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QoS provisioning by EFuNNs-based handoff planning in cellular MPLS networks

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Abstract

In recent years, Multi Protocol Label Switching (MPLS) has been considered as the preeminent technology to incur Quality of Service (QoS) for integrated services. However, in wireless networks the remotes mobility endangers resource management procedure and QoS provisioning. In this paper we propose a new location prediction method based on Evolving Fuzzy Neural Networks (EFuNNs), to manage Label Switched Paths (LSPs) in an MPLS domain. The proposed predictor employs geographical characteristics of underlying area and the movement history of a remote, to produce a set of confidence ratios as the output. That set is considered as a criterion for establishing and managing LSPs so that QoS preserved. The simulation results have shown superior performance in terms of prediction accuracy and utilization improvement for the proposed methods.

Keywords: Cellular MPLS networks; LSP management; Evolving Fuzzy Neural Networks; Quality of Service; Mobility prediction

1. Introduction

The third generation of mobile systems provides different services to end users, extending the scope of second generation mobile from simple voice telephony to complex data applications such as voice over IP, web browsing and file transfer as discussed in [7]. As the result, QoS support for different traffic requirements will be necessary in next generation wireless networks. However, nodes mobility jeopardizes the resource allocation process, and decreases the quality of service provided to delay sensitive traffic. Limited bandwidth and mobility of users in wireless networks, accentuates that traditional QoS engineering methods are insufficient.

In the other hand, increasing number of subscribers and bandwidth demand have pushed the mobile networks to be designed with smaller area cells to attain higher frequency reuse. It is widely accepted that as long as the area cell shrinks, an increment in the number of handovers is unavoidable [12]. To have smooth and robust handover procedure, necessary measures such as minimizing erroneous handover decisions, protecting connections from disruption and preserving QoS during handovers should be considered. In performing such procedures, *location prediction* plays an essential role in allocating enough resources before handing over a moving remote.

To incur QoS for different services, MPLS [8] has been considered as the preeminent technology in recent years. In the core networks, MPLS is emerging as the technology of facilitating traffic engineering and internetworking. Label Switched packet transferring is an extension to packet forwarding whereby short fixed length labels are attached to packets at entry nodes. The labels are assigned according to packets FECs[1] which are determined based on traffic engineering metrics and QoS policies. Packets would be delivered to their destinations (or mediating nodes)

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[1] Forwarding Equivalence Classes.

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through LSRs[2] that swap labels according to traversing paths. These paths are established between egress and interior nodes in MPLS domain according to FEC of traffic and minimum expenditure. MPLS technology can provide QoS by employing CR-LDP[3] [10] or RSVP-TE[4] protocols. These protocols utilize traffic attributes for setting up and holding LSPs and providing resources for them. MPLS can provide both COS[5] and virtual path objectives. So, it has advantages of both IP Diffserv and ATM in providing QoS for different types of traffic. Owing to MPLS advantages, there are a lot of efforts to exert it to wireless networks for QoS improvement.

In this paper, we consider service quality provisioning in an MPLS cellular network. A method is proposed to maintain QoS requirements for offered services by properly managing handoff procedure. To provide adequate resources to the service given to a remote, the LSPs are established and managed based on the predicted next cell of presence of that remote. The location prediction is done by a new method based on EFuNNs. Each output of the predictor indicates the degree of confidence for the corresponding neighboring cell, showing that how likely the remote may move to that cell.

In the next section of this paper, we will review related works on location prediction, handoff management and MPLS and its employment in wireless cellular networks for QoS implementation. In Section 3 EFuNNs is explained. The proposed location predictor is presented in Section 4. In Section 5, our proposed method for QoS-based resource management in an MPLS domain using location prediction is described. Simulation results and discussions are presented in Section 6, and finally, the paper is concluded in Section 7.

2. Related works

This paper contributes in three issues: location prediction, handoff management and cellular MPLS. In this section, we review some related works on each of these areas.

2.1. Location prediction methods

Predicting the next cell of presence may be employed in various cellular network procedures such as resource management, admission control [16,39] and handoff procedure. Location prediction methods may perform some of the following techniques as mentioned in [38]:

– Predicting next cell of presence for a remote,
– Predicting time of presence in a cell for a remote,
– Historical-based prediction,
– Topography-aware prediction,
– Per-user prediction,
– Per-cell prediction.

In [13], authors have proposed a simple prediction scheme using pattern matching. The predictor stores the historical movement pattern of each user in a database and compares the recent states with previous tracks to predict future movement. Authors in [14] use a statistical method to predict the number of channels needed in each cell to be reserved for mobile nodes in neighboring cells. This predictor uses speed, direction and node arrival elapsed time as parameters. To improve call connectivity, authors of [17] have proposed the concept of *shadow cluster*. A shadow cluster defines the area of influence of a mobile node and indicates a set of BS[6]s to which the MN would likely be connected in future. Each BS in the shadow cluster anticipates the MN arrivals and reserve resources for them.

