

Article

Multi-Objective Stochastic Optimization for Determining Set-Point of Wind Farm System

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Abstract: Due to the uncertainty in output power of wind farm (WF) systems, a certain reserve capacity is often required in the power system to ensure service reliability and thereby increasing the operation and investment costs for the entire system. In order to reduce this uncertainty and reserve capacity, this study proposes a multi-objective stochastic optimization model to determine the set-points of the WF system. The first objective is to maximize the set-point of the WF system, while the second objective is to maximize the probability of fulfilling that set-point in the real-time operation. An increase in the probability of satisfying the set-point can reduce the uncertainty in the output power of the WF system. However, if the required probability increases, the set-point of the WF system decreases, which reduces the profitability of the WF system. Using the proposed method helps the WF operator in determining the optimal set-point for the WF system by making a trade-off between maximizing the set-point of WF and increasing the probability of fulfilling this set-point in real-time operation. This ensures that the WF system can offer an optimal set-point with a high probability of satisfying this set-point to the power system and thereby avoids a high penalty for mismatch power. In order to show the effectiveness of the proposed method, several case studies are carried out, and the effects of various parameters on the optimal set-point for the WF system are also analyzed. According to the parameters from the transmission system operator (TSO) and wind speed profile, the WF operator can easily determine the optimal set-point using the proposed strategy. A comparison of the profits that the WF system achieved with and without the proposed method is analyzed in detail, and the set-point of the WF system in different seasons is also presented.

Keywords: energy management systems; multi-objective function; optimal set-points; stochastic optimization; wind farm operation



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1. Introduction

Wind energy, along with other renewable energy sources, is expected to grow substantially in the coming decades and play an important role in fulfilling future world energy needs as well as contributing to reducing global warming. The International Energy Agency (IEA) estimates that the annual wind power could increase to more than 2180 TWh by 2030, which is seven times higher than accumulative wind power production up to 2009 [1,2].

In order to convert wind energy into electricity, a vast number of wind turbine generators (WTGs) and the WF systems have been under construction recently and injecting huge amounts of power into the power system. However, due to the rapid increase in the penetration of wind power, future power systems may face numerous challenges from the supply variability and uncertainty in the output power of WF systems. For small WF systems, this uncertainty can be neglected because the total output power of the WF system

is small compared with the power system capacity. Recently, however, WF systems are designed with a huge installed capacity of up to several GW [3]. Therefore, the uncertainty in such large WF systems cannot be neglected, which adversely affects the operation of the power system in terms of power quality, system security, and system stability [4,5]. Various methods have been proposed to handle the uncertainty in the output power of the WF system in the operation of the power system [6,7].

The most common approach to reducing the effect of the uncertainty in the output power of the WF system is to use auxiliary supplies or reserve capacity, such as battery energy storage system (BESS) [8,9], power-to-hydrogen-to-power system [10], power-to-gas energy storage [11], controllable distributed generators [12], etc. The optimal control of these auxiliary systems can reduce the effect of wind power curtailment by peak shaving as well as by compensating for the power mismatch by the uncertainty in WF's output power. However, the operation and investment costs for this reserve capacity are quite expensive due to the installation of additional controllable distributed sources. In order to reduce these costs, the optimal scheduling and sizing of the reserve capacity are required, considering the uncertainty in the output power of the WF system.

There are several optimization algorithms and strategies for the operation of power systems that have been proposed for optimal sizing and scheduling of the reserve capacity using robust optimization [13], stochastic optimization [14,15], dynamic programming [16], and reinforcement learning (RL)/deep RL [17]. The authors in [13] have proposed a two-stage distributed robust optimization model to investigate the optimization scheduling for the multi-energy coupled system, considering the uncertainty in wind power. This model aims to minimize the expectation of the operation cost under the worst-case condition. The authors in [14,15] have developed a two-stage stochastic programming model for optimal unit commitment and dispatch decisions. The authors in [16] have proposed a capacity sizing method for wind power–energy storage systems using dynamic programming. The authors in [17] have developed a double deep Q-learning-based distributed operation strategy for a BESS considering the uncertainty in the output of wind power. However, these studies in [13–17] only focus on the optimal operation of the power system with a certain uncertainty in the output power of the WF system. The transmission system operators (TSOs) attempt to optimize the operation scheduling of resources outside the WF system, such as power plants and BESSs, to ensure the service reliability in the worst-case (i.e., the output power of the WF is at the lowest bound). A large uncertainty bound can lead to a significant increase in the operation and investment costs due to the requirement of the huge amount of reserve capacity in the power system.

In order to reduce the amount of reserve capacity in the system, the uncertainty in the output power of the WF system should be decreased by optimizing the set-point of the WF system. Various methods have been proposed to determine the set-points of WTGs and the WF system with different objectives [18–20]. The authors in [18] have proposed an operation strategy to optimize the set-point of each WTGs for maximizing the total output power of the WF system. The authors in [19] have investigated the wind power smoothing effect considering the different number of WTGs and the operation of WTGs in the WF system. The authors in [20] have developed an operational strategy to minimize the power deviation in the WF system by optimizing the set-point for each WTGs. However, most studies have focused on maximizing the output power of a WF system [18], smoothing wind power output [19], or minimizing power deviation in the WF system [20]. Determining the set-point of the WF system to reduce the uncertainty of the output power has not been considered in the literature.

