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Paper

Multiobjective Dynamic Economic Emission Dispatch Using Evolutionary Algorithm Based on Decomposition

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Due to the pressures of energy and environment problems, the dynamic economic emission dispatch (DEED), which is more in line with actual dispatching requirements, has become an important research issue in recent years. In this paper, the highly dimensional, strongly coupled, nonlinear and nonconvex multiobjective DEED model is established considering both the fuel costs and pollution emissions objectives. Furthermore, an improved multiobjective evolutionary algorithm based on decomposition with constraints handling (IMOEA/D-CH) is proposed to obtain the optimal dispatching schemes. The IMOEA/D-CH method first decomposes the DEED problem into a number of scalar optimization subproblems and then evolves them simultaneously using the neighborhood information. The real-time heuristic constraints adjustment and modification methods and the adaptive threshold punishment mechanism are adopted in allusion to the complex constraints of the dispatching model. An evolutionary control strategy is also utilized to avoid excessive evolution of the algorithm toward a certain objective. In addition, the fuzzy decision-making strategy is used to provide the decision maker with the optimal compromise solutions. To validate the effectiveness of the IMOEA/D-CH method, the IEEE 30-bus 6-generator system and 10-generator system and 118-bus 14-generator system are studied as test cases. The simulation results indicate the validity and superiority of the proposed method compared with the other reported methods. © 2019 Institute of Electrical Engineers of Japan. Published by John Wiley & Sons, Inc.

Keywords: constraints handling; DEED; MOEA/D; multiobjective optimization

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1. Introduction

Economic dispatch (ED) is a key problem of power system optimal operation. Its main task is to allocate available generator outputs in order to minimize the total operating cost while fulfilling all the equality and inequality constraints [1]. Nowadays, environmental problems have seriously restricted the sustainable development of the world's economy and society. However, the majority of the modern society's power plants are still generating electricity with nonrenewable fossil fuels such as coal, oil and gas, which produce atmospheric pollution emissions like sulfur oxides (SO_x), nitrogen oxides (NO_x), etc. [2].

The economic emission dispatch (EED), which optimizes the generation cost and emission level simultaneously based on the traditional ED, has gradually become an important approach to reduce emissions of the power industry [3]. EED only needs to modify the existing power dispatch strategies compared with upgrading generation equipment or adopting renewable energy [4], and much work has recently been conducted about this issue [5–12]. Nevertheless, this research mainly focuses on the static model, which does not consider the correlation between different dispatching time intervals and cannot ensure the global optimization from the whole schedule horizon. As an extension of static EED, the dynamic economic emission dispatch (DEED), which is more in line with the actual short-term dispatching requirements, has gained more and more academic attention [13], but the DEED problem is a highly dimensional, strongly coupled, nonlinear and nonconvex multiobjective optimization problem (MOP) considering the conflicting objectives and the practical constraints. If the real power network loss, the variation of the load demand and the prohibited operating zone are also included, the problem would be particularly complicated.

In view of the complexity and importance of the DEED problem, it is quite necessary to establish an appropriate dispatch model and, furthermore, develop efficient solving algorithms to obtain the optimal dispatching schemes. Some research has been reported to address this problem. At first, the pollution emission was just considered a constraint in the dynamic economic dispatch (DED). In [14,15], such a model was built without the generators' ramp rate limits, and Song added the emission, as well as the security constraints, to the DED problem in [16]. With the development of high-performance solving algorithms, the research direction of the DEED problem has switched to consider both cost and emission as objectives in recent years. Basu [17] used an evolutionary programming-based fuzzy satisfying method to solve the DEED as a single-objective problem. Benhamida [18], Pandit [19], Thenmalar [20] and Mohammadi [21] converted DEED to a single objective problem on the basis of the price penalty factor approach and solved it using the flexible Hopfield neural network, the improved bacterial foraging algorithm (IBFA), the opposition-based differential evolution algorithm (ODEA) and the random drift particle swarm optimization (RDPSO) method. In [22–26], the weight sum-based single-objective DEED models are handled

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by the PSO, θ-PSO, hybrid DE-SQP and PSO-SQP, the harmony search method with a new pitch adjustment rule (NPAHS) and the differential harmony search (DHS) method, respectively.

All of this research mentioned above has achieved good results. However, due to the limitation of the single-objective DEED model, it is difficult to obtain more than one optimal solution in a single run, and the true pareto-optimal front (PF) is certainly hard to reach. Basu [27,28], Jiang [29], Zhu [30] and Roy [31] formulated the nonlinear constrained dynamic models and proposed the Nondominated Sorting Genetic Algorithm-II (NSGA-II), the Multiobjective Differential Evolution (MODE), the Modified Adaptive Multiobjective Differential Evolution (MAMODE), the modified NSGA-II and the Chemical Reaction Optimization (CRO) algorithms to solve the DEED as a true MOP with competing and noncommensurable objectives. In addition, Guo [32] developed the Group Search Optimizer with Multiple Producers (GSOMP) algorithm and modeled DEED as a series of static EED according to the dispatching time intervals, which would have difficulties in the combination of global optimal solutions from different period of time.

At present, DEED has become the basic issue in the dynamic dispatch domain of smart grid, micro-grid and active distribution networks. For such complicated MOPs, it would be always the focus of research to find a better solving algorithm and further improve the quality of the solutions according to the specific characteristics of the problems. The multiobjective evolutionary algorithm based on decomposition (MOEA/D), which is developed by Zhang and Li [33], has demonstrated potential in dealing with complex MOPs [34–36], and MOEA/D has been successfully implemented in many applications [37–39]. The author of this paper has also used MOEA/D in the field of static EED problem and obtained a better result [40]. However, when it comes to DEED, the relationships of variables are more intricate due to the couplings between the dispatching intervals. So, related research about MOEA/D in DEED problem remains to be conducted.

In this paper, the power DEED model is established with the multiobjective, highly dimensional, strongly coupled, nonlinear and nonconvex characteristics, and an improved multiobjective evolutionary algorithm based on decomposition with constraints handling (IMOEA/D-CH) is proposed to solve the DEED problem. Moreover, to demonstrate the performance of the IMOEA/D-CH, the IEEE 30-bus 6-generator system and 10-generator system and 118-bus 14-generator system are used as test cases. Compared with other reported methods, the results obtained by IMOEA/D-CH show its validity and superiority.

The rest of the paper is organized as follows. Section 2 gives the mathematical model of the DEED problem. Section 3 shows the details of the proposed IMOEA/D-CH method. Section 4 provides a specific solution procedure to implement IMOEA/D-CH for the DEED problem. Section 5 presents the simulation results and discussions. Conclusions are drawn in Section 6.