Two neural network-based predictors have proposed in [11,12]. Both of these predictors are per user. In [11], authors have employed a feed-forward 3-layer neural network. Inputs to this predictor are a set of BSs taken from the movement history of MN. The outputs are 8 possible directions and the distance (number of hops) of the future movement. The simulations has showed 93% average accuracy for uniform movement, 40–70% average accuracy for regular movement and 2–30% average accuracy for random movement patterns. In [12], feedback neural network structures (Joredan-, Elman- and Hierarchical Elman-Networks) are used for the same purpose as [11].

As the mentioned predictors are *per-user* and *movement-dependent*, their operation is broadly based on movement patterns and movement history of mobile nodes. Although noticing to the topography of underlying area, such as a high-way in a cell, may facilitate the next presence cell prediction, these methods do not benefit from topography.

Authors of [18] have proposed a neural network-based topography aware predictor for handoff management. This predictor combines the mobile nodes movement history, current state and topography of the cells as inputs. To take the properties of underlying area into account, RSSIs[7] of surrounding BSs is measured by MNs as movement history. To utilize the movement history for prediction, this model employs a predictor per each BS. This predictor is a feed-forward 3-layer neural network which anticipates the next RSSIs for a remote. Simulations by authors have shown that the proposed method is more accurate in predicting mobility patterns when topographical features have impact on users' movements.

2.2. Handoff management methods

Handoff management methods may be classified according to the metrics used to decide about the necessity of

[2] Label Switched Routers.
[3] ConstRaint-based Label Distribution Protocol.
[4] ReSerVation Protocol & Traffic Engineering.
[5] Class Of Service.
[6] Base Station.
[7] Received Signal Strength Indicators.

handover. These metrics include signal strength [18,21], distance [22] and bit error rate [23]. Due to the fuzzy nature of parameters such as distance or RSS, the handoff planning is a complex procedure. There are several algorithms that employ advanced techniques such as Neural Networks [15,24–28], fuzzy logic [24–27] and pattern recognition algorithms [29–31].

Authors of [32] have proposed a fuzzy inference system for handoff decision. The input metrics of this system are RSS[8] from the current and candidate neighboring access points, ratio of used capacity to the total capacity of those access points and relative direction and speed of MNs. The outputs of this system (which are numbers between 1 and 9) are the membership value of a mobile node for currently serving and candidate access points. The MN does not handover if its membership value for its current access point is above a predetermined threshold. When handoff is necessary, the access point with better membership hysteresis value than the current access point will be selected. The results of simulations have been shown on VCL[9]-based tactical communication systems.

In [19], a fuzzy technique has been represented for microcellular handoff. In this method, RSSI and distance have been selected as metrics for planning. The output of this algorithm is called *hand-over factor* (*HO-Factor*). A value of *HO-Factor* close to 1.0 is interpreted as strong case of handoff and a value close to 0.0 is the opposite. When the *HO-Factor* value for current BS exceeds the value for another target BS (neighboring BS), the handover is necessary.

Authors of [41] have proposed an adaptive fuzzy logic-based algorithm that can adapt itself with the dynamic conditions of hybrid networks.[10] It uses the mobile terminal speed estimation and the traffic volume in wireless LAN as additional input parameters.

In [42], a fuzzy logic-based scheme has been presented for selection of the best base station at the time of handoff. This scheme considers three criteria, namely, received power level, user population and utilized bandwidth of each base station.

The approach proposed in [43] is based on Fuzzy Logic to evaluate the average and variation in signal strength received by a mobile station. To lessen the handoff latency, the mobile station performs an active scan process only once to obtain the complete handoff parameters.

A serious issue in handoff planning is frequent unnecessary handovers. For example an RSS-based algorithm may encounter a problem which is called "ping-pong" effect. This problem occurs when the remote locates around the mid-point between two access points so that the received signal strength oscillates and the remote may be handed over several times. To remedy this problem, in [33] a threshold is introduced to avoid the MN from handover until the RSS from the currently serving BS degrades below predetermined threshold. Another technique is to introduce a hysteresis to the RSS-based algorithm [33]. Although both of the above methods reduce the ping pong effect, but introduce delay to handoff procedure and are not able to respond fast enough in microcellular environments [32]. Such a problem indicates that the handover algorithm requires making crisp decision in a region of uncertainty with metrics that are fuzzy in nature as implied in [40].

2.3. MPLS in cellular networks

In many existing models for MPLS employment in wireless networks, Mobile Nodes need not to know any about MPLS technology. MPLS domain starts from Base Stations or interconnecting Routers. In fact, base stations or routers are responsible for connecting wireless domain to MPLS domain [6]. In [4] a wireless network architecture which is based on MPLS has been proposed. In this architecture, MPLS domain does not include base stations, so the LER[11]s are the routers which are connected to base stations (MLSN[12]s).

In mobile internet connectivity, MIP[13] has been chosen as the core of mobility management mechanism for recent cellular networks. However, basic MIP inherits its bases from IP, so is incapable of providing QoS. The interest in MPLS, as an underlying forwarding scheme for MIP, is justified by its capability to accommodate scale and QoS guarantees [35]. In [2,3], authors have proposed a method which is based on integration of MPLS and MIP.

