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MULTILAYER PERCEPTRON WEIGHT OPTIMIZATION USING BEE SWARM ALGORITHM FOR MOBILITY PREDICTION

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ABSTRACT

The progress in wireless networks has led to the rising demand of quality in service, reduced delay, seamless network, communication anytime/anywhere, and a lot more. The wireless network provides global services/communication through integrated networks. The wireless networks and beyond (4G) makes people free from cable and guarantee a fully distributed communication with promising Quality of Service (QoS). Hence, Mobility prediction or precise and competent forecast of mobile users trail is of prevailing significance for entire network performance. Mobility prediction along with wireless communication protocols helps in better energy, resource management in a network scenario and provides improved quality to the wireless users. This paper proposes mobility prediction based on a Multi-Layer Perceptron (MLP) network optimized with Bee Swarm Algorithm (BA). The proposed model evaluates mobility prediction using mobility traces from wide production wireless network. The Swarm Intelligence (SI) is used in many complex optimization problems in continuous search. The BA is the foraging behaviour of bees in searching food sources. The BA algorithm integrates the network for optimization of weights.

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KEY WORDS

Wireless Networks, Mobility Prediction, Multi-Layer Perceptron (MLP), Bee Swarm Algorithm (BA)

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INTRODUCTION

Wireless networks serve as the transport mechanism among devices and between devices and the traditional wired networks (enterprise networks and the Internet). Wireless-networks make people free from predetermined locations and introduce mobility in most of the aspects in the human life. The wireless networks have bandwidth and resource usage constraints due to increases in the number of users, which lead to termination in communication with reduction in success rate. Since the users are mobile most of the time mobility must be introduced in the systems. The mobility management schemes should be efficient enough to ensure seamless communication.

Wireless network, are classified into two divisions: With and without infrastructure. A mobile node which has free access to move around, even while conducting communication among other nodes, also known as an infrastructured wireless networks, can allow free nodal access whilst the base stations remain fixed. Whereas Ad hoc networks or infrastructureless networks, have no fixed stations although the nodes are feww to move about while communicating, and all the nodes act as routers. Ad Hoc Network mobile networks try to dynamically esablish themselves to form routes and form their own 'on the fly' networks [1].

Wireless technology communications have a vast range of capacities which concentrate on a unique needs, and offers multiple benefits like fleixibility, portability, increased productivity, and lowered installation costs. For example, WLAN or wireless local area networks allow users to shift their laptops witin the surroundings of their office space, without the need for additional items like cables, wires or the worry of losing network connectivity. The lack of wires enables greater flexibility, increased efficiency rates and reduction in wiring costs [2].

Data synchronization in network systems are visible in Ad Hoc networks, enabled through Bluetooth technologies and it allows sharing application among devices. Bluetooth technology reduces cable connectivity in any peripheral devices, such as printers. Personal digital assistants (PDAs) and mobile devices, such as cell phones, enable synchronization to personal databases and give access to wireless e-mail features, browsing the web and general internet access. The above technologies save costs and enable diverse applications to fulfill their goals, such as manufacturing shop floors to first responders.

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Wireless networks provide optimal services to mobile terminals and it is a fundamental function of the above networks to be aware of where the points of attachment exist at any given point of time. Predictions made by mobile networks are commonly used to aid many network management tasks and at a network level, such mechanisms reduce congestins and engance service provision qualities. But at an application level, mobile networks are exploited to enable multiple location services. Thus, mobility predictions are an important function of the above technques and it can determine the location of mobile terminals by manipulating available information carefully. And the accuracy of prediction devices highly depends on movement of user models and the predictio algorithm adopted [3].

The mobility prediction is helpful in allocating resources since it predicts the movement of the user priorly which depends on the past movement of the user. Mobility prediction may be defined as finding the next Access Point (AP) that a user will attach to in a network. The mobility of the user is determined from mathematical models that depict human mobility. The proactive methods like mobility prediction guarantee QoS to the users. Mobility predictions of wireless devices helps the users in smart access and useful to the service provider in planning of the infrastructure and to provide better QoS. GSM based mobile prediction networks also contain multiple routers and Aps, like other mobile networks. Mobility prediction essentially tries to predict the movement of mobile users based on prior mobility models. The user's next location as the user is traveling in the network is helpful for infrastructure planning, resource allocation and future network requirement prediction [4].

All connections to its wireless network have been stored as trace files which is a valuable mine of information. The trace files contain the wireless Network Interface Card (NIC), Medium Access Control (MAC) addresses and the time of connection/disconnection for each access point. Since MAC addresses are unique, can safely assume that each connection/disconnection associated with a MAC ID belongs to a unique user and can be treated as a mobile node.

The wireless trace dataset contains user histories for thousands of wireless users. This data to perform simulation to verify the accuracy of the model versus actual movement, study user movement, prediction benefits, etc. [5]. A large portion of recent research still assumes that user mobility and the connection trace for a MT are strongly dependent.

There are a large number of prediction systems that have been proposed which attempt to measure or capture some regularity of the user's mobility in order to extrapolate from this knowledge about the future behaviour of the user's MT. Real life mobility traces have Mobility Prediction in Wireless Networks Using NN 323 shown that this assumption of user mobility and connection trace of the MT is not as valid as most researchers believe [6].

User movement trajectories are generally logged in at the time when a mobile device is connected to an Access Point (AP), which represents a specific AP of the nth user location has moved from defined time [7-9]. Mobile devices actual movement is called User Actual Path (UAP) which has the form

$$u_i = < ap_1, ap_2, ..., ap_n >$$

The User Mobility Pattern (UMP) is traced from the logs obtained from all APs which show the frequent path used by a mobile device [10-12].

The UMP is used to form the mobility rules. The user's mobility pattern from its actual movement is obtained called as user's real path,

$$U_j = \{\mathrm{AP}_1, \mathrm{AP}_2, \mathrm{AP}_3, ...\mathrm{AP}_n\}$$

The mobility rules obtained from the users real path are

$$l_1 \to l_2$$

$$l_1, l_2 \to l_3$$

$$l_1, l_2, l_3 \to l_4, ..., l_n$$

Each rule has a confidence 'c' and support's'. The rule that generate highest confidence is selected.

