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A Combination of Genetic Algorithm and Particle Swarm Optimization for Power Systems Planning Subject to Energy Storage

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Abstract

With the ever-increasing growth of electrical energy consumption in different fields of a power plant, expanding strategies in power plants is a vital, important and inevitable action. Generally, greenhouse gas emissions can be reduced by replacing wind energy instead of using fossil fuels in power plants for electricity generation. A physical system that is capable of harnessing energy for distribution and compensation electricity at a desired and determined later time is called a typical energy storage system. In this paper, a proper optimization method for expansion planning of electrical energy storage is presented. Since the meta-heuristic algorithms are a very suitable tool for optimization purposes, a hybrid of genetic algorithm (GA) and particle swarm optimization (PSO) technique are used in this research. The main objective of the optimization problem is to increase the energy storage. The implementation of the proposed method is performed using MATLAB and GAMS tools. The simulation results strongly validate the correctness and effectiveness of the proposed method.

Keywords: *Energy storage, Optimization, MATLAB, Energy distribution, GAMS, PSO, GA.*

1. Introduction

Typical Optimization models for solving planning problems concerned with power distribution and dispatching systems have been studied and utilized in recent decades. The main purpose is to optimize investments and minimize total costs, involving investment and operation costs [1]. Optimization tools used in such power plants are becoming significantly essential to support the complex task of efficiently providing electricity to the power network. The power plant areas where these optimization tools are needed include power plant operations, analysis, scheduling, and energy management systems.

Fundamentally, problems coped with such fields require study of the objective functions and constraints in various ways [2]. Optimization problems, which contain uncertain parameters, have been challenged in different papers in recent years by using different optimization methods and uncertainty modeling techniques [3].

In order to assure using an efficient and reliable performance of power plant components, optimization methods are used at each level of planning and operations. For example, they are widely used for planning power plant expansion, generator scheduling, regulating control devices, measuring security margins, and for several other important tasks [4]. Utilizing an improved planning process, it is practically performable to cost-efficiently maintain the reliability of a power plant and functioning of the electricity business markets. The power plant planning process and

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planning techniques are further developed based on the identified lack of existing planning practices. The improved planning techniques, appearing in various planning steps, are combined with the existing planning process, making it much better and versatile [5].

This is considered to be extremely essential since the power generated from these renewable power sources is really depended on natural conditions; therefore, unpredictable fluctuations will be inevitable [6].

Regarding worldwide growing trend of clean energy utilization and attention of legislators system to this subject, the presence of renewable energy sources (RESs) in the power plant is increasing. In addition to significant benefits of using RESs, uncertainties in their amount and dependence on natural resources have compounded the growing trend of these resources. The operation and planning of the power plant in the presence of RESs have faced uncertainties that result in the complexity of problem. Using controllable distributed generation (DG) sources with rapid changes in amount of generated power, application of power storage systems and using demand-side sources to reduce the impact of uncertainty in the presence of RESs has been one of the most important parts of utilization of such systems. Due to rapid response, no demand to invest in expanding power plant capacity, development of smart tools and controllability, demand response sources are considered as a suitable and reliable source from the utility point of view [7]. The technical progress inefficiency of renewable energy sources, have been raised involved with greenhouse gas emission, significant power losses within transmission and distribution networks, unpredictable and unreliable fossil fuel cost, and expansion of reliable communication infrastructure provided by smart grids have all led to an increasing interest in deployment of new renewable energy sources [8]. An increase in the amount of RESs is essential. Over the past decades, this amount has increased in Germany and many developed countries [9]. The South Korean government has been actively promoting an educational-facility improvement program as part of its main energy-saving attempts [10]. In 2015, 195 countries signed the Paris Agreement under the United Nations Framework Convention on natural Climate Changes. In order to attain the ambitious greenhouse gas-reduction targets therein, the electric power sector must be transformed fundamentally [11].

Most power plant units currently use fossil fuels. Fossil fuel resources are scarce and contribute to numerous environmental effects. In recent years, special attention has been paid to renewable power plants in order to overcome these critical problems. Generally, investment cost in renewable power plants is exorbitant and the produced power by this type of power unit is non-dispatchable and uncertain. On the other hand, the investment costs of fossil fuel power plant units are lower than those of renewable power plants and their production capacity is dispatchable. Accordingly, in order to obtain an optimal expansion plan, it is necessary to use fossil fuel power plants besides renewable power plant units to reach a trade-off in investment costs [12]. The simultaneous expansion plan of generation and transmission systems has been accomplished using mixed-integer linear programming (MILP) and mixed integer nonlinear programming (MINLP) [13]. The development of electrical energy storage technology for power generation in emergencies has a special place in the power plant. Energy storage is one of the most important topics in the electrical engineering field.

Moreover, the constant use of electricity is not possible because a load of low in some hours and all power plant units are not always operating simultaneously. Optimizing energy consumption means that using equipment or better management we can do the same work with less energy.

