An optimal algorithm based on kinetic-molecular theory with artificial memory to solving economic dispatch problem

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Economic dispatch (ED) problem exhibits highly nonlinear characteristics, such as prohibited operating zone, ramp rate limits and non-smooth property. Due to its nonlinear characteristics, it is hard to achieve the expected solution by classical methods. To overcome the challenging difficulty, an improved optimization algorithm based on kinetic-molecular theory (KMTOA) was proposed to solve the ED problem in this article. Memory principle is employed into the improved algorithm. By accepting strengthened or weakened stimulus strength, the memory is divided into four states; instant-term, short-term, long-term and forgotten states to update the memory value iteratively. In this way, more and more elites appear in the long-term memory library. Simultaneously, the improved KMTOA, according to the elite population-based guide on the other population, enhances the search ability and avoids the premature convergence which usually suffered in traditional KMTOA. The designs are able to enhance the performance of KMTOA, which has been demonstrated on 12 benchmark functions. To validate the proposed algorithm, we also use three different systems to demonstrate its efficiency and feasibility in solving the ED problem. The experimental results show that the improved KMTOA can achieve higher quality solutions in ED problems.

Keywords: Artificial memory, benchmark function, economic dispatch, KMTOA.

TO improve the effectiveness and efficiency of a given industrial system, several optimization techniques are employed, which achieves the ultimate goal of the system. They are also widely used in industrial fields, especially in the energy industry and other major industries, including telecommunications, transportation, manufacturing, and so on[1].

In the electric power system operation, the objective of the economic dispatch (ED) problem is to determine the outputs of all generating units from a system, with minimum fuel cost and meeting the required constraints. The characteristics of the ED problem presented are highly nonlinear due to the valve-point effect loadings, rate ramp limits, etc. The complexity of ED problems depends on the scale of the system[2]. Optimal allocation of generating units can guarantee the system load to be the most economical. Traditionally, the ED problem can be solved by classical mathematical programming methods, such as the interior point method[3], the linear programming method[4], the dynamic programming method[5], and so on. However, the deterministic numerical methods are not effective for non-smooth and non-convex cost function. In order to overcome the shortcoming of the nonlinear characteristic of practical power systems, a large number of heuristics and other computer intelligence methods have been developed to solve ED problems.

The current mainstream heuristic algorithms can be divided into three main categories. The first optimization algorithm simulates the natural evolution law. Genetic algorithm (GA)[6] is a heuristic search algorithm inspired by Darwin's evolutionary theory and learning from the biological evolution process. GA[7] can find the global optimal solution of the optimization problem, but it has the shortcomings of slow convergence and premature convergence. Subbaraj *et al.*[8] use Taguchi method to propose Taguchi self-adaptive real-coded genetic algorithm (TSARGA) which can exploit the potential offspring. Training on the basis of GA[9], artificial neural network (ANN) is proposed. Different evolution (DE)[10,11], which is similar to the principle of GA, is proposed by introducing differential strategy. Ant colony optimization (ACO) algorithm[12] is a probabilistic algorithm for finding optimal paths. The second optimization algorithm simulates the living habits and activities of biological populations. Particle swarm optimization (PSO)[13–16] is based on the predatory behaviour of birds and has very high speed to the optimal solution, but it is easy to produce premature convergence. Grey wolf optimization (GWO)[17] is proposed according to the predatory behaviour of wolves. The firefly algorithm (FA)[18] is derived from simulating the natural phenomena of fireflies in the night. The algorithm is easy to operate and implement, however, it also gets stuck in local optima value easily due to excessive reliance on excellent individuals. The third optimization algorithm simulates physical laws or physical phenomena.

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Gravitation search algorithm (GSA)[19] is a swarm intelligence optimization method derived from the simulation of gravitation in physics. The algorithm has a good effect on optimization accuracy and convergence speed, but GSA also has the shortcomings of poor local optimization ability and premature convergence. There are other algorithms for solving such problems. Immune algorithm (IA)[20] which is based on the principle of the biological immune system is proposed. Nandan[21] proposed a fuzzy reinforcement learning approach (MAFRL), which is effective for solving unit commitment problem (UCP).

In view of the significance of heuristic algorithm, the KMTOA, a physics-inspired algorithm, was put forward first by Chao-dong Fan in 2013 and applied in optimizing the problem of test function[22]. KMTOA takes into account the convergence and diversity of the population on a better condition. While the fitness value converged rapidly, the algorithm can avoid falling into local extremum as far as possible and show good performance. Although KMTOA has favourable performance, it still has some shortcomings. For example, it is slightly one-sided because it only relies on the current best individual to guide the searching process. When a problem has only extreme values, the efficiency of the algorithm is good. However, when the question includes a plurality of local extreme values, the searching mechanism seriously affects the efficiency of the algorithm.

To overcome the shortcoming of KMTOA, the principle of memory is introduced into the algorithm. Molecular individuals are divided into individual long memory library and short memory library, instantaneous memory library, forgetting memory library according to the calculation of the memory value. The memory value of every individual is updated continuously according to the model of updating memory and the model of forgotten attenuation. It can improve the diversity of the population. To avoid falling into local optimum, the guiding strategy of memory is designed. It uses memory leader selection strategy to guide other molecules. The guided process can be achieved by the random individual whose memory value is higher than the long-term memory group. Hence, this paper proposes an optimization algorithm based on kinetic-molecular theory with artificial memory (AMKMTOA). The experimental results show that the AMKMTOA not only has better accuracy and stability, but also achieves satisfactory results for solving the ED problem.

The model of economic dispatch problem

In ED problem, the main target is optimizing the combination of power generation to minimize the total fuel cost. In the optimized process, equality constraints and inequality constraints should be satisfied.

In short, the total cost function of generation units is usually formulated into a smooth and single function, such as eq. (1)

$$\min f = \sum_{i=1}^{n} F_i(P_i), \tag{1}$$

where $F_i(P_i)$ is the fuel cost equation, in \$/h, for ith unit.

At the same time, the fuel cost function can be defined as smooth or non-smooth.

If the valve-point effects are not taken into the power system, the fuel cost function can be modelled by a smooth and quadratic polynomial equation, such as eq. (2)

$$F_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i, \tag{2}$$

where α_i, β_i and γ_i are the fuel cost coefficients of the ith unit.

