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Research Article

Optimisation and Management of Virtual Power Plants Energy Mix Trading Model

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Abstract. In this study, a robust optimisation method (ROM) is proposed with aim to achieve optimal scheduling of virtual power plants (VPPs) in the day-ahead electricity markets where electricity prices are highly uncertain. Our VPP is a collection of various distributed energy resources (DERs), flexible loads, and energy storage systems that are coordinated and operated as a single entity. In this study, an offer and bid-based energy trading mechanism is proposed where participating members in the VPP setting can sell or buy to/from the day-ahead electricity market to maximise social welfare (SW). SW is defined as the maximisation of end-users benefits and minimisation of energy costs. The optimisation problem is solved as a mixed-integer linear programming model taking the informed decisions at various levels of uncertainty of the market prices. The benefits of the proposed approach are consistency in solution accuracy and traceability due to less computational burden and this would be beneficial for the VPP operators. The robustness of the proposed mathematical model and method is confirmed in a case study approach using a distribution system with 18-buses. Simulation results illustrate that in the highest robustness scenario, profit is reduced marginally, however, the VPP showed robustness towards the day-ahead market (DAM) price uncertainty.

Keywords: Migration to smarter energy systems, Renewable energies, Distributed generation, Robust optimisation, Energy storage systems

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1. Introduction

Present-day electricity grids have been built under the technological limitations of the past. In many ways, their fundamental structures have been little upgraded since they were built a long time ago. Under the existing power system design, centralised high-capacity power stations, which are mainly carbon-dependent energy producers, play a predominant role in power generation and supply of energy services (Rangu *et al.* 2020; Podder *et al* 2020). On the other hand, the integration and participation of distributed energy resources (DERs), a decentralised small-scale power generating units with traditional bulk power stations have been limited by the existing passive distribution networks, driven by a one-way energy flow mechanism (Ullah & Mirjat, 2021).

Climate concerns have also accelerated renewable power generation (Sun *et al.* 2019). However, despite considerable technological advancements over the past decade, many operational challenges are still impeding the wide integration of renewable energy output into existing generation portfolios. Their intermittent and weather-driven output is one of the obstacles to their participation in energy markets (Shayegan *et al* 2019; Lin, *et al.* (2020). One possible solution is the coupling of renewable energy sources (RES), including photovoltaics, wind turbines and hydropower with other smart technologies such as traditional high-capacity generation plants, storage installations, and flexible loads could either solve energy supplies when the output of RES is low or store energy when the generation of RES is high. This combination gives rise to the idea of the VPP, described to be a collection of various DERs functioning as a single entity (Ju *et al* 2019; Sarker *et al* 2021; Pudjianto, *et al* 2007). An appropriate illustration of the VPPs in real life could be found in (Ullah & Mirjat, 2021). Furthermore, the interested readers are directed to (Ullah *et al.* 2019) for a "comprehensive review of VPPs planning, operation and scheduling considering the uncertainty of renewable energy sources"

This work gives an overview of a VPP offers and bids trading mechanism within the scope of the energy market environment where participating members can sell or purchase to/from the DAM to maximise SW. The VPP under study is a collection of DERs, flexible loads, and energy storage systems. The scheduling problem decides the amount of energy to be traded in the market one day in advance. The only uncertainty taken into account in this study is market price. A robust optimisation method

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is used to manage the uncertainties of market price as uncertainty sets. The method assesses the optimal scheduling of the VPP over the short-term planning horizon, which is specific to this study. Simulation studies have shown robustness in response to the day-ahead market price volatility.

Some of the suitable and closely related studies on VPPs proposed in the literature review are as follows: A price-based unit commitment mechanism is implemented by (Saniei, 2013) to effectively manage the VPP bidding strategy. The authors of (Zhao, 2015), find a solution to devise a VPP cheapest bidding strategy in the DAM and balancing market (BM) through the implementation of two-stage stochastic optimization. A robust, non-recourse method is applied by (Rahimiyan & Baringo, 2015) to solve the VPP bidding strategy in the DAM and real-time market (RTM) markets despite volatile market prices and output of wind power. The risk-averse offering approach is discussed by (Correa *et al*. 2015) in response to a VPP energy and reserve trade. The authors of (Shabanzadeh *et al*. 2017) have suggested a stochastic medium-term optimization of the VPP schedule, which works closely with adjacent VPPs and exchanges energy with the electricity market. A proactive concept of a VPP offering strategy in the energy market is presented in recent work (Baringo, & Baringo 2016) where volatilities in the market prices and output of wind power are modeled on trust limits. In (Sučić, 2011), the authors have proposed an advanced VPP control system mechanism for the provision of ancillary services. In (Liu *et al.* 2015), a centralised VPP control scheme consisting of several solar panels and flexible loads is used to sustain and support frequency services of island microgrids. The authors of (Mohammad *et al* 2011; Pandzic *et al* 2013; Riveros *et al* 2015), proposed a trading mechanism for a VPP that maximises their anticipated daily profit in the pool-based energy market.

Some relevant research studies in the literature exist, elaborated VPPs in-depth, and potentially highlighted the possible advantages of integrating different forms of DERs within the VPP environment. However, what is lacking in the literature reviewed is a systematic investigation of the VPP energy trading model's response to market price uncertainty. The use of the stochastic optimisation model will generate a huge number of scenarios and will impose a massive computational burden, therefore, in this study; we propose a model based on ROM to handle the financial risk related to the day-ahead market prices. The following are the main contributions of this work in relation to the literature reviewed.

1. To model a cluster of diversified DERs, flexible loads, and energy storage systems as a VPP that purchases power during off-peak hours, stores and sells it at appropriate times.
2. A robust optimization method is employed to address market price uncertainties as a new non-possibilistic approach, allowing a VPP to make an informed decision concerning the contribution of its participating members.
3. To illustrate the performance of the proposed method by thoroughly evaluating the findings through a case study.

