Economic Load Dispatch—A Comparative Study on Heuristic Optimization Techniques With an Improved Coordinated Aggregation-Based PSO

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Abstract—In this paper an improved coordinated aggregation-based particle swarm optimization (ICA-PSO) algorithm is introduced for solving the optimal economic load dispatch (ELD) problem in power systems. In the ICA-PSO algorithm each particle in the swarm retains a memory of its best position ever encountered, and is attracted only by other particles with better achievements than its own with the exception of the particle with the best achievement, which moves randomly. Moreover, the population size is increased adaptively, the number of search intervals for the particles is selected adaptively and the particles search the decision space with accuracy up to two digit points resulting in the improved convergence of the process. The ICA-PSO algorithm is tested on a number of power systems, including the systems with 6, 13, 15, and 40 generating units, the island power system of Crete in Greece and the Hellenic bulk power system, and is compared with other state-of-the-art heuristic optimization techniques (HOTs), demonstrating improved performance over them.

Index Terms—Adaptive velocity limits, coordinated aggregation, economic dispatch, heuristic optimization techniques, nonsmooth cost functions, particle swarm optimization.

I. INTRODUCTION

IN the electric power supply systems, there exist a wide range of problems involving optimization processes. Among them, the power system scheduling is one of the most important problems in the operation and management [1].

Recently, modern meta-heuristic algorithms are considered as effective tools for nonlinear optimization problems with applications to power systems scheduling, e.g., economic load dispatch (ELD) [2]–[26]. The algorithms do not require that the objective functions and the constraints have to be differentiable and continuous. A particle swarm optimization (PSO) is such an algorithm that can be applied to nonlinear optimization problems.

PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling. In general, swarm behavior can be modeled with a few simple information rules. The decision process of particles in the swarm takes into account two important operators. The first one is their own experience (cognitive operator); that is, they have tried the choices and know which state has been better so far, and they know how good it was. The second one is other particles' experiences (social operator); that is, they have knowledge of how the other particles around them have performed [1]. Unlike other heuristics optimization techniques (HOTs) 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. Since PSO seems to be sensitive to the tuning of its parameters, many researches are still in progress in regulating these.

Recently, the coordinated aggregation based PSO (CA-PSO) was introduced for optimal steady-state performance of power systems [27]. The main idea of CA-PSO is based on the fact that the achievement of each particle is distributed in the entire swarm. At each iterative cycle, each particle updates its velocity taking into account the differences between its position and the positions of better achieving particles. These differences play the role of coordinators as they are multiplied as weighting factors. The best particle in the swarm is excluded from this process, as it regulates its velocity randomly [27]. However, a drawback in the CA-PSO [27] is that particles do not take into account the cognitive operator and do not adaptively organize their search.

This paper focuses on the performance evaluation of a newly introduced improved coordinated aggregation-based particle swarm optimization (ICA-PSO) algorithm in the ELD problem. Specifically, ICA-PSO is produced enhancing the CA-PSO algorithm [27]. Specifically, the CA-PSO is modified with a cognitive operator in the particles, adaptively selected number of search intervals for the particles, variable population size and search accuracy for particles up to two digit points, resulting in the improved convergence of the process.

The ICA-PSO is implemented in the ELD problem. Since 2003 the ELD problem has been solved by various modern HOTs [2]–[26], and some of them have been implemented into practice [1]. The obtained results by ICA-PSO are compared with those given by other state-of-the-art HOTs on power systems with 6, 13, 15, and 40 generating units, the island power system of Crete and the Hellenic bulk power system with various loads subjected to all operating constraints.

II. PREVIOUS WORKS ON HOTs FOR ELD

The state-of-the-art HOTs for ELD are presented in this section in the reverse chronological publishing order:

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1) *Simulated annealing-PSO (SA-PSO):* This paper proposes a new approach and coding scheme for solving economic dispatch problems in power systems through simulated annealing like particle swarm optimization [2].

2) *Quantum-inspired version of the PSO using the harmonic oscillator (HQPSO):* The HQPSO is inspired by the classical PSO and quantum mechanics theories, using a harmonic oscillator (HQPSO) to solve economic dispatch problems [3].

3) *Self-organizing hierarchical particle swarm optimization (SOH-PSO):* In the SOH-PSO the particle velocities are reinitialized whenever the population stagnates at local optima during the search [4].

4) *Bacterial foraging with Nelder–Mead algorithm (BF-NM):* This paper proposes a stochastic optimization approach to solve constrained economic load dispatch problem using hybrid bacterial foraging technique. In order to explore the search space for finding the local minima, the simplex algorithm called Nelder–Mead is used along with BF algorithm [5].

5) *Adaptive-PSO (APSO):* This paper presents a novel heuristic optimization approach to constrained ELD problems using the adaptive-variable population-PSO technique [6].

6) *Uniform design with the genetic algorithm (UHGA):* This paper presents an efficient method for solving the economic dispatch problem (EDP) through combination of genetic algorithm (GA), the sequential quadratic programming (SQP) technique, uniform design technique, the maximum entropy principle, simplex crossover and nonuniform mutation [7].

7) *Differential evolution (DE):* The DE is a classical differential evolution algorithm attempting to solve ELD problem [8].

8) *Particle swarm optimization with chaotic and Gaussian approaches (PSO-CG):* In the PSO-CG a Gaussian probability distribution and chaotic sequences to generate random numbers into velocity update equation are used [9].

9) *Directional search genetic algorithm (DSGA):* The DSGA instead of GA-searching for final best fit chromosome in the entire random search space follows a directional procedure to reach the solution. The total search space is narrowed down to single route. The DSGA is a special algorithm for ELD problem with prohibited operating zones [10].

10) *Real-parameter quantum evolutionary algorithm (RQEA):* The RQEA is a modern population-based probabilistic EA that integrates concepts from quantum computing for objective functions with real parameters [11].

11) *Hybrid differential evolution (HDE) and self-tuning HDE (STHDE):* The HDE is a differential evolution algorithm where the fittest of an offspring competes one by one with that of the corresponding parent, which is different from the other evolutionary algorithms (EAs). The STHDE utilizes the concept of the 1/5 success rule of evolutionary strategies in the original HDE to accelerate the search for the global optimum [12].

12) *Artificial immune system (AIS):* This paper presents a novel optimization approach to constrained ELD problem using artificial immune system. The approach utilizes the clonal selection principle and evolutionary approach wherein cloning of antibodies is performed followed by hypermutation [13].

