Optimizing the Power System Operation Problem towards minimizing Generation and Damage Costs due to Load Shedding

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ABSTRACT

Optimizing the operational parameters and control of the power system in steady-state conditions is a crucial issue in reducing the costs of power generation and operation. In the case of long-term operation of a power system, besides aiming to minimize power generation costs, the cost of damage caused by load shedding also needs to be considered. This paper presents the optimization of the total cost of a power system including minimizing the generation cost function of power plants or power companies and minimizing the damage cost function caused to customers due to load shedding or power outages. At the same time, the objective function must also ensure the constraints on the operating conditions of the power system. This contributes to maintaining the continuity of the power supply to critical loads and minimizing damage. Base loads, priority loads, or loads that are not allowed to be shed are considered as constraints. The optimization problem is addressed by using the Particle Swarm Optimization (PSO) algorithm and the Cuckoo Search Algorithm (CSA). The IEEE 30-bus test system is applied to validate the reduction in total cost. The result comparison shows that when applying the CSA, the total cost is significantly reduced by 3.75% in comparison with the PSO algorithm. The algorithms are implemented in Matlab to demonstrate the efficiency and accuracy of the proposed method.

Keywords-optimal load shedding; PSO; CSA; economic dispatch, cost function

I. INTRODUCTION

Maintaining the stable and continuous operation of a power system is a fundamental task that power system operators must ensure. In some cases, the power system cannot maintain its power balance due to prolonged generator failures or rapid increases in load beyond the generation capacity. At this time, shedding a portion of the load is the most effective solution if initial measures fail to restore power balance. Optimal load shedding has become an area of significant interest and development in power system operation optimization. In [1], an algorithm based on fuzzy logic that responds to load shedding in order to provide an under-frequency load shedding scheme is introduced. Compared to the conventional load shedding solutions, the effectiveness of this method increases in the case of major disturbances and reduces in the case of small and medium failures. In [2], under-frequency load shedding is discussed with specific provisions for acceptable parameters, including the number of load shedding steps, the percentage of load shedding in each step, and the accuracy of the frequency measurement conducted in protective relays. Optimization techniques using algorithms such as Improved PSO (EPSO), Artificial Bee Colony PSO (ABC-PSO), Artificial Neural

Network-PSO (ANN-PSO), and Genetic Algorithm (GA) [3-5] are proposed to address under-voltage load shedding issues. These methods rely on the concept of voltage stability margin and its sensitivity at the maximum load ability point. The Grasshopper Optimization Algorithm (GOA) is employed to optimize frequency-responsive load shedding in [6], resulting in highly cost-effective load shedding solutions. Prominent artificial intelligence technologies such as ANNs, GAs, Fuzzy Logic Systems, etc., have been used to study effective and reliable load shedding measures [7-9]. These studies provide an overview of the above techniques when applied in the field of load shedding, aiming to highlight the advantages compared to the implementation of traditional techniques as well as the limitations when implementing. GA is used to design precise load shedding in [10]. The authors incorporated real-time decision-making to select appropriate load reduction levels for power system disturbances. However, the main disadvantage of GA is its slow response time. Higher effectiveness of load shedding was achieved by using the Chaotic Slime Mold Algorithm (CSMA) [10] with a sinusoidal diagram. It happens when constraints are imposed on the Voltage Stability Margin (VSM) and the total remaining load after shedding. Besides optimal load shedding, the operation optimization of power plants is also studied. Advanced algorithms such as PSO are applied to solve this problem in [12], and especially economic-environmental problems when optimally operating power plants in [13].

The above studies were evaluated as effective for individual objectives based on the specified problem statements. However, the comprehensive optimization of the overall cost of the entire power system has not been thoroughly examined. The objectives and constraints of this approach need further investigation and development. Therefore, this paper aims to apply the PSO and CSA optimization algorithms to find the optimal generation costs and minimize the costs associated with load shedding. To achieve the best efficiency in power generation operations for utility companies, the objective function for optimization is designed based on minimizing power generation costs with additional constraints. Furthermore, minimizing the cost of load shedding along with its associated constraints is considered a parallel objective. These constraints relate to the base loads or loads that are not allowed to be shed. In a competitive electricity market, optimizing all costs is crucial. The optimized cost includes power generation and load shedding costs while considering base load constraints, thus helping to decide whether load shedding should be implemented, and if so, how much power should be shed at different buses with varying consequential costs. As a result, the damage caused by load shedding is minimized, and the total cost is optimized.

