Economic Dispatch Solution Using Hybrid Salp Swarm Algorithm and Simulated Annealing Approach

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***Abstract*—In this paper, a new optimization technique called SSA-SA approach has been suggested. This proposed technique, which is the hybridization of two meta-heuristic techniques named Salp Swarm Algorithm (SSA) and Simulated Annealing (SA) method aims to improve the global optimal solution of ED problem in electrical power systems, considering the various complexities of practical operational constraints, such as valve point effects, active transmission losses, Prohibited Operating Zones (POZ) and Ramp Rate Limits (RRL). The SSA algorithm is used as a global optimization approach, while the SA algorithm is employed to enhance the quality and the exploitation of the best global solution found at each iteration of the SSA. Three electrical test systems, which are the 06-units, 15-units and 40-units are implemented in order to investigate the performances of the SSA-SA approach. The simulation results using the proposed approach are compared to those of the basic SSA method and other optimization techniques, newly published in literature.**

***Index Terms*—Economic Dispatch; Meta-Heuristic Method; Salp Swarm Algorithm; Simulated Annealing.**

I. INTRODUCTION

Due to the huge growth of electric power demand in both public and industrial areas, the Independent System Operator (ISO) of electrical power system is facing major challenges to manage electric power generation, considering deregulated electric energy market and various electricity companies based on thermal, hydro-electric and nuclear power plants. One of the main challenges is the electric power economic generation recognized as the Economic Dispatch (ED) problem. This issue relates to the provision of an optimal allocation of electric power from all committed power plants, while satisfying the total load demand at a minimal total fuel cost and verifying the equality and inequality constraints of power system [1]. The ED problem is known as an optimization problem, which is traditionally assumed to be convex with continuous and quadratic objective function. In practice, the modern power systems are supplied with generating units characterized by practical constraints as valve-point effects, Prohibited OperatingZones (POZ) and multiple fuel options [2-3]. Such practical constraints make the ED problem more complex with non-smooth, discontinuous and non-differentiable objective function depicting highly non-linear operating constraints.

Traditionally, the ED problem has been solved via classical optimization methods when assuming this issue purely convex as Linear Programming (LP) [4], Non-Linear Programming (NLP) [5] and Quadratic Programming (QP) [6] among other methods. Unfortunately, these conventional optimization methods have proved their inaptitude to deal with ED problem when considering the practical constraints as valve-point effects, prohibited operating zones and multiple fuel options. These practical constraints make the ED problem more complex, non-convex and highly non-linear, where the application of conventional optimization techniques suffers from the huge dimensionality and local optimum of practical ED problem solution. Therefore, meta-heuristic techniques as Genetic Algorithms (GA) [7], Particle Swarm Optimization (PSO) [8], Simulated annealing (SA) [9], Differential Evolution (DE) [10], Artificial Bee Colony (ABC) [11] and Grey Wolf Optimization (GWO) [12] algorithms are recently imposed as alternative and global optimization techniques to solve practical and complex ED problems. The main privileges of these meta-heuristic techniques are concerning to their ability to cover the entire search space (to find the best global solution and accordingly escape from the trap of the local minimum), and their capacity to differentiate between solutions according to the fitness of potential solution and their independence of the mathematical kind of the objective function (unaffected by the non-differentiability or the discontinuity of the cost function when they are compared with the classical methods).

In the last decade, new meta-heuristic algorithms have been developed to improve the solution quality of the problems related to the engineering area. Indeed, no single meta-heuristic technique can be judged as better than the other one to solve all optimization issues based on “No Free Lunch” theorem [13]. Recently, a new meta-heuristic technique named Salp Swarm Algorithm (SSA) has been proposed by S. Mirjalili in 2017 to solve various optimization problems. This algorithm is inspired from the swarming behavior of salps moving in deep oceans under salp chains to search for food sources [14]. In the work related to [15], the ED problem has been solved using SSA considering multiple fuels and valve point effects, where a small test system (ten units) has been considered for investigating the SSA algorithm without considering medium and large scales of power systems. Moreover, based on the knowledge of the author, there has been no other modifications introduced in the pseudo code of basic SSA to improve the solution quality of ED problems.

