IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal
IEEE POWER & ENERGY SOCIETY SECTION

Received 12 September 2023, accepted 28 October 2023, date of publication 7 November 2023, date of current version 13 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3330906

RESEARCH ARTICLE

Implementing a Flexible Penalizing Mechanism for Wind Power Producers in the Regulating Market

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This work was supported in part by the Ministry of Research, Innovation and Digitalization under Project PNRR-C9-I8-760090/23.05.2023 CF30/14.11.2022; and in part by the Horizon Europe project DiTArtIS, grant agreement number: 101079242.

ABSTRACT The balancing market as a significant part of the spot market addresses fair transaction settlements to eliminate the system imbalances in real time. However, traditional penalty mechanisms that have been also adopted for renewable generators may incur unintended consequences for such intermittent producers and even drive them out of the market. Therefore, here a flexible penalty mechanism (FPM) is adopted instead of the traditional policies to decrease the undesired impacts of traditional penalty mechanism (TPM) on the WPP's revenue. Aligning with the FPM, making a contract between the WPP and the insurance provider in which the system operator (SO) is in charge of system balance is proposed as a remedy instrument to control the risks of wind volatilities. The proposed framework is formulated as a bi-level trilateral problem, in which in the upper level, the WPP maximizes its expected profit and in the lower level, the SO determines the market clearing prices (MCP) and maximizes the social welfare. Due to the importance of forecasting wind power generation, three deep learning algorithms are also used. Simulation results show that by applying FPM, the WPP's profit improves depending on the contract it signed with the insurance provider while the SO preserves social welfare.

INDEX TERMS Electricity market, market clearing price (MCP), flexible penalty mechanism (FPM), wind power producer (WPP).

NOMENCLATURE

Abbreviations

DA	Day- ahead.
DER	Distributed energy resource.
DR	Demand Response.
FPM	Flexible penalty mechanism.
GRU	Gated Reference Unit.
LSTM	Long Short-Term Memory.
MCP	Market clearing price.
RNN	Recurrent Neural Network.
SO	System operator.
TPM	Traditional penalty mechanism.
WPD	Wind power deviation.
WPP	Wind power producer.

Sets and indices

$(\bullet)_{t,\omega}$	At time t and in scenario ω.
k	Line number.
n	Bus number.
$t \in T$	Set of time.

The associate editor coordinating the review of this manuscript and approving it for publication was Yifan Zhou.

$G \in NG$ Set of generation units.
$D \in ND$ Set of demand load D.
$s(k) = n$ Sending-end bus of line k.
$r(k) = n$ Receiving-end bus of line k.

Parameters

α Confidential level.
β Risk averse parameter.
B_k Susceptance of line k (p.u).
$\Delta\rho_{t,\omega}^{reg}$ The difference between up and down regulating market prices of the network.
C_I^P Premium cost paid by the WPP'to the insurance provider (€).
$\bar{P}_D$ Upper limit of demand D (MW).
$\bar{P}_G$ Upper limit of generation DG unit (MW).
$\bar{P}_W$ Wind power capacity of the WPP (MW).
$P_{t,\omega}^P$ The forecasted wind power generation of the WPP (MW).
$L_{t,\omega}^{up/dn}$ Up/down penalizing value in real-time (€).
$f_k^{\max}$ Transmission capacity of line k (MW).
ρ_t^P Marginal cost of the WPP (€/MWh).
$\rho_{t,\omega}^{up/dn}$ Up/down-regulating market prices (€/MWh).
ρ_G Marginal cost of generation DG unit (€/MWh).
π_ω Probability of scenario ω.

Variables

$\rho_{n,t,\omega}^{DA}$ prices at bus n (€/MWh).
$P_{t,\omega}^{cl}$ Wind power cleared in the DA market WPP W (MW).
$P_{t,\omega}^{of}$ Wind power offered to DA market by the WPP (MW).
$P_{G,t,\omega}$ Power scheduled to be produced by the generation DG unit (MW).
$P_{t,\omega}^{up/dn}$ Up/down regulation power (MW).
$\mathrm{Rev}_{t,\omega}$ Revenue of the WPP (€).
$P_{D,t,\omega}$ Scheduled power to be consumed by demand D (MW).
$\alpha_{W,t}$ Offer price of wind power unit W (€/MWh).
$\rho_{D,t,\omega}$ Marginal utility of demand D (€/MWh).
δ_n Voltage angle of bus n.
f_k Power flow through line k (MW).
η_ω auxiliary variable for calculating risk.
ξ Value at risk.

I. INTRODUCTION

WIND power is increasingly contributing to the electricity supply worldwide because of its low environmental impact and negligible generation costs [1]. The stochastic nature of wind generation creates uncertainty for system operation and market trading, which is the main challenge for the development of wind power resources. On the other hand, in most European countries, if a wind power producer (WPP) cannot supply the scheduled energy in the day-ahead (DA) or intraday (if exists) due to the inability to accurately predict wind speeds, it would be financially punished in the regulating market [2], [3]. In other words, if the WPP cannot provide the allocated capacity in real-time, it has to purchase the shortage energy at higher prices and sell the excess energy at cheaper prices, which affects its profit, significantly. In some electricity markets, the difference between the regulating price and the DA price can even exceed 80% [4]. In such conditions, the associated balancing penalties of WPPs may be up to 10% of the total generated revenue which is almost equal to its profit margin [5]. In this context, the penalty mechanism should be such that its undesired effects do not cause WPPs to go out of competition in the market.

Penalty mechanisms are implemented in the balancing markets to force all participants to fulfil their negotiations in the DA market. However, a traditional penalty mechanism (TPM) has been adopted for also intermittent renewable resources, recently. Results of the research show that implementation of such traditional policies would cause more negative impacts on the revenue of decision-makers due to higher uncertainties associated with stochastic parameters [6]. In this regard, up to now, many attempts are made to reduce the imbalance penalty costs in the regulating market. In [7], a novel decision-making model has been presented in electricity market frameworks to manage distributed energy resources (DERs) and perform transactions optimally such that the overall profit increases. By incorporating a penalty mechanism in the electricity market, the market operator obtains genuine bids to reduce the impact of penalty costs on microgrids' operators and encourage small-scale players to participate in local markets. In [8], a decision-making model has been presented with a reduced risk of penalties in electricity markets. In the proposed model, the microgrids' operator tries to bid in the various markets with different penalty factors such that a fair return on investment is obtained. Due to renewable variabilities, different risk factors are included in a variety of previous works. For instance, in [9], the probability of insufficient supply is compensated by pairing the risk-averse WPP and demand response. In [10], the reserve provided by responsive loads supports the volatile generation of conservative WPP. In [11], a three-stage bi-level stochastic programming approach is proposed for joint energy and reserve scheduling of a virtual power plant. In that framework, the virtual power plant can provide DR services and reserve capacity from external DR providers by participating in a local intraday demand response exchange market and trading with internal load aggregators. In that case, a proper balance between allocating spinning reserve and DR services is provided to reduce the penalty costs resulting from the DA scheduling and the real-time dispatching.

To enhance the supportive effects of WPPs, it is necessary to replace the TPM with a flexible penalty mechanism (FPM) that decreases the undesired impacts of the penalty mechanism on WPPs' revenue. A WPP should not be treated the same as traditional generators as observed in most of the European markets [12]. Because, unlike those traditional generators, uncertainties related to wind generation are inevitable and out of their owner's control. Therefore, the

TABLE 1. The contribution of the proposed method given the existing state of the art in literature.

