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Operation of a Technical Virtual Power Plant Considering Diverse Distributed Energy Resources

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***Abstract*—Virtual Power Plants (VPP) have emerged as a way to coordinate and control the growing number of Distributed Energy Resources (DERs) within power systems. Typically, VPP models have focused on financial or commercial outcomes and have not considered the technical constraints of the distribution system. The objective of this paper is the development of a technical VPP (TVPP) operational model to optimize the scheduling of a diverse set of DERs operating in a day-ahead energy market, considering grid management constraints. The effects on network congestion, voltage profiles and power losses are presented and analyzed. In addition, the thermal comfort of the consumers is considered and the trade-offs between comfort, costs and technical constraints are presented. The model quantifies and allocates the benefits of the DER operation to the owners in a fair and efficient manner using the Vickrey Clarke Grove mechanism. This paper develops a stochastic mixed-integer linear programming (MILP) model and various case studies are thoroughly examined on the IEEE 119 bus test system. Results indicate that electric vehicles provide the largest marginal contribution to the TVPP, closely followed by solar PV units. Also, the results show that the operations of the TVPP improve financial metrics and increase consumer engagement while improving numerous technical operational metrics. The proposed TVPP model is shown to improve the ability of the system to incorporate DERs, including those from commercial buildings.**

***Index Terms*—Virtual Power Plant, Flexibility Services, Consumer comfort, Electric Vehicles, Demand Response, Heating Ventilation and Air Conditioning.**

NOMENCLATURE

Set/indices

s/Ω^s	Index/set of scenarios
h/Ω^h	Index/set of hours
g/Ω^g	Index/set of generators
ev/Ω^{ev}	Index/set of electric vehicles
$\varsigma/\Omega^\varsigma$	Index/set of market
l/Ω^l	Index/set of lines
$n,m/\Omega^n$	Index/set of nodes
k/Ω^k $\{r,c,id \in n\}$	Index/set of loads
HVAC$/\Omega^{HVAC}$	Index/set of HVAC system
ω/Ω^ω	Index/set of normal operation

Parameters

g_l, b_l, S_l^{max}	Conductance, susceptance and flow boundaries of each branch l (S, S, MVA)
R_l, X_l	Resistance, Reactance (Ω, Ω)
MP_l, MQ_l	Big-M parameters related with active and reactive power flows over each branch l
ρ_s	Probability of scenario s
OC_g	Cost of unit energy production
λ_h^{TOU}	TOU price associated with customers (€/MWh)
λ_h^{ς}	Day-ahead market price (€/MWh)
λ_h^{ev}	EV discharging cost (€/MWh)
$PD_{s,h}^n$	Demand at node n (MW)
$QD_{s,h}^n$	Reactive demand at node n (MVAr)
V_{nom}	Nominal voltage (kV)
η_{ev}^{ch}	Charging efficiency
η_{ev}^{dch}	Discharging efficiency
$E_{ev,n}^{min}, E_{ev,n}^{max}$	Energy Storage limit
μ_{ev}	Scaling factor
$P_{g,n,s,h}^{DG,min}$, $P_{g,n,s,h}^{DG,max}$	Power generation limits (MW)
pf_g	Power factor of DG's
pf_{ss}	Power factor of substation
$T_{k,n,s,h}^{ideal}$	Ideal temperature set-point in house k (°C).
$P_{HVAC,k,n,s,h}^{cool\_max}$	Actual HVAC unit power consumption of house k in time h
$T_{k,t,n,s,h}^{in}$	Indoor temperature increase with respect to the set-point in house k in period h (°C).
$T_{k,t,n,s,h}^{dec}$	Indoor temperature decrease with respect to the user-selected set-point in house k in period h (°C).
COP_{HVAC}	Coefficient of performance of HVAC in house k.
M_k	Mass of air in household k (kg).
c_{air}	Thermal capacity of air (kJ/kg·°C).
$T_{k,n,s,h}^{initial}$	Initial indoor temperature of household k (°C).
$T_{k,n,s,h}^{Dead-band}$	Dead-band around the temperature set-point for the HVAC unit of house k (°C).
$T_{kt,n,s,h}^{therm}$	Thermostat set-point of house k in period h (°C).

Variables

$P_{\varsigma,n,s,h}^{market}, Q_{\varsigma,s,h}^{market}$	Power purchased from grid (MW, MVAr)
$E_{ev,n,s,h}$	Reservoir level of EV (MWh)
$I_{ev,n,s,h}^{dch}, I_{ev,n,s,h}^{ch}$	Charging and discharging binary variables
$P_{g,n,s,h}^{DG}, Q_{g,n,s,h}^{DG}$	DG power (MW, MVAr)
$P_{\varsigma,n,s,h}^{market}$	Power purchased from market (MW)
P_l, Q_l, θ_l	Active and reactive power flows respectively, and voltage angle difference of branch l (MW, MVAr, radians)
PL_l, QL_l	Active and reactive power lines of each branch l (MW, MVAr)
$x_{l,h}$	Binary variable to indicate line status
$\Delta V_{n,s,h}$	Voltage deviation magnitude (kV)
$P_{HVAC,k,n,s,h}^{cool}$, $Q_{HVAC,k,n,s,h}^{cool}$	Active and reactive power flows of HVAC system
$T_{(t-1)}^{amb}$	Ambient temperature in period h in house k [°C].

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I. INTRODUCTION

In the age of rapidly increasing numbers of Distributed Energy Resources (DERs), the optimal control of these devices to benefit both the owners and the wider electricity distribution is becoming a challenge [1]. Various control strategies for the optimal scheduling of these devices exist, and among those the introduction of a Virtual Power Plant (VPP) has emerged [2]. This VPP is an entity that aggregates the disparate DERs to ensure that they act as a coordinated group in energy markets and has shown promise both in academic research and real-world applications [3]. Typically, VPPs have focused on optimizing the scheduling of DERs to reach some financial or commercial objectives. These types of VPPs are called Commercial Virtual Power Plants (CVPP) and neglect important technical considerations related to the impact of DERs on the physical distribution grid.

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In order to account for these physical impacts, a Technical Virtual Power Plant (TVPP) has emerged [4]. This agent schedules the optimal output level of generators and DERs to meet commercial as well as technical considerations. This increases the feasibility of the proposed schedule of flexible generators as well as controllable loads. This can increase the efficiency, reliability and penetration of these DERs within a given distribution system [5].

Within a given distribution system, there may be a diverse set of consumers, including prosumers who both produce and consume energy. Commercial, industrial, and residential consumers have different load profiles, differing choices of DERs as well as preferences. In order to maximize the ability of this diverse set of consumers and prosumers to engage in the energy sector, optimization models should incorporate various types of consumers. This will help to maximize the potential complimentary effects that may be present and reduce uncertainty or variability during operation. Uncertainty may be introduced into the model through fluctuating load profiles from the consumers or by the output from renewable energy generators, such as solar photovoltaic or wind generation [6].

To deal with this variability, energy storage systems may be used. Using electric vehicles (EVs) as this storage is intriguing as they may have predictable charging requirements, are mobile, and through smart charging the power withdrawn during charging may be modulated to increase during periods of high renewable energy generation or reduce during periods of high system load. These actions may improve the resilience of the network.

Another device that may provide system flexibility within low voltage networks are Heating Ventilation and Air Conditioning (HVAC) systems. These devices may be operated in a controlled manner to reduce peak load or to operate in anticipation of high heating/cooling demand, such as pre-heating an office building during winter. In fact, thermal loads account for between 40% and 46% of energy consumers in commercial buildings [7]. These devices, when aggregated, can offer important sources of flexibility for low voltage networks.