In this paper, the hybridization of the population based algorithm SSA with the meta-heuristic method Simulated Annealing (SA) is proposed, with the aim to improve the global optimal solution of ED problem considering various complexities due to valve point effects, active transmission losses and ramp rate limits. The SSA algorithm is used as a global optimization approach, while the SA algorithm is employed to enhance the exploitation of the best global solution found at each iteration of the SSA. The SA is a probabilistic optimization technique based on iterative process that is trying to improve a competitive solution. It was developed by Kirkpatrick et al. [16] using Metropolis criterion of annealing in metallurgy area. The hybrid SSA-SA approach was developed as the main contribution in this paper and applied for the first time to solve ED problem. It was tested using three test systems, involving six, fifteen and forty units. The simulation results using the proposed hybrid SSA-SA paradigm were compared with those given by the basic SSA algorithm and other meta-heuristic optimization techniques in the literature for the same test systems. The comparison has proved the superiority and the improved performances of SSA-SA approach in comparison to the basic SSA version and the competitive comparison algorithms.

II. Economic Dispatch Problem

A. ED Problem Formulation

The economic dispatch is a useful tool to look for the optimal generation of all power plants connected to the electrical network in order to minimize the total generation cost, while satisfying the operating constraints. This problem is stated as optimization problem and the mathematical formulation can be given as follows:

$$min\ F_{CT} = \sum_{i=1}^{N_G} F_{ci}(P_{Gi}) \tag{1}$$

where: F_{CT} = Total fuel cost from all power plants as objective function to minimize
$F_{ci}(P_{Gi})$ = Associated fuel cost of producing active power P_{Gi} at power plant i
N_G = Number of generating units (power plants)

Conventionally, the generation cost function $F_{ci}(P_{Gi})$ is expressed in the following quadratic form [8]:

$$F_{ci}(P_{Gi}) = (a_i P_{Gi}^2 + b_i P_{Gi} + c_i)\ \ (\$/h) \tag{2}$$

where: a_i = Cost coefficients of generating unit i
b_i = Cost coefficients of generating unit i
c_i = Cost coefficients of generating unit i

The value a_i, b_i and c_i are subjected to the following constraints:

1) Power balance constraint: (equality constraint)

$$\sum_{i=1}^{N_G} P_{Gi} = P_D + P_L \tag{3}$$

where: P_D = Total active power demand
P_L = Total active transmission losses

The active total losses of the transmission system P_L can be calculated by introducing the B-coefficients as below [15].

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_G} B_{Oi} P_{Gi} + B_{OO} \tag{4}$$

where: B_{ij} = ij-th component of loss coefficient matrix
P_{Gi} = Active power generated from i-th generating unit
P_{Gj} = Active power generated from j-th generating unit
B_{0i} = i-th component of loss coefficient vector
B_{00} = Constant of loss coefficient

2) Generating capacity constraints: (inequality constraint)

The generated active power P_{Gi} from each generating unit i should be located between the maximum and minimum limit represented by $P_{Gi,max}$ and $P_{Gi,min}$, respectively, as shown below.

$$P_{Gi,min} \le P_{Gi} \le P_{Gi,max} \quad i = 1,2,..\,N_G \tag{5}$$

B. Practical Constraints of Generating Units

In modern electrical power system, the generating units are submitted to some practical constraints given by:

1) Ramp rate limits

For on-line units, the generated power can be restricted in the operating range with respect to the time response, reflecting the Ramp Rate Limits (RRL) using the expression below.

$$max(P_{Gi,min}, P_{Gi}^O - DR_i) \le P_{Gi} \le min(P_{Gi,max}, P_{Gi}^O - UR_i) \tag{6}$$

where: $P^O{}_{Gi}$ = Previous power output of i-th unit (in MW)
U_{Ri} = Up-ramp limits of the i-th unit (in MW/h)
D_{Ri} = Down-ramp limits of the i-th unit (in MW/h)