Therefore, this study mainly focuses on developing a strategy for the WF operator to determine the optimal set-point of the WF system to reduce the uncertainty in the output power. In the proposed strategy, a multi-objective stochastic optimization model is developed based on mixed-integer linear programming (MILP). The multi-objective function consists of two single objectives; the first objective is to maximize the set-point of the WF system, while the second objective is to maximize the probability of fulfilling

the set-point of the WF system in real-time operation. As aforementioned, the set-point of the WF system helps TSO in determining the optimal scheduling for all external resources to fulfill the electric demands. In order to reduce the uncertainty of the output power, the WF operators need to assure that they can satisfy the set-point in the real-time operation and inject it into the power system. Any power mismatch between the actual output power and the committed power may result in a high penalty for the WF operator. To increase the profit of the WF by selling power to the grid, it is easy to observe that the WF should inform a high set-point to the TSO. However, if the set-point for WF systems increases, the probability of fulfilling such high set-point decreases. By using the proposed method, the WF operator is able to determine the set-point for the WF system by deciding a trade-off between maximizing the set-point and increasing the probability of fulfilling that set-point. A high probability of fulfilling the set-point helps the WF system avoiding a penalty for power mismatch between the actual output power and the set-point of output power and also reduces the uncertainty of the output power of the WF system. This helps the TSO to significantly reduce the reserve capacity and thereby reducing the investment and operation costs for the whole system. The effect of the ratio of weight factors and the minimum probability requirement on the set-point of the WF system are analyzed in detail in the simulation section. In addition, a comparison of the profits that the WF system achieved with and without the proposed method is analyzed in detail and the set-point of the WF system is also presented with different wind speed profiles for the four seasons in a year. The major contributions of this study are listed as follows:

- A multi-objective stochastic optimization model is developed to determine the optimal set-point of WF with different wind probability density functions. This helps to reduce the uncertainty of the output power of WF and thereby to reduce the requirement of reserve capacity;
- A novel algorithm is proposed for a trade-off between maximizing the set-point of WF and increasing the probability of satisfying this set-point in real-time operation. With any input information, the WF operator is able to find out the optimal set-point with a required probability;
- By increase, the probability of fulfilling the set-point in real-time operation, the uncertainty of the output power of WF can be decreased. This results in the reduction of operation cost of the whole system.

This paper is arranged as follows: In Section 2, the system configuration and operation of the system are presented. In Section 3, the detailed strategy for determining the optimal set-point of the system WF is presented. In Section 4, a MILP-based mathematical model for multi-objective stochastic optimization is formulated. In Section 5, the numerical results are analyzed, and the comparison on the set-point of the WF system is also presented. The conclusion of this study is summarized in Section 6.

2. System Configuration

Figure 1 depicts a typical WF system, which is connected to the power system to supply electric demands. The whole system is operated by a transmission system operator (TSO). The TSO's primary task is to determine the optimal scheduling for supply resources (i.e., power plants and renewable energies sources) and manage the operation of the entire system in real-time operation. To optimize the scheduling for power plants, TSO requires the set-point from the WF system. The WF system normally operates by the WF operator, and this management system is also responsible for determining the optimal set-point of the WF system and informing the TSO. This set-point of the WF system plays a vital role in the optimal scheduling of other resources. Therefore, the WF system must be able to fulfill its set-point in real-time operation. Any power mismatch between actual output and committed power results in a massive penalty for the WF system from TSO. Therefore, this study mainly focuses on determining the optimal set-point of a WF by a trade-off between maximizing the set-point and increasing the probability of satisfying the set-point in the

real-time operation. The operation strategy for the WF system is presented in detail in the next section.

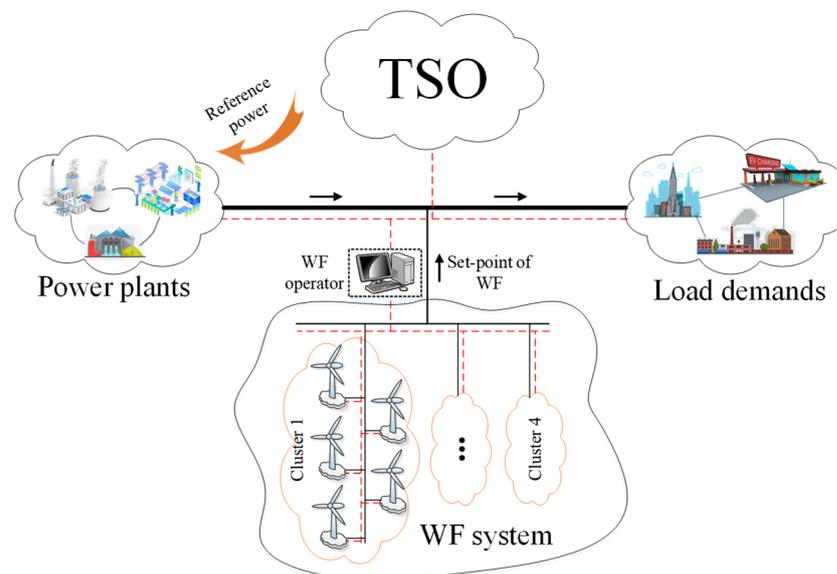


Figure 1. A typical wind farm (WF) system configuration.

3. A Strategy for Determining the Optimal Set-Point of WF System

In this section, we present a strategy for the WF operator to determine the optimal set-point of the WF system, as shown in Figure 2. First, the wind speed parameter is assumed to comply with the Weibull distribution, and the detailed information about the Weibull parameters (i.e., Weibull shape and scale) are taken as input data. Based on the probability density function (PDF) of wind speed data, numerous scenarios for wind speed at each interval is generated to ensure the accuracy of the proposed method. However, a large number of scenarios significantly increases the computation burden for the simulation system. Therefore, a scenario reduction algorithm was developed to merge similar scenarios, as shown in detail in Algorithm 1. After merging all similar scenarios, the output capacity of each WTGs is calculated using (7) with the corresponding wind speed in each scenario. The total output power of the WF system in each scenario is used to determine the optimal set-point of the WF system by solving a multi-objective stochastic optimization model. The first objective is to maximize WF's profitability by selling power to the power system (i.e., maximizing the set-point). However, the WF operator cannot always ensure that the WF system always meets the maximum set-point in real-time operation. Therefore, the WF operator may try to make a trade-off between maximizing the set-point of the WF system and increasing the probability of fulfilling that set-point considering the ratio of weight factors and the minimum probability requirement. In order to determine the actual probability for each set-point of the WF system, we also developed Algorithm 2, and the detailed explanation for Algorithm 2 is presented in Section 4.

