Parameter Optimization for Conventional Soft Frequency Reuse in Multi Cell Networks using Extreme Learning Machine and Genetic Algorithm

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***Abstract*—Soft Frequency reuse (SFR) has been used as a method to reduce the inter-cell interference between cell edge user and cell center users. With a proper adjustment of the system, it can gives us the best throughput of the SFR. The objective of this study is to optimize the three parameters of the SFR obtained from Taguchi model. These three parameters consist of power ratios of the base station (β), concentration of cell-edge user and user distribution of sub-subcarriers. Firstly, the SFR data is modeled using Extreme Learning Machine (ELM). The model is then validated using the unseen samples based on the mean square error (MSE) criterion. Secondly, the best model with the lowest MSE is then used for the parameters optimization by using genetic algorithm (GA) in order to obtain the highest throughput. In the series of experiments, the obtained results offer the highest throughput with reliable and consistent selected parameters. In this paper, the combination ELM-GA technique has been proven to increase the throughput of the system.**

***Index Terms*—Soft Frequency Reuse; Extreme Learning Machine; Genetic Algorithm; LTE.**

I. INTRODUCTION

The world now is evolving on a much faster rate than we anticipated. New technologies are being born from daily basis. At this times, the needs for a faster and better connectivity throughout the world is needed to overcome the slow connection that exist in order to make the data transmission throughout the world to be more efficient and faster. That is why the internet has become one of the important things that we need to have in today's world. The network technologies have evolved from 2G to 4G LTE since the discovery of the 2G network [1].

In 2010, the LTE technology has taken a step that can further increase the speed and efficiency of the data by introducing to LTE advanced which offers more data capacity. A more data capacity will make the mobile broadband users to have a faster and better internet. Basically, the mobile 4G LTE complements the 3G to boost data capacity of the network itself [2]. The multimode of 3G/LTE is the foundation for a successful 4G LTE. The multimode consist of LTE FDD, WCDMA/HSPA+, CDMA2000/EV-DO, TD-SCDMA, and GSM/GPRS. The 3G network enabling a consistent broadband experience outside 4G LTE coverage delivering voice services and global roaming. While the 4G LTE role is to provide more data capacity for richer content and more connections [1].

4G LTE uses orthogonal frequency-division multiple access (OFDMA). With this, it can open up a wider channel and support for channels up to 20MHz. Furthermore, with more antennas, advanced multiple in multiple out (MIMO) technique to create spatially separated paths. Not just that, 4G LTE also can do carrier aggregation up to 100MHz for higher data rates. The 4G LTE network also have been optimized for low latencies response time for both user and control plane to improve the user experience [1].

The 4G LTE network has been configured to use all the OFDMA channels. The backlash of this network is when it is being used by the mobile users, a co-channel interference (CCI) will exist. Especially terminals located at the cell border largely suffer from the power radiated by the base station of neighboring cells in their communication band. There are three major alternatives for mitigating CCI in cellular OFDMA systems [3], the first one will be hard frequency reuse (HFR) [4], the second will be fractional frequency reuse (FFR) [5] and the last will be soft-frequency reuse (SFR) [6]. This paper will explain more on soft-frequency reuse as it will discuss more on the optimization of the conventional SFR's parameters.

There are some ways that can be used to optimize the SFR network. One of the methods is single cell SFR optimization technique. The single cell SFR optimization problem aims to find the major and minor subcarrier allocation and their transmit power for a given cell so that the single cell throughput is maximized by assuming the resource allocation in adjacent cells is fixed [7]. They focus on the optimization of the power level by using the algorithm that has been formulated from the model. The optimization technique is composed into two-step based on iterative algorithm. First, they need to find the minimum transmit power that satisfies the inner and the outer data rate requirements. Then, they re-allocate the subcarriers and the remaining power in a way that the cell throughput is being increased. Next, the inner and the outer cell data rates are being calculated and use them as new inner and outer cell data requirements in the next iterations. This two-step process is repeated until the single-cell throughput does not change anymore. By doing this, we can control the iterative process so that the single cell throughput is monotonously increasing since the data rate requirements are increased every iteration [7]. This method mainly uses a model to simulate the process of the model throughput.