2. Methods

This section proposes a VPP electricity market model. The electricity market model is a platform that facilitates end-users to participate in the electricity market in order to achieve economic benefits. It also regulates power procurement of operational facilities through bilateral contracts or the wholesale energy market.

2.1. VPP electricity market model and description

The generators (stochastic and dispatchable) units submit their hourly active power offer with prices to the VPP- market operator (MO) platform in form of blocks as shown in Fig 1, whereas flexible loads (FLs) submit their hourly bid of load with prices to the VPP-MO platform in form of blocks. The difference between offers and bids of distributed generators and flexible loads are known as social welfare that can be calculated as follows:

Maximise SW = Bid (cost of loads) – Offer (cost of generators).

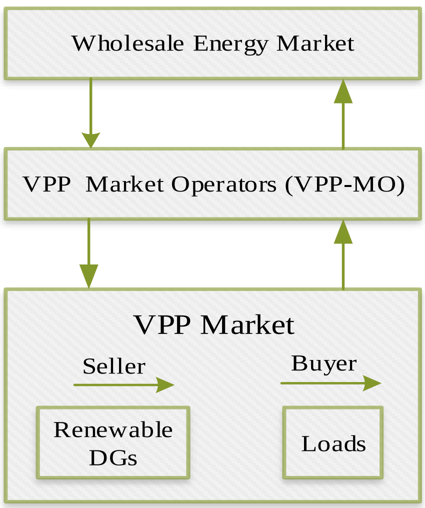

Fig. 1 Proposed VPP Electricity Market Structure.

Within the proposed electricity market design, the VPP-MO has two main tasks, and their operation is explained as follows:

1. The VPP-MO, receives offers and demand bids information from the VPPM and a joint bid to the wholesale power market.
2. The VPP-MO also receives wholesale energy market schedule requests for FLs, stochastic and dispatchable units a day-ahead at the market prices. Flexible loads (FLs) and generators (stochastic and dispatchable) are bound to present their quantity of power and associated offer and bid prices one day ahead of operation.

VPPM will send its bids to the VPP-MO and the quantity of power awarded would be informed later by the VPP-MO. VPP- market operator (MO) allocates the quantity of power exchange with the distribution grid; therefore, the VPP-MO is known in advance, which helps in reducing the variability's generated by the VPPM. Once the transfer of power with the distribution network and VPPM schedule is known one day ahead of operation. The VPPM could resolve the energy market scheduling problem to boost the scheduling of its flexible loads and distributed generators.

2.2 Modelling approach

GAMS, optimisation software has been used to test the proposed approach. The robust optimisation model of energy management of a VPP is solved on a personnel computer with an i7 CPU and 16 GB RAM. Optimal active power flow on the power market is being used to maximise SW subject to system constraints. The stepwise solution structure of the proposed approach is presented as follows:

Step 1 : Initialize $t = 1$

Step 2 : Collecting the historical data of the day-ahead market price, DERs power output, load demand and specifying the technical limits of the VPP elements.

Step 3 : The VPP operators receive information of energy offer price from the main grid at the current time period t.

Step 4 : the DGs owners send their power-producing capacity in each hour t to the VPP operators.

Step 5 : Price-responsive flexible loads offer their load levels and services to the VPP operators for current hour t and rest of the day hours.

Step 6 : The VPP operators using the historical data of the day-ahead market price and DERs power output, to determine upper and lower bounds for the midpoint of DERs production and energy prices for the next 24 hours of the day.

Step 7 : Solving the VPP robust model and gets the energy fractions to be delivered by the utility grid, the DERs units, and the storage unit, and also, the energy delivered to each load, the energy fraction to be stored, and the energy fraction sold to the utility grid at each period of time t.

Step 8: the VPP operators convey the decision procured to both the load demands and the energy suppliers.

3. Deterministic model

The VPP model is designed through the integration of various DERs, energy storage systems, and flexible loads. A VPP sells energy to its associated customers and delivers the distributed generators (DGs) owners surplus production capacity to the day-ahead power market. All decisions made are based on the viewpoint of the VPP, under which the owners of the DGs do not intervene with the decision. The DERs owners are responsible for the uncertainty of RESs and their associated risks (Kardakos *et al* 2015; Kang, 2017; Luo *et al* 2018).

3.1. Objective function

The aim of the VPP optimisation problem is the maximisation of social welfare (SW) (1) under the short-term planning horizon. Collectively, it maximises the benefits of the consumers and minimises the total energy costs. The objective function (1) maximises the SW function determined based on the projected income minus total costs for a given time period. The first term refers to the income earned from the trade-in of energy to its associated customers. The second term refers to the revenue earned from selling or buying the DERs owners surplus production capacity to the day-ahead power market at different grid supply points (GSPs), a point of common coupling for a given time period. The third term shows the cost of charging/discharging of energy storage system at time t. The fourth and the fifth elements are the costs of dispatchable and stochastic units' power generation. And the final element is the cost of curtailing is viewed as a peak load demand reduction over each period of time.

3.2. Constraints

The volume of energy exchanges hourly between the electricity market and the VPP through GSPs is constrained to the required consumer demand per hour and interconnection capacity with the main grid. When a VPP requires to buy power from the grid, the first part of Eq (2) is enforced but when the VPP wants to sell energy through GSPs, then the second part of Eq (2) is enforced. Eq (3) indicates that the necessary contractual and requested amount of power in the VPP setting should be satisfied.

Eq (4) specify the commitment of each flexible load over each period of time. This commitment is viewed as a peak load demand reduction. Eq (5) implements the max/min power output limits of non-dispatchable DGs. Based on historical data and estimation, the owners should assess the maximum capacity of their Stochastic generators (SGs), and provide this information to the VPP to achieve optimal scheduling. Eq (6) implements the max/min power output limits of dispatchable DGs. Similarly, the commitment (0, 1) of dispatchable units and the start-up/shut-down status are stated as (7) and (8).

