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Development of hybrid artificial intelligent based handover decision algorithm

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A B S T R A C T

The possibility of seamless handover remains a mirage despite the plethora of existing handover algorithms. The underlying factor responsible for this has been traced to the Handover decision module in the Handover process. Hence, in this paper, the development of novel hybrid artificial intelligent handover decision algorithm has been developed. The developed model is made up of hybrid of Artificial Neural Network (ANN) based prediction model and Fuzzy Logic. On accessing the network, the Received Signal Strength (RSS) was acquired over a period of time to form a time series data. The data was then fed to the newly proposed $k-step$ ahead ANN-based RSS prediction system for estimation of prediction model coefficients. The synaptic weights and adaptive coefficients of the trained ANN was then used to compute the $k-step$ ahead ANN based RSS prediction model coefficients. The predicted RSS value was later codified as Fuzzy sets and in conjunction with other measured network parameters were fed into the Fuzzy logic controller in order to finalize handover decision process. The performance of the newly developed $k-step$ ahead ANN based RSS prediction algorithm was evaluated using simulated and real data acquired from available mobile communication networks. Results obtained in both cases shows that the proposed algorithm is capable of predicting ahead the RSS value to about ±0.0002 dB. Also, the cascaded effect of the complete handover decision module was also evaluated. Results obtained show that the newly proposed hybrid approach was able to reduce ping-pong effect associated with other handover techniques.

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1. Introduction

With recent increase in the demand for wireless communications services, there is need to address the problem of inefficient communication and sometimes poor Quality of Service (QoS) associated with wireless mobile communication. Seamless mobility with minimal packet loss and low latency across various mobile network operators have been a mirage [1–5].

In solving the problem of poor QoS coupled with the high demand for quality and efficient on-the-go communication capabilities, network operators have resulted into deployment of mobile cellular network stations in form of Base Transceiver Station (BTS). Signal coverage is usually segmented into cells and each cell is covered by overlapping BTS coverage areas. Movement of communication nodes or mobile stations sometimes refers to as cellular phones or mobile phones in wireless mobile communication system is handled by mobility management protocols which tracks the location of mobile stations in the network (known as location management) and ensures accurate delivery of packets as mobile nodes transverses from one BTS coverage area to another (Handover management) [6].

Handover (also known as Handoff) refers to the process of transferring the point of attachment of mobile station to the network from a BTS to another BTS as the mobile station moves from the region of coverage of the initial BTS to the coverage region of the target BTS. This process is expected to be seamless, thus ensuring that the ongoing process is not dropped and the user does not experience poor QoS.

Efforts in solving the aforementioned problem have resulted in the use of more than one mobile phone with multiple subscriber identification module cards. Despite the short term measures adopted by users, the identified problem especially handover problem across various networks of the same technology has not been solved. Hence, the development of hybrid artificial intelligent

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based handover decision algorithm has been developed in this paper. The hybrid approach consists of a cascade of $k-step$ ahead Artificial Neural Network (ANN) based prediction algorithm and Fuzzy inference system for handover decision making in wireless mobile communication system.

The remaining part of this paper is organized as follows: Detailed review of application of artificial intelligent approaches in handover process is discussed in Section 2. Mathematical derivation of the $k-step$ ahead ANN based prediction algorithm and Fuzzy logic system is presented in Section 3. Results obtained and conclusion are contained in Section 4 and Section 5 respectively.

2. Review: application of artificial intelligence techniques in handover scheme

Several efforts have been reported in the literature regarding application of various artificial intelligent techniques in Handover processes [1–5,7–9]. In this paper, review of reported efforts have been grouped into: ANN based approach; Fuzzy logic based approach; Genetic Algorithm based approach and prediction based approach. Review of ANN based approaches in handover decision process are presented in Section 2.1, while Fuzzy logic based approaches are contained in Section 2.2. Handover decision processes using Genetic Algorithm are presented in Section 2.3 and prediction based are contained in Section 2.4.

2.1. Application of ANN approach in handover Process

The use of a three-layer ANN in Cellular handover management was reported in [3]. The proposed approach involve the use of received signal strength and traffic intensities from the serving and target BTSs in implementing handover decision system. A threshold and hysteresis margin based scheme was adopted and handover decision was triggered only when the received signal is above certain value. Thus, handover decision was based on signal based measurement approach [3].

Development of an ANN based pattern recognition handover Algorithm for micro-cellular systems was proposed in [4]. The scheme adopted the use of Received Signal Strength (RSS) as the measured network parameter for handover decision system. The algorithm works on the assumption that two BTS between which a mobile device moves has the capacity to provide same services. Though, this is often not true due to differences in cell capacity and other conditions. The proposed algorithm involves sampling of the RSS and spatial averaging to formatting pattern at each sampling point as the mobile device moves from one BTS to another. It then assign patterns to different BTS to represent the classes after which ANN was then used for pattern classification. The scheme keeps the average number of handovers and call-drops low, though there was a negligible handover decision delay with the introduction of threshold technique. The method also requires only one training vector of each path and environment which makes the method simpler than other pattern recognition based schemes.

The development of handover performance enhancement in heterogeneous wireless network using ANN was reported in [10]. It involve access modeling along with an adaptive parameter adjustment algorithm using ANN technique. The reported scheme has an adaptive parameter adjustment which makes the handover adaptive to the destination network environment quickly and the variation of the throughput can be avoided efficiently.

