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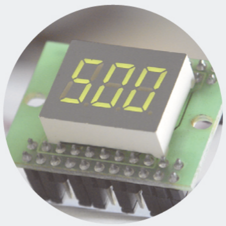

Modified Particle Swarm Optimization for Day-Ahead Distributed Energy Resources Scheduling Including Vehicle-to-Grid

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by
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“The difficulty in life is the choice.”

George Moore

Abstract

This thesis proposes a modified Particle Swarm Optimization (PSO) approach for the day-ahead scheduling of Distributed Energy Resources (DER) in smart grids, considering Electric Vehicles (EVs) with gridable capability (vehicle-to-grid).

The proposed methodology introduces several changes in traditional PSO meta-heuristic to solve effectively the scheduling problem of DER with EVs. This thesis proposes an intelligent mechanism for adjusting the velocity limits of the swarm to alleviate violations of problem constraints and to improve the quality of the solution, namely the value of the objective function. In addition, a hybridization of PSO method is used, which combines this meta-heuristic with an exact method, a full ac power flow in order to validate network constraints of the solutions explored by the swarm.

This thesis proposes a trip reduce demand response program for EVs users. A data-mining based methodology is used to support the network operator in the definition of this program and to estimate how much demand response is adequate for a certain operation condition.

The case studies included in the thesis aim to demonstrate the effectiveness of the modified PSO approach to the problem of DER scheduling considering EVs. An application named EV Scenario Simulator (EVeSSi) has been developed. EVeSSi allows creating scenarios considering EVs in distribution networks. A case study comparison of the modified PSO with an accurate mixed integer non-linear programming is presented. Furthermore, it is also compared with other variants of PSO, and the traditional PSO. Addionatly, different methods of EV battery management, namely uncontrolled charging, smart charging and vehicle-to-grid, are compared. Finally, a test case is presented to illustrate the use of the proposed demand response program for EVs and the data-mining methodology applied to a large database of operation scenarios.

Keywords

Electric Vehicles, Electric Vehicles Demand Response, Optimization, Particle Swarm Optimization,

Resumo

Esta tese apresenta uma aplicação modificada e adaptada da meta-heurística *Particle Swarm Optimization* (PSO) para o escalonamento de recursos energéticos em redes de distribuição inteligentes vulgo *smart grids*, considerando a utilização de veículos eléctricos. Este conceito em que os veiculos podem carregar e descarregar energia para a rede eléctrica é denominado na giria anglo-saxónica por *vehicle-to-grid*.

Esta tese apresenta várias modificações na meta-heuristica PSO original para resolver mais eficazmente o problema do escalonamento de recursos energéticos com veículos eléctricos. Realça-se nesta tese a prosposta de um mecanismo inteligente para o ajustamento do limite das velocidades do *swarm* com vista a aliviar violações de restrições do problema e a melhorar a qualidade da solução, isto é, o valor da função objectivo. Adicionalmente, refere-se a hibridização desta meta-heurística com um método exacto, nomeadamente um trânsito de potências com o objectivo de verificar o cumprimento das restrições da rede eléctrica das soluções exploradas pelo *swarm*.

Um programa de *demand response* para veículos eléctricos é apresentado na tese. Além disso, uma metodologia baseada em técnicas de *data-mining* é proposta para suportar as decisões do operator de sistema na definição e na estimativa do uso desse programa.

Os casos de estudo incluídos nesta tese pretendem demonstrar a eficácia do PSO modificado no problema do escalonamento de recursos energéticos considerando os veículos eléctricos. Uma aplicação com a designação de EVeSSi foi desenvolvida e apresentada nesta tese para criar cenários de penetração de veículos eléctricos e simular os movimentos dos veículos ao longo dos nós das redes de distribuição. Um caso de estudo de comparação com um método exacto de programação não linear inteira mista é apresentado. Além disso, a aplicação proposta é comparada com outras variantes do PSO, incluindo a versão original. São ainda incluídos casos de estudo que abordam diferentes metodologias de interação do veículo com a rede, nomeadamente *uncontrolled charging, smart charging e vehicle-to-grid*. Por fim, é apresentado um caso de estudo com o programa de *demand response* e a metodologia de *data-mining.*

Palavras Chave

Gestão da Procura para Veículos Eléctricos. Optimização, Particle Swarm Optimization, Veículos Eléctricos,

Table of Contents

List of Acronyms

Acronym	Description
BEV	Battery Electric Vehicle
CC	Commerce Consumers
DER	Distributed Energy Resources
DM	Domestic Consumers
DNO	Distribution Network Operator
DOD	Depth Of Discharge
DR	Demand Response
EPSO	Evolutionary Particle Swarm Optimization
EREV	Extended Range Electric Vehicle
EV	Electric Vehicle
EVeSSi	Electric Vehicle Scenario Simulator
ILP	Integer Linear Programming
LC	Large Commerce
LI	Large Industrial
MI	Medium Industrial
MILP	Mixed Integer Non-Linear Programming
MINLP	Mixed Integer Non-Linear Programming
NPSO	New Particle Swarm Optimization
PHEV	Plug-in Hybrid Electric Vehicle
PSO	Particle Swarm Optimization
SC	Smart Charging
UC	Uncontrolled Charging
V2G	Vehicle-to-Grid
VPP	Virtual Power Player

List of Figures

List of Tables

Nomenclature

Notation	Description
Δcd	Duration of charging, typically $\Delta cd = 1$
Δt	Period *t* duration (e.g. 15 min. (0.25), 30 min. (0.50), 1 hour (1)…)
δ	Learning parameter with a range between 0 and 1
θ_b	Voltage angle at bus *b* (rad)
B_{bk}	Imaginary part of the element in Y_{BUS} corresponding to the *b* row and *k* column (S)
θ_b^{max}	Maximum voltage angle at bus *b* (rad)
θ_b^{min}	Minimum voltage angle at bus *b* (rad)
θ_k	Voltage angle at bus *k* (rad)
$\eta_{c(V)}$	Grid-to-Vehicle Efficiency when the Vehicle *V* is in charge mode (%)
$\eta_{d(V)}$	Vehicle-to-Grid Efficiency when the Vehicle *V* is in discharge mode (%)
age	Actual age of the battery considering 6 years of calendar life
batCap	Limit of battery capacity
b_i	Best past experience of particle *i*
bG	Best global experience of all the particles
boostSpeed	Vector with the variables boost speed
classesNum	Total number of classes available
$classesSet_j$	Set of model types *i* that belong to class *j*
$classesWeigth_j$	Weight for class type *j* (e.g. 90% passenger vehicles, 10% commercial vehicles)
$c_{(j,t)}$	Price for generator *j* in period *t*
$c_{Discharge(V,t)}$	Discharge price of vehicle *V* in period *t* (m.u.)
$c_{DG(DG,t)}$	Generation price of *DG* unit in period *t* (m.u.)
$c_{EAP(DG,t)}$	Excess available power price of *DG* unit in period *t* (m.u.)
$c_{NSD(L,t)}$	Non-supplied demand price of load *L* in period *t* (m.u.)

$c_{Supplier(S,t)}$	Energy price of external supplier *S* in period *t* (m.u.)
$c_{TripRed(V,t)}$	Trip reduce price contracted with vehicle *V* in period *t* (m.u.)
Damage	Represents the damage caused to the battery 0 (new battery) and 1 (wear-out)
DOD	Depth of discharge between 0 and 1
d_i	Represents the damage caused by cycle *i* using equation of Damage with DOD of the given *i* cycle.
$E_{BatteryCapacity(V)}$	Battery energy capacity of vehicle *V* (Wh)
$E_{Charge(t)}$	Energy charged in period *t* (W)
$E_{MinCharge(V,t)}$	Minimum stored energy to be guaranteed at the end of period *t*, for vehicle *V* (Wh)
$E_{Stored(t)}$	Battery's energy stored in period *t* (Wh)
$E_{Trip(t)}$	Energy consumed by vehicle trip in period *t*
$E_{Trip(V,t)}$	Vehicle *V* energy consumption in period *t* (Wh)
$E_{TripRed(V,t)}$	Demand response energy reduce of vehicle trip *V* in period *t* (Wh)
$E_{TripRedMax(V,t)}$	Maximum energy reduce for vehicle *V* trip in period *t* (Wh)
$E_{Stored(V,t)}$	Active energy stored in vehicle *V* at the end of period *t* (Wh)
evNum	Total number of electric vehicles
G_{bk}	Real part of the element in Y_{BUS} corresponding to the *b* row and *k* column (S)
initialBatState	Initial battery state of the battery
modelNum	Total number of models available
nCycles	Represents the total number of cycles of the battery
$n_{slowCharge}$	Charging efficiency in slow charge mode
$n_{fastCharge}$	Charging efficiency in fast charge mode
N_b	Total number of buses *b*
N_{DG}	Total number of distributed generators
N_{DG}^b	Total number of distributed generators at bus *b*
N_L	Total number of loads
N_L^b	Total number of loads at bus *b*
N_S	Total number of external suppliers
N_S^b	Total number of external suppliers at bus *b*

N_V	Total number of vehicles
N_V^b	Total number of vehicles at bus *b*
$P_{Charge(V,t)}$	Power charge of vehicle *V* in period *t* (W)
$P_{Charge(V,t)}^b$	Power charge of vehicle *V* at bus *b* in period *t* (W)
$P_{ChargeLimit(V,t)}$	Maximum power charge of vehicle *V* in period *t* (W)
$P_{DG(DG,t)}$	Active power generation of distributed generation unit *DG* in period *t* (W)
$P_{DG(DG,t)}^b$	Active power generation of distributed generation unit *DG* at bus *b* in period *t* (W)
$P_{DGMaxLimit(DG,t)}$	Maximum active power generation of distributed generator unit *DG* in period *t* (W)
$P_{DGMinLimit(DG,t)}$	Minimum active power generation of distributed generator unit *DG* in period *t* (W)
$P_{Discharge(V,t)}$	Power discharge of vehicle *V* in period *t* (W)
$P_{Discharge(V,t)}^b$	Power discharge of vehicle *V* at bus *b* in period *t* (W)
$P_{DischargeLimit(V,t)}$	Maximum power discharge of vehicle V in period t (W)
$P_{EAP(DG,t)}$	Excess available power by *DG* unit in period *t* (W)
$P_{EAP(DG,t)}^b$	Excess available power by *DG* unit at bus *b* in period *t* (W)
$P_{FastCh\arg eRate(t)}$	Fast charge rate in period *t*
$P_{SlowCh\arg eRate(t)}$	Slow charge rate in period *t*
$P_{Load(L,t)}^b$	Active power demand of load *L* at bus *b* in period *t* (W)
$P_{NSD(L,t)}$	Non-supplied demand for load *L* in period *t* (W)
$P_{NSD(L,t)}^b$	Non-supplied demand for load *L* at bus *b* in period *t* (W)
$P_{Supplier(S,t)}$	Active power flow in the branch connecting to upstream supplier *S* in period *t* (W)
$P_{Supplier(S,t)}^b$	Active power flow in the branch connecting to upstream supplier *S* at bus *b* in period *t* (W)
$P_{SupplierLimit(S,t)}$	Maximum active power of upstream supplier *S* in period *t* (W)
$Q_{DG(DG,t)}^b$	Reactive power generation of distributed generation unit *DG* at bus *b* in period *t* (var)
$Q_{DGMaxLimit(DG,t)}$	Maximum reactive power generation of distributed generator unit *DG* in period *t* (var)
$Q_{DGMinLimit(DG,t)}$	Minimum reactive power generation of distributed generator unit

	DG in period *t* (var)
$Q^{b}_{Load(L,t)}$	Reactive power demand of load *L* at bus *b* in period *t* (var)
$Q^{b}_{Supplier(S,t)}$	Reactive power flow in the branch connecting to upstream supplier *S* at bus *b* in period *t* (var)
$Q_{SupplierLimit(S,t)}$	Maximum reactive power of upstream supplier *S* in period *t* (var)
S^{max}_{bk}	Maximum apparent power flow established in line that connected bus *b* and *k* (VA)
signalingPositives	Vector with the signaled variables (positive velocity)
signalingNegatives	Vector with the signaled variables (negative velocity)
techTypesNum	Total number of technology types available
$techTypeSet_j$	Set of model types i that belong to tech type j
$techWeigth_j$	Weight for technology type *j* (e.g. 40% BEV, 60% PHEV)
tLast	Last connected period of vehicle *V* before current trip
T	Total number of periods
V_b	Voltage magnitude at bus *b* (rad)
V^{max}_{b}	Maximum voltage magnitude at bus *b*
V^{min}_{b}	Minimum voltage magnitude at bus *b*
V_k	Voltage magnitude at bus *k* (rad)
$v_{i,j}$	Velocity of variable *j* of particle *i*
${}^{*}v_{i,j}$	New calculated velocity of variable *j* of particle *i*
$Vel^{\max}{}_{j}$	Original initial max. velocity of variable *j*
$Vel^{\max}{}_{j,t}$	Maximum velocity of particle’s variable *j* for period *t*
$Vel^{\min}{}_{j,t}$	Minimum velocity of particle’s variable *j* for period *t*
$VechicleNeeds_V$	Vehicle *V* total periods trips energy consumption
w_i	Weights of particle *i*
${}^{*}w_i$	New mutated weights of particle *i*
${}^{*}w_{i(coop)}$	Cooperation weight component of particle *i*
${}^{*}w_{i(inertia)}$	Inertia weight component of particle *i*

${}^{*}w_{i(memory)}$	Memory weight component of particle *i*
x_i	Integer variable where each x_i represents the number of vehicles of model *i*
${}^{*}x_{i,j}$	New calculated position of *j* variable the *i* particle
$x_{i,j}$	Position of variable *j* of particle *i*
X_t	Slow charge binary variable in period *t*
$X_{(V,t)}$	Binary variable of vehicle *V* related to power discharge in period *t*
y_{bk}	Admittance of line that connect bus *b* and *k* (S)
y_{Shunt_b}	Shunt admittance of line connected bus *b* (S)
Y_t	Fast charge binary variable in period *t*
$Y_{(V,t)}$	Binary variable of vehicle *V* related to power charge in period *t*
Z_t	Boolean trip decision in period *t* (0/1) and fixed before optimization

1 Introduction

1.1 Motivation

Power systems are one of the most complex systems built by man. It is a field where several optimization goals must be pursued but that is plagued with pervasive nonlinearities and uncertainties, and that it is also limited by various operational constraints. Therefore, these optimization problems are far from trivial and include optimal power flow, voltage and frequency control and power generator scheduling, among others.

The optimization problems, in which both the objective functions and the constraints often contain nonlinearities and binary variables, have traditionally been addressed by various techniques which include Non-Linear Programming (NLP) and Mixed Integer Non-Linear Programming (MINLP) [1]. This and other deterministic optimization techniques have difficulties dealing with uncertain variables and require increasing computational resources to deal with real-world problems [2, 3]. In fact, large complex problems such as the ones in future power systems, characterized by an intensive use of Distributed Energy Resources (DER), are hard to be addressed with deterministic approaches due to the time constrainsts related with operation tasks.

Therefore, some alternative techniques, coming from Artificial Intelligence (AI) quarters, like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been used to address this problem purpose. GAs draw inspiration from the field of evolutionary biology, offering operators for crossover, mutation and selection of the best solutions [4]. For certain optimization problems though, the overhead resulting from the application of these operators make this technique less efficient than other simpler algorithms, like PSO [5, 6].

The PSO began with a simulation of simple social systems like the flocks of birds or the schools of fish [7]. The main advantage of PSO is its simplicity, while being capable of delivering accurate results in a consistent manner. It is fast and also very flexible, being applicable to a wide range of problems, with limited computational requirements [6].

That said, the present work focuses on metaheuristics optimization approaches, namely PSO, applied to the energy resource scheduling at the distribution system level and including charging and discharging of Electric Vehicles (EVs). The possibility of using the energy stored in the gridable EVs batteries to supply power to the electric grid is commonly referred to as Vehicle-to-Grid (V2G) and is also considered in the present thesis.

The energy resource scheduling problem is become increasingly important, as the use of distributed resources is intensified and massive V2G use is envisaged. Governments in Europe as well as in United States and Asia are promoting and implementing incentives to increase electric mobility use of EVs. The transportation sector will change from fossil fuel propelled motor vehicles to EVs as fossil fuels are being depleted and rules about CO_2 emissions are getting stricter worldwide [8, 9]. EVs can include Plug-in Hybrid Electric Vehicle (PHEV), Battery Electric Vehicle (BEV), Extended-Range Electric Vehicle (EREV) and Fuel-Cell Vehicle (FCV). Although there are several prototypes of FCVs, they are less likely to be introduced as fast as the PHEV and BEV because fuel-cell units are currently very expensive. FCVs are behind EVs in terms of development and the hydrogen economy is still not competitive [10, 11].

The electrification of the transportation sector brings more challenges and offers new opportunities to power system planning and operation. Continued improvements of EVs envisage EVs massive use, meaning that large quantities of EVs must be considered by future power systems, in terms of the required supply to ensure their users' daily travels [12, 13]. In future scenarios of intensive EVs penetration, the typical electric load diagram can be significantly changed. On the other hand, power systems can use V2G as DERs when the vehicles are parked. This adds further complexity to the planning and operation of power systems. Therefore, new scheduling methods are required to ensure low operation costs while guaranteeing the supply of load demand.

Apart from EVs, power systems will have to deal with other types of DERs at the distribution network level, such as Distributed Generation (DG), Storage Systems (SS), and Demand Response (DR). DER management can be executed by Virtual Power Player (VPPs) or by Distribution Network Operators (DNO) [14, 15]. All the mentioned resources have to be considered in the energy scheduling problem, consequently considering their characteristics and requirements [16].

The energy resource scheduling problem is a MINLP problem when including binary variables and network constraints. If the problem does not consider network constraints it can be addressed with a quadratic or a linear programming model. However, to have a suitable solution in a real-world application, the network constraints must be considered. This thesis considers a multi-period optimization within a day-ahead time frame with the forecasted demand.

When including V2G resources in the optimization scheduling it is necessary to take into account the available resource information, namely accurate information of electric vehicles (EVs). This information must be detailed including the geographical area where vehicles are parked during each considered period, as well as the minimum battery energy requirement defined by the users to allow their daily trips. This information enables to determine EVs minimum battery charge required for each period in order to guarantee the aimed range [17].

Depending on the network size, the optimization can turn naturally into a large combinatorial problem due to the huge number of network elements and to the diversity of energy resources with different specifications and requirements. This fact makes the optimization problem suitable for the use of Artificial Intelligence (AI) based techniques, namely metaheuristics such as PSO.

This thesis introduces several changes in traditional PSO meta-heuristic to solve effectively the scheduling problem of energy resources with electric vehicles. One of the changes is the hybridization of PSO method combining this meta-heuristics with an exact method, including a full ac power flow in order to enable the verification of network constraints of the solutions explored by the swarm. In addition, this thesis proposes an intelligent mechanism for adjusting the velocity limits of the swarm to alleviate violations of problem constraints and to improve the quality of the solution, namely the value of the objective function.

Demand response programs in the context of EVs is proposed in the scope of this thesis, namely trip reduce demand response program for EVs users. A data-mining based methodology is presented to support network operator in the definition of trip reduce demand response program. This methodology enables to estimate how much demand response is adequate for a certain operation condition.

The case studies included in this thesis aim to demonstrate the effectiveness of the modified PSO to the problem of DER scheduling considering electric vehicles. An application named Electric Vehicle Scenario Simulator (EVeSSi) was developed in the scope of this thesis to create scenarios simulating penetration and movements of vehicles in distribution networks. A comparison of the modified PSO with an accurate MINLP method is presented. Furthermore, the modified PSO is compared with other variants of PSO, including the traditional version and some of its most successful variants. A case study is included to compare different methods of vehicle grid interaction, particularly uncontrolled charging, smart charging and vehicle-to-grid. To conclude case studies chapter, the proposed trip reduce demand response program for EVs is demonstrated and the data-mining methodology is applied to a large database of operation scenarios.

1.2 Objectives

The key contribution of this thesis is the proposal of a modified Particle Swarm Optimization to effectively address the hard combinatorial problem of the day-ahead DER scheduling considering EVs in future smart grids context.

To accomplish that goal the following list of work objectives were proposed:

- Design and develop electric vehicle scenario simulator tool to allow the creation of scenarios that simulate the movements of vehicles in distribution networks;
- Provide a comparison of performance and solution quality analysis using deterministic and metaheuristics tools, specifically PSO, to solve the problem of day-ahead scheduling of DER, including V2G, in the context of smart grids;
- Improve metaheuristics methods, namely Particle Swarm Optimization (PSO), to address the envisaged problem in a more effective and efficient way;
- Address the design and use of DR programs for electric vehicles in the context of demand side management;
- Test the proposed methodologies with large-scale test cases, in order to demonstrate their advantages to address realistic problems.

1.3 Outline of the thesis

This thesis is composed by five chapters, including introduction and conclusions, and two appendices regarding case studies data.

After the introduction chapter, chapter 2 presents a brief review of EVs technology including battery modeling and battery costs. A general overview of EVs market penetration and driving patterns is presented. The electric vehicle scenario simulator tool developed in the scope of this thesis is also presented in this chapter.

Chapter 3 starts with a brief state of the art of the day-ahead DER scheduling and PSO. After that, the modified PSO is exposed and the intelligent mechanism for adjusting the velocity limits of the swarm is described. The implementation of the modified PSO approach to the DER scheduling problem considering V2G is also presented in this chapter. Finally, a model of demand response for electric vehicles users is proposed.

Chapter 4 presents several case studies. A comparison of the modified PSO approach with an exact method (MINLP) is included using a 33 bus distribution network. Moreover, the modified PSO is compared with Evolutionary Particle Swarm Optimization (EPSO), New Particle Swarm Optimization (NPSO) and the traditional PSO. A large-scale case study with a 180 bus distribution system with 8000 gridable vehicles is presented. A case study comparing uncontrolled charging, smart charging and vehicle-to-grid is presented and analyzed using a 33 bus distribution network.

Chapter 5 presents the most significant conclusions of the undertaken work as well as some ideas for its future development. This thesis opens excellent opportunities to continue the research in scheduling optimization including V2G in smart grids. Some of the potential ideas are already being worked by the author and are presented in this chapter as future and present research directions.

Some of the work related and presented in this thesis already resulted in some high quality publications. The following list of publications is presented:

Published:

- J. Soares, T. Sousa, H. Morais, Z. Vale, and P. Faria, "An Optimal Scheduling Problem in Distribution Networks Considering V2G," in *IEEE SSCI Symposium on Computational Intelligence Applications in Smart Grid (CIASG)* Paris, France, 2011.
- T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares, "Intelligent Energy Resource Management Considering Vehicle-to-Grid: A Simulated Annealing Approach," *IEEE Transaction on Smart Grid, Special Issue on Transportation Electrification and Vehicle-to-Grid Applications.*, 2011.
- Sérgio Ramos, Hugo Morais, Zita Vale, Pedro Faria, and J. Soares, "Demand Response Programs Definition Supported by Clustering and Classification Techniques," *presented at the ISAP 2011 - 16th International Conference on Intelligent System Application to Power Systems, Hersonissos, Crete, Greece, 2011.*
- P. Faria, Z. Vale, J. Soares, and J. Ferreira, "Demand Response Management in Power Systems Using a Particle Swarm Optimization Approach," *Intelligent Systems, IEEE, vol. PP, pp. 1-1, 2011.*
- P. Faria, Z. Vale, J. Soares, and J. Ferrante, "Particle Swarm Optimization Applied to Integrated Demand Response Resources Scheduling," *in IEEE SSCI Symposium on Computational Intelligence Applications in Smart Grid (CIASG) Paris, France, 2011.*

Additionally the following papers are under review:

- T. Sousa, H. Morais, J. Soares, Z. Vale, “Day-ahead Resource Scheduling in Smart Grids Considering Vehicle-to-Grid and Network Constraint”

- J. Soares, S. Ramos, Z. Vale, H. Morais, P. Faria, “Data Mining Techniques Contributions to Support Electrical Vehicle Demand Response”

2 Electric Vehicles in Smart Grids

The present power systems have several resources available that should be adequately managed, requiring players in a liberalized market to change their strategies and the way they act. Some of these resources such as Distributed Generation (DG), Demand Response (DR), and storage systems have been gaining increased importance [2]. Electric Vehicles (EVs) are emerging as a reliable alternative solution to the typical internal combustion vehicles, with the advantage of being a good way to reduce CO_2 emissions [8, 9], as well as to decrease dependence from fossil energy sources [18-20].

Power system operators and other power system players should consider the use of EVs as a new Distributed Energy Resource (DER) in the scope of the diverse resources connected to the system. However, EVs have very specific characteristics, namely in what concerns location change and their possible dual role as energy sources (discharging batteries when connected to the power grid) or loads (when charging their batteries, consuming energy from the grid) [2]. In an adavanced stage of network automation, the EVs charge and discharge should be controlled by the system operator, maintaining the constraints on the whole system including electric vehicle customers' requirements. However, this requires an appropriate infrastructure that is expensive but allows intelligent integration with the grid and efficient use of energy [20].

Fig. 2.1 shows a diagram of electric vehicles in the smart grid context. Vehicle-to-Grid (V2G) can be anywhere between home, parking lots and companies parks with V2G capabilities. The communication with the Distribution Network Operator (DNO) or the

Virtual Power Player (VPP) (referred as aggregator in the figure) can be done using wireless communication when vehicles are not connected to the grid, for instance, with Global System for Mobile (GSM) communications technology or by wire with Power Line Carrier (PLC) when vehicles are plugged in [21]. The communications between DER and VPPs should be based on contracts respecting legal policies. These communications should be secured through computer security mechanisms such as data encryption and authentication.

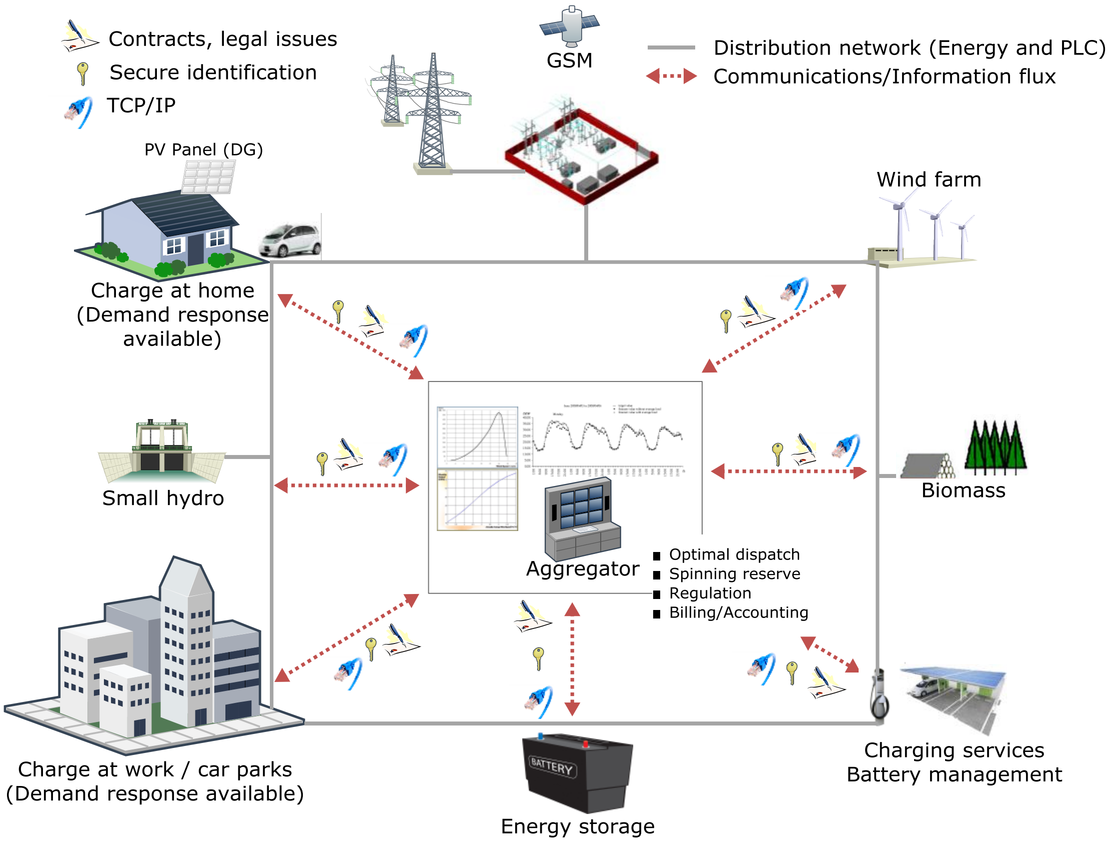

Fig. 2.1 – Electric vehicles in smart grids context [3]

The work in this thesis assumes that adequate infrastructure is in place, namely in what concerns charging points and devices as well as integrated communications. Thus, EV batteries charging and discharging can be used in the scope of intelligent resource management, using the V2G concept.

2.1 Current EV technology

This section provides a review of the current available EV technology; furthermore, EV battery parameters for use in electricity grid system modeling are presented. Part of this review was supported by a recent deliverable of MERGE European project provided in [22]. In that report a database containing more than 100 published specifications of current and proposed EVs (up to 2010) can be found. The EVs included in this database are of the following types:

- Plug-in Hybrid Electric Vehicle (PHEV): It is a regular hybrid vehicle that combines both an electric motor and an internal combustion engine for motive power and has a large capacity battery bank. However, unlike hybrids, PHEVs can be charged using the electricity grid (usually connecting a plug to an electric socket). Batteries in a PHEV can be charged using the on-board charging capabilities of normal hybrids as well;
- Extended Range Electric Vehicle (EREV): The main energy source is the battery for daily trips; however, an internal combustion engine running on hydrocarbons is present and works as a range-extender by recharging battery on-board;
- Battery Electric Vehicle (BEV): the only source of energy is the battery. The range is far more limited than in PHEVs and EREVs. However, this type of vehicles does not use up fuel, instead the charging of batteries depends on the electricity grid. Typically, the batteries of BEVs are of larger capacity than those installed on PHEVs and EREVs, though making the vehicle expensive.

In Europe, motor vehicles fall into the categories presented in Table 2.1 [23].

Table 2.1 – Europe vehicle categories

Vehicle class	Common definition	Passenger/Commercial	Seats(excluding driver)	Mass limit
M1	Passenger car	Passenger	Limit of 8	-
M2	Bus	Passenger	More than 8	5 tonnes
M3	Bus	Passenger	More than 8	-
N1	Van	Commercial	-	3.5 tonnes
N2	Light truck	Commercial	-	12 tonnes
N3	Heavy truck	Commercial	-	-
L1 to L7	Motorcycles, Tricycles and Quadricycles (L7e)			

The majority of the vehicles that are sold in Europe are passenger vehicle, i.e. M1 vehicles representing 87% of the total vehicle fleet [24]. The vehicles considered in the EV review presented in [22] belong to the categories presented in Table 2.2. This table concerns the European vehicles categories of EV that were found in that review, i.e. only M1, N1, N2 and L7e vehicle classes.

Table 2.2 – Electric vehicle categories [22]

Vehicle class		**Vehicle examples [22]**
M1		81
N1		12
N2		4
L7e		19

2.1.1 Battery parameters modeling

A summary of the battery specifications of the models presented in the MERGE review report can be seen in Table 2.3. This data provides support for EV battery modeling and enable the creation of different scenarios based on BEVs, PHEVs and EREVs. It can be seen that the present EREVs models in the market do not allow the fast charge mode.

