An Aggregator-Based Market Modelling with an Impact of Risk Under Uncertainty

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***Abstract*—— In the electricity market the increased penetration of renewable energy sources (RES) and associated uncertainties impose challenges to determine the day-ahead distribution locational market prices effectively and also these uncertainties can jeopardize grid stability and reliability.RES aggregators compete to increase their profit but their intermittent nature adds financial risks to aggregators (A's). The main objective of this paper is to model a day-ahead electricity market by considering RES aggregators as participants to trade energy effectively to maintain a dynamic energy balance. Instead of relying on existing probabilistic forecast methods to account for the variable uncertain nature of RES, this paper uses a novel data-driven forecasting method to predict variable RES power generation accurately.The proposed model follows a three-stage approach. The first stage involves forecasting PV and wind output power with multiple scenarios. In the second stage, a scenario-based multi-aggregator market modelling is performed where aggregators submit their bids to the distribution network operator, who then clears the market by generating price signals. Uncertainties of RES aggregators lead to financial risk for aggregators. Hence, the third stage involves, risk assessment using value at risk (VaR) and conditional value at risk (CVaR) are applied to different scenarios for evaluating the potential portfolio losses within a specified time horizon and confidence level. To evaluate the effectiveness of the proposed model, it is tested on a modified 33-bus test system which shows effective energy trading at a distribution system with a considerable marginal range of voltage violations.The proposed novel three-stage model aims to improve the distribution level electricity market's efficiency and reliability, benefiting RES market participants and consumers alike.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9507

***Index Terms*—Aggregators, Conditional Value at Risk, Distribution Network Operator, Renewable Energy Sources, Value at Risk.**

I. Introduction

Renewable power generation has experienced a remarkable growth in recent years, driven by its environmental benefits and absence of fuel costs. Wind and solar energy stand out as the most significant renewable resources. Over recent years, numerous supportive schemes and policies have been implemented across various countries to increase the contribution of renewable production. Renewable energy sources (RES) increasingly capture attention in society and the electricity market, offering a solid alternative to enhance environmental and economic benefits. However, factors such as season, climate, temperature, geographical location, wind and PV power generation exhibit variable, intermittent, and uncertain outputs. Also, the widespread integration of renewable energy has not only heightened the severity of uncertainties but also introduced new uncertain parameters like solar and wind power forecasting variability, demand and electricity price forecasting errors [1].

These characteristics pose significant challenges in maintaining stability and conducting system planning and operation, which requires a thorough investigation of RES's economic participation in the electricity market [2]. Hence, selecting a suitable approach to model the uncertainty of wind and solar energy holds supreme importance for achieving more precise system planning and operation. Most of the existing studies suggest probabilistic-based forecast methods to study the uncertain nature of RES. A novel and accurate analysis is essential for effective electricity market modelling. Fig. 1 shows the classification of methods used to assess uncertainty.

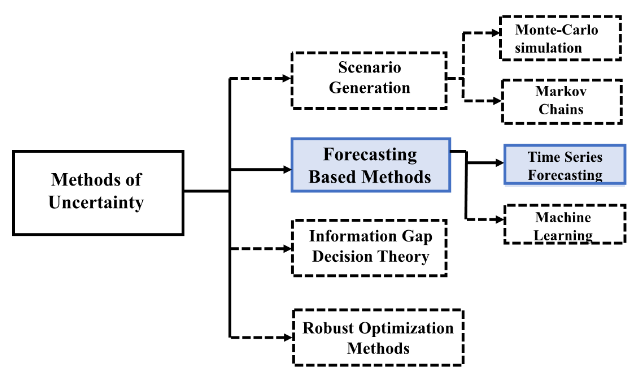

Fig. 1. Classification of Uncertainty Handling Methods (with Proposed method highlighted).

Given the intermittent and variable nature of RE sources, addressing the uncertainty they introduce is crucial, which consequently impacts the electricity market. The scenario-based method, a key approach in the probabilistic forecasting method has been widely adopted. The main approach involves determining the probability density function (PDF) of photovoltaic and wind power using statistical methods followed by generating scenarios through sampling methods. Several scenario-based methods have been explored in existing research [3]- [8]. For instance, in [3] and [4], the forecasting error for solar power, which depends on solar irradiance, is

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considered to follow a beta distribution, while the error for wind power, which depends on wind speed is considered to follow a Weibull distribution. This approach typically employs scenario-based methods such as Monte Carlo (MC) [5] simulation where a substantial number of simulations has to be performed to assess the probabilistic distribution nature of uncertain parameters thoroughly. Though MC simulation is one of the most considered scenario-based methods, it has the drawbacks of taking more simulation time and imposing a significant computational burden. Various technologies have been proposed to assess accurately the grid impact of these uncertain resources without imposing a significant computational burden. Numerous studies address various uncertainties, predominantly utilizing stochastic optimization methods over other techniques. However, few studies have explored robust optimization and information gap decision theory (IGDT) models. Implementing stochastic optimization requires random number generation implemented with method like Monte Carlo simulation being one of the commonly used methods. Study [6] employs, the quantile regression method to establish the PDF. The empirical cumulative distribution function (CDF) is explored in [7]. Additionally, studies [8] and [9] introduce the kernel density estimation (KDE) model.

The above-mentioned studies aim to represent the long-term frequency distribution of PV and wind power generation. Recently, the electricity market has relied on advanced forecasting methods for accurate forecasting of parameters like demand, PV, wind generation and electricity prices. This emphasized forecasting-based methods that use training models with historical data to generate scenarios, bypassing any assumptions about distribution functions. Our focus here is to develop a novel data-driven method which replicates the time series behavior of PV and wind. Given the coherence of PV and wind output power over time, recent research has begun to focus on time series characteristics for accurate estimation that relies on precise forecasting methods. Studies [10]- [12] show forecasting using such advanced methods. Auto regression integrated moving average (ARIMA) is one of the most suitable methods for forecasting load, wind power and solar power. These studies indicate that considering time series characteristics can significantly reduce irregular fluctuations [13]. Parameters such as mean absolute error (MAE) and root mean square error (RMSE) measure the difference between actual and predicted values. Lower values of these parameters indicate smaller errors. Although this method is effective, its applicability is restricted to univariate data.

