PSO of Neural Networks to Predict Busy Times of Cellular Traffic for Assignment to TV Idle Channels by Cognitive Radio

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Abstract: **Kenya has identified radio spectrum as a key driver in its development. Yet, globally, radio spectrum is inefficiently utilized due to ITU's static spectrum allocation. In Kenya, mobile operators are running short of bandwidth due to deployment of 4G services, which enable superfast mobile broadband/internet. In the USA and UK, FCC and Ofcom, respectively, have made effort to allow opportunistic 'poaching' of licensed spectrum as long as communication of licensed user is not interfered with. This has focused research on use of cognitive radio, which would use its sensor networks to establish which TV channels are idle in order to allocate them temporarily to cellular networks. Enabling the cognitive radio to predict which channels shall lie idle at what times introduces better planning and more temporally-efficient allocation. This study explores the viability of predicting the times of mobile telephony traffic jam for a mobile service operator with poor QoS rating within a cell of perennial mobile traffic jam in order to explore whether those times can map well with the TV spectrum holes. The times of the TV spectrum holes shall be determined in a later study.**

Keywords: Cognitive Radio, Mobile Telephony Traffic, NN, PSO

I. INTRODUCTION

Frequency spectrum is a resource in great shortage due to its potential as a vehicle for wealth creation for development. In Kenya, the ICT sector has been identified as a key driver in the economic pillar of Kenya's Vision 2030. Yet, the country identifies low bandwidth as one of the key challenges in the ICT sector [6].

Regulatory bodies in the world (including the Federal Communications Commission in the United States and Ofcom in the United Kingdom) found that most radio frequency spectrum was inefficiently utilized [15]. Cellular network bands are overloaded in most parts of the world, but other frequency bands are insufficiently utilized. International Telecommunications Union (ITU)'s fixed spectrum allocation policy prevents rarely used frequencies (those assigned to specific services) from being used. Due to ITU's strict policy, some national regulatory bodies in the world have been considering allowing unlicensed users in licensed bands if they would not cause any interference to licensed users. These initiatives have focused cognitive-radio research on dynamic spectrum access.

In Kenya, there is huge growth in intelligent mobile devices such as smartphones and pads which has driven major cultural changes in communication that is resulting in increasing user demand for high quality, seamless broadband experiences, across fixed and mobile networks. Furthermore, the last one of the annual audits carried by Communications Commission of Kenya (CCK) on mobile phone service providers' quality of service was damning with average call-blocking and dropping rates approaching 30% within Nairobi city. Is dynamic spectrum access viable in the Kenyan situation? This study has conducted two surveys which indicate that TV consumption is inefficiently-used within the city of Nairobi, and may be 'poached' in instances of cellular over-burden. One survey established strong indications to habitual TV-viewing, with most viewers following certain programs at certain times of the day. The other survey established that certain channels are more popular with certain residential areas, which also constitute mobile cells. This may be due to the fact that a residential estate mostly represents people of a certain level of affluence with various TV broadcasters targeting a specific level. The two surveys imply that within certain mobile cells, consumption of certain TV channels is hardly existent. The surveys also imply that these TV spectrum holes are consistent due to habit-viewing and are, therefore, predictable.

Can cognitive radio network be used to consistently establish the TV spectrum holes within a mobile cell of perennial traffic jam and therefore predict future holes? Cognitive radio (CR) is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which are not, and instantly move into vacant channels while avoiding occupied ones. CR is a hybrid technology involving software defined radio (SDR) as applied to spread spectrum communications. The concept of cognitive radio was first proposed by Joseph Mitola III in a seminar at KTH (the Royal Institute of Technology in Stockholm) in 1998 [11]. Apart from the primary receiver detection technique, all the others attempt to detect the primary transmitter. For establishing TV idle channels, detection of the receivers and the channels they are tuned into is

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more appropriate. This is because transmitter signals may exist within a geographical location yet no receiver is tuned into it. Such a channel is, for all practical purposes, idle. Cognitive radio main operation stages are: Spectrum Sensing and Spectrum Management [1]. So much study has been leveled at spectrum management to enable the Cognitive Radio to select a most technically and temporally appropriate idle channel for a waiting unlicensed user. To enable TV spectrum holes to be used to serve over-burdened cellular networks efficiently, two things must be achieved:

A) Modeling of mobile traffic pattern within a cell of perennial traffic jam and predict times of heaviest jam

B) model patterns of TV-viewing within the cell and predict the channels that would be idle in the times of the heaviest jam

The scope of this paper is outlined in A), above. The study hypothesis, therefore, is;

Can mobile traffic of any of the major mobile service providers be successfully modeled to predict the times of worst mobile traffic jams within a cell of perennial mobile traffic jam?