2. Model of DEED

2.1. Objective functions

The fuel cost of each generating unit considering a pulsatile valve point effect (VPE) can be modeled as the sum of a quadratic and a sinusoidal function. So, the total fuel cost of N generating units over T dispatching time intervals is expressed as:

$$F = \sum_{t=1}^{T}\sum_{i=1}^{N}\{a_i + b_i P_{i,t} + c_i (P_{i,t})^2 + |d_i \sin[e_i (P_{i,\min} - P_{i,t})]|\} \tag{1}$$

where $P_{i,t}$ is the active power output of the ith generating unit at the dispatching time interval t. $P_{i,\min}$ is the lower output limit, and a_i, b_i, c_i, d_i and e_i are the coefficients of fuel cost function for the ith generating unit.

Usually, atmospheric pollutants such as SO_x and NO_x caused by fossil-fueled thermal units can be modeled as the sum of a quadratic and an exponential function. Thus, the total pollution emission of N generating units over the whole dispatching period is expressed as:

$$E = \sum_{t=1}^{T}\sum_{i=1}^{N}[\alpha_i + \beta_i P_{i,t} + \gamma_i (P_{i,t})^2 + \zeta_i \exp(\varphi_i P_{i,t})] \tag{2}$$

where α_i, β_i, γ_i, ζ_i and φ_i are the coefficients of pollution emission function of the ith generating unit.

2.2. System constraints

1. Real power balance constraints: The real power balance constraints are equality constraints that are expressed as

$$\sum_{i=1}^{N} P_{i,t} - P_{D,t} - P_{L,t} = 0 \tag{3}$$

where $P_{D,t}$ and $P_{L,t}$ are the load demand and power loss at the time interval t, respectively. The value of $P_{L,t}$ can be calculated using Kron's loss formula:

$$P_{L,t} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{N} P_{i,t} B_{i0} + B_{00} \tag{4}$$

where B_{ij}, B_{i0} and B_{00} are the transmission network power loss B-coefficients.

2. Generators' capacity constraints

$$P_{i,\min} \le P_{i,t} \le P_{i,\max} \tag{5}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum output capacity of the ith generating unit, respectively.

3. Generators' ramp rate limits

$$\begin{cases} P_{i,t} - P_{i,t-1} - U_{Ri} \times \Delta T \le 0 \\ P_{i,t-1} - P_{i,t} - D_{Ri} \times \Delta T \le 0 \end{cases} \tag{6}$$

where U_{Ri} and D_{Ri} are the ramp up and down rate limits of the ith generating unit, respectively. ΔT is the length of each dispatching time interval.

2.3. Problem formulation

Based on the objective functions and system constraints, the DEED model can be described as an MOP with nonlinear constraints following formula (7)

$$\begin{cases} \min \;\; [F(P), E(P)] \\ \text{s.t.} \;\; g_i(P) = 0, \;\; i = 1, 2, \ldots, p \\ \qquad h_j(P) \le 0, \;\; j = 1, 2, \ldots, q \end{cases} \tag{7}$$

where $F(P)$ and $E(P)$ are the fuel cost and pollution emission objective functions, respectively. $g_i(P)$ and $h_j(P)$ are the equality and inequality constraints, and p and q are the corresponding formula numbers, respectively. P is the active power decision control vector of the generating units.

The objectives of such DEED optimization problems are constrained and even conflicting, and it is usually impossible to find the absolute optimal solutions. The Pareto-optimal solution (PS), which shows tradeoff relations of the objectives, becomes more important for decision support. All of these solutions within the entire search space constitute the PF. In fact, the aim of the DEED problem is to find the PS as much as possible during the whole dispatching period and distribute them on the PF evenly.

3. Proposed Algorithm-based MOEA/D

3.1. MOEA/D for DEED The MOEA/D algorithm, composed of decomposition and evolutionary algorithms, provides a new framework for solving MOPs. The decomposition algorithm transforms the PF approximation problem into a certain number of scalar objective optimization subproblems. For each subproblem, the evolutionary algorithm makes use of the neighborhood information to evolve the subproblems concurrently and collaboratively. Finally, the PF of the optimization problem is achieved by iterations.

3.1.1. Decomposition algorithm MOEA/D can use several algorithms to decompose an MOP into a set of scalar subproblems [33]. Previous research showed that the weighted Tchebycheff approach is less sensitive to the shape of PF and can be used to find the PSs in both convex and nonconvex PFs. So, it is adopted in this paper, and the objective function of each subproblem can be formulated as follows:

$$\begin{cases} \min g^{\mathrm{te}}(x|\lambda, z^*) = \max\limits_{1\le i\le m} \{\lambda_i |f_i(x) - z_i^*|\} \\ \text{s.t. } x \in S \end{cases} \tag{8}$$

where g^{te} is the optimization subproblems after Tchebycheff decomposed approach. x and m are the decision vector and the number of objective functions, respectively. $z^* = [z_1^*, z_2^*, \ldots, z_{\mathrm{m}}^*]^{\mathrm{T}}$ is the reference point. $f_i(x)$ is the ith objective function value. S is the feasible region. $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_{\mathrm{m}}]^{\mathrm{T}}$is the weight vector, and for each $i = 1, \ldots, m$, there should be

$$\begin{cases} z_i^* = \min\{f_i(x)\,|x \in S\} \\ \sum\limits_{i=1}^{m} \lambda_i = 1 \end{cases} \tag{9}$$

3.1.2. Evolutionary algorithm MOEA/D has several distinctive versions based on different evolutionary algorithms (e.g. MOEA/D-SBX [33], MOEA/D-DE [34] and MOEA/D-DRA [35]). Based on previous research, the differential evolution (DE) algorithm is also used to evolve the population of subproblems in this paper. It randomly selected different parent solutions within a certain neighborhood and utilizes the DE operator to generate new child solutions in order to improve the population diversity and the exploration ability of the optimization. The detailed procedures can be found in Section 4.2.

3.2. Improvement of MOEA/D MOEA/D algorithm was originally used to solve unconstrained and general MOPs [33–35], but the dispatching model in this paper has high-dimensional, strong coupling decision variables and various nonlinear, multiscale equations and inequality constraints, which make the feasible solution domain narrow and the topology complex. Therefore, the algorithm must be improved according to the characteristics of this specific DEED problem. The effective processing method of complex constraints and the practical strategy for evolutionary direction controlling and decision making are used to obtain the optimal feasible solution and dispatching scheme.