The introduction of more RE sources at the distribution side necessitates a change of decentralized form of the power system from a centralized one which facilitates a flexible market. Market participants like prosumers, consumers participate in the electricity market locally at the distribution side through an operator known as a distribution network operator (DNO) [15]. Market modelling in the distribution network thus becomes challenging considering many participants and the uncertainties. Reference [16] shows the optimal clearing of the market price by the operator from the submitted bids of aggregators at the distribution end. In [17] risk-constrained stochastic optimization model using mixed integer programming is suggested in which uncertainty of concentrated solar power is investigated using a scenario-based approach considering risk, also a comparative analysis of risk-averse and risk-neutral performance is given. The work in this paper is limited only to solar power plant modelling when other sources like wind and batteries are considered which are not explored. The study of changes in market outcomes with multi-energy systems is important while performing resource optimization. In [18], a day-ahead and intra-day dispatch model for profit maximization is suggested in which uncertainty is modelled using the information gap decision theory (IGDT) approach. In [19], [20] IGDT-based uncertainty modelling is explained. In [19] solar, load and market price uncertainties are handled using IGDT and in [20], a mixed CVaR-IGDT model for DA and real-time market for the solar plant is formulated. Value at risk (VaR) and conditional value at risk (CVaR) are the two parameters for risk assessment [21]. To handle optimization problems with uncertainties stochastic programming is one of the most considered methods. Stochastic optimization problems demand attention not only to the expected values of decision outcomes but also to the risks caused by their variability. Thus, in the decision process's objective, it's essential to incorporate both expected outcomes and the associated uncertainties to make informed choices. As shown in [22], the worst scenario in California's electricity market crisis, led to severe loss, so the risk should be included in the decision-making process where VaR and CVaR are considered as risk parameters. Some works have been explored so far addressing the risk associated with monetary gain in the context of microgrid aggregators. The author in [23] addressed the risk for demand response aggregators and renewable sources aggregators. In [24], risk-constrained stochastic optimization of concentrated solar plants is studied using the scenario-based method to analyse uncertainties of solar radiation and electricity market price. Reference [24] proposes risk measures such as VaR and marginal VaR to analyze risk in the day-ahead market and PDF-based analysis is used to study the uncertainty of solar irradiation and wind speed. Table I presents a comparative analysis showcasing the methodologies employed by different researchers addressing uncertainty through different risk assessment methodologies.

In light of the above studies, there is a need of an effective market modelling to be designed considering the impact of uncertainty on RES. The proposed model uses VaR and CVaR to estimate risk and its variation with uncertain parameters. While most of the available literature focuses on the uncertainty handling of RES, very minimal literature demonstrates both risk assessment and management while designing an RES-dominated day-ahead market model. Our study introduces a 'three-stage market model' exploring the impact of RES uncertainty on day-ahead local electricity market modelling and thus offering insights for renewable energy aggregators to perform better risk management. The key contributions are summarized as follows:

1. This paper utilizes a time series-based forecasting method as a novel method of measuring the uncertainty of RES, thus addressing the gap of dependency on the generalized probabilistic-based scenario generation methods.

TABLE I
COMPARATIVE ANALYSIS OF EXISTING LITERATURE ON UNCERTAINTY HANDLING METHODS AND RISK ANALYSIS METHODS

Reference	Forecasting	Scenario Reduction Method	Uncertainty Modelling	PV Uncertainty	Wind Uncertainty	Risk Method
[3], [17], [25]	PDF	—	PDF	Beta PDF	Weibull PDF	CVaR based
[14], [18]	—	—	IGDT	IGDT	IGDT	IGDT based Risk
[29]	Kantorovich distance matrix (KDM) and MCS	MCS	—	—	Weibull PDF	CVaR based
[26]	Fast forward selection algorithm and MCS	MCS	—	Normal distribution	Weibull PDF	—
[28]	ANN	—	ANN	—	—	
[30]	MCS	MCS	MCS	—	—	VaR & CVaR based
[31]	MCS	MCS	MCS	Beta PDF	Weibull PDF	CVaR
[11]	Wavelet transform-ARMA	K-Means Clustering	MCS	Beta PDF	Weibull PDF	CVaR
[32], [12]	MCS	—	MCS	Log-normal	Weibull PDF	VaR, CVaR
[33]	MCS	—	MCS	Log-normal PDF	Weibull PDF	—
[34], [25]	PDF	—	PDF	Beta PDF	Weibull PDF	CVaR

2. An ARIMA forecasting method is applied to forecast solar and wind output power and its parameters like MAE and RMSE measure the accuracy of predictions. Existing literature focuses on PDF and Monte Carlo methods which are computationally intensive with randomness that may lead to misleading results. Addressing this gap, this paper aims to provide an effective value proposition for managing the uncertain power output of RES.

3. With the limitation of RES's capacity to participate in the electricity market, aggregating various dispatchable and non-dispatchable energy sources is one of the possible solutions for effective market participation of RES with attention to comprehending the value of aggregators for flexible integration with the grid. This paper considers RE-based aggregators as market participants in trading energy with an operator.

4. In market modelling, a bi-level interaction between the operator and aggregator is designed to facilitate the exchange of market information between the operator and aggregator, thus generating market price signals for considered scenarios.

5. It applies Value at Risk (VaR) and Conditional Value at Risk (CVaR), common risk measurement indices in the financial market, to estimate and analyse risk as it varies with changes in uncertain parameters.

6. Since risk levels fluctuate in the pursuit of maximizing market gains, the study also presents the net financial profit for aggregators in the results section.

7. To evaluate the effectiveness of the proposed market model outcome on the power network parameters, a test is performed on a modified IEEE 33 bus test system.

Fig. 2 illustrates the schematic depiction of the proposed model, consisting of three distinct stages; training model, market model and risk model. In the training model, an ARIMA model is employed to forecast future output power based on historical output power data of PV and WT. AGs submit their bids to an operator for market clearing in a market model based on the forecasted generations. Due to the uncertain nature of forecasted generation risk is to be assessed which is modelled in the risk model. The proposed paper is structured as follows: Section II provides the proposed model comprising a training model, market model, and risk model, followed by elucidating the mathematical formulations. Additionally, it explores how the K-means clustering algorithm is employed to reduce forecasted scenarios. Subsequently, Section III analyses the results obtained from the proposed model, resulting in a conclusion in Section IV.

