Determining Generator Contributions to Transmission System Using Parallel Vector Evaluated Particle Swarm Optimization

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***Abstract*—In this paper, the generator contributions to the transmission system are determined by an evolutionary computation technique. Evaluating the contributions of generators to the power flows in transmission lines is formulated as a multiobjective optimization problem and calculated using a parallel vector evaluated particle swarm optimization (VEPSO) algorithm. Specifically, the contributions are modeled by particles of swarms whose positions are optimally determined while satisfying all multiobjectives and other physical and operating constraints. The VEPSO method is parallelized by distributing the swarms in a number of networked PCs. The proposed parallel VEPSO algorithm accounts for nonlinear characteristics of the generators and transmission lines. The applicability of the proposed parallel VEPSO algorithm in accessing the generator contributions is demonstrated and compared with analytical methods for four different systems: three-bus, six-bus, IEEE 30-bus, and 136-bus test systems. The experimental results show that the proposed parallel VEPSO algorithm is capable of obtaining precise solutions compared to analytical methods while considering nonlinear characteristics of the systems.**

***Index Terms*—Evolutionary computation techniques, generator contribution to transmission system, multiobjective optimization, parallel vector evaluated particle swarm optimization (VEPSO).**

I. INTRODUCTION

SINCE competition has been introduced in generation and energy supply sector, it is widely agreed that the transmission system is a natural monopoly and should remain centrally controlled. It is also recognized that the operation of transmission system can have an enormous impact on a competitive market. To achieve the benefits of a robust, competitive bulk power market, all buyers and sellers must have equal access to the transmission grid, and it has become necessary to determine the capacity usage of different transmissions happening simultaneously [1]–[4].

Various analytical [1]–[4] and approximate methods [5]–[11] have been proposed to estimate the contribution of the generator units to the power flows, loads, and losses of the transmission grid in the literature.

Among them, in the analytical method [1]–[4], some closed formulae are introduced to express the above contributions, derivations of which are based on the sensitivity and corrective action analysis [1] and on graph theory [2]–[4]. Although, these contributions are more precise than other methods, the drawbacks are that they do not take into account the nonlinear characteristics of the generators such as prohibited operating zones and the operating constraints of the transmission lines such as thermal limits.

Among approximate and widely spread methods is the power flow comparison (PFC) [5], which assumes the constant voltage. Other methods are the topological trace algorithm [6], [7] and the up-stream and down-stream looking algorithms [8], [9], which assume proportional contribution factors. The circuit-based method is also used challenging the flow-based proportional sharing method [10], [11]. However, inaccurate assumptions were made in all previous methods, ignoring various nonlinear characteristics of the generators and operating constraints of transmission lines, which resulted in the reduction of their applicability, accuracy, and flexibility in complex and large-scale power systems.

Since the contributions of generators satisfy simultaneously different objectives such as the real power flow balance at each line, generator real power outputs, and real power balance at each node of the system, it is an urgent need to develop a new multiobjective method, which offers accuracy in determining the generator contributions, taking into account at the same time nonlinear characteristics of the real power systems. Although someone can claim that the multiobjective problems can be faced by single-objective methods (e.g., creating an aggregation between objectives using weighting factors), this would possibly lead to unsatisfactory solutions due to the additional effort of determining the appropriate weights and possible competitive objectives. However, recent studies [20], [32] have proven that the whole computing time of aggregating multiobjective algorithms is comparable with Pareto dominance but greater than coevolutionary meta-heuristic algorithms. Moreover, up to this point in power engineering, a basic particle swarm optimization (PSO) has been used to combine many objective functions (using weighted sum with equal/unequal weights [22], [23], [27]), but the advantages of additional multiobjective methods have not been evaluated yet.

Recently, modern meta-heuristic algorithms are considered as effective tools for nonlinear optimization problems with applications to power systems [12]. The algorithms do not require that the objective functions and the constraints have to be differentiable and continuous. A PSO introduced by Kennedy and Eberhart [13] is such an algorithm that can be

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applied to nonlinear optimization problems [14]–[20]. PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling. Unlike other heuristics techniques such as genetic algorithm (GA), PSO has a flexible and well-balanced mechanism to enhance and adapt to the global and local exploration and exploitation abilities within a short calculation time [15]. Although PSO seems to be sensitive to the tuning of its parameters, many researches are still in progress in solving complex power systems [21]–[28]. Vector evaluated particle swarm optimization (VEPSO) [32], [33] belongs to coevolutionary meta-heuristic algorithms and is a multiswarm variant of PSO, which is inspired by the vector evaluated genetic algorithm (VEGA) [34]. In VEPSO, each swarm is evaluated using only one of the objective functions of the problem under consideration, and the information it possesses for its own objective function is communicated to the other swarms through the exchange of their best experience [20], [32], [33]. The VEPSO method can be straightforwardly parallelized by distributing the number of swarms in the same number of networked PCs, which accelerates the convergence time [32].

Recently, PSO has been very successfully developed in solving problems in power systems. For example, Yoshida, *et al.* [21] applied PSO to the reactive power and voltage control problem that also considers voltage security assessments. Park *et al.* [22], Gaing [23], and Aruldoss *et al.* [24], [25] also applied PSO to the economic dispatch problem that considers nonlinear characteristics of power systems. Naka *et al.* [26] solved a practical distribution state estimation problem with PSO. Other problems where the PSO was used are the OPF by Abido [27], generation expansion planning by Kannan *et al.* [28], optimal capacitor placement with harmonic distortion consideration by Yu *et al.* [29], robust tuning of power systems stabilizers by Mendonca *et al.* [30] and identification of dynamic security border by Kassabalidis *et al.* [31].

In this paper, evaluating the contributions of generators to the real power flows in transmission lines is formulated as a multiobjective optimization problem and calculated using the VEPSO algorithm. Specifically, the contributions of generators to real power flows in transmission lines are modeled as positions of agents in swarms. Their aim is the correct determination of the generator contributions to transmission system, respecting generator constraints such as prohibited operating zones and line thermal limits.