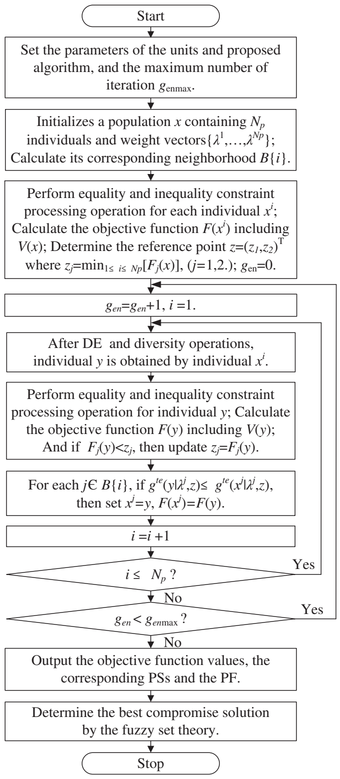

Fig. 1. Flow chart of IMOEA/D-CH for DEED

3.2.1. Constraints handling method (1) Equality constraints handling

For the real power balance constraints in different time intervals of the DEED system, the heuristic constraint processing method [29] is adopted to adjust the output of the generating unit dynamically.

The specific procedure is as follows

i. Set the maximum number of unit output adjustments K for each dispatching time interval, $t = 1, 2, \ldots, T$.
ii. Calculate the constraint violation of equality constraints.

$$\Delta P_t = P_{D,t} + P_{L,t} - \sum_{i=1}^{N} P_{i,t} \tag{10}$$

If $\triangle P_t$ is less than the threshold of the constraint violation ε, or the number of adjustments is greater than the maximum adjustment number K, go to step iv; otherwise, step iii is executed.

iii. Adjust the output of each generating unit at time interval t.

$$P_{i,t} = P_{i,t} + \Delta P_t / N \tag{11}$$

If the result violates the unit capacity or the ramp constraints after such adjustments, $P_{i,t}$ will be handled according to the inequality constraints method in the following section (2) and then returns to step ii.

iv. After all the unit output adjustments are completed, the equality constraint process is ended.

(2) Inequality constraints handling

The inequality constraints involve the active power outputs of the generating units during the whole dispatching period. The dimension of these variables is high, and their coupling relations between every time intervals are serious. All of these factors make

Table I. Description of the test cases

Case	N	NO. of buses	x	Data sources: Unit data	Load demand	Loss coefficients
A	6	30	$6 \times 24 = 144$	Ref. [42]	Ref. [32]	Ref. [42]
B	10	—	$10 \times 24 = 240$	Ref. [27]	Ref. [27]	Ref. [27]
C	14	118	$14 \times 24 = 336$	Ref. [42]	Ref. [32]	Ref. [43]

— = not available.

it difficult to solve the constraints using conventional constraint-handling methods. Therefore, constraints such as unit capacity constraints and ramp rate limits are incorporated into the range of unit output adjustment in this paper, which will implement constant modification of the active power output. The specific methods are as follows:

i. Set the upper and lower limits of the units output for different time interval.

$$\begin{cases} P_{i,t,\min} = \begin{cases} P_{i,\min}, & t = 1 \\ \max\left(P_{i,t-1} - D_{\mathrm{R}i}, P_{i,\min}\right), & \text{otherwise} \end{cases} \\ P_{i,t,\max} = \begin{cases} P_{i,\max}, & t = 1 \\ \min\left(P_{i,t-1} + U_{\mathrm{R}i}, P_{i,\max}\right), & \text{otherwise} \end{cases} \end{cases} \tag{12}$$

ii Adjust the output of the unit according to the following formula:

$$P_{i,t} = \begin{cases} P_{i,t,\min}, & P_{i,t} < P_{i,t,\min} \\ P_{i,t}, & P_{i,t,\min} \le P_{i,t} \le P_{i,t,\max} \\ P_{i,t,\max}, & P_{i,t} > P_{i,t,\max} \end{cases} \tag{13}$$

(3) The constraint-handling approach is based on adaptive penalty function

In the process of adjusting the equality constraint, the solution may still be infeasible after reaching the maximum number of adjustments, and there is a certain equality constraint violation. To address this issue, a constraint-handling approach based on adaptive penalty function is proposed to penalize the infeasible solutions. The steps are as follows:

i. Calculate the total constraint violations of equality constraints for all intervals.

$$V(\boldsymbol{x}) = \sum_{t=1}^{T} \left| \sum_{i=1}^{N} P_{i,t} - P_{\mathrm{D},t} - P_{\mathrm{L},t} \right| \tag{14}$$

ii. Let P be the mating and update neighborhood range in MOEA/D. Then, set

$$\begin{cases} V_{\min} = \min\left\{V\left(x^i\right), i \in P\right\} \\ V_{\max} = \max\{V(x^i), i \in P\} \end{cases} \tag{15}$$

where $V(x^i)$ is the degree of constraint violation of solution x^i. $V_{\min}$ and $V_{\max}$ are the minimum and maximum values, respectively. The threshold value τ is defined as [41]

$$\tau = V_{\min} + s(V_{\max} - V_{\min}) \tag{16}$$

Table III. The result of case A obtained by the proposed method

Method	Objectives	Fuel cost ($)	Emission (lb)
IMOEA/D-CH	Best cost	**25 367.0**	6.9218
	Best emission	26 679.0	**5.6677**
	Best compromise	25 676.0	5.9720

The minimum values are in bold type.

where the parameter s controls the threshold value. The total objective function is given in the form of a penalty function containing constraint violations.

$$F(\boldsymbol{x}) = \begin{cases} f(\boldsymbol{x}) + s_1 V^2(\boldsymbol{x}), & \text{if } V(\boldsymbol{x}) < \tau \\ f(\boldsymbol{x}) + s_1\tau^2 + s_2(V(\boldsymbol{x}) - \tau), & \text{otherwise} \end{cases} \tag{17}$$

where s_1 and s_2 are two scaling parameters with $s_1 \ll s_2$. The proposed penalty function encourages the algorithm to search the feasible region and the infeasible region near the feasible region. The penalty increases sharply when $V(\boldsymbol{x})$ exceeds the threshold. Obviously, for any of the feasible solutions, there must exist

$$V(\boldsymbol{x}) = 0 \tag{18}$$

3.2.2. Evolutionary control strategy The fundamental idea of the MOEA/D algorithm is to calculate the difference between the objective value and the optimal value, including the weight vectors, using formula (8) and then evolve in the direction of narrowing the maximum difference to realize the approximation of the optimal value in a single subproblem. In this process, the diversity in dimension and magnitude of the objective function would make the algorithm overevolve to certain objective with a large difference value. In order to eliminate such a negative influence, the evolutionary direction control strategy is adopted in this paper, described by the following formula:

$$f_i' = \frac{f_i - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \tag{19}$$

where f_i, f_i' are the real and the normalized value of the ith objective, respectively. $f_i^{\max}$, $f_i^{\min}$are the maximum and minimum value of corresponding objective function, respectively.