The combination of PSO algorithm and the genetic algorithm in power plants has been of interest to scholars [14, 15]. In [14] a hybrid usage of GA and PSO is presented for optimal location and sizing of DG on distribution networks and their objective is to minimize network power losses, better voltage regulation and improve the voltage stability within the frame-work of system operation and security limitations in radial distribution systems. While discussing the optimal use of energy storage systems, this new hybrid approach has received less attention.

In this paper, a hybrid usage of GA and PSO for power plants subject to energy storage is considered. The novelty of this paper can be described as follows.

• Hybrid usage of GA and PSO algorithms for simultaneous optimization

• GA is used to obtain the best value and best quality. PSO algorithm is used to get the best position in the fastest time.

• Using energy storage systems in order to enhance network reliability.

In this paper, energy management of the system is determined by considering the security constraints, power flow of generated power by power plant units, and power generation cost. In order to obtain generation costs and annual costs of power generation units as well as the power generation of units, GAMS software is used. Then MATLAB software is employed for optimization purposes.

In the remainder of this paper, Section 2 presents an uncertainty planning model of a power plant with energy storage and power optimization. A brief description of the optimization problem is provided in section 3. Then in Section 4, the proposed model is performed on the IEEE 24-bus test system [14]. The obtained results of the paper are provided in Section 5.

2. Uncertain Model of Power Plant Planning with Energy Storage and Power Optimization

Main purpose of solving the uncertain model of power plant expansion plan considering optimal transmission lines switching is determining the accurate amount of power plant units and new transmission lines, reducing investment cost and optimizing the system consumed energy. In order to cope with this static problem, we should consider uncertainties associated with load demand and power generation of non-dispatchable RESs, the following model that is based on MILP is proposed [13]:

$$\begin{aligned}&\sum_s N_S^H(\sum_i C_i^T P_{s.i}^G + \sum_i C_w^W P_{s.w}^G \\ &+\sum_c C_c^{CSP} P_{s.c}^G + \sum_b C_b^B P_{s.b}^G + C^{US}\sum_j d_{s.j}^{US}) \\ &+\sum_i C_i^T P_i^T + \sum_w C_w^W P_w^W + \sum_i C_i^{CSP} P_i^{CSP} \\ &+\sum_b C_b^B P_b^B + \sum_i C_i^L P_i^L\end{aligned} \tag{1}$$

Constraint (2) provides the power balance at each buses of the system for different scenarios,

$$\begin{aligned}&\sum_{i\in\Omega^{T(n)}} P_{s.i}^G + \sum_{w\in\Omega^{W(n)}} P_{s.w}^G + \sum_{c\in\Omega^{C(n)}} P_{s.c}^G + \\ &\sum_{b\in\Omega^{B(n)}} P_{s.b}^G - \sum_{j\in\Omega^{D(n)}} d_{s.j} + \sum_{\frac{i}{S(i)}=n} P_{s.i}^C + \\ &\sum_{\frac{i}{R(i)}=n} P_{s.i}^C = 0\end{aligned} \tag{2}$$

and (3), (4), (5), and (6) are constraints of active power generated by thermal, biomass, wind, concentrated solar units for different scenarios.

$$0 \le P_{s.i}^G \le P_i^T, \forall i.\forall s \tag{3}$$

$$0 \le P_{s.b}^G \le P_b^B, \forall b.\forall s \tag{4}$$

$$0 \le P_{s.w}^G \le F_{s.w}^W P_w^W, \forall b.\forall s \tag{5}$$

$$0 \le P_{s.c}^G \le P_c^{CSP}, \forall c.\forall s \tag{6}$$

Also, constraint (7) denote the capacity of each concentrated solar unit (with maximum number of hours this unit can operate during a year in full capacity).

$$\sum_{S\in\Omega_K^S} (N_S^H P_{S.C}^G) \le F_{C.K} P_C^{CSP} \sum_{S\in\Omega_K^S} N_S^H, \forall c, \forall s \tag{7}$$

It should be noted that the main difference between cold and hot seasons is modeled through the capacity factor.

Constraint (8) indicates the load demand in each scenario, and the constraint (9) denotes the maximum amount of the demand not supplied.

$$d_{s.i} = D_{s.j} - d_{s.j}^{US}, \forall j.\forall s \tag{8}$$

$$0 \le d_{s.j}^{US} \le D_{s.j}, \forall j.\forall s \tag{9}$$

Constraint (10) also denotes the flowing power and its limitations for new transmission lines.

$$-P_{max.l}^E \le P_{s.l}^E \le P_{max.l}^E, \forall l \in \Omega^{EL}.\forall s \tag{10}$$

Constraints (11), (12) and (13), respectively, denote maximum capacity that can be considered for each corresponding renewable technology:

$$0 \le P_w^W \le P_{max.w}^W, \forall w \tag{11}$$

$$0 \le P_c^{CSP} \le P_{max.c}^{CSP}, \forall c \tag{12}$$

$$0 \leq P_b^B \leq P_{max.b}^B, \forall b \tag{13}$$

According to (1), the objective function of this optimization problem is to minimize the investment clear units, and Susceptance of transmission lines. Constraint (2) provides the power balance at each bus of the system for different scenarios, and (3), (4), (5), and (6) are constraints of active power generated by thermal, biomass, wind, concentrated solar units for different scenarios. Also, constraint (7) denotes the capacity of each concentrated solar unit (with maximum number of hours this unit can operate during a year in full capacity). It should be noted that the main difference between cold and hot seasons is modeled through the capacity factor.

