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Providing Flexibility in Distribution Systems by Electric Vehicles and Distributed Energy Resources in the Context of Technical Virtual Power Plants

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***Abstract*—In the recent past structural changes in the operation and topology of the electrical system have occurred. These changes have coincided with the emergence of distributed energy resources (DERs). Relating to supply side technologies, distributed generation (DG) units have become increasingly common. The demand side has also seen the growth of new technological applications, including electric vehicles (EVs). These changes to the electrical system are being especially felt at the low voltage network level. Technical Virtual Power Plants (TVPPs) have been used to optimally schedule these DERs to increase the network flexibility and at the same time increasing the reliability and power quality of the network and this can bring economic benefits to both the TVPP operator and the customer. This paper develops a stochastic mixed-integer linear programming (MILP) optimization model to maximize the profit of a TVPP. The main objective of the TVPP is to increase operational flexibility of the low voltage network by aggregating DERs, including DG units, Heating Ventilation and Air Conditioning units, and EVs. The model is examined through the use of the IEEE 119-Bus test system. Results demonstrate that the inclusion of DG units and EVs, the profit of the TVPP increases by approximately 45% and system flexibility is increased while respecting the technical constraints of the network and the thermal comfort of the consumers.**

***Keywords*—Flexibility, Distribution System, Distributed Generation, Electric Vehicles, Technical Virtual Power Plant**

I. NOMENCLATURE

A. Sets/Indices

d/Ω^d	Index for of power demand
ev/Ω^{ev}	Index for of electric vehicles
g/Ω^g	Index for of generators
h/Ω^h	Index for of hours
l/Ω^l	Index for of lines
$n/\Omega^n\{i,j \in n\}$	Index for of nodes
s/Ω^s	Index for of scenarios
$\varsigma/\Omega^\varsigma$	Index for of market

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B. Parameters

$E_{ev,n}^{min}$, $E_{ev,n}^{max}$	EV energy storage limit
S_l^{max}, b_l, g_l	Flow boundaries, susceptance and conductance of each branch l (MVA, S, S)
K	Total number of linear segments
MP_l, MQ_l	Big-M parameters for active and reactive power flows in branch l
OC_g	Cost of unit energy production (€)
$P_{g,n,s,h}^{DG,min}, P_{g,n,s,h}^{DG,max}$	Min, max power generation bounds (MW)
$P_{ev,n,h}^{ch,max}, P_{ev,n,h}^{dch,max}$	Charging and discharging power limits of the EVs (MW)
P_r	DG unit rated power (MW)
$P_{sol,h}$	PV output per hour (MW)
$P_{wind,h}$	Wind output per hour (MW)
$PD_{s,h}^n$	Active demand at node n (MW)
pf_g	DG power factor
pf_ς	Power factor of substation
$QD_{s,h}^n$	Reactive demand at node n (MVAr)
V_{nom}	Nominal voltage (kV)
R_h	PV radiation per hour (W/m^2)
R_l, X_l	Resistance and reactance (Ω, Ω)
R_{std}	Standard test condition for radiation (1000 W/m^2)
v_{ci}	Cut-in wind power (m/s)
v_{co}	Cut-out wind speed (m/s)
v_h	Measured wind speed (m/s)
v_r	Rated wind speed (m/s)
α_k, β_k	Slopes of linear segments
η_{ev}^{ch}	EV charging efficiency
η_{ev}^{dch}	EV discharging efficiency
λ_h^{ev}	V2G price (€/MWh)
λ_h^{TOU}	TOU price associated with customers (€/MWh)
λ_h^{ev}	EV discharging cost (€/MWh)
λ_h^ς	Day-ahead market price (€/MWh)
μ_{ev}	Scaling factor
ρ_s	Probability of scenario s

C. Variables

$E_{ev,n,s,h}$	Reservoir level of EV (MWh)
$I_{ev,n,s,h}^{dch}, I_{ev,n,s,h}^{ch}$	EV charging and discharging binary variables

