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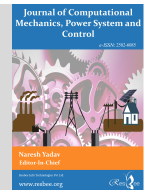

Hybrid PSO-BF Algorithm for Economic Dispatch of a Power System

Rekha .P. Nair
Heera College of Engineering and Technology
Nedumangadu, Thiruvananthapuram, Kerala.
rekhapnair2@gmail.com

Kanakasabapathy P
Amrita School of Engineering
Amritapuri, Vallikavu, Kerala

Abstract: Generally, Economic dispatch (ED) represents the heart of economic operation of a power system. Besides sustaining the system reliability, meeting the forecasted system load at the lowest possible cost is one of the important objectives in power system operation. Nevertheless, the ED problem chiefly based on the generating unit cost function. This paper presents a novel hybrid Particle Swarm optimization and Butterfly Optimization (PSO-BF) algorithm to optimize the economic dispatch of the electric power system. Here, the load distribution problem for various time periods given multiple objectives of the power market is described. Moreover, different weights are assigned for different objectives to change multiobjective optimization issues into fuzzy single-objective optimization issues. Thus, the solution exploiting the idea of maximum satisfaction is attained. This proposed algorithm is used to establish a widespread dispatching optimization technique with the objective of minimization of coal consumption, pollution emission and purchasing cost. Finally, the computation time for the proposed algorithm is summarized and shows better results than the conventional methods such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO).

Keywords: Economic Dispatch; Optimal Power Flow; Constraints; Optimization Model; Cost Function

Nomenclature

Abbreviations	Descriptions
PSO	Particle Swarm Optimization
EED	Economic Environmental Dispatch
WOA	Whale Optimization Algorithm
FN	Functional Network
ABC	Artificial Bee Colony
WG	Wind Generation
ACO	Ant Colony Optimization
EP	Evolutionary Programming
ED	Economic Dispatch
OPF	Optimal Power Flow
BESS	Battery Energy Storage System
MINLP	Mixed-Integer Non-Linear Programming
TVD	Truncated Versatile distribution
DE	Differential Evolution
CHP	Combined Heat and Power
GSA	Gravitational Search Algorithm
SQP	Sequential Quadratic Programming
MPC	Model Predictive Control
DDMPC	Dual Decomposition-based Distributed Model Predictive Control
ACI	Adjustable Confidence Interval
ABC	Artificial Bee Colony
IGDT	Information Gap Decision Theory
GA	Genetic Algorithms

1. Introduction

Generally, ED issue concentrates on the economic problems for the existing electric power system. Moreover, it indicates to assign demand for the system load to each generating units. When meeting diversities of operational limitations the ED attempts to reduce the total cost of the fuel. Nevertheless,

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the necessity of sufficient and secure electricity is inexpensive cost and also reduced pollution [3]. EED problem augments emission effect with increasing distress regarding environmental issues. Moreover, it is considered as a recent enchanting alternative scheme, which has the ability to reduce the problem regarding the emission and fuel cost minimization concurrently without fuel switching [4].

In order to supply adequate total output to fulfill given demand of the total consumer, the multiple generators are implemented in a usual power system [10]. Generally, each of these generating stations has different characteristics of cost-per-hour for its operating range of output. The power station possesses maximum fuel cost for operating as well as the preservation and the fixed cost related to the station itself. Moreover, in the nuclear power plant scenario, it can be entirely appreciable. For instance, while utilities attempt to elucidate transmission line losses, as well as the fluctuating changes related to hydroelectric plants, it will get a high risk.

In the power system, the aim of the ED is to allocate the outputs of all accessible generation units, so the cost of the fuel is reduced and the constraints of the system are also fulfilled. In addition, it can be described as the procedure of allocating generation between the committed units, so the constraints foisted are fulfilled as well as the minimization of energy requirements are also attained.

For the interconnected power system, the economic power dispatch is considered as the procedure to find out the total reactive and real power schedule for each power plant so that to reduce the operating cost. It refers that the generators reactive and real power has the ability to permit the deviation within the particular restrictions; hence it has the capability encounter the demand with reduced fuel cost, which is represented as the Optimal Power Flow (OPF) [9]. In a large scale power system, the OPF is exploited to optimize the power flow solution. With respect to the generators ability restrictions and the output of the compensating devices, the OPF is performed by reducing chosen objective models.