Eqs (9) and (10) represent up/down ramp rate of dispatchable DGs. ΔBC in Eqs (11) and (12) indicates the allowable discrepancy between the energy delivered and the contract with a permissible deviation. While Eq (13) ensures that the contractual and supplied energy during the 24h planning horizon should be equal.

$$Max\,SW = \left[\sum_{t=1}^{T}\left(\begin{array}{l}\left(P_t^{Demand} * \lambda_t^{Chrge}\right) + \sum_{k\in GSP}\left(P_{kt}^{GSP} * \lambda_{kt}^{LMP}\right) + \left(\left(P_{bt}^{Dischge} - P_{bt}^{Chrge}\right) * C_t^{B}\right) \\ -\sum_{i\in DG}\left(P_{it}^{DG} * \lambda_i^{COST} + SUC_{it}^{COST} + SDC_{it}^{COST}\right) \\ -\sum_{j\in SG}\left(P_{jt}^{SG} * \lambda_j^{COST}\right) - \left(P_t^{FL} * \lambda_t^{FL\_\cos t}\right)\end{array}\right)\right] \tag{1}$$

$$-\zeta k\overline{P_k^{MAX}} \le P_{kt}^{GSP} \le \zeta k\overline{P_k^{MAX}}, \quad \forall k \in GSP, \forall t \tag{2}$$

$$\sum_{i\in DG} P_{it}^{DG} + \sum_{j\in SG} P_{jt}^{SG} + P_t^{FL} - \sum_{k\in GSP} P_{kt}^{GSP} + P_{bt}^{Dischrge} \ge P_t^{Demand} + P_{bt}^{Chrge} + P_t^{BC}, \quad \forall t \tag{3}$$

$$0 \le P_{\ell t}^{FL} \le \overline{P_t^{FL}}, \quad \forall \ell \in \mathrm{FL}, \forall\, \mathrm{t} \tag{4}$$

$$0 \le P_{jt}^{SG} \le \overline{P_j^{SG}}, \quad \forall j \in SG, \forall\, \mathrm{t} \tag{5}$$

$$\underline{P_i^{DG}} \cdot X_{it}^{DG} \le P_{it}^{DG} \le \overline{P_i^{DG}} \cdot X_{it}^{DG}, \quad \forall i \in DG, \forall t \tag{6}$$

$$SUC_{it}^{COST} - SDN_{it}^{COST} = X_{it}^{DG} - X_{i(t-1)}^{DG}, \quad \forall i \in DG, \forall t \tag{7}$$

$$SUC_{it}^{COST} + SDN_{it}^{COST} \le 1, \quad \forall i \in DG, \forall t \tag{8}$$

$$RUP_i\left(P_{i(t-1)}^{DG} - P_{it}^{DG}\right) \le T_i^{ON}, \quad \forall i, t \tag{9}$$

$$RDN_i\left(P_{it}^{DG} - P_{i(t-1)}^{DG}\right) \le T_i^{OFF}, \quad \forall i, t \tag{10}$$

$$P_t^{BC} \le \left(1 + \Delta BC\right) * P_t^{Contract}, \quad \forall t \tag{11}$$

$$P_t^{BC} \ge (1 - \Delta BC) * P_t^{Contract}, \forall t \tag{12}$$

$$\sum_{t=1}^{24} P_t^{BC} = \sum_{t=1}^{24} P_t^{Contract} \tag{13}$$

$$0 \le P_{bt}^{Chrge} \le \overline{P_{bt}^{Chrge}} * U_{bt}^{Chrge} \quad \forall b \in B, t \in T \tag{14}$$

$$0 \le P_{bt}^{Dischge} \le \overline{P_{bt}^{Dischrge}} * U_{bt}^{Dischrge} \quad \forall b \in B, t \in T \tag{15}$$

$$\underline{P_{bt}^{S}} \le P_{bt}^{S} \le \overline{P_{bt}^{S}} \quad \forall b \in B, t \in T \tag{16}$$

$$P_{bt}^{Chrge} \le P_{b(t-1)}^{Chrge} + P_{bt}^{Chrge} \Delta t \eta_b^{Chrge} - \frac{P_{bt}^{Dischrge}}{\eta_b^{Dischrge}} \Delta t, \quad \forall b \in B, t \in T \tag{17}$$

$$U_{bt}^{Chrge} + U_{bt}^{Dischrge} \le 1, \quad \forall t, \forall b \tag{18}$$

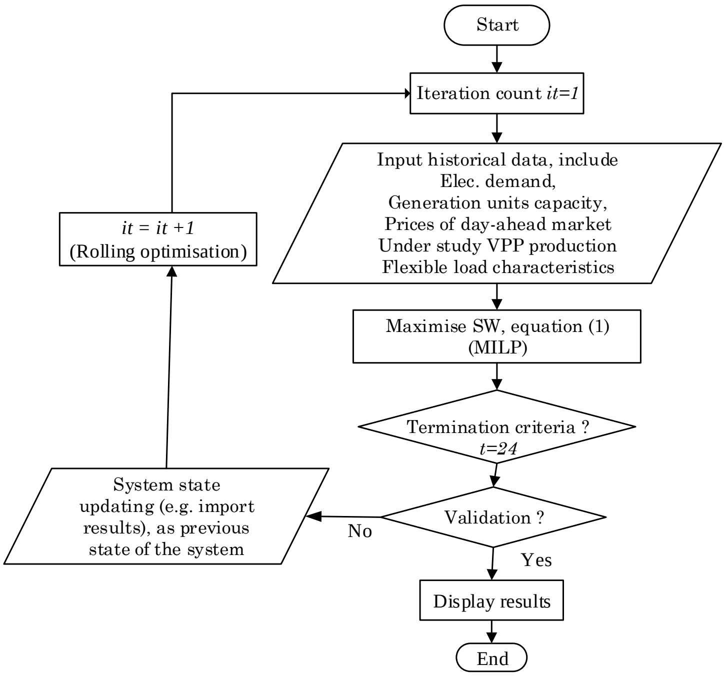

Fig. 2 Solution structure of the proposed algorithm.