References	From the viewpoint of	Price maker/taker	Insurance contracts	Penalizing in regulating market	Forecasting tools	Bi-level modelling	Network constraint
[3]	Virtual power plant	Price taker	-	✓	-	-	✓
[4]	Wind generation	Price taker	-	✓	Fuzzy-NN	-	-
[5]	Wind power producer	Not mentioned	-	✓	-	-	-
[6]	Renewable resources	Not mentioned	-	✓	-	-	-
[7]	Renewable resources	Not mentioned	-	✓	PSO-GA	-	-
[8]	Renewable resources	Not mentioned	-	✓	PSO-GA	-	-
[9]	Wind power producer	Price taker	-	✓	Probability distributions	✓	-
[10]	Wind power producer	Price taker	-	✓	Probability distributions	✓	-
[11]	Virtual power plant	Price taker	-	✓	Probability distributions	✓	-
[13]	Wind generation	Not Mentioned	-	-	Machine learning/ probabilistic wind power ramps	-	-
[14]	Wind generation	Not Mentioned	-	-	Diffusion-based kernel density estimator	-	-
[15]	-	Not Mentioned	-	-	Deep learning methods	-	-
[16]	-	Not mentioned	-	-	Deep learning methods	-	-
[17]	Distribution system operator	Not mentioned	-	-	Particle swarm optimization/ genetic algorithm, etc	✓	-
[19]	Renewable resources	Not Mentioned	-	✓	-	-	✓
[20]	Renewable resources	Not Mentioned	-	✓	-	-	-
[21]	Retailers	Strategic	-	-	-	✓	-
[22]	Renewable resources	Not mentioned	-	✓	-	-	-
[23]	Renewable resources	Not Mentioned	✓	-	-	-	✓
[24]	Renewable resources	Not Mentioned	✓	-	-	-	-
[25]	Market participants	Not Mentioned	✓	-	-	-	✓
This paper	Wind power producer	Price maker	✓	✓	Deep learning algorithms	✓	✓

penalty mechanism should be designed more enough flexibly to incentivize the effects of developing wind production. To address this challenging issue, this paper suggests an FPM instead of a TPM to improve WPPs' utility. Most existing methods to manage wind power deviations (WPDs) focus on improving wind power forecast accuracy [13] and [14] by introducing a deep learning model [15] and in [16], deep learning was used for the prediction of the two components of solar irradiation. In [17], four deep learning models are compared with time series inputs and in [18] optimal settings of particle swarm optimization, genetic algorithm and other methods are identified based on which the bi-level model is solved to obtain the best investment decision for planning a community based energy system.

Some works have devised market clearing algorithms in which the uncertain deviations are addressed by procuring storage devices [19] and [20]; nevertheless, their balancing strategies involve additional costs due to the beforehand purchase of reserve capacity for the DA process. A local power exchange market is also developed for retailers to facilitate power balancing [21]. Utilizing storage systems to tackle undesired deviations via the ancillary service market is an effective way, however, installing storage systems does not always bring benefits because of their high investment costs [22].

There are a few research works that investigate the effects of purchasing insurance contracts to cover uncertain deviations of renewable producers. For example, in [23] an insurance contract between a renewable producer and an energy storage owner is suggested, in which the storage reserves some energy to be used in case of renewable shortfalls. In [24], a management instrument is introduced that allows a risk-averse WPP to purchase the insurance offered by insurance providers to reduce WPD risks. A centralized market mechanism for insurance contracts is designed in [25] that matches buyers and sellers and is a complement to the wholesale design. Although the above-mentioned works investigated the effect of insurance contracts on the WPP's utility function, they didn't address any mechanism for minimizing the undesirable effect of the existing penalty policies on the imbalance settlement of WPPs in the balancing markets.

To address the mentioned issue, the main contribution of this paper is as below:

- A flexible penalizing mechanism (FPM) is proposed to augment the utilization of WPPs in the balancing market. Through this mechanism, the WPP will make a contract with an insurance provider to cover its risks through some specified policy limitations. Then, the insurance provider will support the SO in implementing FPM. In addition, to provide the financial budget for the SO for implementing FPM, flexible DR resources can support the SO by providing DR services.
- The proposed FPM is applied in a trilateral bi-level decision-making model among the WPP, SO, and insurance providers. In this problem, at the upper level, the WPP maximizes its expected profit using the FPM framework and at the lower level, the SO determines the cleared quantities and MCP to maximize its social welfare. The impacts of FPM on the WPP's profit in two types of insurance contracts and different forecasted wind errors are investigated and compared with the TPM framework. This work designs a flexible penalizing scheme for renewable resources in the balancing markets which can be used by the policymakers, insurance providers, and stakeholders in the electricity market sectors.
- Three deep learning algorithms with powerful computational resources are used to predict short-term wind power generation.

The remainder of this paper is organized as follows. The problem description is provided in Section II. The formulation of the proposed bi-level decision-making model of the WPP is presented in Section III. Section IV is designated to show the numerical studies, and Section V devotes to some concluding remarks.

II. DECISION-MAKING MODEL OF THE WPP WITH FPM

As mentioned before, applying a TPM on WPPs can strongly decrease their revenue in the DA market due to the unpredictable nature of wind power [13]. In this regard, a decision-making model is proposed for WPPs considering FPM in the regulating market. Instead of TPM, the proposed FPM can create more efficient decision support for the WPP by reducing penalizing costs in real-time. In this study, the Nordic power market is considered which consists of a DA market followed by an imbalance settlement that penalizes energy deviations. In this market structure, in the DA market, all the WPP and the other generators and DR resources offer/bid the amount of energy they are willing to commit for delivery on the next operating day. Here, the focus is on the offering strategy of the WPP which has a strategic position in the DA market and can affect the market clearing prices (MCP).

The proposed framework is formulated as a bi-level problem that in the upper level, the WPP maximizes its expected profit by modifying the MCP and decreasing its imbalance payments using FPM implemented by the SO. At the lower level, the SO is responsible for determining the cleared quantities and MCP to maximize its social welfare. In this bi-level problem, network constraints such as transmission line congestion and also the emergence of prices are considered in the mathematical model.

Due to production uncertainty, the WPP may be unable to meet its scheduled power in DA and thus be subjected to the imbalance penalty. To reduce the effects of these penalties, a flexible mechanism is proposed that is called FPM. The penalty payments of the WPP to the market operator in the FPM are lower than their corresponding values in the TPM.

A. TRILATERAL RELATION FOR SUPPORTING FPM FRAMEWORK

The structure of the trilateral relation for the FPM framework in the decision-making problem of the WPP is illustrated in Figure 1. As seen, there exists a trilateral contract between the insurance provider, WPP, and SO. The insurance provider designs some insurance contracts for renewable resources and suggests them to the WPP. As seen from the algorithm, the WPP decides whether to choose an insurance contract or choose the TPM. If the WPP is not motivated to purchase any insurance product, the SO will activate TPM framework as a penalizing mechanism for WPP in the regulating market. But, if the WPP tends to purchase an insurance product by making an insurance contract with the insurance provider, the SO will activate the related FPM for the WPP.

