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New Optimization Algorithm Inspired by Kernel Tricks for the Economic Emission Dispatch Problem With Valve Point

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ABSTRACT With the increasing concern over environment protection, Economic Emission Dispatch (EED) problem has received much attention. It is essentially a Multi-objective Optimization Problem, which minimizes both fuel cost and emission pollution simultaneously, as well as meets some system limits. This study transforms EED problem to a single-objective problem with weighted sum method, and then use Newton method to solve the equality constraint iteratively and introduce a common penalty function to deal with the inequality constraint. Moreover, this study tries to propose a new meta-heuristic algorithm inspired by kernel tricks to solve EED problem with no hyper parameters to be tuned. The new algorithm can map a non-linear objective function into a linear one with higher-dimension. Thus the optimization process could be transformed into a linear process, which is more likely to get the optimum solution. When applied in the 3 real-world EED cases with valve point, the new algorithm achieved a better performance compared with other algorithms in the literature.

INDEX TERMS Economic emission dispatch, Kernel search optimization, meta-heuristic algorithm, swarm intelligence.

I. INTRODUCTION

Economic emission dispatch problem (EED) has become an interesting and important task in power system as the environment protection gets more and more attention. EED problem is essentially a Multi-objective Optimization Problem (MOP) [1], which minimizes both fuel cost and emission pollution simultaneously, as well as meets some system limits such as power balance and generation limits.

In the recent decades, a large number of researches have been proposed to solve EED problem. However, conventional methods such as linear programming [2], quadratic programming [3] or interior point technique [4] are not satisfactory for solving EED as they are sensitive to the initial solution and often trapped in the local optimum. Therefore, many meta-heuristic optimization algorithms have been proposed in the literature to solve the dispatch problem. In general, there are mainly two approaches to solve the EED problem, one is converting the MOP into a single objective optimization problem(SOP). For instance, Abdelaziz introduced a modified price penalty factor to convert two objectives of fuel cost and emission into a single one and used flower pollination algorithm (FPA) [5] to solve it. Simulation results of both small and large scale power system indicate the robustness of FPA. Mahdi et al. used a unit-wise price penalty factor to convert all the objectives into a single objective and showed the inclusion of quantum computing idea to bat algorithm for CEED problem was a useful and reliable tool for solving such many-objective optimization problem [6]. Dosoglu et al. presented symbiotic organisms search (SOS) algorithm to solve CEED problem with price penalty factor [7]. In the meantime, many researchers have applied the weighted sum method to solve multi-objectives optimization. Hota et al. presented a fuzzy base modified bacterial foraging

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algorithm (MBFA) [8] for dealing with the EED problems. Shubham et al. used a Fuzzy Clustering based Particle Swarm Optimization algorithm (FCPSO) [9] to tackle the nonlinear multi-objective EED problems. Jadoun et al. combined two objectives into a single one by suggesting adjusted fuzzy membership functions and solved it with Modulated Particle Swarm Optimization (MPSO) [10].

As for the second approach, many Pareto-based multi-objective meta-heuristic algorithms are developed for minimizing both the fuel cost and emission pollution simultaneously. Abido has first developed and successfully applied Niched Pareto Genetic Algorithm (NPGA) [11], Non-dominated Sorting Genetic Algorithm (NSGA) [12], Multi-objective Particle Swarm Optimization (MOPSO) [13], Strength Pareto Evolutionary Algorithm (SPEA) [12], Multi-objective Evolutionary Algorithms (MOEA) [12] to solve EED problems and the experiment results confirm the potential and effectiveness of these algorithms. Zhao et al. used a variant of NSGA-II algorithm and an external penalty function to deal with a dynamic economic dispatch model of micro-grid [14]. Silva proposed a new scheme for the combination method to improve scatter search (ISS) for the EED problem [15], which is a capable candidate for dealing with EED problem. Roy and Bhui proposed quasi-oppositional teaching learning based optimization (QOTLBO) [16] to cope with EED problem with valve point loading. The simulation experiments of four test systems show the comparatively better cost and emission results compared with other algorithms. Qu et al. used summation based multi-objective differential evolution (SMODE) [17] algorithm to solve EED problem with stochastic wind power which yields superior solutions. Zhu et al. used an improved multi-objective evolutionary algorithm based on decomposition to solve CEED problem [18]. Chen and Zeng et al. proposed a constrained multi-objective population extremal optimization (CMOPEO) algorithm to solve EED problem with renewable power generations and the the experimental results showed the better performance compared with the algorithms in the literature [19], [20].

From the meta-heuristic algorithms applied in the EED problems above, it is difficult to choose the best comprise solution on the Pareto Front. And even little improved solutions are crucial and rewarding to the environmental protection and economic operation. Moreover, no matter SOP algorithms or MOP algorithms, they usually need to tune the hyper parameters carefully to find the best solution. Thus the present study tries to propose a new meta-heuristic optimization algorithm based on kernel tricks to deal with EED problem with no hyper parameters to be tuned, and use weighted sum method to transform MOP into SOP. The new meta-heuristic algorithm, named Kernel Search Optimization (KSO), can map a non-linear function into a linear one with higher-dimension. Thus the optimization process of nonlinear function could be transformed into a linear optimization process. When applied in the 3 real-world EED cases with valve point, the new algorithm achieved a better performance compared with other algorithms in the literature.

The remaining parts of this paper is arranged in this order; section 2 gives the basic theoretical model of EED problem. Section 3 presents the principle and details of new optimization algorithm of KSO. Section 4 elaborates the results of 3 real-world EED cases of KSO compared with other algorithms in the literature. Then section 5 has notable remarks and the conclusion.

II. ECONOMIC EMISSION DISPATCH PROBLEM

The EED problem needed to minimize both the total fuel costs and harmful pollutant emission with various power constraints by adjusting the output of each power plant. The objective function of the fuel costs was stated as follows [21]:

$$C = \sum_{i=1}^{N} [a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin(f_i(P_i^{\min} - P_i)) \right|] \tag{1}$$

where C is the fuel cost; a_i, b_i, and c_i are the cost coefficients of the ith generator; e_i and f_i are the valve point effect coefficients; P_i is the real power output; and N is the number of generating units in the system. If e_i and f_i are both 0, it is called EED problem without valve point; else it is called EED problem with valve point.

The objective function of the pollution emission was stated as follows [22]:

$$E = \sum_{i=1}^{N} [\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \eta_i \exp(\delta_i P_i)] \tag{2}$$

where E is the pollution emission, and α_i, β_i, γ_i, η_i, and δ_i are the emission coefficients.

This is a multi-objective optimization problem that has two conflicting objectives of C and E. There are many methods to choose the best comprise solution by transforming MOP into a single-objective problem. One is weighted sum method (WSM) that introduces a weight factor to combine the two objectives together. The final objective function had the following form [23]:

$$F = wC + \gamma(1 - w)E \tag{3}$$

where w is a weight factor, γ is scaling factor.