If the valve-point effects are considered, the fuel cost function for the ith unit includes a sine factor. It can be formulated by a non-smooth and quadratic polynomial function, which is shown in eq. (3).

$$F_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i + |\varphi_i \sin(\omega_i (P_i^{\min} - P))|, \tag{3}$$

where ω_i and φ_i are the coefficients of the ith unit reflecting the valve-point effects.

The constraints of the ED problem can be expressed by relations (4)–(9).

(i) Minimum and maximum of operating limits

$$P_i^{\min} \le P_i \le P_i^{\max}, \quad i = 1, 2, ..., n, \tag{4}$$

where $P_i^{\min}$ and $P_i^{\max}$ represent the minimum and maximum operating power limits of the ith unit.

(ii) The ramp-rate limits of the generator.

$$-LR_i \le P_i - P_i^0 \le UR_i, \tag{5}$$

where P_i^0 is the output power of the ith unit in the previous hours. UR_i and DR_i are the down-ramp limit and up-ramp limit of the ith generator (MW/h). The ramp-rate limits are shown as inequality (eq. (5)). Combining the relations (4)–(5), the following output power (P_i) limits for the ith unit, can be re-formulated as inequality (eq. (6))

$$Po_i^{\min} \le P_i \le Po_i^{\max}, \tag{6}$$

where $Po_i^{\min} = \min(p_i^{\min}, P_i^0 - LR_i)$ and $Po_i^{\max} = \max(p_i^{\max}, P_i^0 + UR_i)$.

(iii) For the ith unit operating zones considering the prohibited zones, the relations are shown as inequality.

$$\begin{cases} P_i^{\min} \le P_i \le P_{i,1}^l \\ P_{i,k-1}^u \le P_i \le P_{i,k}^l \,, & i = 1, 2, ..., n \\ & k = 2, 3, ..., K_i, \\ P_{i,K_i}^u \le P_i \le P_i^{\max} \end{cases} \tag{7}$$

where K_i is the number of prohibited zones of the ith unit. $P_{i,k}^{l}$ and $P_{i,k}^{u}$ are the lower and upper boundary of the mth prohibited operation zones of the ith unit.

(iv) Power balance constraints: The total generation should satisfy the total demand and the transmission loss as shown in eq. (8).

$$\sum_{i=1}^{n} P_i = P_d + P_l, \tag{8}$$

where P_d is the load demand of the power system, in MW. P_l is the transmission line losses, in MW.

The transmission line losses at the entire system are a quadratic function in relation to P_i, which can be calculated by B-matrix coefficients (Kron's loss formula) as eq. (9).

$$P_l = \sum_{i=1}^{n}\sum_{i=1}^{n} P_i b_{ij} P_j + \sum_{i=1}^{n} b_{i0} P_i + b_{00}, \tag{9}$$

where b_{ij} is an element of the loss coefficient matrix of size $n \times n$, b_{i0} an element of the loss coefficient vector of size $n \times 1$ and b_{00} is the loss coefficient constant.

An optimized algorithm based on kinetic-molecular theory

In the population-based optimization, the algorithm, by some search strategy, converges to the optimal solution according to the value of the objective function which starts from a random point of the feasible region. Each algorithm uses different searching strategies depending on various principles. The KMTOA, inspired by the kinetic-molecular theory, is put forward as a global optimized algorithm. In KMTOA, each solution of the problem is regarded as a molecule. The current optimal individual guides each molecule in the attraction–repulsion molecule to complete the searching process. To enhance the ability of jumping out of the local extremum, the algorithm adds into random disturbances for the balanced molecule by simulating the thermal motion of molecules. Based on molecular interactions and thermal motion mechanism, KMTOA can arrive at a better compromise between convergence and population diversity in the searching process.

KMTOA model

Assume that the total number of molecules is n and the problem of dimension is d. The position and quality of the ith molecule are X_i and M_i. The position and quality of the current best molecule are X_{best} and M_{best}. $P_{\text{attraction}}$ is the probability of the current optimal molecule for attracting the molecule. $P_{\text{replusion}}$ is the probability of the current optimal molecule for repelling the molecule. P_{wave} is the probability of the current optimal molecule for the balanced molecule ($P_{\text{attraction}} + P_{\text{replusion}} + P_{\text{wave}} = 1$). When the molecule is balanced, it is added into the random disturbance in order to enhance the global search capability of the algorithm. The KMTOA can be briefly described as follows:

When $rand < P_{\text{attraction}}$ ($rand$ is the random variable from 0 to 1), the ith molecule is attracted by the current optimal molecule. The attracted acceleration can be formulated as eq. (10).

$$a_i = \frac{GM_{\text{best}} M_i (X_{\text{best}} - X_i)}{M_i} = GM_{\text{best}}(X_{\text{best}} - X_i), \tag{10}$$

where G is the gravitational constant.

When $P_{\text{attraction}} < rand \le (P_{\text{attraction}} + P_{\text{repulsion}})$ ($rand$ is the random variable from 0 to 1), the ith molecule is repelled by the current optimal molecule. The repulsive acceleration can be formulated as eq. (11).

$$a_i = -\frac{GM_{\text{best}} M_i (X_{\text{best}} - X_i)}{M_i} = -GM_{\text{best}}(X_{\text{best}} - X_i). \tag{11}$$

When $(P_{\text{attraction}} + P_{\text{repulsion}}) < rand \le 1$ ($rand$ is the random variable from 0 to 1), the KMTOA adds the random disturbance operator to prevent the molecule to get stuck in local optima. The disturbed acceleration can be formulated as eq. (12).

$$a_{ij} = \begin{cases} A(X_{\max j} - X_{\min j})N(0,1) & rand' \le P_m \\ 0 & P_m > rand', \end{cases} \tag{12}$$

where a_{ij} is the jth dimension of the molecule X_i, P_m the mutable rate, ($rand'$ is the random variable from 0 to 1), $X_{\max j}$ and $X_{\min j}$ respectively, stand for the upper bound and lower bound of the jth dimension. $N(0,1)$ is a random variable satisfying the standard normal distribution, A(A = 1–0.9t/T) the vibrant amplitude; where t the current number of iterations and T is the total number of iterations.

