Impact of Dynamic Pricing on Stakeholder's Welfare using Storage under a Virtual Power Plant Operation in Demand Response

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***Abstract*—A major barrier to the deployment of Virtual Power Plants (VPPs) with energy storage under Demand Response (DR) programs is the absence of a clear dynamic pricing (DP) framework that simultaneously addresses the objectives of all stakeholders (prosumers, VPP aggregator, and the grid) under a bidirectional energy flow. This work investigates a DP regime for a VPP integrating battery storage, aimed at optimizing stakeholder objectives in the day-ahead market. The UK national rolling demand data are employed to capture the time-varying nature of wholesale electricity prices. A Cumulative Performance Index (CPI) is used to quantify the VPP's contribution to dynamic load leveling. A Genetic Algorithm (GA) is utilized to optimize the transaction of prices and energy exchanges for stakeholders' welfare maximization. Results show that optimal prices and energy transactions within the DR framework depend strongly on stakeholder objective priorities. The price margin significantly influences the amount of financial rewards received by the stakeholders.**

Keywords— Battery storage, Virtual Power Plant, Aggregator, Dynamic Pricing, Demand Response

I. Introduction

The global restructuring of electric power utilities is transforming the industry from vertically integrated systems into competitive market environments. A key driver of this transition is the smart grid, which enables active consumer participation through demand response and demand-side management. This evolution enhances electricity trading at both wholesale and retail levels, where synchronization between markets is essential for improving grid efficiency and operational performance [1].

At the wholesale level, electricity trading occurs through electricity pools and bilateral agreements between producers and suppliers [2]. These transactions are influenced by factors such as time of day, weather conditions, fuel prices, and regulatory policies [3]. Key stakeholders include the Independent System Operator (ISO), producers, and suppliers. In electricity pools, trading follows a double auction mechanism where the Market Operator (MO) determines the market clearing price based on aggregated supply and demand curves [3–4]. In contrast, bilateral trading involves negotiated forward contracts specifying electricity quantities and prices over defined periods. This approach reduces exposure to spot market volatility and maintains confidentiality without direct MO involvement. Bilateral trading has been widely implemented in England and Wales under the New Electricity Trading Arrangement since 2001 [5].

Electricity procured in wholesale markets is then sold to consumers in retail markets. Traditionally, retail pricing has relied on regulated flat tariffs [6]. While flat tariffs protect consumers from wholesale price fluctuations, they expose suppliers to financial risks [2], [7] and are inefficient because they do not encourage consumers to modify consumption behavior [6], [8]. This lack of responsiveness increases peak demand, affects grid stability, and requires additional reserve capacity for system balancing [1], [8]. Therefore, flat tariffs are no longer suitable for competitive electricity markets [6], [8].

To overcome these limitations, dynamic pricing (DP) has been introduced, supported by widespread smart meter deployment. For example, the UK government aims to achieve high smart meter penetration by 2030 [9]. Dynamic pricing enables demand response by encouraging consumers to adjust consumption according to price signals, typically shifting usage from peak to off-peak periods. This reduces peak demand and improves grid stability. A recent UK pilot study by the Centre for Net Zero (2025) confirmed that consumers respond positively to dynamic pricing, with lower prices increasing off-peak consumption [10].

Dynamic pricing is classified into time-differential and quantity-differential pricing [11]. Time-differential pricing varies rates based on time periods, such as peak and off-peak hours, while quantity-differential pricing increases rates once consumption exceeds predefined thresholds [11]. Historically, these mechanisms were designed for unidirectional energy flow from grid to consumer.

However, advancements in smart grids and distributed energy resources have transformed consumers into prosumers who both consume and generate electricity [12]. Energy storage enables prosumers to purchase electricity during low-price periods and sell it during high-price periods, supporting peak shaving and valley filling. This introduces bidirectional energy flow between prosumers and the grid. Despite this capability, individual prosumers cannot directly participate in wholesale markets and instead rely on aggregators, commonly referred to as Virtual Power Plants (VPPs), which coordinate distributed resources and enable market participation. A key challenge in VPP implementation is the lack of pricing frameworks that balance stakeholder objectives under bidirectional energy conditions. Existing models do not adequately address prosumer incentives, battery operational constraints such as depth-of-discharge limits, aggregator profitability, and grid load balancing requirements.

To address this gap, this study proposes an optimized transaction pricing and energy exchange framework for a community-based VPP in a day-ahead electricity market. The approach utilizes UK national rolling demand data and a Genetic Algorithm (GA) to determine optimal pricing and transaction strategies. A multi-objective optimization framework is applied to maximize stakeholder welfare while ensuring efficient grid operation, economic viability, and effective integration of distributed energy resources.

