Short-Term Wind Power Forecasting Based on a New Feature Selection Technology and Support Vector Machine

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Abstract—**This paper proposes a simpler while more accurate wind power output forecasting method. To solve the stochastic problem, a scenario based operation and control system is required by many situations. Therefore, an efficient wind forecasting and simulation technique is mandated. In this paper, a support vector regression method is applied because of its simplex. To not lose the accuracy, wavelet analysis and an information theory based feature selection technology are also added to the algorithm. Finally, a case study on a wind farm is conducted, and the results are compared with some existing models to prove its superiority.**

Index Terms—wind power prediction, forecasting, machine learning, SVM, feature selection, information theory

I. INTRODUCTION

Renewable energy has received extensive interests over the past decade, resulting from increasing concerns about energy security and sustainability. Wind energy generation, in particular, has been growing rapidly around the world and has become one of the most mature renewable generation technologies. The E.U. has set a binding target of 20% of its energy supply coming from wind and other renewable resources by the year 2020 [1]. In the U.S., a scenario of wind energy contributing 20% of the total energy supply by 2030 is envisioned by the Department of Energy [2]. Renewable Portfolio Standard (RPS) mandates (or their equivalents) with renewable-production tax credits have been enacted in many countries and states to accelerate the development of the wind industry [3]. By the end of 2009, the worldwide installed wind capacity reached 159 GW, showing a 31.7 % increase from 2008 [4]. In the U.S., nearly 10 GW of wind capacity came online in 2009, bringing the U.S. total installed wind capacity to over 35 GW [5], yet the wind energy penetration level in 2009 was only around 2% [6].

The greatest problem of wind power integration in the existing power system is the intermittent nature of wind power due to high correlation with stochastic non-stationary wind speed. Wind integration imposes many challenges to system operators such as operational problems (maintaining system frequency, power balance, voltage support, and quality of power), planning and economic problems (including uncertainty in wind power in to unit commitment, economic load scheduling, and spinning reserve calculations), etc. An accurate wind power forecasting tool to mitigate the undesirable effects in the growing wind penetration scenario is very much essential.

The existing wind power forecasting methods can be generally classified into two categories: the physical models and the statistical models.

The physical models try to use physical considerations as much as possible to reach the best possible estimate of the local wind speed. It takes the wind results from NWP (Numeric Weather Forecast) as its inputs. The NWP model results are usually for the geographical point of the wind farm or for a grid of surrounding points. However, it is the wind speed at the turbine position that is needed, thus more procedure is necessary, which is usually called 'downscaling'. The physical model uses a meso-scale or micro-scale model for the downscaling, which transfer these wind speed forecasts to the level of the wind generators. For running the downscaling models, it is necessary to have a detailed description of the terrain surrounding the wind generators. However, collecting the information of terrain conditions is one of the main difficulties in the implementation of physical models. After the downscaling process, the wind speed at each wind generator calculated into wind power, thus giving the prediction.

Physical models are usually complex models, are run on super computers, which limits the usefulness of NWP methods for on-line or very-short-term operation of power system. The performance of physical models is often satisfactory for long (larger than 6 hours ahead) time horizons and they are on the other hand inappropriate for short-term prediction (several minutes to one hour) alone due to difficulty of information acquisition and complicated computation. As with short-term prediction, the physical models are usually not taken into consideration.

Statistical models in their pure form try to find the relationships between a wealth of explanatory variables including NWP results, and online measured power data, usually employing recursive techniques. On one hand, tradition statistical models, usually uses traditional statistical method. For examples, typical time series models are developed based on historical values. Recursive technique is also usually used in this kind of models.

To specify, statistical models can be divided into two groups: the time sequence independent model and the time sequence based model. The former one only uses a wind power distribution function to generate a wind power curve. Stochastic approaches are used to sample every single point

of the wind power curve. The latter one also considers the intensity of wind power variation as a time sensitive element, and such time series related forecasting methods are often employed in these models.

The time sequence independent models were successfully applied in the early 21th century based on a Monte Carlo chronological simulation methodology, a Wei-bull distribution function based stochastic modeling and a multiple correlated wind speed series based modeling, respectively.[7-8] However, several studies discuss the limitation of these time sequence independent models in terms of their accuracy problems.[9-10] To set up a more robust time sequence based model, much research has been conducted into numerical and analytical modeling during the last decade, [11-13]. Among them, the stochastic differential equation with given marginal distribution and autocorrelation function have been adopted by many researchers. However, there are still many limitations for the numerical methods since it is difficult to set up a successful dynamic and stochastic predictor without artificial intelligence learning. Several researchers have tried to introduce some computational intelligence methods in this area, including genetic algorithm methods, Support Vector Machine methods (SVM), Self-organized Map (SOM) methods, kernel method and Neural Network (NN) methods [14-19], respectively. These methods work well in dynamic system simulation, but not for the stochastic dynamic systems.

In this paper, a simulator combining the stochastic differential equation and SVR will be studied. This algorithm is the one of the most popular in the world, for its simple form and high performance in supervised learning problems. Recent results have shown that SVM-based models either compare favorably with [20] or outperform [21] the ANN-based models in WPP. For example, SVM-based models have been found to take less computational time compared to ANN-based models [22]. This gives the possibility to solve stochastic optimization problem by enumerating as many as scenarios.

In addition, to reduce the calculation time without sacrificing the accuracy, it's important to select a compact subset of all the features in statistical learning models. A proper scale of the training set is both necessary for improving the efficiency and avoiding overfitting. An information theory based feature selection technology is employed here.

This paper is organized as follow. Section II illustrates the basic mathematical form of support vector machine and the feature selection technology. In section III the proposed model is constructed and all the information is given in detail. Its performance on a specific case is evaluated and compared with existing models to show its superiority in section IV. Finally, conclusions and further discussions are given in section V.

II. WAVELET SUPPORT VECTOR MACHINE

A. Support Vector Machine

An SVM is a general learning method developed from statistical learning theory with a better performance than many other routine methods. Statistical learning theory is based on a set of harder theory foundations, which provides a united frame in order to solve the problem of limited sample learning. The basic idea of SVM applied to regression prediction is described as follows [23] and [26].

Given the observed sample set:

$$P(x, y), (x_1, y_1), (x_2, y_2)..., (x_n, y_n) \in R^n \times R$$

suppose the regression function is

$$F = \{f \mid f(x) = \omega^T \cdot x + b, \omega \in R\}$$

Introduce the risk function

$$R_{reg} = \frac{1}{2} ||\omega||^2 + C \, R_{emp}[f]$$

where $||\omega||^2$ is the describing function, $f(\cdot)$ is the complexity term, and C is a constant which determines the tradeoff between the empirical risk and the model complexity.

The main idea of nonlinear support vector regression is to map the input vector x into a high-dimensional feature space by using a nonlinear mapping function $\Phi(x)$ and then perform linear regression on the feature space. In this higher space, there is a greater possibility that the data can be linearly separated. Then, the problem can be described as

$$\min \frac{1}{2} ||\omega||^2 + C \sum_{i=1}^{l} \xi_i$$

Subject to

$$y_i(\omega \cdot \phi(x_i) + b) \geq 1 - C \sum_{i=1}^{l} \xi_i$$

$$\xi_i \geq 0; i = 1, ..., l; C > 0$$

The inner products $\varphi(xi)$ in the high-dimensional space can be replaced by some special kernel functions $K(x_i, x_j)$, which can be calculated. All the necessary computations can be performed directly in input space by calculation kernels. The popular kernels are shown as follows:

1) radial basis function (RBF) kernel

$$K(x, x_i) = exp(-\gamma ||x - x_i||^2)$$

2) polynomial kernel

$$K(x, x_i) = (1 + x \cdot x_i)^d$$

where γ and d are parameters. Different learning machines with arbitrary types of decision surfaces can be constructed by using various kinds of kernel functions $K(x_i, x_j)$.

In actual application, the kernel function has an influence on the realized effect. It is important to select a proper kernel function to optimize the kernel-function solution. As mentioned earlier, polynomial kernel function, RBF kernel

functions, and sigmoid functions are the three routine methods for kernel functions [24-25].

B. Feature Selection Technology

Wind power can be seen as a nonlinear mapping function of several exogenous meteorological variables and its past values. Assuming the past and forecast values of the exogenous variables, such as wind speed, wind direction, temperature, and humidity, are available at the wind farm location or a weather station close to the wind farm, a set of candidate forecasting features (inputs), say, can be constructed as follows:

Wind Power: $WP(t-1), ..., WP(t-N_{WP})$

Wind Speed: $WS(t), WS(t-1), ..., WS(t-N_{WS})$

Wind Direction: $WD(t), WD(t-1), ..., WD(t-N_{WD})$

Temperature: $T(t), T(t-1), ..., T(t-N_T)$

Humidity: $H(t), H(t-1), ..., H(t-N_H)$

The candidate inputs WP(t-1)….WP(t- N_{WP}) are the historical values of wind power, since wind power is dependent on its past values. WS(t) is the forecast value of wind speed for time interval 't' and WS(t-1)….WS(t-N_{WS}) are its past values, considering that wind speed is an important driver for wind power. Similarly, the forecast and past values of wind direction, temperature, and humidity are included in the set of candidate features. In the above formula, N_{WP} indicates the order of back shift for the wind power candidate features, which sometimes is referred to as the order of the dynamical forecast system [27]. Similarly, $N_{WS}, N_{WD}, N_T, and N_H$ are defined. From a data mining view point, these orders should be considered high enough so that no useful information is missed. However, a compromise is always necessary to avoid a too large set of candidate features. For instance, even by considering the low orders of $N_{WP} = N_{WS} = N_{WD} = N_T = N_H = 24$ (only including the features of 24 hours ago for hourly wind power forecast), we reach 124 candidate features. Moreover, if the exogenous variables related to the wind farm are measured in more than one place, the candidate inputs of the exogenous variables should be repeated by the number of measurement sites. However, such a large set of inputs is not directly applicable to a forecasting engine, since it may include ineffective features, which complicate the extraction of input/output mapping function of the prediction process for the forecast engine and degrade its performance. Thus, the set of candidate inputs should be refined by a feature selection technique such that a minimum subset of the most informative features is selected and the other unimportant candidates are filtered out.

Correlation analysis has been proposed for the feature selection of wind power forecast in [27] and [28]. However, wind power is a nonlinear mapping function of several input variables, whereas correlation analysis is a linear feature selection technique. Thus, it may not correctly evaluate the information value of the candidate inputs for wind power forecasting. Moreover, correlation analysis only considers the relevancy between the target variable and candidate inputs to rank them. However, in feature selection, it has been recognized that the combinations of individually good features do not necessarily lead to good estimation performance. In other words, "the m best features are not the best m features" [29]. It should also be noted that relevant features in a forecasting process may include redundant information. Redundant features can potentially degrade the learning process of the forecasting engine, besides the associated unnecessary extra computation burden. Hence, an efficient nonlinear feature selection technique, which can evaluate both relevancy and redundancy of the candidate features, is necessary.

