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A NOVEL SOCIAL-ENVIRONMENTAL-ECONOMIC DISPATCH MODEL FOR THERMAL/WIND POWER GENERATION AND APPLICATION

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Abstract. *A novel model including social, environmental and economic benefits is proposed in hybrid thermal/wind power system and studied by Karush-Kuhn-Tucker and hybrid particle swarm optimization techniques. Our work is the first to develop social dispatch model by calculating risk caused by wind power. Then the novel multi-objective optimization model of social-environment-economic dispatch is established. Karush-Kuhn-Tucker method is used to convert multi-objective model into single-objective one. Particle swarm algorithm and multiplier method are combined to solve constraint optimization problem. So an improved Karush-Kuhn-Tucker and hybrid particle swarm optimization algorithm is proposed. Several scenarios are discussed to evaluate the simulation of three optimization models respectively considering economic dispatch, environmental-economic dispatch, and social-environmental-economic dispatch. The experimental studies show that the proposed algorithm is more accurate with less computational time than commonly used optimization methods. The actual implementation results demonstrate that the model and algorithm are effective and practical to improve the security of power system and reduce power operation costs, energy consumption and emissions.*

Keywords: Social-environmental-economic dispatch, Karush-Kuhn-Tucker, Hybrid particle swarm optimization, Thermal/wind power generation, Multi-objective optimization

1. **Introduction.** Energy conservation and emission reduction have attracted worldwide attention in 21st century. Clean power generation and joint dispatch are effective methods for energy conservation and emission reduction in power system. As a kind of clean energy, wind power is attracting increasingly attention. With fundamental character, the electric power enterprise has to provide reliable power to society. On the contrary, power outage can make social losses. However, thermal power and wind power have different characters. Thermal power has advantages of low cost and stable power, but causes serious pollution, especially carbon dioxide; whereas, clean energy power has the disadvantages of high cost and instability, but is highly environmentally friendly. Because of different economic, environmental and social influences, it is of practical significance to choose scientific and reasonable dispatch methods to achieve the maximum comprehensive benefit of hybrid power system. Because of randomness and instability of wind power [1-3], some literature studied wind power dispatching model with security constraints [4,5]. With proposing of energy conservation and emission reduction, many experts from home and abroad have started to research energy conservation and emission reduction dispatch in power system. Energy conservation dispatch mode was proposed in [6]; Literature [7] comprehensively analyzed environment/techno-economic methods for energy market to establish the environment/techno-economic model; Literature [8] studied dynamic economic dispatch

with energy conservation and emission reduction in power system integrated wind power and proposed a novel quantum genetic optimization algorithm; Energy conservation and emission reduction dispatch and economic dispatch were studied in [9,10].

Above all, the economic dispatch, or energy conservation and emission reduction dispatch (environmental dispatch), or both of them were studied in existing literature. However, none has researched the dispatch model integrated with social dispatch. Comprehensively considering social benefit, environmental benefit, and economic benefit, a novel multi-objective optimization model of social-environmental-economic dispatch with several constraint conditions is established for the first time.

Different techniques have been reported in the literature concerning dispatch problem. In the Artificial Intelligence field, many optimization methods have been developed recently, such as Simulated Annealing (SA) [11], Evolutionary Programming (EP) [12], Evolutionary Strategy (ES) [13], Genetic Algorithm (GA) [14], Particle Swarm Optimization (PSO) [15], Ant Colony System (ACS) [16]. These optimization methods are effective to find the global optimal solution. However, when adopted in large-scale real-world system, it would take a long computational time. In other research papers, focus has shifted towards analytical methods. Literature [17,18] converted multi-objective function into single-objective one using weight functions, but certain disputes and difficulties still exist in weight distribution. Combining KKT and Artificial Intelligence methods in this paper, a novel technique is proposed which avoids weights distribution and uses less computational time with more accuracy.

Based on characteristics of multi-objective optimization and advantages of intelligent algorithms, the Karush-Kuhn-Tucker algorithm [19], multiplier algorithm [20] and particle swarm optimization [21-27] are combined. Convert multi-objective problem into single-objective one by KKT, establish hybrid particle swarm optimization combing multiplier algorithm and particle swarm optimization, and then the KKT-HPSO algorithm is established.

