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Research paper

A risk-aware bidding model for virtual power plants: Integrating renewable energy forecasting and carbon market strategies

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ABSTRACT

Integrating renewable energy resources (RES) into the energy market through a virtual power plant (VPP) framework is an effective strategy for reducing carbon emissions while enhancing system efficiency, reliability, and cost-effectiveness. However, RES-based power generation is inherently uncertain due to weather variability, making it crucial to incorporate uncertainty modelling. Additionally, carbon emissions can serve as a revenue source through carbon reduction policies such as carbon taxes and cap-and-trade schemes. An alternative approach to carbon reduction is the uplift payment scheme, which promotes a more carbon-efficient energy market (EM). This study introduces a novel bidding model within a VPP environment that leverages Extreme Gradient Boosting algorithm (XGBoost) algorithm to predict RES generation, addressing uncertainty through advanced forecasting techniques. The associated prediction risks are quantified using the Conditional Value at Risk (CVaR) method. Furthermore, the proposed bidding model is integrated with the carbon market, incorporating various carbon reduction policies to determine carbon credit prices dynamically. In addition to this, the proposed model is also optimized with a very new meta-heuristic algorithm called White Shark Optimizer (WSO) Algorithm to check the possibility of convergence of the model. A comprehensive comparative analysis is conducted to evaluate the performance of the proposed approach. The model's effectiveness is demonstrated through case studies, illustrating its potential to optimize bidding strategies while mitigating risks associated with RES uncertainty and carbon pricing fluctuations. By integrating advanced forecasting methods, risk assessment, and carbon market mechanisms, this work contributes to the development of a more sustainable, reliable, and economically viable energy market.

1. Introduction

The burning of fossil fuels in conventional power plants is a major contributor to carbon emissions, posing a significant challenge that must be addressed for a sustainable climate. In the era of renewable energy, the conventional grid meets rising energy demands by integrating power generated from renewable energy sources (RES). As a result, aggregating RES within the existing energy market has gained the attention of policymakers. These geographically dispersed RES units not only generate electricity for their own use but can also sell surplus energy to the grid, creating revenue opportunities. Incorporating RES into the electricity exchange market enhances both the efficiency of renewable energy systems and the reliability of the energy market.

The concept of a Virtual Power Plant (VPP) represents a virtual marketplace where all RES units aggregate and participate in the energy market as a single entity. Each small, distributed generation unit functions collectively to optimize energy distribution and market participation. The idea of VPPs was introduced to make use of several individual facilities to achieve a better goal (Seven et al., 2022). While researchers have proposed various definitions of VPPs, a standardized definition remains to be established. According to the European project FENIX (The Virtual Power Plant Concept from an Economic Perspective, 2008), a VPP is defined as a group of diverse distributed energy

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Nomenclature

Variables

Φ Set of the VPP units
$P_{b,pv,t}$/ $P_{b,wt,t}$ Bidding quantity of PV, and WT at time t respectively.
$P_{f,pv,t}$, / $P_{f,wt,t}$ Forecasted power of PV and WT at time t respectively.
$P_{pv,max,t}$,/$P_{wt,max,t}$ Maximum power output of PV and WT at time t respectively.
ρ_c Carbon market revenue in VPP
C_{mt} Operational cost of Micro turbine (MT)
C_{esd} Operational cost of energy storage device
C_c Operational cost of carbon market
$\delta_{b,t}$ Price of EM
$\delta_{c,bid}$ Bidding Price of carbon credit in EM
$\delta_{c,bid(r)}$ Modified carbon credit bid price with the reduction rate α
$\hat{\delta}_c$ Maximum (capped) carbon credit price corresponding to the set emissions cap
$\hat{\delta}_{c,uplift}$ Modified carbon credit bid price with uplift payment scheme
$\delta_{up,t}$/ $\delta_{dn,t}$ Ramp up and down price of the VPP units
R_{ramp} Revenue of VPP from ramp up and down
$P_{up,i,t}$/$P_{dn,i,t}$ Bidding capacity of the market for ramp up and down at time t respectively.
ρ_{em} Revenue of VPP
$P_{b,ev,t}$,/$P_{b,bat,t}$ Bidding quantity of EV, and battery at time t respectively.
$P_{b,mt,t}$,/$P_{b,cpp,t}$ Bidding quantity of MT and CPP at time t respectively.
$P_{pv,min,t}$,/$P_{wt,min,t}$ Minimum power output of PV and WT at time t respectively.
SW Social Welfare of the EM
C_{cpp} Operational cost of Conventional power plant
η Penalty coefficient
$P_{dis,bat,t}$/$P_{char,bat,t}$ Charging and discharging power of battery at time t respectively.
$P_{dis,ev,t}$/$P_{char,ev,t}$ Charging and discharging power of electric vehicle at time t respectively.
$\delta_{c,bat}$/$\delta_{c,ev}$ Battery and electric vehicle charging and discharging price
λ_{pv} Penalty for Solar Photovoltaic (PV) generation
λ_{wt} Penalty for Wind Turbine (WT) generation
η_{char}/η_{dis} Charging and discharging efficiency of energy storage devices
$S_{bat,t}$ /$S_{ev,t}$ Current status State of Charge of battery and electric vehicle respectively.
$S_{bat,t,\min}$ /$S_{bat,t,\max}$ Maximum and minimum SOC of the electric vehicle
$S_{ev,t,\min}$ /$S_{ev,t,\max}$ Maximum and minimum SOC of the battery electric vehicle

resources (DERs) that collectively form a unified operational profile while considering network effects on aggregated output. VPPs incorporate multiple technologies, function across multiple locations, and can operate in isolated networks (Nadeem et al., 2019). RES units in VPPs can include electric vehicles, solar photovoltaic systems, wind farms, microturbines, battery storage systems, controllable loads, micro-CHP units, and fuel cells—most of which produce little to no carbon emissions. The general layout of VPP system is presented in Fig. 1. Expanding the use of these generation units is a key strategy for reducing greenhouse gas emissions and addressing global climate challenges. The following are some of the key features of VPP:

- Enhanced integration of RES within a VPP framework significantly decreases the reliance on fossil fuels in conventional generation units, thereby mitigating greenhouse gas emissions and contributing to improved environmental sustainability.
- The incorporation of VPP components into the existing power infrastructure promotes enhanced grid security, economic operation, and long-term sustainability of the energy system.
- VPPs contribute to increased system lifecycle, operational efficiency, and reliability through coordinated control and optimal dispatch of DERs.
- Beyond their role in electricity market participation, DERs within a VPP also deliver ancillary services, including ramping support, frequency regulation, and real-time balancing of generation and load, thereby reinforcing grid stability and operational resilience.

However, renewable energy generation is inherently intermittent due to its dependence on weather conditions. When integrated into the energy market, an effective bidding strategy is essential to counter the variability of RES generation. This uncertainty can be managed using forecasting algorithms to predict power generation before bidding, coupled with risk analysis. To further promote carbon reduction, various

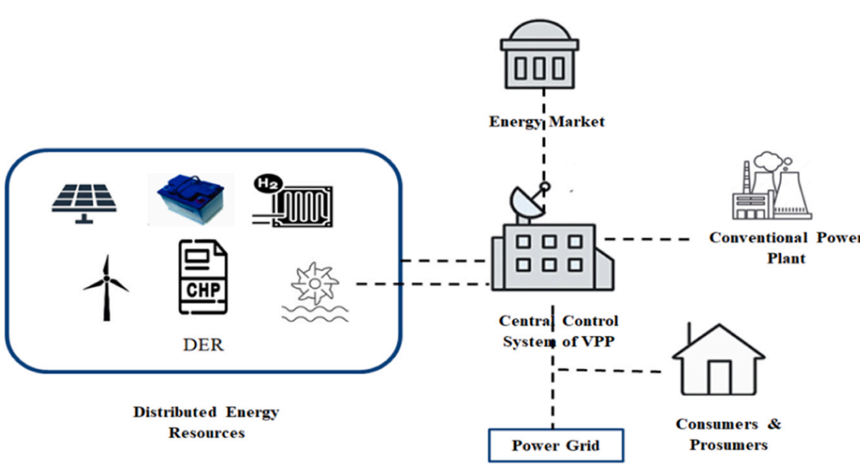

Fig. 1. General layout for VPP system.

policies such as carbon taxes and cap-and-trade schemes have been introduced in the carbon trading market.

This work proposes a bidding model for a VPP system that incorporates forecasted RES power generation to enhance market participation while integrating the energy and carbon markets. Additionally, it examines the pricing of carbon credits within the framework of carbon reduction policies, aiming to maximize the overall profitability of the system while contributing to sustainability efforts.

1.1. Related works

The unpredictable nature of atmospheric conditions makes accurately forecasting solar PV and wind turbine output challenging. Solar power output is influenced by various weather parameters, including air temperature, cloud cover, wind speed, and wind direction. A forecasting algorithm using a support vector machine was proposed in Shi et al. (2011), incorporating weather classification and grid-connected solar PV system implementation. The study utilized four weather models cloudy, rainy, foggy, and sunny achieving an average mean relative error (MRE) of 8.64 % and an average root mean square error (RMSE) of 10.5 %. In Sáez et al. (2015), a fuzzy prediction model was applied to account for RES uncertainty and load prediction, demonstrating better accuracy than linear regression models with MAE (mean absolute error) of 1.27 KW with fuzzy model and 1.72 KW with linear regression model. The fuzzy model in Akhtar et al. (2021) successfully predicted monthly wind power across Indian cities with an average RMSE of 1.12 %. Wind power generation for day-ahead scheduling and real-time applications was forecasted using artificial neural networks (ANN) in Liu et al. (2015), with a mean absolute percentage error (MAPE) of 17.38 %. A 48-h ahead multi-stage wind power forecasting model integrated ANN with SVM, achieving normalized MAE between 9 % and 20 % across 25 wind power plants (Buhan and Çadırcı, 2015).

In Wang et al. (2019), wind power forecasting was refined using a heteroscedastic spline regression model (HSRM) and a robust spline regression model (RSRM), with RSRM providing the most accurate results. Multi-to-multi mapping techniques were applied in Yan et al. (2018) using an ensemble stacked de-noising autoencoder (e-SDAE), yielding a normalized RMSE of 9.60%. Adaptive learning algorithms were employed in Wang et al. (2018) for solar power forecasting, resulting in a MAPE of 13.68% and an RMSE of 16.95%. Short-term solar power forecasting with battery storage was explored in Ando et al. (2021), achieving a MAPE of 17.54%. Meanwhile, Liu et al. (2021) compared day-ahead solar power forecasts using neural networks with LSTM and MLP models over various timeframes, with an average RMSE of 7.30%. Comprehensive reviews of solar power forecasting methodologies were presented in hendouzi and Bourouhou (2020) and a study for a specific location is given in El Robrini (2025). Paper (Andrade and Bessa, 2017) evaluated solar and wind power forecasting using numerical weather prediction (NWP) data with Gradient Boosting Trees (GBT), achieving MAE values of 6.20% and 6.15% and RMSE values of 9.82% and 8.76% for solar and wind forecasting, respectively. ANN-based methods demonstrated superior accuracy and lower error rates compared to other forecasting models. Recent research showed other approaches may perform better than ANNs (Dhananjay Rao et al., 2024).

