Assessing Wind Energy Uncertainty Impact on Joint Energy and Reserve Markets by using Stochastic Programming Evaluation Metrics

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Abstract- Wind energy is considered as a challenging problem for power systems because of its variable nature. As a result of accommodating wind resources with conventional thermal units in the system, performing of electricity markets will be more complicated. The results of the market clearing problem can be improved by proper wind uncertainty modeling. One of the best methods in order to handle wind uncertainty is to use stochastic programming. The expected value of the perfect information (EVPI) and value of the stochastic solution (VSS) are two well-known indices defined to analyse stochastic programming results compared to a case with having full information and a case disregarding uncertainty, respectively. In this paper, impact of the wind uncertainty on the EVPI and VSS indices is investigated in the joint energy and reserve market clearing problem. Wind uncertainty is characterized by two measures, namely wind penetration level and wind forecasting accuracy level. The wind penetration levels are modeled as a fraction of a basic wind power value while various forecasting accuracy levels are modeled by normal probability distribution function with different variances. The problem is investigated and results are analyzed under different levels of the wind penetration and forecasting accuracies. Based on obtained results, the value of the EVPI metric increases with increment of the wind penetration level or forecasting error variance. Also, because of the higher uncertainty level of the wind power arising from penetration level or variance increment, the value of the VSS metric increases.

Keywords- Wind uncertainty, joint energy and reserve market, stochastic programming, Expected Value of Perfect Information, Value of Stochastic Solution.

Nomenclature

Sets

J	Thermal units set
K	Time periods set
S	Scenarios set

Parameters

A(j)	Constant coefficient of piecewise linear generation cost function of unit j
a(j)	Constant coefficient of quadratic generation cost function of unit j
b(j)	First order coefficient of quadratic generation cost function of unit j
c(j)	Second order coefficient of quadratic generation cost function of unit j
$C_{DRB}(j)$	Cost of down-reserve block of unit j
$\overline{C_{DRB}}(k)$	Cost of down-reserve block of demand at period k
$C_{DRD}(j)$	Cost of depleted down-reserve of unit j
$\overline{C_{DRD}}(k)$	Cost of depleted down reserve of demand at period k
$C_{LSh}(k)$	Load shedding cost at period k
$C_D(j,k)$	Shut-down cost of unit j at period k
$C_U(j,k)$	Start-up cost of unit j at period k
$C_{URB}(j)$	Cost of up-reserve block of unit j
$\overline{C_{URB}}(k)$	Cost of up-reserve block of demand at period k

$C_{URD}(j)$ Cost of depleted up-reserve of unit j
$\overline{C_{URD}}(k)$ Cost of depleted up-reserve of demand at period k
$C_{WS}(k)$ Wind spillage cost at period k
$D_{max}(k)$ Maximum demand at period k
$D_{min}(k)$ Minimum demand at period k
Demand(k) Base (constant) demand at period k
DT(j) Minimum down-time of unit j
$E_{PW}(k,s)$ Wind power forecasting error at period k and scenario s
FL(j,l) Slope of segment l of piecewise linear generation cost function of unit j
G(j) Number of time periods unit j must be initially online due to its minimum up-time constraint
L(j) Number of time periods unit j must be initially offline due to its minimum down-time constraint
NL(j) Number of segments of generation cost function of unit j
P(s) Probability of scenario s
$P_D(k)$ Demand price at period k
$P_{max}(j)$ Maximum generation capacity of unit j
$P_{min}(j)$ Minimum generation capacity of unit j
$P_W(k)$ Forecasted mean wind power at period k
RD(j) Ramp-down limit of unit j
RU(j) Ramp-up limit of unit j
$S_0(j)$ Number of time periods unit j has been offline prior to the first period of the time span
SD(j) Shut-down ramp limit of unit j
SU(j) Start-up ramp limit of unit j
$U_0(j)$ Number of time periods unit j has been online prior to the first period of the time span
UT(j) Minimum up-time of unit j
$V_0(j)$ Initial state of unit j

Variables

C_B Sum of power balancing costs in real-time state
$C_P(j,k)$ Generation cost of unit j at period k
$C_{RB}(j,k)$ Sum of reserve block costs of unit j and load at period k
D(k) Demand at period k
$D_{Sch}(k,s)$ Scheduled Demand at period k and scenario s
$DR_B(j,k)$ Down-reserve block of unit j at period k
$\overline{DR_B}(k)$ Down-reserve block of demand at period k
$DR_D(j,k,s)$ Depleted down-reserve of unit j at period k and scenario s
$\overline{DR_D}(k,s)$ Depleted down-reserve of demand at period k and scenario s
LSh(k,s) Amount of load shedding at period k and scenario s
$P_{avail}(j,k)$ Available generation capacity of unit j at period k
$P_G(j,k)$ Generated power of unit j at period k
$P_{Sch}(j,k)$ Scheduled generated power of unit j at period k and scenario s
$t^{off}(j)$ Number of time periods unit j has been offline prior to the start-up in period k
$UR_B(j,k)$ Up-reserve block of unit j at period k
$\overline{UR_B}(k)$ Up-reserve block of demand at period k
$UR_D(j,k,s)$ Depleted up-reserve of unit j at period k and scenario s
$\overline{UR_D}(k,s)$ Depleted up-reserve of demand at period k and scenario s
V(j,k) Binary variable that is equal to 1 if unit j be online in period k and 0 otherwise
WS(k,s) Spilled wind power at period k and scenario s
δ (j,k,l) Generated power in segment l of piecewise linear generation cost function of unit j at period k

1. Introduction

Strong interests toward the use of the renewable energy resources are created because of growing increase of energy consumption, high and increasing cost of the fossil fuels and non-renewable nature and environmental pollution caused by them. In the terms of the use of the renewable energies, the share of the wind energy is more than the other resources of renewable energies because of its characteristics. It is plentiful, renewable, widely distributed, clean, produces no greenhouse gas emissions, and uses little land. But wind energy is considered as a challenging problem for the power systems because of its intermittent and variable nature [1, 2]. In last year, at least 84 countries were utilizing wind power to supply their power demands. Wind power capacity has expanded to 336 GW by June 2014, and wind energy generation is growing fast and has reached around 4% of the worldwide use of electricity [3, 4].