$P_{ev,n,s,h}^{ch}, P_{ev,n,s,h}^{dch}$	EV active and reactive power from charging and discharging (MW)
$P_{\varsigma,n,s,h}^{market}, Q_{\varsigma,s,h}^{market}$	Power purchased from grid (MW, MVAr) each branch l
$P_{g,n,s,h}^{DG}, Q_{g,n,s,h}^{DG}$	Active and reactive DG power (MW, MVAr)
P_l, Q_l	Power flows, active and reactive (MW, MVAr)
$p_{l,s,h,k}, q_{l,s,h,k}$	Step variables used during linearization (MW, MVAr)
PL_l, QL_l	Power losses, active and reactive, for branch l (MW, MVAr)
$P_{ev,n,s,h}^{ch}, P_{ev,n,s,h}^{dch}$	Power charged to and discharged from EVs (MW)
V_n, V_m	Voltage magnitudes at bus n and m (kV)
$\Delta V_{n,s,h}$	Voltage deviation magnitude (kV)
θ_n, θ_m	Voltage angle at node n and m (radians)
θ_l	Voltage angle difference of branch l (radians)
$\chi_{l,h}$	Binary switching variable of line l

II. Introduction

A) Context

The energy sector has benefited in recent years from general economic growth as well as an emergence of new technologies. The amount of energy available to meet demand has become a critical issue. Likewise, generation from renewable energy sources (RES) plays a key role in the decarbonization of the sector. However, RESs are very susceptible to variations, posing new challenges for the operator [1]. Some negative outcomes of RES adoption can be minimized, and system flexibility enhanced, by redesigning market structures; implementing demand response programs; deploying energy storage systems and electric vehicles (EVs) on a large scale; and aggregating heterogeneous distributed energy resources (DERs) for efficient management [2].

It is within this context that EVs and their batteries can go beyond their simple mobility role and be even more relevant and important in the decarbonization of the economy. Depending on the type of EVs, different charging-discharging strategies can be adopted. This factor makes the charge-discharge process of a fleet of EVs a demand-side management (DSM) platform, and rather than simply being one more load on the system, also increases its flexibility [3], [4]. One of these strategies is the vehicle-to-grid (V2G) concept. While some limitations currently exist, especially concerning the life span of EVs batteries, this approach allows for a bidirectional interaction between grid and vehicle. In practice, power may flow either from the network to the vehicle, or from the vehicle to the network. The aggregation of EVs under this process can lead to several advantages, both technical and economic, which is extremely important with the growing adoption rates of RES in electricity generation [5], [6].

To aggregate these forms of production and to increase control of the operational interface of the system, a new entity to analysis and operate the electrical system is introduced. This entity is a technical virtual power plant (TVPP). Figure 1 describes the VPP structure and digital transformation in power systems, both now and in the future[7].

A TVPP aggregates power from different sources, such as DG points or power provided by discharging EVs. It is important to understand how this aggregation can contribute

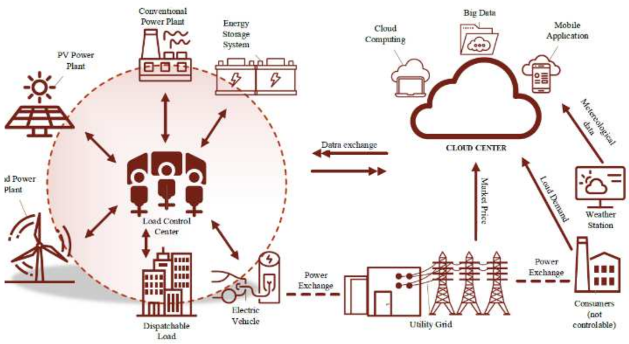

Fig 1. VPP structure.

to increasing the flexibility of the entire system and whether this aggregation will bring both economic and power quality benefits to the system.

B) Literature Review

The development of new tools and technologies, as well as the increasing use of RES-based power generation, both as centralized production units and as distributed generation, has created new challenges for the energy sector. The main concerns arise due to the unpredictability of production, and it is in this context that the concept of VPP appears.