In order to resolve the ED issue, several existing optimization techniques was presented like the Gradient method [11], Lambda Iteration method [13], Linear Programming method [12] and Newton method [14]. However, aforesaid methods fail to attain the optimal solution in order to solve the complex non-linear optimization issues. Hence, to evade the issues in existing optimization techniques, several artificial intelligence approaches was exploited to resolve aforementioned issues like EP [16], PSO [17], DE [19], ABC [18], GSA [20], GAs [15], are few of the techniques that are flourishing in positioning the optimal solution however they are typically slow in convergence.

The main contribution of the paper is to present the hybrid PSO-BF algorithm in order to solve the economic dispatch of the power system operations. Moreover, the proposed method possesses excellent stability, and it provides better computational time than the conventional algorithms.

2. Literature Review

In 2018, Yi-Ming Wei et al. [1], discussed the study colonist in expressing the ED savings in Chinese coal-fired power sector. Moreover, the rates of heat in China for all the coal generators were calculated on the basis of that the requirement for ED was also proved. Subsequently, an optimization technique was exploited to compute the potentials for the energy-saving from ED in non-metropolitan, national and geographicall levels. Finally, to change the current dispatch way to ED was recognized in three important economic and political crises.

In 2019, Farhad Nazari-Herisa et al [2], developed a novel optimization method on the basis of the MINLP to resolve ED. Moreover, the most important objective was to recognize the optimal solution of ED of Micro Grids in power systems. Here, dual dependency effects of power and heat generated by CHP units and the electrical energy storage effect and heat buffer tank were examined in the optimal solution of ED of Micro Grids. Renewable generation unit’s uncertainties, grid power price, as well as load, were considered exploiting scenario-based technique, a robust optimization technique, and IGDT.

In 2018, Dustin McLarty et al [3], discussed a complementary convex quadratic optimizations technique, which highly minimizes, and in some circumstances evades, the mixed-integer effect of the issue. The generalized technique exploited to grid-associated energy systems incorporates any variety of electric or combined heat and power generators, heaters, electric chillers, and energy storage systems. It integrates restraints for limitations of ramping, generator operating bounds, and inefficiency of energy storage.

In 2019, Abdelfattah A. Eladl et al [4] modeled a bi-level optimization and its mathematical relations characteristics were formulated considering the stochastic nature of wind and outputs of Photo Voltaic and the constraints of storage. They have solved optimally formulated relations. Hence, hybrid PSO approach and SQP approach were exploited to offer the optimal power distributed from each energy source.

In 2019, Miguel A. Velasquez et al [5], worked on a closed-loop technique in order to solve the ED at runtime when minimizing probable variations of generation schedules. Initially, a conventional centralized technique was presented in order to address the ED issue with probable improvement enabled using MPC approaches. In order to address the stochasticity and variability problem, the MPC application produces it probable for the operators. A Dual Decomposition-based DDMPC technique was also developed, which was adaptable with agreement methods.

In 2017, Jian Xu, Bao Wang et al. [6], presented a day-ahead ED technique exploiting an uncertainty test taking into consideration of utmost cases of wind power. Here, the set enthused by vigorous optimization, which was exploited to define the wind power intermittency. Moreover, four utmost cases on the basis of the aforesaid set were described to indicate the worst cases of wind power variation. An ED technique was presented, which taken into consideration of both the costs of wind curtailment and load shedding. Using a quadratic programming technique through the initiation of four utmost cases and the wind power uncertainty set, the ED framework can be effortlessly solved.

In 2017, Chenghui Tang et al [7], proposed TVD for wind power that was bounded and high precise than traditional techniques. Moreover, they have discussed the fitting effect as well as the mathematical formulation of TVD. Subsequently, a novel look-ahead dynamic ED technique was proposed with an ACI on the basis of the TVD. In order to maintain the admissible predefined risk level, it enables the system operators, and it seeks the optimal risk level to stable the system reserve scheme and power unbalance risk. In the dispatch model, TVD provides a consistent wind power consideration in order to search the optimal risk level with the aid of ACI. Moreover, the exploitation of TVD and its analytical form has the ability to clarify the wind power uncertainties.

