Use of GA-Optimized NN to Predict DVB-T2 Receiver Spectrum Holes to Accommodate Burden GSM Voice Calls

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***Abstract* – Cognitive radio enables opportunistic utilization of under-used spectrum for networks that are overwhelmed. In Nairobi city, mobile telephony networks are overwhelmed while broadcast TV channels lie idle in some parts. Research in cognitive radio concentrates on point-to-point communication and successfully conducts transmitter sensing in order to establish spectrum holes. However, in broadcast communication such as terrestrial TV, transmitter detection is inefficient, as transmitter signals may be present yet that licensed channel is not tuned-into by TV receivers, rendering those frequencies essentially idle. Our paper describes an attempt to use a novel remote technique to detect, model and predict which DVB-T2 channels are not tuned-into by any TV receiver during the worst mobile traffic jam time, within an overwhelmed mobile cell. An MLP that was GA-optimized to an MSE of 0.0046245 indicated predictability of TV-viewing and predicted Channel 514 MHz as being idle during the 5.00-5.03 pm jam time slot.**

Keywords – Cognitive-Radio; GSM; TV-Receiver-Spectrum-Holes; MLP; GA

I. Introduction

Frequency spectrum is a resource in great demand. Cellular network bands are overloaded in most parts of the world, but other frequency bands are insufficiently utilized [1]. Yet International Telecommunications Union (ITU)'s fixed spectrum allocation policy has prevented poorly-utilized frequencies from being assigned to those who need it more. Opportunistic use of under-used bandwidth, however, is viable using the Cognitive Radio (CR) [2]**.** The CR would decide on the best spectrum band, of all bands available, to meet quality of service requirements and not interfere with licensed users according to ITU radio regulations [3].

In Kenya, mobile telephony operators run short of bandwidth and demand the 700 MHz band for deployment of 4G services for super-fast mobile broadband/internet. There is huge growth in intelligent mobile devices that is increasing user demand for high quality, seamless broadband experiences, across fixed and mobile networks. Although the digital migration is bound to release great swathes of spectrum, in the long term, emerging phenomena such as the Internet of Things (IoT), which is expected to spawn 30 billion devices by 2020, shall strain the dividend. The last annual audit by the Communications Authority of Kenya (CAK) on mobile phone service providers' quality of service - CAK Annual Report, 2012/2013 - was damning. Safaricom Kenya Limited, the largest provider, had one of the worst blocked calls rate of 11% against a target of < 5%, with an aggregated compliance of just 50%.

The more popular cognitive radio research has been in detection of transmitter - as primary or licensed user - signals in a given area to establish which broadcaster's signals are missing there. The licensed channel for the broadcaster whose signals are missing is declared a spectrum hole and is opportunistically used as long as it stays idle. The following references are just a few of heavy research work on transmitter detection; [5] [6] [7] [8] [9] [10].

However, the major weakness of this model is that it is so inefficient in evaluating broadcast communication like terrestrial TV in order to opportunistically use its idle channels. It assumes that once a transmitter's signals are detected within an area, then the transmitter's frequencies are being consumed by TV viewers. But suppose there is no receiver tuned into those channels? Aren't those channels essentially idle?

Such channels are idle and can be 'poached' by secondary users. It would require a sensor network that monitors channel occupation by TV receivers in order to establish such spectrum holes. This is feasible, as shall be described in Methods section. The CR cognitive engine which would be coupled to the sensor network would further use the data it records, over time, about spectrum occupation by the TV receivers and use this data to build a predictive model. Rather than just allocating excess cellular burden to the idle TV spectrum as it occurs, the predictive model would allocate channels which are predicted to be idle in advance. Prior mapping of a future-occurring communication burden to its most suitable impending idle channel is then possible. The benefits of prior mapping are: time wasted in determining the most technically-appropriate of all the occurring idle channels is saved as the determination is done in advance; and temporal matching of idle channel to cellular burden is more efficient, considering that a long-occurring burden may be allocated a shortly-occurring idle channel,

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then demanding expensive seamless infrastructure to handle handover of communication burden to another channel.

