

Bi-objective Layout Optimization for Multiple Wind Farms Considering Sequential Fluctuation of Wind Power Using Uniform Design

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Abstract—The fluctuation of wind power brings great challenges to the secure, stable, and cost-efficient operation of the power system. Because of the time-correlation of wind speed and the wake effect of wind turbines, the layout of wind farm has a significant impact on the wind power sequential fluctuation. In order to reduce the fluctuation of wind power and improve the operation security with lower operating cost, a bi-objective layout optimization model for multiple wind farms considering the sequential fluctuation of wind power is proposed in this paper. The goal is to determine the optimal installed capacity of wind farms and the location of wind turbines. The proposed model maximizes the energy production and minimizes the fluctuation of wind power simultaneously. To improve the accuracy of wind speed estimation and hence the power calculation, the time-shifting of wind speed between the wind tower and turbines' locations is also considered. A uniform design based two-stage genetic algorithm is developed for the solution of the proposed model. Case studies demonstrate the effectiveness of this proposed model.

Index Terms—Wind farm layout optimization (WFLO), wind power fluctuation, bi-objective optimization, uniform design.

I. INTRODUCTION

SIGNIFICANT efforts to explore wind energy resources have been made all around the world to cope with the growing energy demand [1]. Wind turbines play a vital role

in the energy conversion by extracting energy from wind. In the downstream, there is a wake from the wind turbine that slows down the wind speed. The wake effect is the aggregated influence on the energy production of wind farms [2]. And the layout optimization of the wind farm is important to the efficiency of energy production.

Many studies have been investigated on the formulations and algorithms for wind farm layout optimization (WFLO), as shown in Table I. The research conducted by Mosetti *et al.* [3] in 1994 can be considered as the beginning of the systematic study for WFLO. The genetic algorithm (GA) is employed to address the WFLO problem with the maximum energy at minimum cost formulated as the objective, and the Jensen wake model is used to find the wake effect between different turbines. Since this pioneering work, some single-objective or multi-objective optimization models have been established considering the wake effect between turbines. The primary goal is to optimize the amount of energy or the financial index of wind farm.

Wan *et al.* propose a novel particle swarm optimization algorithm [4] to determine the optimal wind turbine locations for maximum wind energy production. Further, a particle swarm optimization based WFLO model is also proposed in [5]. This model copes with the uncertainty of wind speed and wind direction by means of the joint probability distribution function. In [6] the approach for the optimal determination of the turbine type, position and the hub height is designed to maximize the expected profits considering the main risk management aspects. Chen and MacDonald [7] develop an enhanced leveled cost model of wind farm by taking into account the landowner remittance fees and land-plot shapes. In [8], the annual economic benefit (AEB) is designed as the objective of WFLO problem, considering the annual benefit of production and the costs of energy, cable and land. In [9], a wind farm cost model for WFLO formulation considering the investment cost and the present value of operation cost during the entire wind-farm life span is discussed by González *et al.*, the evolution algorithm is used for the optimum wind farm configuration. Recently Ju *et al.* [10] propose a support vector regression guided GA to solve the WFLO problem. The landowners' willingness is considered in the objective.

On the other hand, the computational complexity of WFLO is also a concern. Some mathematical programming approaches are developed to reduce the computational cost.

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TABLE I
EXISTING APPROACHES FOR THE WFLOP

Category	Objective	Algorithm	References
<i>Heuristic algorithm</i>			
Single-objective	Wind energy production	Improved Gaussian PSO	[4]
	Wind energy production	PSO	[5]
	Maximum energy production at minimum cost	Genetic algorithm (GA)	[3]
	Expected profits of the wind farm	GA	[6]
	Cost of energy in \$/MW·h	GA	[7]
	Annual economic benefit (AEB)	GA	[8]
	Global wind farm cost	Evolution algorithm	[9]
	Wind power production	Support vector regression guided GA	[10]
	<i>Mathematical programming</i>		
	Net power production	Mixed Integer Programming	[11], [12]
Multi-objective	Wind energy production	Mixed integer linear and quadratic programming formulations	[13]
	Wind power production	Gradient-based optimization	[14], [15]
	Wind power production	Sequential convex programming (SCP)	[16]
	<i>Heuristic algorithm</i>		
	Wind power production and noise level	NSGA-II	[17], [18]
	Energy generation, Wind farm area and cable length	NSGA-II	[19]
	Energy generation and cost	Multi-objective genetic algorithm (MOGA)	[20]
	Efficiency and cost	MOGA	[21]
	Energy output and cost of the turbines and land area	Multi-Objective PSO	[22]
	Ratio of net AEP to the gross AEP and the uniformity of wake effect	Simulated annealing algorithm (SAA)	[23]
	Wind power production, cable length and land area	Selection hyper-heuristic high-level search method	[24]
	Power output and average deviation of the power	MOEAs	[25]
	Energy production and usage of installed turbines	MOGOMEA	[26]
	Energy production, cable length, enclosed area and noise level	Modified reference vector based evolutionary algorithm	[27]
	Minimum leveled energy cost and maximum capacity factor	Self-organizing maps	[28]

Donovan [11], [12] presents a multiple mixed integer linear formulation based on the vertex packing problem. In addition, the mixed integer linear and quadratic programming formulation and the gradient-based optimization are investigated in [13] and [14], [15], respectively. In [16], Park employs the sequential convex programming (SCP) as the solving algorithm to determine the optimal locations of wind turbines efficiently, for the maximum wind energy production.

The literatures mentioned above determine the optimal wind farm layout with a single objective function. However, the WFLO is a comprehensive problem and many objectives need to be considered simultaneously. As shown in Table I, some studies on the multiple objective model have been conducted recently. In addition to energy production and financial index, the wind farm area, cable length, environmental impact and other objectives are designed.

The noise level as well as wind farm area and cable length are considered as the objective besides wind energy production in [17], [18] and [19]. The NSGA-II is employed as the solver. In [20] and [21], the multi-objective genetic algorithm (MOGA) is used for optimum of turbine position with the maximum energy production and efficiency. An efficient multi-objective PSO algorithm is presented in [22] to minimize the cost of the turbines and land area and maximize the wind energy output. The uniformity of wake effect is developed as the objective by Yang *et al.* [23], to make the wake effect of each turbine uniform, thereby improving the wind turbine operation stability. In [24], a three-objective model is established for the optimal wind farm layout using the selection hyper-heuristic method. The objectives include the energy production, the minimization of the covered land

and the cable length connecting all turbines. Montoya et al in [25] propose a multi-objective optimal model for WFLO and wind turbine selection considering the standard deviation of wind energy production. In [26], the maximum wind energy production and the usage of the installed turbines are designed as the objectives, the performance of the Multi-Objective Gene-pool Optimal Mixing Evolutionary Algorithm (MOGOMEA) is compared with NSGA-II. To cope with the irregular land boundaries, a variable discretization scheme is proposed in [27] and a multi-objective formulation is used for maximizing the energy production and minimizing the cable length, enclosed area and noise level. In [28], the ANN-based algorithm called self-organizing map (SOM) is used to address the WFLO formulation with highly complexity, non-convexity, multi-variable and multi-purpose.