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$$\begin{aligned} Min \sum_s N_S^H (& \sum_i C_i^T P_{s.i}^G + \sum_i C_w^W P_{s.w}^G \\ & + \sum_c C_c^{CSP} P_{s.c}^G + \sum_b C_b^B P_{s.b}^G + C^{US} \sum_j d_{s.j}^{US}) \\ & + \sum_i C_i^T P_i^T + \sum_w C_w^W P_w^W + \sum_i C_i^{CSP} P_i^{CSP} \\ & + \sum_b C_b^B P_b^B + \sum_i C_i^L P_i^L \end{aligned}$$

$s.t.$

$$Equations\ (2) - (13)$$

2.1. DC Power Flow Formulations

For the purpose of fast solution and determination of active power lines, DC power flow must be used.

Respectively DC power flow is carried out based on the following assumptions:

$$\sin(\delta_i - \delta_j) \cong \delta_i - \delta_j \tag{14}$$

- Voltage amplitudes of all system buses are equal to unity,
- Ohmic characteristics of lines are neglected and lines are modeled by using only their reactance,
- The reactive power of the lines is neglected. Hence, load power factors are equal to unity and the following equation can be used for calculating active power:

$$p_{ij} = \frac{\sin(\delta_i - \delta_j)}{x} = \frac{\delta_i - \delta_j}{x} \tag{15}$$

- In this case, power flow is conducted just by having δ_i, δ_j (in radian) and without using iterative solution methods.

2.2. Energy Storage Systems

Every grid includes several batteries used as storage systems in the grid. Equations (16) to (25) show the equations related to the battery [12].

$$\begin{aligned} & 0 \leq p_{bat-ch}(t) \leq \\ & U_{bat-ch}(t).P_{bat-cap}.(1 - SOC(t-1)).\frac{1}{1 - P_{bat-ch}^{loss}}.\frac{1}{\eta_{conv}} \end{aligned} \tag{16}$$

$$\begin{aligned} & 0 \leq P_{bat-disch}(t) \leq \\ & U_{bat-disch}(t).P_{bat-cap}.SOC(t-1).(1 - p_{bat-disch}^{loss}).\eta_{conv} \end{aligned} \tag{17}$$

$$0 \leq P_{bat-ch}(t) \leq U_{bat-ch}.\frac{P_{conv-cap}}{\eta_{conv}} \tag{18}$$

$$0 \leq P_{bat-disch}(t) \leq U_{bat-disch}(t).\frac{P_{conv-cap}}{\eta_{conv}} \tag{19}$$

$$U_{bat-ch}(t) + U_{bat-disch}(t) \leq 1, \tag{20}$$

$$U_{bat-ch}(t), U_{bat-disch}(t) \in \{0,1\} \tag{21}$$

$$SOC(t) = SOC(t-1) - \frac{1}{P_{bat-cap}}.Px.\eta_{conv}.P_{bat-ch}(t) \tag{22}$$

where

$$Px = \frac{1}{1 - P_{bat-disch}^{loss}}.\frac{1}{\eta_{conv}}.P_{bat-disch}(t) - (1 - P_{bat-ch}^{loss})$$

$$0 \leq SOC(t) \leq 1 \tag{23}$$

$$SOC(t_0) = SOC_{initial} \tag{24}$$

$$SOC(T) = SOC_{final} \tag{25}$$

Parameters in the simulated system above are defined as follows.

$P_{bat\_ch}(t)$: Charging rate,

$P_{bat\_disch}(t)$: Discharging rate,

P_{bat_cap} : Maximum capacity of the battery,

SOC : Charging and discharging level,

η_{conv} : Efficiency,

P_{conv_cap} : Capacity of the mediate power electronics converter between the battery and the grid.

Equations (16)-(25) represent the constraints related to charge and discharge rates of batteries. Since the battery cannot charge or discharge at the same time, constraint (22) is defined, whereas parameters are given as follows:

$U_{bat\_ch}(t)$ and $U_{bat\_disch}(t)$: binary variables of the function.

Equation (22) represents the dynamic model of energy at any time for the battery. And, (23) and (25) state constraint of energy storage in the battery, initial and final energy at the beginning and end of the energy management time interval.