II. RELATED WORK

The following review of existing literature outlines instances where modeling of mobile telephony traffic has been done using machine learning algorithms. The review further outlines neural networks as the most popularly-used machine learning algorithm for event prediction and further outlines Particle Swarm Optimization as a technique for improving the performance of the neural network.

A. Instances of Prediction for Cognitive Radio

In [14], it is apparent that research has been going on about opportunistic use of TV bands after the migration, due to the fact that TV bands are one of the least-efficiently used. In [2] [8], prediction of busy mobile traffic times are done with significant accuracy, although the two studies use two machine learning algorithms; Hidden Markov Model (HMM) and Support Vector Machine (SVM). In [10], a multilayered feedforward NN with backpropagation algorithm was used to model the telephone traffic situation. Matlab was used as a platform for all simulations. Regression analysis between predicted traffic congestion volumes and corresponding actual volumes gave a correlation coefficient of 87% which clearly shows the utility and effectiveness of Neural Networks in traffic prediction and control.

The literature in [18] [16] [17] [9] describe studies that have successfully applied Neural Networks (NN), the Hidden Markov Model (HMM), Bayesian Inference (BIF), Autoregressive Model (ARM) and Moving Average (MA), to model and predict occurrence of spectrum holes for secondary allocation to users by cognitive radio.

B. Predictive Analysis: Artificial Neural Networks and Particle Swarm Optimization

An artificial neural network is the most popularly-used predictive algorithm. A neural network learns from experiential data and does not need to be reprogrammed. As its biological predecessor, an artificial neural network is an adaptive system [3]. One of the most popularly-used neural network models is the multi-layer feedforward network. Its training by gradient descent to approximate an unknown function, based on some training data consisting of pairs *(x,t)* is outlined here below. The vector **x** represents a pattern of input to the network, and the vector t the corresponding target (desired output). The overall gradient with respect to the entire training set is just the sum of the gradients for each pattern. The mathematical modeling below describes how to compute the gradient for just a single training pattern. The units shall be numbered and the weights shall be denoted from unit j to unit *i* by w_{ij}.

Definitions:

error signal for unit j: $\partial j = - \partial E/\partial net_j$ …………(1)

gradient for weight w_{ij}: $\Delta w_{ij} = \partial E/\partial w_{ij}$ …………(2)

set of nodes anterior to unit i: $A_i = \{j: \exists\ w_{ij}\}$ ……(3)

set of nodes posterior to unit j: $P_j = \{i: \exists w_{ij}\}$ …..(4)

The gradient: We expand the gradient into two factors by use of the chain rule:

$\Delta w_{ij} = - \partial E/\partial net_i * \partial net_i/\partial w_{ij}$ ……… …………… (5)

The first factor is the error of unit i. The second is

$\partial net_i / \partial w_{ij} = \partial / \partial w_{ij} * \sum w_{ik} y_k = y_j$ ……………… (6)

Putting the two together, we get

$\Delta w_{ij} = \delta_i y_j$.. ………………………………………… (7)

To compute this gradient, there is need to know the activity and the error for all relevant nodes in the network. **Forward activation:** The activity of the input units is determined by the network's external input x. For all other units, the activity is propagated forward:

$y_i = f_i(\sum w_{ij} y_j)$ …………………………………… (8)

Note that before the activity of unit i can be calculated, the activity of all its anterior nodes (forming the set A_i) must be known. Since feedforward networks do not contain cycles, there is an ordering of nodes from input to output that respects this condition.