To reduce carbon emissions, carbon tax and cap-and-trade programs are widely implemented. A carbon tax imposes fees based on the market value of carbon-emitting fuels, while cap-and-trade allows companies to buy or sell carbon credits based on government-imposed emission limits. The concept of carbon pricing was introduced by Glomsrod et al. (1992) and its economic impact was analysed in Metcalf and Weisbach (2009). The cap-and-trade mechanism was pioneered by Stavins (2008) and Paltsev et al. (2008), with emission cap allowances and regulatory factors examined in Hahn and Stavins (2011). He et al. (2012) compared the two schemes across multiple dimensions to highlight their advantages. Alternative carbon reduction strategies that do not disrupt energy market dispatch have been explored in Hogan and Ring (2003) and Gribik et al. (2007). Paper (Zhang et al., 2022a, 2022b) analysed the impact of these schemes on power grid efficiency and strategic dispatch, while (Shin et al., 2021) addressed their role in minimizing energy market side payments. A combined bidding model and uplift payment strategy were proposed to minimize overall system costs.

As the majority of DER units in VPPs are weather-sensitive, an effective energy management system (EMS) is essential. The EMS manages power scheduling and dispatch before and after market bids are received (Latif et al., 2021). A day-ahead and real-time market bidding model was proposed in Baringo and Baringo (2017), focusing on price volatility and wind power uncertainty. Risk-constrained stochastic programming for revenue-maximizing VPP bidding was explored in Vahedipour-Dahraie et al. (2021); Afzali et al. (2020); Liang et al. (2019). Paper (Mashhour and Moghaddas-Tafreshi, 2011) introduced a rotating reserve market with a day-ahead bidding mechanism, while (Dabbagh and Sheikh-El-Eslami, 2016; Baringo and Baringo, 2017), and (Wang, 2018) incorporated spinning reserve markets. Reliability-based VPP bidding was analyzed in Pourghaderi et al. (2022). Paper (Chen et al., 2021) proposed a frequency regulation strategy involving solar PV, battery storage, and wind farms, using the Nash Harsanyi Bargaining solution for optimization. A bi-level optimization model for day-ahead and balancing markets was presented in Zhao et al. (2016), aiming to reduce costs and control inelastic demand. Fuzzy optimization was employed in Al-Awami et al. (2017) to examine demand response strategies like load curtailment and shifting for profit maximization. While most studies focused on single VPP units, (Wang et al., 2016) introduced a multi-VPP concept for unified energy management, using a game-based interactive dispatch model. A bi-level distributed robust optimization approach was used in Song and Jing (2023) to determine optimal bidding strategies under VPP uncertainty. Paper (Singh et al., 2022) was the first to explore energy market coordination with the carbon market, presenting a VPP-based energy management and bidding strategy under cap-and-trade schemes. This analysis underscores the need to integrate RES-based power generation into the energy market to meet growing demand while ensuring optimal bidding and dispatch strategies with minimal carbon emissions. The study (Peng et al., 2023) proposes a tiered carbon trading-based economic dispatch strategy for VPPs, integrating emission pricing into operational decision-making. While innovative in carbon market modelling, the paper lacks comprehensive treatment of uncertainty and real-time market dynamics. The authors introduce a low-carbon scheduling model that incorporates carbon emission flow and demand response, improving environmental and economic coordination (Wang et al., 2024). The work proposed in Ding et al. (2022) addresses optimal VPP operation by incorporating carbon trading mechanisms into the market-based scheduling framework. While practical, the work relies on deterministic modelling and does not explore adaptive or intelligent bidding strategies under uncertainty. The study (Zhang and Liu, 2023) presents a dispatching model for VPPs integrated with carbon capture systems and dual trading mechanisms: green certificates and carbon credits. It offers a comprehensive framework, but the complexity of modelling multiple market layers is not addressed in optimization terms. The paper (Guo et al., 2025) develops an optimal VPP scheduling model combining carbon trading and green certificate markets, aiming to maximize environmental and economic benefits. Despite strong policy integration, the solution methodology could benefit from advanced metaheuristics for better performance under dynamic conditions.

Traditional optimization techniques typically produce effective optimization with the global optimal solution, when applied to simple engineering issues, problems of moderate complexity, or other difficulties. Despite of that, Meta heuristic methods are now becoming the choice for engineering optimization problems. These methods are nature inspired algorithms able to optimize the problem and provides the global best solution (Singh et al., 2021), for example: genetic algorithm which is evolutionary based algorithm, article swarm optimization which is mimics the behaviour of bird swarm for finding the global best solutions and many more methods. The paper (Ul Ain Binte Wasif Ali et al., 2022) proposes an Improved Multilevel Optimization (MLBO) framework for smart energy management in VPPs, leveraging a hybrid GA and local search. While the hierarchical structure enhances coordination, the method suffers from slow convergence and computational overhead in large-scale bidding scenarios. The study presented in Yuvaraj et al. (2025) proposes a robust 3-phase bidding strategy using a hybrid IGWO-PSO algorithm, significantly enhancing resilience and profitability in smart microgrids. Despite its strong performance, the model involves high algorithmic complexity and requires extensive parameter tuning, which may limit real-time applicability. Paper (Liu et al., 2023) introduces an Improved Whale Optimization Algorithm (IWOA) with levy flight and elite learning for optimizing microgrid operations. While it improves exploration capabilities, the method remains sensitive to control parameters and may experience stagnation in complex, high-dimensional VPP bidding problems. The authors develop a three-stage coordinated approach to enhance operational efficiency and reliability of VPPs through deterministic control (Amissah et al., 2024). Although effective in structured scenarios, the absence of metaheuristic optimization limits its flexibility and performance under market and renewable uncertainties.

A new algorithm White Shark Algorithm (WSA), which copies the behaviour of white shark that forages in the deep ocean in order to successfully survive, is getting attention in these optimization problems (Braik et al., 2022). WSA is expected to come out with greater options than the ones that are now available. Since the two key components of any meta-heuristic's success are exploration and exploitation, WSA successfully designs them to maintain a healthy balance between the two. The study presented in Fathy and Alanazi (2023), explored the WSA technique to optimize error in performance of the design parameters of fuel cell and successfully optimizes evaluation metric within small range. With the uncertainty condition of RES, the author in Farhat et al. (2024) proposes a modified WSO algorithm for optimal power flow for modified IEEE- 30 and IEEE-57 bus systems incorporated with solar and wind energy systems. The application of WSO is not only in power sector but the study presented in Ravishankar et al. (2023) explores the in the field of Unmanned Aerial Vehicles (UAVs) clustering. By modifying the clustering process to maximize communication and interaction inside the network, the approach demonstrates dynamic features. Therefore, this work proposes a very novel white shark algorithm for optimizing the revenue for a day ahead market bidding strategy of proposed VPP system integrated with carbon market.

Existing literature is largely focused on isolated aspects of forecasting, carbon policies, and bidding strategies. Papers (Sáez et al., 2015; Akhtar et al., 2021; Liu et al., 2015) and (Wang et al., 2019, 2018; Yan et al., 2018) primarily address solar and wind power forecasting, while (Shi et al., 2011; Buhan and Çadırcı, 2015; Ando et al., 2021), and (Liu et al., 2021) integrate RES forecasting with the energy market, but without carbon market considerations. The models like SVM, fuzzy logic, ANN, autoencoders, and gradient boosting have been applied for forecasting solar and wind power. These models have shown varying degrees of accuracy, but challenges remain in handling the highly stochastic behaviour of RES, especially for short-term and day-ahead operations. Papers (Glomsrod et al., 1992; Metcalf and Weisbach, 2009; Stavins, 2008; Paltsev et al., 2008; Hahn and Stavins, 2011; He et al., 2012; Hogan and Ring, 2003; Gribik et al., 2007) discuss carbon taxation schemes but do not link them to energy market operations. The review highlights carbon pricing strategies such as carbon tax and cap-and-trade and their influence on energy markets. While some studies have attempted to integrate carbon trading into VPP operations, the coordination with market dispatch, uncertainty management, and strategic bidding is still underexplored. Studies on VPP bidding strategies (Shin et al., 2021; Latif et al., 2021; Baringo and Baringo, 2017; Vahedipour-Dahraie et al., 2021; Afzali et al., 2020; Liang et al., 2019; Mashhour and Moghaddas-Tafreshi, 2011; Dabbagh and Sheikh-El-Eslami, 2016; Wang, 2018; Pourghaderi et al., 2022; Chen et al., 2021; Zhao et al., 2016; Al-Awami et al., 2017; Wang et al., 2016) analyse day-ahead, real-time, and reserve markets. Energy management and market participation strategies of VPPs have been developed using methods like stochastic programming, robust optimization, and bi-level models (Song and Jing, 2023; Singh et al., 2022; Peng et al., 2023; Wang et al., 2024; Ding et al., 2022; Zhang and Liu, 2023; Guo et al., 2025). While early works address reliability, frequency regulation, and risk constraints, integration with carbon trading has been only partially addressed. Moreover, the use of metaheuristics (e.g., GA, PSO, IWOA) shows promise in enhancing optimization, but suffer from issues like algorithmic complexity, stagnation, or poor scalability. Finally studies (Singh et al., 2021; Ul Ain Binte Wasif Ali et al., 2022; Yuvaraj et al., 2025; Liu et al., 2023; Amissah et al., 2024; Braik et al., 2022; Fathy and Alanazi, 2023; Farhat et al., 2024; Ravishankar et al., 2023) give an insight of WSO algorithm in different research aspects. Recently, the White Shark Algorithm (WSA) has emerged as a promising metaheuristic that balances exploration and exploitation efficiently. Though WSA has shown success in power systems and UAV applications, its application in VPP bidding under uncertainty with carbon trading mechanisms is novel and yet to be fully explored. From this comprehensive review the identified research gap can be stated as:

1. There is inadequate integration of carbon trading mechanisms in VPP bidding strategies, especially under real-time and day-ahead market uncertainties.
2. Limited use of advanced metaheuristics that can adaptively handle non-linear, high-dimensional VPP optimization problems under carbon and energy market coupling.
3. Lack of models combining forecasting uncertainties (of RES and market prices), carbon cost dynamics, and multi-market participation in a unified optimization framework.
4. Insufficient exploration of WSA or modified WSA in energy markets despite its potential for better convergence and global optimality in complex optimization problems.

Hence the novelty of this work is to develop a day-ahead bidding strategy for a VPP integrated with the carbon market, leveraging the White Shark Optimization (WSO) algorithm to maximize revenue while accounting for renewable energy uncertainty, market price volatility, social welfare and emission cost constraints.

1.2. Contribution

The electricity market is responsible for 40 % of global carbon emissions, highlighting the need to integrate renewable energy sources with the carbon market to minimize fossil fuel dependence. This paper introduces a bidding model that facilitates RES participation in the energy market through carbon trading. A carbon reduction strategy is implemented via an uplift payment scheme, ensuring an efficient dispatch mechanism for the grid. Key contributions include designing a bidding framework for RES, optimizing market participation, and proposing a cost-effective dispatch strategy that enhances sustainability while maintaining market stability. The primary contributions of this paper are as follows:

1. Forecasting of RES: This work proposes solar and wind power forecasting using the Extreme Gradient Boosting (XGBoost) algorithm. Since the forecasted value of these RES has been considered for bid submission, there will be a risk in participation in EM. Analysis of that risk was calculated using the CVaR method.
2. Carbon tax and uplift payment scheme: Carbon market incorporation with EM is the main contribution of this work, which has been done by calculating carbon credit bidding price by carbon tax and uplift payment schemes (details are in section II). These values have been considered for bid submission and carbon market revenue calculation.

3. Bidding model: A day-ahead market with a carbon reduction policy is represented with the aim of maximizing the total revenue of the existing EM. In this model, all components of the work have been integrated. The details of the system components have been described in section IV.
4. WSO Algorithm: The nature inspired algorithm named, White Shark Optimizer (WSO) algorithm has been proposed for same bidding model for finding best optimized revenue.