II. PROBLEM FORMULATION

In this paper, the optimization problem consists of two parts as described in (1). The first part involves the generation cost of power plants $F_1(x)$ or the costs of the utility company during the considered period t. The second part encompasses the costs incurred $F_2(x)$ by customers due to power outages or load shedding.

$$\min F(x) = \min\left(F_1(x)t + F_2(x)\right) \quad (1)$$

where $F(x)$ is the total cost, including the generation cost and load shedding cost (\$), $F_1(x).t$ is a function of the generation cost for the period t (\$), and $F_2(x)$ is the cost function of the damage incurred by electricity consumers due to power cuts or load shedding (\$).

A. *Minimizing the Generation Cost of Power Plants*

The cost function of power plants, or the generation cost of the power company $F_1(x)$, is presented in (2):

$$\min F_1(\mathrm{x}) = \min \sum_{i=1}^{N_G} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) \quad (2)$$

where $F_1(x)$ is the generation cost function (\$/h), N_G is the total number of generators, including the slack bus, P_{Gi} is the active power output of the i^{th} generator (MW), and $\alpha_i, \beta_i, \gamma_i$ are the cost coefficients of the i^{th} generator.

B. *Minimizing the Cost of Load Shedding*

The cost function of the damage caused by load shedding is presented in (3):

$$\min F_2(x) = \min \sum_{j=1}^{NL} (P_{LS_j} C_j) \quad (3)$$

where P_{LS_j} is the amount of load shedding power at bus j (MW), and C_j is the cost of damage caused by load shedding at bus j (\$/MW).

C. *Constraints of the Power System*

When performing the optimization of functions $F_1(x)$ and $F_2(x)$, the constraints of the power system include equality and inequality constraints. This includes equations for balancing active and reactive power at the buses. In addition, the inequalities for the limits of apparent power, active power, reactive power, voltage, and phase angle at the buses are also considered when taking into account the constraints. In (2), the constraints include [14]:

$$f(x, y) = 0 \quad (4)$$

$$x^T = \left[P_{G_1}, V_{L_1} ... V_{L_{NL}}, Q_{G_1} ... Q_{G_{NL}}, S_{IJ_1} ... S_{IJ_{NTL}}\right] \quad (5)$$

$$y^T = \left[V_{G_1} ... V_{G_{NG}}, P_{G_2} ... P_{G_{NG}}, T_1 ... T_{NT}, Q_{c_1} ... Q_{c_{NC}}\right] \quad (6)$$

where x is the vector of dependent variables consisting of the slack bus P_{G1}, load bus voltage V_L, generator reactive power output Q_G, and transmission line loading S_{IJ}, y is the vector of independent variables consisting of generator voltage V_G, generator active power output P_G except at the slack bus P_{G1}, transformer tap setting T, and shunt VAR compensation Q_c. NL, NG, NTL, NT, and NC are the number of load buses, generators, transmission lines, regulating transformers, and shunt compensators, respectively.

$$P_{gi}^{\min} \le P_{Gi} \le P_{gi}^{\max}, i = 1, ..., NG \quad (7)$$

$$Q_{gi}^{\min} \le Q_{Gi} \le Q_{gi}^{\max}, i = 1, ..., NG \quad (8)$$

$$V_{gi}^{\min} \le V_i \le V_{gi}^{\max}, i = 1,...,NG \quad (9)$$

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max}, i = 1,...,NL \quad (10)$$

$$S_{IJ} \le S_{IJ_{NTL}}^{\max}, i = 1,...,NTL \quad (11)$$

$$\delta_{gi}^{\min} \le \delta_i \le \delta_{gi}^{\max}, i = 1, NG \quad (12)$$

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1,...,NTL \quad (13)$$

$$Q_{c_i}^{\min} \le Q_{c_i} \le Q_{c_i}^{\max}, i = 1,...,NC \quad (14)$$

In (3), the constraints include:

The total load shedding power at load buses P_{LSj} must be equal to the total required load shedding power for the entire system P_{LS}.

$$\sum_{j=1}^{NL} P_{LS_j} = P_{LS} \quad (15)$$

The load shedding power at load buses must not exceed the allowable limit and maintain the base load $P_{base,j}$. A base load is a load that does not allow to be shed and must remain in the power system.

$$P_{L_j \min} \le P_{LS_j} \le P_{LS_j,\max} \quad (16)$$

$$P_{base,j} = P_{L_j} - P_{LS_j,\max} \quad (17)$$

III. PSO AND CSA

A. PSO

The PSO algorithm [15] is a widely used method for solving optimization problems in power system operation [16]. In PSO, each individual in the swarm is represented as a vector. These vectors move towards a position in a multi-dimensional search space. Each individual also remembers its own best historical position, called P_{best}. For each iteration of the PSO algorithm, the best global position G_{best}, is found. Once G_{best} is found, each individual will move closer to its own best position and the global best position. After many iterations, this process finds a good network structure for the objective function. The positions of the individuals during the convergence process of the PSO algorithm are presented in Figure 1. The velocity and position of each individual are described by (18):

$$V_i^{k+1} = w.V_i^k + c_1.r_1(P_{best_i} - x_i^k) + c_2.r_2(G_{best_i} - x_i^k) \quad (18)$$

After each iteration, the position of each individual will be updated according to (19):

$$x_i^{k+1} = x_i + V_i^{k+1} \quad (19)$$

where w is the inertia weight function, i is the iteration step, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are randomly generated numbers within the range of [0, 1], V_i^k is the velocity of an individual, and x_i is the current position of the same individual.

B. CSA

The CSA [17] is based on the survival behavior of cuckoo birds. The algorithm's solution update equation is:

$$X_i^{new} = Xbest_i + a \oplus \text{Levy flights} \quad (20)$$

where X_i is the solution of the i^{th} individual, $Xbest_i$ is the solution of the i^{th} individual from the previous iteration, $p_\propto$ is the probability parameter for a random walk, $a > 0$ is the step size parameter. The product $\oplus$ means entry-wise multiplications. This entry-wise product is similar to those used in PSO, but here the random walk via Lévy flights is more efficient in exploring the search space as its step length is much longer in the long run. The quantity of accessible host nests remains constant, and a host bird detects a cuckoo's laid egg with a probability $p_\propto \in [0,1]$. In such instances, the host bird has the option to either discard the egg or forsake the nest entirely, constructing an entirely new nest. To simplify, this latter assumption can be approximated by the proportion $p_\propto$ of the total nests being substituted with new nests (containing new, random solutions).

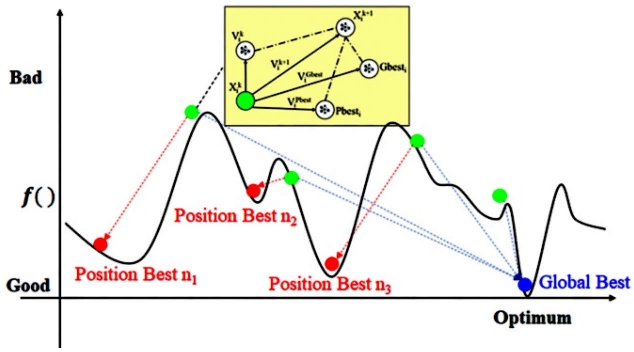

Fig. 1. The positions of the individuals during the convergence process of the PSO algorithm.