II. Generator Contributions to Transmission System

A. Contribution of Generators to Line Flows

Considering a generation and load pattern, the ac load flow calculates the line power flows regarding various operational constraints. However, the contributions of each generator (components of generator's output) to line power flows can possibly violate any of the constraints, either the generator prohibited zones or the thermal limit of lines. None of the currently published methods take into account these constraints in determining generator contributions. Coevolutionary multiobjective optimization techniques are the effective tools for solving this problem. In this paper, the problem of determining the generator contributions to transmission line flows is modeled as a multiobjective optimization problem. We first define the following variables for the optimization problem:

$\mathrm{GC}_{l,g}$	contribution of generator g to line l (state variables);
P_l	real power flow at line l;
P_i^G, P_i^D	real power generation, demand at bus i;
Nl, Ng, Nd	number of lines, generators, and nodes;
Nl_i, Nl_g	number of lines connected to node i, generator g.

If $\mathrm{GC}_{l,g}$ has the same sign with P_l, then they both have the same direction and vice versa.

The multiobjective function is then defined with the following three objectives.

1) The total contribution of generators to each transmission line must be equal to the line flow

$$\min F_1 = \min \sum_{l=1}^{Nl} \left(P_l - \sum_{g=1}^{Ng} \mathrm{GC}_{l,g} \right)^2. \tag{1}$$

2) The real power balance between all generator contributions and the local generation and demand at each nodes must be satisfied

$$\min F_2 = \min \sum_{i=1}^{Nd} \left(P_i^G - P_i^D - \sum_{g=1}^{Ng} \sum_{l=1}^{Nli} \mathrm{GC}_{l,g} \right)^2. \tag{2}$$

3) The total contribution of a generator injected to the transmission system must be equal to the generator's real power output minus a local demand

$$\min F_3 = \min \sum_{g=1}^{Ng} \left(P_g^G - P_g^D - \sum_{l=1}^{N\,\mathrm{lg}} \mathrm{GC}_{l,g} \right)^2. \tag{3}$$

For simplicity, there is no consideration of real power losses in the above objective functions. However, we consider the line capacitances and no assumption that values of voltages are of 1.0 p.u. is made. Therefore, the ac load flow method is used for the calculation of line power flows. This sets the scene for a further study, where contribution of reactive generations to reactive power flows can be calculated replacing the real powers with reactive powers in (1)–(3). In addition to the objective functions, the optimization is subject to the following constraints.

4) In practical operation, the contribution of generators must avoid values in the prohibited operating zones of generators due to their valve operations:

$$P_{g,r}^{\mathrm{low}} \leq \mathrm{GC}_{l,g} \leq P_{g,r}^{\mathrm{upper}}, \qquad r = 1, 2, 3, \ldots, np \tag{4}$$

with $P_{g,r}^{\mathrm{low}} = P_g^{\min}$ and $P_{g,np}^{\mathrm{upper}} = P_g^{\max}$,

where np is number of prohibited operating zones, and $P_g^{\min}$ and $P_g^{\max}$ are the upper and lower limits of generator g.

III. Vector Evaluated PSO

A. PSO

The PSO is a swarm intelligence algorithm, inspired by the social dynamics and emergent behavior that arises in socially organized colonies. The PSO algorithm exploits a population of individuals to probe promising regions of search space. In this context, the population is called swarm, and the individuals are called particles or agents. Each particle moves with an adaptable velocity within the regions of search space and retains a memory of the best position it ever encountered. The best position ever attained by each particle of the swarm is communicated to all other particles.

In PSO, assume an n-dimensional search space $S \subset \mathbb{R}^n$, where n is the number of control or decision variables in the optimization problem and a swarm consisting of N-particles. The position of the ith particle at time t is an n-dimensional vector denoted by

$$S_i(t) = (s_{i,1}, s_{i,2}, \ldots, s_{i,n}) \in S. \tag{5}$$

The velocity of this particle at time t is also an n-dimensional vector

$$V_i(t) = (v_{i,1}, v_{i,2}, \ldots, v_{i,n}) \in S. \tag{6}$$

The best previous position of the ith particle is a point in S, denoted by

$$P_i = (p_{i,1}, p_{i,2}, \ldots, p_{i,n}) \in S \tag{7}$$

and the global best position ever attained among all particles is a point in S denoted by

$$P_{gb} = (p_{gb,1}, p_{gb,2}, \ldots, p_{gb,n}) \in S. \tag{8}$$

The swarm is manipulated by the equations [13], [18], [26]

$$\begin{aligned} V_i(t+1) = k \cdot [&w_i \cdot V_i(t) + c_1 \cdot \text{rand}_1 \cdot (P_i - S_i(t)) \\ &+ c_2 \cdot \text{rand}_2 \cdot (P_{gb} - S_i(t))] \end{aligned} \tag{9}$$

$$S_i(t+1) = S_i(t) + V_i(t+1) \tag{10}$$

where $i = 1, 2, \ldots, N$, c_1 and c_2 are the cognitive and the social parameters, respectively, and rand_1 and rand_2 are random numbers uniformly distributed within $[0, 1]$.

The inertia weighting function for the velocity of particle i is defined by the inertial weight approach

$$w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \cdot iter \tag{11}$$

where $iter_{\max}$ is the maximum number of iterations, and $iter$ is the current number of iterations.

The role of the inertia weighting function is considered critical for the PSO's convergence behavior. It is employed to control the influence of the previous history of the velocities on the current one. Accordingly, the inertia weighting function regulates the tradeoff between the global and local exploration abilities of the swarms [32].

In order to guarantee the convergence of the PSO algorithm, the constriction factor k is defined as

$$k = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \qquad \varphi = c_1 + c_2, \ \ \varphi > 4. \tag{12}$$

When the system behavior is controlled by constriction factor and parameter φ, it has the following features [18], [26].

1) The system does not diverge in a real value search space and finally can converge.
2) it can search different and discrete regions of search space efficiently by avoiding premature convergence.

B. Parallel VEPSO

In spite of the robustness and computational efficiency of the PSO algorithm in solving single-objective optimization problems, it does not face satisfactorily multiobjective optimization problems. On the other hand, the VEPSO method [20], [32] can be effective in solving multiobjective optimization problems such as the determination of generator contributions to transmission systems. The VEPSO method [20], [32] has been inspired by the concept and main ideas of the VEGA [34]. In this paper, the parallel implementation of VEPSO [32] is adopted in solving our multiobjective problem.