II. PROPOSED MODEL

Figure 3 shows the stepwise representation of the proposed model which is a three-stage approach categorised as,

- Training Model
- Market Model
- Risk Analysis Model

1. The training model is executed in 2 steps:

A. Forecasted scenario generation to predict future events.

B. Reduced scenarios adequately represent the uncertainty and variability of the original set.

A. Forecasted scenario generation: The main objective is to get the best forecast such that the mean square deviation from the actual value to the forecast value will be as small as possible. Time series forecasting is a model to predict future values based on previous values in a time-sequential

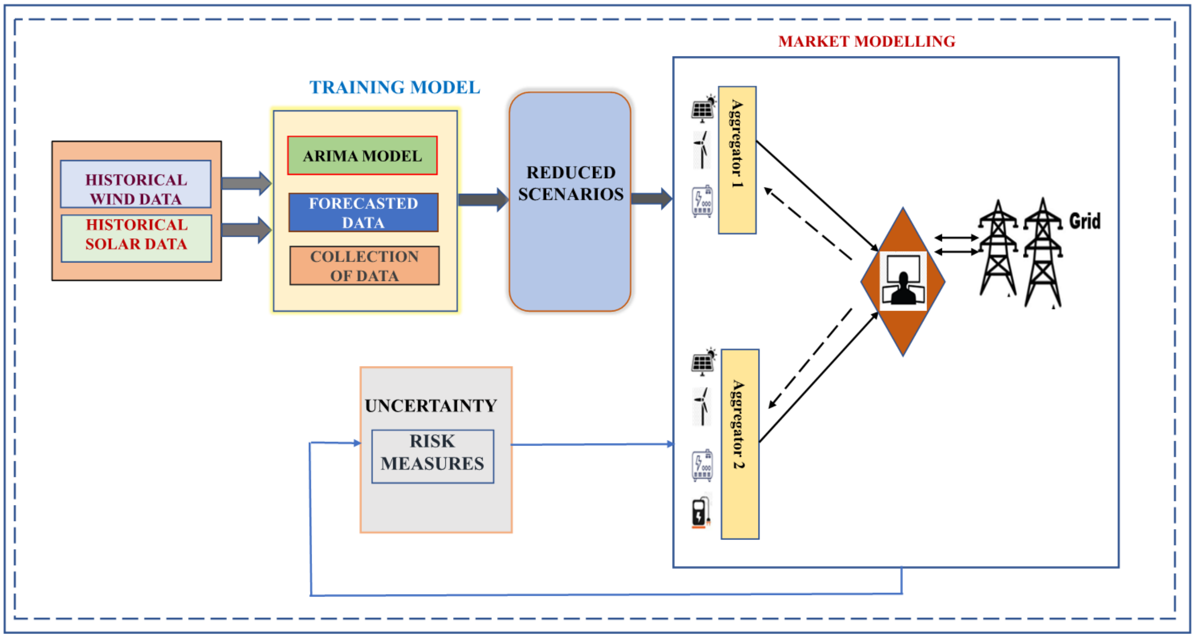

Fig. 2. Schematic Representation of the Proposed Model Illustrating Data and Functional Relations.

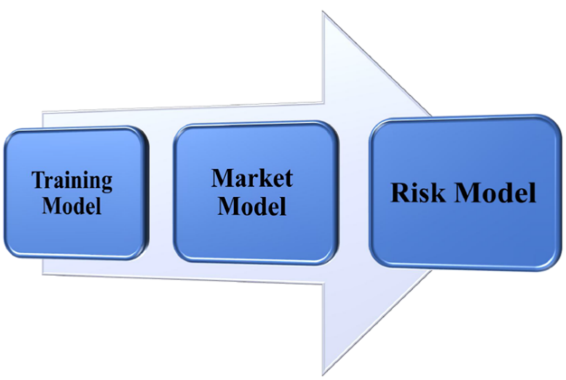

Fig. 3. A Stepwise Visualization of the Proposed Three-Stage Approach.

order by capturing patterns and trends of historical data. To apply the time series forecasting model, historical data of the Texas synthetic test case system's PV and WT output power is used here [30], [36]. ARIMA is one of the most widely used univariate time series models for forecasting, it mainly consists of three parameters (p, d, q) where 'p' is considered as order of autoregression (AR), 'q' is considered as the order of moving average (MA) and 'd' as the order of integration (I). In the AR(p) process, current values depend on previous values; in the MA(q) process, the current deviation from the mean depends on previous deviations. ARIMA approach is also called Box-Jenkins's approach [13]. The general representation of the AR & MA model is shown in equation (1) where C is constant and (ε_t) is white noise for time:

$$AR(p) = C + \sum_{i=1}^{p} a_i x_{t-i} + \varepsilon_t \ , \quad MA(q) = \sum_{i=1}^{q} b_i \varepsilon_{t-i} + \varepsilon_t \tag{1}$$

To assess the accuracy of predictions metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are employed as shown in equations (2) and (3). Y_i is the actual observation, $\hat{Y_i}$ is the predicted observation and 'N' is the total number of observations.

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |Y_i - \hat{Y}_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |Y_i - \hat{Y}_i|^2} \tag{3}$$

This model focuses on forecasting the hourly output power of photovoltaic (PV) and wind turbine (WT) systems. Given the short-term nature of the prediction task, historical data spanning three months from January to march is utilized as input. Once the model is trained, future forecasts are generated as shown in Figs. 4 and 5, and their accuracy is assessed using metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). This process is repeated each hour, and the resulting data is collected for further modelling.

B.k-Means Clustering Scenario Reduction: k-means clustering is one of the most popular unsupervised algorithms. It is considered as a partitional algorithm which classifies the data into clusters based on their similarity. The k-means algorithm is mainly a distance-based clustering algorithm [37], [38]. It computes "centroids" and iterates such that an optimal centroid is attained. The number of clusters identified is represented as 'k'. Generally 'k' value is considered as a predefined value choosen according to a value less than the number of data points. When 'k' value is not predefined value methods like the Elbow method can be used to determine the optimal 'k' value. Partitioning datasets into clusters entails the process of minimizing the squared error between data points and the centroid of a cluster, subsequently assigning each data point to the nearest cluster centroid. Here, the forecasted wind and solar predictions are reduced into five scenarios by using the k-means clustering algorithm in Python.

2. Market Model: Here a bi-level market model is proposed in which the lower-level aggregators (A's) perform economic dispatch to submit their generation bid to DNO. In the upper-level DNO performs day-ahead social welfare maximization to clear the market. Aggregators with various combinations of photo voltaic (PV), wind turbine (WT), diesel generators (D_G) and batteries (BA) are considered. In this analysis, two A's are modelled and can also be extended for multi-aggregators. A1: Combination of 1 WT, 1 PV, 5 (D_G)'s.

A2: Combination of 1 WT, 1 PV, 4(D_G)'s, 2 BA.

Where the number of aggregators is represented as 'a', diesel generators as 'i', PV as 'p', WT as 'w' and BA as 'b'.