Handover decision in wireless mobile communication system using ANN approach was carried out in [11]. A model of 7 cells with different traffic intensities was adopted. The adopted model uses the principle that mobile station in the hysteresis area can connect to more than one BTS and may decide to handover to the BTS with the lowest traffic intensity. ANN was used in taking decision to handover to target BTS. Reduction in the number of handovers was achieved using the proposed approach despite the fact that it considered traffic intensity instead of the number of free channels. Although, incoming calls from mobile stations not in the hysteresis area were blocked.

Using predictive RSS and dwell time, handover decision using ANN was reported in [12]. Adaptive dwell time and merit function were defined, with the dwell time being adjusted according to the movement of the mobile station. In evaluating the proposed approach, heterogeneous wireless network integrating the UMTS, Mobile WiMAX and WLAN was modeled and the proposed network selection algorithm was tested using mobile Internet protocol.

Nasser et al. in [5] presented a handoff network arrangement that depends on neural networks to choose the best cellular network. The developed approach is expected to add into the arrangement of predefined users inclinations, and network parameter. The criteria of weighted elements like cost function, security and bandwidth utilization were normalized between 0 and 1 before being fed into ANN algorithm for handover decision. Performance analysis shows that higher success rate was achieved when compared to other handover techniques.

The use of Cell-based neural networks and K-Means clustering in estimating road traffic congestion from Cellular handover information was reported in [1]. By performing multiple rounds of data collection covering various times of the day, traffic data of various degrees of congestion were obtained. Cell down time information were measured by a cellular phone with specialized features and classified accordingly by K-means clustering algorithm and ANN. The results were then compared against human classification. The results obtained from ANN approach shows better performance with high true positive rate for all degrees of congestion as compared to other techniques. However, the proposed method only estimated for non-signaled road which expert consider to be simple and the pooled cell down time values from all cell sites, without their associated cell identification information, were not adequate to train the network.

2.2. Application of Fuzzy logic approach in handover process

In [7], three separate fuzzifier namely: RSS, speed, and load-balancing were obtained from three distinctive wireless networks in initiating handover process. The approach aimed at applying Fuzzy logic to accomplished the standardization of network parameters so that the same parameters measured from various wireless network would be examined by the fuzzy induction technique. The yield of the fuzzy deduction framework is a numerical measure that is utilized to rank every candidates network. The ranked networks in conjunction with the user inclinations was then utilized in deciding the optimal network.

A multi-adaptive handover technique implemented with Fuzzy logic and optimized with Elman neural system was proposed in [8]. RSS was fundamentally used to trigger handover procedure while the neural system was used to forecast the number of network users in terminal network. The number of users and the mobile station speed, and the bandwidth of the terminal network served as input data to the fuzzy network. The normalization and the converging velocity pace of a conventional Elman neural technique is very slow which needs to be modified by the adjoining network nodes and adjusting the weights to obtain better performance. The technique was benchmarked against the traditional-based vertical handover approach and results obtained shows that the proposed technique gives better precision during handover execution and decision making process.

In [9], Fuzzy logic handover system capable of avoiding ping-pong effect in wireless mobile communication system was proposed. The method reported the use of three RSS based parameters namely: change in RSS of the original BTS; signal strength from the neighboring BTS, and the distance between mobile station and BTS. The performance evaluation of the system via simulations shows that the method can avoid ping-pong effect and has a good handover decision.

A novel handover decision for overlapped networks using Fuzzy logic was established in [13]. The terminal network was chosen using a fuzzy logic based standardized quantitative selection algorithm. It involve the development of multi-criteria handover choice scheme with capability of selecting network with the highest optimal value of the parameters for executing network handover decision. In the model, system parameters used includes bandwidth, latency, SNR and throughput. The network with the least latency value, cost-effective, SNR and high throughput will be selected.

2.3. Application of genetic algorithm approach in handover process

Call Admission Control (CAC) for mobile station in wireless mesh networks was reported in [14]. The method involve the development of a proportional threshold based optimal access bandwidth policy for CAC on the mesh route. The development of Genetic Algorithm (GA) based approximation in achieving differentiated priorities during the mobile station based handover was also proposed. The simulation results shows that the proposed CAC scheme had a satisfying trade-off between differentiated priorities and statistical access bandwidth in real life handover environment. The performance of the CAC scheme was evaluated by extensive analysis and simulation study, giving differentiated priorities for CAC of ongoing calls and new calls, but it doesnt take into cognizance the effects of multi-users during peak periods.

In [15], optimizing vertical handover performance parameters in heterogeneous wireless networks was reported. Multiple optimization problem concept was used to represent multiple numbers of vertical handover criteria which was then used to select the best available network with optimized parameter values. The formulated multiple objective functions were implemented using GA. Results obtained shows that the number of unnecessary handover was reduced compared to other schemes. No effective mobility framework was introduced and the rate at which users access the networks was not given consideration.

Genetic Algorithm was used to reduce number of handovers in [23]. The method focuses mainly on the handover decision problems and it was designed on a three-phase approach. The first phase minimizes the handover latency, operation cost and avoid unnecessary handovers. The second phase satisfies network requirement such as maximizing network utilization. The third phase satisfies user requirement such as providing active application with required degree of QoS. The method was able to eliminate the bottle neck in the traditional vertical handover by providing a faster and seamless handover in the heterogeneous mobile network. Other associated advantages from the proposed approach include: handover is done fast and its delay is as low as possible, Number of handover is minimized which avoids degradation in signal quality and additional loads of the network, handover procedure is reliable and successful, handover algorithm is simple and has less computational complexity.