In this paper, ELM and GA will be employed to determine the best configuration of the SFR parameters. The objective is to obtain the best configuration that to be used in the existing SFR model. The best configuration will produce higher system throughput then the conventional SFR. We proposed to use ELM to model the problem using the simulated data. Then we will use the SFR model to optimize the SFR parameters using GA. The proposed ELM-GA will be investigated in order to tune the entire model's parameter including number of hidden node for ELM and GA's parameter to obtain the best throughput.

Next, in section II, we will introduce SFR model and the parameters that needed to be optimized. In section III and IV, we will discuss on the employed techniques and the proposed methodology, respectively. In section V, we will discuss the results of the experiment. Finally, conclusion is presented in section VI.

II. SFR MODEL

A. Soft Frequency Reuse

Soft Frequency Reuse (SFR), the overall bandwidth is shared by all base station, but for the transmission on each sub-carrier the base stations are restricted to a certain power bound [8].

For the SFR, there are two types of SFR that are being used in the field of network transmission for the time being. The first type is conventional SFR which is a normal SFR and have certain limited functionality. The second type is the Adaptive SFR, this SFR can be adjusted to the environment to produce a better system performance. The conventional SFR is quite independent on cell environment and is considered to be suitable for the macro cell network, where the network layout is quite regular and homogenous such as the classical hexagonal network. Therefore, in conventional SFR, all adjacent cells use the same subcarrier power level and also the same amount of allocated channels for their cell-edge or cell-center users [9] as illustrated in Figure 1.

The backlash of using the convention SFR can be seen in-building networks, the network layout will be irregular and the traffic load changes from time to time. Due to this limitation, adaptive SFR has been introduced to counter this problem. In paper [9], the results of the adaptive SFR have outperformed the conventional SFR in the system performance about 20~35% from the conventional SFR. In that paper, it was proposed that the SFR was using a new SFR scheme where based on the consecutive subcarriers allocation and distributed subcarrier allocation.

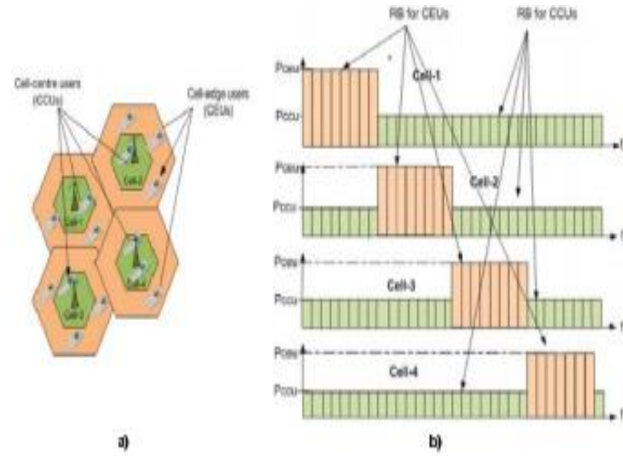

Figure 1: Illustration of the conventional SFR, a) Four adjacent cells with the interior region contains CCUs and the exterior regions contains CEUs, and b) the number of resources and the resource power level in the conventional SFR.

B. SFR Parameter's to be Optimized

SFR has several parameters that determine the throughput rate. In order to carry out the optimization process, the parameters of the system that needed to be optimized for a better system performance are Power Ratios of the base station (β), concentration of cell-edge user, user distribution of sub-carriers. Each of the parameters has been formulated for the SFR use. The power ratios of the base station or β, can be calculated by using Equation (1).

$$\beta = \frac{Power.of.CCU}{Power.of.CEU} \tag{1}$$

The number of resources and the resource of power level, βin the conventional SFR is shown in Figure 2. As we can see, we will use the green part of the power level and will divide by the peach part of the power level to get the power ratios for the base tower.

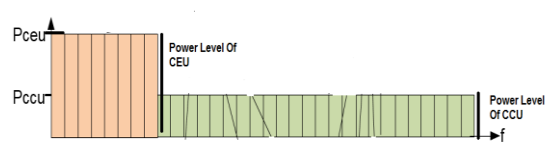

Figure 2: Indications of power levels

The next parameter is the concentration of cell-edge user; this parameter is formulated using Equation (2).

$$Con.CellEdgeUser = \frac{total.cell.edge.user}{no.of.user.in.a.cell} \tag{2}$$

Figure 7 shows the illustration of the conventional SFR. The concentration of cell-edge users can be calculated for an example if the total user for the single cell network is 20 users, the users that are located outside the interior of the SFR, it will be called cell edge user. These users will be used to calculate the concentration of the cell-edge user by dividing it to the total number of users in that same area.