The paper is organized as follows. In Section 2, the multi-objective optimization model is proposed with some relevant constraint conditions. Section 3 introduces Karush-Kuhn-Tucker converting process, the concepts and steps of hybrid particle swarm optimization algorithm in detail. Several scenarios are analyzed for simulation tests aiming to different optimization models in Section 4 which proves effective and practical of the novel model and algorithm. Finally, some concluding remarks are given in Section 5.

2. **Problem Formulation.**

2.1. **Objective functions.**

As clean energy, wind power has advantages of low cost, low energy consumption and pollution. However, wind output is random and predicted wind speed is often large different from actual wind speed, which brings uncertainty to power grid. As two kinds of main power energies, reasonable configuration thermal and wind power output to meet not only economic benefit but also social benefit and environmental benefit at the same time is a multi-objective optimization problem.

Based on the characteristics of thermal and wind power generations, the multi-objective social-environmental-economic dispatch function is established. The economic benefit is expressed by power operation cost, environmental benefit by energy conservation and emission reduction, social benefits by risk cost.

1) Economic benefit

The maximal economic benefit equals minimal power operation cost, which is expressed by a quadratic equation:

$$f_1 = \sum_{t=1}^{T} \sum_{i=1}^{Ng} a_i P_i^2(t) + b_i P_i(t) + c_i \tag{1}$$

where Ng is the number of thermal units in a system; $P_i(t)$ is the real power output of the ith generator in tth time point; T is total time points of one day; a_i, b_i, c_i represent the coefficients of the economic benefit function.

2) Environmental benefit

Environmental benefit is composed of energy conservation and emission reduction. Maximal environmental benefit equals minimal energy consumption and pollutant emission. One of the proposed approaches for modeling energy consumption is to use the quadratic function, these emissions to exponential terms. So the proposed approach for modeling environmental benefit is to use a combination of the polynomial and exponential terms for each generating unit:

$$f_2 = \sum_{t=1}^{T} \sum_{i=1}^{Ng} \alpha_i + \beta_i P_i(t) + \gamma_i P_i^2(t) + \xi_i \exp(\omega_i P_i(t)) \tag{2}$$

where α_i, β_i, γ_i, ξ_i, ω_i are the emission coefficients of the ith generator.

3) Social benefit

The electric power enterprise needs to provide reliable power to society. On the contrary, power outage can make social losses. So it is necessary to calculate risk cost caused by wind power. The social benefit function is as follows:

$$f_3 = \sum_{t=1}^{T} R(t) P_{Dt} \tag{3}$$

where $R(t) = \begin{cases} 1 - \frac{R_{sv(t)}}{P_{j(t)}}, & R_{sv} \le P_j \\ 0, & R_{sv} > P_j \end{cases}$

P_{Dt} is the total power demand in time t; $R_{sv(t)}$ represents the spinning reserved in tth hour; $P_{j(t)}$ is the power output of jth wind turbine in tth time point.

4) Objective models

Then the economic dispatch model min f_1, environment-economic dispatch model min (f_1, f_2), multi-objective optimization model of social-environment-economic dispatch min (f_1, f_2, f_3) are established.

2.2. **Constraint conditions.** Due to the physical or operational limits in practical system, there is a set of constraints that should be satisfied throughout the system operation for a feasible solution.

1) Power balance

$$\sum_{i=1}^{Ng} P_i + \sum_{j=1}^{Nw} P_j = P_D + P_L \tag{4}$$

where P_i is the power output of the ith thermal unit; P_j is the power output of jth wind turbine; P_D is the total needed power in corresponding period; P_L is the transmission loss of line which can be calculated based on the Kron's loss formula as follows: $P_L = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00}$, where B_{ij}, B_{0i}, B_{00} are the transmission network power loss B-coefficients.

2) Power operating limits

$$P_{i\min} \le P_i \le P_{i\max} \tag{5}$$

$$P_{j\min} \le P_j \le P_{j\max} \tag{6}$$

where $P_{i\min}$, $P_{i\max}$ are lower and upper limits of real power output for the ith thermal unit, $P_{j\min}$, $P_{j\max}$ are lower and upper limits of real power output for the jth wind unit, respectively.