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For a given set of patterns for mobility, Head class label determine the next location prediction and is given by

$$a_1, a_2, ..., a_n \rightarrow b_i$$

Where $a_i \in A$ and $b_i \in B$

Optimization can be defined as the process of finding best solution or result under given circumstances. Generally optimization is used for maximizing or minimizing the value of a function, it may be local optimum or global optimum. In optimization there are different types of problems are being utilized like, Liner optimization, Non liner optimization, Dynamic optimization etc. and all have different techniques for solving. Efficiency in system optimizations and processes is ssential for the proper function and economics of mant engineering and science domains. This process is key for the proper functioning of many domains and many problems are solved by adopting approximate and rigorous mathematical search techniques. These intensive approaches have used linear, integer and dynamic programming to arrive at optimal solutions for moderately sized problems. But real life optimmmization problems have encountered engineering problems because of its huge size and complex solution space. Thus, finding exact solutions to these problems is quite difficult and requires an emponential amount of computing time and power to increase the number of decision variables. In order for researchers to overcome such problems. Approximate evolutionary-based decisions and proposals have been created to overcome the search for near-optimum solutions [13].

This paper suggests MLP weight optimization using BA. Section 2 reviews related literature. Section 3 describes the methods employed in this work. Section 4 describes experiment results and Section 5 concludes the work.

RELATED WORKS

A new geo-statistical unsupervised learning technique to identify useful information on mobile phone using hidden patterns was presented by Manfredini et al., [14]. These are regarding different use of the city in time and space related to individual mobility, outlining the technology's potential for the urban planning community. The methodology ensured a reference base that reports the specific effect of activities on recorded Erlang data and a set of maps showing each activity's contribution to local Erlang signal. This technique chose results as significant to explain specific mobility/city use patterns and tested their significance and interpretation from an urban analysis and planning perspective at a Milan urban region scale.

Prediction-based replication methods which achieved service coverage through replication of a central server proposed by Surobhi&Jamalipour [15] were unable to accurately predict future topological changes and maintain service coverage in a post-emergency network. The realistic mobility model including users' post-emergency complex behavioral changes were proposed. A Machine-To-Machine (M2M) networking-based service coverage framework for post-emergency environments accurately predicted new user mobility and optimal replication. It used these predictions to achieve continuous service coverage. Simulation verified the proposals effectiveness.

A complete framework that proactively defined QoS/QoE-aware policies for Long-Term Evolution (LTE)-connected vehicles to select most adequate radio access from available access technologies that maximized QoE throughout mobility path was introduced by Taleb&Ksentini [16]. The policies were communicated to users following 3GPP standards and enforced by user equipment devices. Two different models to model the network selection process were proposed. Network selection process was modeled using a time-continuous Markov chain, and its performance was evaluated through NS2-based simulations considering two wireless access technologies like WiFi and cellular networks.

A framework, with schemes which integrate user mobility prediction models with bandwidth availability prediction models to support mobile multimedia services requirements was proposed by Nadembega et al., [17]. It specifically proposed schemes that predict paths to destinations, times when users enter/exit cells along predicted paths, and available bandwidth in cells on predicted paths. A request for mobile streaming service was accepted with these predictions, only when there was enough (predicted) bandwidth, along the destination path, to support the service. Simulation showed that the new approach outperformed current bandwidth management schemes in supporting mobile multimedia services better.

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Topology design problem in a predictable Delay Tolerant Networks (DTN) where time-evolving topology was known a priori or is predicted was studied by Li et al., [18]. The purpose of reliable topology design problem was to build a sparse structure from original space-time graph so that (1) for any pair of devices, there was a space-time path connecting them with reliability higher than required thresholds; (2) total structure cost is minimized. Finally, simulations on random DTNs, a synthetic space DTN, and a real-world DTN tracing data proved the efficiency of the new method.

Location-based adaptive video quality planning approaches, in-network caching, content prefetching, and long-term radio resource management were discussed and proposed by Abou-zeid&Hassanein [19]. Insights on energy savings were provided. Then a cross-layer framework that jointly optimized resource allocation and multi-user video quality using location predictions was presented. Finally, some future research directions for location-aware media delivery in conclusion were highlighted.

A scalable hybrid bandwidth-efficient Adaptive Service Discovery Protocol (ASDP) for Vehicular Networks presented by Abrougui et al., [20] finds service provider and routing information simultaneously resulting in overall bandwidth savings. The new service discovery protocol adapted the service provider's advertisement zone size based on an adaptation mechanism. Results showed the protocol's scalability. They indicate that the techniques can achieve significant success (more than 90 percent), while guaranteeing low response time (in milliseconds) and low bandwidth use compared to current service discovery techniques.

A novel physical layer authentication scheme exploiting time-varying a Carrier Frequency Offset (CFO) associated with pairs of wireless communications devices was proposed by Hou et al., [21]. Combining these biases and mobility-induced Doppler shift, characterized as a time-varying CFO, is used as a radiometric signature for wireless device authentication. In the new authentication scheme, variable CFO values at different communication times were estimated. Kalman filtering predicted current value by tracking past CFO variations, modeled as an autoregressive random process. Simulation confirmed the effectiveness of the new scheme in multipath fading channels.

A new, fast location-based handoff scheme designed for vehicular environments was presented by Almulla et al., [22]. The protocol was able to accurately predict several APs that a vehicle may visit in the future with the position/movement direction of the vehicle and location information of surrounding APs. It assigned the APs to different priority levels. APs on higher priority levels are scanned first. Simulation showed that the new scheme attained lower prediction error rate and lower link layer handoff latency with limited influence on jitter/throughput.

DTN-Meteo, a new unified analytical model that maps an important class of DTN optimization problems over heterogeneous mobility/contact models to a Markov chain traversal over relevant solution space was proposed by Picu&Spyropoulos [23]. Local optimization algorithms accept/reject candidate transitions (deterministically/randomly), thereby "modulating" transition probabilities. Performance of state-of-the-art algorithms in various real/synthetic mobility scenarios showed that surprising precision is possible against simulations, despite problems complexity and settings diversity.