2) Prohibited operating zones

Operating faults in power plant related to generators or their associated auxiliary equipment (such as feed pump or boiler) cause instability in some ranges of generated active power. As a result, various discontinuities can be created in fuel cost curve engendering Prohibited Operating Zones (POZ). For economical and secure operation, it is necessary to avoid these zones for producing active power. The POZ constraint can be described in the following expression [11].

$$P_{Gi} \in \begin{cases} P_{Gi,min} \le P_{Gi} \le P_{Gi,1}^l \\ P_{Gi,k-1}^u \le P_{Gi} \le P_{Gi,k}^l & k = 2,......npz \\ P_{Gi,zi}^u \le P_{Gi} \le P_{Gi,max} \end{cases} \tag{7}$$

where: $P_{Gi,m}{}^{u/l}$ = Lower/upper bound of the m^{th} prohibited zone of i-th unit
npz = Number of prohibited zones

3) Valve point loading effects

By considering the valve point loading effects, a sine component is added to the quadratic fuel cost function $F_{ci}(P_{Gi})$ of the corresponding i-th generating unit as given below [1].

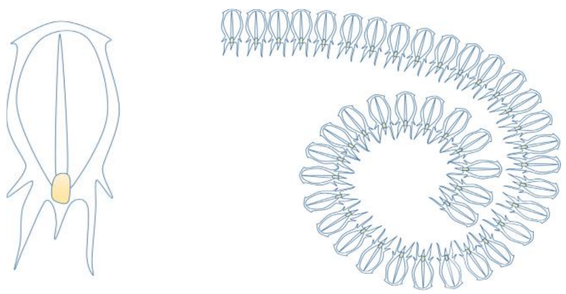
$$F_{vpei}(P_{Gi}) = F_{ci}(P_{Gi}) + \left|e_i \times sin\left(f_i \times \left(P_{Gi,min} - P_{Gi}\right)\right)\right| \qquad (8)$$

where: $F_{vpei}(P_{Gi})$ = Non quadratic fuel cost function of *i-th* generating unit considering valve point loading effects
e_i = Constant for the cost coefficients of *i-th* generating unit reflecting the valve point loading effects
f_i = Constant for the cost coefficients of *i-th* generating unit reflecting the valve point loading effects

III. PROPOSED HYBRID SALP SWARM AND SIMULATED ANNEALING ALGORITHMS

A. *Main Inspiration of SSA*

Salp Swarm Algorithm (SSA) is a recently developed meta-heuristic optimization method by S. Mirjalili [14] to solve various optimization issues in engineering area. It is inspired from the swarming attitude of salps forming chains to navigate in ocean. Salps appertain to the species of Salpidae with transparent barrel-shaped body and they are characterized by specific body tissues resembling to jelly fishes. The salp moves in similar manner to jelly fish by pumping the water through its body in order to swim forward. In such manner, the formed salps chain changes the position to achieve the best locomotion and foraging. Figure 1 describes an individual salp in (a) and salps chain in (b).



(a) (b)

Figure 1: (a) Individual salp, and (b) Swarm of salps (salps chain)

B. *Mathematical Approach to Model the SSA*

To mathematically model the salp chains, the population is first divided to two groups: leader and followers. The leader is the salp at the front of the chain, whereas the rest of salps are considered as followers. As the name of these salps implies, the leader guides swarm and the followers follow each other (directly or indirectly). Similar to other swarm based techniques, the position of salps is defined in an *n-dimensional* search space where *n* is the number of variables of a given problem. Therefore, the position of all salps are stored in a two-dimensional matrix called *x*. It is also assumed that there is a food source called *F* in the search space as the swarm's target. The position of a leader is updated based on the equation indicated as follows:

$$x_j^1 = \begin{cases} FS_j + cr_1.((ub_j - lb_j).cr_2 + lb_j) & cr_3 \geq 0 \\ FS_j - cr_1.((ub_j - lb_j).cr_2 + lb_j) & cr_3 < 0 \end{cases} \qquad (9)$$

where: x^1_j = Position of the first salp (leader) in the *j-th* dimension
FS_j = Position of the food source in the *j-th* dimension
cr_2 = Random numbers in the range [0,1]
cr_3 = Random numbers in the range [0,1]
ub_j = Upper bound of *j-th* dimension
lb_j = Lower bound of *j-th* dimension