To enable TV receiver spectrum holes to be used to serve over-burdened cellular networks efficiently, two things must be achieved;

1) modeling of mobile traffic pattern within a cell of perennial traffic jam and predict times of heaviest jam

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

In [11], we outline how we modeled mobile traffic within the Umoja-Moi Drive mobile cell which Safaricom Ltd data had indicated to be perennially-jammed. Results of the prediction indicated 5.00-5.03 pm as the time slot experiencing the worst mobile traffic jam within the cell. This paper attempts to model patterns of TV-viewing within the same cell and predict channels that would lie idle in the time of worst traffic jam.

Study Objective: To model TV channel occupation by TV sets within the cell of perennial mobile traffic jam, for prediction of idle channels at the predicted 5.00-5.03 pm jam time.

II. RELATED WORK

Prediction of mobile telephony jam times has been done in [12] [13] using derivatives of SVM with good results. SVM, however, is a new concept with no interfaces yet designed for optimizing algorithm, unlike neural networks.

A study on patterns of TV channel occupation by TV sets was also carried out in [14]. They did a survey of a housing estate by interviewing members of households and leaving behind a paper questionnaire. The study was an attempt to determine if there was times of the day when TV sets were uniformly turned off. The TV frequencies during such times could then be suitable for opportunistic use by overwhelmed networks. The study designed times of the day into slots of 30 minutes each and required participants to state in which slots their sets were off or on. The results indicate that on weekdays, TV activity peaked at 8 pm consistently. Over weekends, there was heavy activity between 10 am and 9 pm, with peaks at 2 pm and 9 pm.

Such a questionnaire is similar to the TV diary used by the global Nielsen Survey Company to determine the TV channels that sample TV sets were tuned to and at what times [15]. TV diary is an option for collection of data on occupation of TV channels by TV sets. However, its weakness is forgetfulness of participants in the household to record viewing. The novel technique of programming a set top box remains the best.

III. METHODS

To enable TV receiver spectrum holes to be used to serve over-burdened cellular networks efficiently, the model on Fig. 1 must be implemented. On the left hand side of the study model, the mobile base station controller, the ‘brain’ of the mobile transceiver station, has the normal burden of allocating frequency to communicating mobile stations or mobile phones within the cell. It also computes and keeps a record of the level of call traffic, true blocking value, half rate proportion value, date, time of day, among other values. This record, in the appropriate format, would be transferred to build a mobile traffic predictive model. The predictive model would use this data to predict the time of day with the highest true blocking values. On the right hand side of the model, a Cognitive Radio Base Station Controller (CRBSC) with a cognitive engine would couple to a sensor network and would harvest the channels that the TV sets within the mobile cell are tuned into at any time. The technique used for monitoring these channels is detailed in the following sections.

The data on TV channel occupation by the TV sets would be used to develop a TV receiver spectrum hole predictive model that would use the mobile telephony jam times as input to predict the TV frequencies that would be idle at those jam times. These predicted idle channels would, in turn, be passed back to the mobile base station controller for prior allocation of predicted mobile telephony burden.

While our paper cited in ‘[11]’ outlines the left hand side of the model in Fig. 1, this current paper outlines work done on the right hand side of the model. This current paper models channel occupation of TV receivers within the cell of study, and uses the predicted time slot of worst mobile traffic jam to predict which TV channels shall be idle or untuned-into by all the TV sets in the cell of study. The following section describes the steps taken in that modeling and prediction.

Let us recall the study objective: To model TV channel occupation by TV sets within the cell of perennial mobile traffic jam, for prediction of idle channels at the predicted 5.00-5.03 pm jam time. In order to obtain data of TV channels that were idle in the mobile traffic jam time, the channels tuned into by all the TV receivers within the cell of study must be collated to identify the channels that all the viewers uniformly kept off during the jam time slot. A remote method was employed to monitor and keep a record of these channels. We purchased 500 pieces of the AllWinner A10-based Mele A1000 Set Top Box (STB), at aliexpress.com, at $70 per piece. Using steps described in [16] [17], we were able to install Ubuntu on SD cards of each STB, leaving un-tampered the Android OS that each box came with in the flash memory. We were then able to install GNU Radio version 3.7.4, on the Ubuntu within the STB. GNU Radio has pre-coded software-based blocks for many functionalities, one being an FM transmitter [18]. It is implemented by integrating structured C++ code into the GNU Radio hybrid C++/Python framework.