2.4. Handoff management in cellular MPLS

In previous research, generally, handoff management is performed by MPLS nodes (LSRs) in backbone. In [1] two methods for handoff management have been proposed in which there are special LSPs from the nearest router to the base station, for every connection between an MN[14] and its destination. In the first method which is named "Dynamic Rerouting", during handover, the new BS detects the nearest LSR in the previous LSP (between the previous BS and destination) and establishes a new LSP between itself and that LSR. Actually a new LSP is provided to transfer data from MN to its destination, considering Make-Before-Break policy. This scenario is shown in Fig. 1 where LSR2 is the nearest common LSR.

In the second method called "pre-established paths", a set of pre-established LSPs is used. There is a pre-established LSP from each BS to the destination node of a connection. While an MN is moving from a cell to another, packets sent from this remote traverse through a new LSP in the corresponding cell. The communicating node

[8] Received Signal Strength.

[9] Virtual Cell Layout.

[10] Internetworking between wireless LANs and mobile networks.

[11] Label Edge Router.

[12] Mobile Label Switched Node.

[13] Mobile IP.

[14] Mobile Node.

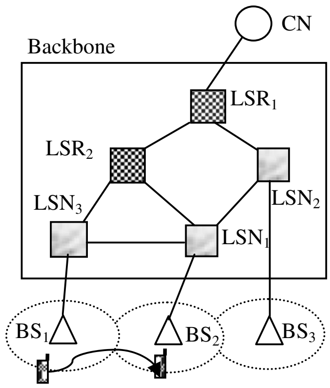

Fig. 1. Dynamic rerouting process.

recognizes the handover from LSP change, and uses the new LSP for sending packets to that remote.

An important problem in handoff management is handling handoff in a diversity area. In a diversity area a remote can receive and transmit packets from and to two or more base stations. MPLS has the inherent capability to support multiple parallel LSP tunnels between multiple nodes and merge these LSPs using Label Merging capability. As considered in Fig. 2, in "Dynamic Rerouting" scenario, when the mobile is transmitting packets to two or more base stations, these base stations forward the packets with different labels to the same LSN (the nearest LSR to the new BS in old LSP) [1]. In this LSN labels will be merged and packets will be forwarded with the same label.

2.5. QoS support in wireless MPLS

There are two approaches to provide QoS in an MPLS-based wireless network [5]. The first one is to use a single LSP to connect each BS to backbone. So, multiple classes of traffic from a base station will be carried within one LSP which is named "E-LSP". QoS differentiation, in this method, is provided by packet marking and per-hop-behavior using COS field of headers.

The second way is to use multiple LSPs named "L-LSP" to connect each BS to the backbone. Each LSP carries one class of traffic. These approaches are shown in Fig. 3.

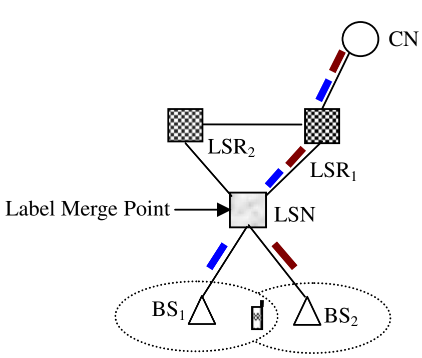

Fig. 2. Handling handoff in the diversity areas.

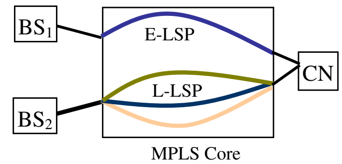

Fig. 3. QoS support in WMPLS networks.

Another proposed way for QoS support in MPLS architecture is using CR-LSP.[15] CR-LDP[16] defines two properties for each CR-LSP called *setup priority* and *hold priority*. CR-LDP reserves resources for each LSP according to its QoS requirements and establishes a new LSP if there is enough resources for it or there is a previously established LSP with smaller *hold priority* than *setup priority* of emerging LSP.

Our proposed location predictor is based on EFuNN. This network will be discussed in the next section.

3. Evolving Fuzzy Neural Network

EFuNN is based on ECOS[17] framework for building online, adaptive intelligent systems that have both their structure and functionality evolving in time. The model is called evolving because of the nature of the structural growth and structural adaptation of the whole evolving connectionist system which it is a part of that. EFuNN suggests a neuro-fuzzy systemic approach that employs growing supervised/unsupervised, knowledge-based learning methods [34]. While new connections and new neurons are created during the operation of the system, EFuNNs can accommodate new input data, including new features and new classes through local elements tuning. These characteristics are useful in cases where the number of features or classes is not determined. The reports in [36] exhibit that the EFuNN model not only gives the analogous performance compared to other complex neuro-fuzzy systems, but also provides the feature of the expeditious one pass parameter training which makes it highly suitable for the low power requirement. Authors of [44] have used EFuNNs for zone radius estimation which is used for zone routing protocol in Bluetooth networks.