13) *Variable scaling hybrid differential evolution (VSHDE):* The VSHDE is an HDE with nonlinear scaling factor [14].

14) *New particle swarm optimization with local random search (NPSO-LRS):* The NPSO-LRS uses the classical PSO splitting up the cognitive operator into best and worst memories integrating with simple local random searches [15].

15) *Improved genetic algorithm with multiplier updating (IGAMU):* The IGAMU integrates an improved evolutionary direction operator and a migrating operator to avoid deforming the augmented Lagrange function [16].

16) *Differential evolution combination with sequential quadratic programming method (DEC-SQP):* The DEC-SQP combines the differential evolution algorithm with the generator of chaos sequences and sequential quadratic programming technique [17].

17) *Evolutionary strategy optimization (ESO):* The ESO is based on classical evolutionary strategy $(\mu + \lambda)$-ES paradigm, considering Gaussian mutation operator [18], [19].

18) *Taguchi method (TM):* The Taguchi method involves the use of orthogonal arrays in estimating the gradient of the cost function and has been widely used in experimental designs for problems with multiple parameters where the optimization of a cost function is required [20].

19) *Modified particle swarm optimization (MPSO):* The MPSO introduces a mechanism in classical PSO to deal with the equality and inequality constraints in the ELD. A constraint treatment mechanism is devised in such a way that the dynamic process inherent in the conventional PSO is preserved. Moreover, a dynamic search-space reduction strategy is devised to accelerate the optimization process [21].

20) *Evolutionary programming algorithm with non-linear scaling factor (EP-NSF):* In the proposed EP-NSF algorithm, mutation changes nonlinearly with respect to the number of generations avoiding premature condition [22].

21) *Hybrid particle swarm optimization with sequential quadratic programming (PSO-SQP):* The PSO-SQP combines the PSO with the conventional sequential quadratic programming technique [23].

22) *Particle swarm optimization (PSO):* The classical PSO algorithm is introduced as a solution method of ELD [24].

23) *Real GA:* The developed real-coded GA is based on a floating-point coding scheme observing transmission line power-flow limits [25].

24) *Improved fast evolutionary programming (IFEP):* The proposed IFEP algorithm uses both Gaussian and Cauchy mutations to create offspring from the same parent and the better ones are chosen for next generation [26].

III. ECONOMIC LOAD DISPATCH

The main purpose of this paper is the performance evaluation of the proposed ICA-PSO in optimal ELD. Therefore, the

ICA-PSO algorithm is tested and compared with other state-of-the-art HOTs on this problem. Thus, a clear picture of the effectiveness of the proposed ICA-PSO is given. The objective of the ELD problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system. Therefore, it can be formulated mathematically with an objective function and two constraints (equality and inequality).

A. Equality Constraint

In the power balance criterion, the equality constraint should be satisfied as

$$\sum_{i=1}^{N_G} P_i - P_D - P_{\text{Loss}} = 0 \tag{1}$$

where N_G represents the total number of generators. So, the total generated real power should be the same with the total load demand P_D plus transmission losses P_{Loss} of the system. The P_{Loss} are calculated using power flows coefficients B_{ij} by the following formula:

$$P_{\text{Loss}} = \sum_i \sum_j P_i B_{ij} P_j + \sum_i B_{0i} P_i + B_{00}. \tag{2}$$

B. Inequality Constraints

The real power output P_i of each generator-i should lie between maximum $P_{i,\text{max}}$ and minimum $P_{i,\text{min}}$ limits represented by

$$P_{i,\text{min}} \leq P_i \leq P_{i,\text{max}}. \tag{3}$$

Also generators have certain prohibited operating zones due to steam valve or vibration in shaft bearings

$$
\begin{aligned}
P_{i,\text{min}} &\leq P_i \leq P_i^{\text{lower}_1} \text{ or} \\
P_i^{\text{upper}_{j-1}} &\leq P_i \leq P_i^{\text{lower}_j} \quad j = 2, \ldots, \text{np}_i \text{ or} \\
P_i^{\text{upper}_{\text{np}_i}} &\leq P_i \leq P_{i,\text{max}}
\end{aligned}
\tag{4}
$$

where $P_i^{\text{lower}_j}$ and $P_i^{\text{upper}_{j-1}}$ are, respectively, the lower and upper bounds of prohibited zone j of generator-i and np_i is the number of prohibited zones in generator-i.

C. Fitness Function

The total fuel cost function (in \$/h or €/h) addressing the valve-point loadings of generating units to be minimized is given by

$$
\begin{aligned}
\min_{P_i} F_C &= \sum_{i=1}^{N_G} F_i \\
&= \sum_{i=1}^{N_G} \left(\alpha_i + b_i P_i + c_i P_i^2 + |e_i \sin(f_i(P_{i,\text{min}} - P_i))| \right)
\end{aligned}
\tag{5}
$$

where a_i, b_i, c_i, e_i, f_i are the fuel cost coefficients of generating unit-i.

In order to speed up the convergence of iteration procedure, the evaluation value is normalized into the range between 0 and 0.5. Specifically, the evaluation function f is adopted as in [24]

$$f = \frac{1}{F_{C,\text{Norm}} + F_{L,\text{Norm}}} \tag{6}$$

where

$$F_{C,\text{Norm}} = 1 + \frac{F_C - F_{\text{min}}}{F_{\text{max}} - F_{\text{min}}} \tag{7}$$

$$F_{L,\text{Norm}} = 1 + \left(\sum_{i=1}^{N_G} P_i - P_D - P_{\text{Loss}} \right)^2. \tag{8}$$

Here, F_{max} and F_{min} are the total cost of generating units at their maximum and minimum limits, respectively, calculated at the initial population.

Evaluation function (6) is the reciprocal of power balance constraint and the generation cost function as in (1) and (5). This implies that if the values of (7) and (8) of a particle are small, then its evaluation value (6) would be large.

In order to limit the evaluation value of each particle of the swarm within a feasible range, before estimating the evaluation value of a particle (6), the generation power output must satisfy the constraints in (4). If a particle satisfies all constraints, then it is a feasible particle and (7) has a small value. Otherwise, the value (7) of the particle is penalized with a very large positive constant.

