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A multi-objective optimization of the active and reactive resource scheduling at a distribution level in a smart grid context

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A B S T R A C T

In the traditional paradigm, the large power plants supply the reactive power required at a transmission level and the capacitors and transformer tap changer were also used at a distribution level. However, in a near future will be necessary to schedule both active and reactive power at a distribution level, due to the high number of resources connected in distribution levels. This paper proposes a new multi-objective methodology to deal with the optimal resource scheduling considering the distributed generation, electric vehicles and capacitor banks for the joint active and reactive power scheduling. The proposed methodology considers the minimization of the cost (economic perspective) of all distributed resources, and the minimization of the voltage magnitude difference (technical perspective) in all buses. The Pareto front is determined and a fuzzy-based mechanism is applied to present the best compromise solution. The proposed methodology has been tested in the 33-bus distribution network. The case study shows the results of three different scenarios for the economic, technical, and multi-objective perspectives, and the results demonstrated the importance of incorporating the reactive scheduling in the distribution network using the multi-objective perspective to obtain the best compromise solution for the economic and technical perspectives.

1. Introduction

The introduction of DG (distributed generation) units, particularly based on renewable sources, in the distribution networks has led to a significant change in the operation and planning of these kind of networks [1]. In addition to the integration of DG units, there are other types of distributed energy resources, such as active consumers with demand response programs, storage units and EVs (electric vehicles) [2], that can cause an even more complex operation of the distribution networks.

Over these years, the smart grid has been presented as a good concept to handle with this new power system paradigm and new uncertainties, considering the decentralization of the whole power system management and control [3]. In this new paradigm, the aggregation of distributed energy resources will be essential to improve the management and control of these resources in the smart grid. For this reason, some authors introduced the VPP (virtual power player) concept as an aggregator of distributed energy resources connected to the electric network, mainly at the distribution level [4]. In order, to operate in a complex and competitive environment, VPPs will need to develop new decision support systems for helping the management and control of the aggregator resources. The complexity of this management is expected to increase geometrically with the transition from conventional vehicles to electric ones [5]. However, EVs can be useful in the scheduling as flexible load and backup system of renewable sources [6].

Reactive power scheduling is a task performed by network operators to avoid the voltage instability, to maintain the voltage levels within a proper range, and to minimize the power losses. Conventionally, centralized power plants were responsible to provide a minimum amount of reactive power to maintain the stability and quality of the system, and for this service the network operator did not remunerate them. Furthermore, the distribution network operator participated in the reactive scheduling through capacitors and tap changer transformers in order to improve the voltage profile.

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Nomenclature

Parameters

α	Objective function F_1 weight factor
β	Objective function F_2 weight factor
λ	Penalization factor
η_c	Grid-to-Vehicle efficiency
η_d	Vehicle-to-Grid efficiency
λ	Penalization factor used in the objective function F_2
μ	Membership function
B	Imaginary part in admittance matrix [S]
c_A	Fixed component of cost function [m.u./h]
c_B	Linear component of cost function [m.u./kWh]
c_C	Quadratic component of cost function [m.u./kWh^2]
c	Resource cost in period t [m.u./kWh]
E	Stored energy in the battery of vehicle at the end of period t [kWh]
$E_{Initial}$	Energy stored in the battery of vehicle at the beginning of period 1 [kWh]
E_{Trip}	Energy consumption in the battery during a trip that occurs in period t [kWh]
G	Real part in admittance matrix [S]
M	Total number of non-dominated solutions in the Pareto front
N	Total number of resources
NF	Normalization factor
S_{Lk}^{max}	Maximum apparent power flow in line k [kVA]
T	Total number of periods
$\overline{U}$	Voltage in polar form [V]
$\overline{y}$	Series admittance of line that connects two buses [S]
$\overline{y_{sh}}$	Shunt admittance of line that connects two buses [S]

Variables

θ	Voltage angle
P	Active power [kW]
Q	Reactive power [kVAr]
S	Apparent power [kVA]
V	Voltage magnitude [V]
X	Binary variable

Subscript

1	Operation cost function
2	Voltage magnitude difference function
Asyn_DG	DG unit with asynchronous generator
B	Bus
BatMax	Battery energy capacity
BatMin	Minimum stored energy to be guaranteed at the end of period t
CAP	Shunt capacitor
Ch	Charge process
Dch	Discharge process
Deg	Battery degradation
DG	Distributed generation unit
DGForecast	Forecast power of distributed generation unit in period t
EV	Electric vehicle
GCP	Generation curtailment power
i, j	Bus i and Bus j
L	Load
Max	Upper bound limit
Min	Lower bound limit
NSD	Non-supplied demand
o	*o*th objective function
obj	Total number of objectives
REF	Slack bus
SP	External supplier
Step	Step of a shunt capacitor with discrete regulation
Stored	Stored energy in the battery of the vehicle
TFR_HV_MV	Transformer that connects from high voltage to medium voltage
TFR_MV_LV	Transformer that connects from medium voltage to low voltage

Superscript

i	Bus i
s	Non-dominated solution s

The VPP will require the use of adequate optimization techniques for handling with the active and reactive power scheduling of distribution networks considering a specific objective [7]. Typically, this problem is formulated to minimize the operation cost of the available distributed energy resources [8], or just considering the DG units [9], but in a competitive environment, as the smart grid, it is also important to consider other issues than just this economic perspective. Therefore, the VPP needs to be aware about the power quality, voltage stability, and active power losses. The optimal resource scheduling problem handled by the VPP requires the incorporation of new strategies to deal with these issues. Hence, the incorporation of reactive power control is essential to enable the VPP to present an optimal scheduling that considers all the issues mentioned above.

The optimization methodology proposed in this paper is based on a multi-objective approach to handle with day-ahead optimal resource scheduling of a VPP in a distribution network considering different reactive power management strategies. The proposed methodology will determine an optimal resource scheduling considering two competing objective functions. One objective function is expressed as the minimization of the operation cost of all distributed energy resources managed by the VPP, and the other one as the minimization of the voltage magnitude differences in all buses of the distribution network. The main goal is helping the VPP's management of a distribution network with high penetration of several distributed energy resources, such as distributed generation units, electric vehicles, and capacitor banks.

The proposed methodology will obtain the Pareto front of the envisaged optimal resource scheduling problem, which it will help the decision maker to have a clear view of all non-dominated solutions of the problem. After determining the Pareto front, a fuzzy-based mechanism [10] is applied to obtain the best compromise solution for the VPP.

The results presented in the case study are expected to show that is relevant to take into account the reactive power control in the optimal resource scheduling for the distribution network's operation with the inclusion of the voltage magnitude difference function (technical perspective). In the case study, it has been used three scenarios with different reactive control strategies to evaluate the impact of the reactive scheduling into the distribution network.

This paper is structured with the following sections: after the introductory section, Section 2 presents a literature review related to the reactive optimal resource scheduling. Section 3 focuses on the proposed methodology and describes the mathematical formulation. A case study is presented in Section 4, and the last section presents the conclusions.

2. Related work

The optimal resource scheduling problem is an optimization problem with the purpose of obtaining the best scheduling of the distributed energy resources managed by a certain player. In the smart grid paradigm, this optimization problem can be undertaken by a diversity of players in a decentralized operation, including distribution system operator and VPPs [11]. In this decentralized operation, each player might need to manage his own distributed resources and network area by a strictly economic objective. As a possible consequence, the electric network might be often operated under stress and closer to its operating limits [12] resulting in voltage instability, congested lines, and reduced power quality. The voltage stability is important for the future distribution network due to the large penetration of distributed energy resources [13]. As mentioned before, a proper reactive power scheduling is important to avoid the electric network's operation under a stress scenario. In these circumstances, a single player should consider an optimal resource scheduling with technical concerns related to the reactive power scheduling, instead of just considering the economic perspective in the optimal resource scheduling. Moreover, a coordinated reactive power scheduling of all involved resources can also lead to a better quality and efficiency of the smart grid operation, instead of considering the centralized perspective used in the traditional paradigm [14].

In order to prevent the voltage instability, the reactive power management is divided into preventive measures and corrective measures [15]. In terms of preventive measures there is: the reactive power scheduling, the active power rescheduling, and the load shedding. In the reactive scheduling, external suppliers, distributed generation, and capacitor banks can have different cost as it is proposed in Ref. [16] which allows the operator to achieve the more profitable solution to dispatch the reactive power. Furthermore, a novel scheme price for the reactive markets is proposed in Ref. [17] which is based on a multi-objective approach.

Over the years, artificial intelligence techniques have been used for solving the reactive power scheduling. In Ref. [18], it is proposed a multi-objective approach based on hybrid fuzzy multi-objective evolutionary algorithm to obtain the Pareto front of a multi-objective reactive power scheduling considering the total power cost related with reactive services, total power losses and voltage stability index. A particle swarm optimization technique has been presented in Ref. [19] to solve the reactive dispatch of a wind farm. Shaw et al. [20] proposed a gravitational search algorithm for the reactive power scheduling with the goal of minimizing the active power losses. Another multi-objective approach is also proposed in Ref. [21] to deal with the reactive power scheduling problem. In these methodologies, it is determined the optimal setting of the control variables: reactive power of the generators, tap positions of the tap changing transformers, and the reactive power of the capacitor banks. In Ref. [22], a multiple-input-multiple-output servo controller is proposed for a synchronous generator that keeps the active power at the desired level and adjusts the reactive power of the generator to a certain desired level.

Beyond a substantial number of methodologies proposed in the literature, the joint active and reactive optimal resource scheduling is not considered by the several authors in this field of research. For instance, in Ref. [15] is presented a reactive power scheduling formulation without considering the active power rescheduling and load shedding contribution for the voltage stability of the network. In Ref. [23], it is also proposed a method for the reactive scheduling problem to stabilize the voltage profile, but this method did not enable the joint scheduling of the active and reactive power because the active power is fixed before the reactive scheduling. Additionally, a particle swarm optimization technique is proposed in Ref. [24] for the reactive scheduling to minimize the active power losses considering a fixed active power scheduling obtained before. This method did not take into account the joint active and reactive scheduling to improve the voltage stability and active power losses while reducing the operation cost. A four-stage multi-objective approach is proposed in Ref. [25] to deal with the reactive scheduling considering the reactive cost, active power losses and voltage stability, but the active power scheduling is not included in the multi-objective approach as another aspect to improve the voltage stability and to reduce the active power losses. In Ref. [26], a multi-objective approach is also proposed to solve a reactive scheduling considering renewable sources without including the joint active reactive scheduling for the economic and technical perspectives of the future distribution networks.