In 2017, Muhammad Khalid [8]worked on a novel real-time forecast technique on the operating revenues and cost of a WG microgrid with a related BESS. An ED scheme was formulated using a predictive optimization policy named receding horizon control to sell energy to the electricity grid by an energy market. This power dispatch model has the ability to integrate multi-step ahead forecasts of wind power and energy price, which required to decide the operational profits income of the WG microgrid. By radial-basis FN, an innovative intelligent forecast model was designed, which provides high precision.

3. Problem Formulation

3.1 Objective Model

(a) Objective model of total fuel consumption:

In eq. (1), x_i, y_i and z_i indicates the constant coefficients representing the curve of consumption; t indicates the time period; n the number of generator units in the power system; i indicates the unit number; N is the number of periods; $M_{c_i}(t)$ indicates the i^{th} unit output at a time period t.

$$f_1(C) = \sum_{t=1}^{N} \sum_{i=1}^{n} \left[x_i M_{C_i}^2(t) + y_i M_{c_i}(t) + z_i \right] \tag{1}$$

(b) Objective model of oxynitride emission function:

In eq. (2), a_i, b_i and c_i indicates the coefficients constant represents the quadratic curve properties.

$$f_2(C) = \sum_{t=1}^{N} \sum_{i=1}^{n} \left[a_i M_{C_i}^2(t) + b_i M_{c_i}(t) + c_i \right] \tag{2}$$

(c) Objective model of electricity purchase cost function:

In eq. (3), $M_{c_i}(t)$ indicates the price of electricity purchase price for each unit at t period, and $M_{c_i}(t) = \max\{f(M_{C_i}(t))R_{i,t}\}$; N indicates the pre-dispatching period; N_C indicates the number of registered units in the system; G_i indicates the forecast of load in time period t; $f(M_{Ci}(t))$ indicates the function of the quotation at time period t for the i^{th} unit; $M_{i,t}$ indicates the unit output; $R_{i,t}$ indicates the running indicator at time period t for the i^{th} unit.

$$f_3(C) = \sum_{t=1}^{N} \sum_{i=1}^{n} \left| \left[M_{C_i}(t) \delta_{C_i}(t) \right] \right. \tag{3}$$

If the i^{th} unit is running at time period t, $R_{i,t} = 1$; if the i^{th} unit is not running at time period t, subsequently $R_{i,t} = 0$. $(M_{Ci}(t))$ indicates the consumption of the electricity for the i^{th} unit at time period t .s

3.2 Constraints Conditions

(a) Node flow balance:

In eq. (4), B represents the related matrix in the network; $M_{G,t}$ represents the active power flow vector, $G_{MH,t}$ node active load vector at time period t; and $M_{H,t}$ represents the node active output vector. $L_{G,t}$ represents the reactive power flow vector, $L_{H,t}$ indicates the node reactive output vector, $L_{LH,t}$ the node reactive load vector at the time period t.

$$\begin{cases} BM_{G,t} = M_{H,t} - G_{MH,t} \\ BL_{G,t} = L_{H,t} - L_{LH,t} \end{cases} \tag{4}$$

(b) System active power balance:

In eq. (5), $M_{i,t}$ represents the system active loss and G_i indicates the system load at the time period t.

$$\sum_{i=1}^{N_C} M_{i,t} R_{i,t} = G_i + M_{i,t} \tag{5}$$

(c) System positive and negative reserve constraints:

In eq. (6) $M_{i,max}$ indicates the maximum output and $M_{i,min}$ minimum output of the i^{th} unit; S_{t+} positive reserve rates and S_{t-} represents the negative reserve rates of the system.