The EFuNN employs a feed forward neural network to process fuzzified data and defuzzifies the fuzzy data as the output. Generally, an EFuNN includes five processing stages, which are network initiation, inputs feed forward, parameters tuning, node aggregation and pruning, and rule extraction, respectively. The fuzzy input layer carries out fuzzy quantization of the inputs. The rule layer contains rule nodes that can evolve through learning. As shown in Fig. 4, after each input vector is fed into the EFuNN, the network updates its parameters, evolves connections, aggregates and prunes nodes based on the output error

15 ConstRaint-based LSPs.
16 ConstRaint-based Label Distribution Protocol.
17 Evolving Connectionist Systems.

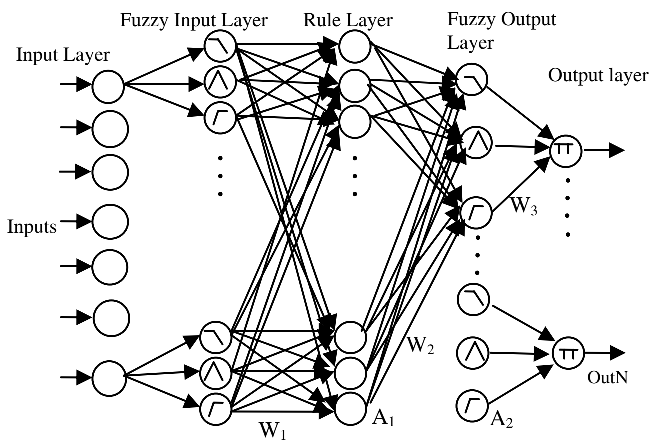

Fig. 4. Sample EFuNN structure.

during the last epoch if necessary. Then the EFuNN propagates the signals forward, and computes the output error again. Then the defuzzification for the fuzzy output layer gets done in the output layer [34].

3.1. Network initiation

At the network initialization phase, the connection weight matrixes W_1 and W_2 (as shown in Fig. 4) are set to some predefined values based on the past experience of the network. W_1 and W_2 represent the coordinates of the sphere center in the fuzzy input space and in the fuzzy output space respectively. The membership functions, the number of the rule nodes and the connection patterns of W_1 and W_2 are decided based on specifications of the problem.

3.2. Input feed-forward layer

When a new sample is fed as input, first it is fuzzified at the fuzzy input layer, then the Fuzzy Distance (FD) between the output of the fuzzy input layer and the connection weights W_1 are calculated to determine if the input falls into the receptive distance of some specific rule node. The fuzzy distance between the two fuzzy membership vectors of input X_f and the connection weights of the jth rule node, $W_{1,j}$ is defined as follows:

$$FD(X_f, W_{1,j}) = \frac{\|X_f - W_{1,j}\|}{\|X_f + W_{1,j}\|}, \ j = 1, \ 2, \ldots, N \tag{1}$$

where N is the number of rule nodes, $W_{1,j}$ is the jth column vector of matrix W_1, $\|X_f - W_{1,j}\|$ denotes the sum of all the absolute values of the vector obtained by subtraction of vectors X_f and $W_{1,j}$. Likewise, $\|X_f + W_{1,j}\|$ is the one obtained by summation of vectors X_f and $W_{1,j}$.

We then select the rule node with the highest activation which is the lowest FD value. The activation set for the rule layer is defined as matrix A_1 with the row vectors given by:

$$A_{1,j} = 1 - FD(X_f, W_{1,j}) \tag{2}$$

If the activation of the selected rule node is smaller than a predetermined sensitivity threshold, a new rule node is created and the new connection weights are established for the new fuzzy input and fuzzy output pair X_f and Y_f. So, the new network has two new weight vectors $W_{1,(N+1)}$ and $W_{2,(N+1)}$ where

$$\begin{aligned} W_{1,(N+1)} &= X_f \\ W_{2,(N+1)} &= Y_f \end{aligned} \tag{3}$$

On the other hand, when the activation of the selected rule node is larger than the sensitivity threshold, it will be passed forward to the next layer to compute the output of Fuzzy Output Layer A_2 as follows:

$$A_2 = \mathrm{satlin}(W_2 \cdot A_1) \tag{4}$$

where $W_2 = [W_{2,1}\ W_{2,2} \ldots W_{2,N}]$ and satlin(.) represents the saturating linear transfer function. Similarly, a new rule node will be created if the following fuzzy output error is larger than a predefined threshold value,

$$FE_{\mathrm{out}} = \|A_2 - Y_f\| \tag{5}$$

At last, crisp output value Y_c can be derived by Eq. (6):

$$Y_c = W_3 \cdot A_2 \tag{6}$$

where W_3 denotes the connection weight matrix between the fuzzy output layer and the output layer.

3.3. Parameter tuning

The training process of the network includes the updates of the connection weights W_1 and W_2, the learning rate and the sensitivity thresholds for each rule node. W_1 is adjusted using unsupervised learning based on the similarity between the fuzzy input vector X_f and the stored prototypes $W_{1,j}$ for the jth rule node as follows:

$$W_{1,j}(t+1) = W_{1,j}(t) + \eta_j(W_{1,j}(t) - X_f) \tag{7}$$

and W_2 is updated according to the Widrow–Hoff least mean square (LMS) algorithm [37] that minimizes the fuzzy output error,

$$W_{2,j}(t+1) = W_{2,j}(t) + \eta_j(A_2 - Y_f).A_{1,j} \tag{8}$$

In both equations, η_j stands for the learning rate of the jth rule node. Note that η_j can be expressed as $\eta_j = 1/\mathrm{ACC}_j$, where ACC_j is the accumulated number of accommodated examples for the jth rule node.