3) Ramp rate limits

$$-R_{idown} \le P_{i(t)} - P_{i(t-1)} \le R_{iup} \tag{7}$$

where R_{idown}, R_{iup} are the ramp rates for the ith thermal unit, respectively.

4) Spinning reserve

$$\sum_{i=1}^{Ng} (P_{it\max} \times U_{it}) \ge P_{Dt} + R_{svt} \tag{8}$$

where P_{Dt} is total power deeded in tth hour; R_{svt} is the spinning reserved in tth hour; U_{it} is the ON and OFF status of the ith conventional unit at the tth time point. ($U_{it} = 0$ represents OFF status, $U_{it} = 1$ represents ON status.)

3. KKT-HPSO Algorithm Application to Social-Environmental-Economic Dispatch.

3.1. Multi-objective model conversion by KKT.

For social-environmental-economic dispatch, as the sub-object, environment benefit is changed firstly by KKT.

$$\begin{aligned} \min \sum_{t=1}^{T} \sum_{i=1}^{Ng} \alpha_i + \beta_i P_i(t) + \gamma_i P_i^2(t) + \xi_i \exp\left(\omega_i P_i(t)\right) \\ \text{s.t.} \quad (4),\ (5),\ (7) \end{aligned} \tag{9}$$

The Lagrangian equation for (9):

$$\begin{aligned} L = & \sum_{t=1}^{T} \sum_{i=1}^{Ng} \alpha_i + \beta_i P_i(t) + \gamma_i P_i^2(t) + \xi_i \exp(\omega_i P_i(t)) \\ & + \lambda \left(\sum_{t=1}^{T} \sum_{i=1}^{Ng} P_{it} + \sum_{t=1}^{T} \sum_{j=1}^{Nw} P_{jt} - D \right) \\ & + \mu_{11}(P_i - P_{i\min}) + \mu_{12}(P_{i\max} - P_i) + \mu_{21}(P_{i(t)} - P_{i(t-1)} - R_{idown}) \\ & + \mu_{22}(R_{iup} - P_{i(t)} + P_{i(t-1)}) \end{aligned} \tag{10}$$

$$\text{s.t.} \quad \beta_i + 2\gamma_i P_{i(t)} + w_i \xi_i \exp(w_i P_{i(t)}) + \lambda + \mu_{11} - \mu_{12} = 0 \tag{11}$$

$$\sum_{t=1}^{T} \left(\sum_{i=1}^{Ng} P_i(t) + \sum_{j=1}^{Nw} P_j(t) \right) = D \tag{12}$$

$$0 \le \mu_{11} \perp P_i - P_{i\min} \ge 0 \tag{13}$$

$$0 \le \mu_{12} \perp P_{i\max} - P_i \ge 0 \tag{14}$$

$$0 \le \mu_{21} \perp P_{i(t)} - P_{i(t-1)} - R_{idown} \ge 0 \tag{15}$$

$$0 \le \mu_{22} \perp R_{iup} - P_{i(t)} + P_{i(t-1)} \ge 0 \tag{16}$$

Then we can get the economic and social benefits function $f = f_1 + P_{risk} f_3$, where P_{risk} is the risk weight coefficient of wind farms. In a general way set P_{risk} as 0.1.

$$\begin{aligned} \min \sum_{t=1}^{T} \sum_{i=1}^{Ng} \left(a_i P_i^2(t) + b_i P_i(t) + c_i \right) + P_{risk} \sum_{t=1}^{T} R(t) \left(\sum_{i=1}^{Ng} P_i(t) + \sum_{j=1}^{Nw} P_j(t) \right) \\ \text{s.t.} \quad (11)\text{-}(16) \end{aligned} \tag{17}$$

$$P_{j\min} \le P_j \le P_{j\max} \tag{6}$$

$$\sum_{i=1}^{Ng} (P_{it\max} \times U_{it}) \ge P_{Dt} + R_{svt} \tag{8}$$

where $0 \le a \perp b \ge 0$ equals $a \ge 0$, $b \ge 0$, $ab \ge 0$.