The contributions of this paper are:

1. To propose a model to obtain the combined active and reactive optimal resource scheduling of the distributed energy resources. This aspect allows the joint optimization of both active and reactive power considering the global technical constraints and not only the reactive power constraints, such as the methods proposed in Refs. [15,23,24]. This means an optimization process considering less approximation and, consequently, more realistic model and constraints.
2. To propose a model with a multi-objective function combining the minimization of the operation cost and the minimization of the voltage magnitude difference, leading to an optimal scheduling with a proper balance between the economic and the technical perspectives. In this sense, the methodology provides a set of solutions and not only one solution, such as the methodologies in Refs. [20,25,26]. With this multi-objective approach, the VPP can decide based not only in the operation cost (economic perspective) and also regarding the technical implication of its decision.
3. To implement a new function of controlling the voltage profile, through the minimization of the voltage magnitude difference of all buses with respect to the voltage in the slack bus. The reduction of voltage differences means less power flow in the lines and consequently less power losses. On the other hand, decreasing the voltage magnitude difference means that the bus voltage will be far from the voltage operation boundaries and, subsequently a voltage slack change will have more impact in all buses.
4. To integrate the management of distributed energy resources, such as DG units and EVs, in the improvement of the voltage stability of a distribution network. The participation of all types of distributed resources in the ancillary services will be important in a near future to assure a reliability of hierarchical power systems. Thus, all hierarchical levels should assure a part of their own ancillary services requirements. In this sense, the inclusion of EVs and DG units in the reactive power control should be addressed.

3. Optimal resource scheduling formulation

The proposed methodology will obtain the active and reactive optimal resource scheduling for the next day of a VPP considering two non-commensurable and competing objective functions. First objective is to obtain the minimum cost of all distributed energy resources, and the minimum voltage magnitude differences in all buses is the second objective. The proposed methodology will schedule the active and reactive generation power of DG units, the active charge power and active discharge power of EVs, and the reactive power of shunt capacitors.

In this section, the mathematical formulation of the proposed multi-objective methodology is described. This section is divided into five subsections. Subsection 3.1 shows the expression used to determine the operation cost of the distributed energy resources. Subsection 3.2 shows the expression applied to minimize the voltage magnitude differences in all buses in the distribution network. Subsection 3.3 presents the multi-objective function used in the proposed methodology and Subsection 3.4 shows the related constraints. Subsection 3.5 describes the fuzzy-based mechanism used to determine the best compromise solution.

3.1. Objective function − F_1

The minimization of the operation cost F_1 used in the proposed methodology can be formulated as

$$\begin{aligned} \min F_1 = \sum_{t=1}^{T} \Bigg[\sum_{DG=1}^{N_{DG}} \begin{pmatrix} c_{A(DG,t)} \times X_{DG(DG,t)} + c_{B(DG,t)} \times P_{DG(DG,t)} + \\ c_{C(DG,t)} \times P^2_{DG(DG,t)} + c_{GCP(DG,t)} \times P_{GCP(DG,t)} \end{pmatrix} \\ + \sum_{EV=1}^{N_{EV}} \Big(\big(c_{Dch(EV,t)} + c_{Deg(EV)} \big) \times P_{Dch(EV,t)} - c_{Ch(EV,t)} \\ \times P_{Ch(EV,t)} \Big) + \sum_{SP=1}^{N_{SP}} c_{SP(SP,t)} \times P_{SP(SP,t)} + \sum_{L=1}^{N_L} c_{NSD(L,t)} \times P_{NSD(L,t)} \Bigg] \end{aligned} \tag{1}$$

where the VPP's goal is to obtain a minimum F_1 for the next day while satisfying the consumers' demand and EV users' requirements. Concerning to EVs, the user must indicate to the VPP the amount of energy that allows him to travel with the EV for the next day, and consequently, the VPP needs to respect to this user's requirement. In order to achieve these demand requirements, the VPP can use the DG units (controllable units) connected to its distribution network that use a quadratic function (typically generators based on fossil fuels) [27]. The DG based on non-controllable renewable sources do not follow the quadratic polynomial function, in which it is possible to establish a unitary energy price in the linear cost (c_B) for these renewables and the other coefficients are zero. Additionally, the generation curtailment power (c_{GCP}) is included to prevent emergency situations of high generation form non-controllable renewable sources turning the proposed methodology more robust to deal with the optimal resource scheduling problems. Another way to achieve the VPP's requirements is through the use of the EVs battery for discharging that is commonly referred to as V2G (vehicle-to-grid) [2]. It is assumed that the EVs battery charging can be controlled by the VPP (i.e. smart charging). In terms of EVs, the costs for the VPP consider the charge and discharge processes. Moreover, degradation cost associated with additional cycling [28] from the charge and discharge processes is also formulated, as proposed in Ref. [29]. External suppliers located outside of the distribution network are other option for the VPP's requirements for the next day with a respective cost for this energy acquired (c_{SP}). It is also considered a penalty cost for the VPP related with the non-supplied demand (c_{NSD}), preventing critical situations with high consumer demands.

3.2. Objective function − F_2

The objective function F_2 minimizes the voltage magnitude differences of all buses in the distribution network and is given by

$$\begin{aligned} \min F_2 = \sum_{t=1}^{T} \Bigg[\sum_{i=1}^{N_B} \left| V_{(REF,t)} - V_{(i,t)} \right| + \lambda \times \Bigg(\sum_{L=1}^{N_L} c_{NSD(L,t)} \times P_{NSD(L,t)} \\ + \sum_{DG=1}^{N_{DG}} c_{GCP(DG,t)} \times P_{GCP(DG,t)} \Bigg) \Bigg] \end{aligned} \tag{2}$$

The objective is to approximate the voltage magnitude of all buses to the voltage magnitude fixed in the slack bus. The increase of the reactive generation power of the available distributed energy resources and shunt capacitors will enable the VPP to achieve the proposed minimization of the voltage magnitude differences. This function will reduce the voltage magnitude differences and it will directly minimize the active power losses in the distribution network, enabling economic savings in the energy resource management of the VPP. The inclusion of non-supplied demand and generation curtailment power variables in this function is important to avoid the cut of power demand or to avoid the excess of generation from DG units with the only purpose of increasing the voltage magnitude of a particular bus. These variables are multiplied by a penalization factor (λ) to penalize the objective function.

3.3. Multi-objective function − F

The proposed multi-objective function F is formulated as

$$\begin{aligned} &\min F = \alpha \times F_1 + \beta \times F_2 \times NF \\ &\alpha + \beta = 1 \ ; \ \alpha \text{ and } \beta \in [0,1] \end{aligned} \tag{3}$$

where the two previous objective functions are considered. In this paper, the weighted sum method is used to deal with the proposed multi-objective function F [30]. The weighted sum method (3) will transform the multi-objective function F into a single function by summing all objective functions, where each objective is multiplied by a different weight factor. The sum of the two weight factors must be equal to 1, and each weight factor is between 0 and 1. Several simulations with different weight factor values will be executed in order to determine the Pareto front of the multi-objective problem. For levelling purposes, the function F_2 uses an additional factor NF.

3.4. Optimization problem constraints

In a smart grid context, the VPP requires an adequate representation of the network with the purpose of obtaining a scheduling result that is also feasible in the distribution network (avoiding lines congestion and voltage magnitude or angle violations). In this paper, the use of an AC power flow [27] is essential to determine the active and reactive power that flows in each line of the distribution network, the power losses and the voltage magnitude and angle. The AC power flow will be executed during the optimal resource scheduling problem, and the power injected in each bus is obtained from the sum of the power flow through the lines that connect each bus with the rest of the network. The active and reactive power injected in each line depends on a non-linear combination between the admittance matrix, on the voltage magnitude, and on voltage angle [27]. The equations that compose the problem constraints are exposed in Appendix A.

Eq. (4) establishes an equality constraint between the active power injected in bus i and the active power generation minus the active power demand in the same bus. The active power generation is the sum of the active generation power of DG units of the active generation power of external suppliers, and of the active discharge power from EVs. On the other hand, the active power demand is determined through the sum of the consumers' active load consumption and the EVs battery charging. Eq. (5) is a reactive power equality constraint considering the reactive power injected and consumed in the bus *i*. The reactive power generation can be obtained from reactive generation power of DG units, reactive generation power of external suppliers, and reactive power from capacitor banks. The reactive power demand results from the consumers' reactive demand and reactive consumption corresponding to the asynchronous generators used by some DG units. The asynchronous generators consume reactive power and do not have the capability of generating reactive power [31]. For this reason, the use of a capacitor with asynchronous generators is essential to suppress the reactive power consumption of these generators and to generate reactive power in order to help the VPP's reactive power scheduling.

The voltage magnitude and angle are important variables to determine the power injected in each bus, and these variables must have maximum and minimum limit. Eqs. (6) and (7) will keep the voltage magnitude and angle between their own limits. A slack bus is previously selected in the network, and the fixed voltage magnitude and angle are specified for it.

The power flow must be below a maximum power limit in each line (line thermal limit). Eqs. (8) and (9) define the inequality constraint to maintain the power flow from bus *i* to bus *j* and vice versa below the maximum power limit of each line, respectively. The term $\overline{U}$ represents the voltage in polar form.

As mentioned before, the VPP's distribution network is connected to upstream networks through transformers that change the voltage level from high voltage (HV) to medium voltage (MV). From these connections comes the energy from the external suppliers that are located outside of the network. The energy exchanged between the VPP and the externals suppliers is limited by the maximum capacity of the transformer HV/MV that connects the distribution network with the upstream network. Eq. (10) establishes that the power from external suppliers must be lower or equal to the maximum capacity of the HV/MV power transformer.

The same happens with the buses in the distribution network. For each bus *i*, there is a transformer from MV to low voltage (LV) that connects small resources, such as photovoltaic units and EVs, to the MV side of the respective bus *i*. Eqs. (11) and (12) determine the active and reactive power that flows in the transformer MV/LV of bus *i*. Eq. (13) establishes that the power from distribution network to the LV side must be lower or equal to the maximum capacity of the respective MV/LV power transformer in bus *i*.

In this paper, the apparent generation power of the DG units must be kept within a minimum limit (14) and a maximum limit (15). The VPP can only choose to use the active generation power (P_{DG}) to minimize the function F_1 (1), or it can just use the reactive generation power (Q_{DG}) to minimize the function F_2 (2), or it can also combine the active and reactive generation power until it reaches the maximum limit (15). Eqs. (14) and (15) are only applied for DG units that use a synchronous generator, because this generator is capable of generating active and/or reactive power. The binary variable (X_{DG}) is included in both equations with the object of deciding whether the DG unit is turning on or turning off.

On the other hand, Eqs. (16) And (17) define the maximum and minimum limit for the active generation power of DG units with asynchronous generator, respectively. As referred before, the asynchronous generator consumes reactive power, instead of generates reactive power and the parameter Q_{Asyn_DG} is not considered in these expressions.