The speed and position can be defined by the acceleration of the molecule. The updated function can be formulated as eq. (13).

$$\begin{cases} V_i(t+1) = \left(\dfrac{0.9 - 0.5t}{T}\right) V_i(t) + a_i \\ X_i(t+1) = X_i(t) + V_i(t+1). \end{cases} \tag{13}$$

Comparison with gravitational search algorithm

The differences between the two algorithms are as: (1) Gravitational search algorithm (GSA) is a random searching algorithm which originates from the physics gravity by simulating the phenomenon. KMTOA is a global search algorithm and is based on the properties and laws of molecular thermal motion. (2) For GSA, particles can be attracted to each other through gravity and move by following the rule of kinematics. A particle that has greater fitness value has larger mass quality. Hence all particles can move towards the particle which has the largest quality and converge to the optimal solution. However, in view of the attraction–repulsion rule between molecules in molecular dynamics theory for KMTOA, the conditions that the molecules are subjected to gravitation, repulsion and no force are put forward. For molecules without force, the particles can jump out of the local solution by simulating the irregular thermal motion of molecules. (3) The search particles in GSA are a group of objects running in space. However, the KMTOA uses a single molecule to complete the search process.

An optimized algorithm based on kinetic-molecular theory with artificial memory

Fundamentally, AMKMTOA sets up the cell of memory and divides the population into four stages, such as instant-term, short-term, long-term and forgotten process, by calculating the value of memory. If the current individual is not forgotten, an individual which comes from the long-term population is randomly selected to achieve direct search. If it is forgotten, an individual, by moving randomly, will be reminded at some point. At the same time, it constantly updates the memory value according to the intensity of the external stimulus. The following part is designed for the key operator of AMKMTOA.

Model of updating memory

The external stimulus includes the ordinary and typical stimulate. If the individual moves to a new better position, it shows that the event is beneficial for searching the global optimal solution. It will be regarded as the ordinary stimulate and increase the value of memory. On the contrary, it will also be regarded as the typical stimulate. The model of calculating the value of memory is shown as eq. (14).

$$m_i^t = m_i^{t-1} + h(f(X_i^{t-1}) - f(X_i^t)), \qquad (14)$$

where m_i^t is the value of memory in the t period, $f(X_i^t)$ the objective function of the t period and $h(h > 0)$ is the adjust coefficient stimulate and the value is selected by the specific situation.

Model of the forgotten attenuation

The memory of instant-term, short-term and long-term will decrease inch by inch with the passage of time. The function of the damped memory is shown as eq. (15) according to the forgetting curve of H. Ebbinghaus.

$$\begin{cases} m_i^t(t+\Delta t) = m_i^t(t)\mathrm{e}^{-\delta t} \\ \delta = \begin{cases} \delta_i & s_i = i \\ \delta_s & s_i = s, \\ \delta_l & s_i = l \end{cases} \quad s_i = \begin{cases} i, & m_i^t(t) \le m_s \\ s, & m_s < m_i^t(t) \le m_l \\ l, & m_i^t(t) > m_l, \end{cases} \end{cases} \qquad (15)$$

where i, s and l are the state of the memory of instant-term, short-term and long-term respectively. m_s, m_l are the critical constants of the short-term and long-term memory. $\delta(\delta > 0)$ is the adjust coefficient of the speeding of the damped memory.

Guiding strategy of memory

Since those entering long-term memory are better individuals, an individual from long-term memory is randomly chosen according to the guiding strategy of memory. The selected individual guides the others to achieve the searching progress. The method can avoid the misleading of the traditional KMTOA because of the guidance from long-term memory. The guiding strategy of memory is shown as eq. (16). If $f(X_i^t)$ is smaller and m_i^t is larger, it explains that the individual is better. Otherwise, the individual is worse.

$$\rho = \frac{f(X_i^t)}{m_i^t} \le \theta, \qquad (16)$$

where θ is a critical constant.

Detailed steps of AMKMTOA

The detailed steps of AMKMTOA are listed as follows. Step 1. Initialize the population and parameters. Step 2. For each individual, calculate the optimal value of the objective function and compute the value of memory based on eq. (14). At the same time, the value of damped memory is also computed according to eq. (15). Step 3. Based on the guiding strategy of memory eq. (16), randomly select an elite-individual (X_{best}) which comes from the long-term memory. Step 4. If the condition of attraction is satisfied, calculate the attracted acceleration based on eq. (10). If the condition of repulsion is met, calculate the repulsive acceleration according to eq. (11). Otherwise, the molecular thermal motion operator will be carried out, and the disturbed acceleration can be calculated by eq. (12). Step 5. Calculate the speed and position of each individual by eq. (13) and save the optimal individual from the population. Step 6. Check termination condition. If the counter k of the generation is achieved at maximum generation value, then output the solution. Otherwise, return to step 2.

Design and analysis of key parameters

For the experiment, the parameters of AMKMTOA are set as follows: the maximum number of function evaluation is 100,000 (the population size is 50 and the maximum number of iterations is 2000); M_{best} and the mutable rate (P_m) are set to 2 and 0.05 respectively. G is the gravitational constant; h, θ are set to random numbers (from 0 to 1), 0.05, 0.01 respectively. $P_{\text{attraction}}$, $P_{\text{replusion}}$ and P_{wave} are the key parameters and decide the next movement of the individual, which greatly affects the performance and efficiency of AMKMTOA. Hence the key parameters of AMKMTOA are investigated. The mean and standard deviation of the best solutions are obtained from 50 trial runs.

Since F_5 is relatively smooth near the optimal value, it is difficult to identify the search direction. F_8 is the global extreme point and all the local extreme points around them are far away from them; so it is easy to fall into the wrong collection in the process of searching for the optimal solution convergent direction. In view of the complexity of F_5 and F_8, this section selects the representative functions to test different values of $P_{\text{attraction}}$, $P_{\text{replusion}}$ and P_{wave}. In order to facilitate the discussion, firstly, $P_{\text{replusion}} = 0.2$, $P_{\text{replusion}} = 0.4$ and P_{wave} is selected from 0 to 0.1 (by genetic algorithm, the mutation rate is very small). The value of $P_{\text{attraction}}$ is determined by $P_{\text{attraction}} = 1 - P_{\text{replusion}} - P_{\text{wave}}$. As shown in Tables 1 and 2, for $P_{\text{replusion}} = 0.2$ and $P_{\text{replusion}} = 0.4$, when P_{wave} takes 0.02–0.06, AMKMTOA can achieve better results.