The rest of the paper is organized as follows: Section II represents the elementary idea of various carbon reduction policies such as Carbon tax, Cap-and-trade scheme, and Uplift payment scheme. The solar and wind power forecasting model is presented in section III, and problem formulation is given in section IV. The proposed WSA algorithm and flowchart for bidding model is presented in section V which is followed by case study in section VI, where the capability of proposed model has been investigated with detailed discussion on results. And finally, a conclusion has been presented in section VII.

2. Carbon reduction strategies

2.1. Carbon tax

The carbon tax policy is a fundamental strategy aimed at reducing and eventually eliminating the use of fossil fuels, which are major contributors to greenhouse gas emissions. The combustion of fossil fuels releases carbon dioxide and other harmful gases into the atmosphere, destabilizing the environment and accelerating climate change. By imposing a carbon tax, governments and regulatory bodies can create a financial incentive for industries to adopt cleaner energy alternatives.

A carbon tax is levied on each ton of GHG emissions produced by industries, power plants, and other major emitters. Since this tax is categorized under pollution taxes, it not only discourages excessive emissions but also generates significant revenue that can be redirected towards renewable energy initiatives, green infrastructure development, or climate adaptation strategies. Many countries, regions, and local governments worldwide have integrated carbon taxes or similar fees into their environmental policies. The tax is often applied directly to carbon-containing fuels like coal, oil, and natural gas, ensuring that carbon-intensive energy sources bear a higher cost.

2.1.1. Integration with Independent System Operator (ISO)

In power systems, the Independent System Operator (ISO) plays a crucial role in balancing supply and demand while ensuring grid stability. By integrating the carbon tax policy into ISO operations, the system can optimize energy dispatch strategies based on predefined carbon reduction targets. This integration involves the following key steps:

1. Emission-Based Dispatch Profile: The ISO modifies the energy dispatch schedule to prioritize low-carbon and renewable energy sources. This adjustment aligns with the targeted reduction in emissions.
2. Carbon Credit Pricing Adjustment: The price of carbon credits is recalculated based on the desired reduction in emissions. This adjusted price helps maintain a balance between economic efficiency and environmental sustainability.

The recalculated carbon credit price incorporates the carbon reduction target (α%) and is determined using the following equation:

$$\alpha = \quad 1 - \frac{\delta_{c,bid(r)}}{\delta_{c,bid}} \tag{1}$$

The carbon reduction rate (α) represents the proportion by which carbon credit prices are adjusted to align with emission reduction targets. A higher reduction target results in a larger decrease in the modified carbon credit bid price ($\delta_{c,bid(r)}$). This pricing strategy encourages energy producers to adopt low-carbon technologies and promotes cleaner energy generation.

The integration of **carbon tax policies** with ISO dispatch strategies presents a powerful solution to mitigate carbon emissions while maintaining energy market efficiency. By adjusting carbon credit prices based on reduction targets, this approach creates a financial incentive for cleaner energy investments and encourages industries to transition toward low-carbon technologies.

2.2. Cap-trade market

The cap-and-trade system is a market-driven approach to reducing greenhouse gas emissions by setting an upper limit (cap) on total emissions while allowing companies to trade carbon credits. This method provides both incentives for emission reduction and flexibility for industries in managing their carbon footprint. Cap-and-Trade Mechanism can be stated as follows:

- Under this system, each company is allotted a cap on the maximum amount of carbon emissions it can produce.
- Companies that emit less than their allocated cap can sell their surplus carbon credits to other firms.
- Companies that exceed their cap must buy additional carbon credits from the market to comply with regulations.
- The market determines the price of carbon credits, promoting cost-effective emissions reduction strategies.
- Since there is a fixed cap on total emissions, the price of carbon credits naturally stabilizes within a certain range.

Unlike a carbon tax, which sets a fixed price on emissions but allows uncertain reductions, cap-and-trade ensures a clear emissions reduction target but allows market forces to determine the price of carbon credits.

Let, P_{CO_2} is the total permit for CO_2 emission and $\widehat{P}$ is the set cap for the emission such that $P_{CO_2} \leq \widehat{P}$. This will target to achieve α % carbon emission reduction. The cap on the carbon credit price is given in Eq. (2).

$$\widehat{\delta_c} = (1-\alpha)\delta_{c,bid} \tag{2}$$

$$\delta_{c,\mathrm{bid(r)}} \leq \widehat{\delta_c} \tag{3}$$

Eq. (2) provides the cap on carbon credit prices is reduced in proportion to the target emission reduction (α). And Eq. (3), adjusted carbon credit price in the market cannot exceed the capped price, ensuring that carbon costs remain within the limit imposed by emission targets. This scheme provides high certainty in future emission reductions (because emissions are capped).

The cap-and-trade system is a flexible and market-driven approach that guarantees emissions reduction by capping total emissions, while allowing the carbon credit price to fluctuate based on market demand. Compared to a carbon tax, it provides certainty in emissions control but introduces uncertainty in pricing. When well-implemented, cap-and-trade can drive innovation, encourage cost-effective carbon reduction strategies, and create economic opportunities in the carbon market.

2.3. Uplift payment

ISO can first define the uniform pricing for the generation units and then support any dispatch profile for the bidding quantity P_{bid}. At that pricing, the generating units aim to make the most profit feasible. However, the equilibrium solution might not be supported by this uniform price, in which case an uplift payment becomes necessary. Suppose an ISO have n numbers of units for its dispatch with some dispatch profile having load demand $P_L = [p_i, \forall_i \epsilon n]$. For the individual profit maximization each unit in the system may have power generations $p_1, p_2, \ldots, p_n$, with their own power limits: $p_{i(min)} \leq p_i \leq p_{i(max)}$. But this solution may not support the overall profit maximization of the system, i.e. the equilibrium solution. For that the payment should be uplifted and so, the distinction between the energy profits realized at the suggested solution and the profits indicated by the suggested price is known as the uplift payment. The actual energy profit is the optimal results of profit maximization. So, for lowest generation cost in the submission of bid in the energy market and to achieve α % carbon emission reduction, the cap on the carbon credit price and the value of bid price for carbon credit is given by Eqs. (3) and (4) respectively.

$$\widehat{\delta}_{c,uplift} = \quad (1-\alpha)\delta_{c,bid} \tag{4}$$

Key Advantages of the Uplift Payment Scheme can be summarized as follows:

- Greater Flexibility: Unlike cap-and-trade, which has a fixed emission cap, uplift payments allow for dynamic dispatch adjustments.
- Fair Compensation: Ensures that power producers receive fair compensation without excessive carbon credit price fluctuations.
- More Social Welfare Benefits: By reducing unnecessary costs and stabilizing prices, this scheme promotes energy affordability.
- Robust against Market Manipulation: Unlike cap-and-trade, uplift payments prevent strategic price increases by market participants.

Table 1 provides the status of above mentioned 3 carbon reduction techniques with various criteria. Since both uplift payments and cap-and-trade start with a cap on emissions, they ensure controlled emissions. However, the uplift payment scheme is more predictable and robust, making it a preferable choice for carbon pricing and energy dispatch.

2.4. VPP Integration with Carbon trading market (CTM)

The **CTM** is a market-based mechanism that allows entities to buy and sell carbon credits, which represent a reduction or removal of GHG emissions. Integrating VPPs with CTMs creates opportunities for cleaner energy production, optimized grid operations, and financial incentives for reducing carbon footprints (Li et al., 2024; Huang et al., 2022). VPPs play a crucial role in reducing carbon emissions by enabling a shift from fossil-fuel-based power generation to renewable energy sources. Their integration with CTMs allows:

- Carbon Credit Generation: VPPs can earn carbon credits by reducing emissions through renewable energy production and demand-side management.

Table 1
Comparing Uplift Payment, Cap-and-Trade, and Carbon Tax Schemes.

Criteria	Uplift Payment Scheme	Cap-and-Trade Scheme	Carbon Tax
Flexibility	Highly flexible, supports multiple dispatch profiles	Less flexible due to fixed emission cap	Moderate flexibility
Certainty in Emissions	Allows control over total emissions through price cap	Directly controls emissions with strict limits	Uncertain emission reduction
Certainty in Prices	Maintains a regulated price cap, minimizing volatility	Prices fluctuate based on market forces	Fixed price per ton of CO_2 emitted
Economic Impact	Reduces unnecessary costs and improves social welfare	Risk of price manipulation in carbon credit markets	Generates government revenue
Market Manipulation Risk	Low (due to regulated price cap and uplift payments)	High (as firms may artificially raise credit prices)	Low (directly imposed tax)

- Real-Time Emission Tracking: VPPs use advanced data analytics and AI to track energy generation and consumption patterns, ensuring accurate reporting for carbon trading.
- Grid Decarbonization: By facilitating the integration of distributed renewable energy, VPPs help reduce reliance on carbon-intensive power plants.

The integration of VPPs with CTMs involves several mechanisms: Carbon credit mechanism (Li et al., 2024), Blockchain-based smart contracts mechanism (Hussain and Farooq, 2019) and as demand response participation (Latif et al., 2020). VPP operators must comply with carbon trading standards to certify emission reductions. The benefits of integrating VPP with CTM can be summarized as:

- Financial Incentives: VPP operators and participants (households, businesses) can generate additional revenue by selling carbon credits.
- Grid Stability: Reduced reliance on fossil fuel plants lowers grid congestion and enhances reliability.
- Regulatory Compliance: Industries with emission reduction targets can meet their obligations by purchasing VPP-generated carbon credits.
- Increased Renewable Energy Adoption: Encourages investments in distributed renewables by making them more profitable.

Despite its potential, VPP integration with CTMs faces challenges such as: Lack of standardized global carbon trading regulations. VPP participation requires accurate emissions tracking, which may be complex for smaller operators. There is also lack of technology infrastructure which will insure interoperability between VPP platforms and CTM registries. Future developments, such as AI-driven energy optimization and blockchain-based carbon credit systems, can further streamline VPP participation in carbon markets.

In this section various carbon reduction schemes have been discussed with their advantages and limitations. In this work carbon tax scheme and uplift payment scheme has been used for the further calculation of bidding price of carbon credit with the presented equations, which will participate in the EM. In the next section the forecasting of the RES units has been discussed.

3. Forecasting of the RES

Various researches in forecasting of renewable energy have been discussed in previous section and seen the accuracy of the models. With GBT forecasting model both solar and wind power with minimum MAE and RMSE. So, in this work, Extreme Gradient Boosting algorithm (XGBoost) (Phan et al., 2021) has been used for the forecasting model of the solar and wind power generation. An ensemble approach of predicting is the XGBoost Tree. Each tree improves characteristics that caused the prior tree to be incorrectly classified. In Fig. 2, the internal operations of XGBoost are depicted. It runs a primary model before identifying its flaws. Losses are used to illustrate the weakness, and as

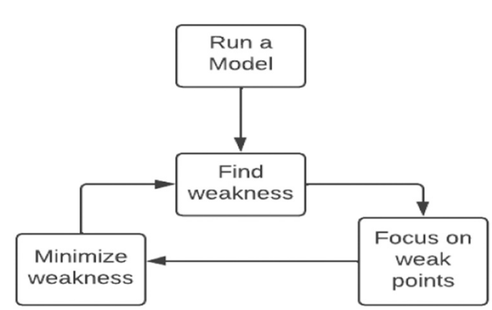

Fig. 2. Internal Process of XGBoost.

new models are built to reduce losses, the process continues. The procedures mentioned below are followed for successfully implementation of XGBoost algorithm for energy forecasting:

i. Data Collection
ii. Pre-processing of the raw data
iii. Split the data into training (80 %) and testing (20 %)
iv. Evaluating the model

K-fold cross validation is performed during training to evaluate the model's effectiveness. After successful forecasting, the model result is usually validated by comparing it with the pre-existing testing data set.