While the coefficient cr_1 is defined as below.

$$cr_1 = 2.e^{-\left(\frac{4l}{L}\right)^2} \qquad (10)$$

where: l = Current iteration
L = Maximum number of iterations

To update the position of the followers, the following equation is used (Newton's law of motion).

$$x_f = \frac{1}{2}.\gamma.t^2 + v_0 t \qquad (11)$$

where: x_f = Follower position
t = Time
γ = Acceleration coefficient
v_o = Initial speed

Because the time in optimization is iteration, the discrepancy between iterations is equal to *1* and considering $v_0=0$, the update of follower position can be expressed as follows:

$$x^i_{f,j} = \frac{1}{2}(x^i_{f,j} - x^{i-1}_{f,j}) \qquad (12)$$

where: $i >= 2$
$x_{f,j}^i$ = Positions of *i-th* follower salp in *j-th* dimension
$x_{f,j}^{i-}$= Positions of *(i-1)-th* follower salp in *j-th* dimension

The pseudo-code of SSA is indicated in Algorithm 1.

Algorithm 1
Pseudo-code of the SSA Algorithm

Initialization of the salp population based on lower and upper limits of each variable of the problem
while *(end condition is not satisfied)*
Calculate the fitness of each search agent (salp)
F *is adopted as a best search agent (food source)*
Update C_1 using (10)
for *each Salp (xi)* ***do***
if*(i==1)*
Update the position of the leading salp by (9)
else
Update the position of the follower salp by (12)
end if
end for
Rectify the salps based on the upper and lower bounds of variables
end while
return F

C. *Simulated Annealing (SA)*

The Simulated Annealing (SA) is a meta-heuristic technique based on a unique solution; it has been developed by Kirkpatrick et al. [16] and inspired from the metropolis process describing a probabilistic jumping. The metropolis mechanism is controlled by the adjustment of the temperature

T. The SA begins at a high level of temperature T_O and a succession of generated points is carried out until certain equilibrium is achieved (T periodically decreases during the search process according to the cooling rate α).The algorithm is equivalent to a random visit of the solution space. But as the temperature decreases, most energy enhancing solutions are rejected, and the algorithm becomes a classic iterative process. For the intermediate temperature, the algorithm allows from time to time, the transformations that degrade the objective function. It thus gives a chance for the system to get out of a local minimum. The acceptance probability of the worst solution is evaluated based on Boltzmann probability given by $P=e-\theta/T$, where θ is the evaluated difference between the objective function corresponding to the best solution and that corresponding to the trial solution. The pseudo-code of Simulated Annealing is given in the Algorithm 2.

Algorithm 2
Pseudo-code of SA

```
Introduce an initial solution as BestSol
Set the cooling ratio α
Set an initial temperature T_O
Set the temperature length T_L (number of iterations at a given
temperature)
Compute fitness(BestSol)
while T> T_O (end condition is not satisfied)
for i=1 to T_L
generate a randomly  solution TrialSol
Calculate the fitness(TrialSol)
Compute the change of fitness:
θ= fitness(TrialSol)- fitness(BestSol)
if θ>0
BestSol= TrialSol, (accept new state)
else
generate q=random(0,1)
if q< e −θ/T
BestSol= TrialSol,
end if
end if
end for
set the temperature T=α×T (update temperature)
end while
Output BestSol
```

D. Hybrid SSA-SA Approach

Due to the capacity of SA for searching a best solution (*BestSol*) in the vicinity of a trial solution (*TrialSol*), a global search approach using SA is introduced at iteration end of SSA method (at each iteration). This hybrid process is employed in order to enhance the solution quality of SSA method, which allows the escape from a local minimum and hence avoiding a premature convergence of the algorithm. The proposed approach is developed as the main contribution for the first time to enhance the solution quality of practical ED problem, recognized as a complex issue in engineering area. The best global solution (food source) *FS* achieved by SSA (in each iteration) is introduced in SA algorithm as (*BestSol*) attempt to enhance the exploitation capability of SSA.