The EED constraints were as follows:

(i) Power balance constraints: The total power of all the generators must meet the demand and the loss of power system [24].

$$\sum_{i=1}^{N} P_i = P_D + P_L, P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{4}$$

where B_{ij} is the loss coefficient, N is the number of generators, P_L is the transmission losses and P_D is the system load.

(ii) Power capacity constraints: The output of each generator ranged from its minimum and maximum outputs.

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{5}$$

where $P_i^{\max}$ and $P_i^{\min}$ are the upper and lower bounds for the ith power output.

To solve EED problem with swarm intelligence algorithm, the inequality constraint of Eq.5 is generally satisfied, because the upper and lower limits can be set in the initialization stage of swarm intelligence. But the equality constraint of Eq.4 is difficult to be satisfied. So Newton method is introduced here to solve the equality constraint iteratively.

Supposing P_i is the output of the ith generator, $i = 1, 2, \ldots, N-1$.

$$P_i = P_i^{\min} + rand[0, 1] \times (P_i^{\max} - P_i^{\min}) \tag{6}$$

$P_i(i = 1, 2, \ldots N-1)$ can satisfy the inequality constraint of Eq.5. The output of the Nth generator P_N can be solved iteratively by equation 4 and the iterative solving steps are as follows:

Step 1: Calculate the original output of the Nth generator P_N by Eq.4

$$P_N^{old} = P_D - \sum_{i=1}^{N-1} P_i \tag{7}$$

where P_N^{old} is the original output of the Nth generator.

Step 2: Calculate the power loss according to the output of the N generators by Eq.5.

$$P_L^{old} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{8}$$

where $P_N = P_N^{old}$.

Step 3: Calculate the new output of the Nth generator P_N

$$P_N^{new} = P_D - \sum_{i=1}^{N-1} P_i - P_L^{old} \tag{9}$$

Step 4: Calculate the error $\varepsilon = \left|P_N^{new} - P_N^{old}\right|$. If $\epsilon >$ preset error, then goto step 2 for the next round; else $P_N = P_N^{new}$.

The output of the Nth generator P_N solved by the steps above, can satisfy the equality constraint of Eq.4, but it is not certain that P_N must fall in the feasible range of $[P_N^{\min}, P_N^{\max}]$. So to deal with the inequality constraint for P_N, a common penalty function is introduced as follows:

$$\widetilde{F} = F + \lambda[\max(P_N^{\min} - P_N, 0) + max(P_N - P_N^{\max}, 0)] \tag{10}$$

where λ is a penalty factor.

In the model of EED problem above, the total transmission line loss P_L is a function of the output level of the system generators, and it is commonly approximated by Kron's loss formula [27]. Due to the simplicity, the model above has been widely used in a large number of references, and it is one of the most common forms for the real power balance constraint in the EED problem. The loss coefficient B of Kron's loss formula is determined by the network configuration and parameters. And the loss P_L is just the approximation of the real network loss, which has a model error from the real loss. Generally, the solution of the approximate model can meet the requirements of engineering applications. This study proposed a new optimization algorithm for solving EED model based on B-coefficient. So the results obtained by KSO had the same model error just as the traditional incremental transmission losses algorithms. For the fair comparison with other algorithms in the literature, this widely used model of EED problem was chosen in this study.

III. THE PRINCIPLE OF KSO ALGORITHM

In spite of so many dazzling meta-heuristic algorithms to solve optimization problem, one algorithm may obtain optimal solutions only on some special problems and the hyper parameters of which needs to be tuned carefully. Even if with the same hyper parameters but on the different problems, the results may be far away from the optimal solution. It has been criticized that the hyper parameters of meta-heuristic algorithms need to be tuned carefully to fit the special objective functions. So in this section, we try to propose a robust optimization algorithm inspired by kernel tricks with no hyper parameters needed to be tuned. The inspiration is as follows.

As all the meta-heuristic algorithms search the optimal solution of the objective function through a nonlinear iterative process, which is essentially a linear incremental (finding maximum) or decremental (finding minimum) process in a higher dimensional space. And kernel trick can map the nonlinear objective functions to the linear ones with higher dimensions. Therefore, the optimization process for nonlinear functions can be transformed into that for linear ones by kernel trick, which can thus adapt different objective functions and no hyper parameters need to be tuned. The details of KSO are as follows.

For any nonlinear function $y = f(x)$, $x = (x_1, x_2, \ldots x_n)$, it could be transformed into a linear function when mapped into a higher-dimensional space by the mapping function $u = \varphi(x)$,where u is an m-dimensional vector and $m \gg n$. The schematic diagram is shown in Fig.1.The higher the dimension is, the more likely it is transformed to a linear

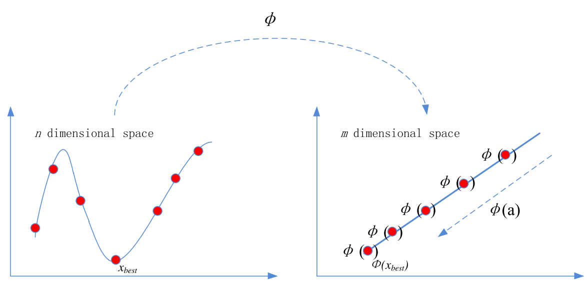

FIGURE 1. Low dimensional space mapped into high dimensional space.

one [25]. That is

$$y = f(x) = \omega^T \bullet u + b$$

where $\omega = (\omega_1, \omega_2, \ldots \omega_m)$ and $u = (u_1, u_2, \ldots u_m)$ are both m-dimensional vectors.

Meanwhile, the original vector in the n-dimensional space mapped to the m-dimensional vector ω is set to be a, that is $\omega = \varphi(a)$, $a = (a_1, a_2, \ldots a_n)$. $\varphi(a)$ is the slope of the hyper-plane in the m-dimensional space, which indicates the direction of optimal value of the hyper-plane. So,

$$y = f(x) = \omega^T \bullet u + b = \varphi(a) \bullet \varphi(x) + b = K(a, x) + b \tag{11}$$

where $K(a, x)$ is kernel function.

