J. Electrical Systems 20-7s (2024): 287-301

[1]Muhammad Zharif Mat Aziz

[2]Ismail Musirin

[3]Mohd Helmi Mansor

[4]Saiful Amri Ismail

[5]Azlina Abdullah

[6]Sharifah Azwa Shaaya

[7]A.V. Senthil Kumar

Embedded Real-Swarm Evolutionary Programming Technique for Intelligent Load Curtailment Strategy

Abstract: - Some traditional optimization techniques are inaccurate and failed to reach their optimal solutions since the solutions normally stuck at local optimal. Thus, any optimization technique cannot be generalized as a reliable optimizer since some optimization techniques are unique to solve optimization problems. This may also occur in power system optimization problem. Load curtailment is one of the important issues in power systems since its approach can help control the power system loss. In general, it is termed as loss minimization so that the delivery of electricity to the consumers can be smoothened. This paper proposes a new optimization technique, Embedded Real Swarm Evolutionary Programming (ERSEP) for identify contingencies occurrence in power system. ERSEP is the integration of real mutation swarm operator with the traditional evolutionary programming (EP) which aims to produce better results in terms of achieving lower optimal solution. Comparative studies were conducted to observe the advantages of ERSEP over the traditional. Results exhibited that the proposed ERSEP outperformed the traditional EP in achieving lower optimal solution validated on IEEE 30-Bus Reliability Test System (RTS). Significant results deduced from this study revealed that total transmission loss reduction worth 52.83% was achieved by EP, 54.09% solved by PSO and 74.09% by ERSEP in Case 1 for chosen load condition. In Case 2, ERSEP maintains to achieve the highest loss reduction worth 54.97%, while EP achieved 51.03% and PSO achieved 52.98% loss reduction. ERSEP maintains to achieve highest loss reduction worth 61.63%, while EP achieved 51.03% and PSO achieved 52.98% loss reduction. This implies that ERSEP is superior in all cases to reach the lowest minimized transmission loss.

Keywords: load curtailment; optimization techniques; evolutionary programming; particle swarm, embedded

I. INTRODUCTION

The increasing demand in current transmission system has caused most of the power system network to undergo increasing current leading to power loss increase. Other than compensation strategy such as the installation of distributed generation (DG), flexible AC transmission system (FACTs) devices installation, reactive power management, power scheduling or reactive power; optimal load curtailment or load shedding can be an allowable option. However, this initiative can be possibly unfair as the electricity utility needs to consider other factors such as technical or non-technical issues. The occurrence of voltage collapse phenomenon could be one of the technical issues, while non-technical issues are such as the political influence or geographical considerations. Load shedding

[1] [1,2,4]Power System Operation Computational Intelligence Research Group (POSC), School of Electrical Engineering,

College of Engineering, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor, Malaysia

[3,5,6]Department of Electrical and Electronics Engineering, College of Engineering, Universiti Tenaga Nasional,

43000 Kajang, Selangor, Malaysia.

[7]Hindusthan College of Arts and Science, Coimbatore, India.

Email: [1]mzharifaziz@gmail.com, **[2]ismailbm@uitm.edu.my, [3]MHelmi@uniten.edu.my, [4]saiful370@uitm.edu.my, [5]aazlina@uniten.edu.my, [6]Shazwa@uniten.edu.my, [7]avsenthilkumar2007@gmail.com

**Corresponding author: ismailbm@uitm.edu.my

is a controlled and deliberate power reduction strategy employed by utility companies to manage and balance the demand and supply of electricity within a given power grid. It involves temporarily cutting off or reducing electricity supply to specific areas or consumers during times of high demand or when the power generation capacity falls short of meeting the total energy requirements. Load shedding is utilized to prevent grid overload, maintain system stability, and avoid the risk of widespread and uncontrolled blackouts. It can be categorized as under-voltage load shedding (UVLS) or under-frequency load shedding (UFLS). Load shedding or in this article referred to as load curtailment requires optimization techniques since its non-optimality will lead to unsolvable power restoration. Among the important load curtailment techniques are the work conducted by Susan et. al [1], Wazir *et. al* in [2] and [3]–[5]. In these studies, optimization techniques have been utilized to solve the issues raised in load curtailment as optimal solutions are required to ensure the amount of loads to be curtailed adhered the desired objectives. Most optimization techniques make use of the elements of artificial intelligence algorithms which are based on population within the variables. In [5], Moazzami *et. al* proposed A new optimal unified power flow controller placement and load shedding coordination approach using the Hybrid Imperialist Competitive Algorithm-Pattern Search method for voltage collapse prevention in power system. This effort is important as this effort managed to prevent the power system from experiencing voltage collapse and complete blackout. In [6], chaotic slime mould optimization algorithm for optimal load-shedding in distribution system. The strength of this work is its ability to address load shedding or curtailment in a bulk distribution system. It managed to achieve greater efficiency in a distribution system considering a constrained function with static voltage stability margin (VSM) index and total remaining load after load shedding. A rigorous review has also been conducted to highlight the significance of load shedding in a broader spectrum. Several critical reviews have also been conducted as reported in [7]–[10]. This implies that this study is significant in the power system community. Another important study that can be highlighted is online voltage stability integrated with load shedding initiative. The load shedding strategy using online voltage estimation process for mitigating fault-induced delayed voltage recovery in smart networks is also an important past work to be addressed due to its capability to perform voltage estimation in power system. This has been highlighted in [8] as one of the important works in load shedding strategy. Other than these works, other work which addressed load shedding using the application of artificial intelligence is the work conducted by Isa et. al in [11], where fuzzy logic was applied to make decision in under-voltage load shedding approach. Numerous optimization have been applied in solving power system problems as reported in [12]–[19]. These studies involved the investigation of compensation schemes, congestion management, load dispatch and voltage stability improvement. However, in some cases the introduced optimization techniques stuck at local optimum which do not allow the searching process into a broader scope. Thus, hybridization or integration of several operators in the original optimization algorithm can be implemented as an effort to alleviate this phenomenon. Among the important integrated optimization techniques are the work conducted in [20], [21], [30], [22]–[29]. This effort has led to convincing results which can be subsequently applied to solve chosen problems within the constraints subject to considerable modifications.

This paper presents a new optimization technique which integrates several operators in particle swarm optimization (PSO) to be embedded in the evolutionary programming. This is termed the Embedded Real Swarm Evolutionary Programming (ERSEP). ERSEP is applied to address the intelligent load curtailment strategy for loss control in power systems. The IEEE 30-Bus reliability test system (RTS). In this study, ERSEP is used to solve load curtailment in power system for achieving lower optimal solution through a comparative study conducted between EP and PSO, the effectiveness of ERSEP can be shown. Results from the study managed to reveal the superiority of ERSEP over the traditional PSO and EP when tested on several significant cases.

II. INTELLIGENT LOAD CURTAILMENT ALGORITHM

This section describes intelligent load curtailment algorithms. It describes the whole description of the method, followed by the explanation of the EP based load curtailment algorithm, followed by the PSO based load curtailment algorithm and ERSEP based load curtailment algorithm.