In order to determine the reasonable values of $P_{\text{attraction}}$, $P_{\text{replusion}}$ values of 0–0.94 and $P_{\text{wave}} = 0.06$ are used. The optimization results of AMKMTOA are compared. Table 3 shows that when $P_{\text{replusion}}$ takes 0.1–0.3, the optimization results of F_5 and F_8 are better. In conclusion, $P_{\text{attraction}} = 1 - P_{\text{replusion}} - P_{\text{wave}} = 0.64$, $P_{\text{replusion}} = 0.3$, $P_{\text{wave}} = 0.06$ are more reasonable.

Simulation experiments

To evaluate the performance of AMKMTOA, we first tested AMKMTOA based on 12 benchmark functions, which are the classical functions utilized in many studies. Then AMKMTOA was used to solve the ED problems. Each algorithm was run 50 times on each benchmark function and the results of algorithms were analysed using statistic measures (mean and standard deviation). In solving the ED problem, three cases with different number of units were used. The cases include 6-unit system, 13-unit system and 40-unit system for verifying the performance of AMKMTOA over practical problems.

Validation of AMKMTOA based on test benchmark function

Test of low-dimensional function

In this section, AMKMTOA is compared with the traditional KMTOA[22], grey Wolf Optimizer (GWO)[23] and differential evolution (DE)[24], particle swarm optimization with random position (RPPSO)[25]. The comparison of algorithms was validated on 12 benchmark functions from reference 22. The benchmark functions used minimization functions and can be divided into three groups: $F_1(x) - F_6(x)$ are the unimodal benchmark functions, $F_7(x) - F_{10}(x)$ are the multimodal benchmark functions, $F_{11}(x) - F_{12}(x)$ are the fixed-dimension benchmark functions.

In Table 4, the average values, standard values and CUP Time are presented. The table illustrates that AMKMTOA was superior to KMTOA considering the quality of the results. Its performance and time was better than the other algorithm on the whole benchmark function. The leading individuals are from long-term library and the selection scope of leading elites is narrowed. Hence, the optimized result is more stable and the robustness of the proposed algorithm is better.

The largest difference in performance between AMKMTOA and other algorithms can be found in F_4, F_5 and F_7. At the same time, the accuracy and stability of AMKMTOA is obviously improved when compared to the four algorithms.

Analysis of convergence

In verifying the AMKMTOA, the population size is 50 and the maximum number of iterations is 2000. At the same time, each algorithm is linked with various parameters, which have a significant impact on the desired results. The identical parameters of each algorithm were set as: (i). RPPSO: $\omega = (0.9–0.5*t/T)$, $c_1 = c_2 = 2$; (ii) DE: $F_{\text{scaling}} = 0.9$, $P_{\text{cross}} = 0.05$; (iii) GWO: $\alpha = [2, 0]$; (iv) KMTOA: $pm_1 = 0.64$, $pm_2 = 0.3$ and (v) AMKMTOA: $pm_1 = 0.64$, $pm_2 = 0.3$.

In Figure 1, it is shown that the convergence speed of AMKMTOA is the fastest. The most obvious difference is reflected in F_7 that tends to find the global optimum faster than the others. In short, AMKMTOA performed better with convergent characteristics and achieved the solution with high accuracy.

Analysis of high-dimensional function

To test the ability of AMKMTOA for complex problems and analyse the influence on the algorithm, the algorithm was tested on high dimensional functions. The complexity of the algorithm was analysed from two aspects, the average value and average running time of the algorithm. The average value shows the optimization precision of the algorithm. The average running time is average time required for completion of a search algorithm. The high dimensional functions include noisy quadric (unimodal benchmark functions and special noise function) and Rastrigin (multimodal benchmark functions).

Table 1. The P_{wave} effects on AMKMTOA

	$P_{replusion}$ = 0.2, $P_{attraction}$ = 1 – $P_{replusion}$ – P_{wave}	
P_{wave}	F_5 (Rosenbrock)	F_8 (Rastrigin)
0.00	2.5485 (44.6098)	–1.0741E+03 (8.1053E-03)
0.01	1.3609E–01 (1.8201)	–1.1991E+04 (6.1231E-04)
0.02	7.3604E–02 (2.9133)	–1.2107 E+04 (6.1310E-04)
0.03	7.6448E–02 (1.2380)	–1.2319 E+04 (4.8252E-04)
0.04	7.4502E–02 (1.9465)	–1.2408 E+04 (5.7590E-04)
0.05	7.3444E–02 (3.6323)	–1.2445 E+04 (5.6380E-04)
0.06	6.8109E–02(2.6199)	–1.2468 E+04 (6.6896E-04)
0.07	1.1473E–01 (1.6324)	–1.2453 E+04 (5.3722E-04)
0.08	7.0022E–02 (3.6951)	–1.2442 E+04 (7.5710E-04)
0.09	7.2944E–02 (2.4292)	–1.2315 E+04 (4.3214E-04)
0.10	1.5405E–01 (2.1152)	–1.2308 E+04 (6.6732E-04)

Table 2. The P_{wave} effects on AMKMTOA

	$P_{replusion}$ = 0.4, $P_{attraction}$ = 1 – $P_{replusion}$ – P_{wave}	
P_{wave}	F_5 (Rosenbrock)	F_8 (Rastrigin)
0.00	1.6860(3.6190)	–1.0995E+03 (7.4794E-03)
0.01	1.4143E–04 (0.7997)	–1.1259E+04 (4.7708E-04)
0.02	1.6288E–04 (0.4883)	–1.1882E+04 (5.7566E-04)
0.03	2.6444E–04 (0.9159)	–1.2080 E+04 (8.0714E-04)
0.04	1.9127E–04 (0.6037)	–1.2141E+04 (4.6174E-04)
0.05	1.8390E–04 (0.4854)	–1.2077 E+04 (4.5774E-04)
0.06	1.6498E–04 (0.4536)	–1.2341E+4 (5.1544E-04)
0.07	1.9147E–04 (0.3518)	–1.2315E+04 (5.3364E-04)
0.08	2.7324E–03 (0.9044)	–1.2255 E+04 (4.9324E-04)
0.09	3.3911E–03 (1.8089)	–1.2104E+04 (5.6963E-04)
0.10	3.2563E–03 (1.2563)	–1.2005E+04 (6.3311E-04)