On the other hand, the power industry has been led to the restructuring in many countries because of problems arising from the inefficiency and inability of governments to supply the costs of investment and operation of this industry. As a result of the restructuring, the power industry that operated as a vertically integrated structure in the long-term became a competitive industry. Formation of the free and competitive markets for electricity and companies with various tasks was one of the results of the restructuring and deregulation. It should be noted that the independent system operator (ISO) clear the electricity market using the pool market strategy that is one of the best methods for market clearing. Also, performing the real time market is one of the best ways to compensate the imbalances between the power production and consumption in the real time state. The real time market is formed to utilize the ancillary services such as depleted up and down reserves at the moment of energy delivery. As a result, the energy and reserve markets should be cleared by the ISO at the same time [5-7].

By adding the wind energy to the system, solution of the joint energy and reserve market clearing problem become more complicated and appropriate uncertainty modeling of the wind power will have a significant impact on the results of this problem. One of the best tools to model the effect of the wind power uncertainty on the market clearing problem is stochastic programming [8, 9]. Stochastic programming is used to formulate and solve the problems that have uncertain parameters and two or more stages of decision-making. In this type of programming, each uncertain parameter is modeled by means of the possible scenarios set. By taking into account the stochastic solution instead of its deterministic counterpart, optimal decisions maximize the ISO expected profit in the market clearing problem [10, 11]. Although, accuracy of the wind power forecasting is acceptable in the literature, but it is not equal to 100 percent and there is some forecasting errors. So, the stochastic programming can be used to model the wind power uncertainty properly. Because in this type of programming, a number of scenarios can be defined to model the different wind power realizations and at the same time, the objective function is depending on these scenarios. Furthermore, in the stochastic programming different stages are defined that can simulate our problem model properly.

Many studies on the settlement of electricity markets have been conducted using the stochastic programming so far. Authors in [12] have considered a mixed integer linear stochastic programming for the generation scheduling of the units in the day ahead electricity market. In this model, spinning reserves pricing and different scenarios are taken into account in the real time. Also, instead of considering all possible scenarios, a certain number of them have been considered to limit the size of the model. In [13], a model with stochastic programming has been considered to optimize biding strategies of the hydroelectric units. The one-day short-term planning and Pumped-storage units have been utilized to maximize profit, too. In [14], the power production of the units in the day ahead joint energy and reserve markets has been scheduled by use of the stochastic programming. This stochastic model has considered both of the uncertainties of the forecasted prices and unit outages. Authors in [15], have utilized a stochastic model to determine the optimal bidding strategy for the profit maximization of the thermal and wind units in the joint energy and reserve markets. In [16], the storage units belong to the independent investors have been considered to sell energy in the day ahead market. The generated power of the wind farms and other renewable sources has been considered as the main source of the electrical power. Also, the stochastic programming has been used to model the variable nature of the market prices and to select the optimal pricing strategy of the storage units. In [17], authors have proposed a model for the short-term electricity market in order to analyze the impact of the wind farms. As well, in this model, uncertainty of the wind power and power balancing methods has been considered.

In the literature, the advantages of using the stochastic programming instead of its deterministic counterpart in the electricity markets have not been analyzed mathematically. The advantages of the stochastic programming can be showed by use of the two main metrics: the Expected Value of Perfect Information (EVPI), and the Value of Stochastic Solution (VSS). In this paper, the impact of the wind power uncertainty level on the EVPI and VSS metrics is analyzed in the joint energy and reserve market clearing problem. Using EVPI metric, the additional profit obtained for the ISO because of accurate forecasting of the wind power, is calculated. By use of VSS metric, the additional profit obtained for the ISO because of using the stochastic programming instead of the deterministic one, is calculated.

The wind power uncertainty level is modeled by use of two methods. First, the wind power penetration level is considered as a portion of the base case wind power and then, the wind power forecasting error is modeled as a normal probability distribution function that its variance can change. Also in the proposed model for the market clearing problem, the thermal units offer bids including power / Price / unit characteristics unlike most of the articles in this field that consider simple bids including power / price. In other words, the generation, start up and shut down costs, as well as all technical constraints of the thermal units are considered by the ISO. Therefore, the average proposed price of the generated power will be reduced. These thermal constraints include ramp up limit, ramp down limit, start up ramp limit, shut down ramp limit, minimum up time limit and minimum down time limit of the units. Also, the spinning up and down reserves provided by the thermal units and demand are considered to balance the power production and consumption in the real time state. In addition, the concepts of the wind spillage and load shedding are utilized in the model.

The study case consists of five thermal units and one wind unit and generation scheduling of the units is done of the GAMS software environment. The remaining sections after this introduction are outlined as follows. In section 2, the concepts of the stochastic programming, EVPI and VSS metrics and modeling of the wind power uncertainty will be studied. The proposed model will be formulated in Section 3 and input parameters and Simulation results are analyzed in Section 4. Finally, in section 5, relevant conclusions will be presented.

2. Mathematical Concepts

In this section, the concepts of the stochastic programming and EVPI and VSS metrics as well as uncertainty modeling of the wind power are described. The two-stage stochastic programming is utilized to clear the joint energy and reserve markets. To evaluate the efficiency of the stochastic programming, two metrics including EVPI and VSS are considered.

2.1. Stochastic Programming

One of the best methods to model the problems with uncertain parameters is stochastic programming. In our proposed approach, the stochastic programming is used to model the uncertainty on the wind power output, which is characterized as a random variable [22, 23]. A limit number of the scenarios should be generated by sampling of this random variable to represent the realizations of the wind power uncertainty. This sampling can be carried out by utilization of the forecasted wind power, mean and standard deviation of the wind power forecasting error. Generated scenarios can be shown as a scenario tree according to Figure 1 [24, 25]. Also, in the stochastic programming to express when a new realization of the uncertain parameter is observed and the related information is available for the decision maker (ISO), different stages are defined [13].