A. Method Description

This section describes the mechanics for particle swarm optimization (PSO), evolutionary programming (EP) and the newly proposed embedded real-swarm evolutionary programming (ERSEP). ERSEP integrates the operators in the traditional PSO into the traditional EP for the purpose of finetuning the mutation process which can possibly lead to exhausted computational burden due to it weakness which stuck at the local optima. Inclusion of the updating process through the velocity and position can help the individuals learn to reach better convergence. In the traditional PSO, there exist quite a few randomness which may cause exhausted computational burden. On the other hand, EP has been found to be superior to achieving optimal solution. However, sometimes its solution is deviated due to the high dependency of the initial generated individuals. Thus, finetuning is required to compensate between the traditional EP and PSO. Utilization of updating process in PSO really helps the traditional EP to reach the optimal solution within acceptable computational time. That is the beauty of the proposed ERSEP.

B. Evolutionary Programming (EP)

Lawrence J. Fogel first invented evolutionary programming (EP) in 1960 with the goal of developing artificial intelligence using evolution simulation as a learning process. Evolutionary programming is one of the artificial intelligence methodologies for optimization based on evolutionary algorithms (EA) based on natural selection mechanics. EP now uses real-valued representations on a frequent basis and has nearly totally blended with evolutionary strategies (ES). EP has no recombination mostly due to biological inspiration, as each individual is regarded as belonging to a different species.

Initialization, statistics, mutation, and competition are all part of the EP process. The initial population of control variables is picked at random from a collection of uniformly distributed control variables spanning their upper and lower boundaries during startup. The objective function and the environment both influence the fitness score fi. For statistics, the value of maximum fitness, minimum fitness, sum of fitness, and average fitness for this generation are determined. During the mutational process, a new population known as offspring is created from the present population known as parent. Any altered value that exceeds its limit is given the limit value. Mutation allows a more fit individual to produce more children for the next generation. The intelligent load curtailment scheme using EP is illustrated in Figure 1.

EP Initialization Part:

In the initialization part, several processes are conducted such as the setting of system loading, evaluation of system status and random number generation. It is then followed by the filling up process of the population pool. A random generator determines both the locations and the amount of power to be curtailed during load when the system is subjected to load variation. Apparently, the number of control variables will very much depend on how many locations to experience the load curtailment process. Other than that, the sizing of load to be curtailed needs to be randomized as well, which will involve the real and reactive power values on the random locations. For three locations to experience load curtailment, nine variables will be generated to represent 3 locations, 3 variables to be assigned as the real power to be curtailed and 3 variables to be assigned as the reactive power to be curtailed. In general, the control variables would be generally written as:

$$l = [x_{i1}\ x_{i2}\ x_{i3}\ \ldots.\ x_{ik},\ P_{i1},\ P_{i2},\ \ldots\ P_{ik},\ Q_{i1},\ Q_{i2},\ \ldots.\ Q_{ik}] \tag{1}$$

The symbol i denotes the number of individuals, k denotes the number of control variables for each category namely the locations, real power, P and reactive power, Q to be curtailed in achieving the minimum fitness. In this study, it is the power loss equation, if the objective function is the minimization of total transmission loss, i.e. *min(transmission loss)*. Mathematically, the loss equation and objective function can be written by: -

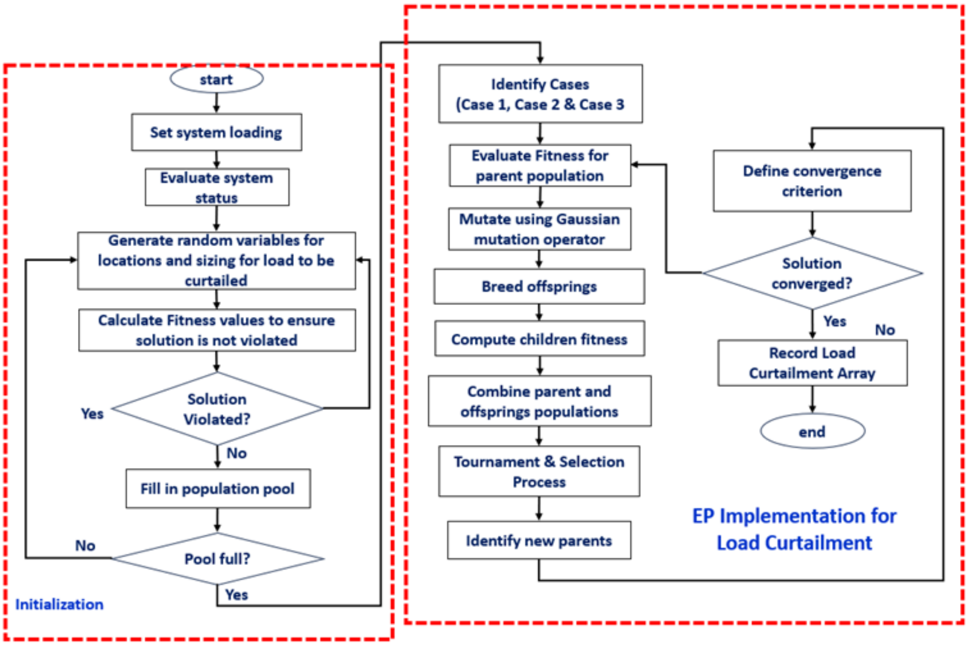

Figure 1: Intelligent Load Curtailment Using EP

$$P_{tot\_loss} = (I_1^2R_1 + I_2^2R_2 + I_3^2R_3 + \ldots.. + I_n^2R_n) \qquad (2)$$

Objective function,

$$O.F. = min(P_{tot\_loss})$$

$$= \min (I_1^2R_1 + I_2^2R_2 + I_3^2R_3 + \ldots.. + I_n^2R_n) \qquad (3)$$

For this study, setting a system loading is important to know the initial status of the system in terms of voltage value, loss, loading condition and its current limit of the power system network. Evaluation of system status gives ideas to the optimizer on how much the system can be subjected to load variation and how many load variation can be conducted during the study. We will also know whether the system is in a secure condition, critical or insecure for further load increment. In this initialization part, an array is formed to record the individuals which satisfied the constraints involving the inequality and equality constraints.