Therefore, the optimal value of the original objective function in the low-dimensional space can be obtained by solving the optimal value of linear function in the high-dimensional space. Unfortunately, it is difficult to solve the optimal value of the high-dimensional linear function directly, but it is easier to solve the optimal value of fitted kernel function corresponding to the objective function. So the optimal value of the objective function can be obtained by solving the optimal value of the fitted kernel function. Any function which satisfies Mercer's theorem can be used as kernel function [26], such as linear kernel function, polynomial kernel function and radial basis (RBF) function, etc. The RBF function can map the objective functions to the infinite dimensional space [22] in which the possibility of being linear functions arises. So the RBF function is used here

$$K(x, y) = \exp(\frac{\|x - y\|^2}{\sigma})$$

Then

$$y = f(x) = K(a, x) + b = \exp(\frac{\|x - a\|^2}{\sigma}) + b \tag{12}$$

It should be noted that the objective function and the fitted kernel function are not equal at all the points, only at some fitted points. The fitted function is used to fit the objective function approximately. Although the optimum of fitted kernel function may not be the strict minimum of the objective function, it can get close to the optimal value gradually by several iterations. As long as the optimal value of the fitted kernel function of Eq.12 is obtained, the approximate optimum value of the objective function in an iteration of optimization is obtained. Here the minimum of Eq.12 in different cases are given as follows directly (proof omitted), assuming that $x \in [x_{\min}, x_{\max}]$, the minimum is x_{best}.

$$x_{best} = \begin{cases} x_{\min} & \sigma < 0 \text{ and } a \geq \frac{1}{2}(x_{\min} + x_{\max}) \\ x_{\max} & \sigma < 0 \text{ and } a < \frac{1}{2}(x_{\min} + x_{\max}) \\ x_{\min} & \sigma > 0 \text{ and } a < x_{\min} \\ a & \sigma > 0 \text{ and } x_{\min} \leq a \leq x_{\max} \\ x_{\max} & \sigma > 0 \text{ and } a > x_{\max} \end{cases} \tag{13}$$

As is seen from Eq.13, the minimum value x_{best} is at the boundary, or is equal to vector a, which is the preimage in the low-dimensional space mapped to the hyper-plane slope in the high-dimensional space. After obtaining σ and a, the minimum x_{best} of fitted kernel function could be obtained according to Eq.13, which is the approximate minimum of the objective function in an iteration. Therefore, the minimum x_{best} which may be equal to the vector a plays a key role in the optimization process actually. It gives the search direction in the iterative optimization process. In view of this, the vector a is named as the kernel vector especially here.

Next, σ and a are solved in detail as follows, from Eq. 12 we can obtain

$$\begin{aligned} \sigma \ln(y - b) &= \|x - a\|^2 \\ &= (x_1 - a_1)^2 + (x_2 - a_2)^2 + \ldots (x_n - a_n)^2 \end{aligned} \tag{14}$$

This is the equation for σ and $a_1, a_2, \ldots a_n$, a total of $n+1$ unknowns, so $n + 1$ non-linear equations are needed to be established for solving the roots, which needs large amount of computation. Here proposes an easier method. Assuming that another vector $temp1 = (x'_1, x'_2, \ldots x'_n)$, the ith item of original vector x and form a new vector $(x_1, x_2, \ldots x'_i, \ldots x'_n)$. The function evaluation of the new vector is y'_i, and n new vectors form a matrix $x' = \begin{pmatrix} x'_1, x_2, \ldots x_i, \ldots x_n \\ \ldots \\ x_1, x_2, \ldots x'_i, \ldots x_n \\ \ldots \\ x_1, x_2, \ldots x_i, \ldots x'_n \end{pmatrix}$, the function evaluation of the matrix x' is $y' = (y'_1, y'_2, \ldots y'_i, \ldots y'_n)$, then

$$\begin{aligned} \sigma \ln(y'_i - b) = (x_1 - a_1)^2 + (x_2 - a_2)^2 \ldots \\ + (x'_i - a_i)^2 \ldots + (x_n - a_n)^2 \end{aligned} \tag{15}$$

Eq. 14- Eq. 15, we have

$$\begin{aligned} \sigma \ln(\frac{y - b}{y'_i - b}) &= (x_i - a_i)^2 - (x'_i - a_i)^2 \\ &= (x_i + x'_i - 2a_i)(x_i - x'_i) \end{aligned} \tag{16}$$

That is,

$$a_i = \frac{1}{2}[x_i + x'_i - \sigma \ln(\frac{y - b}{y'_i - b})/(x_i - x'_i)] \tag{17}$$

Assuming that one more vector $temp2 = (x''_1, x''_2, \ldots x''_n)$, the jth item x''_j, j is one random value in the range of $[1,n]$, is taken out to replace the corresponding jth item of original vector x and form a new vector $x'' = (x_1, x_2, \ldots x''_j, \ldots x_n)$. The function evaluation of new vector is $x'' = (x_1, x_2, \ldots x''_j, \ldots x_n)$, then

$$\begin{aligned} a_j &= \frac{1}{2}[x_j + x'_j - \sigma \ln(\frac{y - b}{y'_j - b})/(x_j - x'_j)] \\ &= \frac{1}{2}[x_j + x''_j - \sigma \ln(\frac{y - b}{y'' - b})/(x_j - x''_j)] \end{aligned}$$

Therefore

$$\sigma = \frac{x'_j - x''_j}{\ln(\frac{y-b}{y'_j-b})/(x_j - x'_j) - \ln(\frac{y-b}{y''-b})/(x_j - x''_j)} \tag{18}$$

Because b is irrelevant to obtaining the minimum in a linear optimization, the values of $y-b$, $y'-b$, $y''-b$ are normalized in the range of [1,e] by the values of y, y', y''. That is

$$y-b=\frac{(y-y_{\min})(e-1)}{y_{\max}-y_{\min}}+1$$

where $y_{\min}$ is the minimum of y, y', y'', $y_{\max}$ is the maximum of y, y', y'', e is natural exponent.

Thus after σ is obtained, a can be obtained when i ranges from 1 to n in turn according to Eq. 17. And the approximate optimum x_{best} of the objective function in this iteration can be obtained according to Eq. 13.

A. THE STEPS OF KSO ALGORITHM

The optimum x_{best} obtained by Eq. 13 is just the approximate to the optimum of the original objective function. So some iterations are needed to improve the accuracy of the global optimal value x_{gbest}, where the update equation plays a key role. In the iterative process of getting close to the real optimal value of the objective function, the approximate optimum x_{gbest} and the global optimum x_{best}, both indicate the search direction of the optimization. Furthermore, in order to accelerate the convergence, the equation above is multiplied by an exponential reduction factor and the final update equation is:

$$x_{new}=\begin{cases} x_{best} \\ \quad If\ f(x_{best})<f(x_{gbest}) \\ x_{gbest}+rand*\exp(\frac{-t}{T_{max}})*(x_{best}-x_{gbest}) \\ \quad Else \end{cases} \tag{19}$$

where T_{max} is the maximum number of iterations, t is the current number of iterations.

Let 's make a summary of the KSO algorithm. With the points initialized randomly, σ and a are calculated according to Eq. 18 and Eq. 17. Then x_{best}, is obtained according Eq. 13. Finally, the points are updated according to Eq. 19 and go to the next iteration until the maximum iteration is met. The detail process of KSO algorithm is shown in Fig. 2, and the pseudo code is shown as Algorithm 1.