As stated previously, Algorithm 1 was developed to reduce the number of scenarios by merging similar scenarios in the scenario set. First, the Kantorovich distances are calculated for each pair of scenarios in the scenario set, and then a similar pair of scenarios (k, s) is determined, as shown in Algorithm 1. Because the two similar scenarios often do not contribute much in evaluating the proposed method, one scenario can be omitted, and the probability for the other is updated simply by the sum of the probabilities of both scenarios [21,22]. This process is repeated until the number of scenarios reduced to the minimum scenario requirement.

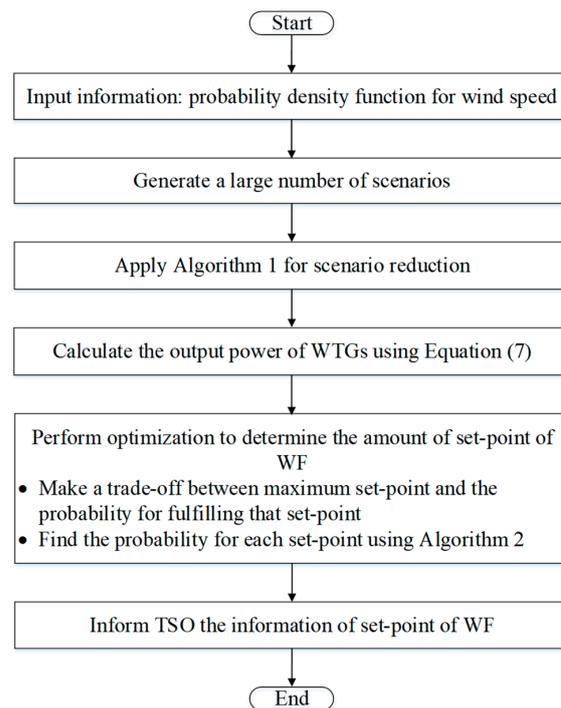


Figure 2. The strategy for determining the set-point of the WF system.

Algorithm 1: Scenario Reduction

Generate S scenarios

Scenarios i : $s(i) = \{\lambda_1^i, \lambda_2^i, \lambda_n^i, \dots, \lambda_N^i\}$

while $S < S_{req}$ **do**:

for $s = 1$ to S **do**:

for $k = 1$ to S **do**:

 //Calculate Kantorovich distance

$$d(s, k) = \left(\sum_{n=1}^N (\lambda_n^s - \lambda_n^k)^2 \right)^{1/2}$$

end

end

 //determine scenario s that is reduced

$$\min_{s \in S} p(s) \cdot \left\{ \min_{\substack{k \neq s \\ k \in S}} (p(k) \cdot d(s, k)) \right\}$$

 //update number of scenarios

$$S \leftarrow S - 1$$

 //determine scenario k that nearest the reducing scenario s

$$k = \arg \min_{\substack{k \neq s \\ k \in S}} \{ p(s) \cdot p(k) \cdot d(s, k) \}$$

 //change probability of scenario k

$$p(k) \leftarrow p(k) + p(s)$$

end

In the next section, a detailed mathematical model is developed to determine the set-point of the WF system with different input data.

4. Mathematical Model

In this section, a mathematical model is developed based on mixed-integer linear programming (MILP) to determine the optimal set-point of the WF system. This optimal set-point is determined by making a trade-off between maximizing the set-point of WF and increasing the probability of fulfilling this set-point in real-time operation. Suppose the WF operator informs a high set-point, which is more profitable; however, the probability of fulfilling that set-point may significantly reduce. Hence, it is important having a trade-off between these two factors (i.e., maximizing the set-point and increasing the probability of fulfilling that set-point). The following mathematical model is developed to analyze the effects of different parameters on determining the set-point of the WF system.

First, in order to evaluate the effectiveness of the proposed method, we assume that the wind speed at WTGs follows Weibull distribution during each season as in [22,23]. The probability density function (PDF) and cumulative distribution functions (CDF) of the Weibull distribution are shown in (1) and (2), respectively. The Weibull shape (k) and Weibull scale (λ) are taken as input parameters in different seasons, and these parameters are taken from [23].

$$f(v) = \frac{k}{\lambda} \left(\frac{v}{\lambda}\right)^{k-1} \exp\left[-\left(\frac{v}{\lambda}\right)^k\right] \quad (1)$$

$$F(v) = 1 - \exp\left[-\left(\frac{v}{\lambda}\right)^k\right] \quad (2)$$

To ensure accuracy in determining the optimal set-point of a WF system, numerous scenarios (S) needs to be generated using PDFs and CDFs. Each scenario is a row vector V_s consisting of the wind speed at each interval of the day from $v_{1,s}$ to $v_{T,s}$, as shown in (3). The probability of each scenario ($prob_s$) is determined by multiplying the probability of each time interval having a certain wind speed $v_{s,t}$, as shown in (4). In this study, we assume that the number of scenarios is large enough, and therefore the total probability of occurrence of the entire scenario set (S) is 1, as shown in (5).

$$V_s = (v_{s,1}, v_{s,2}, \dots, v_{s,t}, \dots, v_{s,T}) \quad \forall s \in S \quad (3)$$

$$prob_s = \prod_{t=1}^T (p_{s,t}) \quad \forall s \in S \quad (4)$$

where: $p_{s,t}$ is the probability of interval t having wind speed $v_{s,t}$

$$\sum_{s=1}^S prob_s = 1 \quad (5)$$

The total output power of the WF system is determined by the total output power of each WTGs, as shown in (6), where the amount of output power of each WTG is calculated by (7) for each corresponding input of wind speed. In order to determine the optimal set-point of the WF system, a multi-objective function is developed, as shown in (8). The first part of (8) represents the normalization of the set-point of the WF system, where the minimum and maximum value of the WF system's output power is determined using (9) and (10), respectively. The second part of (8) is the probability of satisfying the set-point in real-time operation for the WF system. The weight factors α and β show the importance of every single objective in the multi-objective function. The constraints (11) and (12) show the relationship between the weight factors α and β , the values of α and β must be in the range (0, 1) and their sum needs to be 1. If the value of α is close to 1, the WF operator is more concerned with maximizing the set-point of the WF system. On the contrary, if the value of α is close to 0, the WF operator is more concerned about the possibility that the