IV. SIMULATION AND RESULTS

The IEEE 30-bus test system is utilized to test the effectiveness of the proposed technique. This system includes 6 generators, 21 loads, and 41 transmission lines. The single-line diagram of the system is shown in Figure 2. The detailed parameters of the diagram are presented in [18]. In the case study, the IEEE-30 bus system has a load profile as shown in Figure 3. The load parameters for different time intervals t are presented in Table I and Figure 3. There are two times when the system is overloaded, and the total generated power value cannot meet the load demand at times t_3 (8:01 h ÷ 12:00 h) and t_5 (16:01 h ÷ 20:00 h). The power needs to be shed at t_3 and t_5 are 20.87 MW and 50.05 MW. The optimization of the generation cost function $F_1(x)$ using the PSO algorithm has been calculated and presented in [18]. The results of the cost coefficient values $\alpha_i, \beta_i, \gamma_i$ and the optimal generation power values P_{Gi} are shown in Table II. The cost function of load shedding damage $F_2(x)$ is applied when the system has to perform load shedding. In this case study, the generators have generated power according to the optimal result of the function $F_1(x)$. However, the total generated power cannot meet the load demand. At times t_3 and t_5, the system must perform load shedding with a power of $P_{LS,t3}$ being 20.87 MW, and $P_{LS,t5}$ being 50.05 MW. To achieve the minimum value of the function $F_2(x)$, corresponding to the amount of power shed at each load bus must be the optimal value, the PSO and CSA are continued to be used to solve this optimization problem. As a result, the load shedding cost function achieves its lowest. Solving the economic optimization problem of load shedding costs reduces the damage to customers due to power outages.

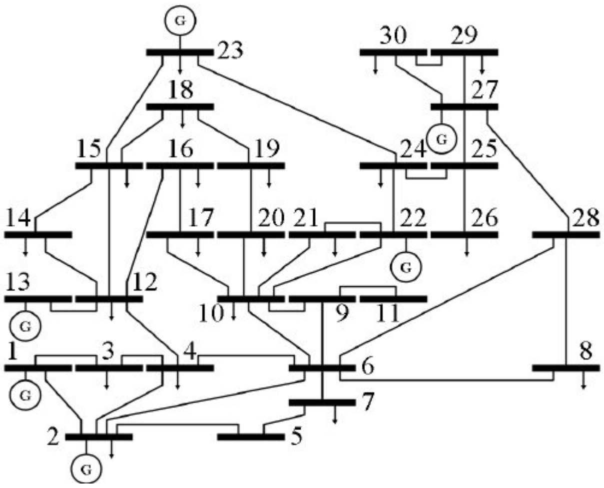

Fig. 2. The diagram of the IEEE-30 bus power system.

In this paper, the base load is proposed as a constraint parameter that must be complied with. The value of load shedding power must not exceed this base load limit. In this case, the value of the base load that needs to be maintained is 20% of the load value at bus j. The results in Table III show that the operating costs of the power plants at t_3 and t_5 are the same, with a value of \$3144.12. However, the load shedding costs at each time interval t have different values. At t_5, the PSO algorithm optimizes the objective function $F_2(x)$ for a cost value of \$13488.28×10^3, corresponding to a load shedding power of 50.40 MW. On the other hand, if the objective function $F_2(x)$ is optimized using the CSA, the cost value is \$13000.85×10^3, corresponding to a load shedding power of 50.45 MW. The calculation of total cost shows that the CSA reduces \$487427.6 (i.e. 3.75%) the damage cost due to load shedding. This cost reduction is very significant in the system. The CSA has better performance than the PSO algorithm because the CSA uses Lévy flights to generate new solutions. This increases the ability to produce diverse solutions and facilitates finding better optimal solutions easily. The convergence characteristics of the PSO and CSA are presented in Figure 4.

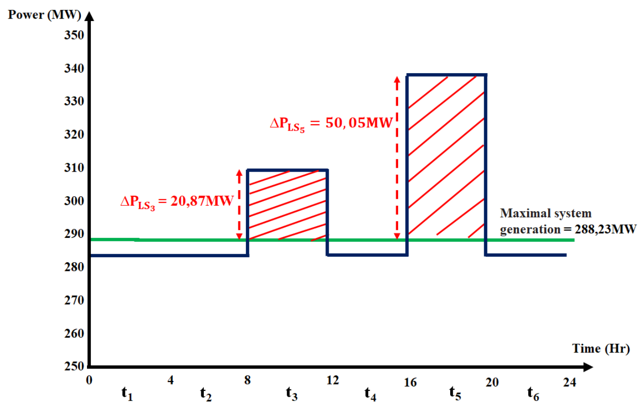

Fig. 3. Load profile versus time for the IEEE 30-bus system.