These insurance contracts differ in insurance premium values. The WPP that wants to take advantage of the FPM discount should sign an insurance contract with an insurance provider and choose one insurance contract. Based on the chosen contract, the insurance provider supports the WPP to use a specific FPM in the regulating market and consequently reduces its penalizing costs. Then, SO implements a predefined FPM for managing WPDs of the WPP who contracted with the insurance provider. At the end of the algorithm, it can be seen DR services support the FPM framework. Practically, the flexibility of FPM originates from DR services provided by flexible demand-side resources. The amount of demand flexibility is determined by the SO based on DR resources' historical data. The SO schedules flexible DR resources and determines the MCP, considering bids of DR providers, offers of the WPP, costs of generation units as well as the amount of support that the insurance provider guarantees.

After the market clearing, the SO sends specific signals to DR providers for adjusting their responsive loads based on the pre-defined scenarios defined under a peer-to-peer agreement between the SO and DR providers. DR providers receive the calling signals and determine their support in fulfilling the request of the SO for implementing the FPM. The payment to DR providers by the SO is supported by the insurance provider.

According to the insurance rules, there exist different options for the WPP to choose any type of insurance contract to reduce its WPD risks. In this study, two types of insurance services are considered and the WPP can choose any of them based on the economic and technical conditions. With the option that the WPP chooses the associated FPM, the WPP pays the insurance premium to receive compensation costs. After making a contract between the WPP and the insurance provider, the type of insurance contract is informed to the SO to implement the associated FPM for that WPP in the regulating market.

In a two-settlement market, such as the Nordic power market, up-regulating price is greater than or equal to the DA price, and down-regulating price is less than or equal to the DA energy price [31]. In the FPM, up (down) regulating price is less (greater) than or equal to the up (down) regulating price in the TPM. Therefore, by implementing FPM, the WPP will get a discount on the imbalance penalty in the regulating market and improve its utility. In the next section, the formulation of the proposed FPM framework for the decision-making of the WPP will be explained extensively.

B. WIND FORECASTING USING DEEP LEARNING ALGORITHMS

Deep learning is a subset of machine learning being a neural network with some layers. Wind power is a promising form of renewable resource but the uncertainty of the available wind energy every day is a challenge as a reliable source of energy. Based on recent research and literature, wind power forecasting methodologies can be obtained with artificial methods. Here, to further increase model accuracy, deep learning is used to overcome the uncertainty phenomenon. Compared with the existing models of forecasting, the performance and accuracy of deep models are high [32]. In this work, three deep learning algorithms are used to predict short-term wind power generation based on wind speed. These algorithms include Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Reference Unit (GRU) [26]. The RNN method is the major model for solving time-dependent problems. One of the significant characteristics of the RNN model is the capability to memorize information from previous data. Using a feedback loop, the information in RNN would be processed. RNN is the neural network that includes connections among internal loops. In RNN, the inputs are provided as a sequence of vectors encoded as a 2D tensor. The output of the RNN would be obtained based on the h_t. The current state equation is:

$$h_t = f(h_{t-1}, X_t) \tag{1}$$

After applying the activation function:

$$h_t = \tanh(W_{h,h}h_{t-1} + W_{xh}X_t) \tag{2}$$

where W is the weight, h stands for the single hidden vector, W_{hh} is the previous hidden layer weight and W_{xh} shows the current input state weight. The output of the RNN model is y_t as:

$$y_t = W_{hy}h_t \tag{3}$$

where, W_{hy} is the weight at the output state.

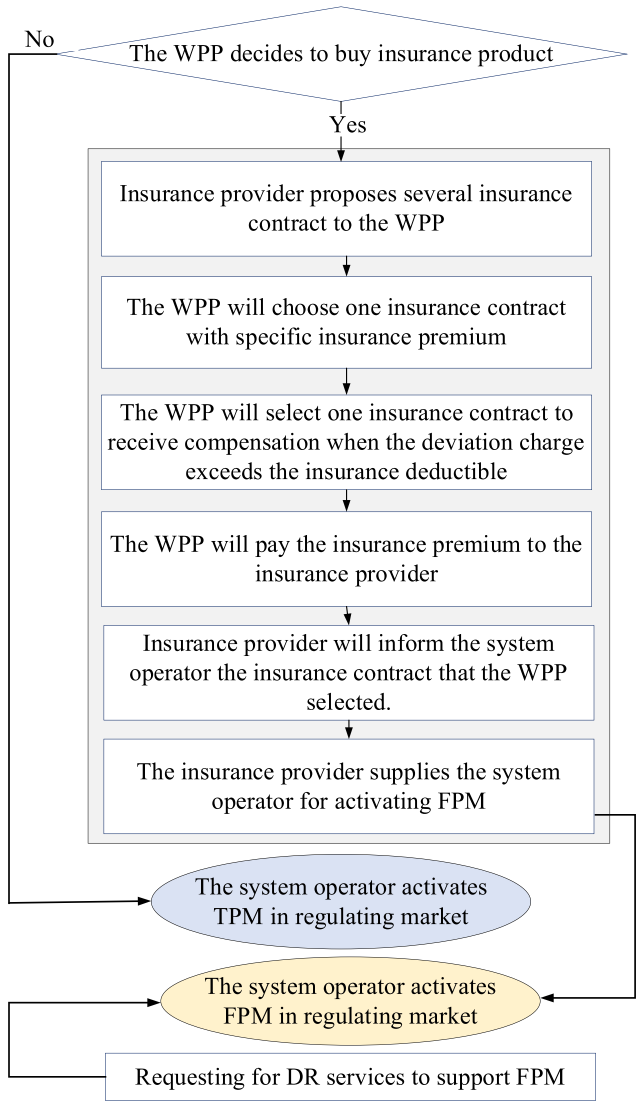

FIGURE 1. The trilateral relationship in the proposed framework.

The LSTM network is part of the deep RNN groups. In usual RNNs, the gradient problem of vanishing is one of the major drawbacks which is omitted in LSTM by integrating self-connected gates in the hidden units. The LSTM is first utilized for time series deep learning. Weather conditions which are mainly a form of time series are used to generate wind power. Nevertheless, deep learning can approximate complex functions. The LSTM method includes three input gates, one output gate, and a forgotten gate. The input sequence is sent to the input gate and the memory would be refreshed.

In RNN, gating system strategies such as GRU methods are also used. GRU is such a long, short-term memory with a forgotten gate while it has few parameters compared with LSTM that is because of the lack of an output gate. More information can be found in [26] that is not explained here due to avoid wordiness.

To investigate the efficiency of each algorithm, the mean square error (MSE) is calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{4}$$

where n stands for the data point number, Y_i and $\hat{Y}_i$ are the observed and the predicted values, respectively.

III. MATHEMATICAL FORMULATION OF THE PROBLEM

The structure of liberalized power market such as Nordic often includes the regulating market in addition to the DA market where any energy deviation can be balanced. In such a power market, up-regulating price is higher or equal to the DA market price, while down-regulating price is less or equal to the DA price [27].