IV. IMPROVED COORDINATED AGGREGATION-BASED PSO

The coordinated aggregation is a new operator introduced recently in the swarm, where each particle moves considering only the positions of particles with better achievements than its own with the exception of the best particle, which moves randomly. The coordinated aggregation can be considered as a type of active aggregation where particles are attracted only by places with the most food. Specifically, at each iterative cycle-t of ICA-PSO, each particle-j with better achievement than particle-i regulates the velocity of the second. The velocity of particle$-i$ is adapted by means of coordinators multiplied by weighting factors. The differences between the positions of particles-j and the position of particle-i, $S_j(t) - S_i(t)$, are defined as coordinators of particle-i velocity. The ratios of differences between the achievement of particle-i, $f(S_i)$, and the better achievements by particles-j, $f(S_j)$, to the sum of all these differences are the weighting factors $w_{ij}(t)$ of the coordinators

$$w_{ij} = \frac{f(S_j) - f(S_i)}{\sum_l (f(S_l) - f(S_i))} \quad j, l \in T_i \tag{9}$$

where T_i represents the set of particles$-j$ with better achievement than particle-i.

Also, the ICA-PSO considers the following additional concepts and techniques.

1) The cognitive operator of the particles (the ability of the particles to retain a memory of its best position ever achieved) for better exploitation of the search space.

2) He adaptively selected number of search intervals for the particles and the variable population size, resulting in the improved convergence of the process for better exploration of the search space. Specifically, the maximum velocities are constricted in a small number of search intervals, Nr, in the search space for better balance between exploration and exploitation. A small Nr facilitates global exploration (searching new areas), while a large one tends to facilitate local exploration (fine tuning of the current search area) [see (13)]. 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 [27]. In the ICA-PSO, the number of search intervals (Nr) is selected adaptively during the iterative process in the areas with the rate of search in (10) at the bottom of the page, where $n_{\text{Allow}}, n_{\text{Emer}}$ and n_{Fail} are, respectively, the limits on the allowed, emergency and failed number of iterations (t); $\text{Nr}_{\min,N}$, $\text{Nr}_{\max,N}$ are the limits of Nr in the area of normal search rate; $\text{Nr}_{\min,I}$, $\text{Nr}_{\max,I}$ are the limits of Nr in the area of intensive search rate, and $\text{Nr}_{\min,S}$, $\text{Nr}_{\max,S}$ are the limits of Nr in the area of scrutiny. Moreover, if no improvement in the global best achievement is observed for n_{Fail} number of iterations the population size is increased by 15%.

3) The particles search the decision space with accuracy up to two decimal points. So, they avoid many local minima, premature convergence and explore/exploit better and faster only three surfaces (0–2 digit points) of the decision space.

The steps of ICA-PSO for ELD are listed in the following.

Step 1) *Initialization:* Generate N-particles. For each particle-i choose initial position vector $S_i(0)$ (initial vector of generators' real power outputs) randomly and set it as best position $P_i(0)$ of particle-i. Calculate its initial achievement $f(S_i(0))$ using the evaluation function (6) and find the maximum $(f_g(0) = \max_i f(S_i(0)))$ called the global best achievement. Then, particles update their positions (generators' real power outputs) in accordance with the following steps.

Step 2) *Swarm's manipulation:* The particles, except the best of them regulate their velocities in accordance with the equation

$$V_i(t+1) = \text{rand}_i \cdot (V_i(t) + c \cdot (P_i - S_i(t))) + \sum_j \text{rand}_j \cdot w_{ij}(t) \cdot (S_j(t) - S_i(t)), \quad j \in T_i \quad (11)$$

where $i = 1, 2, \ldots, N$; c is the cognitive parameter; P_i is the best position of the particle-i it ever encountered; the random parameters rand_i and rand_j are used to maintain the diversity of the population and are respectively uniformly distributed within the ranges [0.999, 1] and [0, 1]; $w_{ij}(t)$ are the weighting factors of the coordinators (9).

Step 3) *Best particle's manipulation:* The best particle in the swarm updates its velocity using a random coordinator calculated between its position and the position of a randomly chosen particle in the swarm.

Step 4) *Velocity bounds' oscillations:* Check if the bounds of velocities are enforced, (12), (13). If the bounds are violated then they are replaced by the respective limits. The velocities of the ith particle in the n-dimensional decision space are limited by

$$[-V_i^{\max}, V_i^{\max}] \quad (12)$$

where the maximum velocity in the l-th dimension (generator-l) of the search space is proposed as

$$v_{i,l}^{\max} = \frac{s_{i,l}^{\max} - s_{i,l}^{\min}}{\text{Nr}}, \quad (i = 1, 2, \ldots, n) \quad (13)$$

where $s_{i,l}^{\min}$ and $s_{i,l}^{\max}$ are the limits in the l-dimension of the search space [limits of real power outputs of generator-l, (3)] and Nr is the chosen number of the search intervals (10). Normally, choose a random integer number in the range of $[\text{Nr}_{\min,N}, \text{Nr}_{\max,N}]$.

Step 5) *Position update:* The positions of particles (generators' real power outputs) are updated on the basis of

$$S_i(t+1) = S_i(t) + V_i(t+1). \quad (14)$$

Step 6) *Position limits:* Check if the limits of particles' positions (generators prohibited operating zones) are enforced (4). If any of the limits are violated then a high penalty is added in (7) and the corresponding number of search interval (10) is set at the lowest value $\text{Nr} = \text{Nr}_{\min,N}$.

Step 7) *Evaluation:* Calculate the achievement $f(S_i(t))$ of each particle-i using the evaluation function (6) and calculate the maximum one among them.

Step 8) *Update search intervals and population size:* If no improvement in the global best is achieved for t number of iterations with: a) $n_{\text{Allow}} < t \leq n_{\text{Emer}}$ choose a random integer number of search intervals in the range of $[\text{Nr}_{\min,I}, \text{Nr}_{\max,I}]$, b) $n_{\text{Emer}} < t <$

$$\text{Nr} \in \begin{cases} \text{Normal} : [\text{Nr}_{\min,N}, \text{Nr}_{\max,N}] \text{ if } t \leq n_{\text{Allow}} \\ \text{Intensive} : [\text{Nr}_{\min,I}, \text{Nr}_{\max,I}] \text{ if } n_{\text{Allow}} < t \leq n_{\text{Emer}} \\ \text{Scrutiny} : [\text{Nr}_{\min,S}, \text{Nr}_{\max,S}] \text{ if } n_{\text{Emer}} < t < n_{\text{Fail}} \end{cases} \quad (10)$$

n_{Fail} choose a random integer number of search intervals in the range of $[\mathrm{Nr}_{\min,S}, \mathrm{Nr}_{\max,S}], c)t \geq n_{\mathrm{Fail}}$ increase the population size every $n_{\mathrm{Allow}} + n_{\mathrm{Emer}} + n_{\mathrm{Fail}}$ iterations by 15% up to 90% of the initial size.

