 \leq WS_\omega \leq U_{ci} \text{or} WS_\omega \geq U_{co} \\ P^{RP}(a' + b' \times WS_\omega + c' \times WS_\omega^2) & U_{ci} \leq WS_\omega \leq U_{rs} \\ P^{RP} & U_{rs} \leq WS_\omega \leq U_{co} \end{cases} \tag{6.3}$$

In equation (6.3), U_{ci}, U_{co}, and U_{rs} represent cut-in speed, cut-out speed, and rated speed, respectively. Different realizations of wind power generation are modeled through scenario generation process based on Roulette Wheel Mechanism (RWM). At first, the distribution function is divided into some class intervals. Moreover, each interval is associated with a probability. Subsequently, according to the different intervals and their probabilities obtained by the PDF, RWM is applied to generate scenarios for each hour. Finally in a similar way, the RWM technique is applied for scenario generation at each hour. It is obvious that a higher number of scenarios produces a more accurate model to consider the mentioned uncertainties. However, this yields an unmanageable optimization problem. Hence, a scenario reduction technique is considered, the K-means clustering technique, resulting in a scenario tree with three independent scenarios. The reduced scenarios that are generated for RER in this study are shown in figure 6.3.

Four price scenarios are used in the process to enable a more comprehensive study. These scenarios are based on day-ahead market prices. Each scenario represents the average price of 90 days for each season. As a result, price scenarios are the average seasonal prices that are applied to the problem. The average prices of the energy and reserve markets based on these scenarios are shown in figure 6.4.

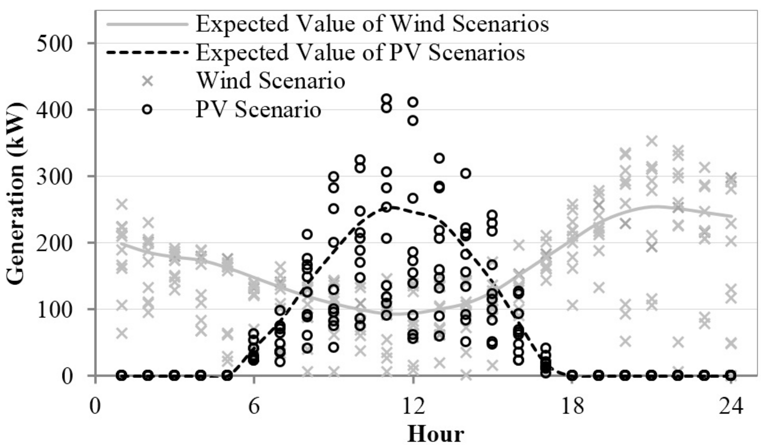

Figure 6.3: Output generation of RERs.

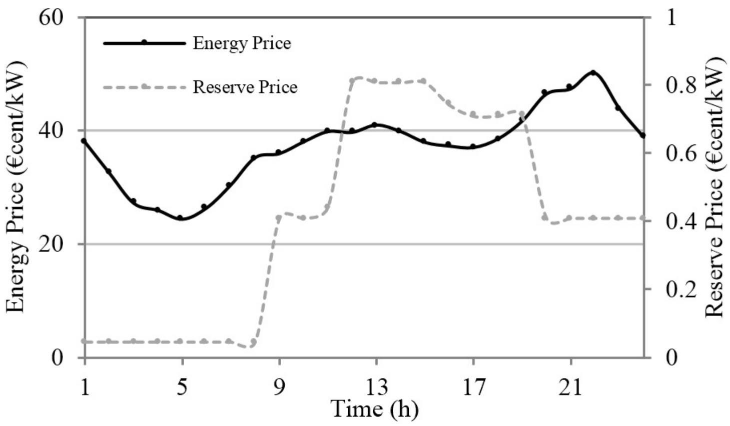

Figure 6.4: Average price of energy and reserve.

6.3 First Stage: PL Model

The first stage models the behavior of PEV's PLs as stochastic storage devices. Here, the non-linear formulation is presented while the model has been linearized for solving the problem. The problem is solved with various price and PEV traffic scenarios:

$$\omega \in \{\Omega_{PL}, \Omega_{Pr}\} \tag{6.4}$$

6.3.1 Objective Function

The objective function at this stage maximizes the profit from operating the PLs from the PL operator's perspective. As shown in equation (6.5), the profit is obtained through energy and reserve market interactions as well as individual contracts with PEV owners that use the PLs in a V2G state. For a better illustration of the objective function terms, a separate formulation for each interaction is presented in equations (6.6)-(6.3.1). The energy market interaction provides revenue to the PL from selling energy to the upstream network minus the cost of purchasing energy:

$$Maximize\{profit^{PL}\} = Max\Bigg\{\sum_{\omega}\rho_{\omega}\sum_{t}\Bigg(profit^{EMI} + profit^{RMI} + profit^{POI}\Bigg)\Bigg\} \quad (6.5)$$

$$profit^{EMI} = p^{out,PL}_{\omega,t}\pi^{E}_{\Omega_{pr},t} - p^{in,PL}_{\omega,t}\pi^{E}_{\Omega_{pr},t} \quad (6.6)$$

The revenues and costs from reserve market interaction are shown in equation (6.7). The income from reserve declaration and the income from selling power in the reserve market multiplied by the probability of a reserve call are the revenues from reserve market interaction. On the other hand, the penalty for not being ready whenever a PL is called to take part in the reserve market is the cost produced by reserve market interaction. In equation (6.7), FOR^{PL} is the forced outage rate which indicates the inability of a PL to deliver power to the upstream grid and may be caused by a system failure or by the PL itself.

$$profit^{RMI} = r^{PL}_{\omega,t}\pi^{Re}_{\Omega_{Pr},t} + r^{PL}_{\omega,t}\rho^{del}_{t}\pi^{E}_{\Omega_{pr},t} - r^{PL}_{\omega,t}\rho^{del}_{t}FOR^{PL}\pi^{Outage}_{t} \quad (6.7)$$

The revenue and income due to the interactions of the PLs with PEV owners that use PLs is shown in equation (6.3.1). The revenues are caused by the amount received from the PEVs for charging their batteries and the parking usage tariff. Besides, the costs of PEV owner interactions come from the value that should be paid to vehicle owners when they participate in a V2G interaction in the reserve and energy markets, respectively. However, it should be noted that the decreased SOC from PEV batteries is the amount that should be paid as the power contributing in the V2G mode. Another cost is the battery depreciation cost, which is calculated based on the amount of power taken from PEV batteries and sold to the energy and/or reserve markets multiplied by the cost of equipment depreciation.

$$\begin{aligned} profit^{POI} &= soc^{PL,up}_{\omega,t}\pi^{G2V}_{t} + n^{PL}_{\omega,t}\pi^{Tariff} - re^{PL}_{\omega,t}\rho^{del}_{t}\pi^{V2G}_{t} - soc^{PL,down}_{\omega,t}\pi^{V2G} \\ &-(p^{out,PL}_{\omega,t} + \rho^{del}_{t}re^{PL}_{\omega,t})Cd^{PL} \end{aligned} \quad (6.8)$$

6.3.2 Constraints

The total power that can be injected into a PL or purchased from it is restricted to fixed charging and discharge rates, as shown in equations (6.9) and (6.10). A PL is also restricted to these rates based on the characteristics of the charging stations as well as the number of stations.

$$p^{in,PL}_{\omega,t} \leq \Gamma^{cha,PL}n^{PL}_{\omega,t} \quad (6.9)$$

$$p^{out,PL}_{\omega,t} + r^{out,PL}_{\omega,t} \leq \Gamma^{dcha,PL}n^{PL}_{\omega,t} \quad (6.10)$$

Each PEV owner that agrees to participate in a V2G mode at a PL may have expectations based on its usage pattern. Mainly, these expectations are declared as the minimum required SOC. On the other hand, the PL owner may expect an approximate duration of the stay at a PL in order to reduce uncertainty. It is assumed that a contract is signed between the PL owner and the PEVs that want to contribute in a V2G mode. In that case, a PL should aggregate the expected minimum SOC assigned in the contracts for each hour to put a limit to the maximum power exchange with the grid. The calculation of ϕ is based on the computations presented in Chapter 4. However, in this chapter an aggregated percentage for the total PEVs regardless of their categories is employed.

In equation (6.11), it is shown that the total PL interaction with the grid should be less than required SOC of the PL due to the contracts with the PEV owners.

$$p_{\omega,t}^{out,PL} + re_{\omega,t}^{PL} \leq \phi_t^{PL} soc_{\omega,t}^{PL} \tag{6.11}$$

In order to specify the SOC and the power capacity of a PL, it is necessary to estimate the approximate number of PEVs at a PL in each hour. On the other hand, as the study is based upon certain PL scenarios (number of PEVs, SOC, and capacity), the allowed number of stations in a PL has to be scaled on this basis. For this reason, equation (6.12) is defined, showing that, if the total number of PEVs in a scenario is less than the number of stations, is fine, but, when it exceeds the number of stations, the presumed amount of PEVs will be limited by the number of stations at the PL.

$$n_{\omega,t}^{PL} = \begin{cases} NS^{PL} & \text{if } NS^{PL} \leq NS_{\omega,t}^{PL,Sc}; \\ NS_{\omega}^{PL,Sc} & \text{if } NS_{\omega,t}^{PL,Sc} < NS^{PL}. \end{cases} \tag{6.12}$$

The total capacity of a PL has to be scaled. It is assumed that the ratio of vehicle numbers in a PL with respect to the number of vehicles in a scenario is proportional to the PL capacity:

$$c_{\omega,t}^{PL} = C_{\omega,t}^{PL,Sc} \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}} \tag{6.13}$$

A PL's SOC at each hour depends on the remaining SOC of the PL from the previous hour, the power exchanged with the upstream network multiplied by the charge/discharge efficiency and the SOCs of arriving or departing vehicles as in equation (6.14). Moreover, the amount of SOC is restricted by the capacity of the PL in each hour and cannot exceed this limit based on equation (6.15).

$$soc_{\omega,t}^{PL} = soc_{\omega,t-1}^{PL} + p_{\omega,t}^{in,PL}\eta^{PL,Cha} - \frac{p_{\omega,t}^{in,PL}}{\eta^{PL,dCha}} + soc_{\omega,t}^{PL,ar} - soc_{\omega,t}^{PL,dep} \tag{6.14}$$

$$soc_{\omega,t}^{PL} \leq c_{\omega,t}^{PL} \tag{6.15}$$

The total SOC of a PL cannot exceed the minimum and maximum SOC of each PEV multiplied by the number of PEVs at each PL:

$$\underline{SOC}^{PEV} n_{\omega,t}^{PL} \leq soc_{\omega,t}^{PL} \leq \overline{SOC}^{PEV} n_{\omega,t}^{PL} \tag{6.16}$$

The number of vehicles that arrive at a PL and depart from it in each hour provides the initial SOC of the PL. Moreover, the available SOC in each hour is the main factor that affects the behavior of the PL. As a result, it is important to estimate its amount based on the stochastic behavior of PEVs. In order to have an approximation of the SOC in each hour, the approximated number of arrivals and departures in each hour should be specified. In this study, PEV scenarios that have been generated are used as a benchmark to indicate arrival/departure patterns. In each hour, the SOC in a scenario is compared with the SOC of the previous hour. If the SOC increases, this means that several PEVs have arrived at the PL (because no interaction is considered between the PL and the grid in the scenarios and the only change in the SOC is due to PEVs' arrivals and departures). However, in order to implement this increase in the SOC, it has to be scaled based on the number of the stations that are installed in the PL. For this purpose, equation (6.17) has been designed. In equation (6.17), it is shown that, if the SOC does not increase in the following hour, no arrival is considered for the PL. However, if the SOC in a scenario is higher than in the previous hour, the increase in the PL's SOC is calculated by scaling the SOC increase by the ratio between the number of PEVs in the PL and the ones in the scenario.

$$\begin{cases} \text{if} \quad SOC_{\omega,t}^{PL,Sc} \leq SOC_{\omega,t-1}^{PL,Sc} \Rightarrow soc_{\omega,t}^{PL,ar} = 0; \\ \text{if} \quad SOC_{\omega,t-1}^{PL,Sc} < SOC_{\omega,t}^{PL,Sc} \Rightarrow soc_{\omega,t}^{PL,ar} = \left(SOC_{\omega,t}^{PL,Sc} - SOC_{\omega,t-1}^{PL,Sc}\right)\frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}}. \end{cases} \tag{6.17}$$

On the other hand, when the SOCs between two consecutive hours decrease, this does not indicate that the number of vehicles has decreased. The reason is that, in some cases, fewer vehicles with higher SOCs may depart from the PL and more PEVs with lower SOCs may arrive at the PL in the same hour. As a result, the scaling procedure used for the SOCs related to PEVs arrivals cannot be used for determining the SOCs related to PEVs departures. Therefore, in equation (6.18), the same comparison is used, but the SOC of a PL is calculated scaling the amount of SOC decrease by the ratio between the SOC in the PL and the one in the scenario.

$$\begin{cases} \text{if} \quad SOC_{\omega,t-1}^{PL,Sc} \le SOC_{\omega,t}^{PL,Sc} \Rightarrow soc_{\omega,t}^{PL,dep} = 0; \\ \text{if} \quad SOC_{\omega,t}^{PL,Sc} < SOC_{\omega,t-1}^{PL,Sc} \Rightarrow soc_{\omega,t}^{PL,ar} = \left(SOC_{\omega,t}^{PL,Sc} - SOC_{\omega,t-1}^{PL,Sc}\right) \frac{soc_{\omega,t}^{PL}}{SOC_{\omega,t}^{PL,Sc}}. \end{cases} \tag{6.18}$$

In scenario generation, the PL does not have any interaction with the network. As a result, the PEVs will enter the PL with a certain amount of SOC and will depart with the same amount. However, as the PL trades with the grid, the total SOC of the PEVs leaving the PL may be higher or lower than the SOC in the same hour for the scenario. The reason is that, while the PEVs stay in the PL, they may be charged or discharged, having a SOC different from the one that they had when they arrived at the PL. The extra charge or discharge of the initial SOC of the PEVs is the basis that produces the PL's profit. Therefore, in order to calculate the revenue/cost of a PL, it is necessary to compute the surplus SOC that remains within the PEVs when they depart. This can be achieved through equations (6.19) and (6.20). In equation (6.19), if the SOC of the departed PEVs that have left is higher than the scaled amount of the departed SOCs in a scenario, this means that the PEVs have been overcharged comparing to their initial SOCs. Hence, the owners have to pay for the excess charge (SOC^{up}). On the other hand, in equation (6.20), if the SOC of the departed PEVs is lower than the one of the initial scenario, the owners should be paid by the PL based on SOC^{down}.

$$\begin{cases} \text{if} \quad SOC_{\omega,t-1}^{PL,dep} \le \left(SOC_{\omega,t}^{PL,Sc} - SOC_{\omega,t-1}^{PL,Sc}\right) \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}} \Rightarrow soc_{\omega,t}^{PL,up} = 0; \\ \text{if} \quad \left(SOC_{\omega,t-1}^{PL,Sc} - SOC_{\omega,t}^{PL,Sc}\right) \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}} < soc_{\omega,t}^{PL,dep} \\ \quad \Rightarrow soc_{\omega,t}^{PL,up} = soc_{\omega,t}^{PL,dep} - \left(SOC_{\omega,t-1}^{PL,Sc} - SOC_{\omega,t}^{PL,Sc}\right) \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}}. \end{cases} \tag{6.19}$$

$$\begin{cases} \text{if} \quad \left(SOC_{\omega,t-1}^{PL,Sc} - SOC_{\omega,t}^{PL,Sc}\right) \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}} \le soc_{\omega,t}^{PL,dep} \Rightarrow soc_{\omega,t}^{PL,down} = 0; \\ \text{if} \quad SOC_{\omega,t-1}^{PL,dep} < \left(SOC_{\omega,t}^{PL,Sc} - SOC_{\omega,t-1}^{PL,Sc}\right) \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}} \\ \quad \Rightarrow soc_{\omega,t}^{PL,down} = soc_{\omega,t}^{PL,dep} - \left(SOC_{\omega,t-1}^{PL,Sc} - SOC_{\omega,t}^{PL,Sc}\right) \frac{n_{\omega,t}^{PL}}{N_{\omega,t}^{PL,Sc}}. \end{cases} \tag{6.20}$$

6.4 Second Stage: Allocation of PEV's Parking Lots

At the second stage, the allocation of PLs in a distribution network is modeled based on various network-constrained objectives. In this study the objectives are to minimize the costs of power loss, voltage deviation, and network reliability. The study examines various PL scenarios and renewable resources including wind generation and photovoltaic (PV) sources:

$$\omega \in \{\Omega_{PLA}, \Omega_{Wind}, \Omega_{PV}\} \tag{6.21}$$

As mentioned before, the outputs of the first stage are treated as inputs at the second stage. This means that the optimal trading behavior of the PLs based on maximizing the PL owner's profit is considered as an input at this stage. The second stage is conducted from the DSO's point of view using the PLs to enhance network operation as much as possible. It should be mentioned that, at the first stage, PEVs are considered as a whole and assumed to belong to a single owner. However, at the second stage, the DSO tries to distribute the PEVs among network buses, thus, the SOC and power injected from/into the PLs should be scaled based on the number of stations that are allocated at each bus. The interface between the first and second stages is done through:

$$p_{j,\omega,t}^{in,PLA} = p_{\omega,t}^{in,PL} \frac{ns_{j,\omega}^{PLA}}{NS^{PL}} \tag{6.22}$$

$$p_{j,\omega,t}^{out,PLA} = p_{\omega,t}^{out,PL} \frac{ns_{j,\omega}^{PLA}}{NS^{PL}} \tag{6.23}$$

$$soc_{j,\omega,t}^{PLA} = soc_{\omega,t}^{PL} \frac{ns_{j,\omega}^{PLA}}{NS^{PL}} \tag{6.24}$$

The objective function shown in equation (6.25) denotes that the DSO wants to minimize the total cost subject to network constraints.

$$Min\{Cost^{Sys}\} = \sum_{\omega} \rho_{\omega} (cost_{\omega}^{Ins} + cost_{\omega}^{Reli} + cost_{\omega}^{VD} + cost_{\omega}^{loss}) \tag{6.25}$$

Each of the cost functions in equation (6.25) is described in the sub-sections below.