Ganguly et al., [24] proposed a location based mobility prediction scheme that helped in selecting the appropriate forwarder by predicting the mobility pattern of nodes. DTN specific user mobility involved both periodic and slightly chaotic patterns; chaotic behavior being attributed to the sudden causal events triggering instantaneous node mobility. In this approach, the authors approximate the periodicity of the DTN node mobility and use that knowledge to facilitate forwarding. The authors compared the results, thus obtained and with real location of the nodes in future mentioned time instances and simulation results showed that scheme provided satisfactory results in predicting mobility of nodes to a great extent.

METHODOLOGY

In this section, datasets, MLP methods and Bee swarm algorithm are described.

Dataset

The mobility traces used by researchers is provided by Dartmouth College as a community service. In this work one month syslog data is used however mobility trace collected over three years in Dartmouth College is available.

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There were 5500 students and 1200 faculty housing the college over the three years during the data collection period. At the outset 476 APs were available and over a point in time it increased to 566. The users were able to use the network across the campus seamlessly as all the APs shared the same SSID. 115 subnets enclosed 188 buildings and hence the wireless gadgets required to acquire new IP addresses at times.

A syslog server log had the AP name, address of the MAC card and message type. It included the timestamp to every message. The messages used by the devices are authenticated, associated, reassociated, roamed and disassociated.

While a mobile gadget selects a network it is primarily authenticated and it associates itself with an AP to enable all traffic linking the device and the network. The mobile gadget reassociated when another AP with better signal strength is available. The device is in roaming when it reassociated with a new access point. When the device moves out of the network coverage or needs the network no more, disassociated message is sent.

In this work trace from users in the Dartmouth College of a single day is used. It is proposed to take into account four attributes with three attributes providing the prior location of the user and the fourth attribute considering the time.
Sample syslog data is given in **Table- 1**.

Table: 1. Sample syslog data

Unix Time Stamp	Specific Access Point Associated with the User
1035100785	AdmBldg19AP3
1035100842	AdmBldg20AP3
1035100851	AdmBldg24AP1
1035100908	AdmBldg20AP3
1035100963	AdmBldg24AP1
1035101020	AdmBldg20AP3
1035101022	AdmBldg24AP1
1035101080	AdmBldg20AP1
1035101082	AdmBldg24AP1
1035101139	AdmBldg20AP3

Establishment of mobility rules

The UMP is

$$l = < l_1, l_2, l_3, \ldots l_n >$$

Mobility rules established from this pattern are

$$l_1, l_2, l_3, l_4 \rightarrow l_{c5}$$

$$l_2, l_3, l_4, l_5 \rightarrow l_{c6}$$

$$l_3, l_4, l_5, l_6 \rightarrow l_{c7}$$

....

$$l_{k-4}, l_{k-3}, l_{k-2}, l_{k-1} \rightarrow l_{ck}$$

Where l_{ck} represents clustered value of AP in the head and represented by all APs close to each other in the network. **Figure- 1** shows frequent item set for minimum support of 35% and confidence of 10%.

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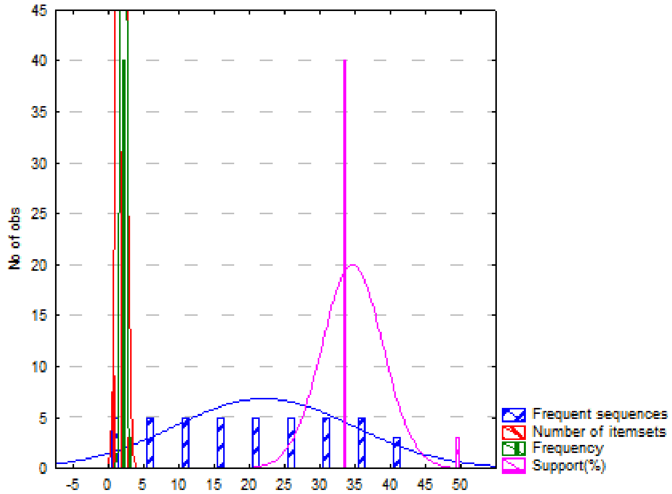

Fig:1 .Frequent Item Set for One Month Data

Multi-Layer Perceptron (MLP)

A MLP constructs on the architecture of the single layer perceptron. The single layer perceptron is not very practical for the reason that it has limited mapping capability. It is merely pertinent to linearly separable inputs. The MLP yet, can be used as a building block for larger, a lot more practical structures. The restrictions of a simple perceptron may be overcome by using multiple layer architectures, difficult training algorithms and activation functions which are non-binary. A classic MLP arrangement consists of source nodes in the input layer, one or more hidden layers which compute the inputs by applying activation function, and an output layer of nodes illustrated in **Figure- 2**. The network has an input layer, single hidden layer with non-linear activation and an output layer with linear function. The input signal flows through the hidden layer from the input layer to output layer. The computations performed by this feed forward network can be written mathematically as

$$t = f(s) = B\varphi(As + a) + b$$

s = inputs
t = outputs
A = first layer weight matrix
a = first layer bias vector
B = second layer weight matrix
b = second layer bias vector
φ = non-linearity function.