In our case, the two-stage stochastic programming is used. The first-stage decisions are the on/off states of the thermal units and their output power and reserve blocks, and the second-stage ones are the depleted reserves and amounts of the wind spillage and load shedding. It should be noted that in the stochastic programming the expected value of the objective function should be calculated because it is a multivalued function considered as a random variable.

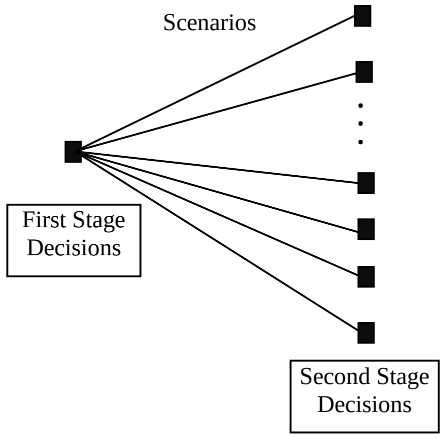

Figure 1: Scenario tree in the stochastic programming

2.2. EVPI and VSS Metrics

The Expected Value of the Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS) are two metrics used to evaluate the efficiency of the stochastic programming. The EVPI metric shows the cost that the ISO can pay for receiving perfect information of the wind power future realizations. Suppose that in the joint energy and reserve market clearing problem, P1 be the optimal value of the objective function. This value shows the ISO expected profit by taking into consideration of the all wind power scenarios. Also, suppose that P2 be the optimal value of the objective function of the joint energy and reserve market clearing problem when perfect information is available for the ISO. Then, the EVPI metric is defined as follows:

$$\text{EVPI} = (P2 - P1) > 0 \quad (1)$$

The value of the stochastic solution is a metric to calculate the additional profit obtained from using the stochastic programming instead of its deterministic counterpart. In the stochastic programming of the joint energy and reserve market clearing problem, the random variable describing wind power is replaced by the expected value of the wind power. The optimal values of the first-stage variables are obtained from the solution of this deterministic problem. Then, the stochastic market clearing problem can be solved by fixing the values of the first-stage variables to those provided by the deterministic one. Suppose that P3 be the optimal value of the objective function of the joint energy and reserve market clearing problem with fixed first stage variables [10]. Therefore, the VSS metric is calculated as follows:

$$\text{VSS} = (P1 - P3) > 0 \quad (2)$$

2.3. Uncertainty Modeling of the Wind Power

The hourly power demand and different penetration levels of the wind power are shown in Figure 2. It should be noted that this demand curve have two peaks in the hours 12 and 20. According to this figure, the amount of the wind power in the state with name of wind1 is considered as the base case wind power. Other states (wind2, wind3, and wind4) show the amounts of the wind power with penetration levels 0.75, 0.5, and 0.25, respectively. In other words, the penetration level is equal to 1 in the base case and in the other cases the amount of the wind power is reduced to 75 percent, 50 percent, and 25 percent of the base case wind power [18].

Also, the wind power forecasting error can be modeled as a normal probability distribution function with zero mean and different variances. Different variances are equal to 0.025, 0.050, 0.075, and 0.100 according to Figure 3. Each normal probability distribution can be discretized into thirteen equal sections and thirteen error values with their relevant probabilities can be calculated. Therefore thirteen scenarios with their relevant probabilities can be considered for the wind power [19-21].

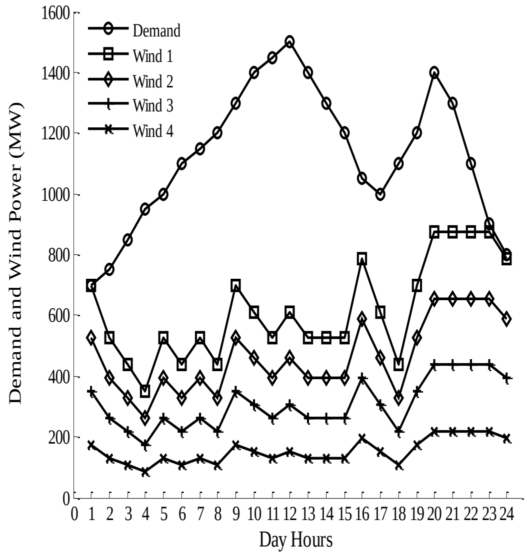

Figure 2: Different penetration levels of the wind power

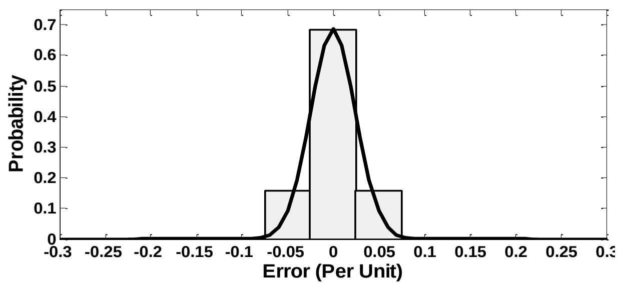

Figure 3a: variance 0.025

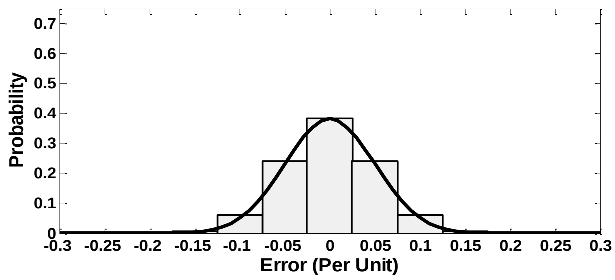

Figure 3b: variance 0.050

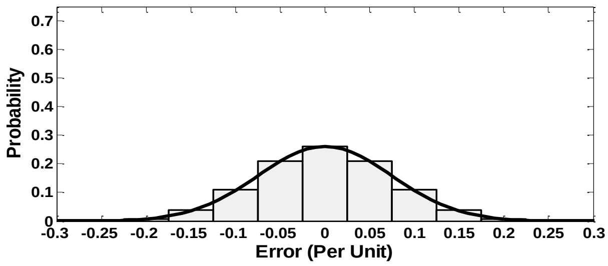

Figure 3c: variance 0.075

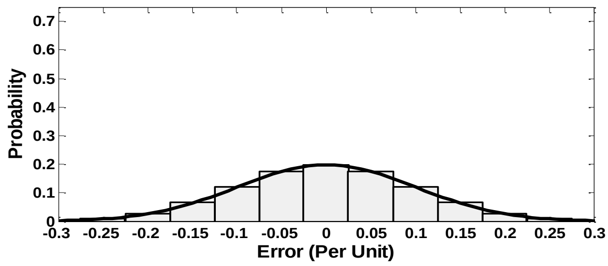

Figure 3d: variance 0.100

Figure 3: Normal probability distribution of the wind power forecasting error with variance 0.025 (Figure 3a), variance 0.050 (Figure 3b), variance 0.075 (Figure 3c), and variance 0.100 (Figure 3d)