The capacitors used in the proposed methodology can have a continuous or discrete regulation. In the continuous regulation, the capacitor can have a reactive power between zero and a maximum limit (Eq. (18)). In the discrete regulation, the capacitor can have several steps ($X_{CAP(CAP,Step,t)}$) with different amounts of reactive power for each step ($Q_{Max(CAP,Step,t)}$) (Eq. (19)), and the VPP can choose the adequate step. In this paper, two types of use for the capacitors in the distribution network are considered. The first one is associated with the asynchronous generator in the DG unit to enable the generation of reactive power by that DG unit. The second is the VPP's possibility of having its own capacitor installed in strategic buses in order to increase the voltage level.

The VPP can also establish “take-or-pay” contracts with DG units, mainly based on renewable sources. Therefore, the VPP is forced to dispatch all the active generation power by the DG units with this type of contract (Eq. (20)). Eqs (21) and (22) represent the maximum active and reactive power of each external supplier.

In terms of electric vehicle constraints, Eq. (23) expresses the amount of energy stored at the end of period *t* for each EV. In this constraint, it is necessary to consider the typical daily travel profile of each EV user, as the VPP is forced to guarantee the energy required for the EV user to travel in the time horizon of the optimal resource scheduling. This trip consumption can be sent by the EV owner [32] or it can be used a forecast tool [33] to predict the EVs owners behaviour. The proposed methodology takes into account the behaviour of the users, driving pattern, travel distance, driving route, vehicles' internal characteristics and batteries performance as influences of the trip consumption in the EVs [34]. The charging (η_c) and discharging (η_d) efficiency battery are also used in Eq. (23). The efficiency to charge and discharge considers the efficiency of the equipment used to plug the EV to the network (ac/dc converters and so on) and the round trip efficiency.

The energy stored on the battery requires a maximum and minimum limit of energy in all optimization periods. Eq. (24) defines a minimum energy stored in the battery for each period of the optimization process. The EV users should inform the VPP which is the minimum amount of energy stored in the battery and in which period that energy must be guaranteed. The VPP and the EV users need to use an adequate communication system to exchange information about the minimum energy stored in the battery [35]. Eq. (25) maintains the energy stored on the EV battery lower than its capacity.

The charge/discharge rates have their own maximum limit (26) and (27), respectively. In this formulation, it was considered that the charge/discharge rate limit can change depending on the different parts of the network that the EV user is connected. Each EV can be connected in a single phase (e.g. at home), with the rate limit being lower than when EVs are connected in three phases (e.g. a parking lot at the work). In this formulation, two binary variables for each EV are used to control the charge/discharge power, avoiding that the two operations occur in the same period (28).

The mathematical formulation of the proposed multi-objective methodology has been implemented in mixed-integer non-linear programming (MINLP) approach (deterministic technique) using the software GAMS (general algebraic modeling system) [36].

3.5. Best compromise solution

After determining the Pareto front, a fuzzy set theory has been used to choose the best candidate solution for the VPP [10]. The membership function μ_o related with the oth objective function of each solution in the Pareto set F_o is defined as

$$\mu_o = \begin{cases} 1 & , \quad F_o \leq F_o^{min} \\ \dfrac{F_o^{max} - F_o}{F_o^{max} - F_o^{min}} & , \quad F_o^{max} < F_o < F_o^{min} \\ 0 & , \quad F_o \geq F_o^{max} \end{cases} \tag{29}$$

where F_o^{max} and F_o^{min} are the maximum and minimum values of the oth objective function, respectively. For each non-dominated solution s, the normalized membership function μ^s is calculated as

$$\mu^s = \frac{\sum_{o=1}^{N_{obj}} \mu_o^s}{\sum_{s=1}^{M} \sum_{o=1}^{N_{obj}} \mu_o^s} \tag{30}$$

where M and N_{obj} are the total number of non-dominated solutions and the total number of objective functions, respectively. The best compromise solution is the one with the maximum μ^s value. For the decision maker, it could be interesting to arrange all Pareto solutions in descending order according to their membership function and having a priority list of Pareto solutions. This will give a better view of the best solutions for the proposed multi-objective problem for the next day [10]. Readers who are interested can find more details of this method in Ref. [37] and fuzzy set theory in Ref. [38].

4. Case study

The results of the proposed methodology to solve the multi-objective optimal resource scheduling problem will be presented in this section. The proposed methodology will be applied to a VPP that manages distributed energy resources and a distribution network. The VPP can handle DG units, external suppliers, capacitor banks and EVs. The charge and discharge processes of the EVs are controlled by the VPP, in terms of amount of power, time and duration. The discharge capability of an EV is called V2G option.

This section is divided into six subsections. Subsection 4.1 presents the information and input data used in the case study of this paper. Subsection 4.2 explains the three scenarios adopted in the present case study. Subsection 4.3 shows the results of the simulation considering the objective function F_1. Subsection 4.4 shows the results of the simulation considering the objective function F_2. In Subsection 4.5 a comparison of the results obtained in Subsections 4.3 and 4.4 is presented. Subsection 4.6 presents the results of the proposed methodology considering the multi-objective F.

4.1. Case study's characterization

A 33-bus distribution network [39] is used to evaluate the performance of the proposed methodology. Fig. 1 depicts the 33-bus distribution network with a projection of DG and EVs for the year 2040 [39]. Bus 0 connects the distribution network to the rest of the electric network, enabling the VPP to buy and/or sell energy to the rest of the network (external suppliers). In this figure, each DG unit has a different colour, which depends on the primary energy source used in each unit. The VPP will manage this 33-bus distribution network with: 66 DG units, 1000 EVs connected to the network, and the possibility to negotiate with 10 external suppliers. It is necessary to satisfy the consumption of 218 consumers spread over the 32 buses [39]. The case study considers a specific consumption scenario, however the VPP can use the proposed methodology to obtain the optimal resource scheduling for a different set of consumption scenarios.

In terms of EVs' projection, a simulator tool proposed in Ref. [33] was used to generate the daily travelling profiles for the 1000 EVs. The simulator tool considers 7 EV models: Renault Zoe Z.E., Renault Kangoo Z.E., Renault Fluence Z. E., Nissan Leaf, Toyota Prius, Citroen C-Zero and Mitsubishi i-MiEV. The technical information of all EV models used in this case study is presented in Table 1. The charge rate considers the slow and fast charging modes, and the discharge rate only considers the slow mode in order to prevent more damage of the batteries' cycle life. The case study uses a charging (η_c) and discharging (η_d) efficiency battery of 76.5%, respectively.

The price and installed capacity of each available resource are presented in Table 2. For this case study, the photovoltaic DG units have a "take-or-pay" contract with the VPP, which establishes the duty by the aggregated player to dispatch all the active power generated by the photovoltaic generators. For the DG units, the linear cost coefficient (c_B) of objective function F_1 (Eq. (1)) is the

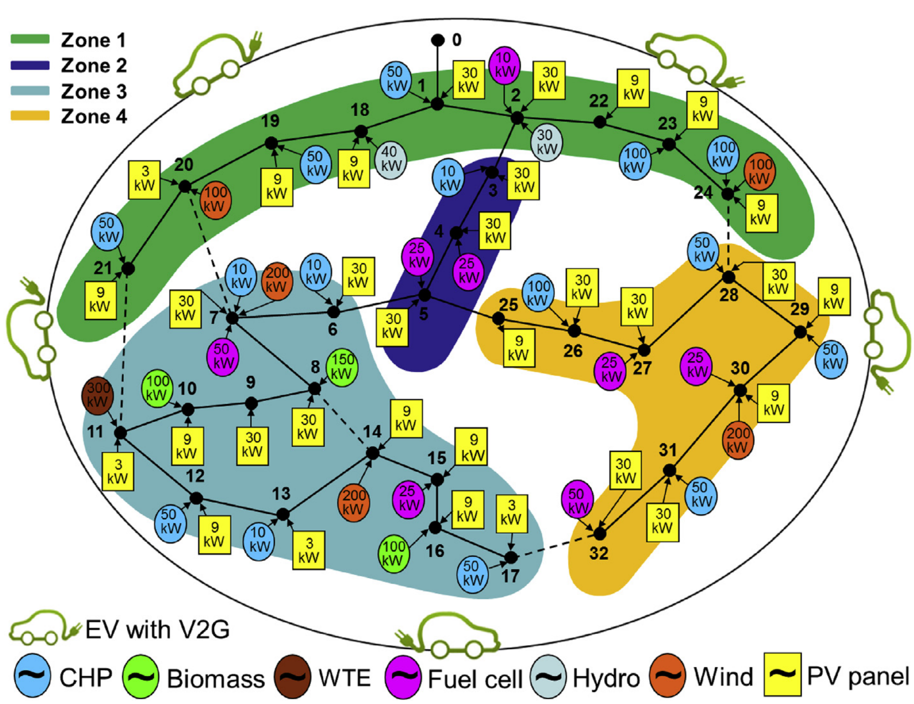

Fig. 1. 33-bus distribution network and resources projection in 2040 (based on [39]).

Table 1
Electric vehicle technical information.

EV model	Battery		Charge rate (kW)	Discharge rate (kW)
	Capacity (kWh)	Range (km)		
MiEV	16.0	160	3	3
C-Zero	16.0	150	2.2	2.2
Fluence Z.E.	22.0	185	3	3
Leaf	24.0	160	6.6	6.6
Kangoo Z.E.	22.0	170	3	3
Zoe	22.0	150	3	3
Prius	4.4	20	3	3

only one used in this case study. In terms of EVs information, the EV charge price is considered equal to zero, because the objective is to minimize the operation cost, and to minimize the voltage magnitude difference, and for this reason, the consumer consumption and EV charge are assumed as a “mandatory” service provided by the VPP in the proposed methodology. The discharge price for the EVs was established in 0.08 m.u./kWh and the degradation cost of the battery is equal to 0.042 m.u./kWh, as can be seen in Ref. [29].

Table 3 shows the shunt capacitors used in the case study. In the table, the type of resource that manages the shunt capacitor is indicated. The DG units based on wind and hydro require the use of capacitors, because they have asynchronous generators to supply active power. The VPP also has its own capacitor banks placed in buses 5, 17, 21, 24 and 32 of the distribution network. The type of regulation and the number of steps are also indicated in this table. The capacitors used by the DG units have discrete regulation, and the VPP uses continuous regulation in the capacitors. The last column of Table 3 indicates the maximum reactive power injected by each capacitor bank.

The simulations of the proposed methodology were executed in a computer with two processors Intel® Xeon® W3520 2.67 GHz, each one with two cores, 3 GB of RAM (random-access-memory) and Windows 7 Professional 64 bits operating system.

