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Optimization of Fuel Cost in Electric Power Systems using Harmony Search Algorithm

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Abstract

Fuel Cost Optimization emerges as an important issue in electrical load distribution systems. In this study, the performance of Harmony Search Algorithm, which has a significant place in the literature, has been observed for sample problems in the field of fuel cost optimization. It is aimed to distribute the load provided by 3-unit, 13-unit and 40-unit power plants with minimum cost. Economic load dispatch problem emerges as a multi-objective optimization problem. For this reason, equal weighted scalarization method has been used. Transmission line losses are taken into account in the solution of unit-3 and unit-13 test systems. For this purpose, Kron's transmission line loss formula are used. In the solution of the unit-40 test system, transmission line loss is ignored. The results obtained are presented in comparison with various mathematical, evolutionary and heuristic/meta-heuristic algorithms used in the literature to solve the same problems. The results show that the Harmony Search Algorithm is a successful algorithm for fuel cost optimization in electric load dispatch systems.

Key Words

"Multi-objective optimization, Harmony search algorithm, Fuel cost optimization, Electric power systems, Power distribution systems, Economic load dispatch"

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1. Introduction

Reducing energy production cost is an important issue that can provide great savings in all areas. With the increase of the population and the industrial establishments using energy resources, the energy need is increasing day by day. To provide this need for energy, power plants are expanding, and energy systems are becoming more complex. The use of biofuels such as coal, lignite, and fuel oil in thermal power plants, which account for a significant portion of electricity generation, raises fuel costs and, as a result, production costs. In thermal power plants, as in all fields, lowering energy production costs is critical. In order to save energy, dynamic load management systems in thermal power plants use load estimates obtained from feedback systems. Thus, it aims to develop optimum generator outputs. For these power plants, the fuel cost is calculated by the 2nd order equations that depend on the output power. Optimization algorithms are used in these systems to keep the output power and total cost to a minimum. Because the economic load dispatch problems are discrete optimization problems including nonlinear equations, these problems are difficult to solve with mathematical methods. For this reason, meta-heuristic optimization algorithms that provide fast, easy to apply and effective solutions are preferred instead of classical optimization methods (Chowdhury and Rahman, 1990; Song et al, 1999; Kök and Yalçınöz, 2005; Öztürk et al, 2011; Mohamed, 2017).

Harmony Search Algorithm has an important place among meta-heuristic algorithms as it can exchange candidate solutions between convergent and divergent regions. In this way, the chances of reaching the global optimum without getting stuck at the local optimum are higher than most current optimization methods. Harmony Search Algorithm is reputable among meta-heuristic optimization algorithms with clarity and simplicity in application, having few design parameters, work fast thanks to random operators and its success in achieving optimum. Due to its success in solving many complex problems such as university schedule, congestion management, job shop scheduling, clustering, structural design, renewable energy, water distribution and data mining, it has been preferred for economic load distribution optimization, which is the focus of this article (Abualigah et al, 2020).

In recent years, the heuristic methods that offer fast, practical and effective solutions as an alternative to mathematical methods are mostly used in studies to provide fuel cost optimization in electric power systems. Ross and Kim (1980) proposed the dynamic programming successive approximations (DPSA) algorithm for dynamic economic load distribution with their work. By applying DPSA to two different systems, they have achieved economic load dispatch in the systems with partially more units. Irving and Sterling (1983) created a fast and low memory requirement system with an algorithm developed using the dual revised Simplex method in order to optimize large-scale and dynamic power systems. Yang et al. (1996) have developed an algorithm based on evolutionary programming for electric power dispatch systems with non-linear function. They applied their method to two sample problems and compared the results with dynamic programming, simulated annealing, and genetic algorithms. They also observed the performance of the proposed method for Taipower system. Song et al. (1999) investigated the effectiveness of the Artificial Ant Colony Algorithm for a real system containing up to 40 units of data. Yalçınöz et al. (2002) solved the economic load distribution problem by using Tabu Search Algorithm in test system with 6 generators. Sinha et al. (2003) et al. tested the performance of evolutionary algorithms in the field of economic load distribution. Firstly, they proposed improvement in the basic method based on scaled cost. Secondly, it measured the performance of evolutionary algorithms for problems with non-convex cost curves where gradient-based methods cannot be used. Ah King and Rughooputh (2003) used the Elitist Multi-Objective Evolutionary Algorithm for both environmental friendly and economical load distribution in their studies. Brini et al. (2009) examined the problem of fuel cost optimization for system consisting of thermal energy and wind power plants and tested the IEEE network (30 nodes, 8 machines and 41 lines) using Strength Pareto Evolutionary Algorithm. Tosun et al. (2009) studied on the fuel cost optimization using the method of Simulated Annealing. Duman et al. (2010) presented their solutions, which they obtained using three heuristic algorithms as Genetic Algorithm, Simulated Annealing and Tabu Search Algorithm in comparison for 6 thermal power plants in Turkey. Öztürk et al. (2011) realized the application of economic load distribution for the system with 3 thermal power plants using Genetic Algorithm. Adaryani and Karami (2013) solved and tested multi-objective optimal power flow problem with the IEEE 9-bus system, IEEE 30-bus system and IEEE 57-bus system using Artificial Bee Colony Algorithm. Xiong et al. (2013) applied a multi-strategy ensemble biogeography-based optimization (MsEBBO) algorithm to the load distribution systems including 13, 15, 38 and 40 generators. Sahoo et al. (2015) comparatively analyzed the optimum load distribution applications solved using evolutionary algorithms. Aliyari et al. (2017) proposed a new approach that combines Particle Swarm Optimization with Genetic Algorithm. They evaluated the results by applying their work on 13-unit and 40-unit test systems by without considering the transmission line loss. In their study, Tefek et al. (2018) applied meta-heuristic methods such as Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Teaching Learning Based Optimization (TLBO) and Gravitational Search Algorithm (GSA) to 3-unit and 13-unit generation systems with valve point load. They evaluated the performance of these algorithms in the economic load dispatch problem. Li et al. (2019) have proposed a multi-population Differential Evolution Algorithm for the economic load distribution problem and solved the problem in different ways by taking and without considering the transmission line loss for 13-unit, 40-unit, 80-unit and 140-unit test systems. Fu et al. (2020) used an Improved Bird Swarm Algorithm (IBSA) for the economic load distribution problem. They applied the algorithm for 6-unit and 15-unit test systems by considering transmission line loss.

