Enhanced Adaptive Traffic Dependent Handover Decision System for Wireless Mobile Networks

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***Abstract*—Integrated network architectures have the potential to provide ubiquitous and seamless services over wide areas of mobility, with adequate quality of service and favourable price. To fully exploit such architectures (heterogeneous networking environments) multiple handovers often become necessary. Furthermore, in view of the growing demand for real-time applications, the inclusion of QoS-related parameters in the handover decision process is essential. This requirement inevitably increases the overall number of decision parameters, leading to unacceptably long algorithm execution time for a typical monolithic fuzzy-based handover decision system (MHDS), which employs a single fuzzy decision engine. In this paper, an adaptive traffic dependent fuzzy-based handover decision system (ATDHDS), which employs multiple fuzzy decision engines, each dedicated to a specific traffic type, is presented. The results show that, comparing with the MHDS, the proposed ATDHDS significantly improves the network selection performance and algorithm execution time. The ATDHDS is then enhanced by introducing additional fuzzy engines, which perform a QoS aggregation process, with the aims to further improve the overall network selection performance and to further reduce the algorithm execution time. The simulation results suggest that the enhanced ATDHDS (EATDHDS) successfully achieves both objectives.**

***Keywords*-fuzzy logic; handover; traffic dependent; QoS aggregation; wireless mobile.**

I. INTRODUCTION

Mobile users in the 'Information age' expect ubiquitous and seamless services over wide areas of mobility, with adequate quality of service and favourable price. It appears that integrated network architectures have the potential to satisfy the above requirements. Integrated network architectures (referred to as heterogeneous networking environments) require interconnections of various wireless technologies such as WLAN, WiMAX and Cellular networks as illustrated in Figure 1. To ensure continuous connection, required quality of service and acceptable usage price, over a wide area of mobility, multiple handovers (switching connection from one wireless network to another) often become necessary. A handover may take place in a homogeneous networking environment (horizontal handover) or in a heterogeneous networking environment (vertical handover). In either case some form of decision mechanism needs to exist within the mobile device.

A horizontal handover decision is normally a straightforward process as the decision is based simply on the received signal strength (RSS). However, due to varied characteristics of different wireless networks, a simple RSS based decision cannot achieve the required results in a vertical handover decision process. Clearly there is a need for a much more intelligent handover decision system (HDS) for heterogeneous networking environments. Several deterministic algorithms for handover decision engines have been proposed in the literature, however they suffered from two limitations: 1) inability to deal with imprecise data efficiently, 2) inconsistencies in the decision outcomes, due to the fact that the procedures used for assignment of parameter weight are subjective.

The fuzzy logic techniques are regarded to have the ability to deal with the above limitations. Thus, numerous fuzzy logic based solutions, which enhance intelligence of the vertical handover process, have been proposed in the literature. However, in most of the existing work the decision process is based on a single monolithic decision engine, and with no regard

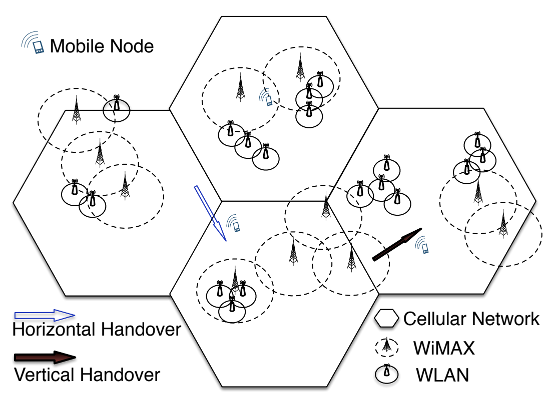

Figure 1. Architecture of Heterogeneous Wireless Mobile Networks

to the traffic type. Furthermore, only a limited number of decision parameters are generally considered. The restriction on the number of decision parameters seems to be due to the fact that as the number of decision parameters increases, the number of decision rules increases exponentially, which leads to computational complexity and very long algorithm execution time (τ). Despite these constraints the QoS-related parameters (latency, jitter and packet loss) need to be included in the decision process, if real-time services (VoIP, video streaming, etc.) are demanded by the users (noting the global demand for real-time services).

To address the above issues, we proposed an adaptive traffic dependent fuzzy-based HDS (ATDHDS) in our previous publication [1]. The performance of the proposed ATDHDS was compared, in terms of the network selection and τ, with monolithic fuzzy-based HDS (MHDS), tailored MHDS and Simple Additive Weighting (SAW). The simulation results showed that the ATDHDS gave an improvement in terms of network selection and a reduction in the value of τ. However, the simulation model did not take into account the fact that the output scores generated by the fuzzy engines follow a random process (the input parameter values are randomly selected). In this paper a statistical averaging procedure is included, which produces more reliable results. In addition, the WiMAX data range is extended from (3 - 6 Mbps) to (1 - 6 Mbps) to represents a more realistic WiMAX capability.

The ATDHDS is further enhanced by introducing two new fuzzy engines, which perform a QoS aggregation process. The aims of the Enhanced ATDHDS are to improve the overall network selection performance and, at the same time, to further reduce τ. The results suggest that the Enhanced ATDHDS gives some improvements in the network selection performance but huge benefit in reducing τ.

Finally, the battery consumption analysis is carried out and the results suggest that the power consumption of the proposed fuzzy-based algorithm is unlikely to have a major impact on the battery life in real-life implementations.

The paper is organized as follows. Related vertical handover decision algorithms are given in Section II. In Section III, the design and development of a monolithic fuzzy-based HDS and the adaptive traffic dependent fuzzy-based HDS are presented. The simulation results and comparisons of performance are also given in Section III. The design and development of the enhanced adaptive traffic dependent HDS is presented in Section IV. A comparison between the ATDHDS and Enhanced ATDHDS and the battery life analysis are also given in Section IV. Section V gives conclusions and future work.

II. Related Vertical Handover Decision Algorithms

Numerous vertical handover decision algorithms have been developed over the past several years [2]–[4]. They have varying degree of complexity and intelligence. These algorithms can be broadly classified into two categories: deterministic algorithms and heuristic algorithms. The former algorithms use mathematical functions to select the best candidate wireless network for handover, whilst decisions in the latter algorithms are made on the basis of some pre-defined decision (IF-THEN) rules, which identify the inter-relationships of the decision parameters considered. Mathematic-based algorithms are simple to use but suffer from two limitations: 1) it is often difficult to acquire very precise data [5], as a result, the network selection performance is degraded, 2) the methods used for assigning the parameter weight to individual decision parameters are subjective [6], as a result, the outcomes are often inconsistent.

