Integrated Immune Chaotic Evolutionary Programming (IICEP) for Integrating Battery Energy Storage System in Transmission Network

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***Abstract*—Energy consumption has experienced significant growth on a global scale in the past decade. This has caused the growing demand of renewable energy resources into grid systems which has led to the need for technological solutions that can improve the stability of power systems. Electrical transmission network is an essential component for effectively and reliably transporting electricity. However, they are prone to power losses, which reduce overall system efficiency and raise operational expenses. Any remedial action to include compensating devices into the current system will require optimal sizing and sizing so as to avoid any over-compensation or under-compensation phenomena. This research investigates an approach of mitigating these losses by incorporating Battery Energy Storage Systems (BESS) into the transmission network. BESS is known to be a promising technology, providing several advantages such as peak shaving, load leveling, and improved grid stability. The purpose of this study is to find the optimal location and sizing of battery energy to minimize loss dissipated by the system using a newly proposed technique termed Integrated Immune Chaotic Evolutionary Programming (IICEP). IICEP is proposed to integrate BESS into the transmission network with a focus on loss minimization. IICEP integrates the operators of clonal features of Artificial Immune System (AIS) with the addition of a chaotic element into the original Evolutionary Programming (EP). It offers a better solution in optimization performance. Three battery energy storages are integrated into the network, each with the placement and sizing to meet the goal. The algorithm of IICEP is tested on IEEE 30- Bus RTS to observe its effectiveness. The results are compared with the traditional EP and AIS, resulting in a lower optimal solution of power losses.**

Keywords*—Battery Energy Storage System (BESS), optimization process, loss minimization, Immune Chaotic Evolutionary Programming (IICEP)

I. INTRODUCTION

Since the twenty-first century, worldwide electricity consumption has grown even faster, with an average annual increase of 3.4 percent, 1.2 percentage points greater than energy consumption's average annual growth [1]. The energy landscape is experiencing a major shift due to the rising demand of electricity, the incorporation of renewable energy sources, and the need for environmentally friendly practices. Installing battery energy storage systems (BESS) is an important approach in power scheduling to increase the network's energy efficiency. Besides, it also provided numerous benefits such as improved power quality, lower operating, and maintenance costs, and many more [2].

In transmission network, the existence of energy storage can relieve transmission congestion and deferral transmission upgrades [3]. Deferring transmission upgrade investments involves postponing utility investments by utilizing modest quantities of storage capacity or in certain instances, by completely skipping such investments. Transmission congestion occurs when energy from dispatched power plants is unable to reach all or some loads due to insufficient transmission facilities. Transmission systems become congested when transmission capacity increases and do not keep pace with the increase in peak electric demand. Electricity storage can be used to minimize congestion-related expenses and charges, particularly if the costs become prohibitively expensive due to severe transmission line congestion. In addition, the appropriate placement, sizing and operation of BESS can improve overall network performance.

The integration of energy storage can be made more efficient and effective by using optimization techniques. Optimization is the process of searching for the best possible solution for a particular problem, under given circumstances. It aims to maximize or minimize a fitness function by searching and selecting its best values [4]. Optimization techniques have long been recognized as useful methods for dealing with complicated mathematical issues. To address the shortcomings of traditional algorithms, many stochastic optimization algorithms known as meta-heuristic algorithms have been created in recent decades [5].

This paper proposes a new integrated optimization technique which made use the chaotic element and clonal process, embedded in EP to allocate and identify the size of energy storage systems into the transmission network. Optimization algorithms are utilized to find the optimal combination of battery locations and sizes for minimizing power loss. Performance evaluation was conducted by comparing the results solved using proposed IICEP with respect to the traditional EP and AIS. It is fair to highlight that the results of BESS installation for reducing the loss in power transmission system solved using IICEP are convincing.