Step 9) *Stopping criteria:* The ICA-PSO algorithm will be terminated if the maximum number of allowed iterations is achieved ($\mathrm{iter}_{\max} = 1000$). If the stopping criteria are not satisfied, go to *Step 2*.

Step 10) *Global optimal solution:* Choose the optimal solution as the global best achievement

$$S_g = \arg\max f_g(S_g). \tag{15}$$

V. PERFORMANCE EVALUATION

To assess the efficiency of the proposed ICA-PSO, the following seven case studies of ELD with various loads are applied.

Case 1) Six-generating units of IEEE 30-bus system. In this application the obtained results are compared with those given by EP-NSF [22].

Case 2) 13-generating units. In this application the results are compared with those given by SA-PSO [2], HQPSO [3], BF-NM [5], UHGA [7], DE [8], RQEA [11], HDE and STHDE [12], IGAMU [16], DEC-SQP [17], ESO [18], [19], PSO-SQP [23], and IFEP [26].

Case 3) 15-generating units. In this application the results are compared with those given by SA-PSO [2], SOH-PSO [4], BF-NM [5], APSO [6], DE [8], PSO-CG [9], DSGA [10], AIS [13], HDE and VSHDE [14], IGAMU [16], ESO [18], [19], and PSO [24].

Case 4) 40-generating units. In this application the results are compared with those given by SA-PSO [2], SOH-PSO [4], BF-NM [5], UHGA [7], DE [8], HDE and STHDE [12], NPSO-LRS [15], IGAMU [16], DEC-SQP [17], ESO [18], [19], TM [20], MPSO [21], PSO-SQP [23], and IFEP [26].

Case 5) Autonomous power system of island of Crete, Greece. In this application the results are compared with those given by Real GA [25].

Case 6) Hellenic bulk power system. The version with 32 combined cycle co-generation plant (CCCP) generating units is considered.

Case 7) A six-generating units with prohibited operating zones considering power loss. In this application the obtained results are compared with those given by SA-PSO [2], BF-NM [5], APSO [6], DE [8], AIS [13], NPSO-LRS [15], ESO [18], [19], and PSO [24].

The performance of ICA-PSO is quite sensitive to the various parameter settings. Tuning of parameters is essential in all PSO based methods. Based on empirical studies on a number of mathematical benchmarks, we [27], [28] have reported the best range of variation for cognitive and social parameters, inertia weighting factor, number of search intervals, and population size. This paper further explores the best range of newly

TABLE I
PARAMETERS OF ICA-PSO

Parameter	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
n_{Allow}	10	10	10	10	10	10	10
n_{Emer}	20	20	20	20	20	20	20
n_{Fail}	50	50	50	50	50	50	50
$Nr_{min,N}$	10	20	15	15	50	15	20
$Nr_{max,N}$	50	500	500	500	500	500	500
$Nr_{min,I}$	50	500	1200	1200	1200	500	500
$Nr_{max,I}$	150	1500	1700	1700	1700	1500	1500
$Nr_{min,S}$	150	1500	2500	4000	2500	1500	1500
$Nr_{max,S}$	250	2500	3500	5000	3500	2500	2500
N-(initial)	20	40	40	70	40	70	20
c	0.5	0.5	0.5	0.5	0.5	0.5	0.5

TABLE II
ICA-PSO FOR SIX-GENERATING UNITS: RESULTS
AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)	Generating units	Outputs (MW)
1	172.89	4	10.10
2	51.20	5	13.48
3	20.10	6	15.87
Load demand (MW)		283.40	
Power loss (MW)		0.24	
Minimum cost ($/h)		697.73	
Mean cost ($/h)		698.02	
Maximum cost ($/h)		700.15	
Number of iterations		197	
CPU time / per iteration (sec)		0.025	

introduced parameters in (10), where sensitivity analysis was performed with respect to the parameters: allowed, emergency and failed limits in the number of iterations; chosen limits of search intervals for the particles in the normal, intensive and scrutiny search areas; population size (N); and cognitive parameter (c). The stochastic parameters of ICA-PSO shown in Table I are those, which yielded best solution for each case study. They were selected after many trial runs by means of sensitivity analysis. The minimum, mean and maximum of cost functions (8) are estimated with up to 1000 iterations in 100 trials on a 1.4-GHz Pentium-IV PC.

A. Case 1

The ICA-PSO is applied to the IEEE-30 bus system with six-generating units, 41 transmission lines, four tap changing transformers, and two injected VAR sources. The total system load demand is 283.4 MW. The cost coefficients of IEEE 30-bus system are slightly modified to incorporate nonsmooth fuel cost functions as given in EP-NSF [22]. The first generating unit is a combined cycle co-generation plant (CCCP), the second generating unit has piecewise cost function, the third and fourth generators have valve point loadings, and the last two have quadratic cost functions. The ramp rate limits of generating units are also given in EP-NSF [22]. Table II shows the best dispatch solution obtained by ICA-PSO for this system. They are better than those given by EP-NSF (total minimum cost: 747.3 $/h) [22].

TABLE III
ICA-PSO FOR 13-GENERATING UNITS: RESULTS
AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)	Outputs (MW) "Constrained"	Outputs (MW)	Outputs (MW)
1	628.32	628.32	628.32	628.32
2	149.60	299.20	299.19	299.19
3	222.75	291.90	294.51	294.51
4	109.86	159.73	159.73	159.73
5	109.86	159.73	159.73	159.73
6	60.00	159.73	159.73	159.73
7	109.87	159.73	159.73	159.73
8	109.87	159.73	159.73	159.73
9	109.87	159.73	159.73	159.73
10	40.00	114.80	114.80	114.80
11	40.00	75	77.40	116.45
12	55.00	60	55.00	55.00
13	55.00	92.40	92.40	92.40
Load demand (MW)	1800.00	2520.00	2520.00	2520.00
Power loss (MW)	0.0	0.0	0.0	39.05
Minimum cost ($/h)	17960.37	24246.60	24168.91	24540.06
Mean cost ($/h)	17967.94	24252.65	24175.34	24561.46
Maximum cost ($/h)	17978.14	24263.56	24184.92	24589.45
Number of iterations	192	324	479	413
CPU time / per iteration (sec)	0.052	0.052	0.052	0.052