IV. SIMULATION AND RESULTS

In order to investigate the hybrid SSA-SA approach and SSA in solving the ED problem, three test systems have been considered: 06-units, 15-units and 40-units. The simulation results were extracted by running the computation code in MATLAB environment for each test system using P-IV Processor, 2.2 GHz, and 1 GB personal computer. The execution of SSA or hybrid SSA-SA computing code was accomplished after the adjustment of SSA and SA parameters for each test system. The minimal total fuel cost was obtained from the optimal solution (achieved for 30 independent trial runs). This optimal solution corresponds to the optimal generated active powers (optimal decision variables) from the committed power plants. To demonstrate the effectivness of SSA-SA approach in achieving better minimal total fuel cost (best optimal solution), famous meta-heuristic optimization techniques have been selected from the literature review to be compared with our approach. These comparison methods have been applied to solve ED problem for the same implemented test systems using SSA and SSA-SA approach. The improved versions and hybrid versions of meta-heuristics were also included in the competitive methods. To examine the feasibility of an optimal solution, the optimal generated power for each power plant was displayed to verify the followings: (a) if this optimal generated power is in the permissible interval between $P_{gi,min}$ and $P_{gi,max}$ (verifying the inequality constraint in (5)), (b) if the power balance described in (3) is accomplished (verifying the equality constraint). The following abbreviations were adopted for each test system after the extraction of the optimal results:

- TP: Total generated Power (MW)
- PL: active Power Losses (MW)
- OTC: Optimal Total fuel Cost ($/h)

A. Six Units Test System

The test system for this case consists of 06 generating units. The total active power losses are considered, while the total load demand is 1263 MW. The POZ characteristics and cost coefficients for such test system are depicted in [17]. The objective function F_{CT} in (1) is considered for quadratic fuel cost function $F_{ci}(P_{Gi})$ in (2) for each power plant. The setting parameters of SSA and SA algorithms for this test system are given as follows:

- For SSA: Salp Population $SP=200$, $n=6$ and $L=150$
- For SA: $\alpha=0.99$, $T_O=0.1$ and $T_L=30$.

The simulation results using the basic SSA and hybrid SSA-SA approach are reported in Table 1.

Table 1
Simulation Results Using SSA, SSA-SA and Comparison Methods for 06-Units System

Unit	PSO[8]	ABC[11]	HBB-BC[18]	SSA	HYBRID SSA-SA
Pg_1	440.576	445.809	441.36	442.282	448.318
Pg_2	167.436	172.922	175.68	77.010	171.496
Pg_3	278.235	262.124	262.82	64.003	265.349
Pg_4	150.000	142.778	134.57	37.711	137.370
Pg_5	157.606	166.373	169.98	80.826	165.745
Pg_6	81.224	85.455	91.16	73.603	86.942
TP	1275.07	1275.46	1275.57	1275.43	1275.22
PL	12.079	12.464	12.57	12.638	12.423
OTC	15445.4	15444.2	15444.26	15444.0	**15439.7**

These simulation results are compared with those of other meta-heuristic optimization methods in literature for the same test system (06-units) and they are reported in Table1. It can be seen from this table, that the proposed SSA-SA approach provides the best minimal total fuel cost (15439.70 $/h) compared to the basic SSA (15444 $/h) and other optimization methods in the literature, such as the PSO [8], ABC [11] and HBB-BC [18]. The convergence characteristics of the Hybrid SSA-SA approach are better than those of the basic SSA based on the convergence curves in Figure 2.

B. Fifteen Units Test System

The second test system used to investigate the effectiveness of hybrid SSA-SA approach in solving the ED problem that contains 15 generating units. The objective function is that of the quadratic total fuel cost function given by (1) for a total load demand of 2630 MW, considering the total active transmission losses. The cost coefficients and ramp rate limits of generating units are taken from [19]. The setting parameters of SSA and SA algorithms are given in the following manner.