The sensitivity threshold for the rule node, which has been referred in Eqs. (5), (6) or (7), is given by

$$S_j(t+1) = S_j(t) + FD(W_{1,j}(t+1), W_{1,j}(t)) \tag{9}$$

3.4. Rule node aggregation

After certain number of training samples has been presented, some neurons and connections may be pruned or aggregated. If the fuzzy distance as given in Eq. (1) for every two out of K nodes is less than a predefined threshold for both connections W_1 and W_2, the K nodes can be aggregated into one single rule node with the following connection weights and sensitivity threshold:

$$W_{r,\text{agg}} = \frac{\sum_{i=1}^{K} W_{r,i}}{K}, r = 1,2 \qquad (10)$$
$$S_{\text{agg}} = 1 - \underset{i\in 1..K}{\text{Max}}(FD(W_{1,\text{agg}}, W_{1,i}))$$

where $W_{1,\text{agg}}$, $W_{2,\text{agg}}$ and S_{agg} represent the connections and sensitivity threshold for the aggregated node, respectively.

3.5. Rule extraction and insertion

Every rule node in the network can generate a fuzzy rule from W_1 and W_2 connections. We assume that there exists a fuzzy rule in the network as in Fig. 5.

In Fig. 5 the number after each fuzzy label represents the degree to which the centers of the input and the output hyper-sphere belong to the respective membership function. The degrees associated with the premise and the consequent parts of the rule are the connection weights of W_1 and W_2, respectively.

For manual insertion of new fuzzy rules, a new rule node, r_i, will be inserted in the rule layer such that the connection weights $W_1(r_j)$ and $W_2(r_j)$ of the rule node represent this rule. It means that only for corresponding linguistic terms in rule, values of $W_1(r_j)$ and $W_2(r_j)$ are one and for others are zero.

4. Proposed predictor

In this section, we propose an EFuNN-based predictor which considers uncertainty characteristics of handover process. The proposed model is a motion predictor with the following characteristics:

– It considers the topographical characteristics of underlying area, in addition to motion history of users.
– There is a predictor per each cell which predicts the next cell of presence for all of the remotes in that area cell.
– The proposed predictor is velocity adaptive.

The predictor is illustrated in Fig. 6. The inputs to this predictor are ASSI[18] of currently serving BS and neighboring BSs, AV[19] and AD[20] of an MN. The outputs are the predicted RSSIs of that MN, velocity and direction which may be used in handoff decision.

To collect the training data set, each BS uses the movement history of alive MNs in its area cell. Each movement history element includes a set of RSSs from the neighboring BSs, current velocity (V) and direction (D) of that MN. An example of a training data set is in the form of below:

Rj : IF In1 is "low" with a degree of 0.45, and is "medium" with a degree of 0.65,
AND In2 is "Low" with a degree of 0.67, and is "High" with a degree of 0.39,
AND In3 is "Low" with a degree of 0.44, and is "High" with a degree of 0.68,
, …
THEN Out1 is "low" with a degree of 0.35, and is "medium" with a degree of 0.88

Fig. 5. The fuzzy rule extracted from EFuNN network.

$$\text{patt} = \langle\langle S_N, S_{N-1}, \ldots, S_2, S_1\rangle, \langle S_0\rangle\rangle \qquad (11)$$

where S_i is the motion history in ith previous time step and S_0 is the current motion status which is recorded by MN. The first part of patt vector will be used as the input component and the second part, $\langle S_0\rangle$ is the corresponding target output. S_i is a vector of the following form:

$$S_i = \langle \text{RSS}(\text{BS}_{\text{cur}(i)}), \text{RSS}(\text{BS}_{1(i)}), \ldots, \text{RSS}(\text{BS}_{M(i)}), D_i, V_i\rangle \qquad (12)$$

where M is the number of neighboring cells. The received signal strength and the velocity (V) values are normalized to lie in the range of $[0,1]$ and direction (D) is a value within $[0,360]$ interval. The $\text{RSS}(\text{BS}_{J(i)})$ value in S_i is the received signal strength value from Jth Base Station where BSs are numbered in a clockwise direction around the current cell in ith history element.

