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Towards an Aggregator that Exploits Big Data to Bid on Frequency Containment Reserve Market

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***Abstract*—The increased penetration of distributed and volatile renewable generation requires the demand-side to be actively involved in energy balancing operations. This paper proposes a solution in which big data and machine learning methods are employed to enhance the capabilities of a Virtual Power Plant to participate and intelligently bid into a demand response energy market. The energy market being investigated consists of the frequency containment reserve market. First, we define the core decision-making required to overcome the uncertainties in the frequency containment reserve market participation for a Virtual Power Plant. Then, we focus on forecasting the frequency containment reserve prices for the day-ahead. We analyze the price data, and identify and collect the relevant features for the prediction of the prices. In addition, we select several regression analysis methods to be utilized for the prediction. Finally, we evaluate the performance of the implemented methods by executing several experiments, and compare the the performance with the performance of a state of the art autoregression method.**

***Index Terms*—smart grid, energy market, demand response, frequency containment reserve, price forecasting, machine learning, regression analysis.**

I. Introduction

The introduction of distributed energy resources into the smart grid has raised the problem of how to integrate these resources without tax payer supported solutions, such as feed-in tariffs. One solution is to empower small consumers with the information and market opportunities needed to profitably offer their flexible capacities for the purpose of improving the energy efficiency of the smart grid. For example, this approach has been chosen in Europe where the Energy Efficiency directive specifically includes a "Consumer information and empowering programme" for this purpose [1].

This paper focuses on consumer owned smart loads that are able to perform demand response to adjust their consumption when there is an imbalance of production and consumption in the smart grid. There are several market mechanisms for demand response, and this paper investigates frequency containment in more detail. In frequency containment, the Transmission System Operator (TSO) makes contracts with customers that own loads, this will automatically reduce or increase their consumption in case of overfrequency or underfrequency in the grid. Unfortunately, the TSOs that have the monopoly position in the demand response market are currently not advancing the cause of consumer empowerment. For example in Finland, Fingrid requires customers to place bids on the frequency containment market the day before, so that it can then accept the cheapest bids until it has obtained the required volume of frequency reserves [2]. As shown in section IV, the volume and price of frequency containment reserve is highly volatile, and is very difficult to predict, resulting in a situation in which the numerous small consumers lack the information that they need to effectively make profit with their resources, presumably lowering consumers' motivation to invest in such resources, and thus hindering the uptake of innovative energy efficient distributed energy resource technologies.

In this paper, we propose that big data and machine learning can be used to empower the consumers by providing frequency containment price forecasts enabling consumers to bid intelligently. However, we also recognize that a solution relying solely on an auction is bound to result in sub-optimal energy efficiency, as it does not exploit the big data available from smart meters of the domestic customers. Thus, we also propose an architecture involving a Virtual Power Plant (VPP) that is able to handle the intelligent bidding on the TSO market using the frequency containment price estimates as well as the consumption estimates derived from the smart meter data of the numerous small consumers. We describe such a system concept, and a detailed technical contribution is made for one major aspect of the concept, namely the frequency containment for normal operation (FCR-N) price forecasting using big data and machine learning.

This paper is structured as follows. Section II reviews related work both in machine learning and in electricity markets. Section III proposes a system architecture that aims at energy efficiency through sharing information and empowering consumers at the VPP and domestic consumer level. Section

IV formulates in detail one major aspect of the system in Section III, namely the frequency containment price forecasting. Section V presents the results of the forecasting, while Section VI concludes the paper and outlines further work.

II. Related work

In the smart grid context, the ever-growing amount of data, available from countless distributed sources provides the basis for enabling big data analysis [3]. The analysis allows the optimization of several operational strategies, such as operations of planning, monitoring and grid protection [4]. Moreover, the analysis can enhance the decision-making capabilities of several actors, such as electricity retailers [5], and aggregators [6]. In fact, these actors can benefit from available market and smart meters data to minimize the uncertainties of the operations in which they are involved [7].