In this study, Harmony Search Algorithm, which is a music based meta-heuristic method, is used to optimize the fuel cost utilized during load distribution of electric power plants. In Chapter 2, Harmony Search Algorithm is introduced in detail and the algorithm steps, operators (HMCR, PAR, RS) and flow diagram are given. In Chapter 3, the information is given about the fuel cost optimization problem in electric power systems and the problem and constraints to be used in this study are presented. In Chapter 4, the solution of fuel cost optimization problem is implemented by Harmony Search Algorithm. The experimental results for Harmony Search Algorithm are given in Chapter 5. It is compared with the solutions of Lagrange and Artificial Bee Colony Algorithm. In the Conclusion part, the results obtained are interpreted.

2. Harmony Search Algorithm

Harmony Search Algorithm has been proposed by Geem et al.(2001). It is a meta-heuristic algorithm based population that models the effort of catching harmony among the sounds of musical instruments. The pitch of a musical instrument determines its harmony quality. Similarly, for an optimization problem, the fitness function determines the importance of decision variables. If the musician gets good harmony, she/he will record it in her/his memory. Likewise, if the algorithm achieves better fitness value, it stores this value in harmony memory. Using these similarities, Harmony Search Algorithm has been designed for optimization problems. Due to its random-based operators, Harmony Search Algorithm is an intuitive method that is fast to operate and easy to design (Geem et al., 2001; Geem, 2009; Mahdavi et al., 2007; Alia and Mandava, 2011).