Here a new kind of feature selection technology called mRMR (max-relevance, min-redundancy method) is used based on mutual information in information theory. In information theory, the mutual information of two random variables, given their probability distribution function, is defined as follows:

$$I(x; y) = \iint p(x, y) \log \frac{p(x, y)}{p(x)p(y)} dx dy$$

Max-Relevance is to search features satisfying (4), which approximates D(S, c) with the mean value of all mutual information values between individual feature x_i and target variable c:

$$\max D(S, c), \; D = \frac{1}{|S|} \sum_{x_i \in S} I(x_i; c)$$

It is likely that features selected according to Max-Relevance could have rich redundancy, i.e., the dependency among these features could be large. When two features highly depend on each other, the respective class-discriminative power would not change much if one of them were removed. Therefore, the following minimal redundancy (Min-Redundancy) condition can be added to select mutually exclusive features [30]:

$$\min R(s), \; R = \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I(x_i; x_j)$$

The criterion combining the above two constraints is called "minimal-redundancy-maximal-relevance" (mRMR) [30]. We define the operator $\phi(D, R)$ to combine D and R and consider the following simplest form to optimize D and R simultaneously:

$$\max \phi(D, R), \; \phi = D - R$$

In practice, incremental search methods can be used to find the near-optimal features defined by ϕ. Suppose we already have feature set S_{m-1}, the feature set with m-1 features. The task is to select the mth feature from the set$\{X - S_{m-1}\}$.This is done by selecting the feature that maximizes ϕ. The respective incremental algorithm optimizes the following condition:

$$\max_{x_j \in X - S_{m-1}} [I(x_j; c) - \frac{1}{m-1} \sum_{x_i \in S_{m-1}} I(x_j, x_i)]$$

III. PROPOSED MODEL

The proposed wind power forecasting model consists of two stages, the feature selection stage, and the support vector machine stage. The feature selection stage selects the most informative and the least redundant feature set from a various candidate features, and then these features are chosen as inputs of our support vector machine. Then it is used to train the data and test on the test set to evaluate its performance. For that in our feature selection algorithm, we need the joint probability distribution between our features and between our features and the target variable wind power, a simple method to estimate the joint probability distribution of two random variables is introduced here.

A. Feature Selection

Firstly the data is normalized to be within the range of [0, 1].

Feature representation, which aims to extract certain characteristics from the original data, plays a key role in determining the performance of WPP. In the previous section, we have introduced the mRMR methods; here we use the more practical form of incremental searching.

Each step in the incremental searching algorithm, we get a new set of selected features, and we list them below:

$$S_1 \subset S_2 \subset \cdots \subset S_N$$

Here comes the problem, how many features should we really use, that is, which of the feature set we should really use above. The answer to this question should be related to our training sample set. According to statistical learning theory, too many features in a model might cause overfitting problems; however, if the training set is large enough, the overfitting problem can be avoided. The gives light to our feature selection strategy: just go through the N feature set above and see which one has the best performance. This is done by the cross-validation method, which is a powerful tool to estimate the generalization error of a model trained by a specific training set, using the training set itself. Details of cross-validation will be given below. Here we use our sample set to calculate the cross-validation error for each of our feature set. For cross-validation is a good estimation of generalization error, the feature set with the least cross-validation error is chosen as our feature set.

B. Estimation of Probability Distribution Function

The basic definitions of the mutual information technique use logarithms in base 2. So, this fact motivates using binomial distributions for the inputs and output [31]. For this purpose, at first, all the candidate inputs and target variable are linearly normalized in the range of [0, 1]. Then, the median of each normalized variable is computed. Half of the values of the normalized variable are more than its median which are rounded to 1 and the other half are less than it which are rounded to 0. After this process, a binomial distribution is obtained for each candidate:

$$p(x = 1) = \frac{\sum_{i=1}^{n} 1\{x_i = 1\}}{n}$$

where the n is the number of samples.

The joint probability function can also be deduced from this simplified binomial distributions.

C. Support Vector Machine

After we have got our selected feature set, we use training sets consisting of these features to train our model. Among the kernel functions, we choose the RBF kernel function.

In general, it is suggested to use RBF kernel function to realize the non-linear regression. A recent result by Keerthi and Lin shows that if RBF is used with model selection, then there is no need to consider the linear kernel. The kernel matrix using sigmoid may not be positive definite and in general its accuracy is not better than RBF.

By now we have determined all the parameters of the models except for the two: C, which is the penal factor in SVM; and the γ in the kernel function.

To maximize the performance of SVM model, a grid-search algorithm on cross-validation accuracy of SVM models will be conducted.

The cross-validation allows us to evaluate the trained model with specific parameters only by the training data. We divide the training data into two equal half, and then two models with the given parameters will be trained by the two data sets separately and then each of them will be used to predict the other part of the whole training set. The average of two MSE we get will be used as the measurements of this trained model with the parameters. The cross-validation just points out that we cannot measure our model using the data with which the model is trained and data outside the training set should be used. It's a practical algorithm to measure the one model with particular parameters.

The grid search of (C,γ) over cross-validation means that go through a sets of parameters of $C = [2^0 \ 2^1 \ 2^2 \ ... \ 2^9], \gamma = [2^{-1} \ 2^{-0.5} \ ... \ 2^4]$. Each combination of the above C and γ will be used to conduct the cross-validation and the one with the least cross-validation MSE will be adopted to train the model with the whole training set. This method is an easy, practical and generally-used approach to select the parameters to maximize the performance of a model.

IV. MODEL VALIDATION

A. Data Description

In the dataset, the hourly data measured wind power data in one wind farm from 2009/07/01 at 0'o clock to 2010/12/31 at 23'o clock is given. The 48-hour ahead Numerical Weather Prediction data, given every 12 hours, from 2009/07/01 at 0'o clock to 2010/12/31 at 12'0 clock is also available, and the one piece of NWP is consisting of two values: wind speed and wind direction.

Our prediction target is to give 48-hours ahead prediction every 12 hours.

Our data is consisted of 1097 12-hours, In total we have 1097 samples for the 48-hour ahead

B. Prediction Schemes

Since the prediction horizon is larger than the time resolution of the data samples, we develop a separate SVM for each prediction ahead hour. Thus, different prediction schemes can be used, including the fixed-step scheme, recursive scheme.

For a given prediction horizon, the fixed-step scheme predicts the value at the next h^{th} hour by using actual historical data only:

$$\hat{y}_{t+h} = f(x_t, x_{t-1}, \dots)$$

In the recursive scheme, the one-step scheme is applied iteratively times to predict at the next h^{th} step. In each iteration, the predicted values from previous iterations are used as additional historical data to predict at the next step

$$\hat{y}_{t+h} = f(\hat{y}_{t+h-1}, \hat{y}_{t+h-2}, \dots, \hat{y}_{t+1}, x_t, x_{t-1}, \dots)$$

In our model we will use the recursive scheme, for the advantage of the recursive scheme is that it is accurate to predict the next-step value in each iteration.

C. Selected Features

Based on the feature selection method in section III, some of the chosen features are listed below:

Wind Power: $WP(t-1), WP(t-2), \dots, WP(t-12)$

Wind Speed: $WS(t), WS(t-1), \dots, WS(t-11)$

Wind Direction: $WD(t), WD(t-1), \dots, WD(t-11)$

D. Evaluation

The main index to evaluate our model is the RMSE (Root Mean Squared Error) as below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

Where the y_i stands for wind power measurements, and the $\hat{y}_i$ stands for the predicted wind power at the corresponding time interval. The real measurements and predicted values should be normalized into [0, 1] to get a percentage RMSE.

After we training process, we use our model to give prediction on our test sets, we'd like to give the time-domain plot of our predicted wind power and real measurements. However, our prediction horizon is 4 times bigger as the prediction interval, so there are multiple schemes. We can use the first 12 hours of each prediction to give our results. Another choice is that, in industry, it's often useful that we give the24-hour prediction of the next day at 12:00 clock this day. So we can use the 13 to 36 hour ahead prediction at 12:00 each day to construct a time domain plot. Here we give both the results:
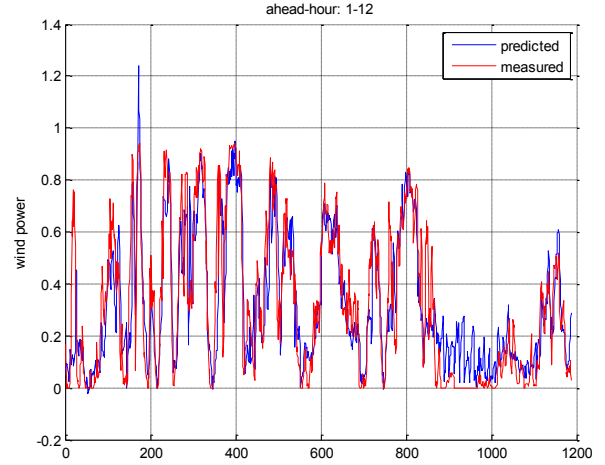

Time domain plot using 1-12th hour prediction
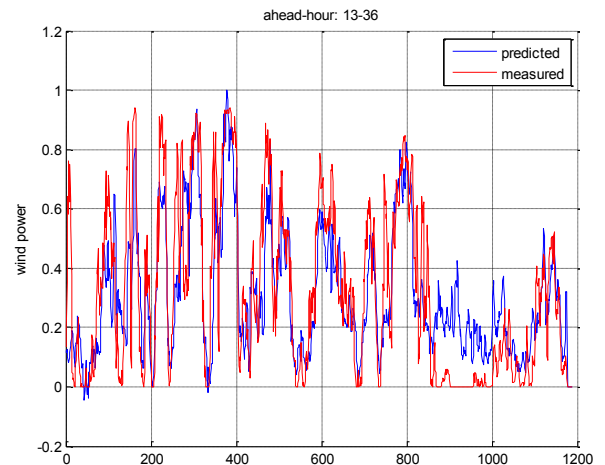
Time domain plot using 13-36th hour prediction

From the above plot we can see that the blue line basically catches up the red line, and no evident can be found. Note that between hour 850-1000, the red line is zero however the blue line is around 0.2. After examining the wind-speed data of this period, we can judge that during this period the wind farm is shut down manually, due to unknown reasons. Later, the error computation will ignore this period.

It's also useful to examine the relationship between the RMSE and the ahead hour. Generally speaking, the higher the ahead hour is, the higher the error is. In the following plot, the relationship between the ahead hour and the error is shown, besides, in order to show that the feature selection technology actually works in our proposed model, persistence model and SVM without feature selection is also shown as a benchmark.