Traditionally, the frequency containment reserves are controlled by means of a droop control, in which power plants adjust their production based on the frequency deviations. However, with the increase of renewable generation, which is replacing the conventional production [8], power plants can not solely guarantee the provision of the ever increasing required reserves [9], thus threatening the stability of the entire power grid. For this reason, the participation of a VPP to the provision of frequency containment reserves is foreseen to have an important role in the balancing of the future power grid [10]. Nevertheless, the new participants are required to consider several uncertainties, and they need to minimize their operational risks. The main uncertainties of a VPP are: the forecastig of the day-ahead flexibility [11], the definition of the dynamic prices combined with the day-ahead scheduling of the demand [12], and the prediction of the demand as well as the energy prices [13].

The prediction of energy prices has been widely studied by means of several methods for time series forecasting [14]. Traditionally, the energy prices (i.e. for the day-ahead market) have been predicted using autoregressive integrated moving average (ARIMA) models [15]. More recent attention has focused on the prediction of market prices through regression analysis methods [16] [17], in which a set of independent variables (X), also called features, are utilized to predict the energy prices, defined as the dependent variable (Y). Nevertheless, no study has been found that aims to identify the fundamental features, and then to forecast the frequency containment reserves prices through regression analysis, enabling VPPs to participate in the reserves provision.

III. Virtual Power Plant market participation

The participation of a VPP in a demand response market, such as the frequency containment reserves, involves several actors, which are required to consider multiple risks and uncertainties. Figure 1 presents the scenario in which a VPP, composed of an aggregator and a set of consumers, is participating to the frequency containment reserves market. Both, the required operations and the main data flows are represented in the figure. To participate in the market, the operations required

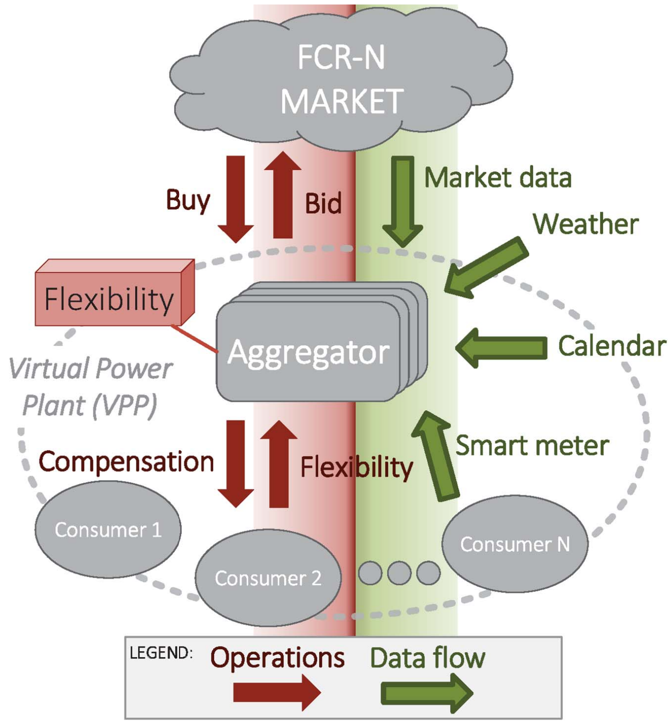

Fig. 1. The required operations and the data flows needed for the participation of the Virtual Power Plant to the Frequency Containment Reserve market

are as follows. The aggregator acts as a mediator between the consumers and the market [6]. The consumers, in exchange of a fair compensation, provide a certain amount of hourly flexibility to the aggregator. Consequently, the aggregator holds a flexibility asset, and uses this asset to bid in the market, with the final aim of participating in the provision of reserves. However, the operations of planning the hourly flexibility provided and bidding to the frequency containment reserves market needs to be executed and optimized one day-ahead [2].

To optimize the bidding strategy, the aggregator has to consider several uncertainties. The aggregator needs to predict the prices of the frequency containment reserves market for the next day. Furthermore, the aggregator has to establish the sensitivity of the consumers to different compensations, and estimate, in cooperation with the consumers, the hourly amount of flexibility that the VPP will be able to provide. Therefore, the aggregator can employ big data and machine learning methods to enhance its ability to make decisions and reduce the uncertainties. In fact, the aggregator can acquire and utilize historical data, such as market data, smart meters data, consumers data, and several other factors that are affecting the presented scenario (i.e. data flows in Figure 1).