II. PROBLEM FORMULATION

The integration of BESS into the transmission network requires an excellent strategy to ensure the reliability and steadiness of power transmission. First step is to find the best location and sizing of battery energy storages. The objective of this new technique is to search for the optimal location and sizing of battery energy storages in transmission network with focusing on loss minimization. In this case, the criteria used to determine the location and sizing of BESS include the resistance, distance and network topology. The range of battery capacity is set below than 200MW, the best possible value is targeted below than 100MW. Three battery storage units are inserted into the system, which means three possible locations and three battery sizes must be chosen.

The objective function of this optimization is set to minimize the total system loss which can be mathematically presented in eqn. (1) [6]. By applying the Newton-Raphson method, the precise voltage and phase angle at each bus are determined, allowing for accurate calculation of line currents and line losses. Thus, the objective function can be written by:

$$Minimize \sum_{i=1}^{n} P_{loss,i} \tag{1}$$

where:

- n is the number of lines in the system
- P_{loss} is the power loss at i

The power loss calculation is represented by the following formula:

$$P_{loss} = I^2 \times R \tag{2}$$

where:

- P_{loss} is the real power loss in MW
- I is the current flowing through the line in Amperes
- R is the resistance of the line in Ohms

III. OPTIMIZATION TECHNIQUE

There are several optimization strategies that have been developed and proposed for power network planning. On the same problem, certain optimization strategies have proven to be more effective than others [7]. After a brief studied and reviewed, the following techniques have been chosen to be integrated to produce IICEP.

A. Evolutionary Programming

Evolutional Programming (EP) is one of the pioneer approaches to the application of evolutionary techniques to machine learning and to the automatic design of artificial intelligence systems [8]. EP algorithm uses only a mutation operator, making it less susceptible to the dependency violation issue [9]. EP techniques can be presented in three distinct EP models: classical evolutionary programming (CEP), fast evolutionary programming (FEP), and improved fast evolutionary programming (IFEP). FEP was reported to exhibit the shortest computational time [10]. Later, various multi-objective of EP was developed to minimize the multi-objective functions and to determine the optimal location and sizing of Distributed Generation [11]. EP works with the principle involving initialization, fitness computations in two-phases, mutation, tournament selection and combination. The initial population is confined by several random variables within a set of individuals. The number of individuals is conventionally 20 as this amount is considered adequate to allow proper search during the optimization process. The control variables depend on how many BESS is planned to be installed into the system. For instance, in this study six control variables are required to denote 3 locations and 3 BESS sizing.

The fitness computation deals with the evaluation of loss, utilizing all the individuals inserted into the system data. Fitness computations are conducted in 2 phases. The first phase utilizes the parents' population, while the other one uses the offsprings. Offsprings are bred through mutation process. The Gaussian mutation process was the most popular mutation technique. Other than this, Levy or Cauchy mutation technique can also be adopted.

Once the fitness computations in both phases have been conducted, a combination needs to be performed which integrates both populations in cascode mode, which in turns doubles the number of individuals. In this case, it would be 40. A subsequent tournament selection process is conducted to identify the survivors for the next evolution. The stopping criterion is determined by evaluating the difference between the maximum and minimum fitness values. This value needs to be less than a pre-defined criterion. This value is normally small, typically 0.0001. The process keeps on iterating until a converged solution is achieved.

B. Artificial Immune System

Artificial Immune System (AIS) is a computational system that is adaptive and diversified, based on the principles of the natural immune system [12]. The natural immune system is an intelligent pattern recognition system that is capable of classifying all cells in the body as self-cells or nonself-cells.

The immune system employs the clonal selection principle as an algorithm to define the fundamental characteristics of its immunological response to an antigenic stimulus [13]. The clonal selection principle is used in power optimization to create a set of candidate solutions known as antibodies. These antibodies indicate potential power optimization options, with each antibody consisting of a unique configuration or set of adjustable parameters. These antibodies are subjected to a selection and mutation process during the optimization process, simulating the immune system's natural selection and diversification mechanisms. This strategy is more accurate since it gets closer to the perfect solution with each iteration [14].