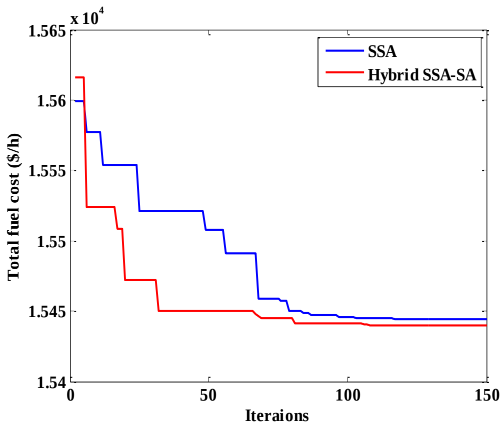


Figure 2: Total fuel cost convergence characteristic for 6-units test system
Note: For SSA: Salp Population SP=400, n=15 and L=200; For SA: α =0.99, T_O =0.1 and T_L =60.

For the present test system, two cases are considered to solve ED problem using SSA and hybrid SSA-SA approach, with and without Ramp Rate Limits (RRL).

The simulation results are reported in Tables 2 and 3 with and without RRL, respectively. After the examination of these tables, it can be concluded that the basic SSA and hybrid SSA-SA converges to 32547.299 $/h and 32545.645 $/h, respectively, and that without RRL. With RRL, the optimal total fuel cost obtained by the basic SSA and hybrid SSA-SA approach are 32710.72 $/h and 32704.48 $/h, respectively. Tables 2 and 3 show the simulation results of other optimization techniques reported in the literature.

Table 2
Simulation Results Using SSA, SSA-SA And Comparison Methods for 15-Units System Without RRL

Unit	DE-PSO [20]	KHA [21]	NAPSO [22]	SSA	HYBRID SSA-SA
1	455.000	455.0000	454.9999	455.0000	454.9731
2	420.000	455.0000	454.9999	455.0000	454.9957
3	130.000	130.0000	130	130.0000	130.0000
4	130.000	130.0000	130	130.0000	130.0000
5	270.000	233.8017	234.2005	233.6641	43.9733
6	460.000	460.0000	460	460.0000	59.9999
7	430.000	465.0000	464.9999	465.0000	65.0000
8	60.000	60.0000	60	60.0000	60.0000
9	25.000	25.0000	25	25.0000	25.0012
10	62.966	31.2698	30.9939	31.0321	25.7030
11	80.000	76.7013	76.7014	77.0675	73.3606
12	80.000	80.0000	79.9999	79.9999	78.7544
13	25.000	25.0000	25	25.0000	25.0414
14	15.000	15.0000	15	15.0000	15.0414
15	15.000	15.0000	15	15.0000	15.0000
TP(MW)	2657.966	NA	2630	2656.763	2656.843
PL(MW)	27.976	26.7673	26.8959	26.8572	27.0440
OTC($/h)	32588.81	32547.370	32548.585	32547.299	**32545.645**

Table 3
Simulation Results Using SSA, SSA-SA And Comparison Methods For 15-Units System With RRL

Unit	SOH-PSO [23]	DSPSO-TSA [24]	APSO [25]	SSA	HYBRID SSA-SA
1	455	453.627	455.000	455.000	455.000
2	380	379.895	380.010	380.000	380.000
3	130	129.482	130.000	130.000	130.000
4	130	129.923	126.520	130.000	130.000
5	170	168.956	170.010	160.497	170.000
6	459.96	459.907	460.000	459.999	460.000
7	430	429.971	428.280	430.000	430.000
8	117.53	103.673	60.000	83.934	60.937
9	77.90	34.909	25.000	25.205	70.268
10	119.54	154.593	159.790	153.195	159.997
11	54.50	79.559	80.000	79.121	79.374
12	80	79.388	80.000	79.999	79.999
13	25	25.487	33.700	25.025	25.000
14	17.86	15.952	55.700	53.728	15.000
15	15	15.640	15.000	15.272	15.000
TP(MW)	2660.8213	2660.96	2658.32	2660.98	2660.57
PL(MW)	30.8319	30.9520	28.3700	31.4813	31.0779
OTC($/h)	32706.55	32715.06	32742.78	32710.72	**32704.48**