WF system can satisfy the set-point in real-time operation. Constraints (13), (14) represent the bound of the set-point of the WF system and constraint (15) represents the minimum probability requirement for satisfying the set-point of the WF system in real-time operation.

$$P_{WF,s,t}^{Out} = \sum_{n=1}^N P_{n,s,t}^{WTG} \quad \forall s \in S, t \in T \quad (6)$$

$$P_{n,s,t}^{WTG} = \begin{cases} 0 & v_{n,s,t} < v_{cut-in} \text{ or } v_{n,s,t} > v_{cut-out} \\ \frac{1}{2} C_p(\beta, \lambda) \rho \pi R^2 v_{n,s,t}^3 & v_{cut-in} \leq v_{n,s,t} < v_{rate} \\ P_{n,rate}^{WTG} & v_{rate} \leq v_{n,s,t} \leq v_{cut-out} \end{cases} \quad \forall n \in N, s \in S, t \in T \quad (7)$$

$$\text{Max} \left\{ \alpha \cdot \left(\frac{P_{WF}^{Sch} - P_{WF,min}^{Out}}{P_{WF,max}^{Out} - P_{WF,min}^{Out}} \right) + \beta \cdot \left(\text{prob} \left(P \geq P_{WF}^{Sch} \right) \right) \right\} \quad (8)$$

$$P_{WF,min}^{Out} = \min \left(\sum_{t=1}^T P_{WF,s,t}^{Out} \right) \quad \forall s \in S \quad (9)$$

$$P_{WF,max}^{Out} = \max \left(\sum_{t=1}^T P_{WF,s,t}^{Out} \right) \quad \forall s \in S \quad (10)$$

$$\alpha + \beta = 1 \quad (11)$$

$$0 \leq \alpha, \beta \leq 1 \quad (12)$$

$$0 \leq P_{WF}^{Sch} \leq T \cdot P_{WF,rate}^{Out} \quad (13)$$

$$P_{WF,rate}^{Out} = \sum_{n=1}^N P_{n,rate}^{WTG} \quad (14)$$

$$\text{prob} \left(P \geq P_{WF}^{Sch} \right) \geq \text{prob}_{req} \quad \forall t \in T \quad (15)$$

The probability of fulfilling the set-point of WF in the left-side of constraint (15) is determined by Algorithm 2. This algorithm helps the WF operator determine the probability that the WF system can meet the set-point in real-time operation. Algorithm 2 checks the output power of the WF system in each scenario and compares it with a certain set-point (P_{WF}^{Sch}) of WF. Suppose the output power of a scenario is greater than P_{WF}^{Sch} , the probability for satisfying the set-point is updated by adding that scenario's probability. After checking all scenarios, the WF operator can determine the probability of satisfying the set-point.

Algorithm 2: Determining probability of a set-point

Input: all N_s scenarios

for $s = 1$ to N_s do:

if $\sum_{t=1}^T P_{WF,s,t}^{Out} \geq P_{WF}^{Sch}$ do:

$\text{prob} \left(P \geq P_{WF}^{Sch} \right) \leftarrow \text{prob} \left(P \geq P_{WF}^{Sch} \right) + \text{prob}_s$

end

end

In the next sections, the optimal set-point of the WF system is presented in detail with different PDFs of wind speed. Furthermore, the effects of various parameters on the optimal set-point of the WF system is analyzed in detail.

5. Numerical Results

In this section, different probability density functions (PDFs) are presented for the four seasons in a year, respectively. In each season, the optimal set-point is analyzed in detail based on the minimum probability requirements and the ratio of weight factors in the objective function (8).

5.1. Input Data

As stated earlier, wind speed follows the Weibull distribution. In this study, we analyze the changes in the set-point of the WF system during different seasons in a year. Each season has different parameters for the Weibull distribution. PDFs and CDFs of wind speed are shown in Figure 3a,b for different seasons, respectively. It can be observed the average wind speed in fall and summer is higher than in spring and winter. This means that the set-point in fall and summer is usually higher in spring and winter. Detailed parameters for Weibull shape and scale are tabulated in Table 1 for different seasons.

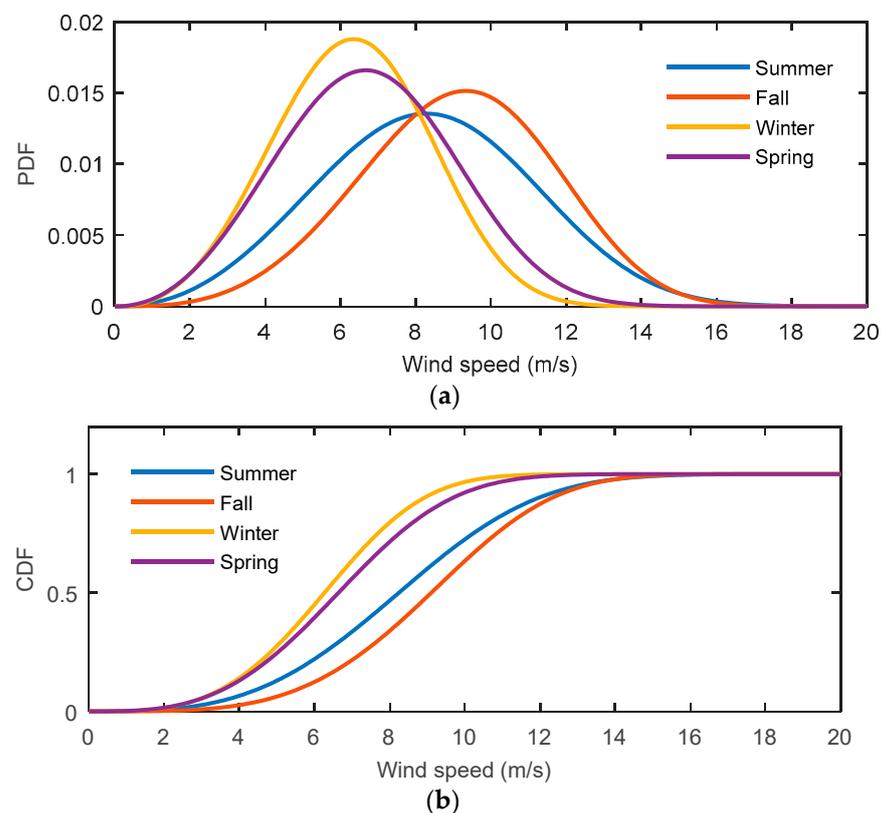


Figure 3. Weibull distribution model of wind speed in different seasons: (a) probability density function; (b) cumulative distribution function.