2.4. Review of prediction algorithm in handover process

Various artificial intelligence based prediction techniques have been reported in literature [16–30]. In [16], the use of ANN based parametric model prediction was reported. The proposed approach can only handle one-step ahead prediction and has not been used for RSS prediction in handover decision making process.

In [25], handover decision algorithm with parameter prediction was reported. Using available network history, prediction of network parameters followed by QoS computation was adopted. The proposed cascaded approach was able to eliminate unnecessary handover during evaluation.

In [26], the combination of RSS prediction scheme and hysteresis algorithm for enhancing handover decision under different shadowing environments was reported. A cascade approach of prediction and hysteresis scheme was adopted in the work. Performance analysis shows that the optimal and best results was obtained using a cascaded scheme instead of a single scheme.

A robust prediction techniques to control micro-cellular handover technique was proposed in [30]. The work adopted the use of next-cell prediction and RSS prediction method for handover decision system. The reported work was based on a heuristic next-cell prediction mechanism in selecting appropriate BTS and RSS in initiating handover requests. However, it was observed that the network weight in the method used was huge due to the combination of two different approaches.

A predictive mobility management scheme that continuously monitors the mobile node, pre-scanned and predicts the next possible access point before handover was reported in [24]. Though, it reduces the packet drop during handover process and improve the QoS, however the method involve pre-authentication and pre-association of mobile node to the predicted new access point hence prediction results are sometimes not accurate.

Other prediction based approaches reported in literature are contained: Adaptive prediction based algorithm for optimizing handover decisions [27]; a study of vertical handover using Micro-Mobility prediction scheme [28]; a service-aware proactive vertical handover algorithm based on bandwidth requirement prediction [29].

It is evident that the use of $k-step$ ahead ANN-based RSS prediction algorithm in handover management system has not been given due consideration. Though in [16], effort was made in developing a one-step ahead algorithm but its applicability in RSS prediction for handover has not been reported. Consequently, it is envisioned that the use of artificial intelligent based approaches that has capability of making a $k-step$ ahead RSS value prediction cascaded with Fuzzy logic will be appropriate in making better handover decision across various mobile networks with little error margin and ping-pong effect.

3. Development of hybrid artificial intelligent based handover algorithm

In this section, the development of the hybrid artificial intelligent based handover algorithm is presented. The proposed algorithm is based on a two-stage approach, the first stage involves the mathematical development of a novel $k-step$ ahead ANN based prediction algorithm while the second stage involves the development of Fuzzy logic based Handover decision making algorithm. The block diagram of the proposed system is as shown in Fig. 1.

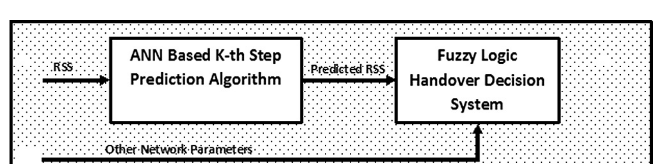

Fig. 1. The block diagram of the proposed Hybrid AI based Handover Decision Algorithm.

The choice of cascaded approach has been justified in [26], in addition, the choice of ANN and Fuzzy logic for handover decision algorithm is based on the performance analysis of some of the existing artificial intelligent techniques. Table 1 shows some of the criteria used in the selection of ANN and FL for the handover system.

The mathematical derivation and computation associated with the development of $k-step$ ahead ANN based prediction algorithm is presented in Section 3.1 while in Section 3.2, the development of Fuzzy Logic based handover decision subsystem is presented.

3.1. Development of K-th step artificial neural network based handover prediction algorithm

Consider the ANN structure shown in Fig. 2 representing $k-step$ ahead ANN based prediction model, the various outputs of the system can be expressed as

$$y(n+(k-1)) = \alpha_k \mathrm{F}\left(\sum_{l=1}^{M} w_{lk}\vartheta_l + h_{0k}\right) \tag{1a}$$

Thus for $k=1$, we have the $y(n)$ output expressed as

$$y(n) = \alpha_1 \mathrm{F}\left(\sum_{l=1}^{M} w_{l1}\vartheta_l + h_{01}\right) \tag{1b}$$

where: M is the number of neurons in the hidden layer; w_{l1} is the weight connecting node l in the hidden layer to neuron $1 i.e k = 1$ in the output layer; h_{01} is the bias term of neuron 1 in the output layer; ϑ_l is the output of the neuron l^{th} in the hidden layer; and α_k is the adaptive coefficient of the linear activation function of the kth output neuron; $y(n-1), y(n-2)\ldots y(n-p)$ are the past p RSS values obtained the system; $y(n), y(n+1)\ldots y(n+1)$ are the expected predicted values of the system.

Similar to (1b), the two-step ahead output $y(n+1)$ can be expressed as

$$y(n+1) = \alpha_2 \mathrm{F}\left(\sum_{l=1}^{M} w_{l2}\vartheta_l + h_{02}\right) \tag{1c}$$

Thus, the $k+1$-step ahead output $y(n+k)$ can be expressed as

$$y(n+k) = \alpha_{k+1} \mathrm{F}\left(\sum_{l=1}^{M} w_{l(k+1)}\vartheta_l + h_{0(k+1)}\right) \tag{1d}$$