6.4.1 Installation Costs

The installation cost consists of the fixed and variable costs to install the PL:

$$cost_{\omega}^{Ins} = \sum_{j} si_{j,\omega}^{PLA} cost_{j}^{PLA,fix} + ns_{j,\omega}^{PLA} cost_{j}^{PLA,var} \tag{6.26}$$

The fixed costs refer to site-dependent costs such as the municipal license payment to install the PL and other wiring or construction licenses. Variable costs refer to the installation cost of the PL which varies, because the optimal number of parking stations in each PL can differ. The variable cost includes the cost of purchasing a station, land needed for installing the station, wiring costs, and vehicle on-board device costs. To select a node for installation of a PL, equation (6.27) is used.

$$si_{j,\omega}^{PLA} \leq Can_{j}^{PLA} \tag{6.27}$$

where *si* is a binary variable indicating whether a bus is selected for the installation of a PL and *Can* is a binary parameter representing whether a bus is a candidate for PL location or not. However, this selection can be based on electrical or urban planning issues. In the process of selecting a bus when a bus is a candidate, then, the binary variable *si* shows whether the candidate bus is also selected by the optimization model.

If a bus is selected for PL installation ($si = 1$), then the number of stations that will be allocated at this bus should not exceed the limit of the total number of available stations in the network as in equation (6.28). Moreover, the total number of stations distributed along network buses should be equal to the whole number of stations to be installed in the system:

$$ns_{j,\omega}^{PLA} \leq si_{j,\omega}^{PLA} NS^{PL} \tag{6.28}$$

$$\sum_j ns_{j,\omega}^{PLA} = NS^{PL} \tag{6.29}$$

6.4.2 Loss Costs

The equation denoting the cost of loss is given by:

$$cost_{\omega}^{loss} = \sum_t \sum_b R_{j,k,\omega,t} (i_{j,k,\omega,t})^2 \Pi^{loss} \tag{6.30}$$

In order to calculate the above-mentioned function, a power flow is solved. In this study, a linear power flow is obtained based on [139] and [138]. The power flow model linearization takes into account the radial nature of the distribution network. For this purpose, the term $\tilde{i}$ is considered as a block to avoid nonlinearities. The formulation of the active and reactive power balance is shown in:

$$p_{j,\omega,t}^{Sys,in} + p_{j,\omega,t}^{W} + p_{j,\omega,t}^{PV} + p_{j,\omega,t}^{out,PLA} - p_{j,\omega,t}^{in,PLA} + \sum_b p_{j,k,\omega,t}^{Line} + R_{j,k}(i_{j,k,\omega,t})^2 = p_{j,t}^{D} \tag{6.31}$$

$$q_{j,\omega,t}^{Sys,in} + \sum_b q_{j,k,\omega,t}^{Line} + X_{j,k}(i_{j,k,\omega,t})^2 = q_{j,t}^{D} \tag{6.32}$$

The relations to obtain $\tilde{i}$ and $\tilde{v}$ are shown in:

$$(v_{j,\omega,t})^2 - 2(R_{j,k} p_{j,k,\omega,t}^{Line} + X_{j,k} q_{j,k,\omega,t}^{Line}) - (Z_{j,k})^2 (i_{j,k,\omega,t})^2 - (v_{k,\omega,t})^2 = 0 \tag{6.33}$$

$$(i_{j,k,\omega,t})^2 = \frac{(p_{j,k,\omega,t}^{Line})^2 + (q_{j,k,\omega,t}^{Line})^2}{(v_{k,\omega,t})^2} \tag{6.34}$$

As in any power flow, the voltage and current limits applied are shown in:

$$\tilde{\underline{V}}_j \leq \tilde{v}_{j,\omega,t} \leq \tilde{\overline{V}}_j \tag{6.35}$$

$$0 \leq \tilde{i}_{j,k,\omega,t} \leq \tilde{\overline{I}}_{j,k} \tag{6.36}$$

RERs in the system should be also limited to the possible amount of generation defined in their scenarios for wind and PV, respectively:

$$0 \leq p^{W}_{j,\omega,t} \leq P^{W,Sc}_{j,\omega,t} \tag{6.37}$$

$$0 \leq p^{PV}_{j,\omega,t} \leq P^{PV,Sc}_{j,\omega,t} \tag{6.38}$$

6.4.3 Voltage Deviation Costs

In this study, the cost imposed to the DSO for having the bus voltages within a specified range is calculated in equation (6.39). It is assumed that the voltage deviation is fixed by means of installing capacitors in the system. Adding a capacitor to the system adds a variable cost term, based on the required reactive power capacity and dependent on the amount of reactive power in the system, as well as a capacitor installation cost (fixed cost).

$$cost^{VD}_{\omega} = \sum_j si^{C}_{j,t} cost^{Cap,fix} + \Delta q_{j,\omega} cost^{Cap,var} \tag{6.39}$$

The amount of reactive power required at each bus can be obtained from:

$$\Delta q_{j,\omega} = -|\Delta v_{j,\omega}| \cdot B_{j,j} \cdot |v_{j,\omega}| \tag{6.40}$$

In order to minimize Δv at each bus, equation (6.38) is used. To keep the equation linear, the minimization of $\Delta \tilde{v}$ has been implemented based on equation (6.39).

$$\Delta q_{j,\omega} = -B_{j,j}\left(\frac{(\underline{v}^{VD}_j)^2 - (v_{j,\omega})^2}{2}\right) - \frac{(\Delta v_{j,\omega})^2}{2} \approx -B_{j,j}\frac{(\Delta \tilde{v}_{j,\omega})^2}{2} \tag{6.41}$$

$$Min\{\Delta v_{j,\omega}\} \quad \Delta \tilde{v}_{j,\omega} \geq \begin{cases} 0 & \text{if } (\underline{v}^{VD}_j)^2 \leq (v_{j,\omega,t})^2 \\ (\underline{v}^{VD}_j)^2 - (v_{j,\omega})^2 & \text{if } ((v_{j,\omega,t})^2 < \underline{v}^{VD}_j)^2 \end{cases} \tag{6.42}$$

6.4.4 Network Reliability Costs

As this study is conducted on a distribution network, the Expected Energy not Served (EENS) index is used to measure reliability. Previous studies, such as [145], use the same concept, but the difference is that the battery is replaced instead of charged. The objective function implemented is shown in:

$$cost_{\omega}^{Reli} = EENS_{\omega}CDC \tag{6.43}$$

where the cost of reliability is calculated through the payment of damages to end users for the period of time where the required energy is not supplied. It is assumed that the PL operator has an extra contract with the PEV owners whereby the operator can use more of the PEV's SOC during contingencies compared to the normal condition. This leads to a higher amount of power injection of the PLs into the grid, based on:

$$p_{j,\omega,t}^{inj,PLA} = soc_{j,\omega,t}^{PLA}\mu_{t}^{PL,Con} \tag{6.44}$$

Whenever a contingency occurs in the system, the DSO aims to reduce load shedding by using the energy injected from PLs, wind farms, and PV units. However, it should be noted that all of these resources (PL, wind and PV) are time-dependent with variable output amounts. On the other hand, a contingency is resolved after the required repair time. Thus, the total power that can be injected by these resources should be computed during the repair time period:

$$\begin{cases} p_{b,\omega,t}^{inj,Res} = \sum_i p_{j,\omega,t}^{inj,PL} + \sum_{h=t}^{h=t+rep_b} p_{j,\omega,h}^{W} + \sum_{h=t}^{h=t+rep_b} p_{j,\omega,h}^{PV} \\ p_{b,\omega,t}^{aff,D} = \sum_j \sum_{h=t}^{h=t+rep_b} p_{j,\omega,h}^{W} \end{cases} \tag{6.45}$$

where, for each interruption (on branch b), the summation of possible injections is made for the buses affected by the interruption, starting from the time when the interruption starts (t) until the repair time is finished ($t + r_b$). The same procedure is performed for those loads that exist in affected buses. Finally, the amount of load shedding is obtained from equation (6.46) [145].

$$p_{b,\omega,t}^{Shed} = Max\big(0, p_{b,\omega,t}^{aff,D}, p_{b,\omega,t}^{inj,Res}\big) \tag{6.46}$$

The total energy not supplied due to contingencies in a network is related with the probability of failure in the network multiplied by the load that has been shed:

$$EENS_{\omega,t} = \frac{1}{T}\sum_{t}\sum_{l} p_{b,\omega,t}^{Shed}\lambda_b \tag{6.47}$$

6.5 Case Studies

The proposed model of the problem explained in this chapter is tested on the IEEE 13-bus radial distribution test system [146]. Various references, including [54] and [147], have previously used the same network for studying the allocation of DG and PLs or PEV stations. All data used are based on real data from Madrid, Spain. Data for the day-ahead market are obtained from the Spanish electricity market [140] and data for wind and PV resources are taken from [148]. It is assumed that only one kind of charging station can be used. Based on [149] and [150], it is assumed that the PL owner purchases the quick charging station at a charging rate of 11 kW per hour. The tariff for PL contracts with PEV owners is based on [142]. The network load is adapted to the hourly-based load of the Spanish market for two reasons: first, the operation problem is calculated for each hour of the day and second, the hourly load has to follow the same pattern as market prices, thus, the Spanish market load is used. This process has been conducted for both active and reactive loads assuming that the system power factor is constant (0.85). In the original version of the IEEE 13-bus system, there is a switch between buses 671 and 692. However, in this study the switch between buses 671 and 692 is considered to be closed. As a result, bus 692 is eliminated from the figures. In addition, the transformer between buses 633 and 634 is assumed not to change the voltage level between these two nodes.

6.5.1 PL Behavior Results

In order to determine the most profitable behavior of the PLs' owner in market transactions, the first stage of the problem has been computed in two cases. In the first case, the PL owner participates in both energy and reserve markets. In the second case, it is assumed that only the energy market is available to the PL owner. The purpose is to compare these two different situations and observe the PLs behavior and if either the reserve or the energy market is more profitable for the PLs owner.

The main results of this stage are shown in figure 6.5 and 6.6 for cases 1 and 2, respectively. These results are reported for 200 parking stations. The derived capacity, SOC, and power exchanged with the grid (input and output) are shown in each case. As it can be seen in both figures, a higher SOC is achieved in case 1 (where a reserve market exists). This shows a specific behavior in the case of having a reserve market. In case 1, more power is purchased from the grid and, hence, a higher SOC is achieved to be offered in both energy and reserve markets. In addition, in both figure 6.5 and 6.6, the PLs' SOCs is considerably higher than in a scenario. This is due to the power exchange of the PL with the grid, which is not considered in the process of scenario generation.

The comparison of the input power in the two cases is illustrated in figure 6.7. It is shown that, in case 1, where the possibility of participating in the reserve market exists, a higher amount of input power is purchased from the energy market. As can be seen in the figure, where both energy and reserve markets are available, the PL owner tries to buy more energy from the grid, in order to maximize its SOC, thus, it has more power available to offer in the market. In case 2, where only the energy market is available to the PL, the owner also charges the battery's SOC but less than in the first case.

However, results in figure 6.8 indicate that there is a considerable difference in the output power of

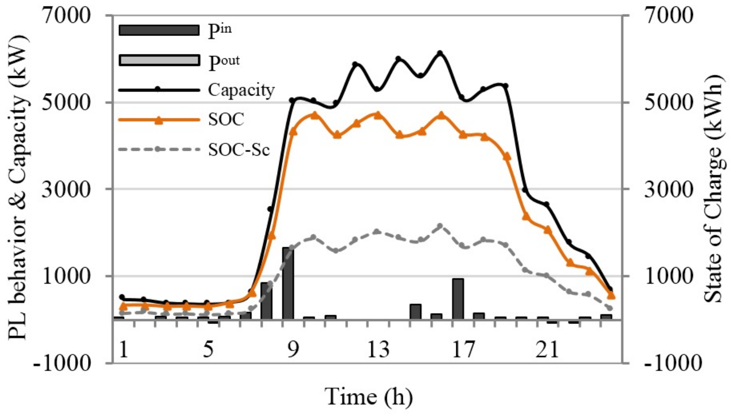

Figure 6.5: PL behavior, capacity, and state of charge in case 1.

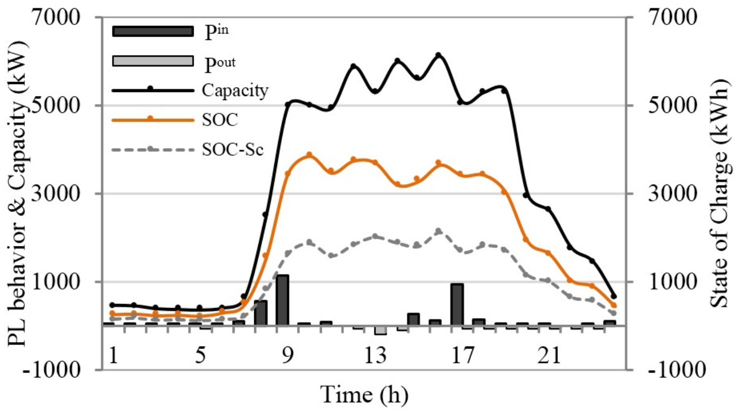

Figure 6.6: PL behavior, capacity, and state of charge in case 2.

the two cases. It shows that the amount of energy sold to the grid in case 2 is significantly higher than in the case 1. This means that PLs tend to offer most of its available power in the reserve market. On the contrary, when it cannot participate in the reserve market, it sells most of its SOC to the energy market.

The reason is revealed by analyzing the details of cost and revenue in each case. It appears that in case 1, the PLs' owner can earn more profit through both reserve declaration and tariff for charging PEV batteries other than selling energy to the grid. As a result, it manages its operation by charging the batteries and provides a sufficient degree of SOC to participate in the reserve market. Then, instead of discharging the batteries, it profits from reserve declaration, reserve call, and the extra benefit of charging PEV batteries.

The comparison of profits in two cases is shown in figure 6.9. The results for four price scenarios and the expected values of profit in the two cases are shown. These results are presented without the revenue from the PEV entrance tariff with the aim of having a better analysis of the behavior. It is obvious that in case 2, although a higher amount of input energy is purchased from the market (figure 6.7) and less energy is sold to the market (figure 6.8), yet a higher profit can be obtained in this case. This is due to the reserve market. A considerable increase in the profit of the PLs indicates that, although they can participate in the market as energy resources, they can gain more profit participating in the reserve market. In this case, PLs are more likely to behave as loads that offer a potential reserve service to the DSO. The analysis denotes that in order to make

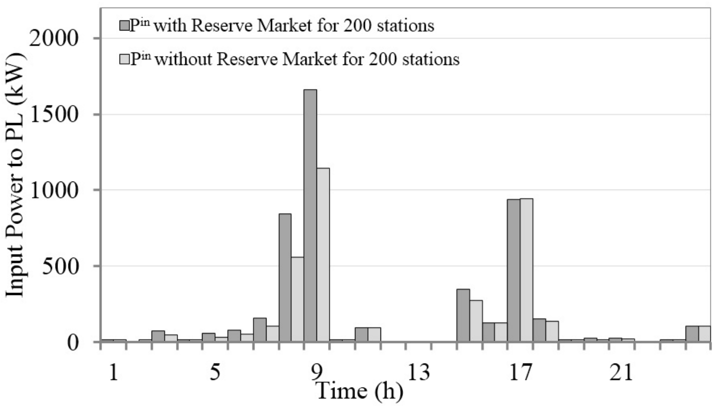

Figure 6.7: Comparison of PL input power in cases 1 and 2.

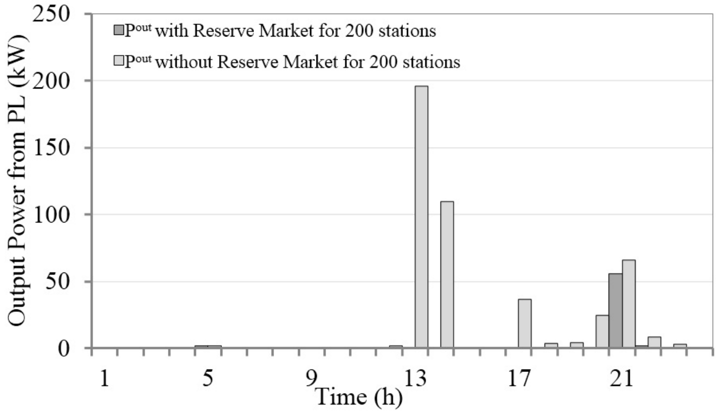

Figure 6.8: Comparison of PL output power in cases 1 and 2.

a PL installation profitable to the owner apart from governmental incentives, it is better to rely on PL storage as a reserve element than as an energy source.