The operating cost of the battery storage system is given as (26).

$$\begin{aligned} C_{bat} = {} & \\ & \alpha_{bat} \cdot \textstyle\sum_t \left[P_{bat-ch}^2(t) + P_{bat-disch}^2(t)\right] \\ & +\beta_{bat} \cdot \textstyle\sum_t \left[P_{bat-ch}^2(t) + P_{bat-disch}^2(t)\right] \\ & +\gamma_{bat} \cdot \textstyle\sum_t [min(SOC(t) - \delta_{bat}, 0]^2 \end{aligned} \tag{26}$$

In this model, three costs are considered for probable damages that battery may experience during the operation: fast charging cost, cost of successive charge and discharge modes, and severe battery depletion costs.

The proposed model in this section overcomes the successive charge and discharge modes. Parameters given in (26) are defined as follows:

α_{bat} , β_{bat} , γ_{bat} : are constant values to make a compromise between different costs.

δ_{bat} : Minimum energy stored in the battery to prevent severe battery discharge.

For example, δ_{bat} = 0.15 means that if the energy level of the battery drops to less than 15% of the rated capacity of the battery, it will absolutely harm the whole battery and causes additional costs.

2.3. Models of Shortage and Surplus Powers

Concepts of shortage power ($P_{shortage}$) and surplus power ($P_{surplus}$) are presented in the operation of microgrids due to the stochastic intrinsic nature of RESs and/or lower or higher price of energy in the upstream grid than the operating costs of local controllable power sources.

The operational characteristic of each microgrid is so that every grid can sell its corresponding surplus power to the upstream grid. On the other hand, in case of power not being supplied, shortage of energy within the microgrid, and lack of local sources in supplying the customers, the utility purchases power from the upstream grid by considering the electricity price.

2.4. Loads

Two types of loads have been considered for the proposed network in this section. The first type is time-variable and interruptible loads, and the second type is fixed loads. For the former one, it is necessary to supply a specific amount of required energy within different time intervals. Concerning interruptible loads, they can be interrupted by paying a penalty for this type of load. Therefore, loads of the first type can participate in demand response programs. On the contrary, fixed loads are sensitive and uninterruptible loads and their demanded power must be supplied at the requested exact time.

Equation (27) shows the minimum, maximum and the amount of energy for time-variable loads, load shifting costs, and load interruption cost, respectively.

$$P_{def}^{Min} \le P_{def}(t) \le P_{def}^{Max}$$

$$E_{def}^{Min} \le \sum^{24} E_{def}(t) \le E_{def}^{Max}$$

$$C_{def} = \Psi.\left[E_{def}^{Max} - \sum_{t=1}^{24} E_{def}(t)\right]$$
$$C_{curt} = \zeta.\left[\sum_{t=1}^{24} P_{def}(t)\right] \tag{27}$$

In the above equations, parameters are defined as follows.

$P_{def}(t)$: Shiftable load,

$P_{def}^{Max}, P_{def}^{Min}$: Minimum and maximum values of the shiftable load,

$E_{def}^{Max}, E_{def}^{Min}$: Energy limitations of the shiftable load,

C_{def}: Load shifting cost,

ψ : Constant value,

$P_{curt}(t)$: Interrupted load,

C_{curt}: Load interruption cost,

ζ: A constant value as load interruption penalty.

2.5. Energy management

Wide usage of micro grids, contributes to attempts of minimizing their operating costs by solving the energy management problems. Following equation presents optimal objective function of a microgrid, which includes costs of generators, battery, power purchase from upstream grid, obtained profit by selling power to the upstream grid and costs related to the demand response programs.

$$\min \sum_t \sum_t \left[C_t\left(P_{gen}^i\right) + C_{startup}^i\right] + C_{bat} + \sum_t \left[pr_t^{buy,DN}.P_t^{shortage} - pr_t^{sell,Dn}.P_t^{surplus}\right] + \sum_i C_{def,i} + \sum_i C_{curt,i} \tag{28}$$

In the above equations, $pr_t^{sell,DN}$ and $pr_t^{buy,DN}$ are the prices of selling electricity to and purchasing electricity from local distribution networks.

2.6. Energy Management of Power Plant

After determining the output power of microgrids, distribution network starts the energy management process. The objective function in this section, given in (29), is minimizing the costs related to the operation of the power distribution grid in presence of microgrids and DGs.

$$\min \sum_t \sum_i \left[C_t\left(P_{gen_{DN}}^i\right) + C_{startup_{DN},t}^i\right] + \sum_t \left[pr_t^{buy,utility}.P_t^{buy_{DN}} - pr_t^{sell,utility}.P_t^{sell_{DN}}\right] + \sum_t \left[pr_t^{buy,DN}.P_{t,i}^{surpluss-MG}\right] + \sum_i C_{def\_DN,i} + \sum_i C_{shed\_DN,i} \tag{29}$$

where $pr_t^{buy,DN}$, $pr_t^{buy,utility}$ are the electricity selling and purchasing prices to and from the distribution network, and $P_{t,i}^{surpluss-MG}$ is the amount of electricity the distribution network purchases from the surplus power of the i-th microgrid. Each microgrid re-plans its units after its situation is specified. Larger system results in complicated energy management problems in distribution network level; and apparently using mathematical methods to solve them become much more difficult.