The VEPSO method [20], [32] assumes that M swarms $S_1, S_2, \ldots, S_M$ of size N aim to optimize simultaneously M-objective functions. Each swarm is evaluated according to one of the objective functions. Let $S_i^{[j]}$, $V_i^{[j]}$, $P_i^{[j]}$, $P_{gb}^{[j]}$ be the current position, velocity, the best previous position of the ith particle, and the global best in the jth swarm, respectively, at a given time t. Then, the VEPSO's swarms should be manipulated according to the equations

$$\begin{aligned} V_i^{[j]}(t+1) = k^{[j]} \cdot \Big[& w_i^{[j]} \cdot V_i^{[j]}(t) + c_1^{[j]} \\ & \cdot \text{rand}_1 \cdot \left(P_i^{[s]} - S_i^{[j]}(t)\right) + c_2^{[j]} \\ & \cdot \text{rand}_2 \cdot \left(P_{gb}^{[s]} - S_i^{[j]}(t)\right) \Big] \end{aligned} \tag{13}$$

$$S_i^{[j]}(t+1) = S_i^{[j]}(t) + V_i^{[j]}(t+1) \tag{14}$$

where the superscripts represent the PSO parameters for the jth swarm. The VEPSO assumes that the search behavior of a swarm is affected by a neighboring swarm. Specifically, it proposes the use of the global best position $P_{gb}^{[s]}$ and the best position of the particles $P_i^{[s]}$ until now in the sth swarm for the evaluation of the velocities of the particles in the jth swarm, assuming a "ring" migration topology (see Fig. 1) defined in [32]

$$s = \left\{ \begin{array}{ll} M, & \text{if } j = 1, \\ j-1, & \text{if } j = 2, 3, \ldots, M \end{array} \right\}. \tag{15}$$

In the case of the multiobjective optimization problem with the three objective functions (1)–(3), three swarms are employed, and each objective function is enforced by each swarm in order to determine the generator contributions. The parallel implementation of VEPSO assumes that each swarm is

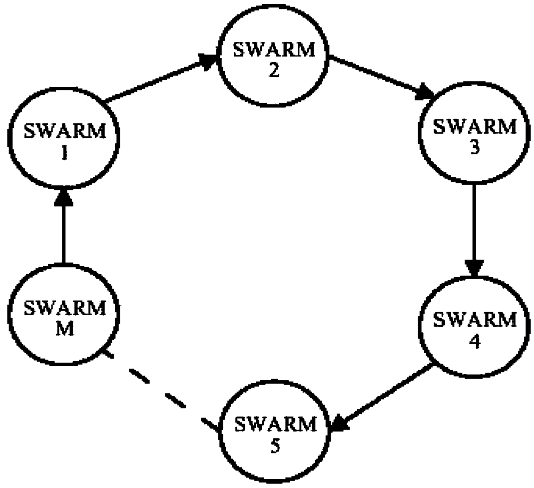

Fig. 1. Ring-migration scheme [32].

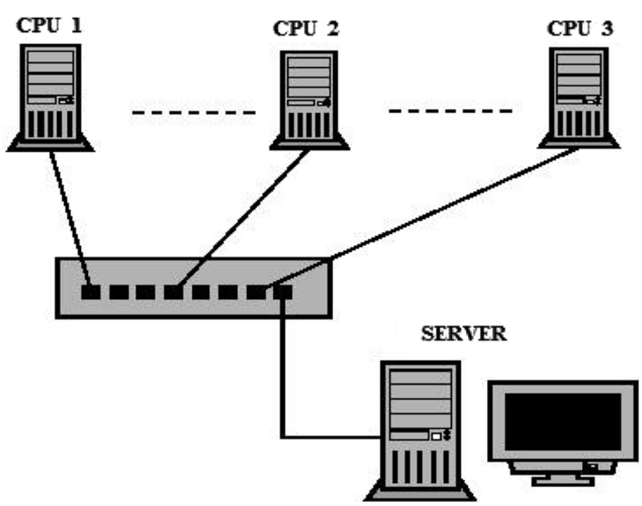

Fig. 2. Ethernet network for ring-migration scheme [32].

evaluated in one of the three PCs, which are connected in an Ethernet network allowing the migration of server from CPU to CPU (see Fig. 2).

In this way, the positions of particles for the three swarms are the contribution of generators to real power flows in transmission lines ($\mathrm{GC}_{l,g}$). The number of dimensions of search space in our study is $n = Nl \times Ng$. The positions of the ith particle belonging to the jth swarm in the n-dimensional search space are limited by the minimum and maximum positions expressed by vectors

$$\left[S_i^{[j],\min}, S_i^{[j],\max}\right], \qquad j = 1,2,3 \tag{16}$$

where the vectors of minimum and maximum positions comprise terms, respectively, (4)

$$\begin{aligned} s_{i,lg}^{[j],\max} &= P_{g,r}^{\mathrm{upper}}, \qquad lg = 1,2,\ldots,n, \\ r &= 1,2,\ldots,np \end{aligned} \tag{17}$$

$$\begin{aligned} s_{i,lg}^{[j],\min} &= P_{g,r}^{\mathrm{low}}, \qquad lg = 1,2,\ldots,n, \\ r &= 1,2,\ldots,np. \end{aligned} \tag{18}$$

The velocities of the ith particle belonging to the jth swarm in the n-dimensional search space are limited by

$$\left[-V_i^{[j],\max}, V_i^{[j],\max}\right], \qquad j = 1,2,3 \tag{19}$$

where the vector of maximum velocities comprises terms

$$V_{i,lg}^{[j],\max} = \frac{s_{i,lg}^{[j],\max} - s_{i,lg}^{[j],\min}}{Nr}, \qquad lg = 1,2,\ldots,n. \tag{20}$$

Here, Nr is a chosen number of search intervals for the particles. It is an important parameter in the proposed parallel VEPSO algorithm. A small Nr facilitates global exploration (searching new areas), while a large one tends to facilitate local exploration (fine tuning the current search area). A suitable value for the Nr usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate the optimum solution.

Incorporating the above modifications the proposed parallel VEPSO algorithm for determining generator contributions to transmission system can be described in the following steps.

Step 1 (Initialization): Set the time counter $t = 0$ and generate $3N$ particles. For each particle in the three swarms (N particles for each swarm) generate, with uniform probability distribution, initial positions $S_i^{[j]}(0)$ limited by (16), and initial velocities $V_i^{[j]}(0)$ limited by (19). To enforce the "ring" migration topology defined by (15), each particle in the initial population is evaluated using (1) if it belongs to the third swarm, (2) if it belongs to the first swarm, and (3) if it belongs to the second swarm. Set as best positions $P_i^{[j]} = S_i^{[j]}(0)$ and as global positions $P_{gb}^{[1]} =$ global best of $P_i^{[3]}$, $P_{gb}^{[2]} =$ global best of $P_i^{[1]}$ and $P_{gb}^{[3]} =$ global best of $P_i^{[2]}$. Set the cognitive and the social parameters $c_1^{[j]}$, $c_2^{[j]}$, $(j = 1,2,3)$.