IV. EXPERIMENTAL RESULTS

In the present study, three classic cases of EED problem with valve point are introduced to validate the performance of KSO, with scale from small to large. Case A: the standard IEEE-30 bus system (P_D = 2.834pu), is a widely used test case,and the results of all the compared algorithms have no big difference and even little improvement was difficult for the algorithms [27]; Case B: 10-unit system (P_D = 2000MW), is a medium scale power system; Case C: 40-unit system (P_D = 10500MW), is more complex and difficult, which can verify the performance of KSO better. The detailed data of the three cases are extracted from the previous studies [27].

In the proposed KSO, the population size N = 10, maximum iteration M = 100, the final results are the best solutions of 30 runs. The application of KSO to EED problem is implemented on the computer with 2.4-GHz Intel Xeon central processing unit E5-2665 and 32G of random-access memory using Matlab2014b.

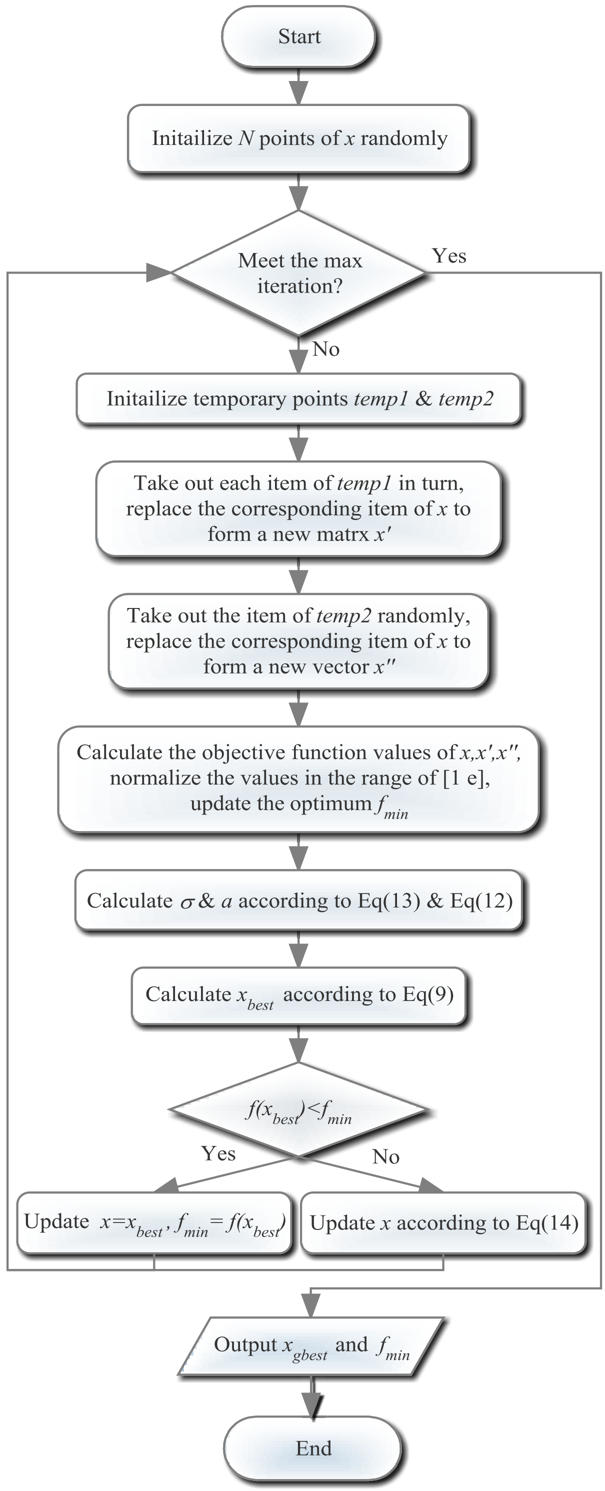

FIGURE 2. The flowchart of kernel search optimization algorithm.

TABLE 1. The best solutions for the fuel cost, total emission and transmission loss for *w* values of case A.

w	P_1	P_2	P_3	P_4	P_5	P_6	V(pu)	P_L(pu)	C($/h)	E(ton/h)
0.0	0.4111	0.4624	0.5436	0.3909	0.5479	0.5156	2.09E-03	0.0353	646.6009	0.1942
0.1	0.3603	0.4387	0.5498	0.4795	0.5472	0.4916	1.62E-03	0.0315	635.1410	0.1948
0.2	0.3189	0.4155	0.5571	0.5562	0.5482	0.4684	1.26E-03	0.0289	626.7375	0.1962
0.3	0.2849	0.3922	0.5599	0.6251	0.5468	0.4534	9.75E-04	0.0273	620.6124	0.1983
0.4	0.2526	0.3732	0.5676	0.6882	0.5481	0.4311	7.00E-04	0.0260	615.7948	0.2008
0.5	0.2231	0.3588	0.5594	0.7506	0.5502	0.4180	3.99E-04	0.0256	612.2380	0.2037
0.6	0.1855	0.3418	0.5687	0.7981	0.5559	0.4091	7.20E-05	0.0250	609.6861	0.2068
0.7	0.1858	0.3314	0.5634	0.8388	0.5519	0.3879	9.18E-05	0.0251	608.4666	0.2089
0.8	0.1650	0.3251	0.5587	0.8895	0.5544	0.3665	1.46E-04	0.0254	607.1467	0.2123
0.9	0.1364	0.3096	0.5766	0.9395	0.5342	0.3627	3.71E-04	0.0254	606.2090	0.2163
1.0	0.1127	0.2917	0.5811	0.9953	0.5261	0.3524	5.18E-04	0.0258	605.8960	0.2211

Algorithm 1 Kernel Search Optimization

Initialize points x
While $t \le Tmax$ **do**
  Initialize new points $temp1$ and $temp2$
  For i from 1 to D step 1
    $x'(i) \leftarrow temp1(i)$
  End for
  Take a random integer j
  $x''(i) \leftarrow temp2(j)$
  $y \leftarrow \{f(x), f(x'), f(x'')\}$, $y_{best} \leftarrow min(y)$,
  $y_{worst} \leftarrow max(y)$, $x_{gbest} \leftarrow arcmin(y)$
  $y \leftarrow \frac{(y-y_{\min})(e-1)}{y_{\max}-y_{\min}} + 1$
  $sigma \leftarrow \frac{x'_j - x''_j}{\ln(\frac{y-b}{y'_j-b})/(x_j-x'_j) - \ln(\frac{y-b}{y''-b})/(x_j-x''_j)}$
  For i from 1 to D step 1
    $a_i \leftarrow \frac{1}{2}[x_i + x'_i - \sigma \ln(\frac{y-b}{y'_i-b})/(x_i - x'_i)]$
    Calculate x_{best} according to Eq.13
  End for
  $y_a \leftarrow f(x_{best})$
  If $y_a < y_{best}$ **then**
    $x_{new} \leftarrow x_{best}, y_{best} \leftarrow y_a$
  Else
    $x_{new} \leftarrow x_{gbest} + (x_{best} - x_{gbest}) * rand * e^{-t/T_{\max}}$
  End if
End while
Print y_{best}