3.2.3. Fuzzy decision making When obtaining the final PS, the decision makers can make a compromise between the objectives according to the actual situation of the system using the best compromise solution. Due to the imprecise nature of the decision makers' judgment, the ith objective value of the solution in the pareto-optimal set F_{i} is represented by a fuzzy-based membership function defined as:

$$\mu_i = \begin{cases} 1, & F_i \le F_i^{\min} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, & F_i^{\min} \le F_i \le F_i^{\max} \\ 0, & F_i \ge F_i^{\max} \end{cases} \tag{20}$$

where $F_i^{\min}$ and $F_i^{\max}$ are the minimum and maximum values of the ith objective, respectively. For each pareto-optimal solution k,

Table II. Optimal parameter setting for IMOEA/D-CH

Case	N	H	C_R	F	η	p_m	ε	K	s	s_1	s_2	$g_{en\max}$
A	100	20	0.9	0.6	20	1/144	10^{-6}	10	0.7	0.01	20	2000
B	100	20	1	0.6	20	1/240	10^{-6}	10	0.7	0.01	20	2000
C	100	30	0.9	0.7	20	1/336	10^{-6}	10	0.7	0.01	20	2000

Table IV. Comparison of the minimum objective values of case A

	IMOEA/D-CH	MAMODE [29]	GSOMP [32]	MOPSO [32]	NSGA-II [32]
Fuel cost ($)	25 367.0	25 732.0	25 493.0	25 633.2	25 507.4
Emission (lb)	5.6677	5.7283	5.6847	5.6863	5.6881
Average time (s)	198.7	428	1262.9	1095.8	4341.3

Table V. Comparison of the compromise (final) solutions of the case A

	IMOEA/D-CH	MAMODE [29]	GSOMP [32]
Fuel cost ($)	25 676	25 912.89419	25 924.45557
Emission (lb)	5.9720	5.979548	6.004152

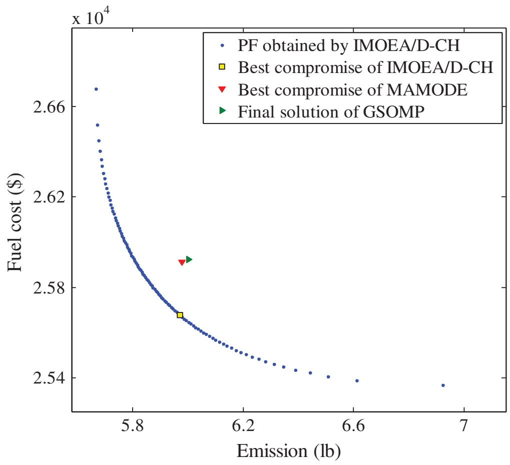

Fig. 2. PF of case A obtained by IMOEA/D-CH and comparison of optimal solutions

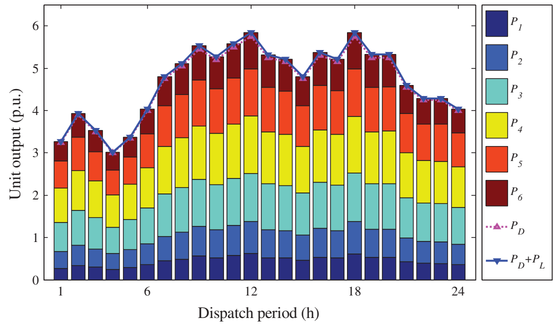

Fig. 3. Constraints check for the best compromise solution of case A

the normalized membership value μ^k is then calculated using

$$\mu^k = \frac{\sum_{i=1}^{m} \mu_i^k}{\sum_{k=1}^{N_{\mathrm{PF}}} \sum_{i=1}^{m} \mu_i^k} \tag{21}$$

where N_{PF} is the number of solutions in PF. The best compromise solution is the one that has the maximum value of μ^k. Then, all the solutions with their different membership function values will help the decision makers obtain the tradeoff relations between different objectives in view of the current operating conditions.

4. Implementation of Proposed Algorithm

4.1. Initialization (1) Population setting: The output of each generating unit is considered the decision variables

Table VI. The best compromise solution of case A obtained by IMOEA/D-CH (p.u.)

t	P_1	P_2	P_3	P_4	P_5	P_6	ΣP_i	P_L	P_D
1	0.2736	0.4015	0.6757	0.8200	0.6343	0.4668	3.2719	0.0219	3.25
2	0.3388	0.4766	0.8245	0.9457	0.7839	0.5635	3.9330	0.0330	3.90
3	0.2985	0.4273	0.7457	0.8635	0.6887	0.5017	3.5254	0.0254	3.50
4	0.2448	0.3735	0.6200	0.7653	0.5847	0.4299	3.0182	0.0182	3.00
5	0.2932	0.4167	0.7163	0.8305	0.6407	0.4756	3.3730	0.0230	3.35
6	0.3609	0.4894	0.8475	0.9542	0.8032	0.5803	4.0355	0.0355	4.00
7	0.4511	0.5770	1.0042	1.1148	0.9668	0.6898	4.8037	0.0537	4.75
8	0.4895	0.6400	1.0460	1.1833	1.0132	0.7420	5.1140	0.0640	5.05
9	0.5626	0.7013	1.1056	1.2673	1.0841	0.8089	5.5298	0.0798	5.45
10	0.5210	0.6625	1.0702	1.2078	1.0488	0.7594	5.2697	0.0697	5.20
11	0.5781	0.7056	1.1088	1.2875	1.0870	0.8155	5.5825	0.0825	5.50
12	0.6268	0.7503	1.1393	1.3555	1.1084	0.8643	5.8446	0.0946	5.75
13	0.5221	0.6626	1.0837	1.2244	1.0537	0.7743	5.3208	0.0708	5.25
14	0.5215	0.6409	1.0659	1.2082	1.0217	0.7600	5.2182	0.0682	5.15
15	0.4603	0.5947	0.9999	1.0934	0.9682	0.6882	4.8047	0.0547	4.75
16	0.5348	0.6846	1.0848	1.2373	1.0556	0.7765	5.3736	0.0736	5.30
17	0.5165	0.6467	1.0698	1.2024	1.0329	0.7493	5.2176	0.0676	5.15
18	0.6166	0.7595	1.1441	1.3381	1.1213	0.8639	5.8435	0.0935	5.75
19	0.5273	0.6678	1.0793	1.2268	1.0476	0.7728	5.3216	0.0716	5.25
20	0.5294	0.6721	1.0743	1.2415	1.0410	0.7637	5.3220	0.0720	5.25
21	0.4248	0.5630	0.9528	1.0625	0.9299	0.6659	4.5989	0.0489	4.55
22	0.3908	0.5220	0.9009	1.0050	0.8633	0.6090	4.2910	0.0410	4.25
23	0.3852	0.5156	0.9006	0.9963	0.8772	0.6157	4.2906	0.0406	4.25
24	0.3582	0.4838	0.8673	0.9589	0.8054	0.5608	4.0344	0.0344	4.00