Table 2.3 – EV battery specifications [22]

Vehicle class		**Battery capacity (kWh)**			**Charging rates (kW)**	
		Max	**Mean**	**Min**	**Slow charge rate**	**Fast charge rate**
BEV	M1	72	29	10	2-8.8	3-240
	N1	40	23	9.6	1.3-3.3	10-45
	N2	120	85	51	10	35-60
	L7e	15	8.7	3	1-3	3-7.5
PHEV	M1	13.6	8.2	2.2	3	11
	N1	13.6	8.2	2.2	3	11
EREV	M1	22.6	17	12	3-5.3	-
	N1	22.6	17	12	3-5.3	-

The typical slow charge rate mode is 3 kW for the majority of classes [22]. N2 class vehicles present a higher slow charge rate mode of 10 kW because the battery capacity tends to be much larger than normal passenger vehicles [22].

In spite of different fast charge rates between vehicle classes, 80% of EV's potential users answered in a survey that the preferred charging place would be at home [22]. This means that the slow charge rate, which is available at home, will be often used.

2.1.2 Battery cell ageing and effects of discharge cycles on battery lifetime

The battery capacity is known to be reduced over its lifetime with discharge and charge cycles. The Miner's Rule method of evaluating battery aging was first introduced by Facinelli [25, 26]. Facinelli observed that cycling damage to a battery is primarily a function of the depth of discharge (and corresponding recharge) to which the battery is subjected. For example, going from 10% to 30% discharge and back was seen to be approximately the same as from going from 50% to 70% and back. Facinelli's Miner's Rule method was originally developed for discrete, non-overlapping cycles, which might typically be found in photovoltaic based battery charging system. These would be subjected to approximately one cycle per day. When batteries are subjected to more irregular cycling, Facinelli's Miner's Rule approach cannot be applied directly [26]. Such irregular cycling has been found to occur in modeling of wind/diesel systems [26, 27].

In [28] the authors suggested a set of equations for battery capacity reduction over cycles number depending on its technology. The reduction of battery capacity as proposed by the authors can be seen in Fig.2.2.

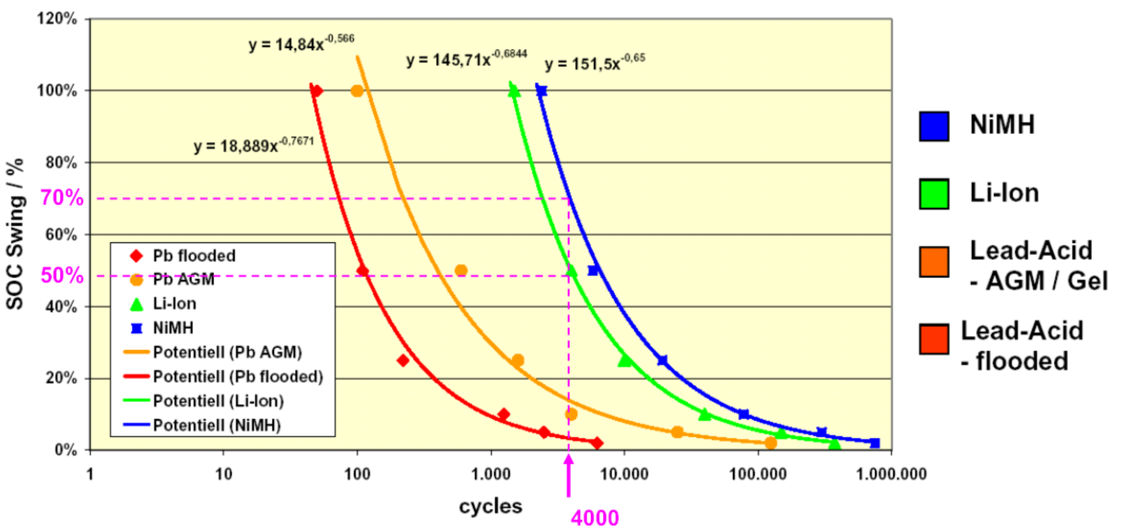

Fig.2.2 – Reduction of battery capacity as a function of cycle nymber [28]

Li-ion batteries are recognized by their superior characteristics in terms of energy and power density and are preferred in applications for which size, weigth and performance are considered very important [29]. Li-ion batteries are expected to be used in mass by electric vehicles because of their higher energy density instead of Nickel-Metal-Hybride (NiMH) batteries. The present energy density of Li-ion batteries is around 180 Wh/kg with prospects for even higher densisites and lower weigth in the near future [30].

Li-ion battery curve equation as presented in Fig.2.2 is:

$$y = \frac{145.741}{x^{0.6844}} \tag{2.1}$$

where, y represents the State Of Charge (SOC) swing for the desired battery life cycles (x).

The above equation assumes that y, i.e. the SOC swing (depth of discharge) remains constant in each battery charge/discharge cycle.

Solving equation (2.01) in order to battery life cycles (x), we obtain:

$$x = \frac{1449.26}{y^{1.46}} \tag{2.2}$$

Using the above equations (2.1) and (2.2) together, the damage of a battery, considering a lifespan of 6 years, can be calculated as follows [22]:

$$\text{Damage} = \frac{\text{Number of cycles}}{1449.26 * \text{DOD}^{-1.46}} + \frac{\text{age}}{6} \tag{2.3}$$

where:

- Damage represents the damage caused to the battery: 0 (new battery) and 1 (wear-out);
- DOD is the depth of discharge between 0 and 1;
- age is the actual age of the battery considering 6 years of calendar life.

To calculate battery capacity and internal resistance the following rules apply:

- Capacity (%) = 100 - (20*Damage).
- Internal resistance (%) = 100 + (20*Damage).

The reduction of battery capacity is represented in Fig. **2.3**, for a 3 year old battery using equation (2.3). The flat red square is the limit of acceptable battery wear-out, which is 80% of the battery capacity [22]. It can be seen that for high depth of discharges this limit is rapidly reached. For a depth of discharge around 0.9 the battery wears-out after 900 cycles. Considering a battery which is 3 years old with around 1000 cycles of charge/discharge, and with a constant DOD of 0.7 (70%), results in an actual capacity of 82% over the original.

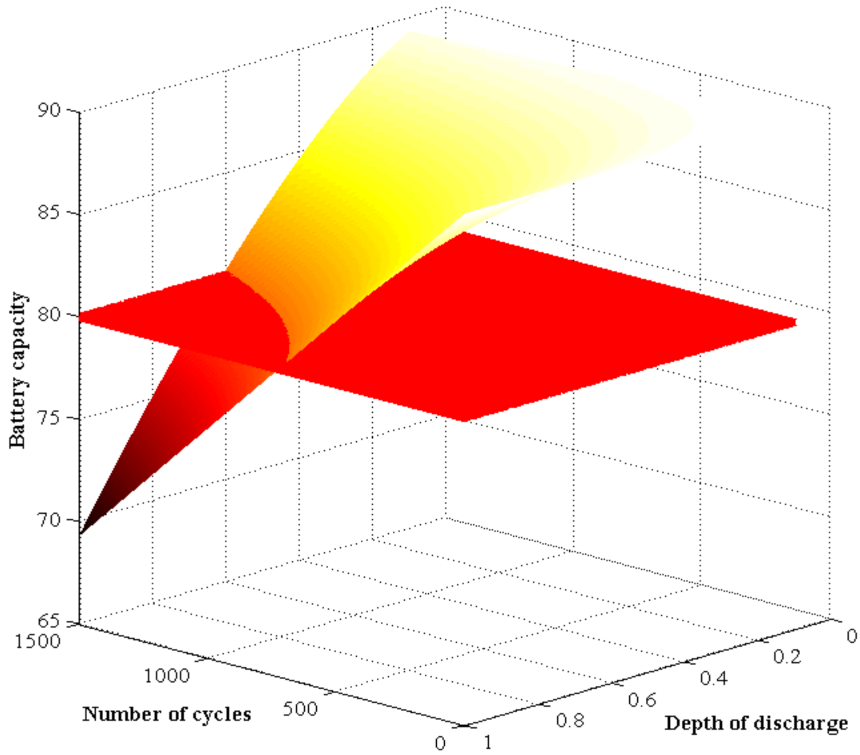

Fig. 2.3 – Reduction of battery capacity for a 3 years old battery

The approach presented above does not allow calculating damages caused to the battery when different *DOD* applies. Therefore Facinelli's Miner's Rule can be used allowing the estimation of the total wear-out damage caused by subjecting the battery to different *DOD* over its lifetime. This allows modeling the effects of different combinations of charge/discharge cycles in simulation and optimization models. The damage caused to the battery as the calculated by the Facinelli Miner Rule (*DamageFMR*) can be represented by equation (2.4):

$$\mathrm{DamageFMR} = \sum_{\mathrm{i}=1}^{\mathrm{ncycles}} \frac{1}{\mathrm{d_i}} \tag{2.4}$$

where:

- $ncycles$ represents the total number of cycles of the battery.
- d_{i} represents the damage caused by cycle *i* using equation (2.3) with DOD of the given *i* cycle.

2.1.3 Battery costs

EVs are projected to cost an additional $6,000-16,000 more than a conventional vehicle in the next 5-10 years [31]. Fig. 2.4 presents the impact of the battery pack on a PHEV drive system cost. It can be seen that it represents about 80% of the total cost.

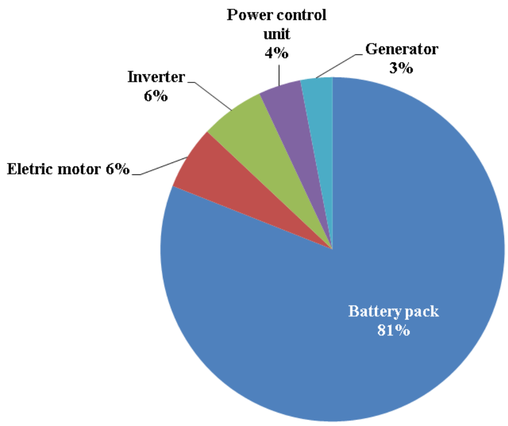

Fig. 2.4 – Breakdown of PHEV drive system cost by component [31]

Nowadays, battery cost estimates vary widely from $260/kWh to $1,300/kWh [31]. These costs should be taken into account by the network operators or VPPs managing V2G cars, due to the use of the battery to supply energy back to the grid that causes extra battery wear-out with no-travelling purposes. The extra battery wear-out resulting from the discharging for this purpose should be paid by the operator. As the price of current battery varies with the type and the quantity of battery units producted and also with the battery technology, the tariff or the contracted price to use the energy of a V2G car should be negotiated with the respective owner.

Fig. 2.5 presents an estimate of battery wear-out cost as a function of battery cost. This cost is to be supported by the operator that uses the V2G concept. This estimate assumes the following:

- Battery capacity equal to 28.5 kWh;
- 1000 battery life cycles using a depth of discharge of 80%;
- A new battery pack is bought by the owner after 1000 cycles of use;
- The battery cell ageing model presented in subsection 2.1.2.

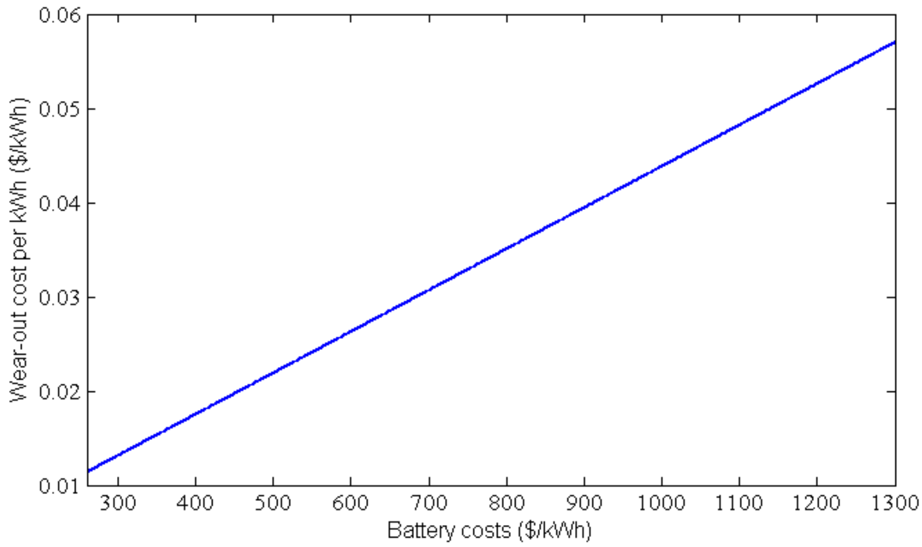

Fig. 2.5 – Battery wear-out cost per kWh as a function of battery cost per kWh

For the best battery cost scenario ($260/kWh) the cost to be supported by the operator would be about 1.1 cents of dollar per kWh (not taking into account the energy itself). The V2G owner should contract a higher price of battery discharging, e.g. 1.5 or 2 cents of dollar per kWh (plus energy) in this case, to make a profit by placing his vehicle resource to the operator.

2.2 EV market penetration and driving behaviors

The authors in [32] claim that the impact of EVs on the distribution network can be determined using driving patterns, charging characteristics, charge timing and vehicle market penetration. A study from department for business enterprise and regulatory reform in United Kingdom estimated that with adequate policy incentives to electric mobility, a fleet penetration of 37% in 2030 can be expected [18]. Fig. 2.6 shows how many EVs, PHEVs, and Internal Combustion engine Vehicles (ICVs) will predictively be on the UK car park if proactive measures are taken to bring EVs to the market. The graph displays predictive data of accumulated EVs and PHEVs as well as ICVs sales until 2030. It can be seen that the simulated penetration predicts a slower and gradual infiltration on the first decade. Power system and network investments must be planned for the future considering this expected significant market share of EVs [18, 32-35].

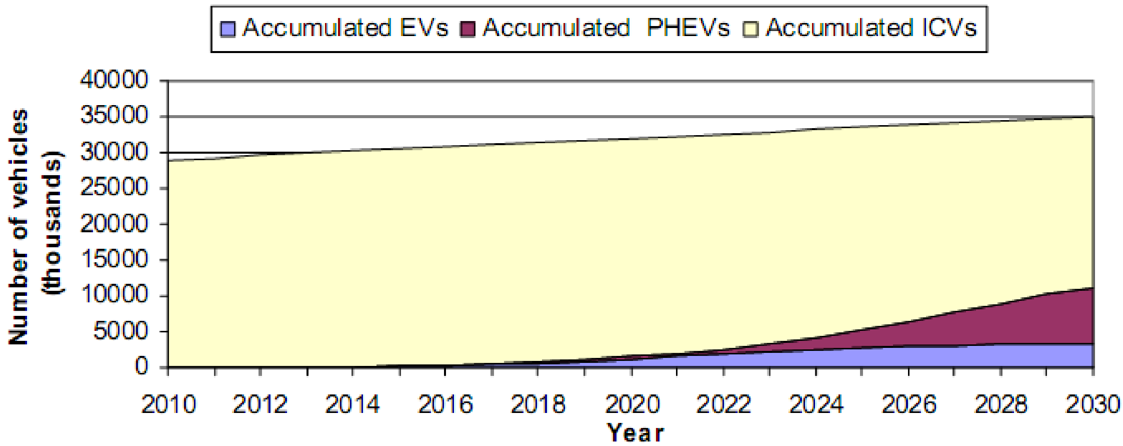

Fig. 2.6 – Number of predicted cars in UK by 2030 [18]

The charge rate is another important characteristic that must be considered, e.g. in the U.S. a 120V 15A socket in theory would be 1.8 kW, while a 20A circuit would ensure about 2.4 kW. In Europe, the standard home outlet is 230V 16A corresponding to a maximum load of 3.7 kW. The proposed faster charging connections in Europe are expected to enable to reach much higher power values [36].

The driving patterns are important because the impact on the power system depends on where and when the vehicles are charging which affects the energy costs. Let us consider a typical daily drive for a person: starting from his/her house, then going to work, maybe the person has lunch in another place, comes back home and/or makes a detour to the store. This means that during the day the vehicle can be in different places: for instance in the garage, in an employer's parking lot, a store parking lot and on the road. The main issue is to know where and when will the EV charge the battery and how many of them will do it simultaneously. This behavior must be studied in order to allow an adequate resource management. Controlled charging of EV can help to reduce consumption impacts on the grids [34, 37]; however, good control strategies must be implemented to avoid secondary system peaks.

In the U.S. [35] near 50% of the Americans drive less than 42 km per day and 90% drive less than 150 km per day. In Western Europe Cities (WEU), these values are lower: an average of 41 km driven per capita and per vehicle in European cities contrasting with 85 km in the US cities [38] (see Fig. 2.7). Thus, the EVs in general have the potential to meet almost America's daily automotive transportation and certainly WEU cities needs on battery alone, considering that most future commercial EVs will have more than 150 km of vehicle range [22]. In 2009, the U.S. Department of Transportation studied the percentage of trips in a day, and the results have shown that almost all cars are parked at night [39] (see Fig. 2.8).

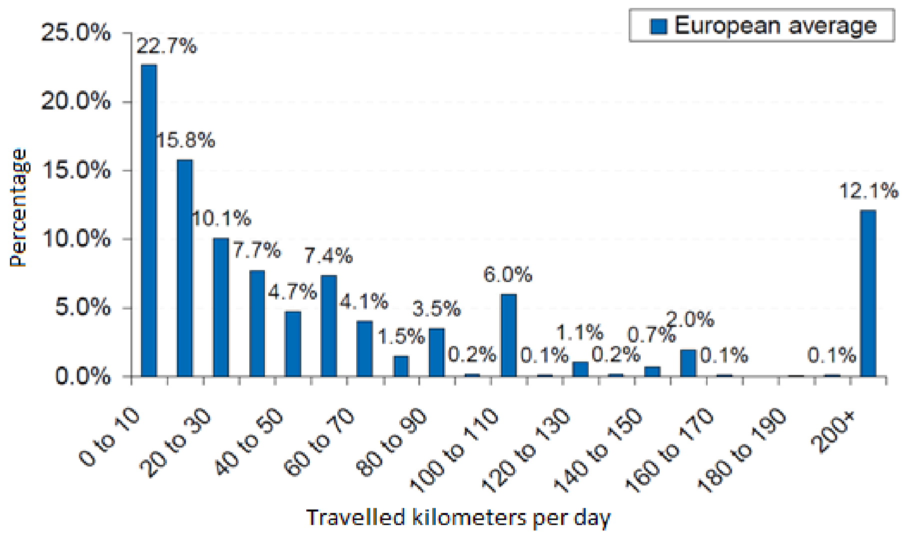

Fig. 2.7 – European average travelled per day on weekday [22]

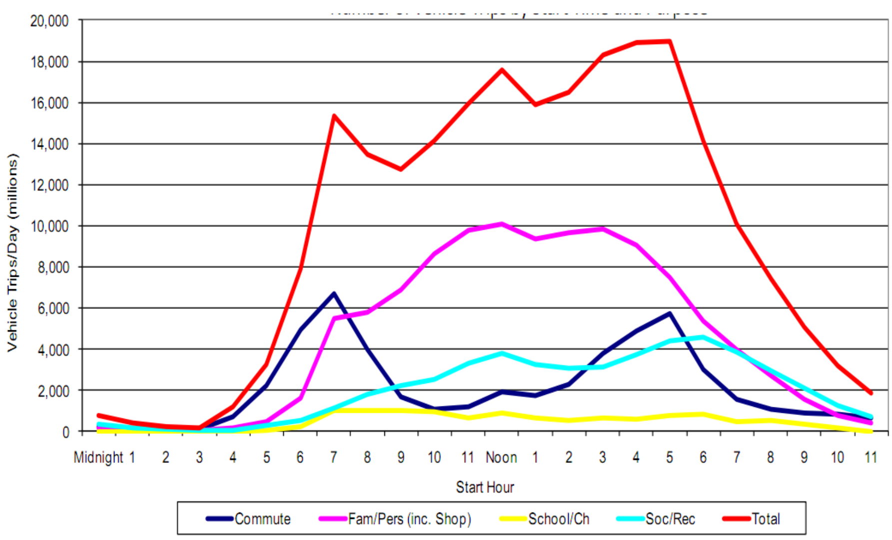

Fig. 2.8 – Distribution of vehicle trips by trip purpose and start time of trip [39]

2.3 EVs scenario simulator tool

An application named Electric Vehicle Scenario Simulator (EVeSSi) was developed in the scope of this thesis to allow the creation of different scenarios in distribution networks. This tool enables a fast and organized way to deploy different case studies. The EV scenarios case studies presented in this thesis were created using this tool.

2.3.1 Parameters of EVeSSi

EVeSSi enables to create EV custom tailored scenarios in a flexible and rapid way. This section presents the parameters used by EVeSSi, which are organized in the following way: global parameters, trip parameters, EV classes and types parameters, and EV specific model parameters.

Table 2.4 presents EVeSSi global parameters. These parameters are related to general considerations of the scenario. For instance, the value of *chargingEfficiency*, *batteryEfficiency*, *initialStateOfBats*, *batteryMaxDoD* parameters are applied for every EV present in the scenario. This is the default setting although these parameters can be applied individually. The recommended values according to [22] are 90% and 85% for *chargingEfficiency* and *batteryEfficiency*, respectively.

Table 2.4 – EVeSSi global parameters

Parameter	Description	Example value
initialStateOfBats	Initial state of batteries	30%
stepRate	Simulation time step (30 min, 1 hour)	1 hour
totalStep	Total number of steps (periods)	24
batteryMaxDoD	Battery max. depth of discharge permitted (DoD)	80%
chargingEfficiency 1	Slow charge mode efficiency	90%
chargingEfficiency 2	Fast charge mode efficiency	90%
batteryEfficiency	Battery efficiency	85%
evNum	Number of electric vehicles	2000
sameInitalEndBusProb	Probability of the EV to end in the same starting network bus in the simulation scenario	85%
parkedAllDay	Cars percentage that are always parked and connected to the grid	1%
carsInsideNetwork	Cars percentage that remain inside distribution network	50%
carsGoingOutsideNetwork	Cars percentage that leave distribution network	25%
carsGoingInsideNetwork	Cars percentage that arrive from other distribution network	25%

Table 2.5 presents the trip parameters. It is possible to define the distribution of trips along each period to simulate real-world conditions; for instance, using data supplied

from [39] (see Fig. 2.8). The same is applied to define trip distance distribution (see Fig. 2.7).

Table 2.5 – EVeSSi trip parameters

Parameter	Description
Trip distribution by period	Distribution of trips by each period
Trip distance distribution	Distribution of travelled distance

Table 2.6 presents the parameters related to the definition of vehicle classes and types. Recalling Table 2.1 and Table 2.2 of vehicles classes, it is possible to define the desired classes using EVeSSi parameters and setting classes distribution of the car fleet according to the aimed values, e.g. 90% of class M1 and 10% of class N2. Vehicle types and their distribution on the scenario can also be defined, e.g., 50% BEV and 50% PHEV. The tool accepts any number of vehicles types as well as vehicles classes.

Table 2.6 – EVeSSi classes and types parameters

Parameter	Description
Vehicle classes	Specification of vehicles classes present in the network
Vehicle classes distribution	Distribution of vehicle classes
Vehicle types	Specification of vehicles types present in the network
Vehicle types distribution	Distribution of vehicle types

Table 2.7 presents specific EV model parameters. The tool enables to specify any number of desired models. The parameters that are available for each model are depicted in the table. The parameter *average km day,* when supplied, overrides the average of *trip distance distribution* parameter (see Table 2.5), however a similar pattern distribution is adjusted to the *average km day* parameter.

Table 2.7 – EVeSSi EV model parameters

Parameter	Example value
Battery capacity	29 kWh
Slow charging rate	3 kW
Fast charging rate	57 kW
Average economy	0.16 kWh/km
Average km day	38 km
Average speed	35 km/h
Vehicle type	Plug-in hybrid vehicle
Vehicle class	M1

2.3.2 EVeSSi process

A schematic view of the process used by EVeSSi to create a given scenario is presented in Fig. 2.9. The parameters described in subsection 2.3.1 are supplied to EVeSSi using a database. In the figure two main models can be identified:

1. Distance for each EV;
2. Generated scenario.

The parameters required by each module are highlighted within a label. In the figure only EV and global parameters appear due to figure size restriction and design appeal. However, all the parameters described in 2.3.1 are loaded from the database.

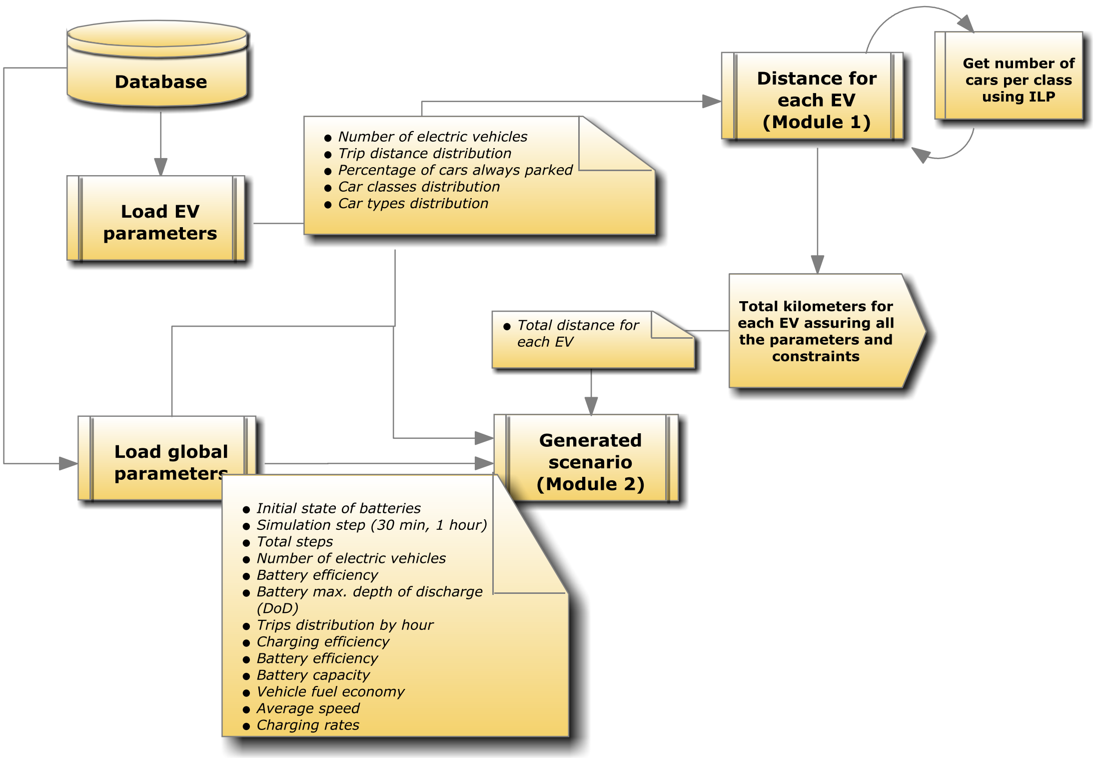

Fig. 2.9 – EVeSSi framework

In module 1 – Distance for each EV – a sub-module to calculate number of cars of each model was developed. This sub-module intends to guarantee user defined parameters and the mathematical formulation uses an Integer Linear Programming (ILP) model. The objective function is neutral (0 – neither minimizing or maximizing the objective function) because the reason of using ILP method in this sub-module is to guarantee problem constraints. These constraints depend on the defined parameters. This sub-module will return the number of cars per each defined model (see Table 2.7) according to classes and types parameters (Table 2.6).

The mathematical model is defined bellow:

$$Min. f = \sum_{i=1}^{modelNum} x_i \times 0 \tag{2.5}$$

Subject to the following constraints:

$$\sum_{i=1}^{modelNum} x_i = evNum \tag{2.6}$$

$$\sum_{j=1}^{techTypesNum} \sum_{i \in techTypeSet_j} x_i = evNum \times techWeight_j \tag{2.7}$$

$$\sum_{k=1}^{classesNum} \sum_{i \in classesSet_j} x_i = evNum \times classesWeight_k \tag{2.8}$$

where:

- $evNum$ is the total number of electric vehicles including all models
- x_i is an integer variable where each x_i represents the number of vehicles of model *i*
- $techWeigth_j$ is the weight for technology type *j* (e.g. 40% BEV, 60% PHEV)
- $classesWeigth_j$ is the weight for class type *j* (e.g. 90% passenger vehicles, 10% commercial vehicles)
- $techTypeSet_j$ is the set of model types i that belong to tech type *j*
- $classesSet_j$ is the set of model types i that belong to class *j*
- $modelNum$ is the total number of models available
- $techTypesNum$ is the total number of technology types available
- $classesNum$ is total number of classes available

With the information returned by the sub-module, module 1 – Distance for each EV – will use EV parameters (Table 2.7) and trip distance distribution parameters (see Table 2.5) to calculate the total distance allocated to each EV. Also in this module, the *carsParkedAllDay* parameter (Table 2.4) is used for setting some cars to be parked all day. Module 1 – Distance for each EV – will return the total distance for each EV.

Module 2 – Generated scenario – depends from the result of module 1. With the EVs' distance information returned by the first module, a scenario is attempted to be created. Fig. 2.10 presents a flowchart of the algorithm thst is the basis of module 2. Travelling-periods are calculated using the distance for each EV returned by module 1. This value corresponds to the number of periods that each vehicle will be disconnected from the grid for travelling purposes. As an example, if the distances returned by module 1 for vehicle 1 and vehicle 2 are 10 km and 50 km, respectively, using *average speed* parameter for the corresponding model of each vehicle (see Table 2.7), assuming 35 km/h for both vehicles, then the travelling-periods would be 1 and 2 for vehicle 1 and 2, respectively, considering a time step of 1 hour, i.e. ceiling the result to the neareast integer of the divisions 10/35 and 50/35. If vehicle 1 distance was 35 km and the *average speed* parameter the same 35 km/h the corresponding travelling-periods would also be 1, however, the energy consumption during the disconnected period would be different.

In this stage, there is only the information of the number of traveling-periods (disconnected periods) for each EV. The next step of the algorithm is to calculate the number of trips that will occur in each period using travelling-periods information and *trip distribution by period* (see Table 2.5) resulting in a vector with the information of scenario trips number per period.