TABLE I. LOAD PARAMETERS AND COSTS OF LOAD SHEDDING OVER TIME

Name of Bus	C_j (\$/kW)	Load t_1 (MW) (0.00h-4.00h)	Load t_2 (MW) (4.01h-8.00h)	Load t_3 (MW) (8.01h-12.00h)	Load t_4 (MW) (12.01h-16.00h)	Load t_5 (MW) (16.01h-20.00h)	Load t_6 (MW) (20.01h-24.00h)
Claytor	300	19.18	19.18	22.9	19.18	23.48	19.18
Kumis	300	5.92	5.92	3.9	5.92	6.38	5.92
Hancock	300	9.49	9.49	9	9.49	10.81	9.49
Fieldale	280	69.97	69.97	95.4	69.97	88.73	69.97
Blaine	280	19.99	19.99	24	19.99	24.47	19.99
Reusens	300	25.03	25.03	31.2	25.03	30.95	25.03
Roanoke	300	8.09	8.09	7	8.09	9.17	8.09
Hancock	280	11.87	11.87	12.4	11.87	14.03	11.87
Bus 14	280	8.37	8.37	7.4	8.37	9.53	8.37
Bus 15	245	9.77	9.77	9.4	9.77	11.33	9.77
Bus 16	220	6.48	6.48	4.7	6.48	7.1	6.48
Bus 17	280	10.33	10.33	10.2	10.33	12.05	10.33
Bus 18	220	6.27	6.27	4.4	6.27	6.77	6.27
Bus 19	245	10.68	10.68	10.7	10.68	12.6	10.68
Bus 20	280	5.57	5.57	3.4	5.57	5.93	5.57
Bus 21	280	16.28	16.28	18.7	16.28	19.7	16.28
Bus 23	220	6.27	6.27	4.4	6.27	6.77	6.27
Bus 24	220	10.12	10.12	9.9	10.12	11.78	10.12
Bus 26	300	6.48	6.48	4.7	6.48	7.1	6.48
Bus 29	220	5.71	5.71	3.6	5.71	6.11	5.71
Bus 30	245	11.45	11.45	11.8	11.45	13.49	11.45
Total		283.4	283.4	309.1	283.4	338.28	283.4

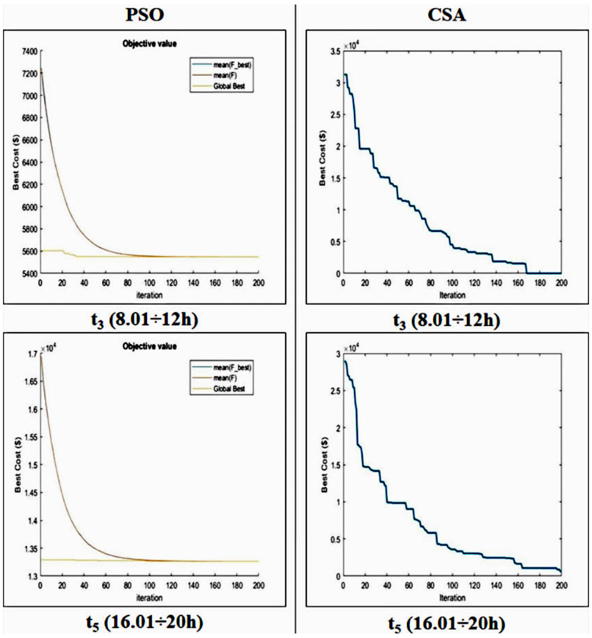

Fig. 4. The convergence characteristics of PSO and CSA algorithms at time intervals t_3 and t_5.