The remainder of this paper focuses on the prediction of the frequency containment reserves prices for normal operation (FCR-N) [2], considering the Finnish market as use case. The FCR-N consist in a balancing market that provides constant reserves to contain the frequency deviations of +/- 0.01 Hz from the nominal frequency value of 50 Hz, and thus it contributes in maintaining the power balance of the grid. The following sections highlight the main characteristics and behaviors of the FCR-N prices, the big data employed in the process of forecasting, and the exploited machine learning regression methods. The further work outlined in section VI complements this work on price prediction with estimates of what level of flexibility customers are expected to provide at specific prices. However, this prediction in itself is a complex problem as the volume of flexibility provided by customers as a function of the financial compensation is highly nonlinear [18]. At the time of writing, there is a lack of available smart meter data on this type of consumer behavior, since demand response has traditionally been limited to large industrial loads. Recent frequency containment reserves piloting has focused on small and medium sized enterprises, with domestic customer pilot projects possibly emerging in the near future [19].

IV. FCR-N PRICE FORECASTING

A. Price Analysis

To analyze the FCR-N market prices, two year data (i.e. 2015 and 2016) were collected from the Open Data Service provided by Fingrid [20]. Figure 2 presents the analysis of the FCR-N price behavior in terms of average price and standard deviation for each month of the collected data. The average and standard deviation of the prices show large variations between different months. The high volatility of the prices is caused by the nature of the FCR-N market, which is utilized to provide reserves when an imbalance occurs in the grid. Thus, it does not present high seasonal correlation between the prices during long time periods (i.e. over the years). Indeed, the continuous transformation of the power grid (i.e. increase of renewable), combined with the changes of the market policies, contributes to the evolution of prices throughout the years. At the same time, as shown in Figure 3, the autocorrelation of the analyzed prices presents peaks at 24-hours intervals, among which the largest autocorrelation is with the price of the same hour of the previous day.

For the two years analyzed, the prices of the FCR-N market were equal to zero for about 30% of the total hours. This is due to the fact that when the FCR-N reserves are not utilized, i.e. the FCR-N volume is zero, hence the prices are also equal to zero. The high rate of zero-price hours increases the uncertainties for the participation of a VPP to the FCR-N market. Thus, the aggregator has to predict the zero-price hours in order to avoid to make an erroneous planning of the reserves.

B. Features Selection

Since the objective of this paper is to forecast the FCR-N prices using data-driven machine learning methods, the selection of the input features for training and generating the prediction models plays a key role in the price forecasts. Thus, input features have been selected in order to represent the main aspects affecting the FCR-N market. These input features incorporate data representing:

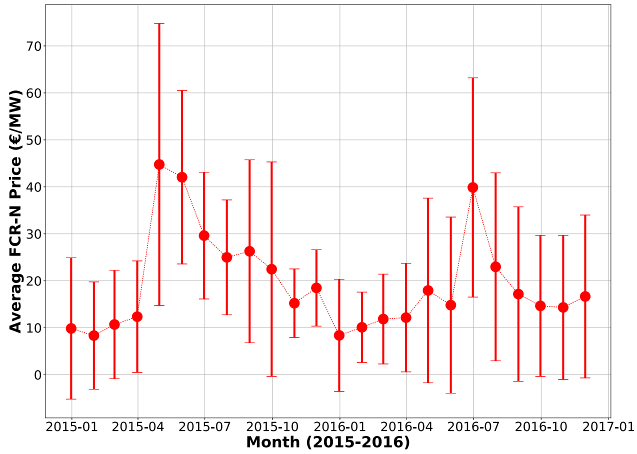

Fig. 2. The mean and the standard deviation for the FCR-N prices for every month of the collected data.