Moreover, studies are conducted at this stage for an increasing number of available stations at the PLs, from 50 to 400. However, as it can be seen in figure 6.9, from a certain number of stations, the amount of profit is saturated. This implies that a higher number of stations does not specifically produce a higher profit for the PLs owner. In case 1, where both energy and reserve markets exist, with more than 330 stations, no more profit is gained. As a result, the rest of the study is conducted for numbers between 50 and 250 in order to make sure that the behavior of the PLs is not affected by the saturation in the profit.

6.5.2 PL Allocation

At the second stage, three different allocation objectives are defined, including grid power loss, network reliability, and bus voltage deviation. In each of these case studies based on a network-constrained objective, a cost function has been defined. The purpose of the DSO is to minimize the cost of each objective. The assumption in all cases is that there are two kinds of renewable resources (wind and PV) at bus number 680 simultaneously. Moreover, it is assumed that, except for buses 650 and 632, all other buses can be candidates for PL allocation. The cases are studied for an increasing number of available charging stations: from 50 up to 250. No limitation has been

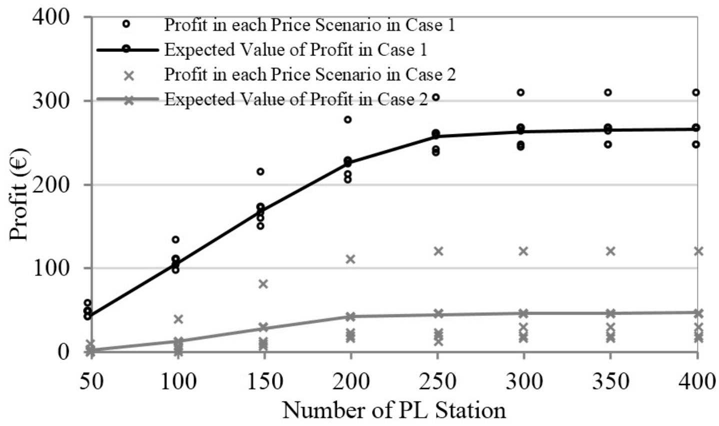

Figure 6.9: PL profit comparison in the two cases.

applied to the problem for the possible number of buses that can be selected for installing PLs. As a result, based on the number of available stations, the model decides how many locations should be selected to keep costs at a minimum level as well as installing the predefined number of stations. However, the maximum amount of possible power injection from each PL into the grid is limited to 1 MW, based on [151]. The results are obtained solving the problem with individual objectives as well as concurrently. The distribution of PLs at the network buses is shown in Figs. 10 to 12 for each individual objective. The overall solution for the three objectives is shown in figure 12 for a PL with 200 stations.

6.5.2.1 Case I: Power Loss Cost Minimization

In figure 6.10, the selected buses and the number of stations in each PL are shown for the grid power loss cost function. As can be observed, bus number 633 is the preferred choice for installing a PL. This is probably due to the load-like behavior of PLs. Considering the distribution of loads, the major loads are located in the lower half of the system. As a result, extra loads, such as PLs, tend to be placed in the upper section of the system. However, as seen in figure 6.4, the model mostly locates PLs at buses near an energy resource. This is more obvious when the number of stations increases. In figure 6.10 (d) and (e), it is shown that the third location for installing a PL is at the same bus as the RERs.

6.5.2.2 Case II: EENS Cost Minimization

To determine PL locations with a reliability cost function, it is assumed that the PL operator has a secondary contract with the PEV owners who can use the excess amount of their SOCs in case of a contingency. This means that, when a contingency occurs, the PL operator will be able to inject more power into the grid to help the DSO to minimize its EENS costs. In addition, a PL will not charge the PEV batteries during a contingency but will use the remaining SOC up to the limit defined in the secondary contract with the PEV owners. This situation results in the distribution of PLs as in figure 6.11. Differently from the grid power loss case, when the objective function consists of minimizing reliability costs, the lower section of the network is mostly selected for PL locations. The reason is that, when a contingency occurs, the DSO tries to use each possible resource in the system to reduce the amount of energy that cannot be served. In this

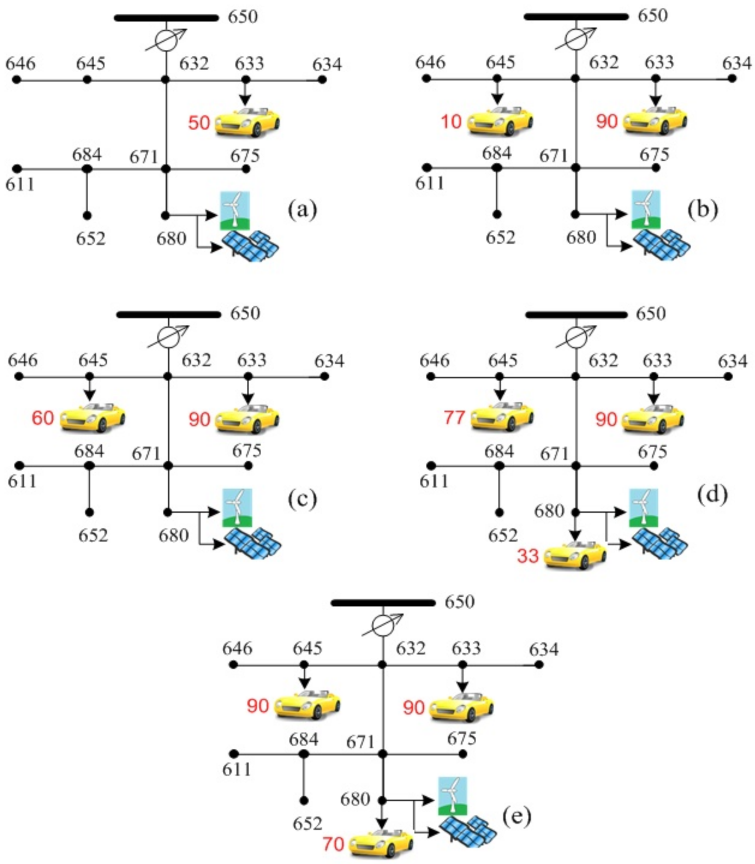

Figure 6.10: PL distribution in the network with a loss cost function: (a) 50 stations; (b) 100 stations; (c) 150 stations; (d) 200 stations; (e) 250 stations.

case, according to the aforementioned assumptions, the PLs are considered as resources that can supply part of the isolated load.

The results show a reduction in the amount of EENS in the system (figure 6.12). Although the PL owner has to spend more money because of the secondary contract (which means it will buy PEV's excess SOC at a higher price than in normal condition), this is still profitable for the DSO. This can serve as a guide for designing incentives to encourage investors to install PLs also considering contingency situations.

Based on figure 6.12, in a system with PLs and no RERs, a lower number of stations at the PLs may increase EENS as PLs act mostly as loads in the system. However, with an increase in the number of stations, EENS can decrease significantly. Figures 6.13 and 6.14 show the costs imposed on the system for enhancing reliability. Although the total system cost (including the DSO and the PL owner) has increased, the DSO cost for reducing the amount of EENS has decreased, see figure 6.14. This shows that not only PLs are useful for enhancing reliability, but also they have positive interactions with RERs. This proves that PLs are fundamental element towards sustainable energy systems. Adding PEV-based PLs to renewable-based electric systems can bring in major improvements to the system, such as reliability.

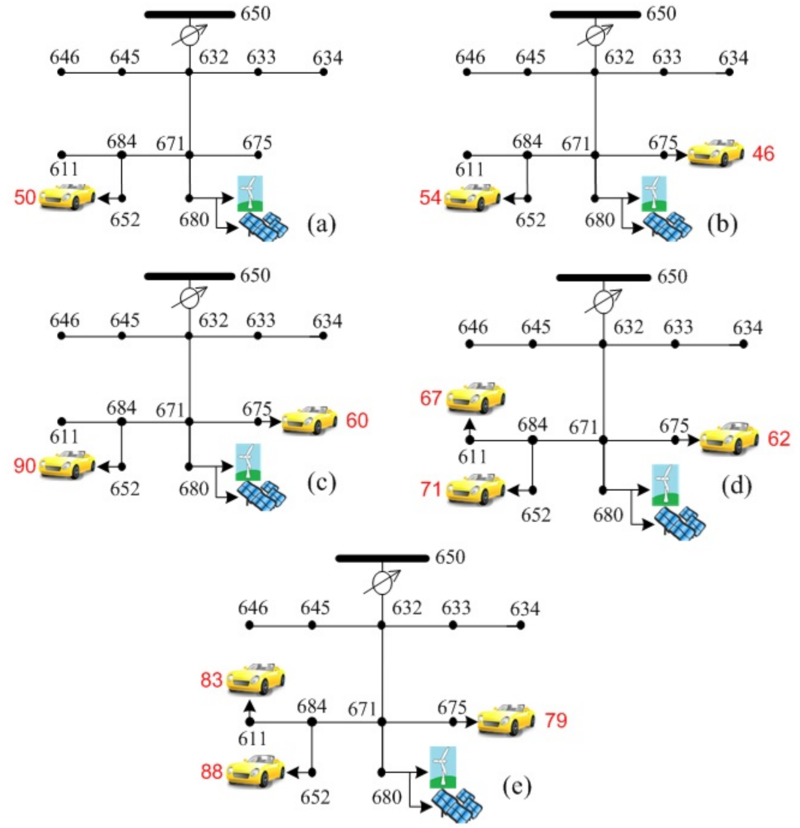

Figure 6.11: PL allocation with a reliability cost function: (a) 50 stations; (b) 100 stations; (c) 150 stations; (d) 200 stations; (e) 250 stations.

6.5.2.3 Case III: Voltage Deviation Cost Minimization

The study examines PL allocation with a voltage deviation cost function. It is assumed that a capacitor will be installed at the same bus where voltage deviates to overcome this problem. Cost data for installing the appropriate capacitor are obtained from [152]. As mentioned before, PLs behave mostly load-like; therefore, the results show that it is better to locate PLs in the upper section of the network, as seen in figure 6.15. This is due to the topology of the network and lines' current limit.

According to the test system data, the line between buses 632 and 671 has the highest current limit in the system. Hence, if more loads are added to the lower section of the network, more voltage deviation may occur at those buses. As it is shown, with a higher numbers of stations, there is a tendency to allocate the PLs at buses with shorter line lengths and lower current limits. One thing should be noted in studying the results in figure 6.15.

As it is shown, the location of a PL with 50 stations differs from the other results. This is due to the behavior of the PL with various numbers of stations. As mentioned before, PLs mostly behave like loads, but also have the capability of injecting power into the grid. With a PL with 50 stations, the amount of load that is added to the system is still lower than the system's peak load. Therefore, it does not cause the voltage to deviate. However, when the number of stations is higher, the approach is different and the allocation will be done in order to reduce the voltage deviation.

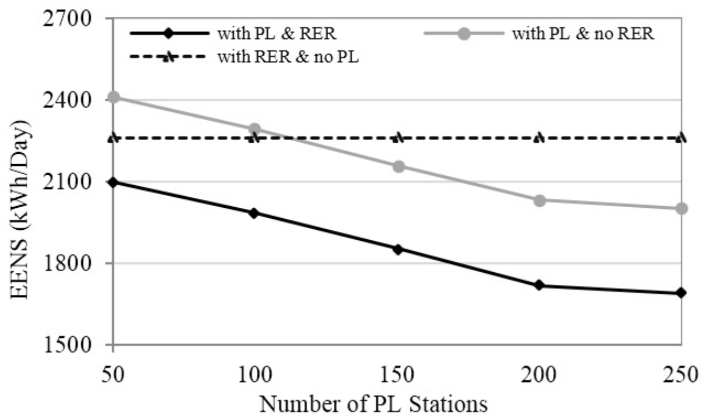

Figure 6.12: EENS for various numbers of PL stations.

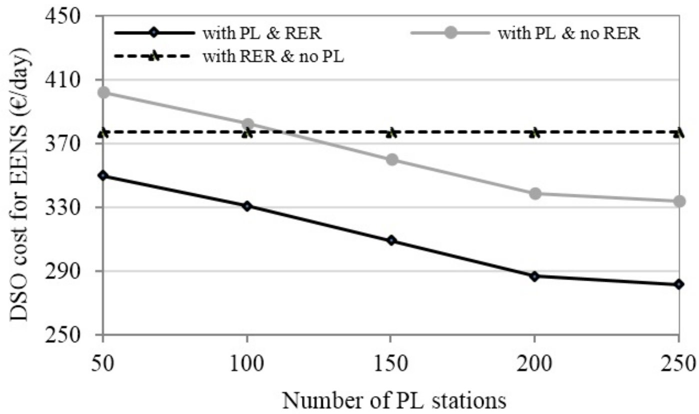

Figure 6.13: DSO cost for EENS only.

6.5.2.4 Case IV: Total Cost Minimization

For the last case study, the overall system's cost minimization is conducted. In this case, all three objectives (loss, reliability, voltage deviation) are solved simultaneously. The selected buses for PL installation with 200 stations are shown in figure 6.16. Moreover, the objective function for each of the individual objectives in both the individual and the collective cases is compared in Table 6.1. By comparing the locations of the PLs in all cases, the locations that are chosen for the individual reliability study are similar to the ones obtained in the collective case. However, comparing the objective functions, there is a change in the amount of the objective function. This indicates that the buses have higher sensitivities to the reliability index of the problem. The same conclusion can be obtained for voltage deviation.

Table 6.1: Results for each Objective Function

		Individual optimization	Overall Optimization
Objective (€)	Loss	437	440
	Reliability	420	432
	Voltage Deviation	105	120
Location	Loss	633,645,680	646,652,675
	Reliability	611,652,675	
	Voltage Deviation	633,645,646	

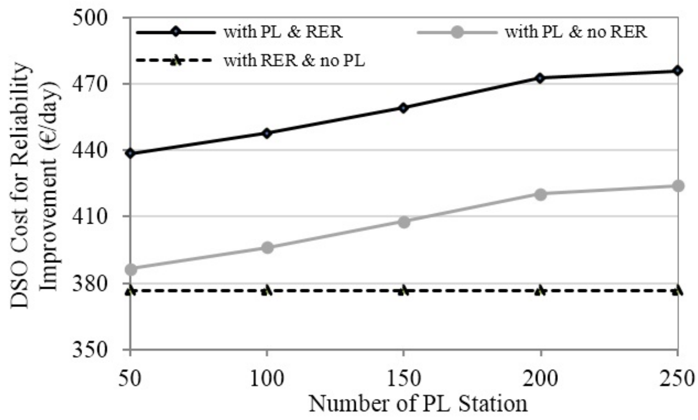

Figure 6.14: Total system cost for reliability improvement.

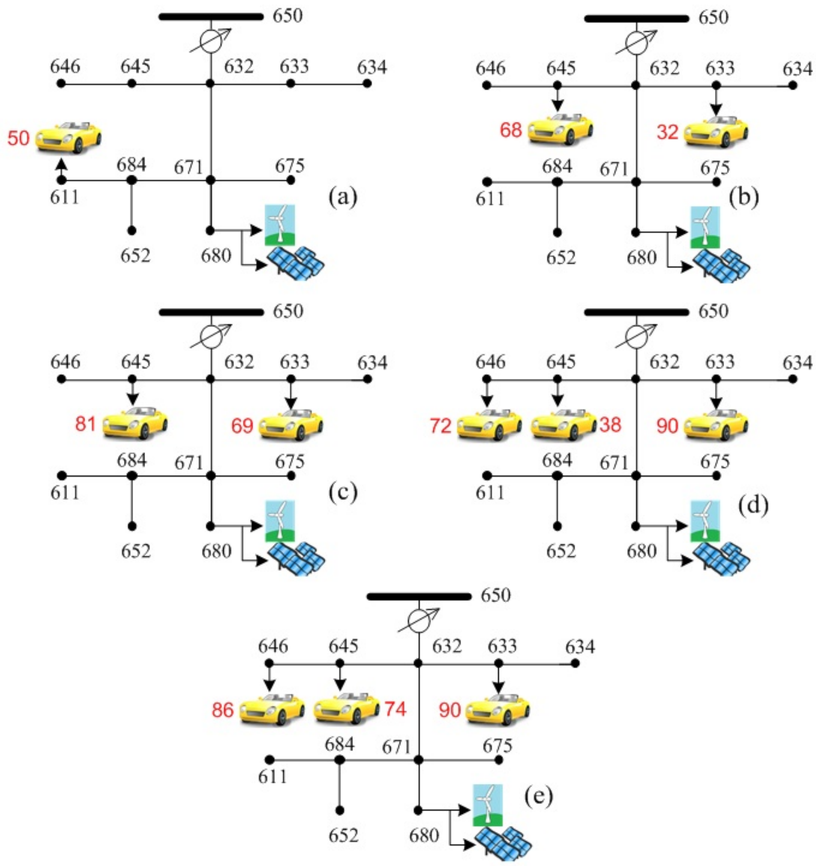

Figure 6.15: PL allocation with a voltage deviation cost function: (a) 50 stations; (b) 100 stations; (c) 150 stations; (d) 200 stations; (e) 250 stations.