$$\begin{cases} \sum_{i=1}^{N_C} \left(M_{i,max} R_{i,t}\right) N_{i,on} \geq G_i \left(1 + S_{t+}\%\right) \\ \sum_{i=1}^{N_C} \left(M_{i,min} R_{i,t}\right) N_{i,on} \geq G_i \left(1 - S_{t-}\%\right) \end{cases} \tag{6}$$

(d) Transmission capacity constraints:

In eq. (7), $R_{i,t}$ represents the actual apparent power and $R_{g,max}$ represents the maximum apparent power of line l at the time period t.

$$R_{i,t} \leq R_{g,max} \tag{7}$$

(e) Unit output constraint:

$$M_{i,max} \leq M_{g,t} \leq M_{i,min} \tag{8}$$

(f) Node voltage constraint:

In eq. (9), $B_{h,max}$ indicates the minimum voltage; $B_{h,t}$ indicates the actual voltage and $B_{h,min}$ indicates the maximum voltage of node h at the time period t.

$$B_{h,max} \leq B_{h,t} \leq B_{h,min} \tag{9}$$

(g) Rate of unit output power rise constraint:

In eq. (10), D_{i-} represents the output drop and D_{i+} represents the increasing rate of the i^{th} unit in one period.

$$M_{i,t-1} - D_{i-} \leq B_{g,t} \leq M_{i,t-1} - D_{i+} \tag{10}$$

(h) Unit minimum runtime and downtime constraints:

In eq. (11), $N_{i,on}$ represents the runtime and $N_{i,off}$ are represents the downtime of the i^{th} unit; $N_{i,on-mim}$ indicates the minimum runtime and $N_{i,off-min}$ indicates the downtime of the i^{th} unit.

$$\begin{cases} N_{i,on} \geq N_{i,on-mim} \\ N_{i,off} \geq N_{i,off-min} \end{cases} \tag{11}$$

3.3 Optimization Model by Integrating Weightage Dispatch

Let us consider $f_i, \min$ as the optimal solution of the i^{th} object, and $f_i, \min > 0$ for the i^{th} objective model $f_i(C)$. Moreover, α_i indicates the degree of the elasticity for the i^{th} object, within the range of elasticity $(-\infty, f_{i,min} + \alpha_i f_{i,min})$. Hence, the transfer model $\lambda(f_i(C))$ of the objective model $f_i(C)$ is formulated as eq. (12).

$$\lambda(f_i(C))=\begin{cases}1 & f_i(C)<f_{i,min}\\ \dfrac{f_{i,min}+\alpha_i f_{i,min}-f_i(C)}{\alpha_i f_{i,min}} & f_{i,min}\le f_i(C)\le f_{i,min}+\alpha_i f_{i,min}\ (i=1,2,3)\\ 0 & f_i(C)>f_{i,min}+\alpha_i f_{i,min}\end{cases} \tag{12}$$

During this transfer model, the optimization model by integrating weightage dispatch for the power is formulated as eq. (13) and (14).

$$\min[\beta_1\lambda(f_1(C))+\beta_2\lambda(f_2(C))+\beta_3\lambda(f_3(C))]$$

$$st\begin{cases}\sum_{i=1}^{N_C}(M_{Ci}(t)R_{i,t})-M_d(t)-M_{rc}(t)=0\\ \sum_{i=1}^{N_C}(M_{Ci},\max(t)R_{i,t})\ge M_d(t)(1+S_{t+}\%)\\ \sum_{i=1}^{N_C}(M_{Ci},\min(t)R_{i,t})\le M_d(t)(1+S_{t-}\%)\end{cases} \tag{13}$$

$$\begin{aligned}&M_{C_i},\ \min(t)\le M_{C_i}(t)\le M_{C_i},\ \max(t)\\ &M_{C_i},(t-1)-D_{i-}\le M_{C_i}(t)\le M_{C_i},(t-1)+D_{i+}\\ &0\le t\le N;\ R_{i,t}\in\{0,1\};\ i=1,2,\ldots N_{Ci}\end{aligned} \tag{14}$$

4. Optimization of Economic Dispatch in the Power System Using the Proposed Hybrid PSO-BF Algorithm

In this section, the solution procedure of the power system dispatching issue is primarily focussed to arbitrarily create a swarm of intelligent particles on the basis of the constraints, and assess the issue on the basis of the objective value function, as well as subsequently update the value of the intelligent particles using the proposed hybrid PSO-Butterfly Algorithm.