The previous researches on WFLO usually consider the energy production, cost and environmental impact as the objectives. However, the layout of wind turbines (WTs) has a significant impact on the sequential fluctuation of power output, because of the wind speed time-correlation and the wind turbine wake effect.

Therefore, our motivations of this work are as follows.

- Firstly, owing to the random and intermittent nature of wind power, adequate spinning reserve generally is needed to guarantee power system operational reliability. The sequential fluctuation of wind power brings great challenges to secure, and cost-efficient operation of power system [29]. Thus, the fluctuation of wind power should be considered in the WFLO.
- Secondly, a large wind power base usually consists of several wind farms with different wind speed profiles.

The proper capacity of multiple wind farms would help to alleviate wind power fluctuation. The optimization of wind farm capacity and wind turbines' locations for multiple wind farms should be conducted simultaneously.

- Thirdly, the wind speed recorded by wind tower cannot represent that through the rotor of turbines, to make the wind speed estimation and hence the power calculation more accurate, the time-shifting of wind speed between the wind tower and turbines' locations should also be considered.

The main contributions and conclusions are:

- Firstly, a bi-objective layout optimization model for multiple wind farms is proposed for the optimal determination of wind farm capacity and the turbines' locations, taking the sequential fluctuation of wind power into account. The proposed model maximizes the energy production as well as minimizes fluctuation of power output. Moreover, for large wind power base optimizing the wind farm capacity and the turbines' locations simultaneously can make full use of the wind energy resources based on the wind speed profiles of each wind farm.
- Secondly, the time-shifting of wind speed between the wind tower and turbines' locations is also considered to improve the accuracy of the power calculation.
- Thirdly, the uniform design based two-stage genetic algorithm is developed. The uniform design is employed to increase the diversity of population, hence to improve the solving efficiency of algorithm. The two-stage evolution is used to improve the feasibility of Pareto optimal solutions.

This work is organized as follows. Section II presented the power output of turbines in multiple wind farms. The time shifting of wind speed and wake effect of turbines are considered. Section III formulates the bi-objective layout optimization for multiple wind farms. Section IV introduced the uniform design based two-stage genetic algorithm. The case studies were demonstrated in Section V. And Section VI summarized the conclusions.

II. POWER OUTPUT OF TURBINES IN MULTIPLE WIND FARMS

The power output of a WT relies on the wind speed through its rotor. However, the recorded wind speed data usually are measured by wind tower, which cannot represent the wind speed of all turbines. Therefore, the time shifting of wind speed and wake loss between WTs should be considered to estimate the wind speed through each WTs' rotor accurately and hence the power output calculation. In this section, the power output calculation of turbines will be introduced.

A. Time-shifting of Wind Speed

Before wind farm planning, the wind tower is installed to access the wind energy information about the wind farm. Because of wind farm layout, the wind speed measured by the wind tower differs from the wind speed through the rotor of a WT. Therefore, time-shifting of wind speed between wind

tower and WT should be considered [30], [31]. The wind speed through the rotor can be got as follows.

$$v_k(t) = v_0(t - \tau_k) \quad (1)$$

$$\tau_k = d_k / v_0(t - \tau_k) \quad (2)$$

where $v_k(t)$ denotes wind speed through the rotor of WT k at time t ; $v_0(t - \tau)$ is the speed measured by wind tower at time $t - \tau$; τ_k is the time-shifting between the wind tower and WT k , which can be calculated by (2); d_k distance along wind direction between WT k and wind tower, if the wind tower is in the upstream of WT k , $d_k > 0$, otherwise, $d_k < 0$.

Figure 1 presents the relative position between the wind tower and a turbine. The coordinates of wind tower and WT k are assumed to be $(0, 0)$ and (x_k, y_k) respectively, and the wind direction and the directions of x-axis are θ_W and θ_x . Therefore, the distance along wind direction between the WT k and wind tower, d_k , can be calculated as (3) and (4).

$$d_k = \cos(\theta_{k \rightarrow W}) \times \sqrt{x_k^2 + y_k^2} \quad (3)$$

$$\theta_{k \rightarrow W} = \theta_W - \left(\theta_x - \arctan\left(\frac{y_k}{x_k}\right) \right) \quad (4)$$

where $\theta_{W \rightarrow k}$ is the angle between wind direction and line connecting wind tower and WT k , as shown in Fig. 1.

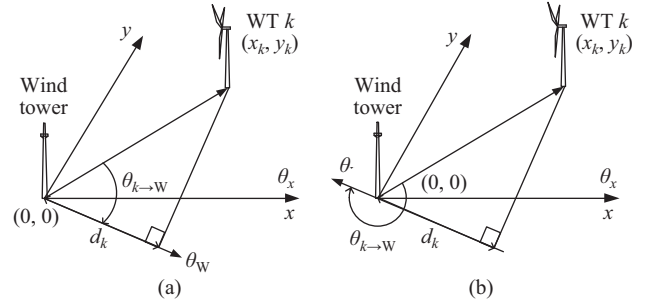


Fig. 1. Relative position between the wind tower and a turbine. (a) is WT k in the downstream of wind tower; (b) is WT k in the upstream.

B. Wake-effect Model of Wind Turbines

Because of wake effects, the kinetic energy extracted by the WT at the downstream location along the wind direction is smaller than that by upstream WT. The losses of wake depend on both wind speed and wind direction.

In this paper, the Jensen model [32], [33] is employed to represent the wake effect. As depicted in Fig. 2, v_{in} denotes the wind speed through the rotor of upstream WT; r_W is the WT rotor radius; $d_{i \rightarrow k}$ and $h_{i \rightarrow k}$ are the horizontal and deviating distances between WT i and k along the wind direction. l is the wake decreasing constant and C_t the thrust coefficient [33]; The wake effect of the upstream WT i to the downstream WT k depends on r_W , $d_{i \rightarrow k}$, $h_{i \rightarrow k}$, l , and C_t simultaneously.

The wind speed that blows to the downstream turbine considering the wake effect of the upstream turbines can be calculated by (5).

$$v' = d_{Wake} \times v_{in} \quad (5)$$

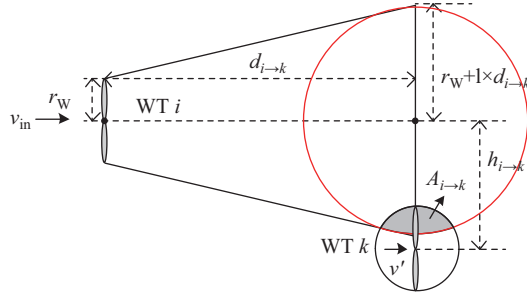


Fig. 2. Wake effect with a deviating distance.

$$d_{\text{Wake}} = 1 - \sum_{i=1}^{N_{\text{up}}} \left(1 - \sqrt{1 - C_t} \right) \left(\frac{r_W}{r_W + l \cdot d_{i \rightarrow k}} \right)^2 \left(\frac{A_{i \rightarrow k}}{\pi r_W^2} \right) \quad (6)$$

where v' is the wind speed that blows to the downstream WT; d_{Wake} represents the wind speed loss coefficient considering the wake effect of upstream WT; N_{up} is the number of upstream WTs and $A_{i \rightarrow k}$ is the size of the shaded area, which is the overlapped area between the wake of the WT i and the rotor of the WT k , the area can be modeled using r_W , $d_{i \rightarrow k}$ and $h_{i \rightarrow k}$.