EP Implementation for Load Curtailment:

In the second part of Figure 1, EP is implemented to optimize the locations and sizing of both real and reactive power to be curtailed at the randomized locations generated in the first place. These individuals are called the parents which consist of all the control variables such as the locations and sizing, P_{dk} and Q_{dk}. These individuals will undergo mutation process which breeds new individuals, called the offsprings or children. The matrix size is the same as those of the parent population. Mutation process is executed using the Gaussian mutation operator which can be referred to several previous studies [ref…]. The Gaussian mutation operator is given by: -

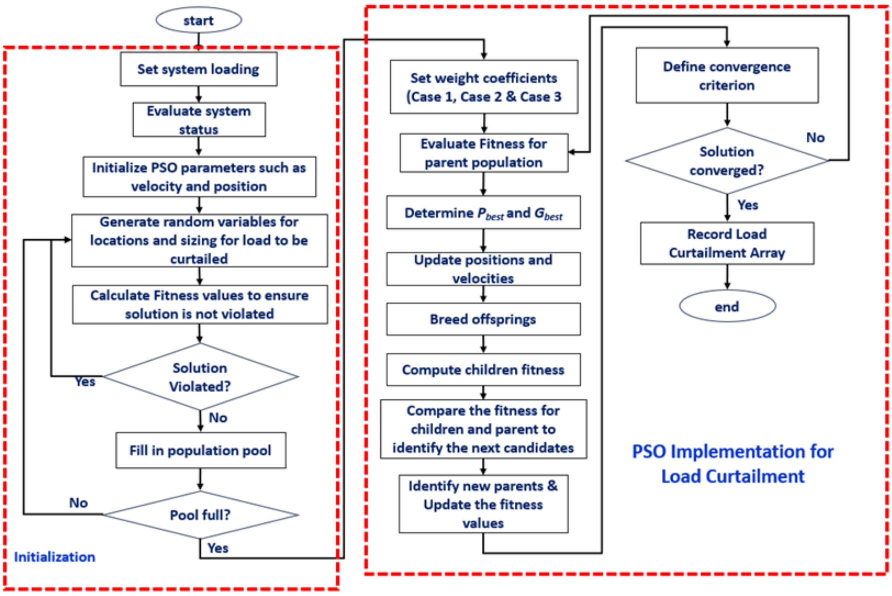

Figure 2: Intelligent Load Curtailment Using PSO

$$X_{i+m} = X_{i,j} + N(0, \beta(X_{j\max} - X_{j\min}) \cdot \frac{f_i}{f_{\max}}) \qquad (4)$$

Once offsprings have been bred, recalculation of fitness values using the offsprings is conducted to see the effect of mutation process. The next process to be done is the combination of the parent's population and the offsprings population with their corresponding fitness values. This process makes the total number of individuals double. If the initial parent's population has a size, let say 20 rows by 9 columns; the population size for the combined population is 40 rows by 9 columns. Number of columns denoted the number of control variables. Upon completion of the combination process, tournament and selection is implemented to identify the survivors for the next evolution. These survivors become the parents for the next evolution. The stopping criterion is determined by the difference between the maximum and minimum fitness, which normally set to be less than 0.0001. This can be mathematically given by: -

$$Fit_{max} - Fit_{min} < 0.0001 \qquad (5)$$

A converged solution will result in identical individuals for each control variable. That means, only one value is obtained for each control variable. This also leads to the identical value for fitness.

C. Particle Swarm Optimization (PSO)

The intelligent load curtailment scheme using PSO is illustrated in Figure 2. As explained in the previous section for EP, the intelligent load curtailment using PSO is also sub-divided into 2 main parts as can be seen in the figure.

PSO Initialization Part:

In the initialization part, the same process is conducted. In the initialization part, several processes are conducted such as the setting of system loading, evaluation of system status and random number generation. It is then followed by the filling up process of the population pool. A random generator determines both the locations and the amount of power to be curtailed during load when the system is subjected to load variation. Apparently, the number of control variables will very much depend on how many locations to experience the load curtailment process. Other than that, the sizing of load to be curtailed needs to be randomized as well, which will involve the real and reactive power values on the random locations. For three locations to experience load curtailment, nine variables will be generated to represent 3 locations, 3 variables to be assigned as the real power to be curtailed and 3 variables to be assigned as the reactive power to be curtailed. In general, the control variables would be generally written as: l = [x_{i1} x_{i2} x_{i3} …. x_{ik}, P_{i1}, P_{i2}, … P_{ik}, Q_{i1}, Q_{i2}, …. Q_{ik}]. The symbol *i* denotes the number of individuals, k denotes the number of control variables for each category namely the locations, real power, P and reactive power, Q to be curtailed in achieving the minimum fitness. In this study, it is the power loss equation, if the objective function is the minimization of total transmission loss, i.e. *min(transmission loss)*. In this technique, PSO parameters such as the velocity and positions are initialized.

PSO Implementation for Load Curtailment:

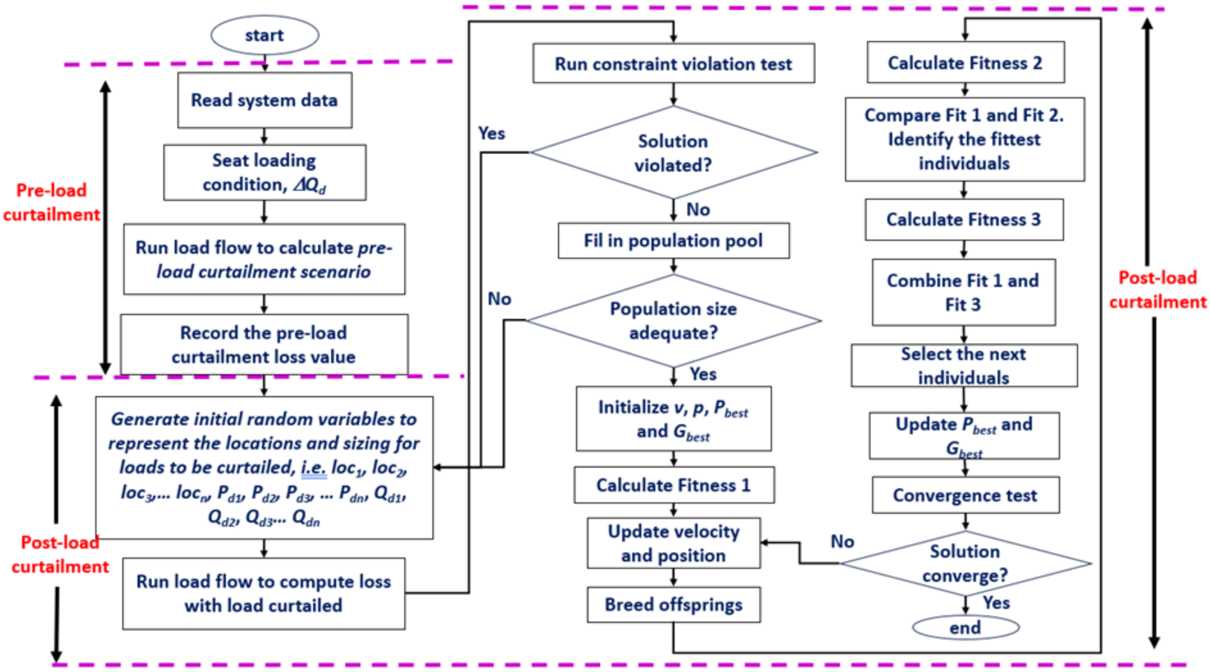

Figure 3: Intelligent Load Curtailment Using ERSEP

This process begins with the identification of cases, namely Case 1, Case 2 and Case 3. In these cases, the weight coefficients are also initialized as the raw data to the PSO optimization parameters. Evaluation of fitness is subsequently conducted to utilizing the parents' population. The personal best, P_{best} and global best, G_{best} are then identified using the individuals available in the parents' population. The next process is the updating of the position and velocities of each individual in the parents' population. This will then be followed by the breeding process of the children or offsprings. The updating process for velocity and position is conducted based on the following equation: -

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{6}$$

$$V_i^{t+1} = wV_i^t + c_1r_1(P_{\text{best}} - X_i^t) + c_2r_2(G_{\text{best}} - X_i^t) \tag{7}$$

where v is the velocity, w is the inertia weight, P_{best} is personal best of particle, G_{best} is global best values of the particles, c_n is acceleration coefficients and X_i is the position of i_{th} value.