3. Optimization

Main purpose of optimization is finding the best acceptable solution regarding the constraints and requirements of a given problem. For a particular problem, there may be several solutions that a function called the objective function is defined to compare and select the optimal solution among the provided solutions. Selecting a suitable function depends on the nature of the problem. For example, the shortest time or cost is among the common objectives of optimizing transportation networks. However, selecting the appropriate objective function is one of the most important steps in optimization process.

Optimization is the art of finding the best solution among the available situations. Optimization is used in designing and maintenance of many engineering, economic and even social systems to minimize costs or minimize energy waste.

Due to the widespread application of optimization in different sciences, this topic has grown significantly during last decades. In order to solve an optimization problem, firstly it must be modeled. Modeling means describing a problem with corresponding mathematical variables and equations so that it simulates optimization problem correctly.

3.1. Optimization Using PSO

PSO is one of the most famous group optimization techniques based on a random search, and its modified versions are used in solving complicated engineering problems.

In this method, a group of particles search the search space to reach the final optimal solution or to a solution close to that. Each of the particles is considered as a random solution within the search space of the problem. PSO is a population-based random optimization technique inspired by the group behavior of birds and flock of fish.

The procedure of PSO is described as follows.

- Initialization: initializing a population of particles with random positions and velocities in D dimensions within the search scope
- Estimation: estimating the fitness of each section in the population
- Update: calculating velocity of each part and moving to the next position
- Termination: stopping the algorithm if an ending criterion happens; otherwise, switching to next Estimation step.

3.2. Optimization Using GA

GA is also a special type of evolutionary algorithm that uses inheritance and mutation. In fact, GAs use Darwin's natural selection principles to find the optimal formula for pattern prediction or matching. GA is generally an iteration-based algorithm that most parts of it are selected by random processes. Furthermore, it is a search technique in computer sciences to find an approximate solution for search problems, and it is one of the most important algorithms used for the optimization of different functions.

The procedure of GA is as follows:

- Initialization: Individuals with random chromosomes are produced that form the initial population of N.
- Reproduction: the degree of fitness of each object is calculated and the individual is multiplied by static law that depends on degree of fitness. Then individuals with low fitness values are eliminated, while those with high fitness values are maintained.
- Crossover: New individual is generated by crossover operation.
- Mutation: This is performed by operations that are defined by mutation probability or mutation, and a new individual is produced.
- Final judgment: If final conditions are satisfied, the best individual obtained is the final solution, otherwise; go to step 2.

3.3. Proposed Method

The proposed method is an enhanced search method for suitable and fast optimization. The purpose of presenting this novel method is to introduce a fast and high-performance optimization technique in comparison to other common techniques. To achieve the best quality optimization we use GA, and to achieve the fastest solution we employ PSO. The former has fast synchronization and is suitable for an iterative and time-demanding problem. Combined flowchart of these two algorithms is shown in Fig. 1.

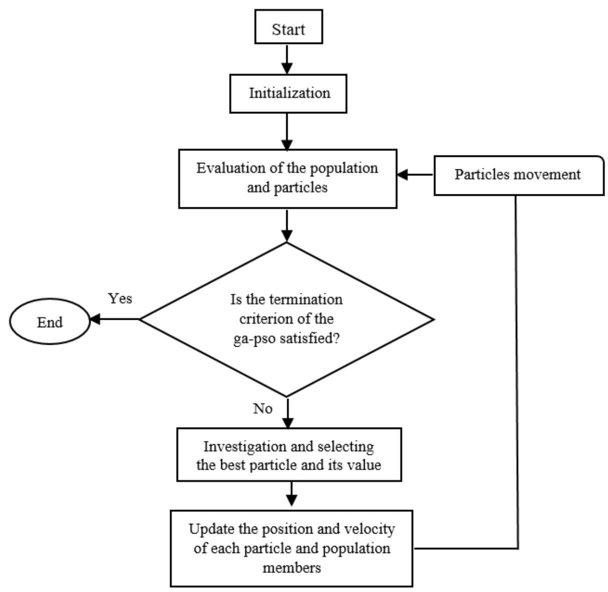

Fig. 1. Flowchart of combined GA-PSO method.

3.4. Optimization Algorithm (BOA)

Butterfly optimization algorithm (BOA) is an interesting meta-physical algorithm inspired by nature; in which butterflies are search agents of BOA for performing optimization [16-18].

The natural phenomenon of butterflies is founded on two vital problems: Variety (I) and formula (f).