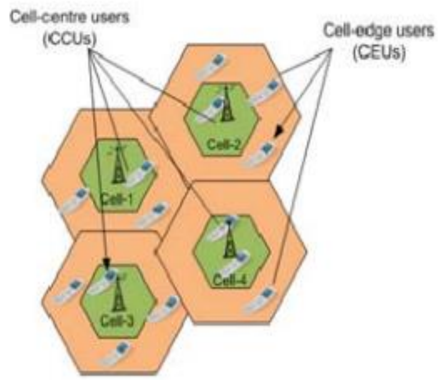

Figure 3: Coordination's of users

As refer to Figure 4. The contribution of the network's sub-carriers can be formulated using Equation (3).

$$User.distribution = \frac{no.of.subcarriers.for.CEU}{total.no.of.subcarriers} \tag{3}$$

III. Employed Technique

In this section, we will discuss on the techniques that will be employed to meet the objectives of this paper.

A. *Extreme Learning Machine*

Feedforward neural network has been widely used as a learning machine for past decades [10]. However, the learning speed of feedforward neural network is slower than required [11]. This is because traditional learning process may require multiple layer of hidden nodes which produce multiple parameters and each of them exists dependencies towards another. This process is however being eliminated by implementing ELM where only single hidden layer feedforward neural network (SLFNs) exists within the learning module [12].

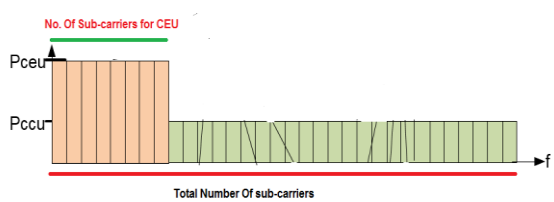

Figure 4: User Distributions

ELM will train the input parameters by implementing a single hidden layer feedforward neural network (SLFNs) which randomly chooses the input weights and analytically determines the output weights of SLFN [12]. The diagram in Figure 5 represents the ELM model.

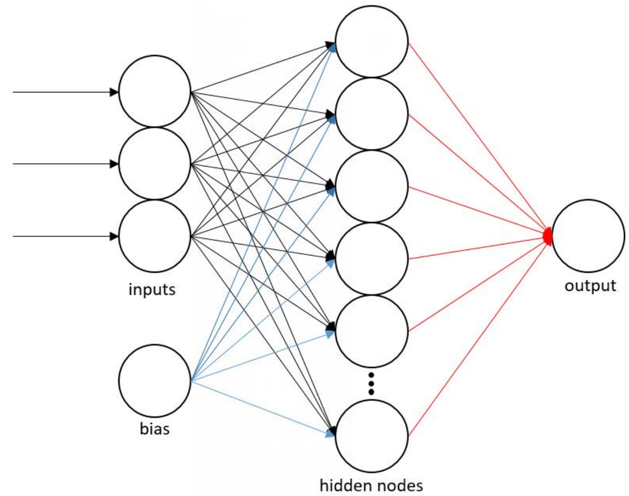

Figure 5: ELM SLFNs model

Firstly, by supplying input samples, $x(t)$ to ELM, random weights and biases are first assigned. Since the fixed input weights w_i and hidden layer b_i is available without any tuning, the process can be done within a short duration and SLFN can be trained by simply finding the least-square solution $\hat{\beta}$ of the linear system $H\beta = T$:

$$\begin{aligned}&\|H(w_1, \dots, w_n, b_1, \dots, b_n)\beta - T\| \\ &\qquad = \min_{\beta}\|H(w_1, \dots, w_n, b_1, \dots, b_n)\beta - T\|\end{aligned} \tag{4}$$

However due to inconsistence matrix size produced from the number of hidden nodes and training samples. The non-squared matrix produced by these differences can be overcome by the implementation of Moore-Penrose generalized inverse [11]. Implementation of Moore-Penrose is necessary to compute the linear system of smallest norm least squares solution by using:

$$\hat{\beta} = H^{\dagger}T \tag{5}$$

where $H^{\dagger}$ is the Moore-Penrose generalized inverse of matrix H. In general, the learning process of ELM can be summarized as follows:

1. Given training set$x_i(t)$, activation function $g(x)$ and hidden node number N
2. Randomly assign input weight w_i and bias b_i
3. Calculate the hidden layer output matrix
4. Calculate the output weight β

B. *Genetic Algorithm*

GA represents a powerful, general purpose optimization paradigm in which the computational process resembles the theory of evolution which is proposed by Darwin [13]. Genetic Algorithms have been used successfully for process parameter optimization and global optimization of absorption chiller system[14, 15].

GA starts with a randomized population of parent's chromosomes representing various possible solutions to a problem. The individual components within a chromosome are referred to as gene. New child chromosomes are created by crossover and/or mutation operations. Crossovers occur as a probabilistic exchange of genes between two or more chromosomes. Mutation involves the random replacement of genes in chromosome. All chromosomes are then evaluated according to a fitness or objective function, with the fittest surviving into the next generation. The result is a gene pool that "evolves" over time to produce better and better solutions to a problem.

GA has been used to explore various parts of the decision space with a high probability of finding improved solutions [15]. There are no guarantee that the final solution obtained using GA will be the best for global optimal solution to a problem, Holland proved theoretically and empirically that these algorithms provide robust searches in complex-spaces [13].

IV. METHODOLOGY

The flow of process of the proposed technique is shown in Figure 6. The data obtained is from the Taguchi conventional SFR model [2]. As mentioned previously, firstly the model is developed using SFR data by using ELM. Secondly, the optimization process will pick the best configurations of the three parameters and will give the best expected throughput for the system model.

The input data for the ELM consists of the 3 input parameters which is a power ratio (β), concentration of cell edge users and user distribution and the throughput as the output from 50 training sets. In the real application, these 3 parameters can be adjusted by adjusting the number of the sub-carriers, power ratios and the number of the cell users in order to obtain higher throughput. The training sets are used to build model using ELM. The models are then subject to the GA process in order to optimize the parameters.

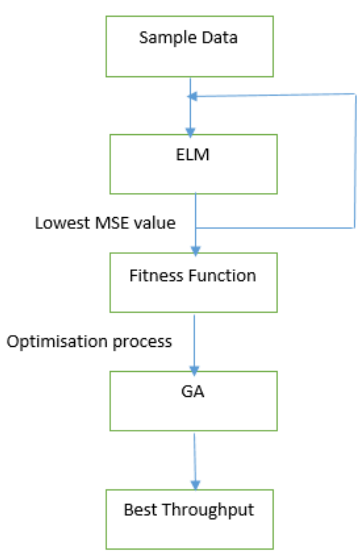

Figure 6: Flow of the proposed technique

In this case, the fitness function will consists of power ratios, cell edge users and user distribution. The ELM algorithm will generate a random number of weightage to be used in the algorithm. The next step, the best model will be selected based on the lowest MSE values of the trained data. From the model, we will obtain the fitness function to be used in the genetic algorithm. The genetic algorithm will find the best configurations to be used in the SFR model to predict the best throughput for the system.

A. Designing ELM model based on the SFR data

For this study, ELM consists only 1 layer of hidden nodes. ELM can be used to find the relationship of the input and output of the system via regression or it can be used to classify different features of the data as classifiers. In this case, the ELM model was used to find the relationship of the inputs and outputs of the system. The mean squared error (MSE) is used to evaluate the relationship of the input and output which implicitly determine the model quality at training stage. The lower the MSE value, the higher probability of the model to be accepted to be used as the fitness function in GA later. The maximum hidden nodes that were being used in this system is 25. It is based on Equation (6):

$$Max\ Hidden\ Node = \frac{Number\ of\ Neuron\ Inputs}{2} \tag{6}$$

The above formula limits the usage of hidden nodes and prevents the usage of different values for the hidden nodes as to avoid over-fitting. However, in order to obtain the best model for SFR parameter's, several number of hidden nodes configuration are investigated. The best model with the least MSE value will be chosen as model to formulate the objective or fitness function for optimization process to get the fitness function. Table 1 shows the result of experimenting different numbers of hidden nodes.

