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Load Management for Voltage Control Study Using Parallel Immunized-computational Intelligence Technique

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ABSTRACT

The increase of power demand is a crucial issue in the power system community in many parts of the world. Malaysia has also witnessed the familiar scenario due to the current development throughout the country has invited the urgency of increase in the power supply. Since Malaysia practices vertical system; where the electricity is supplied by only one utility, load management is an important issue so that the delivery of electricity is implemented without discrimination. Parallel Computational Intelligence will be developed which can alleviate and avoid all the unsolved issues, highlighting the weakness of current schemes. Parallel Computational Intelligence is developed to manage the optimal load in making sure the system maintains the stability condition, within the voltage limits. This paper presents evolutionary programming (EP) technique for optimizing the voltage profile. In this study, 3 algorithms which are Gaussian, Cauchy and Parallel EP were developed to solve optimal load management problem on IEEE 26-bus Reliability Test System (RTS). Results obtained from the study revealed that the application of Parallel EP has significantly reduced the time for the optimization process to complete.

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1. INTRODUCTION

Evolutionary algorithms since based on the concept of natural evolutionary processes. Survival is the element of evolution where a population of individuals needs to adapt to an environment in order for survival and to root out the harmful traits and to rewarding the useful behavior [1]. Evolutionary algorithms are considered as a stochastic optimizer that is well appropriate for discontinuous and multimodal objective functions that have successfully implemented to a variety of complex real-world applications ranging from aerodynamics, circuit design, scheduling and design optimization [2]. In recent years a vast number of parallel computer architectures have emerged and are present in every desktop, notebook PC and mobile phones [3]. With these resources readily available, it has become more critical than ever to design algorithms that can be efficiently implemented in a parallel architecture and as such Evolutionary algorithms can be easily parallelized.

This project presents the load management for voltage control study by using parallel immunized-computational intelligence technique. This study is being implemented on a 26-bus system to demonstrate the load management of that particular system by injecting a reactive power support of the voltage in order for the system to be optimized. The load management has been achieved by implementing the system in an evolutionary programming. The test system will be used to test with varying reactive power individuals in order to determine the optimal way to implement the reactive power support.

Load demand and profile variation in the power system network is an essential issue in the present power system community [4], [5]. Most of the time, electrical utilities relied on cooperation from individual or industry to reduce power consumption. However, with the constant capacity of power generation facilities, better solutions are needed to reduce the electrical demand. In such scenario, the best solution is to go for load management and make the best use of the available generating capabilities of a power utility. Load management is defined as sets of objectives designed to control and modifies the patterns of demands of various consumers of a power utility [6]. The aim of this modification and control is to enable the supply system to meet the demand at all times in the most economical manner. Load management can be applied to all the load experienced by the power utility. Research on load management in power system commenced in the early 70s [7][8], but it did not attract the attention from the research community due to the availability of power during those days. However, with high demand and rapid smart grid technology development, many researchers concerned with load management issues in power system. In general, load control is one of the leading criteria for load management and have been implemented in many competitive power markets. In [9], the development of the load control programs for system stability and price in the United States have been discussed. There are several load flow toolboxes. Amongst others are; Load Curtailment Program, Participating Load Program, and Demand Bidding Program. Controllable load management approaches in the smart grid environment are discussed in [10].