Calculating output error: Assuming that we are using the sum-squared loss

$E = ½ \sum (t_o - y_o)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$

the error for output unit **o** is simply; $\delta_o = t_o - y_o$

Error backpropagation: For hidden units, the error must be propagated back from the output nodes (hence the name of the algorithm). Again using the chain rule, the error of a hidden unit in terms of its posterior nodes can be expanded:

$\delta_j = - \sum \partial E/ \partial net_i * \partial net_i/ \partial y_j * \partial y_j / \partial net_j \ldots\ldots(10)$

Of the three factors inside the sum, the first is just the error of node i. The second is

$\partial net_i / \partial y_j = \partial / \partial y_j * \sum w_{ik} y_k = w_{ij}, \ldots\ldots\ldots (11)$

while the third is the derivative of node j's activation function:

$\partial y_j / \partial net_j = \partial f_j (net_j) / \partial net_j = f^{'}_j (net_j) \ldots\ldots(12)$

For hidden units h that use the tanh activation function, use of the following special identity can be made:

$tanh(u)' = 1 - tanh(u)^2, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$

giving;

$f^{'}_h (net_h) = 1 - y^2_h \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$

Putting all the pieces together results into;

$\delta_j = f^{'}_j (net_j) \sum \delta_i w_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$

PSO-trained neural network, on the other hand, is proven to outperform standard back-propagation neural network, such as the MLP mentioned above [12]. PSO training is also compared in [4] against Differential Evolution (DE) training of neural networks with better results for PSO-trained network. Compared to the genetic algorithm (GA), PSO is easier to implement, reaches optima faster and with fewer parameters to adjust, thereby using computer resources sparingly [7].

PSO is initialized with a group of random particles (solution) and then searches for optima in a conceptual 3D space by updating generations. In every iteration, each particle is updated by following two best 'values'. The first one is the best solution (fitness) it has achieved so far. The fitness value, called *pbest* is also stored. Another 'best' value that is tracked by the particle swarm optimizer, obtained so far by any particle in the swarm. This best value is a global best and called *gbest*. When a particle takes part of the population as its topological neighbors, the best value is a local best and called *lbest*. After finding the two best values, the particle updates its velocity and position with the following equations (1) and (2), respectively [7]:

*[v]=[v]+c1*rand()*(pbest[]–present[]) +*
*c2*rand()*(gbest[]– present[]) …......................(1)*

present[] = present[] + v[]……………………….(2)

where *v[]* is the particle velocity; *present[]* is the particle (solution); *pbest[]* and *gbest[]* are defined as stated before; *rand[]* is a random number between (0,1); *c1* and *c2* are learning factors, usually both equal to 2.

III. METHOD

To conduct prediction of an event, it is essential to identify the factors which influence the occurrence of the event. Manifestations of these factors are studied repetitively to establish a pattern that relates the values of these factors and the event to be predicted. Machine learning involves use of software that have the ability to model these resulting variations of the event with respect to the varying values of the influencing factors.

In order to model mobile telephony traffic, the study has considered data often collected in the process of managing mobile telephony. These data are; Date, Time, Cell ID, Site ID, Cell Name, Base Station Controller Name, Actual Traffic (in Erlang), True Blocking Value (%age value for blocked calls), Utilization Value (%age enhancement through mitigation) and Half Rate Proportion Value (%age half-rate mitigation) [5]. The study chose to use; True-blocking-value, Day-of-the-week and Half-rate-proportion-value as input variables with Time-of-day as the predicted value or target. Once Time-of-day at a high True-blocking-value has been predicted, a further study to this current one shall attempt to predict the TV spectrum holes for those times of mobile traffic jam. Table 1 below illustrates hint of the format of data used for modeling traffic patterns;

TABLE 1 – MOBILE TRAFFIC DATA TRAINING FORMAT

	True Blocking Value	**Day of the Week**	**Half Rate Proportion Value**	**Time of Day**
1	V1	D1	H1	T1
2	V2	D2	H2	T2
.				