The revenue of the WPP at each timeslot t and each scenario ω is obtained by the production of the DA cleared power times the corresponding DA energy price and the actual power production in regulating market times the regulating market prices as follows:

$$\begin{aligned}\mathrm{Rev}_{t,\omega} &= P^{cl}_{t,\omega}\rho^{DA}_{n,t,\omega} \\ &+ \begin{cases}(P^{P}_{t,\omega} - P^{cl}_{t,\omega})\rho^{reg,up}_{t,\omega}; & P^{P}_{t,\omega} - P^{DA}_{t,\omega} < 0 \\ (P^{P}_{t,\omega} - P^{cl}_{t,\omega})\rho^{reg,dn}_{t,\omega}; & P^{P}_{t,\omega} - P^{DA}_{t,\omega} \geq 0\end{cases}\end{aligned} \tag{5}$$

In the Nordic power market, the penalizing value in the regulating market is considered a deviation value that depends on the shortage or excess of energy. It means that if the energy shortage exists and the WPP should compensate it in the up-regulation market with higher prices than DA ones and receives the penalty $L^{up}_{t,\omega} = (P^{P}_{t,\omega} - P^{cl}_{t,\omega})\rho^{reg,up}_{t,\omega}$.

Also, when the actual wind power production in real-time is more than the cleared energy, the WPP should sell its energy excess in the down-regulation market with prices lower than the DA ones. In this condition, the WPP loses a part of its revenue, and it receives a penalty $L^{dn}_{t,\omega} = (P^{P}_{t,\omega} - P^{cl}_{t,\omega})\rho^{reg,dn}_{t,\omega}$.

A. MODEL OF FPM WITH CONSIDERING INSURANCE CONTRACT

The TPM may result in unintended consequences for participants with uncertain nature such as renewable resources. Although implementing more accurate prediction methods would reduce the uncertainties originating from the intermittencies, here, an FPM framework is used to support green productions. Based on the proposed FPM, the multilateral contracts between the SO, WPP, and insurance providers are encouraged to take into account the associated risks of wind production. Since the insurance providers expect to be profit-seeking, these agents will suggest various contracts for renewables with different contents and provisions. Selecting which insurance contract depends on the preferences and policies of the WPP to choose the level of risk measurement. If the WPP selects an insurance contract with higher values for premium, the insurance provider will support the SO and so, the WPP will receive less penalty costs in the balancing market.

In FPM, firstly, the WPP makes a contract with an insurance provider and selects one of the insurance contracts that are suggested to it. Each insurance contract consists of a specific insurance premium that the risk-averse WPP should pay to the insurance provider to receive compensation. Then, based on the insurance contract, the SO implements an FPM for the WPP. This mechanism is based on the forecasted wind power that the WPP submits to the insurance provider. Be noted that the data only includes some forecasting wind power generation and the data privacy of the WPP won't be deteriorated. The forecasted wind power contains some scenarios. The FPM is applied by the SO based on the chosen insurance program. Therefore, some discounts are considered for the WPP such that the regulating prices would get moderate values and get closer. To this end, the value defined in (6) as $\Delta\rho^{reg}_{t,\omega}$ would be subtracted or added to the regulating prices.

$$\Delta\rho^{reg}_{t,\omega} = \rho^{up,TPM}_{t,\omega} - \rho^{dn,TPM}_{t,\omega} \tag{6}$$

where, $\rho^{up,TPM}_{t,\omega}$ and $\rho^{dn,TPM}_{t,\omega}$ denote up and down regulating prices in TPM, respectively; that are attained from historical data from the electricity market. Up-regulating prices in the FPM framework would be obtained from the subtraction of the TPM up-regulating price and $\Delta\rho^{reg}_{t,\omega}$ as in (7).

$$\rho^{up,FPM}_{t,\omega} = \frac{\rho^{up,TPM}_{t,\omega} - \Delta\rho^{reg}_{t,\omega}}{(1+\ell)} \quad \ell = 0, 1, 2, 3, 4, \ldots \tag{7}$$

Also, for the down-regulating prices in the FPM framework, the $\Delta\rho^{reg}_{t,\omega}$ is added to $\rho^{dn,TPM}_{t,\omega}$ to get higher values as in (8).

$$\rho^{dn,FPM}_{t,\omega} = \frac{\rho^{dn,TPM}_{t,\omega} + \Delta\rho^{reg}_{t,\omega}}{(1+\ell)}; \quad \ell = 0, 1, 2, 3, 4, \ldots \tag{8}$$

It should be noted that ℓ depends on the insurance contracts that are made between the WPP and the insurance provider and it is already known based on the contract.

The values of ℓ forecasted scenarios for wind generation. scenarios in the problem. For example, as shown in Figure 2 for a seven segments normal probability density function for wind generation, for the middle scenarios with the highest probability, the WPP will receive the highest value of the discount from the insurance provider in the balancing market. With getting far from the middle scenarios, the probability of the scenarios will reduce. So, the discount that the WPP will receive based on the insurance contract diminishes. So, $\ell = 2$ and $\ell = 3$ are given to account the balancing prices. Finally, in the furthest scenarios, no discount is given to the WPP, due to the lowest accuracy in the forecasting method.

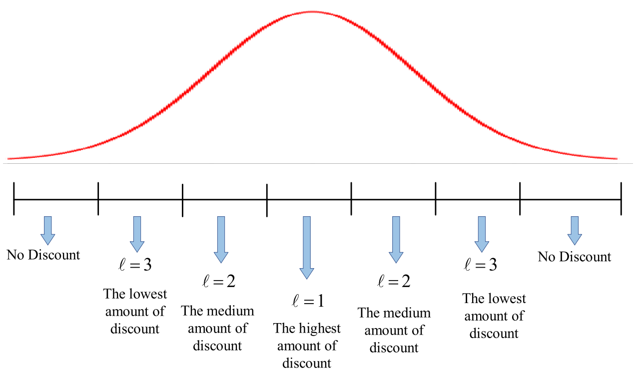

FIGURE 2. Pricing procedure for a sample insurance contract in FPM.

B. THE BI-LEVEL MODEL FOR DECISION-MAKING OF THE WPP

The objective of the WPP is to maximize its production profit as below:

$$Max \sum_{\omega\in\Omega} \pi_\omega \sum_{t\in T} [C_I^P - P_{t,\omega}^{cl}\rho_{t,\omega}^{DA} - P_{t,\omega}^{P}\rho_{t}^{P} + P_{t,\omega}^{dn}\rho_{t,\omega}^{dn} - P_{t,\omega}^{up}\rho_{t,\omega}^{up}] + \beta(\xi - \frac{1}{1-\alpha}\sum_{\omega=1}^{\Omega}\pi_\omega\eta_\omega) \quad (9)$$

In the objective function of the WPP, the first term is its profit and the second term shows conditional value at risk (CvaR). Here, the trade-off between the profit and CVaR would be determined with β. The constraints related to CVaR are also as below:

$$\sum_{\omega\in\Omega} \pi_\omega \sum_{t\in T} [P_{t,\omega}^{cl}\rho_{t,\omega}^{DA} - P_{t,\omega}^{P}\rho_{t}^{P} + P_{t,\omega}^{dn}\rho_{t,\omega}^{dn} - P_{t,\omega}^{up}\rho_{t,\omega}^{up}] + \eta_\omega - \xi \geq 0; \quad \eta_\omega \geq 0 \quad (10)$$

The objective function is subject to the equality in (11) that the cleared power in DA equals the estimated wind power and the compensation power in the regulating market. The inequality in (12) ensures that the estimated wind power is restricted to its maximum capacity.

$$P_{t,\omega}^{P} - P_{t,\omega}^{dn} + P_{t,\omega}^{up} = P_{t,\omega}^{cl} \quad (11)$$
$$P_{t,\omega}^{P} \leq \bar{P}_W \quad (12)$$

The WPP decision-making model and the market-clearing problem are described as bi-level optimization problems. The upper-level problem is from the perspective of the WPP while the lower level is from the SO viewpoint.