$$Min-\left[\sum_{t=1}^{T}\left(\begin{array}{l}\left(P_t^{Demand}*\lambda_t^{Chrge}\right)+\sum\limits_{k\in GSP}\left(P_{kt}^{GSP}*\lambda_{kt}^{LMP}\right)+\left(\left(P_{bt}^{Dischge}-P_{bt}^{Chrge}\right)*C_t^{B}\right)\\ -\sum\limits_{i\in DG}\left(P_{it}^{DG}*\lambda_t^{COST}+SUC_{it}^{COST}+SDC_{it}^{COST}\right)\\ -\sum\limits_{j\in SG}\left(P_{jt}^{SG}*\lambda_t^{COST}\right)-\left(P_t^{FL}*\lambda_t^{COST}\right)+Z*\Gamma_0+\sum\limits_{t=1}^{T}\xi_t\end{array}\right)\right] \tag{19}$$

$$P_t^{Demand}=a*\lambda_t^{DA,\max}+b,\ \ \forall t \tag{20}$$

$$\lambda_t^{LMP}=\alpha^{k}*\lambda_t^{DA,\max},\ \ \forall k,t \tag{21}$$

$$\lambda_t^{Chrge}=\alpha^{0}*\lambda_t^{DA,\max},\ \ \forall t \tag{22}$$

$$\varpi_t*\left(\lambda_t^{DA.\max}-\lambda_t^{DA.\min}\right)\le Z+\xi_t,\ \ \forall t \tag{23}$$

$$y_t=\alpha^{0}*\left(a*\lambda_t^{DA.\max}\right)+\sum_{k\in GSP}\left(\alpha^{k}*\lambda_t^{DA.\max}\right)*P_{kt}^{GSP},\ \ \forall t \tag{24}$$

$$\varpi_t\ge y_t,\ \ \forall t \tag{25}$$

Eqs (14) and (15) indicate the max/min bounds of battery charge/discharge of unit b at time t. While the max/min energy storage capacity of unit b at time t is represented by (16). Battery SOC is formulated by using Eq (17). Eq (18) indicates that the storage device cannot be charged/discharged at the same time period

4. *Robust optimisation model*

In the literature exist, different methods have been suggested for coping with the uncertainties of the parameters described above. These methods are classified as possibilistic and probabilistic methods and/or (combination of both). All of the above methods require some historical data on the nature of the parameter's uncertainties (Soroudi & Amraee, 2013). If a VPP is subject to major variability (i.e. unavailability of information regarding the behavior of unknown parameters) then the aforementioned techniques may not be very helpful and advantageous.

ROM has come out to be a useful strategy of optimisation, lowering the sensitivity of the desired outcome in parameter values deviations. This approach can be viewed as a replacement for the stochastic approach in dealing with uncertainty in mathematical models. ROM is a risk management technique with the less computational burden compared to the above methods (Soroudi & Ehsan, 2012). ROM is used in this study because of three main advantages over the stochastic method as follows:

1. Good computational traceability of results in contrast to stochastic programming due to less calculations.
2. Reliability of results due to worst-case scenario consideration.
3. It does not require distribution of probabilities, unlike stochastic programming.

In the deterministic decision-making model of VPP (1) - (18), the market price is the only uncertain parameter that exists in the objective function, which is formulated in robust form as shown in Appendix 1. The main variable of the optimisation problem (19)-(25) is y_t interacting with VPP power interchanges with the day ahead market (DAM), where energy can be sold/purchased for the next 24h via various GSPs of the grid. The dual variables of the main problem are Z and ξ_t which is used to take into consideration the variance of coefficients λ_t^{Chrge}, and the auxiliary variable ϖ_t is being used to acquire corresponding linear expressions. Γ_0 takes values at the interval {0, 24}, if $\left[\left(\lambda_{kt}^{DA.\max}-\lambda_{kt}^{DA.\min}\right)\geq 0\right]$, while Γ_0 = 0, if $\left[\left(\lambda_{kt}^{DA.\max}-\lambda_{kt}^{DA.\min}\right)=0\right]$.

5. Case study

The performance of the proposed approach is validated by simulation studies using a distribution network of 18 buses (Fig 3) (Bertsimas & Sim, 2003). This system was derived from the known IEEE 30-bus system and we are only giving consideration to 33 kV network. The VPP setting integrates and regulates four Dispatchable and two stochastic DGs and a storage unit. Buses 2, 7, 8, and 14 are assumed to be four possible locations for the installation of dispatchable DGs, while buses 15 and 18 are assumed to be two possible locations for the installation of stochastic DGs. Bus 17 is assumed to be a possible location for the installation of the storage unit. Also, the energy trade with the market is carried out by three substations with different LMPs clustered at buses 1, 11, and 16 (Fig 3). At these three GSPs, the day-ahead market prices are thus projected to be 95, 105, and 100% of market price predictions ($\lambda_t^{DA.forecast}=\lambda_t^{DA.\max}$). Therefore, the a^0 value is set to 1, while the different ratings on each substation transformer can be seen in Fig 2. Parameters (#a and #b) are assumed to be 0.07 and 8. The main characteristics of DERs included in the VPP setting, energy storage data, the day-ahead market price information, and flexible loads information for 24 hours are reported in Tables 1-4. Market-based optimal power flow scheduling is used to maximise the social welfare of VPP in both generation and demand portfolios.