4.2. Case study's scenarios

The case study has been divided into three different scenarios, considering different reactive control perspectives by the VPP. The objective is to evaluate the impact of the different reactive control perspectives in the optimal resource scheduling. Fig. 1 presents four areas in the 33-bus distribution network regarding the voltage profile. These areas will contribute to a better evaluation of the different reactive control scenarios established in this case study.

Table 2
Distributed energy resources information.

Resource	Units #	Total installed capacity (kW)	Linear cost -c_B (m.u./kWh)		
			Max.	Mean	Min.
Photovoltaic	32	1320	0.254	0.187	0.11
Wind	5	505	0.136	0.091	0.06
Small hydro	2	80	0.145	0.117	0.089
CHP	15	725	0.105	0.075	0.057
Biomass	3	350	0.226	0.201	0.186
WTE	1	10	0.056	0.056	0.056
Fuel cell	8	440	0.2	0.055	0.01
External suppliers	10	5800	0.15	0.105	0.06
EVs charge	1000	–		0	
EVs discharge				0.08	
EVs battery degradation cost				0.042	

Table 3
Shunt capacitor information.

Resource	Bus	Type regulation	Number of steps	Maximum reactive power (kVAr)
Wind	7, 14, 20, 24 and 30	Discrete	1	50
Small hydro	2 and 18			40
VPP	5	Continuous	–	50
	17, 21, 24 and 32			30

In the first scenario, the VPP can only use the reactive power from external suppliers located outside the 33-bus distribution network. In this scenario, the DG units only generate active power and the capacitor banks are not considered.

In the second scenario, the VPP established a minimum amount of reactive generation power by the DG units in the peak periods. In these periods, the reactive power consumption is usually high and the DG units must contribute to reduce the impact of this reactive consumption. DG units must guarantee an amount of reactive power equal or higher than 40% of the active power generated. The DG units with asynchronous generators will have capacitor banks to inject the required amount of reactive power in the peak periods. In the off-peak periods, the DG units will only generate active power. The VPP can also use the external suppliers to supply reactive power to the distribution network.

In the third scenario, the DG units will generate active and reactive power without the reactive requirement in the peak periods that is used in the second scenario. In this scenario, the VPP can select properly the amount of active and reactive generation power for each DG unit without violating the constraints (14)–(19). The DG units with asynchronous generators will also have capacitor

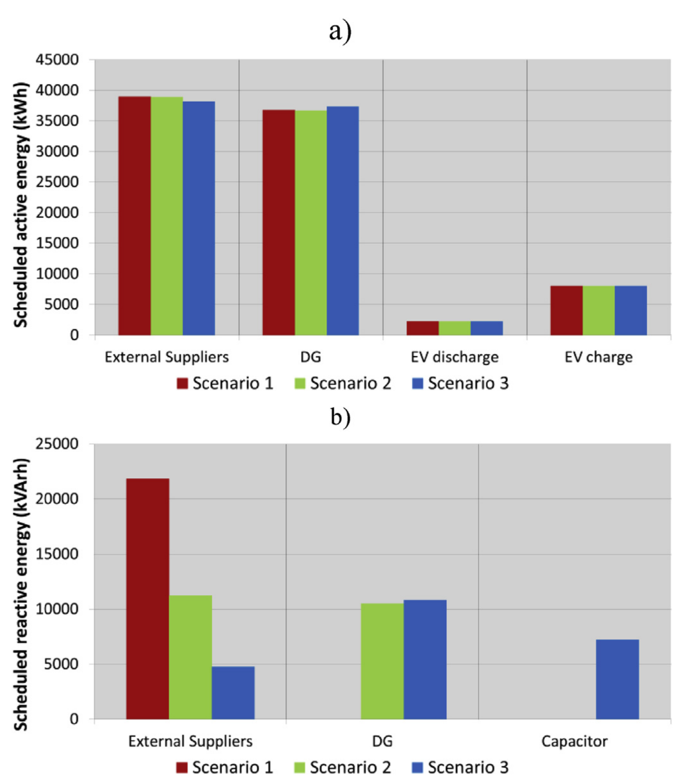

Fig. 2. Scheduled energy for the three scenarios with objective function F_I: a) Active energy; b) Reactive energy.

Table 4
Performance of the proposed methodology with objective function F_1.

Scenario	Operation cost – F_1 (m.u.)	Voltage difference – F_2 (pu.)	Active power losses (kW)
1	6963.14	14.77	823.10
2	6948.89	13.63	684.29
3	6898.10	12.44	603.05

banks to inject the reactive power required by the VPP, but these capacitor banks can only be used if the respective DG unit is turning on. Otherwise, the capacitor cannot be used in the reactive management, because it does not belong to the VPP. The VPP owns itself several capacitor banks strategically located in the 33-bus distribution network that will be used in this scenario to control the voltage magnitude.

4.3. Simulation 1 – objective function F_1 ($\alpha = 1; \beta = 0$)

In simulation 1, it is only considered the objective function F_1, and the three scenarios presented before are used in this simulation. Fig. 2 and Table 4 show the results of the three scenarios to determine the optimal resource scheduling minimizing the operation cost (objective function F_1). In this table, the voltage magnitude difference and the active power losses are also presented.

Scenario 3 presents the best result in terms of operation cost, voltage difference, and active power losses. On the other hand, scenario 1 presents the worse results in these three indicators. The operation cost's variation between the best scenario (scenario 3) and scenarios 1 and 2 is around 0.94%, 0.74%, respectively. The voltage magnitude's variation is of approximately 18.92%, 9.74% between scenario 3 and scenarios 1 and 2, respectively. For the active power losses, the difference is around 36.65%, 13.60% between scenario 3 and the scenarios 1 and 2, respectively. The voltage profile and active power losses present a much higher difference than the operation cost due to the different reactive control perspectives implemented in each scenario. The different reactive control perspectives do not affect much the operation cost result of the optimal scheduling, yet they affect directly the voltage profile and active power losses.

The total active and reactive energy scheduled obtained by the three scenarios in simulation 1 is presented in Fig. 2a and b) respectively. The three scenarios obtained solutions very similar. For this reason, the operation cost results are very close, as it is

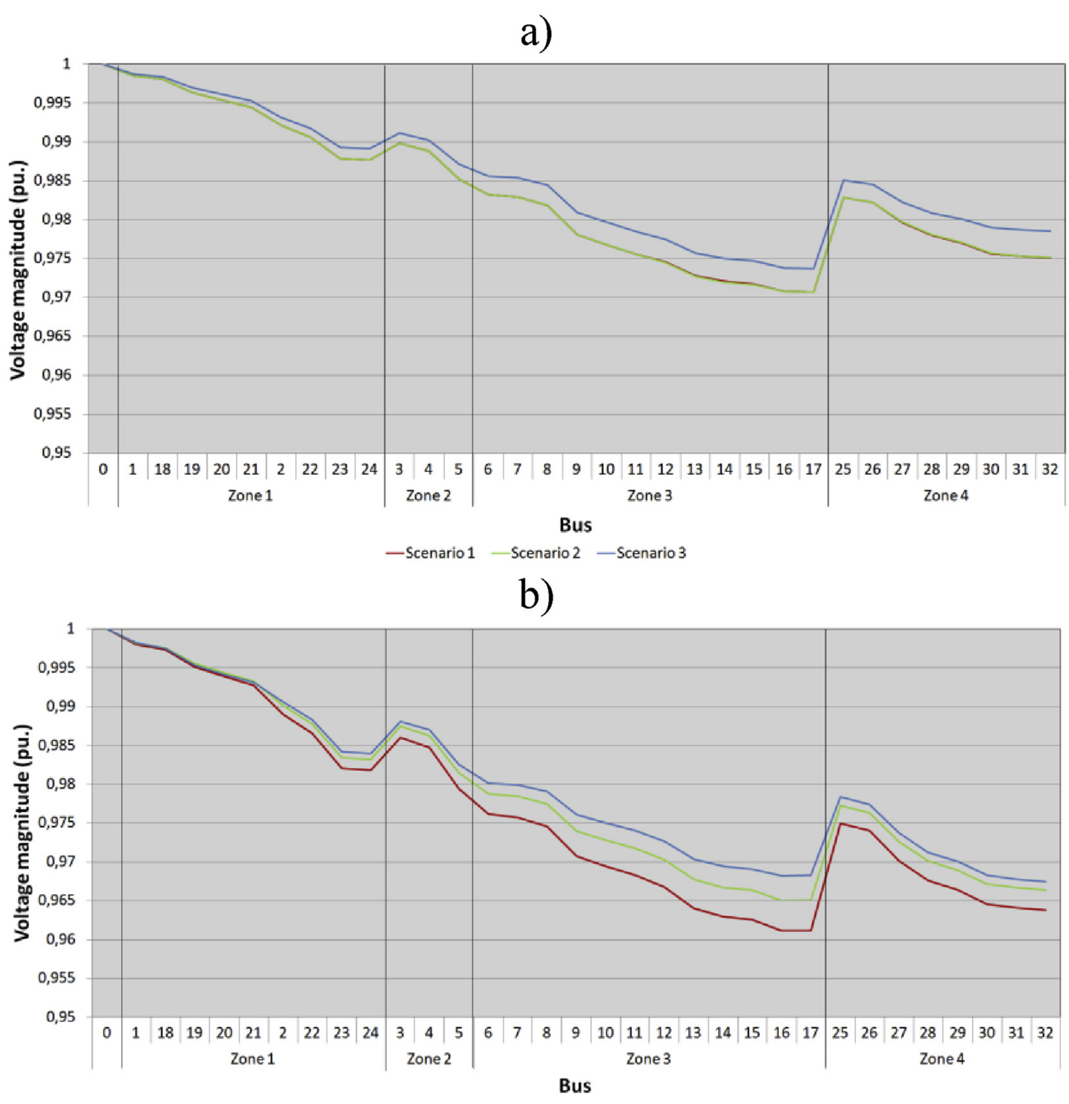

Fig. 3. Bus voltage profile for all scenarios with objective function F_1: a) In period 4; b) In period 20.

shown in Table 4. The different reactive control strategies interfere directly on the voltage profile and active power losses, but not in the optimal scheduling of the active power. Regarding to the reactive energy scheduled, in scenario 1, the external suppliers generate all the reactive power resulting in the highest active power losses value. In scenario 2, the external suppliers and DG units generate similar amounts of reactive power. In scenario 3, the distributed resources, such as DG units and capacitors, generate more reactive power than the external suppliers, which enables the VPP to obtain the lowest active power losses value.