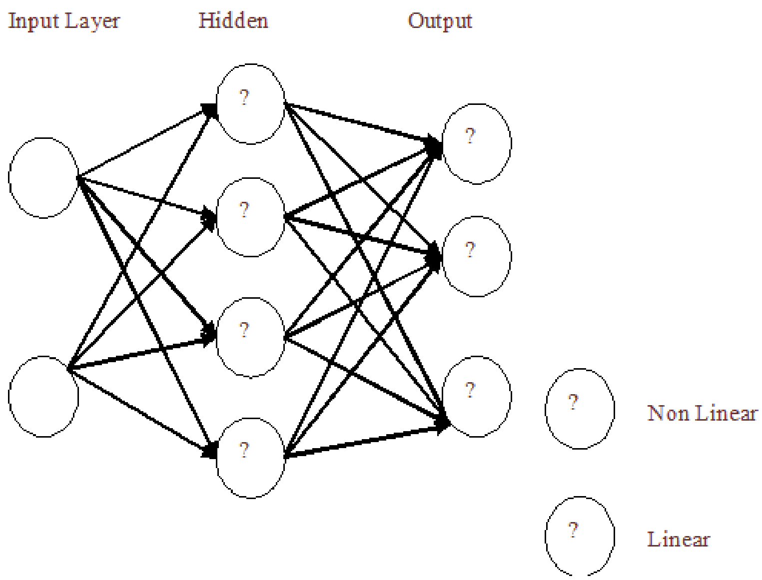

Fig: 2. Multi-Layer Perceptron Architecture

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MLP can estimate any continuous function to any level of accuracy of a compact set. On the other hand, the number of hidden layers and weight matrix that ensure optimum network convergence is never known. The solutions to each NN for the input and output data applied is unique. An MLP can categorize non-linear problems successfully.

The network is governed with equations that steer the network to provide precise result with minimum training error [25]. Commonly the training algorithms concentrate on synaptic weights, number of hidden layers, activation function etc. for assuring optimal result. The familiar supervised learning technique that trains the NN is BP. On the other hand, BP gets trapped in local minima and has slow convergence at some time. However to overcome this trapping of local minima some evolutionary algorithm can be used.

Multi-layered feed forward NNs are appropriate for complex pattern classification since it has various characteristics that provide solution for the same. However, the lack of a suitable training algorithm restricts its application for some of the real world environment. Finding a training algorithm which provides a near global optimal set of parameters in a comparatively short interval of time is a complicated task. Evolutionary Algorithms (EA) like Particle swarm intelligence and Genetic Algorithms (GA) explore a large and composite space in an intellectual way to locate parameters nearer to the global optimum [26]. Therefore, they are appropriate to train feed forward networks. MLP-NN have been generally used for forecasting. The common algorithm used for training this network is BP [27, 28].

Another popular NN used for prediction is the partially recurrent networks. They have a special neurons group in the input layer, called context neurons/neurons of state. Thus, in an input layer of partially recurrent networks two neuron types are seen, those which act like the input, receiving outside signals and context neurons receiving output values of a layer delayed by a step. They are useful for time series prediction problem [29-33]. Jordan in 1986 proposed Jordan NN, characterized as context neurons receive a copy from output neurons and themselves. The Jordan network has as many context neurons as output neurons. Recurrent output layer connections to the context neurons have an associated parameter, m, that, usually take a constant value positive smaller than 1.
For time series prediction, a network will have an output neuron representing predicted time series value at futures instances. The network will thus have only a context neuron and its activations at instant t is given by the following expression:

$$c(t) = mc(t-1) + x(t-1)$$

Where x (t-1) is output network at instant t-1.

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Remaining network activities are calculated as in multiplayer perceptron, where it is enough to consider as input vector a concatenation of the external input activations and context neurons activations:

$$u(t) = \left(x(t),...,x(t-d),\ c(t)\right)$$

Taking into account the expression of the context neuron activation, it is possible to write:

$$c(t) = \sum_{j=1}^{t-1} \mu^{j-1} x(t-j)$$

Therefore, parameter m equips Jordan network with certain inertia for this network's context neurons. It was previously seen that context neuron accumulates network output at all previous instants and parameter value m determines context neuron's sensitivity to retain information.

Popular Jordan NN training algorithm include BPTT and its operation can be summarized by:

- Context neurons activations initialized as zero at the initial instant.
- External input (x(t)...,x(t-d)) at instant t and context neurons activations at instant t are concatenated to determine input vector u (t) to network and propagated towards network output obtaining prediction at instant t+1.
- BP algorithm modifies network weights
- Time variable time increases in one unit with procedure goes to step 2
- Weight adjustment between BP processing elements is carried out based on the difference between NN's target and output values. Error difference in BP is measured by mean square error, as exposed below:

$$E = \sum_{k=1}^{m} \sum_{j=1}^{q} \left(t_{kj} - z_{kj}\right)^2$$

Where t_{kj} is the j_{th} target value of the k_{th} compound, and z_{kj} is the output. Weights are adjusted to a gradient direction with better fitness [34] as shown in the equation:

$$w_{ji}^{new} = w_{ji}^{old} + \alpha \sum_{k} \delta_{kj} y_{ki} + \beta \Delta w_{ji}^{old}$$

Where j, i are adjacent layer indices, $w_{ji}$is weight from the previous layer i_{th} neuron to the j_{th} neuron in the current layer and Δw_{ji} is the preceding weight change. The variable y_{ki} represents the i^{th} output for the k^{th} pattern. Parameters α and β are positive constants called learning rate and momentum rate which controls weight adjustments amount during weight updation.

BP algorithm, a gradient based method, is the most commonly used in NN training. BP algorithm's inherent problems are encountered when this algorithm is used. First, BP algorithm is easily trapped in local minima for non-linearly separable pattern classification problems/complex function approximation problem [35], leading to back-propagation failure to locate a global optimal solution. Second, BP Optimization algorithm's convergent speed is too slow even if learning goal, a given termination error, is achieved. What is to be emphasized is that BP algorithm's convergent behavior depends on initial values choices in network connection weights as also algorithm parameters like learning rate and momentum. To improve original BP algorithm performance, researcher's concentrated on two factors:

- Better energy function selection [36 & 37];
- Dynamic learning rate and momentum selection [38 & 39].

But these have not removed BP algorithms disadvantages of being trapped in local optima. Specifically, convergent speed will be slower as NN's structure is more complex. The BP has a very high likelihood to be trapped in local minima during the training process. Hence some variation in the PSO is proposed in this chapter.

Proposed Bee Swarm Optimization Algorithm

Optimization techniques are significant in practice mostly in soft computing. EAs have been used extensively to solve complex optimization problems. They are powerful class of stochastic optimization algorithms which provide solution to problems which cannot be solved analytically.