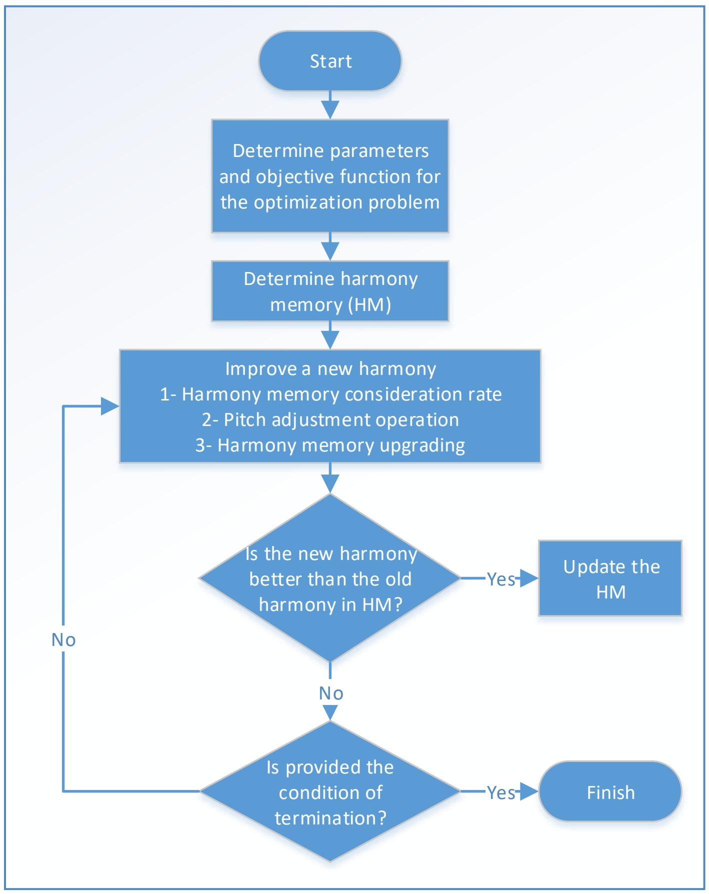

Fig 1. The flowchart of Harmony Search Algorithm

In Fig. 1, the flow diagram of Harmony Search algorithm is given. As shown in the figure, the algorithm starts with the creation of the parameters and the harmony memory (HM) according to the problem parameters (Alia and Mandava, 2011). The HM is initially filled with random values that are compatible the parameter boundaries. At the same time, the objective function appropriate for the problem is determined. At this stage, if it is a constrained optimization problem, a method is chosen related to how the constraint function will be effected on the objective function. Then, a new harmony is generated in three ways. These ways are harmony memory consideration rate (HMCR), pitch adjustment rate (PAR) and random selection. If the obtained new harmony is better than anyone in HM, the new harmony is stored instead of the worst harmony in HM. Unless the termination conditions are met, the process of creating new harmony and if necessary, the process of updating the HM is repeated (Fesanghary, 2010; Ceylan and Ceylan, 2013).

2.1. Harmony Memory Consideration Rate (HMCR)

In the applications of Harmony Search Algorithm, the new harmony is determined using three different methods. The first of these is the method of HMCR. HMCR is the process of selecting from existing values in the HM for the new harmony. Accordingly, while the new harmony (x_i') is randomly chosen from the HM $(x_i^1, x_i^2, x_i^3, \ldots, x_i^{HMS})$ with the HMCR probability, the new harmony (x_i') is randomly selected from the solution space (X_i) with (1-HMCR) probability (Gao et al., 2015; Lee and Geem, 2004).

$$x_i' = \begin{cases} HMCR\ probability & x_i' \in \{x_i^1, x_i^2, x_i^3, \dots, x_i^{HMS} \\ (1-HMCR)\ probability & x_i' \in X_i \end{cases} \quad (1)$$

The construction of the selection process is shown in Equation 1.

2.2. Pitch Adjustment Rate (PAR)

Another method used to determine new harmony is Pitch Adjustment Rate (PAR). With the process of PAR, $\pm rand(0,1) \times bw$ is added to randomly selected harmonies from the existing HM in the probability of PAR. In the case of (1-PAR), HM is not changed.

$$x_i' = \begin{cases} PAR\ probability & x_i' \pm\ rand(0,1) \times bw \\ (1-PAR)\ probability & x_i' \end{cases} \quad (2)$$

Pitch Adjusting is performed according to Equation 2. Here, $rand(0,1)$ shows the randomly generated value between 0 and 1. bw also indicates the bandwidth value calculated in accordance with the algorithm (Lee and Geem, 2004).

2.3. Random Selection (RS)

If the condition of HMCR is not provided, the random selection process is applied (Gao et al., 2015; Lee and Geem, 2004). The new harmony vector is generated randomly as Equation 3:

$$x_{ij}' = l_{ij} + (u_{ij} - l_{ij}) \times \mathrm{rand}(0,1) \quad (3)$$

Where l is the lower bound and u is the upper bound for the parameter of the given problem. And, $rand(0,1)$ shows the randomly generated value between 0 and 1.

3. The Fuel Cost Optimization Problem in Power Systems

In power distribution systems, the power requested by the customers are different magnitude. Since, it is not possible to change the location of plant according to the unit fuel cost ($/MW), in order to minimize the line losses on the system, the system must be fed by evaluating the fuel cost of the power plant (Rahman et al., 2006).

The fuel cost of each producing thermal power plant is calculated according to Eq. 4.

$$F_i = c_i + b_i P_i + a_i P_i^2 \quad (4)$$

Total fuel cost for all thermal power plants is calculated by Eq. 5-7.

$$F_T = F_1 + F_2 + \cdots + F_K = \sum_{i=1}^{n} F_i \quad (5)$$

$$F_T = \sum_{i=1}^{n} (c_i + b_i P_i + a_i P_i^2) \quad (6)$$

$$F_T = \sum_{i=1}^{n} F_i(P_i) \quad (7)$$

For economic load distribution problem, load capacities should be limited. Moreover, in economic load distribution problems, fuel cost functions are usually expressed as a quadratic equation (Yalcinoz and Altun, 2001; Altun and Yalcinoz, 2008).

Eq. 11 gives the load balance in electrical power systems.

$$\sum_{i=1}^{n} P_i - P_L = P_D \quad (11)$$

Here, P_L indicates line loss. P_D shows load demand. In addition, Eq. 12 is used as constraint function.

$$\sum_{i=1}^{n} P_i - P_L - P_D = 0 \quad (12)$$

3.1. 3-Unit Test System

In the first application, fuel cost was calculated for three different thermal power plants using different fuel types. The coefficients and limits used for this purpose are given in Table 1.

Table 1. Fuel cost coefficients and limits for the 3 thermal units system

Generators	P_{min} (MW)	P_{max} (MW)	a_i ($/(MW)^2)	b_i ($/MW)	c_i ($)
P_{G1}	150	600	0.00142	7.2	510
P_{G2}	100	400	0.00194	7.85	310
P_{G3}	50	200	0.00482	7.97	78

For this application, line loss is taken into account for 3-unit test system. The line loss function is given in Eq. 13.

$$P_L = 0.00003P_1^2 + 0.00009P_2^2 + 0.00012P_3^2 \tag{13}$$

In addition, load demand (P_D) is 850.