Despite the advantages that the increasing penetration of DERs can bring to power systems, there may also be some disadvantages. These may include power quality issues related to fluctuations in both voltage and frequency profiles [8]. Also, there may be issues related to the bidirectional flow of power within the network which may lead to congestion issues. High numbers of EVs at a certain location without smart charging may dramatically increase the load faced by the system and the intermittent nature of renewable energy sources may also increase reserve requirements to account for rapid increases or decreases of power generation. These issues may be addressed through smart charging of EV's or by improved weather forecasting to reduce the unpredictability of renewable energy sources (RESs) generation or through the use of Demand Response (DR) programs [9]. The technical constraints considered in this paper can be summarized as follows; minimizing the deviations in the voltage profile of the buses, reducing congestion in the lines, and reducing the power losses experienced by the system.

The introduction of DERs in distribution grids can bring either financial benefits or costs to the individual owner as well as the wider range of participants in the grid. These additional benefits or costs may not be accounted for in the initial price of the DER.

Thus, an ex-post allocation mechanism to account for and distribute these costs or benefits to the DER owners in a fair, efficient and equitable manner may be needed. There are many such allocation mechanisms from coalitional game theory including the Vickrey Clarke Grove (VGC) mechanism which has been widely used in power systems and energy markets [10].

Using these mechanisms can ensure that the various impacts are allocated to the individuals who are responsible and thus increase the fairness and equitability of the TVPP. This may help to increase consumer engagement with the TVPP as consumers will be fairly rewarded for actions which benefit the grid such as investing in DERs and enrolling in the TVPP program [11].

II. State of the Art

A. Literature Review

This section presents recent published research which deals with the optimization of energy systems considering DERs from prosumers and VPPs.

Many papers considering VPPs do not consider the technical constraints of the network. For example, the model presented by [12] is a combined energy scheduling and trading model for prosumers but does not consider technical constraints. This model used the principles of transactive energy and results showed an improvement in grid operations via prosumer's participation.

A further example of technical constraints not being considered is shown in the study conducted by [13]. This paper considered the participation of a CVPP in both the day-ahead and intraday energy markets was studied by. Various types of uncertainty were included in the model and notably a penalty function was introduced to minimize the deviation between the day-ahead and intraday dispatch schedules.

An optimization model for the aggregation of prosumers which took network constraints into account was developed by [14]. This model considered a decentralized approach to determine feasible bidding schedules between aggregators of prosumers and the distribution system operator. The objective was to minimize the aggregator's net cost of bidding in both the energy and secondary reserve markets. Uncertainty related to market price, renewable energy generation or electric vehicles was not considered. Results show that by including network constraints in the problem, costs are slightly increased due to penalties for network violations.

Network congestion, an important technical consideration, was included in the energy management framework for prosumers proposed by [15]. The behavior of aggregated prosumers was modeled using a virtual battery model and used to schedule various small-scale resources to minimize the amount of congestion in the network. The results show a reduction in congestion as well as the preservation of consumer privacy within the model. The model relied on EVs as the main source of flexibility and did not consider other distributed energy resources. By introducing these other forms of responsive demand or generation, the network congestion may be reduced further, especially if there are demand response programs used within the model.

In contrast to the above model, the authors of [16] considered other types of DERs but not EVs in their model. The authors aimed to increase flexibility of distribution systems. The objective was to minimize operational costs by the optimal scheduling of various DERs. While this paper considered other DERs it did not consider network constraints.

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TABLE I
A SYNOPSIS OF SURVEYED RELEVANT LITERATURE IN CONTRAST WITH THE CURRENT WORK.

Paper	Type of optimization	Objective function	Types of DERs	Thermal comfort	Allocation mechanisms	Voltage profiles	Congestion issues	Power losses
[12]	MILP	Minimize costs	Solar PV, ESS	No	No	No	No	No
[13]	MILP	Max revenue	Wind, BESS,	No	No	No	No	No
[14]	Alternating direction method of multipliers	Min cost of energy traded	EV, solar PV	No	No	Yes	Yes	No
[15]	Iterative distribution locational marginal price	Max consumer profit	EV, BESS	Yes	No	No	Yes	No
[16]	MILP	Min costs	ESS, wind energy, solar PV	No	No	No	No	No
[4]	MILP	Max TVPP profits, min contingency costs	Solar PV, EV	No	No	No	No	No
[17]	MILP	Max VPP profit	EV	No	No	Yes	No	No
[5]	Robust optimization	Not included	None	No	No	No	No	No
[18]	MILP	Min consumer cost, Min system fluctuations	BESS	No	No	No	No	No
This paper	**MILP**	**Max VPP profit**	**Solar PV, wind, EV, HVAC**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

The vast majority of VPP models neglect technical constraints of the system. However, a model considering a TVPP was formulated by [4] to maximize the profit of the TVPP while minimizing the outage costs due to contingency occurrences. While the constraints of the distribution grid were considered, there was little analysis of the impacts of the TVPP's operation on the grid, such as congestion management, voltage profile fluctuations and losses in the lines. Instead, the model focused on reliability indicators such as expected energy not served, system average interruption frequency/duration indices (SAIFI/ SAIDI) and expected interruption costs (EIC).

A multi-stage stochastic energy management framework for VPPs was developed in [17]. This model used a mixed-integer linear programming (MILP) approach to investigate the impacts of DR and EVs on minimizing the operating costs of a VPP. The technical constraints of the test system were not considered. A model which considered the effects of a TVPP on both active and reactive power flows was proposed by [5]. This model accounted for uncertainty using a robust capability curve and adjustable robust optimization to formulate a two-stage scheduling and optimization problem. In this paper, congestion management, voltage profile fluctuations and line losses were not investigated.

A decentralized model for the optimal scheduling of flexible resources was developed by [18]. This model aimed to meet certain techno-social-economic objectives for the prosumers and ensure the reliability of the grid. Results show that coordinated scheduling of flexible resources reduced the peak load of the system by 83% and increased prosumer costs by 28% relative to a scenario of non-coordinated scheduling. The model did not consider the effects of EVs or RESs. Impacts of the coordinated scheduling on the technical operations of the grid, such as voltage profiles, congestion or power losses were also not considered.

B. Paper Contributions

The objective of this paper is to investigate the ability of a TVPP to positively impact the operation of a distribution system with a high penetration of DERs, considering both technical and economic impacts. This paper addresses this through the use of a three-stage model for the optimal operation of a TVPP. These stages are shown in Fig. 1.

The first stage involves collecting data and accounting for the various forms of uncertainty using scenario decomposition strategies. The second stage deals with the optimal energy management within the distribution system.

The final stage of the model handles the technical constraints of the system and compensates for the uncertain parameters.

From the previous section, it can be seen that there has been significant research carried out on the concept of VPPs but limited research into their technical impacts on the distribution grid. Table I shows how this paper investigates the impacts of a TVPP in a novel manner as the impact of a VPP on power losses, line congestion as well as average voltage profile deviations has not been investigated to the best of the authors knowledge. This investigation can then provide a comprehensive investigation into the effect that a TVPP can have in a distribution system. In addition, very few existing papers consider thermal comfort considerations for a TVPP. Also, only a few papers consider congestion and line losses within the system. In the existing literature, the impact of a VPP on this combination of technical constraints has not been investigated previously, to the best of the authors knowledge. Finally, no paper surveyed quantified and allocated the benefits of DER using allocation mechanisms.

Thus, the paper has the following major contributions:

- A stochastic (MILP) model that considers technical constraints of the network to optimize the scheduling of a diverse set of generators and loads within a distribution system is developed.
- The concept of a TVPP is extended to investigate the technical impacts of aggregating diverse DERs and quantifies the benefit that the TVPP can bring to the system. To the best of the authors knowledge, this is the first time, the impact of a TVPP on the combination of power losses, voltage profiles and line congestion has been studied.
- The benefits of the different types of DERs are quantified. These marginal benefits are allocated in a fair and efficient manner using the VCG mechanism from cooperative game theory. This quantification is important to highlight which DERs can provide the largest benefit to the system.
- The impact of a TVPP on the thermal comfort of building occupants under different HVAC operational strategies is quantified. This quantification allows for an evaluation of the trade-offs between thermal comfort, financial outcomes and technical impacts of different operating strategies of commercial HVAC systems in the presence of DR programs. By providing this information, commercial building managers become more informed of their possible impacts on the larger electrical system.