II. Virtual Power Plant Stakeholders Model

Fig. 1, is a diagram describing the VPP stakeholders' model developed. N is the total number of prosumers within the community aggregated as a VPP. t is the time interval. $E_{1,t}^{dis}$ to $E_{N,t}^{dis}$ is the discharge energy from prosumer 1 to N battery respectively at t. $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$ is the charge energy for prosumer 1 to N battery respectively at t. β_t^{sell} is the prosumer sell price of energy from battery, or the price at which the VPP buys energy from the prosumer's battery. $L_{1,t}$ to $L_{N,t}$ is the fixed load demand of prosumer 1 to N respectively at t. α_t^{buy} is the price at which the prosumer buy energy from the VPP to meet its load, or the price at which VPP sells energy to the prosumer to meet load demand at t. E_t^{imp} and E_t^{exp} are the amount of energy imported from the grid, and exported to grid by the VPP at t. δ_t^{imp} and γ_t^{exp} are the VPP import and export price of energy to the grid respectively at t. In this work, the VPP's stakeholders includes; VPP aggregator also known as the operator, prosumers, and the grid. Typically, each of the stakeholders has its market objective in participating in demand response to ensure efficient grid operation.

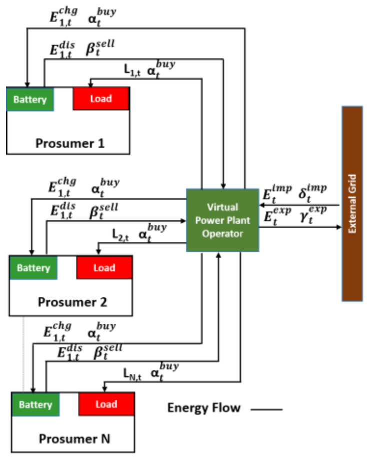

Fig. 1. Architecture of the virtual power plant stakeholders' model.

Fig. 2. Depicts the market participation of all VPP stakeholders. As can be seen, both the VPP operator and the prosumers participates at the aggregation market. While the operator and the grid participate at the wholesale market. The interest of each stakeholders is discussed subsequently.

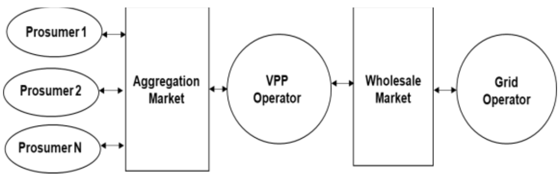

Fig. 2. Virtual power plant stakeholders' market framework.

A. Prosumers

Each prosumer has a fixed load and a battery storage embedded inside their home and participates in day ahead market via the VPP operator. Each prosumer's battery is use for participation in the wholesale power market via the VPP operator. The prosumer buys energy from the VPP operator for meeting its fixed load and for charging its battery via the aggregation market. The prosumer sells energy to the VPP operator via the aggregation market which can be exported to the grid for the curtailment of peak via the wholesale market. The prosumers requires the VPP operator to set its α_t^{buy} and β_t^{sell} as well as allocate $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$ and $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$ in such a way that at the end of their day ahead market participation they get financial incentive, their battery state of discharge is not too low, and the rate at which the change in α_t^{buy} and β_t^{sell} with respect to time t from its current value to its next value is relatively small respectively.

B. Virtual power plant operator

At t the VPP operator can buy energy from the grid E_t^{imp} at a price δ_t^{imp} via the wholesale market and from prosumer 1 to prosumer N $E_{1,t}^{dis}$ to $E_{N,t}^{dis}$ at price β_t^{sell} via the aggregation market. The VPP operator buys E_t^{imp} in bulk from the grid's via the wholesale market to meet the prosumers' load demand ($L_{1,t}$ to $L_{N,t}$) as well as to charge the prosumers' battery ($E_{1,t}^{chg}$ to $E_{N,t}^{chg}$). In this model, the VPP can combine both energies from the grid and the prosumer's battery to meet the load demand of all prosumers ($L_{1,t}$ to $L_{N,t}$). The energy bought from each prosumer ($E_{1,t}^{dis}$ to $E_{N,t}^{dis}$) are aggregated by the VPP operator. The aggregated energy is first used within the community to meet each prosumer's fixed load demand before it can be sold/exported to the external grid the VPP operator.