However, the output ϑ_l of each of the neuron in the hidden layer can be expressed as

$$\vartheta_l = \beta_l \mathrm{F}\left(\sum_{r=1}^{p} \upsilon_{rl} y(n-r) + g_{0l}\right) \tag{2}$$

where υ_{rl} is the weight connecting input node r to hidden node l, g_{0l} is the bias of the hidden node l and β_l is the adaptive coefficient of hidden node linear activation function. Substituting (2) into (1b) to (1d) gives

$$y(n) = \alpha_1 \mathrm{F}\left(\sum_{l=1}^{M} w_{l1}\left(\beta_l \mathrm{F}\left(\sum_{r=1}^{p} \upsilon_{rl} y(n-r) + g_{0l}\right)\right) + h_{01}\right) \tag{3a}$$

$$y(n+1) = \alpha_2 \mathrm{F}\left(\sum_{l=1}^{M} w_{l2}\left(\beta_l \mathrm{F}\left(\sum_{r=1}^{p} \upsilon_{rl} y(n-r) + g_{0l}\right)\right) + h_{02}\right) \tag{3b}$$

and can be generalized up till the k-th step predicted value as

$$y(n+k) = \alpha_{k+1} \mathrm{F}\left(\sum_{l=1}^{M} w_{l(k+1)}\left(\beta_l \mathrm{F}\left(\sum_{r=1}^{p} \upsilon_{rl} y(n-r) + g_{0l}\right)\right) + h_{0(k+1)}\right) \tag{3c}$$

on expanding (3a)–(3c) and using linear activation functions in both the hidden and output layer (i.e F is linear), the $k-step$ ahead ANN based prediction model coefficients can be obtained from the extracted synaptic weights and adaptive coefficients of a well trained ANN with the general equation given as

$$a_{pk} = \alpha_{k+1} \sum_{l=1}^{M} w_{lk+1}\, \upsilon_{pl} \beta_l \tag{4}$$

Thus, $k-step$ ahead ANN based RSS prediction model coefficients a_{pk} are estimated from the synaptic weights and the coefficients of the adaptive activation function of a properly trained two-layer ANN shown in Fig. 2.

In implementing the $k-step$ ahead ANN based prediction algorithm in handover decision making module The coefficients were used to form a matrix from which appropriate prediction level can be easily obtained. Thus the prediction problem shown in Fig. 2 reduces to matrix multiplication given as

$$\begin{bmatrix} a_{11} & a_{21} & a_{31} & \ldots & a_{p1} \\ a_{12} & a_{22} & a_{32} & \ldots & a_{p2} \\ a_{13} & a_{23} & a_{33} & \ldots & a_{p3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{1p} & a_{2p} & a_{3p} & \ldots & a_{pk} \end{bmatrix} \begin{bmatrix} y(n-1) \\ y(n-2) \\ y(n-3) \\ \vdots \\ y(n-p) \end{bmatrix} = \begin{bmatrix} y(n) \\ y(n+1 \\ y(n+2) \\ \vdots \\ y(n+k) \end{bmatrix} \tag{5}$$

$$\mathbf{A}\mathbf{Y}_p^- = \mathbf{Y}_k^+ \tag{6}$$

where $\mathbf{A}$ is a $(p \times k)$ matrix of model coefficients; $\mathbf{Y}_p^-$ is a $p \times 1$ vector of past RSS values and $\mathbf{Y}_k^+$ is a $(k+1) \times 1$ matrix of step ahead predicted RSS values. One advantage of (5) is its implementation using low configuration embedded platform such as ATMEGA 328 that otherwise would not have been able to handle implementation of ANN can now handle the matrix multiplication given in (5). Thus, in this work a new technique for implementing a trained multilayer neural network on a low cost and low specification Micro-controller system has also been introduced.

Table 1
Performance comparison of selected artificial intelligent based techniques.

Criteria	FL	ANN	GA	Choice
Mathematical model	×	✓	×	Already in existence
Learning ability	×	✓	×	ANN
Initialization capability	×	✓	✓	ANN
Knowledge representation	✓	×	×	FL
Non-linearity	✓	✓	×	ANN
Optimization ability	×	✓	✓	ANN
Decision Making	✓	×	×	FL

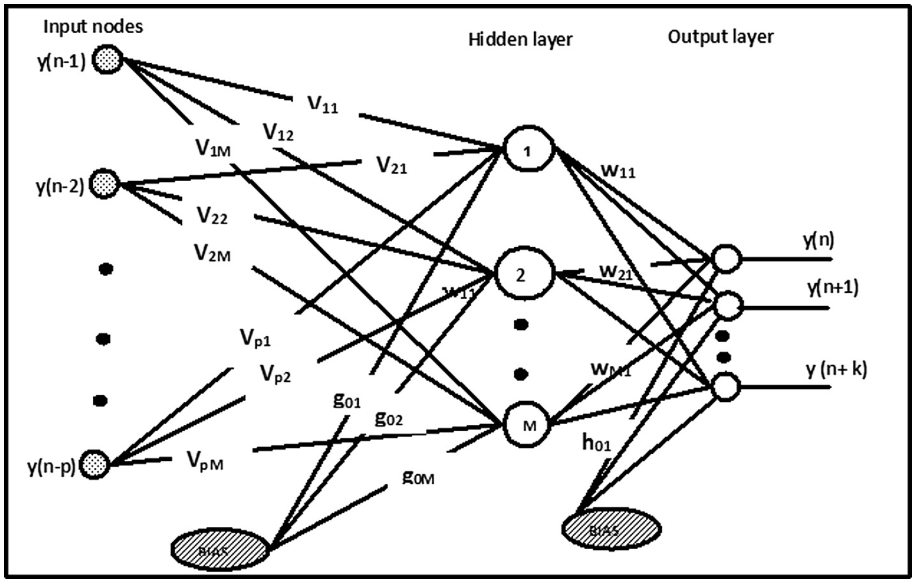

Fig. 2. ANN structure showing synaptic weights connection for the K-th Step Artificial Neural Network Based Handover Prediction System.