Define $\Phi(a,b) = a + b - \sqrt{(a^2+b^2)}$, $0 \le a \perp b \ge 0$ equals $\Phi(a,b)$.

So the single-objective model converted by KKT is:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{Ng} (a_i P_i^2(t) + b_i P_i(t) + c_i) + P_{risk}\sum_{t=1}^{T} R(t)\left(\sum_{i=1}^{Ng} P_i(t) + \sum_{j=1}^{Nw} P_j(t)\right) \tag{17}$$

$$\text{s.t.} \quad \beta_i + 2\gamma_i P_{i(t)} + w_i \xi_i \exp(w_i P_{i(t)}) + \lambda + \mu_{11} - \mu_{12} = 0 \tag{18}$$

$$\sum_{i=1}^{Ng} P_i(t) + \sum_{j=1}^{Nw} P_j(t) = P_{Dt} \tag{19}$$

$$\Phi(\mu_{11}, P_i - P_{i\min}) = 0 \tag{20}$$

$$\Phi(\mu_{12}, P_{i\max} - P_i) = 0 \tag{21}$$

$$\Phi\left(\mu_{21}, P_{i(t)} - P_{i(t-1)} - R_{idown}\right) = 0 \tag{22}$$

$$\Phi\left(\mu_{22}, Riup - P_{i(t)} + P_{i(t-1)}\right) = 0 \tag{23}$$

$$P_{j\min} \le P_j \le P_{j\max} \tag{24}$$

$$\sum_{i=1}^{Ng} (P_{it\max} \times U_{it}) \ge P_{Dt} + R_{svt} \tag{25}$$

3.2. **Single-objective optimization based on HPSO.** Intelligent methods have been successfully applied into optimization problems. Constraint condition dealing is the key for particle swarm algorithm to solve optimization problem. Due to weakness of easily into local minimum, particle swarm algorithm and multiplier method are combined to solve constraint optimization problem. During random search of particles, if the searched particles do not meet constraint conditions, particle swarm algorithm will be replaced by multiplier method, otherwise continue to search. The basic process is as follows.

Step 1. Set current iteration algebra $t = 1$, population size N, searching space dimension D, initial position x_i^0 and velocity v_i^0 in the whole search space. If some particle x_i^0 $(i = 1, 2, \cdots, N)$ does not meet constraint conditions, take x_i^0 as the initial point, and replace x_i^0 with $(x_i^0)^*$ got from multiplier method. Then calculate adaptive value.

Step 2. Let best position p_i of ith particle be current position and p_g be the position of best particle.

Step 3. Perform the following operations of particle swarm algorithm for all particles:

Step 3.1. Update each speed and current position as the original particle swarm.

Step 3.2. If some particle $x_i(t)$ does not meet constraint conditions, take $x_i(t)$ as initial point, replace x_i^0 with $(x_i^0)^*$ got from multiplier method. Then calculate adaptive value.

Step 3.3. If current fitness is better than p_i fitness, set p_i as current adaptive value.

Step 3.4. If current i fits better than p_g, set p_g as current adaptive value.

Step 4. Update $t = t + 1$, return to Step 3, until getting an expected adaptive value or reaching the given maximum iterating times. End.

4. **Simulation Results and Discussion.** The simulation is in a modified IEEE30-Bus 6-Unit system and a wind farm. Six conventional thermal units are assumed. The wind farm represents the parallel operation of 20 units with the same type of wind turbine. Set T = 24. The associated parameters are shown in Table 1. The real output for wind

TABLE 1. Associated parameters of six thermal units

i	a_i	b_i	c_i	R_{iup}	R_{idown}	α_i	β_i	γ_i	ξ_i	ω_i
1	0.00144	5.88	80.62	35	45	4.071	−5.104	5.561	2.1 × 10-3	3.881
2	0.00532	4.61	100.12	30	40	3.321	−5.544	6.046	5.2 × 10-3	4.621
3	0.00415	6.09	234.08	30	40	3.746	−4.615	5.719	6.7 × 10-3	4.951
4	0.00384	6.22	220.78	30	40	3.981	−6.381	4.618	4.0 × 10-3	5.764
5	0.00277	7.04	240.19	30	40	4.351	−5.516	6.348	4.5 × 10-3	6.138
6	0.00508	7.88	320.47	35	45	4.120	−6.181	5.617	6.4 × 10-3	3.198