The VPP operator and the grid negotiate and agrees δ_t^{imp} and γ_t^{exp} in day ahead. This is based on the grid's day ahead demand and its requirement for dynamic load levelling (peak and off-peak support). The VPP operator has a day ahead forecast of $L_{1,t}$ to $L_{N,t}$. The VPP operator then optimally allocates α_t^{buy}, β_t^{sell}, $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$, and $E_{1,t}^{dis}$ to $E_{N,t}^{dis}$. The VPP operator uses $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$, and $E_{1,t}^{dis}$ to $E_{N,t}^{dis}$ to control the amount of energy to be imported E_t^{imp} and exported E_t^{exp} to the grid. From the VPP operator's perspective α_t^{buy}, β_t^{sell}, δ_t^{imp}, γ_t^{exp}, $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$, and $E_{1,t}^{dis}$ to $E_{N,t}^{dis}$ should be set in a way that it makes profit at the end of the day ahead market.

C. Grid balancing service

The grid relies on balancing services provided by the VPP to maintain stability under variable load conditions. These services encompass both peak and off-peak service. VPP can provide peak service to the grid by reducing its dynamic load. This is by discharging of its prosumer battery $E_{1,t}^{dis}$ to $E_{N,t}^{dis}$ to meet the prosumers load demand $L_{1,t}$ to $L_{N,t}$, and also by exporting energy E_t^{exp} to the grid. VPP can provide off-peak service to the grid by increasing its dynamic load through energy E_t^{imp} from the grid to meet its prosumers load as well as charging of its prosumer's battery $E_{1,t}^{chg}$ to $E_{N,t}^{chg}$. This provision of peak and off-peak service by the VPP is to help the grid flatten its demand, and to reduce the peak to average ratio of the grid. The grid's energy balancing need are reflected by the prices δ_t^{imp}, and γ_t^{exp}. More clarity on this is presented in section V.

III. Pricing Based on UK National Rolling Demand

In this work, the UK national rolling demand was used to reflect the cost as well as the time varying nature of the wholesale market price of electricity for both the peak and off-peak period, used as day ahead. The rolling system demand D

for 288-time interval (K number of samples) was taken. It represents UK national demand D at a resolution of 5 minute. This is presented as follows:

$$D = \begin{bmatrix} d_1 \\ . \\ d_K \end{bmatrix} \quad (1)$$

D is use as a basis for setting the VPP import price and export price. D is normalize using its mean $\overline{D}$.

$$\overline{D} = \frac{\sum_{k=1}^{K} d_k}{K}; \forall k \in \{1,2 \ldots\ldots K\} \quad (2)$$

$$D^{norm} = \frac{D}{\overline{D}}; D^{norm} = \begin{bmatrix} d_1^{norm} \\ . \\ d_K^{norm} \end{bmatrix} \quad (3)$$

The normalized D^{norm} represents the VPP import price in pence per unit for K number of samples. k is the index number for each sample. The grid demand is considered best when it is flat or rather equal to its mean. Using D^{norm}, it means that the price at which D equals to $\overline{D}$ is 1 pence per unit. Therefore, the price at which the VPP export electricity must be higher than 1 pence per unit when D is greater than $\overline{D}$, and less than 1 pence per unit when D is less is less $\overline{D}$. This is to encourage the VPP to reduce its dynamic load when D is greater than $\overline{D}$, and to increase its dynamic load when D is lesser than $\overline{D}$. This is to assist the grid in flattening of its demand. Thus, the criteria for setting the VPP export price is based on the deviation of each sample σ_k of D from $\overline{D}$as it infers both peak and off-peak period. The deviation reflects the extent to which the grid demand deviate from its flat load requirement (4)

$$\sigma_k = d_k - \overline{D} \quad (4)$$

The peak deviation is use to normalize the deviation of each sample from the mean and is presented as follows:

$$\sigma_{peak} = max(|\sigma_k|) \quad (5)$$

Using the both the normalized deviation and the price at which D equals to $\overline{D}$, the VPP export price for K samples E^{norm} is formulated as follows:

$$E^{norm} = \theta_1 . sign(\sigma_k) . \left(\frac{\sigma_k}{\sigma_{peak}}\right)^{\theta_2} + 1 \quad (6)$$

Θ_1 and Θ_2 in equation (6) are price margin which represents the degree to which the grid is willing to encourage the VPP to provide dynamic load levelling. They determine the grid's budget constraint. Increasing Θ_1 will increase the price paid by the grid to the VPP operator at time period when the grid load is greater than its average load, and reduce the price paid by the grid to VPP operator at time period when the grid load is less than its average load, vis a vis. Increasing Θ_2 raises the price paid by the grid to the VPP operator when the grid load is below its average level, and lowers the price when the load exceeds the average. In effect, Θ_2 exponentially scales the normalized load deviation. In other convert D^{norm} and E^{norm} in to a 48-time interval (T) of import price δ^{imp} and export price γ^{exp} respectively, moving average was applied. This is calculated as follows:

From D^{norm}, for each $1 \le t \le T$

$$\delta_t^{imp} := \frac{T}{K} . \sum_{j=6(t-1)+1}^{\left(\frac{K}{T}\right)t} d_t^{norm} ; \delta^{imp} = \begin{bmatrix} \delta_1^{imp} \\ . \\ \delta_T^{imp} \end{bmatrix} \quad (7)$$

From E^{norm}, for each $1 \le t \le T$

$$\gamma_t^{exp} := \frac{T}{K} . \sum_{j=6(t-1)+1}^{\left(\frac{K}{T}\right)t} E_i^{norm} \quad \gamma^{exp \begin{bmatrix} \gamma_1^{exp} \\ . \\ \& \gamma_T^{exp} \end{bmatrix}} \quad (8)$$

From δ_t^{imp}, and γ_t^{exp}, the VPP operator determines α_t^{buy}, and β_t^{sell}. This done for all T in day ahead.

IV. Mathematical Formulation

A. Rate of Change of Prosumer Price

The rate at which the change in α_t^{buy} and β_t^{sell} with respect to time t from its current value to its next value occur respectively is also considered as part of the of criteria for determining the prices at which the prosumer buys and sells energy in the day ahead market. This is to enable the VPP operator to give the prosumer preference in terms of how they would prefer the rate at which the change in price to occur. In this work, the prosumers want the rate at which the change in α_t^{buy} and β_t^{sell} with respect to time from its current value occur to be small as possible respectively. The rate of change was modelled using a second order derivative with a forward difference, and is presented in (9) and (10) as follows:

$$\sum_{t=1}^{T-2} \nabla^2 \alpha_t^{buy} = \sum_{t=1}^{T-2} abs\left(\frac{\alpha_{t+2}^{buy} - 2\alpha_{t+1}^{buy} + \alpha_t^{buy}}{\Delta t^2}\right) \quad (9)$$

$$\sum_{t=1}^{T-2} \nabla^2 \beta_t^{sell} = \sum_{t=1}^{T-2} abs\left(\frac{\beta_{t+2}^{sell} - 2\beta_{t+1}^{sell} + \beta_t^{sell}}{\Delta t^2}\right) \quad (10)$$

Δt is the incremental step size in time.

B. VPP Operator Profit

The VPP operator profit VPP_t^{profit} at each time interval t over the day's total number of time interval *(T)* is calculated as follows:

$$\sum_{t=1}^{T} Vpp_t^{profit} = \sum_{t=1}^{T} (Vpp_t^{rev} - Vpp_t^{cost}) \quad (11)$$

Where VPP_t^{rev} and VPP_t^{cost} are the VPP revenue and cost respectively at t. Both VPP revenue and cost are calculated respectively in (12) and (13) as follows:

$$\sum_{t=1}^{T} VPP_t^{rev} = \sum_{i=1}^{N} \sum_{t=1}^{T} (\alpha_t^{buy} . (L_{i,t} + E_{i,t}^{chg}) + \gamma_t^{exp} . E_t^{exp}) \quad (12)$$

$$\sum_{t=1}^{T} VPP_t^{rev} = \sum_{i=1}^{N} \sum_{t=1}^{T} (\alpha_t^{buy} . (L_{i,t} + E_{i,t}^{chg}) + \gamma_t^{exp} . E_t^{exp}) \quad (13)$$

Where i is an index number for the prosumer, N is the total number of prosumers aggregated in to the VPP.

The prosumer's net cost P_t^{net} at each time interval t over the day's total number of time interval T is calculated as follows:

$$\sum_{t=1}^{T} P_t^{net} = \sum_{i=1}^{N}\sum_{t=1}^{T}(\alpha_t^{buy}\,(L_{i,t} + E_{i,t}^{chg}) - \beta_t^{sell}.E_{i,t}^{dis}) \quad (14)$$

C. Battery State of Charge.

The battery state of charge (SOC) gives an information on the battery energy level. The SOC is measured in percentage. The cumulative battery energy level measured at *t* is calculated as follows:

$$E_{i,t}^{stored} = E_i^{init} + \sum_{t=1}^{T} E_{i,t}^{cd} \quad (15)$$

$$Ecd_{i,t} = \begin{cases} E_{i,t}^{chg}, \text{If charging occur} \\ E_{i,t}^{dis}, \text{If discharging occur} \\ 0, \text{if battery is idle} \end{cases} \quad (16)$$

$E_{i,t}^{stored}$ is prosumer *i* cumulative battery energy level in per unit measured at *t*. $E_{i,t}^{init}$ is prosumer *i* initial battery energy level in per unit before participation in the day ahead power market. The prosumer battery SOC is calculated as follows:

$$SOC_{i,t} = 100\frac{E_{i,t}^{stored}}{E_i^{batt}} \quad (17)$$

$SOC_{i,t}$ is the state of charge of prosumer *i* battery measured in percentage during *t*. E_i^{batt} is the actual battery capacity in per unit of prosumer *i*.