Accuracy(MSE) versus Ahead-Hour
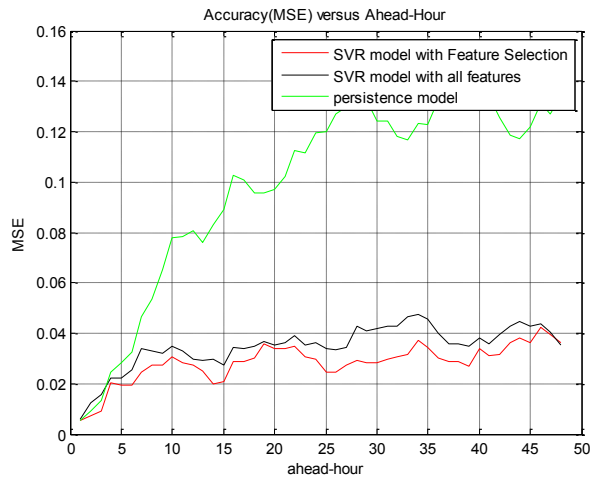
From the above figure we can see our proposed model has the highest accuracy compared with the persistence model and the SVM without feature selection. It also proves that our proposed feature selection algorithm is effective to improve the model accuracy.

The results are listed below:

Algorithm	1-12h	13-36h	overall
SVM+mRMR	14.33%	17.18%	16.86%
SVM+all features	15.81%	19.38%	18.66%
Persistence	20.73%	33.47%	31.52%

From the above table we can see that the with the mRMR feature selection technology, the RMSE of the SVM decreases by round 2%, and is only half of the RMSE of persistence model.

V. CONCLUSION AND DISCUSSION

Wind power forecasting is the one of the most challenging problem in the world, due to the stochastic and uncertain nature of wind speed. Recent years lots of statistical learning algorithms has been introduced into this problem to try to predict the wind power, including ANNs, SVM. However, seldom have people dealt with feature selection problems. The selection of feature has a great impact on the efficacy of the model. Actually the model itself is only a statistical one, and it does not contain any information of the physical characteristics of our predicted object; however, physical information lies in the feature we select, thus feature selection is the door to connect the physical world to the statistical models. To some extend it's the key of our prediction problem.

In this paper, an information theory based feature selection algorithm is proposed, using the mutual information to select the most relevant and the least redundant features. Existing feature selection technology are linear ones like covariance analysis, PCA, however the relation between the inputs and outputs in wind power prediction problem is not linear, so these existing technologies are not good enough. The proposed feature selection technology, however, solves the problem, and its powerful to select features that is non-linearly connected with the outputs. Then this technology then combined with the powerful support vector machine.

Results show that this feature selection technology is a powerful one that effectively selected useful features. Comparisons have been made to existing models to show the superiority of this model.

However, the mutual information method relies on the estimation of joint distribution of variables; this is usually hard given limited sizes of sample sets. In this paper only a simple version based on binomial distribution is used, further studies might focus on a better estimation of joint-distribution of variables.

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The Impact of Trading Wind Power in Both Energy and Regulation Reserve Market on System Operation

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Abstract—With the significant growth of the installed capacity of wind power, the variability of wind energy production puts greater stress on the power system operation. In this situation, more rapid regulation reserve is required, which escalates the scarcity of balancing service. A combined energy and regulation reserve market model is proposed in previous work by introducing wind energy into reserve market, but the previous work mainly concentrates on the bidding strategy and its relative revenue on the side on wind producer. This paper focuses on evaluating the new bidding strategy on the side of system operation by simulating a day-ahead unit commitment problem, and it is derived that in this new market mechanism, more secure system operation can be achieved with lower dispatch cost, through comparing the scheduling results under different bidding strategies.

Nomenclature

k	Index for unit.
N	Number of non-wind units.
Nw	Number of wind power units.
$P_k(t)$	Amount of electricity generated by generator k in time period t.
$P_{w,k}(t)$	Actual output of wind power unit k at time t.
$Z_k(t)$	Binary variable to indicate if generator k is on in time period t.
$UR_k(t)$	Amount of up regulation reserve capacity provided by generator k in time period t.
$DR_k(t)$	Amount of down regulation reserve capacity provided by generator k in time period t.
C_{onk}	Start-up cost for generator k if it is turned on.
C_{offk}	Shut-down cost for generator k if it is turned on.
C_{ak}	Half of start-up cost plus shut down cost.
C_{bk}	Half of start-up cost minus shut down cost.
$D(t)$	Forecasted system demand at time t.
$UR_{req}(t)$	System up regulation reserve requirement at time t.
$DR_{req}(t)$	System down regulation reserve requirement at time t.
UR_{rampk}	Ramp-up rate limit of unit k.
DR_{rampk}	Ramp-down rate limit of unit k.

$P^f_{w,k}(t)$	Forecasted generation of wind power unit k at time t.
$P^b_{w,k}(t)$	Bidding generation of wind power unit k at time t.
$P^s_{w,k}(t)$	Generation of wind power unit k at time t in scenario s.
$P^c_{w,k}(t)$	Committed output of wind unit k at time t.
P_{min}	Lower limit of real power generation.
P_{max}	Upper limit of real power generation.
UR_{kmax}	Up regulation reserve limit of unit k.
DR_{kmax}	Down regulation reserve limit of unit k.
a, b, c	Quadratic energy cost coefficients.
b_{ur}, c_{ur}	Quadratic up reserve cost coefficients.
b_{dr}, c_{dr}	Quadratic down reserve cost coefficients.
π_{UR+}	The price for over-provision of UR reserve.
π_{E+}	The price for over-generation.
π_{UR-}	The price for under-provision of UR reserve.
π_{E-}	The price for under-generation.
π_{UR}	Market price for up regulation reserve.
π_E	LMP.
T_{UR}	Penalty from imbalance UR output.
R	Revenue from the combined market.
R_E	Revenue from the energy market.
R_{UR}	Revenue from the up regulation reserve market.

I. Introduction

Wind generation is one of the fastest growing sources of energy in the world. Several regions have already set targets for the level of wind energy penetration into power grids. The target set by the U.S. Department of Energy is 20% by 2030 [1]. The European Union's target is 14%-17% by 2020 and 26%-34% by 2030 [2]. However, due to the stochastic nature of wind, even if the state-of-the-art wind forecasting methods are utilized, the average day-ahead wind production forecast errors are still around 25%-30% for a single wind plant and 15-18% for a control region [3]. As a result, some of the power systems with large wind penetration increase a considerable amount of additional spinning reserve to cover the potentially large deviations from the day-ahead wind power forecast [4]. Many works on establishing stochastic unit commitment(UC) problems are conducted to reduce the reserve requirement and

the dispatch cost without violating the system security and reliability requirement [5]–[7]. At the same time, there are some other systems which normally use conservative wind forecasts, 80% exceedance forecasts for example, in the day-ahead scheduling process to ensure enough capacity online. In regulated market, this method is equivalent to curtailing wind power generation so as to minimize the impact of wind uncertainty, such as the market in China. This results in under-utilization of wind power. However, in deregulated market, due to the much lower cost of the wind power and lack of over-provision penalty during real-time operation, the actual wind commitment will exceed the bided energy most of time. Therefore, a significant amount of down reserve (DR) will be needed for energy balancing. On the side of wind plants, Frequent wind curtailments will reduce their revenue as well, since no compensation is paid for curtailments in most electricity markets [8]. Thus neither side obtains a benefit from the present mechanism.

The new mechanism allows wind plants to participate in both the energy and reserve markets, and incentives wind plants to reduce their short-term production variations through a proper deviation-penalty design. It has been shown in [9] that with the proposed market mechanism, 1) compared to the existing market operation, wind plants can increase their revenues by optimally bidding into the energy and reserve markets; 2) real-time wind productions are closer to their day-ahead commitments; and 3) additional fast, although variable, reserve from wind can be used towards grid frequency regulation, benefiting grid security. However, it has only analysed the benefits of this model on wind producers side [9]. Still, there are not any system operation analysis model, and its relative potential impacts on the grid side have never been discussed. This paper focuses on analysing the new incentive mechanism based on the combined market [9], to encourage wind producers to regulate their wind generation bids. Persistent price forecasts are used in this paper, and different market schemes are compared. Impacts of different wind penetration levels on the balancing reserve requirements and electricity prices will be evaluated. This paper is organized in the following way. In Section III, an introduction of this combined market mechanism is presented, and the optimal bidding outputs are also calculated to be used in system operation. In Section IV, system unit commitment is formulated as a mixed integer quadric programming problem, and a single bus case study is presented. Section V gives the analysis of operation results and summarizes the paper.

II. Introduction of Combined Market and Wind Bidding Strategy

This section discusses the wind plant's optimal bidding scheme given price signals and probabilistic forecasts proposed in [9]. It assumes that in the following discussions, the market prices are estimated based on the electricity and reserve price of the former day. It is reasonable that bids from any individual wind plant do not affect the market prices

because the clearing price in settlement is decided by the most expensive accepted offer.

A. Energy Market

With sufficient transmission capacity, the revenue of a wind producer for a certain settling interval is related to its committed output and the actual production, as in

$$R_E = \pi_E P_{w,k}^c + T_E \tag{1}$$

T_E is given by

$$T_E = \begin{cases} \pi_{E+}(P_{w,k} - P_{w,k}^c), & P_{w,k} \geq P_{w,k}^c \\ \pi_{E-}(P_{w,k} - P_{w,k}^c), & P_{w,k} \leq P_{w,k}^c \end{cases} \tag{2}$$

In general, $0 \leq \pi_{E+} \leq \pi_E \leq \pi_{E-}$. It is because the wind plant revenue monotonically increases as the wind plant output power increases. In deregulated market, ISOs cannot affect the short-term wind plant output power. All of the wind power variations must then be absorbed by regulation reserve from other controllable resources.