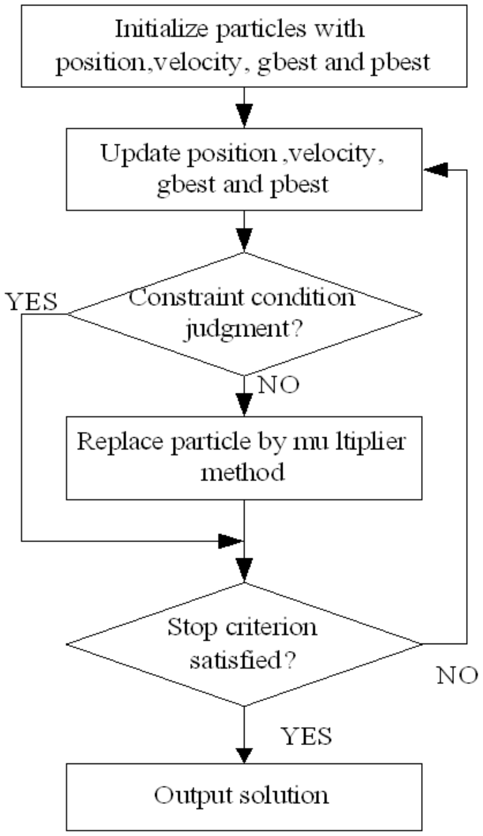

FIGURE 1. Flow chart diagram for HPSO

power, real output for thermal power, load demand and spinning reserved on some day are drawn in Figure 1. The B-coefficients [11] are shown as follows.

$$
\begin{aligned}
&[B] = \begin{bmatrix} 0.0234, 0.0105, 0.0018, -0.0042, -0.0007, -0.0012 \\ 0.0105, 0.0167, 0.0020, -0.0064, -0.0005, -0.0023 \\ -0.0042, -0.0064, -0.0637, 0.3326, -0.0105, 0.0532 \\ -0.0007, -0.0005, -0.0060, -0.0105, 0.0118, 0.0006 \\ 0.0012, -0.0023, -0.0350, 0.0532, 0.0006, 0.2137 \end{bmatrix} \\
&[B_0] = [-0.0006, 0.0015, -0.0039, 0.0062, 0.0015, 0.0013] \\
&B_{00} = 0.0012
\end{aligned} \tag{26}
$$

In order to evaluate the influence of environmental benefit and social benefit to dispatch decision making, three simulations are discussed in this paper: economic dispatch, environmental-economic dispatch and social-environmental-economic dispatch. According to analysis of the simulation results, the influences of wind power and thermal power to the comprehensive benefit are proved, based on which, different dispatch decision making can be made according to preference and need of decision maker. In order to validate the proposed KKT-HPSO, four other commonly used optimization algorithms including Evolutionary Programming (EP), Particle Swarm Optimization (PSO), Hybrid Particle Swarm Optimization (HPSO), and Quantum Genetic Algorithm (QGA) are calculated for comparison.