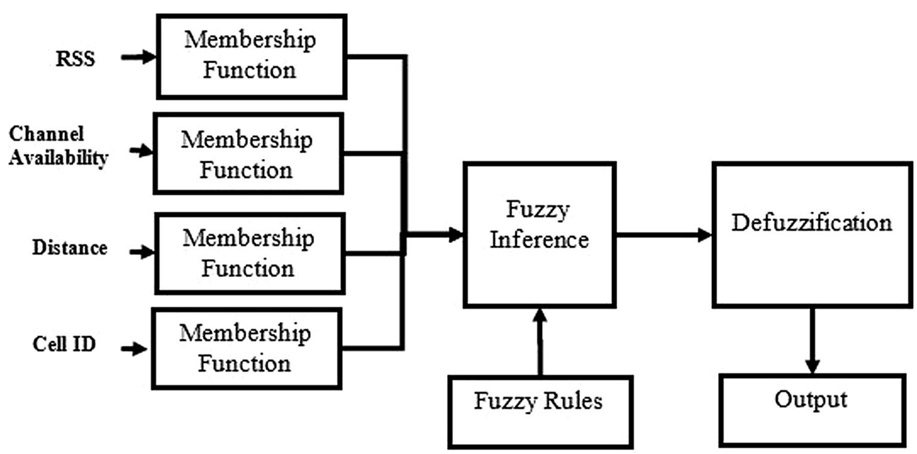

Fig. 3. The FL based Handover Decision Algorithm.

3.2. Development of Fuzzy logic based handover decision algorithm

The development of Fuzzy logic based Handover decision algorithm shown in Fig. 3 is presented in this section. The developed system consists of three different stages, namely Fuzzification stage, Fuzzy inference stage and Deffuzification stage. Detailed discussion of each of the stages is provided herewith.

3.2.1. Fuzzy logic based handover decision fuzzification stage

The fuzzification stage involves defining the membership function of each of the input to the FL. In this work, triangular membership function was adopted. Aside from the predicted RSS level, other inputs used in this work include mobile station GPS coordinates for calculating the distance of the mobile station from the surrounding BTSs; Channel availability and Cell ID.

The Fuzzy sets for each of the input parameters are:

$$RSS = \mathrm{F}(VL, L, H, VH, EH) \tag{7a}$$

where *VL* means Very Low RSS value; *L* means Low RSS value; *H* means High RSS value; *VH* means Very high RSS value and *EH* means Extremely High RSS value,

$$CA = \mathrm{F}(A, NA) \tag{7b}$$

where *A* means Channel is available; and *NA* means No available channel for communication.

$$D = \mathrm{F}(VF, F, N, VN) \tag{7c}$$

where *VF* means Very Far from the BTS; *F* means Far from the BTS; *N* means Near to the BTS and *VN* means Very near to the BTS.

$$CI = \mathrm{F}(VB, NT) \tag{7d}$$

where *NT* means known terrain and *VB* means Very new terrain

The output linguistic variable Handover Decision (HD) Fuzzy set is defined as

$$HD = \mathrm{F}(HG, HM, HHEHG) \tag{7e}$$

where *HG* means Handover to Glo, *HM* means Handover to MTN, *HE* means Handover to Etisalat and *HA* Handover to AIRTEL.

Every element in the input and output fuzzy sets have a corresponding value of membership. Triangular membership function was used in this work and a typical membership functions for Predicted RSS value and Handover Decision are shown in Fig. 4a-c.