GA and PSO are some of the EA that have been used in optimization problems. The Bees Algorithm (BA) is among the newer optimization techniques [40] developed upon bees foraging behavior. Formerly proposed the Bee Colony algorithm motivated by the behavior of bees with enhanced performance in optimization problems in contrast to GA, Differential Evolution (DE), and PSO [41].

It is a population-based algorithm that mimics the food foraging behavior of bee swarms. The basic version of the algorithm performs a neighborhood and random search combined. A bee hive simultaneously explores plenty of food sources by stretching itself in many directions and over long distances [42]. Hypothetically, more bees will visit the flower patch with plenty of nectar/pollen that is gathered with less work, while the flower patch with less amount of nectar/pollen is visited by smaller number of bees [43]. Exploring commence in a colony by scout bees inspecting for potential flower patches. They progress unsystematically patch to patch. Some of the bees in the population called as scout bees continue exploration during searching.

The threshold is defined as a mixture of ingredient such as sugar content. The scout bees locating a patch that are rated higher than a threshold dump nectar/pollen and advance to the "dance floor" to show cast its "waggle dance" after returning to hive. The colony communicates through this strange dance. This dance communicates three information's concerned with the flower patch: Location of the flower patch, distance of the patch from the hive and its status of the quality (i.e. fitness). Based on this information, the bee hive sends bees to the flower patches accurately. The colony assesses the different patches for its relative merit in respect to food quality and energy needed to yield it. The colony understands every bee's knowledge of outside environment from the waggle dance [44].The scout bees (i.e. dancer) along with the follower bees goes to the flower patch after the completion of the waggle dance. Furthermore follower bees are sent to the potential flower patches to collect food rapidly and efficiently.

To decide the next waggle dance, the bees observe for the quality of food when yielding from the patch. If the quality of the flower patch is good and is still a potential food source, then it is publicized in the waggle dance and hence further more bees are employed to that patch.

Figure- 3 shows the flowchart of the BA in its simplest form which is dependent to some parameters described in **Table- 2**.

Table: 2. Parameters for Bee algorithm

Number of Scout bees	N
Sites selected	m
Best sites	e
Bees required for best e sites	n e p
Bees required for other selected (m-e) sites	n s p
Initial patch size	n g h
Iteration	i

The process begins as the scout bees starts harvesting randomly (random search). The fitness of the visited site is evaluated in step 2

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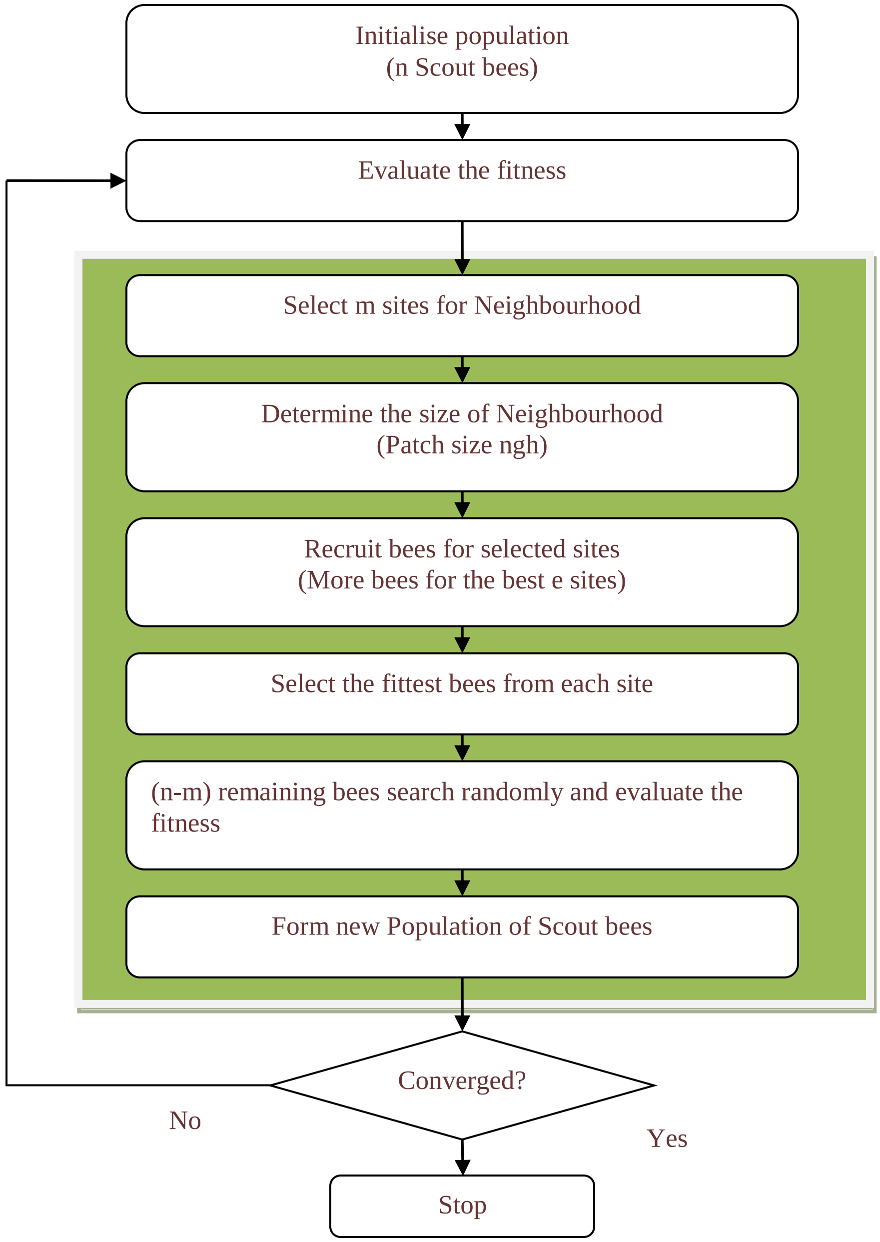

Fig: 3. Pseudo Algorithm for Bee swarm

The Optimization algorithm is used for searching the optimum values of weights, it speeds up the training.