Step 2 (Time update): Update the time counter $t = t + 1$. Set random numbers rand_1 and rand_2 uniformly distributed within the range $[0,1]$.

Step 3 (Velocity update): Using the global best $P_{gb}^{[j]}$ of each swarm $(j = 1,2,3)$ and the best positions of each particle in the three swarms $P_i^{[j]}$ $(j = 1,2,3)$, update the velocities of particles in three swarms using (13). Check if the limits of (19) are enforced. If the limits are violated, then they are replaced by the respective limits.

Step 4 (Position update): Based on the updated velocities, each particle in all swarms moves to new positions according to (14). Check if the limits of (16) are enforced. If the limits are violated, then they are replaced by the respective limits.

Step 5 (Particles best position update): Each particle in the swarms is evaluated according to its updated positions using (1)–(3), where (1) is for the third, (2) is for the first, and (3) is for the second swarm.

TABLE I
CHARACTERISTICS OF TEST SYSTEMS AND VEPSO ALGORITHM

Test System	Ng	Nl	n	VEPSO parameters	
3-bus	2	3	6	N	80
6-bus	3	8	24	Nr	15
IEEE 30-bus	4	41	164	c_1=c_2	2.05
136-bus	79	199	15721	(w_{min}, w_{max})	(0.1, 0.9)

Step 6 (Global best position update): Based on the updated best positions, each swarm updates the global best position $P_{gb}^{[j]}$.

Step 7 (Stopping criteria): The search will terminate if the number of iterations reaches the maximum allowable number (1500 in this study), or the following criteria 1), 2) and 3) are all satisfied.

1) The maximum of the relative errors between the line flow and the sum of all generator contributions to the line is less than 0.5%

$$\operatorname*{Max}_{l}\left|1-\frac{\sum\limits_{g=1}^{Ng}\mathrm{GC}_{l,g}}{P_l}\right|\cdot 100\leq 0.5. \tag{21}$$

2) The maximum of the errors of the real power balance of each generator at each node of the system is less than 0.1%

$$\operatorname*{Max}_{i,g}\left|P_i^G-P_i^D-\sum_{l=1}^{Nld}\mathrm{GC}_{l,g}\right|\cdot 100\leq 0.1. \tag{22}$$

3) The maximum of the relative errors between the real power injection of each generator and its total contributions is less than 0.5%

$$\operatorname*{Max}_{g}\left|1-\frac{\sum\limits_{l=1}^{Nl}|\mathrm{GC}_{l,g}|}{P_g^G-P_g^D}\right|\cdot 100\leq 0.5. \tag{23}$$

IV. SIMULATION RESULTS

To verify the feasibility of the proposed parallel VEPSO algorithm in determining the generator contributions to the transmission system, power systems in four different sizes are tested. In these systems, the thermal power limits at lines and the prohibited operating zones of generators are taken into consideration for practical application, and the proposed parallel VEPSO algorithm is compared with the analytical method whose formulae are based on the sensitivity and corrective action analysis [1].

The characteristics of power systems, which are tested, are given in Table I. Specifically, the dimension of each optimization problem is given in the column of parameter n resulting from the product of the number of generators by the number of lines in the system ($n = Ng \times Nl$). The table also gives the parameters of parallel VEPSO and the dimensions of the swarm's search space chosen in the case studies. The parameters $w_{\min}, w_{\max}, Nr, c_1$, and c_2 are those that lead the proposed parallel VEPSO algorithm faster in convergence and were selected after many empirical runs on the test power systems. Especially for the parameter Nr, this is determined among the candidate values of $[1, 5, 10, 15, 20, 50]$, and $Nr = 15$ is chosen as the best.

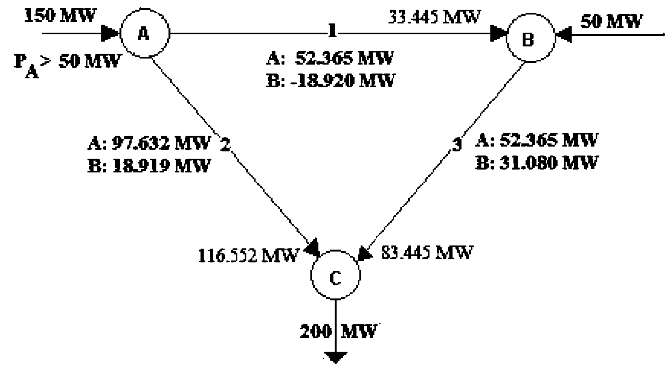

Fig. 3. Contribution of generators to line flows in the three-bus test system.

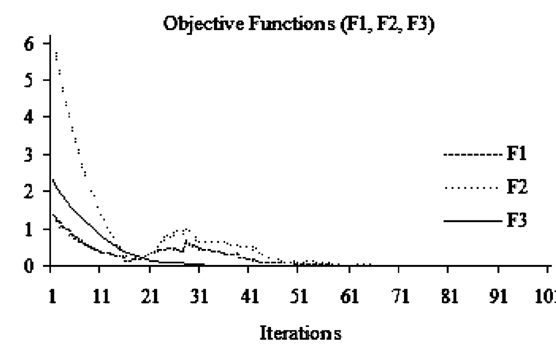

Fig. 4. Convergence of objective functions for the three-bus test system.

A. Three-Bus Test System

In the three-bus test system, the line resistances are 0.01 p.u., the reactances 0.1 p.u. and the distributed capacitance is considered with π model in all transmission lines [1], [5]. Fig. 3 shows the base case power flow result and contribution of each generator to each line flow, resulting from the proposed parallel VEPSO algorithm.

In this case, the minimum real power output at generator A is considered at 50 MW. This case study took about 65 iterations for the objective functions F1, F2, and F3 to converge (see Fig. 4).

B. Six-Bus Test System

Fig. 5 shows the topology of the six-bus test system, the base case power flow results [1], and the contribution of each generator to each line flows, resulting from the proposed parallel VEPSO algorithm.