The voltage magnitude of the slack bus was fixed at 1 pu. The voltage profile of the three scenarios will be shown for one off-peak period (period 4) in Fig 3a) and for one peak period (period 20) in Fig 3b). In period 4, scenarios 1 and 2 present a worse voltage profile than scenario 3. Scenario 1 uses the external suppliers to supply the reactive power requirement, which leads to a reduction of the voltage magnitude in the buses further of the slack bus, such as buses 16 and 17 (zone 3). Scenario 2 had the same behaviour as scenario 1, because in this scenario the endogenous resources (DG units and capacitors) can only be used in the peak periods. In period 4, the voltage magnitude achieves a low value around 0.97 pu in the further buses of the distribution network (buses 16, 17, 31 and 32). As expected, scenario 3 presents better results than the other two scenarios, even considering that in simulation 1 the objective is just to minimize the operation cost. This scenario has more flexibility to schedule the active and reactive resources, where the VPP can use the external suppliers and the endogenous resources to increase the voltage profile.

Concerning the period 20, scenario 1 presents the worse voltage profile of the three scenarios, because the external suppliers are the only ones to supply reactive power. One way to increase this voltage profile comprises the use of distributed energy resources to supply reactive power. The voltage magnitude achieves the lowest value of 0.96 pu. in buses 16, 17, 31 and 32. Scenario 2 presents a better result than scenario 1 due to the requirement by the DG units to supply a minimum of reactive power equal to 40% of the active power generated in the same period. With this requirement, the VPP was able to increase the voltage magnitude of 0.005 pu. in buses 16, 17, 31 and 32 (further buses). With the reactive control strategy, adopted in scenario 3, the VPP was able to achieve the best voltage profile in this period. There is more flexibility to schedule the available resources in terms of active and reactive power, which enables the VPP to mitigate the voltage drop in the further buses of the network. For instance, the minimum voltage magnitude is around 0.97 pu. In both periods, it is possible to observe that the network operates near by the boundaries regarding the minimum voltage limits (0.95 pu).

The performance presented by the three scenarios in simulation 1 can be problematic in the future smart grid paradigm with a higher resources penetration. The VPP must consider more technical indicators that simulate the impact of the resources in the network performance, avoiding the operation of the networks under stress. In the next simulation, it will be presented the results using the objective function F_2 that is a technical indicator.

4.4. Simulation 2 — objective function F_2 ($\alpha = 0$; $\beta = 1$)

In simulation 2, the objective function F_2 is used in the three considered scenarios. The proposed methodology will obtain an optimal scheduling that minimizes the voltage magnitude difference (see equation (3)) of all buses regarding the voltage in the slack bus. The obtained results are presented in Table 5.

Table 5
Performance of the proposed methodology with objective function F_2.

Scenario	Voltage difference − F_2 (pu.)	Operation cost − F_1 (m.u.)	Active power osses (kW)
1	7.91	9485.59	474.30
2	6.73	9102.16	330.32
3	5.66	8719.84	274.84

In terms of voltage magnitude difference, scenario 3 presents the best result with 5.66 pu (sum of the differences of the voltage magnitude in all buses during the 24 periods); scenario 2 achieved the second best result with 6.73 pu; and scenario 1 obtained the worse result with 7.91 pu. These values represent a variation of 39.75% and 18.90% comparing the scenario 3 with the scenarios 1 and 2 respectively. The active power losses present a similar behaviour as it is possible verify in Table 5. In terms of operation cost, scenarios 1, 2 and 3 obtained a result of 9485.59 m.u., 9102.16 m.u. and 8719.84 m.u., respectively. The cost variation between scenario 3 and scenarios 1 and 2 is around 8.78% and 4.38%, respectively. Again, the voltage magnitude difference and the active power losses presented variations between scenarios much higher than the ones obtained in the operation cost's results. This fact proves the importance of the reactive scheduling to the network operation. Scenario 3 presents again the best results in terms of voltage magnitude difference, active power losses and operation cost.

Fig. 4 depicts the active and reactive energy scheduled obtained by the three scenarios with objective function F_2. Again, in this simulation the different scenarios present similar results in terms of active energy scheduling. In terms of reactive scheduling (see Fig. 4b), the scenario 3 uses DG units and capacitor banks to supply the reactive requirement in order to increase the voltage profile of

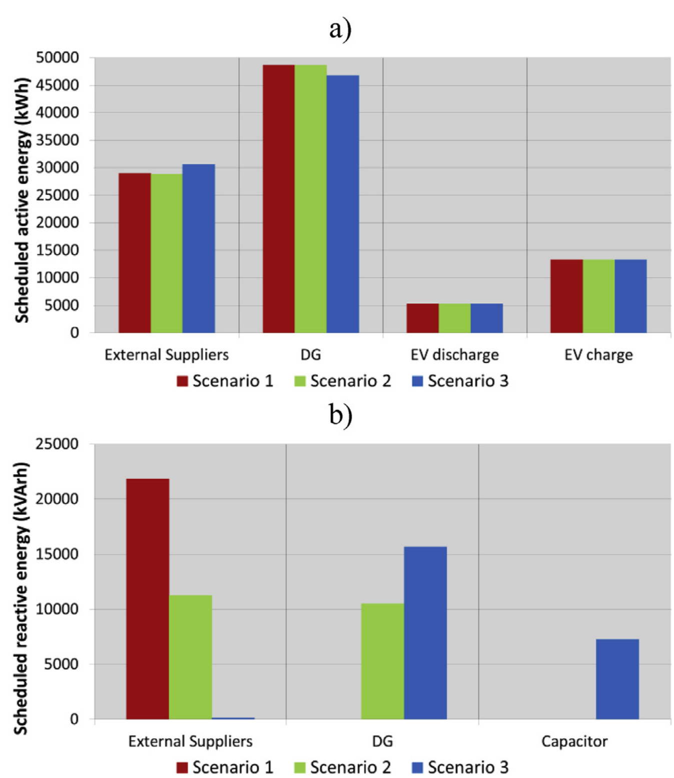

Fig. 4. Scheduled energy for the three scenarios with objective function F_2: a) Active energy; b) Reactive energy.

the buses, scenario 2 uses the external suppliers and the DG in equal percentage and in scenario 1 only considers the external suppliers.

The voltage profile in periods 4 and 20 obtained for each scenario is illustrated in Fig. 5. The three scenarios present similar voltage profile. However, scenario 1 presents the worse result of the three scenarios. In scenario 3, the proposed methodology was able to manage the reactive power in order to obtain a voltage profile in all buses near to the voltage fixed in the slack bus (1 pu). Buses 31 and 32 (the further buses) achieved the lowest voltage magnitude of around 0.991 pu. The voltage drop of these buses was of approximately 0.7%, and in simulation 1 the voltage drop achieved 3%. In period 20, the three scenarios present more distinct results in terms of voltage magnitude, because of the peak demand obtained in this period. In scenario 3, buses 31 and 32 obtained the lowest voltage magnitude of approximately 0.977 pu. In simulation 1, for the same scenario, the methodology achieved a voltage profile below 0.97 pu. With this objective function F_2, the VPP was able to increase the voltage profile in 0.07 pu.

The results obtained in this simulation proved the importance of technical indicators, such as the one used in function F_2 (see Eq. (3)) in the management of the future networks. The use of function F_2 helped the VPP achieving a good voltage profile, and very close to 1 pu. This technical indicator was able to avoid the instability point presented in simulation 1. However, the operation cost obtained in this simulation is higher than the one achieved in simulation 1. These two objectives are in conflict and it requires the use of a multi-objective approach to deal with this kind of behaviour.

4.5. Simulation 3 – multi-objective function F ($\alpha \in [0,1]$; $\beta \in [0,1]$)

In simulation 3, the results of the multi-objective optimal resource scheduling approach are presented. As referred before, the weighted sum method has been implemented to determine the Pareto front for the proposed multi-objective function F in the three scenarios. For each scenario, the proposed methodology had run 501 times and in each run the weighted factors changed from 0 to 1 in steps of 0.002. For each run, the sum of weighted factors (α,β) must be equal to 1. Fig. 6 shows the obtained Pareto.

The Pareto front presents 393, 385 and 382 non-dominated solutions for the scenarios 1, 2 and 3, respectively. The Pareto front solutions are well spread in the three scenarios. As it

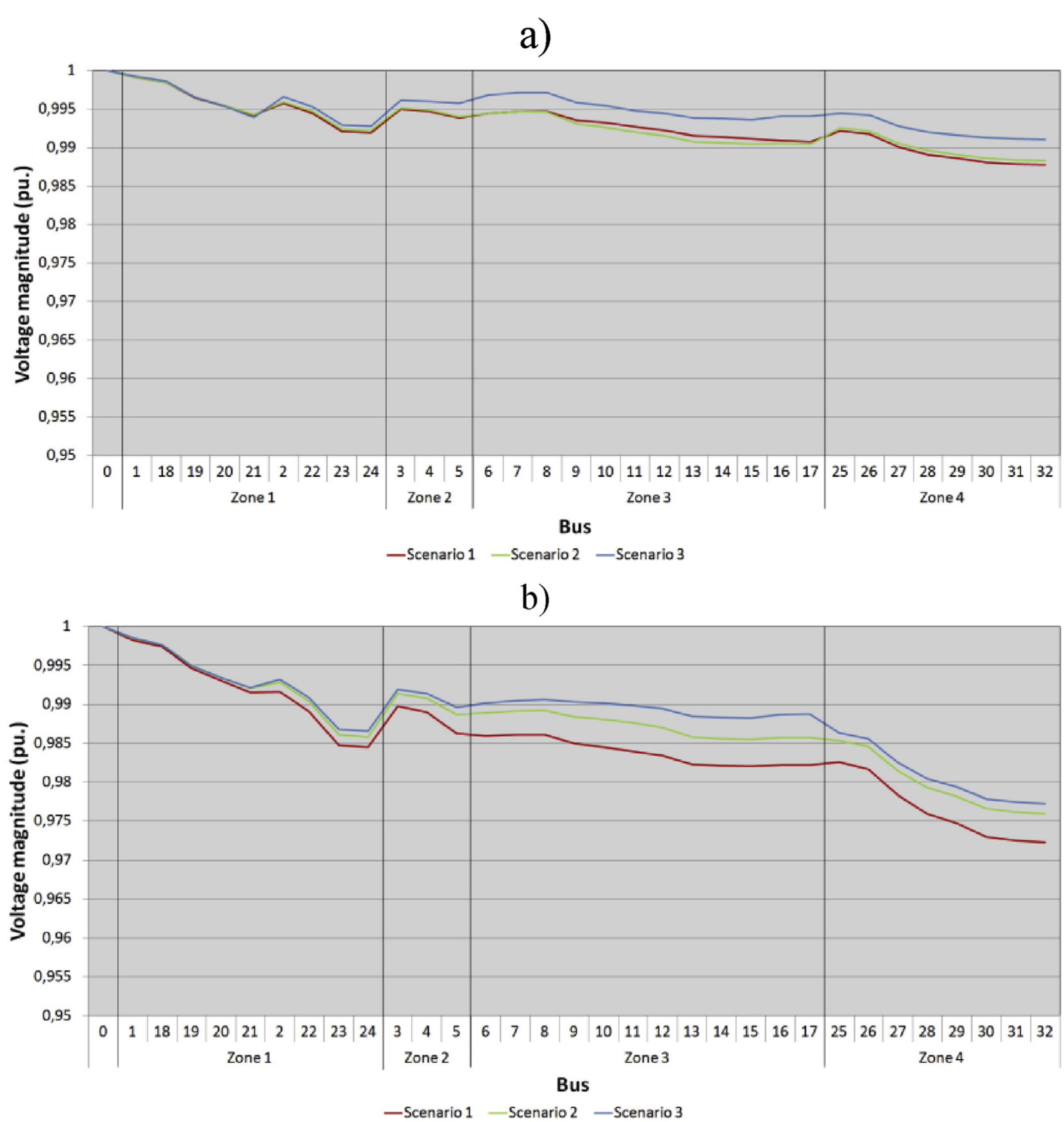

Fig. 5. Bus voltage profile for all scenarios with objective function F_2: a) In period 4; b) In period 20.