The SO objective is to minimize the expression in (13) so that social welfare is maximized. The equation in (14) denotes the energy balance; the power flow from each branch is given in (15) which is limited based on (16). The inequalities in (17) and (18) enforce the constraints in demand and generation, respectively. Be noted that the right side of the columns shows the dual variables associated with each constraint. Constraint (19) ensures that the cleared power is restricted with the offering power. In addition, the bound for the voltage angle and the fixed reference voltage angle are given in (20) and (21).

$$Min \sum_{\omega\in\Omega} \pi_\omega \sum_{t\in T} \begin{bmatrix} P_{G,t,\omega}\rho_{G,t} \\ +\alpha_{W,t}P_{t,\omega}^{cl} \\ -P_{D,t,\omega}\rho_{D,t,\omega} \end{bmatrix} \quad (13)$$

$$\sum_{G\in NG} P_{G,t,\omega} + P_{t,\omega}^{cl} - \sum_{D\in ND} P_{D,t,\omega} - \sum_{k|s(k)=n} f_k + \sum_{k|r(k)=n} f_k = 0 \quad (14)$$

$$f_k = B_k(\delta_{s(k)} - \delta_{r(k)}) \quad (15)$$
$$-f_k^{\max} \leq f_k \leq f_k^{\max} \quad (16)$$
$$0 \leq P_{D,t,\omega} \leq \bar{P}_D \quad (17)$$
$$0 \leq P_{G,t,\omega} \leq \bar{P}_G \quad (18)$$
$$0 \leq P_{t,\omega}^{cl} \leq P_{t,\omega}^{of} \quad (19)$$
$$-\pi \leq \delta_n \leq \pi \quad \forall n\backslash n : ref \quad (20)$$
$$\delta_n = 0 \quad n : ref \quad (21)$$

The inter-dependent variables in the upper and lower levels indicate the coupling of the two optimization problems. In this problem, the prices are obtained as the outputs of the market-clearing problem and the demand or supplies of the lower level depend on the scheduling of the upper level. The detailed mathematical formulations for the bi-level problem are presented in [29].

The bi-level program is formulated as a mathematical problem with equilibrium constraints (MPEC). In this case, the lower level is inserted into the upper level using Karush-Kuhn-Tucker (KKT) optimality conditions.

C. SINGLE-LEVEL MODEL OF THE PROBLEM

The obtained KKT optimality conditions of the lower-level problem are provided here:

$$\rho_G - \rho_{n,t,\omega}^{DA} - \varepsilon_G^{\min} + \varepsilon_G^{\max} = 0 \quad (22)$$
$$\alpha_{W,t} - \rho_{n,t,\omega}^{DA} - \varepsilon_W^{\min} + \varepsilon_W^{\max} = 0 \quad (23)$$
$$\rho_{D,t,\omega} - \rho_{n,t,\omega}^{DA} - \varepsilon_D^{\min} + \varepsilon_D^{\max} = 0 \quad (24)$$
$$\rho_{n(s),t,\omega}^{DA} - \rho_{n(r),t,\omega}^{DA} - \beta_k - \beta_k^{\min} + \beta_k^{\max} = 0 \quad (25)$$
$$\sum_{k|s(k)=n} B_k\beta_k - \sum_{k|r(k)=n} B_k\beta_k - \mu_n^{\min} + \mu_n^{\max} = 0, \quad \forall n\backslash n : ref \quad (26)$$
$$\sum_{k|s(k)=n} B_k\beta_k - \sum_{k|r(k)=n} B_k\beta_k - \gamma_n = 0, \quad n : ref \quad (27)$$
$$0 \leq \beta_k^{\max} \perp f_k^{\max} - f_k \geq 0 \quad (28)$$
$$0 \leq \beta_k^{\min} \perp f_k + f_k^{\max} \geq 0 \quad (29)$$
$$0 \leq \varepsilon_D^{\max} \perp \bar{P}_D - P_{D,t,\omega} \geq 0 \quad (30)$$
$$0 \leq \varepsilon_D^{\min} \perp P_{D,t,\omega} \geq 0 \quad (31)$$
$$0 \leq \varepsilon_G^{\min} \perp P_{G,t,\omega} \geq 0 \quad (32)$$
$$0 \leq \varepsilon_G^{\max} \perp \bar{P}_G - P_{G,t,\omega} \geq 0 \quad (33)$$
$$0 \leq \varepsilon_W^{\max} \perp P_{t,\omega}^{of} - P_{t,\omega}^{cl} \geq 0 \quad (34)$$

$$0 \leq \varepsilon_W^{\min} \perp P_{t,\omega}^{cl} \geq 0 \tag{35}$$

$$0 \leq \mu_n^{\max} \perp (\pi - \delta_n) \geq 0, \quad \forall n \backslash n : ref \tag{36}$$

$$0 \leq \mu_n^{\min} \perp (\pi + \delta_n) \geq 0, \quad \forall n \backslash n : ref \tag{37}$$

In the above equations, the Lagrangian variables corresponding with each expression are given on the left side of the sign $\perp$.

The non-linear term $P_{t,\omega}^{cl}\rho_{t,\omega}^{DA}$ is linearized using strong duality theory and some mathematical relaxations as below:

$$\begin{aligned} P_{t,\omega}^{cl}\rho_{t,\omega}^{DA} = &\sum_{D\in N_D} P_{D,t,\omega}\rho_{D,t,\omega} - \sum_{G\in N_G} P_{G,t,\omega}\rho_{G,t} \\ &- \sum_{k\in N_k} f_k^{\max}(\beta_k^{\min} + \beta_k^{\max}) \\ &\sum_{G\in N_G} (-\varepsilon_G^{\max}\bar{P}^G - \varepsilon_D^{\max}\bar{P}^D) \\ &- \sum_n \pi(\mu_n^{\min} + \mu_n^{\max}) \\ &- P_{t,\omega}^P\rho_t^P + P_{t,\omega}^{dn}\rho_{t,\omega}^{dn} - P_{t,\omega}^{up}\rho_{t,\omega}^{up} \end{aligned} \tag{38}$$

IV. CASE STUDY AND NUMERICAL RESULTS

A. CASE STUDY AND INPUT DATA

In this section, an illustrative example based on IEEE 33 bus test system is used to show the effectiveness of the proposed FPM mechanism. For this purpose, a WPP and an insurance provider are considered to verify the utility improvement of the WPP as a risk-averse decision-maker under different insurance contracts. Here, two types of insurance contracts with different premium costs are considered. The premium costs of contracts#1 and contract #2 are considered to be about 2% and 1% of the WPP's profit, respectively. The value of l for the first contract is 1, 2, 3 and for the second contract is 2, 3, 4, respectively and the WPP can choose each of them. In the first type of contract, l in equations (7) and (8) is considered to be equal to 1 and in this case, the WPP's premium to the insurance provider is low while in the second type of contract, $\ell = 2$ and the WPP's premium to the insurance provider has a higher value.