In this case, the generator constraints and the thermal power flow limits at lines 30–50, 40–60, and 50–60, shown in Table II,

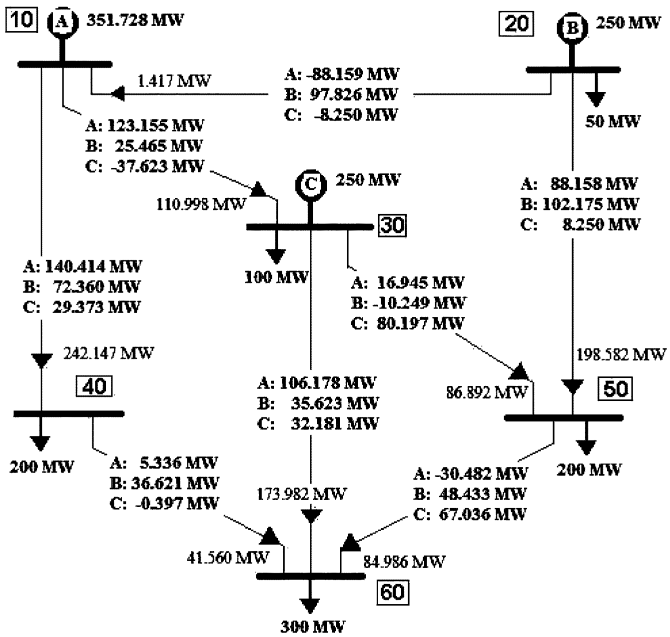

Fig. 5. Contribution of generators to line power flows of six-bus test system.

TABLE II
CONSTRAINTS OF THE SIX-BUS TEST SYSTEM

Gen	Prohibited Operating Zones (MW)	Line	Thermal Limit (MW)
A	(20-30), (40-80), (90-100), (110-120), (130-140), (150-160)	30-50	90
B	(50-60), (80-90), (110-120)	40-60	45
C	(10-20), (40-60), (100-120)	50-60	85

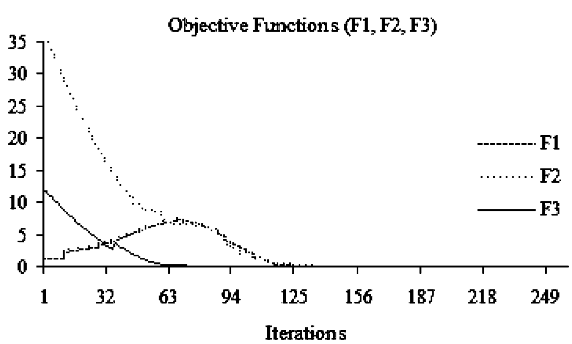

Fig. 6. Convergence of objective functions for the six-bus test system.

are satisfied. Fig. 6 shows that all objective functions (F1, F2, F3) took about 125 iterations in order to converge.

We declare that the minus sign of generator contribution $GC_{l,g}$ means that the influence of a generator g on the flow of line l has inverse direction from the real power line flow. So, the contribution of generator C to line 10–20 results from the power balance of the generator C contribution to lines 10–30 and 10–40, on bus 10 (there is no load at bus 10). The contribution of generator C to line 10–40 results from the power balance of generator C contributions to line 40–60 and the load on bus 40 and so on. In order to interpret the contribution of generator C to real line power flows (from where they come), one can "hide" the outputs of generators A and B and their contributions to lines and loads from Fig. 5 and then examine the power balance of generator C contributions at every bus of the system. Generally, as it is depicted in Fig. 5, the contributions of each one of the generators to each line satisfy the real power balance of the six-bus system and the generator and line constraints regardless of the contributions of other generators.

C. IEEE 30-Bus System

The proposed parallel VEPSO algorithm is tested on the IEEE 30-bus power system. The topology and the complete data of this network are given in [35]. The network consists of four generators, 41 lines, four transformers, and two capacitor banks. Loads were set at the values referred in [35] multiplied by a factor of 0.6 (nominal load). The results for the cases when generators are both constrained and unconstrained are given in Table III. In the case of constrained generators, the upper limits of generators 2 and 3 are 30MW and 8MW, respectively. Comparing the results of the unconstrained case with those given by [1], it is concluded that the last are similar to those given by the proposed parallel VEPSO algorithm.

Fig. 7 demonstrates that all objective functions lead to convergence after about 550 iterations. In this case, the total CPU time is 5 sec while the CPU time of [1] is 0.6 sec since the generator contribution demand only one calculation of Newton power flow.

The Appendix shows the parameter sensitivity analysis of VEPSO. In the simulation, the parameters Nr, c_1, c_2, $w_{\min}$ and $w_{\max}$ are changed. The average and minimum of F_1, F_2, and F_3 with up to 1500 iterations in 100 trials for each case are shown in the table in the Appendix. The results reveal that the appropriate values for $w_{\min}$ and $w_{\max}$ are 0.1 and 0.9, respectively. The appropriate value for c_1 and c_2 is 2.05 and for Nr is 15. Consequently, the appropriate parameter values for VEPSO are the same with the ones suggested in Table I, which were found empirically. Alternatively, the determination of optimum parameters (Nr, c_1, c_2, $w_{\min}$, $w_{\max}$) of VEPSO algorithm can be achieved by incorporating any of the modern evolutionary algorithms such as cultural algorithms [36] in the proposed parallel VEPSO. This can be studied in future research.

D. 136-Bus System

The proposed parallel VEPSO algorithm is also applied to compute the contributions of 79 generators on 199 transmission lines in the 136-bus system. This system consists of 136 buses (33 PV and 103 load buses), 24 transformers, and 17 reactive compensations [37], [38]. The results in this case are similar to those given by [1] with 0.5% precision. Fig. 8 shows that all objective functions are converged after approximately 440 iterations. The total CPU time for the 136-bus system is calculated at 157.2 s. The CPU time of [1] is only 16.8 s since the generator contribution demands only one calculation of Newton power flow.

Finally, Fig. 9 shows the statistical evaluation results by VEPSO in 100 trials. In this case, the maximum, average, and minimum values of the objective functions F_1, F_2, and F_3 are shown in Table IV.