The research concluded that the controllable load management is an efficient approach to provide fast balancing services to the system in the active distribution system and future renewable energy penetration. Load interruption can also help to assure grid stability or handle emergency situations. The amount of used energy usually does not decrease; the load is only shifted to off-peak periods. Load reduction is achieved by demand limiter or signals sent from the utility [11]. Among the most commonly used direct load control programs are ripple control, direct load control, and interruptible services. In case of indirect load control programs various tariffs schemes and bidding programs are used [12]. Ripple control is used to deal with emergency situations. Ripple control was understood as a temporary change in frequency or voltage or as superimposed signals sending. The ripple control is used in many developed countries from the United States through Europe to Japan and Australia. The appliances with the highest contribution to consumption are controlled, switches on and off. Signals to appliances are sent through power line carrier, telecommunication technologies or radio frequency. The primary goal is to either increase or decrease power consumption right when it is needed, the change in power consumption occurs within minutes. Ripple control is a direct control method applied to customer's appliances, for example, water heaters, public lighting, based on the contract between the utility and the customer [13]. Direct load control programs allow a utility to control users load and in case of emergency to turn it on or off remotely [14]. In [15], dynamic programming algorithm is successfully implemented to provide an optimal solution to the demand bidding program and produces different solutions as bids change. Nowadays, Artificial Intelligence (AI) and nature-inspired algorithm (NIA) based optimization method are applied to solve for load control in the smart grid. One of AI methods that have been implemented to solve such problems is fuzzy logic, Load management with fuzzy logic was introduced by James Momoh in 2001 [16]. In [17], fuzzy logic has been applied for load forecasting for smart grid and buildings. Load controller with fuzzy logic was successfully applied in [18]-[20] to mitigate the excessive consumptions when the energy consumptions prices are very high without any adverse impact on the consumer level in the renewable energy environment. Another optimization technique to solve for optimization is Evolutionary Algorithm (EA). Genetic Algorithm (GA) is applied in [21] for cost reduction between unscheduled and schedule load is 11.26%.

2. RESEARCH METHOD

2.1. Problem Formulation

In this paper, the objective of the optimization problem is to improve the voltage profile in a power system through optimal load management in the system by using EP. In the study, 3 types of mutation operator are considered namely Gaussian, Cauchy as well as Parallel mutation. Parallel mutation operator is defined as the combination of Gaussian and Cauchy mutation operator which working parallel with each other. The voltage profile in this paper is indicated by the minimum voltage magnitude in the test system, *f*. Therefore, the objective function *O.F.* can be expressed as:

$$O.F. = \text{maximize}(f) \tag{1}$$

$$f = \min(V) \tag{2}$$

In this paper, the total real power loss P_{Tl} in the system is also considered in the optimization process. However, power loss is not considered as the objective of the optimization process, but it is only taken as consideration to investigate the effect of the optimization process in solving the objective function. Total power loss in a system can be computed by:

$$P_{Tl} = \sum_{k=1}^{N_{line}} I_k^2 R_k \tag{3}$$

where I_k is the current flowing on k^{th} transmission line and R_k is the resistance value of the k^{th} transmission line. While managing the loads in the test system, the voltage profile should be maintained in the suitable operating region because undervoltage and overvoltage condition can cause harm to the power system [22]. Therefore, the safe voltage range is constrained with the minimum value of 0.95 p.u and maximum of 1.05 p.u. The constraint can be expressed as:

$$0.95 \leq V \leq 1.05 \tag{4}$$

Another parameter known as execution time is also considered in the optimization process. The execution time can be used to measure the performance of the optimization algorithm. The execution time is determined by measuring the time required to execute the optimization algorithm until it reaches its convergence.

2.2. Parallel Evolutionary Programming

In this paper, Parallel EP is proposed to solve the optimal load management problem in the attempt to improve the voltage profile in a power system. Parallel EP is developed based on the novel EP algorithm and inspired by the capability of Cauchy mutation operator in improving the performance of the novel EP algorithm. In this paper, the mutation operator will incorporate the implementation of Gaussian and Cauchy mutation operator running in parallel with each other. Brief explanation of Parallel EP is given as follows:

Step 1: Data Initialization

In this step, the optimization process is started by setting the required parameter such as number of individuals, N and the value of EP search step value β. Then, N number of possible solution is generated through random number generation. In this paper, the possible solutions are defined to be the possible optimum load value in the test system. There are 4 locations of loads are proposed to be managed.