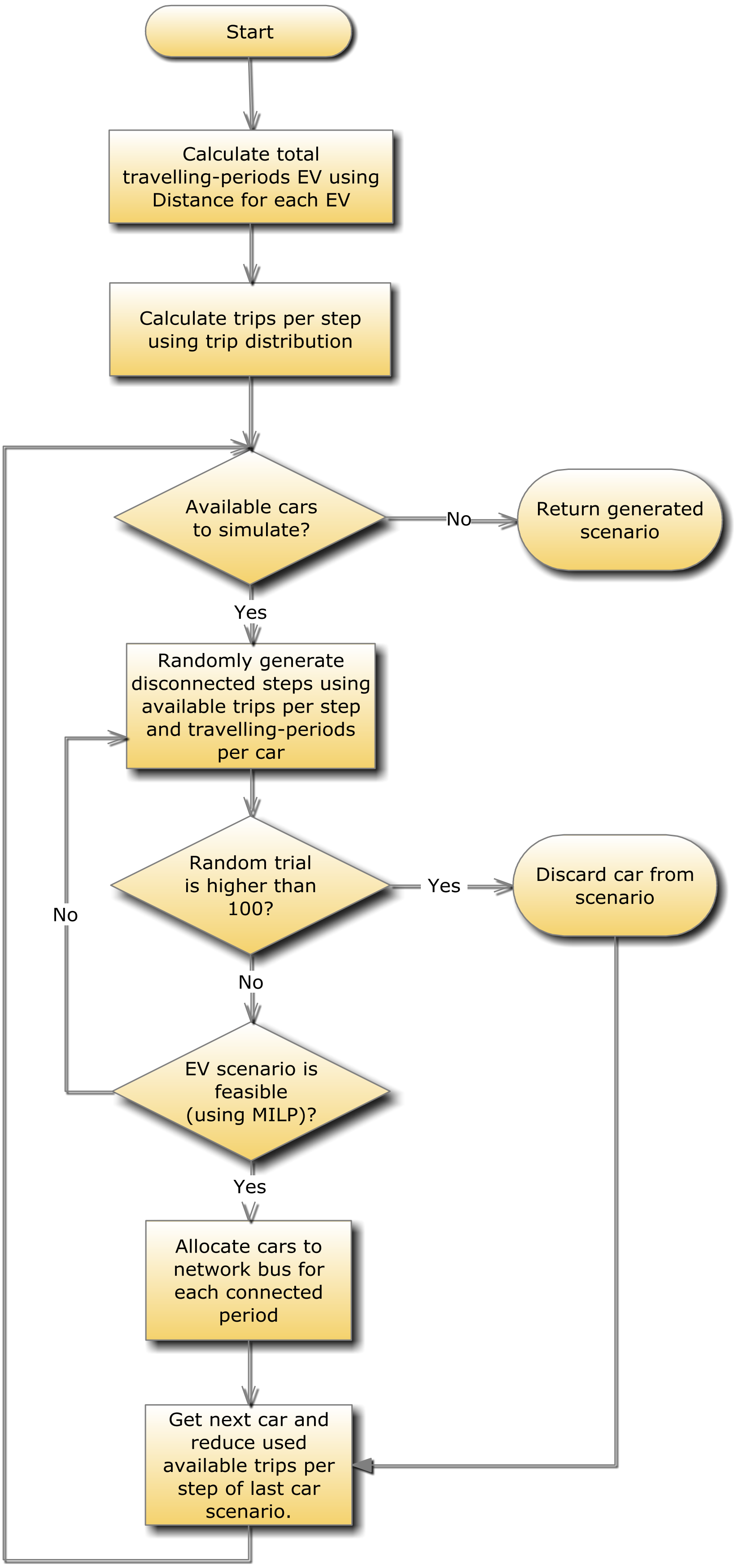

Fig. 2.10 – Module 2 algorithm flowchart

After that, with the number of trips per period, the algorithm will attempt different possibilities of disconnected periods. For example, if vehicle 2 has 2 travelling-periods, then the algorithm randomly allocates this 2 travelling-periods to the available number of periods, for instance, periods 8 and 18. This guarantees the *trip distribution by period* parameter. Mixed Integer Linear Programming (MILP) is used to ensure feasibility of the randomly generated EV disconnected scenario. The objective function minimizes the use of fast charge in order to avoid early battery wear-out. If a feasible solution is found using MILP, the disconnected scenario is accepted for the given EV; otherwise, another randomly disconnected scenario is attempted. In the case of continued failed trials, the EV is marked as infeasible on the network and discarded from the scenario. The mathematical formulation of the feasibility check is defined as follows:

$$Min. f = \sum_{i=1}^{T} Y_t \tag{2.9}$$

Subject to the following constraints:

$$E_{Stored\ (t)} = initialBatState, \qquad with\ \ t = 0 \tag{2.10}$$

$$E_{Stored\ (t)} = E_{Stored\ (t-1)} + E_{Charge(t-1)} - E_{Trip(t-1)}\ , \qquad \forall\ t\ \in \{1, \dots, T\} \tag{2.11}$$

$$E_{Trip(t)} * Z_t - E_{Stored\ (t)} \leq 0 \tag{2.12}$$

$$E_{Stored\ (t)} \leq batCap\ , \quad \forall\ t\ \in \{1, \dots, T\} \tag{2.13}$$

$$\begin{aligned} E_{Charge(t)} = n_{slowCharge} * P_{SlowChargeRate(t)} * X_t * \Delta cd + n_{fastCharge} \\ * P_{FastChargeRate(t)} * Y_t * \Delta cd, \quad \forall\ t\ \in \{1, \dots, T\} \end{aligned} \tag{2.14}$$

$$X_t + Y_t + Z_t \leq 1, \quad \forall\ t\ \in \{1, \dots, T\}$$

where:

- $E_{Charge(t)}$ is the energy charged in period *t*
- $E_{Stored\ (t)}$ is the battery's energy stored in period *t*
- $E_{Trip\ (t)}$ is the energy consumed by vehicle trip in period *t*
- $P_{FastChargeRate(t)}$ is the fast charge rate in period *t*
- $P_{SlowChargeRate(t)}$ is the slow charge rate in period *t*

- X_t is the slow charge binary variable in period *t*
- Y_t is the fast charge binary variable in period *t*
- Z_t is a Boolean for trip decision in period *t* (0/1) and fixed before optimization
- Δcd is the duration of charging, typically $\Delta t = 1$
- $batCap$ is the limit of battery capacity
- $initialBatState$ is the initial battery state of the battery
- T is the number of periods
- $n_{slowCharge}$ is the charging efficiency in slow charge mode
- $n_{fastCharge}$ is the charging efficiency in fast charge mode.

2.4 Conclusions

This chapter starts by addressing several important aspects that support this thesis work, namely the state of the art concerning EV technology regarding types of EVs, current batteries capacity and charging rates.

Battery cell ageing as well as battery costs of EVs are also addressed as they should be taken into account in V2G applications. Estimated battery wear-out cost can be between 1 and 6 cents of a dollar per kWh of used energy.

Market penetration and driving behaviors studies are also considered in this thesis. The impact of EVs on the distribution network can be determined using driving patterns, charging characteristics, charging time and EVs market penetration.

The EVeSSi tool designed and developed in the scope of this thesis has been presented in this chapter. It enables the creation of specific EV scenarios in distribution networks according to the defined parameters that catch EV technology, driving behaviors and market penetration.

3 Optimization Methodologies

Optimization methodologies for the day-ahead Distributed Energy Resources (DER) scheduling problem require adequate and competitive tools. In this thesis Particle Swarm Optimization (PSO), firstly introduced by Kennedy et al. in 1995 [40], was selected as the preferred optimization method due to previously demonstrated benefits in scheduling problems [2, 15]. Though, a deterministic approach method is also presented in this chapter, namely Mixed Integer Non-Linear Programming (MINLP). The use of MINLP is used in this thesis for comparison purposes, since it is important to have a reference technique to be compared with stochastic methodologies such as metaheuristics, in this case PSO.

The mathematical model of the day-ahead DER scheduling problem is presented in this chapter including all the relevant constraints related to distribution network operation, Distributed Generation (DG), Electric Vehicles (EVs) and batteries requirements needs, and Demand Response (DR) programs for EVs.

During this work, the original version of PSO was modified to better suit the day-ahead scheduling problem. PSO problem-specific heuristics, user independent parameterization and an intelligent mechanism were developed in this thesis. It can be considered a new PSO variant but, at the same time, an application-specific implementation of PSO to the problem of day-ahead DER scheduling. The modified PSO model includes an algorithm to identify which problem variables can improve the objective function and relieve constraint violations. Thus, the identified variables will be marked to be differently addressed by the modified PSO in the successive iteration in order to achieve the desired objective.

3.1 State of the art

This section is divided in two parts for better readability. The first part concerns the optimization problem of day-ahead DER scheduling considering Vehicle-To-Grid (V2G). The second part concerns the state of the art regarding PSO.

3.1.1 Day-ahead DER scheduling

A review literature of day-ahead DER scheduling with V2G reveals very few works. Authors in [41, 42] present a unit commitment model with V2G using the meta-heuristic PSO to reduce costs and emissions in smart grids. In these works no comparisons are made with other methodologies, namely in what concerns the use of an exact method for solution quality comparison. Besides that, the network model is not considered because these works address the unit commitment problem. In [2] a PSO approach is presented for the DER scheduling problem using V2G resources. A case study using 500 vehicles is addressed. The results of the case study show that PSO is about 148 times faster than Mixed Integer Non-Linear Programming (MINLP). Authors in [3] propose a simulated annealing approach to solve the DER scheduling problem with V2G resources using a single objective function (operator costs). The methodology is compared with MINLP and the case study results with 1000 V2G units show that the meta-heuristic approach presents a worst objective function value with 3%. Both works from [2] and [3] lack the inclusion of a power flow model in the metaheuristics methodology approach. Instead, a validation of solution after optimization is made. A hybrid approach using power flow could result in better solution quality and avoid network solution validation after optimization. Besides that, vehicles are aggregated in groups of 10 to reduce the number of variables and, consequently, the problem size. An improved model using individual V2G contracts should be further investigated.

Several research works concerning DR programs for loads are reported in the literature [43-46]. However, DR opportunities for V2G are not yet addressed and further investigation is required in this field [47].

3.1.2 Particle Swarm Optimization review

The PSO concept began as a simulation of simple social systems like the flocks of birds or the schools of fish [7]. The main advantage of PSO is its simplicity, while being capable of delivering accurate results in a consistent manner. It is fast and also very flexible, being applicable to a wide range of problems, with limited computational requirements [6]. A PSO system starts with an initial population of random individuals, representing solutions of a problem, to which are assigned random velocities. The individuals, called particles, evolve throughout the problem space, searching for the optimal solution for the specific problem. In every PSO iteration every particle is evaluated against a fitness function to determine the one that offers the best solution found so far. Each particle keeps also track of its own best. Therefore, every particle flies through the problem space chasing two beacons: the global best and its own best. Usually its velocity is clamped to avoid overshooting. Fig. 3.1 represents the flowchart of the basic algorithm of PSO. The particle velocities are governed by three main vectors: particle's inertia, the attraction towards its best position so far and the attraction to the best global position.

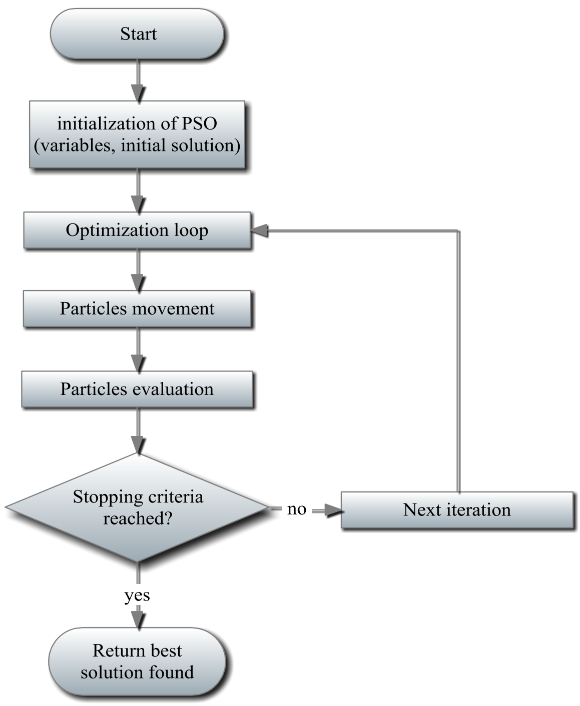

Fig. 3.1 – Traditional PSO flowchart

Nevertheless, the traditional PSO algorithm is not immune to limitations that hang mainly on the fact that it depends on several user-defined and problem-dependent parameters [48, 49]. In fact, the weights of the velocity equation are tuned by the system implementer to fit then to the specific problem. For instance, the inertia weight value carries a strong influence on the evolution of the particle, determining to a certain extent whether it will fall into a local optimum, converge to a global maximum or simply overshoot. It is therefore common to apply to this component a function that decreases as it converges to the global solution, but even the decreasing rate of this function must be carefully defined. This method is also complemented with the clamping of the particle's velocity to maximum and minimum allowed values [50]. The setting of these values is another externally defined operation, which is critical to obtain accurate results: if the velocity is too high the particle risks passing beyond a good solution, but if it is too low it is probable that it will get stuck in a local optimum.

The acknowledgment of this and other limitations led to the proposal of variants to the traditional PSO algorithm. One possible path to the improvement has been the hybridization of PSO with evolutionary algorithms [51]. A good example of this technique is the Evolutionary Particle Swarm Optimization (EPSO) algorithm [48]. EPSO can be seen as a self-adaptive evolutionary algorithm where the recombination is replaced by an operation called particle movement. It does not rely on the external definition of weights and other PSO crucial parameters. The basic gist of this method can be summarized as follows:

- Every particle is replicated a certain number of times;
- Every particle's weights are mutated;
- A movement rule is applied to each mutated particle;
- Each new particle is evaluated according to the problem-specific fitness function;
- Using stochastic tournament, the best particles are picked to form the new generation.

In [52] the authors proposed a modification to the velocity equation in order to include particle's bad experience component besides the global best memory introduced before [40, 53]. The bad experience component helps to remember the previously visited worst position. The method is called New Particle Swarm Optimization (NPSO). The authors claim superiority over conventional PSO in terms of convergence and robustness properties. Time execution is slightly worsened when compared with classic PSO due to the additional computation requirements to process bad experience component.

Another interesting approach is Gaussian PSO (GPSO) that has its acceleration factors replaced by random numbers using Gaussian distributions, discarding the weight factor and avoiding the fixed external definition of the other weights [54].

3.2 Day-ahead scheduling mathematical model

The energy resource management [14] methodology is described in this section, in terms of problem description and mathematical formulation. This methodology is used to support Virtual Power Players (VPP) or Distribution Network Operators (DNO) to obtain an adequate management of the available resources, including V2G, in the smart grid context.

In terms of problem description, VPPs have contracts for managing the resources installed in the grid, including load demand. The load demand can be satisfied by the distributed generation resources, by the discharge of electric vehicles, and by external suppliers (namely retailers, the electricity pool, and other VPPs). The use of V2G discharge, and the respective charge, considers V2G user profiles and requirements. The network influence is included in this methodology, through ac power flow calculation, voltage limits and line thermal limits.

The energy resource scheduling problem is a Mixed Integer Non-Linear Programming (MINLP) problem. The objective function aggregates all the costs with the energy resources. The energy resource model includes: DG, energy acquisition to external suppliers, the V2G discharge or charge energy, the non-supplied demand, the excess available power [2, 3] and trip reduce demand response model for electric vehicles. All the involved resources costs function are considered as linear. The VPP goal is to minimize the objective function value or, in other words, the total operation cost.

In order to achieve a good scheduling of the available energy resources, it is necessary to apply a multi-period optimization; the presented formulation is generic for a specified time period (from period t=1 to t=T) [3, 14]. The model includes an ac power flow algorithm that allows considering network constraints, leading to a Mixed Integer Non-Linear Programming (MINLP) problem.

$$min\ \ f=\sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum_{DG=1}^{N_{DG}} P_{DG(DG,t)}\times c_{DG(DG,t)}+\\ \sum_{S=1}^{N_S} P_{Supplier(S,t)}\times c_{Supplier(S,t)}+\\ \sum_{V=1}^{N_V} P_{Discharge(V,t)}\times c_{Discharge(V,t)}-\\ \sum_{V=1}^{N_V} P_{Charge(V,t)}\times c_{Charge(V,t)}+\\ \sum_{L=1}^{N_L} P_{NSD(L,t)}\times c_{NSD(L,t)}+\\ \sum_{DG=1}^{N_{DG}} P_{EAP(DG,t)}\times c_{EAP(DG,t)}\end{array}\right)\times\Delta t+ \atop +\sum_{V=1}^{N_V} E_{Trip\,Red(V,t)}\times c_{TripRed(V,t)}\right] \tag{3.1}$$

where:

Δt	Period *t* duration (e.g. 15 min., 30 min., 1 hour…)
$c_{Charge(V,t)}$	Charge price of vehicle *V* in period *t*
$c_{DG(DG,t)}$	Generation price of *DG* unit in period *t*
$c_{EAP(DG,t)}$	Excess available power price of *DG* unit in period *t*
$c_{NSD(L,t)}$	Non-supplied demand price of load *L* in period *t*
$c_{Supplier(S,t)}$	Energy price of external supplier *S* in period *t*
$c_{Discharge(V,t)}$	Discharge price of vehicle *V* in period *t*
$c_{Trip\,Red(V,t)}$	Trip reduce price contracted with vehicle *V* in period *t*
$E_{Trip\,Red(V,t)}$	Demand response energy reduce of vehicle trip *V* in period *t*
N_{DG}	Total number of distributed generators
N_L	Total number of loads
N_S	Total number of external suppliers
N_V	Total number of vehicles

$P_{Charge(V,t)}$	Power charge of vehicle *V* in period *t*
$P_{DG(DG,t)}$	Active power generation of distributed generation unit *DG* in period *t*
$P_{Discharge(V,t)}$	Power discharge of vehicle *V* in period *t*
$P_{EAP(DG,t)}$	Excess available power by *DG* unit in period *t*
$P_{NSD(L,t)}$	Non-supplied demand for load *L* in period *t*
$P_{Supplier(S,t)}$	Active power flow in the branch connecting to external supplier *S* in period *t*
T	Total number of periods.

The objective function considers Δt to allow different period *t* duration. For instance, for a 30 minutes period *t* duration, the value of Δt should be 0.5 if the costs function are specified in an hour basis.

In order to improve the solution feasibility the mathematical model includes variables concerning the excess available power ($P_{EAP(DG,t)}$) and non-supplied demand ($P_{NSD(L,t)}$). $P_{EAP(DG,t)}$ is important because the VPP can establish contracts with uninterruptible generation ("take or pay" contracts) with, for instance, producers based on renewable energy sources. In extreme cases, when the load is lower than uninterruptible generation the value of $P_{EAP(DG,t)}$ is different from zero. $P_{NSD(L,t)}$ is positive when the available resources are not enough to satisfy load demand.

The minimization of objective function (3.1) is subject to the following constraints:

- The network active (3.2) and reactive (3.3) power balance with power loss in each period *t*:

$$\begin{aligned}&\sum_{DG=1}^{N_{DG}^{b}}\left(P_{DG(DG,t)}^{b}-P_{EAP(DG,t)}^{b}\right)+\sum_{S=1}^{N_S^b}P_{Supplier(S,t)}^{b}+\sum_{L=1}^{N_L^b}(P_{NSD(L,t)}^{b}-P_{Load(L,t)}^{b})\\&+\sum_{V=1}^{N_V^b}(P_{Discharge(V,t)}^{b}-P_{Charge(V,t)}^{b})=\\&\sum_{k=1}^{N_B}V_{b(t)}\times V_{k(t)}\left(G_{bk}\cos\left(\theta_{b(t)}-\theta_{k(t)}\right)+B_{bk}\sin\left(\theta_{b(t)}-\theta_{k(t)}\right)\right)\\&\forall t\in\{1,..,T\};k\neq b\end{aligned} \tag{3.2}$$

$$\sum_{DG=1}^{N_{DG}^b} Q_{DG(DG,t)}^b + \sum_{S=1}^{N_S^b} Q_{Supplier(S,t)}^b - \sum_{L=1}^{N_L^b} Q_{Load(L,t)}^b = \\ \sum_{k=1}^{N_B} V_{b(t)} \times V_{k(t)} \left(G_{bk} \sin\left(\theta_{b(t)} - \theta_{k(t)}\right) - B_{bk} \cos\left(\theta_{b(t)} - \theta_{k(t)}\right)\right) \\ \forall t \in \{1,..,T\};\ k \neq b \tag{3.3}$$

where:

θ_b	Voltage angle at bus *b* (rad)
θ_k	Voltage angle at bus *k* (rad)
B_{bk}	Imaginary part of the element in Y_{BUS} corresponding to the *b* row and *k* column
G_{bk}	Real part of the element in Y_{BUS} corresponding to the *b* row and *k* column
N_b	Total number of buses *b*
N_{DG}^b	Total number of distributed generators at bus *b*
N_L^b	Total number of loads at bus *b*
N_S^b	Total number of external suppliers at bus *b*
N_V^b	Total number of vehicles at bus *b*
$P_{Charge(V,t)}^b$	Power charge of vehicle *V* at bus *b* in period *t*
$P_{DG(DG,t)}^b$	Active power generation of distributed generation unit *DG* at bus *b* in period *t*
$P_{Discharge(V,t)}^b$	Power discharge of vehicle *V* at bus *b* in period *t*
$P_{EAP(DG,t)}^b$	Excess available power by *DG* unit at bus *b* in period *t*
$P_{Load(L,t)}^b$	Active power demand of load *L* at bus *b* in period *t*
$P_{NSD(L,t)}^b$	Non-supplied demand for load *L* at bus *b* in period *t*
$P_{Supplier(S,t)}^b$	Active power flow in the branch connecting to upstream supplier *S* at bus *b* in period *t*
$Q_{DG(DG,t)}^b$	Reactive power generation of distributed generation unit *DG* at bus *b* in period *t*
$Q_{Load(L,t)}^b$	Reactive power demand of load *L* at bus *b* in period *t*
$Q_{Supplier(S,t)}^b$	Reactive power flow in the branch connecting to upstream supplier *S* at bus *b* in period *t*

V_b	Voltage magnitude at bus *b* (rad)
V_k	Voltage magnitude at bus *k* (rad)

- Bus voltage magnitude and angle limits:

$$V_b^{min} \le V_{b(t)} \le V_b^{max} \quad \forall t \in \{1,..,T\} \tag{3.4}$$
$$\theta_b^{min} \le \theta_{b(t)} \le \theta_b^{max} \quad \forall t \in \{1,..,T\} \tag{3.5}$$

where:

θ_b^{max}	Maximum voltage angle at bus *b* (rad)
θ_b^{min}	Minimum voltage angle at bus *b* (rad)
V_b^{max}	Maximum voltage magnitude at bus *b*
V_b^{min}	Minimum voltage magnitude at bus *b*

- Line thermal limits:

$$\left| V_{b(t)} \times \left(\left[\left(V_{b(t)} - V_{k(t)} \right) y_{bk} \right]^* + \left[V_{b(t)} \times \frac{1}{2} y_{Shunt\_b} \right]^* \right) \right| \le S_{bk}^{max} \quad \forall t \in \{1,..,T\} \tag{3.6}$$

where:

S_{bk}^{max}	Maximum apparent power flow established in line that connected bus *b* and *k*
y_{bk}	Admittance of line that connect bus *b* and *k*
y_{Shunt_b}	Shunt admittance of line connected bus *b*

- Maximum distributed generation limit in each period *t:*

$$P_{DGMinLimit(DG,t)} \le P_{DG(DG,t)} \le P_{DGMaxLimit(DG,t)} \\ \forall t \in \{1,...,T\}; \forall DG \in \{1,...,N_{DG}\} \tag{3.7}$$

$$Q_{DGMinLimit(DG,t)} \le Q_{DG(DG,t)} \le Q_{DGMaxLimit(DG,t)} \\ \forall t \in \{1,...,T\}; \forall DG \in \{1,...,N_{DG}\} \tag{3.8}$$

where:

$P_{DGMaxLimit(DG,t)}$	Maximum active power generation of distributed generator unit *DG* in period *t*
$P_{DGMinLimit(DG,t)}$	Minimum active power generation of distributed generator unit *DG* in period *t*
$Q_{DGMaxLimit(DG,t)}$	Maximum reactive power generation of distributed generator unit *DG* in period *t*
$Q_{DGMinLimit(DG,t)}$	Minimum reactive power generation of distributed generator unit *DG* in period *t*

- Upstream supplier maximum limit in each period *t:*

$$P_{Supplier(S,t)} \le P_{SupplierLimit(S,t)} \quad \forall t \in \{1,...,T\}; \forall S \in \{1,...,N_S\} \tag{3.9}$$

$$Q_{Supplier(S,t)} \le Q_{SupplierLimit(S,t)} \quad \forall t \in \{1,...,T\}; \forall S \in \{1,...,N_S\} \tag{3.10}$$

where:

$P_{SupplierLimit(S,t)}$	Maximum active power of upstream supplier *S* in period *t*
$Q_{SupplierLimit(S,t)}$	Maximum reactive power of upstream supplier *S* in period *t*

- Vehicle technical limits in each period *t:*
  - The vehicle charge and discharge are not simultaneous:

$$\begin{gathered} X_{(V,t)} + Y_{(V,t)} \le 1 \\ \forall t \in \{1,...,T\};\ \forall V \in \{1,...,N_V\}; X_{(V,t)} \text{ and } Y_{(V,t)} \in \{0,1\} \end{gathered} \tag{3.11}$$

where:

$X_{(V,t)}$	Binary variable of vehicle *V* related to power discharge in period *t*
$Y_{(V,t)}$	Binary variable of vehicle *V* related to power charge in period *t*

- Battery balance for each vehicle. The energy consumption for period t travel has to be considered jointly with the energy remaining from the previous period and the charge/discharge in the period:

$$
\begin{aligned}
& E_{Stored(V,t)} = E_{Stored(V,t-1)} + \eta_{c(V)} \times (P_{Charge(V,t)} \times \Delta t) \\
& E_{Trip(V,t)} - \frac{1}{\eta_{d(v)}} \times P_{Discharge(V,t)} \times \Delta t \\
& \forall t \in \{1,...,T\}; \quad \forall V \in \{1,...,N_V\}; \; E_{Trip(V,t)} = P_{Trip(V,t)} \times \Delta t;
\end{aligned}
\tag{3.12}
$$

where**:**

$E_{Stored(V,t)}$	Active energy stored in vehicle *V* at the end of period *t*
$E_{Trip(V,t)}$	Vehicle *V* energy consumption in period *t*
$\eta_{c(V)}$	Grid-to-Vehicle Efficiency when the Vehicle *V* is in charge mode
$\eta_{d(V)}$	Vehicle-to-Grid Efficiency when the Vehicle *V* is in discharge mode

- Discharge limit for each vehicle considering the battery discharge rate:

$$
\begin{aligned}
& P_{Discharge(V,t)} \le P_{DischargeLimit(V,t)} \times X_{(V,t)} \\
& \forall t \in \{1,...,T\}; \; \forall V \in \{1,...,N_V\}; X_{(V,t)} \in \{0,1\}
\end{aligned}
\tag{3.13}
$$

where**:**

$P_{DischargeLimit(V,t)}$	Maximum power discharge of vehicle *V* in period *t*

- Charge limit for each vehicle considering the battery charge rate:

$$
\begin{aligned}
& P_{Charge(V,t)} \le P_{ChargeLimit(V,t)} \times Y_{(V,t)} \\
& \forall t \in \{1,...,T\}; \; \forall V \in \{1,...,N_V\}; Y_{(V,t)} \in \{0,1\}
\end{aligned}
\tag{3.14}
$$

where**:**

$P_{ChargeLimit(V,t)}$	Maximum power charge of vehicle *V* in period *t*

- Vehicle battery discharge limit considering the battery balance:

$$\frac{1}{\eta_{d(V)}} \times P_{Discharge(V,t)} \times \Delta t \le E_{Stored(V,t-1)} \\ \forall t \in \{1,...,T\};\ \forall V \in \{1,...,N_V\};\ \Delta t = 1; \tag{3.15}$$

- Vehicle battery charge limit considering the battery capacity and previous charge status:

$$\eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t \le E_{BatteryCapacity(V)} - E_{Stored(V,t-1)} \\ \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}; \tag{3.16}$$

- Battery capacity limit for each vehicle:

$$E_{Stored(V,t)} \le E_{BatteryCapacity(V)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\} \tag{3.17}$$

where:

$E_{BatteryCapacity(V)}$	Battery energy capacity of vehicle *V*

- Minimum stored energy to be guaranteed at the end of period *t*. This can be seen as a reserve energy (fixed by the EVs users) that can be used for a regular travel or a unexpected travel in each period:

$$E_{Stored(V,t)} \ge E_{MinCharge(V,t)} - E_{TripRed(V,t)} \tag{3.18}$$

$$E_{MinCharge(V,tLast)} \ge E_{Trip(V,t)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\} \tag{3.19}$$

$$E_{TripRed(V,t)} \le E_{TripRedMax(V,t)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}$$

where:

$E_{MinCharge(V,t)}$	Minimum stored energy to be guaranteed at the end of period *t*, for vehicle *V*
$E_{TripRedMax(V,t)}$	Maximum energy reduce for vehicle *V* trip in period *t*
$tLast$	Last connected period of vehicle *V* before $E_{Trip(V,t)}$

3.2.1 Problem dimension

The introduction of V2G resources in the optimization problem represents new demands in terms of computational power requirements. Considering a future scenario [2] of a distribution network with 66 DG units and 2,000 V2G contracts, the day-ahead optimization problem size would correspond to about 100,000 problem variables in a scheduling for 24 periods intervals, just by considering DG and V2G resources and excluding network variables. 96,000 of the 100,000 variables are from V2G resources alone. The total number of variables results from 66 DG * 24 periods * 2 (active and reactive power) + 2,000 V2G * 24 periods * 2 (discharge and charge active power). When including network constraints and more resources such as demand response, this value can easily reach 500,000 variables without even increasing the number of V2G resources.

In [2], the MINLP technique took 858 seconds to solve the optimization problem with 500 grouped V2G resources and including network constraints. A similar scheduling problem with 1000 grouped V2G in [3] took more than 5 hours on the same network using MINLP deterministic approach. Both works were performed in similar machines, thus meaning that the given problem presents an exponential complexity with the increase of problem size. It is important to note that both works use grouped V2G resources that simplify the optimization problem by reducing the amount of V2G variables by a fold of ten. This can be a good technique to reduce computational time when evaluating network impacts or generation cost estimation. However, in real scheduling applications individual V2G contracts should be considered and cannot be simplified this way. In this thesis only individual contracts were used.

Taking into account that this type of scheduling problem will increase with every new V2G contract with the owner of an electric vehicle, it is important to develop specific optimization packages and evolve the present optimization tools to handle hard combinatorial large scale problems more effectively and efficiently. In this case, the use of metaheuristics to solve DER scheduling is of high value to network system operators.

3.3 Modified Particle Swarm Optimization

In this section the modifications introduced to the early versions of Particle Swarm Optimization (PSO) [40, 53] are presented. Modifications to PSO have the goal of improving robustness, convergence time and solution quality and, at the same time, requiring less tinkering of parameters by the user.

This new adaptation of the standard PSO technique developed during this work is somewhat inspired by some already published PSO variants [48, 51, 55]. It may be considered a hybrid algorithm, but being a hybrid it leans more heavily to PSO than to Genetic Algorithms (GA) side. From the GA-PSO hybrids it takes the use of mutation in the definition of the inertial weight but discards the recombination and selection steps. The mutation is governed by a Gaussian distribution. The major feature of the proposed method, though, lies in the manipulation of the upper and lower bounds of the particles velocity.

As already referred, the bounds limiting this velocity are keys to ensure the convergence of the process. These boundary values are problem-specific. Work has been done by other authors [56] showing that PSO performance can be improved by the dynamic modification of the velocity upper limit.

3.3.1 Velocity limits intelligent adjustment

The traditional PSO relies on externally fixed particles' velocity limits, inertia, memory and cooperation weights without changing these values along the swarm search process (PSO iterations) [40, 57]. In very complex problems this can compromise solution diversity because swarm movements are limited to the initially fixed velocities and weights.

In [48] the authors introduced mutation of the strategic parameters (inertia, memory, cooperation) and selection by stochastic tournament. The method is called Evolutionary Particle Swarm Optimization (EPSO) and proved to be proficient in several optimization problems [48]. The authors also propose replicating the particles in order to increase the probability of finding more solutions that enhance the diversity of the search space.

Although with EPSO it is possible to change weights through the search process adding more diversity to the search space, particles velocity limits remain unchanged during the iterative process. In some cases it can be desirable to change the velocity limits based on an intelligent mechanism, since mutation implemented in EPSO is still a stochastic process. This idea is discussed in the present work and originated a new method to implement PSO.

In the proposed method, mutation of the strategic parameters already seen in EPSO is used due to its benefits. The originality of the methodology proposed in this thesis is that variables can be marked up to allow changing the maximum and minimum velocity limits along the search process. These changes are undertaken according to the results of an intelligent mechanism. The main innovative characteristic of the algorithm consists in the communication between particles' evaluation stage and movement stage. That is, when evaluating a given solution, it may be possible to conclude that changing certain variables in a specific direction (velocity) could improve solution fitness or even help in constraints violations. Therefore, a mechanism called signaling has been adopted. This mechanism allows an intelligent adjustment of the velocity limits that are initially set. In the traditional version of PSO the velocity limits are prefixed and cannot be changed during PSO iterations. In other words, with this algorithm it is possible to boost velocity magnitude during the evolving process in an intelligent way with the objective to significantly change its value.