In this part, the data for the economic load distribution problem is as above. Here, it is aimed to minimize the fuel cost functions for three different thermal power plants by taking the constraint conditions into account (Öztürk et al., 2011).

3.2. 13-Unit Test System

In the second application, fuel cost was calculated for thirteen different thermal power plants. The coefficients and limits used for the 13-unit test system are given in Table 2 (Aliyari et al., 2017).

Table 2. Fuel cost coefficients and limits for the 13 thermal units system

Generators	P_{min} (MW)	P_{max} (MW)	a_i ($/(MW)^2)	b_i ($/MW)	c_i ($)
P_{G1}	0	680	0.00028	8.10	550
P_{G2}	0	360	0.00056	8.10	309
P_{G3}	0	360	0.00056	8.10	307
P_{G4}	60	180	0.00324	7.74	240
P_{G5}	60	180	0.00324	7.74	240
P_{G6}	60	180	0.00324	7.74	240
P_{G7}	60	180	0.00324	7.74	240
P_{G8}	60	180	0.00324	7.74	240
P_{G9}	60	180	0.00324	7.74	240
P_{G10}	40	120	0.00284	8.6	126
P_{G11}	40	120	0.00284	8.6	126
P_{G12}	55	120	0.00284	8.6	126
P_{G13}	55	120	0.00284	8.6	126

For this application, load demand (P_D) is 2520. In addition, line loss is taken into account for 13-unit test system. For this purpose, the B loss coefficients is used. The $B_{i,j}$ loss coefficient matrix, the $B_{0,j}$ loss coefficient vector and the $B_{0,0}$ loss constant are given in Appendix-1 (Li et al, 2019). The formula of transmission line loss is expressed as in Eq. 14.

$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00} \tag{14}$$

This formula is also known as Kron's transmission line loss account (Wood and Wollenberg, 2006).

3.3. 40-Unit Test System

In the third application, fuel cost was calculated for forty different thermal power plants. The coefficients and limits used for the 40-unit test system are given in Table 3 (Aliyari et al., 2017).

Table 3. Fuel cost coefficients and limits for the 40 thermal units system

Generator	P_{min} (MW)	P_{max} (MW)	a_i ($/(MW)^2)	b_i ($/MW)	c_i ($)	Generator	P_{min} (MW)	P_{max} (MW)	a_i ($/(MW)^2)	b_i ($/MW)	c_i ($)
P_{G1}	36	114	0.0069	6.73	94.705	P_{G21}	254	550	0.00298	6.63	785.96
P_{G2}	36	114	0.0069	6.73	94.705	P_{G22}	254	550	0.00298	6.63	785.96
P_{G3}	60	120	0.02028	7.07	309.54	P_{G23}	254	550	0.00284	6.66	794.53
P_{G4}	80	190	0.00942	8.18	369.03	P_{G24}	254	550	0.00284	6.66	794.53
P_{G5}	47	97	0.0114	5.35	148.89	P_{G25}	254	550	0.00277	7.1	801.32

Table 3 (cont). Fuel cost coefficients and limits for the 40 thermal units system

Generator	P_{min} (MW)	P_{max} (MW)	a_i (\$/(MW)^2)	b_i (\$/MW)	c_i (\$)	Generator	P_{min} (MW)	P_{max} (MW)	a_i (\$/(MW)^2)	b_i (\$/MW)	c_i (\$)
P_{G6}	68	140	0.01142	8.05	222.33	P_{G26}	254	550	0.00277	7.1	801.32
P_{G7}	110	300	0.00357	8.03	287.71	P_{G27}	10	150	0.52124	3.33	1055.1
P_{G8}	135	300	0.00492	6.99	391.98	P_{G28}	10	150	0.52124	3.33	1055.1
P_{G9}	135	300	0.00573	6.6	455.76	P_{G29}	10	150	0.52124	3.33	1055.1
P_{G10}	130	300	0.00605	12.9	722.82	“P_{G30}	47	97	0.0114	5.35	148.89
P_{G11}	94	375	0.00515	12.9	635.2	P_{G31}	60	190	0.0016	6.43	222.92
P_{G12}	94	375	0.00569	12.8	654.69	P_{G32}	60	190	0.0016	6.43	222.92
P_{G13}	125	500	0.00421	12.5	913.4	P_{G33}	60	190	0.0016	6.43	222.92
P_{G14}	125	500	0.00752	8.84	1760.4	P_{G34}	90	200	0.0001	8.95	107.87
P_{G15}	125	500	0.00708	9.15	1728.3	P_{G35}	90	200	0.0001	8.62	116.58
P_{G16}	125	500	0.00708	9.15	1728.3	P_{G36}	90	200	0.0001	8.62	116.58
P_{G17}	220	500	0.00313	7.97	647.85	P_{G37}	25	110	0.0161	5.88	307.45
P_{G18}	220	500	0.00313	7.95	649.69	P_{G38}	25	110	0.0161	5.88	307.45
P_{G19}	242	550	0.00313	7.97	647.83	P_{G39}	25	110	0.0161	5.88	307.45
P_{G20}	242	550	0.00313	7.97	647.81	P_{G40}	242	550	0.00313	7.97	647.83

For this application, load demand (P_D) is 10500. In addition, line loss is neglected for 40-unit test system.