Table 1 shows the solution values of KSO for case A with the weight factor w ranging from 0 to 1, the step size of 0.1 and $\gamma = 1000$. The values of units P_1 to P_6 are the active power of the six generators of the system. The value of V is the violation of the equality constraints calculated by $V = |\sum_{i=1}^{N} P_i - P_D - P_L|$ because the inequality constraints are satisfied easily by the swarm intelligence algorithms. The violation V is an important parameter as the power plants should meet the load demands as much as possible for the stability of the power system. P_L denotes the transmission loss of the power system. And the fuel cost C and emission pollution E together form the Pareto-front as shown in Fig. 3, which also illustrates the best comprise solutions obtained by some algorithms in the literature. The farther the best comprise solutions are above the Pareto-front of KSO, the better performance KSO has compared with theses algorithms. As is seen from Fig. 3, the best comprise solutions of NSGA- [17], NPGA [11], MOPSO [13] are located far away above the Pareto-front and the ones of SPEA [12], FSBF [28] and NSBF [28] are also above the Pareto-front which implies the better performance of KSO than them. Meanwhile, the best comprise solutions of SMODE [17], MOEA/D [12], MBFA [17] and NGPSO [27]are just on the Pareto-front which mean the competitive performance of KSO with them.

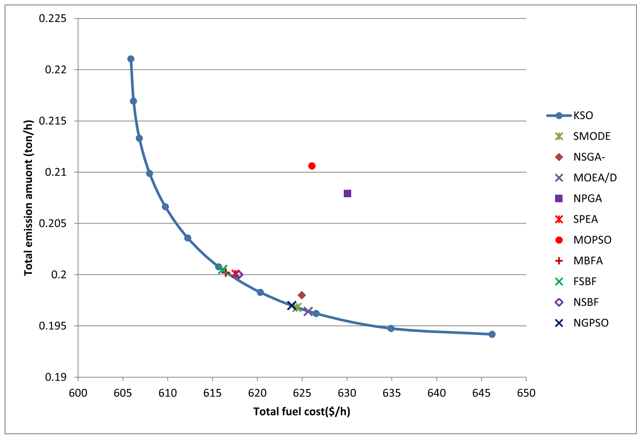

FIGURE 3. The Pareto-front of KSO and the best comprise solutions of other algorithms for case A.

The best fuel cost ($w = 1.0$) and the best pollution emission ($w = 0.0$) of case A are given in Table 2, compared with other results from the literature. At first glance, the results of all the algorithms have no big difference and even little improvement is difficult for the algorithms. In terms of the best cost, KSO obtains a better result of 605.8960($/h) than most of the algorithms except ISS, especially than SMODE [17], MOEA/D [12], MBFA [8] and NGPSO [27] which perform competitive with KSO on the Pareto-front. ISS obtains fewer cost but with a much larger value of V, which means the greater violation of equality constraints. For the best emission, KSO obtains the best result of 0.194178(ton/h)

TABLE 2. Comparison of the best fuel cost and best emission rate of case A with different algorithms.

Algorithm	Best fuel cost (w=1.0)				Best pollution emission (w=0.0)			
	C($/h)	E(ton/h)	P_L(pu)	V(pu)	C($/h)	E(ton/h)	P_L(pu)	V(pu)
MBFA [8]	606.1700	0.2174	0.0255	1.89E-05	643.84	0.194201	0.0345	2.51E-05
MSA [33]	605.9984	0.2207	0.0256	3.96E-05	646.20	0.194179	0.0353	2.71E-05
PSOGSA [27]	605.9984	0.2207	0.0256	6.10E-05	646.21	0.194179	0.0353	2.92E-05
MODE/PSO [28]	606.0073	0.2209	0.0256	1.45E-04	646.02	0.194200	0.0353	4.65E-05
MOPSO [13]	607.8400	0.2192	0.0255	7.38E-03	642.90	0.194230	0.0346	3.82E-03
PSO(wsm) [30]	607.8400	0.2198	0.0257	7.45E-03	645.23	0.194230	0.0352	4.13E-03
MOPSO-II [30]	607.7900	0.2193	0.0257	7.56E-03	644.74	0.194185	0.0350	4.11E-03
GA(wsm) [12]	607.7814	0.2199	0.0256	7.58E-03	645.22	0.194180	0.0352	4.12E-03
NSGA [12]	607.9800	0.2191	0.0265	8.07E-03	638.98	0.194678	0.0327	2.96E-03
NPGA [11]	608.0593	0.2207	0.0251	8.59E-03	644.23	0.194270	0.0355	4.06E-03
SPEA [11]	607.8600	0.2176	0.0258	7.43E-03	644.77	0.194279	0.0347	4.66E-03
DE [34]	608.0658	0.2193	0.0255	8.72E-03	645.09	0.194181	0.0352	4.80E-03
FCPSO [9]	607.7860	0.2201	0.0261	7.39E-03	642.90	0.194218	0.0345	3.64E-03
GSA [29]	605.9984	0.2207	0.0256	1.37E-04	646.21	0.194179	0.0353	6.98E-05
OGSA [29]	605.9982	0.2207	0.0256	5.69E-05	646.21	0.194179	0.0353	2.92E-05
CSS [35]	605.9865	0.2204	0.0254	7.22E-05	645.66	0.194179	0.0329	2.40E-03
NGPSO [27]	605.9984	0.2207	0.0256	1.37E-04	646.21	0.194179	0.0353	6.98E-05
SMODE [17]	619.0700	0.2034	0.0216	2.49E-03	643.01	0.194201	0.0344	4.50E-03
ISS [15]	603.5888	0.2159	0.0245	1.28E-02	633.39	0.194469	0.0318	2.20E-02
BBMOPSO [36]	605.9817	0.2202	0.0256	1.24E-04	646.48	0.194179	0.0354	2.92E-05
MOEA/D [12]	619.5300	0.2017	0.0227	2.39E-03	644.98	0.194187	0.0348	5.02E-03
KSO	605.8960	0.2211	0.0258	5.18E-04	646.22	0.194178	0.0353	6.98E-05

TABLE 3. The statistical results of fuel cost and emission pollution in case A.