The conventional butterfly swarm-based search procedure examines the optimal position based on the sensitivity of flower and nectar probability [22]. In order to perform the optimal position solution, the communication is performed indirectly or indirectly in all butterflies and it also performed in several communication intelligence manners like colors, dancing, chemicals, sounds, and physical actions. The main purpose of the butterfly is to choose the flower that has a suitable probability of nectar with its adequate sensitivity in a random search. It is done for the optimal solution and before finishing the individual flight (iteration) it planned procedure to the subsequently optimal solution. Moreover, this search procedure will carry on until the convergence or termination criterions are attained. In this search, the butterflies are capable to select various local best or p_{best} locations, sensitivity and probability they go towards global best or g_{best} location. In the search area, the decision making of butterfly procedure based on the butterfly communication with the considerably various sensory system. The termination criterion will be the maximum number of flight (iteration) and convergence along with enhancement in individual fitness. The hybridization of PSO-butterfly consistent with the intellect characteristics, behaviors and because of antennal on their mouth by those flowers catches the attention of butterfly while comparing with the others. To present an optimal solution there is extremely better relation among the butterfly and the surrounding atmosphere. In the search procedure, butterfly moves towards the new source of the nectar, immediately subsequent to attractive the food.

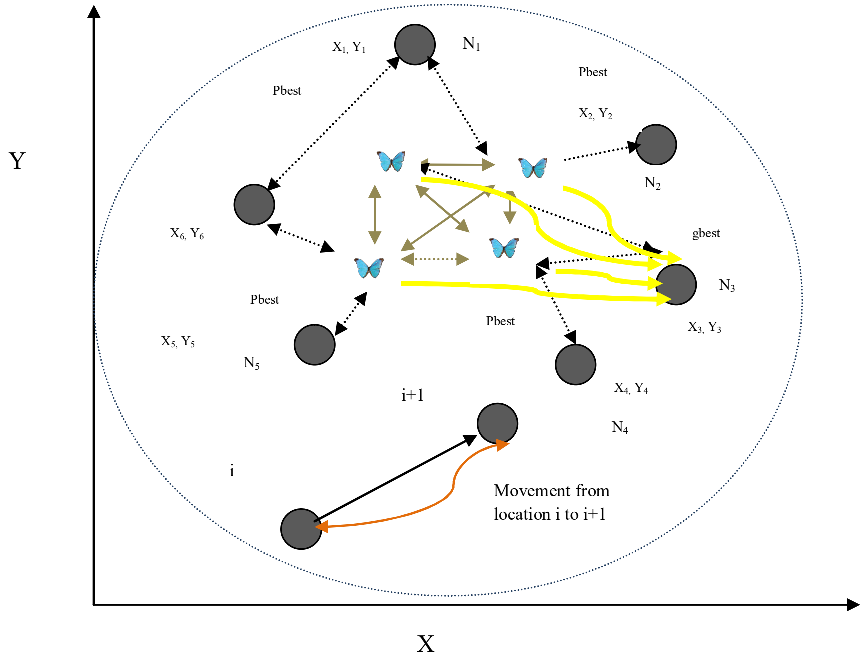

Fig. 1. *Search process of proposed PSO-BF algorithm*

Fig 1 exhibits the demonstrate ion of the proposed method search process for g_{best} solution representing wit with the flower node from N_1 to N_1 and exhibits the butterfly movement from i^{th} position to $i+1^{th}$ position at the search procedure of the proposed method. In the search procedure, the flying decision for each subsequent flight is done on the basis of the butterfly particle swarm's preceding history. Based on the optimal history experience of self and neighborhood of swarms the locations and velocities are altered. The probability and sensitivity ideas go after the survival of the fittest principle such as other evolutionary methods. The local best p_{best} location of a butterfly that has a high sensitivity of butterfly and high probability of nector will become a global optimal g_{best} solution.