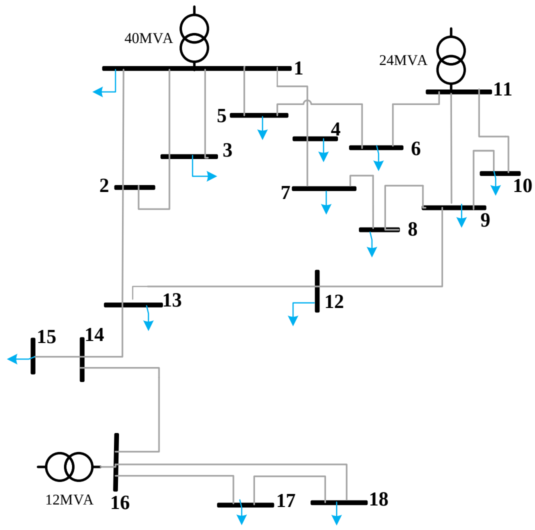

Fig. 3 Single line diagram of 18-bus distribution system

5.1. Numerical studies

The case study presented shows the proposed algorithm's ability to make optimal decisions under uncertainty in order to determine the best possible self-scheduling of a VPP in the day ahead electricity market to maximise the economic gains of its coalition members. The outcome of the simpler deterministic and robust optimization models is compared and presented in this section. In a deterministic approach, the value of benefits earned in a short-term planning horizon (i.e. 24 hours) is \$16,846. Γ_0 represents the degree of robustness in the ROM. This parameter controls the robustness level of the solution within the objective function in relation to market price uncertainty. Allocating the value of Γ_0 = 0 ignores the degree of robustness of the objective function and which is consistent with the result of a simpler deterministic model (\$16846), while maximum robustness is achieved by allocating Γ_0 = 24, and as a result, the minimum benefit is equal to (\$15774). The VPP can handle the financial risk as a decision-maker by correctly choosing the control parameter value (Γ_0). The profit differential between Γ_0= 0 and Γ_0 = 24 is equivalent to \$1072 (15% of \$16846) demonstrates the value of VPP robustness. Fig 4, highlights when the control parameter Γ_0 value is increased, the degree of robustness will be increased, resulting in a more conservative solution.

5.2. Simulation and Results

To assess the ability of the proposed decision-making mechanism, both the simpler deterministic model and the robust optimisation approach must be solved in comparison. The VPP benefits from the ROM for all other Γ_0 values (i.e. Γ_0 = 1…, 24) is demonstrated via Fig 4. The power exchanged between GSPs (#1, #11, and #16) and the upstream grid is shown in Figs 5a, 5b, and 5c. It is worth mentioning that, *+ve* sign indicates the power sold, and the *–ve* sign indicates the power procured from the grid. It is also worth mentioning that, in certain hours, the VPP acts like an arbitrator because, through the cheapest bus 1, it buys energy from the market rather than its needs and sells it especially to the market through high-priced bus (#11).

Table 1
Market price forecasts for 24 hours of the day

t(h)	λ ($/MWh)	t(h)	λ ($/MWh)	t(h)	λ ($/MWh)
1	46.03	9	76.95	17	108.31
2	45.14	10	69.09	18	89.54
3	45.50	11	65.84	19	76.83
4	45.70	12	59.47	20	73.60
5	55.80	13	56.47	21	59.59
6	82.28	14	53.77	22	52.47
7	84.80	15	52.90	23	47.77
8	83.44	16	71.44	24	39.17

Table 2
Energy storage system data

Parameters	Data	Parameters	Data
E_0	0.2	PD_{max}	0.15
E_{max}	0	PD_{min}	0
PC_{max}	0.6	η_C	95%
PC_{min}	0	η_d	90%

Table 3
Characteristics of dispatchable and stochastic units

DER Type	P^{min} (MW)	P^{max} (MW)	DG^{cost} ($/MWh)	DG^{rup} (MW/h)	DG^{rdn} (MW/h)	SUC ($)	SDC ($)
DG	0	4	37	1	1	20	25
DG	0	5	40	1.25	1.25	20	25
DG	0	5.5	35	1.375	1.375	50	25
DG	0	7	45	1.75	1.75	50	25
SG	0	9	65				
SG	0	7	55				

Table 4
Flexible loads characteristics for 24 hours of the day

t(h)	$P_t^{FL,max}$ (MW)	$\lambda_t^{FL,cost}$ ($/MWh)	t(h)	$P_t^{FL,max}$ (MW)	$\lambda_t^{FL,cost}$ ($/MWh)
1	0.591	37.30	13	0.660	46.93
2	0.585	40.96	14	0.689	51.04
3	0.426	51.52	15	0.700	58.35
4	0.589	53.83	16	0.799	85.61
5	0.610	57.80	17	1.017	105.10
6	1.132	74.83	18	0.859	85.44
7	0.852	99.91	19	1.067	81.78
8	1.217	89.50	20	0.696	75.91
9	1.021	61.96	21	0.557	68.03
10	0.871	66.88	22	0.474	44.10
11	0.601	63.87	23	0.656	41.69
12	0.643	50.12	24	0.533	43.90

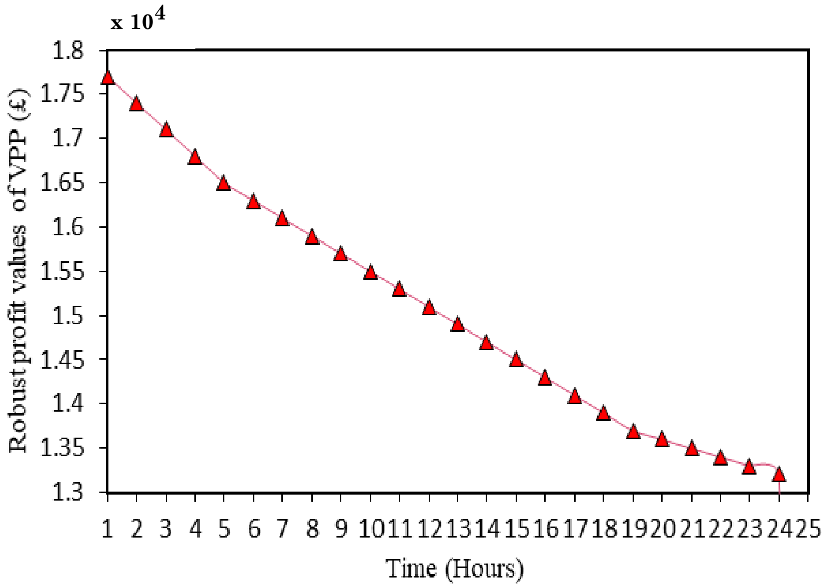

Fig. 4 VPP short-term profit for different control parameter (Γ_0) values.