3. Proposed formulation

In this paper, the impact of the wind power uncertainty level on the EVPI and VSS metrics is analyzed in the joint energy and reserve market clearing problem. To model the uncertainty of the wind power a two-stage stochastic programming is used. The proposed model is in the form of a mixed integer linear programming due to the use of the binary variables to model the on/off states of the thermal units. In this section, first, the objective function of the problem is described and then, the real time constraints and day ahead constraints of the market are presented.

3.1. Objective Function

The ISO expected profit in the joint energy and reserve market clearing problem is considered as follows [10]:

$$\begin{aligned}\text{Max}\quad &\{\sum_{k\in K} P_D(k)\times D(k) - \\ &\sum_{k\in K}\sum_{j\in J}[C_P(j,k)+C_U(j,k)+C_D(j,k)+C_{RB}(j,k)]\text{-}C_B\}\end{aligned} \tag{3}$$

The expected profit in equation (3) consists of two terms. First term is equal to the revenue obtained from selling energy to the consumers. Second term is sum of the of the thermal units power production, start up and shut down costs, reserve block costs, and the expected cost of the power balancing in the real-time state. So, the expectation value of the profit is equal to the difference between this two terms. Usually, a quadratic function is utilized to model the production cost function of a thermal unit and as a result the objective function consisted of this quadratic function is non-linear. So, a linear approximation is applied to the production cost functions of the thermal units in order to guarantee convergence of the solution. The quadratic production cost function of the thermal units can be defined as follows:

$$\begin{aligned}&C_P(j,k)=a(j)\times V(j,k)+b(j)\times P_G(j,k)+c(j)\times P_G^2(j,k)\\ &\forall\, j\in J,\ \forall\, k\in K\end{aligned} \tag{4}$$

This quadratic cost function is approximated by a piecewise-linear cost function according to equations (5), (6), and (7) [26]:

$$\begin{aligned}&C_P(j,k)=A(j)\times V(j,k)+\sum_{L=1}^{NL_j}[F(j,L)\times\delta(j,L,k)]\\ &\forall\, j\in J,\ \forall\, k\in K\end{aligned} \tag{5}$$

$$\begin{aligned}&P_G(j,k)=P_{min}(j)\times V(j,k)+\sum_{L=1}^{NL_j}\delta(j,L,k)\\ &\forall\, j\in J,\ \forall\, k\in K\end{aligned} \tag{6}$$

$$\begin{aligned}&A(j)=a(j)+b(j)\times P_{min}(j)+c(j)\times P_{min}^2(j)\\ &\forall\, j\in J\end{aligned} \tag{7}$$

Also, in objective function (3) there is a cost that pay for purchase the reserve blocks in the day ahead market (CRB). This cost is considered as the reserve block cost and it is equal to sum of the costs of the up and down reserve blocks provided by the thermal units and demand. This cost is considered as equation (8):

$$\begin{aligned}C_{RB}(j,k)=&(C_{URB}(j)\times UR_B(j,k)+C_{DRB}(j)\times DR_B(j,k))\\ &+(\overline{C_{URB}}(k)\times\overline{UR_B}(k)+\overline{C_{DRB}}(k)\times\overline{DR_B}(k))\\ &\forall j\in J,\quad \forall k\in K\end{aligned} \tag{8}$$

The expectation value of the power balancing cost (CB) in the real-time is the last term in objective function (3). This cost is equal to sum of the expected costs of the depleted up and down reserves provided by thermal units and load, wind power spillage and load shedding in the real-time market. The expected power balancing cost is calculated as follows:

$$\begin{aligned}C_B=&[\sum_{s\in S}P(s)\times(\sum_{k\in K}\sum_{j\in J}C_{URD}(j)\times UR_D(j,k,s))]-\\ &[\sum_{s\in S}P(s)\times(\sum_{k\in K}\sum_{j\in J}C_{DRD}(j)\times DR_D(j,k,s))]+\\ &[\sum_{s\in S}P(s)\times(\sum_{k\in K}\overline{C_{DRD}}(k)\times\overline{DR_D}(k,s))]-\\ &[\sum_{s\in S}P(s)\times(\sum_{k\in K}\overline{C_{URD}}(k)\times\overline{UR_D}(k,s))]+\\ &[\sum_{s\in S}P(s)\times(\sum_{k\in K}C_{LSh}(k)\times LSh(k,s))]+\\ &[\sum_{s\in S}P(s)\times(\sum_{k\in K}C_{WS}(k)\times WS(k,s))]\end{aligned} \tag{9}$$

3.2. Market constraints

In this section, the real time market constraints are described first, and then, the day ahead market constraints are studied. The power production and consumption should be balance in the real-time state according to constraint (10). In the left hand side of this equation, power production is equal to the scheduled power of the thermal units plus the generated wind power minus the spilled wind power. On the other hand, Power consumption is equal to the scheduled power demand minus the amount of the load shedding. Also, scheduled power of each thermal unit is equal to the generated power of it plus its depleted up reserve minus its depleted down reserve. Similarly, the scheduled power demand is equal to the power demand plus depleted up reserve minus depleted down reserve of demand side. This variables are given in the equations (11) and (12), respectively:

$$\sum_{j\in J} P_{Sch}(j,k,s)+P_W(k)(1+E_{P_W}(k,s))\text{-}WS(k,s) = D_{Sch}(k,s)-LSh(k,s) \qquad \forall k\in K\,,\quad \forall s\in S \tag{10}$$

$$P_{Sch}(j,k,s)=P_G(j,k)+UR_D(j,k,s)\text{-}DR_D(j,k,s) \qquad \forall j\in J\,,\quad \forall k\in K\,,\quad \forall s\in S \tag{11}$$

$$D_{Sch}(k,s)=D(k)+\overline{UR}_D(k,s)\text{-}\overline{DR}_D(k,s) \qquad \forall k\in K\,,\quad \forall s\in S \tag{12}$$