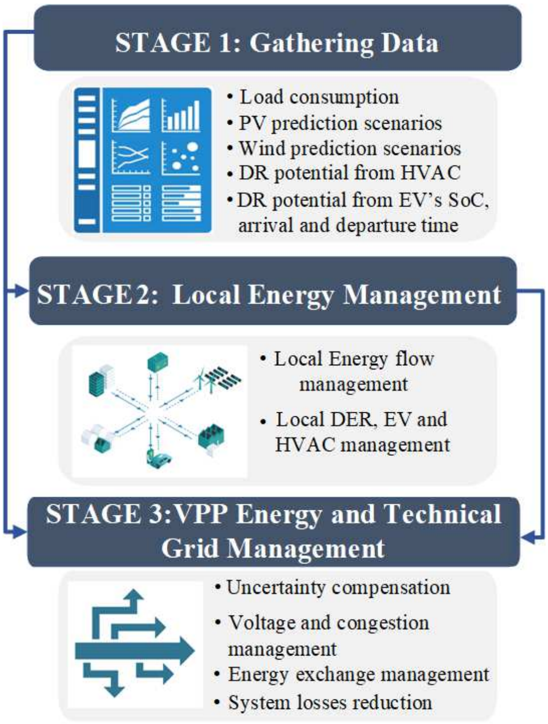

Fig 1: Proposed Three-stage TVPP model.

The work in this paper extends previous research in [8]. This present model introduces the HVAC units and EVs in commercial and service buildings. In addition, this model investigates the impact of TVPP operations on the systems congestion and voltage profiles of the system. Finally, the allocation mechanism used in this paper is also newly introduced. Work carried out in [8] considered the first two stages of Fig. 1 and the complete third stage is a novel introduction.

C. Paper Structure

The rest of the paper has the following structure. Section III contains the mathematical formulation of the model. Section IV presents the details of the case studies investigated and the test system used. The results from the case studies are presented and discussed in detail in Section V. Finally, the conclusions are summarized in Section VI.

III. Mathematical Formulation

A. TVPP Energy Management Model

The stochastic model developed in this paper aims to maximize the TVPP's profit from optimally scheduling various DERs from both residential and commercial consumers. This profit is made up of two terms, revenue from power sold to commercial customers (PSC) and the cost of operating the TVPP (TVPPC) plant while considering the technical and economic constraints. This is shown in (1).

$$Max: \ \sum(PSC - TVPPC) \tag{1}$$

The PSC revenue term is decomposed further in (2). This equation represents each consumer's power consumption from daily loads, EV charging and the usage of HVAC systems. The consumer's power consumption is subject to Time-of-Use (TOU) tariffs.

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

The TVPPC term is shown in (3). These costs include payments to consumer-owned Distributed Generation for electricity produced plus maintenance costs. There are three terms which are subtracted from the operation costs. They are the revenue from power sold in the day-ahead market, revenue from the power sold by discharging EVs and a penalty. The penalty (4) is the price paid to charge EVs or paid to activate the HVAC systems which would not have occurred if the TVPP was not active.

In this model, the control of responsive loads can be performed by the TVPP to achieve the TVPP's goals, but still satisfying the welfare conditions of commercial and service buildings and staff. However, if this control of responsive loads by the TVPP brings additional costs to these buildings, the TVPP pays for the extra cost to the building in the form of a penalty. Therefore, the penalty is the payment to the commercial buildings for the extra cost generated from allowing TVPP to operate the EVs and HVAC.

Therefore, in equations (5)-(6) the EV's penalty term is presented. The penalty is because the TVPP should compensate the surplus cost faced by customers. This cost can be modelled as the difference between customer optimal cost and resulted cost of TVPP's schedule on the charging and discharging cycles of the EVs. This surplus can be interpreted as the incentive paid to customers for participating in energy scheduling of the TVPP.

Customers EVs' Optimal Cost is selected as the optimum cost of each EV introduced in objective function as $Penalty_{ev}$. An independent optimization problem minimizes the following cost function with respect to constraints (9)-(14).

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

$$Penalty = Penalty_{ev} + Penalty_{\,HVAC} \tag{4}$$

$$\begin{aligned} Penalty_{ev} = & \left(\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{k\in\Omega^k}\sum_{ev\in\Omega^{ev}}P_{ev,k,s,h}^{ch}\lambda_h^{TOU}\right. \\ & \left.-\sum_{s\in\Omega^s}\rho_s\sum_{h\in\Omega^h}\sum_{k\in\Omega^k}\sum_{ev\in\Omega^{ev}}\lambda^{ev}P_{ev,k,s,h}^{dch}\right) \\ & -Cost_{ev,\omega}^{NormalOperation} \end{aligned} \tag{5}$$

$$\begin{aligned} & Cost_{ev,\omega}^{NormalOperation} = \\ & \left(\sum_{h\in\Omega^h}\sum_{k\in\Omega^k}\sum_{\omega\in\Omega^\omega}\sum_{ev\in\Omega^{ev}}P_{ev,k,h,\omega}^{ch}\lambda_h^{TOU}\right. \\ & \left.-\sum_{h\in\Omega^h}\sum_{k\in\Omega^k}\sum_{\omega\in\Omega^\omega}\sum_{ev\in\Omega^{ev}}\lambda^{ev}P_{ev,k,h,\omega}^{dch}\right) \end{aligned} \tag{6}$$

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In equations (7)-(8) the HVAC's penalty term is presented. The penalty is due to the fact that the TVPP should compensate the surplus cost faced by customers. This cost can be modelled as the difference between customer optimal cost and resulted cost of TVPP's schedule on the charging and discharging cycles of the HVACs. This surplus can be interpreted as the incentive paid to customers for participating in energy scheduling of the TVPP.

Customers HVAC' Optimal Cost is calculated as the optimum cost of each HVAC introduced in objective function as $\text{Penalty}_{\text{HVAC}}$. An independent optimization problem minimizes the following cost function with respect to constraints (15)-(26).

$$Penalty_{HVAC} = \sum_{s\in\Omega^s} \rho_s \sum_{h\in\Omega^h} \sum_{k\in\Omega^k} \sum_{HVAC\in\Omega^{HVAC}} \lambda_h^{TOU} P_{HVAC,k,s,h}^{cool} - Cost_{HVAC,\omega}^{NormalOperation} \quad (7)$$

$$Cost_{HVAC,\omega}^{NormalOperation} = \sum_{h\in\Omega^h} \sum_{k\in\Omega^k} \sum_{\omega\in\Omega^\omega} \sum_{HVAC\in\Omega^{HVAC}} \lambda_h^{TOU} P_{HVAC,k,h,\omega}^{cool} \quad (8)$$

EVs are modelled by the expressions (9)-(14). The maximum charging and discharging rates are governed by (9) and (10) respectively while (11) ensures that charging or discharging cannot occur simultaneously.

$$0 \leq P_{ev,k,n,s,h}^{ch} \leq I_{ev,k,n,s,h}^{ch} P_{ev,k,n,h}^{ch,max} \quad (9)$$

$$0 \leq P_{ev,k,n,s,h}^{dch} \leq I_{ev,k,n,s,h}^{dch} P_{ev,k,n,h}^{ch,max} \quad (10)$$

$$I_{ev,k,n,s,h}^{ch} + I_{ev,k,n,s,h}^{ch} \leq 1 \quad (11)$$

$$E_{ev,k,n,s,h} = E_{ev,k,n,s,h-1} + \eta_{ev}^{ch} P_{ev,k,n,s,h}^{ch} - \frac{P_{ev,k,n,s,h}^{dch}}{\eta_{ev}^{dch}} \quad (12)$$

$$E_{ev,k,n}^{min} \leq E_{ev,k,n,s,h} \leq E_{ev,k,n}^{max} \quad (13)$$

$$E_{ev,k,n,s,h0} = \mu_{ev} E_{ev,n}^{max};\; E_{ev,k,n,s,h24} = \mu_{ev} E_{ev,n}^{max} \quad (14)$$

The state of charge (SoC) of the EV is modelled in (12) and relies on the SoC of the previous period plus any additional charging and minus any discharging. Inequality (13) ensures that the storage level is always within a permissible range, and (14) sets the initial storage level and requires that the EV returns to this initial SoC at the end of the operational period.