D. Cumulative Performance Index (CPI)

The VPP performance is determined by comparing both the VPP dynamic load E_t^{dyn} and the energy balancing need of the grid. The VPP dynamic load at *t* is the energy imported from the grid by the VPP or the energy exported to the grid by the VPP at *t*. The energy balancing need of the grid at *t* is indicated by the exchange price λ_t at time *t*. This is calculated as the difference between the import and export price of electricity at *t*. This is mathematically represented as follows:

$$\lambda_t = \delta_t^{imp} - \gamma_t^{exp}$$

$$\begin{cases} if\,\lambda_t > 0, \text{gridrequiresoff} - \text{peakservice} \\ if\,\lambda_t > 0, \text{gridrequirespeakservice} \end{cases} \quad (18)$$

When λ_t is positive, the grid requires the VPP to provide off-peak service by increasing its dynamic load. The VPP can increase its dynamic load by importing energy from the grid. When λ_t is negative the grid requires the VPP to reduce its dynamic load. The VPP can reduce its dynamic load by discharging the prosumer's battery to support the load, as well as to export energy to the grid. Therefore, when energy is imported at *t*, E_t^{dyn} is greater than zero. When energy is exported at *t*, E_t^{dyn} is less than zero. Further clarity on E_t^{dyn} is provided in (30) and (31). Both λ_t and E_t^{dyn} are represented with the logic input A_t and B_t respectively, such that:

$$\begin{cases} if\ \lambda_t > 0,\ \ A_t = 1 \\ if\ \lambda_t < 0,\ \ A_t = 0 \\ if\ E_t^{dyn} > 0, B_t = 1 \\ if\ E_t^{dyn} < 0, B_t = 0 \end{cases} \quad (19)$$

If grid requires off-peak service, it means the dynamic load must be increased. On the other hand, if the grid requires peak service, the dynamic load must be decreased. Based on this criterion, a performance state C_t at time *t* is derived as follows:

$$\boldsymbol{C_t = \overline{(A_t \oplus B_t)}} \quad \textbf{(20)}$$

C_t is the output of an EX-NOR logic combination of inputs A_t and B_t. A logic state of 0 for C_t means that the VPP is not performing well and the VPP dynamic load is not in accordance with the grid's energy balancing need. A logic state of 1 for C_t means the VPP has performed well and the dynamic load of the VPP is in accordance with the grid energy balancing need. Based on C_t, a new performance index called the "Cumulative Performance Index" of the VPP (CPI) over the day is computed. *CPI* over *T* is formulated from (14) as follows:

$$CPI = \frac{100\sum_{t=1}^{T} C_t}{T} \quad (21)$$

1. *Problem Formulation*

The optimization problem is the community VPP stakeholders' welfare. This is gotten from (9), (10), (11), (14) (17), and (21). The stakeholders' welfare consists of the rate at which the change in α_t^{buy} and β_t^{sell} with respect to time from its current value to its next value occur respectively, the VPP operator profit, prosumer incentive, the prosumer battery SOC after participation in the day, and the VPP's CPI. The stakeholder's welfare is formulated as follows:

$$[Max]F = \sum_{t=1}^{T}\begin{pmatrix} W1.F1_t - W2.F2_t + W3.F3_t \\ +W4.F4_t - W5.F5_t \end{pmatrix} \quad (22)$$

Where $F5_t$ is calculated from (9) and (10) as follows:

$$F5_t = \nabla^2\alpha_t^{buy} + \nabla^2\beta_t^{sell} \quad (23)$$

$F1_t$ is the VPP operator profit at *t*, W1 is its weighting magnitude. $F2_t$ is the prosumer net cost at *t*, W2 is its weighting magnitude. $F3_t$ is the VPP *CPI* at *t*, W3 is its weighting magnitude. $F4_t$ is the prosumer SOC at *t*, W4 is its weighting magnitude. $F5_t$ is the rate at which the change in α_t^{buy} and β_t^{sell} with respect to time from its current value to its next value occur respectively and W5 is its weighting magnitude.