The scheduled power of the thermal units is limited by the minimum generation capacity and available generation capacity of them according to equation (13). Also, according to equation (14), available generation capacity of the units should be smaller than the maximum generation capacity of them. As well, the scheduled power demand is limited by the supposed minimum and maximum amounts of the power demand in equation (15):

$$P_{min}(j)\times V(j,k)\le P_{Sch}(j,k,s)\le P_{avail}(j,k) \qquad \forall j\in J\,,\quad \forall k\in K\,,\quad \forall s\in S \tag{13}$$

$$0\le P_{avail}(j,k)\le P_{max}(j,k)\times V(j,k) \qquad \forall j\in J\,,\quad \forall k\in K \tag{14}$$

$$D_{min}(k)\le D_{Sch}(k,s)\le D_{max}(k) \qquad \forall k\in K\,,\quad \forall s\in S \tag{15}$$

Constraints (16)-(19) are used to describe the limits of the depleted reserves in the real-time state. The depleted up and down reserves provided by the thermal units and demand should be smaller than the up and down reserve blocks provided by them:

$$UR_D(j,k,s)\le UR_B(j,k) \qquad \forall j\in J\,,\quad \forall k\in K\,,\quad \forall s\in S \tag{16}$$

$$DR_D(j,k,s)\le DR_B(j,k) \qquad \forall j\in J\,,\quad \forall k\in K\,,\quad \forall s\in S \tag{17}$$

$$\overline{UR}_D(k,s)\le \overline{UR}_B(k) \qquad \forall k\in K\,,\quad \forall s\in S \tag{18}$$

$$\overline{DR}_D(k,s)\le \overline{DR}_B(k) \qquad \forall k\in K\,,\quad \forall s\in S \tag{19}$$

Also, the spilled wind power and amount of the load shedding are smaller than the generated wind power and scheduled power demand, respectively:

$$LSh(k,s)\le D(k)+\overline{UR}_D(k,s)\text{-}\overline{DR}_D(k,s) \qquad \forall k\in K\,,\quad \forall s\in S \tag{20}$$

$$WS(k,s)\le P_W(k)(1+E_{P_W}(k,s)) \qquad \forall k\in K\,,\quad \forall s\in S \tag{21}$$

Described constraints were the real time market constraints. The other remaining constraints are the day-ahead market constraints. These constraints consist of technical constraints of the thermal units such as ramp-up limit, ramp-down limit, start-up ramp limit, shut-down ramp limit, minimum up-time, and minimum down time [27]. The ramp-up and the ramp-down limits of the thermal units are described in equations (22), (23), and (24):

$$P_{avail}(j,k)\le P_{Sch}(j,k\text{-}1,s)+RU(j)\times V(j,k) +SU(j)\times[V(j,k)\text{-}V(j,k\text{-}1)]+P_{max}(j)\times[1\text{-}V(j,k)] \qquad \forall\ j\in J\,,\ \forall\ k\in K\,,\quad \forall s\in S \tag{22}$$

$$P_{avail}(j,k)\le P_{max}(j)\times V(j,k+1) +SD(j)\times[V(j,k)\text{-}V(j,k+1)] \qquad \forall\ j\in J\,,\ \forall\ k\in K \tag{23}$$

$$P_{Sch}(j,k\text{-}1,s)\text{-}P_{Sch}(j,k,s)\le RD(j)\times V(j,k) +SD(j)\times[V(j,k\text{-}1)\text{-}V(j,k)]+P_{max}(j)\times[1\text{-}V(j,k\text{-}1)] \qquad \forall\ j\in J\,,\ \forall\ k\in K\,,\quad \forall s\in S \tag{24}$$

The minimum up-time constraints are defined in equations (25)-(28):

$$G(j)=\min\{T,[UT(j)\text{-}U_0(j)]\times V_0(j)\} \tag{25}$$

$$\sum_{k=1}^{G(j)}[1\text{-}V(j,k)]=0 \qquad \forall\ j\in J \tag{26}$$

$$\sum_{n=k}^{k+UT(j)-1} V(j,n)\ge UT(j)\times[V(j,k)\text{-}V(j,k\text{-}1)] \qquad \forall\ j\in J\,,\ \forall\ k=G(j)+1,\dots,T\text{-}UT(j)+1 \tag{27}$$

$$\sum_{n=k}^{T}[V(j,n)-(V(j,k)\text{-}V(j,k\text{-}1))]\ge 0 \qquad \forall\ j\in J\,,\ \forall\ k=T\text{-}UT(j)+2,\dots,T \tag{28}$$

Finally, the minimum down-time constraints are shown in equations (29)-(32):

$$L(j)=\min\{T,[DT(j)\text{-}S_0(j)]\times[1\text{-}V_0(j)]\} \tag{29}$$

$$\sum_{k=1}^{L(j)}V(j,k)=0 \qquad \forall\ j\in J \tag{30}$$

$$\sum_{n=k}^{k+DT(j)-1}[1\text{-}V(j,n)]\ge DT(j)\times[V(j,k\text{-}1)\text{-}V(j,k)] \qquad \forall\ j\in J\,,\ \forall\ k=L(j)+1,\dots,T\text{-}DT(j)+1 \tag{31}$$

$$\sum_{n=k}^{T}[1\text{-}V(j,n)\text{-}(V(j,k\text{-}1)\text{-}V(j,k))]\ge 0 \qquad \forall\ j\in J\,,\ \forall\ k=T\text{-}DT(j)+2,\dots,T \tag{32}$$

4. Case study and simulation results

The considered case consists of five thermal units and one wind farm and the proposed model is solved in the GAMS software version 24.2.2 using CPLEX solver version 11. In this section, the input parameters are given and then, the simulation results are analyzed.