Based on a simple comparison of the hybrid SSA-SA approach with the basic SSA and the remain comparison techniques, it can be seen clearly that the hybrid SSA-SA approach provides lower total fuel cost; hence exhibiting better performances than the DE-PSO [20], KHA [21] and NAPSO [22] (without RRL), and SOH-PSO [23], DSPSO–TSA [24] and APSO [25] (with RRL). The convergence curves of the basic SSA and hybrid SSA-SA for 15-units test system are shown in Figure 3 without RRL and in Figure 4 with RRL, respectively. It is clearly shown that the hybrid SSA-SA converges to a better solution than that of the basic SSA.

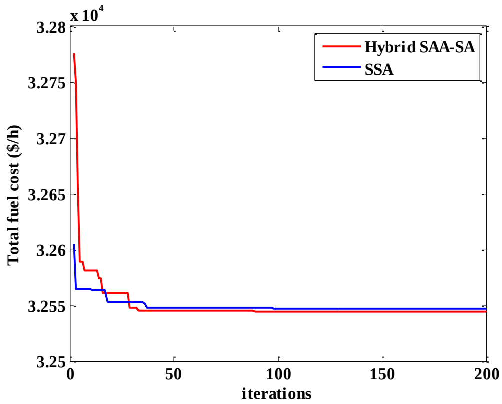


Figure 3: Total fuel cost Convergence characteristic for 15-units system without RRL

C. *Forty Units Test System*

To illustrate the effectiveness and the robustness of the proposed hybrid SSA-SA approach for solving the ED in a large scale electric power system, forty units test system is employed consisting of 40-units without considering the transmission active losses. The total active power demand related to this test system is 10500 MW. The fuel cost function for each generating unit $F_{vpei}(P_{Gi})$ is depicted in (8) considering the valve point effects. Consequently, the objective function representing the total fuel cost in (1) has non-quadratic form.

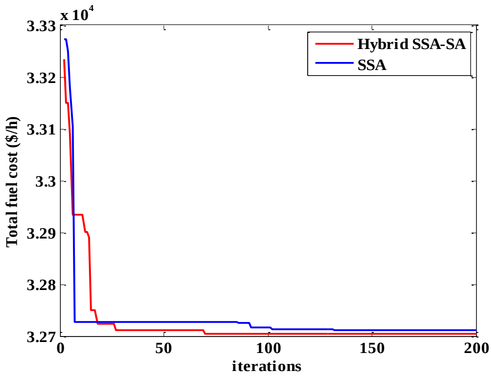


Figure 4: Total fuel cost Convergence characteristic for 15-units system with RRL

The generation capacities and cost coefficients (with valve point effects) for all generating units are carried away from [28]. The simulation is performed by implementing the basic SSA and hybrid SSA-SA approach for 40-units test system and running the computational code in MATLAB software environment. The setting parameters of SSA and SA algorithms for this test system are given as follows:

- For the SSA: Salp Population SP=500, n=40 and L=750.
- For the SA: α =0.99, T_O =0.1 and TL=90.

The simulation results are tabulated in Table 4. The optimal total fuel costs 121578.06 $/h using SSA-SA, and the result from the optimal generated active powers (as decision variables) is better than that provided by the basic SSA 121669.078 $/h and other meta-heuristic optimization methods informed in the literature. The results are shown in Table 4. The convergence characteristics by running basic SSA and hybrid SSA-SA approach are shown in Figure 5, indicating better convergence performances of the hybrid SSA-SA approach than those of the basic SSA.