For simplification, a butterfly is in a relationship with a coded objective function. But, *f* is relative and should be sensitive by other butterflies. Regarding these concepts, fragrance as the physical intensity function of the stimulus is given as follows:

$$f_i = cI^a \tag{30}$$

where f_i is obtained from the fragrance. For instance, common fragrance is understood by butterfly *i*. C is the sensory state, I is the stimulus intensity, and A illustrates the method-dependent power amount, which denotes the degree of absorption. There are two main applicable algorithms [18]:

1. Global search step,

2. Local search step.

In the world wide search step, the butterfly goes one step to the fittest solution butterflyg^*, which can be given as:

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + (r^2 \times \boldsymbol{g}^* - \boldsymbol{x}_i^t) \times f_i \tag{31}$$

here g^* denotes the best current solution among all available solutions of the step. The fragrance of the i-th butterfly is represented by f_i and *r* is a random value in the range of [0, 1]. Local search step can be described as:

$$x_i^{t+1} = x_i^t + (r^2 \times x_k^t - x_j^t) \times f_i \tag{32}$$

where x_j^t and x_k^t are the j-th and k-th butterflies randomly selected from the solution space. If these belong to the same subset and r is chosen as a random value in [0, 1], then Eq. (32) turns into a local random walk. Food search by butterflies could occur in the local and global searches.

Thus, a switching probability (p) in BOA is utilized for switching between common global search and compressed local search. Flowchart of a typical BOA is clearly shown in Fig. 2.

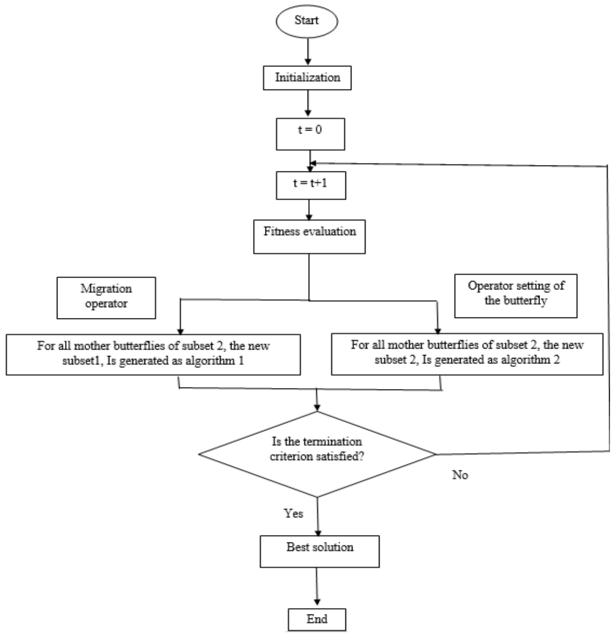

Fig. 2. Flowchart of BOA [17, 18].

4. Simulation

A 24-bus system is considered for simulations, which is shown in Fig. 3[19]. Input data to the system are standard data of an IEEE 24-bus system extracted from [19]. Using GAMS software, annual generation and investment costs of power plant units and power generated by each power unit are obtained and listed in the following table.

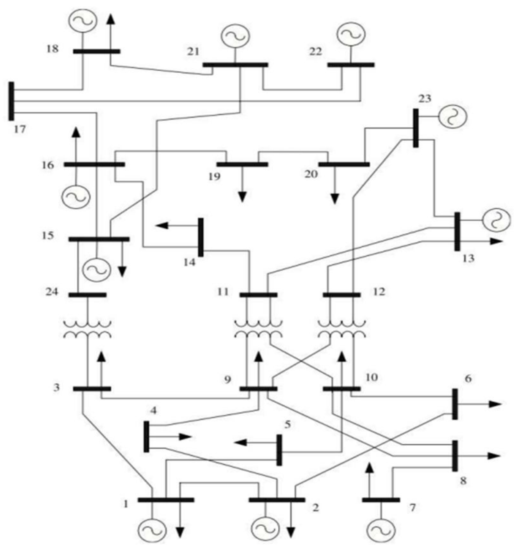

Fig. 3. The 24-bus system [19].

Table. 1. Power plants characteristics

Type of power plant	**Biomass unit**	**Concentrated solar unit**	**Thermal unit**
Number of units	10	13	10
Total generation cost ($/MW)	1/460/000	1/790/000	2/260/000
Total annual investment cost ($/MW)	290/000	290/000	1/010/000
Generation power (MW)	762	472	327/141

Table. 2. Generation power by the biomass unit in different scenarios (MW)

	Biomass units									
Different scenarios	1	2	3	4	5	6	7	8	9	10
1	4	71	58	50	50	98	99	99	93	57
2	87	71	58	50	50	98	99	99	93	57
3	87	71	58	50	50	98	99	99	93	57

Table. 3. Generation power by concentrated solar units in different scenarios (MW)

	Concentrated solar units												
Different scenarios	1	2	3	4	5	6	7	8	9	10	11	12	13
2	20.579	19.8	27	60	53	32	8.674				9.806		
3	8.732		9.36	31.067	11.896	10.311		10.853	15.791	12.32	44	9.289	20.24