RESULTS

The mobility prediction accuracy is evaluated using Multilayer perceptron network. The proposed Multilayer perceptron network is optimized with Artificial Bee Colony (ABC) algorithm. The parameters of the proposed Multilayer perceptron are given in **Table- 3**.

Table: 3.The Parameters of the Proposed Multilayer Perceptron Network

Number of inputs	8

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Number of hidden layer	2
Number of outputs	5
Optimization	Weights ,Learning rate and Momentum using bee swarm algorithm
Activation function	Tanh
Algorithm	Bee swarm

In the proposed Bee swarm optimization, an initial population is randomly chosen. The population is run through the BA (as shown in **Figure- 4.4**). The value used for evaluating the fitness is the best value. The algorithm would have calculated the most favorable solution on convergence. The proposed Bee swarm optimization is used to optimize the MLP network. The weights, learning rate and momentum of the network are optimized using the Bee swarm algorithm. The following **Figure- 4** shows the optimization for a number of iterations.

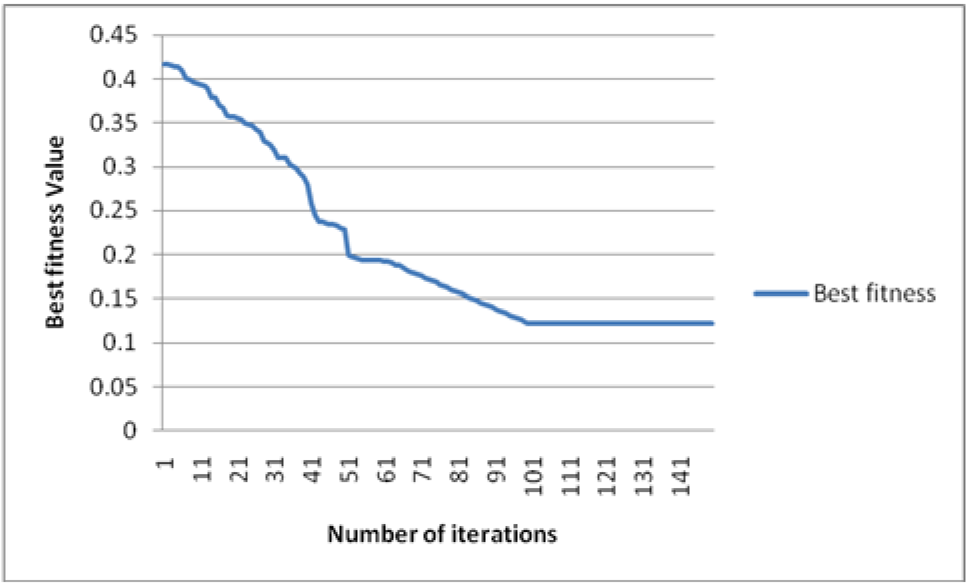

Fig: 4. Best fitness value

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The proposed MLP with proposed bee swarm algorithm is compared with MLP without optimization and with Radial basis network. **Table- 4** shows the classification accuracy and the RMSE achieved by using different techniques. **Table- 5** tabulates the precision and recall. **Figure- 5 and 6** shows the classification accuracy and precision and recall respectively.

Table :4. Classification Accuracy Achieved

Technique Used	Classification accuracy	RMSE
Radial basis function network	0.662295	0.3434
Multi-layer perceptron (two hidden layer)	0.744098	0.2776
Multi-layer perceptron (two hidden layer) with optimization	0.913462	0.1372

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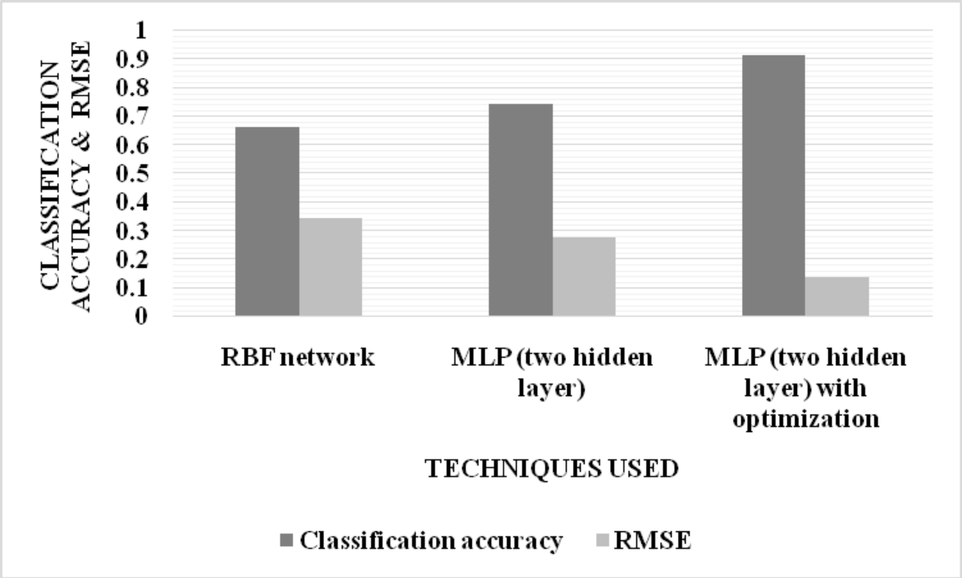

Fig: 5 .Classification Accuracy and RMSE

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From the **figure-5**, it can be observed that the MLP (two hidden layer) with optimization method increased Classification accuracy by 31.87% & 20.43% compared for RBF network and MLP (two hidden layer). The MLP (two hidden layer) with optimization method RMSE decreased by 85.8% & 67.69% compared for RBF network and MLP (two hidden layer).