TABLE IV
MINIMUM GENERATION COST OBTAINED BY DIFFERENT
METHODS ON 13-GENERATING UNITS SYSTEM

Method	Total power 1800 MW	Total power 2520 MW "Constrained"	Total power 2520 MW	Total power 2559.05 MW
ICA-PSO	17960.37	24246.60	24168.91	24540.06
SA-PSO	-	-	24171.39	-
HQPSO	17963.95	-	-	-
BF-NM	17960.49	-	-	-
UHGA	17964.81	-	24172.25	-
DE	17963.83	-	24169.92	-
RQEA	-	24252.05	24164.04	-
HDE	17975.73	-	-	24591.76
STHDE	17963.79	-	-	24560.08
IGAMU	-	-	24169.97	-
DEC-SQP	17963.94	-	-	-
ESO	-	-	24221.77	-
PSO-SQP	17969.93	24261.05	-	-
IFEP	17994.07	-	-	-

TABLE V
ICA-PSO FOR 15-GENERATING UNITS: RESULTS
AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)		
1	455.00	455.00	455.00
2	420.00	419.99	419.99
3	130.00	130.00	130.00
4	130.00	130.00	130.00
5	260.00	260.00	260.00
6	430.00	429.99	429.99
7	465.00	465.00	465.00
8	60.00	60.00	60.00
9	25.00	27.67	25.00
10	62.60	111.29	76.70
11	80.00	80.00	80.00
12	77.40	78.01	54.77
13	25.00	25.00	25.00
14	15.00	15.00	15.00
15	15.00	15.00	15.00
Load demand (MW)	2650.00	2650.00	2630.00
Power loss (MW)	0.0	51.95	11.45
Minimum cost ($/h)	32480.91	33048.32	32393.23
Mean cost ($/h)	32486.76	33060.18	32400.17
Maximum cost ($/h)	32496.47	33078.23	32414.32
Number of iterations	472	465	345
CPU time / per iteration (sec)	0.058	0.058	0.058

B. Case 2

In this application power system has 13-generating units. In the literature there are four different applications with load demand of the system at values of 1800 MW, 2520 MW without power loss (constrained and unconstrained cases), and 2520 MW considering power loss [2], [3], [5], [7], [8], [11], [12], [14], [16]–[19], [23], [26]. In the "constrained" case with load demand at value of 2520 MW without power loss, the outputs of generating units 11 and 12 are fixed at 75 MW and 60 MW, respectively. In the fourth application where power loss is considered the total power generation is 2559.05 MW, namely there is a power loss of 39.05 MW. In this case, the HDE and STHDE [12] achieve power loss of 39.15 MW and 44.33 MW, respectively. Table III shows the best dispatch solution and convergence characteristics of ICA-PSO, for all cases of load demand. The results obtained by ICA-PSO are compared with those available from the literature in Table IV. The results of ICA-PSO are better than all cases except in the case of load demand at value of 2520 MW without power loss, where RQEA [11] achieves better minimum cost.

C. Case 3

In this application power system has 15-generating units, where four units have prohibited operating zones. In the literature there are three applications with the load demand of 2650 MW without power loss, 2650 MW considering power loss, and 2630 MW considering power loss [2], [4]–[6], [8]–[10], [13], [14], [16], [18], [19], [24]. Table V shows the best dispatch solution and convergence characteristics of ICA-PSO for all

cases of load demand. The table also shows the convergence characteristics of ICA-PSO, namely the iteration number achieved, the minimum cost (best iteration), mean CPU time per iteration, and minimum, mean and maximum cost (5). The results obtained by ICA-PSO are compared with those available from the literature in Table VI. It shows that the ICA-PSO performed better than all other HOTs.

D. Case 4

In this application power system has 40-generating units. Total load demand of the system is 10500 MW. In the literature there are many HOTs applications in this system [2], [4], [5],

TABLE VI
MINIMUM GENERATION COST OBTAINED BY DIFFERENT
METHODS ON 15-GENERATING UNITS SYSTEM

Method	Total power 2650 MW	Total power 2701.95 MW	Total power 2641.44 MW
ICA-PSO	*32480.91*	*33048.33*	*32393.23*
SA-PSO	-	-	32708.00
SOH-PSO	-	-	32751.39
BF-NM	-	-	32784.50
APSO	-	-	32742.77
DE	-	-	32588.86
PSO-CG	-	-	32508.12
DSGA	32545.00	-	-
STHDE	-	33343.37	-
AIS			32854.00
VSHDE	-	33282.17	-
IGAMU	32506.33	-	-
ESO	32507.67	-	32640.85
PSO	-	-	32858.00

TABLE VII
ICA-PSO FOR 40-GENERATING UNITS: RESULTS
AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)	Generating units	Outputs (MW)
1	110.80	21	523.28
2	110.80	22	523.28
3	97.41	23	523.28
4	179.74	24	523.28
5	88.52	25	523.28
6	140.00	26	523.28
7	259.60	27	10.00
8	284.60	28	10.00
9	284.60	29	10.00
10	130.00	30	96.39
11	168.80	31	190.00
12	94.00	32	190.00
13	214.76	33	190.00
14	394.28	34	164.82
15	394.28	35	200.00
16	304.52	36	200.00
17	489.28	37	110.00
18	489.28	38	110.00
19	511.28	39	110.00
20	511.28	40	511.28
Load demand (MW)		10500.00	
Power loss (MW)		0.0	
Minimum cost ($/h)		121413.20	
Mean cost ($/h)		121428.14	
Maximum cost ($/h)		121453.56	
Number of iterations		636	
CPU time / per iteration (sec)		0.22	

TABLE VIII
MINIMUM GENERATION COST OBTAINED BY DIFFERENT
METHODS ON 40-GENERATING UNITS SYSTEM

Method	Minimum cost ($/h)	Method	Minimum cost ($/h)
ICA-PSO	*121413.20*	NPSO-LRS	121664.43
SA-PSO	121430.00	IGAMU	121819.25
SOH-PSO	121501.14	DEC-SQP	121741.97
BF-NM	121423.63	ESO	121630.96
UHGA	121424.48	TM	122477.78
DE	121416.29	MPSO	122252.26
STHDE	123598.76	PSO-SQP	122094.67
VSHDE	123496.02	IFEP	122624.35