B. Ancillary Market

It is assumed that deviation penalties also exist in the reserve markets and separate products are available for up and down regulation reserve. Since a wind plant can provide down regulation reserve (up to its minimum output power) at virtually no cost, the price for down regulation reserve is expected to be low with the participation of wind plants. On the other hand, it depends on the availability of wind for a wind plant to provide up regulation (UR) reserve, therefore, the price for UR reserve is expected to be high. In the following discussions, the price for down regulation reserve service is assumed to be negligible and only the revenue from providing UR reserve is considered. The revenue of a wind plant from the reserve markets is given by

$$R_{UR} = \pi_{UR} UR_{w,k}^c + T_{UR} \tag{3}$$

T_{UR} is given by

$$T_{UR} = \begin{cases} \pi_{UR+}(UR_{w,k} - UR_{w,k}^c), & UR_{w,k} \geq UR_{w,k}^c \\ \pi_{UR-}(UR_{w,k} - UR_{w,k}^c), & UR_{w,k} \leq UR_{w,k}^c \end{cases} \tag{4}$$

Similar to the energy market, it is expected that the following price relationship holds

$$Price\ Assumption\ I : 0 \leq \pi_{UR+} \leq \pi_{UR} \leq \pi_{UR-} \tag{5}$$

C. Combined Energy and Regulation Reserve Markets

In general, π_E and π_{UR}, are determined by the simultaneous co-optimization of the energy and reserve markets. Since there is a fuel cost associated with producing energy, the reserve is only an opportunity cost without any actual cost. Thus it is expected the following relationship for imbalanced prices holds

$$Price\ Assumption\ II : \pi_{UR+} \leq \pi_{E+} \leq \pi_{UR-} \leq \pi_{E-} \tag{6}$$

In most of markets, the price for over-generation is zero, *i.e.*, $\pi_{E+} = 0$, after the generation exceeds a certain dead band.

$$R = \begin{cases} \pi_{E+}P_{w,k} + (\pi_E - \pi_{E+})P^c_{w,k} + (\pi_{UR} - \pi_{E+})UR^c_{w,k} & P_{w,k} \in [P^c_{w,k} + UR^c_{w,k}, P_{w,kmax}] \\ \pi_{UR-}P_{w,k} + (\pi_{UR-} - \pi_E)P^c_{w,k} + (\pi_{UR-} - \pi_{UR})UR^c_{w,k} & P_{w,k} \in [P^c_{w,k}, P^c_{w,k} + UR^c_{w,k}] \\ \pi_{E-}P_{w,k} + (\pi_{E-} - \pi_E)P^c_{w,k} + (\pi_{UR-} - \pi_{UR})UR^c_{w,k} & P_{w,k} \in [0, P^c_{w,k}] \end{cases} \quad (7)$$
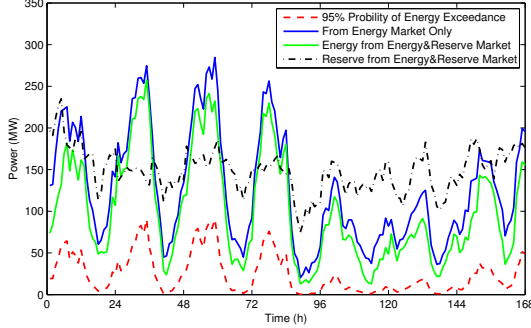

Fig. 1. Bidding curves based on different bidding strategies.

Thus, the assumption of $\pi_{E+} \leq \pi_{UR-}$ in (6) holds under most circumstances. The revenue of a wind plant from the energy and reserve markets is then given by the equation (7) at the top of this page.

This strategy can be explained based on (5). When $P_{w,k}$ is less than $P^c_{w,k} + UR^c_{w,k}$, the wind plant will try to fulfill its committed output power first, because it results in a higher marginal revenue of π_{E-}. After the wind plant fulfills its committed output power, it will then provide UR reserve for a marginal revenue of π_{UR-}. When the total available wind power is more than $P^c_{w,k} + UR^c_{w,k}$, the wind plant will output all of its excessive power, unless being called to curtail, since additional energy now yields a higher marginal revenue ($\pi_{UR+} \leq \pi_{E+}$).

D. Wind Plant Committed Output with Different Market Schemes

As is mentioned in Section II, three bidding schemes will be discussed in this paper, *e.g.* S1 - conservative wind forecasts in the energy market; S2 - optimal bids in the energy market; S3 - optimal bids in the proposed combined energy and reserve market. This part will specify the committed output of wind plants based on these three bidding strategies.

No matter which bidding scheme is taken into application, a probability analysis is required. Since this paper emphasizes the methodology to obtain an optimal bidding strategy, the selection of wind probability distribution can be relatively flexible. An alpha-beta distribution based wind probabilistic forecast is introduced in [10].

For conservative bidding strategy, a 95% exceedance forecast is used in this paper, as is shown in Fig.1. It also shows an example of the wind plant commitment curves from the other two bidding strategies. In one strategy, the wind producer participates only in the energy market, where the optimal committed output power $P^c_{w,k}$, depends on the market prices and wind probabilistic forecast [10]. In the other one, the wind

producer participates in both markets. On the basis of the analysis in [9], the best bidding strategy is solved by:

$$\max E[R(P^c_{w,k}, UR^c_{w,k})] \quad (8)$$

s.t.

$$P_{w,kmax} - P^c_{w,k} - UR^c_{w,k} \geq 0 \quad (9)$$
$$P^c_{w,k} \geq 0, UR^c_{w,k} \geq 0 \quad (10)$$

To explain the results, first define

$$A = \frac{\pi_E - \pi_{UR}}{\pi_{E-} - \pi_{UR-}}, B = \frac{\pi_{UR} - \pi_{E+}}{\pi_{UR-} - \pi_{E+}} \quad (11)$$

Note that according to (4), it can be derived that $B \leq 1$. The optimal bidding scheme depends on the values of A and B, which is summarized in the following cases.

1) Case 1: $0 < A < B$: It is optimal to bid in both energy and reserve markets, and the optimal strategy is

$$P^{c*}_{w,k} = F^{-1}(A), UR^{c*}_{w,k} = F^{-1}(B) - P^{c*}_{w,k} \quad (12)$$

where $F^{-1}(1) = P_{w,kmax}$.

2) Case 2: $A > 0$ and $A \geq B$: In this case, it is optimal to bid only in the energy market, and the optimal strategy is

$$P^{c*}_{w,k} = F^{-1}\left(\frac{\pi_E - \pi_{E+}}{\pi_{E-} - \pi_{E+}}\right), UR^{c*}_{w,k} = 0 \quad (13)$$

Note that since $\pi_{E+} \leq \pi_E \leq \pi_{E-}$ and $0 \leq (\pi_E - \pi_{E+})/(\pi_{E-} - \pi_{E+}) \leq 1$, (13) is valid. The optimal solution in this case is the same as [10], where only the energy market is considered.

3) Case 3: $A \leq 0$, i.e., $\pi_E \leq \pi_{UR}$: In this case, it is optimal to bid only in the reserve market, and the optimal strategy is

$$P^{c*}_{w,k} = 0, UR^{c*}_{w,k} = F^{-1}(B) \quad (14)$$

Note that the condition for this case implies $\pi_{E+} \leq \pi_{UR}$. Thus, $B \geq 0$ in this case and $F^{-1}(B)$ is valid. Note that the reserve bided in the first day is not as much as other days. This is because the predicted energy price and reserve price used in the first day comes from actual database without trading any wind power in reserve market, and relative low level wind penetration. Thus, the reserve price is still not high enough to encourage wind producers to participate in the reserve market. In this paper, all the discussions start from the second day.

III. SYSTEM OPERATION FORMULATION AND CASE STUDY

In current system operation center, day-ahead schedule (UC) and real-time balancing (Optimal Power Flow) are considered separately. In day-ahead schedule, ISOs schedule the startup and shutdown state and the power output of each generator for each time interval in order to minimize the overall cost
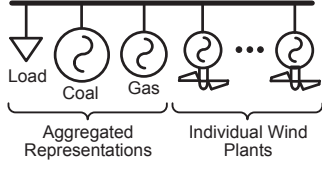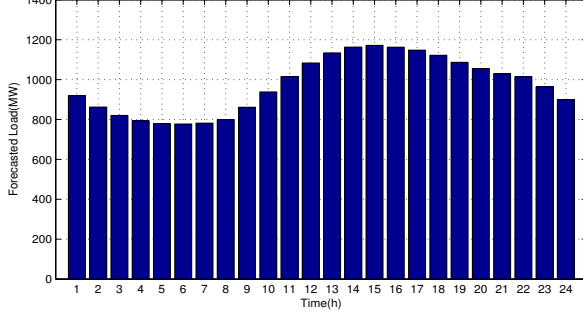
Fig. 2.   Simulation system

Fig. 3.   Hourly load forecast curve (Data selected from ERCOT market and scaled).

Fig. 4.   Hourly forecast wind generation curve and actual wind generation curve (Data selected from NREL EWITS database).

$$\min \sum_{t=1}^{24} \sum_{k=1}^{N} [a_k Z_k(t) + b_k P_k(t) + c_k P_k^2(t)]$$
$$+ C_{ak}[Z_k(t) - Z_k(t-1)]^2 + C_{bk}[Z_k - Z_{k-1}] \quad (15)$$
$$+ b_{UR,k} UR_k(t) + c_{UR,k} UR_k^2(t)$$
$$+ b_{DR,k} DR_k(t) + c_{DR,k}^2(t)$$

s.t.

$$P_k(t) + UR_k(t) - P_{max,k} Z_k(t) \leq 0 \quad (16)$$

$$P_k(t) - DR_k(t) - P_{min,k} Z_k(t) \geq 0 \quad (17)$$

$$\sum_{k=1}^{N} P_k(t) = D(t) - P_{cw,k}^c(t) \quad (18)$$

$$\sum_{k=1}^{N} UR_k(t) = UR_{req}(t) - UR_{w,k}^c \quad (19)$$

$$\sum_{k=1}^{N} DR_k(t) = DR_{req}(t) \quad (20)$$

$$DR_k(t) \leq DR_{kmax} \quad (21)$$

$$UR_k(t) \leq UR_{kmax} \quad (22)$$

$$P_k(t) - P_k(t-1) - [1 - Z_k(t-1)]$$
$$\times P_{kmin} \leq UR_{rampk} \quad (23)$$

$$P_k(t-1) - P_k(t) - [1 - Z_k(t)]$$
$$\times P_{kmin} \leq DR_{rampk} \quad (24)$$

$$0 \leq Z_k(t) \leq 1 \quad (25)$$

$$Z_k(t) \in \mathbb{Z}, P_k(t) \in \mathbb{R} \quad (26)$$

$$\forall k = 1, 2, ..., N, \ \forall t = 1, 2, ..., 24 \quad (27)$$

over the next 24 hours. In real time schedule, ISOs re-adjust each generator's output to balance demand and generation. This study only focuses on day-ahead UC problem.