Table 3. The $P_{attraction}$ and $P_{replusion}$ effects on AMKMTOA

	P_{wave} = 0.06, $P_{attraction}$ = 1 – $P_{replusion}$ – P_{wave}	
$P_{replusion}$	F_5 (Rosenbrock)	F_8 (Rastrigin)
0	3.1805 (2.5361)	–1.2366E+04 (1.7514E-03)
0.1	0.1066 (1.5987)	–1.2187E+04 (2.0183E-04)
0.2	6.8109E–02 (2.6199)	–1.2468E+04 (5.7003E-04)
0.3	1.5109E–04 (0.4242)	–1.2541E+04 (4.1544E-04)
0.4	1.6498E–04 (0.4536)	–1.2441E+04 (5.1544E-04)
0.5	2.0961 E–03 (1.2305)	–1.1988E+04 (7.3462E-04)
0.6	1.0014 E–03 (4.2361)	–1.2373E+04 (7.9635E-04)
0.7	0.3885 E–03 (3.0625)	–1.2229E+04 (1.6896E-03)
0.8	0.4351 (31.2046)	–1.1017E+04 (12.0123)
0.9	32.5624 (66.1132)	–9.1722E+03 (1.5632)
0.94	381.7382 (561.2315)	–7.1125E+03 (9.2380)

The results of AMKMTOA are compared with KMTOA, GWO, DE, RRPSO. The maximum iteration and population size are respectively set to 2000 and 50. Table 5 shows the average values, standard values and CPU time are given in Supplementary Table 1. It illustrates that the performance of AMKMTOA is superior to other algorithms from 100 dimension to 500 dimension. It also fully illustrates the advantages of the algorithm in solving complex problems.

Economic dispatch problem solved by AMKMTOA

For this part, we need to apply AMKMTOA to solve the ED problem in particle issue. In order to verify the feasibility and effectiveness of AMKMTOA, there are three cases to solve the ED problem. For each test problem, the parameter of the population size was set to 50 and the experiments were conducted in 100 trails. The scheduling time horizon for the study was 24 h. For the convergence curves of the three cases, the maximum iterations of algorithms which include AMKMTOA, KMTOA, GSA, DE, RPPSO were set to 200, 500 and 2000. The population size of all algorithms was set to 50. The algorithms were executed with the following parameters: (i) RPPSO: $\omega = (0.9–0.5*t/T)$, $c_1 = c_2 = 2$; (ii) DE: $F_{scaling} = 0.9$, $P_{cross} = 0.05$; (iii) GSA: $m = 100$, $G_0 = 100$, $\alpha = 20$; (iv) KMTOA: $pm_1 = 0.64$, $pm_2 = 0.3$; (v) AMKMTOA: $pm_1 = 0.64$, $pm_2 = 0.3$.

The sets of three cases were conducted and the experimental results of the proposed algorithm were compared with various existing algorithms.

Case I: Six-unit system with a smooth objective function which includes transmission loss, rate ramp limits and prohibited zones was considered. The load demand of the 6-unit system was 1263 MW.

Case II: Thirteen-unit system with a non-smooth objective including value point loading effect was considered. The load demand of the thirteen-unit system was 1800 MW.

Case III: The value point loading effect was taken into account by a 40-unit system. At the same time, it was also a non-smooth objective and the load demand of the 40-unit system was 10,500 MW.

Case I: For the 6-unit system, several constraints was considered, but the value point loading effect was not taken into account. The date and B's loss coefficient matrix of the objective function are from reference 6. Table 5, which includes the best, worst and average costs, presents the results of the 6-unit system. The standard deviation, CPU time, FE are also shown in Table 6. At the same time, the results of AMKMTOA are compared to those of other algorithms including GA[6], DE[10], PSO[6], ICA-PSO[13], SA-PSO[14], IA-EDP[20], MAFRL[21] and KMTOA. The

Table 4. Result of benchmark function

No.	Function name	Value	AMKMTOA	KMTOA[22]	GWO[23]	DE[24]	RPPSO[25]
F_1	Sphere	Mean	0	0	9.2802E-145	1.0544E-11	7.6068E-11
		Standard	0	0	2.2965E-144	7.9337E-12	1.5758E-10
		Time(s)	0.8847	0.9006	1.8050	3.2321	1.4934
F_2	Schwefel P2.2	Mean	0	0	2.3075E-83	1.5298E-7	5.5188E-8
		Standard	0	0	3.8095E-83	5.8829E-8	5.8718E-8
		Time(s)	0.9285	0.9305	1.9101	3.1456	1.4570
F_3	Rotated hyper-ellipoid	Mean	0	0	2.5643E-42	1.6800E+4	1.6706E+3
		Standard	0	0	1.43993E-41	3.2821E+3	2.4112E+3
		Time(s)	1.5886	1.6038	5.1576	3.7862	2.1279
F_4	Nosiy quardric	Mean	9.0211E-7	2.7876E-4	1.9499E-4	0.0423	0.0174
		Standard	2.3801E-4	3.0964E-4	9.3240E-5	0.0101	0.0052
		Time(s)	1.5511	1.5873	2.3287	3.6084	1.5531
F_5	Rosenbrock	Mean	1.5109E-4	0.2126	26.1663	19.3867	82.9348
		Standard	0.4242	0.4688	0.8235	24.1749	216.8880
		Time(s)	1.1827	1.1870	2.4434	3.1968	1.5014
F_6	Step	Mean	0	0	0.4575	0	0
		Standard	0	0	0.3513	0	0
		Time(s)	1.1447	1.1558	1.6783	3.1762	1.4840
F_7	Schwefel	Mean	–1.2541E+4	–1.0918E+4	–6.0670E+3	–1.1845E+4	–1.0296E+4
		Standard	4.1544E-4	420.1210	548.2402	266.3424	436.0910
		Time(s)	1.4418	1.4533	1.8640	3.3208	1.6118
F_8	Rastrigin	Mean	0	0	0	0.9332	205.0490
		Standard	0	0	0	1.1262	37.9783
		Time(s)	1.2511	1.2537	2.1477	3.2720	1.4892
F_9	Ackly	Mean	0	0	7.9936E-15	2.7220E-6	13.0697
		Standard	0	0	3.2059E-30	2.7655E-6	1.2784
		Time(s)	1.4483	1.4666	2.3254	3.3088	1.5774
F_{10}	Griewank	Mean	0	0	0	1.2031E-5	0.0086
		Standard	0	0	0	5.3477E-5	0.0103
		Time(s)	1.4976	1.5063	1.9811	3.3484	1.6554
F_{11}	Branin	Mean	0.3979	0.3979	0.3979	0.3980	0.3979
		Standard	0	0	1.6920E-16	2.4597E-4	0
		Time(s)	0.7966	0.8023	1.0897	2.9927	1.2301
F_{12}	Shubert	Mean	–186.7309	–186.7309	–186.7309	–186.7302	–186.7309
		Standard	0	0	8.8388E-5	0.0031	0
		Time(s)	1.1580	1.1639	1.4065	3.0666	1.2464

