VOL. 10, NO. 23, DECEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

A NEW TECHNIQUE FOR MAXIMUM LOAD MARGIN ESTIMATION AND PREDICTION

Nur Fadilah Ab. Aziz[1], Titik Khawa Abdul Rahman[2], Zuhaila Mat Yasin[3] and Zuhaina Zakaria[3]
[1]Department of Electrical Power Engineering, Universiti Tenaga Nasional, Selangor, Malaysia
[2]King Abdul Aziz University, Jeddah, Saudi Arabia
[3]Universiti Teknologi Mara, Shah Alam, Selangor, Malaysia
E-Mail: nfadilah@uniten.edu.my

ABSTRACT

This paper presents the application of Fast Artificial Immune System (FAIS) for maximum load margin estimation and hybrid Fast Artificial Immune Support Vector Machine (FAISVM) for maximum load margin prediction. The newly developed techniques are marked by its significant fast computation time. A new developed index, Voltage Stability Condition Indicator (VSCI) was used as the fitness function for FAIS and FAISVM in order to evaluate the stability condition of load bus in the system. In FAIS, various mechanisms techniques of AIS were investigated and intensive comparisons were made in order to obtain the best implementation of AIS for maximum load margin estimation. The mechanisms were investigated and compared on three main AIS principles; cloning, mutation and selection. In addition, FAISVM is another new hybrid technique developed for maximum load margin prediction that integrates the application of FAIS and Support Vector Machine (SVM). For validation, FAISVM was compared with Evolutionary Support Vector Machine (ESVM) that uses Evolutionary Programming (EP) as the search algorithm. Based on the results, it shows that FAISVM outperforms ESVM with a higher accuracy prediction value.

Keywords: maximum load margin, artificial immune system, support vector machine, voltage stability index.

INTRODUCTION

Load margin analysis is known as one of the important measurement in voltage stability studies. It is defined as the amount of additional allowable load from a particular operating point in a specific pattern of load increase before the occurrence of voltage collapse [1]. The bus that has the lowest load margin in the system is considered as the weakest bus. Thus, from a load margin analysis, the weakest bus and the maximum load margin (MLM) that the bus can withstand in the system can be identified.

In power system analysis, the number of research related to the system load margin is expanding tremendously due to its importance. Saffarian *et al.* presented a method to predict the Closest Loadability Limit (CLL) for each operating point by using RBFNN [2]. The proposed approach can be used to predict the load margin of individual buses under normal condition and the total load margin under normal condition and critical contingencies. Both RBFNNs employed active and reactive loads on PV and PQ buses as input data. To reduce the number of training data and enhance the speed of RBFNN, a clustering algorithm was applied in the research.

Besides that, Musirin and Abdul Rahman had introduced the application of evolutionary programming (EP) for maximum loadability estimation in electric power system [1]. In the research, EP was used as an optimisation technique to automatically search the maximum reactive power limit prior to the instability of the system when a particular load bus is subjected to load variation. Thus, the reactive power loading maximisation was used as the objective function and a pre-developed line based voltage stability index namely FVSI was used as the fitness of the objective function. In reference [3], the proposed technique was compared with AIS and the conventional voltage stability analysis.

On the other hand, EL-Dib *et al.* [4], had presented another type of evolutionary technique for maximum loading point estimation problem. The proposed solution is based on Particle Swarm Optimisation (PSO). This study introduced a hybrid model that integrates Genetic Algorithm (GA) and the PSO, called as Hybrid PSO (HPSO). A loading factor that represents the increase in the system load from some initial operating point was used. HPSO was utilised as the optimisation technique in which the objective function is to minimise the reciprocal of the loading factor in order to search for the maximum loading point that the system can withstand. The performance of the proposed method was compared with the CPF technique.