Algorithm	C_{min}	C_{max}	C_{mean}	C_{median}	C_{std}	E_{min}	E_{max}	E_{mean}	E_{median}	E_{std}
GQPSO [37]	606.3804	611.86971	609.4986	609.6692	1.18	0.194222	0.194606	0.194451	0.194467	8.70E-05
SAIWPSO [38]	605.9984	606.0008	605.9986	605.9984	4.14E-04	0.194179	0.194179	0.194179	0.19417856	1.30E-07
NGPSO [27]	605.9984	605.9984	605.9984	605.9984	**0.00**	0.194179	0.194179	0.194179	0.194179	**0.00**
KSO	**605.8960**	**605.8960**	**605.8960**	**605.8960**	**0.00**	**0.194178**	**0.194178**	**0.194178**	**0.194178**	**0.00**

TABLE 4. The best solutions for the fuel cost, total emission for *w* values of case B.

w	0.0	0.1	0.2	0.3.	0.4	0.5	0.6	0.7	0.8	0.9	1.0
P_1	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000
P_2	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000
P_3	81.1342	81.1044	81.0657	81.8324	83.0291	84.7412	86.7684	88.4879	90.7984	97.2175	106.8407
P_4	81.3637	81.1148	80.8184	81.2858	82.1261	83.4185	84.9238	85.9576	87.2729	92.9695	100.9243
P_5	160.0000	160.0000	160.0000	160.0000	160.0000	143.7777	126.1310	109.9352	95.9611	88.2551	81.3210
P_6	240.0000	240.0000	240.0000	219.5572	189.0919	164.2877	142.7323	121.8268	103.7307	93.5454	82.9457
P_7	294.4851	292.2569	289.7305	291.3367	294.5841	299.5076	300.0000	300.0000	300.0000	300.0000	300.0000
P_8	297.2701	296.9424	296.5467	300.8221	307.2982	315.4369	321.2865	327.1948	334.0932	340.0000	340.0000
P_9	396.7657	398.0086	399.4298	406.0190	415.3430	427.8255	442.3902	456.2934	470.0000	470.0000	470.0000
P_{10}	395.5763	397.2162	399.1084	406.2862	416.3564	429.7994	445.6240	461.2551	470.0000	470.0000	470.0000
V(MW)	4.69E-05	7.70E-05	1.15E-04	6.13E-05	8.93E-05	1.10E-04	6.95E-05	1.13E-04	8.66E-04	3.20E-03	5.68E-03
P_L(MW)	81.5951	81.6432	81.6994	82.1393	82.8289	83.7946	84.8563	85.9509	86.8572	86.9907	87.0374
C($/h)	116412	116399	116384	115600	114608	113505	112645	112022	111646	111535	111497
E(ton/h)	3932.24	3932.32	3932.58	3961.37	4014.44	4105.62	4210.65	4325.95	4436.05	4497.24	4573.24

among all the algorithms. So in the comparison for both the best fuel cost and the best pollution emission, only KSO obtains the best result. So it can be concluded that KSO performs better than all the algorithms on case A.

Table 3 gives the statistical results of fuel cost and emission pollution in case A over 30 runs. To be more precise, the statistical metrics include the maximum, minimum, mean, median and standard deviation. From Table 3, it can be seen that KSO performed better and more robust than the compared algorithms in the literature.

Table 4 shows the solution values of KSO for case B with the weight factor w ranging from 0 to 1, the step size of 0.1 and $\gamma = 10$. And the fuel cost C and emission pollution E together form the Pareto-front as shown in Fig. 4, which also illustrates the best comprise solutions obtained by some algorithms in the literature. As is seen from Fig. 4, the best comprise solutions of NSGA- [17], FPA [5] are located above the Pareto-front clearly and the ones of MODE [22], PDE [22], SPEA2 [22], GSA [29] and ϵv-MOGA [30] are also above the Pareto-front and locate

TABLE 5. Comparison of the optimal solution values for the fuel cost (w=1) of case B with different methods.

Algorithm	BSA	QOTLBO	TLBO	DE	OGHS	NGPSO	KSO
P_1	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000
P_2	80.0000	79.9991	80.0000	79.8063	80.0000	80.0000	80.0000
P_3	106.9295	107.9231	105.9616	106.8253	106.9916	106.9399	106.8407
P_4	100.6028	98.6479	99.9321	102.8307	100.5354	100.5763	100.9243
P_5	81.4990	82.0180	80.6424	82.2418	81.4450	81.5017	81.3210
P_6	83.0074	83.4878	85.7878	80.4352	83.0670	83.0209	82.9457
P_7	300.0000	300.0000	300.0000	300.0000	299.9998	300.0000	300.0000
P_8	340.0000	340.0000	340.0000	340.0000	339.9999	340.0000	340.0000
P_9	470.0000	469.9706	469.6979	470.0000	470.0000	470.0000	470.0000
P_{10}	470.0000	469.9988	469.9943	469.8975	469.9999	470.0000	470.0000
V(MW)	6.04E-05	2.57E-05	3.86E-05	3.05E-06	3.08E-04	2.29E-05	5.68E-03
P_L(MW)	87.0388	87.0453	87.0161	87.0368	87.0389	87.0388	87.0374
C(\$/h)	111497.63	111498.43	111500.42	111500.79	111497.61	111497.63	111497.27
E(ton/h)	4572.26	4568.69	4563.34	4581.00	4572.27	4572.20	4573.24

TABLE 6. Comparison of the optimal solution values for the total emission (w=0) of case B with different methods.

Algorithm	BSA	QOTLBO	TLBO	DE	OGHS	NGPSO	KSO
P_1	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000
P_2	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000
P_3	81.1749	81.1342	81.1261	80.5924	81.1062	81.1342	81.1342
P_4	81.3585	81.3637	81.3640	81.0233	81.4128	81.3637	81.3637
P_5	160.0000	160.0000	160.0000	160.0000	160.0000	160.0000	160.0000
P_6	240.0000	240.0000	240.0000	240.0000	239.9999	240.0000	240.0000
P_7	294.4430	294.4843	294.4790	292.7434	294.5065	294.4851	294.4851
P_8	297.2970	297.2710	297.2439	299.1214	297.2617	297.2701	297.2701
P_9	396.8075	396.7645	396.8041	394.5147	396.7353	396.7657	396.7657
P_{10}	395.5131	395.5775	395.5788	398.6383	395.5715	395.5763	395.5763
V(MW)	8.70E-05	4.07E-05	1.12E-04	9.04E-05	2.02E-04	4.69E-05	4.69E-05
P_L(MW)	81.5941	81.5952	81.5958	81.6334	81.5941	81.5951	81.5951
C(\$/h)	116412.38	116412.44	116412.35	116404.29	116412.65	116412.44	116412.44
E(ton/h)	3932.24	3932.24	3932.24	3932.42	3932.24	3932.24	3932.24

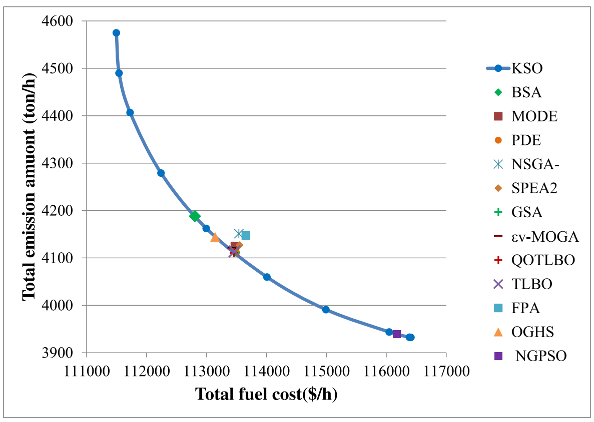

FIGURE 4. The Pareto-front of KSO and the best comprise solutions of other algorithms for case B.

near the solution of KSO when $w = 0.5$, which implies that the solution of KSO dominates the best comprise solutions of these algorithms. Meanwhile, the best comprise solutions of BSA [31], QOTLBO [16], TLBO [16], OGHS [32], NGPSO [27] are just on the Pareto-front which mean the competitive performance of KSO with them.