The UC with wind generation could be formulated as an optimization problem (15)-(25). The objective is to schedule the non-wind unit state and generation, up frequency regulation and down frequency regulation reserve at time $t(t = 1, 2, ..., T)$, so that the total dispatch cost including energy, reserve, startup, and shutdown cost over time horizon $T(T = 24)$ is minimized. Equation(15) is the objective function used in this model. Equation (16) and (17) are the generation limits. Equation (18) is power balance equations. Since wind generators are non-dispatchable units, it is reasonable to assume wind committed outputs are negative loads. The same as wind committed up frequency reserve balance equation shown in (19). $UR_{req}(t)$ is calculated from the system reliability analysis and empirically set as 10% of the peak of loads demand. Equation (20) is the down frequency reserve balance equation. Regulation limits for non-wind units are defined in (21) and (22). Equation (23) and (24) denote generator ramp rate limits; this constraint holds if and only if both $U_{Gi,t}$ and $U_{Gi,t-1}$ are equal to 1. A mixed integer quadric programming solver is implemented to obtain optimal UC. In order to study the combined energy and reserve market model, a single bus system with aggregated coal (1000MW) and gas (500MW) plants, and 10 individual wind plants are selected from the NREL EWITS database, as is shown in Fig.2. The total wind power over a typical summer week is shown in Fig.3 Balancing reserves from the aggregated coal and gas plants are scheduled by solving (15)-(25).
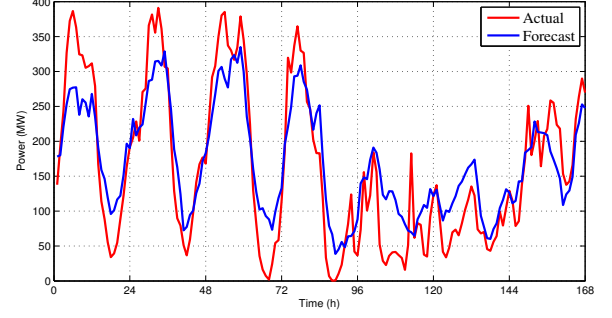
Data for non-wind generators can be found in Table I. The non-wind generator energy bidding data is shown in Table II. The ancillary service bidding data for non-wind generators can be found in Table III. The hourly load forecast curve is shown in Fig.3, while the total wind power over a typical summer week is shown in Fig.4. The committed wind outputs based on different market bidding scenarios are shown in Fig.1 in Section III. The forecast price curve of energy and reserve used by wind producers is shown in Fig.5.
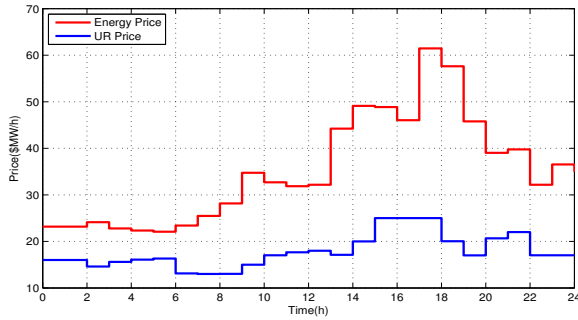
Fig. 5. Day-ahead market prices for energy and up regulation reserve used in the case study (Data selected from the ERCOT nodal market).

TABLE I
GENERATOR DATA

Gen. Unit	P_{min} (MW)	P_{max} (MW)	Ramp Up (MW/h)	Ramp Down (MW/h)	Initial State at time 0
G1	100	1000	200	50	OFF
G2	20	500	200	20	OFF

IV. RESULTS AND DISCUSSIONS

A. Conservative Wind Forecasts in the Energy Market

In conservative wind forecast market, the reserve requirement is 10% of total demands. Additional up reserve for wind power energy is unnecessary because the uncertainty is cramped by the low committed wind energy. Therefore, non-wind generation will be scheduled the most amount of energy among these three kinds of scenarios. The dispatch cost will increase and low efficiency is one of the challenges in conservative wind forecasts based market. In addition, wind curtailment cannot be avoided due to lack of down regulation reserve, shown in Fig.6. In Fig.6, the red line denotes the variation of wind outputs and up/down regulation reserve represented by blue slash line. It is apparent that down regulation is not enough in this situation and wind curtailment will be mandated to execute.

Fig.7(b) shows the day-head non-wind price. This conservative bidding strategy does not affect the reserve and energy price a lot.

TABLE II
GENERATOR ENERGY BIDDING DATA

Unit	Fuel Consumption Function			Start Up Cost ($)	Shut down Cost ($)
	a (MBtu)	b (MBtu/MWh)	c (MBtu/MWh^2)		
G1	650	15	0.017	3500	1
G2	650	50	0.008	3500	1

TABLE III
GENERATOR ANCILLARY SERVICE BIDDING DATA

Unit	b_{ur} (MBtu/MWh)	c_{ur} (MBtu/MWh^2)	b_{dr} (MBtu/MWh)	c_{dr} (MBtu/MWh^2)
G1	13	0.02	10	0.02
G2	35	0.05	12	0.02

TABLE IV
VARIATION PENALTY COEFFICIENTS FOR WIND UNITS

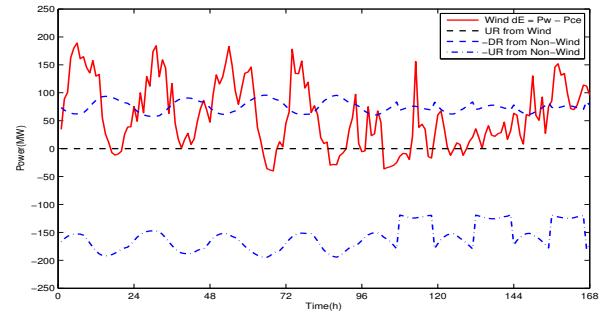| Penalty	π_{E+}	π_{E-}	π_{UR+}	π_{UR-}
Value	$0.1\pi_E$	$2.6\pi_E$	$0.7\pi_E$	$1.2\pi_E$

Fig. 6. Aggregated wind deviations and balancing reserve requirements under conservative forecast scenario.

B. Optimal Bids in the Energy Market

In optimal energy bids scenario, additional up reserve for wind power energy is required to manage the uncertainty. Therefore the reserve requirement is 10% of total demands plus 10% of the wind power capacity, shown in Fig.8. Different from conservative forecast scenario, the derivation of wind power is pulled down paralleled due to no mandated probability limitation applied before wind power bidding. This raises the wind utilization rate, whereas it increases the up reserve requirement especially with a higher wind penetration.

Due to the requirement of up reserve increases, the reserve price also goes up shown in Fig.9(b).

C. Optimal Bids in the Proposed Combined Energy and Reserve Market

In this combined market scenario, additional up reserve for wind power energy is also needed to manage the uncertainty. However, it can be filled by wind power reserve in most of time with a proper penalty selection. The up reserve requirement is 10% of total demands plus 10% of the wind power capacity. From Fig.9(b), the balancing UR requirement is about the same as S1, but the wind production variations are reduced. Part of the wind variations are now presented to the grid as variable UR. As a result, the level of balancing DR can
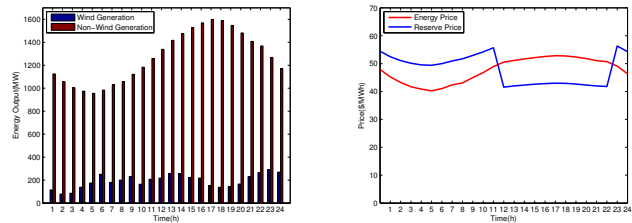
(a) Scheduling results.

(b) Real time price.

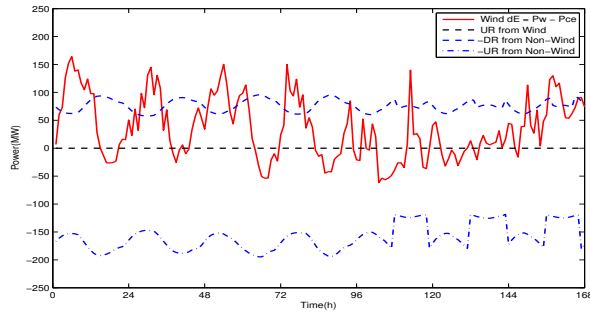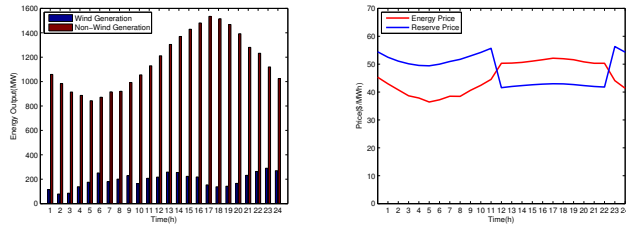Fig. 7. S1 - Under conservative forecast scenario.

Fig. 8. Aggregated wind deviations and balancing reserve requirements under optimal energy bid scenario.

(a) Scheduling results.

(b) Real time price.

Fig. 9. S2 - Under optimal energy bid scenario.

(a) Scheduling results.

(b) Real time price.

Fig. 11. S3 - Under optimal energy and reserve bid scenario.

reducing the need for additional reserve. Besides, the result indicates that this new mechanism requires less short-term reserve, reduces expected dispatch costs and increases the system security. Since this is a completely new area, lots of problems need to be explained, such as follows: 1) real-time analysis of this mechanism: the real time electricity price does affect the bidding strategy and energy balance; 2) the optimal penalty selection strategy: only limited analysis is given in this paper and a more comprehensive analysis should be discussed; 3) the impact of different penetrations on the system operation. More works need to be continued in the later paper.

be reduced. The scheduling results is shown in Fig.10. This bidding strategy accomplishes the objective that reduces wind power committed generation without losing the benefits of both wind producers and grids. The dispatch cost is the lowest one, and the up reserve provided by non-wind unit does not increase, therefore consolidating the efficiency. From Fig.11, the reserve price actually goes down because of the participation of wind power in reserve market. Undoubtedly, the price cannot fall down too low to incentive wind producers bid in reserve market.

V. CONCLUSION AND FUTURE WORK

It is apparent that all of the wind variations are directly exposed to the grid in both S1 and S2, while in S3, part of the wind power variation is diverted into the system reserve,
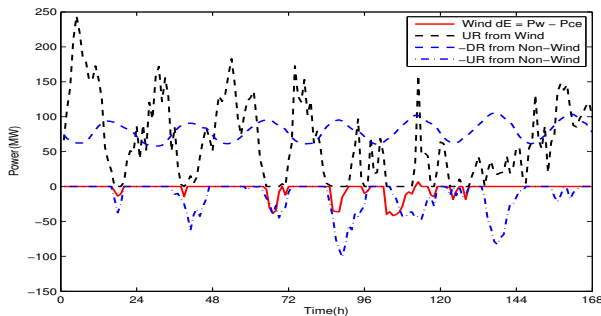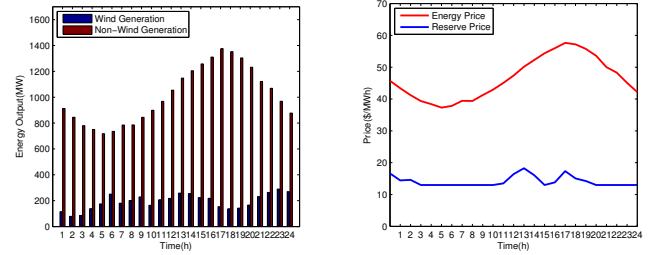
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Fig. 10. Aggregated wind deviations and balancing reserve requirements under optimal energy and reserve bid scenario.