3. Risk Analysis Model: In the electricity market risk management plays a prominent role in assessing the performance of RE generating units. As the microgrid-generating units exhibit uncertainty, hence risk must be considered in the mathematical formulation. Thus, uncertainty about future outcomes is referred to as risk. In the proposed model solar and wind power are forecasted using a time series model. The deviation from the actual and forecast will impact the electricity market which is considered as risk. Hence, risk assessment is necessary for economic analysis, where uncertainty is a factor to integrate risk analysis, enabling how uncertainty influences profit. Value at Risk (VaR) is a statistical tool extensively employed in financial risk management. Its primary purpose is to evaluate the potential loss that a portfolio of financial assets may incur within a predefined time frame while considering a specified level of confidence. Simply VaR expresses the utmost extent of potential loss a portfolio might encounter over a set duration and likelihood. CVaR is a coherent risk measure whose effectiveness has been well justified in financial and risk management areas. It provides optimization shortcuts for many practical large-scale calculations through scenarios and finite sampling. This approach is used to trade energy in the DA electricity market. CVaR or expected shortfall is a risk measure that quantifies the amount of tail end in a portfolio which is computed by taking the average between var(α) and losses exceeding var with confidence interval θ [27].

Mathematical Formulation: The main objective is to maximize the profit of aggregators as represented in equation (4) where π_s is the probability of scenarios. The most common way to include risk in the problem formulation is by adding a risk measuring term CVaR, the risk measure is multiplied by risk aversion factor β where $\beta \in [0,1]$ and expected profit is multiplied by (1-β) to control trading between expected profit and risk measure CVaR which is represented as,

$$\text{Max OF} = \pi_s \left[(1-\beta)\cdot E(p,t,s) + \beta \cdot \text{CVaR}\right] \tag{4}$$

$$\text{CVaR} = \alpha - \frac{1}{(1-\theta)} \sum_{s=1}^{N_s} \pi_s . \eta_s \tag{5}$$

$$\text{subj to } \eta_s \geq 0 \tag{6}$$

$$\alpha - E(p,t,s) - \eta_s \leq 0 \tag{7}$$

Equation (5) represents the formulation of risk parameter CVaR where α is VaR with Θ as the confidence interval and η_s is the auxiliary variable which is a positive variable as shown in equation (6) and (7).

Aggregator Level: The main objective of A's is to reduce their operating costs, increasing aggregators' profit and thereby calculating the optimal schedules of D_G. Profit of the aggregator is represented in equation (8).

$$E(p,t,s) = \sum_s \left(\sum_{t=1}^{24} \left(P_D(a,i,t)\cdot \lambda_D(t)\right) - P_a(t)\cdot \mu_a(t) \right) \tag{8}$$

$P_a(t)$ is the aggregated power to be submitted to the operator to maximize the benefit of selling energy. The price signal $\mu_a(t)$ at the lower level is the aggregator price signal and which is taken as a decision variable with a cap limit of 30 \$/MWh per D_G maximum cost to satisfy economic dispatch criteria, where PD is D_G power and λ_D is the cost incurred for (D_G).

Constraints: Power balance constraint: Equation (9) shows the power balance constraints which ensures the total generated power of the aggregator is equal to the power transferred to the operator.

$$\sum_s \left(\sum_p P_{pv}(p,a,t) + \sum_w P_w(w,a,t) + \sum_i P_D(a,i,t) \right) + \sum_b \left(P_{bch}(b,a,t) - P_{bdch}(b,a,t)\right) = \sum_s P_a(a,t) \tag{9}$$

A's power P_a for considered scenarios is taken as summative of all sources of aggregator with PV power represented as P_{pv}, Wind power as P_w, diesel generator power as P_D, battery charging and discharging powers as P_{bch} and P_{dbch}.

D_G constraints: Equations (10), (11) and (12) show the maximum power capacity of D_G with their minimum up and minimum down limits as RU_D and RD_D.

$$0 \leq P_D(s,a,i,t) \leq P_{D,\max}, \quad \forall t,a \tag{10}$$

$$P_D(s,i,t) - P_D(s,i,t-1) \leq RU_D, \quad \forall t,a \tag{11}$$

$$P_D(s,i,t-1) - P_D(s,i,t) \leq RD_D, \quad \forall t,a \tag{12}$$

From these equations, D_G's output power for considered aggregators can be calculated.

Battery constraints: Equations (13) and (14) represent the charging and discharging limits of the battery and energy stored in the battery E_b is shown in equation (15).

$$P_{\text{bch,min}} \leq P_{\text{bch}}(s,a,b,t) \leq P_{\text{bch,max}}, \quad \forall t,a \tag{13}$$

$$P_{\text{bdch,min}} \leq P_{\text{bdch}}(s,a,b,t) \leq P_{\text{bdch,max}}, \quad \forall t,a \tag{14}$$

$$E_b(s,a,b,t) = E_b(s,a,b,t-1) + P_{\text{bch}}(s,a,b,t)\cdot \eta_{\text{ch}} - \frac{P_{\text{bdch}}(s,a,b,t)}{\eta_{\text{dch}}}, \quad \forall t,a \tag{15}$$

$$E_{b,\min}(s,a,b,t) \leq E_b(s,a,b,t) \leq E_{b,\max}(s,a,b,t), \quad \forall t, a \tag{16}$$

where η_{ch}, η_{dch} are charging and discharging efficiency and the battery energy storage limit is represented in (16).

Price limit Constraints:

$$0 \leq \mu_a(s,t) \leq \mu_{a,\max}(s,t) \tag{17}$$

Equation (17) represents the aggregator's price limit $\mu_a(t)$ constraint with a maximum limit.

Aggregator power Limit Constraints:

$$0 \leq P_a(s,a,t) \leq P_{a,\max}, \quad \forall t, a \tag{18}$$

The aggregator power limit constraint is set by taking the maximum power generated from A's considering all scenarios.

Operator level Model: The distribution network operator upon receiving the generated bids from the Aggregator level model generates an optimal price signal for the A's. The objective function is given as

$$\text{Min OF} = \sum_s \left(\sum_{t=1}^{24} (P_{\text{gr}}(s,t) \cdot \mu_{\text{gr}}(s,t) - P_a(s,t) \cdot \mu_a(s,t)) \right) \tag{19}$$

$$\sum_s P_{\text{gr}}(s,t) = \sum_s P_{\text{load}}(s,t) - P_a(s,t) \tag{20}$$

The main aim of the DNO is to minimize the transmission level market (grid) dependency while meeting the load at the distribution level. Any surplus and deficiency of power is balanced at the grid level as shown in equation (20). $\mu_{\text{gr}}(t)$ is the forecasted grid price signal. The proposed model is detailed in an algorithm as shown below:

Algorithm 1 Algorithm of the Proposed Model

Step 1: Based on the available historical data of PV and wind output power, scenarios are generated using an ARIMA forecasting method. The forecast accuracy is measured using metrics such as MAE and RMSE.