The thermal units parameters are shown in Table 1. The time span is considered 24 hours and it is divided into 24 time periods. Also, the hourly base power demand and hourly demand price are given in Tables 2 and 3.

Table 1: Thermal units parameters [27]

Parameters	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
P_{min} (MW)	125	100	75	50	50
P_{max} (MW)	500	400	300	200	200
UT (h)	7	6	5	4	3
DT (h)	7	6	5	4	3
a ($)	700	900	600	700	400
b($/MW)	16	23	17	21	18
c ($/MW^2)	0.0045	0.0060	0.0035	0.0052	0.0027
C_U($)	700	900	600	700	400
C_D($)	700	900	600	700	400
RU(MW)	250	200	150	100	100
RD(MW)	500	400	300	200	200
SU(MW)	125	100	75	50	50
SD(MW)	500	400	300	200	200

Table 2: Hourly base demand (MW) [27]

Hour	1	2	3	4	5	6
Load	700	750	850	950	1000	1100
Hour	**7**	**8**	**9**	**10**	**11**	**12**
Load	1150	1200	1300	1400	1450	1500
Hour	**13**	**14**	**15**	**16**	**17**	**18**
Load	1400	1300	1200	1050	1000	1100
Hour	**19**	**20**	**21**	**22**	**23**	**24**
Load	1200	1400	1300	1100	900	800

Table 3: Hourly demand price ($)

Hour	1	2	3	4	5	6
Price	20	20.25	20.75	21.25	21.50	22
Hour	**7**	**8**	**9**	**10**	**11**	**12**
Price	22.25	22.50	23	23.50	23.75	24
Hour	**13**	**14**	**15**	**16**	**17**	**18**
Price	23.50	23	22.50	21.75	21.50	22
Hour	**19**	**20**	**21**	**22**	**23**	**24**
Price	22.50	23.50	23	22	21	20.50

The hourly forecasted mean wind power is shown in Table 4. Furthermore, different variances of the discretized normal probability distribution function of the wind power forecasting error and their relevant probabilities are considered according to Table 5.

Table 4: Hourly forecasted mean wind power (MW) [18]

Hour	1	2	3	4	5	6
Power	700	525	435	350	525	435
Hour	**7**	**8**	**9**	**10**	**11**	**12**
Power	525	435	700	610	525	610
Hour	**13**	**14**	**15**	**16**	**17**	**18**
Power	525	525	525	785	610	435
Hour	**19**	**20**	**21**	**22**	**23**	**24**
Power	700	875	875	875	875	785

Table 5: Probabilities of the different variances of the wind forecasting error distribution function [19-21]

Scen.	1	2	3	4	5	6	7
Mean Error	**-0.30**	**-0.25**	**-0.20**	**-0.15**	**-0.10**	**-0.05**	**0**
Prob Var. 1	0	0	0	0	0.0013	0. 1573	0.6827
Prob Var. 2	0	0	0.0002	0.0060	0.606	0.2417	0.3829
Prob Var. 3	0.0001	0.0012	0.0085	0.038	0.1109	0.2108	0.2611
Prob Var. 4	0.0030	0.0092	0.0278	0.0656	0.1210	0.1747	0.1974
Scen.	**8**	**9**	**10**	**11**	**12**	**13**	
Mean Error	**0.05**	**0.10**	**0.15**	**0.20**	**0.25**	**0.30**	
Prob Var. 1	0. 1573	0.0013	0	0	0	0	
Prob Var. 2	0.2417	0.606	0.0060	0.0002	0	0	
Prob Var. 3	0.2108	0.1109	0.038	0.0085	0.0012	0.0001	
Prob Var. 4	0.1747	0.1210	0.0656	0.0278	0.0092	0.0030	

The price of one MW of the reserve block and depleted reserve of the thermal units are equal to 10 and 20 percent of the one MW generated power price of them, respectively. Also, the price of one MW of the reserve block and depleted reserve of the power demand are considered 3 and 5 percent of the hourly power demand price, respectively. The costs of the load shedding and wind spillage are supposed 500 and 10 dollars per MW, respectively.

The simulation results including the obtained expected profit due to the use of the stochastic programming (profit 1), the obtained profit due to the use of the perfect information of the wind power (profit 2), and the value of the EVPI metric are shown in Tables 6a to 6d. These results are given by consideration of penetration levels 0.25, 0.5, 0.75, and 1 of the forecasted wind power as well as variances 0.025, 0.05, 0.075 and 0.1 of the normal probability distribution function of the wind power forecasting error.

Table 6: Values of the profits ($) and EVPI metric ($) for different penetration levels and variance 0.025 (Table 6a), variance 0.050 (Table 6b), variance 0.075 (Table 6c), variance 0.100 (Table 6d)

Table 6a: variance 0.025

PL	Profit 1	Profit 2	EVPI
0.25	126313	150958	**24645**
0.50	205343	253911	**48568**
0.75	283843	355143	**71300**
1.00	360965	454292	**93326**

Table 6b: variance 0.050

PL	Profit 1	Profit 2	EVPI
0.25	125616	150958	**25341**
0.50	203826	253911	**50084**
0.75	282276	355143	**72867**
1.00	360075	454292	**94216**

Table 6c: variance 0.075

PL	Profit 1	Profit 2	EVPI
0.25	124994	150958	**25993**
0.50	202939	253911	**51022**
0.75	281321	355143	**73893**
1.00	357156	454292	**97226**

Table 6d: variance 0.100

PL	Profit 1	Profit 2	EVPI
0.25	124359	150958	**26614**
0.50	201426	253911	**52509**
0.75	279989	355143	**75189**
1.00	356256	454292	**98081**

Based on obtained results, following increasing wind penetration level, the expected profit increases because of less power production of the thermal units and less operating cost of them. Also, the value of the EVPI metric increases with penetration level increment; because more uncertainty is generated in the problem and as a result, difference between the obtained expected profit due to the use of the stochastic solution and the obtained profit due to the use of the perfect information increases. On the other hand, by increasing the variance of the normal probability distribution function of the wind power forecasting error, the expected profit decreases; because the accuracy of the wind power forecasting decreases and as a result, the ISO needs to pay more costs to purchase the reserve blocks and depleted reserves for the power balancing in the real time. Also, the value of the EVPI metric increases with variance increment due to the more uncertainty generated in the problem.