Heuristic algorithms (e.g., rule-based, fuzzy logic, neural network and Adaptive Neural Fuzzy Inference System (ANFIS)) follow a different decision making approach and therefore avoid the drawbacks suffered by the deterministic algorithms. Fuzzy logic, in general, is regarded to have the ability to enhance intelligence in decision making processes. It has been widely used for decision making processes in many different areas, e.g., business forecasting [7] and stock trading [8]. More specific to handover in wireless networks, fuzzy-based algorithms have been used in a handover triggering algorithm [9]; pre-processing of imprecise input data for Analytic Hierarchy Process (AHP) [10] and Simple Additive Weighting (SAW) algorithms [11]. The use of fuzzy logic in all the above applications has been only to assist handover decision engines.

A number of researchers have focused their attention on developing fuzzy-based vertical handover decision algorithms [12], [13]. A fuzzy-based vertical handover decision algorithm, which assumes interconnection between WLAN and WMAN, is proposed in [14]. The decision parameters considered are: RSS, data rate, distance. The main aim of this work is to minimize the number of packet loss and the results presented are encouraging.

Authors in [15] have proposed a network selection algorithm based on fuzzy logic assuming three wireless technologies (Cellular, WiMAX and WLAN). The algorithm takes RSS, network load and available bandwidth into consideration. The results suggest that the proposed algorithm can select the most appropriate wireless network for handover in a given scenario.

In [16], a fuzzy-based algorithm between WWAN and WLAN is proposed. RSS, bandwidth, usage price are included in the decision process. The results show that the proposed algorithm makes accurate handover decisions, reduces the number of unnecessary handovers, balances network resources and improves network performance.

In all the above solutions, no QoS-related decision parameters (i.e., latency, jitter and packet loss) have been considered in the decision process. In view of the growing demand for real-time mobile applications, which require guaranteed QoS (defined by commonly used recommendations [17]), it has become necessary to include the QoS parameters in the decision process. More recently, efforts have been directed to evaluate the performance of a HDS in the presence of multiple QoS parameters.

In [18], bit error rate (BER) and RSS have been considered in their fuzzy-related decision algorithm. The results show improvement in terms of the number of handover reduction. In [19], a fuzzy-based vertical handover algorithm taking data rate, delay and BER (along with other parameters such as cost and security) into consideration is proposed. The algorithm improves the process of wireless network selection, thus avoiding unnecessary handovers. Authors in [20] have proposed a QoS aware fuzzy-based vertical handover mechanism that considers data rate, latency, jitter and BER. The proposed work is found to be effective for selecting a wireless network that meets the requirements of different applications. The results show a reduction in average end-to-end delay and yield a moderate average bandwidth.

The above work clearly suggests that including QoS-related parameters improves the overall decision performance. This inevitably increases the overall number of decision parameters, which generally leads to an unacceptably long algorithm execution time (τ). The time delay as a result of long τ imposes a serious restriction on the number of decision parameters that can be used in fuzzy-based decision algorithms. Thus, a new approach is needed that allows a relatively large number of decision parameters to be included and, at the same time, minimizes τ.

III. Adaptive Traffic Dependent Fuzzy-based HDS Design

We introduced the idea of traffic dependency and proposed an adaptive traffic dependent fuzzy-based handover decision system design (ATD design) in our previous published work [1]. The network selection performance of the ATD design was compared with a conventional monolithic fuzzy-based handover decision system (MHDS design) and a tailored MHDS designs. The ATD design was shown to have given significant improvement for the network selection process as well as a hugh reduction in τ.

In our previous work [1], the simulation model did not take into account the fact that the output scores generated by the fuzzy engines follow a random process (the input parameter values are randomly selected). In this paper a statistical averaging procedure has been used to produce more reliable results.

In the new procedure, for each of the three traffic types (i.e., CBR, VBR and ABR), 1000 runs of simulations (one trial, T) were carried out by each HDS design. The performance criterion chosen was the percentage success (PS), defined as the number of times (expressed as a percentage) the HDS selected the wireless network that had the highest score among the three wireless networks and fully satisfied the QoS requirements. The QoS requirements for CBR and VBR traffics were taken from [17]. In the case of ABR traffic, the packet loss of 7% or less was used. Ten trials were carried out for each traffic and the average of 10 trials was taken as the final outcome, as shown in Figures 2, 3 and 4.

In addition, the WiMAX data range was extended from (3 - 6 Mbps) to (1 - 6 Mbps) in the new simulation model, which represents a more realistic WiMAX capability. The simulation model assumed the following network and traffic scenarios:

(i) Three wireless network technologies, namely, WLAN, WiMAX and Cellular (supporting High Speed Packet Access (HSPA), which supports data rate up to 7.2 Mbps).

(ii) One WLAN, one WiMAX and one Cellular to represent a heterogeneous networking environment.

(iii) Three applications (VoIP, video streaming and file transfer to represent CBR, VBR and ABR traffics, respectively) - VoIP application with voice CODEC (G.711) and a data rate of 64 kbps, video streaming application in H.264 coding format with a bit rate of 0.8–1 Mbps along with an encoded (ACC) audio signal at 96 kbps and file transfer application with a bit rate of 1 Mbps.

The range of values for decision parameters in Tables I, II and III were taken either from real-life tests or commonly used standards [21]–[25].

The simulation results show that the ATD design gives an improvement of 17.2% compared with the MHDS (MD1) design in the case of VoIP traffic (CBR traffic), depicted in Figure 2. However, the performance of tailored MHDS (MD2) design is identical to that of ATD design. This is to be expected as the two designs use identical FMFs and decision rules [1].

For the video streaming traffic (VBR traffic), depicted in Figure 3, the performance of ATD design is 15.71% and 25.49% better than the MD1 and MD2 designs, respectively.

In the case of file transfer traffic (ABR traffic), the performance of ATD design is 4.09% and 13.04% better than the MD1 and MD2 designs, respectively (in Figure 4).