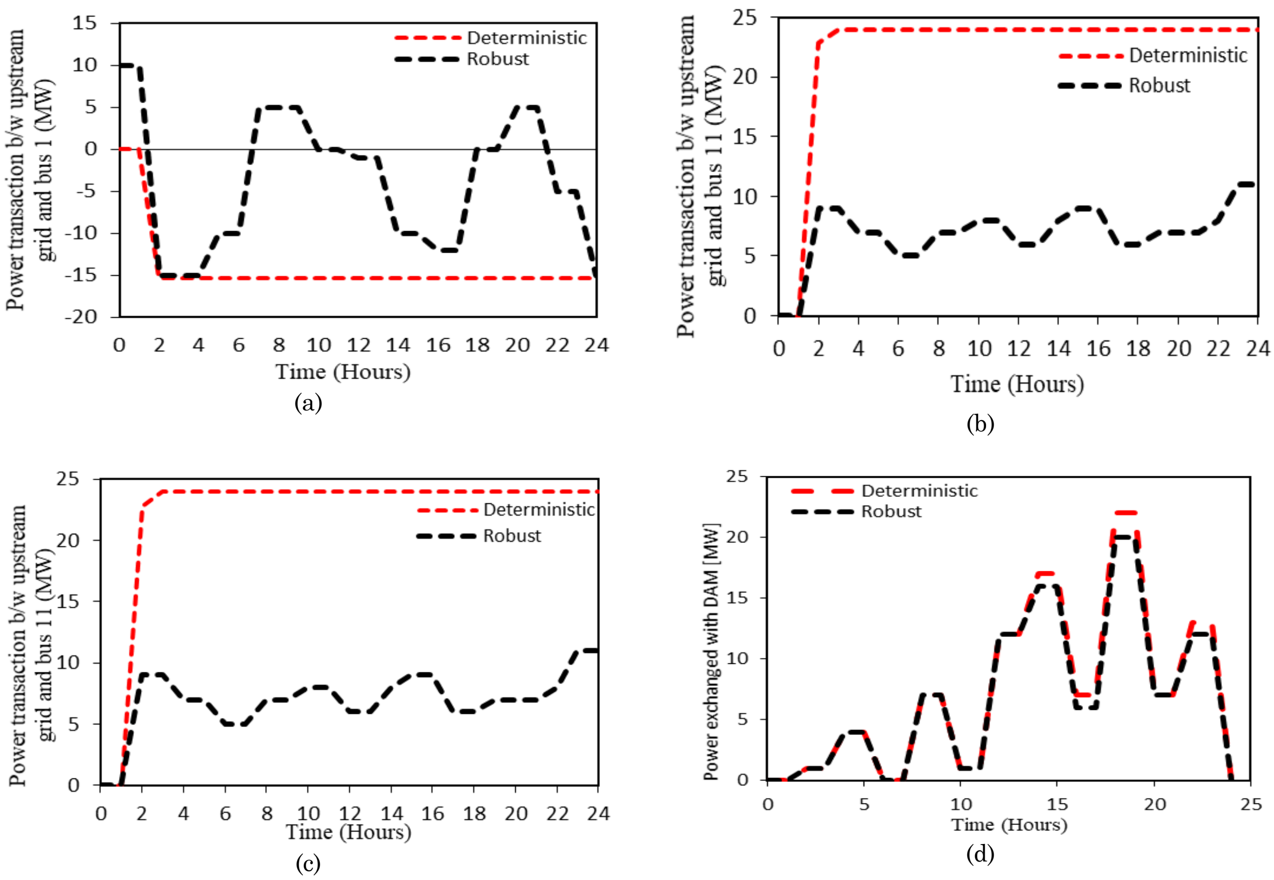

Fig. 5a, b, and c shows Power transaction between upstream substations and bus (#1, #11, and #16) respectively, while **Fig. 5d** shows Power transactions with day-ahead electricity market.