The obtained expected profit due to the use of the stochastic programming (profit 1), the obtained profit due to the use of mean value of the wind power and deterministic programming (profit 3), and the value of the VSS metric with regard to the different penetration levels and variances are given in Tables 7a to 7d. The values and variations of the obtained expected profit due to the use of the stochastic programming are quite similar to the previous results (Tables 6a to 6b). The VSS metric is utilized to calculate the additional profit obtained from using a stochastic programming instead of its deterministic counterpart. This metric is equal to the value of the expected profit obtained from the stochastic solution minus the value of the profit obtained from the deterministic solution. As the results in the Tables 7a to 7b show, all of the values of the VSS metric are positive and this means that the ISO can earn more profit by use of the stochastic programming instead of the deterministic one; so, the necessity of the utilization of the stochastic solution is revealed. It should be noted that, because of the higher uncertainty level of the wind power arising from penetration level or variance increment, the value of the VSS metric increases.

Table 7: Values of the profits ($) and EVPI metric ($) for different penetration levels and variance 0.025 (Table 7a), variance 0.050 (Table 7b), variance 0.075 (Table 7c), variance 0.100 (Table 7d)

Table 7a: variance 0.025

PL	Profit 1	Profit 3	VSS
0.25	126313	117945	**8367**
0.50	205343	192013	**13329**
0.75	283843	266686	**17157**
1.00	360965	337983	**22982**

Table 7b: variance 0.050

PL	Profit 1	Profit 3	VSS
0.25	125616	116207	**9409**
0.50	203826	190013	**13813**
0.75	282276	264687	**17589**
1.00	360075	336302	**23773**

Table 7c: variance 0.075

PL	Profit 1	Profit 3	VSS
0.25	124994	114969	**10025**
0.50	202939	188051	**14887**
0.75	281321	261901	**19420**
1.00	357156	333191	**23965**

Table 7d: variance 0.100

PL	Profit 1	Profit 3	VSS
0.25	124359	112957	**11401**
0.50	201426	186032	**15394**
0.75	279989	259817	**20172**
1.00	356256	330528	**25728**

The hourly generated power of the thermal units in the form of the radar diagrams are shown in Figures 4 and 5. In our problem, the ISO has scheduled the power generation of the thermal units 1, 3, and 5 optimally. Figure 4 depicts the generated power variations of these three units with regard to the different penetration levels of the wind power. According to this figure, when the wind power penetration level (generation) increases, the power generation of these thermal units decreases. For instant, when penetration level has equaled to 0.75 or 1, unit 5 has been shut down in some hours like the first and last hours of the time span. Also, the generated power variations of these three units considering the different variances of the probability distribution function of the wind power forecasting error are shown in Figure 5. As this figure show, generated powers of the units have slight variations when variance changes. In this situation, the values of the reserve blocks and depleted reserves in the real time change significantly to compensate the power imbalance arising from inaccurate wind power forecasting.

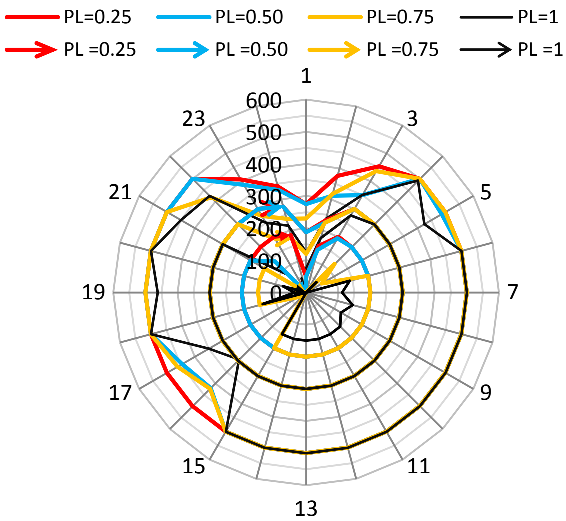

Figure 4: Hourly generated power of units 1(—), 3(→), and 5( ) with regard to the different penetration levels (MW)

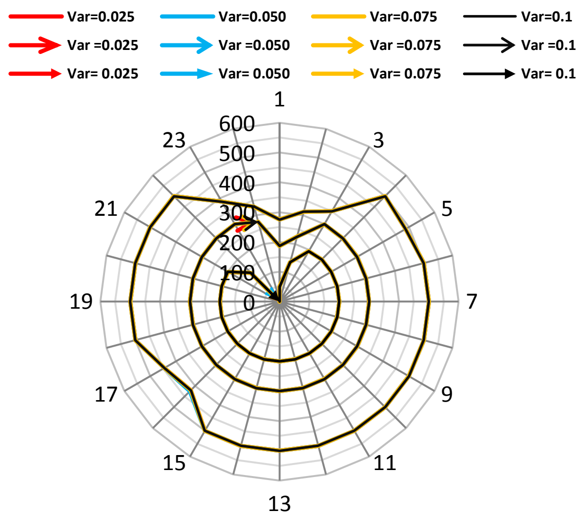

Figure 5: Hourly generated power of units 1(—), 3(→), and 5( ) with regard to the different variances (MW)

Amounts of the up and down reserve blocks (URB & DRB) and expected value (in different scenarios) of the depleted up and down reserves (URD & DRD) are represented in Figure 6. This reserves are sum of the reserves provided by the five thermal units in every hour and their value are calculated for PL=0.5 and Var=0.075. Based on these results, significant part of the reserves is provided as down reserve; in other words, the thermal units decrease their power production to balance the power production and consumption in the real time state. On the other hand, the amounts of the reserve blocks and depleted reserves provided by the demand are shown in Figure 7. For the demand side reserves, up reserves have an important role in the power balancing. It should be noted that the expected value of the depleted reserves is always smaller than the reserve blocks. Also, due to the applying the two stage stochastic programming, in the solution process the amounts of the reserve blocks (first stage decisions) are determined first, and then, the amounts of the depleted reserves (second stage decisions) are calculated.