Therefore, the wind speed through the rotor of downstream WT can be calculated by (7) with the consideration of wake effect between WTs and time-shifting of wind speed.

$$v'_k(t) = d_{\text{Wake}} \times v_k(t) = d_{\text{Wake}} \times v_0(t - \tau_k) \quad (7)$$

After the calculation of the distances between the WT i , k and the wind tower along the wind direction (d_i and d_k), the horizontal and deviating distances between WT i and k ($d_{i \rightarrow k}$ and $h_{i \rightarrow k}$) are easy obtained as (8) and (9).

$$d_{i \rightarrow k} = d_i - d_k \quad (8)$$

$$h_{i \rightarrow k} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 - (d_{i \rightarrow k})^2} \quad (9)$$

From all the above, the wind speed blowing to any turbines can be calculated. Then according to the power characteristic of WT [30], the power output of any WTs can be determined.

C. Wind Power Model

The WT k output at hour t ($P_{W,k}(t)$) can be modeled by the function with respect to wind speed through to its rotor as shown by (10).

$$P_{W,k}(t) = \begin{cases} 0, & 0 \leq v'_k(t) < v_{ci}, \\ (a + bv'_k(t) + cv'_k(t)^2)P_{W,r}, & v_{ci} \leq v'_k(t) < v_r \\ P_{W,r}, & v_r \leq v'_k(t) < v_{co} \end{cases} \quad (10)$$

where $P_{W,r}$ is the turbine rated power; v_{ci} , v_{co} , v_r express cut-in, cut-out and rated speed, respectively. a , b and c are the constants which depend on v_{ci} and v_r [34].

III. BI-OBJECTIVE LAYOUT OPTIMIZATION OF MULTIPLE WIND FARMS

In this section, the bi-objective layout optimization of multiple wind farms is proposed to determine the optimal installed capacity of each wind farm and the location of each WT. This method adopts the energy production and wind power fluctuation as the objectives, which can relieve the wind power fluctuation under the premise of the wind energy production. Therefore, the proposed method can mitigate the effects of wind power volatility on system operational security.

Suppose that each wind farm is a square area in the first quadrant of axes, and wind tower is located at the origin. The proposed model aims to determine the location of each turbine, i.e. x_i , y_i , z_i . z_i represent which the turbine is located in and (x_i, y_i) express the position in wind farm z_i .

A. Objectives of Layout Optimization of Multiple Wind Farms

The goal of the proposed model is to mitigate the impacts of wind power fluctuation on system operation security under the premise of the wind energy production. Therefore, the maximum energy production and the minimum fluctuation of wind power are selected as the objectives simultaneously.

1) Maximizing Energy Production

The total energy production of all the wind farms can be calculated according to the wind power model of WT.

$$\max E_W = \sum_{t=1}^T P_{WB}(t) \quad (11)$$

$$P_{WB}(t) = \sum_{m=1}^{M_W} \sum_{i=1}^{N(m)} P_W(v'_i(t)) \quad (12)$$

where T (h) represents the number of hours; E_W (MW·h) express the total energy production of all the wind farms; $P_{WB}(t)$ (MW) is the output of all wind farms at hour t , which is calculated as (12); M_W and $N(m)$ are the number of wind farms and turbines in wind farm m respectively. $N(m)$ is determined in the optimization in accordance with the installed capacity; $v'_i(t)$ (m/s) is the wind speed of WT i at time t with the consideration of wind speed time-shifting and turbine wake effect.

2) Minimizing Fluctuation of Wind Power

Because of the time-shifting of wind speed and the correlation and complementarity of different wind farms power output, it can mitigate the power output sequential fluctuation to optimize each wind farm capacity and wind turbine locations. To quantify the fluctuation of wind power, the wind power fluctuation risk index (i.e. R_S) based on exponential function is developed. The R_S can express the effects of wind power fluctuation on secure and cost cost-efficient operation of wind-thermal system.

In the unit commitment of wind-thermal system, adequate spinning reserve is needed to accommodate the wind power fluctuation [35]. Therefore, the effects on system secure and cost-efficient operation can be ignored, when the fluctuation is less than the predetermined spinning reserve. If the fluctuation exceeds the spinning reserve and rises further, the effects will kick in and increase rapidly. In this paper, this relationship

between the effects and the fluctuation is assumed as an exponential function. Therefore, the wind power fluctuation risk index is defined as (13) and (14).

$$R_S(t) = \begin{cases} \exp(R_W(t) - \alpha) & R_W(t) > \alpha \\ 0 & R_W(t) \leq \alpha \end{cases} \quad (13)$$

$$R_W(t) = \frac{|P_{WB}(t+1) - P_{WB}(t)|}{P_{WB}(t)} \quad (14)$$

where $R_S(t)$ is the risk index of R_S at hour t ; $R_W(t)$ expresses the relative wind power ramp rate at hour t ; α is the tolerability for wind power fluctuation of wind-thermal system. Since the spinning reserve is usually prearranged in the unit commitment as a percentage of wind power, α indicates that the effects of wind power fluctuation on the system operation are ignored, if $R_W(t)$ is less than α .

In order to relieve the wind power fluctuation, the minimum total fluctuation risk index is designed as an objective for the optimization model.

$$\min RS_W = \sum_{t=1}^T R_S(t) \quad (15)$$

where RS_W is the total fluctuation risk index for multiple wind farms.

B. Constraints of Layout Optimization for Multiple Wind Farms

The constraints contain the turbines' number and wind farm area constraints.

$$N_m^{\min} \leq N(m) \leq N_m^{\max} \quad (16)$$

$$\sum_{m=1}^M N(m) = N_W \quad (17)$$

$$0 \leq x_i \leq L \quad (18)$$

$$0 \leq y_i \leq L \quad (19)$$

where $N_m^{\max}$ and $N_m^{\min}$ are the maximum and minimum number of WTs in wind farm m , respectively; N_W express the total number; L (km) represents the side length of a wind farm.

IV. UNIFORM DESIGN BASED TWO-STAGE GENETIC ALGORITHM

The proposed bi-objective optimization model is formulated as a multi-objective and multi-constraint problem. The NSGA-II [36], [37] can be used to solve such problem [38]. In GA, the initial population is often generated randomly. The diversity is crucial for the performance. In this paper, in order to accelerate the solution of the proposed model and improve the feasibility of the Pareto solutions, the uniform design (UD) based two-stage genetic algorithm is developed. The uniform design (UD) [39] is developed by Professor Fang Kai-Tai and Wang Yuan, which is used to seeks trial points that are uniformly dispersed. In this paper, UD table is employed to increase the diversity of population. The two-stage evolution is used to improve the feasibility of Pareto solutions. At the beginning, the energy production is used as the objective

function. The general GA [40] is employed to direct the evolution of population. After some generations, the energy production of the whole population will ramp to a relative high level rapidly. Then, the NSGA-II is employed taking the maximum energy production and minimum fluctuation of wind power as the objectives.