Over the last few years, several studies concerning VPPs have been carried out. Some studies have addressed topics such as classification, modelling, optimization and solutions for optimization problems concerning VPPs while considering uncertainty such as Yu *et al.* [7], while others focus mainly on the role of VPP in energy management, for example, Naval *et al.* [8], where the design of an optimal VPP management model with two integration levels of RES is discussed. Some other researches, target mainly the financial aspects of VPPs, as is the case of the work done by Hany Elgamal *et al.* [9], where market participation and optimization trading of VPPs stands out when day-ahead prices are unknown and possibly volatile or by Hadayeghparast *et al.* [10], with the main objective is to maximize the VPP daily profit and minimize daily emissions.

The introduction of the TVPP concept has created an emerging additional area of research in this field. Within the scope of optimal scheduling, the operation of a TVPP in the presence of DERs while considering grid constraints. Pourghaderi *et al.* [11] formulate a model to maximize a TVPP's profit during participation in the day-ahead energy market by scheduling the DERs.

The authors in [12] present an energy management framework for a TVPP in an active distribution system with a diverse set of DERs. The performance of a TVPP as a price maker agent participating in the wholesale energy market is presented in [13].

This current paper focuses on the maximization of the profit of a TVPP operating in a day-ahead market, with the integration of DERs and V2G energy supplied by EVs. This work distinguishes itself from previous research through a new mathematical formulation and its approach to provide flexibility to the distribution system, jointly with the economic advantages and technical benefits. This new focus leads to an increase in the quality standards of the power supplied, and consequently to an increase in the system reliability, which are not addressed in the other works.

C) Contributions and Paper Organization

In this paper, a mathematical optimization model is formulated to manage the TVPP in an optimal manner. The literature review has shown that there is a growing area of research considering the technical impacts of VPPs but very few VPP models consider technical impacts from operations. This work extends the state of the art in the following two aspects:

- A stochastic mixed-integer linear programing (SMILP) model for TVPP in a day-ahead energy market using a penalty function to minimize the impacts of the TVPP operation on consumers thus increasing their incentive to engage with the TVPP.
- An extensive analysis regarding the economic and technical impacts of the TVPP operation on the distribution grid focusing on the flexibility delivered by DGs and EVs is carried out. This leads to a holistic investigation of the potential impacts of TVPP operations on consumers.

The rest of the paper is organized as follows: Section III presents the model's mathematical formulation. The results of the model as well as a discussion of these results in shown in Section IV. Section V contained the conclusions and ideas for future research.

III. Mathematical Formulation

A. Objective Function

The main objective of this paper is to maximize the profit of a TVPP through the optimal scheduling of its resources during its participation in the day-ahead energy market. The objective function was formulated in Equation (1) as the difference between two main relevant cost terms, namely, the cost associated with the power sold to the loads (*PSC*) and the cost imposed by the TVPP (*TVPPC*).

$$Profit = PSC - TVPPC \tag{1}$$

The cost term related to the power sold to the loads is presented in Equation (2). It represents the profit generated from retailing power to the loads using the TOU tariff price at a given hour, where the power supplied to the loads is considered, as well as the charging of EVs. In this equation, the probability of a given scenario occurring is shown by ρ_s. In the context of this work, all the different scenarios will have the same probability of occurrence.

$$\begin{aligned} PSC = &\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\lambda_h^{TOU}P_{l,s,h} \\ &+\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{ev\in\Omega^{ev}}\lambda_h^{TOU}P_{ev,n,s,h}^{ch} \end{aligned}\tag{2}$$

The total cost imposed by TVPP is defined in Equation (3) and is the result of the difference between the operating costs of DGs and the sum of the energy cost purchased from the market and V2G power supplied by the EVs. In addition, the TVPP should provide some compensation for the excess costs incurred by customers, with a penalty factor associated with the EVs scheduling.