Step 2: For scenario-based market modeling, forecasted scenarios are reduced to a minimum number of 5.

Step 3: Several dispatchable and non-dispatchable sources are aggregated into aggregators for trading energy at the distribution network.

Step 4: A bi-level market modeling is designed to balance surplus and deficiency levels of aggregators with the grid. The generation of various sources of aggregators and their optimal price signals are calculated for a period of 24 hours.

Step 5: Aggregators conduct scenario analysis to assess the impact of risks and uncertainties on profit. By evaluating multiple scenarios, aggregators can identify potential risks using risk measures such as VaR and CVaR.

Step 6: Based on the power generation of aggregators, an optimal power flow is executed on a modified 33-bus test system, which shows the optimal value of execution.

III. Results and Dsicussion

Based on the historical data of PV and wind output power, the ARIMA time series forecasting model will forecast future power in the short term. Figures 4 and 5 illustrate the forecast scenarios for PV and wind output power with a comparison of the forecasted and actual day-ahead PV and output power. The difference between these predicted values and actual observed values represents the forecast uncertainty. The suggested methodology is tested using Python software for this a 64-bit, core i5 processor-based computer with 3.20Hz clock speed and 4GB RAM is used. The k-means clustering algorithm is also modelled in Python, reducing forecast scenarios into 5 clusters as shown in Fig. 6 (a) and (b). MAE and RMSE bars of PV and wind output power scenarios is shown in Figs. 7 and 8. For market modelling, a non-linear optimization model for reduced scenarios is developed in GAMS software and the non-linearity is handled with the available solvers.

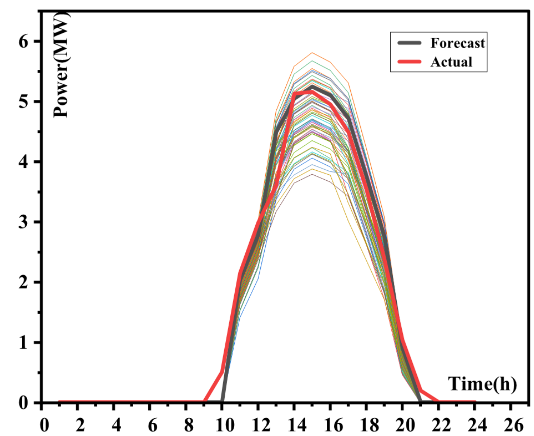

Fig. 4. Forecasted Scenarios of PV Output Power.

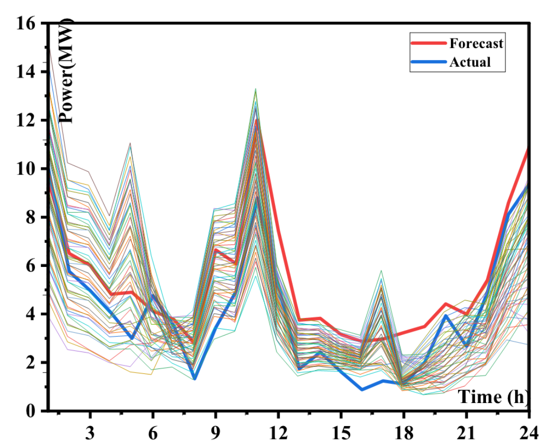

Fig. 5. Forecasted Scenarios of Wind Output Power.

As forecasted output power of PV and wind is intermittent to meet the demand and also for continuous trading of DA market, sources such as (D_G)'s and batteries are considered as per their technical constraints. As various dispatchable and non-dispatchable sources are aggregated as aggregators for energy trading, in this model two A's are considered for market modelling of which A1 is considered to be composed of one PV, one WT, 5 (D_G)'s and A2 is considered to be composed of one PV, one WT, 4 (D_G)'s and 2 batteries, it can also be enhanced to multiple aggregators for energy modelling but in the proposed model for analysis only two aggregators are

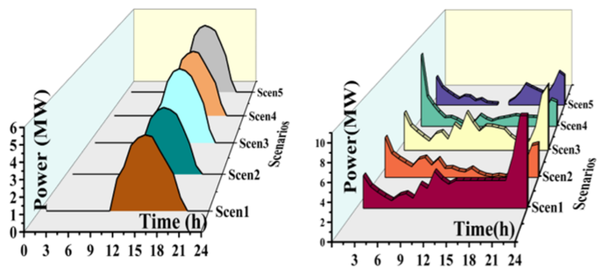

Fig. 6. Reduced Scenarios of (a) PV & (b) Wind Output Power.

considered and also to show the variation of modelling energy, price and risk here aggregator composition is considered to be of with batteries (A2) and without batteries (A1).

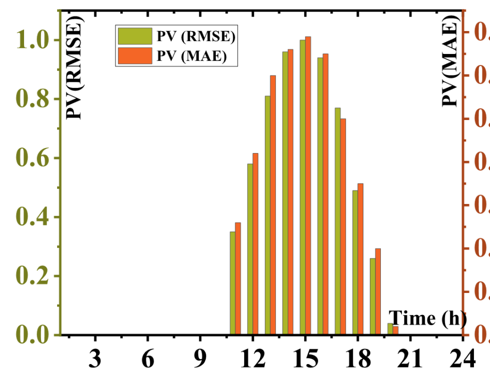

Fig. 7. RMSE and MAE metrics for PV Forecsted Scenarios.

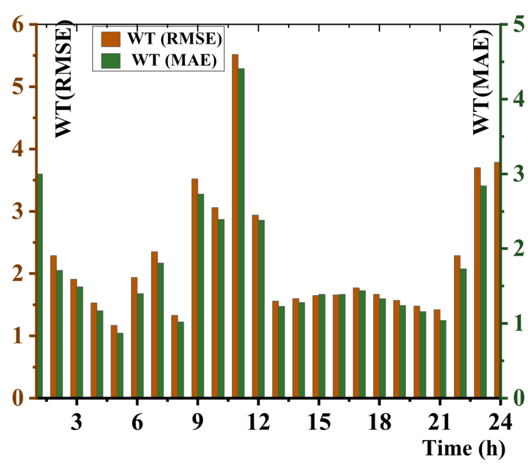

Fig. 8. RMSE and MAE metrics for Wind output power forecasted scenarios.

This model estimates the output power of (D_G)'s of each aggregator and determines the charging and discharging levels of batteries for 24 hours with consideration of scenarios. Based on the generation of aggregators submitted to the operator, the operator clears the market and generates the price signals.