For simplicity, both η_{ev}^{ch} and η_{ev}^{dch} are set to be equal and are expressed as a percentage, depending on the node where the EVs are connected.

HVAC systems are modelled by expressions (15)-(26) which were obtained from [19]. The maximum and minimum temperature limits are set by (15) while (16) bounds the HVAC power use. This model utilizes a thermal resistance model which uses the cooling operation of the HVAC system and is shown in (17). The initial temperature is defined by (18). Equation (22) minimizes the discomfort level of the consumers. Equations (23) and (24) set the upper and lower limits of HVAC operation. The non-negativity constraints for the decision variable are shown in (25) and (26).

$$T_{HVAC,k}^{min} \leq T_{k,n,s,h}^{ideal} \leq T_{HVAC,k}^{max} \quad (15)$$

$$0 \leq P_{HVAC,k,n,s,h}^{cool} \leq P_{HVAC,k,n,s,h}^{cool\_max} \quad (16)$$

$$T_{kt,n,s,h}^{in} = (1 - \frac{\Delta T}{1000\,.\,M_k\,.\,c_{air}\,.\,R_k}) \,.\, T_{k(t-1),n,s,h}^{in} + \frac{\Delta T}{1000\,.\,M_k\,.\,c_{air}\,.\,R_k} \,.\, T_{(t-1)}^{amb} - \frac{COP_{HVAC}}{0{,}000277\,.\,M_k\,.\,c_{air}} \,.\, P_{HVAC,k,n,s,h}^{cool} \;,\; \forall\, k, t > 1 \quad (17)$$

$$T_{kt0,n,s,h}^{in} = T_{k,n,s,h}^{initial} \;,\forall\, k \quad (18)$$

$$P_{HVAC,k,n,s,h}^{cool} = u_{kt,n,s,h} \,.\, P_{HVAC,k,n,s,h}^{cool} \;,\forall\, k, t \quad (u = 0\; OFF, u = 1\; ON) \quad (19)$$

$$T_{kt,n,s,h}^{in} \;\forall\, k, t \in \underset{T_{kt,n,s,h}^{in}, T_{kt,n,s,h}^{dec}, T_{kt,n,s,h}^{therm}, T_{kt,n,s,h}^{in}}{argmin} \Big\{ \frac{1}{N_k} \,.\, \sum_{s\in\Omega^s} \sum_{h\in\Omega^h} \sum_{k\in\Omega^k} (T_{kt,n,s,h}^{in} + T_{kt,n,s,h}^{dec}) \quad (20)$$

subject to:

$$T_{kt,n,s,h}^{therm} \leq T_{kt,n,s,h}^{ideal} + T_{kt,n,s,h}^{in} \;,\forall\, k, t \quad (21)$$

$$-\,T_{kt,n,s,h}^{therm} \leq T_{kt,n,s,h}^{dec} - T_{kt,n,s,h}^{ideal} \;,\forall\, k,\; t \quad (22)$$

$$T_{kt,n,s,h}^{in} \leq T_{kt,n,s,h}^{therm} + T_{k,n,s,h}^{Dead-band} \;,\forall\, k, t \quad (23)$$

$$-T_{kt,n,s,h}^{in} \leq T_{k,n,s,h}^{Dead-band} - T_{kt,n,s,h}^{therm} \;,\forall\, k, t \quad (24)$$

$$-T_{kt,n,s,h}^{dec} \leq 0 \;,\forall\, k, t \quad (25)$$

$$-T_{kt,n,s,h}^{in} \leq 0 \;,\forall\, k, t \;\Big\} \quad (26)$$

Kirchhoff's Current law governs the flows of current into and out of a node. This is applied to the active power flow in (27) and the reactive power flows in (28). In these equations $P_{l,s,h}$ and $Q_{l,s,h}$ represent the active and reactive power flow in the line respectively, and $PD_{s,h}^{n}$ and $QD_{s,h}^{n}$ represent the active and reactive demand at the nodes, respectively. $PL_{l,s,h}$ and $QL_{l,s,h}$ represent the active and reactive power losses in the line, respectively.

$$\sum_{g\in\Omega^g} P_{g,n,s,h}^{DG} + \sum_{k\in\Omega^k} \sum_{ev\in\Omega^{ev}} \left(P_{ev,k,n,s,h}^{dch} - P_{ev,k,n,s,h}^{ch}\right) + P_{\varsigma,s,h}^{market} + \sum_{in,l\in\Omega^l} P_{l,s,h} - \sum_{out,l\in\Omega^l} P_{l,s,h} = \left(PD_{s,h}^{n} + P_{HVAC,k,n,s,h}^{cool}\right) + \sum_{in,l\in\Omega^l} \frac{1}{2} PL_{l,s,h} + \sum_{out,l\in\Omega^l} \frac{1}{2} PL_{l,s,h} \;;\; \forall \varsigma \in i \quad (27)$$

$$\sum_{g\in\Omega^g} Q_{g,n,s,h}^{DG} + Q_{\varsigma,s,h}^{market} + \sum_{in,l\in\Omega^l} Q_{l,s,h} - \sum_{out,l\in\Omega^l} Q_{l,s,h} = \left(QD_{s,h}^{n} + Q_{HVAC,k,n,s,h}^{cool}\right) \quad (28)$$

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$$+ \sum_{in,l\in\Omega^l} \frac{1}{2} QL_{l,s,h} + \sum_{out,l\in\Omega^l} \frac{1}{2} QL_{l,s,h} \forall\varsigma \in i$$

Inequalities (29) and (30) present linearized AC power flows through each feeder, which are governed by Kirchhoff's Voltage Law. Note that $\theta l,s,h$ refer to the angle difference $\theta n,s,h - \theta m,s,h$ where n and m are bus indices corresponding to the same line l, based on [20].

The big-M formulation was used, set to the maximum transfer capacity, to avoid the non-linearity.

$$\left|P_{l,s,h} - (V_{nom}\left(\Delta V_{n,s,h} - \Delta V_{m,s,h}\right)g_l - V_{nom}^2 b_l \theta_{l,s,h}\right| \leq MP_l \quad (29)$$

$$\left|Q_{l,s,h} - (-V_{nom}\left(\Delta V_{n,s,h} - \Delta V_{m,s,h}\right)b_l - V_{nom}^2 g_l \theta_{l,s,h}\right| \leq MQ_l \quad (30)$$

The maximum amount of flow that can pass through a line is given by inequality (31).

Equations (32) and (33) represent active and reactive power losses in each line l.

$$P_{l,s,h}^2 + Q_{l,s,h}^2 \leq \chi_{l,h} (S_l^{max})^2 \quad (31)$$

$$PL_{l,s,h} = R_l\left(P_{l,s,h}^2 + Q_{l,s,h}^2\right) / V_{nom}^2 \quad (32)$$

$$QL_{l,s,h} = X_l\left(P_{l,s,h}^2 + Q_{l,s,h}^2\right) / V_{nom}^2 \quad (33)$$

The active and reactive power limits of the DGs are given by (34) and (35), respectively.