The compensation for consumers extra cost due to the EVs scheduling is thus defined in Equation (4) and it can be seen as an incentive for consumers to participate in the TVPP schedule. This cost is derived from the difference between the optimal cost of customers EVs and the expressed cost of scheduling EVs load cycles.

$$\begin{aligned} TVPPC\ =&\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{g\in\Omega^g}OC_gP_{g,n,s,h}^{DG} \\ &-\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{\varsigma\in\Omega^\varsigma}\lambda_h^{\varsigma}P_{\varsigma,n,s,h}^{market} \\ &-\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{ev\in\Omega^{ev}}\lambda_h^{ev}P_{ev,n,s,h}^{dch} \\ &+Penalty \end{aligned}\tag{3}$$

$$\begin{aligned} Penalty\ =&\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{ev\in\Omega^{ev}}\lambda_h^{TOU}P_{ev,n,s,h}^{ch} \\ &-\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{es\in\Omega^{es}}\lambda_h^{ev}P_{ev,n,s,h}^{dch} \\ &-Cost_{ev}^{Operation} \end{aligned}\tag{4}$$

B. Constraints

The first constraint is related to the linearized AC power flows in each feeder. These are illustrated in inequalities (5) and (6). Both respect Kirchhoff's Voltage Law. The Big-M formulation is used place an upper bound on the transfer capacity. The linearization of the equations is described in [14].

$$\begin{aligned} &\left|P_{l,s,h}-\left\{V_{nom}\left(\Delta V_{n,s,h}-\Delta V_{m,s,h}\right)g_l-V_{nom}^2b_l\theta_{l,s,h}\right\}\right| \\ &\le MP_l \end{aligned}\tag{5}$$

$$\begin{aligned} &\left|Q_{l,s,h}-\left\{-V_{nom}\left(\Delta V_{n,s,h}\right.\right.\right. \\ &\qquad\left.\left.\left.-\Delta V_{m,s,h}\right)b_l-V_{nom}^2g_l\theta_{l,s,h}\right\}\right| \\ &\le MQ_l \end{aligned}\tag{6}$$

Equation (7) and Equation (8) express active and reactive power flow, respectively, with the application of Kirchhoff's Current Law. This requires that all outgoing flows from a node must be equal to the sum of all incoming flows.

$$\begin{aligned} &\textstyle\sum_{g\in\Omega^g}P_{g,n,s,h}^{DG}+\sum_{ev\in\Omega^{ev}}\left(P_{ev,n,s,h}^{dch}-P_{ev,n,s,h}^{ch}\right)+ \\ &P_{\varsigma,s,h}^{market}+\textstyle\sum_{in,l\in\Omega^l}P_{l,s,h}-\sum_{out,l\in\Omega^l}P_{l,s,h}=PD_{s,h}^n+ \\ &\textstyle\sum_{in,l\in\Omega^l}\frac{1}{2}PL_{l,s,h}+\sum_{out,l\in\Omega^l}\frac{1}{2}PL_{l,s,h}\,;\ \forall\varsigma\in i \end{aligned}\tag{7}$$

$$\begin{aligned} &\textstyle\sum_{g\in\Omega^g}Q_{g,n,s,h}^{DG}+\ Q_{\varsigma,s,h}^{market}+\sum_{in,l\in\Omega^l}Q_{l,s,h}-\sum_{out,l\in\Omega^l} \\ &Q_{l,s,h}=QD_{s,h}^n+\textstyle\sum_{in,l\in\Omega^l}\frac{1}{2}QL_{l,s,h}+\sum_{out,l\in\Omega^l} \\ &\tfrac{1}{2}QL_{l,s,h}\ \forall\varsigma\in i \end{aligned}\tag{8}$$

The apparent power flow, S_l , of a given line, is $\sqrt{P_l^2+Q_l^2}$. This power flow cannot be greater than the rated value which is indicated in Equation (9).

$$P_l^2+\ Q_l^2\le\ (S_l^{max})^2 \tag{9}$$

Equation (9) deals with the quadratic expressions of active and reactive power flow. Through piecewise linearization, these expressions can be linearized by considering an adequate number of linear segments K. This easily applied approach uses a first-order approximation of the non-linear curve. In this context, two non-negative additional variables are used for the flows P_l and Q_l. These variables represent the positive and the negative flows and are given as $P_l=P_l^+-P_l^-$ and $Q_l=Q_l^+-Q_l^-$ respectively. Using this approach, only the positive quadrant of the non-linear curve is considered. This results in a reduction in mathematical complexity as well as the computational burden.