Recalculation of fitness values utilizing the offspring needs to be conducted to see the updated fitness values once offsprings have been bred. To identify the updated candidates or individuals, a comparison of fitness values for each individual number in both the parents and offsprings population will be conducted. The updated parents and the corresponding fitness values will be subsequently identified and calculated. The convergence criterion set in this algorithm will determine whether the optimization needs to be stopped or return to the fitness calculation again as shown in the figure. A converged solution will exhibit all the individuals for each variable to be identical. That means if the number of individuals is 20 for x_1, then all these individuals will be similar. This happens to other control variables as well. The fitness values for all the individuals will also be identical, which makes the difference between the minimum and maximum fitness values to be less than 0.0001 or any small value closer to zero. This can also be referred to as equation (4).

III. OVERVIEW OF THE PROPOSED METHOD

Embedded Real Swarm Evolutionary Programming (ERSEP) is a newly developed optimization algorithm that combines the strength of EP and PSO. The population of parameters which have their velocities and positions are updated using PSO equation. The EP segment of this algorithm comes from the combination and selection process for the next iteration. The benefit of this hybridization is that the combination process of EP takes less time to find the optimal positions and velocities for next iterations and the PSO mutation process can find the optimum solution faster than the gaussian equation. The Intelligent Load Curtailment Scheme Using the proposed ERSEP is illustrated in Figure 3. This figure presents the whole algorithm in 2 main parts namely the pre-load curtailment and post-load curtailment.

ERSEP During Pre-Load Curtailment

The first part of the proposed ERSEP intelligent load curtailment algorithm describes the condition of a power system before any load curtailment is conducted, looking at the status of the system. In this phase, normal load flow is conducted to the system to observe the status of the system. The status of voltage level, total transmission power loss and minimum voltage are recorded in this phase. To emulate a disturbance, the system can be subjected to load increment at any chosen load bus or even uniform increment at load buses in the whole system. The initial loss is recorded and can be denoted as $Loss_{set}$ or $Loss_{init}$. This value is taken as the inequality constraint during the initialization process of ERSEP. This can be generally written mathematically as: -

$$Loss_{tot} < Loss_{init} \tag{8}$$

Any total power loss computed during the initialization process will be considered as a failure to the generated candidates or individuals. This will be explained again in detail in the second part of this algorithm. The initial fitness value to indicate the status of the system can be chosen based on the desired objective function. If the load curtailment initiative is meant to control or minimize the total power loss, then the initial fitness value is the $Loss_{init}$; while V_{min} can be taken as the initial preset fitness value if the objective is to maximize the minimum voltage in the system. However, if the optimization process requires to consider both properties, then multi-objective optimization is the best option.

ERSEP During Post-Load Curtailment

In the post-load curtailment part, several steps need to be conducted so that the intelligent load curtailment scheme is successfully established which eventually should manage to identify the locations, sizing of both the real and reactive power to be curtailed at the optimized locations. These are intelligently achieved through the implementation of the proposed ERSEP. To get a detailed understanding, let us go through the following procedural steps to describe the detailed process for post-load curtailment algorithm.

Step 1: Generate initial random variables: In this step, random variables are generated to represent the locations, sizing of load power to be curtailed. In this study, since three load buses are planned for the load curtailment scheme, nine variables will be required with size of population of 20. This is also called as 20 individuals for each random variable. If 3 load buses are randomly planned for the load shedding scheme, then the general equation for this step can be represented by: -

$$A = \begin{bmatrix} l_{11}\ l_{12}\ l_{13} & P_{d11}\ P_{d12}\ P_{d13} & Q_{d11}\ Q_{d12}\ Q_{d13} \\ l_{21}\ l_{22}\ l_{23} & P_{d21}\ P_{d22}\ P_{d23} & Q_{d21}\ Q_{d22}\ Q_{d23} \\ l_{31}\ l_{32}\ l_{33} & P_{d31}\ P_{d32}\ P_{d33} & Q_{d31}\ Q_{d32}\ Q_{d33} \\ \dots\dots\dots\dots\dots & \dots.\dots.\dots. & \dots.\dots.\dots. \\ l_{k1}\ l_{k2}\ l_{k3} & P_{dk1}\ P_{dk2}\ P_{dk3} & Q_{dk1}\ Q_{dk2}\ Q_{dk3} \end{bmatrix} \tag{9}$$

L_{11} is the first individual for the first location, L_{21} is the second individual for the first location and L_{k1} is the k^{th} individual for the first location. L_{12} is the first individual for the second location and L_{k1} is the k^{th} individual for the second location. Same understanding can be applied for other symbols for locations. P_{d11} is the first individual for the first P_d or amount of real power to be curtailed, P_{d21} is the second individual for the first P_d and P_{dk1} is the

k^{th} individual for the first P_d. P_{d12} and P_{d13} represent the first individual for the second and the third P_d values respectively. P_{dk3} is the k^{th} individual for the third P_d variable. Similarly, Q_{d11} is the first individual for the first Q_d or amount of reactive power to be curtailed, Q_{d21} is the second individual for the first Q_d and Q_{dk1} is the k^{th} individual for the first Q_d. Q_{d12} and Q_{d13} represent the first individual for the second and the third Q_d values respectively. Q_{dk3} is the k^{th} individual for the third Q_d variable.

Step 2: Calculate fitness value: In this step, fitness value is calculated utilizing all the individuals contained in the parents' population. In this step, the fitness value is the power loss for the system, which makes used equation (2). Since we have 20 individuals during the random number generation (called as initialization process); then, there will be 20 independent fitness values computed in this step. All the fitness values are tested using the constraint violation test, which ensures that all fitness values are less than the pre-determined inequality quality constraint. In this case, the inequality constraint is $P_{loss}<Loss_{init}$. 20 passed individuals sets containing all the control variables, which satisfied the inequality constraint will make sure the population pull is filled.

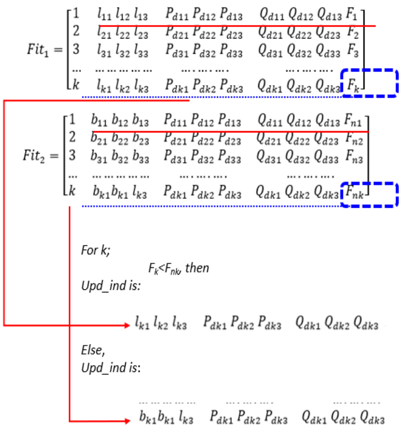

Figure 4: Comparison of fitness to derive updated individuals.