The network selection performance of Simple Additive Weighting (SAW) algorithm is also compared with the ATD design and the results are shown in Figures 5, 6 and 7. The results show that the ATD design is 19.08%, 18.9% and 10.45% better than the SAW design for VoIP (in Figure 5), video streaming (in Figure 6) and file transfer traffics (in

TABLE I
Decision Parameters for CBR Traffic

Network	DR (Mbps)	LA (ms)	JI (ms)	PL (%)	BA (hrs)	PR (p/min)
WLAN	1 - 8				2.5 - 5	1
WiMAX	1 - 6	0-300	0-50	0-1.5	0.55x(2.5-5)	2
Cellular	1 - 5				0.74x(2.5-5)	3

TABLE II
Decision Parameters for VBR Traffic

Network	DR (Mbps)	LA (s)	JI (ms)	PL (%)	BA (hrs)	PR (p/min)
WLAN	1 - 8				2.5 - 5	1
WiMAX	1 - 6	0-7		0-7	0.55x(2.5-5)	2
Cellular	1 - 5				0.74x(2.5-5)	3

TABLE III
Decision Parameters for ABR Traffic

Network	DR (Mbps)	LA (s)	JI (ms)	PL (%)	BA (hrs)	PR (p/min)
WLAN	1 - 8				2.5 - 5	1
WiMAX	1 - 6			0-7	0.55x(2.5-5)	2
Cellular	1 - 5				0.74x(2.5-5)	3

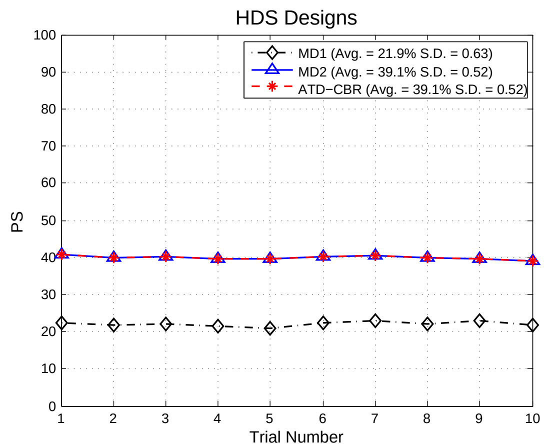

Figure 2. Network Selection Performance - VoIP

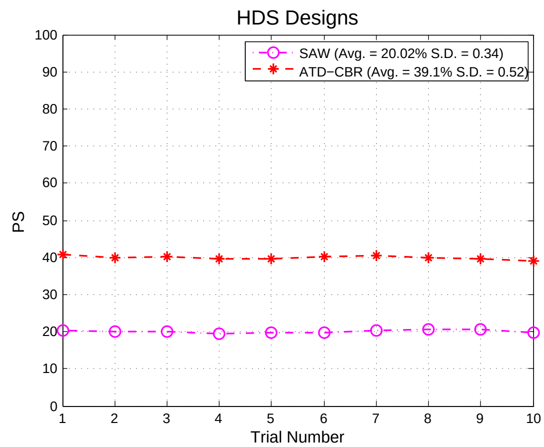

Figure 5. Network Selection Performance - VoIP

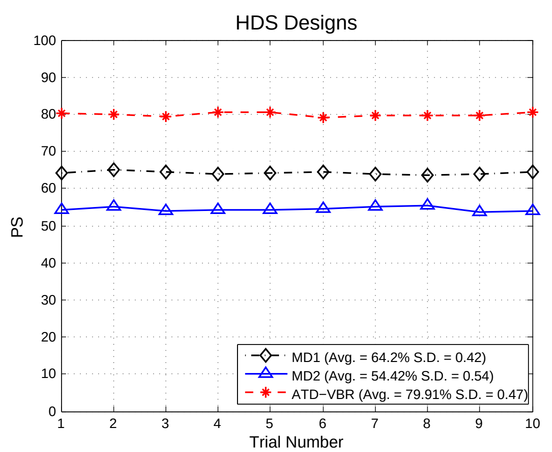

Figure 3. Network Selection Performance - Video Streaming

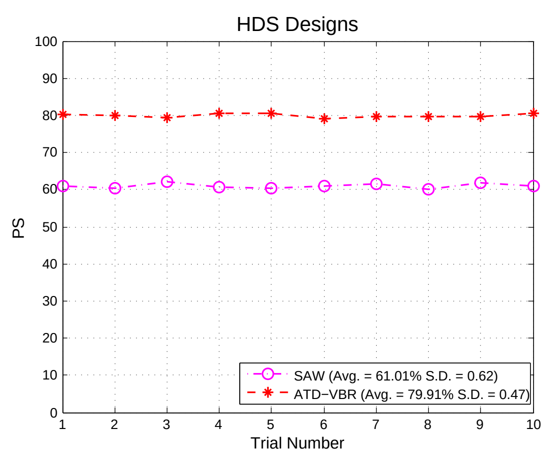

Figure 6. Network Selection Performance - Video Streaming

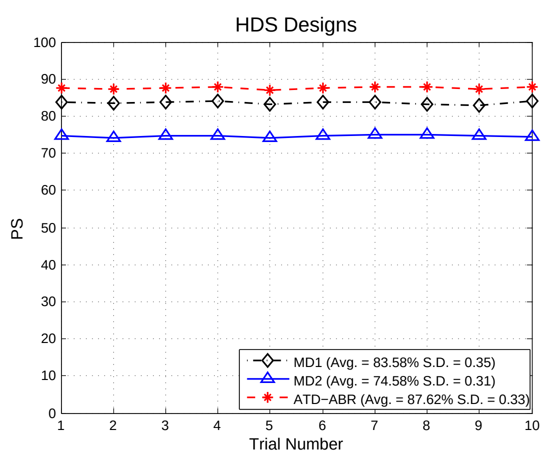

Figure 4. Network Selection Performance - File Transfer

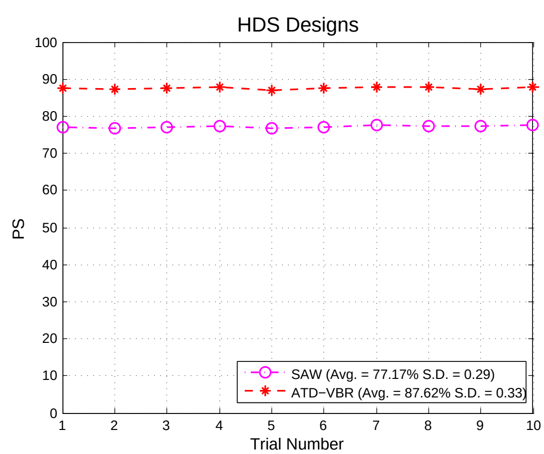

Figure 7. Network Selection Performance - File Transfer

Figure 7), respectively.