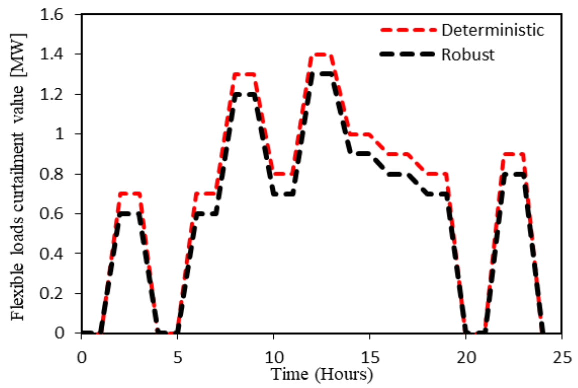

Fig. 6 Total flexible loads contributions

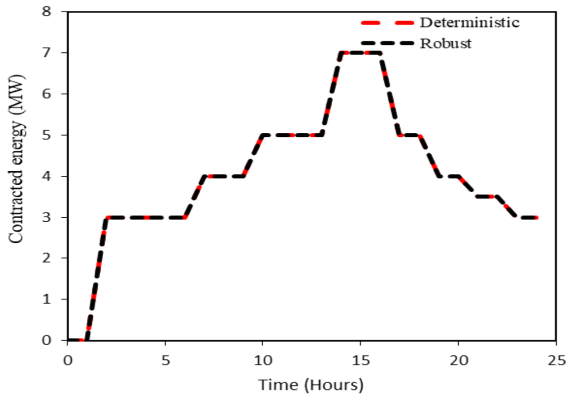

Fig. 7 Power supplied through bilateral contracts

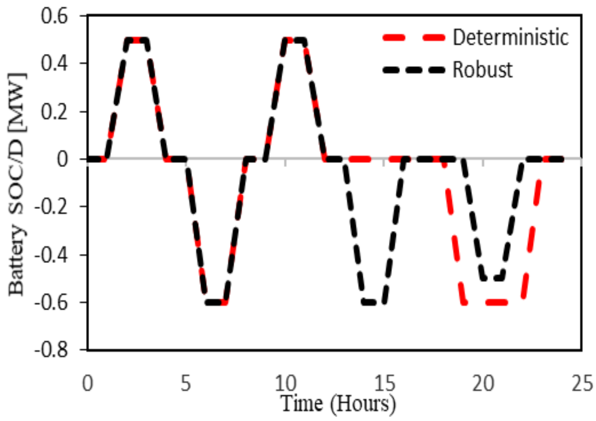

Fig. 8 Battery state of charge/discharge

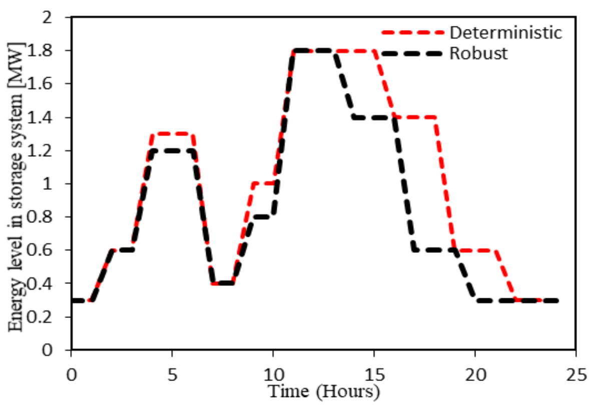

Fig. 9 Energy level in the storage system

According to Fig 5a highlights that the power obtained from GSP (#1), is reduced by ROM compared to a simpler deterministic approach; it is because of obtaining more resilient scheduling of VPP due to market price uncertainty. In addition, Fig 5b, also highlights that the power sold through GSP (#11) is minimized by ROM compared to the deterministic approach and finally, Fig 5c, highlights that the power obtained through GSP (#16) is minimised and the power sold is reduced compared with the deterministic approach.

In fact, the VPP serves as both a consumer and a producer when it generates revenue from different LMPs, even though the coordinated distributed energy resources are capable of satisfying the load demands. Fig 5d, shows the power exchanged between the upstream grid and the VPP in deterministic and RO models. In comparison with the deterministic approach, it has been shown that the power obtained in ROM is reduced because VPP aims to become more resilient against the uncertainty of day-ahead market prices. Thus, less power is derived from upstream networks, while more of its own generation is used to meet consumer requirements. In reality, VPP main objective is to increase energy sell during periods of high price in order to maximise economic gains from the day-ahead electricity market

Flexible loads curtailment of deterministic and RO models is illustrated via Fig 6. In the deterministic approach, load interruption is greater than RO approach. According to Fig 6, the volume of flexible loads would be lower if the flexible loads price is greater than that of the market price, however, the volume of load curtailment raises in other hours when contrasting the market price with the flexible loads price. Due to the conservatism of the ROM, and it is one of the logical reasons why the RO solution would be less economical than a deterministic approach.

The total energy supplied through bilateral contracts is depicted in Fig. 7. As the permitted error for bilateral contracts and supplied energy ΔBC can be as little as 10%. In the case of the deterministic approach, VPP utilises 10% discrepancy as an opportunity and trades a reduced amount of power when energy prices are less, however, as the market price goes up, more power will be sold. Additional power is purchased to compensate for the shortage of energy supplied in hours with high market prices. In accordance with Fig. 7, the power supplied by deterministic and RO approaches are the same and did not change because of the predetermined price. Battery SOC/D of deterministic and RO models for 24 hours is illustrated via Fig 8. Assuming that the battery can either be charged by DERs and/or power bought from the upstream grid through the cheapest bus (#1), and it can be discharged by selling the power supplied to the upstream grid through the expensive bus (#11). +ve sign indicates charging and –ve sign indicates discharging of the battery. Fig 8 indicates the energy storage systems contribution in off-peak hours for both approaches are the same, while in a robust case, at peak hours, more power is drawn from the storage system. The energy storage system contributes by having a fast response time (due to the direct control) to load demand requests, when there is a supply and demand mismatch. It should be observed that the energy storage systems contribution is trivial. Finally, Fig 9, shows the energy stored in the battery system. During the high demand hours when the market price increases, the energy stored in the battery system is released to satisfy some of the demand. It is therefore apparent that the battery is charging in off-peak hours, and the energy stored is used in the high price hours. It is important to note, that the energy storage system cannot charge and discharge simultaneously, it is due to the optimisation model imposes a charge and discharge constraint.

6. Conclusion

In this study, a robust optimisation technique is utilised within the VPP setting to guarantee a minimum level of social welfare for its participating members in the day-ahead electricity market. The market price uncertainty was modelled via uncertainty sets and the optimisation problem is solved as a MILP problem utilising GAMS optimisation software to maximise SW. The usefulness of this approach is its flexibility in terms of better solution accuracy and less computational burden. A case study simulation results indicate that despite the use of robust optimisation method, the social welfare of VPP has been reduced marginally due to market price uncertainty; however, this method demonstrated robustness towards market price volatility. The proposed method of energy management can be advantageous because of its simplicity in terms of the risk management approach. The specific conclusions are given as follows;

1) The proposed model, through a robust optimisation technique, enables the VPP to reflect uncertain data in an acceptable manner.
2) The proposed model makes it possible for the VPP to manage its DERs to purchase and sell energy according to its goals at the required time.
3) The risk management strategy implemented in this study has an impact on the bidding strategy and the power that a VPP trades.