6.6 Chapter Summary

In this study, various cases of PL integration in a distribution network have been studied. Interconnecting resources in the network has effects on the system that should be carefully examined. A holistic view towards PL allocation has been presented. On one hand, PL installation should fulfill different traffic or urban considerations. On the other hand, installing numerous charging stations at a PL may cause problems for the electric system. In this study, it is assumed that different regulatory conditions or urban considerations will address the installation of various numbers of

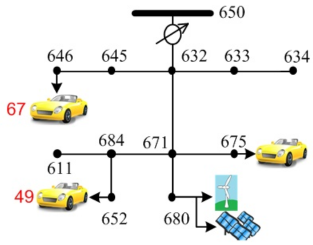

Figure 6.16: PL allocation with a total cost function.

stations in the system. As a result, the problem is solved for an increasing number of available stations. The results show that a PL, due to its nature as a charging station, will behave more likely like a load in the system. However, in certain situations, the V2G mode can be used and the PL will act as a resource in the system. When optimizing the market behavior of PLs, it is concluded that when the PL owner participates in the reserve market instead of the energy market, this can be more profitable because the V2G costs are avoided. Also, more revenue from PEV owners can be obtained due to a higher SOC that will remain in the PEV batteries. Regarding network-constrained objectives, despite the low costs of V2G for PL owners, the DSO can profit significantly from the presence of PLs in the system, not only to reduce its EENS costs, but also to improve system reliability. PLs' interaction with the grid greatly affects the allocation of PLs in the network. Moreover, the overall solution considers all the objectives simultaneously, suggesting that the sensitivity of each bus to each objective imposes the right location of the PLs. In this study, it was shown that an optimal allocation of PLs can produce a significant profit for the DSO when considering reliability criteria.

Chapter 7

Integration of the PEVs PL in the multi-energy system modeling

7.1 Introduction

The multi-energy systems contain key resources driving the evolution of the future systems. However, making MES consistent with all the possible components of the future systems is challenging and requires in-depth studies. The future energy systems should be provided with various facilities to encourage the electric vehicle manipulation. The adequate foreseeing of charging stations compatible to the number of PEVs in the system should be managed by system planners. As a result, the concept of PEV parking lots as an aggregated form of PEVs can provide a proper solution for charging the PEVs as well as establishing an interface for interactions of the PEVs with the grid.

On the other hand, the PEVs' owners' preferences and charging requirements as well as their daily traffic pattern can significantly affect the system operation. The amount of input energy to the PEV batteries and their potential of V2G participation is influenced by their traffic pattern. The interactions of PEV owners with their home-charging aggregators or public charging stations can change the amount of electricity demand for the multi-energy demand. Moreover, considering the PEV PL as a resource in the MES, the status of PEVs entering the PL and their SOC can change the behavior of PL as a resource in the MES operation. As a result, the traffic behavior of the PEVs has to be added to the demand management of a MES.

The intention of this chapter is to provide a comprehensive model for the integration of PEV facilities in the form of PL and aggregated charging stations in the MES. The results will investigate the charging behavior of PL and the strategy of MES operator in providing the demand. The hourly electricity provision of MES and the operation of various MES components (such as CHP) in response to changes in electricity demand (due to PEVs) are analyzed. In order to investigate the effect of PEV owners preference and traffic pattern on the operation of MES, the commuting of PEVs between two micro MEs is considered as the factor affecting the amount of electrical load for the multi-energy demand.

7.2 Problem Description

As the PEVs are inevitable components of the future energy systems, in this study the infrastructure for the charging need of these vehicles is added to the MES model. It is assumed that in a MES serving a MED, the PEVs are owned by the end-users in the MED and can be charged in the charging stations provided on the demand side (presumably residential area) which are referred as Home charging (HC) stations. For commercial purposes, a PEV PL is embedded in the MES. The PL can act as storage in the system deploying the potential of PEV batteries. However, it should be considered that the operation of charging stations on the demand side and the PL's charging strategy causes a dependency between these two elements of the MES. On the other hand, the travel statistics of the PEVs and their consumption pattern also affect PL operation. In figure 7.1 the MES model considered for this study and its components are shown.

As seen in figure 7.1, the PL is considered as a resource in the micro MES while the charging stations (ChS) has the characteristics of a load. Note that all of the PEVs will not be parked during the day and some of them are traveling which leads to energy consumption in their batteries. Therefore, these PEVs are also considered in the model as urban area PEVs which can also be seen in the model. As it is shown, the PL is added as a module to the micro MES while the HC is considered on the MED side. The difference between PL and HC is the traffic pattern of the PEVs that enter or leave them. The PEVs are staying in the PL during the working hours of the day, which makes the PL a potential resource consisting of the batteries SOC. On the other hand, the PEVs are in the HC during early hours in the morning or late at night, which makes it a proper place for charging the batteries in the hours when the energy price is lower. This difference between the patterns and their effect on the operation of the MES is studied.

To expand the idea and examine the further effect of the PEVs traffic pattern on the MES operation, two micro MESs are considered which have different consumption pattern. One of these MESs covers an area with the commercial consumption and the other one is dedicated to the area with residential usage. It is assumed that both of these MESs are equipped with CHP units, auxiliary boilers, heat storage, and photovoltaic unit and operated by a single operator. Each of the MESs serves multi-energy demand regarding the consumption pattern of the area which they cover (i.e., commercial or residential).

It is assumed that each of the MESs is a traffic zone for the vehicles. As the consumption pattern of these two micro-MESs are different, the behavior of the PEVs in them is accordingly different. The PEVs in the supposed model have the opportunity of charging their vehicles either in PEV parking lots or in urban charging stations available in the area. The PEVs PL can be available on both commercial building and residential complexes for PEVs who plan to stay for longer hours in the parking. Consequently, the PL operator will also take benefit from the PEV batteries' storage in the V2G mode to take part in the energy and reserve electricity market. On the other hand, for other PEVs who need a fast charging or have the estimation of a short stay in charging station, the individual charging stations in the urban area are embedded. As a result, the charging stations will only add an extra load due to the charging PEVs to the MED, while the PL other than the added load provide a storage resource for the system operator.

The main challenge is that the charging requirements of PEVs in these two areas are different due to the different traffic pattern of PEVs. Different driving pattern, parking duration, and travel distance in commercial and residential areas will form different load pattern for these two micro-MESs. On the other hand, considering the PEV PLs as storage in the energy hub model requires more accurate modeling of the PL's behavior in the charging/discharging of the PEVs. Addressing the contradictory effects of all these components in an energy hub approach is the main focus of this study.

In this study, it is assumed that the PEVs commute between the residential and commercial area is based on travel purposes. This means that the arrival and departure to or from each zone (micro-MES) is affected by the destination zone. For example, the arrival to the commercial zone is higher during working hours of the day while on the finishing hours of the day the arrival to the residential area will be higher and they stay during the night at residential zone. Moreover, it is assumed

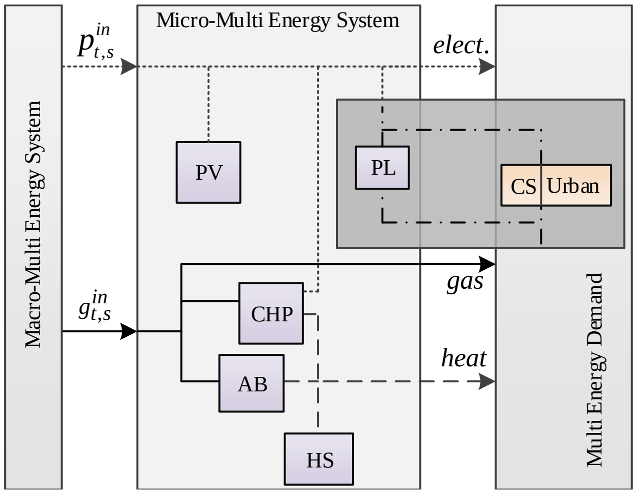

Figure 7.1: The integration of PEV traffic in PL and ChS with MES model.

that some of the PEVs may enter these zones from other micro-MESs which are aggregated in this model and considered as environment's commute. The PEVs from the understudy MESs can also leave for the environment.

On their arrival to a zone, the PEV owners have the choice of entering PL or ChS. Entering the PL is considered to be the first choice of the PEVs. Other PEVs who do not enter the PL keep driving in the area of enter the ChSs. The urban area is defined for those PEVs that are not in the PL nor ChS. When entering the PL, the PEVs owners specify their preferences by declaring their minimum SOC requirement on their departure. This will limit the PL's transaction with the grid while discharging the PEVs batteries and also assures the PEV owners of their adequate charging status for their next travel.

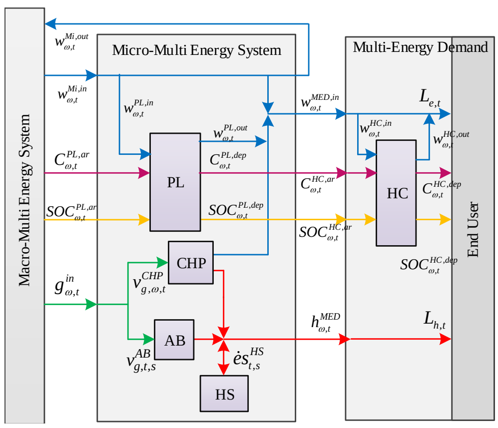

Figure 7.2: Schematic of micro MES with PL and HC.

7.3 Matrix modeling of MES with PL and HC

In this study, a micro multi-energy system is considered that serves multi-energy demand with the demand of electricity and heat. The micro MES consists of a CHP unit, an auxiliary boiler (AB), and a heat storage (HS). It is assumed that the PEV PL is added as a module to the micro MES while the HC stations are on the MED side.

As previously described in Chapter 3, the matrix modeling of the micro MES with storage and the possibility of injecting power to the upstream network can be modeled as presented in equation 7.1. It consists of the coupling matrices C and S representing the conversion due to energy converters in the MES and energy storages, respectively.

$$\begin{bmatrix} \mathbf{c}^{\mathbf{Mi}}_{\omega,\mathbf{t}} & \mathbf{s}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \end{bmatrix} \begin{bmatrix} \mathbf{p}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \\ \dot{\mathbf{e}}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \end{bmatrix} = \begin{bmatrix} \mathbf{L}^{\mathbf{MED}}_{\omega,\mathbf{t}} \end{bmatrix} + \begin{bmatrix} \mathbf{k}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.1}$$

In this section, the modification of the matrix modeling for the micro MES with additional PEVs' PL and HC formulated.

7.3.1 PL model in micro MES

When the PL is added as a module to the micro MES, the coupling matrix of the micro MES is going to be affected. The reason is that the ability of the PL to act as a resource in the system along with its capability to have the role of a storage will change the entries of the coupling matrix, the input vector, and the output vector. As a result, the matrix modeling of the micro MES with the PL will change as:

$$\begin{bmatrix} \mathbf{c}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} & \mathbf{s}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} \end{bmatrix} \begin{bmatrix} \mathbf{p}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} \\ \dot{\mathbf{e}}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} \end{bmatrix} = \begin{bmatrix} \mathbf{L}^{\mathbf{MED,new}}_{\omega,\mathbf{t}} \end{bmatrix} + \begin{bmatrix} \mathbf{k}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.2}$$

Due to the twofold role of the PL as a resource and a storage in the system, the entries in equation (7.2) are shown in:

$$\mathbf{c}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} = \begin{bmatrix} \mathbf{c}^{\mathbf{Mi}}_{\omega,\mathbf{t}} & \mathbf{c}^{\mathbf{Mi,PL}}_{\omega,\mathbf{t}} \\ 0 & \mathbf{c}^{\mathbf{PL}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.3}$$

$$\mathbf{s}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} = \begin{bmatrix} \mathbf{s}^{\mathbf{Mi}}_{\omega,\mathbf{t}} & 0 \\ 0 & \mathbf{s}^{\mathbf{PL}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.4}$$

$$\mathbf{p}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} = \begin{bmatrix} \mathbf{p}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \\ \mathbf{p}^{\mathbf{PL}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.5}$$

$$\dot{\mathbf{e}}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} = \begin{bmatrix} \dot{\mathbf{e}}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \\ \dot{\mathbf{e}}^{\mathbf{PL}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.6}$$

$$\mathbf{L}^{\mathbf{MED,new}}_{\omega,\mathbf{t}} = \begin{bmatrix} \mathbf{L}^{\mathbf{MED}}_{\omega,\mathbf{t}} \\ \mathbf{L}^{\mathbf{PL}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.7}$$

$$\mathbf{k}^{\mathbf{Mi,new}}_{\omega,\mathbf{t}} = \begin{bmatrix} \mathbf{k}^{\mathbf{Mi}}_{\omega,\mathbf{t}} \\ \mathbf{k}^{\mathbf{PL}}_{\omega,\mathbf{t}} \end{bmatrix} \tag{7.8}$$

Based on the above equations, the total conversion matrix for the micro MES with the PL will be as:

$$\begin{bmatrix} \mathbf{c^{Mi}_{\omega,t}} & \mathbf{c^{Mi,PL}_{\omega,t}} & \mathbf{s^{Mi}_{\omega,t}} & 0 \\ 0 & \mathbf{c^{PL}_{\omega,t}} & 0 & \mathbf{s^{PL}_{\omega,t}} \end{bmatrix} \begin{bmatrix} \mathbf{p^{Mi}_{\omega,t}} \\ \mathbf{p^{PL}_{\omega,t}} \\ \mathbf{\dot{e}^{Mi}_{\omega,t}} \\ \mathbf{\dot{e}^{PL}_{\omega,t}} \end{bmatrix} = \begin{bmatrix} \mathbf{L^{MED}_{t}} \\ \mathbf{L^{PL}_{\omega,t}} \end{bmatrix} + \begin{bmatrix} \mathbf{k^{Mi}_{\omega,t}} \\ \mathbf{k^{PL}_{\omega,t}} \end{bmatrix} \tag{7.9}$$

In order to derive the detailed format of the matrices, the interactions that occur within the micro MES should be considered. Referring to figure 7.1, it is shown that the inputs of the micro MES from the upstream network are electricity and gas energy carriers. However, the capacity and the SOC of the PEVs that enter the PL should be considered as the inputs of the micro MES as well. On the other hand, the level of SOC that is maintained in the PEV's batteries and the total capacity of the PEVs' batteries form the characteristics of the PL as a storage. Therefore, the complete format of the micro MES matrix model will be as:

$$\begin{bmatrix} 1 & v^{CHP}_{g,\omega,t}\eta^{CHP}_{e} & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & v^{CHP}_{g,\omega,t}\eta^{CHP}_{h} + v^{AB}_{g,\omega,t}\eta^{AB}_{h} & 1 & 0 & 0 & 0 & {}^{1}/\eta^{HS}_{\omega,t} & 0 & 0 \\ 0 & 0 & 0 & \eta^{PL}_{\omega,t} & 1 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} w^{Mi,in}_{\omega,t} \\ g^{Mi,in}_{\omega,t} \\ q^{Mi,in}_{\omega,t} \\ k^{PL}_{\omega,t} \\ SOC^{PL,ar}_{\omega,t} \\ c^{PL,ar}_{\omega,t} \\ \dot{q}^{HS}_{\omega,t} \\ \dot{C}^{PL}_{\omega,t} \\ s\dot{o}c^{PL}_{\omega,t} \end{bmatrix} = \begin{bmatrix} w^{MED}_{\omega,t} \\ g^{MED}_{\omega,t} \\ q^{MED}_{\omega,t} \\ soc^{PL,dep}_{\omega,t} \\ c^{PL,dep}_{\omega,t} \end{bmatrix} + \begin{bmatrix} w^{Mi,out}_{\omega,t} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{7.10}$$

In the complete format, the efficiency of the heat storage is included in the model based on the charging or discharging mode of the storage as shown in equation (7.11). The same approach is used for the PL in G2V/V2G mode as in equation (7.12).

$$\eta^{HS}_{\omega,t} = \begin{cases} \eta^{HS,cha} & \text{if Charge/Standby} \\ {}^{1}/\eta^{HS,dcha} & \text{if Discharge} \end{cases} \tag{7.11}$$

$$\eta^{PL}_{\omega,t} = \begin{cases} \eta^{PL,cha} & \text{if Charge/Standby} \\ {}^{1}/\eta^{PL,dcha} & \text{if Discharge} \end{cases} \tag{7.12}$$

The potential of the PL as an energy/reserve resource is obtained from the level of SOC that is maintained in the PEV batteries after the transactions of the PL (energy input to the PL and output from the PL). For this computation, the term $\kappa^{PL}_{\omega,t}$ is defined as in:

$$\kappa_{\omega,t}^{PL} = w_{\omega,t}^{PL,in} - w_{\omega,t}^{PL,out} \tag{7.13}$$

The amount of SOC that can be offered in the energy or reserve market in each hour is shown by $s\dot{o}c_{\omega,t}^{PL}$ which is the difference in SOC level in two consecutive time intervals (equation 7.14). In addition, the total available capacity in the PL that limits its maximum input power and consequently its stored energy is computed by equation (7.15).

$$s\dot{o}c_{\omega,t}^{PL} = soc_{\omega,t}^{PL} - soc_{\omega,t-1}^{PL} \tag{7.14}$$

$$\dot{C}_{\omega,t}^{PL} = C_{\omega,t}^{PL} - C_{\omega,t-1}^{PL} = C_{\omega,t}^{PL,ar} - C_{\omega,t-1}^{PL,dep} \tag{7.15}$$

There are other operational constraints that limit the interactions of the PL with the upstream network. The hourly input power to the PL cannot exceed the possible charging of the batteries which is calculated from the charging rate of the PL multiplied by the hourly number of PEVs in the PL (equation (7.16)). On the other hand, the output energy of the PL should not be lower than the possible discharging (based on the number of PEVs in the PL and the discharging rate) and the minimum PEV owners' requirement on their departure SOC (equation (7.17)).

$$w_{\omega,t}^{PL,in} \leq \gamma^{PL} n_{\omega,t}^{PL} \tag{7.16}$$

$$w_{\omega,t}^{PL,out} + r_{\omega,t}^{PL} \leq min\{\gamma^{PL} n_{\omega,t}^{PL}, soc_{\omega,t}^{PL} \phi^{PL}\} \tag{7.17}$$

The SOC in the PL is limited by the maximum and minimum possible SOC of each PEV in ratio to its capacity.