As has been mentioned in Section II, minimization of the algorithm execution time (τ) is an important requirement for handover decision systems. The value of τ required for MD1, MD2, ATD and SAW designs was evaluted on a 2.13GHz Intel Core 2 Duo with 4GB memory. The simulation results (in Figure 8) show that the value of τ for MD1 and MD2 designs is 1.87 second for all the three traffic types. In the case of

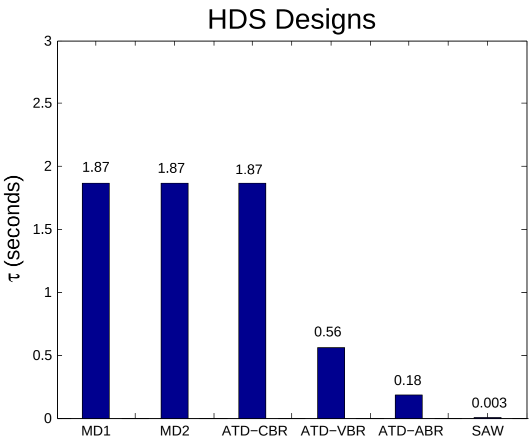

Figure 8. Algorithm Execution Time

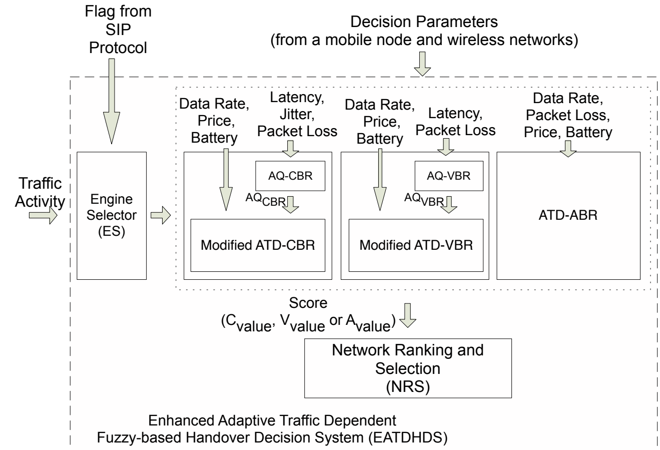

Figure 9. Architecture of EATDHDS

ATD design, the value of τ is 1.87 second, 0.56 second and 0.18 second for VoIP, video streaming and file transfer traffics, respectively.

The results clearly show that the proposed ATD design significantly reduces τ for video streaming (VBR) and file transfer (ABR) traffics when compared with MD1 and MD2 designs. The reduction in τ is 70.05% and 90.37% for video streaming and file transfer traffic, respectively. However, in the case of VoIP, there is no improvement in the value of τ. It is to be expected as the three HDS designs (MD1, MD2 and ATD) employ the same number of decision rules.

Note that the τ of SAW design is lower than that of ATD design since SAW algorithm uses a simple mathematical function to calculate the score used for a decision making. Although, the value of τ in the case of SAW design is relatively low, the overall network selection performance of the ATD design is superior to SAW design. Therefore, it is more beneficial to use fuzzy-based algorithms for a handover decision.

IV. Enhanced ATD Design (EATD Design)

The ATD design has been extended to include two additional fuzzy engines. The aims of the EATD design are: a) to improve overall network selection performance and b) to further reduce τ. The network selection performance of ATD and EATD designs and the corresponding τ are compared.

The general architecture of enhanced adaptive traffic dependent fuzzy-based HDS (EATDHDS) is shown in Figure 9. The two new fuzzy engines, namely AQ-CBR and AQ-VBR, convert individual values of QoS parameters into an aggregated single value (AQ), i.e., AQ_{CBR} and AQ_{VBR} for CBR and VBR traffics, respectively. In the case of ABR traffic only one QoS parameter (packet loss) is relevant, thus no QoS aggregation is neccessary.

A. AQ-CBR and AQ-VBR Engines

Each engine contains a specific set of FMFs and decision rules to match the corresponding traffic. The Engine Selector (ES) identifies the type of incoming traffic and the relevant engine is selected to perform a QoS aggregation process, which generates the corresponding AQ value (AQ_{CBR} or AQ_{VBR}) as shown in Figure 10.

If VoIP (CBR) traffic is identified, three QoS parameters (latency (LA), jitter (JI) and packet loss (PL)), associated with the candidate wireless network, are directed to the AQ-CBR engine. The corresponding input fuzzy sets are denoted by $\widetilde{LA}$, $\widetilde{JI}$, and $\widetilde{PL}$. Each fuzzy set has three memberships (Low, Medium, High). The total number of decision rules required for this fuzzy engine is 27 (using equation 1 from [26]). Each decision rule is then assigned a decision output, which is based on expert knowledge. This process formulates an output fuzzy set, $\widetilde{AQ}_{CBR}$.

For video streaming (VBR) traffic, only two QoS parameters (i.e., latency (LA) and packet loss (PL)) are directed to the AQ-VBR engine. The corresponding input fuzzy sets for the VBR traffic are denoted by $\widetilde{LA}$, and $\widetilde{PL}$. Following the above principle, the total number of decision rules required for this fuzzy engine is 9 (using equation 1 from [26]) and the output fuzzy set is denoted by $\widetilde{AQ}_{VBR}$.

The crisp inputs (the values for each QoS parameter) are fuzzified and provided to fuzzy inference system (FIS). The aggregated fuzzified data, $\mu\widetilde{AQ}_{CBR}$ and $\mu\widetilde{AQ}_{VBR}$, are given by (equation 4 from [26]):

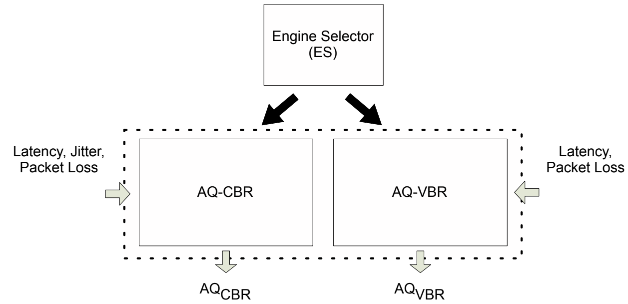

Figure 10. QoS Aggregation Engines

$$\mu\widetilde{AQ}_{CBR}(y) = max_k[min[\mu\widetilde{LA}^k(latency), \mu\widetilde{JI}^k(jitter), \mu\widetilde{PL}^k(packetloss)]], \text{ for k} = 1, 2, \ldots, 27 \quad (1)$$

$$\mu\widetilde{AQ}_{VBR}(y) = max_k[min[\mu\widetilde{LA}^k(latency), \mu\widetilde{PL}^k(packetloss)]], \text{ for k} = 1, 2, \ldots, 9 \quad (2)$$

Finally, defuzzifier converts the aggregated fuzzified data into crisp value. The values generated by AQ-CBR and AQ-VBR engines are AQ_{CBR} and AQ_{VBR}, respectively (as shown in Figure 10). They are calculated using a centroid method, which are given by (equation 5 from [26]):

$$AQ_{CBR} = \frac{\int \mu\widetilde{AQ}_{CBR}(y).ydy}{\int \mu\widetilde{AQ}_{CBR}(y)dy} \quad (3)$$

$$AQ_{VBR} = \frac{\int \mu\widetilde{AQ}_{VBR}(y).ydy}{\int \mu\widetilde{AQ}_{VBR}(y)dy} \quad (4)$$

The AQ_{CBR} and AQ_{VBR} are then fed into the relevant decision engines (modified ATD-CBR or modified ATD-VBR) togerther with input decision parameters as shown in Figure 9.