The training patterns are preprocessed by an adaptive weighted averaging operation with variable weight, γ and constant window length (N) using the following formula:

$$S_{\text{input}} = \sum_{i=1}^{N} \gamma^{i-1} S_i, \gamma \in (0,1] \qquad (13)$$

The parameter γ is the forgetting factor which diminishes the effect of long term history. The variable weight is updated based on the previously predicted MN velocity as shown in Fig. 5. For higher velocities, the long history is less correlated with the current status. As such, the value of γ should be smaller to diminish the effect of long history

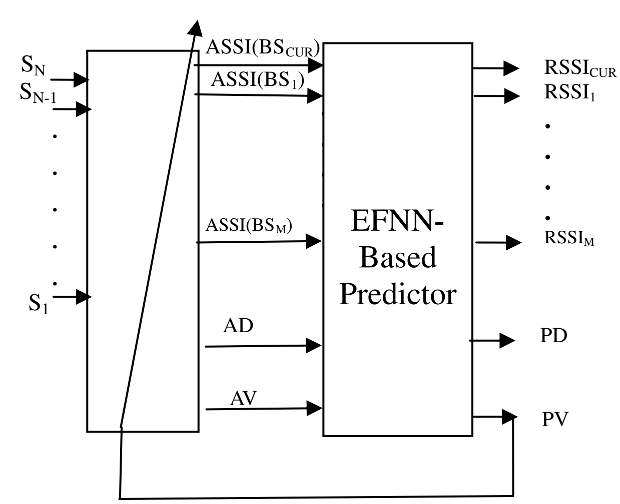

Fig. 6. Proposed mobility predictor.

[18] Averaged Signal Strength Indication.
[19] Average Velocity.
[20] Average Direction.

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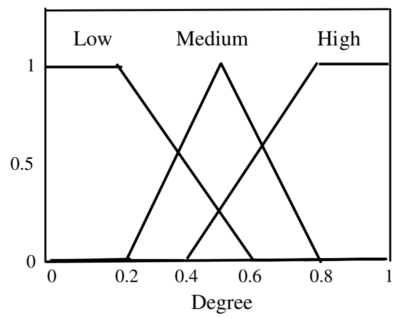

Fig. 7. ASSI, AV, PV and RSSI membership functions.

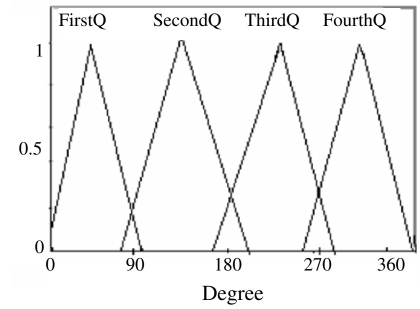

Fig. 8. The membership functions for AD and PD fuzzy variables. There are four fuzzy sets per each quarter of trigonometric circle.

further. Regarding that, γ can be taken proportional to $1 - V_p$ where V_p is the predicted velocity. The S_{input} vector which is the input vector to EFuNN-based predictor can be interpreted as below:

$$S_{\text{input}} = \langle \text{ASSI}(\text{BS}_{\text{cur}}), \text{ASSI}(\text{BS}_1), \ldots, \text{ASSI}(\text{BS}_M), \text{AV}, \text{AD} \rangle \tag{14}$$

where each parameter is the averaged value of the corresponding parameters in the history vectors (S_i).

The training samples which are applied to EFuNN during training phase are in the form of $\langle S_{\text{input}}, S_0 \rangle$ pairs of vectors.

The membership functions of fuzzy variables, ASSI, AV, PV and RSSI, are shown in Fig. 7.

The membership functions of averaged direction (AD) and predicted direction (PD) are represented in Fig. 8.

The predicted values of RSSI and direction PD can be used for handover decision using *the adaptive fuzzy handoff algorithm with direction biasing* which has been proposed in [24]. Also, as the other purpose of this paper, the RSSI part of the output is used in two different proposed policies for LSP management. These policies will be discussed in the next section separately. In the first policy, we select the maximum output as *the most probable next cell of presence*. In the second policy, outputs will be compared with a threshold T to find a set of neighboring cells which are chosen as *the most probable cells of presence* with confidence degrees equal to the respective output values.

5. LSP management using predicted RSSIs

This research is continued by proposing and comparing two policies for LSP management in MPLS domain using location prediction results. We assume that MPLS domain begins in base stations. Therefore, BSs operate as LERs that label packets of subordinate MNs based on their destinations. In the first policy, a temporary LSP will be established in *the most probable next cell of presence* for each existing LSP. In the second policy, a set of temporary LSPs will be established in *the set of most probable cells of presence* for each existing LSP. These LSPs are CR-LSP[21]s [10], which are utilized for QoS provisioning. These two policies are explained in the following subsections in more detail.

[21] ConstRaint-based LSP.

5.1. Pre-established temporary LSPs

As mentioned earlier, the first policy considers simple LSPs in the most probable next cell of presence. Hence, the process of *LSP establishment and management* is presumed in three situations as follows:

(a) When the handover occurs and the MN moves to a new cell. If there are no pre-established temporary LSPs for its traffic, these LSPs will be established between BS and destinations for existing FECs, using LDP protocol [9]. Then, the pre-established or currently established LSP will be used by BS to deliver the traffic of that MN.

(b) At every time step. Each BS predicts next location of its MNs and informs neighboring BSs to establish new temporary LSPs before MNs handover. Moreover, if previous prediction for each MN is different from current prediction, preceding temporary LSPs for that MN should be omitted after a predetermined number of time steps.

(c) When an MN is leaving a cell. Current BS keeps respective LSPs for that MN until it leaves the diversity area. So, that MN can transfer its traffic using both LSPs.