A comparison of different types of PSO in detecting maximum loadability limits was made by Acharjee *et al.* [5-7]. Acharjee and Indira had analysed the application of two types of PSO namely Adaptive PSO (APSO) and HPSO for maximum loading point estimation [5]. Breeding and subpopulation of GA properties were combined in PSO to add the diversity and overcome the local optima. The optimisation problem considers inequality constraints, voltage and reactive power generation limits of PV buses. From the results shown, HPSO gives a better performance under constrained situation. Three types of PSO were compared in [6]. They are APSO, General PSO (GPSO) and Chaotic PSO (CPSO). GPSO is the standard PSO algorithm where the PSO parameters were not made adaptive. In CPSO, chaos was introduced to overcome the local optima and to speed up the convergences. Acharjee *et al.* had proposed an improved APSO in reference [7]. New innovative formulae were developed for a better tuning of PSO parameters. The PSO parameters were not fixed and independent of number and maximum number of iterations. Besides that, decoupling properties of power flow variables were also employed in the proposed CPSO. From the results, GPSO shows the worst performance. Vice versa, CPSO gives the best success rate and more maximum loadability factors under different voltage limits.

Based on the literature reviews, ANN, PSO and GA are the most common methods used by the former researchers to determine the maximum load margin (MLM) of a system. On the other hand, the application of AIS in power system has not been much explored. In this study, a superior performance of AIS to determine the MLM of a system was introduced where an investigation on three main principles of AIS; cloning, mutation and selection was conducted. The approaches that deliver the best performance in terms of accuracy and time were utilised to develop a fast AIS algorithm named as Fast Artificial Immune System (FAIS). In addition, this paper also proposes a new technique to predict the MLM by integrating FAIS with powerful machine learning, Support Vector Machine (SVM) termed as Fast Artificial Immune Support Vector Machine (FAISVM). In this study, a newly developed voltage stability index, VSCI [8] was used as the fitness function for FAIS and FAISVM.

IMPLEMENTATION OF FAIS FOR MLM ESTIMATION

This section describes the application of FAIS for MLM estimation. To obtain the best implementation of AIS for MLM estimation, the investigation was conducted on three main principles of AIS:

Proliferation (Cloning)

Proliferation or cloning refers to a process of reproduction of a single population to generate a group of identical sub-population. Traditionally, a deterministic selection rule is adopted as the cloning method. However, this technique only selects the best individual solutions, and hence may lead to the premature convergence of the algorithm. To avoid premature convergence, two types of cloning methods were explored:

Standard cloning

This type of cloning is a self-reproduction where all populations are being reproduced without any selection. In this study, all individuals were cloned by 10 times.

Proportional cloning

Proportional cloning imitates the phenomenon that only a small number of diverse antibodies can be activated in immune response. It selects only few relatively isolated non-dominated individuals as the active antibodies to do proportional cloning according to their affinity value. The individuals with higher affinity value will be reproduced more than those with lower affinity value. The affinity of the proportional cloning, qi, can be described as,

$$q_i = \frac{f_i}{\sum f_i} \times np \tag{1}$$

Where np = population size and = fitness value, in which the developed VSCI was used as the fitness.

Diversification (Mutation)

In AIS, diversification of antibodies is created by a mutation mechanism. Mutation is an important mechanism that generates a new population by performing a random perturbation in the solution of current population. In order to improve AIS, the performance of three types of mutation are investigated; Gaussian, Cauchy and the combination of the use of either Gaussian or Cauchy mutations.

Selection

In this study, a selection mechanism is used to select a candidate which has the best affinity value for the next generation population. Clonal theory concluded that it is better to maintain only a small set of candidates for the next population that have high affinity value in the immune memory instead of preserving a large number of them [9]. This is one of the important characteristics in AIS as it guarantees the searching for the best solutions along the process. As a result, a faster convergence and fewer entrapments in local minima in comparison to classical AIS can be obtained. Three different techniques of selection were investigated in this study.

Tournament selection

This selection scheme selects a set of individual solutions stochastically and from the set of population the best solution is chosen. The number of individual solutions selected is called tournament size. In this study, 10 individual solutions are chosen randomly as the opponents. This group of opponents together with the individual solution, n are put in the tournament pool for a competition. The number of winnings is recorded. The process is repeated until n is equal to the number of population size, m. The population is then sorted by the number of winnings. 20 individual solutions with the highest number of winnings are then selected as the next generation population.