Triangular and trapezoidal functions are used for fuzzy memberships in the design of input fuzzy sets for the AQ-CBR and AQ-VBR engines. The associated FMFs are shown in Figures 11 and 12. A small portion of the decision rules for the two AQ engines is shown in Tables IV and V.

TABLE IV
DECISION RULES FOR AQ-CBR ENGINE

No.	Latency	Jitter	Packet Loss	Output
1	Low	Low	Low	High
2	Low	Low	Medium	MediumHigh
3	Low	Low	High	Low
4	Low	Medium	Low	MediumHigh
5	Low	Medium	Medium	Medium
:	:	:	:	:
27	High	High	High	Low

TABLE V
DECISION RULES FOR AQ-VBR ENGINE

No.	Latency	Jitter	Packet Loss	Output
1	Low	Low	Low	High
2	Low	Low	Medium	MediumHigh
3	Low	Low	High	Low
:	:	:	:	:
9	High	High	High	Low

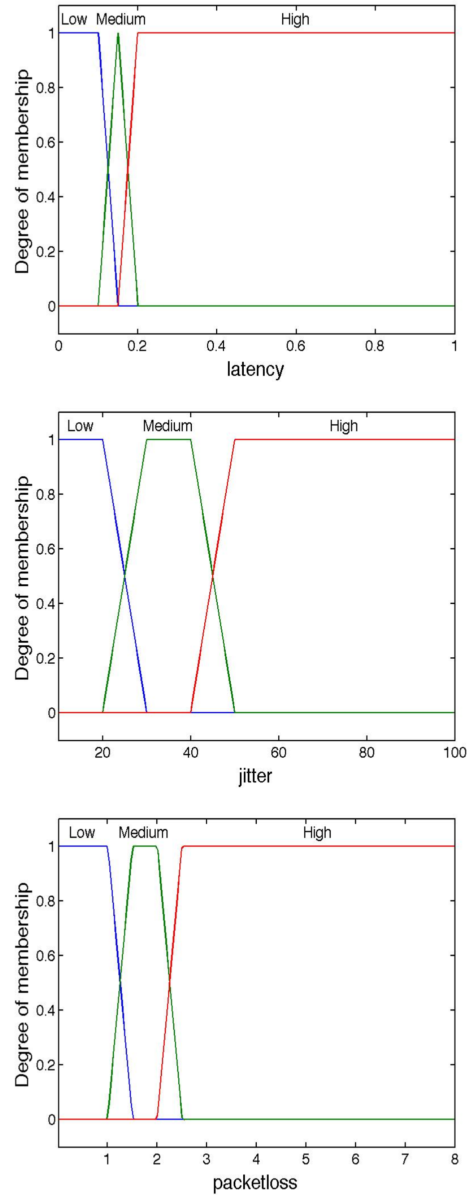

Figure 11. FMFs for AQ-CBR Engine

B. Modified ATD-CBR, Modified ATD-VBR and ATD-ABR Decision Engines

As the QoS parameters are aggregated in the EATD design, fewer inputs are needed for the decision engines, i.e., data rate, usage price, battery life and AQ_{CBR} for the ATD-CBR decision engine and data rate, usage price, battery life and AQ_{VBR} for the ATD-VBR decision engine (as shown in Figure 9). As a result, the existing ATD-CBR and ATD-VBR decision engine designs needed to be modified. The ATD-ABR decision engine is identical to the ATD-ABR decision engine presented in the ATD design [1]. Note that due to the QoS aggregation process, the input parameters to the modified ATD-CBR and modified ATD-VBR decision engines have been reduced, which in turn

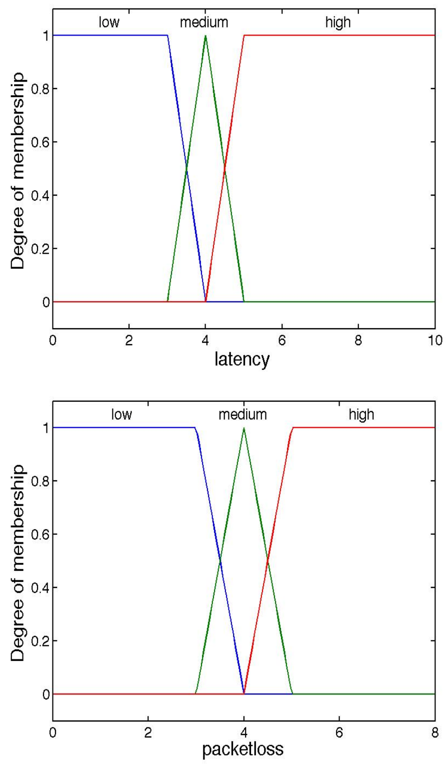

Figure 12. FMFs for AQ-VBR Engine

have reduced the total number of decision rules.

Then, the aggregrated fuzzified data generated by the modified ATD-CBR decision engine, $\mu\tilde{C}(y)$, modified ATD-VBR decision engine, $\mu\tilde{V}(y)$, and ATD-ABR decision engine, $\mu\tilde{A}(y)$, are given by (equation 4 from [26]):

$$\begin{aligned}\mu\tilde{C}(y) =& max_k[min[\mu\widetilde{DR}^k(datarate),\\ &\mu\widetilde{AQ}^k(AQ_{CBR}), \mu\widetilde{PR}^k(price),\\ &\mu\widetilde{BA}^k(battery)]],\\ &fork = 1, 2, 3, \ldots, 81\end{aligned} \tag{5}$$

$$\begin{aligned}\mu\tilde{V}(y) =& max_k[min[\mu\widetilde{DR}^k(datarate),\\ &\mu\widetilde{AQ}^k(AQ_{VBR}), \mu\widetilde{PR}^k(price),\\ &\mu\widetilde{BA}^k(battery)]],\\ &fork = 1, 2, 3, \ldots, 81\end{aligned} \tag{6}$$

$$\begin{aligned}\mu\tilde{A}(y) =& max_k[min[\mu\widetilde{DR}^k(datarate),\\ &\mu\widetilde{PL}^k(packetloss), \mu\widetilde{PR}^k(price),\\ &\mu\widetilde{BA}^k(battery)]],\\ &fork = 1, 2, 3, \ldots, 81\end{aligned} \tag{7}$$

where k is the total number of rules.