Inequality (36) limits the DGs ability to inject or consume reactive power.

$$P_{g,n,s,h}^{DG,min} \leq P_{g,n,s,h}^{DG} \leq P_{g,n,s,h}^{DG,max} \quad (34)$$

$$Q_{g,n,s,h}^{DG,min} \leq Q_{g,n,s,h}^{DG} \leq Q_{g,n,s,h}^{DG,max} \quad (35)$$

$$-\tan\left(cos^{-1}(pf_g)\right) P_{g,n,s,h}^{DG} \leq Q_{g,n,s,h}^{DG} \leq tan\left(cos^{-1}(pf_g)\right) P_{g,n,s,h}^{DG} \quad (36)$$

For stability reasons, the active and reactive power limits at the substations are given by (37) and (38).

$$P_{\varsigma,s,h}^{market,min} \leq P_{\varsigma,s,h}^{market} \leq P_{\varsigma,s,h}^{market,max} \quad (37)$$

$$Q_{\varsigma,s,h}^{market,min} \leq Q_{\varsigma,s,h}^{market} \leq Q_{\varsigma,s,h}^{market,max} \quad (38)$$

The reactive power that is withdrawn from the substation is subject to the bounds presented in inequality (39).

$$-\tan\left(cos^{-1}(pf_{ss})\right)P_{\varsigma,s,h}^{market} \leq Q_{\varsigma,s,h}^{market} \leq tan\left(cos^{-1}(pf_{ss})\right)P_{\varsigma,s,h}^{market} \quad (39)$$

Equation (40) requires that all nodes with a demand at hour h are connected and have a single input flow through line l. The inequality shown in (41) places an upper bound of 1 input flow for the terminal nodes.

$$\sum_{l\in\Omega^l} \chi_{l,h} = 1, \forall m \in \Omega^k; l \in n \quad (40)$$

$$\sum_{in,l\in\Omega^l} \chi_{l,h} - \sum_{out,l\in\Omega^l} \chi_{l,h} \leq 1, \forall m \notin \Omega^k; l \in n \quad (41)$$

B. Allocation Mechanism

The Vickrey-Clark-Groves (VCG) mechanism is a commonly used mechanism within cooperative game theory [20]. This mechanism is an efficient way to ensure that the dominant strategy within a cooperative game is for the individuals to act in a truthful manner.

The outcome of this mechanism a set of truthful private valuations submitted by the agents (the set of agent's valuations are given by $\tilde{v}=\{\tilde{v}_1,\ldots,\tilde{v}_n\}$). This mechanism allows the first-best outcome to be implemented.

This mechanism ensures that the DER owner i receives a monetary transfer equal to the true marginal contribution of that DER to the distribution system. Formally, the transfer ti that agent i receives is described by (42):

$$t_i(\tilde{v}) = \sum_{j\neq i} \tilde{v}_j(f^*(\tilde{v})) - \sum_{j\neq i} \tilde{v}_j(f^*(\tilde{v}_{-i})) \quad (42)$$

The VCG mechanism is used in this model to accurately quantify and allocate the benefits provided by the various types of DERs to the system in such a manner which provides a fair and efficient valuation of the DER's contribution to the TVPP.

IV. System Layout and Case Studies considered

In this section, the layout of the test system and assumptions used in the model are presented. Following this, the various case studies are discussed.

A. System Layout

In this work, the 119-bus test system is used to perform the numerical analysis. The system has a nominal voltage of 11 kV and demand of 22709.72 kW and 17041.068 kVAr [21]. The size and location of RESs, and also the power factor of RESs, are all taken from [21].The type of DG units and the buses to which it is connected, as well as the points of interconnection between the EVs parking lots and HVAC systems and the network, are also shown in Fig. 2 and are taken from [21]. Two types of DG units are considered as illustrated: wind power and solar power.

The installed capacity of these units is 1 MW in both cases. EV characteristics are taken from [8] and the initial value of the SoC is either 50% or 62.5% depending on the individual EV in the EV parking lot. The solar and wind plants are modeled using a set of scenarios to represent the power generated while accounting for uncertainty in the output. These scenarios are derived from real-data taken from [21].

The correlations between solar irradiation, wind speed and demand were considered during scenario generation. This was done to ensure that the generated scenarios closely resemble real-world conditions. Between solar irradiation and wind speed a correlation factor of -0.3 was used. The correlation between wind speed and demand was 0.28 and a correlation factor of 0.5 was used for the relationship between solar irradiation and demand [20]. These factors were used to derive new wind and solar production profiles using Cholesky factorization as was done in [20].

There are three sources of uncertainty, solar generation, wind generation and demand. Three scenarios for each parameter were developed. This resulted in 27 scenarios (three scenarios for each parameter or 3x3x3) which were reduced using k-means clustering techniques as is described in [20]. In addition to the above, the following assumptions and system data are also considered:

- A time horizon of 24 hours is considered;
- In each node a voltage deviation of ±5% is considered;
- The reference node is the substation, with a voltage magnitude set to 1 p.u. and the angle to 0°;
- The value of the power factor of the DG units is 0.95 and the substation is 0.8, both inductive;
- EVs rates of charge and discharge of energy are considered the same and equal to 90%;

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- The operation cost of EVs during charge and discharge is 5 €/MWh;
- The EVs discharge cannot go below 40% of their total load capacity;
- The operation cost of solar DG units is 18.24 €/MWh [22];
- The operation cost of wind DG units is 13.2 €/MWh [23]
- Commercial buildings can also charge EVs at night;
- Optimization for usage during a summer period for a location in Southern Europe.

Commercial and service buildings (hospitals) are distributed throughout the network and are fed through nodes 20, 33, 43, 69, 77, 83, 108 and 112. The demand profile for each type of consumer at each node is obtained from [24].

Each one of these customers have HVAC and EVs units, with each EV park having 25 cars. EVs are to charge at the period with the lowest electricity purchase price, considering demand response. The arrival and departure times for the EVs are sourced from [25]. In this distribution network, there are different line capacities depending on the line's location. These are 500 kVA, 800 kVA and 1200 kVA. In those lines closer to the substation, the line capacities are higher.

B. Case Studies Considered

The developed work was based on four case studies. The first case uses the external grid to meet the demands of the system. This is a benchmark case to examine the various effects of the latter case studies. The second case allows for the aggregation of distributed RES systems (solar PV and wind) to meet a portion of the demand in addition to the external grid. In addition, the impacts of DR, through a TOU tariff (shown in Table II), are investigated. The TOU rate is sourced from [26].

The third case study investigates the potential of EVs and commercial HVAC systems to increase the flexibility of the system. This case investigates the possibility of the EVs to act as mobile energy storage systems to help support the grid's operation in cases where there is a sudden drop off in the generation from RES generators. The case study considers the power purchased from the market and the aggregation of power from the EVs, HVAC use in commercial buildings, and DR flexibility with no generation from RES units.

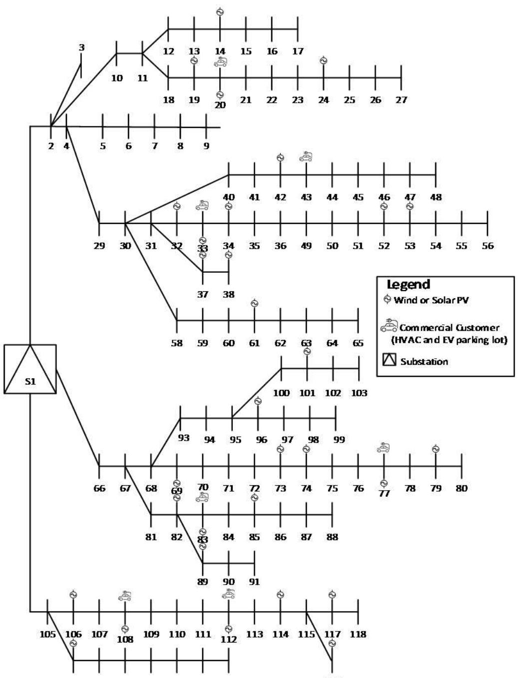

Fig. 2: Layout of test system used.