The GNU Radio would import data on channels occupied by the STB. To import the data from the STB's OS, which is an Android in the flash memory, we emulated Mikael's technique in [19]. We then designed a software based GNU FM transmitter as in [20]. The GNU Radio's transmitter module would, in pulses to reduce interference to other signals, send the channels occupation data by TV STB sets to a remote laptop-based GNU Radio FM receiver which is stationed at the centre of the cell of study to receive such data from all STB's in the study.

In Kenya, after the digital migration, a few broadcasters have been allocated frequencies. Most TV stations have become only content producers who must transfer their content to their broadcaster of choice for broadcast. Signet-KBC, Startimes-PANG, BambaTV-Lancia and ADN were awarded broadcast license. Signet-KBC was allocated 54, Startimes-PANG was allocated 120, BambaTV-Lancia was allocated 11 while ADN was allocated 21 frequencies [21]. Each of these frequencies can carry twenty different multiplexed content. The general practice with broadcasters is to permanently allocate a certain frequency to the content of a group of producers. From the data of spectrum occupation that we collected using the just-mentioned remote technique, we populated a table with 30-day data in the format illustrated in Table I. To reduce amount of data needed to be collected, we focused on the period of the day around the predicted jam time of 5.00-5.03 pm.

TABLE I – TV VIEWING DATA COLLECTION FORMAT

Time of Day (Slots)	Day of the Week	TV content producer	Broad-caster	Frequency (MHz)
1	A	NTV	Signet	514
.	.	.	.	.

Neural networks work better with less fields for every number of training instances. Due to the fact that the fields, 'TV content producer' and 'Broadcaster', duplicate the 'Frequency' field, the two fields were removed from the table of training data. The eventual table of data for training is therefore as in Table II, with 'Time-of-Day' and 'Day of the Week' as inputs. 'Frequency' is the output;

TABLE II - TV VIEWING DATA TRAINING FORMAT

Time-of-Day (Slots)	Day of the Week	Frequency (MHz)
1	A	
.	.	.

In [22] [23] [24] [25], the back propagation neural network or multilayer perceptron neural network (MLP) is proven to conduct high performance of prediction. From various literature, it is also arguably the most popular predictive algorithm. An MLP can have several hidden layers. Formally, an MLP having a single hidden layer forms the function:

$$f : R^D \rightarrow R^L ,$$

where D is the size of input vector $x$and L is the size of the output vector $f(x)$, so that, in matrix notation:

$$f(x) = G(b^{(2)} + W^{(2)} (s(b^{(1)} + W^{(1)}x))), \ldots\ldots\ldots\ldots\ldots(1)$$

with bias vectors $b^{(1)}$, $b^{(2)}$; weight matrices $W^{(1)}$, $W^{(2)}$and activation functions $G$and s.

The vector

$$h(x) = \Phi(x) = s(b^{(1)} + W^{(1)}x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

forms the hidden layer. $W^{(1)} \in R^{D \times Dh}$ is the weight matrix connecting the input vector to the hidden layer. Each column $W_{\cdot i}^{(1)}$ represents the weights from the input units to the i^{th} hidden unit. Usual choices for s include *tanh*, with

$$tan\ h(a) = (e^a - e^{-a}) / (e^a + e^{-a}) \ldots\ldots\ldots\ldots (3)$$

, or the logistic *sigmoid*function, with

$$Sigmoid(a) = 1/(1 + e^{-a}) \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Both the *tanh* and *sigmoid* are scalar-to-scalar functions, however, their natural conversion to vectors and tensors is in applying them element-wise.