In all case studies, the proposed parallel VEPSO was implemented on a network of three 1.4-GHz Pentium-IV PCs so that

TABLE III
CONTRIBUTIONS OF CONSTRAINED AND UNCONSTRAINED GENERATORS TO REAL POWER FLOWS IN IEEE 30-BUS SYSTEM

Line	Line flows (MW)	Contributions of Constrained Generators (MW)				Contributions of Unconstrained Generators (MW)			
		G1	G2	G3	G4	G1	G2	G3	G4
1-2	-12.351	1.457	-16.148	2.348	0.028	4.290	-13.866	-3.275	0.499
1-3	18.554	4.713	16.107	-2.169	-0.061	1.939	14.534	2.672	-0.591
2-4	25.599	-3.955	27.623	2.151	-0.218	0.837	21.441	4.171	-0.850
3-4	16.957	4.710	14.252	-1.950	-0.050	1.850	13.491	2.264	-0.649
2-5	19.779	4.558	14.527	0.007	0.689	1.743	30.851	-14.940	2.124
2-6	28.999	0.740	28.679	0.408	-0.738	1.199	25.263	3.725	-1.189
4-6	15.814	1.412	15.957	-0.813	-0.655	1.579	17.417	-1.681	-1.501
5-7	13.080	4.563	14.163	-6.298	0.651	-0.319	-2.535	18.308	-2.374
6-7	0.741	-4.564	-1.075	6.078	0.219	0.833	10.768	-14.559	3.698
6-8	17.153	3.635	13.402	-2.010	2.036	0.626	10.122	5.091	1.313
6-9	8.669	2.838	11.151	1.379	-6.749	0.608	10.129	5.472	-7.541
6-10	7.990	9.972	5.113	-7.271	0.169	0.352	5.874	3.172	-1.409
9-11	-15.001	-0.043	-0.044	-0.265	-14.635	-0.002	-0.046	-0.023	-14.93
9-10	23.677	2.909	11.229	1.895	7.697	0.615	10.243	5.525	7.294
4-15	23.267	-0.651	22.511	1.230	0.178	1.014	15.757	7.101	-0.605
12-13	0.000	0.045	0.034	-0.127	0.047	0.000	0.000	0.000	0.000
12-14	-0.068	1.349	-0.329	-0.791	-0.295	-0.014	-0.194	-0.047	0.187
12-15	-6.552	5.293	-11.160	-0.106	-0.580	-0.282	-4.408	-2.015	0.154
12-16	-0.102	-7.164	5.786	1.024	0.247	0.054	0.683	0.097	-0.936
14-15	-3.789	1.333	-4.257	-0.578	-0.285	-0.145	-2.317	-1.125	-0.201
16-17	-2.203	-7.165	3.692	1.024	0.246	-0.021	-0.528	-0.515	-1.140
15-18	3.859	3.407	0.640	0.462	-0.651	0.192	2.941	1.246	-0.522
18-19	1.918	3.408	-1.301	0.462	-0.651	0.122	1.804	0.678	-0.687
19-20	-3.788	3.407	-6.965	0.460	-0.690	-0.085	-1.540	-0.994	-1.169
10-20	5.138	-3.414	8.921	-1.111	0.703	0.132	2.313	1.386	1.306
10-17	7.632	7.156	1.287	-1.716	0.825	0.217	3.695	2.103	1.618
10-21	10.298	1.007	10.830	-3.750	2.133	0.340	5.540	2.834	1.584
10-22	5.119	8.217	-4.617	1.502	-0.087	0.164	2.678	1.381	0.896
21-22	-0.255	1.018	1.776	-3.529	0.465	-0.042	-0.638	-0.255	0.680
15-23	4.072	2.542	1.251	0.301	-0.028	0.188	2.849	1.187	-0.151
22-24	4.838	9.223	-2.867	-1.828	0.330	0.125	2.092	1.141	1.480
23-24	2.120	2.534	-0.908	0.511	-0.018	0.117	1.709	0.616	-0.322
24-25	1.683	11.756	-8.518	-1.099	-0.506	0.047	0.659	0.202	0.775
25-26	2.116	0.951	1.439	-0.217	-0.009	0.076	1.238	0.619	0.183
25-27	-0.513	10.758	-10.003	-0.720	-0.538	-0.033	-0.637	-0.451	0.607
27-28	-8.444	6.033	-13.769	-0.116	-0.572	-0.321	-5.301	-2.789	-0.033
27-29	3.685	7.990	-3.881	0.505	-0.890	0.133	2.157	1.078	0.316
27-30	4.219	-3.299	7.606	-0.933	0.877	0.153	2.469	1.234	0.362
29-30	2.212	7.961	-5.579	0.719	-0.887	0.080	1.295	0.647	0.190
8-28	-0.900	3.641	-2.336	-1.793	-0.441	-0.029	-0.457	-0.201	-0.212
6-28	9.270	-9.648	16.131	1.718	1.065	0.352	5.781	3.005	0.230
Gen. Real Power Outputs		6.203	100.0	50.0	15.0	6.203	100.0	50.0	15.0

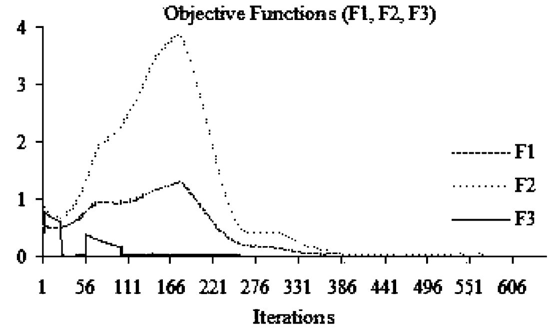

Fig. 7. Convergence of objective functions for the IEEE 30-bus test system in the case of constrained generators.

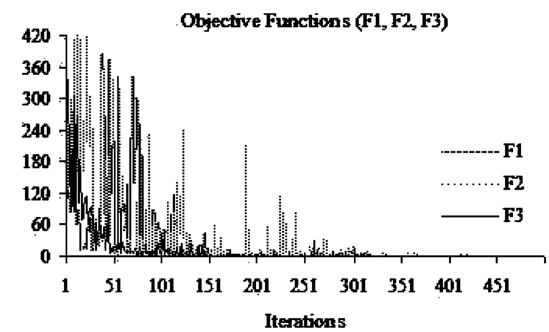

Fig. 8. Convergence of objective functions for the 136-bus test system.