Chance Constrained Unit Commitment With Wind Generation and Superconducting Magnetic Energy Storages

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Abstract—**System operation reserve requirement keeps going up in the past 3 years to compensate for the variation of wind power. This reduces the efficiency of thermal units by limiting their energy output. Superconducting magnetic energy storage (SMES) as a novel technology was proposed to provide up and down regulation reserve due to its fast response to charge and discharge. However, given the cost and utilization ratio of SMES, an optimal unit commitment (UC) with the integration of SMES is necessary. This paper modifies the traditional UC model into a chance-constrained stochastic problem to realize the optimal schedule objective. To solve this non-convex problem, a Branch/Bound (BB) Technique and Particle Swarm Optimization (PSO) algorithm is introduced, while the initialization of PSO is achieved by the simplex algorithms. Finally, a comparison between the deterministic UC and stochastic UC is given. The result indicates that the model in this paper offers independent system operators (ISO) more freedom to balance the system dispatch cost and reliability and it can successfully reduce the SMES costs.**

Index Terms—**SMES, wind power, regulation reserve, unit commitment, chance constraint, branch and bound, PSO.**

I. INTRODUCTION

T he installation of wind power plants has rapidly increased in many countries. Due to its uncertain and uncontrollable nature, wind power raises many difficulties for reliable operation. In order to maintain the reliability of a power system, one traditional way is to increase regulation and operating reserves dramatically against wind power fluctuations, and the other way is to curtail wind power entirely during peak hours.

Superconducting Magnetic Energy Storage (SMES) systems is a good way to reduce the high regulation and operating reserves, for its fast response to charge and discharge. Moreover, recent research shows that SMES can bring more benefit than cost in small scale power systems [1]. Previous papers discussed the feasibility for coordinating SMES with thermal units in an Economic Dispatch problem, which is a static model without considering a time horizon [2]. The dynamic and stochastic unit commitment problem was

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introduced in [3] for evaluating the penetration of large amounts of intermittent wind power, however, this model ignores the generation unit status. Probabilistic-based Security Constraint Unit Commitment problem was introduced in [4], but it requires scenario simulation and thus consumes a large amount of time. In [5], the probability distribution of wind was assumed to be a combination of Gaussian distribution and Laplace distribution, and Monte-Carlo simulation is applied to solve the chance-constrained problem, but it is still a scenario based method. In this paper, instead of the scenario-based stochastic method, chance constraints are introduced to determine both energy and ancillary service schedules. This will greatly reduce the computing complexity, and offers independent system operators (ISOs) more freedom to balance the system dispatch cost and reliability.

Generally, the common methods to solve a UC problem can be divided into two categories, e.g. numerical optimization techniques and evolutionary programming techniques. The former contains dynamic programming, Lagrangian-relaxation methods, branch and bound methods, and mixed-integer programming [6-11]; the latter includes genetic algorithms, particle swarm optimization, simulated annealing, etc.[12-14].To get a numerical solution, a convex prerequisite is mandated however it obviously cannot be satisfied for a chance constrained UC problem. In [18], a general Mixed Integer Linear Programming algorithm is introduced and is generally applied in many situations. However it is impossible to solve a chance-constraint problem with multiple probability distribution spaces, which is a non-convex model. In this paper, a combined method which processes the advantages of both numerical optimization techniques and evolutionary programming techniques is introduced. It is referred to as a branch/bound particle swarm optimization algorithm. To get a heuristic solution, a proper and feasible initialization and evolution strategy is required to improve convergence efficiency of algorithms. The branch and bound techniques provide a way to update the binary variables, and the particle swarm optimization solves the nonlinear problem in each step of the iteration. The initialization problem of PSO is solved by using basic initial variables which are frequently used in the simplex method.

The paper is organized as follow: In section II the unit commitment problem with wind generation is formulated. In section III, the integration of branch/bound technique and PSO is discussed in detail. In section IV, three cases are studied and come to the conclusions that a chance constrained UC model

with SMES could compensate for the variability of wind power while reducing the dispatch cost.

II. PROBLEM FORMULATION

Present practice is to consider day-ahead schedule (Unit Commitment) and real-time balancing (Optimal Power Flow) separately. This paper only focuses on the day-ahead UC problem and assumes that storage devices could provide a frequency regulation service. Compared with conventional high ramp reserves such as hydro, the response time of SMES are negligibly small.

The unit commitment with wind generation and SMES could be formulated as an optimization problem (1)-(16). The objective is to schedule the thermal unit generation ($P_{Gi,t}$), spinning reserve ($R_{Gi,t}^{spin}$), up-frequency regulation ($R_{Gi,t}^{UR}$) and down-frequency regulation reserve ($R_{Gi,t}^{DR}$) with SMES up and down regulation reserve ($R_{SMES,i,t}^{UR}$, $R_{SMES,i,t}^{DR}$) at time t (t=1,2…T), so that the total energy, reserve, startup, and shutdown cost over time horizon T (usually one day, T=24) is minimized subject to generation and storage constraints:

$$\min \sum_{t=1}^{T} \begin{Bmatrix} \sum_{i=1}^{N_G} U_{Gi,t}[C_{Gi}^E(P_{Gi,t}) + C_{Gi}^{Spin}(R_{Gi,t}^{Spin}) + C_{Gi}^{UR}(R_{Gi,t}^{UR}) + C_{Gi}^{DR}(R_{Gi,t}^{DR})] \\ +[(1-U_{Gi,t-1})U_{Gi,t}C_{Gi}^{ST}(P_{Gi,t}) + U_{Gi,t-1}(1-U_{Gi,t})C_{Gi}^{SD}(P_{Gi,t})] \\ +\sum_{i=1}^{N_M} U_{SMESi,t}[C_{SMESi}^{UR}(R_{SMESi,t}^{UR}) + C_{SMESi}^{DR}(R_{SMESi,t}^{DR})] \end{Bmatrix} \quad (1)$$

where at time t, $R_{Gi,t}^{spin}, R_{Gi,t}^{UR}, R_{Gi,t}^{DR}, P_{Gi,t}$ denote the committed output, spinning reserve, up regulation and down regulation of ith thermal unit respectively, $R_{SMES,i,t}^{UR}$ and $R_{SMES,i,t}^{DR}$ are up and down regulation of the ith SMES. $U_{Gi,t}$ and $U_{SMES,i,t}$ are binary variables; they have a value of 1 if the ith thermal unit or SMES is committed to provide energy/reserve at time t, and 0 otherwise. N_G and N_M are the number of thermal units and SMESs respectively. Here the cost for wind generation is ignored. The cost for energy is assumed to be quadratic:

$$C_{Gi}^E(P_{Gi,t}) = a_i P_{Gi,t}^2 + b_i P_{Gi,t} + c_i \quad (2)$$

while the cost for reserves are assumed linear:

$$C_{Gi}^{Spin}(P_{Gi,t}) = C_{Gi}^{Spin} P_{Gi,t} \quad (3)$$

$$C_{Gi}^{UR}(P_{Gi,t}) = C_{Gi}^{UR} P_{Gi,t} \quad (4)$$

$$C_{Gi}^{DR}(P_{Gi,t}) = C_{Gi}^{DR} P_{Gi,t} \quad (5)$$

$$C_{SMESi}^{UR}(R_{SMESi,t}) = C_{SMESi}^{UR} R_{SMESi,t} \quad (6)$$

$$C_{SMESi}^{DR}(R_{SMESi,t}) = C_{SMESi}^{DR} R_{SMESi,t} \quad (7)$$

The costs for start-up and shut-down are assumed constant:

$$C_{Gi}^{ST}(P_{Gi,t}) = C_{Gi}^{ST} \quad (8)$$

$$C_{Gi}^{SD}(P_{Gi,t}) = C_{Gi}^{SD} \quad (9)$$

In general all the costs would be convex, hence the objective function given $U_{Gi,t}$ and $U_{SMES,i,t}$ is convex.

A. Constraints Used in Traditional Wind UC Problem

a) Power balance equations:

$$\sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t} + P_{Wind,t}^f = P_{Load,t} \quad (10)$$

where $P_{Load,t}$ is the forecasted demand at time t, and $P_{wind,t}^f$ is the forecasted wind output at time t. Since single bus is considered, it is reasonable to assume there is only one wind farm.

b) Generation limits

$$P_{Gi,t} + R_{Gi,t}^{Spin} + R_{Gi,t}^{UR} - U_{Gi,t} P^{max} \leq 0 \quad (11)$$

$$U_{Gi,t} P_{Gi}^{min} - P_{Gi,t} + R_{Gi,t}^{DR} \leq 0 \quad (12)$$

where P_{Gi}^{max} and P_{Gi}^{min} are the maximum and minimum power for i^{th} thermal unit if it is committed at time t. It could be seen in the inequalities that if $U_{Gi,t}$ is 0, then the energy and reserve allocation for the ith are 0s.

c) Spinning reserve limits:

$$\sum_{i=1}^{N_G} R_{Gi,t}^{Spin} U_{Gi,t} \geq R_{Sym}^{Spin} \quad (13)$$

where R_{sym}^{Spin} is the system requirement spinning reserve, this value is calculated from the security analysis.

d) Regulation limits for SMESs:

$$0 \leq R_{SMES,i,t}^{UR} \leq P_{SMES,i}^{charge} \quad (14)$$

$$0 \leq R_{SMES,i,t}^{DR} \leq P_{SMES,i}^{discharge} \quad (15)$$

where $P_{SMES,i}^{charge}$ and $P_{SMES,i}^{discharge}$ are the maximum charge and discharge capability of ith SMES. Here discharging is considered, even if it is costly, because without discharging there will be negative Locational Marginal Prices (LMPs) when the wind farm's output is exceeding its committed output.

e) Ramp rate limits for thermal units:

$$-RR_{Gi}^{Down,max} \leq P_{Gi,t} - P_{Gi,t-1} \leq RR_{Gi}^{Up,max} \quad (16)$$

This constraint holds if both $U_{Gi,t}$ and $U_{Gi,t-1}$ equal 1.