TABLE IX
ICA-PSO FOR CRETE'S POWER SYSTEM (18-GENERATING
UNITS): RESULTS AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)	Generating units	Outputs (MW)
1	15.00	10	12.28
2	45.00	11	12.28
3	25.00	12	24.00
4	25.00	13	3.00
5	25.00	14	34.04
6	4.13	15	35.35
7	4.13	16	37.00
8	12.28	17	36.23
9	12.28	18	3.00
Load demand (MW)		365.00	
Power loss (MW)		0.0	
Minimum cost ($/h)		25430.16	
Mean cost ($/h)		25440.89	
Maximum cost ($/h)		25462.34	
Number of iterations		315	
CPU time / per iteration (sec)		0.059	

E. Case 5

In this application the ELD problem in the autonomous power system of Greek island of Crete is solved. Two subcases are considered. In the first sub-case the system comprises of 18-generating units with quadratic (convex) cost functions, 52 buses, 66 branches, and 18 thermal units. In this subcase branch-power flow limits are considered. The data are given in [25]. Table IX shows the best dispatch solution and the convergence characteristics of ICA-PSO. The results of ICA-PSO in this version of the Crete's power system with various loads are compared with those given by Real GA [25] in Table X. The maximum power capability is $P_{G,\max} = 433.22$ MW. The results given by ICA-PSO are better than those given by Real GA [25]. In the second sub-case the system comprises 19-generating units with cubic (nonconvex) cost functions. In this subcase also branch-power flow limits are considered. The maximum power capability is $P_{G,\max} = 490.3$ MW. Total load demand of the system is 400 MW (medium load). The technical limits and the coefficients of cost functions of 19-generating units are given in Appendix A. Table XI shows the best dispatch solution and convergence characteristics of ICA-PSO.

[7], [8], [12], [15]–[21], [23], [26]. Table VII shows the best dispatch solution and convergence characteristics of ICA-PSO. The results obtained by ICA-PSO are compared with those available from the literature in Table VIII, which shows that the performance of the ICA-PSO is exceeding in all other cases.

TABLE X
ICA-PSO AND REAL GA FOR CRETE'S POWER SYSTEM
(18-GENERATING UNITS-VARIOUS LOADS)

Load demand (MW)	ICA-PSO ($/h)	Real GA ($/h)
95% $P_{G, max}$	29731.03	29731.05
90% $P_{G, max}$	27653.92	27655.53
80% $P_{G, max}$	23854.78	23861.58
70% $P_{G, max}$	20386.00	20396.39

TABLE XI
ICA-PSO FOR CRETE'S POWER SYSTEM (19-GENERATING
UNITS): RESULTS AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)	Generating units	Outputs (MW)
1	5.44	11	15.00
2	15.00	12	15.00
3	15.00	13	3.00
4	25.00	14	18.80
5	25.00	15	5.00
6	25.00	16	30.27
7	11.80	17	30.28
8	11.80	18	62.50
9	11.80	19	62.50
10	11.80		-
Load demand (MW)		400.00	
Power loss (MW)		0.0	
Minimum cost (€/h)		32015.42	
Mean cost (€/h)		32029.93	
Maximum cost (€/h)		32041.10	
Number of iterations		429	
CPU time / per iteration (sec)		0.064	

TABLE XII
ICA-PSO FOR 32-GENERATING UNITS OF HELLENIC BULK
POWER SYSTEM: RESULTS AND CONVERGENCE CHARACTERISTICS

Generating units	Outputs (MW)	Generating units	Outputs (MW)
1	150.00	17	265.00
2	180.00	18	265.00
3	160.00	19	265.00
4	120.00	20	265.00
5	120.00	21	265.00
6	120.00	22	60.00
7	135.00	23	110.00
8	270.00	24	110.00
9	140.00	25	265.00
10	127.00	26	28.00
11	265.00	27	110.00
12	265.00	28	110.00
13	270.00	29	270.00
14	330.00	30	270.00
15	265.00	31	300.00
16	265.00	32	160.00
Load demand (MW)		6300.00	
Power loss (MW)		0.0	
Minimum cost (€/h)		227582.29	
Mean cost (€/h)		227590.21	
Maximum cost (€/h)		227599.13	
Number of iterations		509	
CPU time / per iteration (sec)		0.19	

F. Case 6

In this application the Hellenic bulk power system has 32-generating units. The maximum power capability is $P_{G,max} = 6313$ MW. Total load demand of the system is 6300 MW (heavy load). Technical limits and the coefficients of cost functions for 32-generating units are given in Appendix B. The system is also constrained because generating unit 26 is fixed at 28.00 MW.

Table XII shows the best dispatch solution and the convergence characteristics of ICA-PSO.

G. Case 7

We finalize the results giving full details of ICA-PSO operation on a representative case study. In this case study, the power loss is considered and each one of the six-generating units has two prohibited operating zones. Total load demand of the system is 1263 MW. All correct data are given in [19]. In the literature there are many HOTs applications in this system [2], [5], [6], [8], [13], [15], [18], [19], [24].

Also in this case study, sensitivity analysis [27], [28] was performed with respect to the parameters: allowed n_{Allow}, emergency n_{Emer} and failed n_{Fail} limits in the number of iterations; chosen limits of search intervals for the particles in the normal $[Nr_{min,N}, Nr_{max,N}]$, intensive $[Nr_{min,I}, Nr_{max,I}]$

and scrutiny $[Nr_{min,S}, Nr_{max,S}]$ search areas; initial population size N; and cognitive parameter c. Specifically, the following empirical 4-tuples of stochastic parameters were considered in the simulation results:

$$n_{Allow} = \{5, 10, 15, 20\}$$
$$n_{Emer} = \{20, 25, 30, 35\}$$
$$n_{Fail} = \{35, 40, 45, 50\}$$
$$[Nr_{min,N}, Nr_{max,N}] = \left\{ \begin{array}{l} [10, 50], [15, 250] \\ [15, 500], [20, 500] \end{array} \right\}$$
$$[Nr_{min,I}, Nr_{max,I}] = \left\{ \begin{array}{l} [10, 150], [50, 1700] \\ [500, 1500], [1200, 1700] \end{array} \right\}$$
$$[Nr_{min,S}, Nr_{max,S}] = \left\{ \begin{array}{l} [150, 250], [1500, 2500] \\ [2500, 3500], [4000, 5000] \end{array} \right\}$$
$$N = \{20, 40, 70, 100\}$$
$$c = \{0.5, 1.0, 2.0, 2.5\}. \tag{16}$$

The chosen values were evaluated by minimum of objective function (6) which was calculated with up to 1000 iterations in 100 trials. Due to the space limitation, the simulation results are omitted. They need few large matrices to be presented. The results reveal that the appropriate values for stochastic parameters are those given in the last column of Table I. Alternatively, the determination of optimum parameters of ICA-PSO can be achieved by incorporating any of the modern evolutionary algorithms such as cultural algorithms [29] in the ICA-PSO. This will be studied in a future research on stochastic optimization techniques.