comparative statistics results are summarized in Table 6. It illustrates that all performance indices of the proposed algorithm are obviously better than the others except the fitness evolution. Table 6 shows the power of each generation, transmission loss, and total cost achieved by AMKMTOA for the test system. In addition, the experimental results of AMKMTOA are also compared with GA[6], PSO[6], CBA[26], IA-EDP[20] and KMTOA. This table explains that the total cost of AMKMTOA is much less than the other methods.

The convergence characteristic of AMKMTOA for this case is shown in Figure 2, and the proposed algorithm is compared with a few classical optimization algorithms. The simulation test shows that AMKMTOA has better convergence accuracy and high evolution velocity when compared to algorithms. By means of simulation, it proves the effectiveness and availability of AMKMTOA for the 6-unit system.

Case II: To validate the performance of this optimization method for medium size, the 13 generating units are regarded as the second test system because of the increased complexity. The value point loading effect is taken into account. The date of fuel cost function is from ref. 27. To verify the proposed algorithm for the 13-unit system, the experimental results are compared with methods which include TSARGA[8], DE[10], DECDM[27], HMAPSO[15], ICA-PSO[13], SOMA[28], IA-EDP[20], MAFRL[21] and KMTOA. The comparative results are presented in Table 7. The best, worst and average solution, standard value, CPU time and FE are contained in this table. By analysing the results for all optimization algorithms, we

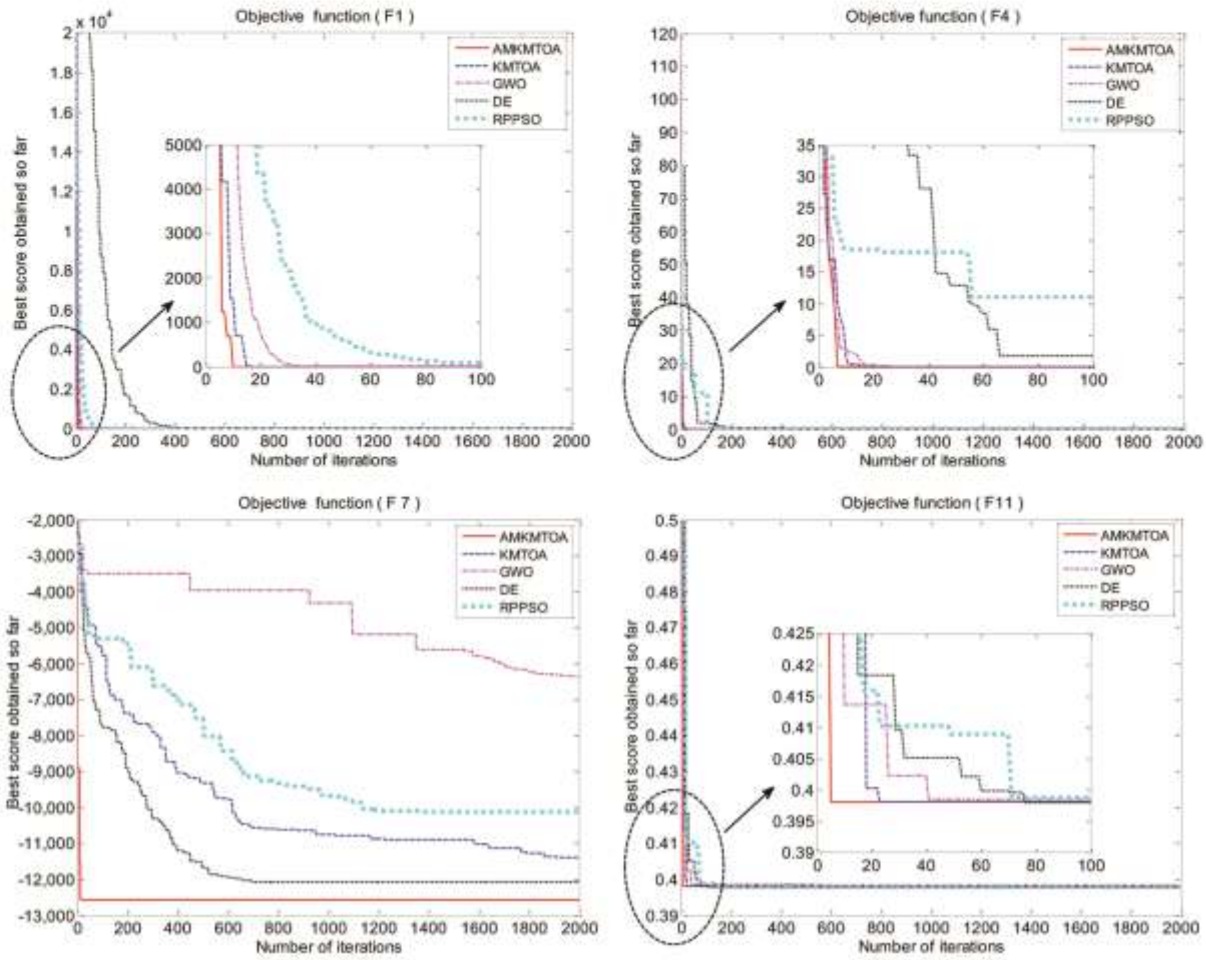

Figure 1. Parameter space of Sphere, Nosiy Quardric, Schwefel, Branin (F_1, F_4, F_7, F_{11}).