Similar to previous EP, Gaussian distribution mutation has been selected to perform mutation process for these two techniques. The main difference between EP and AIS is that EP has combination process, but in AIS. On the other hand, AIS has cloning process, but not in EP.

C. Integrated Immune Chaotic Evolutionary Programming

The design of IICEP involves step-by-step procedure starting with initialization process until finding the best combination result of right location and sizing to get better loss profile. The algorithm is coded with a focus on employing advanced computational and techniques to solve the complexity of power system optimization.

IICEP concept of optimization is created based on EP and AIS techniques with an addition of chaotic sequence. The IICEP algorithm aims to locate energy storage placements to greatly reduce grid energy losses. The Piecewise Linear

Chaotic Map (PLCM) is adopted in this technique due to its simplicity, efficiency and good dynamic behaviour. The PLCM is denoted by (3) given below:

$$cv_{new} = \begin{cases} \frac{cv_i}{p}, 0 \leq cv_i < p \\ \frac{cv_i - p}{0.5 - p}, p \leq cv_i < 0.5 \\ \frac{(1-9-cv_i)}{0.5-p}, 0.5 \leq cv_i < (1-p) \\ \frac{1-cv_i}{p}, (1-p) \leq cv_i < 1 \end{cases} \quad (3)$$

where:

- cv_i is the initial chaotic variable at iteration 0
- p is the control parameter

For this study, p = 0.4 is chosen as suggested in [15]. The update of the chaotic variable, cv_{new} is used in the mutation process in IICEP to breed new individuals called the offsprings.

IV. Result And Discussion

The effectiveness of the proposed technique is validated on IEEE 30-Bus RTS. The procedure begins with running power flow analysis to get the loss set without the installation of BESS. Power flow analysis computes the voltage magnitude and phase angle at each bus in a power network under steady-state conditions. These calculations are necessary to determine the flow of electrical power from producers to consumers while keeping the network operating within safe and stable limits. Once the power flow solution has been determined, the power losses in the transmission lines can be computed. After that, the procedure continues with initialization process to get 20 random combinations of location and sizing of three battery energy storage with its loss profile which need to be lower than the loss during the normal load flow process without BESS installation. To ensure the effectiveness of IICEP, the same combinations or energy storage are also tested using EP and AIS Algorithm. The results of the testing are presented below.

A. Random Plot during Initialization at Q_{d26} = 30 MVAR

Fig.1 shows the random plot of the locations and size of all batteries during initialization process. The locations and sizes of all BESS are scattered randomly within the limit set of 200MW for the batteries. We can notice that all the plots of the individuals in random are not converging towards a particular point. But all the individuals ensure that the computed fitness values during initialization process are lower than the $loss_{set}$ during the normal load flow.

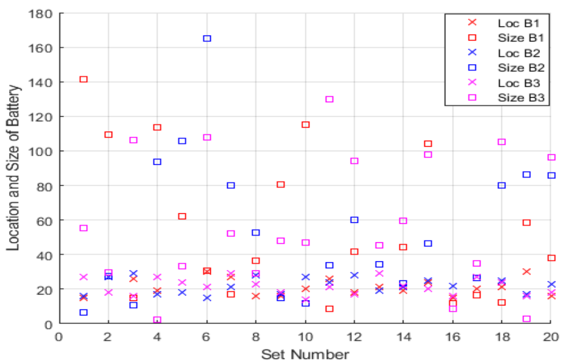

Fig. 1 BESS Initialization.

B. Converged Solution

The performance of all the three optimization techniques is observed when load variations were subjected to Bus 26 and Bus 29. These two buses have both been identified as weak buses in power system analysis as it can contribute to voltage collapse in this system [16]. To ensure the new algorithm can be used effectively, the two bus values were selected for the testing process. The reactive power of 30 MVAR is used for all cases.