TABLE XIII
RESULTS OF ICA-PSO FOR SIX-GENERATING UNITS WITH PROHIBITED
OPERATING ZONES CONSIDERING OF POWER LOSS

Generating units	Outputs (MW)
1	447.09
2	173.15
3	263.90
4	139.05
5	165.63
6	86.64
Load demand (MW)	1263.0
Power loss (MW)	12.47
Minimum cost ($/h)	*15443.24*
Mean cost ($/h)	15443.97
Maximum cost ($/h)	15444.33

Fig. 1. ICA-PSO convergence for six-generating unit system with prohibited operating zones considering power loss (best dispatch solution).

TABLE XIV
RESULTS OBTAINED BY DIFFERENT METHODS ON SIX-GENERATING UNITS
SYSTEM WITH PROHIBITED OPERATING ZONES CONSIDERING POWER LOSS

Method	Minimum cost ($/h)	Total Power (MW)	Power loss (MW)	Power balance (MW)
ICA-PSO	*15443.24*	1275.46	12.47	-0.01
SA-PSO	15447.0	1275.7	12.733	-0.033
BF-NM*	15443.8164	1275.4	12.4437	-0.0437
APSO	15443.5751	1275.3764	12.421628	-0.04522
DE	15449.76	1275.947	12.957	-0.01
AIS	15448.0	1275.655	12.655	0.0
NPSO-LRS	15450.5	1275.94	12.9361	-0.0039
ESO**	15407.527	1272.46	12.824	*-3.374*
PSO	15454	1276.01	12.9584	-0.0516

* Prohibited operating zone of generating unit-6 is violated
** Infeasible solution (power balance violation)

Table XIII shows the best dispatch solution of ICA-PSO. It shows the mean and maximum cost, too. The results obtained by ICA-PSO are compared with those available from the literature in Table XIV, which shows that the performance of the ICA-PSO exceeds all other feasible solutions.

Fig. 1 shows the convergence of ICA-PSO in the best case of generation dispatch. The ICA-PSO converges after only 101 iterations (best iteration $number = 101$).

Table XV represents the performance of ICA-PSO on the best case. Specifically, it gives the intensity of search for the particles iteration by iteration as a function of the global best achievement. It shows clearly how the population size is increased and the number of search intervals of the particles is oscillated adaptively. The rhythm of search the space for the best solution is similar to radio-emission frequency of pulsars (see Fig. 1). The critical numbers of iterations during the convergence process are also shown in Fig. 1. It is demonstrated the fast convergence capability of the coordinately aggregated particles in finding a high quality solution.

H. Advantages of ICA-PSO Over Other HOTs

Observing the comparison results given in Tables II, IV, VI, VIII, X, and XIV, the ICA-PSO algorithm is shown to be more efficient than all other HOTs except a quantum evolutionary algorithm (RQEA [11]) in one case, in finding optimal solutions.
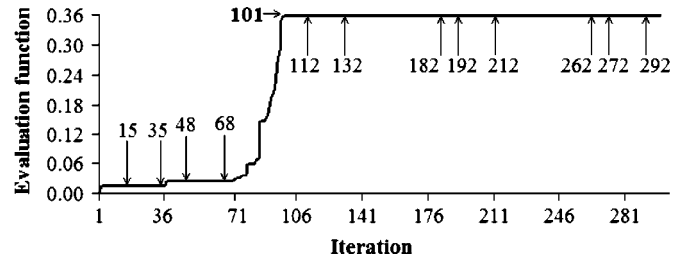
TABLE XV
ICA-PSO OPERATION (BEST CASE) ON SIX-GENERATING UNITS SYSTEM WITH
PROHIBITED OPERATING ZONES CONSIDERING POWER LOSS

Iteration	Global best achievement	Search interval	Search intensity	Population size
[1 , 4]	Increased	[20 , 500]	Normal	20
[5 , 14]	Fixed	[20 , 500]	Normal	20
[15 , 34]	Fixed	[500 , 1500]	Intensive	20
[35 , 36]	Increased	[20 , 500]	Normal	20
[37 , 47]	Fixed	[20 , 500]	Normal	20
[48 , 67]	Fixed	[500 , 1500]	Intensive	20
[68 , 70]	Fixed	[1500 , 2500]	Scrutiny	20
[71 , **101**]	Increased	[20 , 500]	Normal	20
[102 , 111]	Fixed	[20 , 500]	Normal	20
[112 , 131]	Fixed	[500 , 1500]	Intensive	20
[132 , 181]	Fixed	[1500 , 2500]	Scrutiny	20
[182 , 191]	Fixed	[20 , 500]	Normal	23
[192 , 211]	Fixed	[500 , 1500]	Intensive	23
[212 , 261]	Fixed	[1500 , 2500]	Scrutiny	23
[262 , 271]	Fixed	[20 , 500]	Normal	26
[272 , 291]	Fixed	[500 , 1500]	Intensive	26
[292 , 341]	Fixed	[1500 , 2500]	Scrutiny	26
[342 , 351]	Fixed	[20 , 500]	Normal	29
[352 , 371]	Fixed	[500 , 1500]	Intensive	29
[372 , 421]	Fixed	[1500 , 2500]	Scrutiny	29
[422 , 431]	Fixed	[20 , 500]	Normal	32
[432 , 451]	Fixed	[500 , 1500]	Intensive	32
[452 , 501]	Fixed	[1500 , 2500]	Scrutiny	32
[502 , 511]	Fixed	[20 , 500]	Normal	35
[512 , 531]	Fixed	[500 , 1500]	Intensive	35
[532 , 581]	Fixed	[1500 , 2500]	Scrutiny	35
[582 , 591]	Fixed	[20 , 500]	Normal	38
[592 , 511]	Fixed	[500 , 1500]	Intensive	38
[512 , 561]	Fixed	[1500 , 2500]	Scrutiny	38
[562 , 1000]	Fixed	[1500 , 2500]	Scrutiny	38

Regarding ICA-PSO, it has an excellent performance in finding the global best solution in a comparable computing time over other HOTs because of the following main advantages.