The best fuel cost ($w = 1.0$) and the best pollution emission ($w = 0.0$) of case B are given in Table 5 and Table6, compared with other results from the literature. In terms of

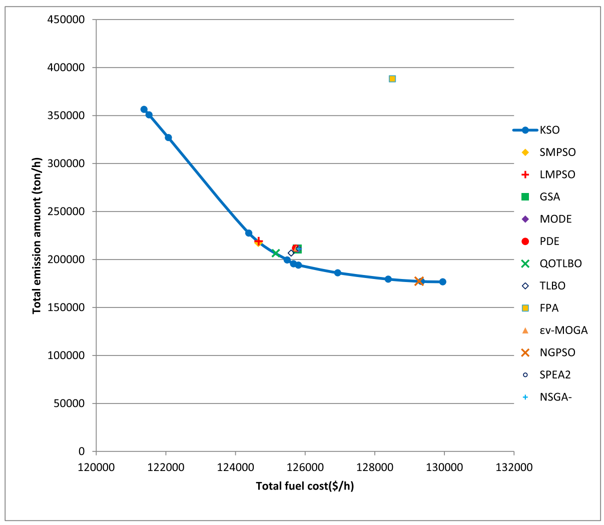

FIGURE 5. The Pareto-front of KSO and the best comprise solutions of other algorithms for case C.

the best cost, KSO obtains the best result of 111497.27(\$/h) compared with all the algorithms especially better than BSA, QOTLBO, TLBO, OGHS, NGPSO which are just on the Pareto-front. KSO saves 0.36(\$/h) fuel cost compared with OGHS which has the second best result. For the best emission, KSO obtains the best result among all the algorithms

TABLE 7. The statistical results of fuel cost and emission pollution in case B.

Algorithm	C_{min}	C_{max}	C_{mean}	C_{median}	C_{std}	E_{min}	E_{max}	E_{mean}	E_{median}	E_{std}
GQPSO [37]	112429.74	113327.07	113102.46	113216.44	2.56E+02	4011.92	4042.19	4032.93	4035.10	7.55
SAIWPSO [38]	111497.63	111497.63	111497.63	111497.63	1.81E-04	**3932.24**	3932.25	3932.25	**3932.24**	2.33E-03
NGPSO [27]	111497.63	111497.63	111497.63	111497.63	1.00E-07	**3932.24**	**3932.24**	**3932.24**	**3932.24**	2.10E-07
KSO	**111497.27**	**111497.27**	**111497.27**	**111497.27**	**1.63E-08**	**3932.24**	**3932.24**	**3932.24**	**3932.24**	**2.02E-07**

TABLE 8. The best solutions for the fuel cost,total emission for *w* values of case C.

w	0.0	0.1	0.2	0.3.	0.4	0.5	0.6	0.7	0.8	0.9	1.0
P_1	114.00	114.00	114.00	114.00	114.00	114.00	112.80	114.00	110.93	111.34	111.38
P_2	114.00	114.00	114.00	114.00	114.00	114.00	112.68	114.00	110.88	111.54	110.84
P_3	120.00	120.00	120.00	120.00	120.00	120.00	119.67	120.00	97.41	98.35	97.50
P_4	169.37	173.09	177.30	179.73	179.73	179.73	179.66	179.73	179.73	179.73	179.84
P_5	97.00	97.00	97.00	97.00	97.00	97.00	96.68	97.00	87.96	89.15	87.91
P_6	124.26	126.03	128.71	132.66	137.42	140.00	139.72	140.00	140.00	139.86	140.00
P_7	299.71	300.00	300.00	300.00	300.00	300.00	298.30	260.06	260.30	260.39	259.91
P_8	297.91	298.45	299.28	300.00	300.00	300.00	284.60	284.60	284.62	284.60	284.83
P_9	297.26	297.71	298.40	299.95	300.00	300.00	284.60	284.70	284.60	284.64	284.60
P_{10}	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.55	130.00
P_{11}	298.41	301.87	306.44	312.23	318.40	318.40	311.46	318.40	243.60	243.59	168.80
P_{12}	298.03	301.39	305.88	311.64	318.11	318.40	315.59	318.40	243.60	168.81	168.80
P_{13}	433.56	433.57	433.68	436.47	394.28	394.28	394.28	394.29	304.52	215.04	214.76
P_{14}	421.73	418.78	411.61	396.68	394.28	394.28	394.28	394.28	394.28	304.65	304.52
P_{15}	422.78	420.18	413.73	398.50	394.28	394.28	394.28	394.44	394.28	304.57	394.28
P_{16}	422.78	420.18	413.73	398.50	394.28	394.28	394.28	394.35	394.28	394.28	394.28
P_{17}	439.41	443.15	450.02	462.41	477.33	489.28	488.33	489.28	489.28	489.37	489.28
P_{18}	439.41	438.77	437.74	436.35	433.75	425.59	497.57	421.56	421.52	511.28	511.28
P_{19}	439.40	443.15	450.04	462.44	477.37	489.28	487.59	489.28	489.28	489.28	489.28
P_{20}	439.41	438.77	437.74	436.35	433.75	425.59	421.52	421.69	511.28	511.28	511.28
P_{21}	439.45	438.69	437.69	436.73	435.77	433.61	433.54	433.74	521.74	523.28	523.28
P_{22}	439.45	438.69	437.69	436.73	435.77	433.61	433.54	433.54	520.46	523.28	523.28
P_{23}	439.77	439.08	438.18	437.33	436.52	434.49	433.62	433.56	521.69	523.28	523.28
P_{24}	439.77	439.08	438.18	437.33	436.52	434.49	433.57	433.65	521.17	523.28	523.30
P_{25}	440.11	439.22	438.03	436.79	435.43	433.52	433.52	433.60	433.52	523.28	523.28
P_{26}	440.11	439.22	438.03	436.79	435.43	433.52	433.52	433.59	433.52	523.28	523.28
P_{27}	28.99	24.56	20.35	16.85	14.14	11.93	10.00	10.00	10.00	10.29	10.00
P_{28}	28.99	24.56	20.35	16.85	14.14	11.93	10.00	10.00	10.00	10.29	10.00
P_{29}	28.99	24.56	20.35	16.85	14.14	11.93	10.00	10.00	10.00	10.00	10.00
P_{30}	97.00	97.00	97.00	97.00	97.00	97.00	97.00	97.00	88.22	90.01	88.47
P_{31}	172.33	173.50	175.29	178.49	184.48	190.00	187.91	190.00	161.20	171.95	190.00
P_{32}	172.33	173.50	175.29	178.49	184.48	190.00	186.12	190.00	190.00	182.37	190.00
P_{33}	172.33	173.50	175.29	178.49	184.48	190.00	188.51	190.00	190.00	189.99	190.00
P_{34}	200.00	200.00	200.00	200.00	200.00	200.00	199.72	200.00	200.00	194.92	166.49
P_{35}	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	168.77	166.10	165.42
P_{36}	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	166.97	194.98	165.27
P_{37}	100.84	101.99	103.75	106.68	110.00	110.00	110.00	110.00	89.91	106.62	110.00
P_{38}	100.84	101.99	103.75	106.68	110.00	110.00	110.00	110.00	89.71	108.94	110.00
P_{39}	100.84	101.99	103.75	106.68	110.00	110.00	110.00	110.00	89.48	90.27	110.00
P_{40}	439.41	438.77	437.74	436.35	433.75	425.59	421.52	511.28	511.28	511.28	511.28
C($/h)	129955	129498	128866	127807	126488	125690	125491	125112	122973	121755	121376
E(ton/h)	176682	176936	178093	181710	188861	195215	199591	206592	285613	346170	356336