Table VII. Comparison of the optimal objective values of case B

Method	Objectives	Fuel cost/10^6 (\$)	Emission/10^5 (lb)	Average time (s)
IMOEA/D-CH	Best cost	**2.4791**	3.1096	360.2
	Best emission	2.5770	**2.9292**	
	Best compromise	2.5167	2.9780	
IBFA [19]	Best cost	**2.481733**	3.27502	5.2017
	Best emission	2.614342	**2.95833**	
	Best compromise	2.517117	2.99037	
NSGA-II [27]	Best compromise	2.5226	3.0994	1211.475
RCGA [27]	Min cost	**2.5168**	3.1740	1080[a]
	Min emission	2.6563	**3.0412**	1080[a]
	Min combination	2.5251	3.1246	1105.363
MODE [28]	Best compromise	2.5224	3.0997	—
MAMODE [29]	Best cost	**2.492451**	3.15119	505
	Best emission	2.581621	**2.95244**	
	Best compromise	2.514113	3.02742	
CRO [31]	Best cost	**2.481613**	3.21214	6.3128
	Best emission	2.519305	**2.98664**	
	Best compromise	2.517821	3.01942	6.9703
HCRO [31]	Best cost	**2.479931**	3.21347	4.9362
	Best emission	2.520067	**2.98456**	
	Best compromise	2.517076	2.99066	5.1366

[a]Estimated value.

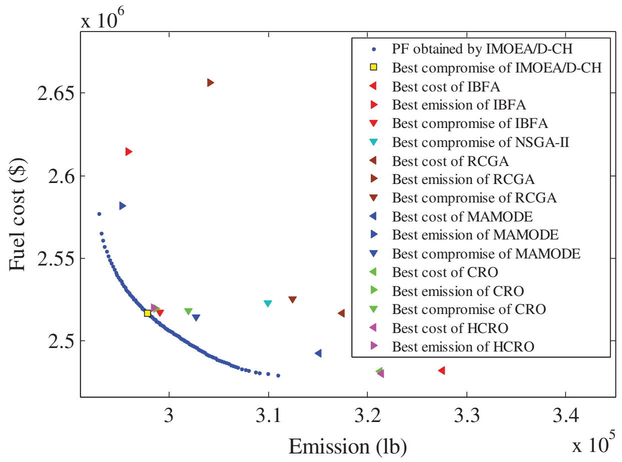

Fig. 4. PF of case B obtained by IMOEA/D-CH and comparison of optimal solutions

to construct the population of the proposed algorithms. N_p is the population size.

$$\boldsymbol{x} = [\boldsymbol{x}^1 \ \boldsymbol{x}^2 \cdots \ \boldsymbol{x}^{N_p}]^{\mathrm{T}} \tag{22}$$

The individual $\boldsymbol{x}^i (i \in N_p)$ represents one of the dispatching schemes.

$$\boldsymbol{x}^i = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,T} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,T} \\ \vdots & \vdots & \vdots & \vdots \\ P_{N,1} & P_{N,2} & \cdots & P_{N,T} \end{bmatrix} \tag{23}$$

Each individual has the dimension of $\mathrm{N} \times T$; in this regard, the dimension decision variables are the output power of thermal generator units, and the output value $P_{i,\,t}$ is randomly generated between its upper and lower bounds according to formula (5).

(2) Weight vectors

The evenly spread weight vector $\{\lambda^1, \lambda^2, \ldots, \lambda^{N_p}\}$of the proposed algorithm is taken from$\{0/(N_p-1),\ 1/(N_p-1), \ldots, (N_p-1)/(N_p-1)\}$ for the two objectives of DEED. Make it conform to the provisions of λ in formula (9) and calculate the Euclidean distance between any two weight vectors; then, find the H-closest vectors for each λ^i as its neighborhood$B(i) = \{i_1, i_2, \ldots, i_{\mathrm{H}}\}$. Then, $\lambda^{i_1}, \lambda^{i_2}, \cdots, \lambda^{i_H}$ are the H-closest weight vectors to λ^i.

4.2. DE operation

For each individual x^i of the population, randomly select three indices r_1, r_2 and r_3 from neighborhood $B(i)$ and $r_1 \neq r_2 \neq r_3 \neq i$. Then, generate a solution $y_k^{'}$ corresponding to the kth decision variable of $\boldsymbol{x}^i$ by a DE operator (DE/rand/1) based on the following formula.

$$y_k^{'} = \begin{cases} x_k^{r_1} + F\left(x_k^{r_2} - x_k^{r_3}\right), & \text{with probability } C_R \\ x_k^i, & \text{with probability } 1 - C_R \end{cases} \tag{24}$$

where C_R and F are two control parameters. In order to increase population diversity, use the mutation operation of probability p_m to produce new y_k as follows:

$$y_k = \begin{cases} y_k^{'} + \sigma_k\,(u_k - l_k), & \text{with probability } p_m \\ y_k^{'}, & \text{with probability } 1 - p_m \end{cases} \tag{25}$$

where $l_k$and u_k are the lower and upper bounds of the kth decision variable, respectively. σ_k is defined as,

$$\sigma_k = \begin{cases} (2\mathrm{rand})^{\frac{1}{\eta+1}} - 1, & \text{if rand} < 0.5 \\ 1 - (2 - 2\mathrm{rand})^{\frac{1}{\eta+1}}, & \text{otherwise} \end{cases} \tag{26}$$

where rand is a uniform random number from [0, 1]. η is the distributed control parameter.

4.3. Procedures for solving DEED

The flow chart of the proposed IMOEA/D-CH algorithm for solving the multi-objective DEED problem is shown in Fig. 1. g_{en} is the number of iterations.

5. Simulation Results and Discussions

The performance of the proposed IMOEA/D-CH algorithm to solve DEED problems has been evaluated using three test cases in this paper. The entire research period is divided into 24 parts with 1-h time intervals based on day-ahead dispatch.