Tournament with elitism selection

In comparison with tournament, elitism mechanism allows the elite of the population to be directly carried forward to the next generation. The best solution is believed to interact with other individual solutions in the population in generating new population members and enhance the probability of creating a better next generation population. Therefore, in tournament with elitism selection method, the population members are first ranked according to their fitness values before the tournament selection takes place. The tournament selection as explained in previous subsection is then conducted with the two solutions from elitism at the top. Similarly, when n equals to the new population size (m–2), the population is ranked according to its number of winnings from the competition. Two elitism members together with the top 18 of the populations from the ranking will then be selected as the next generation population.

Ranking selection

Ranking selection is the simplest selection method. The idea is very straightforward. In this study, the best 20 individual solutions are selected from the mutated population in which the members are ranked according to their fitness function to become the next population.

FAIS ALGORITHM FOR MLM ESTIMATION

Based on the explanation in previous subsections, the algorithm of FAIS for MLM estimation is presented as below:

Step 1: Initialisation - Generate a random initial population for possible solutions of MLM.

Step 2: Fitness Evaluation 1 - Run load flow to evaluate the stability of the system when the generated MLM variable is utilised. If the load flow does not converge, repeat Step1.

Step 3: Proliferation - Adopt either standard or proportional cloning method to produce the identical copies of the solutions. The number of clones for proportional cloning method depends on the VSCI value calculated in Step 2.

Step 4: Diversification – Use Gaussian, Cauchy or the combination of either Gaussian or Cauchy Mutation to mutate the proliferated solutions. In the combination of either Gaussian or Cauchy Mutation, both types of mutations are conducted but only the best mutated solutions are used for the next operation.

Step 5: Fitness Evaluation 2 – For each mutated population member, run load flow to calculate the value of VSCI in order to determine the stability condition of the system.

Step 6: Selection - The VSCI values calculated in Step 5 are used to select the best generation population by either using Tournament, Tournament with Elitism or Ranking Selection.

Step 7: Stopping Criterion - The stopping criterion used for this research can be defined as the specified difference between the maximum and minimum value of the VSCI calculated in Step5. Repeat Step 3 – Step 6 until the stopping criterion is met.

IMPLEMENTATION OF FAISVM FOR MLM PREDICTION

This research also introduces the application of hybrid optimisation approach via FAISVM by integrating FAIS and SVM for MLM prediction. The following subsections describe SVM training and testing process as well as the algorithm used by FAISVM for the prediction.

Selection of input and output features

The selection of input data is very important in any prediction task. The selected input data must provide enough information to predict the MLM of a load bus. In this study, the VSCI value, reactive and active power load at the critical bus and other bus were used as the input data. Since the objective is to predict the MLM of a load bus under a predetermined loading condition, the output feature selected is the loading factor, λ.

SVM training and testing

This study implements SVM from a LS-SVMlab toolbox, Version 1.8 K. Pleckmans and J. A. K. Suykens from Electrical Engineering Department of Katholieke Leuven University developed the toolbox in October 2002 [10]. Three parameters need to be specified to produce a SVM model. A right combination of these parameters will give the best performance of SVM. The parameters are the regularization parameter, gamma (γ), the kernel function parameter, sigma (σ2) and the kernel functions. In this research, RBF kernel function was used as the kernel function in all simulations performed since it has been reported as the best choice of kernel function for SVM [11]. Like any other supervised learning methods, SVM takes a set of input data and makes a prediction using the trained and tested data called support vectors. The input and its corresponding output data were generated by varying the increment of loading at the weakest bus only, or other single bus that may affect the stability of the weakest bus or loading increment at both the weakest bus and the other single bus. The performance of SVM increases as the number of training data over the number of testing data increases [11-12]. 70% of the data generated was used as the training data while the remaining 30% was utilised as the testing data.