The XGBoost model is an accumulative model. Considering N numbers of decision trees (f) the output (Y) is obtained using Eq. (5).

$$Y_i = \sum_{n=1}^{N} f_n(x_i) \tag{5}$$

Where the function of each Tree is denoted by $f \epsilon F$, F. Eq. (6) gives the objective function of an additive θ if "l" is taken to be the loss function and "Ω" is the regularization term,

$$Obj(\theta) = \sum_{i=1}^{M} l(y_i, Y_i) + \sum_{n=1}^{N} \Omega(f_n) \tag{6}$$

The regularization term $\Omega(f)$with hyper-parameterλ, can be expressed using Eq. (7).where, γ is pruning parameter, ω is vector of scores on leaves on the tree and T is the number of leaves.

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \tag{7}$$

Every time a decision tree gets added, XGBoost picks up a new function. So, when it is learning t^{th} step, the prediction is given by Eq. (8).

$$Y_i^t = Y_i^{t-1} + f_t(x_i) \tag{8}$$

Using Eq. (8) in (6), the new objective function of XGBoost is obtained by Eq. (9).

$$Obj(\theta)^t = \sum_{i=1}^{n} l\left(y_i, Y_i^{t-1} + f_t(x_i)\right) + \sum_{m=1}^{t} \Omega(f_m) \tag{9}$$

3.1. Hyper-parameter optimization

A hyper-parameter is a factor whose value is used to control the learning process. A few distinct XGBoost hyper-parameters exist. Booster, Subsample, Learning Rate, and Regularization Parameters (Alpha and Lambda) are a few examples. All of the parameters selected for the suggested model are shown in Table 2. Exhaustive Grid Search (EGS) Method were used to adjust these parameters in order to obtain the best forecasting outcome. It does a thorough search of a manually chosen subset of this model's hyper-parameter space. The model is then specified with the best parameter value. Fig. 3 shows the block diagram for wind power forecasting with XGBoost, and the same procedure will be used for the solar power forecasting. The variables considered for solar power forecasting are: Air Temperature, Azimuth, Cloud Opacity, DHI, DNI, EBH, GHI, and relative humidity. Wind power variables are: Cloud Cover, wind speed, humidity, and temperature, pressure, and wind gust.

Table 2
Hyper-parameter optimization For PV And WT System.

Parameters	Default Value	Updated for Solar	Updated for wind Turbine
Subsample	1	0.7	0.8
Cosample_bytree	1	0.7	0.6
Cosample_bylevel	1	0.8	0.7
Booster	Gbtree	Gbtree	Gbtree
Learning rate	0.1	0.005	0.01
Max_depth	3	6	7
N_estimator	100	900	700
Reg_alpha	0	0.01	0.02
Reg_Lambda	1	3.0	9

The data set for solar and wind power for forecasting has been considered for the duration of 6.5 months and 14 months respectively from north eastern region of India. Data for solar power is in 15-minute durations and for wind power is 1-hour durations. The results with predicted power with actual power for solar and wind system have been given in Figs. 4 and 5 respectively.

3.2. Error calculation

The model's performance has been evaluated by calculating the difference between the expected and actual values. Although other methods for calculating errors have been proposed to evaluate forecast performance, none of them are recognized as the industry standard. Three errors, as mentioned below, have been calculated using Eqs. (10)–(12).

1. Mean Absolute Percentage Error (MAPE): MAPE measures the average absolute percentage difference between the actual and forecasted values.
2. Root Mean Square Error (RMSE): RMSE represents the square root of the average of the squared differences between actual and forecasted values.
3. Mean Absolute Error (MAE): MAE measures the average of the absolute differences between actual and forecasted values.

Here, A and P are actual and predicted value of the output respectively,

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|A-P|}{A} \times 100\% \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{A-P}{2}\right)^2} \times 100\% \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|A-P| \tag{12}$$

The values of MAPE for solar and wind power forecasting are 6.83 %, and 12.96 % respectively. And RMSE for both are 13.61 % and 20.85 % respectively. The MAE values are 17.53 KW for Solar and 0.61 KW for Wind. In this section the forecasting model of solar and wind power has been presented using XGBoost algorithm. The forecasted values of both the powers have been considered in the bid application in the next section of the work.

4. Problem formulation

The critical problem in this work is presenting a bidding strategy within the VPP environment. The components of VPP are most important because they will decide how they participate in the EM bidding and reduce carbon emissions. The proposed VPP system component is presented in Fig. 6 and the components are: a conventional power plant, solar PV units, wind power plants, electric vehicles, micro turbines, loads, and battery storage systems. Fig. 7 also illustrates the primary idea of the workflow of the proposed model, which starts from forecasting the RES units (section III).

The bid will be submitted to EM for all the components, as mentioned above, along with the carbon credit bid. The calculation of carbon credit

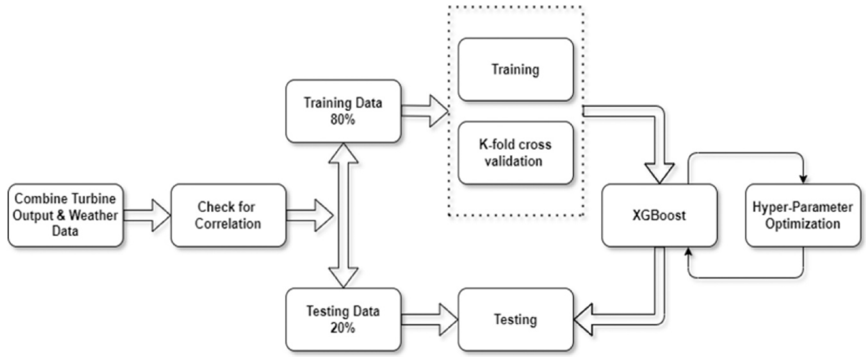

Fig. 3. Block diagram of Wind Power Forecasting using XGBoost.

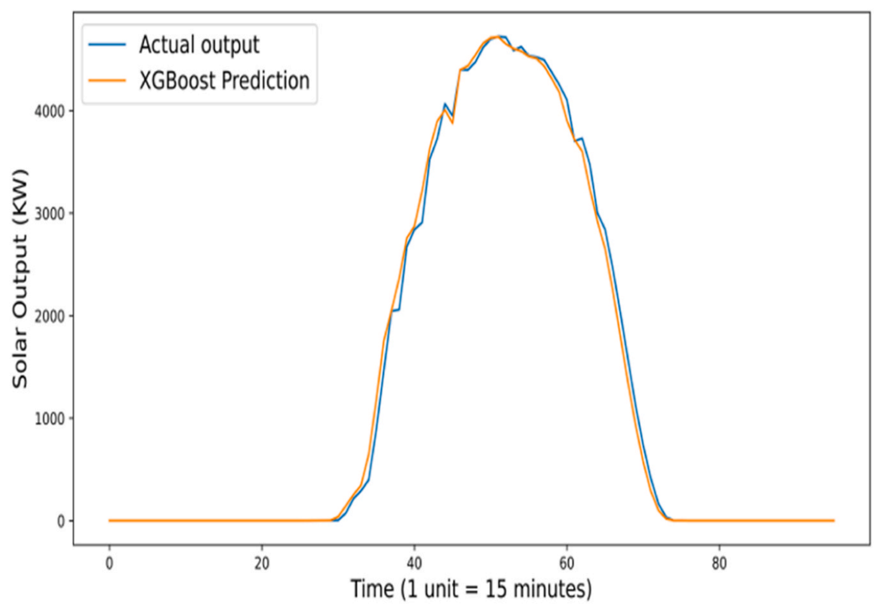

Fig. 4. Solar power forecasting.

price has already been discussed in section II. In this section, the objective function of the proposed work is discussed, along with various constraints. The term "bidding model" refers to a system model offering a strategic approach to the EM to maximize its profit and lower the system's total cost. The schedule for the power generation in which the RES units will participate in EM can be submitted using the bidding model. The objective of the presented model is to maximize the total revenue, which is given by Eq. (13).

$$\max \sum (\rho_{em} + \rho_c + SW - C_{mt} - C_{cpp} - C_{esd} - C_c - \lambda_{pv} - \lambda_{wt}) \tag{13}$$

$$\rho_{em} = \sum_{t=1}^{24} \delta_{b,t} \left(P_{b,pv,t} + P_{b,wt,t} + P_{b,ev,t} + P_{b,bat,t} + P_{b,mt,t} + P_{b,cpp,t} \right) + R_{ramp} \tag{14}$$

$$R_{ramp} = \sum_{\substack{t=1 \\ i \in \Phi}}^{24} \left(\delta_{up,t} * P_{up,i,t} + \delta_{dn,t} * P_{dn,i,t} \right) \tag{15}$$

$$\rho_c = \sum_{t=1}^{24} \delta_c \left(P_{b,pv,t} + P_{b,wt,t} + P_{b,ev,t} + P_{b,bat,t} \right) \tag{16}$$

Eqs. (14)–(16) shows revenue from the energy market and carbon market. For maximizing the revenue the ρ_{em}, ρ_c, and SW should be maximum and the operational cost C_{mt}, C_{cpp}, C_{esd}, andC_c should have minimum value. When the forecasted value of the RES will differ from the bidding value so, penalty will be charged to both PV and WT unit.

With the carbon tax, cap-and-trade programs and uplift payment schemes, the cost of the carbon market will be calculated by modified carbon credit price, $\delta_{c,bid(r)}$ and is given by the Eq. (17).

$$\rho_c = \sum_{t=1}^{24} \delta_{c,bid(r)} \left(P_{b,pv,t} + P_{b,wt,t} + P_{b,ev,t} + P_{b,bat,t} \right) \tag{17}$$

The calculation of $\delta_{c,bid(r)}$ for all policies are already presented in the section II. The energy providers have to pay carbon tax depending on carbon emission, it will in the form of operating cost of the system and not contributes in the revenue generations. Whereas other two programs will contributes in the revenue generation depending on the cap of the emission given to the system and the equilibrium dispatch profile of the system respectively.