Subject to the VPP operator and prosumer budget constraints.

$$(1 - \kappa_1^{buy}).\delta_t \le \alpha_t^{buy} \le (1 + \kappa_2^{buy}).\delta_t \quad ; \quad \forall t \in \{1,2\ldots\ldots T\} \quad (24)$$

$$(1 - \kappa_1^{sell}).\gamma_t \le \beta_t^{sell} \le (1 + \kappa_2^{sell}).\beta_t; \forall t \in \{1,2\ldots\ldots T\} \quad (25)$$

κ_1^{buy} and κ_2^{buy} are the minimum and maximum variation of the prosumer buy price from the VPP import price respectively. κ_1^{buy} represent the maximum reduction of the import price of energy that VPP operator can afford and would be willing to sell to the prosumers. κ_2^{buy} represents the maximum increase of the import price of energy that the prosumers can afford and would be willing to buy energy from the VPP operator. κ_1^{sell} represent the maximum reduction of the export price of energy that prosumer can afford and would be willing to sell to the VPP operator. κ_2^{sell} represents the maximum increase of the export price of energy that the VPP operator can afford and would be willing to buy energy from the prosumer.

Subject to battery inequality constraints:

$$E_{min,i}^{dis} \leq E_{i,t}^{dis} \leq E_{max,i}^{dis} \tag{26}$$

$\forall t \in \{1,2......T\}; \forall i \in \{1,2......N\}$

$$E_{min,i}^{chg} \leq E_{i,t}^{chg} \leq E_{max,i}^{chg} \tag{27}$$

$\forall t \in \{1,2......T\};\forall i \in \{1,2......N\}$

$$SOC_{min,i} \leq SOC_{i,t} \leq SOC_{max,i} \tag{28}$$

$\forall t \in \{1,2......T\}; \forall i \in \{1,2......N\}$

Subject to VPP net dynamic load equality constraint:

$$E_t^{dyn} = \sum_{i=1}^{N}\left(L_{i,t} + Ecd_{i,t}\right) \qquad (29$$

$\forall t \in \{1,2......T\};\forall i \in \{1,2......N\}$

$$E_t^{dyn} = \begin{cases} E_t^{imp}, \text{if } E_t^{dyn} > 0 \\ E_t^{exp}, \text{if } E_t^{dyn} < 0 \\ 0, \text{if } E_t^{dyn} = 0 \end{cases} \tag{30}$$

Subject to the network constraint:

$$E_{max}^{grid} \leq E_t^{dyn}; \forall t \in \{1,2......T\} \tag{31}$$

F is the community VPP stakeholders' welfare, and is the objective function to be maximize. E_{max}^{grid} is the maximum energy exchange, which is to prevent violation of the voltage limit of the network. This was further considered as a black box model. $E_{min,i}^{dis}$ and $E_{max,i}^{dis}$ are the minimum and maximum discharge energy at any t that can be allocated to prosumer i battery. $E_{min,i}^{chg}$ and $E_{max,i}^{chg}$ are the minimum and maximum charge energy at any t that can be allocated to prosumer i battery. SOC_{min_i} and SOC_{max_i} are the minimum and maximum state of charge prosumer i battery can be subjected to.

V. Experimental Setup & Results

N was chosen as 1 for clarity. While E^{batt}=24 per unit; E_o=12 per unit; initial SOC=50%; $E_{d,max}$=1.2 per unit; $E_{d,max}$ =1 per unit; T=24; κ_1^{buy} and κ_2^{buy} was set at 0.2 respectively;$\kappa_1^{sell}$and $\kappa_2^{sell}$was set at 0.2 and 0.3 respectively. The weightings were selected as follows; $W1$=0.3; $W2$=0.25; W3=0.2; W4=0.35; W5=0.05. These were simulated under three scenarios by varying Θ_1 relative to Θ_2 as presented in Table I.

Table I. Scenarios

Scenarios	Θ_1	Θ_2
One	1	1
Two	2	1
Three	4	1

Genetic Algorithm (GA) was used to determine prosumers' optimal day-ahead energy buy and sell prices and battery charge/discharge schedules based on VPP import/export prices and forecasted load, ensuring optimal energy trading and battery operation. Under Scenario One, Fig. 3 shows optimized dynamic pricing, where buy prices exceed sell prices. Fig. 4 presents optimized energy transactions. The grid net price, defined as export minus import price, identifies peak and off-peak periods. Battery load reflects charge and discharge activity. The dynamic load aligns with grid needs by decreasing during peak periods and increasing during off-peak periods, demonstrating effective load shifting and coordinated battery operation.