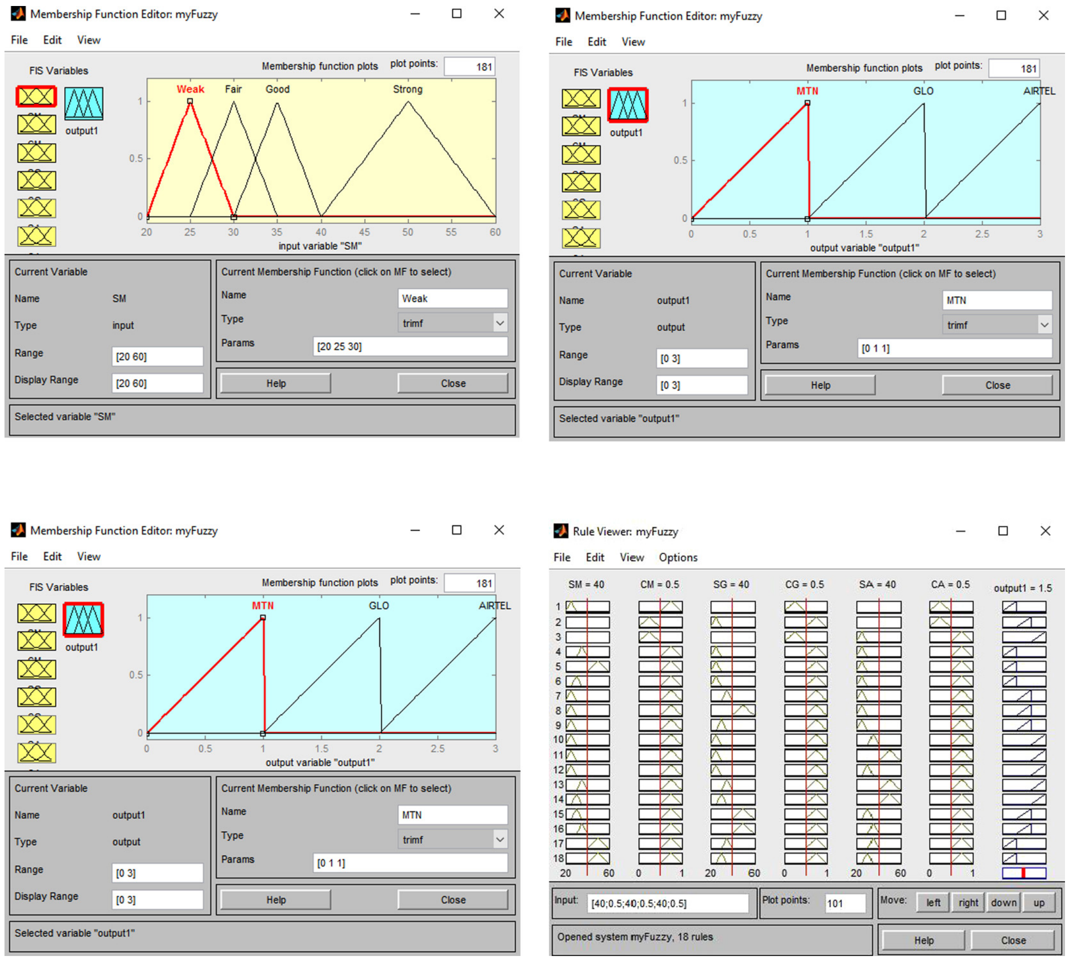

Fig. 4. Fuzzy Inference System (a) Predicted RSS Level Membership Function (a) Predicted Channel Availability (CA) Membership Function (c) Handover Decision Output Membership Function (d) Handover Decision Inference Engine.

3.2.2. Fuzzy logic based handover decision fuzzy inference stage

In the Fuzzy logic based handover decision Fuzzy inference stage, max–min inference was exploited using if-then rules which is as shown in Fig. 4d. The inference applies the minimum linguistic variables of the input parameters to deduce the output of the system based on the set rules.

3.2.3. Fuzzy logic based handover decision deffuzification stage

When the output is obtained, centroid defuzzification is applied to obtain the numerical value of the obtained handover decision. The defuzzification state decides which network to handover to based on the defuzzifier.

4. Results and discussion

Results obtained from the performance analysis of the developed Handover algorithm are reported in this section. Two different metrics were used to measure the accuracy of the predicted RSS prior to taken handover decision. These are: The Prediction Error (PE) and Relative error (RE). The two metrics are defined by (8) and (9) respectively.

$$PE = RSS_{AC} - RSS_{PR} \tag{8}$$

$$RE = \frac{RSS_{AC} - RSS_{PR}}{RSS_{AC}} \tag{9}$$

where RSS_{AC} is the actual RSS level measured and RSS_{PR} is the predicted price RSS level.

4.1. Performance analysis of $k-step$ ahead ANN based prediction (KSABP) algorithm

In evaluating the $k-step$ ahead ANN based prediction algorithm developed in this work, results obtained from two different scenarios have been reported. In Section 4.1.1, results obtained from the prediction of RSS signal acquired from mobile network operators has been provided while in Section 4.1.2, results obtained from application of the developed algorithm in predicting gold coin price has been reported.

4.1.1. Received signal strength prediction using $k-step$ ahead ANN based prediction algorithm

In the first case, a multiple operators enabled sim card system reported in [31] was used to acquire RSS levels of a particular mobile network operator on different time intervals. In this paper results obtained from 5 s acquisition time interval has been reported only as similar results were obtained using other different time intervals. The acquired data was then normalized using

$$y(n) = \frac{\bar{y}_{acq}(n)}{max(\bar{y}_{acq}(n))} \tag{10}$$

where $\bar{y}_{acq}(n)$ is the acquired RSS data using the card and $y(n)$ is the normalized RSS value. The normalized data were then fed into the developed ANN based prediction model for prediction coefficients computation using (4) while (5) was used to compute the predicted value. For a case study, the computed coefficients are now substituted into the prediction model to form a one-step ahead prediction model given as

$$y(n) = -[0.8268y(n-1) + 0.1730y(n-2)] \tag{11}$$

which was then used to predict the RSS value ahead of feeding it into the Fuzzy system for handover decision module. Results obtained are shown in Table 2 and Fig. 5. Results obtained shows that the use of ANN-based prediction technique shows better performance in term of accurately predicting the next RSS level required for Handover than even the use of Linear prediction technique. Furthermore, it was also observed that the predicted RSS level is very close to the measured RSS value with a very low error margin. It can be observed that the proposed algorithm is capable of predicting RSS level to about ±0.0002 error margin.

4.1.2. Gold coin price prediction using $k-step$ ahead ANN based prediction algorithm

In evaluating the developed algorithm and justifying its applicability to other fields, the daily price of Gold coin was obtained over a period of six months. The data was adopted due to the fact that one-day ahead price could now be obtained and can be used to test the accuracy of the proposed algorithm. The obtained data was formatted as an input data to the $k-step$ ahead ANN-based prediction (KSABP) model with p past input data and one step ahead target data as the output of the model.

The designed model was trained using back propagation approach and upon convergence, the synaptic weights and adaptive coefficients of the activation function were extracted from which the required prediction coefficients were computed using (4). The obtained model coefficients were used to predict the future price on a one-day ahead prediction approach. The proposed approach was benchmarked against Yule Walker approach. For the duo, the Prediction Error (PE) and Relative Error (RE) were computed and part of the results obtained are shown in Fig. 6 and Table 3.