The PSO is a well-known optimization algorithm [21] in every part of the PSO algorithm; each particle within the search space goes after particular inertia and velocity with the associated generations and updates its locations.

Let us consider total populations vector as $N \;\; y(i = 1,2,3,\ldots N)$ and individual velocities vector as u. Let us assume u_i represents the velocity and y_i represents the population for i^{th} iteration as well as u_{i-1} represents the velocity and y_{i-1} represents the population for the previous iteration. Therefore, on the basis of the conventional PSO the equations (15 and 16) for velocity and population for i^{th} iteration can be represented as [23].

$$u_i = z_i * u_{i-1} + a_1 r_1 \left(y_{pbest,i-1} - y_{i-1}\right) + a_2 r_2 \left(y_{gbest,i-1} - y_{i-1}\right) \tag{15}$$

$$y_i = y_{i-1} + u_i \tag{16}$$

In eq. (15), a_1 & a_2 represents the acceleration coefficients and r_1 and r_2 represents a random variable (0 to 1). The butterfly leaning on the basis of the PSO technique has elaborated to discover the optimal solutions such as the probability, random parameters, sensitivity, acceleration coefficients, p_{best} and g_{best} for the rapid convergence and additional precise solutions than other approaches. In the hybrid PSO-butterfly optimization algorithm, p_{best} solutions are chosen by the respective optimal solution.

Subsequently, the g_{best} solution is recognized on the basis of individual fitness. The position of the nectar source indicates the potential optimal solution for the issue and the number of nectar (food) indicates the equivalent fitness. The common sensitivity and probability ranges are taking into consideration from 0.0 to 1.0. The velocity limits can be set on the basis of the limits of the difficulty variables. Therefore, the sensitivity and probability as an iterations function are stated as eq. (17).

$$s_f = e^{-\left(iter_{max} - iter_i\right) / iter_{max}} \tag{17}$$

In eq. (18), $iter_{max}$ indicates the maximum number of iterations, and $iter_i = i^{th}$ iteration count.

$$p_f = \frac{fi_{gbest,i}}{\sum fi_{pbest,i}} \tag{18}$$

Where $fi_{gbest,i}$ represents the local optimal fitness solutions with i^{th} iteration, $fi_{pbest,i}$ represents global fitness optimal solutions with i^{th} iteration.

The values of the acceleration coefficients a_1 & a_2 are equals to 2 for the proposed algorithm and also for the existing PSO. The inertia weight range for both the Butterfly and PSO method is set as 0 to 1 and that is represented in eq. (19).

$$Z_f = {(iter_{max} - iter_f)}\big/{iter_{max}} \tag{19}$$

The fundamental idea of velocity-displacement-time is stated in eq. (20), where, u refers velocity, d refers displacement and t refers time

$$u = \frac{d}{t} \tag{20}$$

Using $i_1 = 1/time$; which is suppose that the random time constant i_1 for any immediate speed and distance.

$$u = d \times i_1 \tag{21}$$

In addition, the velocity is directly proportional to the inertia and therefore different velocity values encompass different inertia. For summation, the thumb rule represents the summation that can probable for same or corresponding related quantities. As a result, the common equation for velocity updating is stated in eq. (22).

$$u = d_1 \times i_1' + d_2 \times i_1'' + inertia \times u \times i_1''' \tag{22}$$

Similar to the thumb rule the displacement of the position displacement can update go after if $i_2' = time(t)$ is random instantaneous than,

$$d' = d + u \times i_2' \tag{23}$$

In the above idea, now by using the hybrid PSO-butterfly, the butterfly velocity, and position based on the probability of nectar amount in the search and sensitivity of butterfly. Therefore, the equations for updating the position and velocity are the probability and sensitivity function and it is stated in eq. (24) and (26). Fig 2 demonstrates the flow chart for the proposed algorithm.

$$u_i' = i_1'' \cdot z_i \cdot u_{i-1} + s_f(1-p_f)a_1r_1(y_{pbest,i-1} - y_{i-1}) + p_{fg}a_2r_2(y_{gbest,i-1} - y_{i-1}) \tag{24}$$