The linear constraints associated with this approach are given by Equation (10) to Equation (13) with $p_{l,s,h,k}\le P_l^{max}/K$ and $q_{l,s,h,k}\le Q_l^{max}/K$.

$$P_{l,s,h}^2 \approx \sum_{k=1}^{K} \alpha_{l.k}\, p_{l,s,h,k} \tag{10}$$

$$Q_{l,s,h}^2 \approx \sum_{k=1}^{K} \beta_{l.k}\, q_{l,s,h,k} \tag{11}$$

$$P_{l,s,h}^+ + P_{l,s,h}^- = \sum_{k=1}^{K} p_{l,s,h,k} \tag{12}$$

$$Q_{l,s,h}^+ + Q_{l,s,h}^- = \sum_{k=1}^{K} q_{l,s,h,k} \tag{13}$$

An approximation of the active and the reactive power losses in line l are shown in Equation (14) and Equation (15), respectively. However, these equations are strongly non-linear and non-convex, making the problem difficult to solve.

$$\begin{aligned} PL_l = PL_{l,ij} + PL_{l,ji} \approx 2V_{nom}^2 g_l(1 - cos\theta_l) \\ \approx V_{nom}^2 g_l \theta_l^2 \end{aligned} \tag{14}$$

$$\begin{aligned} QL_l = QL_{l,ij} + QL_{l,ji} \approx -2V_{nom}^2 b_l(1 - cos\theta_l) \\ \approx -b_l V_{nom}^2 \theta_l^2 \end{aligned} \tag{15}$$

To overcome this problem the expressions are rewritten, in Equation (16) and Equation (17), in terms of the active and the reactive power flows.

Expressing the losses in this manner reduces the number of non-linear terms and removes redundant constraints relating to the angle differences when the branch between two nodes is not connected. The complete method used in the linearization is shown in [15].

$$PL_{l,s,h} = \frac{R_l\left(P_{l,s,h}^2 + Q_{l,s,h}^2\right)}{V_{nom}^2} \tag{16}$$

$$QL_{l,s,h} = \frac{X_l\left(P_{l,s,h}^2 + Q_{l,s,h}^2\right)}{V_{nom}^2} \tag{17}$$

The scheduling of EVs by the TVPP should satisfy some technical constraints that can be modeled using Equation (18) to Equation (23).

$$0 \le P_{ev,n,s,h}^{ch} \le I_{ev,n,s,h}^{ch} P_{ev,n,h}^{ch,max} \tag{18}$$

$$0 \le P_{ev,n,s,h}^{dch} \le I_{ev,n,s,h}^{dch} P_{ev,n,h}^{dch,max} \tag{19}$$

$$I_{ev,n,s,h}^{ch} + I_{ev,n,s,h}^{dch} = 1 \tag{20}$$

$$E_{ev,n,s,h} = E_{ev,n,s,h-1} + \eta_{ev}^{ch} P_{ev,n,s,h}^{ch} - \frac{P_{ev,n,s,h}^{dch}}{\eta_{ev}^{dch}} \tag{21}$$

$$E_{ev,n}^{min} \le E_{ev,n,s,h} \le E_{ev,n}^{max} \tag{22}$$

$$E_{ev,n,s,h0} = \mu_{ev} E_{ev,n}^{max};\ E_{ev,n,s,h24} = \mu_{ev} E_{ev,n}^{max} \tag{23}$$

Equation (18) and Equation (19) limit the amount of charging or discharging power, respectively. In addition, Equation (20) safeguards against simultaneous charging and discharging.

On the other hand, (21) model the state of charge of each EV, while inequality (22) guarantees that the EV storage level is always within the allowed range. Equation (23) sets the initial storage level and guarantees at the end of the operating period that the final charge level is the same as the initial level.