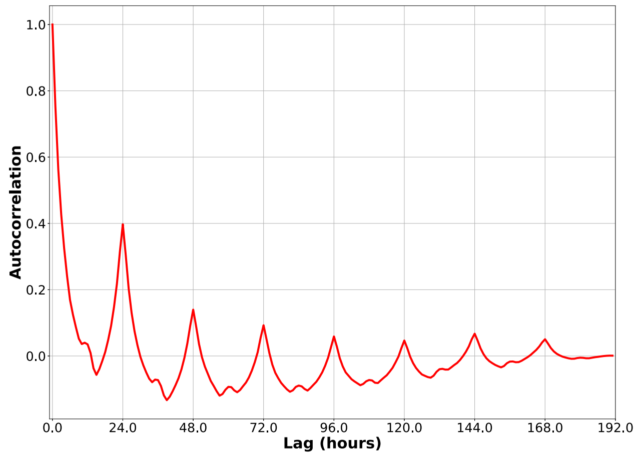

Fig. 3. The average autocorrelation of the FCR-N prices for the entire 2016

- the generation of renewable, the total energy generation, and the consumption of energy in Finland;
- weather data: which affects the consumption and generation of renewable energy in the country;
- data relative to the calendar: i.e. seasons, hour of the day, weekdays, holidays;
- data which is highly correlated to the FCR-N prices: such as the volume and the activated amount of FCR-N, but also the amount of energy imported and exported from Finland, which can be used by the TSOs as FCR-N reserve.

Table I presents the complete list of features that have been collected to predict the FCR-N prices. As for the FCR-N prices, two years data was collected for the selected features from several data sources [20], [21]. Moreover, the selected features have been categorized in two different types, respectively denoted as type 1 and type 2. The common aspect of the type 1 features corresponds to the possibility of acquiring accurate predictions from the data for the future 24 to 72 hours, which can then be used as input to the prediction

TABLE I
FEATURES SELECTED FOR THE PREDICTION OF FCR-N PRICES

Feature Name	Number of features	Feature type
Day-ahead Elspot prices (€/hour)	1	1
Total Energy Generation (MW/h)	1	1
Wind Energy Generation (MW/h)	1	1
Load Forecast (MW/h)	1	1
Solar Radiation	8	1
Temperature	6	1
Wind speed	6	1
Humidity	6	1
Calendar (i.e. weekdays, holidays, seasons, hours)	28	1
Electricity import/export - Commercial flow (MW/h)	5	1
Electricity import/export - Measured flow (MW/h)	5	2
Volume of FCR-N (MW/h)	1	2
Activated FCR-N (MW/h)	1	2
Total	70	

models. On the other hand, type 2 consists of features that are highly correlated to the FCR-N prices out of which no accurate predictions for the future days are available.

The collected features have been pre-processed before being utilized for predicting the FCR-N prices. The features have been normalized using the following rescaling formula:

$$x' = \begin{cases} \frac{x - min(x)}{max(x) - min(x)} & if(x \in \mathbb{R}^+) \\ 2 \cdot \left(\frac{x - min(x)}{max(x) - min(x)}\right) - 1 & otherwise \end{cases} \quad (1)$$

in which x represents one feature of Table I.

C. Regression Analysis

Regression analysis is a form of predictive modeling technique which investigates the relationship between a dependent variable (Y), and one or more independent variables (X). More specifically, regression analysis helps one understand how the typical value of the dependent variable (or 'criterion variable') changes when any one of the independent variables is varied, while the other independent variables are held fixed. Many techniques for carrying out regression analysis have been developed. In this paper, we consider the following method which are regularly used by researchers.

Linear Regression establishes a relationship between the dependent and independent variables using a best fit straight line (also known as regression line) [22]. Linear regression only looks at linear relationships between dependent and independent variables. That is, it assumes there is a straight-line relationship between them, which is often incorrect. Moreover, Linear Regression is very sensitive to outliers. It can terribly affect the regression line and eventually the forecasted values.

Decision tree uses a tree as a predictive model which maps observations about an item to conclusions about the item's target value [23]. Decision trees where the target variable can take continuous values are called regression trees [24]. Decision trees in general have an advantage over other learners in that it is highly interpretable. In addition, they require relatively little effort from users for data preprocessing and they are not sensitive to outliers since the splitting happens based on proportion of samples within the split ranges and not on absolute values. Finally, decision trees do not require any assumptions of linearity in the data. However, decision tree can be extremely sensitive to small perturbations in the data: a slight change can result in a drastically different tree. Furthermore, decision tree can easily overfit. This can be negated by validation methods and pruning [25].

Support vector machine (SVM) constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which was originally proposed for classification tasks [26]. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. A version of SVM for regression is called support vector regression (SVR) [27]. In the same way as with classification approach there is motivation to seek and optimize the generalization margin given for regression.