4.1. Constraints

4.1.1. RES constraints

The equations (18.a) to (18.f) represent the maximum and minimum power limits to the generating units with respect to solar and wind

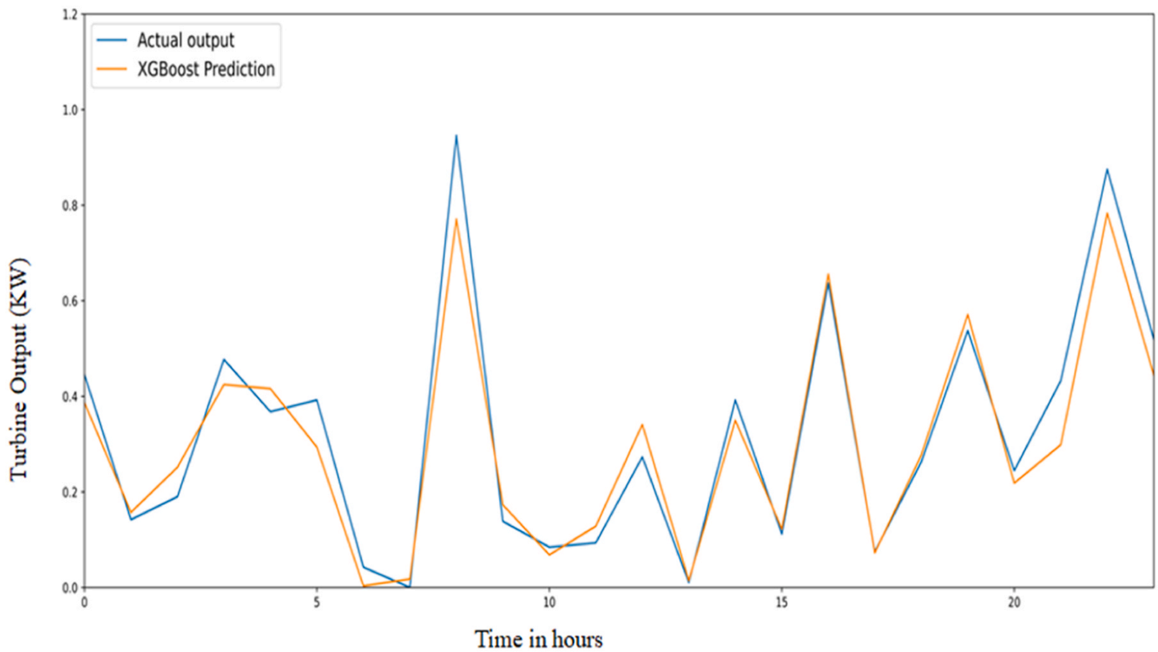

Fig. 5. Wind power Forecasting.

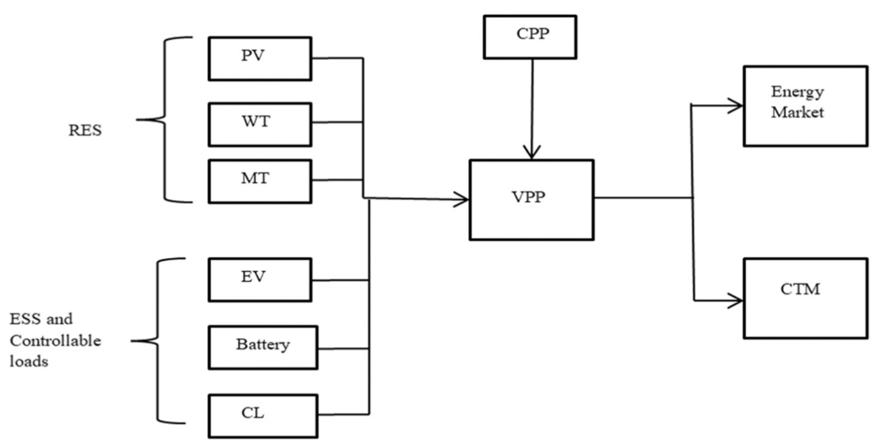

Fig. 6. System components of VPP System integrated with EM and CTM.

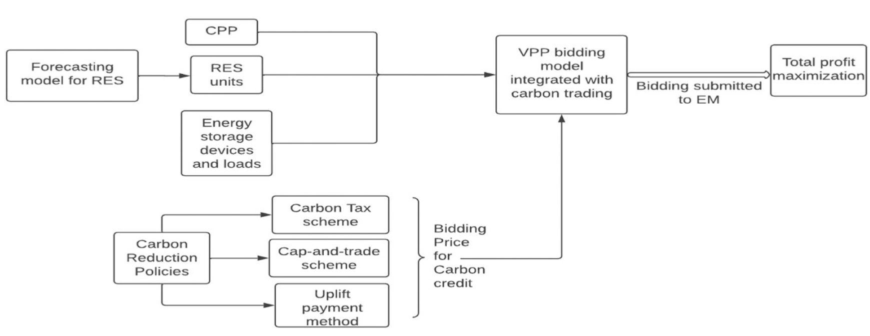

Fig. 7. Block Diagram for work flow of the presented Bidding model.

power generation. The uncertainty in the forecasting has been restricted with the penalty factor η and penalty for both solar and wind units have been calculated by equation (19.a) and (19.b) respectively. The risk analysis in forecasting has been done by CVaR (Mashhour and Moghaddas-Tafreshi, 2011) method. The CVaR has been calculated for different β % of the confidence interval and is represented in Table 3. This interval level expresses the degree of certainty that provided confidence interval for VaR will be exceeded by β%. Moreover, the confidence interval shows the range in which the calculated VaR is likely to fall. As the β increases the risk in the prediction reduces.

$$P_{b,pv,t} \quad + P_{up,pv,t} \quad \leq P_{pv,\max,t} \tag{18.a}$$

Table 3
Risk measures.

Confidence Level	CVaR
0.90	0.0402324
0.95	0.0403231
0.99	0.0411327

$$P_{b,pv,t} + P_{up,pv,t} \geq P_{pv,\min,t} \tag{18.b}$$

$$P_{b,pv,t} \geq P_{dn,pv,t} \tag{18.c}$$

$$\mathrm{P_{b,wt,t}} + \mathrm{P_{up,wt,t}} \leq \mathrm{P_{wt,max,t}} \tag{18.d}$$

$$P_{b,wt,t} + P_{up,wt,t} \geq P_{wt,\min,t} \tag{18.e}$$

$$P_{b,wt,t} \geq P_{dn,wt,t} \tag{18.f}$$

$$\lambda_{pv} = \sum_{t=1}^{24} \delta_{b,t}\eta \left| P_{b,pv,t} - P_{f,pv,t} \right| \tag{19.a}$$

$$\lambda_{wt} = \sum_{t=1}^{24} \delta_{b,t}\eta \left| P_{b,wt,t} - P_{f,wt,t} \right| \tag{19.b}$$

4.1.2. Electric Vehicle and Battery constraints

Due to uncertain nature of the RES, energy storage devices play an important role in VPP. Storage devices have great marketability and in this work EV and battery have been taken for this purpose. The performances EV and battery are characterized by its charging and discharging capacity at time t. So, equations (20.a- 20.b) and (21.a-21.b) gives the constraints of power of battery and EV. SOC of both units need to constraints to prevent from over charging and discharging of units. Equation (20.d - 20.f) and (21.d - 21.f) limits the discharging power of both units by real-time SOC status of the units. The operational cost of these units in a day, C_{bat} and C_{ev} can be calculated by equation (20.g) and (21.g) respectively.

$$P_{b,bat,t} + P_{up,bat,t} \leq P_{dis,bat,t} \tag{20.a}$$

$$P_{dn,i,t} - P_{b,bat,t} \geq P_{char,bat,t} \tag{20.b}$$

$$P_{dis,bat,t} \leq S_{bat,t} \tag{20.c}$$

$$S_{bat,t} - P_{dis,bat,t} + P_{char,bat,t} \leq S_{bat,t,\max} * C_{bat,\max} \tag{20.d}$$

$$S_{bat,t+1} = S_{bat,t} - \frac{P_{dis,bat,t}}{\eta_{dis}} + \eta_{char} * P_{char,bat,t} \tag{20.e}$$

$$S_{bat,t,\min} \leq \frac{S_{bat,t}}{C_{bat,\max}} \leq S_{bat,t,\max} \tag{20.f}$$

$$C_{bat} = \sum_{t=1}^{24} \delta_{c,bat} * P_{b,bat,t} \tag{20.g}$$

$$P_{b,ev,t} + P_{up,ev,t} \leq P_{dis,ev,t} \tag{21.a}$$

$$P_{dn,ev,t} - P_{b,ev,t} \geq P_{char,ev,t} \tag{21.b}$$

$$P_{dis,ev,t} \leq S_{ev,t} \tag{21.c}$$

$$S_{ev,t} - P_{dis,ev,t} + P_{char,ev,t} \leq S_{ev,t,\max} * C_{ev,\max} \tag{21.d}$$

$$S_{ev,t+1} = S_{ev,t} - \frac{P_{dis,ev,t}}{\eta_{dis}} + \eta_{char} * P_{char,ev,t} \tag{21.e}$$

$$S_{ev,t,\min} \leq \frac{S_{ev,t}}{C_{ev,\max}} \leq S_{ev,t,\max} \tag{21.f}$$

$$C_{ev} = \sum_{t=1}^{24} \delta_{c,ev} * P_{b,ev,t} \tag{21.g}$$

$$C_{esd} = C_{bat} + C_{ev} \tag{22}$$

4.1.3. Micro Turbine operational constraints and CPP

When there is a greater demand for power than what can be produced through RES and ESD, Micro-turbines (MT) are crucial. The maximum and minimum power levels of MT limit for its production as shown in Eqs. (23) and (24) and operating cost of MT, C_{mt} can be calculated by Eq. (25) with unit operational cost of $\delta_{c,mt}$. Eq. (26) is power limit constraints for conventional power plant units.

$$P_{b,mt,t} + P_{up,mt,t} \leq P_{\max,mt} \tag{23}$$

$$P_{b,mt,t} \geq P_{dn,mt,t} \tag{24}$$

$$C_{mt} = \sum_{t=1}^{24} \delta_{c,mt} \left(P_{b,mt,t} + P_{up,mt,t} \right) \tag{25}$$

$$P_{\min,cpp} \leq P_{b,cpp,t} + P_{up,cpp,t} \leq P_{\max,cpp} \tag{26}$$

4.1.4. Constraints of carbon market

The operational cost will be determined by the operation of MT, and the carbon bidding power $\mathrm{P_{c,mt,t}}$ will be the bidding power of PV and WT with power during up regulation and represented by Eq. (27). Eq. (28) will be used for calculation of operational cost of carbon market. The carbon credit price δ_c will change for all three policies of the carbon reduction. The calculation of carbon credit price for bidding has already been discussed in section II.

$$P_{c,mt,t} = P_{b,pv,t} + P_{up,pv,t} + P_{b,wt,t} \quad P_{up,wt,t} \tag{27}$$

$$C_c = \delta_c \left(P_{b,mt,t} + P_{b,cpp,t} + P_{up,mt,t} + P_{up,cpp,t}\right) \tag{28}$$

4.1.5. Calculation of social welfare (SW)

Consumer surplus (CS) represents the difference between the prices of goods which an individual wants to pay and the actual price which is paid for those goods. It actually represents the benefit of the consumers for consumption of the product. On the other hand, the difference between any product's market price and its marginal price is represented by the producer surplus. The gap between the company's revenue and its total variable costs is another way to describe this. So, Social Welfare is the sum of CS and PS of a market as given in Eq. (29) and (30). The SW maximization will provide the economic efficiency and hence maximization of CS and PS, as shown in Fig. 8 (Jeremy and Magnago, 2017), where area A1 represents CS and area A2 represents PS and SW is the area (A1 +A2) with $\delta_{b,t,\max}$ and $\delta_{b,t,\min}$ as maximum and minimum value of the bidding price.

$$SW(q) = CS(q) + PS(q) \tag{29}$$

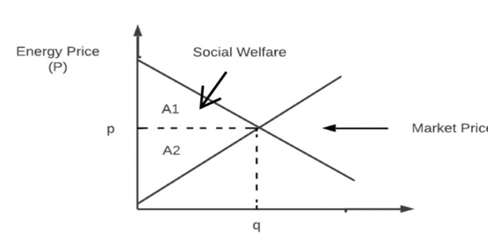

Fig. 8. Social Welfare for an energy market.

$$CS(q) + PS(q) = \frac{1}{2} \quad P_{b,t} \quad (\delta_{b,t,\max} \quad - \quad \delta_{b,t,\min}) \tag{30}$$

4.1.6. Final constraints

Finally, the VPP must meet the total demand from consumer so, to satisfy that the total amount of energy bid $P_{b,t}$ should be more than the load demand at time t, $P_{load,t}$ and is given in Eq. (31).

$$P_{b,t} \geq P_{load,t} \tag{31}$$

5. Methodology

The White Shark Optimizer (WSO) is a nature-inspired meta-heuristic algorithm that simulates the predatory behaviour of white sharks in the ocean. It is designed to solve complex optimization problems, particularly in fields like energy systems (Singh et al., 2021). The algorithm is inspired by the hunting strategies of white sharks, which are apex predators known for their intelligent, strategic, and aggressive hunting techniques. White sharks rely on keen sensory systems, speed, and adaptive strategies to locate and capture prey this forms the biological basis of the WSO. WSO is easy to implement and adapt to various optimization problems. The some advantages of WSO can be summarized as follows:

- Exploration–Exploitation Balance: The encircling and hunting behaviours of sharks are simulated to provide a dynamic balance between exploration and exploitation, essential in avoiding local optima.
- Fast Convergence: Adaptive behaviour ensures faster convergence to optimal or near-optimal solutions in less iteration.
- Robustness under Uncertainty: The stochastic search capabilities make WSO highly suitable for uncertainty-prone environments like VPP with RES and price volatility.
- Low Parameter Sensitivity: Fewer control parameters make WSO easier to tune and more stable across different problem instances.