Table VIII. The best compromise solution of case B obtained by IMOEA/D-CH (MW)

t	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_L	P_D
1	150.09	135.05	94.69	119.77	127.19	126.58	93.86	85.24	79.03	44.09	19.59	1036
2	150.22	135.17	90.84	119.99	171.94	124.61	123.14	90.16	79.77	46.63	22.47	1110
3	150.02	135.29	145.16	129.57	181.99	159.97	129.74	119.80	80.00	55.00	28.54	1258
4	153.85	144.80	186.70	179.57	231.70	160.00	130.00	119.99	80.00	55.00	35.61	1406
5	151.02	212.06	186.48	182.63	242.95	159.98	129.96	119.98	79.98	54.98	40.02	1480
6	224.55	222.23	211.93	230.55	243.00	159.99	130.00	120.00	80.00	55.00	49.25	1628
7	229.18	226.34	263.64	248.75	243.00	160.00	130.00	120.00	80.00	55.00	53.91	1702
8	227.62	277.33	280.52	261.82	243.00	160.00	130.00	120.00	80.00	55.00	59.29	1776
9	298.96	309.51	298.77	299.84	243.00	160.00	130.00	120.00	80.00	54.98	71.06	1924
10	326.64	346.92	340.00	300.00	243.00	160.00	130.00	120.00	80.00	55.00	79.56	2022
11	364.57	401.30	340.00	300.00	243.00	160.00	129.99	120.00	80.00	55.00	87.86	2106
12	413.19	401.33	340.00	300.00	243.00	160.00	130.00	120.00	80.00	55.00	92.52	2150
13	356.52	371.94	340.00	300.00	243.00	160.00	129.99	120.00	80.00	55.00	84.45	2072
14	299.09	309.89	298.12	299.97	243.00	160.00	130.00	120.00	80.00	55.00	71.07	1924
15	228.67	282.08	279.45	257.17	243.00	160.00	130.00	120.00	80.00	55.00	59.37	1776
16	165.73	222.10	202.14	220.36	242.97	160.00	129.99	120.00	80.00	55.00	44.29	1554
17	151.66	210.40	189.41	181.68	241.85	160.00	130.00	120.00	80.00	55.00	40.00	1480
18	220.25	223.20	215.27	230.55	243.00	159.99	129.98	119.99	80.00	54.97	49.20	1628
19	229.81	277.01	277.79	262.76	242.98	159.99	130.00	119.99	79.98	54.99	59.30	1776
20	305.18	319.24	334.52	300.00	243.00	160.00	130.00	120.00	80.00	55.00	74.94	1972
21	303.02	303.06	320.20	280.83	243.00	160.00	130.00	119.99	80.00	55.00	71.10	1924
22	223.03	223.23	240.26	230.83	217.87	158.79	129.71	119.69	79.86	53.98	49.25	1628
23	150.43	143.31	162.07	180.97	182.27	159.93	129.94	120.00	79.99	54.99	31.90	1332
24	150.10	135.00	107.99	131.56	171.87	133.12	129.47	119.79	79.87	50.63	25.40	1184

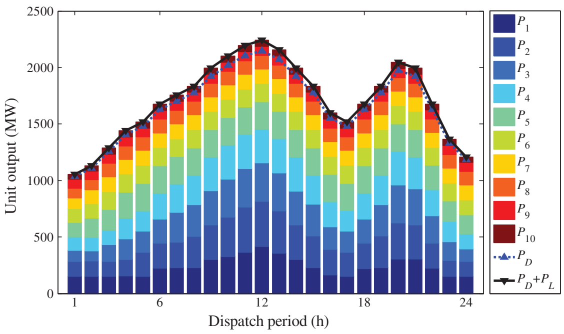

Fig. 5. Constraints check for the best compromise solution of case B

The specific description of the test systems are given in Table I. All the algorithms are implemented using MATLAB 2009b and executed on a computer with Core i5-4570@3.2GHz CPU, 8GB RAM and Windows 10 (64 bit) operating system. All algorithms were run 30 times independently, and the solutions and the average consumption time were recorded.

The experiments and related analysis show that the parameter selection of IMOEA/D-CH is critical in optimization. Parameter N controls a certain size of solution population to cover the whole PF. H gives the proper neighborhood range for evolving from parents to offspring. The other control parameters, such as C_R, F, η, p_m, ε, K, s, s_1 and s_2, guarantee the optimality and diversity of the feasible solutions. After evaluating different parameter combinations, the parameters have been confirmed on the basis of the recommended values in [33–35,40,41]. The parameters of the proposed algorithm are listed in Table II for clarity.

5.1. Case A To validate the efficiency of the proposed method for DEED, the IEEE 30-bus 6-generator test system is used, including nonlinear transmission power loss. The power load demand of the system can be found in [32], and the unit data and power loss coefficients are available in [42].

Table IX. The result of Scenario i obtained by the proposed method

Method	Objectives	Fuel cost ($)	Emission (lb)
IMOEA/D-CH	Best cost	**109 130**	122.070
	Best emission	123 390	**68.879**
	Best compromise	114 090	84.939

Note: The minimum values are in bold type. it has been explained in Table II.

The best cost, best emission and best compromise solution of Case A obtained by the proposed IMOEA/D-CH algorithm are given in Table III. Then, the results are compared to the minimum objective values reported in the literature, including MAMODE [29], GSOMP [32], MOPSO [32] and NSGA-II [32], in Table IV. Table V indicates the difference of the compromise (final) solutions with other methods.

As shown clearly in Table IV, the IMOEA/D-CH gives the minimum fuel cost of $25 367.0 and emission of 5.6677 lb, which are significantly better than those of MAMODE, GSOMP, MOPSO and NSGA-II methods. In Table V, the proposed approach obtains the best compromise solution of $25 676 and 5.9720 lb, which are also the best among the three methods.

The corresponding PF of the proposed approach in a single run is shown in Fig. 2 with the comparison of other reported optimal solutions. It can be clearly seen that the PS are widely and uniformly distributed in the objective space. The best compromise solution of IMOEA/D-CH also has a better location than that of MAMODE and GSOMP. The detailed information of the compromise result obtained by IMOEA/D-CH is shown in Table VI, based on which the power balance constraints, including P_i, P_D and P_L, can be checked at each interval in Fig. 3. In addition, although the computing time varies on the different hardware specification, the time consumed by IMOEA/D-CH demonstrates the efficiency of the proposed technique to solve DEED problem under general computers.