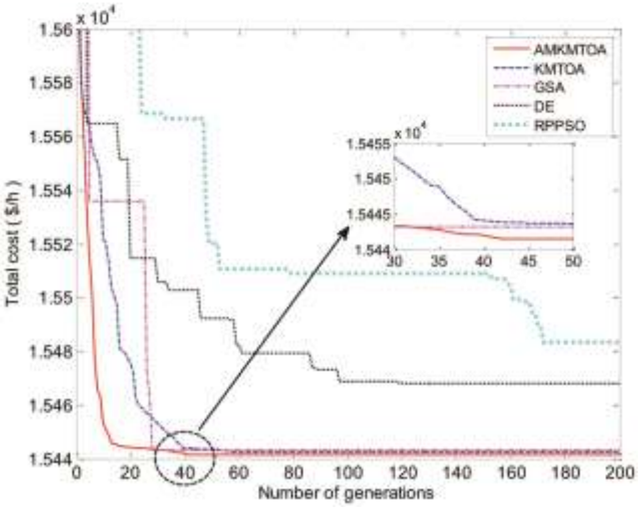

Figure 2. Convergences curves for 6-unit system.

can conclude that AMKMTOA is superior to the other methods in terms of the performance indices. The CPU time of AMKMTOA is less than the six methods expect ICAPAO. At the same time, Table 8 also shows the comparison of the power of each generation and total cost for the proposed algorithms, which include QPSO[29], DFA[18], IA-EDP[20], CBA[26], KMTOA. It illustrates that the total price of AMKMTOA is cheaper than the others.

Figure 3 presents the comparison of convergence curves for the proposed method and some typical methods. The simulation consequence shows that AMKMTOA has characteristics with higher convergence precision and faster convergence speed. It is better than each classic method. Simulation, proves the feasibility and validity of AMKMTOA for the 13-unit system. This is a single step forward to solve the ED position.

Case III: To explore the feasibility of AMKMTOA in large scale power systems, the system is made up of the 40 generating units and has value point loading effects. The date of 40-unit system is from reference 27. The results of the proposed algorithm are also compared with the classical algorithms, such as TSARGA[8], DE[10], DECDM[27], FAPSO-NM[16], ICA-PSO[13], SOMA[28], IA-EDP[20], MAFRL[21] and KMTOA. The statistical conclusion is shown in Table 9. From this table, we see that the synthesized performance of AMKMTOA is still the best

Table 5. Comparison of 6-unit system results (FE = fitness evolution)

Problem/algorithm	Best	Worst	Mean	Standard	CPU time (s)	FE
GA[6]	15,459.00	15,469.00	15,469.00	41.58	–	20,000
DE[10]	15,449.77	15,449.87	15,449.78	–	0.03	36,000
PSO[6]	15,450.00	15,492.00	15,454.00	14.86	–	20,000
ICA–PSO[13]	15,443.24	15,444.33	15,443.97	–	–	20,000
SA–PSO[14]	15,447	15,455	15,447	2.528	7.58	20,000
IA–EDP[20]	15,442.9369	15,449.0294	15,444.0361	1.04109	0.769	3,000
MAFRL[21]	15,441.2610	15,444.2300	15,442.3206	0.8010	0.53	5,000
KMTOA	15,442.3462	15,448.9416	15,445.8941	1.0321	0.031	5,000
AMKMTOA	15,441.2286	15,445.2684	15,442.3082	0.7828	0.025	5,000

Table 6. Best results for 6-unit system

Unit	GA[6]	PSO[6]	CBA[26]	IA-EDP[20]	KMTOA	AMKMTOA
1	474.8066	447.4970	447.4187	446.6761	439.3404	447.8336
2	178.6363	173.3221	172.8255	172.2169	182.7354	173.2712
3	262.2089	263.4745	264.0759	264.1762	263.4227	263.3539
4	134.2826	139.0594	139.2469	143.6750	129.2436	138.3466
5	151.9039	165.4761	165.6526	161.3429	173.3652	165.3621
6	74.1812	87.1280	86.7652	87.2039	87.1183	87.0027
Total power (MW)	1276.03	1276.03	1275.376	1275.2910	1275.2462	1275.2041
Loss power (MW)	13.0217	12.9584	12.9848	12.2903	13.0023	12.2827
Total cost ($/h)	15,459	15,450	15,450.2381	15,442.9369	15,442.3462	155,441.6478

Table 7. Comparison of 13-unit system results

Problem/algorithm	Best	Worst	Mean	Standard	CPU time (s)	FE
TSARGA[8]	17,963.94	18,089.61	17,974.31	3.18	17.69	50,000
DE[10]	17,963.83	17,975.36	17,965.48	–	1.05	130,000
DECDM[27]	17,961.9440	18,061.4110	17,974.6869	20.3066	12.6	25,000
HMAPSO[15]	17,969.31	17,990.31	17,969.31	–	–	280,000
ICA–PSO[13]	17,960.37	17,978.14	17,967.94	1.92	0.12	40,000
SOMA[28]	17,967.4219	18,017.6161	17,985.3242	20.6772	–	25,000
IA–EDP[20]	17,961.4331	18,052.3155	17,980.1898	21.6666	0.876	25,000
MAFRL[21]	17,960.1200	17,964.6012	17,961.9231	0.8720	1.53	10,000
KMTOA	17,961.0670	17,967.2960	17,962.5110	1.0262	0.7555	10,000
AMKMTOA	17,960.1150	17,964.7420	17,961.7863	0.9061	0.6393	10,000

Table 8. Best results for 13-unit system

Unit	QPSO[29]	DFA[18]	IA-EDP[20]	CBA[26]	KMTOA	AMKMTOA
1	538.5600	628.31851	628.3066	628.3185	628.3128	628.3191
2	224.7000	149.59963	149.5246	149.5997	149.5654	149.6342
3	150.0900	222.74899	223.1148	222.7491	222.7908	222.7142
4	109.8700	109.86655	109.8754	109.8666	109.8662	109.8665
5	109.8700	109.86655	109.8489	109.8666	109.8662	109.8665
6	109.8700	109.86655	60.0000	109.8666	109.8662	109.8665
7	109.8700	109.86655	109.8319	109.8666	109.8662	109.8665
8	109.8700	60.00000	109.8434	60.0000	60.0000	60.0000
9	109.8700	109.86655	109.8049	109.8663	109.8662	109.8665
10	77.4100	40.00000	40.0000	40.0000	40.0000	40.0000
11	40.0000	40.00000	40.0000	40.0000	40.0000	40.0000
12	55.0100	55.00000	55.0000	55.0000	55.0000	55.0000
13	55.0100	55.00000	55.0000	55.0000	55.0000	55.0000
Total power (MW)	1,800.0	1,800.0	1,800.0	1,800.0	1,800.0	1,800.0
Total cost ($/h)	17,969.0100	17,963.8286	17,961.4331	17,963.8339	17,961.0670	17,960.1150