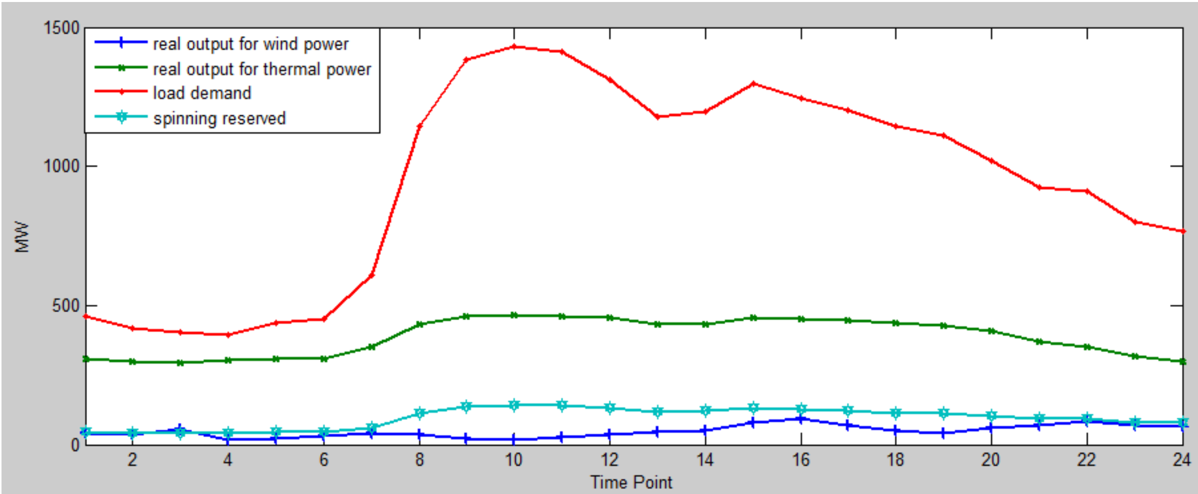

Figure 2. Referred data on some day

4.1. **Scenario 1.** In this scenario, only economic dispatch is considered. So the single-objective model is described as follows:

$$\min \sum_{t=1}^{T} \sum_{i=1}^{Ng} a_i P_i^2(t) + b_i P_i(t) + c_i \tag{27}$$
$$\text{s.t.} \quad (4)\text{-}(8)$$

Calculate it by four optimization algorithms including EP, PSO, HPSO, and QGA. The results can be seen in Table 2. From Table 2, we learn that QGA could obtain faster speed 3.54s and converge to minimum value of the total cost $275,038. On the other wise, EP performs worst which uses most CPU time and spends most total cost.

Table 2. Different total cost and computation time of CPU on some day when using 5 different algorithms

DIFFERENT ALGORITHM	ECONOMIC DISPATCH		ENVIRONMENTAL -ECONOMIC DISPATCH		SICIAL -ENVIRONMENTAL -ECONOMIC DISPATCH	
	Total cost	CPU time	Total cost	CPU time	Total cost	CPU time
EP	$290,782	7.04	$221,637	7.51	$222,094	7.89
PSO	$281,017	5.27	$220,934	5.54	$221,534	5.91
HPSO	$279,462	3.89	$219,762	3.96	$219,981	4.05
QGA	$275,038	3.54	$218,924	3.75	$219,340	3.80
KKT-HPSO	–	–	$218,335	3.14	$219,067	3.24

4.2. **Scenario 2.** In this scenario, both environmental benefit and economic benefit are considered. Then we can get the multi-objective model:

$$\min \left(\sum_{t=1}^{T} \sum_{i=1}^{Ng} a_i P_i^2(t) + b_i P_i(t) + c_i, \sum_{t=1}^{T} \sum_{i=1}^{Ng} \alpha_i + \beta_i P_i(t) \right.$$
$$\left. + \gamma_i P_i^2(t) + \xi_i \exp(\omega_i P_i(t)) \right) \quad (28)$$

s.t. (4)-(8)

Firstly convert environment benefit model by KKT, see chapter 3.1. Then the multi-objective model is changed into single-objective one.

$$\min \sum_{t=1}^{T} \sum_{i=1}^{Ng} a_i P_i^2(t) + b_i P_i(t) + c_i \quad (29)$$

s.t. (18)-(25)

Calculate it by proposed KKT-HPSO and other four commonly used algorithms including EP, PSO, HPSO, and QGA. The results can be seen in Table 2. From Table 2 we learn that proposed KKT-HPSO algorithm converges to optimal objective in 3.14s and gets fewest total cost \$218,335, which is even better than QGA. Similar with scenario 1, EP has the worst performance.