The output vector is therefore:

$$o(x) = G(b^{(2)} + W^{(2)}h(x)) \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

To train an MLP, all parameters of the model is learned. Using Stochastic Gradient Descent with mini-batches, the parameters to learn is in the set:

$$\Theta = \{W^{(2)}, b^{(2)}, W^{(1)}, b^{(1)}\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Gradients $\partial\ell / \partial\Theta$ is obtained using the back-propagation algorithm [26]**.**In our case, D shall be 2 and L shall be one.

Due to the fact that neural networks work best with numerical data which is well-encoded, Date field was encoded as day-of-the-week. The day can be represented using the most natural coding; 1 for Monday, 2 for Tuesday etc. However, performing direct conversion of nominal or categorical values into numerical has the risk that the direct values may not represent the relative essence of the categories. For instance, to give Monday a value of 1 and Friday a value of 5 implies that Friday is five times Monday which is not true. It is more appropriate to use 1-of-7 coding. Monday would be represented by 1,0,0,0,0,0,0 and Tuesday, by 0,1,0,0,0,0,0 etc. Values of the other fields would automatically be scaled to between -1 and 1.

In order to identify and use the most optimal MLP model, we compared the performance of the manually-trained MLP where we manually tried out various values of its models, such as number of neurons, number of layers, activation functions and learning rates, against automatically trying out values of its models using genetic algorithm (GA). The GA would automatically try out various values of the mentioned attributes out of a large solution space, each time testing the performance for most optimal model [27] [28] [29]. Version R2010a of MATLAB was used to develop the script to implement the MLP.

Genetic algorithms are techniques that attempt to establish the most optimal solution within a solution space. The problem would first be encoded as a string of real numbers or, as is more typically the case, a binary bit string. A typical chromosome may look like this:

10010101110101001010011101 10

The following set of steps is a typical algorithm which is repeatable until an optimum solution is found.

- Test each chromosome to see how good it is at solving the problem at hand and assign a fitness score accordingly. The fitness score is a measure of how good that chromosome is at solving the problem to hand.
- Select two members from the current population. The chance of being selected is proportional to the chromosomes fitness. Roulette wheel selection is a commonly used method.
- Dependent on the crossover rate crossover the bits from each chosen chromosome at a randomly chosen point.
- Step through the chosen chromosomes bits and flip dependent on the mutation rate.
- Repeat step 2, 3, 4 until a new population of N members has been created.

For instance, given two chromosomes, one represented by black digits with the second one represented by grey digits;

10001001110010010
01010001001000011

We can choose a random bit along the length, say at position 9, and swap all the bits after that point so the initial chromosomes above become:

10001001101000011
01010001010010010

This would sometimes be followed by mutation. This is where a bit within a chromosome will be flipped (0 becomes 1, 1 becomes 0). This is usually a very low value for binary encoded genes, say 0.001. So whenever chromosomes are chosen from the population the algorithm first checks to see if crossover should be applied and then the algorithm iterates down the length of each chromosome mutating the bits if applicable [30].In our case, the chromosomes of the GA would represent the array of weights of the MLP and the activation function. Fig. 2 represents the operation of the MLP being optimized by GA.

IV. RESULTS

Table III displays the four best manually-trained MLP models. The training of the best performing model, within the four, is illustrated in Fig. 3 with an MSE of 0.022933. However, Fig. 4 shows the process of training the GA-NN. As long as error is above a threshold, defined at 0.005, the GA keeps varying the indicated variables of the network. The trained network was used to predict the frequencies which would be tuned-into by the 500 TV sets within the cell, by querying the network with the 5.00-5.03 pm jam time slot. All the other frequencies were predicted to be occupied apart from 514 MHz, which was predicted to be idle during the jam time slot.

TABLE III – MSE VALUE FOR VARIOUS MODELS OF MLP

No. of Hidden Layers	No. of Neurons	Learning Rate	Training Function	Mean Square Error (MSE)
2	40	0.04	log sigmoid	0.198771
4	20	0.05	log sigmoid	0.026668
1	30	0.02	tan sigmoid	0.022933
3	20	0.4	tan sigmoid	0.083454

V. DISCUSSION

When several MLP models, each with varying parameter values, were trained, the best performing among them achieved an MSE of 0.022933. However, when GA was used to optimize MLP, the lowest MSE achieved during training was a much better value of 0.0046245. When this better network was used to predict the frequencies which would be tuned-into by the TV sets under study in the worst jam time slot of 5.00-5.03 pm, all the active frequencies were tuned-into except 514 MHz.