5.2. Pre-established temporary CR-LSPs

In the second policy, CR-LSPs are used as temporary pre-established paths. The outputs of proposed predictor which are *confidence degrees* are employed for *setup and hold priorities*. These priorities are defined between 1 and 7 in each CR-LDP and the highest priority holder is used for permanent LSPs for each FEC. A *hold and setup priority* between 1 and 6 is assigned to each temporary CR-LSP according to its *confidence degree*. The process of LSP establishment and management is further described in three situations as below:

(a) When the handover occurs and the MN moves to a new cell. If there are no pre-established temporary CR-LSPs for its traffic, these LSPs will be established with maximum hold and setup priority, 7. On the other hand, if there are previously established CR-LSPs, their hold prior-

ities will be modified to 7. Then the BS uses these CR-LSPs for that MN.

(b) At every time step. Each BS predicts next locations of its MNs and obtains the *confidence degrees* for each neighboring cell. Then, the BS chooses a set of next cells of presence for each MN if their confidence degrees are larger than a preset threshold T. Afterwards, BS informs chosen neighboring BSs about establishment of the new temporary CR-LSPs with *setup and hold* priorities according to respective *confidence degrees* (according to heir order in the above set). Those BSs must establish new CR-LSPs for each MN using CR-LDP before handover. Moreover, if previous prediction for each MN is different from current prediction, precedent temporary CR-LSPs for that MN should be omitted or their *hold priorities* should be modified.

(c) When an MN is leaving a cell. Those CR-LSPs in neighboring cells which are not necessary will be removed. Moreover, currently used CR-LSPs for this MN will remain until MN leaves the diversity area.

In the next section, the simulation results for proposed predictor and handoff management in a wireless MPLS domain are presented.

6. Simulations results

The simulations are performed in two phases. First, the accuracy of proposed predictor is evaluated and then, the performance of proposed LSP management method is examined.

Simulation environment has been implemented in NS [20], and includes of 25 circular cells and one highway. A population of 20 MNs is considered where half of MNs have random mobility model while others move with different speeds in highways. The value of N and the initial value of γ are chosen to be 10 and 0.9, respectively. The time step has been considered to be 0.5 s, similar to [44] (as the measurement sampling period is 0.5 s in GSM [24]). We have used the propagation model which has been proposed in [45] to compute the RSS values from the distances. Although the value of velocity is determined by NS, authors of [44] have proposed several methods to estimate the velocity. After online training of EFuNN-based predictor using our proposed method, the prediction error for random and regular movement patterns have been computed and illustrated in Figs. 9 and 10.

In the second phase of simulation, we consider data delivery criterion in a packet-based network to investigate the performance of the proposed method for LSP management. We assume that 1 Mbps links connect each BS to backbone, and there are four MNs which have four established connections with four corresponding nodes (CN1, CN2, CN3 and CN4) in backbone. Each MN transmits 1 Mbps of CBR traffic over its connection. The data delivery ratio is observed using four loss monitors in the corresponding nodes (CNs). The normalized value of delivered data in corresponding nodes is evaluated for three different handoff management methods. The first method is a basic scheme without prediction. The other two methods are the proposed policies for LSP management using predictor. The simulation results are shown in Figs. 11–13 for 3600 time steps using the same traffic pattern for those three methods.

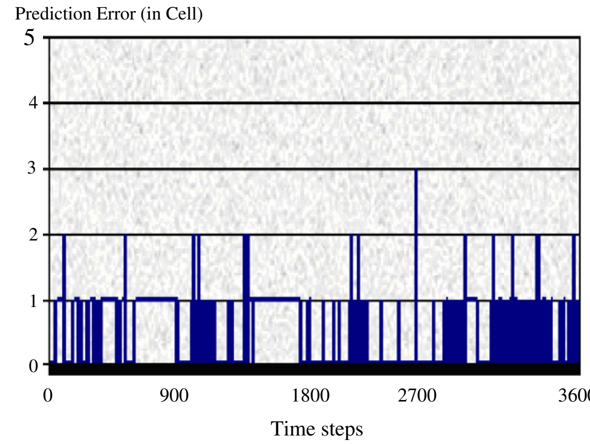

Fig. 9. Prediction error for random movement pattern.

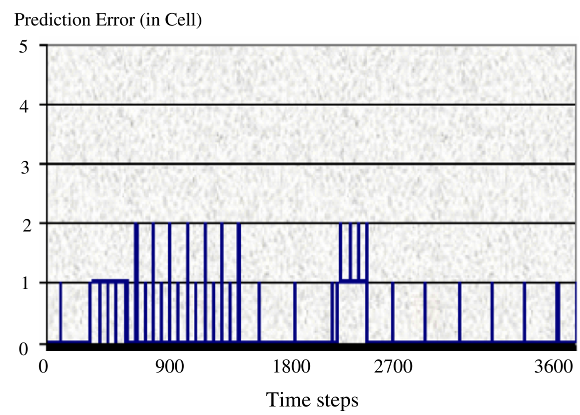

Fig. 10. Prediction error for regular movement pattern.