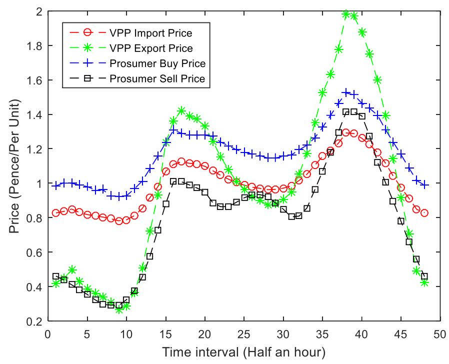

Fig. 3. Optimized day ahead dynamic price (Scenario One).

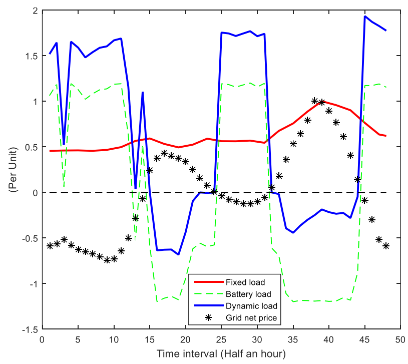

Fig. 4. Optimized day ahead energy transaction (Scenario One).

Under scenario Two, Fig. 5, is the optimized day ahead dynamic price for the community VPP, and Fig. 6, is the optimized energy transaction for the community VPP. In. Fig. 5, It can be seen that unlike in Fig. 3, the prosumer sell price is set relatively higher than the buy price during the night peak. Under scenario Three, Fig. 7, is the optimized day ahead dynamic price for the community VPP, and Fig. 9, is the optimized transaction for the community VPP. In Fig. 4

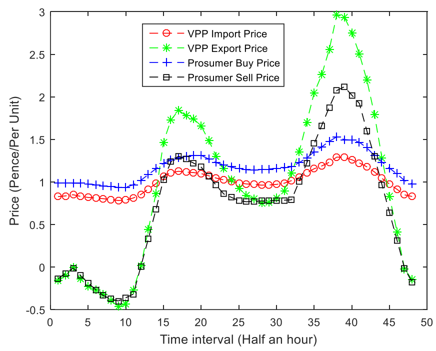

Fig. 5. Optimized day ahead dynamic price (Scenario Two).

Unlike Scenarios 1 and 2, Scenario 3 shows prosumer sell prices higher than buy prices during morning and night peaks, encouraging demand response participation. Across all scenarios (Figs. 4, 6, and 8), dynamic load decreases during peak periods and increases during off-peak periods, supporting grid stability and efficient operation.

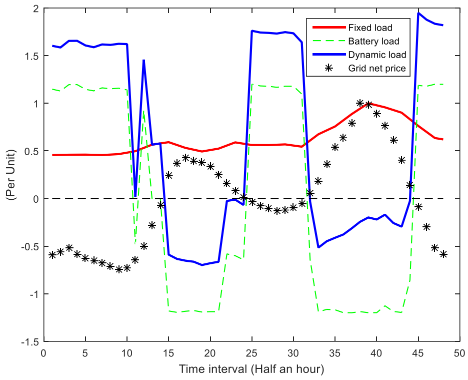

Fig. 6. Optimized day ahead dynamic price (Scenario Two).

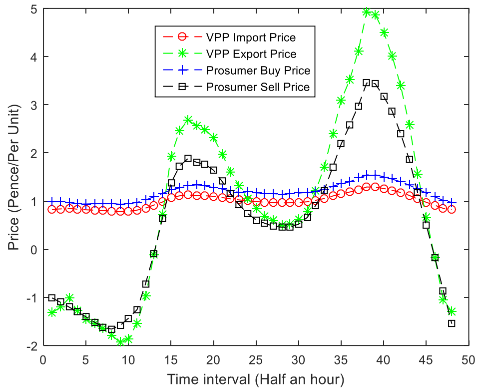

Fig. 7. . Optimized day ahead dynamic price (Scenario III).

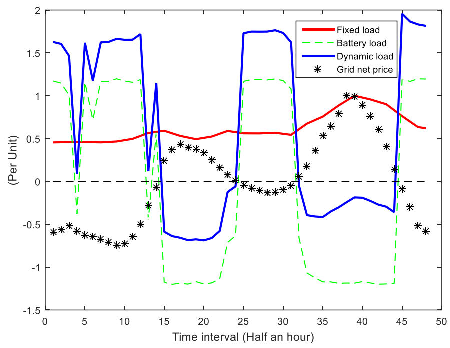

Fig. 8. Optimized day ahead energy transaction (Scenario IV).