7.3.2 HC model in MED

In this study, it is assumed that the individual charging stations are provided in the system; however, they are aggregated and operated by a single MED operator.

In the system depicted in figure 7.1, the MED consists of the end-users with the energy need of electricity and heat. Therefore, the matrix modeling for the input to the MED and the delivered service to the end-use for a MED without HC is defined as:

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} w_{\omega,t}^{MED,in} \\ q_{\omega,t}^{MED,in} \end{bmatrix} = \begin{bmatrix} W_t^{user} \\ Q_t^{user} \end{bmatrix} \tag{7.18}$$

When the HC is added to the MED, the arrival capacity and SOC to the HC will be added as the inputs of the MED to the input matrix. The complete matrix format for MED including all the

HC interactions is shown in:

$$\begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \eta_{\omega,t}^{HC} & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 1 & -1 & 1 \end{bmatrix} \begin{bmatrix} w_{\omega,t}^{MED,in} \\ g_{\omega,t}^{MED,in} \\ q_{\omega,t}^{MED,in} \\ k_{\omega,t}^{HC} \\ SOC_{\omega,t}^{HC,ar} \\ c_{\omega,t}^{HC,ar} \\ \dot{C}_{\omega,t}^{HC} \\ s\dot{o}c_{\omega,t}^{HC} \end{bmatrix} = \begin{bmatrix} W_{\omega,t}^{user} \\ Q_t^{user} \\ soc_{\omega,t}^{HC,dep} \\ c_{\omega,t}^{HC,dep} \end{bmatrix} \tag{7.19}$$

Following the same approach as the PL, the detailed description of each entries in (20) are shown in the following equations:

$$\eta_{\omega,t}^{HC} = \begin{cases} \eta^{HC,cha} & \text{if Charge/Standby} \\ 1/\eta^{HC,dcha} & \text{if Discharge} \end{cases} \tag{7.20}$$

$$\kappa_{\omega,t}^{HC} = w_{\omega,t}^{HC,in} - w_{\omega,t}^{HC,out} \tag{7.21}$$

$$s\dot{o}c_{\omega,t}^{HC} = soc_{\omega,t}^{HC} - soc_{\omega,t-1}^{HC} \tag{7.22}$$

$$\dot{C}_{\omega,t}^{HC} = C_{\omega,t}^{HC} - C_{\omega,t-1}^{HC} = C_{\omega,t}^{HC,ar} - C_{\omega,t-1}^{HC,dep} \tag{7.23}$$

$$w_{\omega,t}^{HC,in} \leq \gamma^{HC} n_{\omega,t}^{HC} \tag{7.24}$$

$$w_{\omega,t}^{HC,out} + r_{\omega,t}^{HC} \leq min\{\gamma^{HC} n_{\omega,t}^{HC}, soc_{\omega,t}^{HC} \phi^{HC}, W_{\omega,t}^{user}\} \tag{7.25}$$

7.4 Case-Studies

The model proposed in this study is tested on the micro MES schematically illustrated in figure 7.1. It is assumed that the CHP unit, AB, and HS are operated within the micro MES and has the characteristics as described in [13]. The PL which is added to the micro MES is considered to have 180 stations with fast charging rate of 11 kW/h. The charging stations installed in the HC have slow charging equipment with the rate of 7 kW/h. In order to implement the different PEV behaviors in the model, five different scenarios are considered for arrival to and departure pattern from PL and HC, which are shown in figures 7.2 and 7.3, respectively. It is assumed that the traffic pattern in the model is unidirectional, which means that the PEVs enter the micro MES directly to PL or HC and do not have travels within the micro MES. The problem is modeled as a mixed integer linear programming (MILP) problem and is implemented in GAMS utilizing the CPLEX12 solver.

In this chapter, 4 case studies are designed for studying the proposed model and examining its efficiency:

- Case I, where only the PL is added to the model;
- Case II, where only HC stations are available in the model and no PL is provided;
- Case III, where both PL and HC are added to the model and a traffic flow between these two elements is considered;
- Case IV, where the flow between two micro MES is considered
  - Individual operation of PEV Aggregator and MES;
  - Coordinated operation of PEV Aggregator and MES

7.4.1 Case I: micro MES with PL and no HC

In this case, the only charging possibility for the PEVs in the system is the PL. It is assumed that the PEVs enter the PL based on the pattern derived in Chapter 4. The electricity balance for the micro MES in this case is illustrated in figure 7.3. As it is shown, the PL charges the PEVs mainly on their arrival (hours 8-10) and before their departure (hours 17-20). However, the PL does not participate in the energy interaction and its strategy is to make profit through reserve participation with its SOC. On the other hand, the CHP can sell the excess of its production to the upstream network.

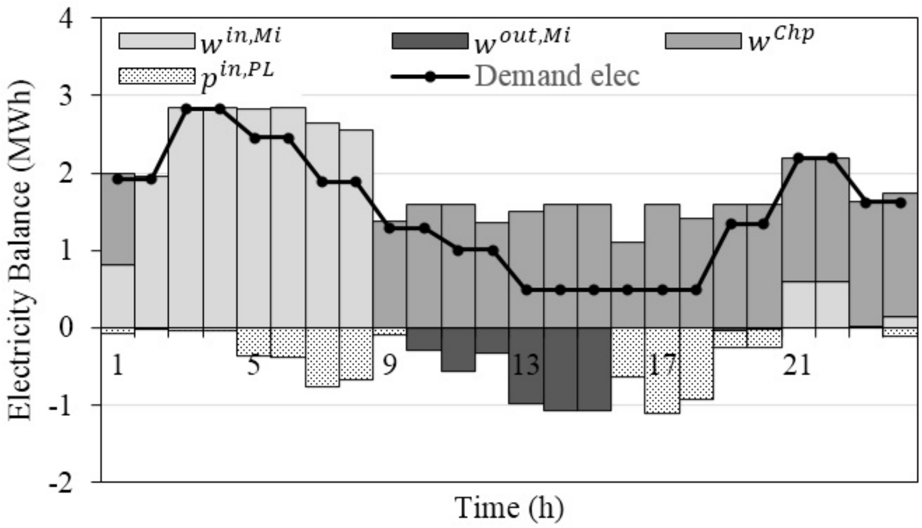

Figure 7.3: Electricity balance in micro MES components in case I.

7.4.2 Case II: micro MES with HC on MED and no PL

In this case, the impact of HC on the MED and electric demand is investigated. The results for the electricity balance of the MED is shown in figure 7.4. The electric demand is increased significantly due to the PEVs' charging requirements and this increase in the demand follows the traffic pattern of the PEVs' arrival to or departure from the HC stations.

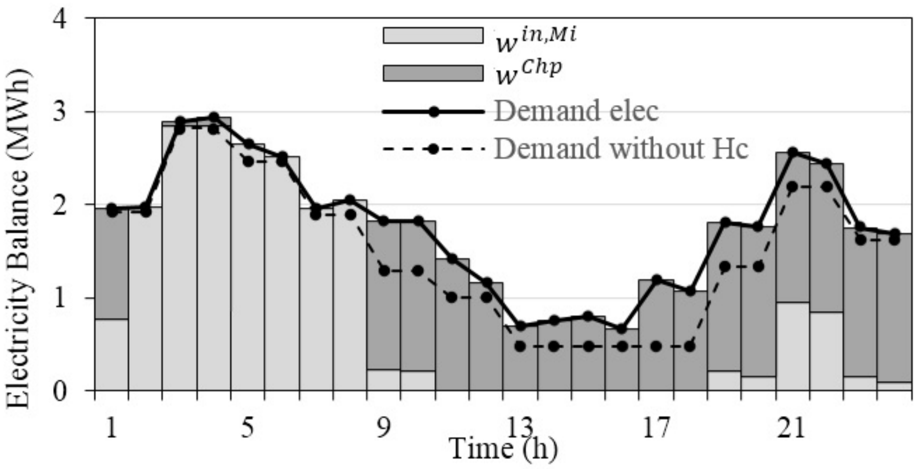

Figure 7.4: Electricity balance in micro MES components in case II.

7.4.3 Case III: micro MES with PL and HC

In this case, both PL and HC are added to the model and a traffic flow between these two elements is considered to occur. It is assumed that a certain percentage (α %) of the PEVs that depart from the PL enters the HC and the rest of the PEVs will not be plugged-in while they are not in the PL. The results for the electricity balance of the micro MES for α=80% is shown in figure 7.5. Here, the input of the HC is shown separately from the electric demand for better comparison of the PL and HC behavior. As it is shown, in this case both PL and HC benefit from participating in reserve market rather than the energy market. The reason is that in this situation they can make a profit from both selling the power to the PEVs as well as receiving the income from participating in the reserve market.

The comparison of costs in the three cases and the base case where no PL or HC is existing is presented in Table 7.1. The reserve profit is the profit gained by the MES operator through taking part in the reserve market with the SOC of the PEVs (whether in PL or HC). The PEV profit is the profit gained through selling energy to the PEV owners for charging their batteries. It can be deduced that the least cost operation of the system can be achieved in Case III where both HC and PL are available. In this situation, not only the preferences of the PEVs and their charging requirements can be fulfilled, but also a better scheme for operation of multi-energy resources can be obtained. It also proves that the profit from the available reserve in the PL and HC can be beneficial enough to reduce the costs imposed by the added load of the PEVs in the MES.

Table 7.1: Cost Profit Analysis

	Base Case	Case I	Case II	Case III
Reserve Profit	nan	454.51	285.75	744.46
PEV Profit	nan	324.55	298.07	341.53
Utility Cost	-3479.3	-3768.06	-3765.02	-3787.93
Total	-3479.3	-2988.96	-3181.19	-2701.93

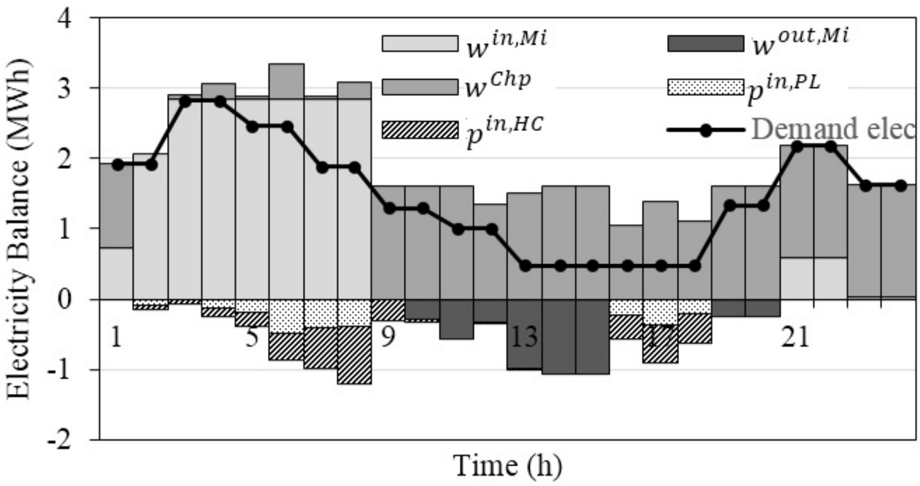

Figure 7.5: Electricity balance in micro MES components in case III.

7.4.4 Case IV: Mutual effect of two micro MESs with PL and HC

For integrating the commute of PEVs fleet and the investigate the impact of traffic patterns and the dependencies they cause between the carriers, this case study is designed. Two micro MESs are considered which have different consumption pattern. One of these MESs covers an area with the commercial consumption and the other one is dedicated to the area with residential usage. It is assumed that both of these MESs are equipped with CHP units, auxiliary boilers, and heat storages and are operated by a single operator. Each of the MESs serves multi-energy demand regarding the consumption pattern of the area which they cover (i.e., commercial or residential).

As shown in 7.6 the micro-MES # 1 covers a residential area while micro-MES # 2 is dedicated to a commercial zone. It is assumed that MES # 2 is also equipped with PV generation. The illustration of the commute between micro-MESs and the exchanged SOC as well as the interaction with the upstream network are shown in the figure.

7.4.4.1 Individual operation of PEV Aggregator and MES

In this case it is assumed that the PEV aggregator autonomously participates in the energy and reserve market to provide the required energy for the PEVs in the system. On the other hand, the micro-MESs operator also operates its components to supply MED. The total input of electricity for PEV aggregator and the MES operator should not exceed the limit of the transformer in the system. The electricity balance for both micro-MESs are shown in figures 7.7 and 7.8. As it is observed, the total production of the CHP unit and input electricity in this case matches the total MED electric load. In these figures Win shows the total electrical energy input to the micro-MESs.

7.4.4.2 Coordinated operation of PEV Aggregator and MES

In this case, the PEV aggregator and the MES operator merge as a single operator who provides energy through two micro-MESs for the PEVs and MED. The operator can take benefit from various elements in the system to manage the best strategy of charging/discharging its PEVs as

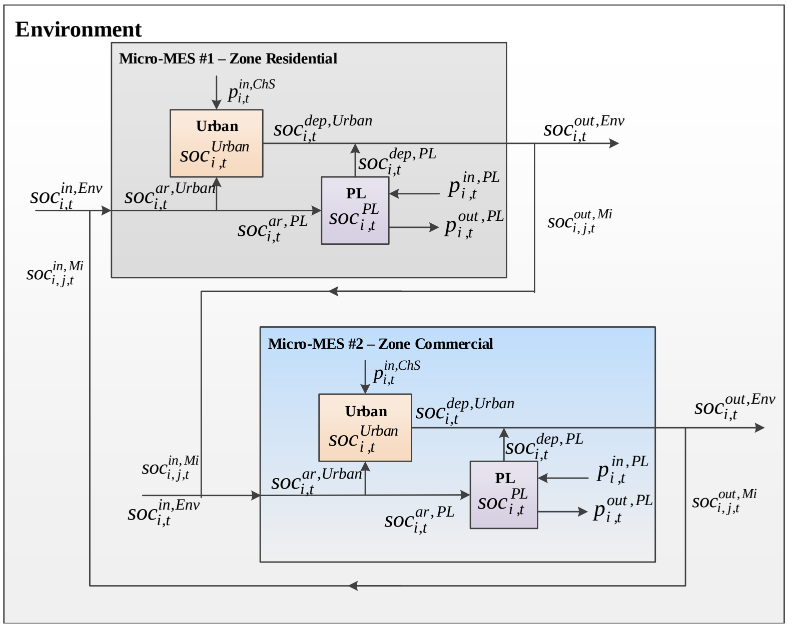

Figure 7.6: The integration of PEV traffic in PL and ChS with MES model.

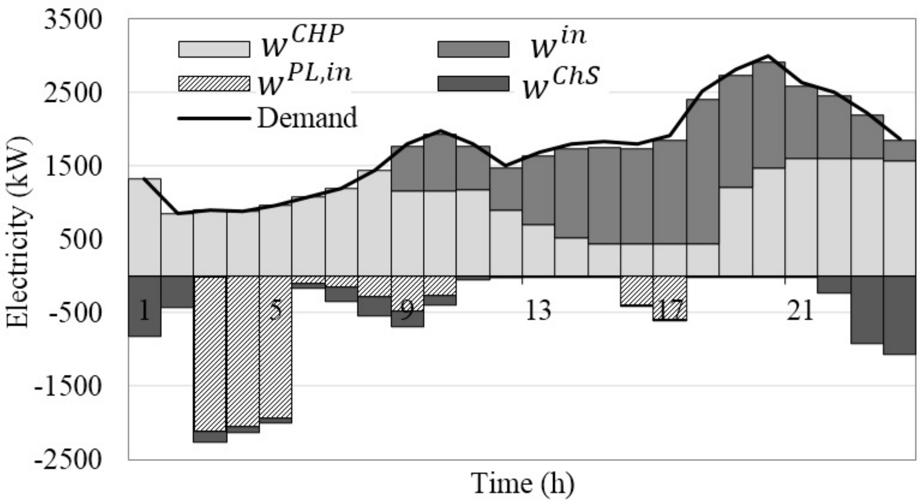

Figure 7.7: Electricity balance for micro-MES # 1 in Case I.

well as reducing the operational cost of the system. The results for the electricity balance in two micro-MESs are shown in figures 7.9 and 7.10. It shows that in this case, the production of the CHP has significant changes comparing to Case I. Moreover, the amount of input energy is also increased due to the extra added load of PEVs.