Consider $i'' = 1$, followed by

$$u_i' = z_i \cdot u_{i-1} + s_f(1-p_f)a_1r_1(y_{pbest,i-1} - y_{i-1}) + p_{fg}a_2r_2(y_{gbest,i-1} - y_{i-1}) \tag{25}$$

$$y_i = y_{i-1} + \beta_i \cdot u_i' \tag{26}$$

In eq. (24), p_{fg} represents the probability of global best (in general consider p_{fg} =1 for global solution), p_f represents the current probability (as stated in eq. (26)) and β_i refers time-varying probability coefficient, $\beta_i = rand * p_i$, rand -is the random number [0, 1].

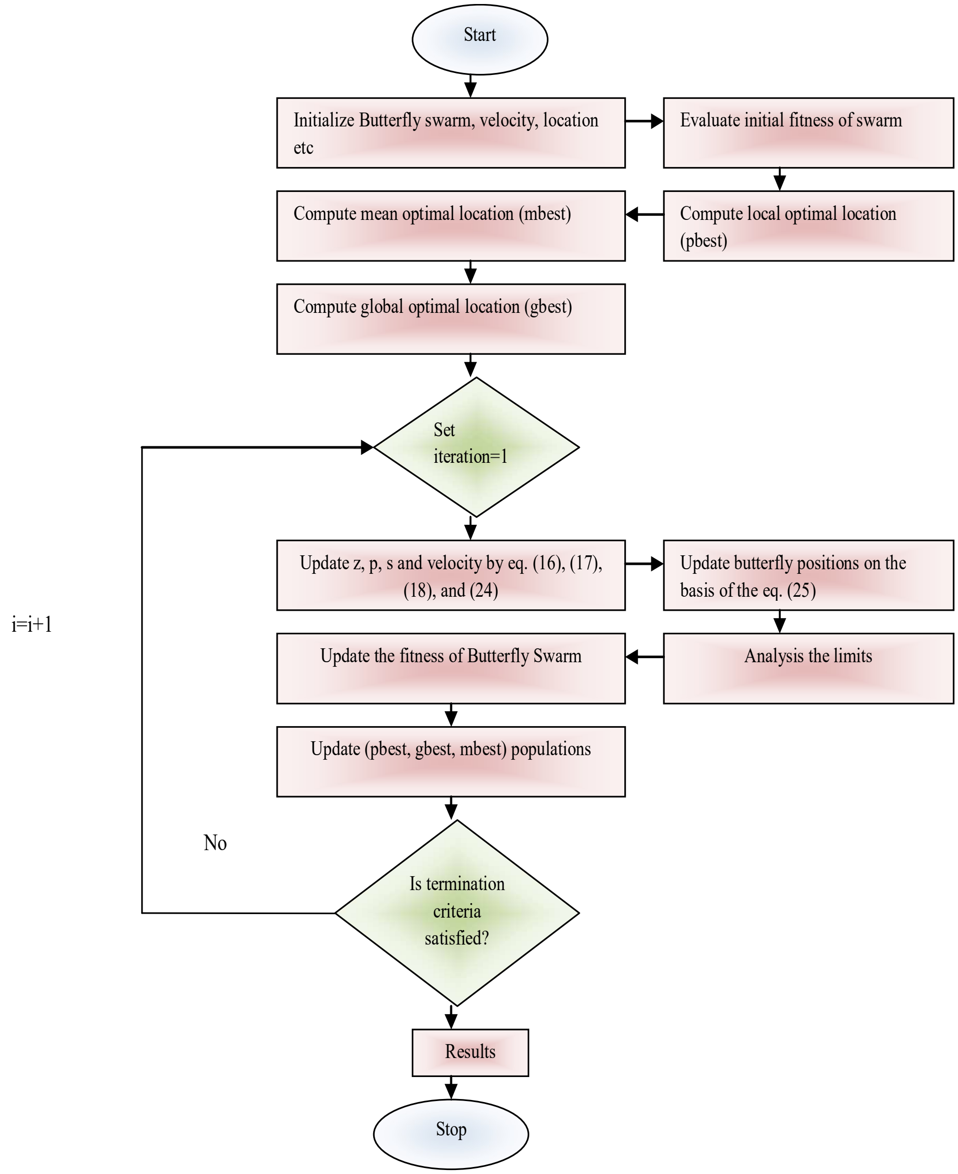

Fig. 2. *Flowchart of a proposed method*

5. Results and Discussions

5.1 Simulation Procedure

In this section, the simulation procedure of the proposed and conventional methods such as PSO, GWO, WOA, ABC, and ACO has presented in order to solve the economic dispatch of the power system. Here, the proposed method and conventional methods are tested on two population sizes such as 30 and 200 in order to check the feasibility of the method.

5.2 Performance Analysis

Table 1 shows the performance analysis of the proposed and conventional methods for population size 30. Here, the proposed method is compared to coal consumption, electronic power cost, and carbon emission. In Table 1, the proposed method is 7% better than the PSO, 9% better than the GWO, 10% better than the WOA, 11% better than the ABC, 13% better than the ACO algorithm with respect to the coal consumption. Hence, the overall analysis states that the proposed method is better than the conventional methods.

Table 1. Comparison analysis of proposed and conventional methods for population size 30

Population size	Methods	Coal consumption	Electric power cost	Carbon emission
30	PSO	31,221.432	17,223.13	13,126.13
	GWO	30,124.238	16,326.29	13,226.21
	WOA	30,189.231	16,321.68	12,321.17
	ABC	29,127.428	16,821.34	12,254.23
	ACO	30,236.812	16,325.91	13,221.26
	Proposed	29,131.821	15,815.25	12,098.32

Table 2 shows the performance analysis of the proposed and conventional methods for population size 200. Here, the proposed method is compared to coal consumption, electronic power cost, and carbon emission. In Table 2, the proposed method is 14% better than the PSO, 15% better than the GWO, 18% better than the WOA, 19% better than the ABC, 21% better than the ACO algorithm with respect to the electric power cost. Hence, the results proved that the proposed method is credible and it is reasonable.