TABLE II
TOU TARIFFS USED

Time	Tariff (€/MWh)
10:00-21:00	61.27
21:00-10:00	40.36

The fourth case study extends Case 3 by including RES generation to the EVs and HVAC systems to examine the combined impact of these technologies on the technical and economic performance of the TVPP. This case study considers the power purchased from the market, the aggregation of power from the DGs, and the aggregation of power provided by a variety of sources such as EVs through Vehicle-to-grid (V2G) interface technologies, HVAC use in commercial buildings, and DR flexibility through the ToU tariff. In this final case, the variation of the temperature range in commercial buildings is assessed.

The model is programmed in GAMS 24.0 and solved using the CPLEX 12.0 solver. The simulations are conducted on an HP Z820 workstation with two 3.1 GHz E5-2687W processors and 256 GB of RAM with a CPU time of 1200s.

V. RESULTS AND DISCUSSION

A. Impact of TVPP on Profits

The revenues from the power sold to the consumers, the operating costs of the TVPP and the final profit of the TVPP for all case studies are shown in Table III. From the table, it can be seen that as more DERs are added to the system, such as solar PV, wind, EVs and HVAC units, the profit of the TVPP increases. This increase is mainly due to the reduction in operating costs as the revenue of the TVPP largely remains constant. This cost reduction is due to numerous factors such as increased local generation which is cheaper than the external grid and smart scheduling of the EV charging and HVAC operation to minimize use during periods of high TOU tariffs.

Table III shows that there is a 48% reduction in the costs of operation when DER are included (case 2) in the system compared to the Case 1. When EVs and HVAC units are added to the DERs (Case 4), costs are reduced by 56% relative to the base case. In terms of profits, Case 2 sees a 94% increase in profits compared to Case 1. When all DERs are included (Case 4), profits increase to € 32026.23. The energy mix of Case 4 is shown in Fig. 3. The contributions of the DERs (wind, solar and V2G) are shown. The charging demand of EVs is also shown. It can be seen that there is a large amount of EV charging during the early hours of the morning and then a slight increase when the solar PV units are generating.

There is a decrease in the EV charging during the peak periods in the evening. Importantly, the implementation of a TOU ensures that there is a reduction in the load during peak hours. If this DR program was not included, we may see an increase in the peak load during the evening as a result of EV charging. This will bring extra costs to the consumers and negatively impact the network.

B. Marginal Contribution of DER Assets

This section investigates the marginal contribution of each DER asset type to the overall profit of the TVPP according to the VCG mechanism. By quantifying the contribution of each DER type, appropriate compensation may be paid to the owners of the DER may be made so that the owners are incentivized to participate in the TVPP.

By using the VCG mechanism, it is ensured that the DERs with the largest positive impact to the TVPP are compensated in a fair and efficient manner.

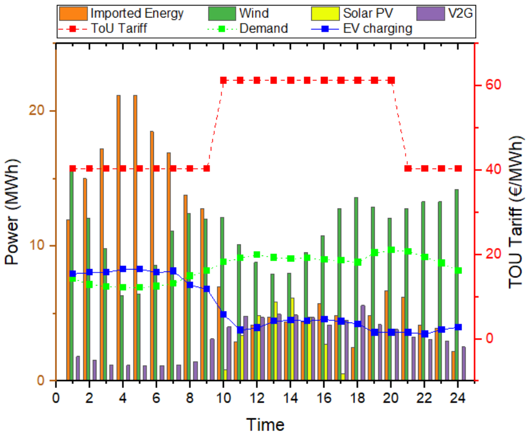

Fig. 3: Energy mix for Case 4.

TABLE III
FINANCIAL COMPARISON BETWEEN TWO CASE STUDIES

	Revenue (€)	Costs (€)	Profit (€)
Case 1	44091.62	28849.79	15241.83
Case 2	44517.26	14992.79	29524.47
Case 3	44143.67	16989.28	27154.38
Case 4	44783.89	12757.65	32026.23

This is important to understand as DER assets may include significant investment costs and the choice of the allocation of capital to these DER assets are a significant factor in the optimal operation of a TVPP agent.

The marginal contribution of the DERs assets to the profit of the TVPP is shown in Table IV. This table shows that EVs can provide the biggest impact to the TVPP operation. This is due to their ability to both absorb and provide power to the TVPP during different times. The ability of the EVs to provide proper power compensation is limited by the size of the battery. HVAC units do not provide significant technical benefits however, they provide important sources of thermal comfort control for commercial buildings and thus are important for the TVPP. HVAC units may also provide important peak reduction services.

C. Technical Impact of TVPP

In this optimization model, the technical constraints of the distribution system are accounted for. These include the capacities of the lines within the system. Table V shows the instances where line loads are exceeded in Case 1 and how the subsequent cases helped reduce or eliminate instances where the line load capacities were exceeded.

In the Case 1 there are 19 instances where the load exceeds the rated line capacity. In Case 2, there are three instances. Case 3 sees 15 instances and in Case 4 the rated line capacities are not exceeded at all. In Case 3, only the EVs and HVAC units are operating. The ability of the EVs to offer power compensation is limited due to their size. This is the reason for the relatively high number of line capacities being exceeded.

Another important technical constraint to consider in the system management is the voltage profile of the nodes within the network. The voltage profile of the buses across the study period is an important metric in terms of reliability of the system. The voltage profiles for all nodes across the 24-hour period for Case 1 is shown in Fig. 4.

In contrast to Fig. 4, the results of the nodal voltage profile seen in Case 4 are shown in Fig. 5. In this case study, the profile of the nodal voltages has been greatly improved. The improvements to the voltage profile are due to the presence of the DG units as they generate power locally which improves the voltage of the local nodes.

The DG units also tend to be located near the end of a line which improves the voltage profile. The largest voltage drops are seen in those nodes located at end nodes of the feeders which can be seen from the grid topology.

The average voltage deviations for each node over the 24-hour period for Case 4 are shown in Fig 6. The figure shows the pu deviation in the voltage profile from the nominal voltage of 11 kV and there are no instances of the voltage profile exceeding the 0.05 pu threshold.

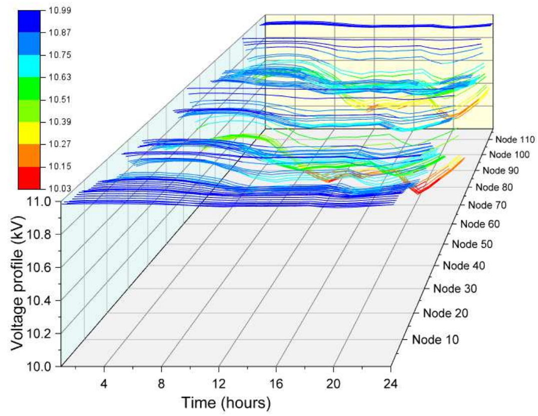

Fig. 4: Voltage profile for Case 1.

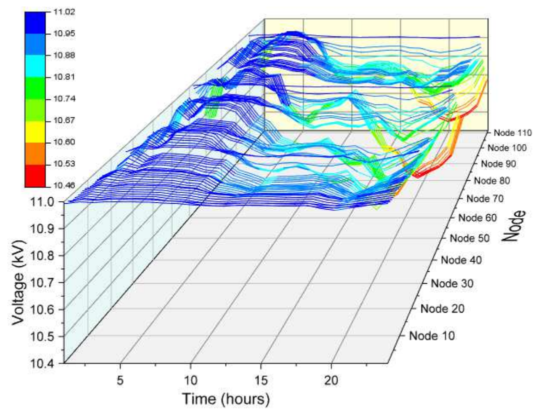

Fig. 5: Voltage profile for Case 4.