The proposed methodology uses three strategic parameters (w_i) already seen in EPSO, namely: inertia, memory, and cooperation. At the beginning of the process the values of these weights are randomly generated between 0 and 1. After that, the particle's weights are changed in each iteration using a Gaussian mutation distribution according to (3.20):

$$^{*}w_i = w_i + \delta N\left(0,1\right) \tag{3.20}$$

where:

$^{*}w_i$	New mutated weights of particle *i*
w_i	Weights of particle *i*
δ	Learning parameter with a range between 0 and 1

A high value of δ adds more importance to mutation whereas *N(0,1)* is a random number following a normal distribution with mean equal to 0 and variance equal to 1. Once again, the strategic parameters are limited to values between 0 and 1 in this stage.

Equation (3.21) allows the calculation of the new particle's velocity that depends on particle's present velocity, best past experience (memory) and best group's experience (cooperation). The traditional PSO uses pre-fixed weights times a random value in memory and cooperation terms of velocity equation [40].

$$^{*}v_{i,j} = {}^{*}w_{i(inertia)} v_{i,j} + {}^{*}w_{i(memory)} \left(b_i - x_{i,j}\right) + {}^{*}w_{i(coop)} \left(bG - x_{i,j}\right) \tag{3.21}$$

where:

b_i	Best past experience of particle *i*
bG	Best global experience of all the particles
$v_{i,j}$	Velocity of variable *j* of particle *i*
$^{*}v_{i,j}$	New calculated velocity of variable *j* of particle *i*
$x_{i,j}$	Position of variable *j* of particle *i*
$^{*}w_{i(inertia)}$	Inertia weight component of particle *i*
$^{*}w_{i(memory)}$	Memory weight component of particle *i*
$^{*}w_{i(coop)}$	Cooperation weight component of particle *i*

The new positions ($^{*}x_{i,j}$) for each particle are then calculated according to the movement equation (3.22).

$$^{*}x_{i,j} = x_{i,j} + {}^{*}v_{i,j} \tag{3.22}$$

where:

$^{*}x_{i,j}$	New calculated position of *j* variable the *i* particle

Fig. 3.2 shows a representative illustration of the particle movement for a given variable using strategic parameters of PSO: inertia, memory and cooperation.

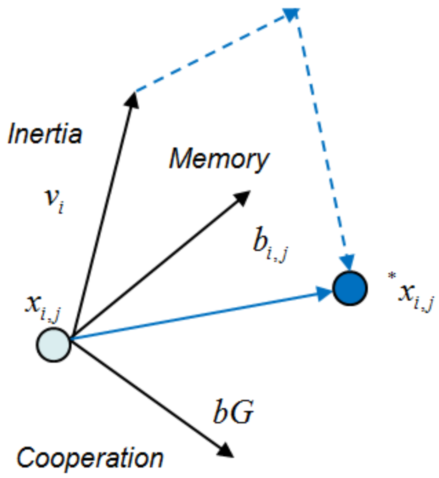

Fig. 3.2 – Illustration of particle movement (adapted from [49])

After applying the movement equation to each particle, the algorithm evaluates the fitness of the new positions and the best *bG* solution is stored across iterations. During the evaluation stage the variables that improve fitness function or eliminate constraints violations are marked. The identification of the variables that should be signaled depends on the optimization problem that is being addressed. The optimization engineer should identify which variables are best suitable to be signaled during the evaluation stage and design an algorithm to recognize which variables should be signaled across iterations to improve solution fitness or handle constraints violations. The criteria to define which variables are selected to be signaled may be included in the following list, although they are not restricted to:

- Variables that can easily relive constraints violations if changed in a certain direction;
- Variables that cannot be changed by direct repair method;
- Variables that are not easily corrected by direct repair method.

Direct repair method is an on fly technique that enables correcting a bad solution to a good solution, e.g. correct problem's variables limits or problem's constraints violations, during or before evaluation phase. An indirect repair method consists in accepting a bad solution throughout the heuristic search. The most common method is adding a penalty to fitness function in order to enable metaheuristics to perceive it as a bad solution. Direct repair methods are generally superior when compared with indirect repair methods in terms of effectiveness and efficiency. However, they are not always trivial to implement in metaheuristics and sometimes impossible or impracticable to program. Thus, indirect repair methods such as penalty functions are used in order to attempt to achieve solutions without constraint violations. As said before, the algorithm proposed here for PSO can be used to improve fitness function but also in constraints handling. In this case it is as an indirect repair method, though without adding penalties to fitness function. Nevertheless, penalties, direct repair methods and the proposed algorithm can be used together in the same implementation. More information on constraints handling techniques can be found in [58].

To support the proposed algorithm, a signaling vector for each particle is maintained across the process to enable the communication between evaluation and movement stages. These array elements assume one of the following values: 0, 1, -1 or special codes. The size of this array (number of columns) corresponds to the number of variables in the problem. The set of signaling vectors constitutes a signaling matrix for the swarm, with as many lines as the number of particles set. The value 0 means that a given variable has not been signaled. The value 1 means that the variable has been signaled to gain more speed in the positive direction and -1 means that the variable has been signaled to gain speed in the opposite direction. Special codes are values different from 0, 1 and -1 that can be used for extended functions of the proposed algorithm. They can be used for, setting some variables of the swarm to a desired value in special conditions of the optimization problem. These variables should be signaled with a given special code for subsequent identification.

The resulting new maximum and minimum velocity limits of a given particle's variable are evaluated according to (3.23) and (3.24), respectively:

$$Vel^{\max}{}_j = Vel^{\max}{}_j + BoostSpeed_j * SignalingPositives_j \tag{3.23}$$

$$Vel^{\min}{}_j = Vel^{\min}{}_j + BoostSpeed_j * SignalingNegatives_j \tag{3.24}$$

where:

$Vel^{\max}{}_j$	Original initial max. velocity of variable *j*
$Vel^{\min}{}_j$	Original initial min. velocity of variable *j*
boostSpeed	Vector with the variables boost speed
signalingNegatives	Vector with the signaled variables (negative

	velocity)
signalingPositives	Vector with the signaled variables (positive velocity)

signalingPositives is obtained from the signaling vector, built with its positive values (equal to 1) and with zeros in the other positions. s*ignalingNegatives* is also obtained from the signaling vector, being built with its negative values (equal to -1) and with zeros in the other positions. The boost speed vector contains the values that influence the change of maximum or minimum velocity limits when a given variable is signaled. This vector can be defined by hand for each variable or using an algorithm, for instance 200% of the initial maximum or minimum velocity limits or other adequate algorithm for the problem under implementation.

Fig. 3.3 presents the signaling process of the modified PSO described in this chapter. In the evaluation stage the variables are identified and in the movement stage the velocity limits of the marked variables are updated. Each iteration, the velocity values are randomly generated between the lower and upper velocity limits. In early versions of PSO the velocities are generated once, in the beginning of the process, according to the fixed maximum and minimum velocity limits.

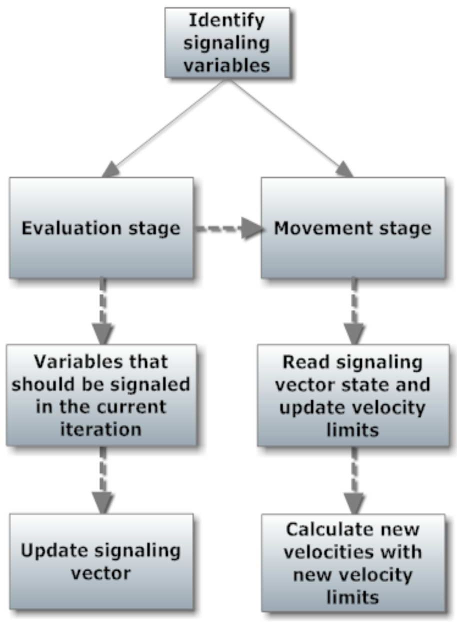

Fig. 3.3 – Modified PSO signaling process

For a better understanding of how the signaling mechanism works, let us follow a simple example for one particle considering an optimization problem of *n* variables.

Table 3.1 presents the data for a given particle with *n* variables (V_1 to V_n column). This table presents the state of variables' velocity limits before and after the signaling. The boost speed vector is initially fixed. The elements of the boost speed vector represent the variation on the velocity limit when the variable is signaled. Let us consider that the vectors were initialized as shown in Table 3.1. The signaling vector is always initialized with zeros.

Table 3.1 – Algorithm example

<table>
<tr><td colspan="3"></td><td colspan="6">Variables</td></tr>
<tr><td colspan="3"></td><td>V_1</td><td>V_2</td><td>V_3</td><td>V_4</td><td>…</td><td>V_n</td></tr>
<tr><td rowspan="7">Signaling</td><td rowspan="3">Before</td><td>Signaling Vector</td><td>0</td><td>0</td><td>0</td><td>0</td><td>…</td><td>0</td></tr>
<tr><td>Max. Velocity</td><td>10</td><td>10</td><td>20</td><td>10</td><td>…</td><td>10</td></tr>
<tr><td>Min. Velocity</td><td>0</td><td>0</td><td>-10</td><td>0</td><td>…</td><td>-5</td></tr>
<tr><td>Initially fixed</td><td>Boost Speed Vector</td><td>100</td><td>50</td><td>150</td><td>200</td><td>…</td><td>100</td></tr>
<tr><td rowspan="3">After</td><td>Signaling Vector</td><td>0</td><td>1</td><td>0</td><td>-1</td><td>…</td><td>0</td></tr>
<tr><td>Max. Velocity</td><td>10</td><td>60</td><td>20</td><td>10</td><td>…</td><td>10</td></tr>
<tr><td>Min. Velocity</td><td>0</td><td>0</td><td>-10</td><td>-200</td><td>…</td><td>10</td></tr>
</table>

The values for max. velocity and min. velocity in Table 3.1 represent the velocity limits for two different states, namely before the signaling process and after the signaling process. After the signaling process, considering that the signaling vector took the values presented in Table 3.1 the resulting values for max. velocity and min. velocity are shown. Analyzing these values, V_2 and V_4 were identified to change their velocity limits in the next PSO iteration movement. For V_2, the maximum velocity, after signaling, changes from 10 to 60; for V_4, the minimum velocity changes from 0 to -200, according to the boost speed vector and to the signaling vector. For instance, V_2 velocity limit was boosted by 50 (boost speed vector) from its initial velocity of 10 (max. velocity before signaling) resulting in a new velocity of 60 (max. velocity after signaling).

3.3.2 Self-parameterization

PSO Parameterization is an important aspect of its implementation success to a given problem. However, optimal parameterization depends on the specific problem and it is not a trivial task. For this reason, a user independent automatic parameterization was implemented.

The initial stopping criterion is defined to be at least 50 iterations. Nevertheless, if during the last 5 iterations (of 50) the best fitness is still improving, the proposed implementation increments 1 iteration. After that, this incrementing occurs until there is no improvement in the fitness function in the last 5 iterations or when a maximum of 300 iterations are reached. The number of swarm particles is 10. When applied to the present scheduling problem this number of particles and the stop criterion proved to be adequate in case studies.

In this thesis a PSO's particle means a solution comprising several variables, i.e. each particle contains the problem variables. The variables controlled by the swarm are the generators active and reactive power variables, the V2G charge/discharge variables and V2G DR when available. In the proposed implementation the variables for charge and discharge of V2G are the same, where a positive value means that the vehicle is charging and a negative value means that it is discharging. This way the binary variables for charge and discharge (3.11) are not required as in MINLP implementation, reducing correspondently the computational execution time. Minimum and maximum positions of variables are set to the lower and upper bound of each problem variable, therefore the maximum and minimum limits of variables are always guaranteed in the swarm.

One of the most important parameters in PSO is the maximum and minimum velocities of particles. It is important to note that if these values are too high, then the particles may move erratically, going beyond a good solution. On the other hand, if they are too small, then the particle's movement is limited and the solution compromised [51, 56]. In the modified PSO the initial maximum and minimum velocity limits are calculated in the beginning of the program according to a specific algorithm. The algorithm that calculates the maximum and minimum velocities is described below.

The maximum velocities for generators (DG and suppliers) active power variables are calculated according to (3.25):

$$Vel^{\max}_{j,t} = \frac{1}{c_{(j,t)}} \quad \forall t \in \{1,...,T\};\ \forall j \in \{1,...,N_{DG}+N_S\} \tag{3.25}$$

where:

$Vel^{\max}_{j,t}$	Maximum velocity of particle's variable *j* for period *t*
$c_{(j,t)}$	Price for generator *j* in period *t*

The minimum velocities for generators (DG and suppliers) active power variables are calculated according to (3.26):

$$Vel^{\min}_{j,t} = c_{(j,t)} \quad \forall t \in \{1,...,T\};\ \forall j \in \{1,...,N_{DG}+N_S\} \tag{3.26}$$

where:

$Vel^{\min}_{j,t}$	Minimum velocity of particle's variable *j* for period *t*

The values of the maximum and minimum velocities described above are normalized between the lower bound and the upper bound of the generation active power limits.

The maximum velocities for generators reactive power variables are set to the upper limits of reactive power. Minimum velocities are the same as maximum velocities, however in the opposite direction.

The maximum velocities for V2G charge active power variables are calculated according to (3.27):

$$Vel^{\max}{}_{j,t} = VechicleNeeds_V * \frac{1}{\sum_{L=1}^{N_L} P_{Load(L,t)}} \tag{3.27}$$
$$\forall t \in \{1,...,T\};\ \forall\ j \in \{N_{DG} + N_S + 1,...,N_V\};$$
$$\forall V\{1,...,N_V\};\forall L\{1,...,N_L\}$$

where:

$VechicleNeeds_V$ Vehicle V total periods trips energy consumption

The maximum velocities of V2G charge variables are normalized between the lower bound and upper bound of V2G charge rate limit.

The minimum velocities for V2G discharge active power variables are calculated according to (3.28):

$$Vel^{\min}{}_{j,t} = \frac{1}{c_{Discharge(V,t)}} \tag{3.28}$$
$$\forall t \in \{1,...,T\};\ \forall\ j \in \{N_{DG} + N_S + 1,...,N_V\};\forall V\{1,...,N_V\}$$

where:

$c_{Discharge(V,t)}$ Price of discharge of vehicle V in period t

The minimum velocities of V2G discharge variables are normalized between the lower bound and upper bound of V2G discharge rate limit.

The maximum and minimum velocity of DR V2G variables are set to zero, because they are only activated in special conditions, e.g. energy cost.

With the above algorithm there is no need for specifying maximum and minimum values empirically and manually. The above problem-specific algorithm is suited for problems with similar mathematical formulation (see subsection 3.2).

3.3.3 Problem implementation

The original PSO relies on fixed velocity limits that are not changed during the swarm search process (PSO iterations) [40, 57]. Research work performed by Fan and Shi [40, 56] has shown that an appropriate dynamic change of maximum velocities can improve the performance of the PSO algorithm.

In the present implementation to the problem of day-ahead scheduling, maximum and minimum values of velocity limits can change dynamically according to the specific mechanism formerly theorized. The initial maximum and minimum velocities are set according to subsection 3.3.2 and changed dynamically as the mechanism described in subsection 3.3.1. In the evaluation phase the mentioned mechanism will check for constraints violations, namely:

- Bus lower voltage violations (3.4-3.5);
- Bus overvoltage violations (3.4-3.5);
- Line thermal limits (3.6).

If there is any violation of the above constraints the algorithm will mark the variables that can possibly help to alleviate these violations. In the case of bus lower voltage violations, the mechanism will mark DG reactive power and V2G resources variables, to increase reactive power and discharges, respectively. In the case of bus overvoltage violations, the mechanism will mark DG reactive power variables to decrease and nearby EVs to charge. The buses selected to get the appropriate V2G and DG resources are the buses where violations occurred as well as the buses that were preceding it.

Line thermal limit violations can be corrected in two ways: reducing V2G charge or increasing generation in the downstream lines. The mechanism marks V2G charge to be reduced and DG generation production to be increased. More information about voltage drop in radial distribution networks can be found in [59].

Fig. 3.4 presents the selection of buses according to the type of violation. It helps to understand the described mechanism above.

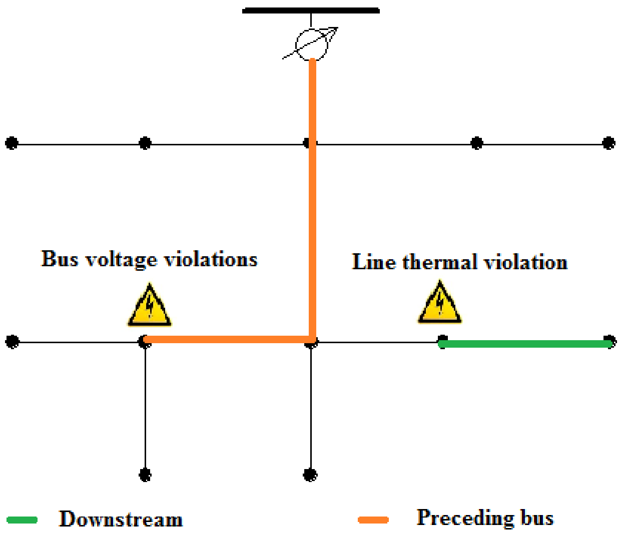

Fig. 3.4 – Described mechanism buses selection in the case of violations

The velocity limits of the marked variables are changed according to the type of signaling. For instance, when DG reactive power variables are marked, the maximum velocities of these variables are increased by 20%. When the DG reactive power variables are marked to decrease, the minimum velocities of these variables are decreased by 20%.

The described mechanism contributes to a faster convergence to a solution without violations, as well as improving the solution fitness. To improve fitness function the mechanism works as follows:

- It tries to increase V2G charge variables values when V2G charge price is lower than mean generation cost acting on maximum velocity limits of corresponding variables;
- It tries to increase V2G discharge variables values when V2G discharge price is lower than mean generation cost acting on minimum velocity limits of corresponding variables;
- It tries to apply DR V2G trip reduce program (when available) by increasing corresponding variables when DR program price is lower than the sum of mean generation cost and the repesctive vehicle charge price.

Looking at the problem formulation presented in 3.2, namely the objective function, it can be seen why the above aspects improve the solution.

The initial swarm population is randomly generated between the upper and the lower bounds of variables, except from V2G variables that are initialized with zeros. During swarm search the algorithm checks whether to charge or discharge vehicles as well as to apply DR programs as needed or advantageous.

A robust power flow model from [60, 61] is included in the modified PSO approach to check solutions feasibility during swarm search process. The load system balance (3.2-3.3) is validated by a power flow algorithm, and the power losses are compensated by the energy suppliers or DG generators. Vehicle battery balance constraints (3.12, 3.15-3.19) are checked before fitness evaluation. If the values from swarm solutions are not according to the constraint limits, the solution is corrected by direct repair method. Direct repair method can be used instead of indirect repair method such as penalty factors providing an efficient way of correcting solutions before evaluating the fitness function [58].

3.4 Electric vehicles demand response

Demand Response (DR) for load management is well addressed in the literature [43-46]. Thus, the focus in the scope of this thesis is concentrated on demand response programs for EVs. Trip reduce demand response program for electric vehicles in the context of day-ahead is proposed.

3.4.1 Trip reduce demand response program

Trip reduce demand response program for EVs is proposed in this thesis. The gist is to provide network operator with another useful resource that consists in reducing vehicles charging necessities. This demand response program enables vehicle users to get some profit by agreeing to reduce their travel necessities and minimum battery level requirements.

Fig. 3.5 presents the proposed framework of DR trip reduce program. An initial optimization is made assuming that EVs which contracted DR option will participate. With the optimization results it is possible to identify if any EVs users are scheduled to participate in the DR programs. After that, these EV users can be invited to participate by some means, e.g. internet application, mobile message. Network operator should wait for a response within a time limit. With the responses of users the network operator should reschedule, by running the optimization program again with the updated information. If new EVs users are given by the optimization results to participate the operator should follow the same procedure in order to lower operation costs. This task should be integrated automatically. The users that do not respond within the time limit should be considered as not participating in the DR program.

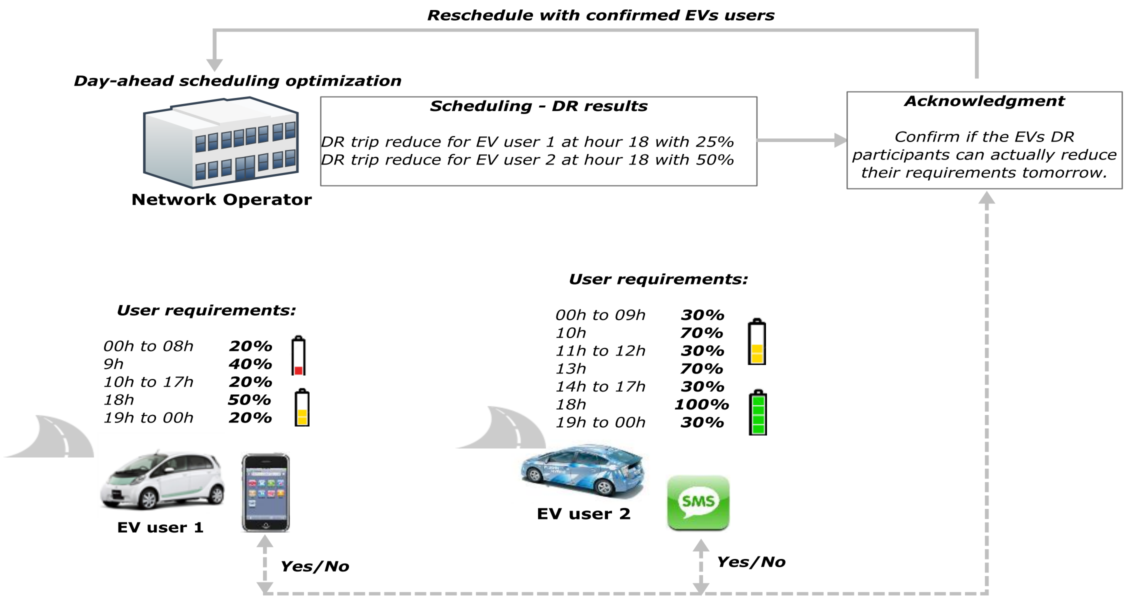

Fig. 3.5 – Framework of DR trip reduce program

In a real environment to enable an attractive commercial model and a fair choice of EV users participating in this type of DR programs a list of already participated should be maintained and included in the optimization model. It can happen that two users have the same contracted DR trip reduce price, however user number one might be chosen often due to network location for instance. If an already participated list is maintained it is possible to work out the users that have never participated and invite them to participate in the next opportunities.

3.4.2 Trip reduce demand response program definition

For supporting network operator in the definition of trip reduce demand response program a methodology is proposed in this section. Fig. 3.6 presents the methodology framework. It enables to estimate how much demand response is adequate for a certain operation condition.

Starting from an initial operation condition, e.g. based on a case study database, a range of scenarios should be created. For instance, the available Distributed Generation (DG), price of network suppliers and base load. The criteria to modify such data should be carefully investigated by the operator taking into account the experience and knowledge of its own network operation. After creating some operation scenrios to simulate real world conditions, the modified PSO technique can be executed for each of the created scenarios and the optimization results stored. If the operator has already a large number of operation scenarios in the database and the corresponding scheduling results this step can be skipped.

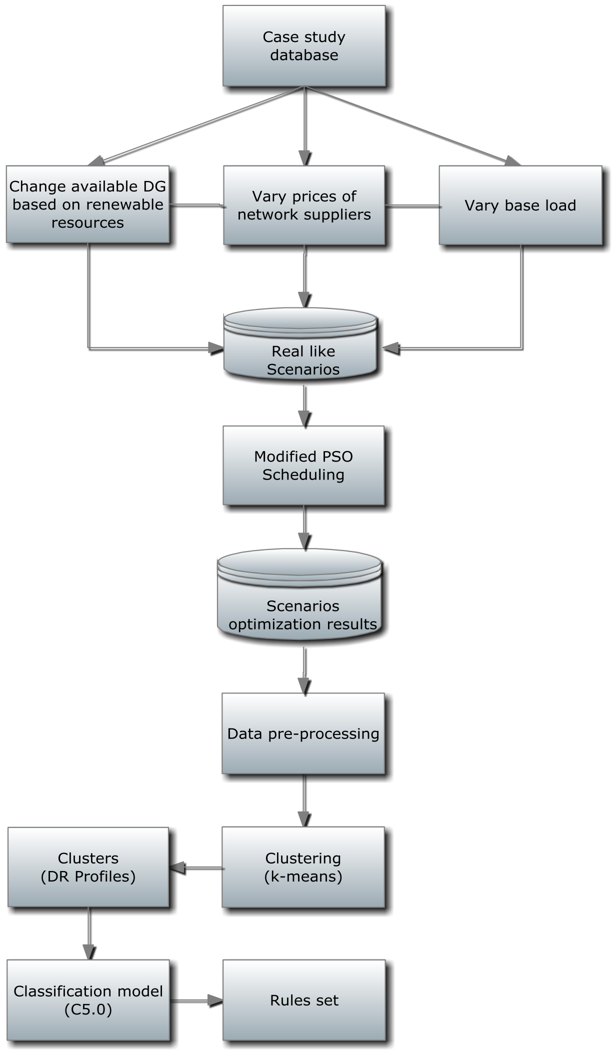

Fig. 3.6 – Implemented methodology framework

Data pre-processing phase consists in converting the optimization results (in a 24 period basis) to a one period basis. After the data pre-processing phase a clustering algorithm is used in order to identify similar patterns among trip reduce demand response usage per period, namely the *K-means* clustering algorithm. Typically the choice of the number of clusters may be supported by the analysis and evaluation of measurement distances [62]. However, the contribution of expert opinions is taken into account.

In order to estimate the usage of trip reduce demand response per period for a given operation condition a classification model is created. For the implementation of the classification model, rule-based modeling technique C5.0 classification algorithm is used. The classification model generates the decision tree to provide the rules set.

3.5 Conclusions

Day-ahead scheduling with Vehicle-to-Grid (V2G) is treated in very few works in the literature. In this chapter the mathematical model of the day-ahead scheduling including V2G is presented. The problem is a Mixed Integer Non-Linear Programming (MINLP) model and due to its nature it is classified as a large combinatorial problem.

Metaheuristics are useful in solving this type of hard problems in reasonable execution time and with satisfactory results. For this reason, PSO is selected in this thesis to be compared with MINLP. A modified version of PSO with application-specific ingredients is proposed in the scope of theis thesis and presented in this chapter as a result of this work.

The described mechanism for the modified PSO can be extended by using other functions. This can be done, for instance, using mark codes to reset some variables to zero or to the upper/lower limit as needed. In the present case only increase/decrease functions on the velocity limits were used. This mechanism allows an intelligent adjustment of the initial velocity limits.

Electric vehicle demand response program for EVs users is proposed in this chapter, specifically the trip reduce demand response model. The aim is to provide the network operator with another useful resource to lower operation costs while at the same time motivating the active participation of EVs users in demand response programs. A data-mining based methodology to support the definition of trip reduce demand response program is proposed in this chapter. The methodology enables to estimate how much trip reduce is adequate for a certain operation condition

4 Case studies

This chapter presents the case studies used in this work to illustrate the application and support the advantages of the modified Particle Swarm Optimization (PSO) approach proposed in this thesis. For that, an exact method, namely Mixed Integer Non-Linear Programming (MINLP), is compared with the aforementioned methodology in terms of execution time and solution quality.

There are many versions of PSO that can be found in the literature [51]. In this work, three versions were selected to be compared with the proposed methodology, specifically traditional PSO, Evolutionary Particle Swarm Optimization (EPSO) and New Particle Swarm Optimization (NPSO). A comparison analysis is made including robustness and convergence tests.

A large-scale case study with a 180 bus distribution system with 8,000 gridable vehicles is included in this chapter.

Three different charging methodologies are compared in a case study: uncontrolled charging, smart charging and vehicle-to-grid. The aim is to demonstrate which concept provides best suitabilitty to deal with the high presence of electric vehicles in the grid.

One case study including electric vehicle demand response is presented in this chapter, namely trip reduce program. A comparison is made with a scheduling that does not include the demand response program model. The same case study conditions, e.g. price conditions, are used in the comparison. The demand response program for electric vehicles aims to provide network operator with more network resources and the possibility to reduce operational costs.

4.1 Implementation tools

MATLAB language (MATLAB 7.10.0 R2010a) [63] and GNU Linear Programming Kit (GLPK) were used to create the EV scenario simulator tool (EVeSSi). This tool enables the creation of a specific EV scenario in distribution networks according to the defined parameters that catch EV technology, driving behaviors and EV penetration.

PSO metaheuristics was developed using MATLAB software. MINLP mathematical model was implememted in General Algebraic Modeling System (GAMS) [64], which is a high-level modeling system for mathematical programming and optimization. This model was developed in the scope of a master thesis [65]. DIscrete and Continuous OPTimizer (DICOPT) was the solver used within GAMS to solve the MINLP optimization problem.

All related data-mining algorithms were executed in Clementine 12 software [66], though data analysis was performed in MATLAB. These algorithms include K-means clustering methods but also classification C5.0 decision tree algorithm.

All the case studies were executed on a machine with two Intel® Xeon® E5620 2.40GHz processors; each one with 4 cores, 6GB of random-access-memory and Windows 7 Professional 64 bits operating system.

The used computer systems have multi-core processors, however, both MATLAB and GAMS applications used only one processor core for the results presented in this work.

4.2 Modified PSO performance

The performance of the modified PSO (see 3.3) is presented in this subsection. The solution quality and execution time are compared with MINLP method developed in GAMS. The case study is also described in this section.

4.2.1 Case study description

This case study considers a 12.66 kV 33 bus distribution network as can be found in [3, 67, 68]. The network in the case study presents a 2040 scenario with intensive use of distributed resources (Fig. 4.1).The distribution network serves 218 consumers with total peak consumption around 4.2 MW (Fig. 4.2) as defined in the consumer set scenario developed in [69]. It includes 66 DG units (33 photovoltaic, 8 fuel cells, 4 wind farm, 2 small hydro, 1 waste to energy, 3 biomass units, and 15 cogeneration units). A time step of 1 hour is used for a total of 24 periods. The data of this case study, including resources and network data can be seen in appendix A.