Table 1. Detailed parameters for Weibull distribution in different seasons [23].

Seasons	Parameters for Weibull Distribution	
	Weibull Shape (-)	Weibull Scale (m/s)
Spring	3.2	7.5
Summer	3.24	9.29
Fall	3.99	10.04
Winter	3.61	7.03

The test WF system consists of 20 WTGs, and the close WTGs are grouped to form a cluster. In this study, we assume that 20 WTGs are grouped into 4 clusters, and each cluster has 5 WTGs, as shown in Figure 1. All WTGs in the WF system has the same configuration, and detailed information for WTGs is presented as follows [24].

- The rated power is 10 MW;
- The minimum operation point is 10% of the rated power, i.e., 1 MW;
- The maximum ramp-up/ramp-down is 20% of the rated power, i.e., 2 MW.

To determine the optimal set-point of a WF system and analyze the effectiveness of the proposed method, the multi-objective stochastic optimization model is implemented in Visual Studio C++ integrated with IBM ILOG CPLEX 12.6 [25].

5.2. Determine Optimal Set-Point of WF in Spring with a Large Scenario Set

In this section, a detailed analysis of the optimal set-point of the WF system is presented with wind speed data in spring. The optimal set-point of the WF system is the total energy that the WF system injects into the power system during a day with a wind speed profile in spring. The scheduling horizon is a day, and each interval is set to 1 h. The effects of minimum probability requirement and ratio of weight factors on the set-point of WF are also presented in detail.

In order to ensure the accuracy of the proposed method, we generate 10,000 scenarios. However, a large number of scenarios increases the computation burden for the simulation system. Therefore, Algorithm 1 is used to reduce the number of scenarios to 1000. In the first case study, the ratio of weight factors (α/β) is fixed to 1/1, and the minimum probability requirement in constraints (15) is varied from 0.1 to 0.95. The optimal set-point of the WF system is shown in Figure 4. It is easy to observe that the set-point of WF decreases if the minimum probability requirement increases. The set-point is nearly 1400 MWh if the minimum probability requirement is 0.1. This means that the WF can only guarantee to satisfy the set-point (i.e., 1400 MWh) with a probability of 10% in real-time operation. However, if the set-point reduces to nearly 950 MWh, the WF can guarantee to satisfy this set-point with a probability of up to 95% in real-time operation. The actual probability of fulfilling a given set-point is shown in detail in the second axes of Figure 4. It requires a trade-off between maximizing the set-point of WF and maximizing the probability of satisfying that set-point. This is because the WF operator may face a massive penalty for the power mismatch between the actual output power and the set-point of output power during the real-time operation of the power system. Therefore, it can be concluded that the set-point should be set at around 1000 MWh in this season, and the WF can guarantee to fulfill this set-point with a probability of up to 85%.

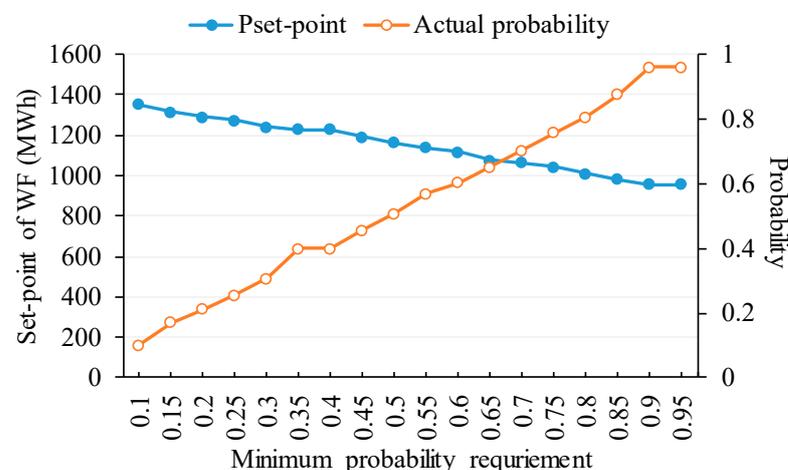


Figure 4. The set-point of WF with different values of minimum probability requirement.

In the second case study, the minimum probability requirement is set to 0.85 to avoid the penalty for power mismatch, while the weight factor α is varied from 0 to 1. The value of α close to 1, the WF operator tended to pay more attention to the maximum the set-point of the WF system. By contrast, if the value of α close to 0, the WF operator tends to pay more attention to the high probability of fulfilling this set-point in real-time operation (i.e., reduce the uncertainty of the output power of WF). Depending on information from TSOs, such as the selling price and the penalty for mismatch power, the WF operator will determine the ratio of weight factors (α/β) to take a trade-off between the profits from selling wind power and the possible penalty of power mismatch. It can be observed from Figure 5 that the set-point of the WF system is determined with different values of the weight factor α . In order to ensure the probability of satisfying the set-point from 90% in real-time operation, the set-point of the WF system should be set in a range from 800 MWh to around 1000 MWh, which corresponds to the value of the α weight factor from 0.05 to 0.8.