We then attempted to compute how many mobile telephony voice calls can be accommodated on the one idle DVB-T2 frequency. Although more advanced and efficient standards have begun to come to Kenya, where the study has been done, the prevalent mobile telephony system for voice calls is Global System for Mobile Communications (GSM). In GSM system, both Frequency Division Multiple Access (FDMA) and Time Division Multiple Access (TDMA) multiple access systems are used in turn, to enable mobile stations share bandwidth. In the FDMA phase, the 900 MHz band employs two-25 MHz bands (890-915 MHz and 935-960 MHz), one for uplink and the other for downlink. Each 25 MHz bandwidth hosts 124 carrier frequency channels, spaced 200 KHz apart. The 1800 MHz band does not differ much. The TDMA phase employs 8 full rate speech channels per frequency channel [31] [32].

For digital TV broadcasting, Kenya uses the Digital Video Broadcasting Terrestrial 2 (DVB T2) standard. In Kenya, the DVB T2 standard is designed to employ 6.66 or 7.61 MHz normal signal bandwidth [33].

50 MHz bandwidth would host (124 * 8 = 992) duplex carrier frequency channels once both FDMA and TDMA have been employed. One 6.66 MHz DVB-T2 channel should then be able to host ((6.66 MHz / 50 MHz) * 992) 132 speech sessions which is able to eliminate the worst true blocking value of 20.44 within the cell of study.

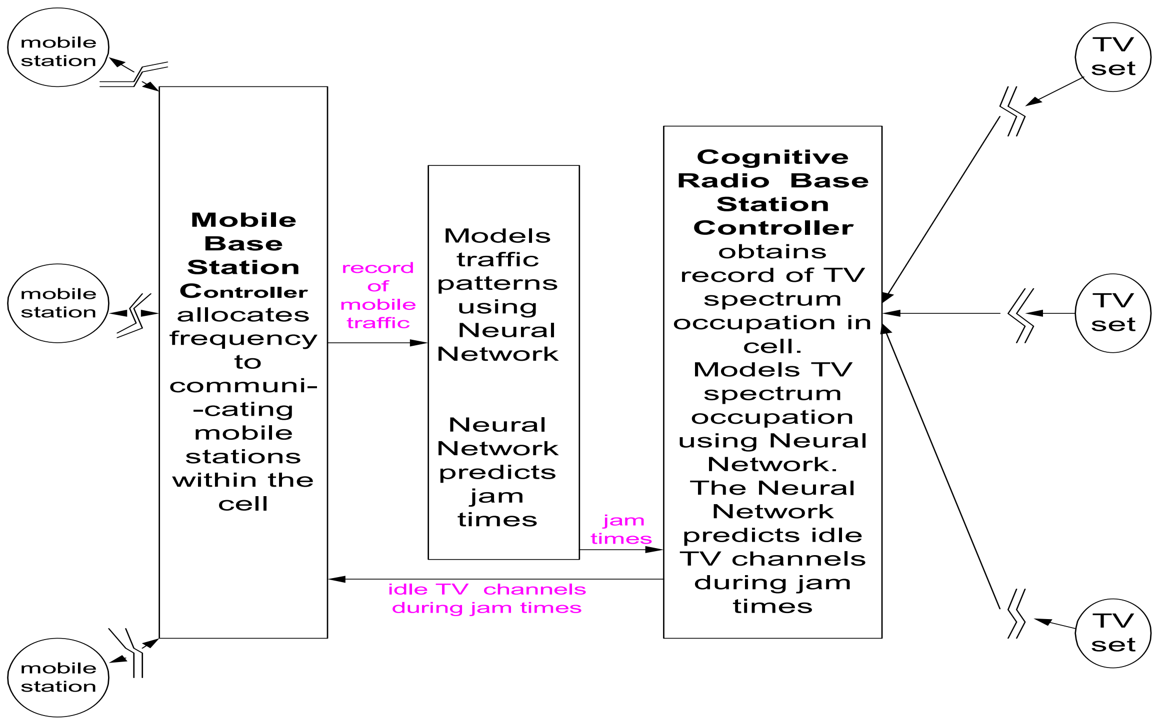

Fig. 1 - Model to Enable TV Receiver Spectrum Holes to be Used to Serve Over-burdened Cellular Networks