Table 2. *Comparison analysis of proposed and conventional methods for population size 200*

Population size	Methods	Coal consumption	Electric power cost	Carbon emission
200	PSO	29,152.331	18,531.82	15,321.21
	GWO	29,223.126	18,345.91	15,124.12
	WOA	31,232.154	17,632.11	15,327.53
	ABC	29,127.428	17,731.96	15,231.12
	ACO	29,154.227	17,325.67	14,123.43
	Proposed	28,432.154	16,246.18	14,143.27

Table 3. Computational time of proposed and conventional methods for population size 30 and 200

Methods	Computation time	
	Population size 30	Population size 200
PSO	16	12
GWO	10	9
WOA	13.5	11
ABC	13	10
ACO	14	13
Proposed	8	7

Table 3 shows the computational analysis of the proposed and conventional methods for population size 30 and 200. In Table 3 for population size 200, the proposed method is 7% better than the PSO, 5% better than the GWO, 7.5% better than the WOA, 6% better than the ABC, 8% better than the ACO algorithm. For population size 30, the proposed method is 13% better than the PSO, 11% better than the GWO, 12.5% better than the WOA, 12% better than the ABC, 10% better than the ACO algorithm. It can be seen from the computational analysis results the population size smaller, the computational time takes to completion is less. Hence, the overall analysis states that the proposed method is better than the conventional methods.

6. Conclusion

Generally, economic dispatch is a significant optimization problem in power system planning. This paper concentrated on the load distribution issues in different time periods for the multiple objectives in the power market. Moreover, a hybridization of PSO-BF optimization method is presented in order to solve the problems in dispatching of the power system. The proposed method has the ability to solve large-scale computation issues in a rapid and precise way. While comparing the computation time, the proposed HPSO-BA exhibits stupendous benefits in saving computation time. Additionally, the proposed method has shown that the power enterprises can enhance the computation effectiveness, and attain optimized dispatched power system.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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