1) It optimally manipulates the swarm with an adapted search rhythm similar to pulsars radio-emission one, namely the adaptively selected number of search intervals for the particles (10). Also the swarm is renewed by the introduced concept of variable population size (see *Step 8* of ICA-PSO algorithm).

2) It manipulates well the violated particles and penalized them, but simultaneously giving them more search opportunities (see *Step 6* of ICA-PSO algorithm).

3) It takes into account much more coordinators for the swarm's manipulation than the other PSO (see *Step 2* of ICA-PSO algorithm). To be specific, the other PSO considers only two coordinators, namely the best position a particle it has ever encountered and the global/local best in the swarm.

TABLE XVI
TECHNICAL LIMITS AND COEFFICIENTS OF THE CUBIC COST FUNCTIONS OF THE 19-GENERATING UNITS OF AUTONOMOUS POWER SYSTEM OF CRETE

Unit	P_{min}	P_{max}	d	c	b	a	Fuel cost
1	4.0	6.2	17.377	-167.2	727.6	0.001	0.173
2	7.0	15.0	0.476	-11.824	378.937	0.001	0.173
3	7.0	15.0	0.476	-11.824	378.937	0.001	0.173
4	13.0	25.0	0.18	-8.053	355.088	0.001	0.173
5	14.0	25.0	0.092	-4.166	300.58	0.001	0.173
6	14.0	25.0	0.092	-4.166	300.58	0.001	0.173
7	3.0	11.8	0.421	-8.378	230.369	0.001	0.173
8	3.0	11.8	0.421	-8.378	230.369	0.001	0.173
9	3.0	11.8	0.421	-8.378	230.369	0.001	0.173
10	3.0	11.8	0.421	-8.378	230.369	0.001	0.173
11	3.0	15.0	3.299	-102.551	1024.0	90.0	0.3366
12	3.0	15.0	3.299	-102.551	1024.0	90.0	0.3366
13	3.0	14.0	0.0	0.008	267.0	2113.0	0.3366
14	3.0	18.8	0.0	0.008	219.0	2865.0	0.3366
15	5.0	28.1	0.0	0.008	275.0	3757.0	0.3366
16	2.4	58.0	0.001	0.01	227.0	5000.0	0.3366
17	2.5	58.0	0.001	0.01	227.0	5000.0	0.3366
18	11.2	62.5	0.001	0.01	145.54	5120.0	0.3366
19	12.0	62.5	0.001	0.01	145.64	5120.0	0.3366

4) It adopts a stochastic coordination for the manipulation of best particles giving them full freedom (see *Step 3* of ICA-PSO algorithm).

5) In the programming code of ICA-PSO algorithm the particles search the decision space only with accuracy of two decimal points. So, swarm does not exhaust its capability of "walking around." This technique is well supported by previous mentioned advantages.

These advantages provide the ICA-PSO more possibilities than the other HOTs, in exploring the decision space around local minima and escaping from them.

VI. CONCLUSION

This paper proposed a new type of PSO algorithm, the ICA-PSO based on the cognitive and coordinated aggregation operators. It also introduced the variable population size, adaptive number of search intervals for the particles and search accuracy of particles up to two digit points, resulting in the improved convergence of the process. The ICA-PSO as well as the state-of-the-art HOTs competed in the optimization of ELD problem considering a number of different types of constrains. The results obtained in the systems with 6, 13, 15, and 40 generating units, the island power system of Crete and the Hellenic bulk power system with various loads indicated an improved performance of the ICA-PSO over other HOTs, and good convergence characteristics.

APPENDIX A

The technical limits and coefficients of the cubic cost functions of the 19-generating units of autonomous power system of Crete are shown in Table XVI.

TABLE XVII
TECHNICAL LIMITS AND COEFFICIENTS OF LINEAR COST FUNCTIONS OF THE 32-GENERATING UNITS (CPPP) OF HELLENIC BULK SYSTEM

Unit	P_{min}	P_{max}	b	a	Fuel cost
1	90.0	150.0	340.0	3560.0	0.18
2	100.0	180.0	335.0	4307.0	0.18
3	100.0	160.0	320.0	3856.0	0.18
4	30.0	120.0	320.0	3856.0	0.18
5	30.0	120.0	325.0	3856.0	0.18
6	30.0	120.0	324.4	3806.0	0.18
7	65.0	135.0	336.0	1232.5	0.18
8	180.0	270.0	330.0	2422.5	0.18
9	80.0	140.0	335.0	1232.5	0.204
10	80.0	140.0	335.5	1232.5	0.204
11	170.0	265.0	1195.49	16560.0	0.02
12	170.0	265.0	1189.27	16560.0	0.02
13	170.0	270.0	1215.14	17100.0	0.02
14	200.0	330.0	1204.12	17100.0	0.02
15	170.0	265.0	1150.46	20100.0	0.02
16	170.0	265.0	1306.66	16560.0	0.02
17	170.0	265.0	1299.95	16560.0	0.02
18	170.0	265.0	1194.54	16560.0	0.02
19	170.0	265.0	1203.64	16560.0	0.02
20	170.0	265.0	1151.89	16560.0	0.02
21	170.0	265.0	1212.27	16560.0	0.02
22	40.0	60.0	1382.85	3900.0	0.02
23	80.0	110.0	1355.06	7020.0	0.02
24	80.0	110.0	1266.89	7020.0	0.02
25	170.0	265.0	1231.14	16560.0	0.02
26	28.0	28.0	1580.74	1800.0	0.02
27	80.0	110.0	1312.41	6780.0	0.02
28	80.0	110.0	1317.68	6780.0	0.02
29	180.0	270.0	1295.16	16200.0	0.02
30	180.0	270.0	1303.79	16200.0	0.02
31	125.0	300.0	1150.23	19800.0	0.02
32	42.0	160.0	324.0	3532.0	0.18

The units of coefficients in Appendix A and B are: P_{max} and P_{min} in MW in Kg-lt/MWh³; c in Kg-lt/MWh²; b in Kg-lt/MWh; a in Kg-lt, and fuel cost €/Kg-lt

APPENDIX B

The technical limits and coefficients of linear cost functions of the 32-generating units (CPPP) of Hellenic bulk system are shown in Table XVII.

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