B. Constraints for Scenarios

At day-ahead schedule, the forecast of wind is not accurate, and sometimes the error is really large. So it is required that the regulation reserves can compensate the variation of wind, for each scenario, this is really time-consuming:

a) Power balance equations:

$$\sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t}^s + \sum_{i=1}^{N_M} U_{SMESi,t} P_{SMESi,t}^s + P_{Wind,t}^s = P_{Load,t} \quad (17)$$

where $P_{Wind,t}^s$ is the scenario wind output at time t.

b) Generation limits:

$$U_{Gi,t}(P_{Gi,t} - R_{Gi,t}^{DR}) \leq U_{Gi,t} P_{Gi,t}^s \leq U_{Gi,t}(P_{Gi,t} + R_{Gi,t}^{UR}) \quad (18)$$

This constraint holds for both committed and non-committed generators.

c) Generation ramp limits:

$$P_{Gi,t-1} - RR_{Gi}^{DR} \leq P_{Gi,t}^s \leq P_{Gi,t-1} + RR_{Gi}^{UR} \quad (19)$$

Again, this constraint holds if and only if both $U_{Gi,t}$ and $U_{Gi,t-1}$ equal 1.

d) Regulation limits for SMESs:

$$-R_{SMESi,t}^{DR} \leq U_{SMESi,t} P_{SMESi,t}^s \leq R_{SMESi,t}^{UR} \quad (20)$$

e) SMES capacity limits:

$$E_{SMES,i}^{min} \leq E_{SMESi,0} + \sum_{t=1}^{t_0} P_{SMESi,t}^s \leq E_{SMES,i}^{max} \quad (21)$$

For $t_0 = 1, 2, \ldots T$. $E_{SMES,i}^{min}$ and $E_{SMES,i}^{max}$ are the minimum and maximum storage capacity for i^{th} SMES.

C. Chance Constraints for Scenarios

The scenario-based model can be converted into a chance-constrained model to reduce the computation time. All the derivations are on the basis of the following assumption, for a wind generator that is operating at Maximum Power Point Tracking (MPPT) mode, the output power is in range of $[0, P_{wind}^{max}]$.

First, equation (17) can be converted into:

$$\sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t}^s + \sum_{i=1}^{N_m} U_{SMESi,t} P_{SMESi,t}^s = P_{Load,t} - P_{Wind}^s \quad (22)$$

In this equation, the right side is in the range $[P_{Load,t} - P_{wind}^{max}, P_{Load,t}]$. Moreover, if the wind outputs follow a probability distribution pattern, then the wind output would fall in the range $[F^{-1}(\alpha/2), F^{-1}(1-\alpha/2)]$ for a probability of $1 - \alpha$. $F_t^{-1}(\cdot)$ is the cumulative distribution function (cdf) of the wind output. The left side of the equation is in the range of $[\sum_{i=1}^{N_G} P_{Gi,t} - \sum_{i=1}^{N_G} R_{Gi,t}^{DR} - \sum_{i=1}^{N_M} R_{SMESi,t}^{DR}, \sum_{i=1}^{N_G} P_{Gi,t} + \sum_{i=1}^{N_G} R_{Gi,t}^{UR} + \sum_{i=1}^{N_M} R_{SMESi,t}^{UR}]$. Thus if the former range is contained by the latter one, then the scenario will not violate any limits for a probability of $1 - \alpha$. Given those special distribution functions which are generally adopted by ISOs, the chance constrained model can be further converted into a deterministic model:

$$\sum_{i=1}^{N_G} U_{Gi,t} R_{Gi,t}^{UR} + \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^{UR} \geq P_{Wind,t}^f - F_t^{-1}(\frac{\alpha}{2}) \quad (23)$$

$$\sum_{i=1}^{N_G} U_{Gi,t} R_{Gi,t}^{DR} + \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^{DR} \geq F_t^{-1}(1-\frac{\alpha}{2}) - P_{Wind,t}^f \quad (24)$$

However, to solve regular chance-constrained problem, more than one distribution density function will be constructed to measure the constraints. In this paper, to better introduce the simplification and derivation, it is assumed that the probability of wind velocity follows a Weibull distribution. Generally, the wind power output is positively related to the wind velocity. It could be seen that as α increases, the up-regulation reserve and down-regulation reserve requirements decrease, making the system more economic and more risky.

The inequalities are derived in the Appendix. Hence the constraints for scenarios could be transformed into constraints for conventional UC problem, so the final constraints for optimal operation are (2)-(16), (23)-(24) with objective function (1). The mathematical model is:

$$\min f(\tilde{\cdot}, \tilde{}) \quad (25)$$

s.t

$$g(\tilde{\cdot}, \tilde{} \quad (26)$$

$$h(\tilde{\cdot}, \tilde{} \quad (27)$$

Where $\tilde{\cdot}$ consists of real-valued variables and $\tilde{\imath}$ consists of binary variables. The optimization problem is a deterministic model within each special distribution space.

III. PROBLEM SOLUTION

A. Particle Swarm Optimization Overview

Particle Swarm Optimization (PSO) suggested by Kennedy and Eberhart in 1995 is based on the analogy of a swarm of bird or a school of fish [16]. In general, this algorithm is faster than genetic algorithm except for small scale systems. However, the PSO algorithm is only applicable for real valued variables, so Kennedy and Eberhart proposed Binary Particle Swarm Optimization (BPSO) [17] method. The structure of BPSO is similar to that of real-valued PSO except that the position of a particle is a binary one. In BPSO, instead of changing to a new position according to the speed of a particle, the particle would turn to 1 from 0 or 0 from 1 based on a probability which is positively related to the velocity of the particle:

$$S(v_{ij}^{k+1}) = \frac{1}{1 + \exp(-v_{ij}^{k+1})} \quad (28)$$

The value of $S(v_{ij}^{k+1})$ can be interpreted as a probability threshold. If a random number selected from a uniform distribution [0,1] is less than $S(v_{ij}^{k+1})$, then the position of the jth element in the ith particle at iteration k+1 is set to 1 and otherwise set to 0. Next the BPSO would be proved ineffective for this problem.

B. Lemma

Lemma: For each unit commitment combination

$$\tilde{\imath} \quad \{U_{Gi,t}\} \cup \quad \underline{\quad\quad\quad} \}$$

The solution space $\tilde{\cdot}$ from constraints would not intersect with another unit commitment combination, i.e., if a solution $\tilde{\cdot}$ is feasible for $\tilde{\imath}_{\_}$, then it cannot be feasible for $\tilde{\imath}_{\_}$.

For two different unit commitment combinations $\tilde{u}_1 = \{U_{1,Gi,t}, i=1,2,\ldots N_G\} \cup \{U_{1,SMESi,t}, i=1,2,\ldots N_M\}$ and $\tilde{u}_2 = \{U_{2,Gi,t}, i=1,2,\ldots N_G\} \cup \{U_{2,SMESi,t}, i=1,2,\ldots N_M\}$, since they are not identical, there must be an i so that $U_{1,Gi,t} \neq U_{2,Gi,t}$ or $U_{1,SMESi,t} \neq U_{2,SMESi,t}$, thus in the solution space of case 1 and 2, there must be one thermal unit or SMES that is committed in the first situation and not committed in the second situation, and vice versa. For the case where the generator is committed, the output power should be larger than P_{Gi}^{Min}, and for the case where the generator is not committed, the output power should be zero. Thus, the two solutions are not identical.

Based on this lemma, it is apparent that the solution spaces for each unit commitment combination are not intersecting with each other. Hence, suppose BPSO is used, then there would be $2^{(N_G+N_M)T}$ possible combinations for the unit commitment, then the particle swarm has to enumerate $2^{(N_G+N_M)T}$ non-intersecting spaces to find the minimum value, otherwise there is no guarantee that global minimum is achieved. The complexity of this technique would be dramatically reduced if there is an algorithm to determine only a fraction of the $2^{(N_G+N_M)T}$ spaces would contain the global optimal solution. In this paper, branch and bound technique is used in selecting solution spaces.

C. Branch and Bound (BB)Technique:

Relaxation provides an excellent way to solve the MIP problem. First of all, assume the binary variables $\tilde{u}$ are real-valued variables in the range of [0, 1], and solve the problem by particle swarm optimization. The Branch and Bound algorithm generally alternates between two main steps:

branching, which is a recursive subdivision of the search space and bounding, which is the computation of lower and upper bounds for the global minimum of the objective function in a sub region of the search space. If all discrete variables take discrete values, then the algorithm is stopped, otherwise split the search space into half (branching) and add bounds for each spaces (bounding), and solve the two sub problems by PSO.

D. Handling of Constraint Violation

When PSO is implemented to solve the optimization problem with a convex objective function and non-convex constraints, the update of the particle would cause it to violate a constraint, thus making it a non-feasible solution. In the context of evolutionary optimization, four popular methods are generally used to handle constraints: the first is to preserve the feasibility of solutions, the second is differentiating between feasible and non-feasible solutions, the third one is a penalty function, and the last one is hybrid method. However, most of the methods need careful design of the parameters.

In this paper, a fly-back mechanism is used to handle the constraints. When each particle is out of its feasible region, it has to fly back to the previous position. Experimental results indicate that this technique can locate better minima with fewer iterations and without penalty functions. The particle update rule is:

$$x_i^t = \begin{cases} x_i^{t-1} + v_i^t & g_j(x_i^{t-1} + v_i^t) \le 0, \forall j \\ x_i^{t-1} & g_j(x_i^{t-1} + v_i^t) \le 0, \exists j \end{cases} \quad (29)$$

After the fly back, the velocity of the particle would change at the next time step according to the different positions of local best particle and global best particle. The above mechanism could successfully handle inequality constraints. In order to handle equality constraints, simple decrease the dimension of the variables, so that the last thermal unit $P_{GN_G,t}$ is determined by:

$$P_{GN_G,t} = P_{Load,t} - P_{Wind,t}^f - \sum_{j=1}^{N_G-1} P_{Gj,t} \quad (30)$$

E. Integrating BB and PSO

In this paper, a hybrid of PSO with BB is proposed. At the start of the algorithm, the PSO is used to determine an optimal feasible solution by assuming $\tilde{u}$ is real-valued variables. This solution is taken as the global best solution Gbest. In alliterations, if an improvement is conducted in the global solution by PSO, the improved Gbest would be sent to BB module as a starting point. During a PSO search, the discrete variables $\tilde{u}$ are truncated to the nearest valid discrete points. The solutions would not exceed boundaries using the fly-back mechanism.

F. Initialization of PSO by Simplex Method

$g(\tilde{x}, \tilde{u})$ is non-convex quadratic constraints when a multiple distribution space is proposed and introduced, thus traditionally, initialization of particles would require security examination. This is rather time consuming, since it is hard to find feasible solutions. In this paper, the initialization is achieved by a two-stage simplex method. Typically, first randomly initialize the binary variable $\tilde{u}$. If $\tilde{u}$ is given, then the

non-convex quadratic constraints would turn into linear constraints, i.e.

$$g_i(\tilde{} \quad (31)$$

The constraints are dependent on $\tilde{u}$ which is randomized. Thus, the linear constraints could be rewritten as:

$$A_i\tilde{} \quad (32)$$

The initialization of $\tilde{y}$, that is subject to the constraint (32), could be achieved with artificial variables. To determine the initial feasible solution, augment the problem to include artificial variables $\tilde{y}$, and then solve this artificial problem:

$$\min 1^T \tilde{} \quad (33)$$

Subject to

$$A_i\tilde{} \quad \tilde{} \quad \tilde{} \quad (34)$$

The artificial problem is already in canonical form, with $\tilde{y} = \tilde{b}$ as its initial basic feasible solution. Since $\tilde{y} \ge b$ is required, then this artificial problem has an apparent minimum solution at $\tilde{y} = 0$, which yields an initial basic feasible solution to the original problem. This solution could be used to initialize one particle, since a basic feasible solution is a feasible solution.