4. The Implementation of Harmony Search Algorithm on Fuel Cost Optimization Problems

The objective function for fuel cost optimization with Harmony Search Algorithm was determined as the sum of the fuel cost functions calculated for thermal power plants (Eq. 15)

$$F_T = F_1 + F_2 + \cdots + F_K = \sum_{i=1}^{n} F_i \tag{15}$$

In this study, static penalty approach was used to handle constraints. With this approach, a fixed penalty was imposed on the objective function when the constraint was violated. For this problems, the constraint function $g(x)$ has been given in Eq. 16.

$$g(x) = P_D + P_L - [\sum_{i=1}^{n} P_i] \tag{16}$$

Accordingly, with the static penalty approach (Smith and Coit, 1997), the constraint function had been imposed on the objective function.

Table 4 shows the parameter settings of Harmony Search Algorithm for the fuel cost optimization problems in detail.

Table 4. Harmony search parameter settings for fuel cost optimization problems

Parameter	Value (Unit-3)	Value (Unit-13)	Value (Unit-40)
Number of variables	3	13	40
Number of constraints	1	1	1
Max Iteration	10000	10000	50000
HMS (Harmony Memory Size)	6	100	50
HMCR (Harmony Memory Consideration Rate)	0.9	0.95	0.95
Min PAR	0.4	0.3	0.3
Max PAR	0.9	0.95	0.95
Min bandwidth	0.0001	0.0001	0.0001
Max bandwidth	1.0	1.0	1.0

After the parameters, objective function and penalty function were determined, the harmony memory (HM) was randomly generated in accordance with the range of variables. Then, fitness function and penalty function were calculated.

The harmony search approach had continued with the new harmony creation step. For this purpose, one of the memory consideration, pitch adjusting and random selection methods had been used. Which method to use was determined by creating two random values between 0 and 1 called x and y. Accordingly, the following algorithm was applied.

$if\ x < HMCR$
    Apply $Memory\ Consideration$
        $If\ y < PAR$
            Apply $Pitch\ Adjusting$
        end
$else\ if\ x > HMCR$
    Apply $Random\ Selection$
end

While applying the step of *Memory Consideration*, the value in an index randomly determined from the HM was taken into the new harmony. In the step of *Pitch Adjusting*, firstly, a random value was generated in the interval $[0,1]$ called p. Then, a constant value (bw) was generated using the bandwidth, current iteration and max iteration values. If $p < 0.5$, the value of $rand(1) * bw$ was added to the old value in HM. Otherwise, the value of $rand(1) * bw$ was subtracted from the old value. It was checked whether the obtained value was within the parameter limits. If it was within the limits, the value was added to the new harmony.

$If\ p < 0.5$
    $old = old + rand(1) * bw$
$else$
    $old = old - rand(1) * bw$

While applying the step of *Random Selection*, a random value was chosen within the parameter boundaries and included in the new harmony.

According to the algorithm, after the new harmony and its fitness value were calculated, the best and worst fitness values were determined. The new harmony value was first compared with the best fitness value in HM. If the new harmony is better than the best value in HM, it is added to HM, while the worst value is subtracted from HM. Depending on the changes made, it has been updated best and worst values. If the new harmony is not better than the best value, but better than the worst value, it is still added to the HM. This time, only the worst value was modified. If the new harmony is worse than the worst value in HM, it is not taken into HM. The process of creating new harmony continued until the specified maximum number of iterations.

5. Experimental Results

Fuel cost optimization with Harmony Search Algorithm was encoded on an Intel Core-i5 2.5 GHz Turbo 3.1 GHz PC using MATLAB 2018b. The application of the economic load dispatch problems with the Harmony Search Algorithm shows the results obtained with 30 independent runs for each system.

5.1. 3-Unit Test System

Firstly, Harmony Search Algorithm has been tested on 3 thermal power plants having limited power capacity and having three different fuel types in order to minimize the fuel cost in electric power distribution systems. In Table 5, it is seen the change of fuel cost optimization results (the power of the thermal plants, power loss, best fitness value and computational time) with Harmony Search Algorithm in terms of the number of iteration.