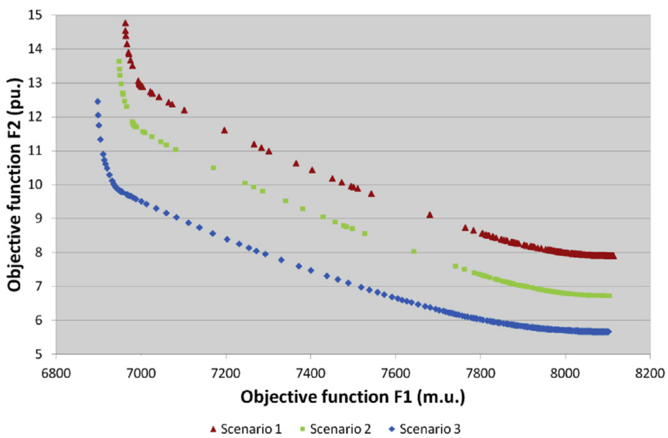

Fig. 6. Pareto front for the scenarios 1, 2 and 3 of simulation 3.

happened in the previous simulations, the best Pareto front was obtained for scenario 3, and the worst result was determined for scenario 1. This happen for the same reasons pointed in the previous simulations.

After determining the Pareto front, the fuzzy set approach has been used to identify the best compromise solution for each scenario. This method helps the VPP to choose the most suitable solution to be applied for the optimal resource scheduling problem. Table 6 shows the membership function μ^s value, the operation cost, the voltage magnitude difference and the active power losses of the best compromise solution.

Scenario 3 presents the best compromise solution with the lowest value of the three scenarios for the operation cost, voltage difference, and active power losses. On the other hand, scenario 1 presents the worst result in these three indicators. In terms of operation cost's variation, it is seen a low difference of 0.59% and 0.35% between scenario 3 and scenarios 1 and 2, respectively. On the other hand, the voltage difference achieved a higher variation of around 32.42% and 20.11% between scenario 3 and scenarios 1 and 2, respectively. Moreover, the active power losses variation between the best one and scenarios 1 and 2 is approximately 48.00% and 31.29%, respectively. Fig. 7 presents the active and reactive energy scheduling obtained by the best compromise solutions in the three scenarios. As expected, the results are between the ones obtained in the previous simulations. The reactive energy scheduling is very close to the one obtained with the objective function F_2. This happens due to the cost of the reactive power is considered equal to zero in the simulations.

Fig. 8 illustrates the voltage magnitude in all buses in periods 4 and 20. As expected, scenario 3 obtains the best voltage profile than the other two scenarios in both periods, presenting a solution that minimizes operation cost and voltage magnitude at the same time. This scenario uses more DG units and capacitor banks to increase voltage in the further buses.

Table 6
Best compromise solution of the proposed methodology with multi-objective function *F*.

Scenario	μ^s	Operation cost – F_1 (m.u.)	Voltage difference – F_2 (pu.)	Active power losses (kW)
1	0.003260	7042.53	12.58	670.39
2	0.003282	7025.75	11.41	528.64
3	0.003582	7001.41	9.50	452.96

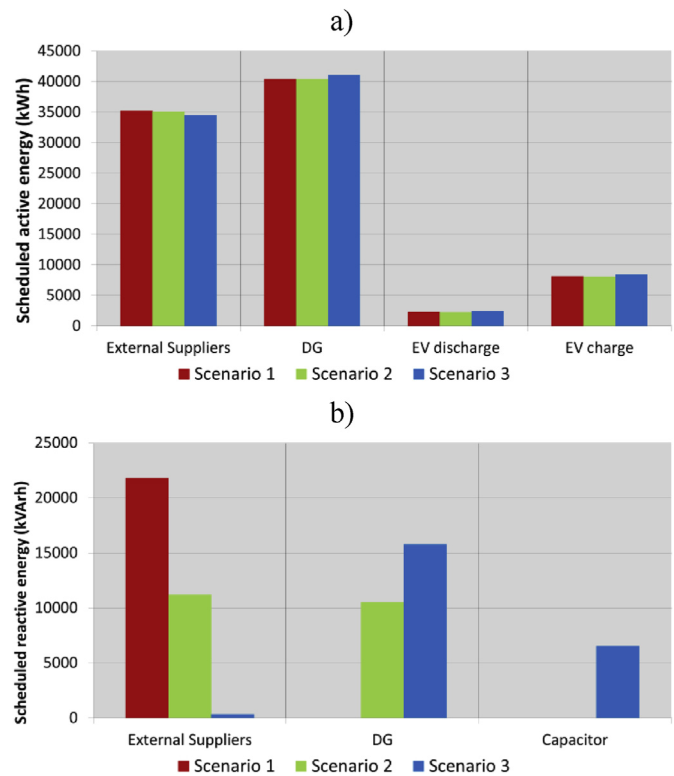

Fig. 7. Scheduled energy for the three scenarios for the best compromise solution: a) Active energy; b) Reactive energy.

In comparison with simulation 1 (see Fig. 3), these voltage profiles are higher in all scenarios. On the other hand, the voltage profiles of this simulation are lower than the ones obtained by simulation 2 (see Fig. 5). The multi-objective approach was able to find a middle-term solution between the individual optimal solutions obtained by the operation cost (simulation 1) and the voltage magnitude difference (simulation 2).

The use of a multi-objective approach is essential to obtain all possible solutions of the active and reactive optimal resource scheduling problem (non-dominated solutions of the Pareto front) with the purpose to help the VPP to select the best solution for its own interests. The multi-objective approach is more useful to the VPP than to optimize individually each objective function such as in simulation 1 and 2. The proposed methodology was able to obtain the Pareto front and the fuzzy set approach presented the best compromise solution for the three scenarios.

4.6. Comparison of simulations 1, 2 and 3

The comparison of the operation cost of simulations 1, 2 and 3 (considering the best solution) is presented in Fig. 9. As expected, simulation 1 achieved a better operation cost for the three scenarios. Simulation 3 presents the second best results with very close results to the ones presented by simulation 1. The operation cost variation between simulation 1 and 3 is around 1.13%, 1.09% and 1.48% for scenarios 1, 2 and 3, respectively. Moreover, the operation cost increased from simulation 1 to simulation 2 in 36.23%, 30.99% and 26.41% for scenarios 1, 2 and 3, respectively.

Fig. 10 depicts the voltage magnitude difference of simulations 1, 2 and 3 in the three scenarios. As expected, simulation 2 achieved a best voltage magnitude difference in the three scenarios.

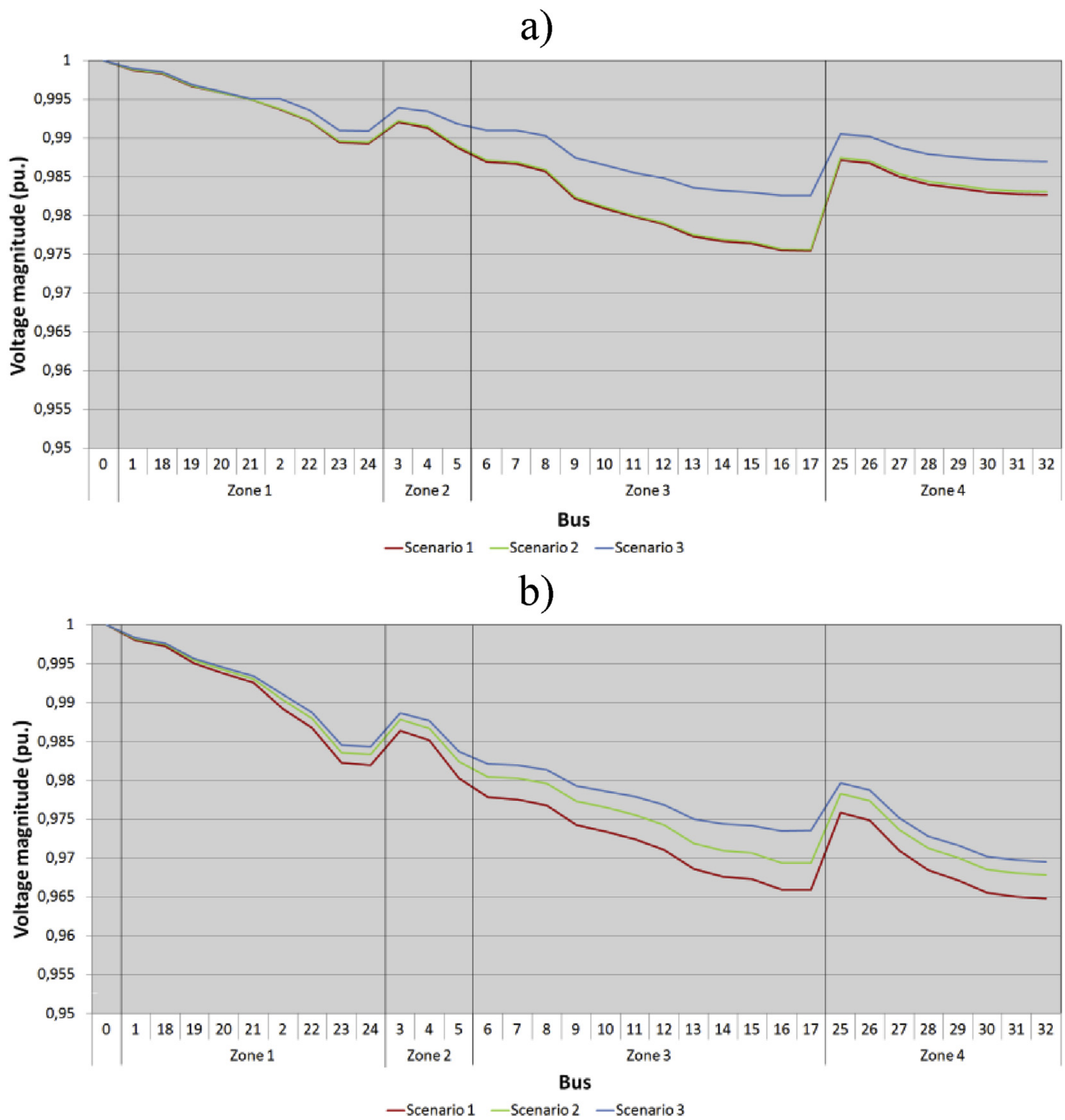

Fig. 8. Bus voltage profile for all scenarios for the best compromise solution: a) In period 4; b) In period 20.