The defuzzifier converts the aggregated fuzzified data into the score (i.e., C_{value}, V_{value} and A_{value} for the modified ATD-CBR, modified ATD-VBR and ATD-ABR decision engines, respectively) using the same principle as above (equation 3 and 4). The score (depending on the decision engine used) is then used by the NRS to rank the wireless networks. The wireless network with the highest score is selected for a handover.

The associated FMFs for the modified ATD-CBR, modified ATD-VBR and ATD-ABR decision engines are shown in Figures 13, 14 and 15, respectively. A small portion of the decision rules for the modified ATD-CBR and modified ATD-VBR decision engines is shown in Table VI. Table VII shows a small portion of the decision rules for the ATD-ABR decision engine.

C. Simulation Results, Comparisons and Discussion

Based on the simulation procedure given in Section III, the performance of EATD design was evaluated. The results are compared with the ATD design in Figures 16 and 17 for VoIP and video streaming traffics, respectively.

The results in Figure 16 show that the network selection performance of the EATD design is 4.28% better than the ATD design for VoIP traffic. In the case of video streaming traffic (Figure 17), the improvement is 3.36%.

The algorithm execution time (τ) of the ATD and EATD designs is also compared (shown in Figure 18) for the two traffic types (VoIP and video streaming). The results show that τ of the EATD design is reduced to 0.25 second for VoIP traffic. This gives a reduction of 86.6% when compared with the ATD design. In the case of video streaming traffic, τ is reduced to 0.21 second. A reduction of 62.5% is achieved.

The network selection performance is improved due to the fact that fewer decision rules facilitate relatively more accurate assignment of the corresponding decision outputs, which are based on expert knowledge. The reduction in τ is due to QoS

TABLE VI
DECISION RULES FOR THE MODIFIED ATD-CBR AND ATD-VBR DECISION ENGINES

No.	DR	AQ	PR	BA	Output
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Medium	Low
3	Low	Low	Low	High	Low
:	:	:	:	:	:
79	High	High	High	High	Medium
80	High	High	High	Medium	MediumHigh
81	High	High	High	High	High

TABLE VII
DECISION RULES FOR THE ATD-ABR DECISION ENGINE

No.	DR	AQ	PR	BA	Output
1	Low	Low	Low	Low	MediumLow
2	Low	Low	Low	Medium	Medium
3	Low	Low	Low	High	MediumHigh
:	:	:	:	:	:
79	High	High	High	High	VeryLow
80	High	High	High	Medium	VeryLow
81	High	High	High	High	Low