In the future, energy efficiency will continue to be improved through multi-energy system designs. Thus, future research will concentrate on investigating optimal dispatch mechanisms, which will enable multi-energy systems with more complex frameworks operating in energy markets

Nomenclature

ROM	:	robust optimisation method
VPP	:	virtual power plant
DER	:	distributed energy resources
SW	:	social welfare
DAM	:	day ahead market
RES	:	renewable energy sources
RTM	:	real time market
VPPM	:	virtual power plant market
VPP-MO	:	virtual power plant market operator
FLs	:	flexible loads
DGs	:	distributed generators
SG	:	stochastic generators
LMPs	:	locational marginal prices
BC	:	bilateral contracts
MILP	:	mixed integer linear programming
T	:	set of time period
DG	:	set of dispatchable DGs
SG	:	set of stochastic DGs
GSP	:	grid supply points for upstream grid connection
FL	:	set of flexible loads
BESS	:	set of battery storage systems
t	:	index of time periods
k	:	index for GSPs
i	:	index for DGs
j	:	index for SGs
l	:	index for FLs
b	:	index for BESS
a, b	:	parameters for demand estimation in the distribution network
α^0	:	the ratio of VPP customer's charge to the upper limit of the market price forecast
ΔBC	:	hourly permissible deviation between the energy contracted and delivered via BC
P_t^{Demand}	:	VPP's customers active power demand in time period t
λ_t^{Chrge}	:	price that is charged to the VPP's customers in time period t
P_{kt}^{GSP}	:	power exchange with the DAM at the GSPs in time period t
λ_{kt}^{LMP}	:	locational marginal price at the GSPs in time period t
C_t^B	:	operating cost of unit b at time period t
λ_i^{COST}	:	generation cost of DG unit i
SUC_{it}^{COST}	:	start-up cost of unit i at t ($)
SDC_{it}^{COST}	:	shut-down cost of unit i at t ($)
$P_t^{Contract}$	:	contracted energy delivered through BC in time period t
λ_j^{COST}	:	generation cost of SG unit j ($)
$\lambda_t^{FL\_cost}$	:	curtailment cost of the FLs in time period t
$\overline{P_k^{MAX}}$	:	power connection capacity of the GSP k, with the main grid
Γ_0	:	uncertainty control parameter in the ROM
P_{bt}^S	:	the stored energy in unit b in time period t
$P_{bt}^{Chrge} / P_{bt}^{Dischrge}$	:	energy charge/discharge of unit b in time period t
$\overline{P_{bt}^{Chrge}} / \overline{P_{bt}^{Dischrge}}$	:	max charge/discharge of unit in time period t
$U_{bt}^{Chrge} / U_{bt}^{Dischrge}$	:	binary variables, one if charge or discharge of unit b in time period t, otherwise
$\underline{P_{bt}^S} / \overline{P_{bt}^S}$	:	min/max level of energy stored in unit b in time period t
$\eta_b^{Chrge} / \eta_b^{Dischrge}$	:	energy efficiency factor used for charge/discharge of unit b
P_{it}^{DG}	:	generation cost of DG unit i in time period t
P_{jt}^{SG}	:	generation cost of SG unit j in time period t
P_t^{FL}	:	the quantity of curtailment by the FLs in time period t
P_t^{BC}	:	energy deliver through BC in time period t [MWh]
X_{it}^{DG}	:	online commitment of unit i in time period t
ϖ_t	:	an auxiliary variable for obtaining a linear expressions
y_t	:	the main variable interacting with the VPP power exchanges with the DAM through GSPs k
z, ξ_t	:	dual variables of the deterministic decision making problem

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Appendix 1: Robust optimisation formulation.

ROM is a mathematical technique used to efficiently solve problems of optimisation with uncertain parameters. Unlike, stochastic programming, RO is less flexible technique of risk management but on the other hand it requires relatively very low computational burden. Typically, the self-scheduling problem (1) of VPP proposed in this article can be defined as follows:

$$Min\left[\sum_{j=1}^{n} C_j * X_j\right] \tag{26}$$

Subject to

$$\sum_{j=1}^{n} a_{ij} * X_j \le b_i, \quad \forall i = 1....,m \tag{27}$$

$$0 \le X_j, \quad \forall j = 1....,n \tag{28}$$

$$X_j \in [0,1] \; for\, some\; j = 1....,n \tag{29}$$

If the coefficients c_j of the objective function is regarded as known, then it is easy to obtain the solution to this problem using MILP solver. But if any of these coefficients are uncertain, in the objective function then we need to use RO technique to solve the optimisation problem. This is the main scenario of VPP self-scheduling problem (1) in which market prices are uncertain. Therefore, a robust counterpart can be developed of the VPP model. In order to achieve that, each coefficient c_j is presumed to have values in the interval [$\mathbf{c_j}$, $\mathbf{c_j + d_j}$] where d_j indicates a divergence from the nominal coefficient. In addition, to develop a robust MILP problem, an integer control parameter representing by Γ_0 is defined, that has values at the interval {**0, /*J*$_0$/**}, where $J_0 = [j/d_j > 0]$. This parameter regulates the robustness level of the objective function. If $\Gamma_0 = 0$, the robustness level is ignored in the objective function, while if $\Gamma_0 = /J_0/$, the maximum impact of cost variation is taken into account, resulting to a relatively more conservative solution.
Reformulation of the original problem (26) - (29), presented as follows:

$$Min\left[\sum_{j=1}^{n} C_j * X_j + Z * \Gamma_0 + \sum_{j=1} \xi_j\right] \tag{30}$$

Subject to Eqs (27) – (29)

$$Z + \xi_j \ge d_j * \varpi_j, \quad j \in j_0 \tag{31}$$

$$0 \le Z \tag{32}$$

$$0 \le \xi_j, \quad \forall j = 1....,n \tag{33}$$

$$0 \le \varpi_j, \quad \forall j = 1....,n \tag{34}$$

$$X_j \le \varpi_j, \quad \forall j = 1....,n \tag{35}$$

Eqs (30) - (35) are derived from the concept of duality theory (Bertsimas & Sim, 2004), and a detailed explanation is given on how the linear robust optimization counterpart approach is precisely formulated is given in (He *et al.* 2016).