Results obtained shows that the proposed technique provides better performance as compared to that of using Yule Walker technique. In most cases, it was also observed that the predicted price using the proposed algorithm gave almost similar results as the ground truth. Thus, low RE values were obtained using the proposed technique.

4.2. Handover decision results using simulated data

In order to evaluate the developed Fuzzy Inference Handover System, MATLAB was used to simulate BTS environment and mobile stations. The environment consist of Ten (10) different BTSs with different mobile stations. The simulated environment is as shown in Fig. 7.

The pseudo-code developed for the simulation of Handover by mobile stations is as presented herewith:

1. Given BTS cell map of an area
2. Find the location of the BTS and its boundary coordinates
3. Display the BTS on the map
4. Randomly generate coordinate for mobile stations
5. For each Mobile Station, do the following
   (a) Find the Euclidean distance to each BTS location
   (b) Estimate the RSS of the BTS using Lagrange interpolation. Taking minimum distance to be 0 Unit and the corresponding RSS value as 80dBm and maximum distance to be 560 units and the corresponding RSS value as 30 dBm
   (c) Display the mobile stations with the corresponding distance from each of the BTS and the corresponding RSS value of each BTS.

Mobility of the mobile stations were also simulated and at each stage in order to take handover decision, network parameters that serves as the input to the FIS system were calculated. Firstly the RSS was predicted using the proposed $k-step$ ahead ANN based prediction model. The predicted RSS value and other network parameters were then fed to the FIS to determine Handover decision. Since the environment was a simulated one, the Handover

Table 2
Performance evaluation of Prediction Algorithm Using Acquired RSS data.

Measured RSS	AR-Pred. RSS	KSABP Pred. RSS	AR Model PE	KSABP PE	AR Model RE	KSABP RE
1.0000	0.9959	0.9998	0.0041	0.0002	0.4105	0.0211
1.0000	0.9959	0.9998	0.0041	0.0002	0.4105	0.0211
1.0000	0.9959	0.9998	0.0041	0.0002	0.4105	0.0211
1.0000	0.9959	0.9998	0.0041	0.0002	0.4105	0.0211
1.0000	0.9959	0.9998	0.0041	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.9565	0.8660	0.8694	0.0905	0.0871	9.4641	9.1101
0.9565	0.9519	0.9413	0.0047	0.0152	0.4879	1.5935
0.9565	0.9526	0.9563	0.0039	0.0002	0.4105	0.0211
0.9565	0.9526	0.9563	0.0039	0.0002	0.4105	0.0211
0.9565	0.9526	0.9563	0.0039	0.0002	0.4105	0.0211
0.9565	0.9526	0.9563	0.0039	0.0002	0.4105	0.0211
0.9565	0.9526	0.9563	0.0039	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211
0.8696	0.8660	0.8694	0.0036	0.0002	0.4105	0.0211

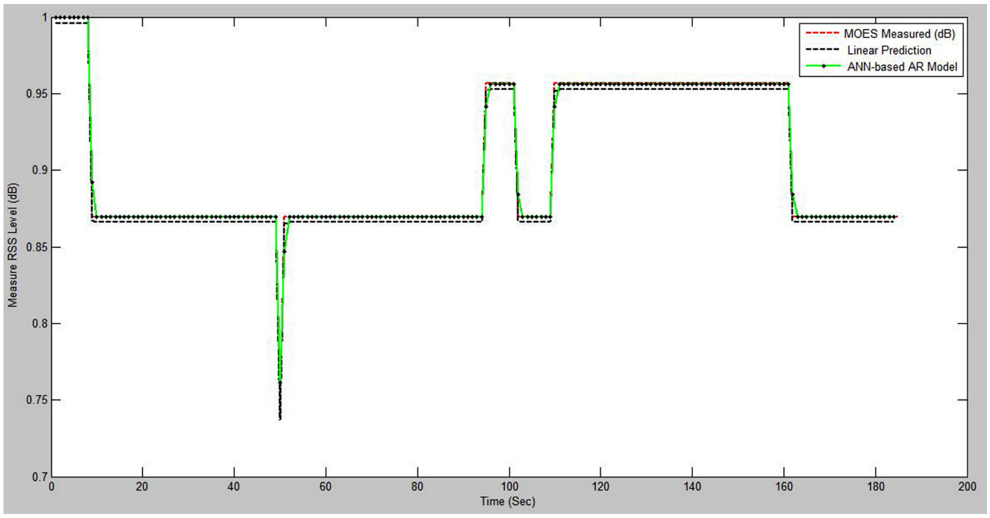

Fig. 5. Performance Analysis of the $k-step$ ahead ANN based prediction using acquired RSS Data.