V. CONCLUSION

In this paper, PSO and CSA have been applied to solve the multi-objective problem in optimizing generation cost and minimizing damages cost caused by load shedding. In the problem of optimizing the cost function of load shedding, the CSA optimizes the damage cost function effectively.

TABLE II. OPTIMAL GENERATION POWER P_{GI} VALUES AND THE CORRESPONDING COST COEFFICIENTS WHEN USING THE PSO ALGORITHM

Control variables	α_i	β_i	γ_i	**PSO**
P_{G1} (MW)	0	200	37.5	189.12
P_{G2} (MW)	0	175	175	47.55
P_{G3} (MW)	0	100	625	19.56
P_{G4} (MW)	0	325	83	10.00
P_{G5} (MW)	0	300	25	10.00
P_{G6} (MW)	0	300	250	12.00
Fuel cost ($/h)				786.03

The achieved value using this method is $487427.6, showing a reduction of 3.75% compared to the PSO algorithm. This reduction in damage cost is crucial in the competitive electricity market. The proposed method has addressed the overall optimization problem, including optimizing power generation and the damage due to power outage. In addition, load shedding takes into account the base load or the maximum allowable load shedding. This helps maintain critical loads in the electricity market. The CSA uses Lévy flight to increase discovery in search and performs a second check after each iteration. However, in this paper, only two algorithms were used for comparison. The proposed method opens up new research directions in applying advanced algorithms to solve the overall optimization problem considering multi-objective constraints and base load to be maintained.

TABLE III. LOAD SHEDDING POWER AT EACH LOAD BUS WHEN APPLYING PSO AND CSA

Name of Bus	**t_3 (8.01h – 12h)**			**t_5 (16.01h – 20h)**		
	P_{LS_j} (PSO)	P_{LS_j} (CSA)	$P_{LS_j,\max}$	P_{LS_j} (PSO)	P_{LS_j} (CSA)	$P_{LS_j,\max}$
Claytor	1.59	0.01	18.32	1.17	0.62	18.78
Kumis	1.64	0.26	3.12	3.36	0.16	5.10
Hancock	1.56	0.03	7.2	0.88	1.39	8.64
Fieldale	0.01	1.69	76.32	1.49	13.26	70.98
Blaine	0.82	0.00	19.2	1.50	0.01	19.57
Reusens	1.63	0.01	24.96	5.29	0.01	24.76
Roanoke	0.46	0.01	5.6	4.45	0.03	7.33
Hancock	1.46	0.81	9.92	0.19	3.03	11.22
Bus 14	0.40	4.27	5.92	4.40	0.00	7.62
Bus 15	0.72	0.67	7.52	2.44	0.01	9.06
Bus 16	0.64	0.00	3.76	0.52	1.98	5.68
Bus 17	0.85	4.19	8.16	1.11	0.11	9.64
Bus 18	2.10	2.38	3.52	3.79	0.01	5.41
Bus 19	1.99	0.00	8.56	0.28	12.81	10.08
Bus 20	0.43	3.76	2.72	2.25	2.23	4.74
Bus 21	0.63	0.00	14.96	4.19	0.00	15.76
Bus 23	0.54	0.32	3.52	3.53	0.01	5.41
Bus 24	1.36	1.11	7.92	1.55	4.51	9.42
Bus 26	0.50	0.00	3.76	2.42	3.58	5.68
Bus 29	0.76	0.03	2.88	4.77	6.70	4.88
Bus 30	0.84	1.33	9.44	0.82	0.00	10.79
Total load shedding (MW)	20.91	20.88		50.40	50.45	
CPU time (s)	42.76	4.58		23.46	2.67	
Load shedding cost: $F_2(x)=\sum_{j=1}^{NL}(P_{LS_j}C_j)$ ($\times 10^3$\$)	5555.59	5551.21		13488.28	13000.85	
Generation cost: $F_1(x).t$ (\$)	3144.12	3144.12		3144.12	3144.12	
Total cost: $F(x)=(F_1(x)t+F_2(x))$ ($\times 10^3$\$)	5558.74	5554.35		13491.42	130004	
Save cost: $\Delta F(x)$ (\$)	**4382.54**			**487427.60**		

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