Table 5. The change of fuel cost optimization results according to the number of iterations

Iteration number	P_1 (MW)	P_2 (MW)	P_3 (MW)	(P_L) (MW)	Best Fitness (F_T) \$/h	Computational Time (sec.)
1000	490.7358	260.6997	113.4505	14.8860	7.9178e+03	0.068
2000	520.6509	245.6365	98.4380	14.7255	7.9082e+03	0.090
3000	524.0522	238.1083	102.4403	14.6008	7.9073e+03	0.127
4000	553.5062	202.4371	108.3447	14.2880	7.9070e+03	0.152
5000	547.7023	220.5247	96.2611	14.4881	7.9048e+03	0.156
8000	550.8535	218.3180	95.3114	14.4829	7.9047e+03	0.210
10000	545.1810	221.9300	97.3760	14.4820	7.9047e+03	0.256

The success of Harmony Search Algorithm in the implementation of fuel cost optimization for electric power distribution system was compared with the Lagrange Multipliers and Artificial Bee Colony Algorithm.

Table 6. Comparative results for 3-unit test system

Algorithm & Method	P_1 (MW)	P_2 (MW)	P_3 (MW)	Best Fitness (F_T) $/h	P_L (MW)	Constraint Function Value
Lagrange Multipliers	435.1	299.9	130.7	7952	15.82	0.1239
Artificial Bee Colony (ABC)	548.764	222.149	93.410	7904	14.38	0.1998
Harmony Search (HS)	**545.181**	**221.930**	**97.376**	**7904**	**14.48**	**$2.8317*10^{-4}$**

The comparative results for the method of Lagrange Multipliers, Artificial Bee Colony Algorithm and Harmony Search Algorithm for solving 3-unit test system are given in Table 6. For best fitness value, the amount of power consumed by 3 thermal power plants has been given by P_1, P_2, P_3. In addition, the results in terms of *best fitness*, *transmission line loss* and *constraint function value* are given in Table 6. *Best fitness* shows the best results achieved with 30 runs. P_L indicates the power loss occurring on the line during transmission. On the other hand, *constraint function value* shows the convergence value of the constraint function to zero for the best fitness.

As seen in Table 6, Artificial Bee Colony Algorithm and Harmony Search Algorithm provides advantage in terms of fitness value according to Lagrange Multipliers method (Öztürk et al., 2011). However, it is seen that the method of Lagrange Multipliers and the ABC algorithm inadequate according to the Harmony Search algorithm in terms of compliance with the constraint function (Öztürk et al., 2011). In addition, Harmony Search algorithm works quite fast due to random-based operators.

5.2. 13-Unit Test System

In the second application, the success of the Harmony Search Algorithm is evaluated on the 13-unit test system. Table 7 presents the best result of the Harmony Search Algorithm in 13-unit test system and the best P_i values obtained accordingly. Transmission line loss is also given in the table.

Table 7. Best result obtained by Harmony Search Algorithm for 13-unit test system

Generators	P_{min} (MW)	P_{max} (MW)	P_i (MW)
P_{G1}	0	680	649.09265
P_{G2}	0	360	326.27103
P_{G3}	0	360	179.50858
P_{G4}	60	180	145.70709
P_{G5}	60	180	169.58356
P_{G6}	60	180	172.98691
P_{G7}	60	180	177.78502
P_{G8}	60	180	173.23779
P_{G9}	60	180	177.04062
P_{G10}	40	120	54.40878
P_{G11}	40	120	110.09333
P_{G12}	55	120	115.38593
P_{G13}	55	120	94.39442
Load Demand (MW)			2520
Transmission Loss (MW)			**25.32522**
Total power output (MW)			**2545.32522**
Total generation cost ($/h)			**24411.46705**

In Table 8, the results of the economic load dispatch problem with Harmony Search approach for 13-unit test system has compared with the results of various heuristic/meta-heuristic and evolutionary methods in the literature. In Table 8, it is seen that Harmony Search Algorithm is superior to other methods in terms of both *total generation cost* and *transmission line loss* (P_{Loss}). In addition, in terms of computational time, it is appears that it is more successful than all of them except BBO and DE / BBO. This methods are seen to have lower performance than Harmony Search Algorithm.

Table 8. Comparative results for 13-unit test system

Algorithm & Method	Best Fitness (F_T) $/h	P_{Loss} (MW)	Computational Time (sec.)
HDE (Wang et al.,2007)	24591.76	39.1582	3.573
ST-HDE (Cai et al., 2012)	24560.08	44.3314	2.9783
ICA-PSO (Vlachogiannis and Lee, 2010)	24540.06	-	-
BBO (Bhattacharjee et al., 2014)	24515.21	-	0.15
SOS (Secui, 2016)	24515.06	40.4393	13.75
CS (Yang, 2014)	24514.98	-	2.7166
DE/BBO (Bhattacharjee et al., 2014)	24514.97	-	0.11
SDE (Reddy and Vaisakh, 2013)	24514.88	40.43	-
MABC (Secui, 2015)	24514.87	40.4266	117.6
MCSA (Zhao et al.,2018)	24514.87	40.4266	2.56
MSOS (Secui, 2016)	24514.87	40.4266	12.80
MPDE (Li et al, 2019)	24514.87	40.4266	5.0
Harmony Search (HS)	**24411.4670**	**25.32522**	**0.848711**

5.3. 40-Unit Test System

In the third application, the success of the Harmony Search Algorithm is evaluated on the 40-unit test system. Table 9 gives the best result of the Harmony Search Algorithm in 40-unit test system and the best P_i values obtained accordingly. Transmission line loss has been neglected for this application.