Equations (24) and (25) are responsible for limiting the active and reactive power from the DG, respectively. The inequality in (26) details the capacity of DGs to inject or use reactive power according to the system's need. It shows that the solar and wind DGs are capable of operating between a lagging power factor leading power factor, pf_g.

$$P_{g,n,s,h}^{DG,min} \le P_{g,n,s,h}^{DG} \le P_{g,n,s,h}^{DG,max} \tag{24}$$

$$Q_{g,n,s,h}^{DG,min} \le Q_{g,n,s,h}^{DG} \le Q_{g,n,s,h}^{DG,max} \tag{25}$$

$$\begin{aligned} -tan\left(cos^{-1}(pf_g)\right) P_{g,n,s,h}^{DG} \le Q_{g,n,s,h}^{DG} \\ \le tan\left(cos^{-1}(pf_g)\right) P_{g,n,s,h}^{DG} \end{aligned} \tag{26}$$

Due to technical reasons, there are limits placed on purchases of active and reactive power from the grid. Such constraints are set by (27) and (28). For this study, the limits of active power generation are placed at 1,5 times the minimum and maximum limits. The inequality (29) governs the bounds of the amount of reactive power that can be transferred from the grid and is determined by the substation's power factor.

$$P_{\varsigma,s,h}^{market,\,min} \le P_{\varsigma,s,h}^{market} \le P_{\varsigma,s,h}^{market,max} \tag{27}$$

$$Q_{\varsigma,s,h}^{market,min} \le Q_{\varsigma,s,h}^{market} \le Q_{\varsigma,s,h}^{market,max} \tag{28}$$

$$\begin{aligned} -tan\left(cos^{-1}(pf_\varsigma)\right) P_{\varsigma,s,h}^{market} \le Q_{\varsigma,s,h}^{market} \\ \le tan\left(cos^{-1}(pf_\varsigma)\right) P_{\varsigma,s,h}^{market} \end{aligned} \tag{29}$$

IV. Numerical Results

A. Data and Assumptions

The model is tested on the standard IEEE 119-Bus system to simulate and validate the mathematical model defined and explained in the previous section. The system is shown in Fig.2. Two types of DG units are considered which are wind power and solar power. The installed capacity of these units is 1MW in both cases. It is also necessary to describe the data used for the Day-Ahead Market pricing and the TOU tariff pricing. Both can be seen in Fig. 3. and are extracted from the Italian energy market since the scenarios used are extracted from this market. Also considering the case of Italy, the penetration level of EVs is set to 1%, a number below those seen globally, due, among other reasons, to the country's focus on vehicles powered by natural gas [16].

The value assumed for the nominal voltage is 12.66 kV, with a voltage deviation of ±5% in each node. The value of the power factor is 0,95 at the DG units and 0.8 at the substation. EVs charging and discharging rates are identical and set at to 90%. The operating cost of EVs during charging and discharging are 5 €/MWh. Operation costs of solar DG and wind DG units are 40 €/MWh and 20 €/MWh, respectively.

The variability and uncertainty associated with RESs are a major challenge facing the electricity system. One of the issues in the operation of a distribution system is the intermittency of renewable sources, which are related to the variations in power output across time. To account for these factors a reasonably large range of possibilities must be assumed, providing a strong variety of potential scenarios. A scenario can be defined as the evolution or the progression of an uncertain parameter over a given period. In the case of the power demand scenarios, long-term demand profiles based on historical data are considered. Each one of the resulting annual scenarios has 8760 snapshots, where a snapshot refers to a specific hour's demand or generation profile.