The operation of the PL also changes in this case. The variation in the PL operation is more considerable in micro-MES # 2. As shown in figure 7.11, the production pattern of PV is similar to the peak hours of PL. Therefore, the PL's charging pattern during hours 10 to 15 is increased without increasing the input electrical energy. Moreover, the PV and the CHP unit has lower marginal cost rather than the upstream electricity market. As a result, the PL purchases the energy produced by PV and CHP unit to charge its PEVs. As in this case the operation of CHP is increased, the heat balance for two micro-MESs are also investigated and shown in figure 7.11. The increased production of the CHP due to PEVs load affects the operation of auxiliary boiler in both cases. The heat demand is covered by the CHP instead of AB. These changes in the operation

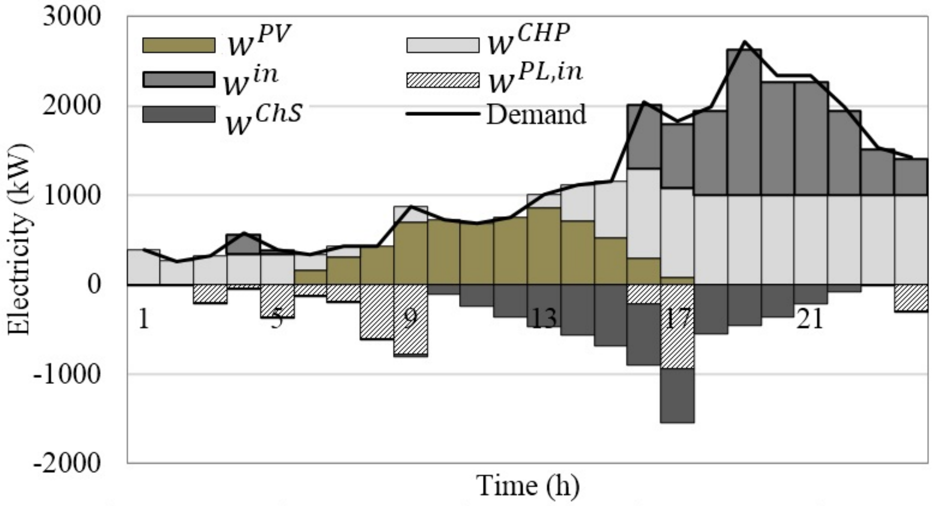

Figure 7.8: Electricity balance for micro-MES # 2 in Case I.

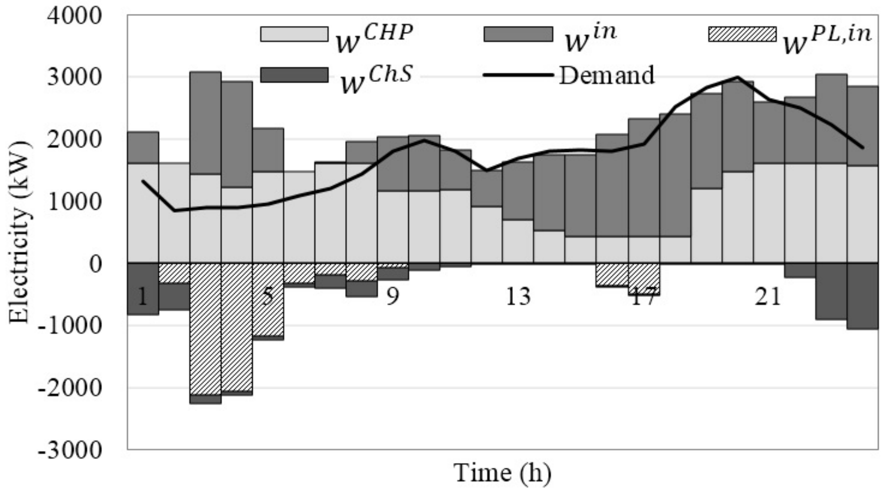

Figure 7.9: Electricity balance for micro-MES # 1 in Case II.

strategy of the MES will lead to a cost reduction of 1.5% for operating MES Case II. Although the cost of the PEVs charging is increased in this case comparing to Case I due to more charging in the PL, the profit of the PL also increases due to higher level of SOC and higher income through participation in reserve market with more SOC.As a result, the total cost is reduced.

In other words, the micro-MES has a variable marginal cost for 24 hours which is due to various energy resources in the system. The dependency between the energy carriers, the uncertainty of production for the renewable resources, and the demand for a certain type of energy affects the marginal cost of each resource in the micro-MES. In this situation, the presence of PEV PL provides a degree of freedom and brings new levels of flexibility for the MES operation. The concept of the PEV PL that can act as a storage in the system enables the MES operator to store the production of its resources. This cross impact of the PEV aggregation and MES resources increases the operational flexibility and enhances the market participation strategies.

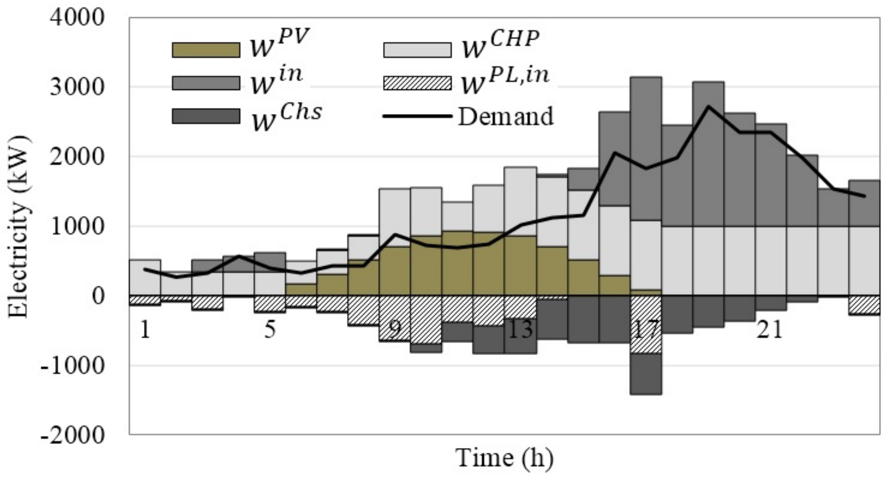

Figure 7.10: Electricity balance for micro-MES # 2 in Case II.

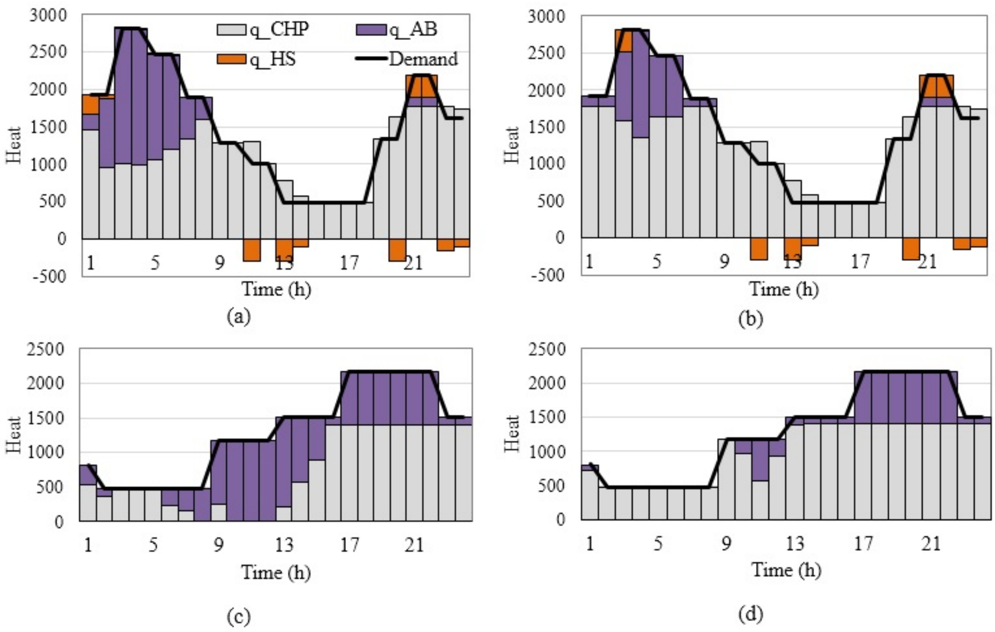

Figure 7.11: Heat balance comparison between two micro-MESs in two Cases: (a) and (c) heat balance in Case I in micro-MES 1 and 2, respectively; (b) and (d) heat balance in Case II in micro-MES 1 and 2, respectively.

7.5 Chapter Summary

In this chapter, an operational model is proposed to integrate the effects of the PEVs traffic pattern on operation of PEVs PL and ChS within the concept of multi-energy systems. The PEVs traffic pattern is included in the matrix modeling of the MES with two charging options within the MES environment: the PL and HC. The effect of the charging needs of the PEVs on the electric demand as well as the effects that it can have on the operation of the micro MES components is investigated. Moreover, the PEVs are considered as the components of the MES better operation strategies can be obtained by the system operator which leads to cost minimization. The results indicated that the purpose of the PEV travels affects the electrical load pattern which should be provided in the system. The availability of the PL and HC, the inevitable added load of PEVs in the future system can be best managed using the internal resources of the MES such as CHP unit. This will not only lead to the satisfaction of the PEV owners but also provide the MES operator with higher levels of profit due to better manipulation of MES resources.

Chapter 8

Conclusions

In this chapter the main conclusions of the thesis are highlighted on the basis of answering the research questions that constituted the main motivation of this research. Then, several points to guide future research are proposed. Finally, the publications of the Author are listed.

8.1 Main Conclusions

The results presented in this thesis allow for answers to be given to the research questions that were initially posed in Section 1.2.

- *How a multi-energy environment can provide the scheme for the multi-energy demand to use the demand side facilities and contribute in the system operation strategies?*
  In a typical multi-energy system, various components of distributed energy resources such as DG, distributed storages and conventional DR programs may exist. Assume that in such system the multi-energy demand is enriched with the technologies that can have various energy carriers as an input and convert them to required services. These converters are located on demand side and are apart from those internal converters that MES may contain. For better comprehension, assume that MES covers a residential urban area. In this case, some DGs such as diesel engines, CHP units and storage units exist in the local network. However, on the demand-side there exist devices that benefit from the multi-carrier input technology. Therefore, this technology will bring the opportunity for both demand-side and system operator to take benefit from it. In this situation, whenever one carrier has higher price compared to another one, the consumer may have the choice to select between two or more carriers to use as an input.
  On the other hand, the system operator will also be able to choose between various sources for supplying one certain service, which is beneficial during system emergencies or resource shortages, as well as high price intervals. Therefore the situation will cause a dependency on demand side. This dependency is due to the fact that the estimation of the demand and the required input resource will be dependent to the customer's choice of carrier. As this dependency occurs on demand-side, it is different from those dependencies that are within the local network system due to its internal converters such as CHP units. As a result it is called external dependency. All components of a local energy network in MES, as well as the dependencies occurred in the system (both internal and external), can be considered as DERs that can be employed by the MES operator in its operation or planning schedules for providing the customers need of energy.
  Based on the definitions, DR is the change in electric usage by end-use customers from their normal consumption patterns in response to various changes such as price, incentive payments, etc. Regarding this definition, the external dependency can be considered as a DR resource. This thesis proposes that the external dependency can be employed in the system

as resource to fulfill the customers' energy requirements. The approach towards this resource is proposed as a DR program called CBDR program. Activating the CBDR program in the system will not only benefit the end-use to enrich their level of participation, but also help the system operator to maintain a higher level of customer satisfaction by deploying their own potentials.

- *What are the uncertainties imposed by the vehicle owners' behavior to the PEVs' potential? How the preferences of the owners can be included in the mathematical model?*
  There are several aspects regarding the PEVs in the system. One of the most challenging issues in PEVs studies is their uncertainty. This uncertainty is initiated by the vehicle owners behavior in using their vehicles as well as the area the vehicles are traveling. The area under study and the average distance that each PEV travels affects the number of available PEVs in the system and their level of SOC. Moreover, the policies, rules, and regulation on encouraging the PEVs purchase also has effects on the public interest towards the PEVs. The traffic flow pattern in the area as well as the usage pattern of the area under study (commercial, residential, industrial, etc.) can have significant influences over the PEV fleet. This will eventually affect the electrical load pattern in the system. Hence, while studying the PEVs in the system and integrating them in a sensitive network such as distribution network, it is necessary to carefully model them in the problem.
  As mentioned, the initial state of charge, the distance traveled, the battery capacity, the speed of the vehicle, and the battery type affect the SOC of the PEV on their arrival to the PL or any charging stations. On the other hand, the charging rate of charging station, duration of stay, required departure SOC, and energy price are factors affecting the charging of the PEVs while they are parked at a station. The arrival/departure pattern of the PEVs to/from the PL or stations have an important influence on the total level of SOC in the PL or for the aggregator agent. The purpose of the PEV travels also affects the charging need of the PEVs. The reason is that their purpose defines the behavior of the owners on their consumption of the vehicles.
  In order to include the preferences of the PEVs in the mathematical model, this thesis proposed a series of coefficients derived from the real data surveys which can be used in different studies. These coefficients are as follows:

  1. Coefficient determining the share of each PEV category from hourly vehicle departure.
  2. Coefficient determining the share of each PEV category from total PEVs in the PL in each hour.
  3. Coefficient determining the minimum departure SOC requirement of each PEV category.

  By means of this coefficients and the hourly equivalent data presented in tables of Chapter 4, the preferences of the PEV owners which is one of main uncertainty of the PEVs' operation can be modeled.

- *How the market strategies can be designed with the availability of the PEVs in the system? What is a better choice in case of PEVs for participating in electricity market?*
  Through the comprehensive bilevel model that is proposed in this thesis,the equilibrium price of energy and reserve trade of PEV PL has been derived considering the preferences of the PEV owners. It is known that the PEVs are going to be an addition to the existing energy systems which are equipped with various resources, i.e., renewable resources, distributed gen-

erations, and DR programs from the demand side. On the other hand, in such environment with various components and complicated interactions, an organized inter-relation should be defined so that all the involved parties in this system could assure their own profit. As a result, the best strategy for participating the PEVs in the market can be designed in a multi-resource environment which has been the focus of this thesis.
From another point of view, it is proved that the aggregated form of the PEVs can have a better identification in system integration or market participation. However, the PEV PL with the unique opportunities that bring in the system has the best vision to compete with other resources in the system. The PEV PL not only has the advantages of aggregated PEV batteries, but also benefits from lower levels of uncertainty in comparison to the individual PEV aggregator.
Regarding the market participation of the PEVs, the proposed model in chapter 5 has comprehensively discussed the advantages of PEV PL in market interaction which can be summarized as:

1. It is shown that in the uniform pricing model where the LL components can have more flexibility the model is more effective and the equilibrium point is found in a more suitable way for all parties' profit. On the other hand, it is shown that in an environment with mixed resources, the model can provide the solution to compromise between all the potentials in the system;

2. It is shown that the equilibrium price is affected by various factors which may change the behavior of the players in the model. When the behavior is changed, the equilibrium price is going to be changed; however, the bilevel model is designed in a way that the optimum solution is found in this compromising situation;

3. Although the PL can be considered as a resource in the system, the compromise between the competitiveness of other resources in the system such as DGs and the expenses of V2G vehicles will lead to less tendency towards V2G mode operation. However, it was deduced from the study that the PL can provide various opportunities for the aggregator in terms of flexibility and increase the total profit. The aggregator can decrease the equilibrium price to increase its own share of the local market, triggering the load flexibility potential of the PL (increasing the quantity in lower level) which causes higher profit for both aggregator and PL;

4. It is deduced that the reserve price also had a critical role with which the aggregator controls the input energy to the PL and encourages the PL for purchasing more energy. From another point of view, other local resources have proved that they influence the problem. With higher levels of local resources penetration in the system, the equilibrium price can go as low as the marginal price of these resources, which affects the charging status of the PL as well.

Through this conclusions, it can be deduced that there is an inter-relation between various aspects of the PEV PL in the system. The tariffs assigned to the PEVs in the PL can be as effective as the energy/reserve price in strategy of the system operator in manipulation of its resources. However, the model proposed in this thesis can provide a proper platform for the system operators to estimate the best strategy.

- *What are the roles that can be assigned to the PEVs in a multi-energy system?*

The first impressions of electric vehicles were their charging needs in the electrical system and the load they add to the distribution grid. Later, by further studies on the subject, the V2G option of these vehicles has emerged to be considered as a resource in the system. Introducing massive integration of PEVs to the system through aggregator agents or PEV PL showed more possible impacts and benefits that the PEVs can cause in the system.
Moreover, although the PEVs' demand is only electrical, while being included in the multi-energy system, the charging of the PEVs should be scheduled compatible to the prospects of the MES and other resources in the MES. Therefore, not a single role is comprehended for the PEVs in the system, but a two-fold role can be assigned to them.
The operation of individual PEVs in the system scale is almost impossible due to high level of uncertainty. Therefore, an aggregated form of PEV (either through and agent or PL) is the main assumption. In this case, with the presumption of availability of V2G infrastructure, the PEVs not only will be the bulk load, but have the potential of act as a resource in the system. This role can be considered both for the commercial PLs or aggregated home-charging PEVs which belong to the multi-energy demand.
Regarding the energy hub approach, while only taking into account the micro-MES block, two main roles can be assigned to the PEV PL. The PEV PL can act as a storage in the system as well as having the characteristics of a converter in the micro-MES. From the studies in this thesis, it is deduced that the PEV PL can act as a converter which accepts electricity and traffic flow as the input carriers and gives out the electricity to the upstream network. This image of the PEVs and considering the PEVs traffic flow as a carrier in the MES has not been discussed in any previous works and is one of main contributions of this study. It should be noted that the home-charging PEVs can also be considered with the potential of having the role of storage/converter; however, due to the dominant need of charging while the PEVs are parked at home rather than discharging preference, this idea has not been developed in this thesis.