Simulation 3 presents the middle-term voltage profile result and simulation 1 obtains the worst result of the three simulations. The voltage profile variation between simulation 2 and 3 is around 59.04%, 69.54% and 67.84% for scenarios 1, 2 and 3, respectively. The voltage magnitude difference decreased from simulation 1 to simulation 2 in approximately 86.73%, 102.53% and 119.79% for the scenarios 1, 2 and 3, respectively. These variations are higher than the ones presented in the previous comparison of the operation cost (see Fig. 9), proving once again the importance of using this technical indicator in order to improve the operation of the future

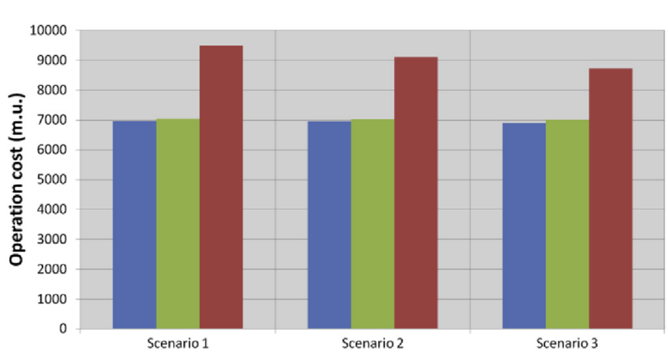

Fig. 9. Operation cost comparison between simulation 1, 2 and 3.

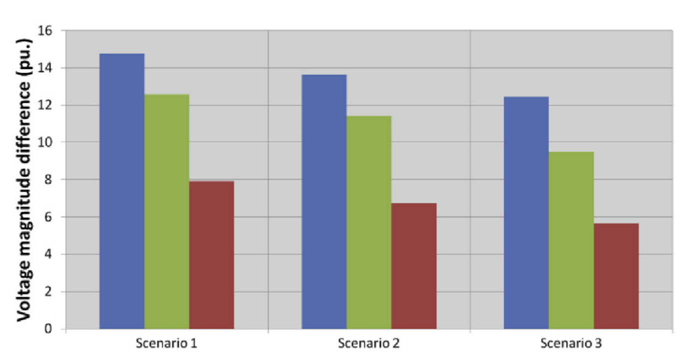

Fig. 10. Voltage magnitude difference comparison between simulation 1, 2 and 3.

networks. For instance, in scenario 3 the operation cost increases in 1.48% with the objective of reducing the voltage magnitude difference in 67.84% between simulation 1 and 3. The reduction in the voltage magnitude differences has more impact than an increase in the operation cost. For the simulation 3, the differences between scenarios 1 and 3 is for the operation cost of 0.6% and for the voltage difference of 32%.

The active power losses comparison between simulations 1, 2 and 3 is shown in Fig. 11. The active power losses results have the same behaviour as the voltage magnitude difference (see Fig. 10), and simulation 2 presents better results than simulation 1 and 3. Simulation 3 presents the second best result and simulation 1 obtains the worst result for the power losses.

The results obtained in this paper have been technically validated using an adequate network transient simulator tool presented in Ref. [39]. This simulator provides a large set of realistic models of the energy resources and network equipment allowing the validation of the proposed methodology.

5. Conclusions

This paper presents a methodology that handles with the active and reactive optimal resource scheduling in a distribution network with a large number of distributed resources. The proposed methodology is helpful to avoid drawbacks introduced by the distributed resources, such as bidirectional power flow, instability in the voltage levels. Three objective functions are used in the resources scheduling, namely: the operation cost minimization, the minimization of the voltage magnitude difference and the minimization of a multi-objective function resulting in a Pareto front. A fuzzy set approach has been used to select the best compromise solution. The proposed function to minimize the voltage magnitude difference in all buses improves the voltage stability of the network while reducing consequently the power losses.

The paper presents a case study for a 33-bus distribution network managed by a VPP with a penetration of 66 DG units and 1000 EVs showing clearly the effectiveness of the proposed approach to significantly increase the voltage profile in all buses of network with a marginal increase in the costs. With a Pareto front, the VPP can choose for different solutions according its profile and the operation scenario. Additionally, the fuzzy set approach gives a good compromised solution between the both considered objectives (costs and voltage profile). Several scenarios have been tested with the three proposed objective functions, considering the generation of reactive power by the DG and/or by the capacitor banks. The best results are obtained when the DG units generate active and reactive power and when the capacitor banks are used (i.e. scenario 3). In this case, a reduction of 32% of voltage differences is obtained with a cost increasing of only 0.6%.

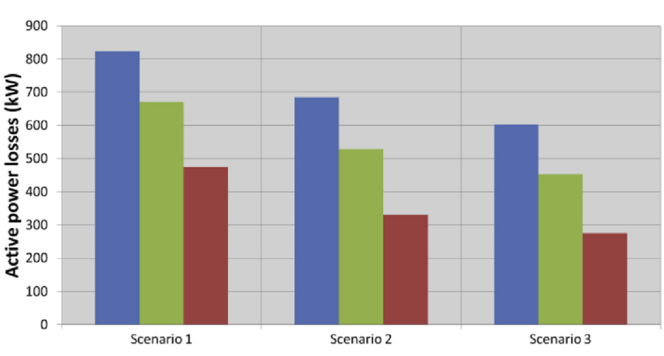

Fig. 11. Comparison of active power losses between simulation 1, 2 and 3.

The main conclusion of this work is the importance of using distributed resources in the reactive power scheduling in order to guarantee a safe operation without any kind of stressful situations. The proposed methodology was able to integrate the active and reactive power scheduling with the objective of obtaining a solution that manages the network for the economic and technical perspectives. The aggregated players must also be aware of the technical indicators of the network, and not just in the economic perspective of cost minimization. The multi-objective approach was able to obtain the Pareto front and the respective non-dominated solution in order to select the most suitable solution based on the VPP's interest. In the future, the authors intend to use multi-objective evolutionary algorithms to deal with the proposed optimization problem.

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Appendix A

$$\sum_{DG=1}^{N_{DG}^{i}}\left(P_{DG(DG,t)}^{i}-P_{GCP(DG,t)}^{i}\right)+\sum_{SP=1}^{N_{SP}^{i}}P_{SP(SP,t)}^{i}+\sum_{EV=1}^{N_{EV}^{i}}P_{Dch(EV,t)}^{i} - \sum_{L=1}^{N_{L}^{i}}\left(P_{Load(L,t)}^{i}-P_{NSD(L,t)}^{i}\right)-\sum_{EV=1}^{N_{EV}^{i}}P_{Ch(EV,t)}^{i}=G_{ii}\times V_{i(t)}^{2} + V_{i(t)}\times\sum_{j\;\in\;L^{i}}V_{j(t)}\times\left(G_{ij}\cos\theta_{ij(t)}+B_{ij}\sin\theta_{ij(t)}\right) \tag{4}$$

$$\sum_{DG=1}^{N_{DG}^{i}}Q_{DG(DG,t)}^{i}+\sum_{SP=1}^{N_{SP}^{i}}Q_{SP(SP,t)}^{i}+\sum_{CAP=1}^{N_{CAP}^{i}}Q_{CAP(CAP,t)}^{i} - \sum_{L=1}^{N_{L}^{i}}\left(Q_{Load(L,t)}^{i}-Q_{NSD(L,t)}^{i}\right)-\sum_{Asyn\_DG=1}^{N_{Asyn\_DG}^{i}}Q_{Asyn\_DG(Asyn\_DG,t)}^{i} = V_{i(t)}\times\sum_{j\;\in\;L^{i}}V_{j(t)}\times\left(G_{ij}\sin\theta_{ij(t)}-B_{ij}\cos\theta_{ij(t)}\right)-B_{ii}\times V_{i(t)}^{2}$$
$$\forall t\in\{1,\ldots,T\};\forall i\in\{1,\ldots,N_{B}\};\theta_{ij(t)}=\theta_{i(t)}-\theta_{j(t)} \tag{5}$$

$$V_{Min}^{i}\le V_{i(t)}\le V_{Max}^{i} \tag{6}$$

$$\theta_{Min}^{i}\le\theta_{i(t)}\le\theta_{Max}^{i} \tag{7}$$

$$\left|\overline{U_{i(t)}}\times\left[\overline{y_{ij}}\times\left(\overline{U_{i(t)}}-\overline{U_{j(t)}}\right)+\overline{y_{sh\_i}}\times\overline{U_{i(t)}}\right]^{*}\right|\le S_{Lk}^{Max} \tag{8}$$

$$\left|\overline{U_{j(t)}} \times \left[\overline{y_{ij}} \times \left(\overline{U_{j(t)}} - \overline{U_{i(t)}}\right) + \overline{y_{sh\_j}} \times \overline{U_{j(t)}}\right]^{*}\right| \leq S_{Lk}^{Max} \quad (9)$$
$$\forall t \in \{1,\ldots,T\};\ \forall i,j \in \{1,\ldots,N_B\};\ i \neq j;\ \forall k \in \{1,\ldots,N_K\}$$

$$\left(\sum_{SP=1}^{N_{SP}^i} P_{SP(SP,t)}^i\right)^2 + \left(\sum_{SP=1}^{N_{SP}^i} Q_{SP(SP,t)}^i\right)^2 \leq \left(S_{TFR\_HV\_MV(i)}^{Max}\right)^2$$
$$\forall t \in \{1,\ldots,T\};\ \forall i \in \{1,\ldots,N_B\} \quad (10)$$

$$\begin{aligned} P_{TFR\_MV\_LV(i,t)} = & \sum_{DG=1}^{N_{DG}^i}\left(P_{DG(DG,t)}^i - P_{GCP(DG,t)}^i\right) \\ & + \sum_{EV=1}^{N_{EV}^i}\left(P_{Dch(EV,t)}^i - P_{Ch(EV,t)}^i\right) \\ & - \sum_{L=1}^{N_L^i}\left(P_{Load(L,t)}^i - P_{NSD(L,t)}^i\right) \end{aligned} \quad (11)$$