However, the artificial variable method could only provide one feasible initialization. To obtain more feasible solutions, simply choose different unit commitment combination $\tilde{u}$ and derive one feasible solution from each combination. The overall diagram is shown in Fig.1.
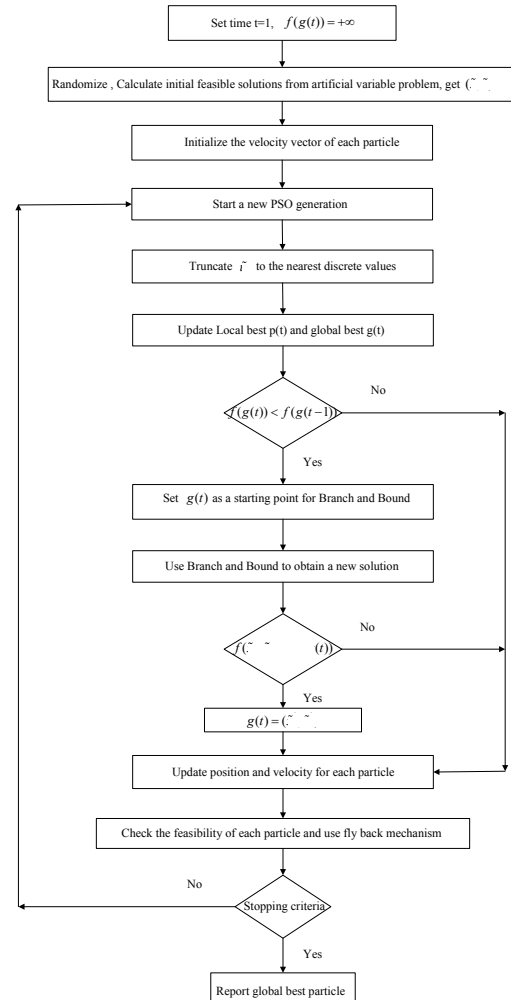

Fig. 1. Overall diagram for integration of branch/bound and PSO

IV. CASE STUDY

In this section, the proposed hybrid Branch/Bound and Particle Swarm Optimization method are tested on a single bus test system, which consists of three thermal units, a wind farm, and a SMES unit as show in Fig.2. Data for thermal generators can be found in Table I. The thermal generators' energy bidding data is shown in Table II. The ancillary service bidding data for thermal generators can be found in Table III. The ancillary service bidding data for SMES can be found in Table IV. The hourly forecast for load and wind output is shown in Table V.
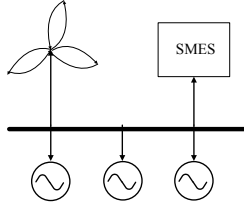

Fig.2.System illustration with three thermal units, one wind farm and one SMES.

Three cases are discussed in this paper:
Case 1: Base case dispatch with $1 - \alpha = 99\%$
Case 2: Base case dispatch with $1 - \alpha = 99.999\%$
Case 3: Base case dispatch without SMESs
And three scenarios are considered during peak hour:
Scenario 1: wind output equals to wind forecast
Scenario 2: wind output at maximum capability
Scenario 3: wind output at minimum capability

Table I
GENERATOR DATA

Unit	Pmin (MW)	Pmax (MW)	Ramp Up (MW/h)	Ramp Down (MW/h)	Initial State at time 0
G1	30	600	200	50	ON
G2	30	600	200	20	OFF
G3	20	400	200	50	OFF

Table II
GENERATOR ENERGY BIDDING DATA

Unit	Fuel Consumption Function			Start up Cost	Shut down Cost	Fuel Price
	a (MBtu)	b (MBtu/MWh)	c (MBtu/MWh^2)			
G1	176.9	13.5	0.04	1200	800	1.247
G2	129.9	40.6	0.001	1000	500	1.246
G3	137.4	17.6	0.005	1500	800	1.246

Table III
GENERATOR ANCILLARY SERVICE BIDDING DATA

Unit	C_{Gi}^{Spin} ($/MWh)	C_{Gi}^{UR} ($/MWh)	C_{Gi}^{DR} ($/MWh)
G1	13.2	26.4	26.4
G2	13.0	26.0	26.0
G3	15.0	28.0	28.0

Table IV
SUPER MAGNETIC ENERGY STORAGE ANCILALRY SERVICE BIDDING DATA

Unit	C_{SMESi}^{UR} ($/MWh)	C_{SMESi}^{DR} ($/MWh)	P_{SMESi}^{charge} (MW)	$P_{SMESi}^{discharge}$ (MW)
SMES1	20	15	30	20

Case 1: The hourly UC solution is calculated in Case 1 and the first 12 hours' dispatching solution is shown in Tables VI. Table VI also contains the scheduling results of the spinning reserve and regulation reserve of thermal units and the

regulation reserve of SMES as well. The total cost of dispatch is \$271,280. The wind power output is assumed to be positively related to the wind velocity, which follows a Weibull distribution.

Table V
HOURLY LOAD FORECAST DATA

Hour	Forecast Load (MW)	Forecast Wind (MW)	Hour	Forecast Load (MW)	Forecast Wind (MW)
1	200	8.2	13	750	59.0
2	200	11.4	14	750	78.1
3	250	66.9	15	700	44.9
4	250	69.8	16	650	19.5
5	250	55.4	17	500	3.7
6	200	50.9	18	600	16.5
7	350	4.6	19	600	72.2
8	500	49.3	20	700	73.3
9	600	45.6	21	650	65.3
10	800	10.1	22	550	24.5
11	800	24.8	23	450	49.9
12	700	37.3	24	350	40.3

Case 2: In comparison with Case 1, additional ancillary services are needed in Case 2 because of the increased reliability. The total cost is \$276,290.

Case 3: In comparison with Case 1, the generation at each thermal unit is decreased, so that they have sufficient regulation reserve for the variation of wind. Hence, the total cost for the system is increased to \$276,330.

It could be seen from the simulation that with the increase of reliability, the total cost for the system is also increased from \$27,129 to \$27,628. The model in this paper has already considered contingency analysis: the variation of wind is compensated by regulation reserve while the trips of generators are compensated by spinning reserve.

Table VI
PART OF CASE 1 DISPATCH RESULTS

Hour	G1 (MW)	Up Regulation Reserve (MW)	Down Regulation Reserve (MW)	G1 (Spin/Up Regulation/Down Regulation) (MW)
1	95.7	2.6	24.0	20.5/2.1/23.4
2	94.0	3.8	22.3	20.3/3.3/23.1
3	91.2	21.7	4.1	20.3/21.7/3.8
4	89.8	23.1	3.4	20.1/22.6/2.8
5	96.9	18.2	7.7	20.4/18.0/7.8
6	74.4	16.7	9.1	20.5/16.6/9.4
7	172.3	1.1	25.1	20.0/1.6/24.4
8	224.9	16.4	9.9	20.1/16.4/10.2
9	276.7	14.6	10.8	19.9/15.1/11.4
10	402.2	4.3	23.1	27.7/4.8/22.6
11	391.9	11.0	18.0	24.8/11.3/18.0
12	331.0	12.1	13.9	20.4/12.5/13.8

V. DISCUSSIONS AND CONCLUSIONS

The common way to specify spinning reserve is that certain amounts of reserves are pre-specified. However, there is not a common what to specify regulation reserve since this is implemented by automatic generation control (AGC). If the system demand is exceeding the generation, then ISOs have to buy emergency power from interconnecting markets.

Traditionally, regulation reserve does not have to be specified because the forecasting technique for demand brings few errors. However, with the penetration of wind and its inability to accurately forecast wind power, it is necessary to

decrease the generation of each thermal unit in order to compensate for the variation of wind, thus decreasing the efficiency of thermal units. With the development of Super Magnetic Energy Storage (SMES) devices, it is more and more economical to use the fast response SMES as regulation reserve. This paper proposes the operation model for a chance-constrained unit commitment problem, and presents simulations to discuss the introduction of SMESs.

Unit Commitment is a mixed integer non-convex quadratic programming problem, which is difficult to solve. In this paper, a hybrid branch/bound and particle swarm optimization is coordinated to solve this problem. The PSO algorithm solves the non-convex quadratic problem, while the branch and bound technique helps to choose the unit commitment combination.

In the simulation part, three cases are presented to compare the cost and reliability of the system. Comparing Case 1 and Case 3, it is concluded that the introduction of SMESs makes the system more economic while maintaining its reliability. Comparing Case 1 and Case 2, it is concluded that the economy of the system makes the system more risky; however, under the three scenarios the system's regulation reserve can still compensate for the variation of wind.

VI. Appendix

Let A represent the event that the regulation reserve could compensate for wind variation at time t. Then

$$P(A) \geq 1 - \alpha$$

$$\Leftrightarrow P(\sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t}^s + \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^s + P_{Wind,t}^s = P_{Load,t}) \geq 1 - \alpha$$

$$\Leftrightarrow P(P_{Load,t} - \sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t}^s - \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^s = P_{Wind,t}^s) \geq 1 - \alpha$$

$$\Leftrightarrow F_t^{-1}(\frac{\alpha}{2}) \leq P_{Load,t} - \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^s - \sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t}^s \leq F_t^{-1}(1 - \frac{\alpha}{2})$$

$$\Leftrightarrow F_t^{-1}(\frac{\alpha}{2}) \leq \sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t} + P_{Wind,t}^f - \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^s - \sum_{i=1}^{N_G} U_{Gi,t} P_{Gi,t}^s \leq F_t^{-1}(1 - \frac{\alpha}{2})$$

$$\Leftarrow \begin{cases} \sum_{i=1}^{N_G} U_{Gi,t} R_{Gi,t}^{UR} + \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^{UR} \geq P_{Wind,t}^f - F_t^{-1}(\frac{\alpha}{2}) \\ \sum_{i=1}^{N_G} U_{Gi,t} R_{Gi,t}^{DR} + \sum_{i=1}^{N_M} U_{SMESi,t} R_{SMESi,t}^{DR} \geq F_t^{-1}(1 - \frac{\alpha}{2}) - P_{Wind,t}^f \end{cases}$$

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