A. Initial Population Generating Method Based on UD

In this paper, the WTs' positions for the initial population are determined based UD table to increase the genetic diversity. The wind farm areas are firstly subdivided into $q \times q$ identical square cells, as shown in Fig. 3. Then, the cell in which the WT locates for an individual is determine based on the UD table.

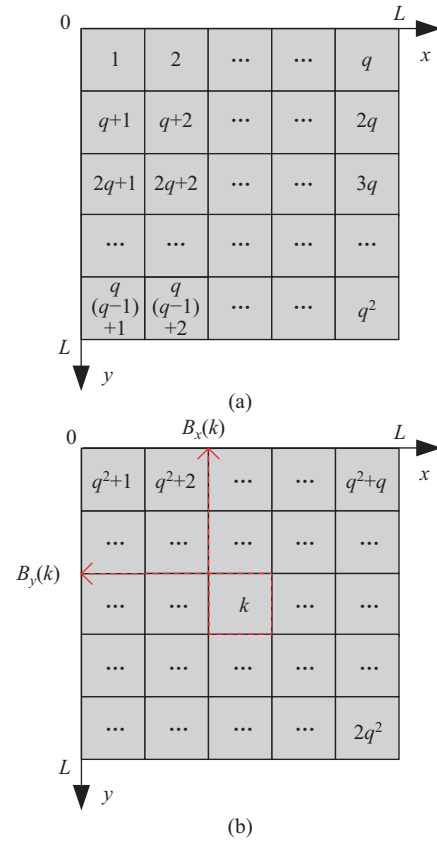


Fig. 3. Cells for wind turbines' positions.

Suppose that N_W WTs are installed in M wind farms. Therefore, there are $N = M \times q \times q$ cells that each WT can be located in. The UD table $U_N(N^{N_W})$ can be used to determine the cell where WTs locate for the initial population. The $U_N(N^{N_W})$ is a $N \times N_W$ matrix. The elements in each row correspond to an individual. And each element corresponds to a WT for the individual.

The detailed procedure of generating initial population based on the UD is described as follows.

Step 1: Generate UD table, $U_N(N^{N_W})$ and set the index of individual $i = 1$ and the index of turbine $j = 1$.

Step 2: According to the element $u_{i,j}$ of $U_N(N^{N_W})$ determine the cell in which WT j is located. $u_{i,j}$ express the UD table's element in row i and column j .

Step 3: Generate two random numbers uniformly distributed over (0, 1), R_1 and R_2 , to determine the location of WT j for individual i , $(x_{i,j}, y_{i,j}, z_{i,j})$,

$$\begin{cases} x_{i,j} = B_x(u_{i,j}) + R_1 \times L/q \\ y_{i,j} = B_y(u_{i,j}) + R_2 \times L/q \\ z_{i,j} = B_z(u_{i,j}) \end{cases} \quad (20)$$

where $B_x(u_{i,j})$ and $B_y(u_{i,j})$ are the edge along the x- and y-axis of cell $u_{i,j}$; $B_z(u_{i,j})$ is the wind farm number of cell $u_{i,j}$.

Step 4: if $j = N_W$, encode all the WTs' locations for the i^{th} individual into one chromosome; otherwise, set $j = j + 1$, go to step back 2.

Step 5: if $i = N$, return the initial population and stop; otherwise, set $i = i + 1$, go back to step 2.

B. Two-stage Evolution for GA

The proposed optimization model aims to relieve the wind power fluctuation under the premise of energy production. Obviously the solution that pursues smaller fluctuation risk index blindly at the expense of the sharp decline of energy production is infeasible. Therefore, the two-stage evolution for GA is proposed to improve the feasibility of Pareto solutions. In the first stage, the WFLO model is considered as a single objective optimization problem to improve the wind energy production for the populations rapidly. Then, the NSGA-II is employed taking the maximum energy production and minimum fluctuation of wind power as objectives simultaneously.

In the second stage, the fluctuation risk index for each individual is modified according to the energy production, as (21). This equation is designed to reduce the ability to survive of the individual that has much lower wind energy production.

$$RS'_W(g, i) = \begin{cases} RS_W(g, i), & E_W(g, i) \geq (1 - \gamma) \times E_W^{\max}(g) \\ \frac{RS_W(g, i)(E_W^{\max}(g) - E_W(g, i))}{\gamma \times E_W^{\max}(g)}, & \text{Otherwise} \end{cases} \quad (21)$$

where $RS_W(g, i)$ and $RS'_W(g, i)$ are the initial and modified fluctuation risk index for the i^{th} individual in the g^{th} generation population; $E_W(g, i)$ is the energy production; $E_W^{\max}(g)$ is the maximum energy production in the g^{th} generation population; γ is maximum sacrifice coefficient of wind energy production which indicates the acceptable maximum of the sacrifice energy production for the reduction of wind power fluctuation, γ can be set to 0 ~ 0.05. The higher γ represents that the planer prefers to relieve the wind power fluctuation at the expensive of more energy production.

C. UD based two-stage genetic algorithm

The process of the UD based two-stage genetic algorithm is presented below and the flowchart is illustrated in Fig. 4.

Step 1: The initialization of parameters, including: the wind farm number (M), the side length of wind farm (L), the number of WTs (N_W), the maximum sacrifice coefficient of wind energy production (γ), population size (N), the maximum generation number ($G_{\max}$), the generation number

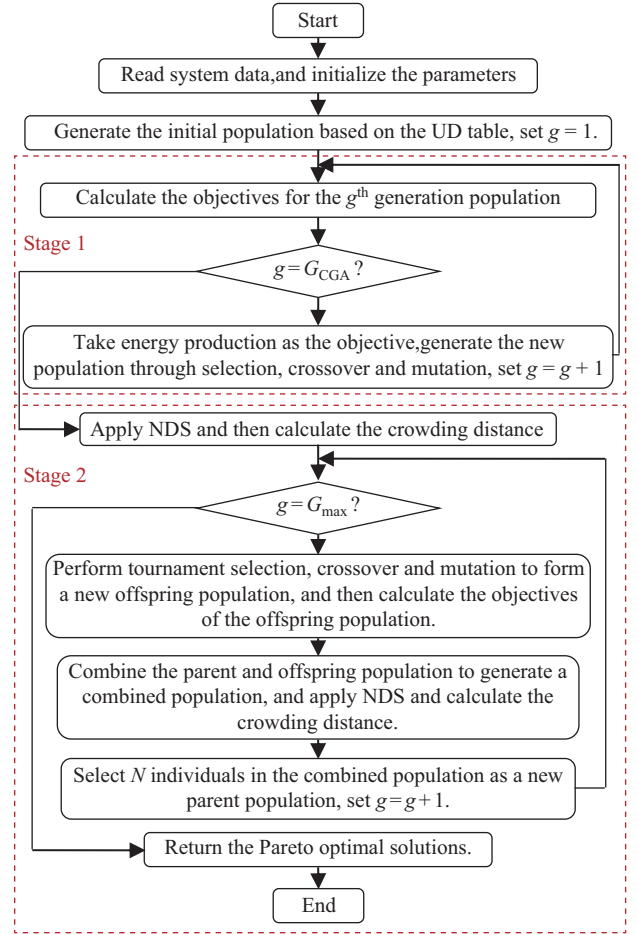


Fig. 4. Flowchart of the UD based two-stage genetic algorithm.

of the first stage (G_{CGA}), the crossover and mutation rate (P_C and P_M).