Step 3: Initialize v, p, P_{best} and G_{best}: The initialized velocity, v and initialized position, p will be later utilized for the next process. Pbest contains all the individuals with the top fitness values, which may have the matrix size of [20 rows by 9 columns], while the P_{best} is only considered the individuals that give the top fitness value. In this case, the best fitness is the lowest power loss value.

Step 4: Calculate Fitness 1: In this step, fitness values are calculated utilizing all the P_{best} values. The matrix size remained the same, but it will become [20 rows by 11 columns] if one column is used to note the individual number and the other column is meant for the fitness value.

Step 5: Update Velocity and Breed Offsprings: At this stage, velocity and position for each individual is calculated. In general, equations (6) and (7) can be used to do this. However, since we have 9 control variables, then we will have 9 derived equations to perform the updating process for the velocity and position. The offsprings are consequently bred from this process. The offsprings which represent the location need to make sure that the new individuals are all integers because they are locations. In the implementation, a simple if-then rule needs to be considered, where if location is greater than 30 or less than 1, then the previous individuals are considered as the offsprings.

Step 6: Calculate Fitness 2 and Comparison of Fit 1 and Fit 2: Fitness values are recalculated utilizing all the updated individuals. The matrix size remained the same as in Step 4. These values are normally slightly different as compared to the ones computed in Step 4. Subsequent comparison for each individual number is conducted between the fitness in Fitness 1 and Fitness 2. Let say, if Fitness 1 for individual 1 is lower than the value of Fitness 2 for individual 1, then all the first individuals are considered as the updated individual 1. On the other hand, if the value of Fitness 1 is higher than the value of Fitness 2 for individual 1, then all individuals 2 are taken as the updated individual. This is illustrated in Figure 4.

Step 7: Calculate Fitness 3: New fitness values are calculated using the updated individuals. The size of this population is going to be the same as those for Fitness 1 and Fitness 2.

Step 8: Combine Fitness 1 and Fitness 3: The population for Fitness 1 and Fitness 3 are combined which eventually makes the combined population double. This process learns the total individuals and evaluates the corresponding fitness values so that fit individuals can later be derived from here.

Step 9: Update P_{best} and G_{best}: The values for P_{best} and G_{best} are updated, derived from the combined population between Fitness 1 and Fitness 3.

Step 10: Convergence Test: This process determines the stopping criterion for the whole optimization process. Similar stopping criterion as those discussed in PSO and EP is implemented here. It is set based on the difference between the minimum and maximum fitness value to be less than 0.0001 or any small value closer to zero. If the solution converged, then the optimal solution will exhibit identical values for each control variable. The fitness values will also be identical.

IV. Results and discussion

The results of this study are presented and discussed in this section. The proposed ERSEP was validated on IEEE 30- RTS. The study was conducted on 3 cases for the sake of comparison which are:

- Case 1: Load curtailment when reactive load was subjected at Bus 30.
- Case 2: Load curtailment when reactive load was subjected at Bus 20.
- Case 3: Load curtailment when reactive load was subjected at Bus 26.

Case 1: Load Variation at Bus 30

Table 1 tabulates the results for load curtailment when reactive load was subjected to Bus 30. The result for P_d and Q_d to be curtailed are shown in this table. Reactive power loading at Bus 30 was varied from 5 MVAR to 25 MVAR increment. In general, load curtailment has made the total loss reduced. The control variable, $x1$, $x2 \ldots x6$ represent P_{d1}, Q_{d1}, P_{d2}, Q_{d2} and P_{d3}, Q_{d3}. These variables are real and reactive powers to be curtailed in the system to reduce the total loss. The amount of power to be curtailed is shown in Table 1, while the optimal location is tabulated in Table 2. For instance, at Q_{d30} = 20 MVAR, 53.7304 MW and 17.8328 MVAR need to be curtailed at Bus 27, 46.7917 MW and 15.3720 MVAR need to be curtailed at Bus 18 and 28.7212 MW and 57.1655 MVAR need to be curtailed at Bus 21. These are results when the problem was optimized using EP. Using ERSEP, 43.3781MW and 8.4353 MVAR need to be curtailed at Bus 21, 55.5421 MW and 72.4823 MVAR need to be curtailed at Bus 12 and 95.9427 MW and 9.5563 MVAR need to be curtailed at Bus 5. The results can be observed from the same table. In general, the proposed ERSEP technique managed to achieve lower optimal loss over the traditional EP.

Table 2: Case 1: Load curtailment Location at load variation Q_{d30}

Techs						
EP	Q_{d30} (MVAR)	5	10	15	20	25
	Loc_1	17	17	17	27	27
	Loc_2	5	5	5	18	18
	Loc_3	21	21	21	21	21
PSO	Q_{d30} (MVAR)	5	10	15	20	25
	Loc_1	4	6	8	11	21
	Loc_2	12	4	5	12	28
	Loc_3	8	1	2	7	29
ERSEP	Q_{d30} (MVAR)	5	10	15	20	25
	Loc_1	4	7	28	21	12
	Loc_2	8	11	21	12	10
	Loc_3	15	5	5	5	5

Table 1: Case 1: Load curtailment sizing with variation at Q_{d30}

Technique						
	Q_{d30}	5	10	15	20	25
	P_{d1}(MW)	41.5816	41.5834	41.5826	53.7304	53.7304
	P_{d2} (MW)	70.0996	70.0994	70.1008	46.7917	46.7917

EP	P_{d3} (MW)	91.0182	91.0172	91.0164	28.7212	28.7212
	Q_{d1} (MVAR)	76.1928	76.1861	76.1848	17.8328	17.8328
	Q_{d2} (MVAR)	26.2258	26.2253	26.2223	15.372	15.372
	Q_{d3} (MVAR)	4.712	4.7152	4.7144	57.1655	57.1655
	Loss set (MW)	17.7038	18.101	18.109	19.5484	20.9266
	Loss (MW)	5.4468	5.7485	5.7485	**9.221**	9.8164
	Q_{d30}	5	10	15	20	25
PSO	P_{d1}(MW)	59.034	165.7502	86.5406	52.58	51.7738
	P_{d2} (MW)	125.8641	54.0327	63.4133	23.3965	63.0342
	P_{d3} (MW)	24.6989	49.3545	5.941	34.5895	15.8698
	Q_{d1} (MVAR)	94.3353	34.7082	7.4344	24.4668	24.1287
	Q_{d2} (MVAR)	63.3324	41.3007	19.4358	8.6626	30.6393
	Q_{d3} (MVAR)	76.8714	75.095	95.9517	3.6704	54.1625
	Loss set (MW)	17.7038	18.1091	18.666	19.5484	20.9265
	Loss (MW)	2.1966	4.9986	5.4034	**8.9742**	9.6013
	Q_{d30}	5	10	15	20	25
ERSEP	P_{d1}(MW)	91.2093	3.102	12.4462	43.3781	38.2042
	P_{d2} (MW)	55.206	35.2406	82.6677	55.5421	29.0214
	P_{d3} (MW)	46.4663	89.4951	96.3823	95.9427	49.2307
	Q_{d1} (MVAR)	58.7575	44.1618	97.1485	8.4353	2.7661
	Q_{d2} (MVAR)	37.2478	28.1911	75.436	72.4823	46.1259
	Q_{d3} (MVAR)	23.8522	7.2359	53.2105	9.5563	56.1433
	Loss set (MW)	17.7038	18.1091	18.666	19.5484	20.9265
	Loss (MW)	5.8125	5.8553	5.7912	**5.0656**	9.2862