The data of the mobile telephony traffic was obtained from the transaction processing system of one of the leading service providers in Nairobi. Three weeks of traffic was used to ensure the weekly repetitions which ensure predictability was captured. The Multi-Layer Perceptron (MLP) neural network built in this study had the three influencing factors; True-blocking-value, Day-of-the-week and Half-rate-proportion-value constitute the inputs x_1, x_2 and x_3. Time-of-Day, was the predicted value or target, **t**, as it is a direct function of times of heaviest traffic. The performance of the neural network was optimized using a Particle Swarm Optimization (PSO) algorithm. Each neural network of specific and unique features (number of layers, number of neurons, activation function, learning rate) constituted a particle out of many within a swarm. The features of each particle were then continuously varied and the performance of each new particle evaluated. The new particle with best performance formed the new neural network to be used for modeling. Version R2010a of MATLAB was used to develop the script to implement the MLP. For the PSONN, the neural network toolbox was linked to the PSORT toolbox in the R2010a using Neural Network add-in for PSORT by Tricia Rambharose [13]. Evaluation of performance uses the Mean Squared Error (MSE) and average error values.

IV. RESULTS

The following TABLE 2 and Fig. 1 illustrate the MSE values for the various models of the MLP.

TABLE 2 – MSE VALUE FOR VARIOUS MODELS OF MLP

No. of Hidden Layers	No. of Neurons	Learning Rate	Training Function	Mean Square Error (MSE)
1	20	0.01	log sigmoid	0.09346
2	20	0.08	log sigmoid	0.07636
3	40	0.01	log sigmoid	0.06930
1	20	0.4	tan sigmoid	0.09834
2	20	0.01	tan sigmoid	0.07980
3	20	0.4	tan sigmoid	0.07215

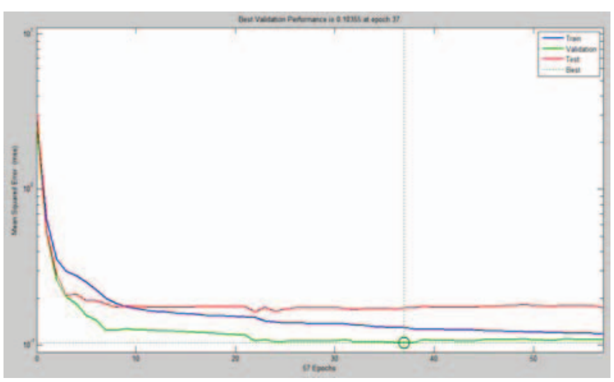

Fig. 1 - Best Validation Performance (in MSE) for One of the 30 Trained MLP Models

For the PSONN architecture, the graph showing the varying average error as the neural network was being optimized by the particle swarm optimization tool decayed down to 0.1369 after about 34 epochs, as illustrated in Fig. 2.

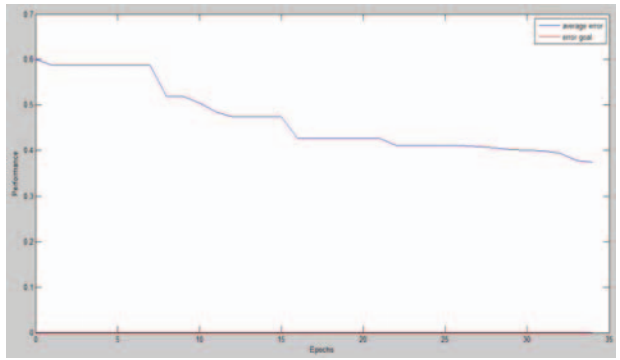

Fig. 2 – Progressive Performance of PSONN Through the Epochs

V. CONCLUSION

In this study, the lowest MSE value recorded for the MLP model is 0.06930 with number of hidden layers at 3, number of neurons at 40, learning rate at 0.01 and logarithmic sigmoid as training function. The graph representing the average error for the PSONN went down to a low of 0.1369 through the epochs. Given that the average error is a square root scale with respect to the MSE, the PSONN has shown better performance than the MLP. The results are a strong indication that training an MLP neural network using the PSO adds value to the standard back propagation neural network. The results from both the MLP and PSONN models also indicate that there is a strong relationship between True-blocking-value, Day-of-the-week and Half-rate-proportion-value as input (influencing) factors and Time-of-Day as the predicted value for mobile telephony traffic of a major service provider within a certain cell of perennial mobile traffic jam within Nairobi city. The second conclusion further indicates that it is viable to predict mobile telephony traffic of the mentioned service provider, within the mentioned cell within Nairobi city. If it shall be established that there are consistent TV spectrum holes at the times of mobile traffic jam within the cell, it should be viable enough to predict and use the TV spectrum holes for excess mobile traffic in order to improve QoS significantly by the service provider.

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