1) Scatter Plot at Q_{d26}=30 MVAR

The scatter plots showing the optimal location and sizing of all batteries optimized using EP, AIS, and IICEP when tested on Bus 26 are shown in Fig. 2, Fig. 3, and Fig. 4. In terms of the position and sizing of all BESS, EP and AIS approaches yield the same results: BESS 1 is located at Bus 27 and has a capacity of 73 MW, BESS 2 is located at location 21 and has a capacity of 51 MW, and BESS 3 is located at location 20 and has a capacity of 27 MW. For IICEP, the location of BESS 1 is Bus 18 and has a capacity of 16 MW, battery 2 is Bus 28 and has a capacity of 97 MW, and battery 3 is Bus 17 and has a capacity of 26 MW.

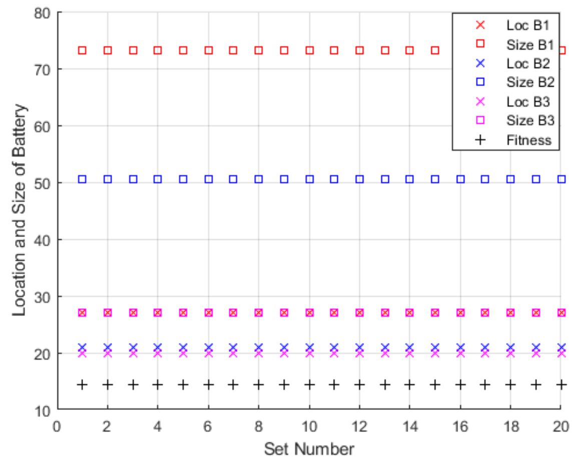

Fig. 2 Converged Solution using EP,

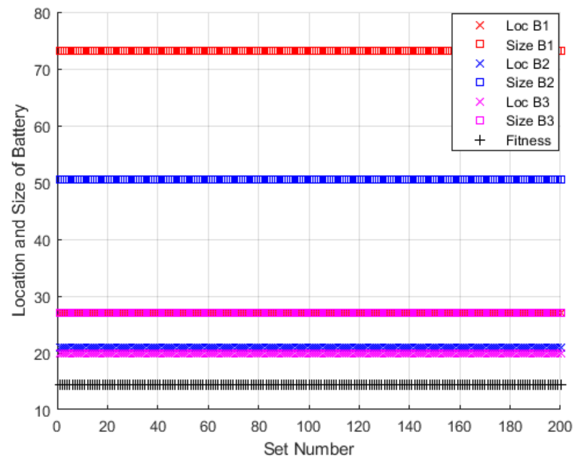

Fig. 3 Converged Solution using AIS.

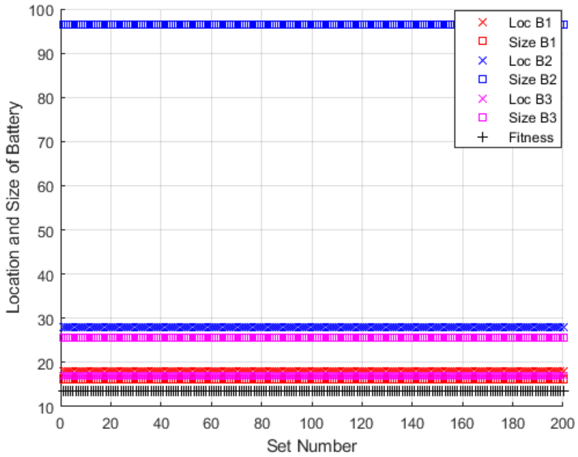

Fig. 4 Converged Solution using IICEP.