Table X. Comparison of the minimum objective values of Scenario i

	IMOEA/D-CH	MAMODE [29]	GSOMP [32]	MOPSO [32]	NSGA-II [32]
Fuel cost ($)	109 130	114 709.2	142 547.2	143 218.3	145 790.5
Emission (lb)	68.879	70.21	331.23	359.07	348.58
Average time (s)	166.5	235	5321.0	4733.0	14 123.2

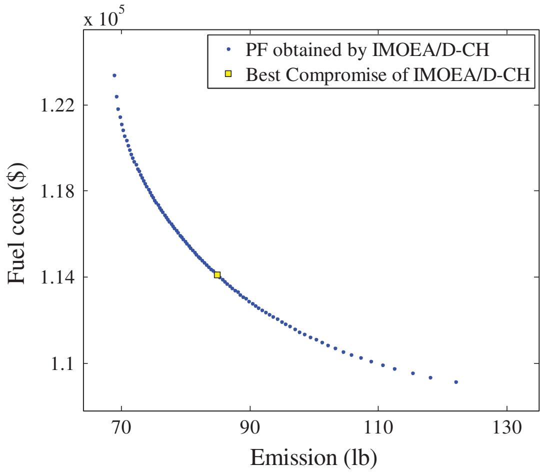

Fig. 6. PF of case C without power loss obtained by IMOEA/D-CH

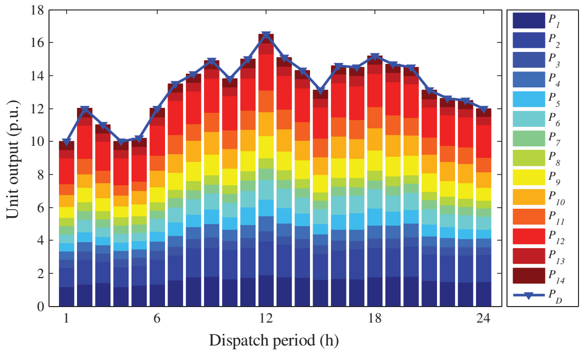

Fig. 7. Constraints check for the best compromise solution of case C without power loss

5.2. Case B This test case is a 10-generator power system [27], and the other parameters can also be found in this reference. In this case, both the nonsmooth fuel cost and the nonlinear power loss are considered through the optimization. The optimal dispatch schedules of generators obtained by the proposed method are compared with the results recently reported in the literature.

The optimal results of Case B obtained by the proposed method are summarized in Table VII, with the comparison of IBFA [19], NSGA-II [27], RCGA [27], MODE [28], MAMODE [29], CRO [31] and HCRO [31]. The minimum fuel cost obtained by IMOEA/D-CH is $\$2.4791 \times 10^6$, which is less than that of IBFA ($\$2.481733 \times 10^6$), RCGA ($\$2.5168 \times 10^6$), MAMODE ($\$2.492451 \times 10^6$), CRO ($\$2.481613 \times 10^6$) and HCRO ($\$2.479931 \times 10^6$). The minimum emission of the proposed method is 2.9292×10^5 lb, which is also better than that of IBFA (2.95833×10^5 lb), RCGA (3.0412×10^5 lb), MAMODE (2.95244×10^5 lb), CRO (2.98664×10^5 lb) and HCRO (2.98456×10^5 lb). In terms of the best compromise solution, the IMOEA/D-CH gives a fuel cost of $\$2.5167 \times 10^6$ and emission of 2.9780×10^5 lb, which is also the best among the other methods except MAMODE. The cost of MAMODE is $\$2.514113 \times 10^6$, which is \$2587 less than that of IMOEA/D-CH, but its emission is 3.02742×10^5 lb, which is 4942 lb more than that of IMOEA/D-CH. Obviously, the increase in emissions of MAMODE accounted for a greater proportion (1.66%) compared to the reduction in cost (0.103%). So, IMOEA/D-CH achieves a better compromise result. Meanwhile, it is worth noting that, although their time consumption are very short, the IBFA, CRO and HCRO are single-objective optimization methods that can obtain only one solution per trail, like RCGA. Their total calculation time would be considerable.

The comparison and the distribution of the optimal solutions are clearly shown in Fig. 4. As the values of the best compromise solution of MODE and NSGA-II, IBFA and HCRO are pretty close, the cost and emission ($\$2.5224 \times 10^6$, 3.0997×10^5 lb) of MODE and HCRO ($\$2.517076 \times 10^6$, 2.99066×10^5 lb) are not shown in the figure for clarity. Table VIII gives the detailed information of the compromise result obtained by IMOEA/D-CH. The power balance constraints check of P_i, P_D and P_L at each time interval is demonstrated in Fig. 5.

5.3. Case C This test case is the IEEE 118-bus 14-generator system [32]. According to whether the power network loss is considered, two scenarios are studied for comparison as conducted in [29]. The unit data can be found in [42], and the transmission loss coefficients are available in [43].

Scenario i: In this scenario, the network power loss of the test case is not considered first. Table IX gives the best cost, best emission and best compromise solution obtained by the proposed IMOEA/D-CH algorithm. Then, the corresponding optimal objective values of IMOEA/D-CH, MAMODE [29], GSOMP [32], MOPSO [32] and NSGA-II [32] are all summarized in Table X.

As can be seen from Tables VIII and IX, the IMOEA/D-CH achieves a minimum fuel cost of \$109 130 and emission of 68.879 lb, which are much better than those of MAMODE, GSOMP, MOPSO and NSGA-II methods. Furthermore, the amount of time consumed by IMOEA/D-CH is relatively small.

Figure 6 demonstrates the PF with uniformly distributed PS in the objective space of the proposed approach in a single run. The detailed information of the best compromise result is not provided for the length of the paper, but the power balance constraints including P_i and P_D can still be checked at each interval in Fig. 7.

Scenario ii: The network power loss of the test case C is included in this scenario, which brings the highly nonlinear equality constraints of the real power in solving DEED problems. Table XI provides the comparison of the optimal objective values of case C with power loss for different methods.

Obviously, the minimum fuel cost and emission obtained by IMOEA/D-CH (\$117 660 and 90.231 lb) are much better than that of MAMODE (\$118 094.70 and 93.597782 lb). With regard to the best compromise solution, although the emission obtained by MAMODE is 107.850296 lb, which is 3.159704 lb less than that of IMOEA/D-CH, its cost is \$125 648.735817, which is \$2348.735817 far more than that of IMOEA/D-CH.

The above results confirm the global search ability of the proposed method once again in dealing with the complex constrained DEED problem-based Scenario i. Figure 8 shows the PF with uniformly distributed PS with power loss and the relative position of the optimal solutions of Scenario ii in the objective space in a

Table XI. Comparison of the optimal objective values of case C with power loss

Method	Objectives	Fuel cost ($)	Emission (lb)	Time(s)
IMOEA/D-CH	Best cost	**117 660**	157.93	295.69
	Best emission	135 910	**90.231**	
	Best compromise	123 300	111.01	
MAMODE [29]	Best cost	**118 094.70**	156.481978	—
	Best emission	134 258.849082	**93.597782**	
	Best compromise	125 648.735817	107.850296	

Note: The minimum values are in bold type. it has been explained in Table II.

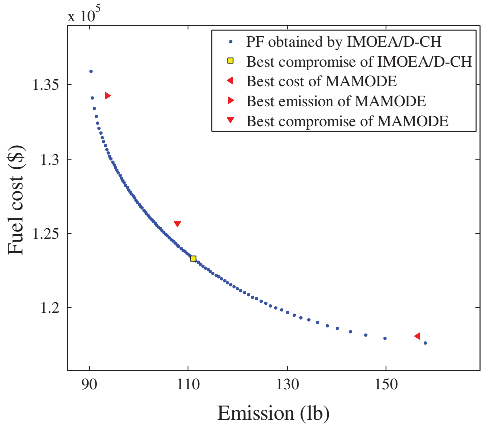

Fig. 8. PF of case C with power loss obtained by IMOEA/D-CH

single run. The detailed information of the best compromise result is also provided in Table XII for solution checking.