EP only managed to reduce the transmission loss from 19.5484 MW to 9.2210 MW, while ERSEP reduced this value to 5.0656 MW. On the other hand, PSO managed to reduce this value to 8.9742 MW. This implies that ERSEP is much superior to EP and PSO to achieve the lowest minimal loss in the system with the 3-load curtailment scheme. This leads to 52.83% loss reduction solved by EP, 54.09% solved by PSO and 74.09% by ERSEP. ERSEP exhibits outstanding results over EP and PSO. The detailed results for other load conditions can be referred to in the same table.

Case 2: Load Variation at Bus 20

Table 3: Case 2: Load curtailment sizing with variation at Q_{d20}

Techniques	Q_{d20}	5	10	15	20	25
EP	P_{d1}(MW)	53.7304	53.7304	8.3582	53.7304	53.7304
	P_{d2} (MW)	46.7917	46.7917	22.8656	46.7917	46.7917
	P_{d3} (MW)	28.7212	28.7212	91.3029	28.7212	28.7212
	Q_{d1} (MVAR)	17.8328	17.8328	15.2133	17.8328	17.8328
	Q_{d2} (MVAR)	15.372	15.372	82.5537	15.372	15.372
	Q_{d3} (MVAR)	57.1655	57.1655	53.8095	57.1655	57.1655
	Loss set (MW)	17.7175	17.868	18.997	20.2516	22.2671
	Loss (MW)	8.0779	8.302	10.2324	**9.5719**	10.6863
	Q_{d20}	5	10	15	20	25
PSO	P_{d1}(MW)	55.2317	80.5998	74.6123	68.8214	42.09
	P_{d2} (MW)	40.4739	40.27	38.9855	48.2335	35.4136
	P_{d3} (MW)	27.3134	17.9365	9.8621	7.9231	41.4853
	Q_{d1} (MVAR)	7.0532	57.9475	36.6255	12.1924	30.4782
	Q_{d2} (MVAR)	10.7121	24.4618	21.5567	35.7783	4.1789
	Q_{d3} (MVAR)	44.9252	29.8907	9.3649	12.2953	1.1806
	P_{d1}(MW)	17.7175	18.2298	18.9997	20.2516	22.2671
	P_{d2} (MW)	5.8282	8.4195	8.1583	**9.1925**	10.67
	Q_{d20}	5	10	15	20	25
ERSEP	P_{d1}(MW)	72.7061	21.6015	79.6014	24.8845	64.4042
	P_{d2} (MW)	71.4369	69.1714	61.4547	34.4363	14.8146
	P_{d3} (MW)	39.7776	73.2942	69.0014	70.6428	51.7002
	Q_{d1} (MVAR)	42.3469	56.3571	6.3473	93.0412	20.249
	Q_{d2} (MVAR)	24.3792	19.0387	78.8735	43.9556	69.6367
	Q_{d3} (MVAR)	41.3018	40.9604	26.3061	61.2684	24.0868
	Loss set (MW)	17.7175	18.2298	18.9997	20.2516	22.2671
	Loss (MW)	5.4941	4.5683	5.2717	**8.8028**	8.1079

Table 3 tabulates the results for load curtailment sizing when reactive load was subjected to Bus 20. The results for locations of loads to be curtailed are tabulated in Table 4. Reactive power loading at Bus 20 was varied from 5 MVAR to 25 MVAR. In general, load curtailment has made the total loss reduced. For instance, when three load curtailment scheme was solved using EP, at Q_{d20} = 20 MVAR, 53.7304 MW and 17.8328 MVAR need to be curtailed at Bus 27, 46.7917 MW and 15.3720 MVAR need to be curtailed at Bus 18 and 28.7212 MW and 57.1655 MVAR need to be curtailed at Bus 21. This load curtailment optimized using EP reduces the loss from 20.2516 MW to 9.5719 MW. Using ERSEP, 24.8845 MW and 93.0412 MVAR need to be curtailed at Bus 4, 34.4363 MW and 43.9556 MVAR need to be curtailed at Bus 20 and 70.6428 MW and 61.2684 MVAR need to be curtailed at Bus 5. This load curtailment reduces the loss from 20.2516 MW to 8.8028 MW. ERSEP managed to reduce the transmission loss to MW, while EP reduced it to 9.5719 MW and by PSO it is 9.1925 MW.

Table 4: Case 2: Load curtailment Location at load variation Q_{d20}

Techs						
EP	*Q_{d20} (MVAR)*	5	10	15	20	25
	Loc_1	27	27	27	27	27
	Loc_2	18	18	18	18	18
	Loc_3	21	21	21	21	21
PSO	*Q_{d20} (MVAR)*	5	10	15	20	25
	Loc_1	5	6	12	9	15
	Loc_2	7	4	5	5	5
	Loc_3	4	7	8	6	9
ERSEP	*Q_{d20} (MVAR)*	5	10	15	20	25
	Loc_1	21	5	11	4	5
	Loc_2	5	12	5	20	6
	Loc_3	8	23	4	5	15

In general, the proposed ERSEP technique managed to achieve lower optimal loss over the traditional EP and PSO. ERSEP maintains to achieve highest loss reduction worth 54.97%, while EP achieved 51.03% and PSO achieved 52.98% loss reduction. The detailed results for other load conditions can be referred to in the same table.

Case 3: Load Variation at Bus 26

Table 5 tabulates the results for load curtailment when reactive load was subjected to Bus 26. In this case, implementation of 3-load curtailment scheme managed to reduce the total transmission loss as those experienced in other cases. The results for locations of loads to be curtailed are tabulated in Table 6. Similar load increments were subjected this bus; varied from 5 MVAR to 25 MVAR. In general, load curtailment has made the total loss reduced. For instance, when three load curtailment scheme was solved using EP, at Q_{d26} = 20 MVAR, 53.7304 MW and 17.8328 MVAR need to be curtailed at Bus 27, 46.7917 MW and 15.3720 MVAR need to be curtailed at Bus 18 and 28.7212 MW and 57.1655 MVAR need to be curtailed at Bus 21. This load curtailment optimized using EP reduces the loss from 20.2516 MW to 9.5719 MW. Using ERSEP, 15.4704 MW and 36.2832 MVAR need to be curtailed at Bus 27, 139.9924 MW and 111.7017 MVAR need to be curtailed at Bus 16 and 102.0418 MW and 79.7979 MVAR need to be curtailed at Bus 15. This load curtailment reduces the loss from 20.2516 MW to 7.5007 MW. EP managed to reduce it to 9.5719 MW and PSO gives 9.1925 MW. In general, the proposed