2) ScatterPlot at Q_{d29}=30 MVAR

The scatter plots in Fig. 5, Fig. 6, and Fig. 7 illustrate the optimal locations and sizing of all the BESS optimized using EP, AIS, and IICEP when tested on Bus 29. EP and AIS techniques produce identical results as tested on Bus 26. For IICEP, BESS 1 is located at Bus 28 and has a capacity of 29 MW, BESS 2 is located at Bus 23 and has a capacity of 30 MW, and BESS 3 is located at Bus 29 and has a capacity of 11 MW.

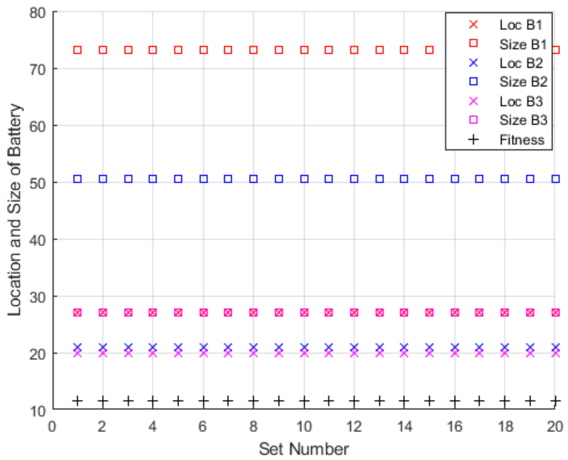

Fig. 5 Converged Solution using EP.

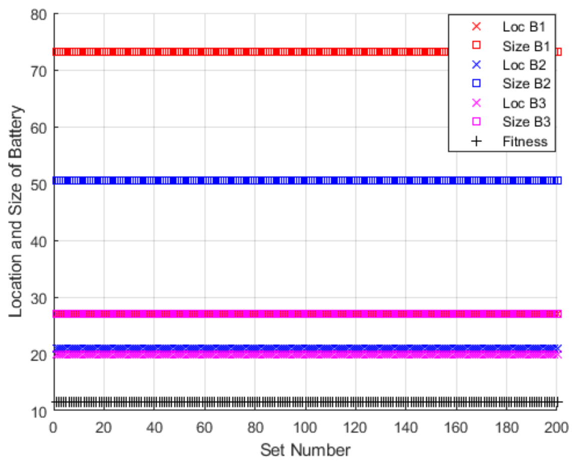

Fig. 6 Converged Solution using AIS.

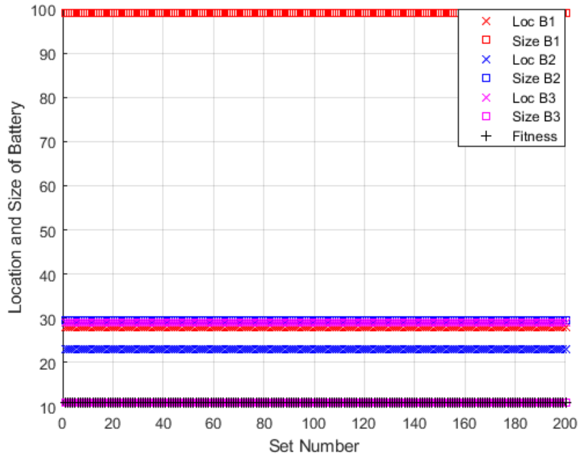

Fig. 7 Converged Solution using IICEP.

3) Loss Profile

To evaluate the loss performance, the algorithms are run with reactive power inputs ranging from 0 MVAR to 30 MVAR on both load buses. In general, as the load increased in steps, the loss values for pre- and post-optimization also gradually increase. All optimization reduces lost value at a rate ranging from 48 to 60%. IICEP performs significantly better than the other two optimization techniques in terms of loss reduction as can be seen in Table I and Table II, also shown in Fig. 8 and Fig. 9.