Performance measure

The performance and accuracy of the prediction for all techniques in this study is verified by using mean square error (MSE). MSE is chosen as the main performance measurement based on its popularity in the literature as SVM regression test [12-13]. The lower the value of MSE indicates a better prediction. In this research, the calculated values of MSE was calculated separately from the training and testing process. They are calculated based on the obtained predicted and actual values. The formula of the MSE is formulated as below

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \qquad (2)$$

where x and y are the targeted and predicted values and n is the number of data patterns.

FAISVM algorithm for MLM prediction

The conventional selection of SVM parameters is not only tedious but also may lead to a local optimal solution [14-15]. Thus in this study, an intelligent selection of the parameters via AIS is proposed so that the

VOL. 10, NO. 23, DECEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

overall training performance of the developed algorithm could be optimised. FAIS works as an evolutionary search technique to determine the best combination value of the SVM parameters. Figure-1 illustrates the flowchart of the developed algorithm. The algorithms for the proposed technique are described as the following:

Step 1: Generate a random initial population for possible solutions within the range of designed variables.
Step 2: Generate several copies (clone) of the generated initial population for all parameters that are needed to be optimised.
Step 3: Mutate each clone.
Step 4: Run SVM by using the mutated parameter values if the values of the mutated parameters are within the specified range, otherwise, repeat step 3.
Step 5: Rank and select the best 20 individual to be prescribed for the next iteration population.
Step 6: Repeat step 2-5 until the number of iterations and the specified performance test, the MSE value are met. If the voltage stability prediction attains the targeted MSE value or the number of iteration reaches its maximum value, the search process is stopped.
Step 7: Repeat step 1-6 for 10 simulations automatically for consistency. To confirm the optimality of the finest values obtained, the best MSE value obtained by each simulation will be the next targeted MSE value. The stopping criterion of this algorithm is the maximum number of automatic simulation. In this study, the maximum number of automatic simulation is set to 10.

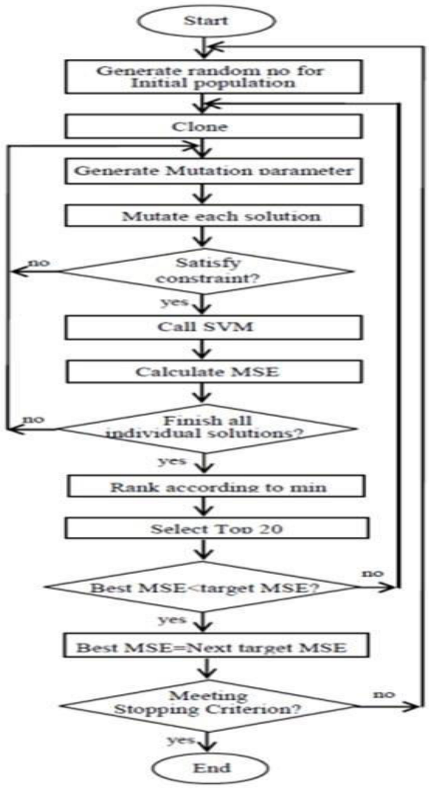

Figure-1. The flowchart of FAISVM for maximum load margin prediction.

ESVM algorithm for MLM prediction

For comparative study, another newly hybrid technique that integrates the application of EP and SVM named Evolutionary Support Vector Machine (ESVM) was also developed. In ESVM, EP is used as the search technique to determine the optimal value SVM parameters. In EP optimisation technique, the optimal solution is generally obtained by evolving a population of candidate solutions over a number of iterations. The first generated population is known as the parents. For every iteration, new solutions or known as offspring are formed from the parents by using a mutation operator. In selection process, the best individuals in parents and offspring population will be used as the next population. The degree of the optimality of the individuals is measured by using a fitness function. These processes are repeated until the fitness of the problem is converged.

RESULTS AND DISCUSSIONS

The proposed algorithms were tested on an adapted IEEE Test 30 bus system. The system consists of 1 slack bus, 5 generators, 24 load buses, 37 transmission lines, 4 tap changing transformers.