6. Conclusions

The multiobjective DEED model is established to deal with the conflicting fuel cost and pollution emission objectives in all dispatching time intervals. The MOEA/D algorithm is applied to solve the dynamic dispatch problem with appropriate improvement, which is termed IMOEA/D-CH. The proposed algorithm first decomposes the DEED problem into a set of subproblems through the Tchebycheff approach and then evolves them simultaneously using DE operation. The real-time heuristic constraints adjustment and modification methods, the adaptive threshold punishment mechanism, the evolutionary control strategy and the fuzzy decision-making approach are adopted in IMOEA/D-CH to obtain the optimal dispatching schemes. The IEEE 30-bus 6-generator system and 10-generator system and 118-bus 14-generator system are tested, and the results obtained by the proposed method are always comparable or better than that of the reported methods. The findings of this paper further prove that MOEA/D is a competitive tool to solve the complex constrained MOPs in a power system.

In the future, it is interesting to investigate the perfect DEED model for the unit commitment problem. With the development of new energy, such as wind power and solar power, due to their randomness, it will be more complicated to optimize the solution. Therefore, it is necessary to explore a more complete model and optimization algorithm. For example, to increase the user's revenue maximization objective function, extend the DEED model to the three-objective optimization problem and solve it with MOEA/DD and NSGA-III [44]. Another important avenue for future research is to analyze the adaptability of the constraint-handling method and to improve other multiobjective optimization algorithms.

Table XII. The best compromise solution of case C obtained by IMOEA/D-CH with power loss (p.u.)

t	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_L	P_D
1	2.1978	1.6455	0.5000	0.7460	0.5008	0.5242	0.5013	0.5040	0.7026	0.8634	0.7750	1.2128	0.5036	0.5028	1.6798	10.0
2	2.4958	1.8904	0.5000	0.9247	0.6197	0.7060	0.5006	0.5000	0.9386	1.0905	0.9395	1.4662	0.5000	0.5000	1.5720	12.0
3	2.3032	1.8478	0.5002	0.7815	0.5001	0.6716	0.5008	0.5003	0.8274	0.9906	0.8690	1.3430	0.5009	0.5006	1.6370	11.0
4	2.2577	1.5773	0.5009	0.7312	0.5069	0.5599	0.5009	0.5010	0.7325	0.8271	0.7183	1.2636	0.5009	0.5009	1.6791	10.0
5	2.2334	1.7073	0.5009	0.7150	0.5005	0.6134	0.5001	0.5009	0.7559	0.9121	0.6919	1.2357	0.5008	0.5001	1.6680	10.2
6	2.3860	1.9166	0.5020	0.8619	0.6920	0.7947	0.5015	0.5015	0.9120	1.1030	0.9584	1.4773	0.5024	0.5024	1.6117	12.0
7	2.5765	1.9861	0.6228	1.0456	0.8231	0.9259	0.5000	0.5000	1.1067	1.2525	1.1500	1.5269	0.5079	0.5000	1.5240	13.5
8	2.6313	2.0718	0.6443	1.0512	0.8598	1.0920	0.5002	0.5002	1.1288	1.3028	1.1774	1.6556	0.5001	0.5019	1.5174	14.1
9	2.7224	2.1454	0.7151	1.1584	0.9065	1.0734	0.5128	0.5041	1.1902	1.3651	1.1909	1.7156	0.6728	0.5010	1.4737	14.9
10	2.6027	2.0791	0.6000	1.1092	0.8425	1.0209	0.5019	0.5046	1.0366	1.3122	1.1367	1.5570	0.5008	0.5024	1.5066	13.8
11	2.7179	2.1525	0.7766	1.1322	0.9375	1.0815	0.5025	0.5568	1.1751	1.4121	1.1548	1.7022	0.6697	0.5000	1.4714	15.0
12	2.7669	2.2746	0.8219	1.2441	1.0691	1.1921	0.6253	0.6822	1.3468	1.5330	1.3559	1.7927	0.7421	0.5020	1.4487	16.5
13	2.7793	2.2109	0.6871	1.0812	0.9618	1.1387	0.5005	0.5005	1.2309	1.4060	1.2853	1.6910	0.5840	0.5056	1.4628	15.1
14	2.5635	2.1550	0.7035	1.1017	0.9120	0.9978	0.5015	0.5008	1.1331	1.3497	1.1719	1.6495	0.5759	0.5004	1.5163	14.3
15	2.5619	1.9655	0.5867	0.9942	0.7537	0.9398	0.5000	0.5000	1.0002	1.2180	1.0255	1.5451	0.5492	0.5000	1.5398	13.1
16	2.7036	2.1217	0.6369	1.1323	0.8717	1.0752	0.5113	0.5001	1.1477	1.3608	1.2183	1.6818	0.6224	0.5001	1.4839	14.6
17	2.6038	2.1382	0.7398	1.1080	0.9111	1.0157	0.5000	0.5075	1.1683	1.4124	1.1323	1.7423	0.5365	0.5000	1.5159	14.5
18	2.6947	2.1903	0.7154	1.1580	0.9389	1.0944	0.5003	0.5003	1.2416	1.4647	1.2777	1.7225	0.6766	0.5009	1.4763	15.2
19	2.6342	2.1534	0.6826	1.1056	0.9521	1.1022	0.5011	0.5209	1.2257	1.3491	1.2225	1.6568	0.5933	0.5000	1.4995	14.7
20	2.5894	2.1617	0.6852	1.1281	0.8865	1.0811	0.5123	0.5385	1.1612	1.3119	1.1718	1.7007	0.5781	0.5093	1.5158	14.5
21	2.5251	1.9508	0.5977	0.9709	0.7527	0.8869	0.5002	0.5023	1.0638	1.2314	1.1235	1.5474	0.5021	0.5002	1.5550	13.1
22	2.4122	2.0011	0.5109	0.9676	0.7126	0.8721	0.5039	0.5000	0.9679	1.2191	0.9978	1.5125	0.5012	0.5060	1.5849	12.6
23	2.4728	1.9239	0.5178	0.9595	0.6653	0.8743	0.5013	0.5013	0.9986	1.1918	0.9834	1.4776	0.5013	0.5013	1.5702	12.5
24	2.4030	1.8843	0.5028	0.9208	0.6444	0.7732	0.5033	0.5027	0.9197	1.1034	0.9614	1.4799	0.5017	0.5017	1.6023	12.0

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