Figs. 9 and 10 show the diesel generator production of Aggregators 1 and 2. Based on the composition of aggregators when PV and wind energy are not supportive, aggregators utilize power from diesel generators. Tables II and III show the technical specifications of (D_G)'s and batteries (BA) of considered A's to model using the above equations.

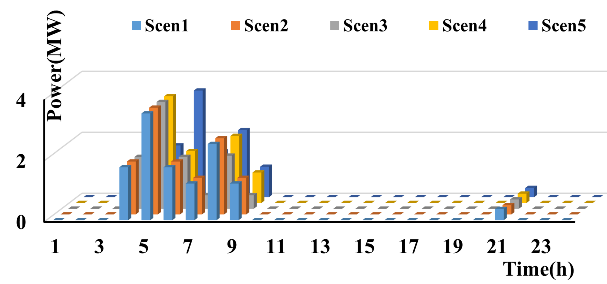

Fig. 9. Diesel Generators production of A1.

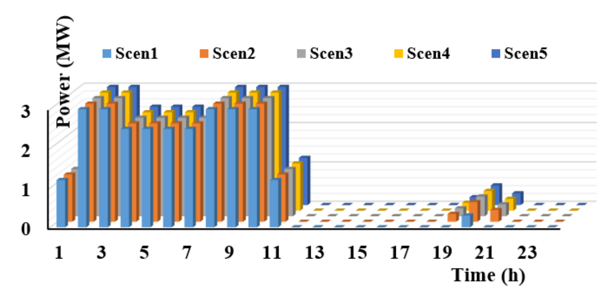

Fig. 10. Diesel Generators production of A2.

Figs. 11 and 12 show the charging and discharging power levels of batteries for the scenarios considered, taking into account battery constraints and(D_G) constraints as outlined in the above equations. Batteries and (D_G)'s are used to balance the energy of the aggregators and support continuous market operation. This production is available at hours when the availability of RES is low, i.e., during mid-day because RES generation is more BA and diesel production is less.

TABLE II
SPECIFICATIONS OF BATTERIES CONSIDERED IN THE PROPOSED MODEL

Battery	$E_{b\,\min}$ (MW)	$E_{b\,\max}$ (MW)	$P_{bch\mathbf{max}}$, $P_{bdch\mathbf{max}}$	$P_{bch\mathbf{min}}$, $P_{bdch\mathbf{min}}$	η_{ch}, η_{dch}
1	0	8.0	4.0	0	0.98
2	0	4.0	4.0	0	0.95

TABLE III
SPECIFICATIONS OF DIESEL GENERATORS FOR AGGREGATORS 1 AND 2

Group	D's	$P_{(D,\mathbf{max})}$ (MW)	λ_D ($/MWh)	RU_D, RD_D
A1	1	1.0	22.5	0.5
	2	1.2	20.0	0.6
	3	1.0	25.0	0.5
	4	0.5	20.0	0.3
	5	1.0	22.5	0.5
A2	1	0.5	20.0	0.3
	2	0.5	25.0	1.0
	3	1.0	28.5	0.5
	4	1.0	22.5	0.5

Figs. 13 and 14 represent scenario-wise individual Aggregator production. The profit of aggregator 1 and aggregator 2

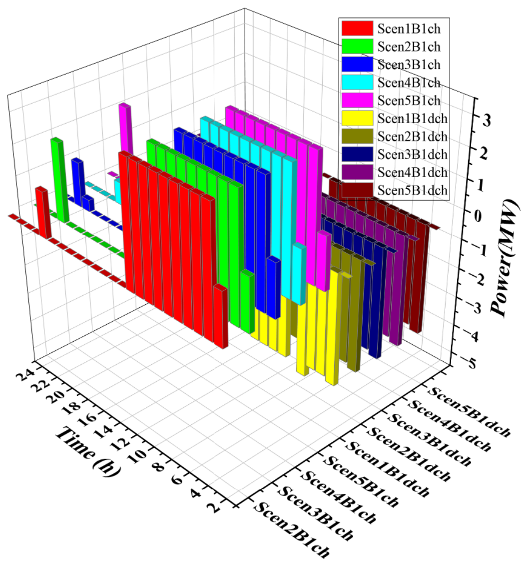

Fig. 11. Charging & discharging levels of Battery 1.

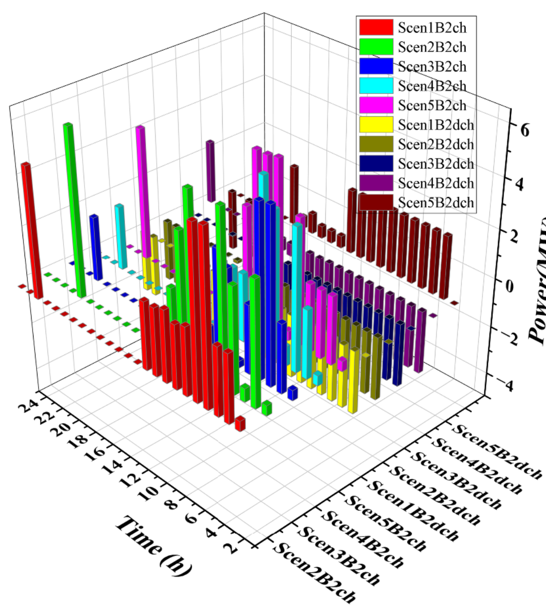

Fig. 12. Charging & discharging levels of Battery 2.

is shown in Figs. 15 and 16. In energy markets, risk considerations play a significant role due to the inherent volatility and uncertainty associated with energy prices, supply-demand dynamics, regulatory changes, and geopolitical factors. Energy market participants, including producers, consumers, traders, and investors, need to effectively manage various types of risks to protect against potential losses. A's conduct scenario analysis to assess the impact of risk and uncertainties on profit, by evaluating multiple scenarios A's can identify potential risks. VaR and CVaR are commonly used risk measures in the trading environment to evaluate the potential losses a portfolio might encounter within a specified time horizon at a particular

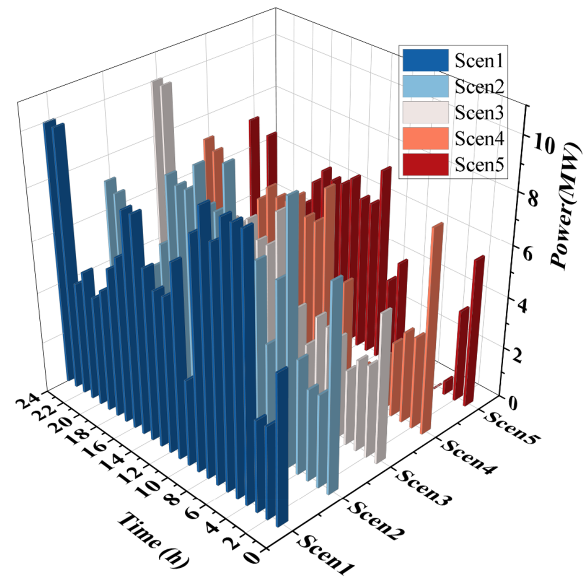

Fig. 13. Scenario-wise total Production of A1.

confidence level. Calculated VaR and CVaR are computed for aggregators 1 and 2 for confidence levels of 95% and 98% as given in Table IV.