WSO simulates a balance between exploration (searching new areas of the solution space) and exploitation (refining the current best solutions). This algorithm able to converge efficiently and also can avoid local optima. The main behavioural patterns modelled in the algorithm include:

1. Tracking and Detection: White sharks use their sensory organs to detect prey over long distances. In WSO, this behaviour is modelled to explore the solution space. This pattern comes as in the behaviour of shark which reflects that shark is moving towards the prey.
2. Encircling the Prey: Sharks circle their target before attacking. This is analogous to local search in the algorithm and the shark will move in direction of optimal prey.
3. Attacking Strategy: A white shark uses sudden bursts of speed to catch prey. In WSO, this corresponds to intensifying the search around promising solutions, i.e., sharks will update their position towards best location of the prey.
4. Dynamic Position Update: The position of each shark (candidate solution) is updated based on a mixture of exploration and exploitation strategies. This step is analogous to the fish school behaviour.

5.1. Mathematical Model of WSO

The generalized mathematical model for WSO algorithm is proposed in this section. The flowchart for WSO with respect to proposed bidding model of VPP in day ahead market is presented in Fig. 9. Let: $\vec{X_i^t}$ be the position vector of the i^{th} white shark (candidate solution) at iteration t, $\vec{X^*}$ be the position of the **best** solution found so far, N be the number of

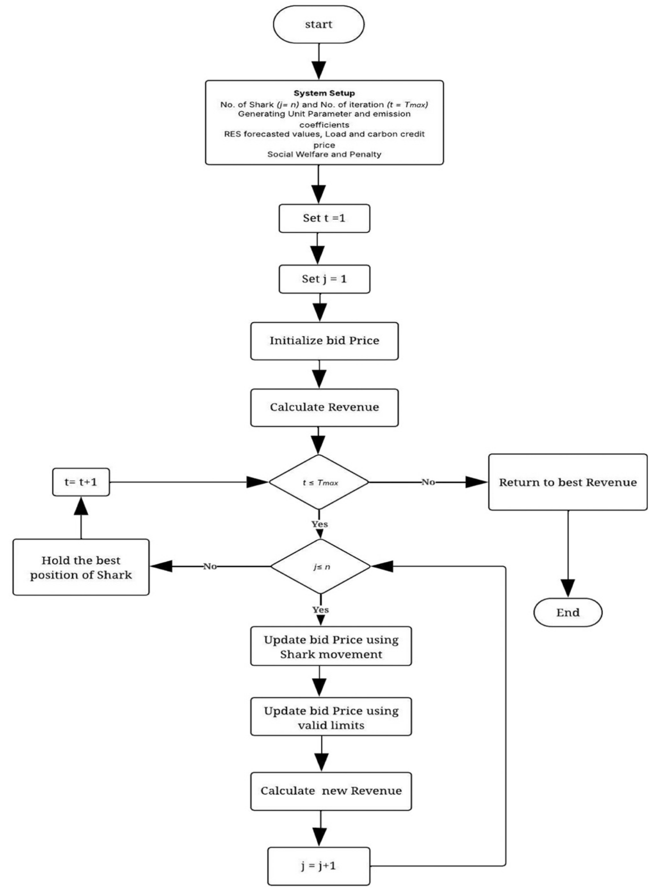

Fig. 9. WSO Flowchart for Bidding Model in VPP.

white sharks, D be the dimensionality of the problem, and T_{max} be the maximum number of iterations.

1. Position Update – Core Behaviour: The position update Eq. (32) simulates white shark behaviour like tracking, encircling, and attacking. This equation helps explore and exploit the solution space adaptively.

$$\vec{X_i}^{t+1} = \vec{X^*} + \vec{A} * (\vec{X_i^t} - \vec{X^*}) + \vec{C} * \vec{R} \tag{32}$$

Where:

- $A{\rightarrow}{=}a{\cdot}\ rand{\cdot}\ sign(r_1{-}0.5)$ → controls the attraction or repulsion toward the best solution,
- a → linearly decreases from 2 to 0 to balance exploration and exploitation,
- $\vec{C} = 2{\cdot}rand$ → adds randomness (exploration), $\vec{R}$ → a random vector in the search space, and $rand$ and r_1 are uniformly distributed random numbers in [0, 1].

2. Hunting Mechanism (Exploitation Mode): If a solution is close to the prey (global best), the shark refines its movement, given by Eq. (33). This guides the algorithm to move closer to the best-known solution while avoiding premature convergence.

$$\vec{X_i}^{t+1} = \vec{X_i^t} - b * (\vec{X_i^t} - \vec{X^*}) + \rho \tag{33}$$

Where, b ϵ [0, 1] is a learning coefficient, and ρ is a small random number vector to intensify the search locally.

3. Exploration Behaviour: To ensure global search and avoid local optima, the algorithm occasionally performs a random movement as presented in Eq. (34)

$$\overrightarrow{X_i}^{t+1} = \overrightarrow{X_i^t} + randn(D) \tag{34}$$

Where, $randn(D)$generates a normally distributed vector of dimension D, This simulates random patrol behaviour of sharks in unexplored regions.
4. Adaptive Parameter Update: To improve convergence, some parameters adapt over time. This ensures that the search becomes more exploitative as iterations proceed. The exploration-to-exploitation factor a reduces over iterations given by Eq. (35):

$$a = 2\,.\,(1 - \frac{t}{T_{\max}}) \tag{35}$$

5. Fitness Evaluation: Each shark's position $\overrightarrow{X_i}$ is evaluated using an objective function $f(\overrightarrow{X_i})$ this could be: either Minimization: min$f(\overrightarrow{X_i})$ or Maximization max$f(\overrightarrow{X_i})$.

6. case study

6.1. Case data

In this section, the proposed uplift payment policy in the bidding model is evaluated using actual day-ahead market load data. The DAM data has been collected from Indian energy exchange for a region in hourly format and adjusted to align with the power generation capacity of the proposed model. To assess the effectiveness of the uplift payment scheme, we compare it with the carbon tax policy. Four distinct cases are analysed: (1) integration of VPP units in the energy market without any carbon market considerations, (2) incorporation of a carbon market alongside the EM but without any specific carbon reduction policy, (3) implementation of a carbon tax as a carbon reduction policy in addition to the second case, and (4) application of the uplift payment scheme as an alternative carbon reduction policy. A summary of these cases is provided in Table 4.

The system components have been described in the previous section, and their respective parameters are detailed in Table 5. The battery storage system has a maximum charging capacity of 9 MW and a discharging capacity of 10 MW, while electric vehicles (EVs) have a maximum charging power of 20 MW and a discharging capacity of 25 MWh. The state of charge (SOC) for both the battery and EVs is maintained between 10 % and 90 %. The bidding analysis focuses on the day-ahead market, with load demand and electricity prices depicted in Figs. 10 and 11, respectively. The electricity price component and other financial components in this work is represented in an international standard currency "Euro (€)". These data points serve as inputs for optimizing the objective function. The optimization problem is solved using the General Algebraic Modeling System (GAMS) with a Mixed-Integer Nonlinear Programming (MINLP) model and also a novel WSO algorithm has been utilized to investigate the proposed model. WSO algorithm has been solved in MATLAB environment. Additionally, the day-ahead solar and wind energy predictions are already presented in Section III to enhance the accuracy of the bidding strategy.

Table 4
Case descriptions.

Cases	Description of the market and carbon policy considered
1	Only EM with VPP units without integration of carbon market
2	With carbon market but without any carbon reduction policy
3	EM aggregated with VPP units and carbon market having carbon tax as carbon emission reduction policy
4	EM aggregated with VPP units and carbon market Uplift payment as carbon emission reduction policy

Table 5
Parameter of the Vpp Units.

Component	Maximum Generation (MW)	Minimum Generation (MW)
CPP	500	0
MT	15	0
Solar PV	220	0
Wind plant	250	0
Penalty factor	2 %	

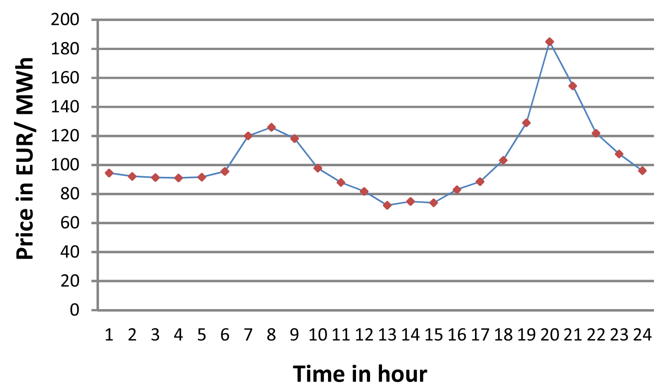

Fig. 10. Energy price in EM for DAM.

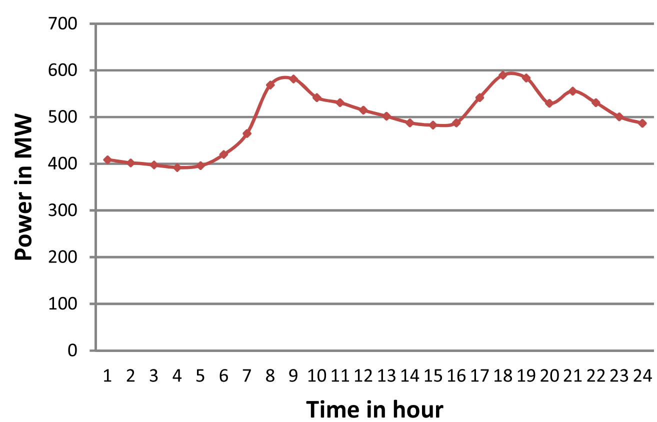

Fig. 11. Load demand for Day-ahead market.

MAPE for solar and wind power forecasting are 6.83 % and 12.96 %. To restrict the error due to this, penalty has been given to both solar and wind power systems. The value of penalty factor for the analysis has been taken as 2 % for which a penalty of.30 € and 3.10 € has to be by solar and wind power forecasting respectively. A 2 % penalty was selected for the forecasting model to balance economic realistic (Zhang et al., 2022a, 2022b), forecasting accountability and enhances system robustness. In Kebriaei et al. (2011) author targeted incentive aligned with operational cost asymmetries encouraging forecasts that balance risk and cost. This value systematically penalizes large deviations, encourages high forecasting accuracy, and ensures system reliability without imposing overly punitive constraints on renewable generation forecasts.