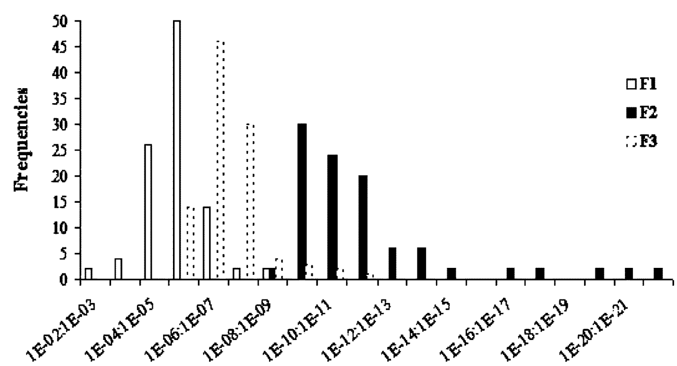

Fig. 9. Statistical results by VEPSO (100 trials) for 136-bus test system.

TABLE IV
MAXIMUM, AVERAGE, AND MINIMUM VALUES OF OBJECTIVE FUNCTIONS (F_1, F_2, F_3) FOR 136-BUS SYSTEM (100 TRIALS)

F_1 max	F_1 aver	F_1 min	F_2 max	F_2 aver	F_2 min	F_3 max	F_3 aver	F_3 min
5.671 E-03	1.674 E-06	2.546 E-09	7.348 E-09	7.760 E-11	8.573 E-22	8.435 E-06	9.354 E-07	3.678 E-12

the three swarms are distributed in parallel on these PCs (see Fig. 2). Therefore, the total CPU time of the proposed parallel VEPSO algorithm was the time in which the last function converged (F2 in the last case study). It must be noticed that although the CPU time of the proposed method is greater than that given in [1], the proposed method can solve the problem, which includes nonlinear characteristics of the power systems. Moreover, the proposed algorithm can be distributed in more than three networking PCs resulting in a further reduction of the computing time.

V. CONCLUSIONS

This paper presented a parallel VEPSO algorithm for determining generator contributions to the transmission system under various generator and transmission line constraints. The problem of determining real power contributions is formulated

TABLE V
PARAMETER SENSITIVITY ANALYSIS FOR IEEE 30-BUS SYSTEM (100 TRIALS)

w_{min}	w_{max}	F	c_1=c_2									
			2.000					2.025				
			Nr									
			1	5	10	15	20	1	5	10	15	20
0.1	0.9	F_1 aver	8.840E-06	2.457E-06	8.234E-06	8.879E-07	4.861E-06	7.044E-07	1.002E-06	6.344E-05	6.746E-06	1.917E-06
		F_1 min	8.141E-07	1.132E-07	4.338E-07	4.123E-08	1.936E-07	5.613E-08	3.582E-08	7.226E-06	7.380E-07	2.225E-07
		F_2 aver	1.439E-20	5.631E-13	6.434E-10	7.758E-10	9.937E-11	5.200E-10	6.870E-10	3.365E-10	3.877E-10	7.590E-10
		F_2 min	1.136E-23	4.863E-15	7.383E-13	2.207E-12	4.734E-13	1.411E-12	2.484E-12	1.051E-12	4.480E-13	1.032E-12
		F_3 aver	5.769E-11	5.546E-08	5.518E-08	4.386E-08	8.670E-08	4.518E-07	1.441E-07	1.576E-06	8.647E-07	6.307E-08
		F_3 min	4.294E-12	1.033E-08	4.840E-09	3.471E-09	4.463E-09	2.525E-08	1.684E-08	1.000E-07	4.158E-08	4.244E-09
0.4	0.9	F_1 aver	5.048E-04	9.696E-06	1.832E-05	3.423E-06	9.713E-06	4.523E-06	1.603E-06	2.180E-05	4.771E-05	6.307E-06
		F_1 min	2.614E-05	1.488E-06	2.233E-06	2.740E-07	3.713E-07	4.204E-07	1.468E-07	1.223E-06	5.131E-06	4.639E-07
		F_2 aver	3.218E-11	8.658E-10	1.266E-10	2.141E-10	4.131E-11	1.561E-16	3.001E-10	9.897E-10	2.088E-10	8.368E-10
		F_2 min	7.074E-15	2.739E-12	2.026E-12	3.173E-13	8.637E-14	1.211E-19	1.515E-13	7.862E-11	3.752E-13	5.785E-12
		F_3 aver	6.388E-08	2.092E-06	1.284E-07	1.294E-06	1.215E-07	7.470E-13	6.597E-08	7.150E-08	4.157E-07	7.004E-07
		F_3 min	9.901E-09	2.196E-07	6.238E-09	1.213E-07	1.222E-08	3.539E-14	5.977E-09	3.180E-09	5.039E-08	4.244E-08
0.1	1.0	F_1 aver	2.229E-05	2.374E-06	3.519E-07	1.441E-05	5.405E-06	6.760E-06	1.363E-06	4.677E-07	6.115E-06	2.256E-05
		F_1 min	3.015E-06	2.395E-07	1.359E-08	1.358E-06	4.588E-07	4.605E-07	5.910E-08	3.354E-08	3.723E-07	2.450E-06
		F_2 aver	1.186E-17	1.624E-12	1.947E-11	7.652E-11	5.695E-10	2.297E-12	8.338E-10	1.902E-10	3.747E-10	8.091E-11
		F_2 min	7.888E-21	3.281E-15	1.310E-13	5.654E-14	3.874E-13	2.683E-15	2.861E-12	2.595E-13	1.378E-12	2.842E-13
		F_3 aver	1.181E-08	5.949E-07	4.965E-08	1.578E-07	6.021E-07	1.118E-08	9.039E-08	1.884E-07	2.945E-06	4.872E-06
		F_3 min	7.079E-10	2.986E-08	2.968E-09	1.320E-08	6.230E-08	6.453E-10	7.472E-09	1.528E-08	3.077E-07	3.573E-07
0.4	1.0	F_1 aver	3.205E-06	1.077E-06	1.199E-06	5.669E-06	6.232E-06	2.239E-03	1.370E-05	5.708E-07	9.800E-07	5.784E-05
		F_1 min	4.941E-07	8.606E-08	1.049E-07	5.185E-07	6.490E-07	3.246E-04	1.000E-06	2.867E-08	3.491E-08	6.761E-06
		F_2 aver	1.460E-21	3.881E-10	1.208E-11	6.950E-12	5.670E-10	2.332E-13	5.342E-10	8.707E-10	1.052E-13	8.311E-10
		F_2 min	5.847E-25	4.306E-13	2.949E-15	1.101E-14	7.514E-13	1.459E-16	1.813E-12	3.933E-12	3.200E-16	1.138E-11
		F_3 aver	2.385E-13	4.481E-08	6.334E-08	4.626E-08	4.529E-08	6.434E-09	2.725E-08	2.776E-08	8.699E-07	6.481E-07
		F_3 min	1.094E-14	3.975E-09	3.908E-09	8.413E-09	2.482E-09	3.985E-10	1.531E-09	9.831E-10	1.376E-07	5.416E-08