Table. 4. The capacity factor of solar unit 1 in seasons 1 and 2

	Counter of seasons	
Counter of concentrated solar units	1	2
1	0.48	0.46
2	0.42	0.15
3	0.59	0.46
4	0.6	0.53
5	0.41	0.45
6	0.45	0.5
7	0.41	0.12
8	0.34	0.12
9	0.45	0.19
10	0.21	0.51
11	0.6	0.48
12	0.46	0.1
13	0.23	0.52

Table. 5. Collected data illustrating the daily consumption of a particular city for optimization of energy consumption of the power plant

Time (hr)	Load (MW)	Time (hr)	Load (MW)
1	1625	16	2150
2	1700	17	2000
3	1820	18	1870
4	1810	19	1700
5	1800	20	1475
6	1740	21	1350
7	1600	22	1350
8	1525	23	1280
9	1450	24	1380
10	1550		
11	1625		
12	1625		
13	1750		
14	1750		
15	2000		

Fig. 4 illustrates a particular city's 24 hours energy consumption that utilizes the proposed optimization technique

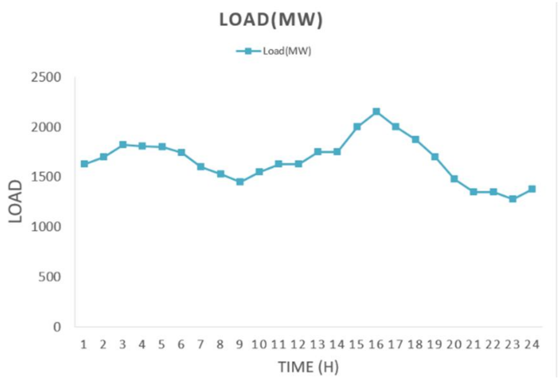

Fig. 4. 24h Consumption linear diagram in MW.

For GA-PSO algorithm parameters have been considered as follows:

Population size: 50, Maximum iteration: 100

Cross over probability: 0.7,

Number of variations: 24,

Minimum Variation: 1450,

Maximum variation: 2150.

Once the generation powers of each of power plant units are obtained, the system is optimized using the combined GA-PSO algorithm. Then the system will be re-optimized using BOA and the obtained results from the optimization will be examined using two different algorithms. Fig. 5 clearly shows the Output curve of the optimized energy using the combined GA-PSO and BOA algorithm. Both algorithms select their best and the most optimum value of their inputs. These data are read by the algorithm and then best value among the inputs will be chosen, subject to modified cost Function. The best value is the value means involving more power and less cost. Comparing results of 100 iterations of evaluation of obtained cost functions contributes to 19.37 (Butterfly algorithm) and 19.20 (GA-PSO algorithm) that obviously infers that GA-PSO algorithm leads to a better performance from the point of access point (time) and optimum point (Fig. 5).

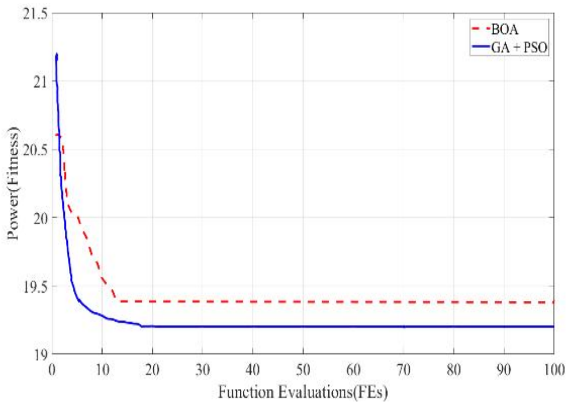

Fig. 5. Output curve of the optimized energy using the combined GA-PSO algorithm.

5. Conclusions

The main purpose of this study was to present an efficient novel optimization method that could give a relatively better solution in terms of both best storage point and convergence rate to reach the optimum point than the other common methods. For this purpose, firstly a background of optimization and energy storage methods is presented. In Section 2, to solve this static problem by considering uncertainties involved with load demand and power generation of non-dispatchable RESs, a model based on MILP is proposed. Optimization is defined in Section 3. Section 4 presents an optimization method and introduces the proposed method. In Section 5, power generation cost, annual cost of each power unit and their corresponding power generation which are obtained by GAMS program are discussed. Then a combined GA-PSO algorithm is used to optimize the system. Next, the BOA is utilized to compare the proposed technique with another optimization technique, and the results of both algorithms are compared. Metaheuristic algorithms are a very useful optimization tool in optimization problems. We used a hybrid usage of genetic algorithm and particle swarm optimization. The output accuracy in this paper was calculated appropriately. Other metaheuristic algorithms can also be utilized to optimize energy consumption. Regarding the structure of the network, DC power flow is implemented. Electrical energy storage systems can be used for load backup, frequency, and voltage amplification, peak load management, energy quality enhancement, and renewable energy support. Utilizing energy-saving systems has special virtues and disadvantages; because built-in battery-banks are very expensive. For example, an individual 12V (120A-h) Battery is about 200$; that stores only 1.44 KW energy and supplies about 300W. Of course usage of battery-banks contributes to significant benefits such as supporting loads, stabilizing voltage and frequency, handling peak consumptions, improving energy quality and supporting renewable energy sources. Thus, according to requirements of power networks to battery-banks, we can make a decision to use or not to use battery-banks. Capacity limitation of each bus depends on its storage capacity and on the value of optimal function that will not be constrained according to the values of buses 3, 6 and 12. Power storage systems are placed between nodes of each bus. Considering outputs and optimizing power consumption of power plants, infers that considering energy storage can reduce operating costs, provide energy, increase reliability and supply operating storage.