Table 1
Accuracy Value for Different Nodes

Number of Hidden Nodes	Train Accuracy (MSE)	Test Accuracy (MSE)	Activation Function
5	7.9110	6.9706	Sin
10	0.1955	0.1220	Sin
15	0.0518	0.1558	Sin
20	0.0807	0.0446	Sin
25	0.0460	0.0871	Sin

From the Table 1, it shows that the hidden nodes of 20 yields the lowest MSE values which is 0.0807 and 0.0446 respectively for the train accuracy and test accuracy. Next step is to test the hidden nodes by using different activation functions. Table 2 summarizes the results of different activation function.

Table 2
Results of Different Activation Function

Number of Hidden Nodes	Activation Function	Test Accuracy (MSE)	Train Accuracy (MSE)
20	Sin	0.0491	0.0476
20	Sig	0.0486	0.0428
20	Hard Lim	0.0389	0.0667

As a result from Table 2, the ELM model that uses 20 hidden nodes with sigmoid function as activation function will be used to model the SFR model. The model of this ELM and weightage for each neurons can be represented as in Figure 7. Therefore, this model is subjected to the optimization for finding the best SFR parameter's using GA.

The weightage of the each nodes lies in the connectors of each of the nodes. From this model, we can acquire the fitness function. The output function can be calculated by using Equation (7).

$$f(x) = \sum_{i=1}^{L} \beta i G(ai, bi, x) \quad (7)$$

where $\boldsymbol{ai}$ are input weights from *c input* nodes to i^{th} hidden node, and $\boldsymbol{bi}$ is the bias of the i^{th} hidden node. $\boldsymbol{ai}$ and $\boldsymbol{bi}$ are called the learning parameters of the i^{th} hidden node. $\boldsymbol{x}$ is the input vector with $\boldsymbol{c}$ dimensions and $\boldsymbol{\beta i}$ is the output weight from the i^{th} hidden node. $\boldsymbol{(ai)}$ is the output of the i^{th} hidden node with respect to input $\boldsymbol{x}$ and *G* activation function. Activation function can be any nonlinear piecewise continuous functions such as sigmoid, Gaussian, etc. [16]. The fitness function that will be used to implement GA is given in Equation (8).

$$f(x) = sig(\sum_{i=1}^{L} \beta i G(ai, bi, x)) \quad (8)$$

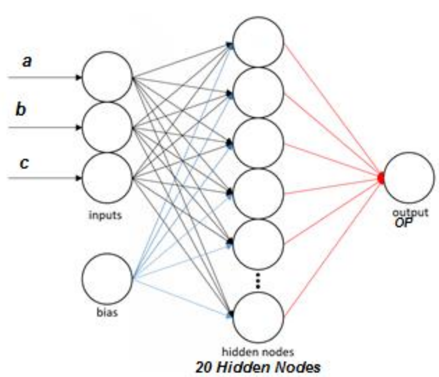

Figure 7: SFR model using ELM

B. Design of Genetic Algorithm for SFR Optimisation

The design of the optimisation process is being done using software. The data that are feed into the ELM algorithm are from Microsoft Excel. The parameters of the SFR model were used as to represent the genes within the population of chromosomes. The ELM model for the SFR data was used to get the fitness function within MATLAB for evaluating individual chromosomes. The goal of the integrated ELM- GA system is to determine the best configuration values for the 3 parameters needed to provide for the SFR model to get the best throughput of the system.

The ELM-GA system receives the current SFR parameters value of power ratios, cell edge user and user distribution and matches it with their respective outputs. In this experiment, the value of 50 populations was used because 50 datasets were obtained through the Taguchi conventional SFR data. The GA component of the system uses the predictive ELM model as its fitness function, and uses the current parameter values as the process input. Next, GA will calculate between the values from the input and throughput of the system. The GA will calculate through the constraint of the perimeters. Figure 7 shows how the GA process works with the ELM model.

Figure 7: How ELM model integrated with GA

V. EXPERIMENTS, RESULTS AND DISCUSSION

With the best ELM model from the previous section, we have performed several experiments to get the best configurations for the SFR model. Basically, the GA will explore new configurations within the ELM model by running through specific constraints of the input. Below are the list of the possible configurations that will boost the throughput of the system.