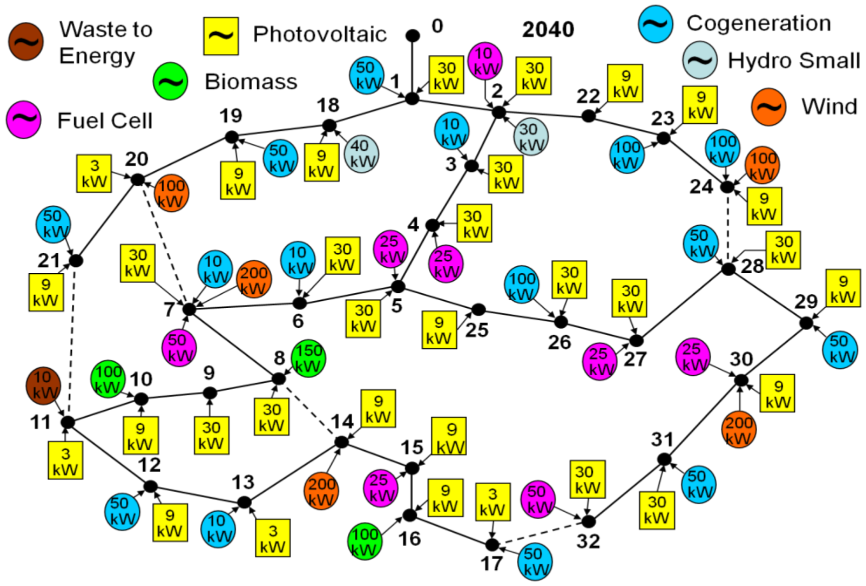

Fig. 4.1 – 33 bus distribution network configuration in 2040 scenario [3, 67, 68]

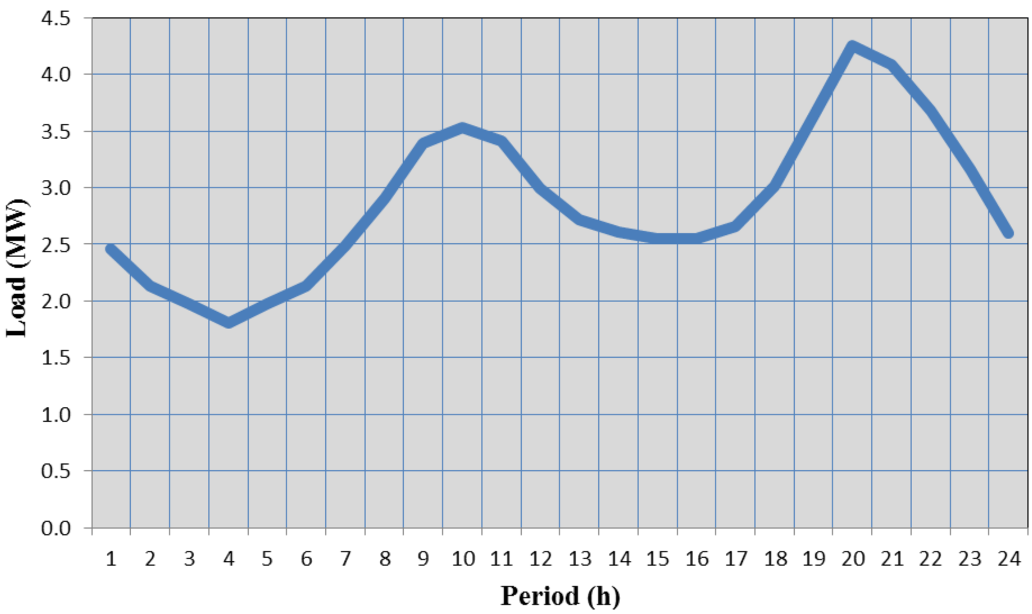

Fig. 4.2 – Load demand without electric vehicles

The number of V2G units will depend on the type and amount of consumers that are connected to the network. The consumers of the distribution network were divided into 6 groups: Domestic Consumers (DC), Commerce Consumers (CC), Medium Commerce (MC), Large Commerce (LC), Medium Industrial (MI) and Large Industrial (LI) [43]. Table 4.1 shows the number of V2G units considered in this case study. The columns and rows contain the consumer type and bus number respectively. For each bus it is indicated the number of consumers for each type and the total number of consumers [69].

Table 4.1 – Consumers and V2G scenario

Bus	Load (kW)	Number of consumers						
		DC	**CC**	**MC**	**LC**	**MI**	**LI**	**Total**
1	113	-	2	2	1	-	-	**5**
2	101.1	2	5	-	-	-	-	**7**
3	136.1	4	4	-	-	-	-	**8**
4	65.9	7	2	-	-	-	-	**9**
5	230.2	8	-	-	-	-	-	**8**
6	230.2	4	1	-	2	-	-	**7**
7	65.9	-	1	1	2	-	-	**4**
8	65.9	9	1	-	-	-	-	**10**
9	48.3	10	-	-	-	-	-	**10**
10	65.9	4	2	-	-	-	-	**6**
11	65.9	6	1	-	-	-	-	**7**
12	136.3	7	-	-	-	-	-	**7**
13	65.9	5	2	2	-	-	-	**9**
14	65.9	6	-	-	-	-	-	**6**
15	65.9	7	1	-	-	-	-	**8**
16	101.1	5	2	-	-	-	-	**7**
17	101.1	2	4	1	-	-	-	**7**
18	101.1	-	-	2	2	-	-	**4**
19	101.1	3	-	3	1	-	-	**7**
20	101.1	-	4	4	-	-	-	**8**
21	101.1	-	2	2	1	-	-	**5**
22	101.1	2	5	-	-	-	-	**7**
23	488.4	2	1	-	-	-	4	**7**
24	488.4	-	1	-	-	1	4	**6**
25	65.9	7	-	-	-	-	-	**7**
26	65.9	5	1	-	-	-	-	**6**
27	65.9	8	-	-	-	-	-	**8**
28	136.3	2	2	3	-	-	-	**7**
29	230.2	-	1	1	-	3	-	**5**
30	171.5	-	1	-	-	3	1	**5**
31	242.4	-	-	2	4	-	-	**6**
32	65.9	5	-	-	-	-	-	**5**
Total	**4,250.9**	**120**	**46**	**23**	**13**	**7**	**9**	**218**
Vehicles/ consumer		3	12	60	200	40	100	-
Assumed penetration (%)		**30**	**28**	**28**	**35**	**34**	**45**	**-**
V2G		108	155	386	910	95	405	**2,059**

The assumed V2G penetration delivers an estimated number of 2,059 cars to the given network. The number of cars set in the simulations was 2,000 for simplifying data analysis. General parameters of the simulated scenario are given in Table 4.2. The stats resulting from the use of EVeSSi tool for this network are shown in Table 4.3. This case study scenario uses the modeling parameters given in subsection 2.1.1 for EVs battery. Identical share of about 33% for EVs types were assumed in the scenario, e.g. for BEV, PHEV and EREV types. The distribution of trips along the day is based on the data provided in [39] (see Fig. 2.8). The data concerning vehicle definition for this case study can be seen in appendix A.

Table 4.2 – Scenario parameters

	Parameter value
Battery efficiency	85%
Cars parked all day (no movements)	1%
Charging efficiency (slow and fast mode)	90%
Initial state of battery	30%
Maximum depth of discharge	80%
Number of EVs	2,000
Number of periods	24
Time step	1 hour

Table 4.3 –Scenario driving stats

		Driving stats
Trip Distance (km)	Mean	29
	Maximum	482
	Minimum	0
Total Distance (km)		58,438
Mean Battery Capacity (kWh)		15

To simulate movements to and from the network, it was assumed that 50% of the cars remained inside the network, i.e. 1,000 cars, 25% of cars remained inside the network from 9AM to 18PM and 25% from 19PM to 8AM. The outcome of movements using such assumptions is expressed in Fig. 4.3.

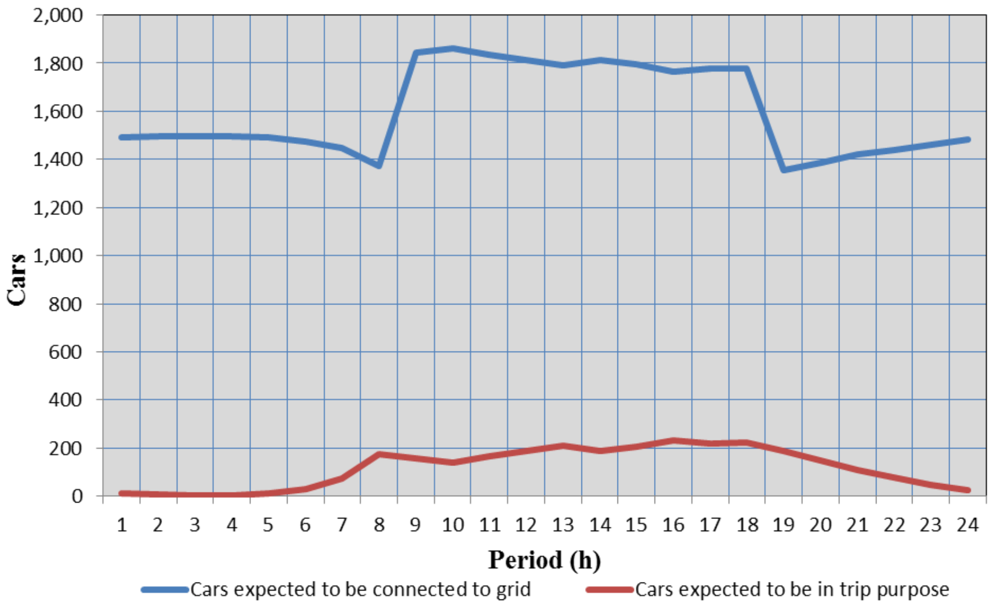

Fig. 4.3 – Cars expected to be connected to the grid

4.2.2 Solution comparison with MINLP

To demonstrate the effectiveness of the modified PSO a comparison with MINLP has been carried out. This section provides the results for both methods and the corresponding analysis.

Fig. 4.4 presents the optimal scheduling resulting from MINLP whereas Fig. 4.5 presents the scheduling for a random run using modified PSO. The optimization corresponds to the formulation presented in subsection 3.2 without EV demand response programs. The objective function cost is 6,175 m.u. and 6,180 m.u. in the case of MINLP and the modified PSO, respectively. This corresponds to an operation cost increase of 0.08% when compared with the solution obtained with MINLP, which is negligible.

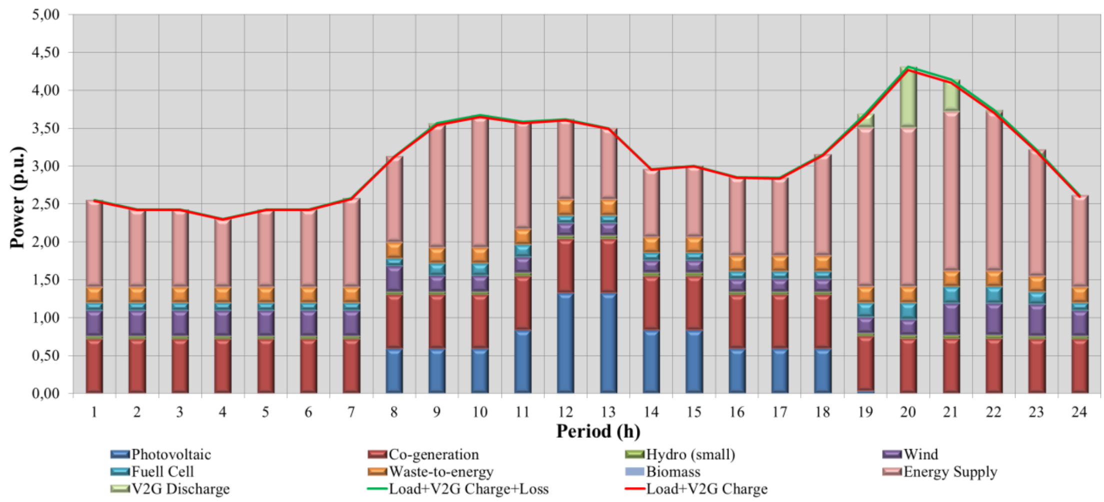

Fig. 4.4 – Optimal scheduling obtained with MINLP in GAMS

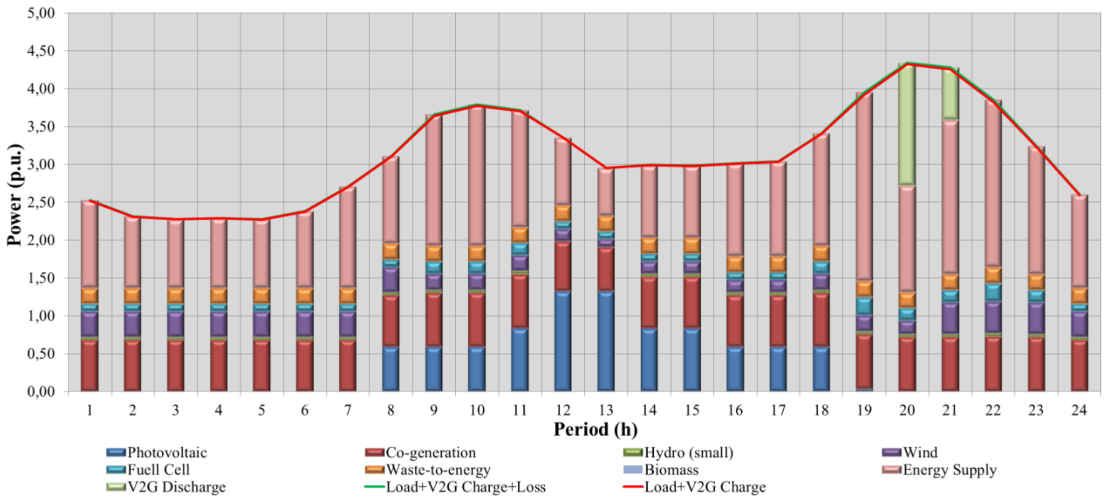

Fig. 4.5 – Scheduling resulting from a random run in modified PSO

In spite of the cost of both solutions being virtually the same, the resulting scheduling from both methodologies carry some differences, even so they are quite similar. The modified PSO discharges more vehicles in period 20 and 21 than MINLP approach. In period 19 only MINLP approach presents vehicles discharge. The peak load in modified PSO is 4.326 MW while in MINLP is 4.309 MW both in period 20. The peak power loss in MINLP solution occur in period 20 whereas in PSO occur in period 19. The power loss in period 20 is alleviated in PSO solution due to the high presence of vehicles discharge, which acts as distributed generation.

Fig. 4.6 shows the objective function of 100 trials using the modified PSO. The maximum objective function cost in 100 trials was 6,209 m.u. and the minimum was 6,179 m.u. with a mean value of 6,192. A random trial for the given case study will fall into these values with high chance. When compared with MINLP this represents almost no variability of the objective function value with a minimum and maximum variation of 0.06% and 0.55%, respectively.

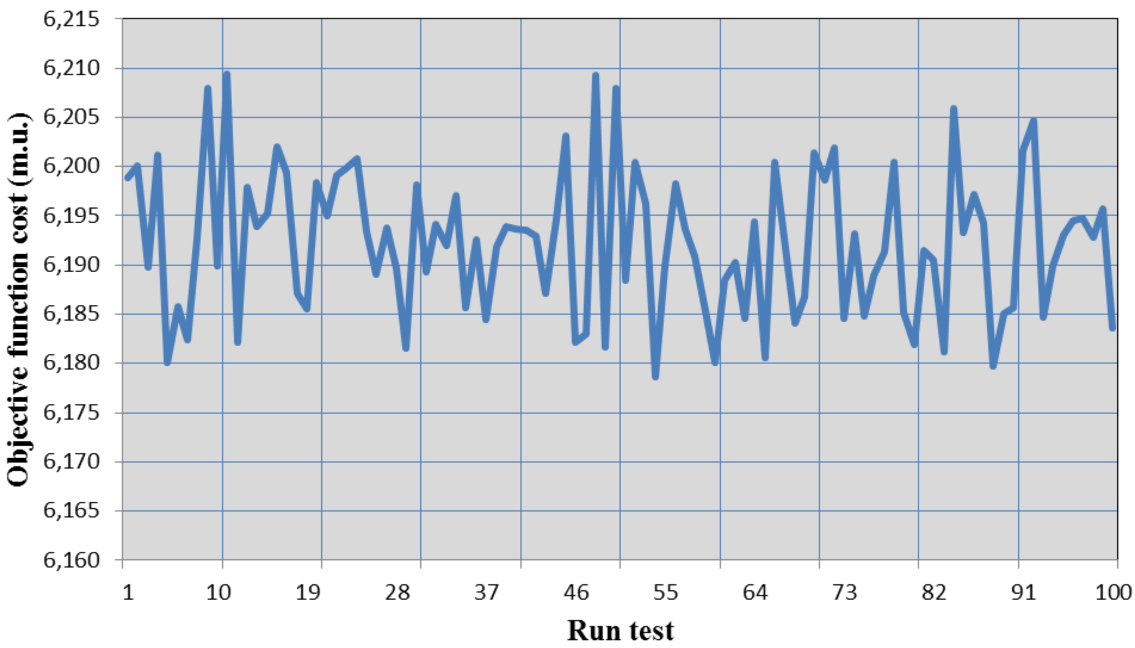

Fig. 4.6 – Objective function cost for 100 trials using the modified PSO

Table 4.4 presents the summary of the results for MINLP and of the modified PSO. In this case study PSO is 2,600 times faster than MINLP methodology and delivers almost the same objective function cost as MINLP. MINLP takes more than 25 hours to solve the optimization problem. This execution time is expected to rise exponentially with the increase of the number of resources and network size. To note that this case study presents a modest 33 bus network size and 2,000 V2G resources without any demand response programs available. The execution time of MINLP approach is high, which is prohibitive for the day-ahead decision.

Table 4.4 – Results comparison over 100 trials

Methodologies	**Best**	**Worst**	**Mean**	**Execution time**	**Violated solutions**
	(m.u.)	(m.u.)	(m.u.)	(s)	(#)
MINLP	6,175	---	---	91,018	---
Modified PSO	6,179	6,209	6,192	35	0/100

4.3 Comparison with other PSO versions

To demonstrate the superiority of the modified PSO in day-ahead scheduling with V2G, the proposed method is compared with other well-known versions, namely Evolutionary Particle Swarm Optimization (EPSO), traditional PSO and New Particle Swarm Optimization (NPSO). There are many more variants of PSO in the literature however it is impracticable to implement all. The metaheuristics parameters used are depicted in table Table 4.5 according to its authors' recommendations. Self-parameterization from proposed implementation of PSO (see subsection 3.3.2) was coded in the comparing versions. The initial swarm population is randomly generated between the upper and the lower bounds of variables for traditional PSO, NPSO and EPSO. For each of the versions a robustness and convergence test was carried out. The data of the used case study is the same as the one presented in subsection 4.2.1

Table 4.5 – Parameters of PSO versions

Parameters	**PSO Methodologies**			
	Traditional PSO [40]	**NPSO [52]**	**EPSO [48]**	**Modified PSO**
Minimum Iterations	50			
Initial swarm population	Randomly between the upper and the lower bounds of variables			Refer to subsection 3.3.3
Stopping Criteria	Refer to subsection 3.3.2			
Max. velocity	Refer to subsection 3.3.2			
Min. velocity	Refer to subsection 3.3.2			
Inertia Weight	1	0.9-0.4 (linearly decreased)	Gaussian mutation weights	
Acceleration Coefficient Worst Position	Not present	0.1	Not present	
Acceleration Coefficient Best Position	2	1.9	Gaussian mutation weights	
Cooperation Coefficient	2	2	Gaussian mutation weights	

4.3.1 Traditional Particle Swarm Optimizaiton

Traditional PSO has been implemented according to [40]. Fig. 4.7 shows the objective function cost over 100 trials using this version. The variability of the costs when plotting the overall trials results is negligible

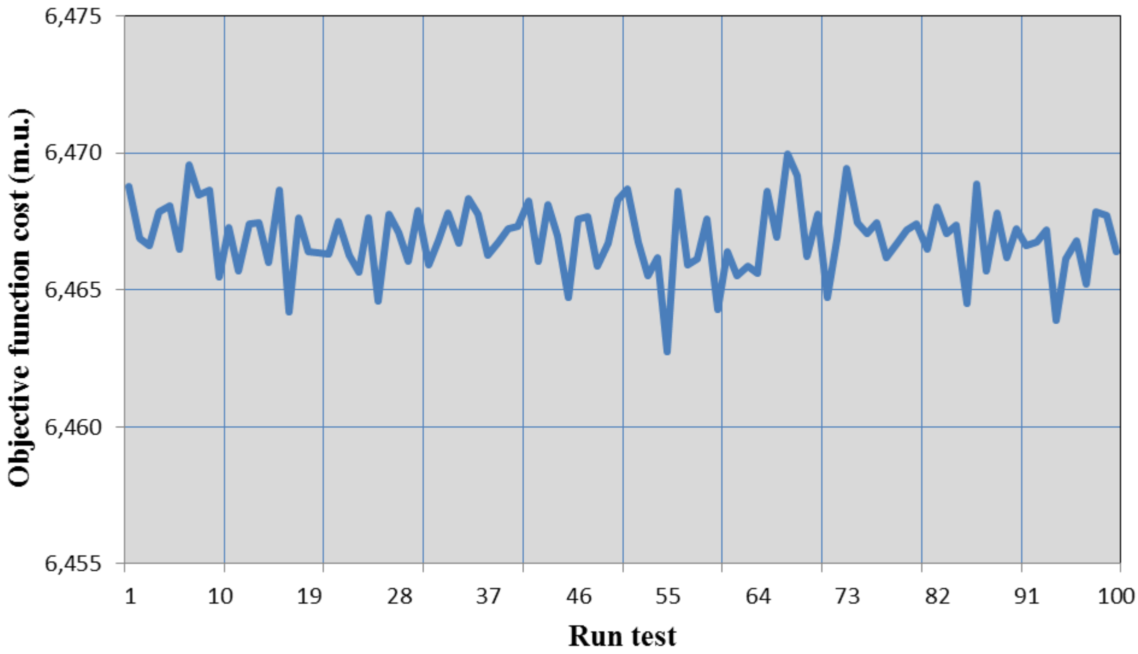

Fig. 4.7 – Objective function cost for 100 trials using traditional PSO

Fig. 4.8 illustrates a convergence test for a random trial in traditional PSO. The objective function decreases smoothly over iterations and improvement stops after some iterations. Due to the definied stopping criteria (see subsection 3.3.2) the optimization stops in 50 iterations.

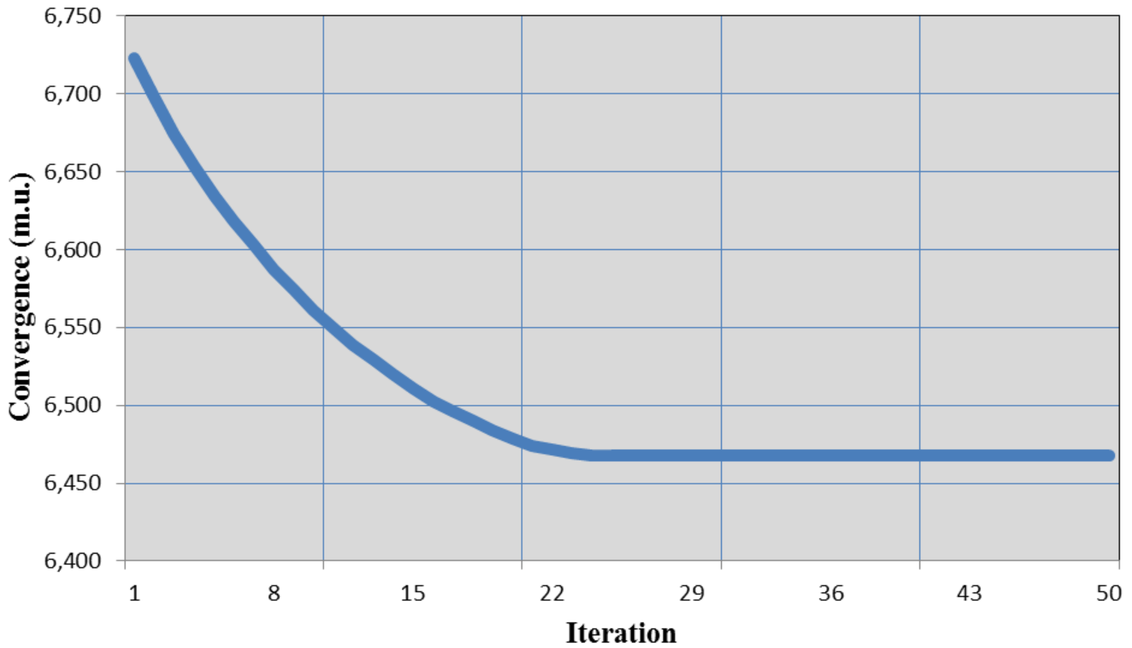

Fig. 4.8 – Convergence of a random trial using traditional PSO

4.3.2 New Particle Swarm Optimizaiton

In [52] the authors propose a modification of the velocity equation to include particle's bad experience component. The traditional PSO includes best experience component. NPSO include both best and bad experience. The bad experience component helps to remember its previously visited worst position. The authors claim superiority over conventional PSO. Time execution is slightly higher when compared with traditional PSO due to the additional computation requirements to process bad experience component.

Fig. 4.9 presents the objective function cost over 100 trials using NPSO. When compared with traditional PSO, NPSO presents slightly improved robustness.

Fig. 4.10 illustrates a convergence test for a random trial in NPSO which turns out to be very comparable with traditional PSO.

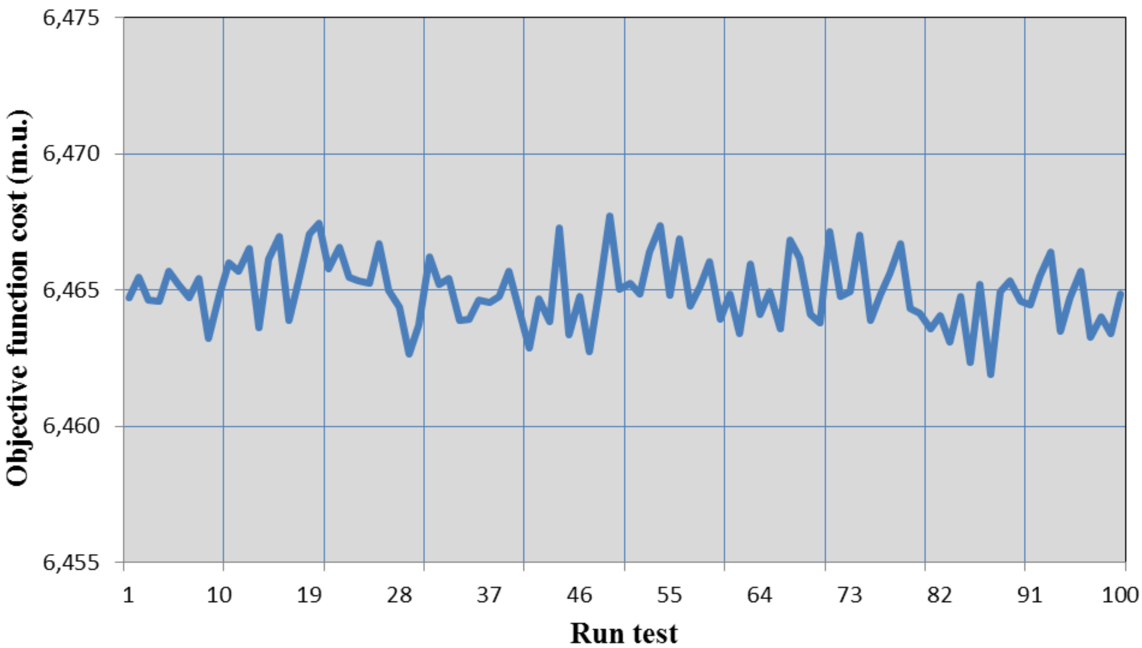

Fig. 4.9 – Objective function cost for 100 trials using NPSO

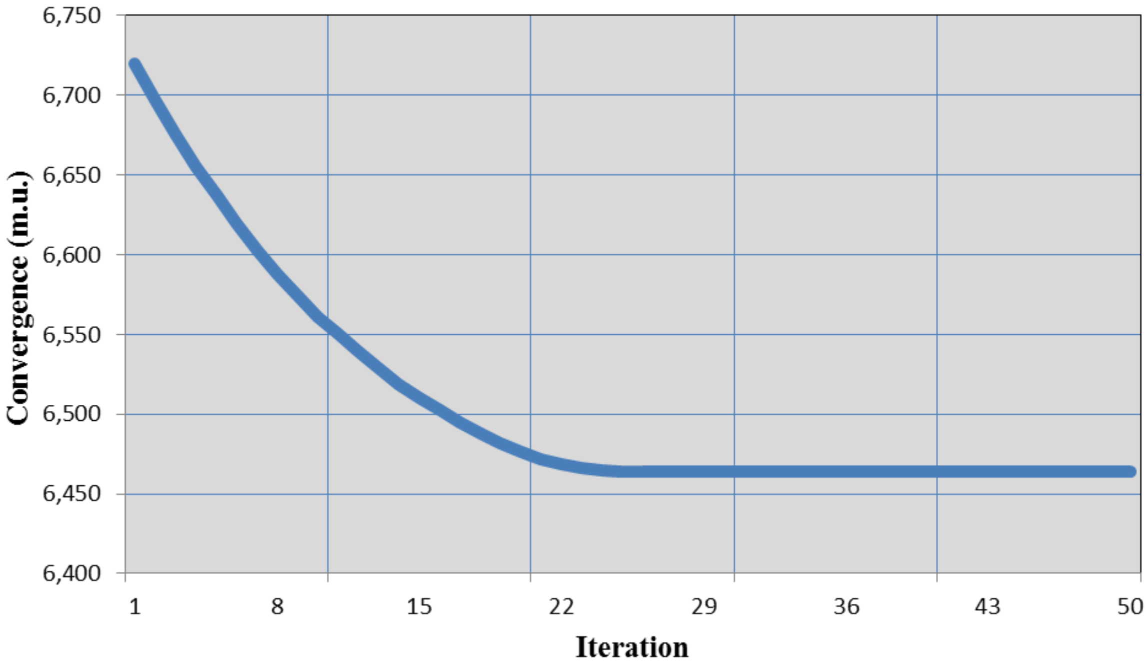

Fig. 4.10 – Convergence of a random trial using NPSO

4.3.3 Evolutionary Particle Swarm Optimizaiton

The EPSO approach, introduced by [48], aims at joining together the benefits of evolutionary programming with the benefits of PSO. It is a self-adaptive algorithm that relies on the mutation of the strategic parameters of the particle movement. EPSO adds replication of each particle and selection of the best particles by stochastic tournament.

Fig. 4.11 depicts the objective function cost for 100 trials using EPSO. This methodology presents more variability when compared with traditional PSO and NPSO, however better solution quality is achieved. Fig. 4.12 shows a convergence test for a random trial in EPSO. In this case study better solutions are expected to be obtained using EPSO instead of traditional PSO and NPSO. The mutation, replication and selection process in EPSO makes it computational heavier than traditional PSO and NPSO.