Step 2: Generate the initial population based on the UD table $U_N(N^{N_W})$, and set the index of generation $g = 1$.

Step 3: Calculate the energy production and the fluctuation risk index for the g^{th} generation population.

Step 4: if $g = G_{CGA}$, go to step 6.

Step 5: Take the energy production as the objective, and generate the new generation through selection, crossover and mutation, set $g = g + 1$ and go back to step 3.

Step 6: Apply non-dominated sorting (NDS) to classify the population into different fronts and get the crowding distance for the same front [37].

Step 7: if $g = G_{\max}$, go to step 11.

Step 8: Perform tournament selection, crossover and mutation to form the offspring population based on the front value and crowding distance, and then calculate the objectives for the offspring population.

Step 9: Combine the parent and offspring population, and apply the NDS to the combined population and get the crowding distance for the same front.

Step 10: Based on the elitist strategy, select N individuals in the combined population as the new parent population, set $g = g + 1$, go back to step 7.

Step 11: Return the individuals belonging to the first front as Pareto solutions, end the algorithm.

V. DETERMINATION OF OPTIMAL SOLUTION CONSIDERING SEQUENTIAL OPERATION FEATURES

A. Determination of the Optimal Solution

The proposed bi-objective layout optimization of multiple wind farms can be used to obtain the Pareto-optimal solutions. However, the optimal solution cannot be determined. It depends on the wind power penetration and the TGU regulating flexibility of power system. If the penetration of wind power is relative small or the TGU regulating flexibility is relative high, the power system has strong ability to accommodate the fluctuation of wind power. Therefore, the solution with larger fluctuation index and large wind power production can decrease the operation cost. On the contrary, the solution with less fluctuation of wind power is more likely to be the optimal.

The focus of this paper is on the consideration of wind power sequential fluctuation, the total installed wind turbine number is assumed predetermined and the impact of wind turbine location on the installation cost is ignored. The optimal solution in Pareto-optimal solutions is determined according to the annual operation cost calculated by the operation simulation of wind-thermal system. The operation simulation model is formulated as a mix-integer linear programming problem and can be solved by commercial solvers.

B. Operation Simulation of Wind-thermal Power System

The operation simulation of wind-thermal power system intends to determine the optimal solution in the Pareto-optimal solutions by calculating the operation cost based on the wind power curve. The total operation cost consists of the production cost, emission cost, startup cost, and shutdown cost of TGUs. All these cost functions are formulated as linear functions or approximated by a series of piecewise linear functions.

The objective function is modeled as follows:

$$\min F_O = \sum_{t=1}^{TO} \sum_{i=1}^{N_T} [F_i(P_i(t)) + E_i(P_i(t)) + C_i^{SU}(t) + C_i^{SD}(t)] \quad (22)$$

where F_O is the total operation cost. N_T is the number of TGUs. T_O denotes the number of hours. $P_i(t)$ is the output of TGU i at hour t . $F_i(\cdot)$ and $E_i(\cdot)$ are the production and emission cost function of TGU i respectively. $C_i^{SU}(t)$ and $C_i^{SD}(t)$ are the startup and shutdown cost of TGU i at hour t .

The fuel cost of TGU including the production, startup, and shutdown costs can be approximated by a series of piecewise linear functions according to [41].

The emission cost considering NO_x , CO_2 , CO and SO_2 is formulated by a linear function of $P_i(t)$,

$$E_i(P_i(t)) = \sum_{k=1}^{N_E} v_k \cdot \varepsilon_{k,i} \cdot P_i(t) \cdot \Delta t \quad (23)$$

where v_k is the emission cost for the k^{th} gas (\$/kg). $\varepsilon_{k,i}$ is the emission coefficient for the k^{th} gas of TGU i (kg/MW·h). N_E is the number of gas types.

The constraints are formulated as follows:

1) Power Balance Constraint

$$\sum_{i=1}^{N_T} P_i(t) + P_{WB}(t) = P_L(t) + P_{CW}(t) \quad (24)$$

$$0 \leq P_{CW}(t) \leq P_{WB}(t) \quad (25)$$

where $P_{CW}(t)$ is the wind power curtailment at hour t .

2) TGU Generation Constraints

The TGU generation constraints indicate the ramp rate limits of TGU including the ramp-down, ramp-up, and startup ramp rate limit.

$$P_i^{\min}(t) \leq P_i(t) \leq P_i^{\max}(t) \quad (26)$$

$$P_i^{\min}(t) \geq U_i(t) \cdot P_{i,r}^{\min} \quad (27)$$

$$P_i^{\min}(t) \geq P_i(t-1) - U_i(t) \cdot DR_i \quad (28)$$

$$0 \leq P_i^{\max}(t) \leq U_i(t) \cdot P_{i,r}^{\max} \quad (29)$$

$$P_i^{\max}(t) \leq P_i(t-1) + U_i(t-1) \cdot UR_i + [U_i(t) - U_i(t-1)] \cdot SR_i \quad (30)$$

where $P_i^{\max}(t)$ and $P_i^{\min}(t)$ are the maximum and minimum available power output of TGU i at hour t . $U_i(t)$ represents the state of TGU i at hour t (1: on, 0: off). DR_i , UR_i and SR_i are the ramp-down, ramp-up, and startup ramp rate limit of TGU i respectively.

3) TGU Minimum on/off Time Constraints

The TGU minimum on/off time constraints can be expressed as the following mixed-integer linear programming formulations

$$\sum_{t=1}^{H_{i,\text{on}}} [1 - U_i(t)] = 0 \quad (31)$$

$$\sum_{n=t}^{t+T_{i,\text{on}}^{\min}-1} U_i(n) \geq T_{i,\text{on}}^{\min} \times [U_i(t) - U_i(t-1)], \quad H_{i,\text{on}} + 1 \leq t \leq T_O - T_{i,\text{on}}^{\min} + 1 \quad (32)$$

$$\sum_{n=t}^{T_O} \{U_i(n) - [U_i(t) - U_i(t-1)]\} \geq 0, \quad T_O - T_{i,\text{on}}^{\min} + 2 \leq t \leq T_O \quad (33)$$

$$\sum_{t=1}^{H_{i,\text{off}}} U_i(t) = 0 \quad (34)$$

$$\sum_{n=t}^{t+T_{i,\text{off}}^{\min}-1} [1 - U_i(n)] \geq T_{i,\text{off}}^{\min} \times [U_i(t-1) - U_i(t)], \quad H_{i,\text{off}} + 1 \leq t \leq T_O - T_{i,\text{off}}^{\min} + 1 \quad (35)$$

$$\sum_{n=t}^{T_O} \{1 - U_i(n) - [U_i(t-1) - U_i(t)]\} \geq 0, \quad T_O - T_{i,\text{off}}^{\min} + 2 \leq t \leq T_O \quad (36)$$

where $H_{i,\text{on}} = \min(T, (T_{i,\text{on}}^{\min} - H_i^0) \cdot U_i(0))$ denotes the number of initial hours during which TGU i must be online. $H_{i,\text{off}} = \min(T, (T_{i,\text{off}}^{\min} - H_i^0) \cdot (1 - U_i(0)))$ denotes the number of initial hours during which TGU i must be offline. H_i^0 is the number of hours TGU i is kept in the initial state prior

to the first hour. $T_{i,on}^{\min}$ and $T_{i,off}^{\min}$ are the minimum on and off time of TGU i .