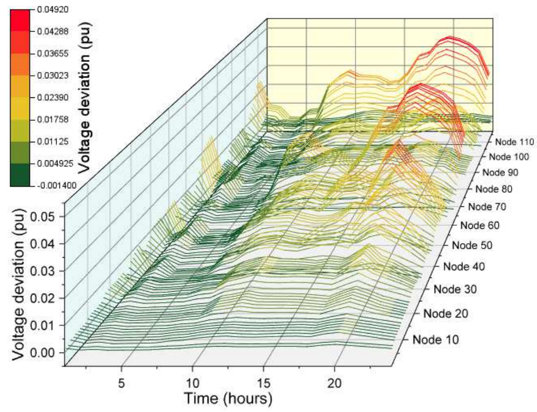

Fig. 6: Voltage deviation for Case 4.

TABLE IV
ALLOCATION OF MARGINAL DER BENEFITS

DER Type	Contribution (%)
Solar PV	36
Wind	18
Electric vehicles	39
HVAC units	7

TABLE V
LINE CONGESTION

Line	Case 1 (MVA)	Case 2 (MVA)	Case 3 (MVA)	Case 4 (MVA)
Line 1	35.03	0.00	9.42	0.00
Line 30	27.66	0.00	0.00	0.00
Line 41	30.56	0.00	0.00	0.00
Line 57	10.98	0.00	10.98	0.00
Line 62	42.12	0.45	29.79	0.00
Line 63	62.65	0.00	44.14	0.00
Line 66	53.16	0.00	53.16	0.00
Line 67	82.35	22.35	82.35	0.00
Line 68	41.09	0.00	41.09	0.00
Line 69	41.09	0.00	41.09	0.00
Line 77	9.44	0.00	0.00	0.00
Line 88	44.86	0.00	0.00	0.00
Line 99	48.94	0.00	8.47	0.00
Line 101	17.02	0.00	17.02	0.00
Line 102	57.45	0.00	57.45	0.00
Line 105	75.64	0.00	75.64	0.00
Line 106	0.63	0.63	0.63	0.00
Line 107	0.63	0.00	0.63	0.00
Line 109	44.24	0.00	25.71	0.00

In addition to the congestion and voltage profile of the system, the power losses were also investigated for all four test cases. The losses experienced by the system across the four cases are shown in Table VI. There is a significant decrease in the losses in Case 2, Case 3, and Case 4. Most significantly, the reduction in losses in Case 2 and Case 4 are due to the presence of the solar PV and wind generators. These local generators help to reduce the losses as they are positioned closer to the demand and thus there are fewer losses in the distribution lines.

D. Impacts of EV Aggregation

In Case 3 and Case 4, EVs and HVAC units in commercial and service buildings were included. Electric vehicles have limited ability to provide power compensation so the EVs had a small impact on the voltage deviations. They were able to charge and discharge according to the system demand and ToU pricing. This is shown in Fig. 7, which shows the active power discharge from the EV aggregators. This Figure only shows the active power discharge and does not show the charging of the EVs which typically occur between 21:00 and 07:00.

The impacts of the TOU tariff are clear to see as there is significant V2G power provided by the EVs during the evening peak periods, between 19:00 and 21:00. This Figure shows the ability of EVs in parking lots equipped with V2G services to contribute to meeting system load balancing requirements and their potential in DR programs. The aggregated charging demand of the various EV aggregators is shown in Fig. 8. This Figure shows that there is very little charging demand during the peak TOU period between 10:00 and 20:00. Only EV aggregator 1 has significant charging which can be explained as this is the aggregator located at the hospital and there exists a minimum demand for EV charging throughout the day.

E. Impacts of HVAC due to Changing Thermal Comfort

In addition to including the effects of EVs in Case 3 and Case 4, HVAC units were also included in these cases. These HVAC units were optimized to respond to the DR program (TOU tariffs) to reduce demand during high demand periods while maintaining the thermal comfort of the consumers within the commercial buildings. There exist trade-offs between thermal comfort of consumers and the amount of flexibility that HVAC units can provide to the system. Stricter thermal comfort requirements will mean that the HVAC units need to operate for longer periods and possibly in high demand periods which have high TOU tariffs.

TABLE VI
SYSTEM LOSSES ACROSS THE FOUR CASES

Case Number	Losses (MWh)
Case 1	20.25
Case 2	9.38
Case 3	14.11
Case 4	6.16

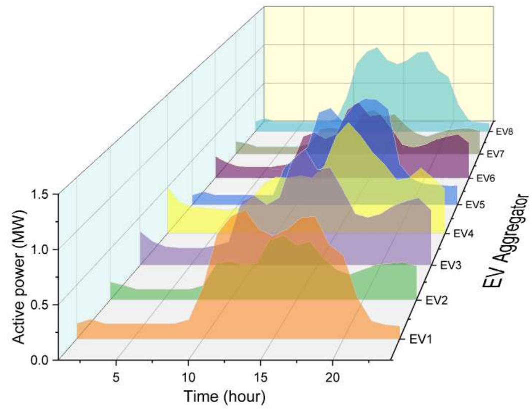

Fig. 7: Aggregated V2G power from EVs.

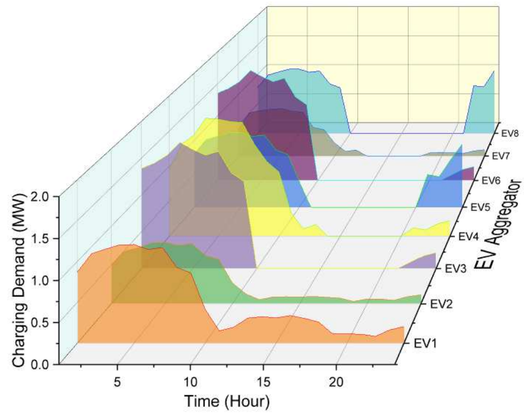

Fig. 8: Aggregated charging demand from EVs.

The three thermal comfort bands are a wide range of 18° and 24°, a standard band of 19° to 23°, and a narrow band of 20° to 22°. This is shown in Fig. 9 that compares the operation of HVAC units within the model with three different thermal comfort requirements. In the narrow thermal operating band, due to stricter operating constraints of the commercial HVAC system and the ToU tariff, the costs of operating the HVAC units increased, therefore there was no HVAC operation during peak times (19:00 and 21.00). In the narrow thermal comfort band, HVAC power demands increased by 13.11% relative to the standard thermal cases in Southern Europe. Despite this increase in power demand, there were no significant technical impacts on the distribution grid. This shows that there is a trade-off between thermal comfort and operating costs but no significant trade-off between thermal comfort and technical aspects of the grid. Due to the DR program, there is a large amount of power used by the HVAC systems at 18:00 in order to pre-cool the buildings, which reduces the need for HVAC use during peak periods (20:00 and 21:00). Fig. 9 shows the ability of HVAC units in commercial and service buildings to contribute to DR programs while maintaining thermal comfort.

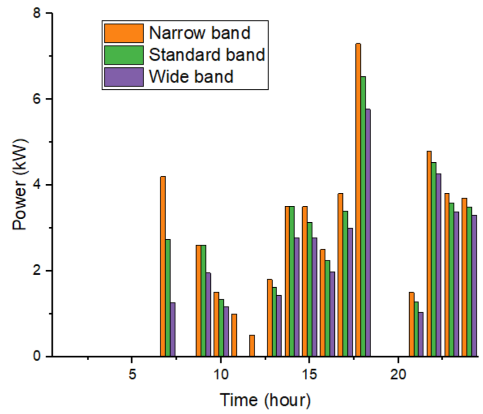

Fig. 9: HVAC power use.