TABLE 9. The solution when *w*=0.6 in the Pareto-front of KSO compared with other algorithms of case C.

Algorithms	GSA	MODE	PDE	NSGA-	SPEA2	QOTLBO	TLBO	ϵv-MOGA	KSO
C	125782	125792	125731	125825	125808	125161	125602	125750	125491
E	210933	211190	211765	210949	211098	206490	206648	211744	199591

although most algorithms are the same as KSO. The statistical results of fuel cost and emission pollution are tabulated in Table 7, which shows that KSO is more robust than the compared algorithms in the literature. In summary, all of this show the better performance of KSO on case B.

Table 8 shows the solution values of KSO for case C with the weight factor *w* ranging from 0 to 1, the step size of 0.1 and $\gamma = 0.1$. And the fuel cost C and emission pollution E together form the Pareto-front as shown in Fig.5, which also illustrates the best comprise solutions obtained by some algorithms in the literature. As is seen from Fig.5, the best comprise solutions of GSA [25], MODE [8], PDE [22], TLBO [16], FPA [5], ϵv-MOGA [30], SPEA2 [22] and NSGA- [17] are located above the Pareto-front clearly and

TABLE 10. Comparison of the best fuel cost and best emission rate of case C with different algorithms.

Algorithm	Best fuel cost (w=1.0)		Best pollution emission (w=0.0)	
	C($/h)	E(ton/h)	C($/h)	E(ton/h)
IABC [39]	129995	176682	121415	356422
IABC-LS [39]	129995	176682	121413	359901
ABCDP [39]	129995	176682	121413	359901
ABCDP-LS [39]	129995	176682	121413	359901
HPSOGSA [40]	129997	176684	121413	360228
MBFA [8]	129995	176682	121416	356424
PSOGSA [40]	129987	176678	121461	358155
MODE [22]	129956	176683	121837	374791
MBFA [8]	1299950	176682	121416	356424
DE-HS [41]	129994	176682	121415	356433
MAθ-PSO [42]	129995	176682	121413	359902
KSO	129955	176682	121376	356336

TABLE 11. The statistical results of fuel cost and emission pollution in case C.

Algorithm	C_{min}	C_{max}	C_{mean}	C_{median}	C_{std}	E_{min}	E_{max}	E_{mean}	E_{median}	E_{std}
GQPSO [37]	146121.50	152214.35	151703.04	151960.24	9.81E+02	270192.37	312560.56	298292.51	297963.51	7.40E+03
SAIWPSO [38]	121676.23	122597.19	121966.30	121906.00	2.27E+02	177276.36	179282.34	177772.49	177674.83	3.73E+02
NGPSO [27]	121513.48	122697.77	122065.12	122119.11	2.67E+02	176682.52	176684.83	176683.40	176683.21	5.58E-01
KSO	121375.87	121927.12	121538.12	121475.87	1.81E+02	176682.26	176682.26	176682.26	176682.26	5.82E-11

near the solution of KSO when $w = 0.6$, shown in Table 9 for details,which implies that the solution of KSO dominates the best comprise solutions of these algorithms. Meanwhile, the best comprise solutions of SMPSO [10], LMPSO [10], QOTLBO [16] and NGPSO [27] are just on the Pareto-front which mean the competitive performance of KSO with them.

The best fuel cost ($w = 1.0$) and the best pollution emission ($w = 0.0$) of case C are given in Table 10, compared with other results from the literature. In terms of the best cost, KSO obtains a minimum result of 121376($/h) especially better than SMPSO, LMPSO, QOTLBO and NGPSO which were just on the Pareto-front. KSO saves 37($/h) fuel cost compared with IABC-LS [37],ABCDP [37],ABCDP-LS [37] HPSOGSA [38] and MAθ-PSO [40] which has the second best result. And for the best emission, KSO also obtains a minimum result of 176682(ton/h) among all the algorithms. The statistical results of fuel cost and emission pollution are tabulated in Table 11, which shows that KSO is more robust than the compared algorithms. So it can be concluded that KSO performs much better than all the algorithms in the literature on case C.

V. CONCLUSION

This study proposed a new meta-heuristic algorithm of KSO to deal with EED problem, which maps a non-linear objective function into a linear one with higher-dimension. When applied in the 3 real-world cases of EED problems, the Pareto-front of KSO is much better than the best comprise solution of most algorithms. Moreover, no matter on best fuel cost or best total emission, KSO performs better than all the compared algorithms in the literature. It is worth noting that KSO performs much better on case C than case A and B, which has more generators. So in general, KSO achieved a better performance on EED problem, and no hyper parameters need to be tuned.

Although the model of EED problem in this study is static, KSO can also deal with the dynamic scenarios(e.g. the external load changes). The study needs to establish the model of EED problem with the external load changing and deal with some new constraints. It can be expected that KSO may perform competitively on the dynamic EED problem which have more decision variables, because it perform better on case C with more generators. Future studies may also aim to introduce some distributed algorithms to decompose the global OPF problem into regional sub-problem for ultra-large scale multi-area power systems, or an interval fuzzy optimization-based technique to choose more optimal trade off solutions, or a non-dominated constraints sorting strategy to improve KSO for an MOP edition.

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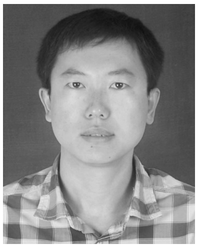

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