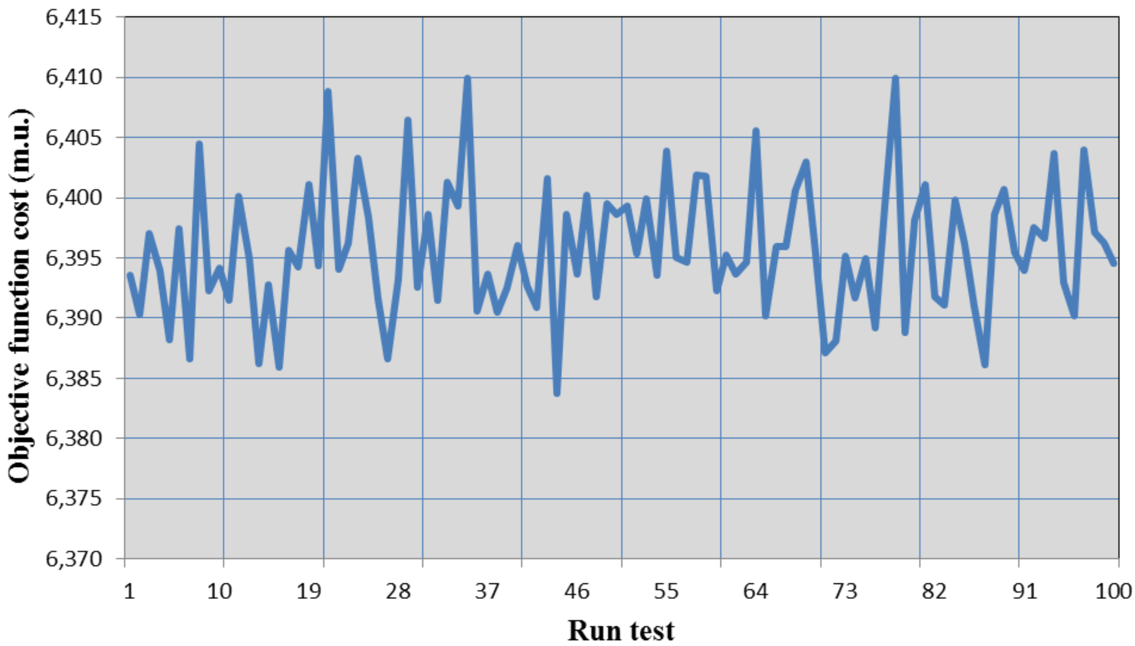

Fig. 4.11 – Objective function cost for 100 trials using EPSO

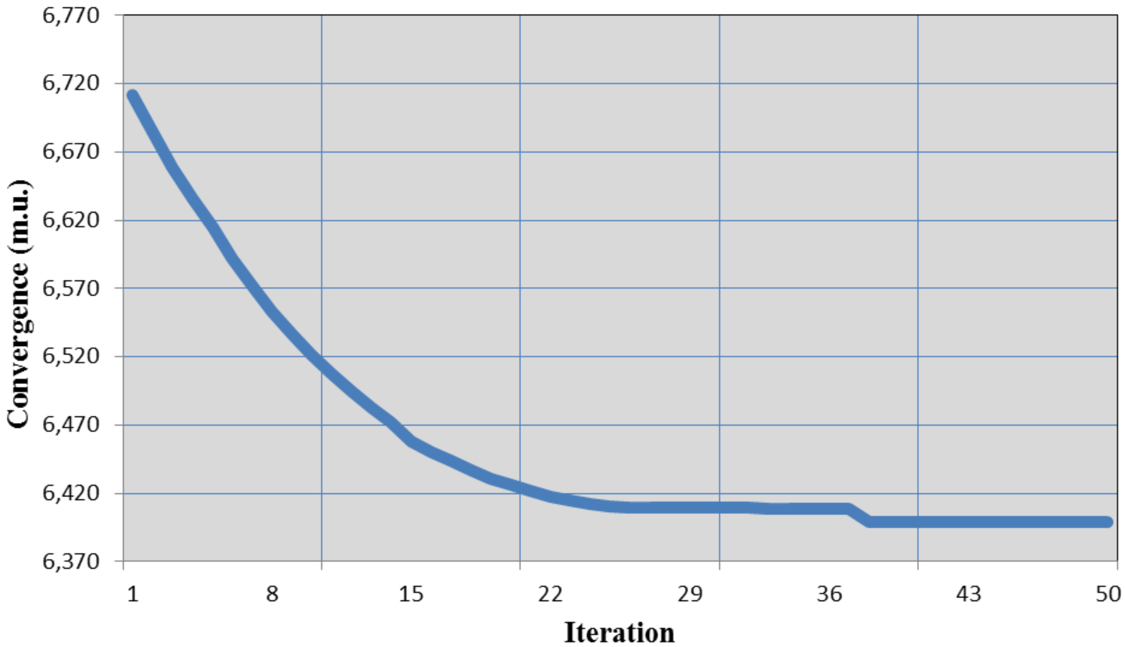

Fig. 4.12 – Convergence of a random trial using EPSO

4.3.4 Comparison analysis

Fig. 4.13 plots the robustness test of each considered methodology together along with the modified PSO test. Traditional PSO is lined up with NPSO, being NPSO relatively better over traditional PSO. The modified PSO meta-heuristic presents better local optimum escaping with consistency results over 100 run tests.

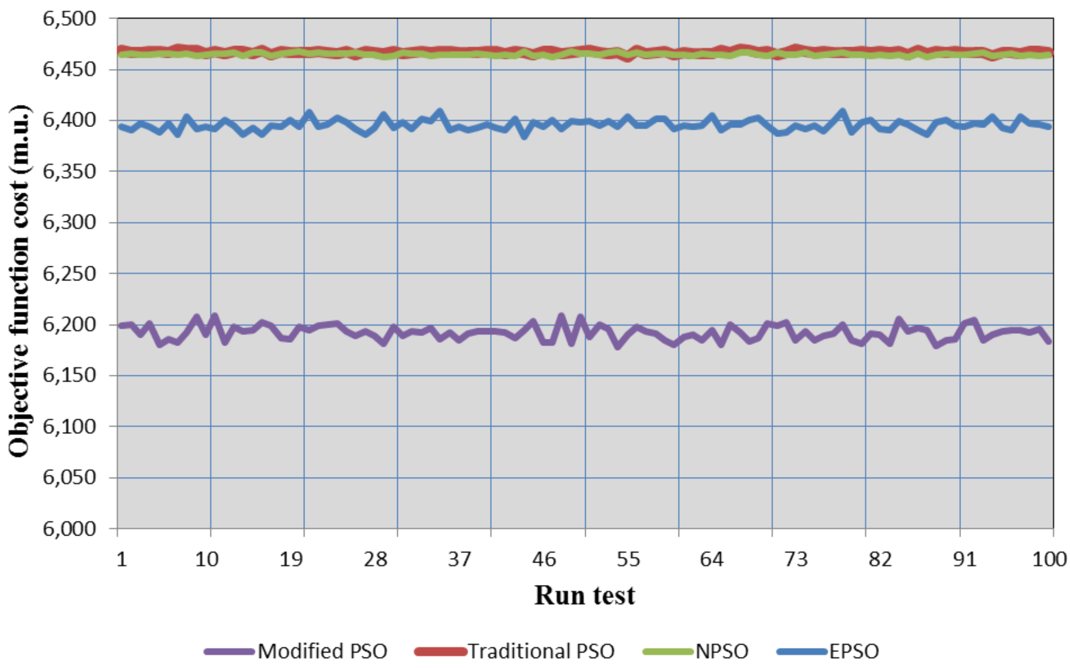

Fig. 4.13 – Robustness test of the modified PSO and PSO versions

Fig. 4.14 depicts the convergence for a random trial including the modified PSO and implemented variants. Clearly, the modified PSO presents a different behavior in convergence test. The sudden drop at iteration 4 in the objective function operation cost is related to quick variations in the swarm positions in the space. The intelligent adjustment included in the modified PSO (see subsection 3.3.1) significantly increases the likelihoods of high solution variations.

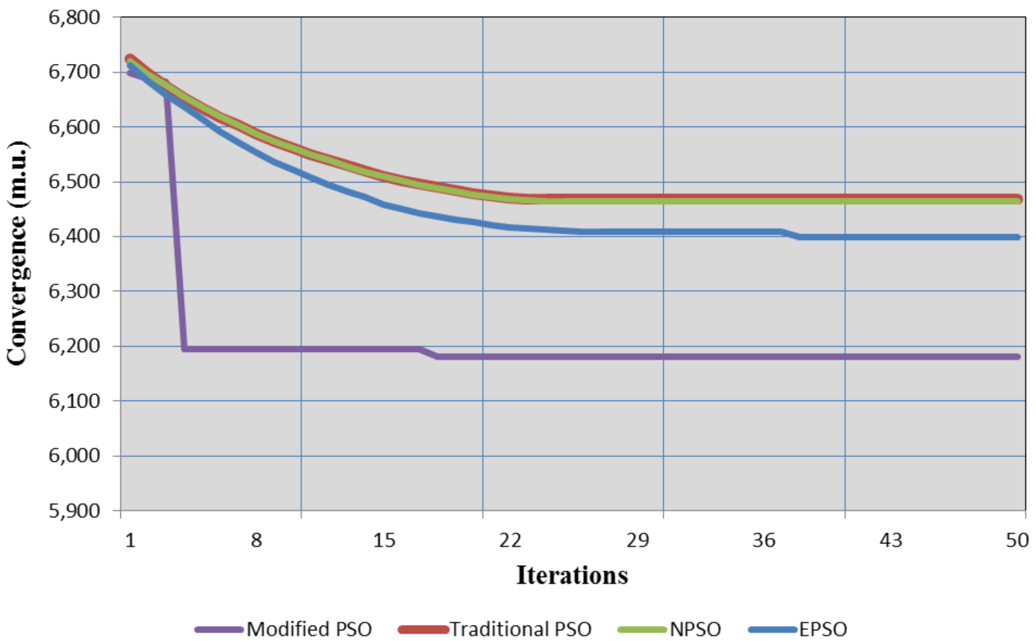

Fig. 4.14 – Convergence test of the modified PSO and PSO versions for a random trial

Table 4.6 shows the resulting robustness test results. The robustness variability coefficient is defined as the ratio between the standard deviation and the mean of the results over 100 trials. MINLP appears in the table for objective function cost reference and execution time comparison with the other techniques. No unfeasible solutions were found in 100 trials for the presented methodologies. Though the modified PSO presents more variability in the results, i.e. the high robustness variability coefficient, the worst objective function over 100 trials is well below from the other tested versions. The execution time of the modified PSO is faster due to the improved convergence properties. EPSO is the meta-heuristic that takes longer execution time due to replication and selection concept.

Table 4.6 – Robustness test result comparison over 100 trials

Methodologies	**Best**	**Worst**	**Mean**	**Robustness variability coefficient**	**Mean execution time per trial**	**Violated solutions**
	(m.u.)	**(m.u.)**	**(m.u.)**		**(s)**	**(#)**
MINLP	6,175	---	---	---	91,018	---
Modified PSO	6,179	6209	6192	0.1192	35	0/100
Traditional PSO	6,463	6470	6467	0.0199	42	0/100
NPSO	6,462	6468	6465	0.0190	45	0/100
EPSO	6,384	6410	6396	0.0846	156	0/100

That said it becomes evident that a specific modified PSO for the problem of day-ahead scheduling with V2G offers advantages in execution time and most importantly solution quality. In critical situations (grid operation on network limits) the proposed PSO can handle with optimization constraints violations better than the tested versions due to the intelligent mechanism.

4.4 Large-Scale case study 180 bus network with 8,000 V2G

The present case study aims to demonstrate the behavior of the proposed PSO with a larger network in order to understand how performance is affected when the number of variables increases. The distribution network is a 30 kV, 180 bus system with 116 DG generators and 1 external supplier. The peak consumption of the case study is around 12.4 MW without EVs. The total number of EVs in the distibution network was set to 8,000. The EVeSSi tool presented in subsection 2.3 was used for simulating the EVs movement in the 180 bus network.

Fig. 4.15 depicts the results of the scheduling using the modified PSO. The high share of generation comes from the network external supplier (energy supply in the figure) meanwhile DG presens lower share of the total generation. The discharging of vehicles did not happen mainly due to cheap supplier energy price.

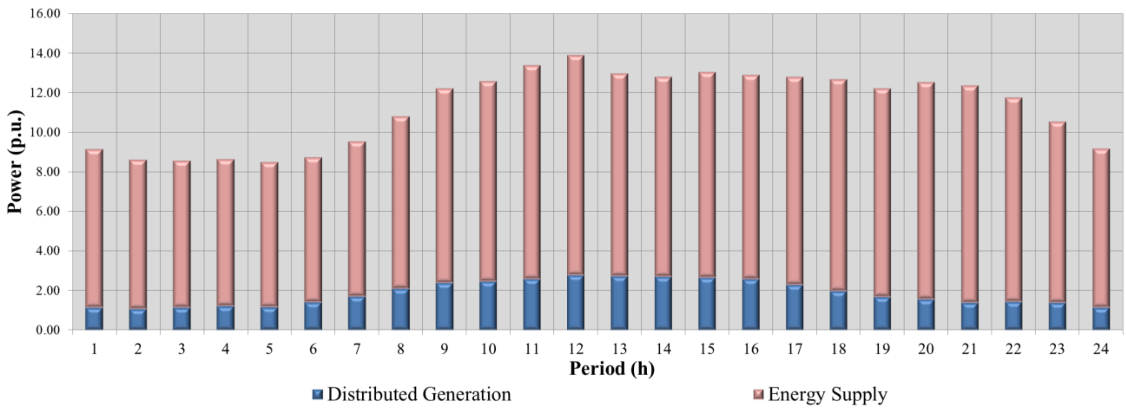

Fig. 4.15 – 180 bus network scheduling using the modified PSO method

Fig. 4.16 shows the load and the vehicles load profile. The peak generation is 13.92 MW whereas the peak load is 13.75 MW in period 12.

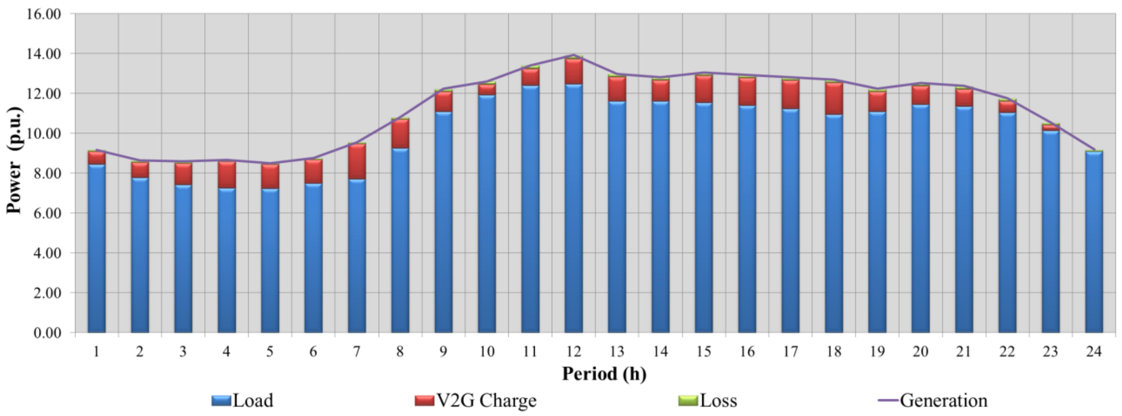

Fig. 4.16 – Load and EVs charge profile

Table 4.7 summarizes the scheduling results using the modified PSO. The execution time of 401 seconds is higher when compared with the previously presented case study of 33 bus distribution network with 2,000 vehicles which took about 35 seconds. However, the execution of this case study is reasonable for the day-ahead context.

Table 4.7 – Scheduling results summary

Objective function cost	**Execution time**	**Peak load**	**Peak power loss**	**Total EVs load**	**Violations**
(m.u.)	(s)	(MW)	(kW)	(MWh)	Yes/No
13,510	401	13.75	167.28	24.71	No

4.5 Different charging methodologies comparison

Three different approaches for managing EVs in the smart grid are used for comparison, namely Uncontrolled Charging (UC), Smart Charging (SC), Vehicle-to-Grid (V2G). The data for this case study is the same as the one presented in subsection 4.2.1. The modified PSO presented in this thesis is used for solving the above approaches scheduling optimizations.

4.5.1 Uncontrolled charging

UC refers to charging EVs whenever possible without grid control. The battery is charged until it has reached maximum charge or the owner has to leave. A case study using this principle is carried out in this section assuming that when vehicles are connected to the grid they charge. Therefore, vehicle charging is not controlled by the operator. The optimization problem do not include discharge of the vehicles to the grid and the vehicles charging decision variables are not considered, instead the charges occur every time that the vehicle is connected unless the battery is already full charged.

Fig. 4.17 depicts the resulting scheduling using UC principle. The solution was obtained in random run of modified PSO. The objective function cost is 7,413 m.u. The peak load occurs at period 1 with a value of 7.12 MW.

The presented solution is unfeasible at network level because the total load at period 1 and 2 creates high voltage drops and lines thermal capacity violations.

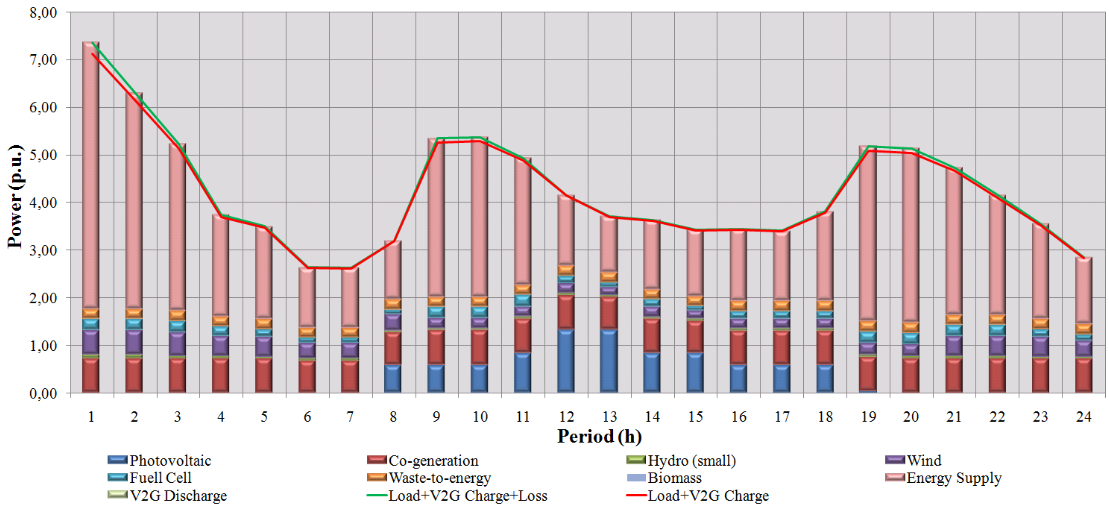

Fig. 4.17 – Uncontrolled charging mode scheduling

4.5.2 Smart charging

In the SC philosophy, there is an increase in the communication requirements between the EV and the grid. The operator can control the EV charging periods, however, respecting users' constraints and minimum levels of battery for users' trips.

Fig. 4.18 show the resulting scheduling using SC. The solution was obtained in random run of modified PSO. The objective function cost is 6,222 m.u. The peak load occurs at period 20 with a corresponding value of 4.50 MW.

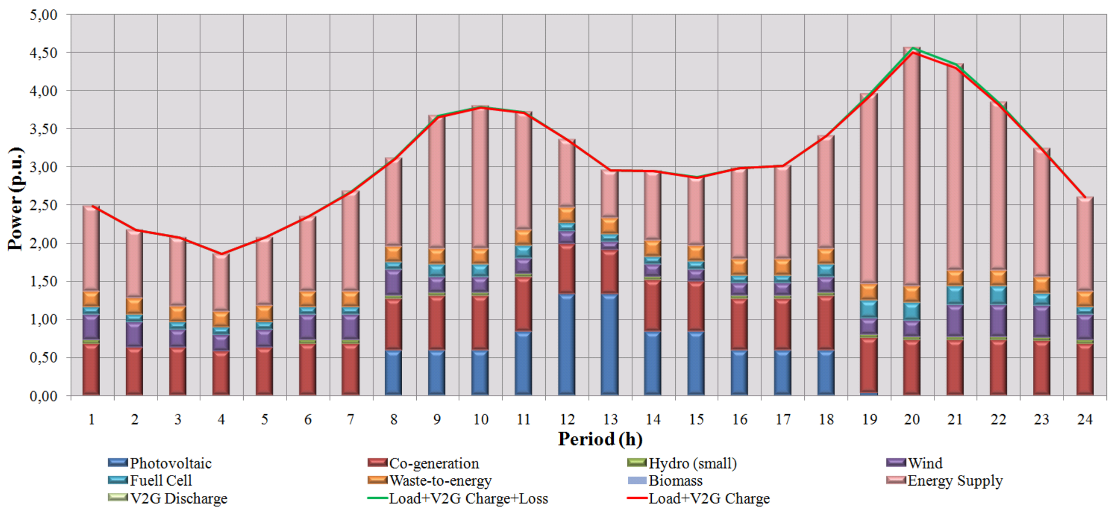

Fig. 4.18 – Smart charging mode scheduling

4.5.3 Vehicle-to-grid opportunities

V2G corresponds to the combined use of SC with the possibility of using EVs as an energy resource available to the grid operator. V2G is the long term goal of EVs smart grid integration

Fig. 4.19 presents the resulting scheduling using V2G concept. The solution was obtained in a random run of modified PSO. The objective function operation cost is 6,193 m.u. The peak load occurs at period 20 with a value of 4.36 MW. It can be seen that for another random run using the same case study situation and the same optimization principle, e.g. V2G, the solution is slightly different than the previously presented in subsection 4.2.2 due to the stochastic nature of the method.

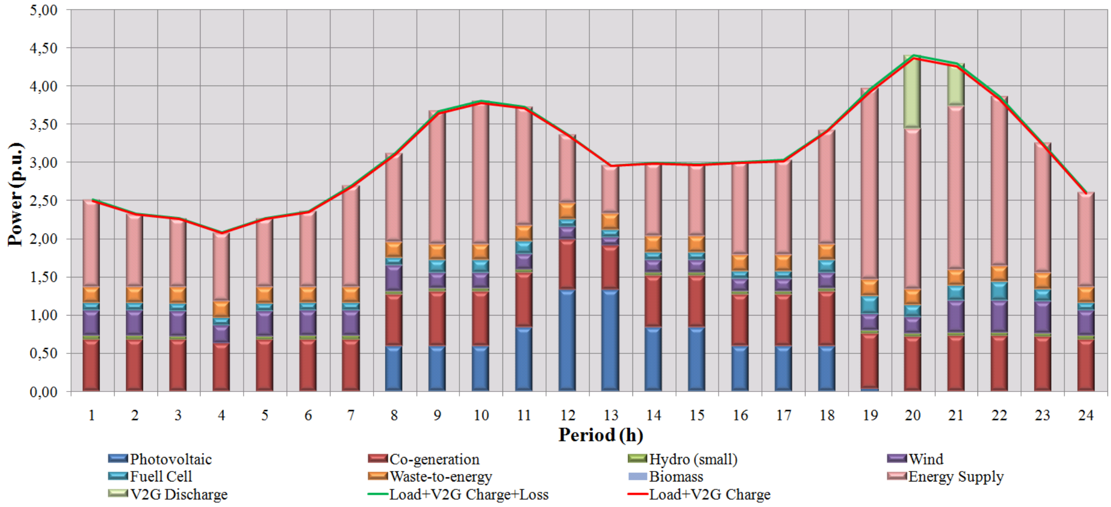

Fig. 4.19 – Vehicle-to-grid mode scheduling

4.5.4 Comparison analysis

Fig. 4.20 shows the total charge load of EVs for UC, SC and V2G methodologies. SC and V2G create similar load patterns while UC is far different.

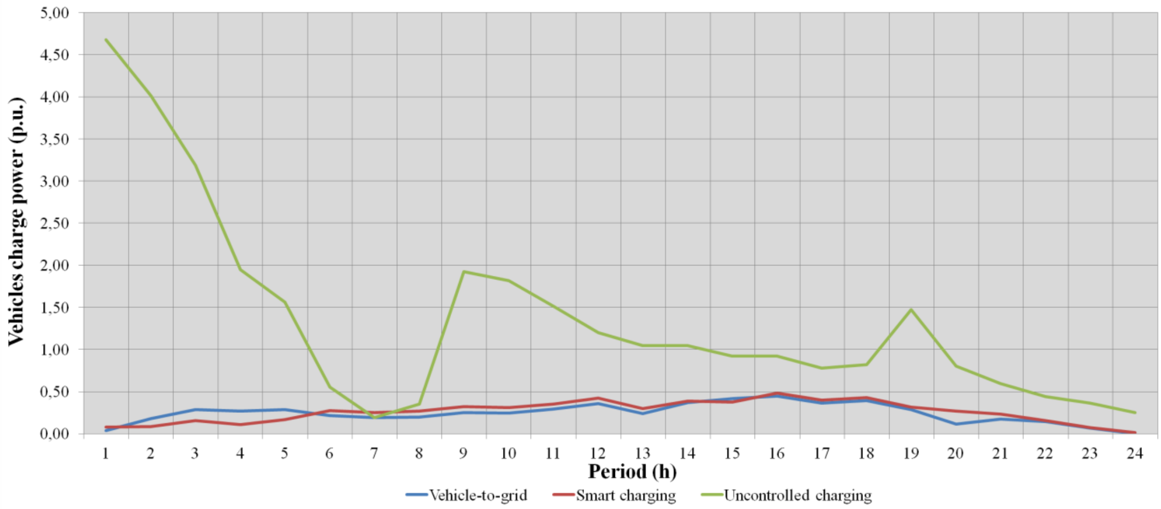

Fig. 4.20 – Vehicle charge load power for the different charging methodologies

Table 4.8 shows a summary of the results for each charging methodology. The total load created by EVs in UC is about 6 times higher than for SC and V2G approaches. Peak power loss is much higher in UC than the two other approaches. With V2G capabilities peak loss was reduced by about 36% when compared to SC in this case study. Peak load, in this case, was reduced from 4.50 MW to 4.36 MW. The total EVs load is higher in V2G than SC methodology because V2G approach uses EVs to discharge. The operation energy costs can be reduced in this case by about 0.5%. It is not conclusive neither significant, however EVs owners can have some profit by letting their vehicles serve the grid in the common well because discharging price includes the energy cost, battery wear-out and battery efficiency.

Clearly, UC is not suited for this number of EVs in the grid. With such approach network contingencies would arise. A smaller limit of EVs would be recommended in this case. SC and V2G are the most appropriate modes for network operation being V2G the ultimate choice.

The execution time presents almost a residual variation among the presented approaches. Even with far less decision variables, UC takes approximately the same execution time as the two other approaches. The most noticeable reason is that this approach integrates extra programming code in PSO to accommodate UC mode thus eliminating the effect of less decision variables.

Table 4.8 – Charging methodologies results comparison

Charging mode	Objective function cost	Execution time	Peak load	Peak power loss	Total EVs load	Violations
	(m.u.)	(s)	(MW)	(kW)	(MWh)	Yes/No
Uncontrolled charging (UC)	7413	35	7.12	239.63	31.46	Yes
Smart charging (SC)	6222	34	4.50	60.67	5.04	No
Vehicle-to-Grid (V2G)	6193	35	4.36	38.84	5.78	No

4.6 Electric vehicles demand response test cases

4.6.1 Trip reduce demand response program test case

A case study following the same conditions of subsection 4.2.1 was carried out to test the trip reduce demand response approach, however with different suppliers energy prices, different base load and different renewable energy availability. See appendix B for the respective data.

Fig. 4.21 presents the results of the scheduling with DR trip reduce available. The reduce occurs mainly between period 9 and period 22. The total reduced energy from vehicle trips amounts to 3.72 MWh.

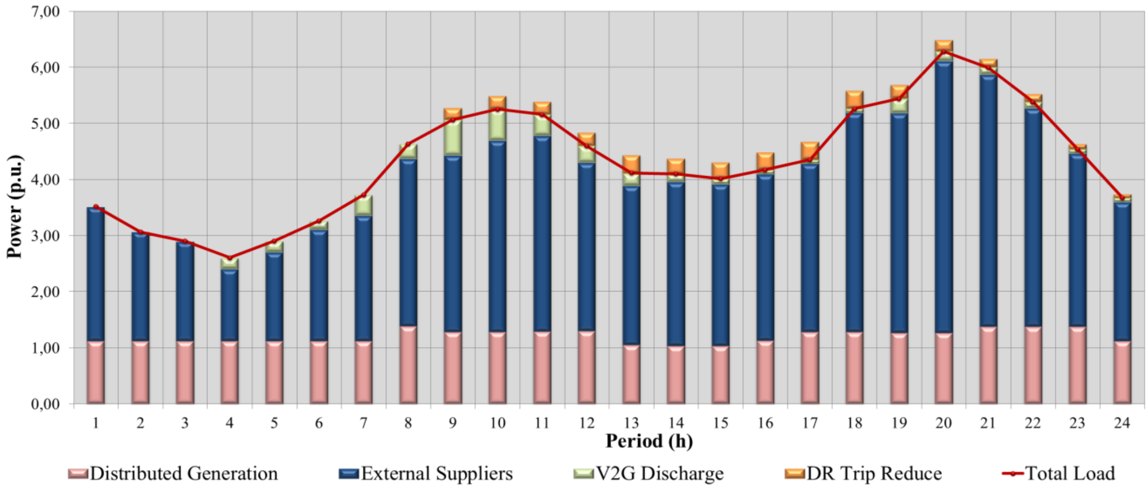

Fig. 4.21 – Scheduling with DR trip reduce available

Fig. 4.22 shows the charge scheduling of the EVs. A total charge of 6.23 MWh was dedicated to EVs. The high EVs charge occurred at period 18.

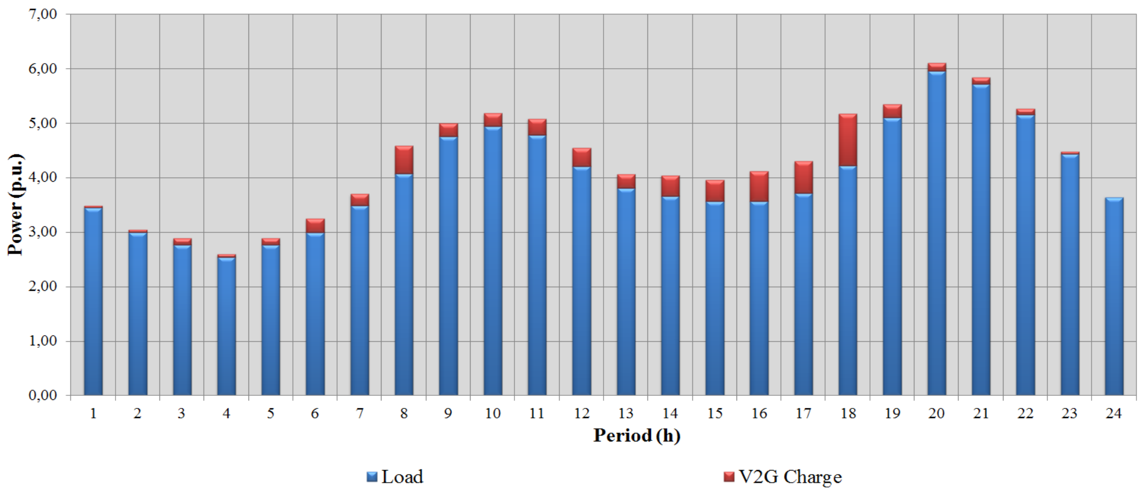

Fig. 4.22 – EVs charge scheduling with trip reduce available

Table 4.9 shows the summary results of trip reduce approach compared with the results of not using trip reduce demand response program.

Table 4.9 – Summary results of using and not using trip reduce

	Objective function cost	**Execution time**	**Peak load**	**Peak power loss**	**Total EVs load**	**Total EVs discharge**	**Total trip reduce**
	(m.u.)	**(s)**	**(MW)**	**(kW)**	**(MWh)**	**(MWh)**	**(MWh)**
With trip reduce available	13,129	50	6.10	180	6.24	4.56	3.72
No trip reduce available	13,208	35	6.25	200	7.41	1.95	-

As seen in the Table 4.9 the execution time is higher when using the demand response option due to added computational programming code. The difference in the objective function cost is residual. However, the peak load is reduced as well as the system power loss. The discharging of EVs is higher mainly because there is less use of EVs battery when using trip reduce.

4.6.2 Trip reduce demand response program definition test case

For supporting network operator in the definition of trip reduce demand response program several operation scenarios were simulated in this case study. The proposed methodology was presented in the previous chapter (see subsection 3.4.2).

Starting from an initial case study database (see subsection 4.2.1) a range of scenarios was created and some data was modified such as the available Distributed Generation

(DG), price of network suppliers and base load. Distributed generation based on renewable energy was varied from 0% to 100% of the original case study in steps of 5% (21 variations). Price of network suppliers was varied from 100% to 150% in steps of 5% (11 variations). Base load was varied from 60% to 140% in steps of 10% (9 variations). With these combinations a total of 2,079 different operation scenarios were created to simulate real world conditions. The modified PSO technique was executed for each of the created scenarios and the optimization results were stored.

Data pre-processing phase consisted in converting the optimization results (in a 24 period basis) to a one period basis. The conversion resulted in the attributes of Table 4.10 from exception of the class attribute. Thus, a total of 49,896 period scenarios were created. After the data pre-processing phase the *K-means* clustering algorithm was used in order to identify similar patterns among trip reduce demand response usage per period. In this case the number of clusters was chosen to be equal to 10 to enable a reasonable analysis by the network operator and a reduced group of rules set. The results of the obtained profiles using 10 clusters can be seen in Table 4.11. 97% of the created scenarios did not used trip reduce demand response program.