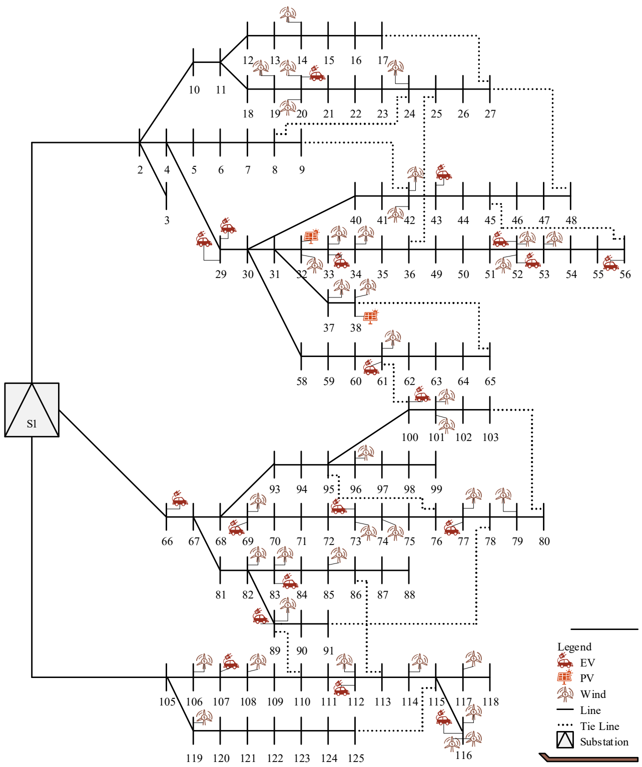

Fig. 1. 119-Bus test system representation.

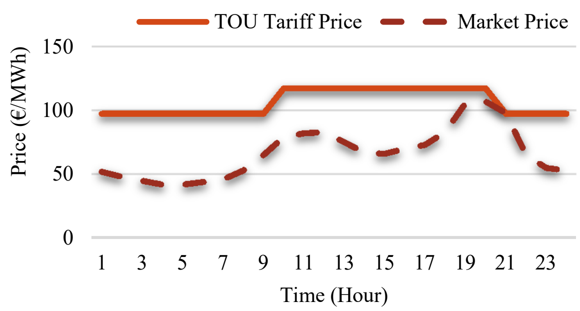

Fig. 2. Time-of-Use Tariff and Day-Ahead Market Price.

To verify the tractability of the problem, this multi-dimensional input data is reduced using the k-means clustering technique which aggregates the snapshots that are more similar, reducing the total number in each scenario. For this study, three different scenarios are considered for the power demand, as well as three different scenarios for solar power production and three different scenarios for wind power generation.

These scenarios are combined to form a set of 27 distinct scenarios, all of them with the same probability of occurring. Importantly, it was verified that considering a larger number of scenarios and all their possible combinations contributes to a more complex matrix. This leads to a higher computational effort, without achieving significant advantages in the final solution. This resulted in 27 scenarios which were reduced using k means techniques as is described in [17].

The model is formulated using GAMS 24.0. The solver used in this paper is CPLEX 12.0. An HP Z820 workstation with two 3.1GHz E5-2687W processors and 256 GB of RAM was used to for the simulations.

B. Discussion of Numerical Results

Three different case studies will be assessed in the analyses:

- Case 1 – Considers that all the power needed to meet the loads will be supplied exclusively by the market;
- Case 2 – Includes the power supplied by the market, as well as the aggregation of RESs-based DGs present in the distribution grid;
- Case 3 – Considers the power obtained from the market, aggregation of power from the DGs and power provided by EVs through V2G operation.

Table I presents the financial results for the TVPP in all three case studies. In the first case, the TVPP schedules only the power provided by the market. In the second case, there is an increase in the total profit of TVPP, with an increase of 45.33% compared to the first case. Similarly, in the third case, there is an increase in the profit of the TVPP by 45.42% compared to the first case and 0,15% compared with the second case. Comparing the three cases, it can be seen that Cases 2 and Case 3 have an increase in revenue from power sold over Case 1 in the order of 1.55% for both cases. Concerning the *TVPPC* there is a decrease of 47.39% in the costs when comparing Case 2 to Case 1. Similarly, there is also a reduction of 47.55% in the costs of Case 3 relative to Case 1 and 0.30% relative to Case 2. Therefore, the presence of aggregation of RESs-based DGs leads to lower costs, which in turn is reflected in an increase in profits. The integration of EVs in Case 3 also contributes to these results in a similar manner, but the magnitude of the effect is lower due to a small percentage of EVs integration.

Studying the generation and demand profiles is an essential part of the flexibility analysis of the system. In this model, the TVPP is organized and aggregates energy to respond to the demand in the day-ahead market, for the various cases considered. With the aggregation of different power sources in the TVPP, the dependence on the market decreases substantially, leading not only to an increase in profit of the TVPP but also to an increase in the flexibility level of the system. The average energy mix (in percentage) for the day-ahead operation of the TVPP for Case 2 is presented in Fig. 4. From this figure, it is possible to calculate an average reduction of 72,55% in the amount of energy needed from the market, in comparison to the first case. The amount of power purchased is reduced from 100% (Case1) to 26,93% of the total. Wind power DG represents the largest share of production, with 66,73% and the remaining 6,34% belong to solar power DG.