Constraints (31)–(33) represent the minimum up time limits of TGU, and describe the situation that TGU is turned off only when TGU is continuously on for a period longer than its minimum on time. These constraints are modeled by dividing the time span into three periods: the initial hours defined by $H_{i,on}$, the subsequent hours, the final ($T_{i,on}^{\min} - 1$) hours. Similarly, constraints (34)–(36) describe the minimum off time limits of TGU.

4) Spinning Reserve Constraints

The up spinning reserve requirement includes the basic and additional spinning reserve. The basic spinning reserve is used to support the sudden changes of the net load demand, and the additional spinning reserve is for the fluctuation of wind power. The downward reserve only considers the additional spinning reserve [42]. The spinning reserve constraints are modeled as follows.

$$\sum_{i=1}^{N_T} [P_i^{\max}(t) - P_i(t)] \geq \mu_1 [P_L(t) - P_W(t) + P_{CW}(t)] + \mu_2 [P_W(t) - P_{CW}(t)] \quad (37)$$

$$\sum_{i=1}^{N_{Ther}} [P_i(t) - P_i^{\min}(t)] \geq \mu_2 \times [P_W(t) - P_{WC}(t)] \quad (38)$$

where μ_1 and μ_2 are the coefficient of basic and additional spinning reserve requirement.

VI. CASE STUDIES

The effectiveness of the bi-objective layout optimization model for multiple wind farms is verified in this section, using the wind data for 10 years of four different sites, i.e. Mayville, Galesburg, Hillsboro and Prosper in North Dakota, US [43]. The wind data of Mayville, Galesburg and Hillsboro are used for the small-scale system studies corresponding to subsection A, B and C. The wind speed data of all the five sites are used for the large-scale wind farms. Suppose that the installation of identical 2.5 MW wind turbines is planned with the hub height and rotor diameter of 85 m and 50 m. The cut-in, rated, and cut-out speeds of the turbine are 3, 11 and 25 m/s. The wake decreasing constant (l) and the roughness length (z_0) are set to 0.075 [44] and 0.03 m [8].

A. Efficiency Analysis of the Initial Population Generating Method Based on UD

In this case, 60 identical turbines are installed in three wind farms. Each wind farm is assumed to be $2.0 \text{ km} \times 2.0 \text{ km}$ square land. The recorded wind data of Mayville, Galesburg and Hillsboro are used. This case takes the maximum energy production as the objective to analysis the effectiveness of the UD based initial population generation method. The UD based method and the random method are employed to generate the initial population. Each wind farm is subdivided into 14×14 square cells. The population size is set to 588. The general GA is employed with the maximum generation number of 300. The evolutionary processes are plotted in Fig. 5.

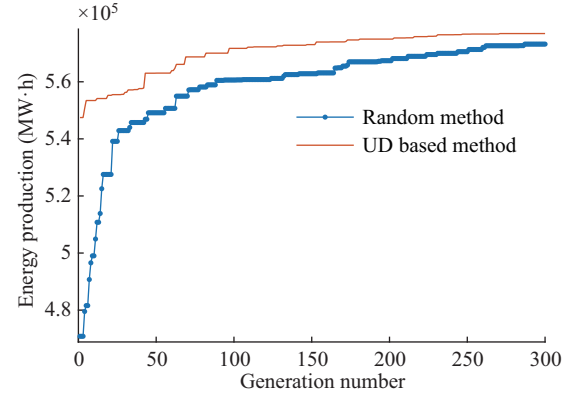


Fig. 5. Evolution of genetic algorithms.

Close examination of Fig. 5 shows that the initial population generating method based on UD can improve the diversity of the population, and performs better than the random generating method in the aspect of evolution efficiency. The UD based method can achieve the goal of lifting the average energy production of the population rapidly to a relatively high level.

B. Bi-objective Optimization for Multi Wind Farms

This case takes the energy production and the fluctuation risk index as the objectives to optimize the layout for the three wind farms. The maximum sacrifice coefficient of wind energy production (γ) is set to 0.02. Fig. 6 shows the Pareto-optimal front of the three wind farms layout.

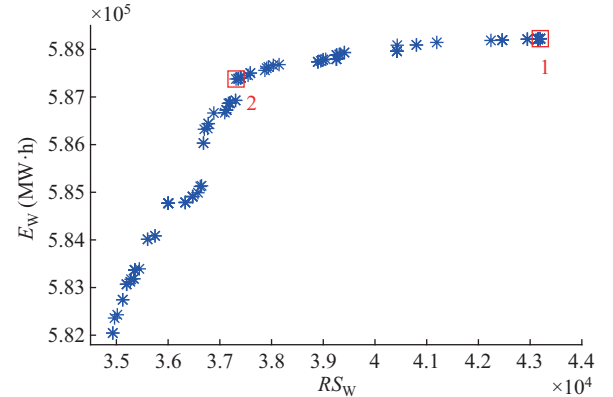


Fig. 6. Pareto-optimal front of the three wind farms layout.

It is observed from Fig. 6 that in the Pareto-optimal front there is a parabolic relationship between the energy production and the wind power fluctuation risk index. The wind power fluctuation risk index drops dramatically from solution 1 to solution 2, where the energy production decreases slightly. The fluctuation risk index drops from 4.3196×10^4 to 3.7313×10^4 by 9.45% with the slight reduction of energy production from $5.8822 \times 10^5 \text{ MW}\cdot\text{h}$ to $5.8738 \times 10^5 \text{ MW}\cdot\text{h}$ by 0.14%. However, the wind power fluctuation risk index begins to reduce slowly from solution 2. According to the relationship between the energy production and the total fluctuation risk index, the proposed bi-objective layout optimization model can

dramatically relieve the fluctuation of wind power with little loss of energy production.

The solution 1 with the maximum energy production is shown in Fig. 7. It is observed that many turbines are located along the boundary that can alleviate the wake-effect when the area of wind farm fixed.

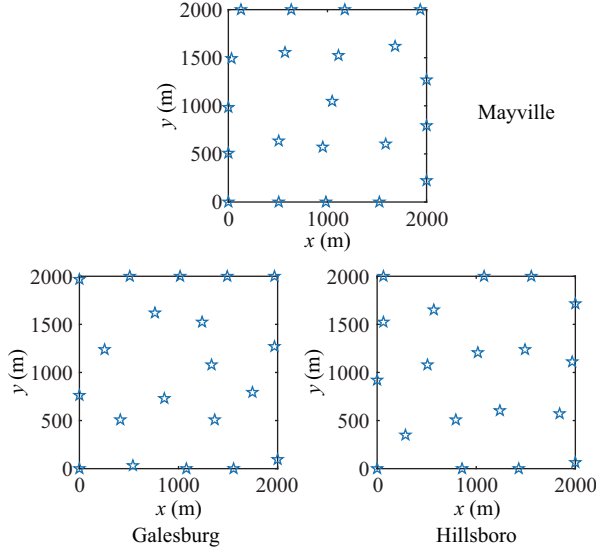


Fig. 7. Wind farms layout of solution 1.