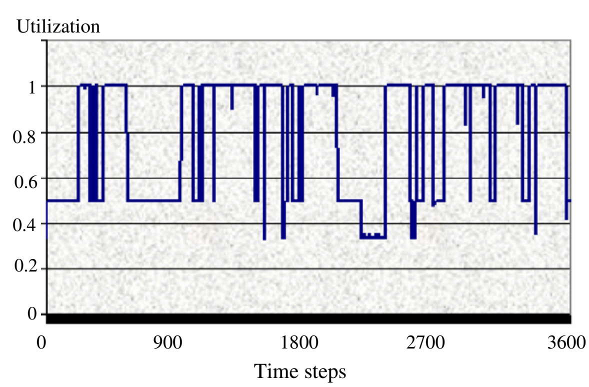

Fig. 11. Utilization for the classic handover method.

The results of simulations show that in the traditional handoff management method, there are quality degradations during handoffs. Furthermore, the bandwidth from a BS to the corresponding node is shared between a numbers of traffic flows in the current cell. For our first proposed method, the process of handoff is faster. Thus, the traffic degradation during handover interval is lower, although there is shared links between different MNs.

Since the bandwidth is reserved for each traffic flow in the second proposed method, the traffic degradation is minimized for admitted flows and providing quality of service for CBR traffic is more convenient. As the BS-to-core links are band-limited, the utilization decrease occurs during some short time intervals due to incorrect prediction and late LSP establishments in a number of traversed cells. This reduction is near 100% because of bandwidth reservation for other previously established LSPs.

To compare the average utilization for the three discussed methods, the utilization is moving averaged over a 500 steps averaging window. The results are shown in Fig. 14. This figure illustrates that the CR-LSP presents better performance, in terms of delivered data, over the two other methods.

7. Conclusions

In this paper we considered QoS provisioning in MPLS wireless networks by means of mobility prediction. To offer adequate resources for a flow before handoff, we proposed two methods for LSP management based on location prediction. A new mobility predictor using evolving fuzzy neural networks is proposed. The predictor provides enough accuracy to reduce the number of unnecessary handovers. Furthermore, two methods for LSP management by the proposed predictor are proposed. Using prediction results in resource management reduces the ping-pong effect because of existing pre-established LSPs. Moreover, using CR-LSPs to pre-reservation of resources for different traffics has significant effects on data delivery. Simulations results show that pre-established CR-LSPs based on the proposed method presents superior performance in terms of utilization and data delivery. The VBR traffic and investigating the effects of proposed schemes on its quality of service will be considered in the future research.

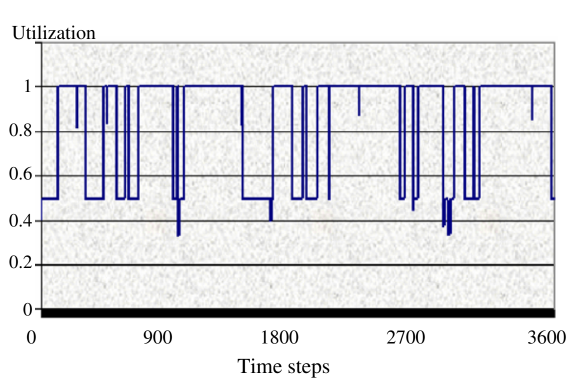

Fig. 12. Utilization for the pre-established LSPs method.

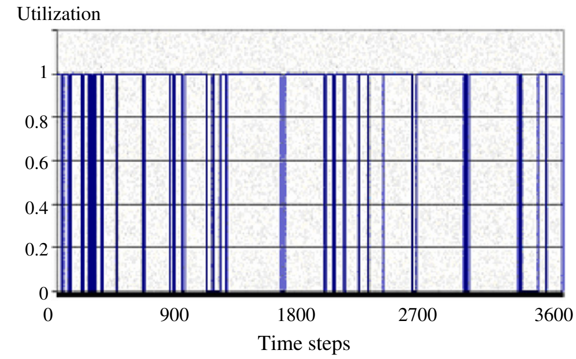

Fig. 13. Utilization for the pre-established CR-LSPs method.

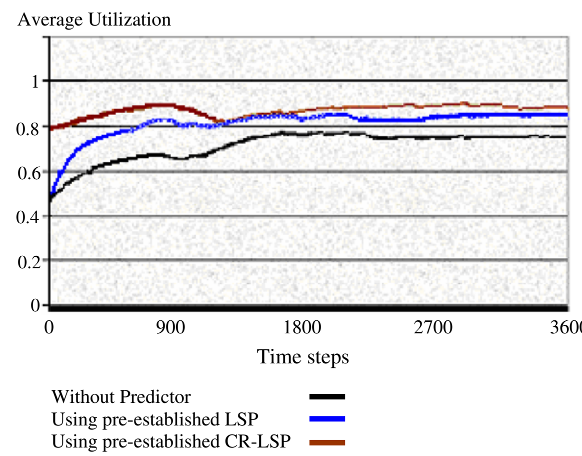

Fig. 14. Averaged utilization for the three methods.

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