In order to estimate the usage of trip reduce demand response per period for a given operation condition it was implemented a classification model using rule-based modeling technique C5.0 classification algorithm. The input attributes data sets have been divided to form a training group and a test group. The separation among test and training classes is to avoid spoiled results, so that the model accuracy is not erroneous influenced. The classification model generates the decision tree to provide the rules set.

Table 4.10 shows the attributes of the database that were used by the clustering algorithm and by the classification model to generate the rules set.

Table 4.10 – Attributes used by the clustering and classification algorithm

Variables	Description	Clust.	Class.
PERIOD	Time interval (1-24h)		X
TOTAL_ LOAD	Total load for the given period		X
DG_GEN	Total generation from distributed generation for the given period		X
SUPLLIERS_GEN	Total suppliers generation for the given period		X
V2G_DR	Total trip reduce demand response program used	X	
LAST_GEN_PRICE	Last generation price for the given period		X
V2G LOAD	Total load from EVs for the given period		X
CLASS	Class obtained by clustering		X
Total number of inputs		1	6

Table 4.11 – Obtained cluster from the k-means clustering algorithm

Class	Average usage (kWh)	Simulations per cluster
1	0,00	48204
2	56,29	197
3	104,04	289
4	139,19	265
5	167,77	386
6	205,12	173
7	236,91	208
8	267,63	132
9	310,79	24
10	359,28	18

As an example, the rules set for class 2 are presented:

Rule 1 for CLASS 2
if PERIOD > 15
and PERIOD <= 17
and TOTAL_LOAD > 4,133
and V2G_LOAD <= 0,697
and DG_GEN <= 1,364
and LAST_GEN_PRIC > 0,189
then CLASS 2
Rule 2 for CLASS 2
if PERIOD > 12
and PERIOD <= 13
and LAST_GEN_PRIC > 0,182
then CLASS 2
Rule 3 for CLASS 2
if PERIOD > 15
and PERIOD <= 17
and V2G_LOAD <= 0,697
and LAST_GEN_PRIC > 0,189
then CLASS 2

The classification model generated a rule set with an overall accuracy of 98.18%. Table 4.12 summarizes the information concerning the overall accuracy of the used C5.0 algorithm for this case study. This methodology supports network operator decisions in the definition of trip reduce demand response program in its daily operation. It enables to estimate how much demand response is adequate for a certain operation condition.

Table 4.12 – Overall accuracy

	Total number	Accuracy (%)
Correct decisions	16596	98.18
Wrong decisions	308	1.82
Total	16904	100.00

4.7 Conclusions

In this chapter several case studies were presented and discussed. The performance of the modified PSO approach proposed in this thesis for the day-ahead Distributed Energy Resources (DER) scheduling was compared with an exact method, namely Mixed Integer Non-Linear Programming (MINLP). The results have shown that the modified PSO approach execution time is faster by a factor of 2,600 times when compared to MINLP in the 33 bus system network case study. The solution quality in terms of objective function varied slightly between 0.06% and 0.55% in a 100 trials run test when compared to the MINLP reference technique. This demonstrates the suitability of using an approximate algorithm such as the modified PSO for the day-ahead energy resources scheduling

The comparison of the modified PSO with the different variants of PSO, namely EPSO, NPSO and the traditional version demonstrated its superiority in terms of solution quality and execution time.

The modified PSO was tested with a small sized 33 bus network with 2,000 V2G and a larger one of 180 bus with 8,000 V2G. The scheduling optimization took an average of 35 seconds on the smaller network and 401 seconds on the larger one. This value even when compared with the 91,018 seconds (more than 25 hous) of MINLP for the 33 bus network case approach is very low. It is expected that MINLP execution time for the 180 bus test case is impracticable for the day-ahead context with the exponential nature of the MINLP problems. Further investigation is required to test MINLP approach with a larger test case using MINLP.

Another important conclusion drawn from the case studies is that vehicle-to-grid and smart charging approaches are the suitable ways to deal with the intensive penetration of EVs. In spite of uncontrolled charging do not requiring investments in car-to-grid communications, this methodology will certainly cause more network contingencies with higher penetration of EVs unless appropriated network investments are made.

A case study with the application of demand response for EVs users, proposed in chapter 3, was illustrated and compared with a case study without demand response. The trip reduce demand response program demonstrated that, in certain operation conditions, it is possible to reduce operation costs, the peak load and the system power loss.

5 Conclusions and Future Work

The expected rise of Electric Vehicles (EVs) use poses new challenges and, at the same time, opens new opportunities for distribution network operators. With the adequate infrastructure in place and with the possibility of EVs being used as an energy resource using the Vehicle-To-Grid (V2G) approach, the day-ahead resource scheduling model needs to be revised in order to include these new requirements. This thesis focuses on that particular case of optimization.

To deal with a high number of variables in the non-linear optimization process, metaheuristics are the appropriate tools to reduce execution time. Particle Swarm Optimization (PSO) was selected in this work due to its proven success in the power system field.

This thesis addressed some aspects in the power system optimization field for the day-ahead Distributed Energy Resources (DER) scheduling, namely providing:

- EVs Scenario Simulator (EVeSSi) for the creation of custom scenarios in distribution networks with EVs;
- Full mathematical model that supports the V2G concept in the day-ahead scheduling context;
- Improved PSO for the presented problem;
- Trip reduce model for electric vehicle demand response.

The thesis presented a brief review of the current electric vehicle technology, including EVs batteries capacity and charging/discharging rates. The battery cell ageing as well as battery costs of EVs should be taken into account in V2G applications involving economy costs. With the present battery production technology the estimated battery wear-out cost can vary between 1 and 6 cents of a dollar per kWh of used energy.

A tool called EVs Scenario Simulator (EVeSSi) has been developed to enable the creation of custom scenarios in distribution networks with EVs. This tool can be parameterized by the user to catch EV technology, driving behaviors and market penetration.

A mathematical model has been developed to include the V2G concept and the trip reduce demand response program. The vehicle users' requirements and technical constraints are considered in the model as well as charging and discharging efficiency. The network constraints are also included for obtaining feasible solutions.

The introduction of V2G resources in the optimization problem represents new demands in terms of computational power requirements. The meta-heuristic PSO was modified to better suit the problem of Distributed Energy Resources (DER) optimal scheduling. A classic method, namely Mixed Integer Non-Linear Programming (MINLP), has been used for comparison purposes. The performance of the modified PSO was compared with MINLP using a case study considering a 33 bus distribution network and 2,000 gridable EVs. The performance of the modified PSO surpassed the MINLP execution time by a factor of 2,600 times with 35 seconds in PSO against 91,018 seconds (more than 25 hours) in MINLP. When compared to MINLP, the modified PSO presented only slightly worse solutions (a residual difference with a maximum of 0.55% in 100 trials). When compared with other variants, the modified PSO still managed to get better execution time and better solutions using the same case study. It is reasonable to conclude that the development of an application-specific PSO for the day-ahead DER scheduling proved its success in the comparison case studies.

A large-scale case study using a 180 bus network with 8,000 V2G demonstrated that the modified PSO execution time is still acceptable when the number of variables is very high. The execution time in the large-scale case study was around 400 seconds against 35 seconds for the 33 bus distribution system network. The execution time of MINLP approach in this case study is expected to be massive what makes it useless even for day-ahead scheduling requirements.

Three different vehicle grid interaction approaches have been tested, namely, Uncontrolled Charging (UC), Smart Charging (SC) and V2G. These approachs differ in the way vehicles interact with the grid. UC is the grid uncontrolled approach, e.g. vehicles starts charging whenether the owner plugs in. In the SC approach the grid operator can control when vehicles charge while respecting the owners requested battery levels for each period. In the V2G approach, besides SC philosophy the grid operator can use the vehicles to discharge power to the grid while paying to its owners. The case study revealed that UC is inappropriate to hold a large number of vehicles in the network because of simultaneous vehicles charges that cause network technical violations. Consequently, the UC approach can expose network operator to critical operation situations if the number of vehicles is high and no network upgrades are considered. SC and V2G are more appropriate for the tested number of vehicles, being V2G the best choice in terms of costs reduction while reducing peak load and network power loss.

Electric vehicle demand response for EVs users has been proposed in this thesis considering the day-ahead context. A trip reduce demand response program has been designed and implemented. The case study considering the trip reduce demand response program demonstrated that it is possible to reduce operation costs, peak load as well as the system power loss. A data-mining based methodology to support the definition of trip reduce demand response program was developed enabling to estimate how much trip reduce is adequate for a certain operation condition. The trip shifting program framework is proposed as future work and further investigation is required to analyze its effectiveness.

The work done in the scope of this thesis opens new horizons for future developments. Thus, the following list gives some suggestions for the upgrade of the proposed methodology:

- Improve EVeSSi tool to create advanced realistic vehicle movements in the distribution network;
- Experiment quadratic cost functions in the mathematical formulation with an appropriate case study;
- Investigate multi-objective function problems in the day-ahead scheduling context using adequate versions of PSO for multi-objective problems;

- Extend the mathematical model to consider the low voltage distribution system level in order to improve the precision of the results, namely what concerns the network power lossin that level;
- Prepare more test cases considering different scenarios of EVs penetration and other distribution networks and compare with MINLP and the modified PSO;
- Demonstrate modified PSO ability to avoid solutions violations in critical network situations, e.g. operation in network limits, and compare with other variants and MINLP;
- Compare the modified PSO with more PSO variants and other approximate algorithms such as firefly algorithm, mean variance optimization and glowswarm optimization;
- Explore the parallelization of the PSO algorithm under a parallel computing plataform to improve execution time in large-scale problems;
- Further investigation is required to analyse the viability of demand response programs for EVs;
- Further investigation on additional demand response programs for EVs including the analysis of the proposed trip shifting demand response program.

In what concerns the trip shifting demand response program for EVs some work has already been done. It aims to provide another useful resource for the network operator. This demand response program enables vehicle users to provide a list of optional travelling periods for their already expected travel trips. This enables the network operator to shift load by paying participating users, reduce operational costs and alleviate network contingencies.

Fig. 5.1 presents the possible framework for this program. This framework is very similar as the presented previously for DR trip reduce program (see Fig. 3.5) however with a different purpose. For instance, in this example EV user 1 expects to travel in periods 9 to 10 and 18 to 19. The initial optimization result returned an EV user 1 travelled in period 7 to 8 instead of 9 to 10. The shifting should be limited to the alternatives that users impose, limiting the computational execution time of optimization process at the same time. The acknowledgment of users' participation in the demand response program is of extreme importance for network operator in order to obtain the appropriate resources scheduling and reduce operational costs.

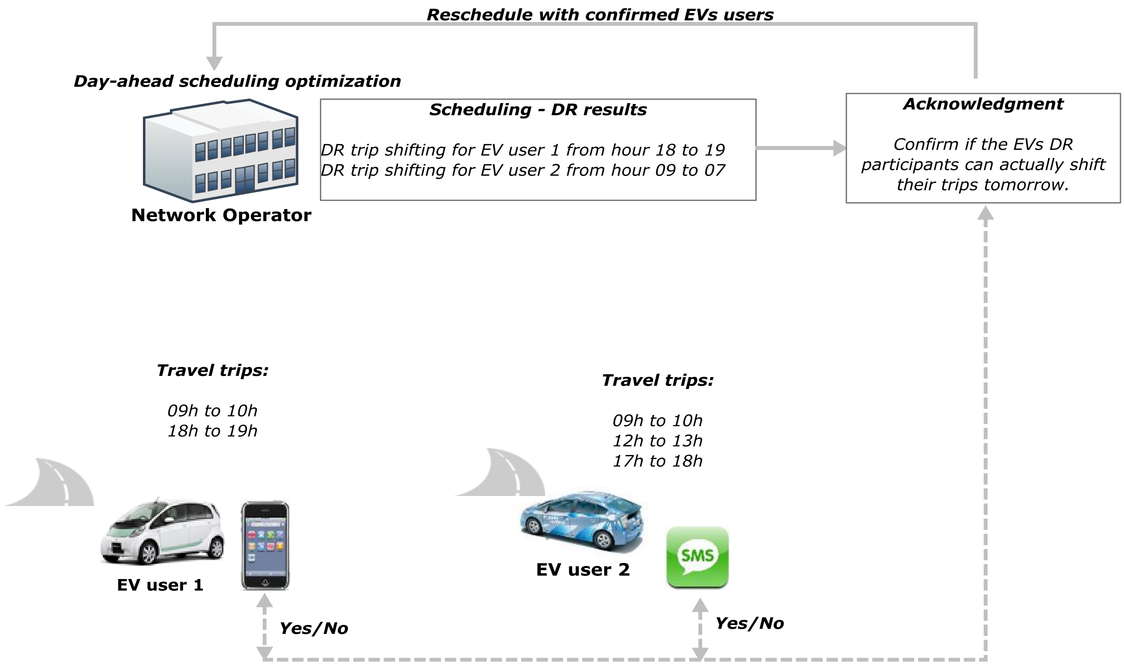

Fig. 5.1 – Framework of DR trip shifting program

Fig. 5.2 presents a brief framework for the future work.

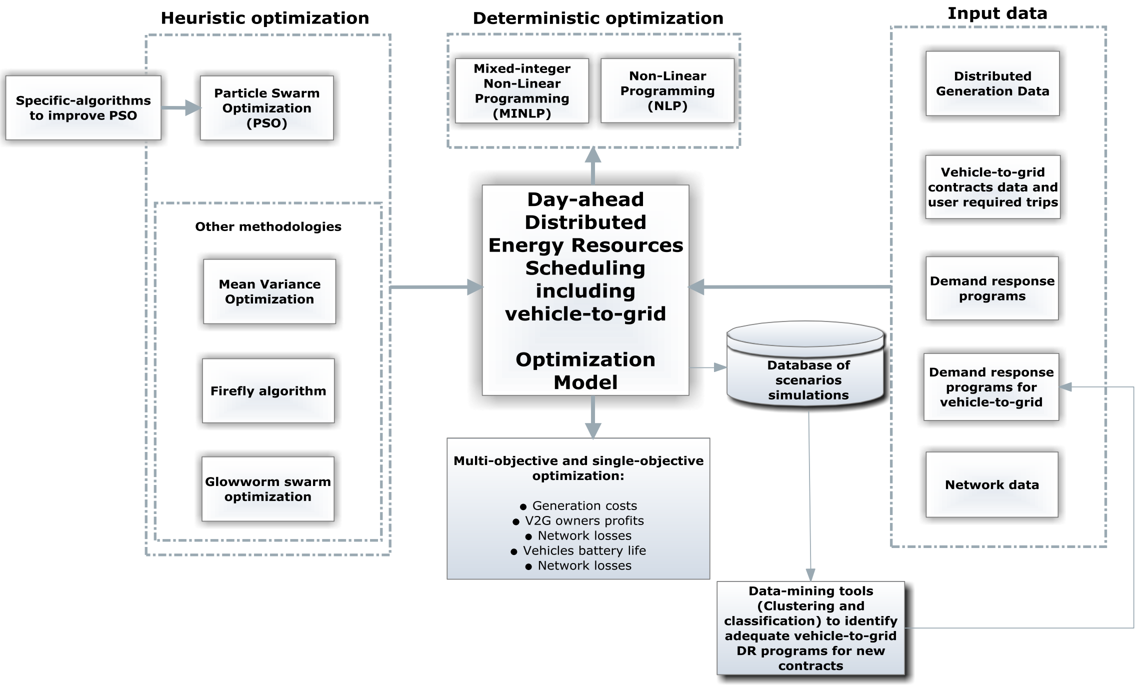

Fig. 5.2 – Future work framework

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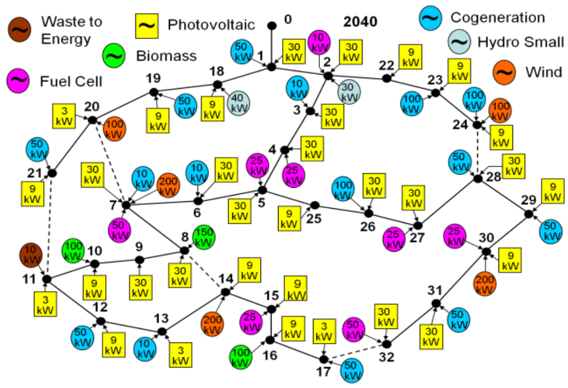
Appendix A – *Case study data 33 bus*

Resources price in monetary units (m.u.) – 33 bus network case study



Resources price (m.u.)

Generator ID	Bus	Price (m.u./MWh)	Generator ID	Bus	Price (m.u./MWh)
		Period 1 to 24			Period 1 to 24
1	**1**	110	**39**	**19**	212
2	**1**	67	**40**	**19**	78
3	**2**	145	**41**	**20**	199
4	**2**	102	**42**	**20**	74
5	**2**	132	**43**	**21**	205
6	**3**	180	**44**	**21**	75
7	**3**	64	**45**	**22**	210
8	**4**	254	**46**	**23**	208
9	**4**	98	**47**	**23**	74
10	**5**	184	**48**	**24**	218
11	**5**	95	**49**	**24**	136
12	**6**	191	**50**	**24**	65
13	**6**	74	**51**	**25**	194
14	**7**	197	**52**	**26**	194
15	**7**	62	**53**	**26**	58
16	**7**	85	**54**	**27**	198
17	**7**	105	**55**	**27**	98
18	**8**	179	**56**	**28**	177
19	**8**	190	**57**	**28**	57
20	**9**	152	**58**	**29**	154
21	**10**	210	**59**	**29**	81
22	**10**	186	**60**	**30**	165
23	**11**	204	**61**	**30**	75
24	**11**	56	**62**	**30**	100
25	**12**	197	**63**	**31**	174
26	**12**	74	**64**	**31**	91
27	**13**	198	**65**	**32**	184
28	**13**	79	**66**	**32**	109
29	**14**	210	**67***	**0**	60
30	**14**	60	**68***	**0**	70
31	**15**	178	**69***	**0**	80
32	**15**	110	**70***	**0**	90
33	**16**	189	**71***	**0**	100
34	**16**	226	**72***	**0**	110
35	**17**	176	**73***	**0**	120
36	**17**	87	**74***	**0**	130
37	**18**	156	**75***	**0**	140
38	**18**	89	**76***	**0**	150

* Network suppliers

Vehicles charge and discharge price (m.u.)

Charge Price (m.u./MWh)	Discharge Price (m.u./MWh)
Period 1 to 24	Period 1 to 24
70	90

Resources technology – 33 bus network case study

Generator ID	Bus	Type	Technology	Generator ID	Bus	Type	Technology
1	**1**	1	Photovoltaic	**39**	**19**	1	Photovoltaic
2	**1**	2	Cogeneration	**40**	**19**	2	Cogeneration
3	**2**	2	Hydro small	**41**	**20**	1	Photovoltaic
4	**2**	2	Fuel cell	**42**	**20**	2	Wind
5	**2**	1	Photovoltaic	**43**	**21**	1	Photovoltaic
6	**3**	1	Photovoltaic	**44**	**21**	2	Cogeneration
7	**3**	2	Cogeneration	**45**	**22**	1	Photovoltaic
8	**4**	1	Photovoltaic	**46**	**23**	1	Photovoltaic
9	**4**	2	Fuel cell	**47**	**23**	2	Cogeneration
10	**5**	1	Photovoltaic	**48**	**24**	1	Photovoltaic
11	**5**	2	Fuel cell	**49**	**24**	2	Wind
12	**6**	1	Photovoltaic	**50**	**24**	2	Cogeneration
13	**6**	2	Cogeneration	**51**	**25**	1	Photovoltaic
14	**7**	1	Photovoltaic	**52**	**26**	1	Photovoltaic
15	**7**	2	Wind power	**53**	**26**	2	Cogeneration
16	**7**	2	Fuel cell	**54**	**27**	1	Photovoltaic
17	**7**	2	Cogeneration	**55**	**27**	2	Fuel cell
18	**8**	1	Photovoltaic	**56**	**28**	1	Photovoltaic
19	**8**	2	Biomass	**57**	**28**	2	Cogeneration
20	**9**	1	Photovoltaic	**58**	**29**	1	Photovoltaic
21	**10**	1	Photovoltaic	**59**	**29**	2	Cogeneration
22	**10**	2	Biomass	**60**	**30**	1	Photovoltaic
23	**11**	1	Photovoltaic	**61**	**30**	2	Wind
24	**11**	2	Waste to energy	**62**	**30**	2	Fuel cell
25	**12**	1	Photovoltaic	**63**	**31**	1	Photovoltaic
26	**12**	2	Cogeneration	**64**	**31**	2	Cogeneration
27	**13**	1	Photovoltaic	**65**	**32**	1	Photovoltaic
28	**13**	2	Cogeneration	**66**	**32**	2	Fuel cell
29	**14**	1	Photovoltaic	**67**	**0**	2	Supplier
30	**14**	2	Wind	**68**	**0**	2	Supplier
31	**15**	1	Photovoltaic	**69**	**0**	2	Supplier
32	**15**	2	Fuel cell	**70**	**0**	2	Supplier
33	**16**	1	Photovoltaic	**71**	**0**	2	Supplier
34	**16**	2	Biomass	**72**	**0**	2	Supplier
35	**17**	1	Photovoltaic	**73**	**0**	2	Supplier
36	**17**	2	Cogeneration	**74**	**0**	2	Supplier
37	**18**	1	Photovoltaic	**75**	**0**	2	Supplier
38	**18**	2	Hydro small	**76**	**0**	2	Supplier

Type:
1 – Network cannot control generation
2 – Network can control generation

Resources active power limits (p.u.) – 33 bus network case study

Resources active power limits (p.u.) from period 1 to 12

Generator ID	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
2	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
3	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
4	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
7	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
9	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
11	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
13	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
15	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
16	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.060	0.060	0.060	0.060
17	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
19	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.050	0.090
22	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
23	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
24	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
25	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.050	0.090
26	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
27	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
28	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
29	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.050	0.090
30	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.060	0.060	0.060	0.060
31	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.050	0.090
32	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
33	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.050	0.090
34	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
35	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
36	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
37	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.050	0.090
38	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040

Generator ID	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
39	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.030	0.030	0.030	0.030
40	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
41	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
42	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.045	0.045	0.045	0.045
43	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
44	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
45	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
46	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
47	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
48	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
49	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.045	0.045	0.045	0.045
50	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
51	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
52	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
53	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
54	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
55	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
56	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
57	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
58	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
59	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
61	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
62	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.045	0.045	0.045	0.045
63	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
64	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
66	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
67*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
68*	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
69*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
70*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
71*	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700
72*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
73*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
74*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
75*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
76*	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000

* Network suppliers

Resources active power limits (p.u.) from period 13 to 24

Generator ID	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
1	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
2	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
3	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
4	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
5	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
6	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
7	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
8	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
9	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
10	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
11	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
12	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
13	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
14	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
15	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200

Generator ID	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
16	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.125	0.125	0.125	0.125
17	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
18	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
19	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150
20	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
21	0.090	0.050	0.050	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000	0.000
22	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
23	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
24	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
25	0.090	0.050	0.050	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000	0.000
26	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
27	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
28	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
29	0.090	0.050	0.050	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000	0.000
30	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.125	0.125	0.125	0.125
31	0.090	0.050	0.050	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000	0.000
32	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
33	0.090	0.050	0.050	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000	0.000
34	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
35	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
36	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
37	0.090	0.050	0.050	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000	0.000
38	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
39	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.000	0.000	0.000	0.000	0.000
40	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
41	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
42	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.085	0.085	0.085	0.085
43	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
44	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
45	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
46	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
47	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
48	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
49	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.085	0.085	0.085	0.085
50	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
51	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
52	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
53	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
54	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
55	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
56	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
57	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
58	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
59	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
60	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
61	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
62	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.085	0.085	0.085	0.085
63	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
64	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
65	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
66	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
67*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
68*	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
69*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
70*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
71*	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700
72*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
73*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
74*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
75*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
76*	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000

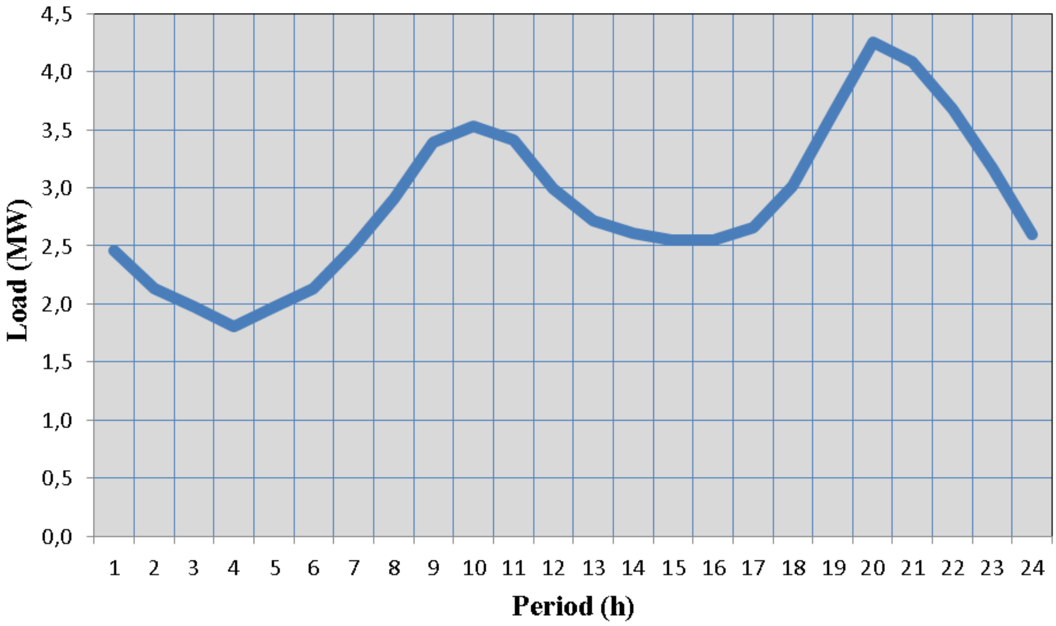
* Network suppliers

Network lines data in per unit system (p.u.) – 33 bus network case study

Network lines data

From bus	To bus	Resistance (p.u.)	Inductive reactance (p.u.)	Capacitance (p.u.)	Thermal limit (p.u.)
0	**1**	0.00083	0.00029	0.00000	5.50
1	**2**	0.00444	0.00157	0.00000	5.50
1	**18**	0.00168	0.00060	0.00000	5.50
2	**3**	0.00243	0.00065	0.00000	4.29
2	**22**	0.00377	0.00133	0.00000	5.50
3	**4**	0.00119	0.00032	0.00000	4.29
4	**5**	0.00453	0.00122	0.00000	4.29
5	**6**	0.00656	0.00177	0.00000	4.29
5	**25**	0.00665	0.00179	0.00000	4.29
6	**7**	0.00125	0.00034	0.00000	4.29
7	**8**	0.00238	0.00064	0.00000	4.29
8	**9**	0.00935	0.00252	0.00000	4.29
9	**10**	0.00345	0.00093	0.00000	4.29
10	**11**	0.00376	0.00101	0.00000	4.29
11	**12**	0.00475	0.00128	0.00000	4.29
12	**13**	0.00821	0.00221	0.00000	4.29
13	**14**	0.00466	0.00126	0.00000	4.29
14	**15**	0.00205	0.00055	0.00000	4.29
15	**16**	0.01877	0.00506	0.00000	4.29
16	**17**	0.00511	0.00138	0.00000	4.29
18	**19**	0.00639	0.00226	0.00000	5.50
19	**20**	0.00407	0.00144	0.00000	5.50
20	**21**	0.00809	0.00286	0.00000	5.50
22	**23**	0.00808	0.00285	0.00000	5.50
23	**24**	0.00093	0.00033	0.00000	5.50
25	**26**	0.00181	0.00049	0.00000	4.29
26	**27**	0.00674	0.00182	0.00000	4.29
27	**28**	0.00512	0.00138	0.00000	4.29
28	**29**	0.00323	0.00087	0.00000	4.29
29	**30**	0.00621	0.00167	0.00000	4.29
30	**31**	0.00198	0.00053	0.00000	4.29
31	**32**	0.00217	0.00059	0.00000	4.29

Load data per period (p.u.) – 33 bus network case study



Active power per period in p.u. – period 1 to 12

Bus	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.0796	0.0575	0.0531	0.0487	0.0531	0.0575	0.0620	0.0988	0.1005	0.1087	0.1095	0.1103
2	0.0849	0.0518	0.0478	0.0438	0.0478	0.0518	0.0786	0.0910	0.0932	0.0942	0.0941	0.0717
3	0.0875	0.0690	0.0637	0.0584	0.0637	0.0690	0.0785	0.1193	0.1254	0.1369	0.1258	0.1105
4	0.0614	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0478	0.0478	0.0478	0.0479
5	0.0510	0.0345	0.0319	0.0292	0.0319	0.0345	0.0702	0.0644	0.0724	0.0910	0.0886	0.0478
6	0.1514	0.1151	0.1062	0.0974	0.1062	0.1151	0.1521	0.1854	0.1899	0.2035	0.1912	0.1565
7	0.1524	0.1151	0.1062	0.0974	0.1062	0.1151	0.1602	0.1814	0.1935	0.2502	0.2345	0.1568
8	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0478	0.0478	0.0478	0.0478
9	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0478	0.0478	0.0478	0.0478
10	0.0279	0.0259	0.0239	0.0219	0.0239	0.0259	0.0279	0.0400	0.0500	0.0358	0.0358	0.0358
11	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0600	0.0700	0.0700	0.0800	0.0600
12	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0600	0.0700	0.0700	0.0700	0.0600
13	0.0743	0.0690	0.0637	0.0584	0.0637	0.0690	0.1000	0.1000	0.1700	0.1800	0.1700	0.1100
14	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0600	0.0478	0.0478	0.0478
15	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0478	0.0478	0.0478	0.0478
16	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0600	0.0478	0.0478	0.0478
17	0.0558	0.0518	0.0478	0.0438	0.0478	0.0518	0.0558	0.0637	0.0900	0.0717	0.0717	0.0717
18	0.0558	0.0518	0.0478	0.0438	0.0478	0.0518	0.0558	0.0500	0.0800	0.0717	0.0717	0.0717
19	0.0558	0.0518	0.0478	0.0438	0.0478	0.0518	0.0558	0.0500	0.0600	0.0717	0.0717	0.0717
20	0.0558	0.0518	0.0478	0.0438	0.0478	0.0518	0.0558	0.0637	0.0600	0.0717	0.0717	0.0800
21	0.0558	0.0518	0.0478	0.0438	0.0478	0.0518	0.0558	0.0637	0.0800	0.0717	0.0717	0.1000
22	0.0800	0.0518	0.0478	0.0438	0.0478	0.0518	0.0558	0.0637	0.0800	0.0717	0.0717	0.1000
23	0.2500	0.2416	0.2230	0.2045	0.2230	0.2416	0.2800	0.2974	0.3000	0.3346	0.3346	0.3000
24	0.2500	0.2416	0.2230	0.2045	0.2230	0.2416	0.2800	0.2974	0.3000	0.3500	0.3500	0.3000
25	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0500	0.0500	0.0700	0.0600	0.0478
26	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0500	0.0500	0.0700	0.0600	0.0478
27	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0425	0.0478	0.0700	0.0478	0.0478
28	0.0743	0.0690	0.0637	0.0584	0.0637	0.0690	0.0743	0.1000	0.1100	0.1400	0.1300	0.0956
29	0.1239	0.1151	0.1062	0.0974	0.1062	0.1151	0.1239	0.1600	0.2000	0.1700	0.1600	0.1593
30	0.0929	0.0863	0.0797	0.0730	0.0797	0.0863	0.0929	0.1100	0.1500	0.1195	0.1195	0.1000
31	0.1301	0.1208	0.1115	0.1022	0.1115	0.1208	0.1301	0.1400	0.2400	0.2000	0.1900	0.1600
32	0.0372	0.0345	0.0319	0.0292	0.0319	0.0345	0.0372	0.0500	0.0478	0.0478	0.0478	0.0400