$$\begin{aligned} Q_{TFR\_MV\_LV(i,t)} = & \sum_{DG=1}^{N_{DG}^i} Q_{DG(DG,t)}^i + \sum_{CAP=1}^{N_{CAP}^i} Q_{CAP(CAP,t)}^i \\ & - \sum_{L=1}^{N_L^i}\left(Q_{Load(L,t)}^i - Q_{NSD(L,t)}^i\right) \\ & - \sum_{Asyn\_DG=1}^{N_{Asyn\_DG}^i} Q_{Asyn\_DG(Asyn\_DG,t)}^i \end{aligned} \quad (12)$$

$$\left(P_{TFR\_MV\_LV}\right)^2 + \left(Q_{TFR\_MV\_LV}\right)^2 \leq \left(S_{TFR\_MV\_LV(i)}^{Max}\right)^2 \quad (13)$$
$$\forall t \in \{1,\ldots,T\};\ \forall i \in \{1,\ldots,N_B\}$$

$$\sqrt{P_{DG(DG,t)}^2 + Q_{DG(DG,t)}^2} \geq S_{Min(DG,t)} \times X_{DG(DG,t)} \quad (14)$$

$$\sqrt{P_{DG(DG,t)}^2 + Q_{DG(DG,t)}^2} \leq S_{Max(DG,t)} \times X_{DG(DG,t)} \quad (15)$$

$$P_{DG(DG,t)} \geq P_{Min(DG,t)} \times X_{DG(DG,t)} \quad (16)$$

$$P_{DG(DG,t)} \leq P_{Max(DG,t)} \times X_{DG(DG,t)} \quad (17)$$

$$Q_{CAP(CAP,t)} \leq Q_{Max(CAP,t)} \quad (18)$$

$$Q_{CAP(CAP,t)} = \sum_{Step=1}^{N_{Step}} Q_{Max(CAP,Step,t)} \times X_{CAP(CAP,Step,t)} \quad (19)$$
$$\forall t \in \{1,\ldots,T\};\ \forall CAP \in \{1,\ldots,N_{CAP}\}$$

$$P_{DG(DG,t)} + P_{GCP(DG,t)} = P_{DGForecast(DG,t)} \quad (20)$$
$$\forall t \in \{1,\ldots,T\};\ \forall DG \in \{1,\ldots,N_{DG}\}$$

$$P_{SP(SP,t)} \leq P_{Max(SP,t)} \quad (21)$$

$$Q_{SP(SP,t)} \leq Q_{Max(SP,t)} \quad (22)$$
$$\forall t \in \{1,\ldots,T\};\ \forall SP \in \{1,\ldots,N_{SP}\}$$

$$\begin{aligned} E_{Stored(EV,t)} = & E_{Stored(EV,t-1)} - E_{Trip(EV,t)} + \eta_{c(EV)} \times P_{Ch(EV,t)} \\ & - \frac{1}{\eta_{d(EV)}} \times P_{Dch(EV,t)} \end{aligned}$$
$$\forall t \in \{1,\ldots,T\};\ \forall EV \in \{1,\ldots,N_{EV}\};\ \Delta t = 1$$
$$t = 1 \rightarrow E_{Stored(EV,t-1)} = E_{Initial(EV)} \quad (23)$$

$$E_{Stored(EV,t)} \geq E_{BatMin(EV,t)} \quad (24)$$

$$E_{Stored(EV,t)} \leq E_{BatMax(EV,t)} \quad (25)$$
$$\forall t \in \{1,\ldots,T\};\ \forall EV \in \{1,\ldots,N_{EV}\}$$

$$P_{Ch(EV,t)} \leq P_{Max(EV,t)} \times X_{Ch(EV,t)} \quad (26)$$

$$P_{Dch(EV,t)} \leq P_{Max(EV,t)} \times X_{Dch(EV,t)} \quad (27)$$

$$X_{Ch(EV,t)} + X_{Dch(EV,t)} \leq 1 \quad (28)$$
$$X_{Ch(EV,t)} \ \ and \ \ X_{Dch(EV,t)} \in \{0,1\}$$

References

[1] Tafarte P, Das S, Eichhorn M, Thrän D. Small adaptations, big impacts: options for an optimized mix of variable renewable energy sources. Energy 2014;72(0):80–92.
[2] Kempton W, Tomic J. Vehicle-to-grid power fundamentals: calculating capacity and net revenue. J Power Sources 2005;144(1):268–79.
[3] Vale Z, Morais H, Faria P, Ramos C. Distribution system operation supported by contextual energy resource management based on intelligent SCADA. Renew Energy 2013;52(0):143–53.
[4] Morais H, Pinto T, Vale Z, Praca I. Multilevel negotiation in smart grids for VPP management of distributed resources. IEEE Intell Syst 2012;27(6):8–16.
[5] Sousa T, Vale Z, Carvalho JP, Pinto T, Morais H. A hybrid simulated annealing approach to handle energy resource management considering an intensive use of electric vehicles. Energy 2014;67(0):81–96.
[6] Madzharov D, Delarue E, D'Haeseleer W. Integrating electric vehicles as flexible load in unit commitment modeling. Energy 2014;65(0):285–94.
[7] Ji B, Yuan X, Chen Z, Tian H. Improved gravitational search algorithm for unit commitment considering uncertainty of wind power. Energy 2014;67(0):52–62.
[8] Li Y, Wu Q, Li M, Zhan J. Mean-variance model for power system economic dispatch with wind power integrated. Energy 2014;72(0):510–20.
[9] Aman M, Jasmon G, Bakar A, Mokhlis H. A new approach for optimum simultaneous multi-DG distributed generation units placement and sizing based on maximization of system loadability using HPSO (hybrid particle swarm optimization) algorithm. Energy 2014;66(0):202–15.
[10] Abido M. Multiobjective evolutionary algorithms for electric power dispatch problem. IEEE Trans Evol Comput 2006;10(3):315–29.
[11] Chun-Hao L, Ansari N. Decentralized controls and communications for autonomous distribution networks in smart grid. IEEE Trans Smart Grid 2013;4(1):66–77.
[12] Mousavi O, Cherkaoui R. Literature survey on fundamental issues of voltage and reactive power control. Deliverable of the MARS Project financially supported by "swisselectric research". 2011.
[13] van Cutsem T, Vournas C. Voltage stability of electric power systems. Springer; 1998.
[14] Zhang A, Li H, Liu F, Yang H. A coordinated voltage/reactive power control method for multi-TSO power systems. Int J Elec Power 2012;43(1):20–8.
[15] Mousavi O, Bozorg M, Cherkaoui R. Preventive reactive power management for improving voltage stability margin. Electr Pow Syst Res 2013;96(0):36–46.
[16] Caldon R, Rossetto F, Scala A. Reactive power control in distribution networks with dispersed generators: a cost based method. Electr Pow Syst Res 2003;64(3):209–17.
[17] Reddy S, Abhyankar A, Bijwe P. Reactive power price clearing using multi-objective optimization. Energy 2011;36(5):3579–89.

[18] Saraswat A, Saini A, Saxena AK. A novel multi-zone reactive power market settlement model: a pareto-optimization approach. Energy 2013;51(0):85–100.
[19] Martinez-Rojas M, Sumper A, Gomis-Bellmunt O, Sudrià-Andreu A. Reactive power dispatch in wind farms using particle swarm optimization technique and feasible solutions search. Appl Energ 2011;88(12):4678–86.
[20] Shaw B, Mukherjee V, Ghoshal S. Solution of reactive power dispatch of power systems by an opposition-based gravitational search algorithm. Int J Elec Power 2014;55(0):29–40.
[21] Zare M, Niknam T, Azizipanah-Abarghooee R, Amiri B. Multi-objective probabilistic reactive power and voltage control with wind site correlations. Energy 2014;66(0):810–22.
[22] Fodor A, Magyar A, Hangos K. Multiple-Input–Multiple-Output linear-quadratic control of the energy production of a synchronous generator in a nuclear power plant. Electr Pow Compo Sys 2014;42(15):1673–82.
[23] Lin X, Yu C, David A, Chung C, Wu H, Xu N. A novel market-based reactive power management scheme. Int J Elec Power 2006;28(2):127–32.
[24] Badar A, Umre B, Junghare A. Reactive power control using dynamic particle swarm optimization for real power loss minimization. Int J Elec Power 2012;41(1):133–6.
[25] Kargarian A, Raoofat M, Mohammadi M. Reactive power market management considering voltage control area reserve and system security. Appl Energ 2011;88(11):3832–40.
[26] Zare M, Niknam T. A new multi-objective for environmental and economic management of Volt/Var control considering renewable energy resources. Energy 2013;55(0):236–52.
[27] Grainger J, Stevenson W. Power system analysis. McGraw-Hill; 1994.
[28] Peterson S, Whitacre J, Apt J. The economics of using plug-in hybrid electric vehicle battery packs for grid storage. J Power Sources 2010;195(8):2377–84.
[29] Peterson S, Apt J, Whitacre J. Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. J Power Sources 2010;195(8):2385–92.
[30] Deb K. Multi-objective optimization using evolutionary algorithms. Wiley; 2001.
[31] Gomez-Exposito A, Conejo A, Canizares C. Electric energy systems: analysis and operation. Taylor & Francis; 2008.
[32] Ferreira J, Monteiro V, Afonso J. Vehicle-to-Anything application (V2Anything app) for electric vehicles. IEEE Trans Industrial Informatics 2013:99. 1-.
[33] Soares J, Canizes B, Lobo C, Vale Z, Morais H. Electric vehicle scenario simulator tool for smart grid operators. Energies 2012;5(6):1881–99.
[34] Garcia-Valle R, Lopes J. Electric vehicle integration into modern power networks. Springer; 2012.
[35] Hong L, Huansheng N, Yan Z, Guizani M. Battery status-aware authentication scheme for V2G networks in smart grid. IEEE Trans Smart Grid 2013;4(1):99–110.
[36] GAMS. GAMS home page.
[37] Sakawa M, Yano H, Yumine T. An interactive fuzzy satisficing method for multiobjective linear-programming problems and its application. IEEE transactions on systems. Man Cybern 1987;17(4):654–61.
[38] Farina M, Amato P. A fuzzy definition of “optimality” for many-criteria optimization problems. IEEE Trans Syst Man Cybern Part A Syst Humans 2004;34(3):315–26.
[39] Silva M, Morais H, Vale Z. An integrated approach for distributed energy resource short-term scheduling in smart grids considering realistic power system simulation. Energ Convers Manage 2012;64(0):273–88.