Table: 5. Precision and Recall

Technique used	Precision	recall
Radial basis function network	0.672	0.662
Multi-layer perceptron (two hidden layer)	0.746	0.741
Multi-layer perceptron (two hidden layer) with optimization	0.929	0.913

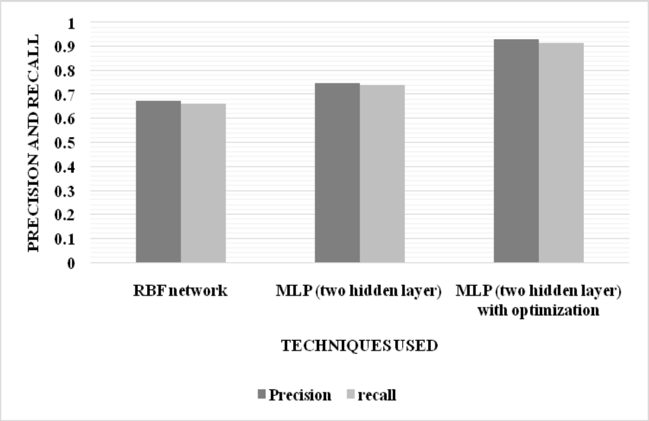

Fig:6. Precision and Recall

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From the **Figure- 6**, it can be observed that the MLP (two hidden layer) with optimization method increased precision by 32.1% & 21.85% compared for RBF network and MLP (two hidden layer). The MLP (two hidden layer) with optimization method recall decreased by 31.87% & 20.79% compared for RBF network and MLP (two hidden layer).

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The MLP and RBF was simulated using 10 fold cross validation. The **Figure- 7 to 15** shows the actual and predicted value for sample cross validation for RBF and MLP.

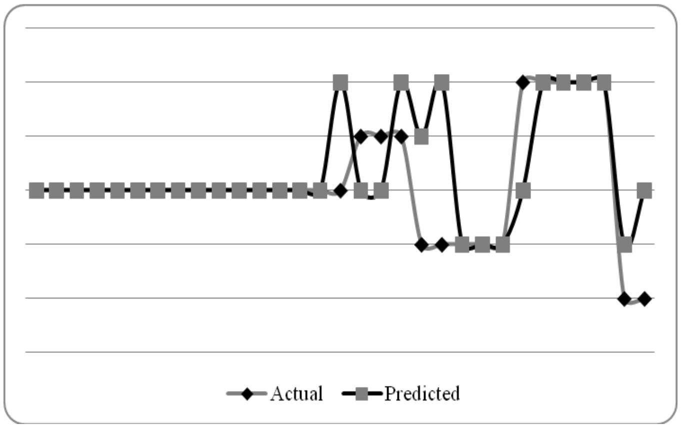

Fig:7. Iteration 4, Multilayer Perceptron

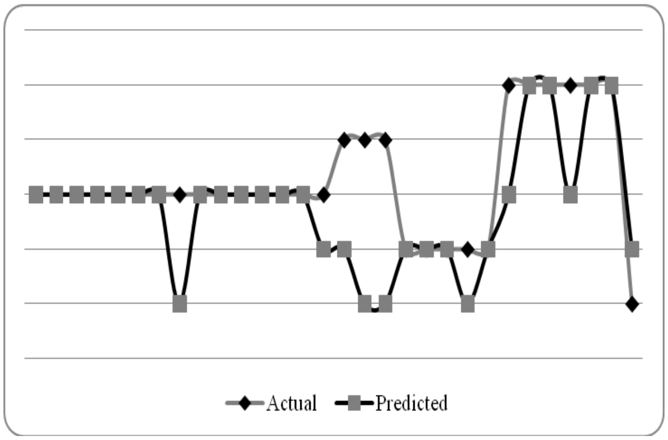

Fig: 8. Iteration 9, Multilayer Perceptron

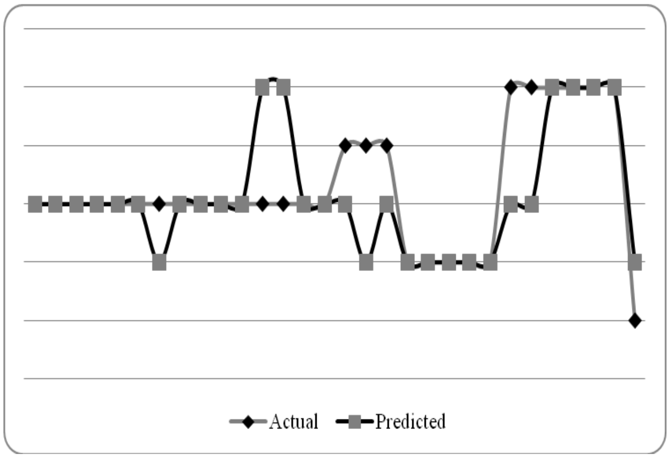

Fig: 9. Iteration 10, Multilayer Perceptron

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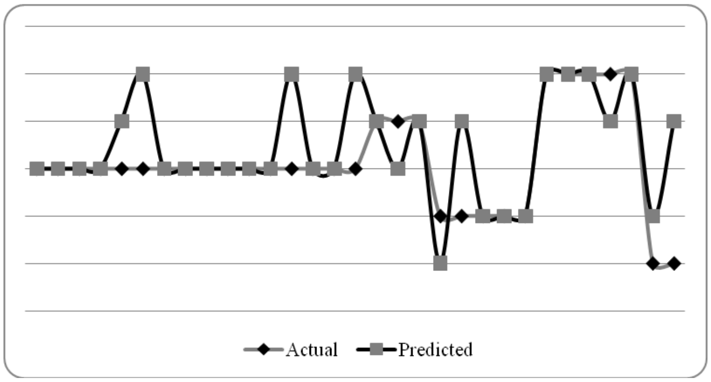