Step 2: Fitness Value Computation

At this stage, the fitness value of the individuals is computed by solving load flow analysis. In this research, the fitness value of the individual is considered as the value of the minimum voltage magnitude in the system. During this phase, the total power loss in the system is also computed.

Step 3: Mutation

Mutation process is used to produce new possible solutions which is known as the offspring from its parents. In novel EP, Gaussian mutation technique is implemented in the mutation process. In this paper, the mutation process will involve Gaussian and Cauchy mutation technique working in parallel with each other. Offspring generated by Gaussian mutation technique can be expressed as in (5) while Cauchy mutation technique is expressed as in (6).

$$x_{new,1} = x + N\left(0, \beta(x_{max} - x_{min})\left(\frac{f}{f_{max}}\right)\right) \tag{5}$$

$$x_{new,2} = x + C(x_{max} - x_{min}) \tag{6}$$

Where x is the parent individual while $x_{new,1}$ and $x_{new,2}$ are the offspring produced from Gaussian and Cauchy mutation technique respectively. Parent with the largest number is indicated by x_{max} while x_{min} represent the smallest parent value. Random number generated by using Cauchy mutation is represented by C while N represents the random number generated by Gaussian distributed random number generation. The fitness value of an individual is denoted by f and f_{max} is the highest fitness value among the individuals while β is the search step value for gaussian mutation technique. After the offspring has been generated, load flow analysis is conducted on the offspring to compute the fitness value.

Step 4: Combination

In this phase, the offspring produced during the mutation process are combined by stacking them on top of each other to become a single array consisting of the offspring produced by the Gaussian and Cauchy mutation technique. The fitness value of the offsprings are also combined in the same manner.

Step 5: Selection

The selection process is conducted using elitism method where the fittest individuals will survive in the competition among all individuals in the pool. The combined individual will be sorted first according to the value of their fitness value. Then, *N* individuals from the pool will be chosen and carried forward to the next iteration of the optimization process while the remaining individuals will be eliminated from the individual pool.

Step 6: Convergence Test

In this stage, the optimization algorithm will determine either it should continue of the optimization process or stopping it. The optimization process can be stopped if the solution has been converged, which is indicated by the difference of maximum and minimum fitness value of the individuals in the pool which is lower than a specified value. The process can also be terminated if the iteration counter has reached its maximum iteration number.

3. RESULTS AND ANALYSIS

In this paper, optimal load management problem will be solved by using the proposed Parallel EP algorithm. The management problem will be tested on IEEE 26-bus Reliability Test System (RTS) and the detail of the test system can be referred in [22]. The optimization process will determine the optimal load for the test system to achieve a better voltage profile. The total power loss and the time required to complete the optimization process are also recorded to assess the performance of the optimization algorithm. The same problem is solved using Gaussian EP and Cauchy EP in order to determine if Parallel EP can perform better compared to the others.

3.1. Load Variation at Bus 2

During the optimization process, the reactive load at bus 2 is increased gradually from 10MVAr to 50MVAr by increment of 10MVAr. The optimization result is then compared with the implementation of Gaussian and Cauchy mutation technique in EP on solving the similar problem. Figure 1 depict the result of the optimized voltage profile over the variation of reactive load at bus 2 of the system. From the results, it can be observed that Parallel Ep has managed to improve the voltage profile in the system. In several loading conditions, Parallel EP has managed to provide better post-optimized voltage profile compared to Gaussian EP and Cauchy EP except when the loading is at 20 MVAr where Cauchy EP has yielded a better result than Parallel EP. However, Parallel EP has provided a better result compared to Gaussian EP and Cauchy EP in most loading cases. While successfully providing good results, the post-optimized voltage profile provided by Parallel EP is situated in the allowable voltage magnitude range, which then satisfies the constraint imposed to the problem.