The regulating market prices extracted from the Nordic power market [31] are given in Figure 3. The forecasted wind power production is also shown in Figure 4. The deviations related to regulating market prices and wind power are generated using normal density function. Based on the historical data of wind power, market prices and demand, some scenarios are also generated and combined.

For wind power forecasting, different algorithms including RNN, LSTM, and GRU are applied to the problem. The models are trained on the training set and validated using the validation dataset.

B. NUMERICAL RESULTS

The WPP tends to compensate for the power deviation by participating in the regulating market. In this case, by applying TPM, the WPP may encounter with unintended results. Therefore, the WPP makes a contract with an insurance provider to get a discount on regulating prices in the case of FPM. Figure 5 illustrates up and down regulating market prices in both TPM and FPM and WPD=10%. By applying FPM, the regulating prices would get moderate values and get closer. Therefore, down-regulating prices would take higher values while up-regulating prices would take lower amounts. Be noted that both up and down prices exist in all hours which implies that both upward and downward services are required. Figure 6 shows cleared energy in the DA market and MCP in cases of TPM and FPM for WPD=10%. The trend of the DA cleared power in both cases follows the trend of wind power production that is presented in Figure 4.

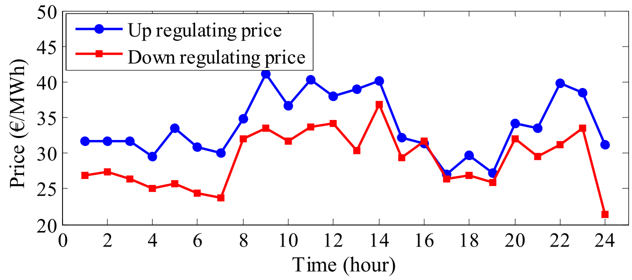

FIGURE 3. Up and down-regulating market prices.

In the case of FPM, the cleared power reduces in most hours that is because the WPP confronts with lower penalties to compensate for its energy deviations. By applying FPM, the WPP sells more energy in the regulating market with more desired prices than those in TPM. The DA clearing prices are also shown in Figure 6 (b). The DA prices will change due to being dynamic and dependent on the network load. In addition, as observed in Figure 6 (b), MCP does not change significantly in the case of FPM compared to TPM. Since the submitted offers of producers and bids of consumers do not change in the two cases, the MCP is settled and remains unchanged.

The energy deviation compensated in the regulating market in both TPM and FPM in WPD=10% is illustrated in Figure 7. The total purchased energy in the cases of TPM and FPM are 1.81 and 2.46, respectively, which shows a 36.5% increment with applying FPM. Moreover, the total excess energy in TPM and FPM are 16.82 and 19.41 which indicates a 15.4% increment. By applying FPM, the WPP faces lower penalty costs and as a result, the energy trading in the regulating market augments. As expected, during high price periods (i.e., 9:00 to 14:00), the associated high price volatility discourages the WPP from aggressive energy trading in up-regulating market. While such high prices encourage the WPP to sell its energy excess in the down-regulating market.

Here, with implementing FPM, since the WPP receives fair discounts, it tends to sell its overproduction in down regulating market. In addition, when the FPM is applied, due to the fair prices in real-time, the WPP is motivated to sell its surplus production in down regulating market instead of DA market.

Figure 8 shows DA energy trading in different WPDs in TPM and FPM frameworks with two types of insurance

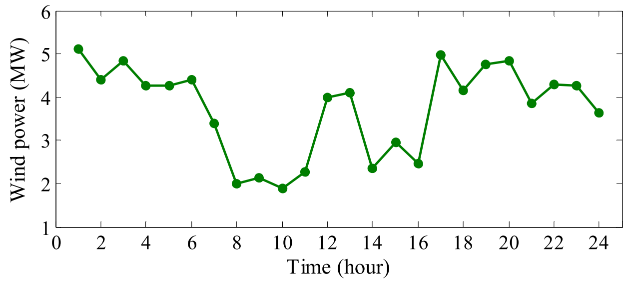

FIGURE 4. Forecasted wind power production.

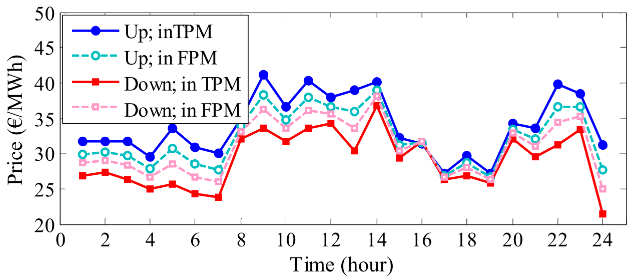

FIGURE 5. Regulating market prices in both TPM and FPM frameworks.

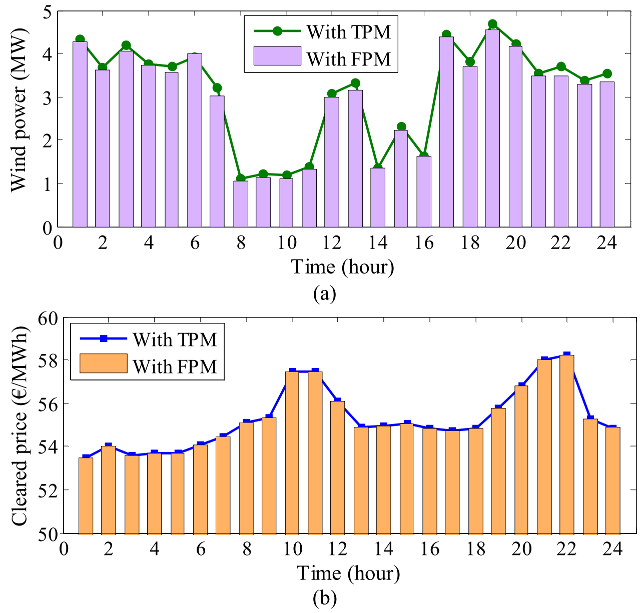

FIGURE 6. (a) Wind power cleared in DA market, and (b) MCP.

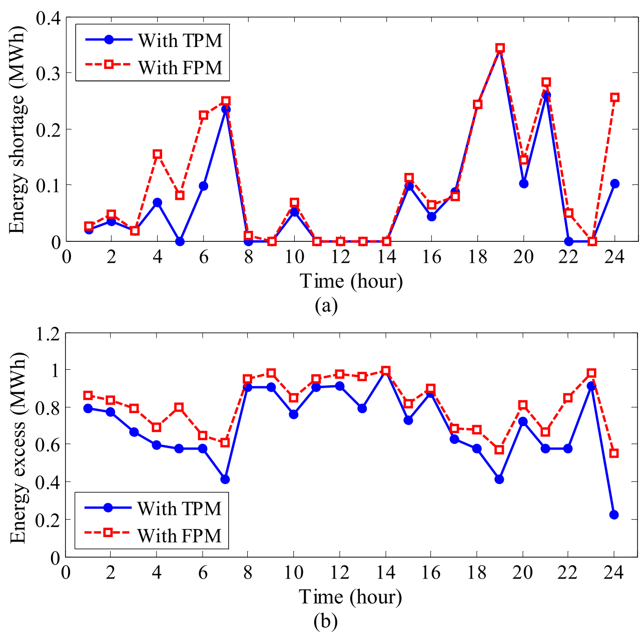

FIGURE 7. Trading energy in both of TPM and FPM mechanisms, (a) energy shortage, and (b) energy excess.