The other second stage decision variables that play a role in the power balancing in the real time state are the spilled wind power and amount of the load shedding. The values of these two variables in the different scenarios during 24 hours are shown in Figures 8 and 9 for PL=0.5 and Var=0.075. According to Figure 8, in the scenarios 10 to 13 all of the generated wind power is not utilized; because wind farm produces abundant power in these scenarios and excess wind power is spilled to balance the power production and consumption in the real time. Also, it can be deduced from the Figure 9 that in the scenarios 1 and 2 the power demand is not supplied completely; in other words, in these scenarios load shedding occurs due to the less power production of the wind farm. In this situation, load shedding is a more economical way than the power production of the thermal units to supply demand.

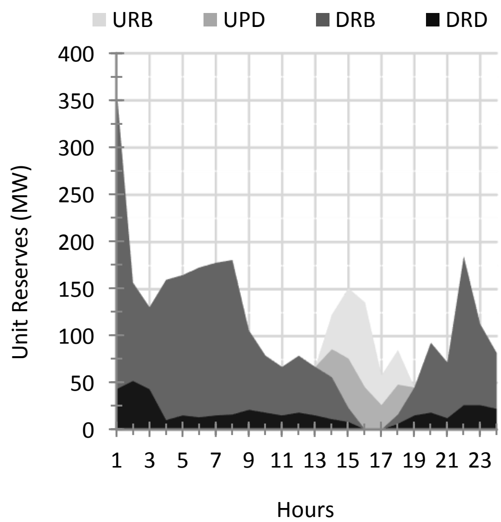

Figure 6: The up and down reserve blocks (URB & DRB) and expected value of the depleted up and down reserves (URD & DRD) of the thermal units (MW)

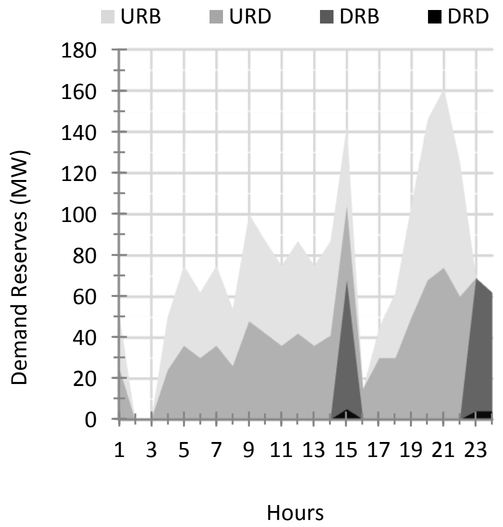

Figure 7: The up and down reserve blocks (URB & DRB) and expected value of the depleted up and down reserves (URD & DRD) of the demand (MW)

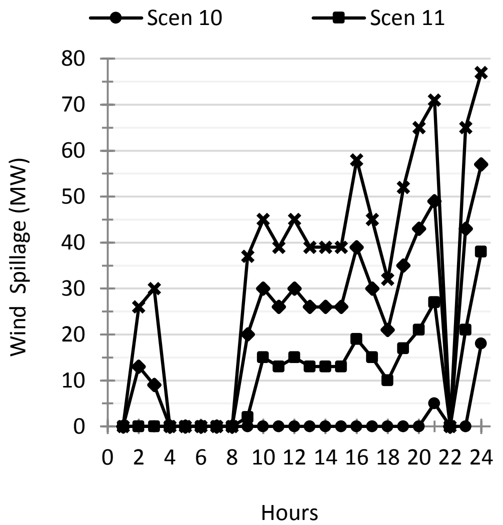

Figure 8: Hourly spilled wind power in different scenarios (MW)

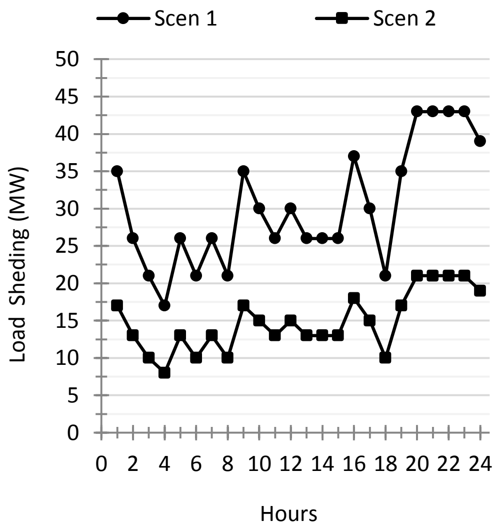

Figure 9: Amount of the load shedding in different scenarios (MW)

5. Conclusion

In this paper, the impact of the wind power uncertainty on the stochastic programming evaluation measures, namely EVPI and VSS metrics is studied. The proposed formulation clears joint energy and reserve markets considering wind energy uncertainty. The EVPI metric has been utilized to show the value of the accurate wind power forecasting. On the other hand, the VSS metric has been used to describe the advantages of the using stochastic programming instead of the deterministic one. The wind power uncertainty level modeled by use of two methods. First, the wind power penetration level considered as a portion of the base case wind power and then, the wind power forecasting error modeled as a normal probability distribution function that its variance can change. Also in the proposed model for the market clearing problem, the thermal units offered bids including power / Price / unit characteristics. Therefore, the average proposed price of the generated power reduced. Based on the obtained results for EVPI metric, it can be deduced that the ISO expected profit increases in the range of 16 to 21 percent if the ISO perform accurate forecasting of the wind power. Also, the values of the abovementioned metrics increase when the penetration level of the wind power or the variance of the wind power forecasting error increases. As the VSS metric variations showed, it revealed that by use of the stochastic programming instead of its deterministic counterpart to solve the market clearing problem, the value of the profit increases in the range of 6 to 9 percent. This profit increment is arising from the correct scheduling of the thermal and wind units and proper wind power uncertainty modeling by use of the first and second stage decision variables in the two stage stochastic programming framework. As a result, the VSS metric demonstrates the superiority of the stochastic programming against deterministic model in order to handle wind energy uncertainty in joint energy and reserve markets.

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