Table 9. Best result obtained by Harmony Search Algorithm for 40-unit test system

Generators	P_{min} (MW)	P_{max} (MW)	P_i (MW)	Generators	P_{min} (MW)	P_{max} (MW)	P_i (MW)
P_{G1}	36	114	110.29158	P_{G21}	254	550	526.50392
P_{G2}	36	114	97.99516	P_{G22}	254	550	541.31560
P_{G3}	60	120	118.79055	P_{G23}	254	550	542.05638
P_{G4}	80	190	166.89665	P_{G24}	254	550	540.77378
P_{G5}	47	97	92.92470	P_{G25}	254	550	543.71069
P_{G6}	68	140	133.81623	P_{G26}	254	550	520.56106
P_{G7}	110	300	292.40465	P_{G27}	10	150	15.90187
P_{G8}	135	300	285.36292	P_{G28}	10	150	15.38631
P_{G9}	135	300	283.30370	P_{G29}	10	150	12.76315
P_{G10}	130	300	156.82297	P_{G30}	47	97	85.63556
P_{G11}	94	375	156.12193	P_{G31}	60	190	186.22376
P_{G12}	94	375	130.10710	P_{G32}	60	190	177.40437
P_{G13}	125	500	219.85852	P_{G33}	60	190	189.16958
P_{G14}	125	500	277.20875	P_{G34}	90	200	198.99970
P_{G15}	125	500	292.31890	P_{G35}	90	200	197.88949
P_{G16}	125	500	352.49031	P_{G36}	90	200	180.34113
P_{G17}	220	500	484.61791	P_{G37}	25	110	98.88074
P_{G18}	220	500	492.57398	P_{G38}	25	110	104.53875
P_{G19}	242	550	510.41547	P_{G39}	25	110	109.97914
P_{G20}	242	550	535.99183	P_{G40}	242	550	521.85052
Load Demand (MW)							10500
Total generation cost ($/h)							**120057.573959**

In Table 10, the results of the Harmony Search Algorithm for economic load dispatch problem are presented in comparison with many artificial intelligence optimization methods that have been studied on the 40-unit test system in the literature. The results show that the Harmony Search Algorithm is superior to other compared methods in terms of total generation cost. In terms of computational time, it is seen that Harmony Search Algorithm is more successful than EP-SQP, PSO-SQP, HCASO, FAPSO, UHGA, AAA, FAPSO-NM, ARCGA, CE-SQP, HAAA, MABC, MPDE.

Table 10. Comparative results for 40-unit test system

Algorithm & Method	Best Fitness (F_T) $/h	Computational Time (sec.)
EP-SQP (Victoire and Jeyakumar, 2004)	122323.97	997.73
PSO-SQP (Victoire and Jeyakumar, 2004)	122094.67	733.97
HCASO (Cai et al., 2012)	121865.63	168.72
FAPSO (Niknam, 2010)	121712.4	87
ST-HDE (Wang et al.,2007)	121698.51	6.92
UHGA (Da-kuo et al., 2008)	121424.48	333.68
AAA (Kumar and Dhillon, 2018)	121421.2	69
DE/BBO (Bhattacharya and Chattopadhyay, 2010)	121420.89	1.23
RCGA (Amjady and Nasiri-Rad, 2009)	121418.72	-
FAPSO-NM (Niknam, 2010)	121418.3	40
ARCGA (Amjady and Nasiri-Rad, 2010)	121410.10	15.67
FA (Niknam, 2010)	121415.05	-
BA (Niknam, 2010)	121414.91	-
CE-SQP (Subathra et al., 2015)	121412.88	137.86
HAAA (Kumar and Dhillon, 2018)	121412.70	20
CBA (Adarsh et al., 2016)	121412.5468	1.55
MABC (Secui, 2015)	121412.5409	115.2
MCSA (Zhao et al.,2018)	121412.5355	3.9948
MPDE (Li et al, 2019)	121412.5355	18.0
Harmony Search (HS)	**120057.573959**	**7.651581**

6. Conclusions

Reducing production and distribution costs in electric power systems is of great importance for all areas of life. Currently, heuristic methods are frequently preferred as well as mathematical methods for economic load distribution (Song et al., 1999; Yalçınöz et al., 2002; Ah King and Rughooputh, 2003; Kök and Yalçınöz, 2005; Brini et al., 2009; Tosun et al., 2009; Duman et al., 2010; Öztürk et al., 2011; Adaryani and Karami, 2013; Xiong et al., 2013; Sahoo et al., 2015; Mohamed et al., 2017; Aliyari et al., 2017; Li et al., 2019; Fu et al., 2020). In this work, the solution of three fuel cost optimization problems, which was previously solved with different mathematical and heuristic methods, was realized by using Harmony Search Algorithm. Harmony Search Algorithm has been developed by modeling the idea of obtaining different melodies using the same notes in the memory (Geem et al, 2001; Geem, 2009, Fesanghary, 2010). The algorithm tries to achieve the local optimum with the help of pitch adjusting operator, and the global optimum with the help of the harmony memory consideration and random selection operators (Ceylan and Ceylan, 2013). Harmony Search algorithm is an easy to apply, fast and efficient meta-heuristic method (Lee and Geem, 2004).