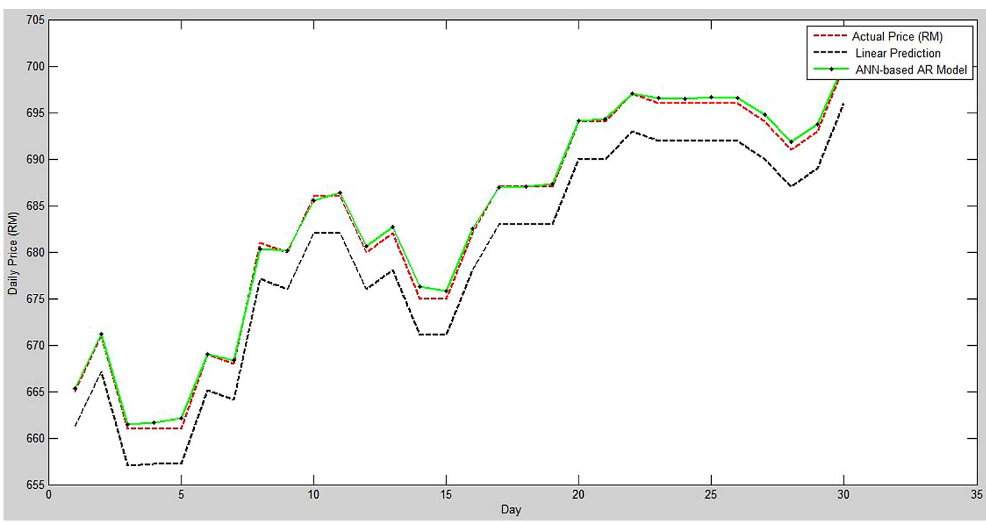

Fig. 6. Gold Coin Prediction Using $k-step$ ahead ANN-based prediction (KSABP) model.

Table 3
Gold Price Prediction Usng $k-step$ ahead ANN based Prediction Algorithm.

Actual Price	AR-Pred. Price	KSABP Pred. Price	AR Model PE	KSABP PE	AR Model RE	KSABP RE
665.000	651.163	656.136	13.837	8.864	2.081	1.333
671.000	661.235	665.294	9.765	5.706	1.455	0.850
661.000	667.088	671.221	−6.088	−10.221	0.921	1.546
661.000	657.056	661.418	3.944	−0.418	0.597	0.063
661.000	657.208	661.640	3.792	−0.640	0.574	0.097
669.000	657.181	662.136	11.819	6.864	1.767	1.026
668.000	665.152	669.045	2.848	−1.045	0.426	0.156
681.000	664.067	668.312	16.933	12.688	2.486	1.863
680.000	677.096	680.310	2.904	−0.310	0.427	0.046
686.000	675.970	680.173	10.030	5.827	1.462	0.849
686.000	682.023	685.495	3.977	0.505	0.580	0.074
680.000	681.981	686.400	−1.981	−6.400	0.291	0.941
682.000	676.009	680.643	5.991	1.357	0.878	0.199
675.000	678.084	682.701	−3.084	−7.701	0.457	1.141
675.000	671.046	676.304	3.954	−1.304	0.586	0.193
682.000	671.117	675.755	10.883	6.245	1.596	0.916

output of the FIS was compared with the ground truth and it was seen that in almost all the situations, Handover decision from the FIS correspond with the ground truth. The error margin obtained from various simulated handover decision was calculated and results obtained show that only 2% error in handover decisions were made by the developed system. The proposed algorithm

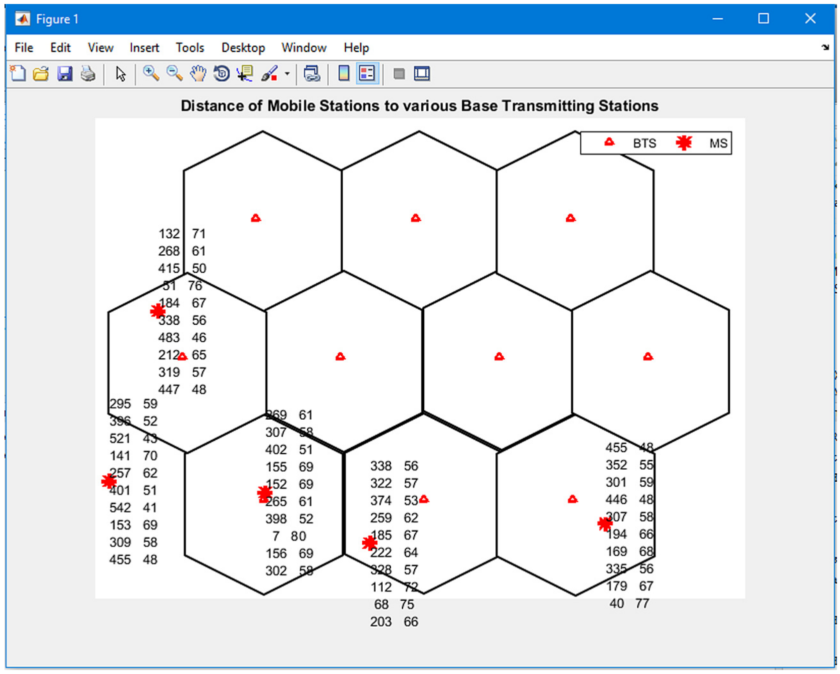

Fig. 7. Simulated BTS Environment for Evaluating Hybrid Handover Scenarios.

was tested and handover without pin-pong effect associated with some other techniques were also obtained.

5. Conclusion

In this paper, the use of a cascaded ANN and Fuzzy logic for handover decision in a wireless mobile communication system has been presented. Basically, the ANN has been used in the determination of model coefficients for effective prediction of RSS level in handover decision management system. The computed coefficients were concatenated to form a matrix and simple matrices multiplication can be undertaken in obtaining the predicted values. The predicted values using the ANN based prediction algorithm was compared with some known techniques and it was observed that the developed approach was able to demonstrate good prediction values as obtained during performance analysis. The output of the prediction system was then fed to the Fuzzy inference system for taking necessary handover decision. Results obtained shows that the proposed approach was able to take necessary handover decision and avoid ping-pong effect when evaluated.

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