Table 5: Case 3: Load curtailment sizing with variation at Q_{d26}

Techniques						
	Q_{d26}	5	10	15	20	25
EP	P_{d1}(MW)	41.5813	41.5834	41.5822	53.7304	53.7304
	P_{d2} (MW)	70.0997	70.1016	70.7917	46.7917	46.7917
	P_{d3} (MW)	91.0183	91.0171	91.1841	28.7212	28.7212
	Q_{d1} (MVAR)	76.1930	76.1860	76.1841	17.8328	17.8328
	Q_{d2} (MVAR)	26.2259	26.2242	26.2226	15.3720	15.3720
	Q_{d3} (MVAR)	4.7122	4.7155	4.7137	57.1655	57.1655
	Loss set (MW)	17.7175	17.868	18.997	20.2516	22.2671
	Loss (MW)	5.4456	5.5890	6.4395	9.5719	10.6863
	Q_{d26}	5	10	15	20	25
PSO	P_{d1}(MW)	55.2317	80.5998	74.6123	68.8214	42.0900
	P_{d2} (MW)	40.4739	40.2700	38.9855	48.2335	35.4136
	P_{d3} (MW)	27.3134	17.9365	9.8621	7.9231	41.4853
	Q_{d1} (MVAR)	7.0532	57.9475	36.6255	12.1924	30.4782
	Q_{d2} (MVAR)	10.7121	24.4618	21.5567	35.7783	4.1789
	Q_{d3} (MVAR)	44.9252	29.8907	9.3649	12.2953	1.1806
	P_{d1}(MW)	17.7175	18.2298	18.9997	20.2516	22.2671
	P_{d2} (MW)	5.8282	8.4195	8.1583	9.1925	10.6700
	Q_{d26}	5	10	15	20	25
ERSEP	P_{d1}(MW)	37.6722	105.6565	39.1787	15.4704	64.4042
	P_{d2} (MW)	56.2115	49.6763	35.3426	139.9927	14.8146
	P_{d3} (MW)	33.9864	35.7272	61.4511	102.0418	51.7002
	Q_{d1} (MVAR)	67.5081	37.2510	80.9558	36.2832	20.2490
	Q_{d2} (MVAR)	25.2464	36.0877	42.5506	111.7017	69.6367
	Q_{d3} (MVAR)	6.8624	49.0362	31.1839	79.7959	24.0868
	Loss set (MW)	17.7175	18.2298	18.9997	20.2516	22.2671
	Loss (MW)	3.3332	3.6078	7.0321	7.5007	8.1079

ERSEP technique managed to achieve lower optimal loss over the traditional EP and PSO. ERSEP maintains to achieve highest loss reduction worth 61.63%, while EP achieved 51.03% and PSO achieved 52.98% loss reduction.

Table 6: Case 3: Load curtailment Location with load variation Q_{d26}

Techs						
	Q_{d26} *(MVAR)*	5	10	15	20	25
EP	Loc_1	27	27	25	27	27
	Loc_2	18	18	16	18	18
	Loc_3	21	21	21	21	21
	Q_{d26} *(MVAR)*	5	10	15	20	25
PSO	Loc_1	5	17	7	9	7
	Loc_2	4	7	4	4	6
	Loc_3	7	21	11	27	22
	Q_{d26} *(MVAR)*	5	10	15	20	25
ERSEP	Loc_1	15	2	8	27	9
	Loc_2	11	5	5	16	3
	Loc_3	6	11	19	15	27

V. CONCLUSION

This paper has presented Embedded Real-Swarm Evolutionary Programming (ERSEP) for solving optimization problems which will involve load curtailment. In this study real swarm mutation operator was embedded into the EP mechanics. Results obtained from ERSEP are superior to the traditional EP and PSO in terms of achieving lower optimal solution for the study, when validated on the IEEE 30-Bus RTS. Significant results deduced from this study revealed that total transmission loss reduction worth 52.83% was achieved by EP, 54.09% solved by PSO and 74.09% by ERSEP in Case 1 for chosen load condition of 20 MVAR. In Case 2, ERSEP maintains to achieve the highest loss reduction worth 54.97%, while EP achieved 51.03% and PSO achieved 52.98%. ERSEP continues to maintain the highest loss reduction worth 61.63%, while EP achieved 51.03% and PSO achieved 52.98%. This implies that ERSEP is superior in all cases to reach the lowest minimized transmission loss. Further study can make use of proposed the ERSEP optimization engine for solving other optimization problems in power system with only simple alteration.

ACKNOWLEDGMENT

The authors would like to acknowledge the Research Management (RMC) UiTM Shah Alam, Selangor, Malaysia and the Ministry of Higher Education, Malaysia (MOHE) for the financial support of this research. This research is supported by MOHE under Fundamental Research Grant Scheme (FRGS) with project code: FRGS/1/2019/TK04/UITM/01/1 and 600-IRMI/FRGS 5/3 (381/2019).8h

REFERENCES

[1] S. M. Kiseng, C. M. Muriithi, and G. N. Nyakoe, “Under voltage load shedding using hybrid ABC-PSO algorithm for voltage stability enhancement,” *Heliyon*, vol. 7, no. 10, Oct. 2021, doi: 10.1016/j.heliyon.2021.e08138.

[2] R. M. Larik, M. W. Mustafa, M. N. Aman, T. A. Jumani, S. Sajid, and M. K. Panjwani, “An improved algorithm for optimal load shedding in power systems,” *Energies*, vol. 11, no. 7, 2018, doi: 10.3390/en11071808.

[3] V. Tamilselvan and T. Jayabarathi, “A hybrid method for optimal load shedding and improving voltage stability,” *Ain Shams Eng. J.*, vol. 7, no. 1, pp. 223–232, 2016, doi: 10.1016/j.asej.2015.11.003.

[4] S. F. A. Shukor, I. Musirin, Z. A. Hamid, M. K. M. Zamani, M. Zellagui, and H. Suyono, “Intelligent based technique for under voltage load shedding in power transmission systems,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 17, no. 1, pp. 110–117, 2019, doi: 10.11591/ijeecs.v17.i1.pp110-117.

[5] M. Moazzami, M. J. Morshed, and A. Fekih, “A new optimal unified power flow controller placement and load shedding coordination approach using the Hybrid Imperialist Competitive Algorithm-Pattern Search method for voltage collapse prevention in power system,” *Int. J. Electr. Power Energy Syst.*, vol. 79, pp. 263–274, 2016, doi: 10.1016/j.ijepes.2016.01.022.

[6] M. S. Abid, H. J. Apon, A. Ahmed, and K. A. Morshed, “Chaotic slime mould optimization algorithm for optimal load-shedding in distribution system,” *Ain Shams Eng. J.*, vol. 13, no. 4, Jun. 2022, doi: 10.1016/j.asej.2021.101659.