4.3. **Scenario 3.** In this scenario, a multi-objective model including social benefit, environmental benefit and economic benefit is proposed. It can be expressed as follows.

$$\min \left(\sum_{t=1}^{T} \sum_{i=1}^{Ng} a_i P_i^2(t) + b_i P_i(t) + c_i, \sum_{t=1}^{T} \sum_{i=1}^{Ng} \alpha_i + \beta_i P_i(t) + \gamma_i P_i^2(t) + \xi_i \exp(\omega_i P_i(t)), \right.$$
$$\left. \sum_{t=1}^{T} R(t) \left(\sum_{i=1}^{Ng} P_i(t) + \sum_{j=1}^{Nw} P_j(t) \right) \right) \quad (30)$$

s.t. (4)-(8)

Firstly convert environment benefit model by KKT. Then the multi-objective model is changed into single-objective one, see chapter 3.1.

$$\min \sum_{t=1}^{T} \sum_{i=1}^{Ng} \left(a_i P_i^2(t) + b_i P_i(t) + c_i \right) + 0.1 \sum_{t=1}^{T} R(t) \left(\sum_{i=1}^{Ng} P_i(t) + \sum_{j=1}^{Nw} P_j(t) \right) \quad (31)$$

s.t. (18)-(25)

Calculate it by proposed KKT-HPSO and other four optimization algorithms including EP, PSO, HPSO, and QGA. The results can be seen in Table 2. From Table 2, we learn that the optimization results are similar with that in scenario 2. The proposed KKT-HPSO method could obtain a faster speed which convergences to a minimum value of the total cost than EP, PSO, HPSO and QGA algorithms.

Only considering economic dispatch, the optimal total cost is \$275,038 which is most compared with other two dispatch models; For environmental-economic dispatch, the optimal total cost is \$218,335 which is significantly reduced compared with economic dispatch; while the optimal total cost of social-environmental-economic dispatch is \$219,067 which is a little higher than environmental-economic dispatch. From simulation results we know that, when considering social benefit, total cost increases compared with environmental-economic dispatch. However, because of randomness of wind power, it is necessary to consider social benefit to prevent power system risk.

At the same time, the weight of social benefit has important influence to optimal result. Different risk weight coefficients correspond to different results and decisions. For social-environmental-economic dispatch, when risk weight coefficient is 0, 0.1, 0.3, 0.5, the total cost is $218,335, $219,067, $219,984, $220,142, respectively. System risk increases with risk weight coefficient, which leads to increase of risk value proportion in objective function. Therefore, the greater the risk weight coefficient is, the more the optimal total cost of dispatch model.

5. **Conclusions.** A novel dispatch model is proposed in this paper which comprehensively considers social-environmental-economic dispatch using improved Karush-Kuhn-Tucker and hybrid particle swarm optimization algorithm in power system integrated wind power. After analyzing social benefit, environmental benefit and economic benefit and their constraint conditions, the novel multi-objective optimization model of social-environment-economic dispatch is established. Karush-Kuhn-Tucker is used to convert multi-objective model into single-objective one. Particle swarm algorithm and multiplier method are combined to solve constraint optimization problem. Then an improved Karush-Kuhn-Tucker and hybrid particle swarm optimization algorithm is proposed. Three scenarios that respectively consider economic dispatch, environmental-economic dispatch, and social-environmental-economic dispatch are discussed. Simulation results show that economic dispatch converges to most total cost and environmental-economic dispatch to fewest. When considering social benefit, optimal total cost of social-environmental-economic dispatch increases compared with environmental-economic dispatch. Also, influence of weight of social benefit to optimal result is evaluated. Different risk weight coefficients correspond to different results and decisions. According to analysis of the simulation results, the influences of wind power and thermal power to the comprehensive benefit are proved, based on which, different dispatch decision making can be made according to preference and need of decision maker. In order to validate the proposed KKT-HPSO, four other commonly used optimization algorithms including Evolutionary Programming (EP), Particle Swarm Optimization (PSO), Hybrid Particle Swarm Optimization (HPSO), and Quantum Genetic Algorithm (QGA) are calculated for comparison. Simulation results prove that the proposed algorithm is more accurate and with less computational time than other optimization algorithms. The actual implementation results prove that the model and algorithm are effective and practical to improve power system security, reduce power operation costs, energy consumption and emission.

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