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VI. Conclusions

This paper has shown that, while the technical constraints of the distribution network have rarely been considered in VPP models, VPPs have positive technical benefits to the distribution grid. These impacts were evaluated by developing a stochastic mixed integer linear programming model for a VPP operating in a distribution system with a number of consumers. The TVPP optimized the generation of a number of DERs to maximize its profit when bidding into a day-ahead energy market. Through this optimization, results have shown an increase in system flexibility, increased consumer engagement and increased RES generation, while maintaining consumer thermal comfort requirements. Line losses were reduced by nearly 70% because of the model. The worst performing node, Bus 79, saw a 66% reduction in voltage deviations. Results show that the TVPP reduces operating costs and increases the revenue from the energy sold in the system. Costs saw a maximum reduction of 56% relative to the base case. These outcomes are combined to increase the profits of the TVPP. The benefits of the various types of DERs have been quantified and can be allocated to the owners of the DERs. This analysis shows that EVs have the largest marginal contribution to the profit of the TVPP, followed by solar PV systems, and then wind turbines. Therefore, various types of DERs can complement each other and a diverse set of DERs operating within a TVPP provides the best outcome for the TVPP operator in terms of both financial and technical outcomes. Different comfort preferences were investigated for the HVAC operation by changing the allowable limits of indoor temperature. These results showed a clear trade-off between consumer comfort and cost savings. However, there was no significant trade-off between thermal comfort and technical impacts in the system. Overall, the results showed the numerous benefits that a TVPP can bring to a distribution grid, including increased financial performance, improved technical operations, improved energy efficiency and enhanced environmental outcomes.

References

[1] Z. Ullah, G. Mokryani, F. Campean, and Y. F. Hu, "Comprehensive review of VPPs planning, operation and scheduling considering the uncertainties related to renewable energy sources," *IET Energy Syst. Integr.*, vol. 1, no. 3, pp. 147–157, 2019.

[2] A. Baringo, L. Baringo, and J. M. Arroyo, "Day-Ahead Self-Scheduling of a Virtual Power Plant in Energy and Reserve Electricity Markets under Uncertainty," *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 1881–1894, 2019.

[3] M. Di Somma, G. Graditi, and P. Siano, "Optimal Bidding Strategy for a DER Aggregator in the Day-Ahead Market in the Presence of Demand Flexibility," *IEEE Trans. Ind. Electron.*, vol. 66, no. 2, pp. 1509–1519, Feb. 2019.

[4] N. Pourghaderi, M. Fotuhi-Firuzabad, M. Kabirifar, M. Moeini-Aghtaie, M. Lehtonen, and F. Wang, "Reliability-Based Optimal Bidding Strategy of a Technical Virtual Power Plant," *IEEE Syst. J.*, pp. 1–12, 2021.

[5] Z. Tan, H. Zhong, Q. Xia, C. Kang, X. S. Wang, and H. Tang, "Estimating the Robust P-Q Capability of a Technical Virtual Power Plant Under Uncertainties," *IEEE Trans. Power Syst.*, vol. 35, no. 6, pp. 4285–4296, Nov. 2020.

[6] J. Naughton, H. Wang, M. Cantoni, and P. Mancarella, "Co-optimizing Virtual Power Plant Services Under Uncertainty: A Robust Scheduling and Receding Horizon Dispatch Approach," *IEEE Trans. Power Syst.*, pp. 1–1, 2021.

[7] J. T. Cousins and T. E. Solutions, *Using Time Of Use (Tou) Tariffs In Industrial, Commercial And Residential Applications Effectively.*

[8] M. Gough *et al.*, "Optimization of Prosumer's Flexibility Taking Network Constraints into Account," in *2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe*, Madrid, Spain, Jun. 2020, pp. 1–6.

[9] W. Wang, P. Chen, D. Zeng, and J. Liu, "Electric Vehicle Fleet Integration in a Virtual Power Plant With Large-Scale Wind Power," *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 5924–5931, Sep. 2020.

[10] P. G. Sessa, N. Walton, and M. Kamgarpour, "Exploring the Vickrey-Clarke-Groves Mechanism for Electricity Markets," *IFAC-Pap.*, vol. 50, no. 1, pp. 189–194, Jul. 2017.

[11] L. F. M. van Summeren, A. J. Wieczorek, G. J. T. Bombaerts, and G. P. J. Verbong, "Community energy meets smart grids: Reviewing goals, structure, and roles in Virtual Power Plants in Ireland, Belgium and the Netherlands," *Energy Res. Soc. Sci.*, vol. 63, p. 101415, May 2020.

[12] M. Khorasany, A. Najafi-Ghalelou, and R. Razzaghi, "A Framework for Joint Scheduling and Power Trading of Prosumers in Transactive Markets," *IEEE Trans. Sustain. Energy*, vol. 12, no. 2, pp. 955–965, Apr. 2021.

[13] H. T. Nguyen, L. B. Le, and Z. Wang, "A Bidding Strategy for Virtual Power Plants With the Intraday Demand Response Exchange Market Using the Stochastic Programming," *IEEE Trans. Ind. Appl.*, vol. 54, no. 4, pp. 3044–3055, Jul. 2018.

[14] J. Iria, P. Scott, and A. Attarha, "Network-constrained bidding optimization strategy for aggregators of prosumers," *Energy*, vol. 207, p. 118266, 2020.

[15] J. Hu, J. Wu, X. Ai, and N. Liu, "Coordinated Energy Management of Prosumers in a Distribution System Considering Network Congestion," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 468–478, Jan. 2021.

[16] M. Mansourlakouraj, M. J. Sanjari, M. S. Javadi, M. Shahabi, and J. P. S. P. S. Catalao, "Exploitation of Microgrid Flexibility in Distribution System Hosting Prosumers," *IEEE Trans. Ind. Appl.*, pp. 1–1, 2021.

[17] F. Sheidaei and A. Ahmarinejad, "Multi-stage stochastic framework for energy management of virtual power plants considering electric vehicles and demand response programs," *Int. J. Electr. Power Energy Syst.*, vol. 120, p. 106047, Sep. 2020.

[18] A. Mashlakov, E. Pournaras, P. H. J. Nardelli, and S. Honkapuro, "Decentralized cooperative scheduling of prosumer flexibility under forecast uncertainties," *Appl. Energy*, vol. 290, p. 116706, May 2021.

[19] A. Tascikaraoglu, N. G. Paterakis, O. Erdinc, and J. P. S. Catalao, "Combining the Flexibility From Shared Energy Storage Systems and DLC-Based Demand Response of HVAC Units for Distribution System Operation Enhancement," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 137–148, Jan. 2019.

[20] S. F. Santos, D. Z. Fitiwi, M. Shafie-Khah, A. W. Bizuayehu, C. M. P. Cabrita, and J. P. S. Catalao, "New Multistage and Stochastic Mathematical Model for Maximizing RES Hosting Capacity—Part I: Problem Formulation," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 304–319, Jan. 2017.

[21] S. F. Santos, D. Z. Fitiwi, M. R. M. Cruz, C. M. P. Cabrita, and J. P. S. Catalão, "Impacts of optimal energy storage deployment and network reconfiguration on renewable integration level in distribution systems," *Appl. Energy*, vol. 185, pp. 44–55, Jan. 2017.

[22] "ATB | NREL." https://atb.nrel.gov/ (accessed Apr. 27, 2021).

[23] B. Steffen, M. Beuse, P. Tautorat, and T. S. Schmidt, "Experience Curves for Operations and Maintenance Costs of Renewable Energy Technologies," *Joule*, vol. 4, no. 2, pp. 359–375, Feb. 2020.

[24] "CaracterizacaodeRedes - CARE 2019." https://www.eda.pt/Regulacao/Lists/CaracterizacaodeRedes1/DispForm.aspx?ID=30&ContentTypeId=0x010400E34242259BFE28459B3929FB5F836DF50300444138EC13909142B011B908DF55F87F (accessed May 17, 2021).

[25] S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, "Investigating the Impacts of Plug-in Hybrid Electric Vehicles on Power Distribution Systems," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1351–1360, Sep. 2013.

[26] Baltimore Gas and Electric Company, "Baltimore gas and electric company, electric rates information." 2016. [Online]. Available: http://www.bge.com/