[7] N. N. A. Bakar, M. Y. Hassan, M. F. Sulaima, M. N. im Mohd Nasir, and A. Khamis, “Microgrid and load shedding scheme during islanded mode: A review,” *Renew. Sustain. Energy Rev.*, vol. 71, no. November 2016, pp. 161–169, 2017, doi: 10.1016/j.rser.2016.12.049.

[8] M. Ghotbi-Maleki, R. M. Chabanloo, and H. Javadi, “Load shedding strategy using online voltage estimation process for mitigating fault-induced delayed voltage recovery in smart networks,” *Electr. Power Syst. Res.*, vol. 214, Jan. 2023, doi: 10.1016/j.epsr.2022.108899.

[9] Z. Hu, Z. Shi, L. Zeng, W. Yao, Y. Tang, and J. Wen, “Knowledge-enhanced deep reinforcement learning for intelligent event-based load shedding,” *Int. J. Electr. Power Energy Syst.*, vol. 148, Jun. 2023, doi: 10.1016/j.ijepes.2023.108978.

[10] Arasteh H, Mirsaeedi H. Parallel GA-PSO Algorithm to Solve the Unit Commitment Problem. sjis 2022; 4 (3) :1-9.

[11] A. I. M. Isa, H. Mohamad, K. Naidu, N. Y. Dahlan, and I. Musirin, “Method of determining load priority using fuzzy logic for adaptive under frequency load shedding technique,” *Pertanika J. Sci. Technol.*, vol. 25, no. S, 2017.

[12] K. W. Hedman, A. S. Korad, M. Zhang, G. Thompson, A. Dominguez-Garcia, and X. Jiang, “The Application of Robust Optimization in Power Systems,” 2014.

[13] C. Wang, C. J. Miller, M. H. Nehrir, J. W. Sheppard, and S. P. McElmurry, “A load profile management integrated power dispatch using a Newton-like particle swarm optimization method,” *Sustain. Comput. Informatics Syst.*, vol. 8, pp. 1–10, 2014, doi: 10.1016/j.suscom.2014.10.001.

[14] K. Muthukumar and S. Jayalalitha, “Electrical Power and Energy Systems Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique,” *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 299–319, 2016, doi:

10.1016/j.ijepes.2015.11.019.

[15] Z. Liu, M. Liu, and W. Xia, "Energy Procedia Comparison of Multi-area Reactive Power Optimization Parallel Algorithm Based on Ward and REI Equivalent," vol. 14, no. 50777021, pp. 1580–1589, 2012, doi: 10.1016/j.egypro.2011.12.1136.

[16] K. C. Tan, C. K. Goh, A. A. Mamun, and E. Z. Ei, "An evolutionary artificial immune system for multi-objective optimization," vol. 187, pp. 371–392, 2008, doi: 10.1016/j.ejor.2007.02.047.

[17] A. H. Fathima and K. Palanisamy, "Optimization in microgrids with hybrid energy systems – A review," *Renew. Sustain. Energy Rev.*, vol. 45, pp. 431–446, May 2015, doi: 10.1016/j.rser.2015.01.059.

[18] V. K. Jadoun, N. Gupta, K. R. Niazi, and A. Swarnkar, "Modulated particle swarm optimization for economic emission dispatch," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 80–88, Dec. 2015, doi: 10.1016/j.ijepes.2015.04.004.

[19] B. Bhattacharyya and V. K. Gupta, "Fuzzy based evolutionary algorithm for reactive power optimization with FACTS devices," *Int. J. Electr. Power Energy Syst.*, vol. 61, pp. 39–47, Oct. 2014, doi: 10.1016/j.ijepes.2014.03.008.

[20] I. Musirin, "Power engineering and optimization," *Int. J. Simul. Syst. Sci. Technol.*, vol. 17, no. 41, 2017, doi: 10.5013/IJSSST.a.17.41.00.

[21] Z. A. Hamid, I. Musirin, and S. H. M. Kerta, "An approach on non-discriminatory losses charge allocation for deregulated power market using meta-heuristic-optimization-based-electricity-tracing (MOET)," *Int. Rev. Electr. Eng.*, vol. 12, no. 2, 2017, doi: 10.15866/iree.v12i2.11295.

[22] N. A. Rahmat, I. Musirin, and A. F. Abidin, "Differential Evolution Immunized Ant Colony Optimization Technique (DEIANT) in solving economic dispatch by considering prohibited operating zones," in *Proceedings of the 2014 IEEE 8th International Power Engineering and Optimization Conference, PEOCO 2014*, 2014. doi: 10.1109/PEOCO.2014.6814472.

[23] N. Kassim, S. I. Sulaiman, Z. Othman, and I. Musirin, "Harmony search-based optimization of artificial neural network for predicting AC power from a photovoltaic system," in *Proceedings of the 2014 IEEE 8th International Power Engineering and Optimization Conference, PEOCO 2014*, 2014. doi: 10.1109/PEOCO.2014.6814481.

[24] N. A. Rahmat, I. Musirin, and A. F. Abidin, "Differential Evolution Immunized Ant Colony Optimization (DEIANT) technique in solving economic emission dispatch," in *Proceedings of 2013 International Conference on Technology, Informatics, Management, Engineering and Environment, TIME-E 2013*, 2013. doi: 10.1109/TIME-E.2013.6611991.

[25] S. A. Jumaat, I. Musirin, M. M. Othman, and H. Mokhlis, "A hybrid meta-heuristics optimization technique for loss minimization and cluster identification in power system network," in *Proceedings of the 2014 IEEE 8th International Power Engineering and Optimization Conference, PEOCO 2014*, 2014. doi: 10.1109/PEOCO.2014.6814493.

[26] S. A. Jumaat, I. Musirin, M. M. Othman, and H. Mokhlis, "Evolutionary Particle Swarm Optimization (EPSO) based technique for multiple SVCs optimization," in *PECon 2012 - 2012 IEEE International Conference on Power and Energy*, 2012. doi: 10.1109/PECon.2012.6450202.

[27] N. A. Rahmat, I. Musirin, A. F. Abidin, and M. R. Ahmad, "Economic load dispatch with valve-point loading effect by using differential evolution immunized ant colony optimization technique," in *2014 Australasian Universities Power Engineering Conference, AUPEC 2014 - Proceedings*, 2014. doi: 10.1109/AUPEC.2014.6966560.

[28] N. I. Abdul Aziz, S. I. Sulaiman, S. Shaari, and I. Musirin, "New technique for sizing optimization of a stand-alone photovoltaic system," *J. Theor. Appl. Inf. Technol.*, vol. 67, no. 2, 2014.

[29] Z. Hamid, I. Musirin, M. N. A. Rahim, and N. A. M. Kamari, "Effective power scheduling via Blended Crossover Continuous Ant Colony Optimization," in *International Conference on ICT and Knowledge Engineering*, 2011. doi: 10.1109/ICTKE.2012.6152415.

[30] S. A. Jumaat, I. Musirin, M. M. Othman, and H. Mokhlis, "Optimal location and sizing of SVC using particle swarm optimization technique," in *Proceedings - 1st International Conference on Informatics and Computational Intelligence, ICI 2011*, 2011. doi: 10.1109/ICI.2011.58.