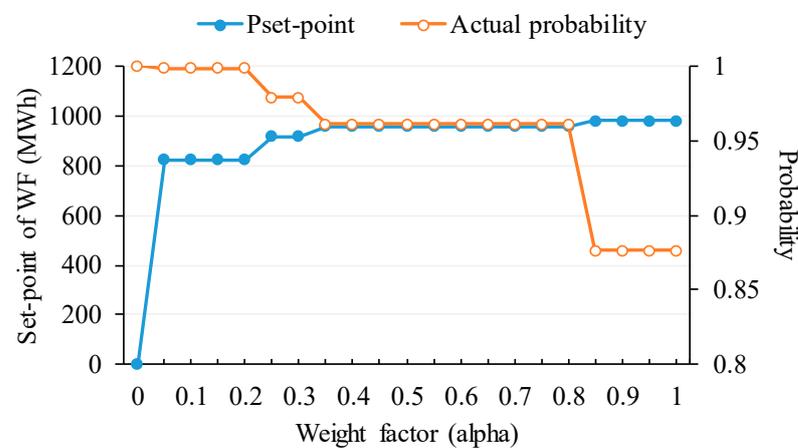


Figure 5. The set-point of WF with different values of weight factor (α).

Finally, the effects of the value of weight factor α and the minimum probability requirement on determining the set-point of the WF system are shown in Figure 6. In this case study, the value of weight factor α was varied from 0.05 to 1, and the minimum probability requirement is varied from 0.5 to 0.9. It can be observed from Figure 6 that the effect of the minimum probability requirement on the set-point of the WF system is negligible, especially in the case of the small value of α , while the value of α has a high effect on the set-point of the WF system. The maximum set-point of the WF system is 1160 MWh, corresponding to a value of α of 1 and the minimum probability requirement of 0.5. However, as mentioned earlier, the value of α and the minimum probability requirement is determined based on a trade-off between the profits from selling wind power and the penalty of power mismatch between the actual output and the committed power of the WF system. Based on the above-detailed analysis, the WF operator can easily determine the optimal set-point with any value of α and the minimum probability requirement.

5.3. Comparison of the Optimal Set-Point with and Without the Proposed Method

To show the effectiveness of the proposed method, a detailed comparison of the set-point of the WF system will be presented using the proposed method and not using the proposed method. As stated in Section 4, the proposed method is to determine the optimal set-point of a WF system by making a trade-off between maximizing the output power of the WF system and maximizing the probability of satisfying this set-point in real-time operation. This can reduce the penalty for mismatch power between the set-point and the actual output power. Without the proposed method, the WF operator usually sets the set-point based on the history data (i.e., PDF). However, this method can lead to the

following two problems, (1) a low set-point with a high probability and (2) a high set-point with a low probability. Both cases can reduce the profit of the WF system.

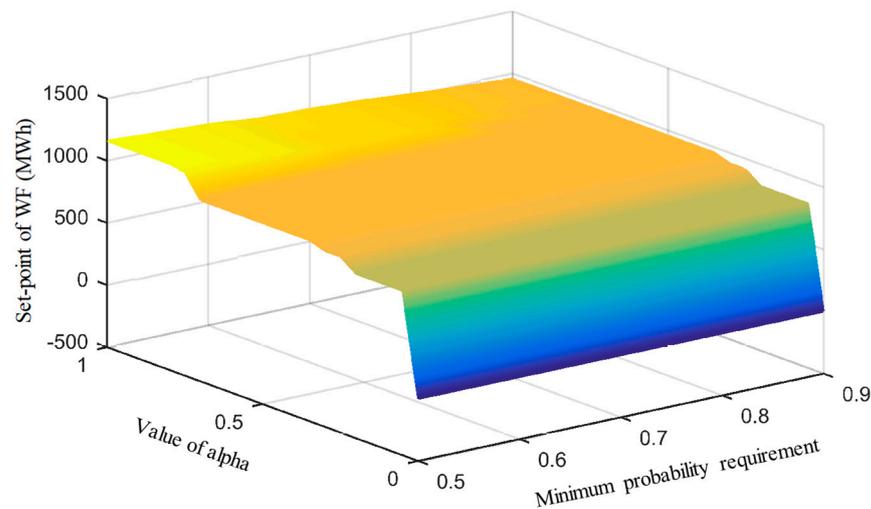


Figure 6. The set-point of WF with different values of weight factor (α) and minimum probability requirement.

Therefore, in this section, we analyze the effect of the set-point on the profit of a WF system using the wind speed profile in spring. Without the proposed method, we assume that the set-point of a WF system is 750 MWh and 1000 MWh. Based on the probability density function in Section 5.1, the corresponding probability to satisfy each set-point in real-time operation is easily determined. The detailed set-points of the WF system and the probability of fulfilling these set-points are tabulated in Table 2.

Table 2. Set-point of WF with and without the proposed method.

Without Proposed Method		With Proposed Method	
Set-Point (MWh)	Probability	Set-Point (MWh)	Probability
750	0.99	980	0.87
1000	0.81	-	-

To calculate the profit of the WF system, we assume that the selling price is 100 KRW/kWh, and the penalty for the mismatched power is 500 KRW/kWh. The profit of the WF system is calculated based on the set-point and the amount of mismatch power between the set-point and the actual output power in real-time operation, as shown in Table 3. When the set-point is small (i.e., 750 MWh), the penalty for the mismatched power decreases significantly because the WF system can ensure to meet this set-point with the probability of 0.99. However, the amount of selling power to the power system is also small and thus significantly reducing the profitability of the WF system. Conversely, when the set-point increases (i.e., 1000 MWh), the probability of fulfilling the set-point in real-time operation is only 0.81. Therefore, the WF system often faces a high penalty due to mismatched power. That is the main reason why we proposed a new algorithm to determine the optimal set-point of the WF system to maximize the total profit for the WF system. It can be seen that the optimal set-point is 980 MWh obtained using the proposed method, which provides the highest profit with a different amount of mismatch power between the set-point and the actual output power.

Table 3. Profit of WF with and without the proposed method ($\times 10^3$ KRW).

Set-Point (MWh)	Possible Power Mismatch (MWh)				
	10	20	30	40	50
750	74,200	74,150	74,100	74,050	74,000
1000	80,050	79,100	78,150	77,200	76,250
980 (optimal case)	84,610	83,960	83,310	82,660	82,010

5.4. Optimal Set-Point of WF in Different Seasons

In the previous sections, the effects of the various parameters on determining the set-point of the WF system were analyzed in detail using the wind speed data in spring. In this section, the set-point of the WF system is determined with different input parameters of wind speed for other seasons (i.e., summer, fall, and winter), and the minimum probability requirement is varied from 0.1 to 0.95.