By analyzing the capacity planning results of multiple wind farms in the Pareto optimal solution set, it is found that there are only four kinds of capacity planning schemes, which shows that the optimal capacity-planning schemes of multiple wind farms are very concentrated. The Pareto-optimal front is re-depicted in Fig. 8 with different colors expressing different planning schemes of multiple wind farms. Here, we note that the solutions with the same capacity-planning scheme are usually lumped together. This shows that the capacity-planning scheme of multi wind farms has greater impact on the wind power production and fluctuation. As such, it is necessary to optimize the wind farm layout for multiple wind farms simultaneously. From the capacity planning results for the three wind farms, it is found that more wind turbines should

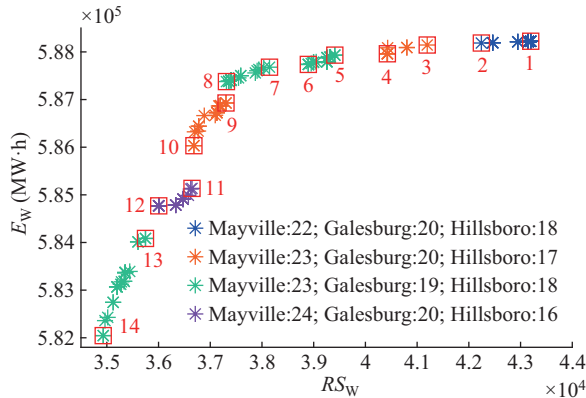


Fig. 8. Pareto-optimal front with the capacity planning results for the three wind farms.

be installed in Mayville than Hillsboro. It could be reason that the Mayville is richer in wind energy resource than Hillsboro.

C. Determination of the Optimal Planning Result of Multi Wind Farm

The bi-objective optimization for multi wind farms could obtain the Pareto-optimal solutions, nonetheless cannot identify the optimal solution. The ability of the power system to compensate wind power fluctuation relies on the operation flexibility of thermal generating units (TGUs). Therefore, the optimal solution would depend on the TGU regulating ability. In this paper, the optimal solution is determined by means of operational simulation of power system for one year.

As shown in Fig. 8, the fourteen solutions are selected based on the capacity-planning schemes and the distribution of solutions, to constitute the wind-thermal system with four TGUs. Table II shows the parameters of TGUs [45], [46]. The load profile follows the IEEE Reliability test syetms-96 [47], and the annual peak is set as 350 MW. The GUROBI is used to determine the yearly operating cost of wind-thermal system by solving diurnal operation simulation model.

TABLE II
PARAMETERS OF THERMAL GENERATING UNITS

Parameters	TGU 1	TGU 2	TGU 3	TGU 4	
$P_r^{\max}$ (MW)*	140	140	58	58	
$P_r^{\min}$ (MW)	70	70	25	25	
$T_{on}^{\min}$ (h)	5	5	1	1	
$T_{off}^{\min}$ (h)	5	5	1	1	
HSU (\$)	550	550	60	60	
CSU (\$)	1100	1100	–	–	
T^{Cold}	4	4	–	–	
a (\$/h)	700	700	660	660	
b (\$/MW·h)	16.7	16.7	25.9	25.9	
c (\$/MW ² ·h)	0.002	0.002	0.004	0.004	
Emission characteristics (kg/MW·h)	NO _x	3.976	3.976	4.101	4.101
	CO ₂	832.954	832.954	840.240	840.240
	CO	0.138	0.138	0.147	0.147
	SO ₂	0.501	0.501	0.553	0.553

The operation costs and wind power curtailment, production and consumption are shown in Table III. The scheduling curves with the solution 1 are available in [48]. It is shown that the total operation cost does not increase with wind energy production decreasing. The solution 1 has the maximum wind power production, the wind power curtailment is also maximum. This confirms that the operation cost has a strong correlation with the fluctuation of wind power, and then demonstrates the effectiveness of the proposed model. With the decrease of wind power production, all the operation cost including the total operation cost, fuel cost and emission cost first reduce and then increase. The wind-thermal system with solution 6 has the minimum total operating cost. Therefore, in this case solution 6 is selected as the optimal solution with the maximum economic efficiency.

Here, we also calculate the rate of wind curtailment and wind power consumption shown in Fig. 9. It is found that the rate of wind curtailment of solution 1 and 2 with greater wind power production is dramatically higher than the other solutions. Accordingly, the wind energy consumption of solution 1 and 2 is less than solution 3–7. Comparing solution 3–4 and

TABLE III
OPERATING COSTS OF THE PARETO SOLUTIONS

No.	Total cost ($\times 10^7$ \$)	Fuel cost ($\times 10^7$ \$)	Emission cost ($\times 10^7$ \$)	Wind power curtailment (MW·h)	Wind power production (MW·h)
1	4.8825	3.5027	1.3798	7.0770	5.8822
2	4.8824	3.5025	1.3798	7.0692	5.8819
3	4.8824	3.5029	1.3795	7.0245	5.8814
4	4.8842	3.5045	1.3797	7.0278	5.8796
5	4.8813	3.5019	1.3794	7.0001	5.8793
6	4.8812	3.5017	1.3795	6.9986	5.8774
7	4.8817	3.5023	1.3794	6.9837	5.8768
8	4.8818	3.5021	1.3797	6.9868	5.8738
9	4.8813	3.5012	1.3801	6.9862	5.8693
10	4.8839	3.5028	1.3805	6.9646	5.8512
11	4.8831	3.5055	1.3808	7.0012	5.8499
12	4.8831	3.5057	1.3808	6.9994	5.8491
13	4.8847	3.5026	1.3805	6.9673	5.8479
14	4.8868	3.5055	1.3814	6.9428	5.8041

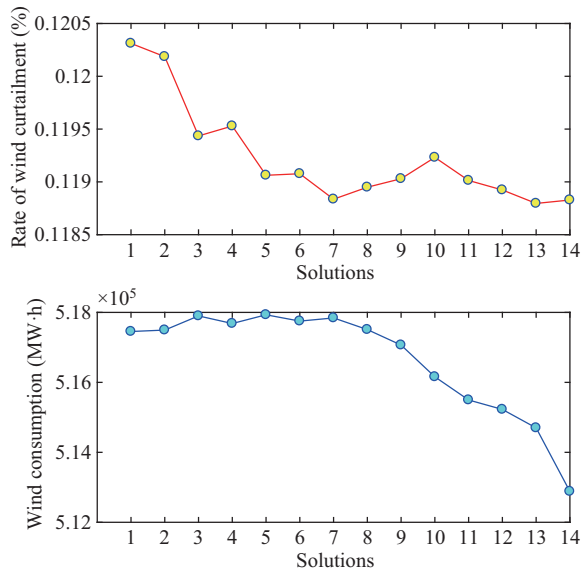


Fig. 9. Rate of wind curtailment and wind consumption along the solutions.

5–6 shows that although the wind power consumptions have little difference, the solutions 3–4 have much higher operation costs. Therefore, the consideration of wind power fluctuation can improve the cost-efficiency of the power system.