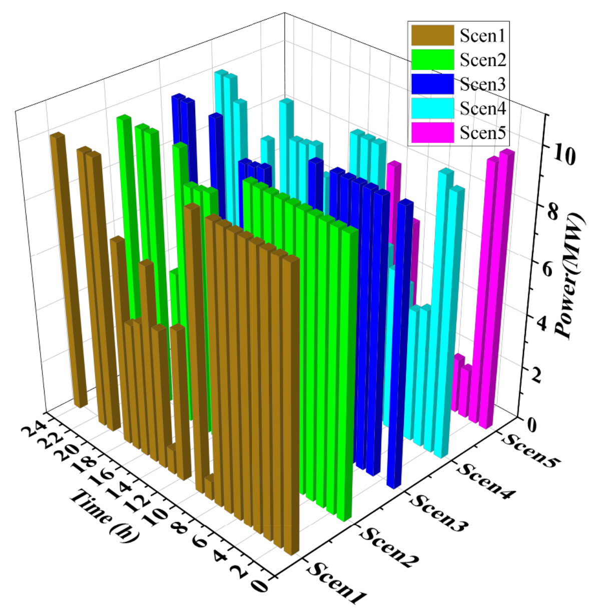

Fig. 14. Scenario-wise total Production of A2.

VaR quantifies the minimum expected loss that a portfolio might experience. A negative VaR indicates that at a particular confidence interval, the returns are expected to be better than a specific amount. If VaR is negative, CVaR will be positive because it is considered as average returns of tail beyond VaR point. In Table IV scenarios 1, 2, and 3 shows positive VaR indicating maximum potential loss and higher CVaR indicates substantial tail end losses. Aggregator 2 with batteries shows more negative VaR compared to aggregator 1 without batteries. This implicates, with support of storage units, aggregator 2 is more risk averse than aggregator 1 in handling DER uncertainties. Fig. 17 depicts market clearing

TABLE IV
VaR OF AGGREGATOR 1 AND 2 AT DIFFERENT SCENARIOS

Scenario	A1-VaR (95%)	A1-VaR (98%)	A2-VaR (95%)	A2-VaR (98%)
Scen1	32.25	18.09	0	-29.5
Scen2	31.25	25.15	0	-5
Scen3	28.43	-10.86	-7.08	-76
Scen4	26.45	19.11	-12.5	-76.5
Scen5	6.87	0	-61.54	-63.5

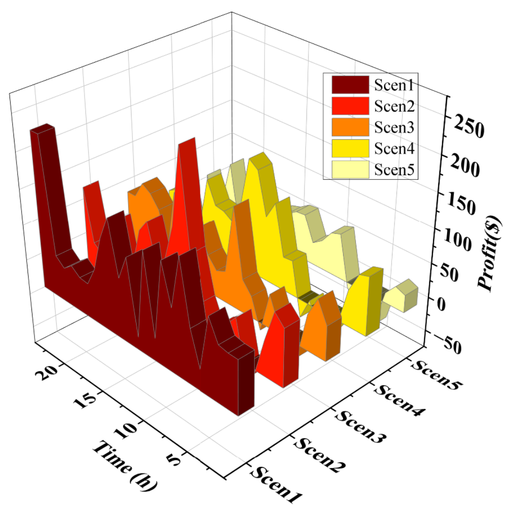

Fig. 15. Scenario-wise Profit of A1.

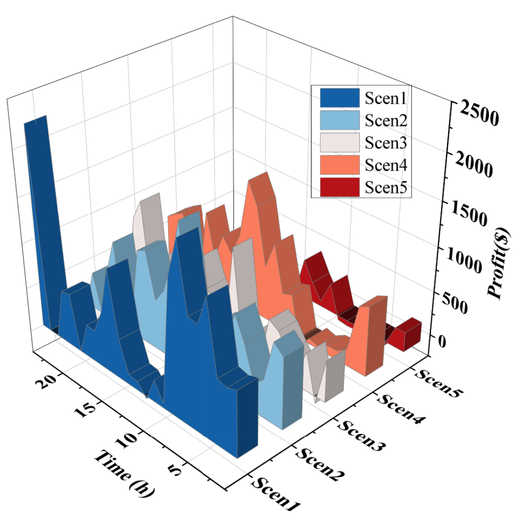

Fig. 16. Scenario-wise Profit of A2.

price signals 'μ_a' of aggregators for 24 hours, the operator calculates price signals '$\mu_{\mathrm{gr}}(t)$' of aggregators based on their generation and grid price is the forecasted price [35]. The inference drawn is that the price of A's is lower than the price of the grid, indicating a lower generation cost at the aggregator level because of the generation of DER. Fig. 18

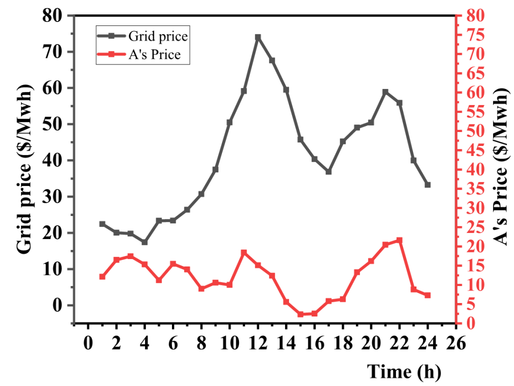

Fig. 17. Comparison of day-ahead price signal of aggregator and Grid Price signal.

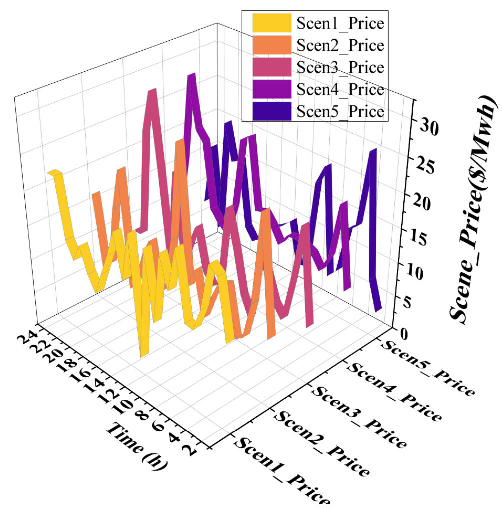

Fig. 18. Aggregators Market clearing price signal Scenarios.

shows the optimal price signals of A's for reduced scenarios. Fig. 19 shows scenario-wise CVaR for aggregators 1 and 2 at a confidence interval 95%.