- *What are the solutions for the system operator to take benefit from the opportunities of the multi-energy system equipped with various resources as well as PEVs?*
  A MES with the presence of the PEVs will have higher levels of flexibility in the system. Although the PEVs will add to the total load that the MES should provide, they add to the flexibility of the MES through their flexible load and storage opportunities. When the PEVs are considered as the components of the MES better operation strategies can be obtained by the system operator which leads to cost minimization. Moreover, the MES operator can have the opportunity of matching renewable resources (if available) with the provided storage capacity by the PEV batteries. As the results of this thesis showed, the PEV usage pattern of the PL provide a proper storage pattern for storing the power generated by the PV arrays as both has their highest capacity during the day hours rather than night.
  The PL as the aggregated form of the PEVs batteries has more control on their charging/discharging schedule and can be considered as a resource in the system. Although in most cases the PL's strategy did not lead to injecting the energy saved in the batteries to the system, the profit gained by the participation in the reserve market can cover the cost of supplying energy for the PEVs. From another point of view, the PL operator can take benefit from higher level of charging which brings more income to the PL. The compatibility of resources production pattern with PL's operating hours as well as the flexible nature of the PL's operation help the system operator to provide a better operation of the system with reduced costs.

8.2 Outlook for the Future Works

The following points may be further studied in order to broaden the understanding of the topics treated in this thesis:

- This study has considered the allocation of the PEV PL in the distribution network. Further studies in this view can be conducted such as the reinforcement or expansion requirements of the network due to the addition of the PEV PL on network nodes.
- It is shown that the PEVs adds to the electrical load of the system. Therefore, it will change the load forecast of the system. This forecast can be performed either in short or long term perspectives. In short term the traffic pattern and behavior of the PEVs will affect the load estimation. In long term, the governmental incentives and policies in increasing the number of PEVs in the system as well as facilitating the charging infrastructure needed to be considered.
- The PEVs causes a time dependency as well as the carrier dependency in the multi-carrier system. The CBDR program proposed in this thesis can be developed considering the time-dependency of the PEVs in the system.
- The correlation and possible conflicts of the charging strategies between the PEV PL and PEV HC deserves further studies as the strategy of these two elements can significantly affect the total available capacity of the PEVs in the system.
- The effects of PL tariffs on PL's strategy in market participation has been shown in this thesis. For future works, the effect of these tariffs on the PEVs behavior in using the PL can be investigated.

8.3 List of Publications

The following Papers have been published or submitted in the course of the work on this thesis:

Journal Papers

1. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, G. Chicco, J.P.S. Catalão, "*Stochastic Modeling of Multi-Energy Carrier Dependencies in Smart Local Networks with Distributed Energy Resources*," IEEE Transactions on Smart Grid, Vol. 6, No. 4, pp. 1748-1762, July 2015.
   Impact factor: 4.252; Q1 (First Quartile) journal in ISI Web of Science and Scopus
2. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J. Contreras, J.P.S. Catalão, "*Allocation of PEVs' Parking Lots considering Network Constrained Objectives*," IEEE Transactions on Power Systems, Vol. 30, No. 5, pp. 2643-2656, September 2015.
   Impact factor: 2.814; Q1 (First Quartile) journal in ISI Web of Science and Scopus
3. M. Shafie-khah, **N. Neyestani**, M.Y. Damavandi, F.A.S. Gil, J.P.S. Catalão, "*Economic and Technical Aspects of Plug-in Electric Vehicles in Electricity Markets*," Renewable and Sustainable Energy Reviews (Elsevier), 2016. Impact factor: 5.901; Q1 (First Quartile) journal in ISI Web of Science and Scopus

4. **N. Neyestani**, M. Y. Damavandi, A. G. Bakirtzis, J.P.S. Catalão, "*PEV Parking Lot Equilibria with Energy and Reserve Markets Considering the PEV Owner Preferences*," IEEE Transactions on Power Systems.
   Impact factor: 2.814; Q1 (First Quartile) journal in ISI Web of Science and Scopus

5. **N. Neyestani**, M. Y. Damavandi, G. Chicco, J.P.S. Catalão, "*Effects of PEV Traffic Flows on the Operation of Parking Lots and Charging Stations*," Submitted to IEEE Transactions on Power Systems.
   Impact factor: 2.814; Q1 (First Quartile) journal in ISI Web of Science and Scopus

6. M. Y. Damavandi, **N. Neyestani**, M. Shafie-khah, J.P.S. Catalão, "*Aggregation of Demand Side Resources under the Concept of Multi-Energy Players as a Flexible Source in the Market Environment*," Submitted to IEEE Transactions on Smart Grid.
   Impact factor: 4.252; Q1 (First Quartile) journal in ISI Web of Science and Scopus

Book Chapters

1. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, "*Modeling Energy Demand Dependency in Smart Multi-energy Systems*," in: Technological Innovation for Collective Awareness Systems, Eds. L.M. Camarinha-Matos, N.S. Barrento, R. Mendonca, DoCEIS 2014, IFIP AICT 423, SPRINGER, Heidelberg, Germany, pp. 259-268, April 2014.

Conference Papers

1. **N. Neyestani**, M. Y. Damavandi, J.P.S. Catalão, "*Integrating the PEVs' Traffic Pattern in Parking Lots and Charging Stations in Micro Multi-Energy Systems*," IEEE UPEC 2016 Conference.

2. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, "*The effect of PEV's traffic behavior on Multi-Energy Demand's Dependency*," IEEE EnergyCon 2016 Conference.

3. M. Shafie-khah, M.H. Shoreh, P. Siano, **N. Neyestani**, M. Yazdani-Damavandi, J.P.S. Catalão, "*Oligopolistic Behavior of Wind Power Producer in Electricity Markets including Demand Response Resources*," Accepted for the 2016 IEEE Power & Energy Society General Meeting, PESGM 2016.

4. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, G. Chicco, J.P.S. Catalão, "*Stochastic Modeling of Multienergy Carriers Dependencies in Smart Local Networks with Distributed Energy Resources*," in Proc. of the 2016 IEEE PES Transmission & Distribution Conference & Exposition, T&D 2016, Dallas, Texas, USA, 2-5 May, 2016 (accepted).

5. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J. Contreras, J.P.S. Catalão, "*Allocation of Plug-in Electric Vehicles' Parking Lots in Distribution Systems Considering Network Constrained Objectives*," in Proc. of the 2016 IEEE PES Transmission & Distribution Conference & Exposition, T&D 2016, Dallas, Texas, USA, 2-5 May, 2016 (accepted).

6. **N. Neyestani**, M. Y. Damavandi, J.P.S. Catalão, "*Assessment of PEV Owners' Preferences Impact on PEV Parking Lot Transactions*," in Proc. of the 25th Australasian Universities Power Engineering Conference, AUPEC 2015 (technically co-sponsored by IEEE), Wollongong, Australia, USB flash drive, 27-30 September, 2015.

7. **N. Neyestani**, M. Y. Damavandi, J.P.S. Catalão, "*Analyzing the Effect of Various PEV*

Owner's Charging Tariffs on PEV PL's Market Equilibrium," in Proc. of the IEEE Region 8 International Conference on Computer as a Tool, EUROCON 2015, Salamanca, Spain, USB flash drive, 8-11 September, 2015. (attended the conference).

8. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, J. Contreras, "*PEV Parking Lot Behavior Equilibria in Energy and Reserve Markets*," in Proc. of the IEEE Power & Energy Society General Meeting, PESGM 2015, Denver, Colorado, USA, July 26-30, 2015.

9. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, "*Modeling the PEV Traffic Pattern in an Urban Environment with Parking Lots and Charging Stations*," in Proc. of the IEEE PowerTech 2015 Conference, Eindhoven, Netherlands, 29 June - 2 July, 2015.(attended the conference).

10. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, G. Chicco, "*Uncertainty Characterization of Carrier-Based Demand Response in Multi-Energy Systems*," in Proc. of the 5th International Conference on Power Engineering, Energy and Electrical Drives, PowerEng 2015 (technically co-sponsored by IEEE), Riga, Latvia, USB flash drive, May 11-13, 2015. (attended the conference).

11. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, G. Chicco, "*Modeling the Carrier Dependencies on Demand-Side in a Smart Multi-Energy Local Network*," in Proc. of the 2014 Smart Grid Conference, SGC'14 (technically co-sponsored by IEEE), Tehran, Iran, CD-R, December 9-10, 2014.(attended the conference).

12. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, J. Contreras, "*Modeling the Optimal Behavior of PEV Parking Lots in Energy and Reserve Market*,"in Proc. of the 5th IEEE PES Innovative Smart Grid Technologies Europe Conference, ISGT Europe 2014, Istanbul, Turkey, October 12-15, 2014.

13. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, J. Contreras, "*Allocation of PEVs' Parking lots in Renewable-based Distribution System*," in Proc. of the 24th Australasian Universities Power Engineering Conference, AUPEC 2014 (technically co-sponsored by IEEE), Perth, Australia, USB flash drive, 28 September, 1 October, 2014.

14. **N. Neyestani**, M. Y. Damavandi, M. Shafie-khah, J.P.S. Catalão, "*Comparison of Various Operational Statuses of PIEV Aggregators with Home-charged EVs and Parking Lots*," in Proc. of the 2014 IEEE Power & Energy Society General Meeting, PESGM 2014, Washington, DC Metro Area, USA, USB flash drive, 27-31 July, 2014.

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Appendix A

Mathematical Formulation for solving the bilevel problem with MPEC

A.1 Lagrangian Equation

The extended version of equation (5.47) is shown in equation A.1.

A.2 Stationary Conditions

Equations (A.1)-(A.15) represent the stationary conditions for all the decision variables of LL as in (5.22). These conditions are resulted from the first derivative of the decision variables in the LL problem. Short version presented in equation (5.52).

$$
\begin{aligned}
&Max\{profit^{PL}\} = Max\{\sum_t (Revenue_t^{PL} - Cost_t^{PL})\} = Min(-l) = \\
&- p_t^{out,V2G}\pi_t^{out,V2G} + (p_t^{in,V2G} + p_t^{in,G2V})\pi_t^{in,PL} \\
&- r_t^{PL}\pi_t^{Re,PL} - r_t^{PL}\rho_t^{del}\pi_t^{out,PL} + r_t^{PL}\rho_t^{del}FOR^{PL}\pi_t^{out,PL} \\
&- (soc_t^{dep,flex1} + \phi_t^{dep,fix1}\beta_t^{dep,fix1}C_t^{dep,PL} - SOC_t^{dep,fix1,Sc} - SOC_t^{dep,flex1,Sc})\Pi_t^{G2V1} \\
&- (\phi_t^{dep,fix2}\beta_t^{dep,fix2}C_t^{dep,PL} - SOC_t^{dep,fix2,Sc})(\Pi_t^{G2V2} + Cd^{PL}) \\
&+ (beta_t^{dep,fix2}C_t^{dep,PL} - \phi_t^{dep,fix2}\beta_t^{dep,fix2}C_t^{dep,PL})\Pi_t^{Extra} \\
&- (soc_t^{dep,flex2} - SOC_t^{dep,flex2,Sc})\Big(\frac{(\Pi_t^{G2V3} + Cd^{PL}) + \Pi_t^{V2G}}{2}\Big) \\
&+ Z_t^{PL}\left|(\Pi_t^{G2V3} + Cd^{PL}) - \frac{(\Pi_t^{G2V3} + Cd^{PL}) + \Pi_t^{V2G}}{2}\right| \\
&+ (\beta_t^{dep,flex2}C_t^{dep,PL} - \phi_t^{dep,flex2}\beta_t^{dep,flex2}C_t^{dep,PL})\Pi_t^{Extra} \\
&+ (p_t^{out,PL} + P_t^{in,PL} + r_t^{PL}\rho_t^{del})Cd^{PL} + n_t^{PL}\pi^{Tariff} - r_t^{PL}\rho_t^{del}\pi_t^{V2G} + \sum_k (p_{k,t}^{DG}\pi_t^{out,PL} - a_k^{DG}p_{k,t}^{DG}) \\
&- p_t^{D}(\Pi_t^{ToU} - \pi_t^{in,PL}) + (p_t^{Demand} - p_t^{D})\Pi_t^{Incentive} \\
&+ \lambda_t^{PL,G2V}\big(soc_t^{PL,G2V} - soc_{t-1}^{PL,G2V}|_{t>1} - SOC_{t_0}^{PL,G2V}|_{t=1} - \theta_t^{PL}C_t^{PL} + soc_t^{dep,G2V} - p_t^{in,G2V}\eta^{cha,PL}\big) \\
&+ \lambda_t^{PL,V2G}\Big(soc_t^{PL,V2G} - soc_{t-1}^{PL,V2G}|_{t>1} - SOC_{t_0}^{PL,V2G}|_{t=1} - (1-\theta_t^{PL})C_t^{PL} \\
&+ soc_t^{dep,V2G} - p_t^{in,V2G}\eta^{cha,PL} + \frac{p_t^{out,V2G}}{\eta^{dcha,PL}}\Big) \\
&+ \lambda_t^{dep,G2V}\big(soc_t^{dep,G2V} - \phi_t^{dep,fix1}\beta_t^{dep,fix1}C_t^{dep,PL} - soc_t^{dep,flex1}\big) \\
&+ \lambda_t^{dep,V2G}\big(soc_t^{dep,V2G} - \phi_t^{dep,fix2}\beta_t^{dep,fix2}C_t^{dep,PL} - soc_t^{dep,flex2}\big) \\
&- \underline{\mu}_t^{PL,G2V}(soc_t^{PL,G2V}) - \overline{\mu}_t^{PL,G2V}(\theta_t^{PL}C_t^{PL} - soc_t^{PL,G2V}) - \underline{\mu}_t^{PL,V2G}(soc_t^{PL,V2G}) \\
&- \overline{\mu}_t^{PL,V2G}\big((1-\theta_t^{PL})C_t^{PL} - soc_t^{PL,V2G}\big) \\
&- \underline{\mu}_t^{dep,flex1}(soc_t^{dep,flex1} - \phi_t^{dep,flex1}\beta_t^{dep,flex1}C_t^{dep,PL}) - \overline{\mu}_t^{dep,flex1}(\beta_t^{dep,flex1}C_t^{dep,PL} - soc_t^{dep,flex1}) \\
&- \underline{\mu}_t^{dep,flex2}(soc_t^{dep,flex2} - \phi_t^{dep,flex2}\beta_t^{dep,flex2}C_t^{dep,PL}) - \overline{\mu}_t^{dep,flex2}(\beta_t^{dep,flex2}C_t^{dep,PL} - soc_t^{dep,flex2}) \\
&- \overline{\mu}_t^{PEV,G2V}(\theta_t^{PL}C_t^{PL}\overline{\chi}^{PEV} - soc_t^{PL,G2V}) - \underline{\mu}_t^{PEV,V2G}(soc_t^{PL,V2G} - (1-\theta_t^{PL})C_t^{PL}\underline{\chi}^{PEV}) \\
&- \overline{\mu}_t^{PEV,G2V}\big((1-\theta_t^{PL})C_t^{PL}\overline{\chi}^{PEV} - soc_t^{PL,G2V}\big) - \underline{\mu}_t^{in,G2V}p_t^{in,G2V} - \overline{\mu}_t^{in,G2V}(\gamma^{PL}\theta_t^{PL}N_t^{PL} - p_t^{in,G2V}) \\
&- \underline{\mu}_t^{in,V2G}p_t^{in,V2G} - \overline{\mu}_t^{in,V2G}(\gamma^{PL}(1-\theta_t^{PL})N_t^{PL} - p_t^{in,V2G}) \\
&- \underline{\mu}_t^{out,V2G}(p_t^{out,V2G} + r_t^{PL}) - \overline{\mu}_t^{out,V2G}(\gamma^{PL}(1-\theta_t^{PL})N_t^{PL} - p_t^{out,V2G} - r_t^{PL}) \\
&- \underline{\mu}_t^{Re,PL}r_t^{PL} - \underline{\mu}_t^{out,PL}p_t^{out,V2G} \\
&- \underline{\mu}_t^{D,total}\big(p_t^{D} - (1-a_t^{D})p_t^{D,total}\big) - \overline{\mu}_t^{D,total}\big(p_t^{D,total} - p_t^{D}\big) + \sum_k\big(-\underline{\mu}_{k,t}^{DG}(p_{k,t}^{DG}) - \overline{\mu}_{k,t}^{DG}(\overline{P}_k^{DG} - p_{k,t}^{DG})\big) \\
&- \underline{\mu}_t^{Aux,PL1}(Z_t^{PL} - soc_t^{dep,flex2} + SOC_t^{dep,flex2,Sc}) - \underline{\mu}_t^{Aux,PL2}(Z_t^{PL} - soc_t^{dep,flex2} + SOC_t^{dep,flex2,Sc})
\end{aligned}
\tag{A.1}
$$

$$\frac{\partial l}{\partial p_{\omega,t}^{in,G2V}} = \pi_t^{PL,in} - \lambda_{\omega,t}^{PL,G2V}\eta^{cha,PL} - \underline{\mu}_{\omega,t}^{in,G2V} + \overline{\mu}_{\omega,t}^{in,G2V} = 0 \tag{A.2}$$