contracts. In contract 1 of FPM, the WPP's premium to the insurance provider is high; therefore low penalty costs are implemented for the WPP rather than those in contract 2. Figure 8 illustrates the cleared energy in DA market in different WPDs. As seen, with increasing WPD, the cleared energy in the DA market augments that is because the WPP operator tends to efficiently utilize wind energy surplus. While, in TPM, there exists the most energy cleared in DA, however, with the implementation of FPM, the cleared energy in DA reduces due to the discount the WPP receives in real-time. Hence, the lack of wind generation is compensated by purchasing energy from down regulating market with cheaper prices. This results directly in a very small amount of DA energy transaction in TPM scheme. In FPM, in contract 2, since the amount of discount the WPP receives is less than the one in contract 1, the cleared energy in DA decreases. In contract 1, the WPP confronts with more discount in real time transactions, so, those cheaper prices in real time reduce the DA energy exchanges; This results the augment in the revenue of the WPP.

To assess the effect of accuracy in wind power prediction in different cases, energy trading in DA and regulating markets are investigated in different WPDs. Figure 9 illustrates energy trading in up and down regulating markets in different WPDs and the TPM and FPM frameworks. As shown, with increasing WPDs, more total energy in regulating market is traded, since, in this condition, the energy imbalance would be more critical and the WPP should compensate it in the regulating market.

Moreover, when TPM is implemented, in both the up and down regulating market, the energy traded has the least value. While, with FPM, due to the discount that is considered for the WPP, both amounts of up and down regulating energy transactions augment. Even, more energy trading in contract 1 occurs compared to the one in contract 2; because more discount is considered for the WPP in contract 1. Totally, in all cases, with increasing WPDs, the DA cleared power would be estimated as more than its actual power causing up trading energy to obtain an increasing trend. While, with increasing WPDs, down-regulating trading reduces due to higher DA cleared power.

Table 2 reveals different items in the two cases with accurate and inaccurate prediction methods in different WPDs and both TPM and FPM for two types of insurance contracts with different payments to insurance providers. It can be justified from the table that the use of an adequate prediction

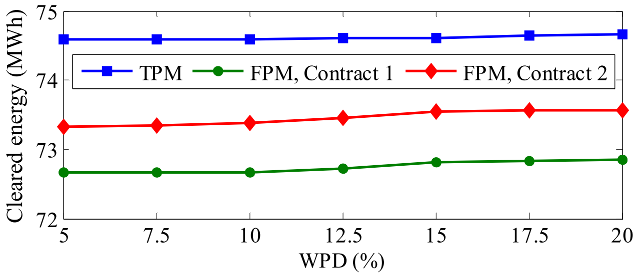

FIGURE 8. Total cleared energy in DA market in different WPDs.

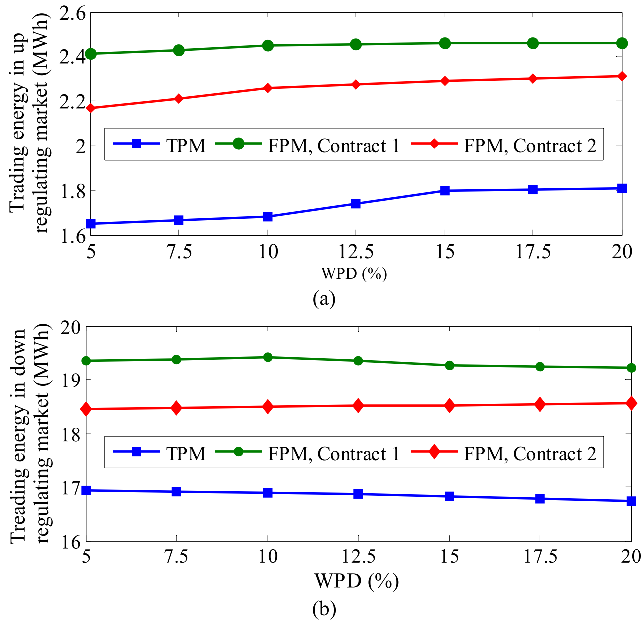

FIGURE 9. Total of trading energy versus different WPDs, (a) in up-regulating market, and (b) in down-regulating market.

tool involving a high degree of accuracy can lead to higher DA energy transactions. As expected, the WPP participates more in the regulating market to cover the energy deviations resulting from inaccurate predictions compared with the case with perfect information tools. As seen, in both cases of TPM and FPM, with increasing the WPD, the cleared power in DA augments that is because the WPP tends to efficiently utilize its high generation. When wind uncertainties are higher, the energy imbalances becomes more critical; therefore, more energy should be transacted in the regulating market. Also, when there is higher uncertainty, the WPP participates in the up-regulation market to cover the probable energy shortage that occurred due to higher DA clearing power, while, it may confront less energy excess. These lead to higher up penalties and lower down penalties. Moreover, in both TPM and FPM cases, with increasing WPD, the expected profit of the WPP reduces. These points to encouraging the implementation of more accurate techniques would reduce the uncertainty associated with the WPP and specifically its expected profit.

In this table, the social welfare of the SO is also shown in both TPM and FPM in different WPDs. It is observed that the social welfare of the SO in the case of FPM has increased. Moreover, the social welfare associated with contract 2 is more than the social welfare in contract 1 which indicates the value of the premium of the insurance contract.

Also, with increasing WPDs, the social welfare augments that is because the SO may tend to correct the energy deviations through balancing markets or other resources. To investigate the impacts of the risk-aversion on the decision-making problem in two penalty mechanisms, the results for different cases are compared in Table 3. Due to the limited space, the results for only two values of risk parameter β corresponding to the relatively risk-neutral and risk-averse behaviors are indicated; $\beta = 0.01$ and $\beta = 100$, respectively. The WPP faces instantaneous and variable resources such as wind generation, market prices, and loads; it may take different strategies to reduce the exposure to the risks. As the WPP becomes more risk averse, it is more intended to increase the expected energy traded in the DA market. The policy that is adopted by the WPP to hedge against the profit variability boils down to trading energy in the balancing market as a penalizing environment. In this circumstance, with existing insurance contracts, energy exchange in the DA market reduces in the hope to sell its additional production in the balancing market. Also, the WPP can compensate for its financial loss from the insurance provider based on the contracted prices in Contract 1 and Contract 2. Based on the penalty prices of the two contracts, since contract 2 consists of higher penalty prices, the WPP augments its participation in the DA market to cover its energy deviations. In fact, when there exists higher wind uncertainty, the WPP tries to compensate the energy shortage/surpluss by participating in the regulating market.

As the risk aversion increases, the energy purchased in up-regulating market augments, at the expense of reducing the energy compensation in the down-regulating market. Moreover, with making an insurance contract with insurance providers, both up and down regulating values augment compared to the values in TPM. Because, by implementing FPM, flexible penalizing prices would be mbproposed to the WPP in Contract 1 and Contract 2. From this table, it can be seen that increasing β decreases the expected profit of the WPP. It is because, as the WPP becomes more risk averse, it purchases its energy deficit in the up-regulating market with high prices. Also, by making a contract with insurance providers, the expected profit of the WPP augments, since more flexible penalizing prices would be considered for the WPP in the regulating market based on the two Contracts.