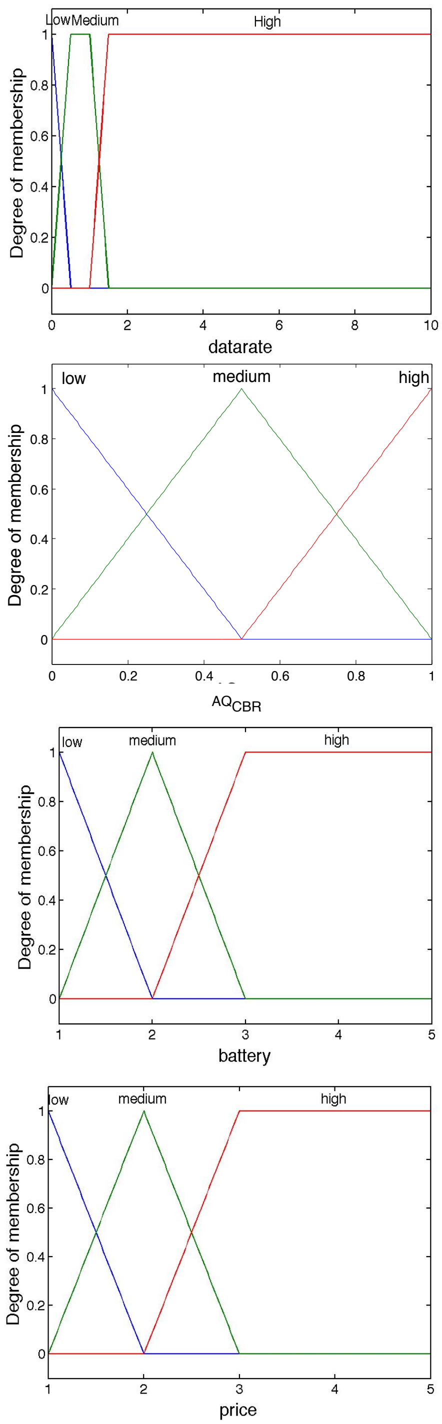

Figure 13. FMFs for The Modified ATD-CBR Decision Engine

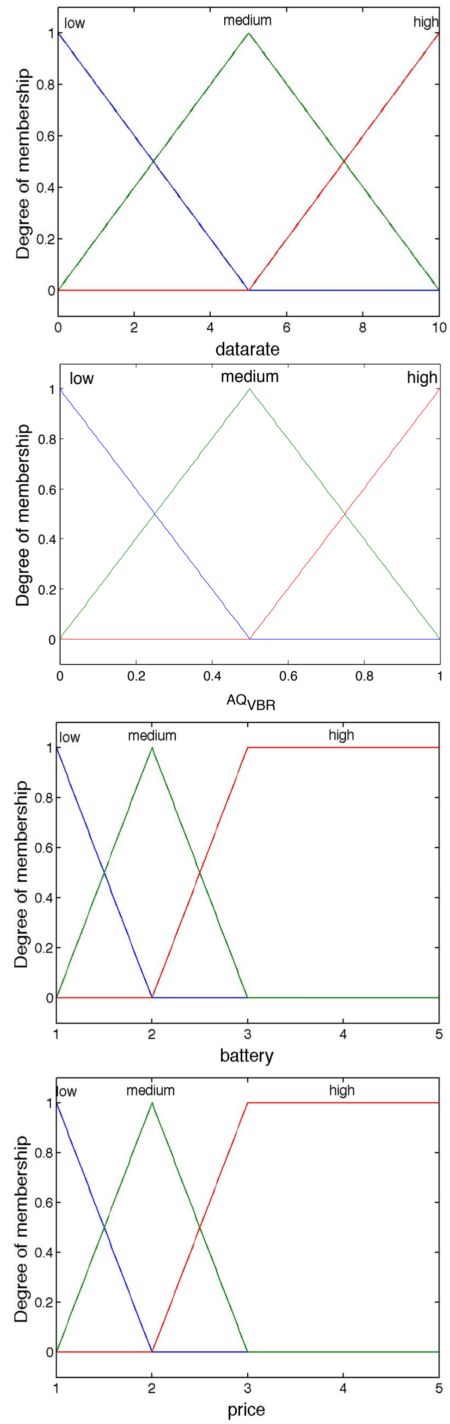

Figure 14. FMFs for The Modified ATD-VBR Decision Engine

aggregation process. The modified ATD-CBR and modified ATD-VBR decision engines require just 81 decision rules when compared with 729 and 243 decision rules required by the ATD-CBR and ATD-VBR decision engines, respectively.

D. Battery Consumption Analysis

Our comparison of fuzzy-based algorithms with SAW algorithm reveals that the superiority of fuzzy-based algorithm comes at a price, i.e., the algorithm execution time of even the best (EATD) decision engine is higher than that required by the SAW. This raises the issue of power consumption and

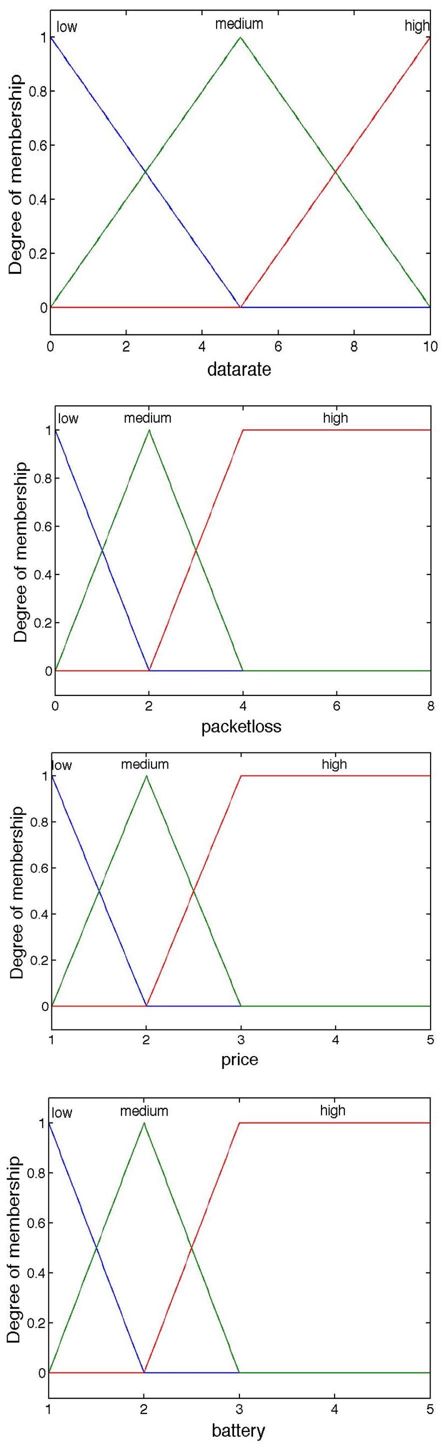

Figure 15. FMFs for the ATD-ABR Decision Engine

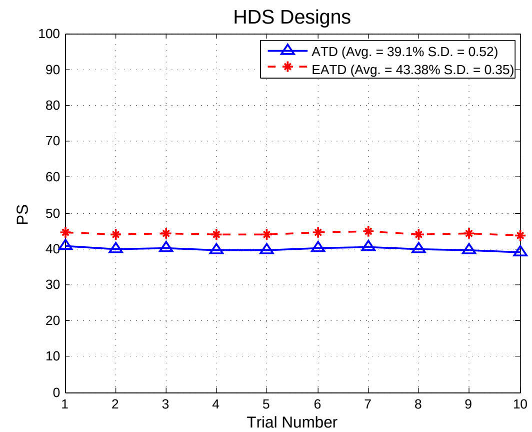

Figure 16. Network Selection Performance - VoIP

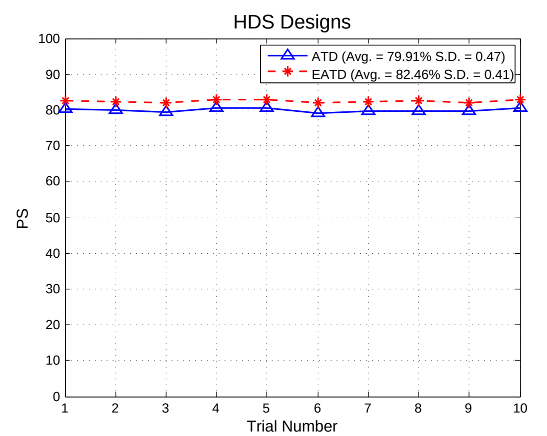

Figure 17. Network Selection Performance - Video Streaming

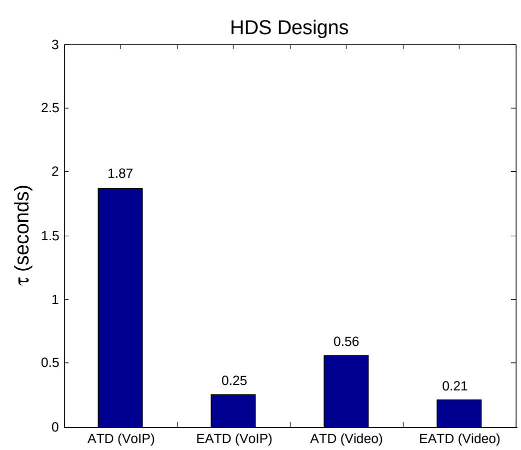

Figure 18. Algorithm Execution Time

the recharging frequency for the battery. In order to address these issues we have made some projections based on the data available to us.