The set-point of the WF system is shown in detail in Figure 7a–c for summer, fall, and winter, respectively. Similar to the discussion in Section 5.2, the set-point of the WF system will decrease if the minimum probability requirement increases. To ensure power supply reliability (i.e., reducing the power mismatch between the set-point of WF's output power and the actual output power), the minimum probability requirement is usually set greater than or equal to 0.85. If the minimum probability requirement is varied from 0.85 to 0.95, it can be seen from Figure 7a–c that the set-point changes from 1710 MWh to 1760 MWh for summer, from 2180 MWh to 2430 MWh for fall, and from 840 MWh to 870 MWh for winter, respectively. The change in the set-point of the WF system is reasonable with the given input data of wind speed in Table 1. The average value of the wind speed in fall and summer is much larger than that in winter. Therefore, although the minimum requirement probability is the same, the WF operator could determine a high set-point for the WF system during summer and fall, while this value usually decreases significantly during spring and winter. A detailed comparison of the set-point of the WF system is analyzed in detail in the next section.

5.5. Comparison of the Optimal Set-Point of WF among the Four Seasons

In this section, the set-point of the WF system and the actual probability to satisfy each set-point in real-time operation are presented and compared among the four seasons in a year with different wind speed parameters. In this case study, the weight factor α is varied from 0 to 1, and the minimum probability requirement is set to 0.85 to avoid a penalty for power mismatch. If the value of α is 0, the WF operator is only interested in maximizing the probability of satisfying the set-point of a WF system. Therefore, the set-point is set to 0, and the probability of fulfilling this set-point is 1. On the contrary, if the value of α varies from 0.4 to 1, the set-point of the WF system does not change much, as shown in Figure 8a. Therefore, the set-point of WF systems can be set at 980 MWh, 1760 MWh, 2430 MWh, 870 MWh for spring, summer, fall, and winter, respectively. It can be observed that the set-point of WF is largest in the fall and the smallest in winter. Corresponding to each set-point of the WF system, the WF operator always ensures that the probability of fulfilling the set-point in real-time operation is greater than or equal to 0.85, as shown in Figure 8b.

To show more clearly the difference in the set-point of the WF system during different seasons in a year, the detailed set-points of the WF system are tabulated in Table 4 with the optimum value in spring as a reference case. It can be observed that the set-points of the WF system increase significantly during summer and fall. If the value of α varies from 0 to 1, the increase in the set-point of WF could be from 72% to 100% in summer and 140% to 153% in fall compared with the set-point in spring, while the set-point in winter is slightly lower than in spring (i.e., from -7% to -12%).

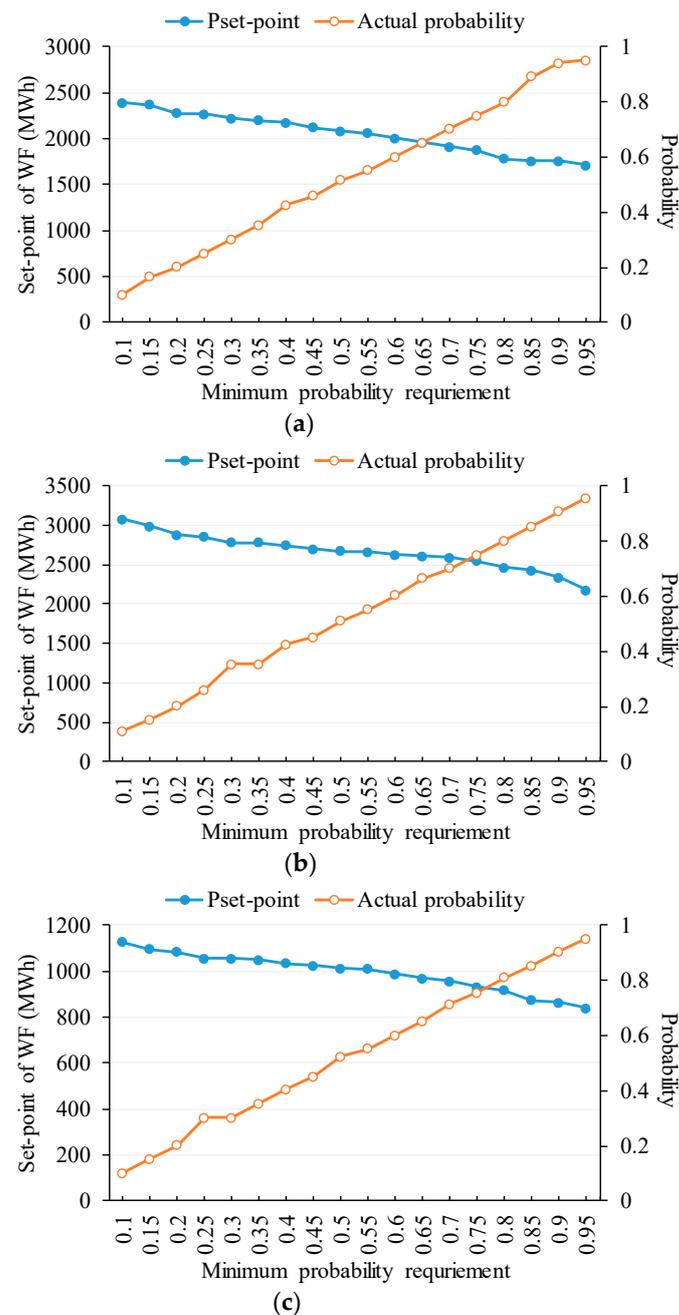


Figure 7. The set-point of WF with a different value of minimum probability requirement: (a) summer; (b) fall; (c) winter.