as a multiobjective optimization problem that takes into account nonlinear characteristics of the power systems such as prohibited operating zones of generators and thermal limit of lines. The feasibility of the proposed method was demonstrated and compared with other analytical methods, for four different systems of various sizes. The experimental results showed that though the proposed parallel VEPSO algorithm is slower than the analytical method, it is capable of obtaining results with high accuracy while considering various nonlinear constraints of the power systems in a short computing time, which is in part due to the fact that the three swarms are distributed in parallel on a network of three PCs. Parallel distribution in a larger PCs network can result in further reduction in computing time. As further research, a hybrid evolutionary algorithm, such as cultural-VEPSO, will be introduced to determine the optimum values of empirical parameters of the VEPSO algorithm.

APPENDIX

Table V shows the parameter sensitivity analysis for the IEEE 30-bus system (100 trials).

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TABLE V
(*Continued*.) PARAMETER SENSITIVITY ANALYSIS FOR IEEE 30-BUS SYSTEM (100 TRIALS)

w_{min}	w_{max}	F	$c_1=c_2$									
			2.050					2.100				
			Nr									
			1	5	10	15	20	1	5	10	15	20
0.1	0.9	F_1 aver	1.024E-05	4.866E-07	1.310E-05	2.105E-09	2.313E-06	2.956E-06	2.617E-06	1.849E-05	1.639E-05	3.681E-06
		F_1 min	1.199E-06	2.974E-08	1.551E-06	1.679E-09	1.905E-07	5.904E-07	1.833E-07	1.263E-06	1.707E-06	4.597E-07
		F_2 aver	8.420E-11	3.034E-10	9.974E-10	2.697E-13	5.052E-10	5.146E-10	7.156E-10	1.001E-09	4.969E-11	5.285E-10
		F_2 min	1.880E-13	6.288E-13	1.663E-10	1.333E-13	3.473E-13	4.072E-13	1.262E-12	6.413E-10	2.987E-14	2.211E-12
		F_3 aver	6.485E-07	1.595E-07	2.271E-07	1.065E-11	9.473E-08	2.378E-11	2.132E-07	8.004E-08	4.293E-06	2.512E-07
		F_3 min	4.080E-08	1.971E-08	1.457E-08	9.313E-12	4.771E-09	1.142E-12	2.443E-08	7.277E-09	2.441E-07	1.548E-08
0.4	0.9	F_1 aver	1.487E-05	7.903E-06	3.952E-06	3.205E-07	1.620E-07	8.247E-06	9.830E-06	1.243E-04	2.505E-06	7.597E-06
		F_1 min	1.121E-06	6.830E-07	2.770E-07	1.613E-08	7.407E-09	5.511E-07	6.005E-07	1.804E-05	4.467E-07	6.060E-07
		F_2 aver	8.370E-10	1.004E-09	6.608E-11	7.740E-10	1.404E-12	5.907E-11	7.786E-10	9.723E-10	1.066E-11	7.470E-12
		F_2 min	1.065E-11	2.896E-10	1.369E-13	1.386E-11	3.279E-15	4.396E-14	2.018E-12	3.131E-11	4.040E-15	1.001E-14
		F_3 aver	8.360E-07	7.970E-07	6.224E-08	2.215E-07	2.039E-06	1.918E-07	4.863E-07	8.430E-07	9.695E-07	5.991E-07
		F_3 min	4.735E-08	1.046E-07	4.522E-09	1.541E-08	1.741E-07	9.794E-09	6.121E-08	1.051E-07	5.411E-08	7.108E-08
0.1	1.0	F_1 aver	1.373E-05	3.709E-07	1.083E-05	2.931E-05	1.005E-05	4.168E-06	6.168E-06	6.311E-06	3.489E-06	7.641E-05
		F_1 min	6.037E-07	2.699E-08	7.878E-07	1.351E-06	9.092E-07	3.064E-07	4.135E-07	4.112E-07	1.590E-07	9.360E-06
		F_2 aver	4.145E-10	7.762E-12	1.094E-10	8.658E-10	9.916E-10	4.919E-11	6.077E-10	6.814E-10	7.355E-10	6.627E-10
		F_2 min	3.334E-13	1.149E-13	1.320E-13	9.975E-12	4.829E-11	6.217E-14	1.332E-12	4.367E-12	4.196E-12	2.055E-12
		F_3 aver	1.857E-07	1.445E-07	1.012E-07	7.767E-06	6.372E-07	1.297E-06	4.596E-07	1.153E-06	2.741E-07	4.401E-07
		F_3 min	1.290E-08	6.708E-09	9.558E-09	7.479E-07	3.592E-08	2.216E-07	8.741E-08	7.562E-08	1.469E-08	3.453E-08
0.4	1.0	F_1 aver	2.788E-06	3.054E-06	1.935E-05	4.291E-06	1.080E-06	4.097E-05	3.617E-06	8.088E-08	1.720E-04	1.070E-05
		F_1 min	2.352E-07	1.870E-07	2.367E-06	3.271E-07	6.537E-08	4.339E-06	2.210E-07	7.284E-09	2.025E-05	8.041E-07
		F_2 aver	3.240E-11	9.637E-10	9.802E-10	3.184E-12	6.883E-10	6.322E-10	1.132E-10	1.050E-12	1.111E-12	9.476E-10
		F_2 min	5.929E-15	3.804E-11	9.747E-11	2.398E-15	4.497E-12	4.832E-13	1.457E-13	1.311E-15	1.751E-15	1.520E-11
		F_3 aver	2.179E-08	1.166E-07	3.687E-07	3.263E-07	1.137E-07	2.001E-07	9.438E-06	7.824E-08	5.219E-11	1.094E-07
		F_3 min	1.441E-09	5.935E-09	3.790E-08	1.874E-08	4.584E-09	2.461E-08	9.025E-07	7.852E-09	1.593E-12	6.176E-09

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