Active power in p.u. per period. – period 13 to 24

Bus	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
1	0.0655	0.0659	0.0666	0.0632	0.0680	0.0752	0.0859	0.0885	0.0797	0.0788	0.0664	0.0620
2	0.0651	0.0604	0.0575	0.0633	0.0685	0.0677	0.0857	0.0797	0.0717	0.0775	0.0597	0.0558
3	0.0830	0.0602	0.0585	0.0634	0.0685	0.0903	0.1234	0.1062	0.0957	0.0956	0.1014	0.0744
4	0.0384	0.0299	0.0247	0.0251	0.0347	0.0451	0.0687	0.0531	0.0479	0.0490	0.0514	0.0372
5	0.0425	0.0425	0.0399	0.0201	0.0425	0.0451	0.0787	0.0531	0.0478	0.0398	0.0398	0.0372
6	0.1478	0.1351	0.1348	0.1399	0.1442	0.1505	0.2025	0.1770	0.1593	0.1225	0.1328	0.1239
7	0.1435	0.1354	0.1325	0.1315	0.1442	0.1505	0.2054	0.1770	0.2321	0.1545	0.1521	0.1239
8	0.0425	0.0425	0.0425	0.0370	0.0425	0.0451	0.0700	0.0531	0.0900	0.0300	0.0398	0.0372
9	0.0425	0.0425	0.0410	0.0360	0.0425	0.0451	0.0478	0.0700	0.0600	0.0398	0.0398	0.0372
10	0.0319	0.0319	0.0300	0.0319	0.0319	0.0339	0.0600	0.0800	0.0800	0.0400	0.0400	0.0279
11	0.0300	0.0300	0.0260	0.0350	0.0360	0.0451	0.0478	0.0900	0.0700	0.0400	0.0398	0.0372
12	0.0425	0.0425	0.0410	0.0425	0.0425	0.0451	0.0478	0.0700	0.0478	0.0400	0.0398	0.0372
13	0.0850	0.0900	0.0850	0.0850	0.0850	0.0903	0.1500	0.1700	0.1800	0.1200	0.0900	0.0743
14	0.0450	0.0420	0.0380	0.0430	0.0460	0.0500	0.0700	0.0700	0.0800	0.0900	0.0600	0.0372
15	0.0425	0.0500	0.0500	0.0430	0.0460	0.0500	0.0478	0.0700	0.0800	0.0398	0.0398	0.0372
16	0.0800	0.0600	0.0500	0.0430	0.0460	0.0500	0.0478	0.0700	0.0700	0.1300	0.0700	0.0372
17	0.0800	0.0637	0.0637	0.0637	0.0637	0.0677	0.0900	0.1100	0.1000	0.1000	0.0597	0.0558
18	0.0800	0.0637	0.0637	0.0637	0.0637	0.0677	0.0717	0.1200	0.0717	0.0900	0.0900	0.0558
19	0.0800	0.0637	0.0637	0.0637	0.0637	0.0677	0.0900	0.0797	0.0717	0.1200	0.0900	0.0558
20	0.0800	0.0900	0.0700	0.0637	0.0637	0.0677	0.0900	0.1200	0.1000	0.1100	0.0800	0.0558
21	0.0800	0.0637	0.0637	0.0637	0.0637	0.0677	0.0900	0.1200	0.1000	0.1500	0.0900	0.0558
22	0.0637	0.0700	0.0670	0.0637	0.0637	0.0677	0.0717	0.0797	0.1000	0.1000	0.0800	0.0558
23	0.2974	0.2974	0.2974	0.2974	0.3000	0.3800	0.3800	0.4500	0.4600	0.3500	0.3000	0.3000
24	0.2500	0.2974	0.2974	0.2974	0.3200	0.3800	0.4500	0.5000	0.4800	0.3500	0.3500	0.2500
25	0.0425	0.0420	0.0410	0.0430	0.0460	0.0700	0.0700	0.1000	0.0800	0.0800	0.0700	0.0600
26	0.0500	0.0360	0.0340	0.0350	0.0460	0.0600	0.0478	0.0531	0.0478	0.0500	0.0600	0.0600
27	0.0425	0.0350	0.0400	0.0425	0.0425	0.0451	0.0478	0.0600	0.0800	0.1000	0.1000	0.0900
28	0.0900	0.0790	0.0700	0.0650	0.0680	0.0800	0.1200	0.2000	0.2000	0.2000	0.1500	0.1500
29	0.1400	0.1380	0.1300	0.1390	0.1400	0.1505	0.1900	0.2500	0.1900	0.1500	0.1000	0.1239
30	0.1200	0.1200	0.1300	0.1300	0.1300	0.1300	0.1195	0.1328	0.1400	0.1900	0.2000	0.1500
31	0.1500	0.1500	0.1450	0.1600	0.1500	0.1700	0.2000	0.3000	0.2500	0.2000	0.2000	0.1500
32	0.0400	0.0390	0.0500	0.0500	0.0410	0.0600	0.0700	0.1000	0.1200	0.1500	0.0800	0.0500

Definition of EVs models in EVeSSi tool – 33 bus network case study

Models definition

Model ID	Description	Battery capacity (kWh)	Slow charging rate (kW)	Fast charging rate (kWh)	Average economy (kWh/km)	Average speed (km/h)	Average km day (km/day)	Vehicle type	Vehicle class
1	Passenger car	8.7	3	0	0.1122	20	20	BEV	L7e
2	Passenger car	28.5	3	57	0.1608	35	38	BEV	M1
3	Commercial van	23.0	3	46	0.1854	30	56	BEV	N1
4	Light truck	85.3	10	60	0.5867	40	136	BEV	N2
5	Passenger car	8.2	3	0	0.1560	35	20	PHEV	M1
6	Commercial van	8.2	3	0	0.1560	30	20	PHEV	N1
7	Passenger car	16.9	3	0	0.2530	35	20	EREV	M1
8	Commercial van	16.9	3	0	0.2530	30	30	EREV	N1

EV classes' definition

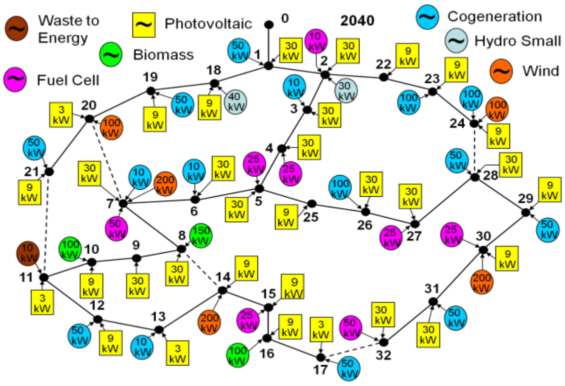
Vehicle class	Share
L7e	0.005
M1	0.870
M2	0.000
M3	0.000
N1	0.100
N2	0.025
N3	0.000

EV types definition

Vehicle type	Share
BEV	0.333
PHEV	0.333
EREV	0.333

Appendix B – *Case study data trip reduce*

Resources price in monetary units (m.u.) – 33 bus network case study



Resources price (m.u.)

Generator ID	Bus	Price (m.u./MWh) Period 1 to 24
67*	**0**	90
68*	**0**	105
69*	**0**	120
70*	**0**	135
71*	**0**	150
72*	**0**	165
73*	**0**	180
74*	**0**	195
75*	**0**	210
76*	**0**	225

* Network suppliers

Vehicles charge and discharge price (m.u.)

Charge price (m.u./MWh)	Discharge price (m.u./MWh)
Period 1 to 24	Period 1 to 24
70	90

Trip reduce demand response price(m.u.)

Trip reduce demand response price (m.u./MWh)
Period 1 to 24
100

Resources active power limits (p.u.) – 33 bus network case study

Resources active power limits (p.u.) from period 1 to 12

Generator ID	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.015	0.015	0.020	0.030
6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.060	0.060	0.060	0.060
17	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
19	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
22	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
23	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
24	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
25	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
26	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
27	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
28	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
29	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
30	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
31	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
32	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
33	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
34	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
35	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
36	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
37	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
38	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
39	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
40	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
41	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Generator ID	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
42	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
43	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
44	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
45	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
46	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
47	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
48	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
49	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
50	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
51	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
52	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
53	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
54	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
55	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
56	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
57	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
58	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
59	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
61	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
62	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.045	0.045	0.045	0.045
63	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
64	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
66	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
67*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
68*	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
69*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
70*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
71*	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700
72*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
73*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
74*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
75*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
76*	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000

* Network suppliers

Resources active power limits (p.u.) from period 13 to 24

Generator ID	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
5	0.030	0.020	0.020	0.015	0.015	0.015	0.000	0.000	0.000	0.000	0.000	0.000
6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.125	0.125	0.125	0.125
17	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
19	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Generator ID	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
22	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
23	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
24	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
25	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
26	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
27	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
28	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
29	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
30	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
31	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
32	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
33	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
34	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
35	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
36	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
37	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
38	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
39	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
40	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
41	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
42	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
43	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
44	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
45	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
46	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
47	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
48	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
49	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
50	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
51	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
52	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
53	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
54	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
55	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
56	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
57	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
58	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
59	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
61	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
62	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.085	0.085	0.085	0.085
63	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
64	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
66	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
67*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
68*	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
69*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
70*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
71*	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700
72*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
73*	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300
74*	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
75*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
76*	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000

* Network suppliers

Load data per period (p.u.) – 33 bus network case study

Active power per period in p.u. – period 1 to 12

Bus	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.1114	0.0805	0.0743	0.0682	0.0743	0.0805	0.0867	0.1383	0.1407	0.1522	0.1533	0.1544
2	0.1188	0.0725	0.0669	0.0613	0.0669	0.0725	0.1100	0.1274	0.1305	0.1319	0.1318	0.1004
3	0.1226	0.0967	0.0892	0.0818	0.0892	0.0967	0.1100	0.1670	0.1756	0.1916	0.1761	0.1547
4	0.0860	0.0483	0.0446	0.0409	0.0447	0.0483	0.0521	0.0595	0.0669	0.0669	0.0669	0.0670
5	0.0714	0.0483	0.0446	0.0409	0.0446	0.0483	0.0983	0.0901	0.1013	0.1274	0.1240	0.0669
6	0.2120	0.1611	0.1487	0.1363	0.1487	0.1611	0.2129	0.2596	0.2658	0.2849	0.2677	0.2191
7	0.2134	0.1611	0.1487	0.1363	0.1487	0.1611	0.2243	0.2540	0.2709	0.3503	0.3283	0.2195
8	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0595	0.0669	0.0669	0.0669	0.0669
9	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0595	0.0669	0.0669	0.0669	0.0669
10	0.0390	0.0362	0.0335	0.0307	0.0335	0.0362	0.0390	0.0560	0.0700	0.0502	0.0502	0.0502
11	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0840	0.0980	0.0980	0.1120	0.0840
12	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0840	0.0980	0.0980	0.0980	0.0840
13	0.1041	0.0967	0.0892	0.0818	0.0892	0.0967	0.1400	0.1400	0.2380	0.2520	0.2380	0.1540
14	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0595	0.0840	0.0669	0.0669	0.0669
15	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0595	0.0669	0.0669	0.0669	0.0669
16	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0595	0.0840	0.0669	0.0669	0.0669
17	0.0781	0.0725	0.0669	0.0613	0.0669	0.0725	0.0781	0.0892	0.1260	0.1004	0.1004	0.1004
18	0.0781	0.0725	0.0669	0.0613	0.0669	0.0725	0.0781	0.0700	0.1120	0.1004	0.1004	0.1004
19	0.0781	0.0725	0.0669	0.0613	0.0669	0.0725	0.0781	0.0700	0.0840	0.1004	0.1004	0.1004
20	0.0781	0.0725	0.0669	0.0613	0.0669	0.0725	0.0781	0.0892	0.0840	0.1004	0.1004	0.1120
21	0.0781	0.0725	0.0669	0.0613	0.0669	0.0725	0.0781	0.0892	0.1120	0.1004	0.1004	0.1400
22	0.1120	0.0725	0.0669	0.0613	0.0669	0.0725	0.0781	0.0892	0.1120	0.1004	0.1004	0.1400
23	0.3500	0.3383	0.3123	0.2862	0.3123	0.3383	0.3920	0.4164	0.4200	0.4684	0.4684	0.4200
24	0.3500	0.3383	0.3123	0.2862	0.3123	0.3383	0.3920	0.4164	0.4200	0.4900	0.4900	0.4200
25	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0700	0.0700	0.0980	0.0840	0.0669
26	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0700	0.0700	0.0980	0.0840	0.0669
27	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0595	0.0669	0.0980	0.0669	0.0669
28	0.1041	0.0967	0.0892	0.0818	0.0892	0.0967	0.1041	0.1400	0.1540	0.1960	0.1820	0.1338
29	0.1735	0.1611	0.1487	0.1363	0.1487	0.1611	0.1735	0.2240	0.2800	0.2380	0.2240	0.2230
30	0.1301	0.1208	0.1115	0.1022	0.1115	0.1208	0.1301	0.1540	0.2100	0.1673	0.1673	0.1400
31	0.1822	0.1691	0.1561	0.1431	0.1561	0.1691	0.1822	0.1960	0.3360	0.2800	0.2660	0.2240
32	0.0520	0.0483	0.0446	0.0409	0.0446	0.0483	0.0520	0.0700	0.0669	0.0669	0.0669	0.0560

Active power in p.u. per period. – period 13 to 24

Bus	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
1	0.0917	0.0922	0.0932	0.0885	0.0952	0.1053	0.1202	0.1239	0.1115	0.1103	0.0929	0.0867
2	0.0912	0.0846	0.0804	0.0887	0.0959	0.0948	0.1199	0.1115	0.1004	0.1084	0.0836	0.0781
3	0.1162	0.0843	0.0819	0.0887	0.0959	0.1264	0.1728	0.1487	0.1339	0.1339	0.1420	0.1041
4	0.0538	0.0418	0.0346	0.0352	0.0486	0.0632	0.0962	0.0744	0.0670	0.0685	0.0719	0.0520
5	0.0595	0.0595	0.0558	0.0282	0.0595	0.0632	0.1102	0.0743	0.0669	0.0558	0.0558	0.0520
6	0.2069	0.1891	0.1887	0.1959	0.2019	0.2107	0.2835	0.2478	0.2230	0.1715	0.1859	0.1735
7	0.2009	0.1896	0.1855	0.1841	0.2019	0.2107	0.2876	0.2478	0.3249	0.2163	0.2129	0.1735
8	0.0595	0.0595	0.0595	0.0518	0.0595	0.0632	0.0980	0.0743	0.1260	0.0420	0.0558	0.0520
9	0.0595	0.0595	0.0574	0.0504	0.0595	0.0632	0.0669	0.0980	0.0840	0.0558	0.0558	0.0520
10	0.0446	0.0446	0.0420	0.0446	0.0446	0.0474	0.0840	0.1120	0.1120	0.0560	0.0560	0.0390
11	0.0420	0.0420	0.0364	0.0490	0.0504	0.0632	0.0669	0.1260	0.0980	0.0560	0.0558	0.0520
12	0.0595	0.0595	0.0574	0.0595	0.0595	0.0632	0.0669	0.0980	0.0669	0.0560	0.0558	0.0520
13	0.1190	0.1260	0.1190	0.1190	0.1190	0.1264	0.2100	0.2380	0.2520	0.1680	0.1260	0.1041
14	0.0630	0.0588	0.0532	0.0602	0.0644	0.0700	0.0980	0.0980	0.1120	0.1260	0.0840	0.0520
15	0.0595	0.0700	0.0700	0.0602	0.0644	0.0700	0.0669	0.0980	0.1120	0.0558	0.0558	0.0520
16	0.1120	0.0840	0.0700	0.0602	0.0644	0.0700	0.0669	0.0980	0.0980	0.1820	0.0980	0.0520
17	0.1120	0.0892	0.0892	0.0892	0.0892	0.0948	0.1260	0.1540	0.1400	0.1400	0.0836	0.0781
18	0.1120	0.0892	0.0892	0.0892	0.0892	0.0948	0.1004	0.1680	0.1004	0.1260	0.1260	0.0781
19	0.1120	0.0892	0.0892	0.0892	0.0892	0.0948	0.1260	0.1115	0.1004	0.1680	0.1260	0.0781
20	0.1120	0.1260	0.0980	0.0892	0.0892	0.0948	0.1260	0.1680	0.1400	0.1540	0.1120	0.0781
21	0.1120	0.0892	0.0892	0.0892	0.0892	0.0948	0.1260	0.1680	0.1400	0.2100	0.1260	0.0781

Bus	Period											
	13	14	15	16	17	18	19	20	21	22	23	24
22	0.0892	0.0980	0.0938	0.0892	0.0892	0.0948	0.1004	0.1115	0.1400	0.1400	0.1120	0.0781
23	0.4164	0.4164	0.4164	0.4164	0.4200	0.5320	0.5320	0.6300	0.6440	0.4900	0.4200	0.4200
24	0.3500	0.4164	0.4164	0.4164	0.4480	0.5320	0.6300	0.7000	0.6720	0.4900	0.4900	0.3500
25	0.0595	0.0588	0.0574	0.0602	0.0644	0.0980	0.0980	0.1400	0.1120	0.1120	0.0980	0.0840
26	0.0700	0.0504	0.0476	0.0490	0.0644	0.0840	0.0669	0.0743	0.0669	0.0700	0.0840	0.0840
27	0.0595	0.0490	0.0560	0.0595	0.0595	0.0632	0.0669	0.0840	0.1120	0.1400	0.1400	0.1260
28	0.1260	0.1106	0.0980	0.0910	0.0952	0.1120	0.1680	0.2800	0.2800	0.2800	0.2100	0.2100
29	0.1960	0.1932	0.1820	0.1946	0.1960	0.2107	0.2660	0.3500	0.2660	0.2100	0.1400	0.1735
30	0.1680	0.1680	0.1820	0.1820	0.1820	0.1820	0.1673	0.1859	0.1960	0.2660	0.2800	0.2100
31	0.2100	0.2100	0.2030	0.2240	0.2100	0.2380	0.2800	0.4200	0.3500	0.2800	0.2800	0.2100
32	0.0560	0.0546	0.0700	0.0700	0.0574	0.0840	0.0980	0.1400	0.1680	0.2100	0.1120	0.0700

Appendix C – *Case study data 180 bus*

Resources price in monetary units (m.u.) – 180 bus network case study

Resources price (m.u.)

Generator ID	Bus	Price (m.u./MWh)	Generator ID	Bus	Price (m.u./MWh)
		Period 1 to 24			Period 1 to 24
***1**	**1**	50	**60**	**83**	45
2	**3**	45	**61**	**84**	45
3	**4**	80	**62**	**85**	45
4	**5**	110	**63**	**86**	45
5	**6**	200	**64**	**87**	45
6	**7**	45	**65**	**88**	30
7	**8**	200	**66**	**89**	200
8	**9**	200	**67**	**91**	45
9	**10**	45	**68**	**93**	45
10	**11**	200	**69**	**95**	45
11	**12**	200	**70**	**97**	45
12	**13**	150	**71**	**99**	200
13	**14**	200	**72**	**101**	45
14	**15**	200	**73**	**103**	45
15	**16**	200	**74**	**105**	45
16	**17**	200	**75**	**107**	45
17	**18**	200	**76**	**109**	200
18	**19**	150	**77**	**111**	45
19	**21**	45	**78**	**113**	300
20	**23**	200	**79**	**115**	200
21	**25**	200	**80**	**117**	200
22	**27**	200	**81**	**119**	45
23	**29**	200	**82**	**121**	45
24	**31**	200	**83**	**123**	45
25	**33**	150	**84**	**125**	200
26	**36**	80	**85**	**127**	45
27	**37**	200	**86**	**129**	300
28	**39**	200	**87**	**131**	45
29	**41**	200	**88**	**133**	45
30	**43**	200	**89**	**135**	45
31	**45**	200	**90**	**137**	45
32	**47**	110	**91**	**139**	45
33	**49**	200	**92**	**141**	45
34	**51**	200	**93**	**143**	45
35	**53**	200	**94**	**145**	45
36	**55**	200	**95**	**147**	45
37	**57**	30	**96**	**148**	45
38	**59**	200	**97**	**149**	45
39	**61**	200	**98**	**150**	45
40	**63**	200	**99**	**151**	45
41	**64**	200	**100**	**152**	45
42	**65**	200	**101**	**153**	200
43	**66**	200	**102**	**154**	200
44	**67**	200	**103**	**155**	150
45	**68**	200	**104**	**156**	45
46	**69**	45	**105**	**157**	150
47	**70**	45	**106**	**158**	45
48	**71**	45	**107**	**159**	150
49	**72**	45	**108**	**160**	45
50	**73**	45	**109**	**161**	200
51	**74**	45	**110**	**162**	45
52	**75**	45	**111**	**163**	45
53	**76**	45	**112**	**164**	200
54	**77**	300	**113**	**165**	200
55	**78**	45	**114**	**166**	200
56	**79**	45	**115**	**167**	30

Generator ID	Bus	Price (m.u./MWh) Period 1 to 24	Generator ID	Bus	Price (m.u./MWh) Period 1 to 24
57	**80**	45	**116**	**170**	300
58	**81**	45	**117**	**173**	45
59	**82**	45			

* Network suppliers

Network lines data in per unit system (p.u.) – 33 bus network case study

Network lines data

From bus	To bus	Resistance (p.u.)	Inductive reactance (p.u.)	Capacitance (p.u.)	Thermal limit (p.u.)
1	2	0.00003	0.00002	0.00000	11.115
2	3	0.00005	0.00008	0.00000	14.04
3	4	0.00019	0.00030	0.00000	7.02
3	5	0.00005	0.00008	0.00000	14.04
5	6	0.00011	0.00018	0.00000	7.02
5	7	0.00007	0.00013	0.00000	14.04
6	8	0.00003	0.00003	0.00000	11.115
7	10	0.00026	0.00042	0.00000	7.02
7	11	0.00004	0.00006	0.00000	14.04
8	9	0.00005	0.00005	0.00000	11.115
11	12	0.00011	0.00018	0.00000	7.02
11	13	0.00004	0.00006	0.00000	14.04
13	14	0.00019	0.00030	0.00000	7.02
13	15	0.00004	0.00006	0.00000	14.04
15	16	0.00023	0.00036	0.00000	7.02
15	17	0.00006	0.00009	0.00000	7.02
15	18	0.00014	0.00025	0.00000	14.04
17	19	0.00015	0.00024	0.00000	7.02
17	22	0.00023	0.00036	0.00000	7.02
18	25	0.00033	0.00049	0.00000	4.68
18	29	0.00017	0.00030	0.00000	14.04
19	20	0.00004	0.00004	0.00000	11.115
20	21	0.00003	0.00002	0.00000	11.115
22	23	0.00019	0.00030	0.00000	7.02
22	24	0.00023	0.00036	0.00000	7.02
25	26	0.00015	0.00024	0.00000	7.02
25	27	0.00008	0.00012	0.00000	7.02
27	28	0.00002	0.00002	0.00000	11.115
29	30	0.00059	0.00088	0.00000	4.68
29	31	0.00014	0.00025	0.00000	14.04
31	32	0.00019	0.00030	0.00000	7.02
31	33	0.00113	0.00180	0.00000	7.02
31	34	0.00018	0.00032	0.00000	14.04
34	35	0.00030	0.00048	0.00000	7.02
34	36	0.00017	0.00030	0.00000	14.04
36	37	0.00025	0.00043	0.00000	9.36
36	95	0.00097	0.00146	0.00000	5.265
37	38	0.00011	0.00019	0.00000	14.04
38	39	0.00034	0.00054	0.00000	7.02
38	42	0.00004	0.00006	0.00000	14.04
39	40	0.00023	0.00036	0.00000	7.02

From bus	To bus	Resistance (p.u.)	Inductive reactance (p.u.)	Capacitance (p.u.)	Thermal limit (p.u.)
39	41	0.00023	0.00036	0.00000	7.02
42	43	0.00008	0.00012	0.00000	7.02
42	44	0.00015	0.00028	0.00000	14.04
44	45	0.00008	0.00012	0.00000	7.02
44	46	0.00009	0.00017	0.00000	14.04
46	47	0.00019	0.00030	0.00000	7.02
46	50	0.00011	0.00018	0.00000	7.02
46	51	0.00015	0.00025	0.00000	9.36
47	48	0.00011	0.00018	0.00000	7.02
47	49	0.00015	0.00024	0.00000	7.02
51	52	0.00078	0.00117	0.00000	4.68
51	53	0.00015	0.00025	0.00000	9.36
53	54	0.00033	0.00049	0.00000	4.68
53	55	0.00017	0.00028	0.00000	9.36
55	56	0.00023	0.00036	0.00000	7.02
55	61	0.00078	0.00117	0.00000	4.68
55	62	0.00023	0.00039	0.00000	9.36
56	57	0.00011	0.00018	0.00000	7.02
56	59	0.00026	0.00042	0.00000	7.02
57	58	0.00004	0.00004	0.00000	11.115
59	60	0.00007	0.00004	0.00000	8.19
62	63	0.00052	0.00078	0.00000	4.68
62	68	0.00025	0.00043	0.00000	9.36
63	64	0.00046	0.00068	0.00000	4.68
63	66	0.00019	0.00030	0.00000	7.02
64	65	0.00010	0.00006	0.00000	8.19
66	67	0.00010	0.00006	0.00000	8.19
68	69	0.00030	0.00048	0.00000	7.02
68	92	0.00039	0.00059	0.00000	4.68
69	70	0.00010	0.00006	0.00000	8.19
69	71	0.00026	0.00042	0.00000	7.02
71	72	0.00046	0.00068	0.00000	4.68
71	73	0.00034	0.00054	0.00000	7.02
73	74	0.00024	0.00014	0.00000	8.19
74	75	0.00018	0.00011	0.00000	8.19
75	76	0.00019	0.00030	0.00000	7.02
76	77	0.00026	0.00039	0.00000	4.68
76	78	0.00046	0.00068	0.00000	4.68
78	79	0.00023	0.00036	0.00000	7.02
78	80	0.00046	0.00068	0.00000	4.68
80	81	0.00046	0.00068	0.00000	4.68
80	83	0.00039	0.00059	0.00000	4.68
80	86	0.00033	0.00049	0.00000	4.68
81	82	0.00008	0.00007	0.00000	11.115
83	84	0.00046	0.00068	0.00000	4.68
83	85	0.00005	0.00005	0.00000	11.115
86	87	0.00026	0.00039	0.00000	4.68
86	88	0.00023	0.00036	0.00000	7.02
86	89	0.00052	0.00078	0.00000	4.68
89	90	0.00039	0.00059	0.00000	4.68
89	91	0.00033	0.00049	0.00000	4.68
92	93	0.00046	0.00068	0.00000	4.68
92	94	0.00033	0.00049	0.00000	4.68
95	96	0.00038	0.00060	0.00000	7.02
96	97	0.00026	0.00039	0.00000	4.68
96	100	0.00023	0.00036	0.00000	7.02
97	98	0.00019	0.00030	0.00000	7.02
97	99	0.00020	0.00029	0.00000	4.68
100	101	0.00019	0.00030	0.00000	7.02
100	102	0.00038	0.00060	0.00000	7.02
102	103	0.00019	0.00030	0.00000	7.02
102	104	0.00038	0.00060	0.00000	7.02
104	105	0.00019	0.00030	0.00000	7.02
104	106	0.00056	0.00090	0.00000	7.02

From bus	To bus	Resistance (p.u.)	Inductive reactance (p.u.)	Capacitance (p.u.)	Thermal limit (p.u.)
106	107	0.00039	0.00059	0.00000	4.68
106	128	0.00034	0.00054	0.00000	7.02
106	142	0.00098	0.00146	0.00000	4.68
107	108	0.00046	0.00068	0.00000	4.68
107	111	0.00046	0.00068	0.00000	4.68
108	109	0.00015	0.00024	0.00000	7.02
108	110	0.00019	0.00030	0.00000	7.02
111	112	0.00033	0.00049	0.00000	4.68
111	114	0.00046	0.00068	0.00000	4.68
112	113	0.00011	0.00018	0.00000	7.02
112	115	0.00023	0.00036	0.00000	7.02
114	117	0.00015	0.00024	0.00000	7.02
114	118	0.00015	0.00024	0.00000	7.02
114	119	0.00065	0.00098	0.00000	4.68
115	116	0.00010	0.00006	0.00000	8.19
119	120	0.00033	0.00049	0.00000	4.68
119	121	0.00072	0.00107	0.00000	4.68
121	122	0.00019	0.00030	0.00000	7.02
121	123	0.00052	0.00078	0.00000	4.68
123	124	0.00033	0.00049	0.00000	4.68
123	125	0.00049	0.00078	0.00000	7.02
125	126	0.00015	0.00024	0.00000	7.02
125	127	0.00019	0.00030	0.00000	7.02
128	129	0.00026	0.00042	0.00000	7.02
128	130	0.00098	0.00146	0.00000	4.68
130	131	0.00046	0.00068	0.00000	4.68
130	134	0.00072	0.00107	0.00000	4.68
131	132	0.00026	0.00039	0.00000	4.68
131	133	0.00019	0.00030	0.00000	7.02
134	135	0.00033	0.00049	0.00000	4.68
134	136	0.00011	0.00018	0.00000	7.02
134	137	0.00059	0.00088	0.00000	4.68
137	138	0.00026	0.00039	0.00000	4.68
137	139	0.00052	0.00078	0.00000	4.68
139	140	0.00019	0.00030	0.00000	7.02
139	141	0.00026	0.00039	0.00000	4.68
142	143	0.00030	0.00048	0.00000	7.02
142	144	0.00023	0.00036	0.00000	7.02
142	145	0.00104	0.00156	0.00000	4.68
145	146	0.00033	0.00049	0.00000	4.68
145	147	0.00059	0.00088	0.00000	4.68
145	150	0.00072	0.00107	0.00000	4.68
147	148	0.00011	0.00018	0.00000	7.02
147	149	0.00026	0.00039	0.00000	4.68
150	151	0.00026	0.00039	0.00000	4.68
150	152	0.00078	0.00117	0.00000	4.68
150	155	0.00085	0.00127	0.00000	4.68
152	153	0.00026	0.00039	0.00000	4.68
152	154	0.00026	0.00039	0.00000	4.68
155	156	0.00072	0.00107	0.00000	4.68
155	159	0.00059	0.00088	0.00000	4.68
155	161	0.00059	0.00088	0.00000	4.68
156	157	0.00026	0.00042	0.00000	7.02
156	158	0.00033	0.00049	0.00000	4.68
159	160	0.00019	0.00030	0.00000	7.02
161	162	0.00026	0.00039	0.00000	4.68
161	163	0.00052	0.00078	0.00000	4.68
163	164	0.00085	0.00127	0.00000	4.68
163	171	0.00059	0.00088	0.00000	4.68
164	165	0.00033	0.00049	0.00000	4.68
164	166	0.00052	0.00078	0.00000	4.68
166	167	0.00033	0.00049	0.00000	4.68
166	168	0.00026	0.00042	0.00000	7.02
168	169	0.00026	0.00042	0.00000	7.02

From bus	To bus	Resistance (p.u.)	Inductive reactance (p.u.)	Capacitance (p.u.)	Thermal limit (p.u.)
168	170	0.00023	0.00036	0.00000	7.02
171	172	0.00046	0.00068	0.00000	4.68
171	176	0.00078	0.00117	0.00000	4.68
172	173	0.00019	0.00030	0.00000	7.02
172	174	0.00052	0.00078	0.00000	4.68
174	175	0.00033	0.00049	0.00000	4.68
176	177	0.00019	0.00030	0.00000	7.02
176	178	0.00072	0.00107	0.00000	4.68
178	179	0.00046	0.00068	0.00000	4.68
178	180	0.00039	0.00059	0.00000	4.68

Network diagram screenshot – 180 bus network case study