Table 3
Sample Original Configurations Without GA

a	*b*	*c*	*OP*
0.4	4	0.3	67.7054
0.4	4	0.55	67.7538
0.4	8	0.3	67.6865
0.4	8	0.55	67.6276
0.4	6	0.3	67.725
0.4	6	0.55	67.7026
0.4	10	0.3	67.6275
0.4	10	0.55	67.7651
0.4	12	0.3	67.6118
0.4	12	0.55	67.6555

Table 4
Configuration Values With GA

a	b	c	OP	Activation Function
0.4003	5	0.5499	68.1190	Sig
0.4027	5	0.4324	70.0920	Sig
0.4005	5	0.4498	64.4044	Sig
0.4002	5	0.3000	67.8881	Sig
0.4003	5	0.4951	69.0095	Sig
0.5999	11	0.4094	68.9301	Sin
0.6000	11	0.4079	69.7732	Sin
0.5998	11	0.3987	69.3735	Sin
0.5981	11	0.4000	69.1027	Sin
0.4000	5	0.5500	69.6826	Sin

Figure 8 shows the convergence curve of the GA in finding the maximum value of throughput from the ELM model. In GA, the process of mutation/crossover will occurs to get the best configuration. The generation is set to be 50. The populations, we can set its random values, the higher the generations, the better the GA can perform.

The optimization process was repeated as many times until the configurations value and the output values are the same. As a result from the continuous runs, we can see from the table, there are significant changes that we can see from the original configurations and the configurations with GA. The maximum output of the original configurations is *67.7498* with the configuration values of *a = 0.6, b= 12 and c = 0.55* while the maximum output for the configuration with GA is 70.0920 with the configurations values of *a = 0.4027, b = 5.00 and c =0.4324*. The activation functions of the ELM model also have an effect on the output of the throughput. As we can see here the sigmoid function will gives a lower value of *b* but the value *OP* is actuating from *64.4044* and *70.0920* which is not very stable. On the other hand, the sin function however gives a stable *OP* values but in exchange it has a very high *b* values.

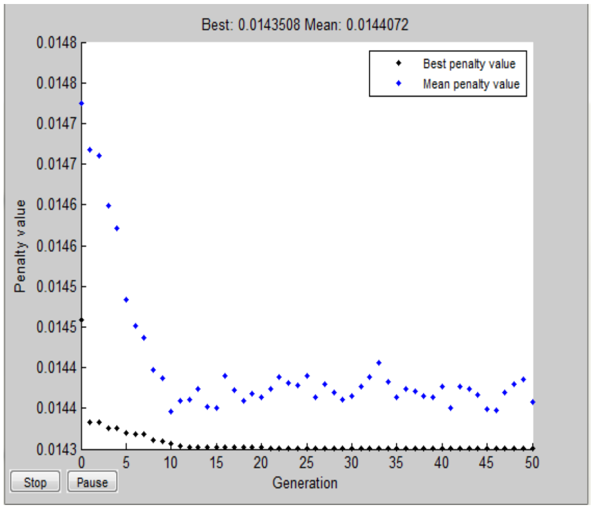

Figure 8: GA process to get the maximum value of throughput

VI. Conclusion

An integrated ELM-GA tool for optimizing the SFR data has been developed to optimize throughput for the conventional SFR. An ELM model, which in this case is the ELM, of the optimisation process was developed using the neural-network model as the fitness function, to determine which configurations values would result in the highest throughput of the SFR model system. The process parameter values derived by the ELM-GA algorithm was based on the functional mapping developed by the neural-network model. That functional mapping is representative of the training data set, and should be as accurate as the training data set. The optimisation process of ELM-GA has been proved to yield the best configuration to be used in the SFR model to get the best throughput. From the experiment, we can see the best values to be used in the configurations are *a = 0.4027, b = 5.00 and c =0.4324* which will produce the highest throughput of *70.0920* but by using this configurations the results are hard to predict because it is not stable in a few runs. The best configuration is by using the sine activation function, the throughput of the system is stable in a few runs. The best configuration for the sine activation function is *a = 0.6000, b = 11.0000, and 0.4079* which will yield the throughput of *69.772*. This shows the model of ELM-GA has succeeded by finding the best configurations that will increase the throughput by 3% of the original conventional SFR.

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