Table 4
Results and Comparison with Various Optimization Techniques Using SSA-SA Approach for 40 Units System

Unit	DAA [26]	NPSO [27]	DEC-SQP[28]	SSA	HYBRID SSA-SA
1	110.9751	113.9891	111.7576	114.0000	111.4418
2	110.9751	113.6334	111.5584	113.4536	111.6520
3	97.88472	97.5500	97.3999	119.6224	98.2729
4	180.0803	180.0059	179.7331	184.4572	179.5980
5	88.1956	97.0000	91.6560	91.5758	90.6821
6	106.1117	140.0000	140.0000	139.9495	138.5316
7	260.2433	300.0000	300.0000	300.0000	259.6009
8	285.1205	300.0000	300.0000	287.1186	285.7925
9	285.1205	284.5797	284.5997	287.5028	287.3461
10	204.9651	130.0517	130.0000	130.0000	130.0002
11	168.9643	243.7131	168.7998	168.7998	94.0000
12	168.9643	169.0104	94.0000	94.0000	94.0000
13	215.0420	125.0000	214.7598	125.0000	304.5196
14	304.2920	393.9662	394.2794	394.2794	394.2794
15	394.5920	304.7586	304.5196	304.5196	394.2794
16	394.5920	304.5120	304.5196	394.2794	304.5195
17	489.5454	489.6087	489.2794	489.2794	489.2794
18	489.5454	489.6024	489.2794	489.2794	489.2888
19	511.7249	511.7903	511.2794	511.2794	511.2793
20	511.7249	511.2624	511.2794	511.2794	511.2794
21	523.4980	523.3274	523.2794	523.2794	523.2795
22	523.4980	523.2196	523.2853	523.2794	523.5014
23	523.4707	523.4707	523.2847	523.2794	523.2795
24	523.0661	523.0661	523.2794	523.2794	523.2794
25	523.3978	523.3978	523.2794	523.2794	523.2795
26	523.2897	523.2897	523.2794	523.2794	523.2794
27	10.0208	10.0208	10.0000	10.0000	10.0070
28	10.0927	10.0927	10.0000	10.0000	10.0021
29	10.0621	10.0621	10.0000	10.0000	10.0001
30	88.9456	88.9456	90.3329	96.4609	92.8901
31	789.9951	789.9951	190.0000	190.0000	190.0000
32	190.0000	190.0000	190.0000	190.0000	190.0000
33	190.0000	190.0000	190.0000	190.0000	190.0000
34	165.9825	165.9825	200.0000	165.1319	167.1213
35	172.4153	172.4153	200.0000	199.7365	193.1173
36	191.2978	191.2978	200.0000	200.0000	166.7209
37	109.9893	109.9893	110.0000	93.2233	108.6343

Unit	DAA [26]	NPSO [27]	DEC-SQP[28]	SSA	HYBRID SSA-SA
38	109.8799	109.8799	110.0000	110.0000	110.0000
39	109.8733	109.8733	110.0000	110.0000	110.0000
40	511.5671	511.5671	511.2794	511.2794	511.2794
TP (MW	10500.0	10500.0	10500.0	10500.0	10500.0
OTC ($/h)	121788.7	121704.7	121741.9	121669.07	**121578.06**

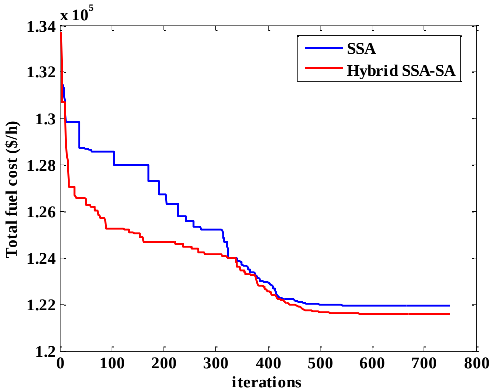


Figure 5: Convergence characteristics for 40-units system using basic SSA and hybrid SSA-SA approach

V. CONCLUSION

The new proposed approach SSA-SA, which is hybridizing the Salp Swarm Algorithm (SSA) and the Simulated Annealing (SA) method has been carried out for solving the economic dispatch problem, taking into consideration the practical constraints of generating units (making the ED problem more complex) due to prohibited operating zones of generation, ramp rate limits, active transmission losses and valve point effects. The effectiveness and the robustness of the SSA-SA approach have been tested on three benchmark electric power systems: 06-units, 15-units and 40-units. The simulation results have confirmed the capacity of the proposed SSA-SA approach in solving the economic dispatch issue, considering various complexities and scales of test power systems, and overcoming the basic SSA and other meta-heuristic optimization methods applied in literature.

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