Gradient boosting decision tree (GBDT) is one of the most widely used learning algorithms in machine learning today [28]. It constructs an additive regression model, utilizing decision trees as the weak learner. Specifically, it builds decision trees one at a time, where each new tree helps to correct errors made by previously trained tree. Advantages of GBDT include adaptability, interpretability, scalability (it can handle very high dimensional spaces as well as large number of training examples) and accuracy. In addition, GBDT is able to model feature interactions and inherently perform feature selection.

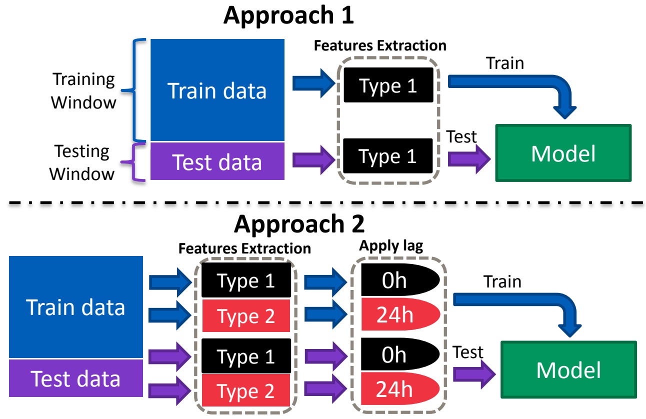

Fig. 4. Configuration settings of the the two approaches: Approach 1 and Approach 2 respectively.

V. Experimental Results

A. Performance evaluation

The first experimental results evaluate and compare the performance of the selected machine learning regression methods (i.e. Linear Regression, Regression tree, SVR, and GDBT). Two different approaches are proposed: Approach 1 (App1) and Approach 2 (App2) respectively. In both the approaches,

TABLE II

Mean Square Error (MSE) performance comparison for Approach 1 (App1) and Approach 2 (App2) for the four tested regression methods: linear regression, regression tree, SVR, and GDBT.

Month (2016)	Linear Regression App1	Linear Regression App2	Regression tree App1	Regression tree App2	SVR App1	SVR App2	GDBT App1	GDBT App2
January	130.43	118.66	188.45	204.50	126.69	133.12	121.92	105.86
February	87.81	75.74	84.42	82.52	55.84	64.25	52.41	48.60
March	170.64	152.83	199.12	166.73	138.13	140.77	95.77	94.51
April	224.04	188.53	217.15	492.71	137.82	147.02	107.30	101.14
May	242.70	245.64	453.14	329.94	285.73	206.29	190.11	190.52
June	189.60	170.35	286.39	282.02	157.75	169.98	120.13	114.60
July	615.19	512.47	524.97	463.75	322.64	309.03	269.84	267.22
August	193.68	159.88	277.47	227.37	164.69	146.80	152.72	125.07
September	196.27	158.52	227.77	201.87	130.33	155.54	90.22	86.63
October	67.15	69.01	134.49	183.78	55.81	65.46	62.67	65.50
November	97.29	71.54	182.00	184.26	102.51	99.08	85.17	70.70
December	214.57	138.16	284.43	256.87	152.57	128.02	144.97	123.81
Average MSE	204.54	**173.76**	259.43	**258.04**	155.02	**148.84**	126.83	**118.97**
P-value	**0.0056615**		**0.9614914**		**0.5041442**		**0.0112685**	

we have predicted the FCR-N prices for the entire year in 2016. Moreover, for every day of 2016 and each implemented method, we have trained a model for predictions, in which the size of the training window was composed of one year sequential data, while the size of the testing window consisted of the 24 hours of the following day.

The differences between the two approaches are presented in Figure 4. In App1, we have used only the features of type 1 to train and test the model for predicting the FCR-N prices. On the other hand, for App2 we have extracted both types of features (i.e. type 1 and type 2) from the data, and then we have added a lag of 24 hours to the features of type 2. The lag of 24 hours was added to the features of type 2 due the fact that while there are no accurate predictions for features of type 2, these features are highly correlated with the FCR-N prices (i.e. FCR-N volume, Activated FCR-N, etc). In addition, the FCR-N prices have presented over the collected data a high correlation with the hourly prices of the previous day (Figure 3). For these reasons, we have decided to apply a lag of 24 hours to the features of type 2 in the App2, and then compare the performance with the App1.