Our simulations were carried out on MATLAB platform using Intel processor of 65watts rating. The longest τ required by the decision engine (worst case for the EATD design) is 0.25 seconds (shown in Figure 18). Therefore, the power consumption for the worst case = 65x0.25 = 16.25 watt-seconds or 0.0045 watt-hours. Now the battery capacity of a modern smart phone is around 5.5 watt-hour. Thus, a smart phone can execute the above algorithm around 1222 times

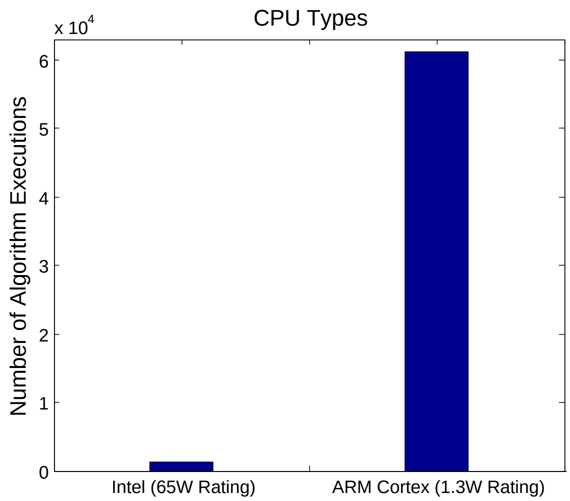

Figure 19. Intel-based vs. ARM-based Processor

as shown in Figure 19 (this does not include the power consumption of other components) before the battery needs recharging.

If we now consider a processor that is actually used in mobile devices (e.g., ARM Cortex A series of approximately 1.3 watts rating), the estimated power consumption reduces to 0.00009 watt-hour. Assuming the same battery as above, a smart phone can execute the algorithm for over 61,111 times (in Figure 19) before the need for recharging. Significant improvement in terms of battery consumption has been observed here. Further improvements will come from the fact that an actual mobile device is likely to use dedicated and embedded software, or dedicated hardware (e.g., FPGA [27], [28]) instead of MATLAB platform to run fuzzy algorithm. This will further reduce τ and hence the power consumption.

E. Discussion

We have addressed the two main issues concerned with the vertical handover decision mechanisms that are widely proposed in the literature. In these mechanisms, a) a single monolithic fuzzy decision engine is generally proposed, and b) the decisions for network selection are made with no regard to traffic type. The former concern restricts the number of decision parameters that can be included in the decision process. This restriction arises due to the fact that as the number of decision parameters increases, the number of decision rules increases exponentially, resulting in computational complexity and an unacceptably long algorithm execution time (τ). However, for real-time applications it becomes very important to include the QoS-related parameters in the decision process, which inevitably increases the overall number of decision parameters. The latter concern impairs the quality of network selection. This limitation on the network selection performance arises due to the fact that a single monolithic decision engine cannot possibly perform equally well for all the different types of traffics.

In order to deal with the above issues we have suggested an adaptive traffic dependent handover decision system (ATDHDS). In our approach multiple decision engines, each dedicated to a specific traffic type, have been proposed. This is achieved by tailoring FMFs to match the QoS requirements of each individual traffic type. As only those QoS parameters that are relevant to a given traffic type are included in the corresponding decision engines, the number of decision rules required for video streaming and file transfer traffics has been reduced, compared with a typical monolithic fuzzy-based handover decision system (MHDS). In the case of VoIP, the two HDS designs have the same number of decision rules. The simulation results show that the ATD design gives a significant improvement in terms of network selection performance and a reduction in τ.

The ATD design has been further enhanced by introducing additional fuzzy engines, which perform a QoS aggregation process for the CBR and VBR traffics. The additional fuzzy engines allow the total number of decision rules required for the enhanced ATD design (EATD design) to be further reduced, which leads to further reduction in τ. Furthermore, fewer decision rules facilitate relatively more accurate assignment of the decision outputs of fuzzy decision engines. As a result, the network selection performance has been enhanced and the value of τ has been further reduced (for the CBR and VBR traffics).

Finally, the battery life analysis has been carried out and it has been shown that the power consumption of the proposed fuzzy-based algorithm is unlikely to have a major impact on the battery life in real-life implementations.

V. Conclusion and Future Work

In our previous work, we introduced the idea of traffic dependency and proposed an adaptive traffic dependent fuzzy-based handover decision system (ATDHDS). In this paper, a new simulation model, which includes a statistical averaging procedure, has been used in order to produce more reliable simulation results.

For evaluation and comparison purposes, three handover decision system designs, namely MHDS design 1 (MD1), MHDS design 2 (MD2) and ATD design, have been developed. Assuming a heterogeneous networking environment and three traffic types (CBR, VBR and ABR), simulation results have been produced to compare the network selection performance and the algorithm execution time of the three HDS designs. In addition, the performance of SAW design has also been compared with the ATD design.

In terms of the network selection performance, the simulation results show that the ATD design gives an improvement of 17.2%, 15.71% and 4.09% for VoIP, video streaming and file transfer traffics, respectively when compared with MD1, and 19.08%, 18.9% and 10.45% for VoIP, video streaming and file transfer traffics, respectively when compared with SAW design.

In the case of VoIP the network selection performance of ATD and MD2 is identical as the two designs use identical

FMFs and decision rules. However, the ATD design is 25.49% and 13.04% better than the MD2 design for video streaming and file transfer traffics, respectively. This result clearly suggests that comparing with MD1, the performance of MD2 has degraded for video streaming and file transfer traffics. The reason for this degradation is that the FMFs and decision rules used for the video steaming and file transfer traffics are in fact tailored to match the VoIP traffic. In other words, the MD2 design is biased towards VoIP traffic, hence rendering this design less attractive for the other two traffics. We conclude that for optimum performance the FMFs and the decision rules must be matched to each individual traffic type.

In terms of τ, the results show that the ATD design gives an improvement of over 70% and 90% for video streaming and file transfer traffics, respectively when compared with MD1 and MD2 designs. In the case of VoIP, τ has the same value for all the three designs, since the three designs use the same number of decision rules for VoIP traffic.

The ATD design has been further enhanced to include a QoS aggregation process. The EATD design has been presented and the performance compared. The simulation results show that the network selection performance of EATD design is 4.28% and 3.36% better than that of the ATD design for VoIP and video streaming traffics, respectively. At the same time a reduction of 86.6% and 62.5% in the value of τ has been achieved by the EATD design for VoIP and video streaming traffics, respectively.

Future work will focus on further enhancement of intelligence of the decision mechanisms, especially when mobility related parameters are considered (e.g., velocity, coverage area, distance, direction of movement, etc.). It is envisaged that the algorithm execution time will be even a greater challenge when mobility related parameters are included in the decision process. Thus, development of new algorithms that require significantly reduced execution time will be part of our future work.

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