MLM estimation by FAIS

From previous study, bus 30 was identified as the most critical bus for the IEEE 30 bus system [12]. There are three types of maximum load margin taken into account; P margin, Q margin, and P&Q margin. Two types of load increment are considered, which are, increase load at a selected load bus and increase load at all load buses. 18 various approaches of AIS optimisation method were compared. The approaches were being applied in three main principles of AIS; proliferation, diversification and selection, as illustrated in Figure-2. Figure-2 described the framework for the development of MLM estimation techniques via AIS. Based on the figure, the best implementation of AIS techniques for maximum load margin estimation is called as FAIS. FAIS was developed from the combination of proportional cloning, Cauchy mutation and ranking selection.

Table-1 shows the best results obtained from five times simulations in determining the MLM of reactive power load at the weakest bus, bus 30 of IEEE 30 bus system by using the techniques as stated in Figure-2. From the table, an AIS approach named as FAIS managed to give the shortest computation time of 400.1 seconds with a high value of MLM, 34.9299 Mvar. Based on Figure-2, FAIS incorporates the combination of proportional cloning, Cauchy mutation and ranking selection. AIS14 that combines proportional cloning, Cauchy mutation and tournament selection technique takes only slightly longer time, 480 seconds. However, FAIS is favourable due to its simplicity of the ranking selection technique compare to tournament with elitism technique as well as higher value of MLM. From the table it is also observed that, techniques that applied proportional cloning method exhibit shorter computation time. This is because the number of clones generated depends on the correlation of the individual solution with the fitness. The more related the solution to the fitness function, the more number of clones is generated.

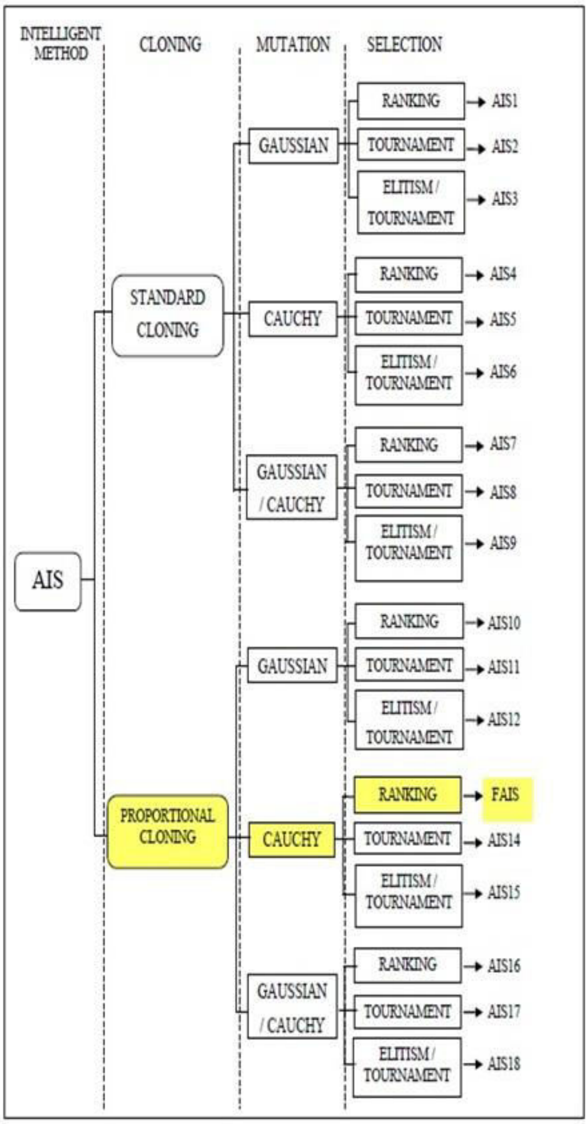

Figure-2. The development of MLM techniques.

In addition, Table-2 presents the comparison between FAIS and the conventional voltage stability analysis (VSA) technique. VSA determines the maximum load margin of the critical bus by using only VSCI as the voltage collapse indicator. Based on Table II, FAIS shows a better result with a slightly higher amount of maximum load margin for all three types of maximum load margin as compared to VSA. This shows that the step size increment used by the AIS approaches implemented in FAIS technique is smaller than VSA technique and hence produced a better result. Therefore, it is proven that FAIS is a better method for estimating the maximum load point of load buses in a system in terms of both computation time and accuracy compare to the conventional voltage stability analysis technique.