Nomenclature

Counters	
b	Counter of biomass units
c	Counter of concentrated solar units
i	Counter of thermal units
j	counter of load demand
K	Counter of seasons. 1: cold season, 2: hot season
l	Counter of transmission lines
n	Counter of buses
s	Counter of scenarios
w	Counter of wind units
$S(I)$	Sending-end bus of line l
$R(I)$	Receiving-end bus of line l
Sets	
$\Omega^A(n)$	Set of nuclear parts connected to bus n
$\Omega^B(n)$	Set of biomass units connected to bus n
$\Omega^C(n)$	Set of concentrated solar parts connected to bus n
$\Omega^D(n)$	Set of load demand connected to bus n
Ω_K^S	Set of biomass parts connected to bus n
Ω^{CL}	Set of candidate transmission lines
Ω^{EL}	Set of available transmission lines
$\Omega^{GHG(n)}$	Set of greenhouse gas emission parts connected to bus l
$\Omega^{T(n)}$	Set of thermal parts connected to bus n
$\Omega^{W(n)}$	Set of wind parts connected to bus n
Constants	
B_l	Susceptance of transmission line l [Mho]
C_b^B	Generation cost of biomass unit [$/MW]
C_{sb}^B	Annual investment cost of biomass part b [$/MW]
C_c^{CSP}	Generation cost of the focused solar unit [$/MW]
C_{sc}^{CSP}	Annual investment cost of the concentrated solar unit [$/MW]
C_i^T	Generation cost of thermal unit i [$/MW]
C_{Si}^T	Annual investment cost of thermal unit i [$/MW]
C_l^L	Annual investment cost of transmission line l [$/MW]
C^{US}	Cost of demand not supplied [$/MW]
C_w^W	Generation cost of wind unit w [$/MW]
C_{Sw}^W	Annual investment cost of wind unit w [$/MW]
$D_{s,j}$	Amount of load demand j in scenario s [$/MW]
$f_{c,k}$	Capacity factor of solar unit c in season k [pu]
$f_{s,w}^W$	Normalized wind generation power of wind unit w in scenario s [pu]
N_S^H	Number of hours containing scenario s [h]
M	A very large number (e.g. 10^6)
$P_{max,b}^B$	Maximum capacity of biomass unit b [MW]
$P_{max,c}^{CSP}$	Maximum capacity of concentrated solar unit c [MW]
$P_{max,w}^W$	Maximum capacity of wind unit w [MW]
$P_{max,l}^C$	Capacity of candidate transmission line l [MW]
$P_{max,l}^E$	Capacity of available transmission line l [MW]
L^{TS}	Maximum number of lines that could be open
y^n	Costs related to each scenario
Variables	
$d_{s,j}$	Consumed power by load demand j in scenario s [MW]
$d_{s,j}^{US}$	Power not supplied for load demand j in scenario s [MW]
P_b^B	Generated power by biomass unit b [MW]
P_c^{CSP}	Generated power by concentrated solar unit c [MW]
P_i^T	Generated power by thermal unit i [MW]
P_w^W	Generated power by wind unit w [MW]
$P_{s,b}^G$	Generated power by biomass unit b in scenario s [MW]
$P_{s,c}^G$	Generated power by concentrated solar unit c in scenario s [MW]
$P_{s,i}^G$	Generated power by thermal unit i in scenario s [MW]
$P_{s,w}^G$	Generated power by wind unit w in scenario s [MW]
$P_{s,l}^C$	Power flow on candidate transmission line l in scenario s [MW]
$P_{s,l}^E$	Power flow on available transmission line l in scenario s [MW]
$Q_{s,l}$	Auxiliary variable
y_l^L	Investment status on transmission line l. $y_l^L = 1$ if the line is constructed; otherwise, $y_l^L = 0$
$Z_{s,l}^C$	A binary variable showing the switching status of the candidate transmission lines l in scenario s. $Z_{s,l}^C = 1$ if the lines are closed; otherwise, $Z_{s,l}^C = 0$
$Z_{s,l}^E$	A binary variable showing the switching status of the available transmission lines l in scenario s. $Z_{s,l}^E = 0$ if the lines are closed; otherwise, $Z_{s,l}^E = 1$
$\theta_{s,n}$	Voltage angle of bus n in scenario s [rad]
a	Auxiliary variable for modeling the regret

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