Fig: 10. Iteration 4, Radial Basis function

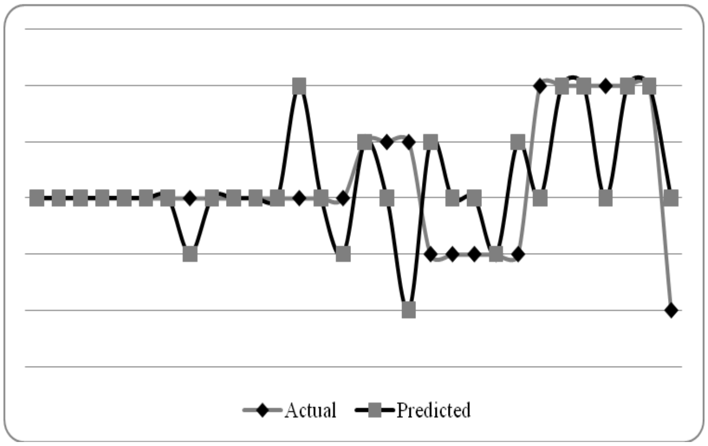

Fig:11. Iteration 9, Radial basis function

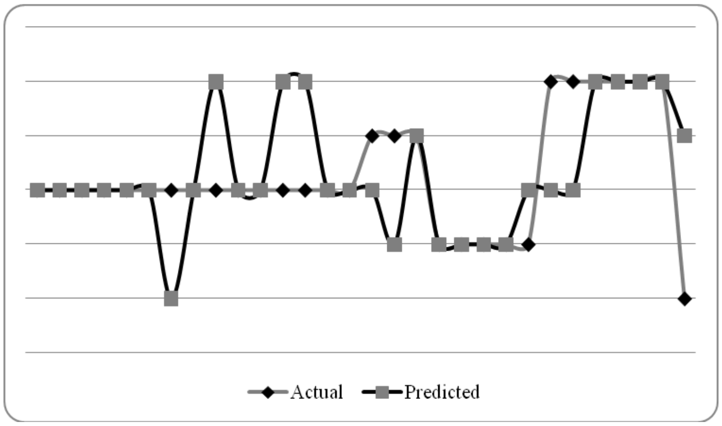

Fig: 12 .Iteration 10, Radial Basis function

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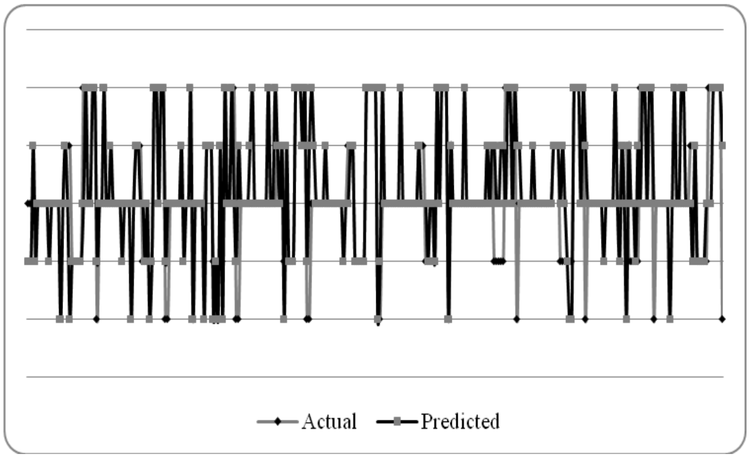

Fig: 13. Radial basis network output: Actual Vs Predicted

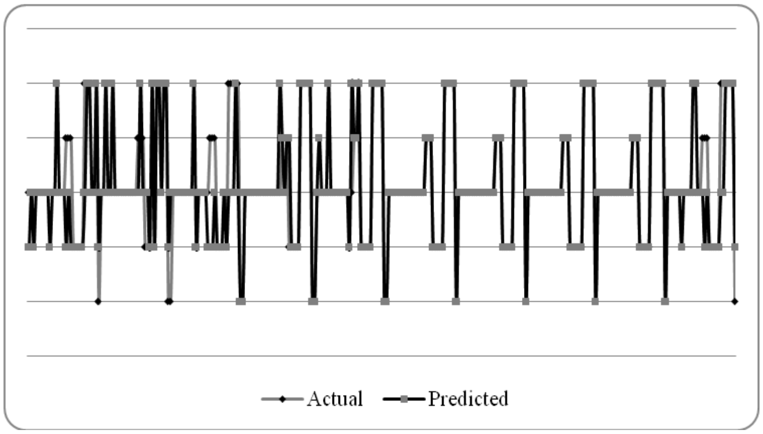

Fig: 14. Multiplayer Perceptron network output: Actual Vs Predicted

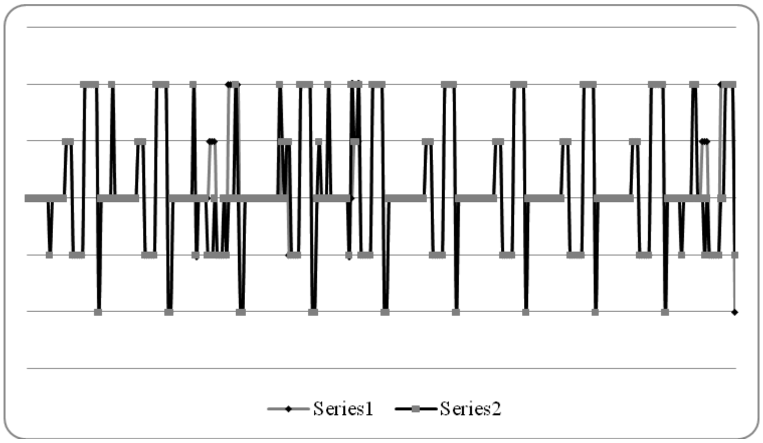

Fig: 15. Multiplayer Perceptron network with bee swarm optimization output: Actual Vs Predicted

It is evident from the Figures and Tables that the Proposed MLP network optimized with bee swarm optimization algorithm performs well compared to MLP without optimization and RBF.

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CONCLUSION

Mobile users expect services to be provided with less latency and better quality. Seamless handoff with least delay in wireless networks is an important criterion to improve QoS. Mobility prediction helps in seamless handoff by allocating resources beforehand. In recent years lot of researches have been done on mobility prediction schemes and models. This work provides a MLP network optimized with bee swarm algorithm in a wireless campus environment for the prediction of mobile user movement. The proposed algorithm predicts the next movement of the user with the help of the mobility rules established from the mobility traces. The data available in the Dartmouth college public domain is used as mobile wireless traces. This one month trace data is used for evaluation in this work. The results of the experiment conducted shows that the MLP network optimized with bee swarm algorithm act upon suitably.

CONFLICT OF INTEREST

No conflict of interest

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