Table-1. Comparison among MLM estimation techniques.

TECHNIQUE	VSCI	MLM (Mvar)	Time (s)
AIS1	1.0000	34.9382	2888.4
AIS2	0.9999	34.9244	3461.7
AIS3	1.0000	34.9299	3237.9
AIS4	0.9976	34.9340	1083.9
AIS5	1.0000	34.9244	1555.3
AIS6	1.0000	34.9292	1720.7
AIS7	1.0000	34.9299	601.6
AIS8	0.9999	34.9292	1057.3
AIS9	1.0000	34.9375	758.9
AIS10	1.0000	34.9306	977.6
AIS11	1.0000	34.9271	1297.3
AIS12	1.0000	34.9299	1238.9
FAIS	1.0000	34.9299	400.1
AIS14	1.0000	34.9250	537.6
AIS15	1.0000	34.9306	480.0
AIS16	1.0000	34.9299	731.0
AIS17	1.0000	34.9382	836.3
AIS18	1.0000	34.9299	728.7

Table-2. Comparison between FAIS and VSA.

TYPE OF LOAD	TYPE OF MLM	FAIS	VSA
Increase at Bus 30	P (MW)	47.449	47.414
	Q (Mvar)	34.932	34.928
	P&Q (MW/ MVar)	33.198/ 21.610	33.197/ 21.609
Increase at all buses	P (MW)	29.606	26.823
	Q (Mvar)	24.388	24.302
	P&Q (MW/ MVar)	22.758/ 14.814	22.754/ 14.812

MLM prediction by FAISVM

To observe the effect of load increment at the critical bus, several loading conditions are chosen which include the effect of load increase at other buses on the critical bus. Bus 29 and bus 7 are chosen as the other load buses involved since bus 29 is closely connected to the bus 30 as the weakest bus, and bus 7 as a load bus that is less connected to the weakest bus. Each loading condition created is treated as a case.

Table-3 tabulates the MLM prediction performance results by using FAISVM and ESVM for three types of MLM. In this study, the prediction performance was measured by using MSE and standard deviation, STD. The MSE values calculated are the

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difference between the predicted and actual MLM values. For every case, at least five simulations had been conducted. The MSE and STD values tabulated in the table were calculated from the simulation that gave the lowest MSE value. The values are the average values that were calculated from the obtained top ten individual solutions.

Based on Table-3, FAISVM has produced much lower MSE values than ESVM for all three types of MLM, when the objective function is the MLM of P, Q or both P and Q. Apart from that, the values of STD produced by FAISVM also are much smaller than the values given by ESVM in all three types of MLM and all cases, which imply that most of the predictions made by FAISVM are closer to the mean value than predictions made by ESVM. In other words, the prediction performance by FAISVM is more consistent than ESVM.

CONCLUSIONS

A superior performance of AIS to determine the MLM of load bus named as FAIS was developed in this work. FAIS offers a better performance of AIS since several available mechanisms for cloning, mutation and selection have been compared. The combination of these mechanisms that delivers the best performance in terms of accuracy and computation time was utilised in FAIS. Based on the results, FAIS gave a better performance than VSA confirming the capability of FAIS in estimating the value of MLM.

Apart from that, a novel Fast Artificial Immune Support Vector Machine (FAISVM) for MLM prediction was also developed. FAISVM is another newly developed algorithm that incorporates the application of FAIS and SVM in one algorithm. The integration of FAIS with SVM has resulted to a very fast and accurate prediction of MLM. For comparison, another newly hybrid algorithm named as Evolutionary Support Vector Machine (ESVM) that uses Evolutionary Programming (EP) as the search algorithm was also developed. The obtained results have shown that FAISVM outperforms ESVM where FAISVM gives a lower MSE and standard deviation value than ESVM in the prediction.

To conclude, this paper has successfully delivered two outstanding techniques for maximum load margin estimation and prediction based on biological optimisation technique and its hybrid with artificial intelligence.

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