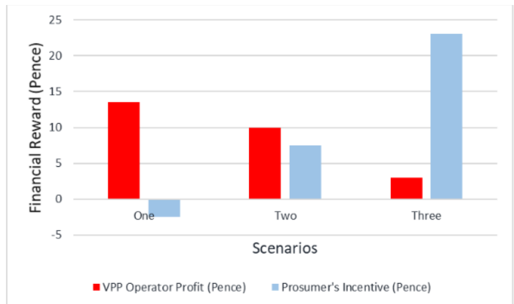

Fig. 9. VPP and Prosumer incentive Financial Rewards

It is essential to evaluate the financial rewards of both the VPP operator and prosumers after providing demand response under day-ahead pricing, as shown in Fig. 9. The VPP operator achieves the highest profit in Scenario 1 and the lowest in Scenario 3. In contrast, prosumers incur a cost in Scenario 1 but achieve the highest incentive in Scenario 3. A key finding is that the price margin between VPP import and export prices strongly influences the financial benefits received by both the VPP operator and prosumers.

VI. Conclusion

In this work, a methodology for setting dynamic pricing for VPP with energy storage under a bidirectional energy flow that allows business transaction among VPP stakeholders' during demand side management has been investigated. The results showed that prices and energy transaction can be set in such a way that it benefits all VPP stakeholders. Using the price margins as a basis of investigation under three different scenarios, the results reveals that the price margin between the import and export price at the wholesale market has a strong influence on the level of financial reward receives by the VPP stakeholders during demand response. This work provides a framework that can be further enhanced through integration with smart metering infrastructure, supporting real-time data exchange and dynamic control, thereby advancing the future realization of smart cities.

References

[1] S. Braithwait, D. Hansen, and M. O'Sheasy, "Retail electricity pricing and rate design in evolving markets," 2007.

[2] D. S. Kirschen and G. Strbac, Fundamentals of power system economics: John Wiley & Sons, 2004.

[3] L. S. Tesfatsion, C. A. Silva-Monroy, V. W. Loose, J. F. Ellison, R. T. Elliott, R. H. Byrne and R. T. Guttromson, *New Wholesale Power Market Design Using Linked Forward Markets: A Study for the DOE Energy Storage Systems Program*, SAND2013-2789, Sandia National Laboratories, Albuquerque, NM, USA, Apr. 2013. Available: https://www.sandia.gov/app/uploads/sites/163/2021/09/SAND2013-2789.pdf

[4] J. Xiao, Y. Meng, L. Li, S. Fan, G. He, and Z. Li, "Market equilibrium with strategic pricing and strategic constraints in renewable energy: the role of private energy storage," *Frontiers in energy research*, vol. 12, Mar. 2024, doi: https://doi.org/10.3389/fenrg.2024.1346528.

[5] Elexon, "The Balancing and Settlement Code (BSC) Arrangements," 2018

[6] J. Yang, J. Zhao, F. Wen, and Z. Y. Dong, "A Framework of Customizing Electricity Retail Prices," IEEE Transactions on Power Systems, vol. 33, no. 3, pp. 2415–2428, May 2018, doi: https://doi.org/10.1109/tpwrs.2017.2751043.

[7] D. S. Kirschen, "Demand-side view of electricity markets," IEEE Transactions on Power Systems, vol. 18, no. 2, pp. 520–527, May 2003, doi: https://doi.org/10.1109/tpwrs.2003.810692.

[8] J. Yang, J. Zhao, F. Luo, F. Wen, and Z. Y. Dong, "Decision-Making for Electricity Retailers: A Brief Survey," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4140–4153, Sep. 2018, doi: https://doi.org/10.1109/TSG.2017.2651499.

[9] Department for Energy Security and Net Zero, "Enhancing the smart meter installation journey towards Clean Power 2030," GOV.UK, Sep. 2025. [Online]. Available: https://www.gov.uk/government/calls-for-evidence/enhancing-the-smart-meter-installation-journey-towards-clean-power-2030/enhancing-the-smart-meter-installation-journey-towards-clean-power-2030

[10] "Dynamic Pricing Electric Vehicle Public Charging Demand," *https://www.centrefornetzero.org*, 2025. https://www.centrefornetzero.org/papers/the-impact-of-dynamic-prices-on-electric-vehicle-public-charging-demand-evidence-from-a?utm_source=chatgpt.com (accessed Oct. 26, 2025).

[11] T. Jiang, Y. Cao, L. Yu, and Z. Wang, "Load Shaping Strategy Based on Energy Storage and Dynamic Pricing in Smart Grid," IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2868–2876, Nov. 2014, doi: https://doi.org/10.1109/tsg.2014.2320261.

[12] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, "Energy Peer-to-Peer Trading in Virtual Microgrids in Smart Grids: A Game-Theoretic Approach," IEEE Transactions on Smart Grid, pp. 1–1, 2019, doi: https://doi.org/10.1109/tsg.2019.2934830.