In this study, a detailed analysis of the set-point of the WF system was presented with different weight factors in the multi-objective function and wind speed profiles. It can be seen that the proposed method plays an important role in determining the optimal set-point for the WF system. This enables the WF operator to maintain a high profit by avoiding a penalty for any mismatch power between the set-point and the actual output power in real-time operation. The proposed method can be integrated into the energy management system of the WF system, and the optimal set-point is updated with any input information, such as wind speed profile and weight factors. In this study, the proposed method was tested with seasonal input data, and the optimal set-point is determined for a day in the season. However, the proposed method is also applicable to the different time scheduling horizons (e.g., an hour, a day, a week, etc.) with the corresponding probability density functions.

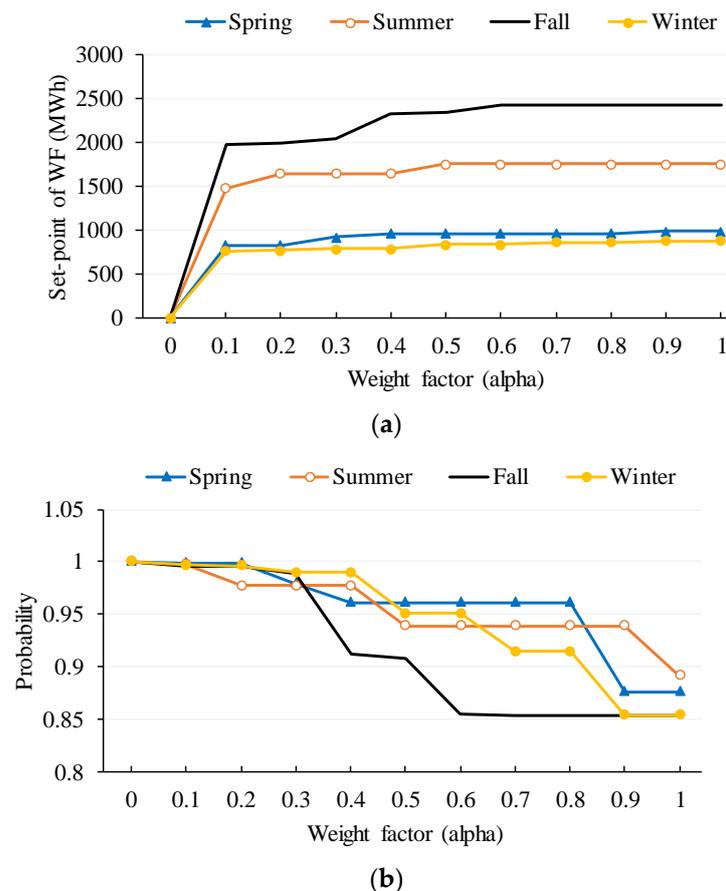


Figure 8. Comparison of the optimal results among different seasons: (a) the set-point of WF; (b) the probability of fulfilling the optimal set-point.

Table 4. Set-point of WF in different reasons and value of weight factors.

Value of Alpha	Increase in the Set-Point of WF			
	Spring (%)	Summer (%)	Fall (%)	Winter (%)
0	0.00	0.00	0.00	0.00
0.1	0.00	79.03	140.46	−7.64
0.2	0.00	100.11	141.34	−7.16
0.3	0.00	80.02	122.18	−14.33
0.4	0.00	72.10	143.30	−18.10
0.5	0.00	83.10	144.43	−12.61
0.6	0.00	83.10	153.06	−12.61
0.7	0.00	83.10	153.19	−10.02
0.8	0.00	83.10	153.19	−10.02
0.9	0.00	78.72	147.14	−11.21
1	0.00	78.83	147.14	−11.21

6. Conclusions

In this study, a multi-objective stochastic optimization model was proposed to determine the set-point for a WF system. The first objective is to maximize the set-point of the WF system, while the second objective is to maximize the probability of fulfilling that set-point in real-time operation. The proposed strategy mainly focuses on determining the set-point of the WF system by a trade-off between these two objectives considering the ratio of the weight factors in the multi-objective function and the minimum probability requirement. A comparison of the profit of the WF system using the proposed method and not using the proposed method were analyzed in detail. The results indicate that the WF system can always ensure the maximum profit at the optimal set-point achieved by

the proposed method. Using the proposed method not only maintains a high set-point for the WF system but also ensures a high probability for satisfying this set-point in real-time operation. According to the wind speed profile in spring, the set-point of the WF system is set from 800 MWh to 1000 MWh with the value of α from 0.05 to 0.8 to ensure the probability of satisfying the set-point greater than or equal to 0.95 in real-time operation. A similar analysis also has been carried out with different wind data for four seasons, and the set-point of WF systems should be set at 980 MWh, 1760 MWh, 2430 MWh, 870 MWh for spring, summer, fall, and winter, respectively. It can be observed that the set-point of the WF system is largest in fall and is lowest in winter. With these set-points of WF in the four seasons, the WF operator always ensures that the probability of fulfilling these set-points in the real-time operation is greater than or equal to 0.85.

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Nomenclatures:

Sets

T	Scheduling horizon
S	Set of scenarios
N	Set of WTGs

Indices

t	Index of time intervals
s	Index of scenarios
n	Index of WTGs

Parameters

$f(v), F(v)$	Probability density function and cumulative distribution function of wind speed
k, λ	Weibull shape and scale parameters
$v_{s,t}$	Wind speed at t in scenario s
V_s	Wind speed vector in scenario s
$prob_s$	Probability of scenario s
$P_{n,s,t}^{WTG}$	Output power of WTG n at t in scenario s
$P_{n,rate}^{WTG}$	Rated output power of WTG n
$v_{cut-in}, v_{cut-out}$	Cut-in, cut-out wind speed
v_{rate}	Rated wind speed of WTGs
$P_{WF,s,t}^{Out}$	Output power of the WF system at t in scenario s
P_{WF}^{Sch}	Optimal set-point of the WF system
$prob(P \geq P_{WF}^{Sch})$	Probability of fulfilling the set-point in real-time operation
$prob_{req}$	Minimum required probability of fulfilling the set-point in real-time operation
α, β	Weigh factors of different objective
$P_{WF,min}^{Out}$	Minimum set-point of the WF system
$P_{WF,max}^{Out}$	Maximum set-point of the WF system
$P_{WF,rate}^{Out}$	Rated output power of the WF system

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