Based on the power generation of aggregators an optimal power flow is executed by considering a modified 33-bus test system as shown in Fig. 20 for the considered aggregators. Fig. 21 shows voltage magnitudes at each bus for the considered generation and the deviation of voltage magnitude is$\pm 8\%$ which is a considerable limit in the distribution network. For this execution Mat-lab based Mat-power tool is used with the considered generation and demand profiles.

Fig. 22 shows a comparative analysis of risk measure CVaR and profit with a variation of the risk aversion factor 'β' ranging from 0 to 1, as shown in the above mathematical modelling in equation (1) it is inferred that when β =0 expected profit is of a greater value and with high value of β the profit decreases and the risk measure increases.

IV. CONCLUSION

In this study, we have proposed a three-stage distribution market model considering the uncertainties of DER generation. The main objective to model a day ahead electricity market

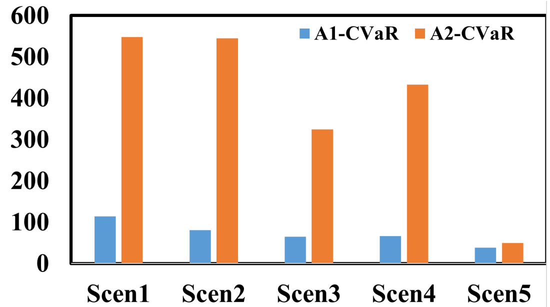

Fig. 19. Comparison of CVaR of A1 and A2 at a confidence interval of 95%.

at distribution end considering the impact of risk due to uncertain RE sources. The ARIMA model captures the temporal dependencies and trends present in the time series solar and wind generation data, performing accurate and reliable forecasts. The proposed risk modelling at the distribution level provides a flexible market environment to communicate with the grid at the transmission side, thereby balancing the surplus and deficiency of market participants. Also, the optimal price signals are generated which enhances the reliable market operation. We have quantified the uncertainty with forecasted data which allows the decision-makers to gain valuable insights into the range of potential outcomes and the corresponding risks. Furthermore, our approach contributes to the existing literature by addressing the limitations of traditional forecasting methods that often neglect uncertainty in their predictions. By explicitly considering uncertainty, our model enables more informed decision-making in the day-ahead electricity market, allowing market participants to better assess and manage risks, optimize trading strategies, and enhance overall market efficiency. However, this approach has its limitations such as the accuracy of the forecasts and uncertainty estimates is contingent upon the availability and quality of historical data, as well as the assumptions and parameter settings of the ARIMA model. With further refinement and validation, this approach has the potential to assess the efficiency and reliability of DER-dominated electricity markets, benefiting both market participants and consumers alike.

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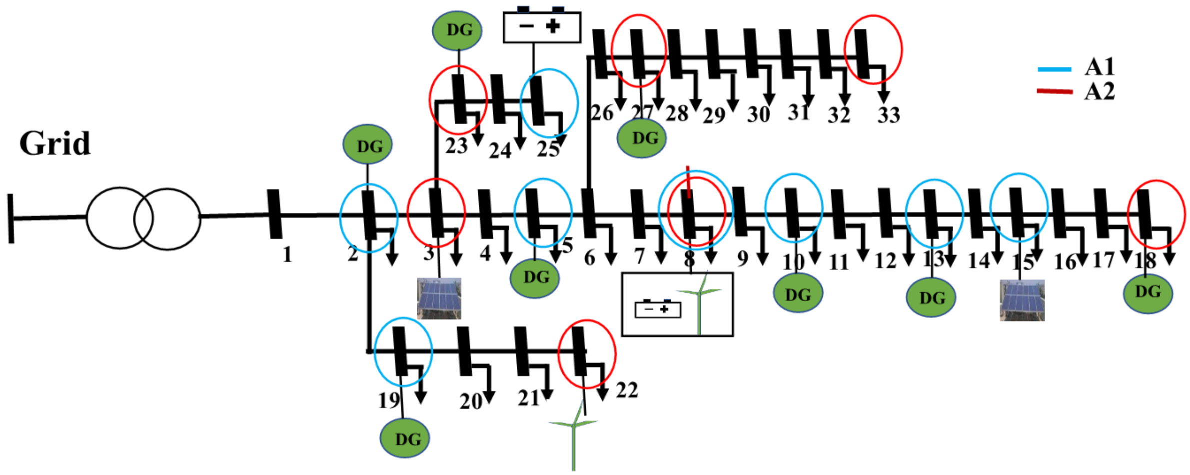

Fig. 20. Modified IEEE 33-bus test system with considered Aggregators generation.

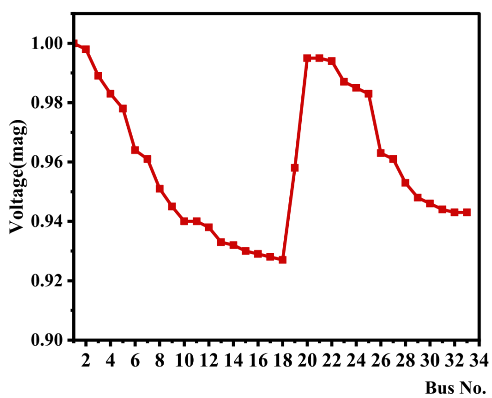

Fig. 21. Voltage profile at each bus of the modified IEEE 33-bus test system.

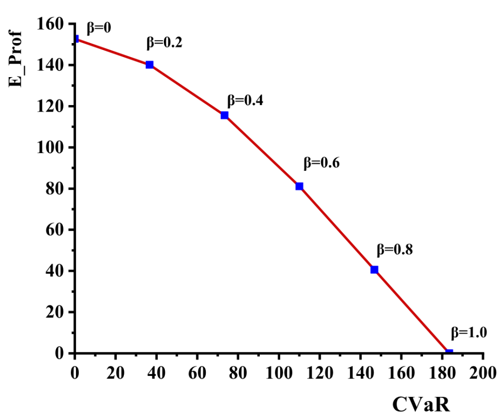

Fig. 22. Comparison of CVaR and Expected Profit for different β values.

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