Initially, the target carbon reduction percentage (α) is selected, and the corresponding bidding price for carbon credits is determined. A higher α value can impact the economic dispatch profile, leading to increased operating costs. Table 6 presents the typical carbon credit prices for various α values. In this study, a 20 % carbon reduction target is considered within the carbon tax and uplift payment scheme integrated into the VPP bidding model. This value aligns with international

Table 6
Carbon bidding price with different carbon reduction target.

% Carbon reduction target (α)	Bidding price for carbon credit (in (€)
10	17.36
20	15.43
30	13.50
40	11.57
50	9.64
60	7.72
70	5.78
80	3.89
90	1.93
100	0

policy trajectories such as the IEA Net Zero Roadmap (IEA, 2021) and national emission reduction commitments. It also reflects a moderate carbon abatement scenario, as adopted in similar academic studies on carbon pricing and VPP dispatch (Peng et al., 2023; IPCC, Climate Change, 2022). From a technological standpoint, the proposed VPP system featuring high RES penetration and storage capability can feasibly achieve this target under optimal bidding strategies.

The operating cost of the carbon market with a 20 % carbon reduction is compared between the Carbon Tax policy and the Uplift Payment scheme for the CPP unit. Fig. 12 illustrates that the operating cost under the carbon tax scheme is consistently higher than that of the uplift payment scheme, supporting the proposed bidding strategy.

To achieve carbon reduction, power systems must transition toward RESs. In the analyzed system, the total load demand is met by all available generating units. For instance, at 15 h, the load demand reaches 485 MW. Fig. 13 illustrates the variation in power generation across different carbon reduction targets at this demand level. As generation from CPP units decreases, RES contributions proportionally increase to compensate for the reduced fossil fuel-based generation.

If the carbon reduction target reaches 100 %, service providers must fully transition to RESs as their primary generation source. In such a scenario, the bidding price for carbon credits becomes zero since carbon trading becomes irrelevant in a fully renewable-based energy market. This highlights the necessity of integrating RESs effectively into the energy market while maintaining a balanced and cost-efficient dispatch strategy. The proposed uplift payment scheme demonstrates a cost-effective approach to achieving carbon reduction goals while minimizing the financial burden on market participants.

6.2. *Result analysis*

6.2.1. *Results from the RES forecasting model*

Section III presents the XGBoost Algorithm, a RES forecasting model that forecasts power from solar and wind and is further integrated with the carbon market in a bidding model. The anticipated outcomes are

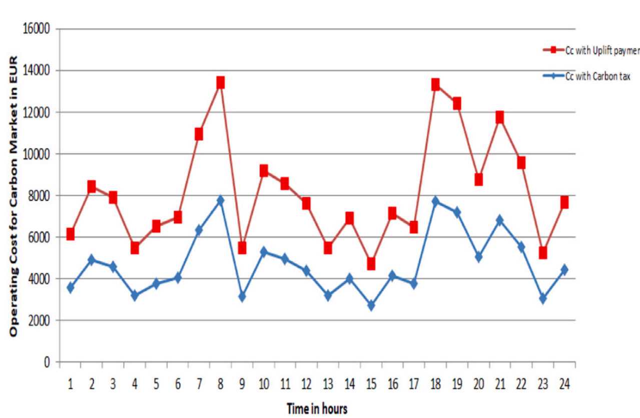

Fig. 12. Comparison of the carbon credit price C_c.

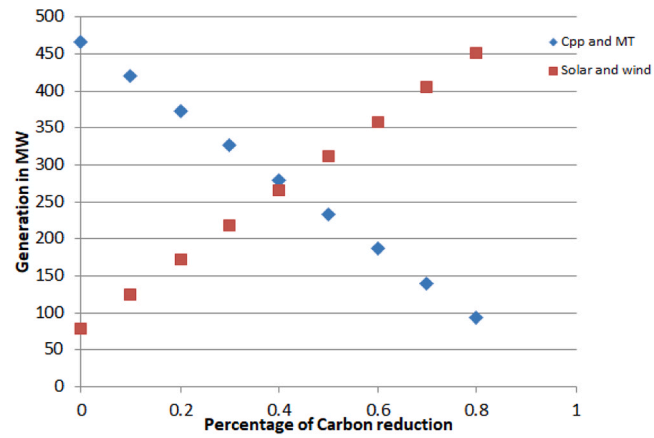

Fig. 13. Variation of power generation from different units with percentage of carbon reduction.

already shown in the section indicated. The performance of the predicted outcome can be assessed by computing several error components, and the performance has been examined in this suggested model using the MAPE, MAE, and RSME evaluation metrics.

The performance comparison of various forecasting models, as summarized in the Table 7, highlights a diverse range of accuracy levels across studies. RMSE values varied widely, with the lowest observed in Akhtar et al. (2021) at 1.12 % for wind power prediction and the highest in Wang et al. (2018) at 16.95 % for solar power forecasting. The MAE values were reported in Sáez et al. (2015), showing improved accuracy using a fuzzy model (1.27 KW) over linear regression (1.72 KW), while

Table 7
Comparison of performance of various forecasting methods.

Ref.	Algorithm	RMSE	MAE	MAPE
(Shi et al., 2011)	SVM	10.5 %	—	8.64 % (MRE)
(Sáez et al., 2015)	Fuzzy Model and Linear Regression	—	1.27 KW (Fuzzy), 1.72 KW (Linear regression)	—
(Akhtar et al., 2021)	Fuzzy Logic	1.12 %	—	—
(Liu et al., 2015)	ANN	—	—	17.38 %
(Buhan and Çadırcı, 2015)	ANN and SVM (48-hour Wind Forecasting)	—	9–20 % (Norm. MAE)	—
(Wang et al., 2019)	Spline Regression Models	—	—	—
(Yan et al., 2018)	Ensemble Stacked Denoising Autoencoder (e-SDAE)	9.60 % (Norm.)	—	—
(Wang et al., 2018)	Adaptive Learning Algorithm	16.95 %	—	13.68 %
(Ando et al., 2021)	Short term forecast	.05 KW	.03 KW	17.54 %
(Liu et al., 2021)	LSTM and MLP	7.30 %	—	—
(Andrade and Bessa, 2017)	GBT and NWP	9.82 % (Solar), 8.76 % (Wind)	6.20 % (Solar), 6.15 % (Wind)	—
This work	XGBoost	13.61 %, (Solar) 20.85 % (Wind)	17.53 KW (Solar) 0.61 KW (Wind)	6.83 % (Solar) 12.96 % (Wind)

(Andrade and Bessa, 2017) demonstrated balanced accuracy for both solar and wind forecasts using gradient boosting trees (6.20 % and 6.15 %, respectively). MAPE, a key metric for percentage-based error, ranged from 6.83 % for solar in the current work to 17.54 % in Ando et al. (2021). Notably, this work presented competitive forecasting performance, particularly for wind power, with a low MAE of 0.61 KW and a MAPE of 12.96 %, indicating its robustness in handling variability. Overall, ANN-based and hybrid models like ANN, SVM and ensemble SDAE achieved promising results, while the integration of adaptive and fuzzy learning methods also contributed to improved forecast accuracy.

6.2.2. Results from the bidding model

Case 1. *Without Carbon market:* When EM is only considered, the calculations are simpler. There is no involvement of the carbon market, so there is no carbon credit price. The system's total revenue has been given in Table 8 (Case 1). Other components of the objective function, such as the various operational costs, social welfare, and penalties for the considered RES, have been given in Table 8. The total revenue from the EM is 10,379.11 €.

Case 2. *With Carbon market without any reduction policy:* In this case, the carbon market has been considered, but no carbon reduction schemes have been considered. Only the base value of the carbon credit price has been considered for calculating revenue from CM. The system's total revenue has been given in Table 8 (Case 2). The carbon credit value is 19.35 €, and the rest of the calculation for other operating costs and profits have been made with this value (for CM). The revenue from CM is 742.99 €.

Case 3. *With Carbon market and carbon tax policy:* For the same condition as in Case 1, with consideration of the carbon tax, various revenues of the system have been given in the table. With 20 % of the carbon reduction target, the value of the bid price for the carbon credit with the carbon tax scheme is 15.44 €, as shown in Table 5. Since the tax has to be paid with a given rate of the governing body for the emission due to the CPP and MT, so the total revenue is approx. 9833.39 € (Table 8), which will be again deducted as EC. The quadratic cost function with the emission coefficient can calculate the emission cost of the generating units. EC calculation is beyond the scope of this work and will be taken for future work.

Case 4. *With Carbon market and with Uplift payment policy:* The uplift payment policy for the carbon bid price will be kept under the cap concerning the solution of the system with maximum profit solution. The cap is again 15.44 €, but the carbon credit price is not equal to this value as that of the carbon tax. The result of the objective function for the profits of the EM with the optimized carbon credit price has been presented in Table 8, and the system's total revenue is 10,018.36 €.

The optimization results and various revenue streams from the system have been summarized in Table 8 across all four cases. In this table the optimized value of best revenue found from WSA is also given which is 44,605.58€, which is best among all the case presented. As in this algorithm the aim is to optimize the maximum revenue so, the results is mentioned in total revenue and other components are not provided. This may be considered as the future research of this work to find optimized value of the entire component present in objective function. Since the base system parameters remain consistent, the revenues from other system components remain unchanged, except for carbon market revenue and operating costs, which are detailed separately in Table 9.

In the proposed VPP system, the operating costs of MT and CPP units are relatively low. However, these units are not operated continuously over the 24-hour scheduling horizon. Instead, their operation is selectively controlled by the EMS, which is responsible for optimally coordinating the dispatch of various distributed energy resources to meet the system's load demand. The EMS follows a prioritized dispatch strategy aimed at minimizing carbon emissions and operational costs. Under this strategy, the EMS first evaluates the availability of power from RES, such as solar PV and wind turbines, as well as from the ESDs, including battery storage systems. The goal is to meet the load demand as much as possible using these clean and low-emission resources. Only when the combined power from RES and ESD units is insufficient to meet the demand does the EMS consider activating the MT and CPP units. This hierarchical scheduling ensures that high-emission generation sources like MT and CPP units are utilized only as a last resort, thereby supporting the overall objective of reducing the carbon footprint of the VPP system. Directly supplying power from CPP units without verifying the availability of cleaner sources contradicts the design philosophy of the proposed VPP. Such an approach would not only increase operational emissions but also undermine the environmental and economic efficiency goals embedded within the EMS strategy.

From Table 8, it is evident that Case 1 yields the highest total revenue among all cases. However, among Cases 2–4, the uplift payment scheme generates the highest revenue, while the lowest revenue is observed in the scenario without a carbon reduction policy. The uplift payment scheme incorporates a fixed cap to optimize carbon credit value for maximum revenue. If the cap-and-trade policy were implemented with the same cap, it would also generate profits, though slightly lower than the uplift payment scheme, as the cap would be used for determining carbon credit prices in that model.

The total profit under the uplift payment scheme is 10,018.36€, which represents the complete profit for the energy service provider. Additionally, the carbon market revenue in this scenario amounts to 391.65€, and approximately 26 carbon credits can be purchased under this policy. These findings demonstrate that an uplift payment scheme, when integrated with the energy market, offers greater operational flexibility, reduces carbon emissions, and maximizes system profitability. This study primarily focuses on the carbon tax and uplift payment schemes; future research can extend the analysis to cap-and-trade schemes and further examine carbon emission reductions.