In this article, the fuel cost optimization of systems including 3-unit, 13-unit and 40-unit thermal plants with active power constraints was performed using the Harmony Search Algorithm. Equal weighted scalarization was preferred as a multi-objective optimization method, as the load distribution cost optimization means optimization of separate functions for different thermal power plants. In addition, the method of Static Penalty Function was used in order to effect the constraint function on the objective function. For the fuel cost optimization problem using Harmony Search Algorithm, the optimal value was identified the reached best result when the algorithm ran 30 times. The results obtained were compared with several mathematical, evolutionary and heuristic/meta-heuristic methods.

The experimental results indicate that the application performed with Harmony Search Algorithm is superior in compared to the other approaches. In the three applications performed using the Harmony Search Algorithm, it is seen that the proposed method reaches the best fitness value. In other words, it gives the best result compared to other algorithms in terms of total transmission cost. It is also successful in minimizing transmission line loss, as seen in the 13-unit test system. In addition, the run-time performance is reasonable and it is better than many algorithms compared.

As a result, it has been shown that the Harmony Search Algorithm, which is an intuitive method, is suitable to be used in the field of fuel cost optimization in electric power systems. It is possible to develop and test the algorithm for more complex power plants in future studies.

Appendix-1

$B_{i,j}=10^{-2}*$

$$\begin{bmatrix}
0.0014 & 0.0012 & 0.0007 & -0.0001 & -0.0003 & -0.0001 & -0.0001 & -0.0001 & -0.0003 & -0.0005 & -0.0003 & -0.0002 & 0.0004 \\
0.0012 & 0.0015 & 0.0013 & 0.0000 & -0.0005 & -0.0002 & 0.0000 & 0.0001 & -0.0002 & -0.0004 & -0.0004 & 0.0000 & 0.0004 \\
0.0007 & 0.0013 & 0.0076 & -0.0001 & -0.0013 & -0.0009 & -0.0001 & 0.0000 & -0.0008 & -0.0012 & -0.0017 & 0.0000 & -0.0026 \\
-0.0001 & 0.0000 & -0.0001 & 0.0034 & -0.0007 & -0.0004 & 0.0011 & 0.0050 & 0.0029 & 0.0032 & -0.0011 & 0.0000 & 0.0001 \\
-0.0003 & -0.0005 & -0.0013 & -0.0007 & 0.0090 & 0.0014 & -0.0003 & -0.0012 & -0.0010 & -0.0013 & 0.0007 & -0.0002 & -0.0002 \\
-0.0001 & -0.0002 & -0.0009 & -0.0004 & 0.0014 & 0.0016 & 0.0000 & -0.0006 & -0.0005 & -0.0008 & 0.0011 & -0.0001 & -0.0002 \\
-0.0001 & 0.0000 & -0.0001 & 0.0011 & -0.0003 & 0.0000 & 0.0015 & 0.0017 & 0.0015 & 0.0009 & -0.0005 & 0.0007 & 0.0000 \\
-0.0001 & 0.0001 & 0.0000 & 0.0050 & -0.0012 & -0.0006 & 0.0017 & 0.0168 & 0.0082 & 0.0079 & -0.0023 & -0.0036 & 0.0001 \\
-0.0003 & -0.0002 & -0.0008 & 0.0029 & -0.0010 & -0.0005 & 0.0015 & 0.0082 & 0.0129 & 0.0116 & -0.0021 & -0.0025 & 0.0007 \\
-0.0005 & -0.0004 & -0.0012 & 0.0032 & -0.0013 & -0.0008 & 0.0009 & 0.0079 & 0.0116 & 0.0200 & -0.0027 & -0.0034 & 0.0009 \\
-0.0003 & -0.0004 & -0.0017 & -0.0011 & 0.0007 & 0.0011 & -0.0005 & -0.0023 & -0.0021 & -0.0027 & 0.0140 & 0.0001 & 0.0004 \\
-0.0002 & 0.0000 & 0.0000 & 0.0000 & -0.0002 & -0.0001 & 0.0007 & -0.0036 & -0.0025 & -0.0034 & 0.0001 & 0.0054 & -0.0001 \\
0.0004 & 0.0004 & -0.0026 & 0.0001 & -0.0002 & -0.0002 & 0.0000 & 0.0001 & 0.0007 & 0.0009 & 0.0004 & -0.0001 & 0.0103
\end{bmatrix}$$

$B_{0,j}$ = [-0.0001 -0.0002 0.0028 -0.0001 0.0001 -0.0003 -0.0002 -0.0002 0.0006 0.0039 -0.0017 0.0000 -0.0032]
$B_{0,0}$ = 0.55

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