Fig. 5 presents the average energy mix for the day-ahead market for the TVPP in Case 3. The aggregation of V2G power in the TVPP, estimated at 0,96%, reducing dependence on the external market and increases the flexibility of the system, with the amount of power purchased being reduced to 26,51% of the total. Wind DG represents 66,18% and the remaining 6,35% belong to solar DG. In this case, it was possible to estimate an average reduction of 73.5% in the amount of energy needed from the market in the first case and 3,30% in the second case. This decrease occurs especially in the periods when EVs are supplying power to the grid, between the 11th and the 22nd hour of the day (as is shown in the black bars of Fig 5).

TABLE I: FINANCIAL RESULTS FOR THE THREE CASES

	Revenue	TVPP Cost	Profit
Case 1	16285.804	44091.619	28498.087
Case 2	29791.099	44783.891	14992.791
Case 3	29836.472	44783.891	14947.419

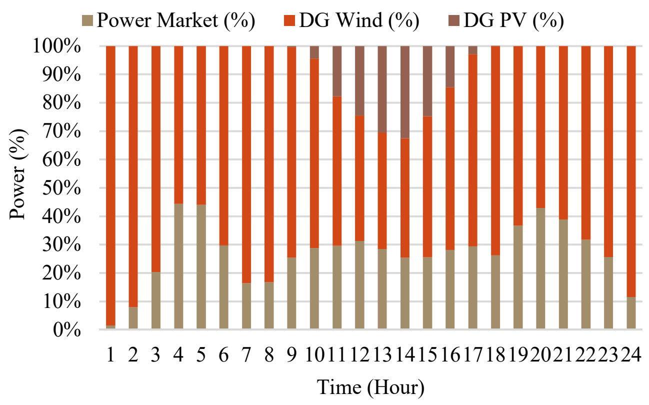

Fig. 3. The energy mix for Case 2.

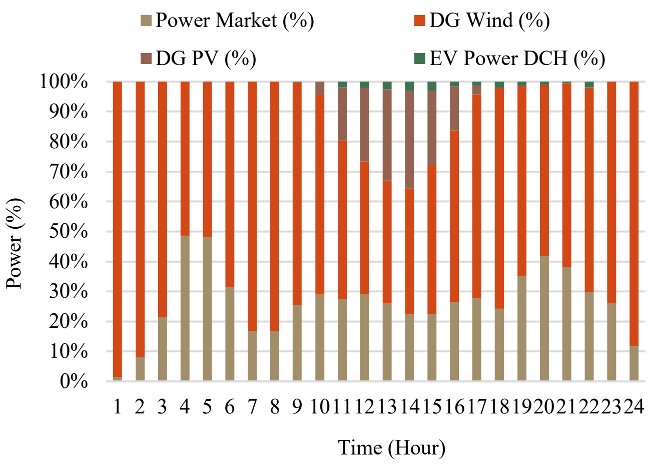

Fig. 4. Energy mix for Case 3.

It is to be expected that the continuous increase in EVs penetration in society will lead to an increase in the available power during discharging, which will mean an increase in the percentage of V2G power and, consequently, an increase in the flexibility of the entire system.

V. CONCLUSIONS

This paper has presented an operational model for a TVPP was developed. This TVPP considered the aggregation of small DERs and diverse energy sources in a specified power generation network. The model was formulated as a stochastic MILP model and was validated through simulations on the IEEE 119–Bus test system, considering the inclusion of DERs as solar power and wind power DG points, and the penetration of EVs that supply power to the distribution system through V2G interface technologies. A linearized AC optimal power flow model was used for the stochastic model. The results show that the use of DERs, in combination with EVs, provides a more efficient use of locally produced renewable generation. This increase in efficiency can also be seen from the economic point of view, where the profit of the TVPP, when these technologies are present, is higher. In general, the results showed that in the context of a TVPP there was an increase in flexibility from the combination of EVs and DERs, making it easier to manage the intermittency of these resources.

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