The Fig. 14 is a WSA Convergence Curve, a metaheuristic optimization algorithm inspired by the hunting behaviour of white sharks. The figure shows how the algorithm progresses in terms of optimizing the objective function—in this case, maximizing revenue for a VPP system. The blue curve represents the best revenue found so far at each iteration. At the start (iteration 1), the revenue is relatively low approx. €41,709. As the iterations progress, the algorithm quickly improves the solution, reaching near-optimal revenue approx. € 44,604 within the first 20–30

Table 8
Comparison of different revenue in all cases.

Cases	Case 1	Case 2	Case 3	Case 4	
				MINLP	With WSA
Total Revenue (€)	10,379.11	9694.75	9833.39	10,018.36	44,605.58
Bidding revenue (€)	3764.24	3764.24	3764.24	3764.24	—
Carbon market revenue (€)	Not Included	742.99	592.47	391.65	—
C_c (€)	Not Included	1427.35	1138.19	752.40	—

Table 9
Various components of objective function.

Components	Values in (€)
SW	6751.11
C_{cpp}	72.49
C_{esd}	42.71
C_{mt}	17.62
λ_{pv}	0.30
λ_{wt}	3.10

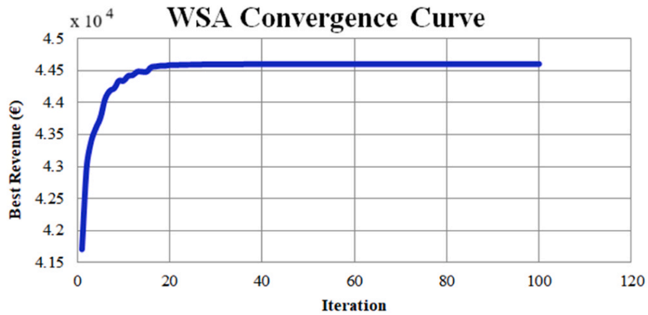

Fig. 14. Convergence curve for WSA.

iterations. After that, the curve flattens out; indicating convergence, i.e., meaning no significant improvement in the objective function is being found. From this convergence curve, this can be stated that, the WSA algorithm is effectively optimizing the revenue. It converges quickly (in fewer than 30 iterations), showing fast performance and stability. After convergence, the solution becomes stable, suggesting the algorithm has found a near-optimal or optimal bidding strategy for the VPP.

The comparative analysis reveals proposed WSO in bidding of VPP has been presented in Table 10 with some other metaheuristics algorithm. The analysis shows that WSO outperforms other approaches in terms of convergence speed, uncertainty resilience, and ease of parameter tuning, making it highly suitable for dynamic VPP bidding environments. While the MLBO method (Ul Ain Binte Wasif Ali et al., 2022) offers structured decision-making, it suffers from high computational burden. The IGWO-PSO hybrid (Yuvaraj et al., 2025) achieves strong performance but is complex and parameter-heavy. The improved WOA (Liu et al., 2023) enhances exploration but remains sensitive to tuning and may stagnate. The deterministic strategy (Amissah et al., 2024) ensures operational efficiency but lacks adaptability under uncertainty. Overall, WSO provides a well-balanced and computationally efficient solution, particularly in scenarios requiring fast and adaptive bidding decisions.

The problem proposed and investigated in this work is very important for the coming energy market with VPP units. So, comparing various works in this area with the presented work is essential. In section I, a review of related work is given, and it has been found that very few works integrate EM with CM. RES units are participating in EM, making the system more efficient, reliable, and environmentally friendly. Table 11 compares the VPP benefit from this study with some of the work from section I.

In previous research works revenues in references Baringo and Baringo (2017) to Wang et al. (2016) range from €2453.56 to €9687.37 with the best revenue among these is from Vahedipour-Dahraie et al. (2021) with €9687.37. These approaches likely used traditional or early

Table 11
Comparison of revenue from various Vpp model in published references.

References	Total Revenue (€) (Best Solution)	References	Total Revenue (€) (Best Solution)
(Baringo and Baringo, 2017)	7858.50	(Zhao et al., 2016)	7078.19
(Vahedipour-Dahraie et al., 2021)	9687.37	(Al-Awami et al., 2017)	2453.56
(Pourghaderi et al., 2022)	2626.96	(Wang et al., 2016)	5324.23
(Chen et al., 2021)	7050.91	This work MINLP model solved in GAMS with BARON solver	10,018.36
		This work with WSO algorithm in MATLAB	44,605.58

metaheuristic optimization techniques or simpler models. The model proposed in this presented work with MINLP Model (solved in GAMS using BARON solver) achieves total revenue of €10,018.36, outperforming all previous references. This shows that the model is well-constructed and better at capturing market dynamics and constraints. And also the approach to solve the model by WSA Algorithm in MATLAB results revenue of €44,605.58 higher than the next best result. This suggests that White Shark Algorithm approach is significantly more effective at finding near-optimal solutions in a complex, nonlinear problem space. The algorithm likely accounts for additional components such as carbon trading, forecasting errors, and social welfare, making it more comprehensive and realistic.

6.2.3. *Impacts on carbon policy*

The integration of carbon market mechanisms, such as carbon taxes, cap-and-trade systems or uplift payment scheme, into VPP bidding models represents a progressive step towards operational decisions with climate policy objectives. However, the effectiveness of such integration depends heavily on the feasibility of implementation, the broader policy implications, and the system-level trade-offs that emerge.

6.2.3.1. Policy feasibility. From a regulatory position, the feasibility of integrating carbon pricing into market-based bidding strategies hinges on the availability of reliable carbon accounting systems, robust market structures, and supportive policy frameworks. Current electricity markets in several countries are gradually maturing to support such hybrid bidding frameworks. The proposed model assumes accurate emission factors for conventional generating units and real-time or day-ahead carbon prices, which are increasingly becoming accessible through policy mandates. Nonetheless, regions without an established carbon

Table 10
Comparison of wso with other metaheuristic algorithms.

Ref.	Algorithm	Bidding Strategy	Uncertainty Handling	Optimization Strengths	Limitations
(Ul Ain Binte Wasif Ali et al., 2022)	**Improved Multilevel Optimization** (MLBO: GA and local search)	Bi-level coordinated VPP bidding	Price and RES uncertainty via probabilistic models	Good adaptability, structured decision hierarchy	Slow convergence, sensitivity to initial settings
(Yuvaraj et al., 2025)	**Hybrid IGWO-PSO**	3-stage dynamic bidding (DAM, RTM, reserves)	Scenario-based modelling of demand & RES	Improved convergence over PSO/ GWO; good resilience	Parameter-heavy; hybrid tuning complexity
(Liu et al., 2023)	**Improved WOA (IWOA)**	Microgrid operation & economic dispatch, bidding integrated	Probabilistic modelling, demand/generation	Enhanced exploration using Levy flight and local search	Performance sensitive to control coefficients
(Amissah et al., 2024)	**Three-stage deterministic-coordinated control**	Centralized bidding-coordination across VPP	Basic uncertainty modelling (load & generation profiles)	Enhanced operational efficiency, reliability	No metaheuristic used; limited global optimization
This work	**White Shark Optimizer (WSO)**	Dynamic day-ahead market bidding	Stochastic modelling of RES and prices	Fast convergence, low tuning burden, exploration–exploitation balance	Relatively new; less benchmarked than GA/ PSO

pricing scheme may face significant infrastructural and technical barriers.

6.2.3.2. Policy implications. The inclusion of carbon cost in the bidding process changes the economic incentives for resource scheduling and dispatch. Units with high emission intensities, such as coal-based CPPs or microturbines, are economically penalized under higher carbon prices, thereby promoting the dispatch of cleaner or renewable sources such as wind, solar, and battery storage. This supports national and international decarbonization goals. On the other side, this may increase electricity procurement costs, particularly in carbon-intensive regions, thereby affecting the competitiveness of conventional generation assets. Furthermore, incorporating carbon signals in the VPP bidding strategy strengthens the role of flexible assets such as EVs and energy storage systems. These units help the VPP adapt to both energy and carbon price fluctuations, enhancing economic resilience and environmental compliance.

6.2.3.3. System-level trade-offs. Several system-level trade-offs arise when environmental objectives are incorporated into economic optimization models:

- Economic and Environmental Goals: While carbon pricing drives emission reductions, it may reduce the total revenue for the VPP operator, especially in carbon-intensive portfolios. The model must thus aim to make balance between profit from system and environmental compliance.
- Short-Term Costs and Long-Term Gains: Introducing carbon pricing can lead to higher short-term operational costs. However, it fosters long-term investments in low-carbon technologies and enhances system sustainability.
- Market Participation: Smaller or less efficient VPPs might be disproportionately affected by carbon costs, leading to potential market imbalances; therefore the policy mechanisms should be such as carbon revenue will maintain the balance and participation in market.
- Operational Complexity: Including carbon pricing adds another layer of complexity to market bidding, requiring more sophisticated forecasting and optimization frameworks.

Overall, the proposed bidding model highlights the importance of policy coordination and system design when introducing environmental signals into market operations. A well-calibrated carbon pricing mechanism, supported by transparent regulations and market readiness, can enhance both the efficiency and sustainability of VPP operations.

7. Conclusion

This paper proposes an effective carbon reduction policy integrated with the energy market, where renewable energy source units, aggregated as a virtual power plant, actively participate in carbon reduction strategies. The uncertainty associated with photovoltaic and wind energy generation has been addressed using a forecasting algorithm combined with a penalty mechanism. The XGBoost algorithm, a method derived from artificial neural networks, has been employed for power prediction, offering improved accuracy. As a result, penalties for RES units due to forecasting errors have been significantly reduced. Additionally, the risk in forecasting has been analysed using the Conditional Value at Risk (CVaR) method, which provides a comprehensive assessment of profit and loss for participating units based on predicted price fluctuations. This risk-based approach enhances the decision-making process for market participants, ensuring a more stable and predictable revenue stream. The energy market has been seamlessly integrated with the carbon market, incorporating specific carbon reduction targets through an uplift payment strategy in the bidding model. Three distinct carbon reduction policies have been examined, with bidding prices for carbon credits determined under both carbon tax and uplift payment schemes. A detailed analysis has demonstrated that the uplift payment scheme provides a more efficient carbon reduction mechanism, offering higher profitability and lower operational costs than the carbon tax approach.

Furthermore, considering various power constraints and bidding strategies, a comprehensive day-ahead energy market bidding model has been developed for the proposed system. The results indicate that the total revenue and carbon market earnings under the uplift payment scheme surpass those of the carbon tax model. Additionally, the overall operational cost of the carbon market is significantly reduced when using the uplift payment strategy, making it a more economically viable and environmentally sustainable solution. The MINLP approach is strong and shows competitive performance, validating model formulation. The proposed WSA-based optimization model in MATLAB clearly well performs in terms of revenue generation. This demonstrates the superior performance, flexibility, and scalability of your method for real-world VPP bidding and carbon market integration. Future research can extend this study by incorporating real-time carbon emission data for further validation with some new meta-heuristic models. Additionally, the proposed model can be applied to other energy market operations, including long-term market forecasting and multi-market coordination, to enhance the sustainability and efficiency of modern energy markets.

CRediT authorship contribution statement

Umit Cali: Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Nalin Behari Dev Chudhury:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Taha Selim Ustun:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Arup Kumar Goswami:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Kumari Nutan Singh:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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