$$\frac{\partial l}{\partial p_{\omega,t}^{in,V2G}} = \pi_t^{PL,in} + Cd^{PL} - \lambda_{\omega,t}^{PL,G2V}\eta^{cha,PL} - \underline{\mu}_{\omega,t}^{in,V2G} + \overline{\mu}_{\omega,t}^{in,V2G} = 0 \tag{A.3}$$

$$\frac{\partial l}{\partial p_{\omega,t}^{out,V2G}} = -\pi_t^{PL,out} + Cd^{PL} + {}^{\lambda_{\omega,t}^{PL,G2V}}/_{\eta^{cha,PL}} - \underline{\mu}_{\omega,t}^{out,V2G} + \overline{\mu}_{\omega,t}^{out,V2G} - \underline{\mu}_{\omega,t}^{out,PL} = 0 \tag{A.4}$$

$$\begin{aligned}\frac{\partial l}{\partial r_{\omega,t}^{PL}} =& -\pi_t^{Re,PL} - \rho_t^{del}\pi_t^{out,PL} + \rho_t^{del}FOR^{PL}\pi_t^{out,PL} + \rho_t^{del}\Pi_t^{V2G} + \rho_t^{del}Cd^{PL} \\ & - \underline{\mu}_{\omega,t}^{out,V2G} + \overline{\mu}_{\omega,t}^{out,V2G} - \underline{\mu}_{\omega,t}^{Re,PL} = 0\end{aligned} \tag{A.5}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{PL,G2V}} = \lambda_{\omega,t}^{PL,G2V} - \lambda_{\omega,t+1}^{PL,G2V} - \underline{\mu}_{\omega,t}^{PL,G2V} + \overline{\mu}_{\omega,t}^{PL,G2V} - \overline{\mu}_{\omega,t}^{PEV,G2V} + \underline{\mu}_{\omega,t}^{PEV,V2G} = 0 \qquad \forall t < T \tag{A.6}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{PL,G2V}} = \lambda_{\omega,t}^{PL,G2V} - \underline{\mu}_{\omega,t}^{PL,G2V} + \overline{\mu}_{\omega,t}^{PL,G2V} - \overline{\mu}_{\omega,t}^{PEV,G2V} + \underline{\mu}_{\omega,t}^{PEV,V2G} = 0 \qquad \forall t = T \tag{A.7}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{PL,V2G}} = \lambda_{\omega,t}^{PL,V2G} - \lambda_{\omega,t+1}^{PL,V2G} - \underline{\mu}_{\omega,t}^{PL,GV2G} + \overline{\mu}_{\omega,t}^{PL,V2G} - \underline{\mu}_{\omega,t}^{PEV,V2G} + \overline{\mu}_{\omega,t}^{PEV,V2G} = 0 \qquad \forall t < T \tag{A.8}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{PL,V2G}} = \lambda_{\omega,t}^{PL,V2G} - \underline{\mu}_{\omega,t}^{PL,GV2G} + \overline{\mu}_{\omega,t}^{PL,V2G} - \underline{\mu}_{\omega,t}^{PEV,V2G} + \overline{\mu}_{\omega,t}^{PEV,V2G} = 0 \qquad \forall t = T \tag{A.9}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{dep,G2V}} = \lambda_{\omega,t}^{PL,G2V} + \lambda_{\omega,t+1}^{dep,G2V} = 0 \tag{A.10}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{dep,V2G}} = \lambda_{\omega,t}^{PL,V2G} + \lambda_{\omega,t+1}^{dep,V2G} = 0 \tag{A.11}$$

$$\frac{\partial l}{\partial Z_{\omega,t}^{PL}} = |\left(\Pi_t^{G2V3} + Cd^{PL}\right) - {}^{\left((\Pi_t^{G2V3}+Cd^{PL})+\Pi_t^{V2G}\right)}/_{2}| - \underline{\mu}_{\omega,t}^{Aux,PL1} - \underline{\mu}_{\omega,t}^{Aux,PL2} = 0 \tag{A.12}$$

$$\frac{\partial l}{\partial soc_{\omega,t}^{dep,flex1}} = -\Pi_t^{G2V1} - \lambda_{\omega,t}^{dep,G2V} - \underline{\mu}_{\omega,t}^{dep,flex1} + \overline{\mu}_{\omega,t}^{dep,flex1} = 0 \tag{A.13}$$

$$\begin{aligned}\frac{\partial l}{\partial soc_{\omega,t}^{dep,flex2}} =& -\left({}^{\left((\Pi_t^{G2V3}+Cd^{PL})+\Pi_t^{V2G}\right)}/_{2}\right) - \lambda_{\omega,t}^{dep,V2G} - \underline{\mu}_{\omega,t}^{dep,flex2} + \overline{\mu}_{\omega,t}^{dep,flex2} \\ & + \underline{\mu}_{\omega,t}^{Aux,PL1} - \underline{\mu}_{\omega,t}^{Aux,PL2} = 0\end{aligned} \tag{A.14}$$

$$\frac{\partial l}{\partial p_{m,t}^{DG}} = -\pi_t^{out,PL} + A_m^{DG} - \underline{\mu}_{m,t}^{DG} + \overline{\mu}_{m,t}^{DG} = 0 \tag{A.15}$$

$$\frac{\partial l}{\partial p_t^{D}} = \pi_t^{in,PL} - \Pi_t^{Incentive} - \underline{\mu}_{t}^{D,total} + \overline{\mu}_{t}^{D,total} = 0 \tag{A.16}$$

A.3 Complementary Conditions

Equations (A.17)-(A.40) are the complementary conditions of the problem. The short version presented in (5.54).

$$0 \leq \underline{\mu}_{\omega,t}^{PL,G2V} \perp soc_{\omega,t}^{PL,G2V} \geq 0 \tag{A.17}$$

$$0 \leq \overline{\mu}_{\omega,t}^{PL,G2V} \perp (\theta_{\omega,t}^{PL} C_{\omega,t}^{PL} - soc_{\omega,t}^{PL,G2V}) \geq 0 \tag{A.18}$$

$$0 \leq \underline{\mu}_{\omega,t}^{PL,V2G} \perp soc_{\omega,t}^{PL,V2G} \geq 0 \tag{A.19}$$

$$0 \leq \overline{\mu}_{\omega,t}^{PL,V2G} \perp \big((1-\theta_{\omega,t}^{PL}) C_{\omega,t}^{PL} - soc_{\omega,t}^{PL,G2V}\big) \geq 0 \tag{A.20}$$

$$0 \leq \underline{\mu}_{\omega,t}^{dep,flex1} \perp (soc_{\omega,t}^{dep,flex1} - \phi_{\omega,t}^{flex1} \beta_{\omega,t}^{flex1} C_{\omega,t}^{dep,PL}) \geq 0 \tag{A.21}$$

$$0 \leq \overline{\mu}_{\omega,t}^{dep,flex1} \perp (\beta_{\omega,t}^{flex1} C_{\omega,t}^{dep,PL} - soc_{\omega,t}^{dep,flex1}) \geq 0 \tag{A.22}$$

$$0 \leq \underline{\mu}_{\omega,t}^{dep,flex2} \perp (soc_{\omega,t}^{dep,flex2} - \phi_{\omega,t}^{flex2} \beta_{\omega,t}^{flex2} C_{\omega,t}^{dep,PL}) \geq 0 \tag{A.23}$$

$$0 \leq \overline{\mu}_{\omega,t}^{dep,flex2} \perp (\beta_{\omega,t}^{flex2} C_{\omega,t}^{dep,PL} - soc_{\omega,t}^{dep,flex2}) \geq 0 \tag{A.24}$$

$$0 \leq \overline{\mu}_{\omega,t}^{PEV,V2G} \perp (\theta_{\omega,t}^{PL} C_{\omega,t}^{PL} \overline{soc}^{PEV} - soc_{\omega,t}^{PL,G2V}) \geq 0 \tag{A.25}$$

$$0 \leq \underline{\mu}_{\omega,t}^{PEV,V2G} \perp \big(soc_{\omega,t}^{PL,G2V} (1-\theta_{\omega,t}^{PL}) C_{\omega,t}^{PL} \underline{soc}^{PEV}\big) \geq 0 \tag{A.26}$$

$$0 \leq \underline{\mu}_{\omega,t}^{in,G2V} \perp p_{\omega,t}^{in,G2V} \geq 0 \tag{A.27}$$

$$0 \leq \overline{\mu}_{\omega,t}^{in,G2V} \perp (\gamma^P L \theta_{\omega,t}^{PL} N_{\omega,t}^{PL} - p_{\omega,t}^{in,G2V}) \geq 0 \tag{A.28}$$

$$0 \leq \underline{\mu}_{\omega,t}^{in,V2G} \perp p_{\omega,t}^{in,V2G} \geq 0 \tag{A.29}$$

$$0 \leq \overline{\mu}_{\omega,t}^{in,V2G} \perp \big(\gamma^P L (1-\theta_{\omega,t}^{PL}) N_{\omega,t}^{PL} - p_{\omega,t}^{in,V2G}\big) \geq 0 \tag{A.30}$$

$$0 \leq \underline{\mu}_{\omega,t}^{out,V2G} \perp (p_{\omega,t}^{out,V2G} + r_{\omega,t}^{PL}) \geq 0 \tag{A.31}$$

$$0 \leq \overline{\mu}_{\omega,t}^{out,V2G} \perp \big(\gamma^P L (1-\theta_{\omega,t}^{PL}) N_{\omega,t}^{PL} - p_{\omega,t}^{out,V2G} - r_{\omega,t}^{PL}\big) \geq 0 \tag{A.32}$$

$$0 \leq \underline{\mu}_{\omega,t}^{Re,PL} \perp r_{\omega,t}^{PL} \geq 0 \tag{A.33}$$

$$0 \leq \underline{\mu}_{\omega,t}^{out,PL} \perp p_{\omega,t}^{out,V2G} \geq 0 \tag{A.34}$$

$$0 \leq \underline{\mu}_{t}^{D,total} \perp \big(p_t^D - (1-\alpha_t^D) \geq 0 \tag{A.35}$$

$$0 \leq \overline{\mu}_{t}^{D,total} \perp (p_t^{D,total} - p_t^D) \geq 0 \tag{A.36}$$

$$0 \leq \underline{\mu}_{m,t}^{DG} \perp p_{m,t}^{DG} \geq 0 \tag{A.37}$$

$$0 \leq \overline{\mu}_{m,t}^{DG} \perp (\overline{P}_{m}^{DG} - p_{m,t}^{DG}) \geq 0 \tag{A.38}$$

$$0 \leq \underline{\mu}_{\omega,t}^{Aux,PL1} \perp (Z_{\omega,t}^{PL} - soc_{\omega,t}^{dep,flex2} + SOC_{\omega,t}^{dep,flex2,Sc}) \geq 0 \tag{A.39}$$

$$0 \leq \underline{\mu}_{\omega,t}^{Aux,PL2} \perp (Z_{\omega,t}^{PL} + soc_{\omega,t}^{dep,flex2} - SOC_{\omega,t}^{dep,flex2,Sc}) \geq 0 \tag{A.40}$$

A.4 Strong Duality

$$\begin{aligned}
&- p_t^{out,PL}\pi_t^{out,PL} + p_t^{in,PL}\pi_t^{in,PL} - r_t^{PL}\pi_t^{Re,PL} - r_t^{PL}\rho_t^{del}\pi_t^{out,PL} + r_t^{PL}\rho_t^{del}FOR^{PL}\pi_t^{out,PL}\\
&- \sum_k p_{k,t}^{DG}\pi_t^{out,PL} =\\
&+ (soc_t^{dep,fix1} + soc_t^{dep,flex1} - SOC_t^{dep,fix1,Sc} - SOC_t^{dep,flex1,Sc})(\Pi_t^{G2V1} + Cd^{PL})\\
&+ (soc_t^{dep,fix2} - SOC_t^{dep,fix2,Sc})(\Pi_t^{G2V2} + Cd^{PL}) - (\beta_t^{dep,fix2}C_t^{dep,PL} - \phi_t^{dep,fix2}\beta_t^{dep,fix2}C_t^{dep,PL})\Pi_t^{Extra}\\
&+ (soc_t^{dep,flex2} - SOC_t^{dep,flex2,Sc})\Big(\frac{(\Pi_t^{G2V3} + Cd^{PL}) + \Pi_t^{V2G}}{2}\Big)\\
&- Z_t^{PL}\left|(\Pi_t^{G2V3} + Cd^{PL}) - \frac{(\Pi_t^{G2V3} + Cd^{PL}) + \Pi_t^{V2G}}{2}\right|\\
&- (\beta_t^{dep,flex2}C_t^{dep,PL} - \phi_t^{dep,flex2}\beta_t^{dep,flex2}C_t^{dep,PL})\Pi_t^{Extra}\\
&- (p_t^{out,PL} + P_t^{in,PL} + r_t^{PL}\rho_t^{del})Cd^{PL} + n_t^{PL}\pi^{Tariff} - r_t^{PL}\rho_t^{del}\pi_t^{V2G} + \sum_k (p_{k,t}^{DG}\pi_t^{out,PL} - a_k^{DG}p_{k,t}^{DG})\\
&+ \lambda_t^{PL}(-SOC_{t_0}^{PL}|_{t=1} - SOC_t^{ar,PL})\\
&+ \lambda_t^{ca,PL}(-C_{t_0}^{PL}|_{t=1} - C_t^{ar,PL} + C_t^{dep,PL}) + \lambda_t^{nu,PL}(-N_{t_0}^{PL}|_{t=1} - N_t^{ar,PL} + N_t^{dep,PL})\\
&- \lambda_t^{dep,fix1}(\phi_t^{dep,fix1}\beta_t^{dep,fix1}C_t^{dep,PL}) - \lambda_t^{dep,fix2}(\phi_t^{dep,fix2}\beta_t^{dep,fix2}C_t^{dep,PL})\\
&- \overline{\mu}_t^{dep,PL}C_t^{dep,PL} - \overline{\mu}^{nu,PL}NS_t^{PL} - \zeta_{t=T}^{PL}SOC_{t_0}^{PL} - \sum_k \overline{\mu}_{k,t}^{DG}\overline{P}_k^{DG}\\
&+ \underline{\mu}_t^{dep,flex1}(\phi_t^{dep,flex1}\beta_t^{dep,flex1}C_t^{dep,PL}) - \overline{\mu}_t^{dep,flex1}(\beta_t^{dep,flex1}C_t^{dep,PL})\\
&+ \underline{\mu}_t^{dep,flex2}(\phi_t^{dep,flex2}\beta_t^{dep,flex2}C_t^{dep,PL}) - \overline{\mu}_t^{dep,flex2}(\beta_t^{dep,flex2}C_t^{dep,PL})\\
&- \underline{\mu}_t^{Aux,PL1}(SOC_t^{dep,flex2,Sc}) + \overline{\mu}_t^{Aux,PL2}(SOC_t^{dep,flex2,Sc})
\end{aligned} \tag{A.41}$$

Appendix B

IEEE 37 bus Radial Distribution Network Data

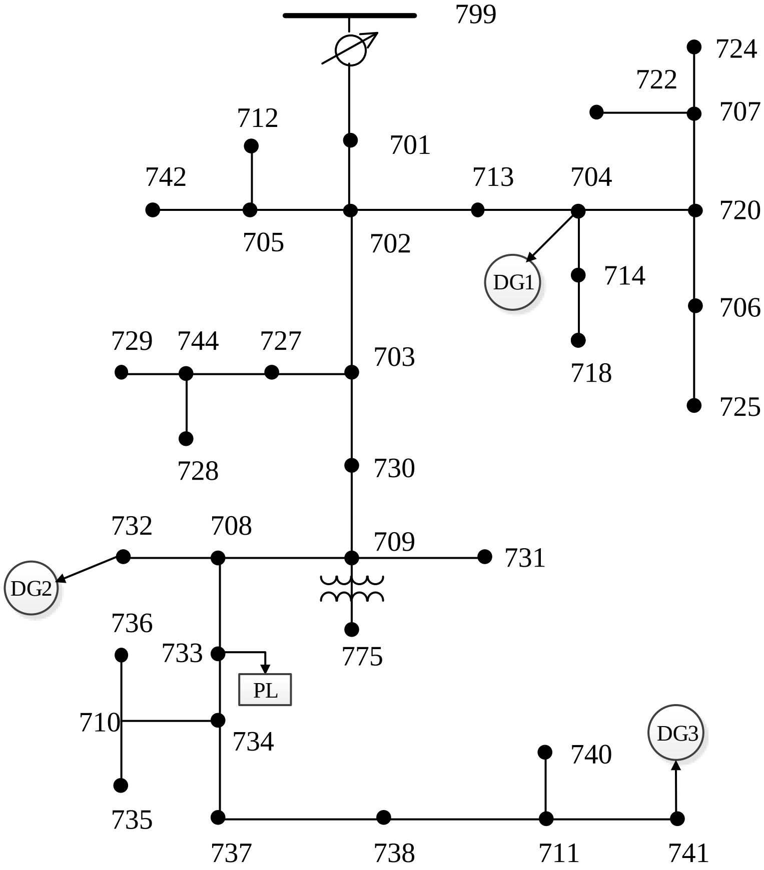

Figure B.1: IEEE 37-bus network under study with added resources.