It can be implied that msximization of the expected profit of the WPP is equivalent to the minimization of the imbalance costs following by implementation of FPM. Here, by implementing TPM and then FPM in contract 1 and Contract 2, the expected profit augments about 3.4% and 2.7%, respectively.

The proficiency of this work is compared qualatively with other published ones. To compare the performance of the proposed penalizing mechanism in this study with the penalty approaches applied in other existing literature, it can be mentioned that in [11], a price signal is extracted from a balancing market to punish the agents who deviate from their scheduling

TABLE 2. Different items in both TPM and FPM for two types of insurance contract and in different WPDs.

Penalty Mechanism	Type of Insurance contract	WPD (%)	Trading energy in DA	Trading energy in up Regulation	Trading energy in down Regulation	Expected profit of the WPP	Up penalty	Down Penalty	Payment to insurance provider	Social Welfare
TPM	No contract	5	74.40	1.68	16.90	2401.56	48.75	516.47	-	4456.77
	No contract	10	74.61	1.80	16.82	2398.14	52.21	513.84	-	4468.83
	No contract	15	74.67	1.79	16.74	2392.11	51.90	510.82	-	4471.44
FPM	Type 1	5	72.67	2.41	19.36	2435.61	69.08	617.62	17.02	4358.20
	Type 2		73.33	2.17	18.56	2424.42	62.56	580.43	11.43	4397.48
	Type 1	10	72.67	2.45	19.41	2431.92	70.12	618.59	16.89	4358.56
	Type 2		73.38	2.26	18.50	2420.72	65.18	581.37	11.29	4400.09
	Type 1	15	72.82	2.46	19.26	2425.87	70.42	613.71	16.88	4365.49
	Type 2		73.55	2.29	18.36	2414.72	65.77	576.70	11.29	4408.49

TABLE 3. Values of various items in different prediction accuracy in TPM and FPM for two pricing contracts.

Penalty mechanism	WPD	β	DA	Down regulating	Up regulating	Expected profit
TPM	5%	0.01	3.687	0.705	0.099	2734
		100	3.689	0.705	0.101	2733
FPM (Type 1)		0.01	3.609	0.811	0.120	2808
		100	3.607	0.811	0.117	2806
FPM (Type 2)		0.01	3.063	0.767	0.128	2804
		100	3.063	0.767	0.121	2803
TPM	15%	0.01	3.611	0.697	0.119	2652
		100	3.111	0.697	0.120	2651
FPM (Type 1)		0.01	3.611	0.815	0.128	2755
		100	3.609	0.813	0.122	2752
FPM (Type 2)		0.01	3.064	0.765	0.127	2724
		100	3.064	0.765	0.127	2721

TABLE 4. Values of various items in different machine learning algorithms in WPD=0.5%.

Penalty mechanism	Point	RNN	LSTM	GRU
TPM	Expected profit	2774	2776	2779
	UP Regulating	0.125	0.120	0.119
	Down Regulating	0.782	0.779	0.774
FPM (Type 1)	Expected profit	2808	2811	2813
	UP Regulating	0.131	0.128	0.124
	Down Regulating	0.771	0.763	0.756
FPM (Type 2)	Expected profit	2804	2806	2809
	UP Regulating	0.128	0.126	0.124
	Down Regulating	0.770	0.765	0.764

programs. In [11], the expected profit of the WPP using a constant price signal reduces, while, with applying FPM, it augments as shown in Table 2.

In [19], an average pricing market mechanism was proposed for renewable generations to mitigate the unintended volatility of those intermittent generations where the penalty scheme was used based on frequency regulation services and energy storage systems. Although the results in [19] show that a less severe penalty price can result in a higher market surplus, it will lead to more severe market volatility. Furthermore, using storage systems bring degradation problems. But, the present work designs a flexible penalizing scheme for renewable resources in the balancing markets using FPM without storage systems with those advantages shown in [19] which can be used by the policymakers, insurance providers, and stakeholders in the electricity market sectors.

Table 4 presents values of various items in different machine learning algorithms in WPD=0.5%. As can be seen from this table in the case of the GRU method, the WPP receives the most profit that is because of the most accurate wind power. In this regard, the WPP confronts penalties in the balancing market when it tries to compensate for the errors originating from inaccurate predictions.

Such a penalty in the balancing market causes a decline in the overall expected profit. From this table, it is also observed that the LSTM model performs better compared to RNN and is even closer to the GRU. Furthermore, it is seen that by implementing a proper FPM, the WPP would insure its profit, and its participation in the balancing market would be reduced.

Also, the MSE is calculated from (4) based on which RNN, LSTM, and GRU are 0.138, 0.129, and 0.124, respectively. It can be interpreted from the results that GRU with the lowest value of MSE provides better results other than the other two methods.

Totally, with considering high degree of wind power generation, implementing the traditional penalties will bring negative effects specifically on the motivation of investigators of renewable resources. But, as can be seen from the table, despite the implementation of FPM, using a perfect forecasting method by the WPP owner is required to avoid revenue losses.

V. CONCLUSION

Applying conventional penalty mechanisms would result in unintended consequences for renewable generations. Therefore, one solution suggested to the problem is to make a contract with insurance providers. So, in this paper, the insurance for wind power deviation is proposed as a risk measurement instrument for risk-averse WPP. In this regard, choosing a proper insurance program for the WPP can bring a certain profit for the WPP operator. To this point, the profit-seeking WPP operator can choose a proper insurance program to reduce its deviation risk. So, choosing different insurance types have a specific effect on real-time energy coverage.

The results show that choosing FPM with different insurance contracts in different WPDs has a specific effect on the energy trading on the DA and regulating markets. Moreover, due to the discount that is considered for the WPP, unlike energy trading in real-time, the energy trading in DA reduces. Furthermore, the expected profit of the WPP augments about 9.45% and 14.14% in the two insurance contracts based on the premium paid by the WPP in each one. It was also pointed mentioning that DR resources provide DR services for the SO to successfully implement the FPM framework. Moreover, it was mentioned that the value of social welfare increases in FPM rather than TPM, and also it changes based on the premium of the insurance contracts. Moreover, the values of social welfare augment by increasing WPDs. In this study, wind forecasting using deep learning algorithms is also driven that it demonstrates that making an insurance contract affects significantly the expected profit of the WPP in case of inaccurate forecasting compared with the case with the best prediction.

A subject of future research will be on developing a coalition of wind power production with other resources to provide an effective way to exploit the reduction in variability of output power of renewable resources. In addition, as transmission networks can surely affect the coalition of wind power in different buses, the present work will be extended to consider multi-bus networks to account for transmission effects.

One of the limitations of this study is that the concept of insurance is not familiar enough with the energy and electricity markets. In other words, the current electricity markets require the revision of some definitions. In other words, a more proficient framework is required for the current electricity markets to provide an environment for insurance providers to support renewables and flexible resources. Therefore, for future studies, more business work should be done specifically on the business models of insurance providers.

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Open Access funding provided by 'Università degli Studi di Salerno' within the CRUI CARE Agreement