Table II presents the performance of the two approaches by comparing the mean square error (MSE) for every month of 2016. As can be seen, for every method implemented, the best prediction results took place during the months where the standard deviation of the prices was smaller (Figure 2). In contrast, the worst prediction results occurred during July 2016, when the average price was more than double than the other averages of 2016 in joint with a large standard deviation (Figure 2). Moreover, comparing the performance of App1 and App2, significant differences in the results were observed for three of the four tested methods. In fact, the predictions of App2 improved the results obtained in App1 for Linear Regression, SVR, and the GDBT method. However, no significant differences between App1 and App2 were found by using the Regression tree method. Considering the average MSE performance for the predictions of 2016, for all the methods implemented, App2 outperformed App1.

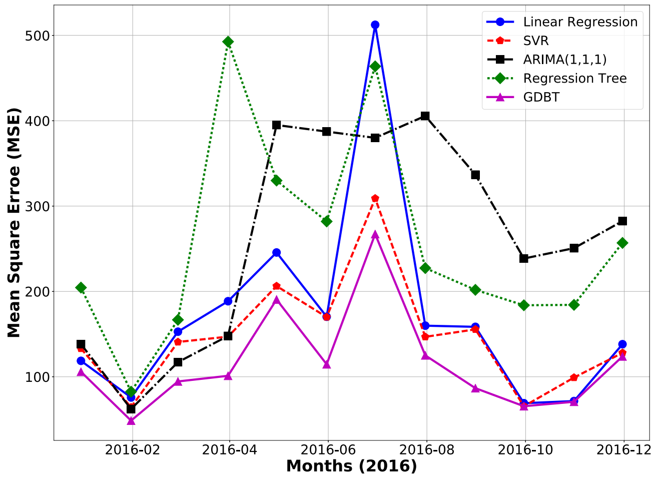

Fig. 5. Performance comparison between ARIMA(1,1,1) and the four implemented machine learning regression methods using the Approach 2 settings

To assess the significance of the prediction improvements of App2 over App1, the performance results were compared using the T-test [29]. The calculated p-values are presented in Table II. The results indicate that adding a lag of 24 hours to the features of type 2 produces a significant improvement for Linear Regression and GBDT (i.e. p-value<0.05). Hence, the strategy implemented in App2 is helpful for improving the accuracy of our predictions. However, we can also observe that this strategy does not significantly improve the results for Regression tree and SVR.

B. Performance comparison

The objective of the second experiment was to compare the best performance between the two approaches above, i.e. App2, with the state of the art ARIMA model. As for App1 and App2, the ARIMA(1,1,1) model was used to make predictions for the entire 2016, in which the training window for the autoregressive FCR-N prices was one year, and the predictions were made for 24 hours ahead. Figure 5 compare the MSE performance of the ARIMA with the results of the four implemented methods in App2. As shown, during the initial months of 2016, i.e. where the average prices are steady and the standard deviations are small, the ARIMA performed similarly to the machine learning methods. However, for the remaining months of the year, three of the four regression methods implemented (i.e. Linear Regression, SVR, and GDBT) significantly outperformed the predictions of the ARIMA model.

VI. Conclusion

The purpose of the current study was to present an architecture involving a VPP capable of exploiting big data to intelligently bid on the FCR-N market. The main objective was to forecast the FCR-N prices for the day-ahead. Thus, we have analyzed two years of historical FCR-N data. In addition, we have selected the set of features and four regression analysis methods to be utilized for the predictions. The performance of the four methods were compared by means of two different approaches for predictions, and the significance of the results were assessed through the T-test. Finally, we have shown that the performance of the implemented regression methods were outperforming the predictions of the ARIMA method.

Further research might explore whether deep learning methods such as neural networks could improve the accuracy for the predictions of FCR-N prices. Moreover, a natural progression of this work would be to continue exploiting big data to enable the optimal operational strategies for the participation of a VPP into an energy market. In fact, smart meter data could be used to predict the amount of flexibility that a VPP could provide and the consumers sensitivity to different compensations. These solutions could enhance the strategic operations of the aggregator by reducing uncertainties, and thus provide a framework that could enable the VPP to actively participate in the FCR-N market.

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