Fig. 8 and Fig. 9 show the results for loss profile with regards to load variation in IEEE 30-Bus RTS. The results

TABLE I. LOSS VALUE BEFORE AND AFTER OPTIMIZATION AT BUS 26

Load (MVAR)	Loss Set (MW)	EP		AIS		IICEP	
		MW	%	MW	%	MW	%
0	17.58	7.60	56.80	7.60	56.80	6.97	60.34
5	17.73	7.77	56.19	7.77	56.19	7.42	58.15
10	18.12	8.07	55.45	8.07	55.45	7.43	59.01
15	18.62	8.54	54.13	8.54	54.13	8.00	57.04
20	19.39	9.22	52.42	9.22	52.42	8.29	57.25
25	20.53	10.20	50.34	10.20	50.34	9.81	52.22
30	22.44	11.59	48.33	11.59	48.33	10.82	51.80

TABLE II. LOSS VALUE BEFORE AND AFTER OPTIMIZATION AT BUS 29

Load (MVAR)	Loss Set (MW)	EP		AIS		IICEP	
		MW	%	MW	%	MW	%
0	17.55	7.56	56.94	7.56	56.94	7.30	58.39
5	17.72	7.74	56.29	7.74	56.29	7.69	56.61
10	18.23	8.15	55.28	8.15	55.28	7.97	56.29
15	19.00	8.84	53.46	8.84	53.46	8.21	56.81
20	20.25	9.92	51.00	9.92	51.00	8.94	55.87
25	22.27	11.59	47.96	11.59	47.96	10.91	51.02
30	26.11	14.30	45.25	14.77	43.43	13.66	47.66

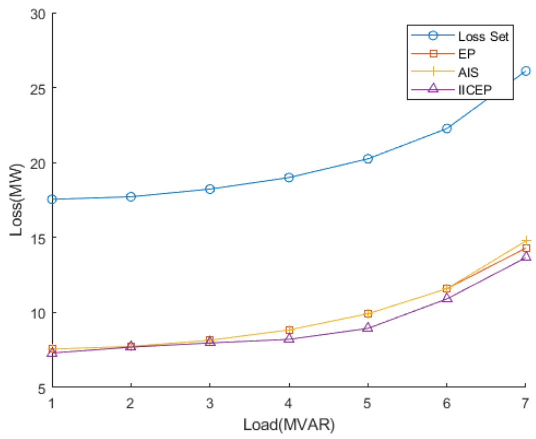

Fig. 8 Loss versus Load tested on Bus 26.

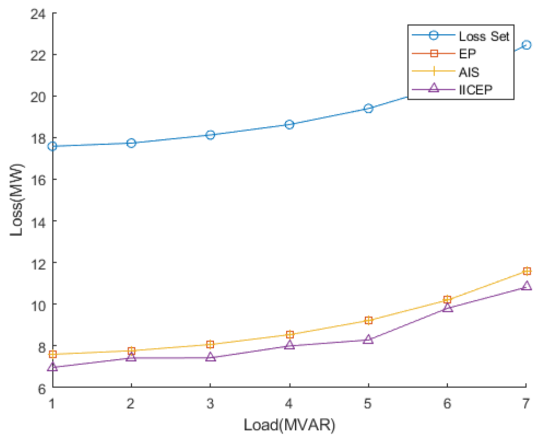

Fig. 9 Loss versus Load tested on Bus 29.

show that implementing any optimization strategies to integrate BESS to minimize loss is worthwhile. Apparently, the loss values after optimization for EP and AIS are similar, just like their optimal solution and sizing. IICEP technique performed slightly better than the other two techniques. This is a promising indicator of the effectiveness of the proposed optimization technique. However, additional research is needed in terms of convergence time and BESS cost.

V. Conclusion

In conclusion, this research focuses on the best way to allocate and size BESS in transmission network to minimize loss. A new algorithm termed IICEP has been developed to find the optimal combination of BESS locations and sizing while keeping the loss profile low. The implementation of BESS is an important approach for increasing a power network's energy efficiency, and their appropriate placement, sizing, and operation can improve overall network performance. BESS maintains a stable and consistent power supply by balancing the supply and demand of electricity.

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