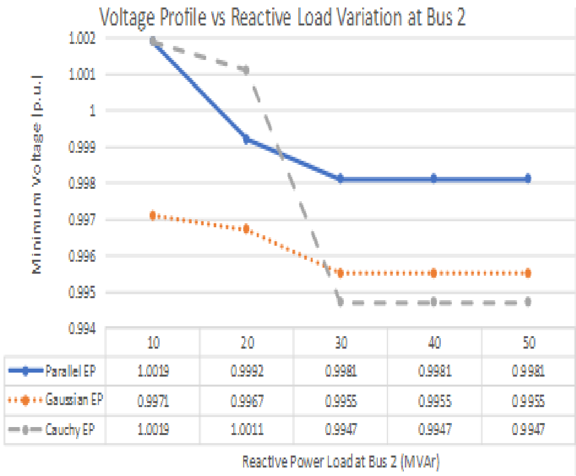


Figure 1. Optimized voltage profile with load variation at bus 2

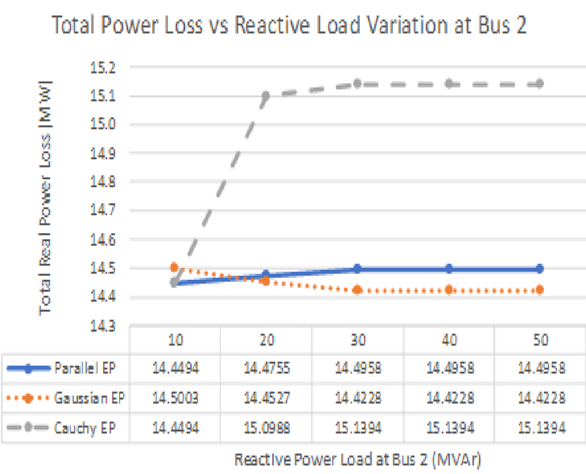
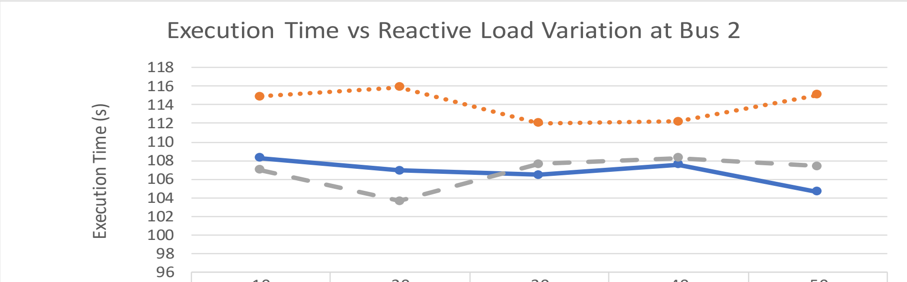


Figure 2. Power loss profile with load variation at bus 2

The power loss after the optimization process and the time required to complete the optimization process were graphically represented on Figure 2 and Figure 3 respectively. From the results depicted in

Figure 2, it can be observed that Parallel EP has yielded lower total real power loss compared to Cauchy EP although Gaussian EP has managed to provide lower power loss compared to Parallel EP. This trend continues when bus 2 of the system is loaded with 20 MVAr reactive load up to 50 MVAr. At 10 MVar, it can be observed that Parallel EP is capable of yielding a lower real power loss compared to Gaussian EP while Cauchy EP provided the same result with Parallel EP. Parallel EP also has clocked the lowest execution time compared to the Gaussian and Cauchy EP at most of the loading cases, which implies that optimization process using Parallel EP can be completed faster.