Table 9. Comparison of 40-unit system results

Problem/algorithm	Best	Worst	Mean	Standard	CPU time (s)	FE
TSARGA[7]	121,463.07	124,296.54	122,292.31	315.18	696.01	25,000
DE[12]	121,416.29	121,431.47	121,422.72	–	–	240,000
DECDM[23]	121,423.4013	121,696.9868	121,526.7330	54.8617	44.3	25,000
FAPSO-NM[11]	121,418.3	121,419.8	121,418.803	–	40	60,000
ICA-PSO[8]	121,413.20	121,453.56	121,428.14	–	139.92	70,000
SOMA[24]	121,418.7856	12,508.3757	121,449.8796	26.8385	–	25,000
IA-EDP[14]	121,436.9729	121,648.4401	121,492.7018	182.5274	1.092	24,000
MAFRL[21]	121,411.7200	124,115.9012	121,413.4311	1.4856	2.63	10,000
KMTOA	121,412.3663	121,418.9533	121,415.9608	1.5217	1.4626	25,000
AMKMTOA	121,411.5644	121,416.6033	121,413.2570	1.4864	1.4461	25,000

Table 10. Wilcoxon signed ranks test

	AMKMTOA versus KMTOA			AMKMTOA versus GSA		
Test problem	*P*-value	R^+	R^-	*P*-value	R^+	R^-
6-units	4.7387e-06	8688	1412	6.9358e-10	9383	717
13-units	3.0916e-04	7862	2238	7.3803e-10	9578	522
40-units	7.6588e-05	8124	1976	4.9752e-10	9644	456
	AMKMTOA versus DE			AMKMTOA versus RRPSO		
6-units	3.0123e-11	10100	0	3.0123e-11	10100	0
13-units	2.9215e-09	9578	521	4.0772e-11	10056	44
40-units	4.9752e-11	9946	154	3.0199e-11	10100	0

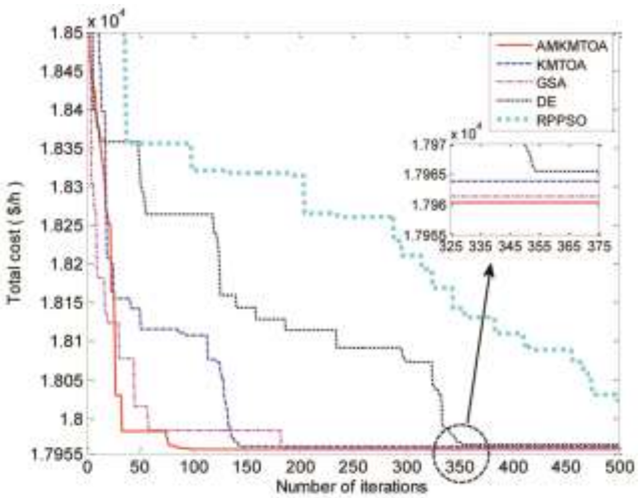

Figure 3. The convergences curves for 13-unit system.

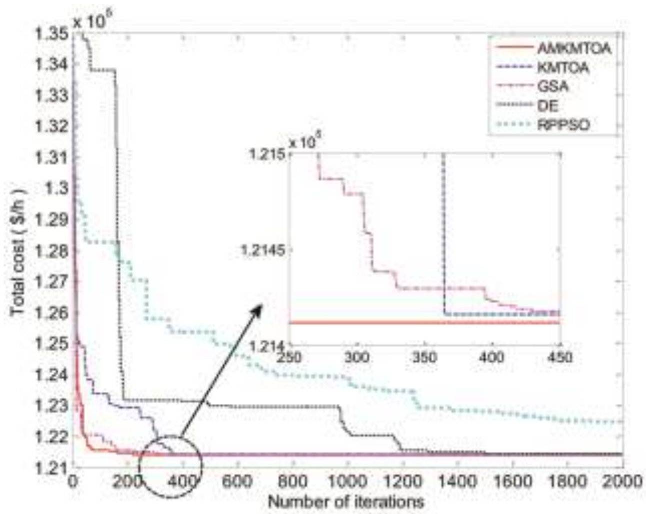

Figure 4. The convergences curves for 40-unit system.

when compared to others. Of course, the CUP time and FE are worse than IA-EDP. Power of each generator is given in Supplementary Table 2. It compares AMKMTOA with the five optimization algorithms, which are EDA/DE[30], DFA[18], IA-EDP[20], CBA[26] and KMTOA. Comparison of the results explains the superiority of AMKMTOA for optimizing the 40-unit system.

In Figure 4, the simulation consequence indicates that AMKMTOA has characteristics with higher convergence precision and faster convergence speed.

Wilcoxon signed ranks test of three systems

To examine the significance of the proposed approach in solving the ED problem, the Wilcoxon signed rank test was used. The principle of the Wilcoxon signed rank test and the meaning of the index is from ref. 31. AMKMTOA was compared with KMTOA, GSA, DE and RRPSO.

The experiments were conducted in 100 trails. The optimized results of five different algorithms were statistically analysed for every trail. The statistical results of 6-units, 13-units and 40-units were tested by the Wilcoxon signed rank test. It can be seen from Table 10 that AMKMTOA is superior to other algorithms in the ED problem.

Conclusion

This paper presents an improved algorithm called AMKMTOA based on kinetic-molecular theory, which is inspired based on the model of artificial memory. This algorithm was used to solve the economic dispatch problem. In the proposed algorithm, we employed the guiding strategy of memory which chose randomly, individuals from long-term memory to achieve the searching progress. The improved algorithm has been demonstrated very efficiently by testing 12 benchmark functions. When compared to the traditional KMTOA, it could greatly increase the searching ability and improve the convergence precision. The experiment simulation proved that AMKMTOA could achieve a better result when compared to other heuristic algorithms and efficiently deal with the constraints in the economic dispatch problem.

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