In order to analyze the impact of power system regulating ability on the determination of optimal solution, the operation cost of the wind-thermal system for each solution is recalculated with the peak load changing from 348 MW to 353 MW at the step of 0.5 MW. Fig. 10 depicts the normalized total operation cost and the optimal solutions (the stars).

It can be seen from Fig. 10 that when the peak load is less than 351 MW, the optimal solution is distributed in solutions 5–9, while when the peak load is greater than 351 MW, the optimal solutions concentrate at solution 1 or 2 with higher wind power production. It is because that the penetration of wind power decreases with the increase of load demand, and the ability of the power system to accommodate the fluctuation of wind power is improved.

D. Large-scale System Study

This case is conducted with a large-scale system to illus-

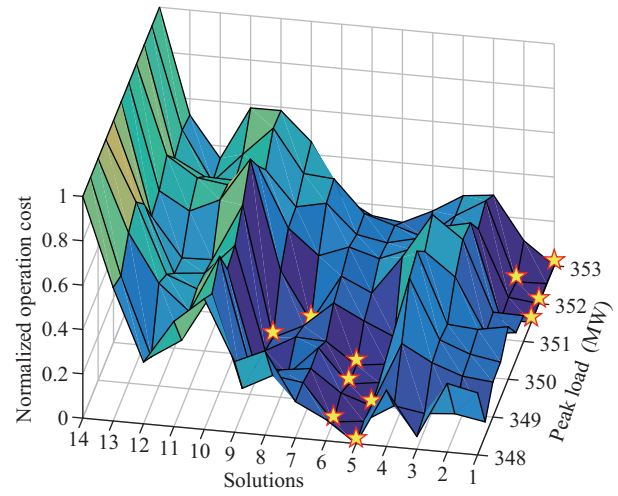


Fig. 10. Normalized operation costs and optimal solutions (the stars) along with the changes of peak load.

trate the effectiveness of the bi-objective layout optimization model. Assume that 300 identical WT are installed in four 4.0×4.0 km² wind farms with the wind speed data of Mayville, Galesburg, Hillsboro and Prosper. Two scenarios are conducted. In Scenario 1, the optimal wind farm capacity and the turbines' locations for four wind farms are optimized simultaneously. In Scenario 2, each wind farm is assumed to prearrange 75 turbines. Fig. 11 shows the Pareto-optimal front for the two scenarios.

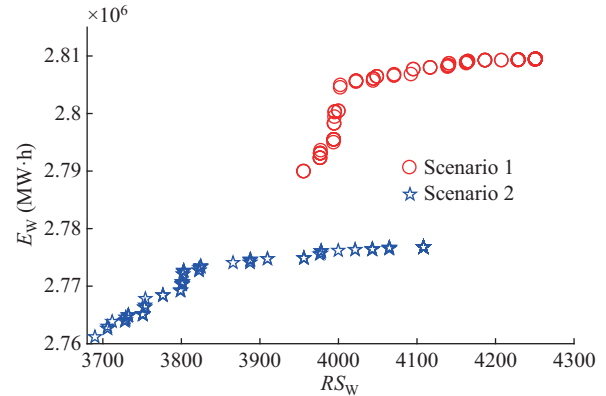


Fig. 11. Pareto-optimal front for large scale system with the scenarios.

Comparing the Pareto-optimal fronts in Fig. 11, it is observed that in Scenario 1, optimizing the wind farm capacity and the turbines' locations simultaneously can greatly improve the wind energy production without significantly increasing the wind power fluctuation risk index. Therefore, the optimization of wind farm layout for multiple wind farms is necessary to be conducted simultaneously, which can make full use of the wind energy resources of each wind farm.

We analyze the capacity planning results of multiple wind farms in the Pareto optimal solution set, and re-depict the Pareto-optimal front using different colors expressing different planning schemes in Fig. 12. The Pareto-optimal solution set contains 7 capacity planning schemes, which more than that

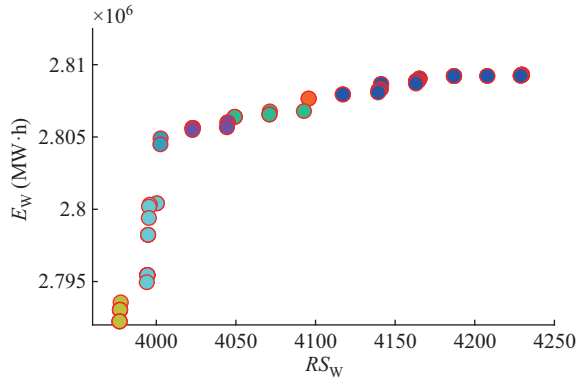


Fig. 12. Pareto-optimal front for large scale system with different planning schemes.

of the small system. Since the number of decision variables is much more than the small system, the capacity planning results would be relatively stable.

Figure 13 shows the capacity planning schemes for the large scale system. The planned number of turbines for each wind farm is relatively concentrated. In addition, the turbine number of Galesburg is only about 40, which is much less than others. It could be the reason that Galesburg has far less wind resources than the other wind farms. On the other hand, it also indicates that the wind turbines are arranged over a relatively large distance, and the influence of wake effect is weak.

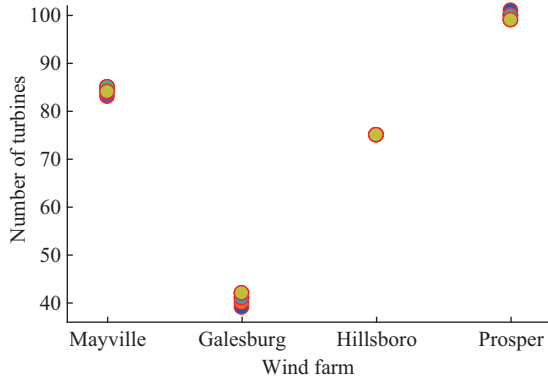


Fig. 13. Capacity planning schemes for large scale system.

VII. CONCLUSION

A bi-objective layout optimization model for multiple wind farms is presented considering the sequential fluctuation of wind power. The proposed model aims to determine the optimal installed capacity of wind farms and the location of wind turbines. Moreover, it can maximize the energy production and minimize the fluctuation of wind power simultaneously, hence improve security and the cost-efficiency of wind-thermal system. A uniform design based two-stage genetic algorithm is developed for the solution. Case studies have been conducted to verify the effectiveness of the proposed model.

Conclusions are summarized below.

1) The proposed bi-objective layout optimization model is effective to determine the Pareto optimal solutions for multiple

wind farm layout and reduce the fluctuation wind power with the slight reduction of energy production.

2) The optimal layout solution for multiple wind farms relies on the operation flexibility of TGUs, which can be found out by the operation simulation of power system with the participation of wind farms.

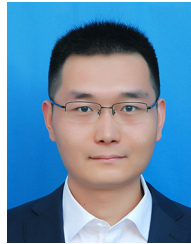
3) The uniform design based genetic algorithm can accelerate the convergence to Pareto solutions and improve the feasibility of Pareto solutions.

4) For large wind power base, it can make full use of the wind energy resources based on the wind speed profiles of each wind farm to optimize the wind farm capacity and the turbines' locations simultaneously.

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