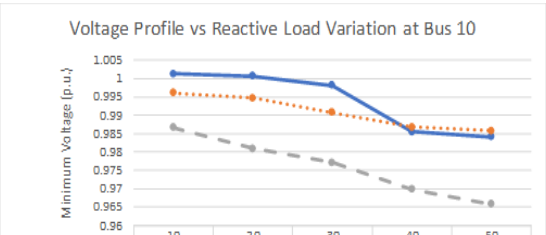
	10	20	30	40	50
Parallel EP	108.25	106.91	106.46	107.55	104.67
Gaussian EP	114.92	115.89	112.04	112.2	115.08
Cauchy EP	106.96	103.64	107.65	108.29	107.42

Figure 3. Execution time of optimization process with load variation at bus 2

3.2. Load Variation at Bus 10

The experimental work as conducted in section 3.1 is repeated while varying the reactive power load at bus 10 of the test system. The reactive power load of the chosen bus is varied from 10 MVAr up to 50MVAr with 10MVAr increment. The optimization result in terms of voltage profile of the system is illustrated as in Figure 4. From the results obtained, it can be observed that Parallel EP has managed to provide a better solution in the first 3 loading condition. However, Gaussian EP has provided a slightly better result compared to Parallel EP while Cauchy EP has provided the worst results among the others. It is also noted that the results provided by Parallel EP are satisfying the voltage magnitude constraint since no results provided has exceeded the maximum or reduced below the minimum allowable voltage magnitude.

The total real power loss after optimization process is conducted has been recorded as in Figure 5. From the figure, Parallel EP has recorded the lowest power loss during the first 2 loading condition. Further increase in the reactive loading at bus 10 has revealed that Gaussian EP has successfully provide a better power loss compared to Parallel EP and Cauchy Ep with Cauchy EP providing a higher total power loss compared to the others. However, it can be observed that Parallel EP has clocked the fastest execution time compared to Gaussian EP and Cauchy EP in most loading cases as recorded in Figure 6.



	10	20	30	40	50
Parallel EP	1.0013	1.0007	0.9982	0.9855	0.9841
Gaussian EP	0.9961	0.9947	0.9908	0.9868	0.9858
Cauchy EP	0.9867	0.981	0.9771	0.9699	0.9658

Figure 4. Optimized voltage profile with load variation at bus 10

	10	20	30	40	50
Parallel EP	14.4659	14.4878	15.2094	15.691	15.7697
Gaussian EP	14.5485	14.5522	14.9554	14.773	14.8489
Cauchy EP	14.7461	14.9648	15.1193	15.7349	16.0671

Figure 5. Power loss profile with load variation at bus 10

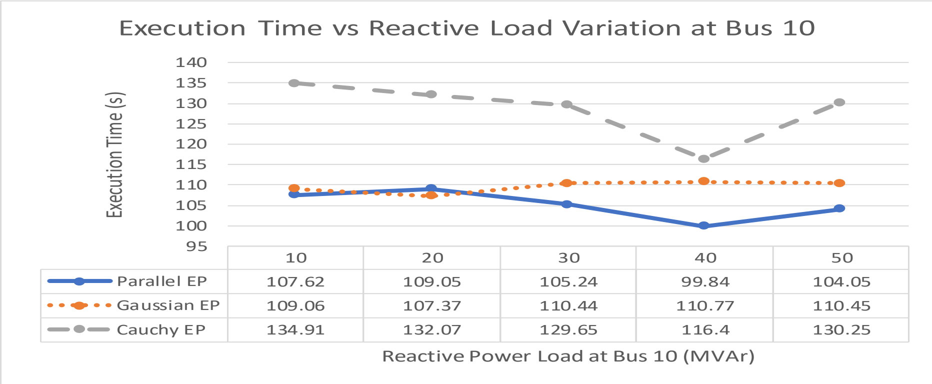


Figure 6. Execution time of optimization process with load variation at bus 10

4. CONCLUSION

This paper has presented the implementation of Parallel EP in the attempt to improve the voltage profile of IEEE 26-bus RTS via optimal load management. Referring to the results obtained from the experimental work, it can be concluded that Parallel EP has the capability of solving the optimization problem as well as performing better in other EP-based techniques. Future work is suggested in terms of improvement of the performance of Parallel EP so that it can provide better optimization results in term of solution quality as well as optimization speed.

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