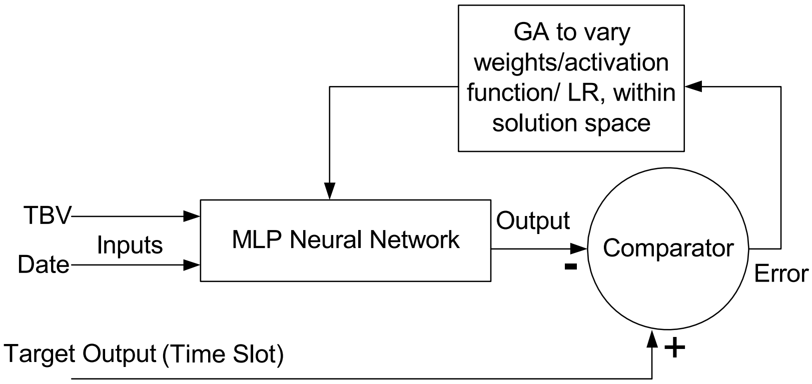

Fig. 2 – Process of GA-NN Training

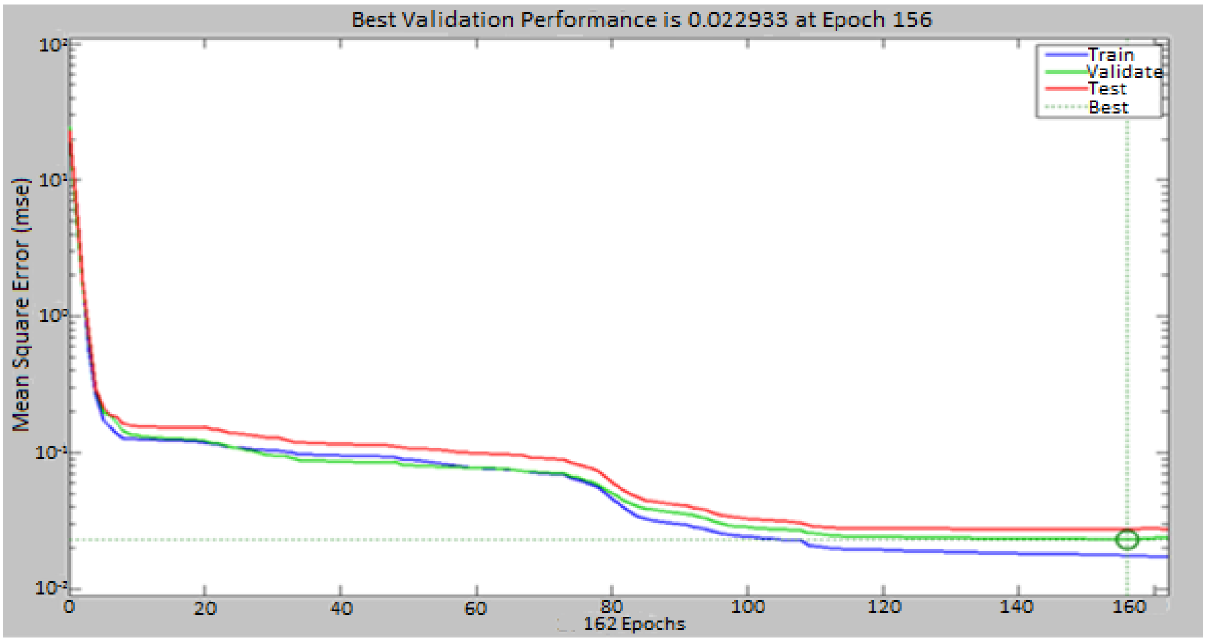

Fig. 3 – Training Graph of the best-performing MLP

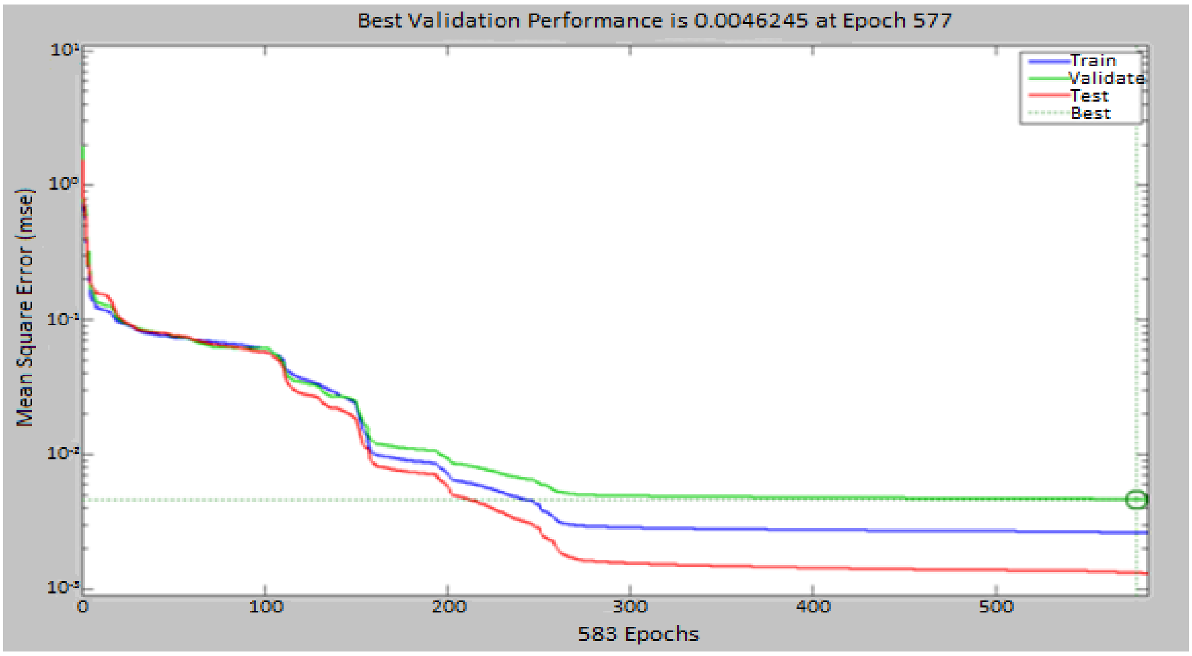

Fig. 4 – Training Graph of the GA-NN

VI. CONCLUSION

From the impressive MSE value of 0.0046245 achieved by the GA-NN network, we can conclude that consumption of TV channels within the cell of study exhibits consistent patterns that can enable prediction of idle channels. Given that the predicted spectrum hole is enough to eliminate the worst recorded true blocking value within one of the worst mobile cells within the city, we can also conclude that such predicted idle channels are enough spectrum resource to eliminate call blocking within any cell in the city of Nairobi.

VII. FUTURE WORK

We intend to eliminate the errors of sampling by providing every household, within the mobile cell of study, with a set top box. The patterns of occupation of TV channels by the TV sets would be perfectly accurate, although costly.

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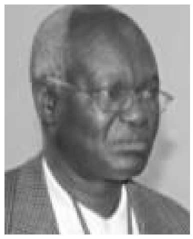

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Prof. Ogao is a recipient of the following awards and scholarships: ICA Young Student Award, Ottawa, Canada; European Science Foundation Scholar, Ulster, UK; ESRI GIScience Scholar, USA; ITC/DGIS, PhD Fellowship; Netherlands Fellowship Programme, MSc Research Fellowship, The Netherlands; Survey of Kenya-IGN-FI Training Award, Paris, France. He is also a member of ACM SIGGRAPH; Associate member, Institution of Surveyors, Kenya; Member of Commission for Visualization and Virtual Environment; Member of Research Group of Visualization and Computer Graphics, University of Groningen, The Netherlands.