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Analysis & Comparison of Decision Tree Algorithms for Vertical Handover in Wireless Networks

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***Abstract*—The main aim of this research paper is to implement Vertical Handover Decision using Decision Tree Algorithms. The accuracy of the decision trees is compared and analyzed using the analytical and statistical frameworks. The main parameters considered for Handover are Received Signal Strength, Quality of Service, Bandwidth and Network Coverage. Quality of Service for a network is derived on the basis of parameters like packet loss, latency and jitter.**

***Index Terms*— Vertical Handover (VHO), Vertical Handover Decision Algorithm (VHDA), Received Signal Strength (RSS), Quality of Service (QoS), Decision Tree, Random Forest, Random Tree, REP Tree.**

I. INTRODUCTION

There has been an ever-growing demand for high data rate by mobile users. The users also expect growth in the traffic carrying capacity of the wireless networks. This demand can be met only by deployment of the heterogeneous wireless networks [1]. For enhanced user experience, the mobile users must be able to connect to the 'Best' network among the available heterogeneous networks. The ability to connect seamlessly to the various wireless networks operating on different radio access technologies is possible due to the Vertical Handovers [2]. The inputs parameters that need to be taken into consideration for efficient Vertical Handover Decision Algorithms (VHDAs) are Received Signal Strength (RSS), cost, network load, bandwidth, QoS, battery status, network coverage etc. Quality of service (QoS) of a network is dependent on parameters like packet loss, latency and jitter [3]. The inaccuracy of Vertical Handover Decision Algorithm (VHDA) may lead to frequent switching between the various networks multiple times. This creates a huge load on the networks. The Ping-Pong effect can be reduced by using decision trees while deciding for handover and subsequent deterioration in the network performance [4].There are various techniques which are employed for the classification of data. Decision tree is one of the important and useful techniques for classification of data. [5] [6] [7]

The organization of the research paper is as follows. Section II captures the mathematical background. Section III captures the design and implementation. Section IV captures the simulation and results followed by conclusion in section V.

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II. BACKGROUND

The decision tree closely resembles a flowchart-type tree structure. Table I captures the various components of the decision tree [6].

TABLE I COMPONENTS OF DECISION TREE

S .No	Details	Represented By
1	Test on an Attribute	Internal Node
2	Result of the test	A branch
3	Class or the distributions	Leaf Node (also called as Terminal Node)

The decision tree is based on Shanon Entropy, Information Gain and Gain Ratio.
(a) Shanon Entropy is given by following equation
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$$Entropy = \sum_{i=1}^{n} p_i * \log p_i \quad (1)$$

Where
p_i denotes probability of event i

(b) Information Gain G (p,T) for a test is given by following equation

$$Gain(p,T) = Entropy - \sum_{j=1}^{n}\left(p_j * Entropy(p_j)\right) \quad (2)$$

Where
T denotes the number of the test [8] [9]

The decision tress considered for the implementation and comparison are as follows-

i. J48 - J48 can be termed as the extension and improvement of Iterative Dichotomiser (ID) 3 decision tree with additional features including pruning and deviation of rules. [10]
ii. REP Tree – It is also known as Reduced Error Pruning Tree. It is a type of decision tree which is based on information gain. [11]
iii. Random Tree – It is a type of decision tree which considers K random features present at each and every node. [11]
iv. Random Forest – Each and Every classifier appears as a decision tree and then the group of the classifiers can be termed as Forest. The random selection of the attributes at each and every node will lead to the generation of the individual decision trees. In Random Forest, the generation of the decision tree is done by choosing the attributes in random order. Random Forest is the fastest among the decision trees and also improves the accuracy. [6]

There are various performance measures which are used to check the performance of the decision trees. They are:

i. Classification Accuracy
ii. Mean Absolute Error
iii. Root Mean Square Error
iv. Confusion Matrix [12]

The confusion Matrix is the grouping of actual and predicted class by the classifiers. Fig 2 shows the Confusion Matrix.

		Actual Class	
		Yes	No
Predicted Class	Yes	True Positives (TP)	False Positives (FP)
	No	False Negatives (FN)	True Negatives (TN)
Total		**P**	**N**

Figure 1 Confusion Matrix

TABLE II. FORMULA FOR DETAILED ACCURACY PARAMETERS

S. No	Parameter	Formula
1	TP Rate (True Positive Rate) Also Known as Hit Rate	Positives correctly classified divided by Total Positives = (TP)/P
2	FP Rate (Also known as False Positive Rate)	Negatives incorrectly classified divided by Total Negatives = (FP)/N
3	Specificity	$\frac{True\ Negatives}{(False\ positives + True\ Negatives)}$ = 1 – FP rate
4	Precision	$\frac{True\ Positives}{(True\ Positives + False\ Positives)}$ $= \frac{TP}{(TP + FP)}$
5	Recall	$\frac{True\ Positives}{(Total\ Positives)}$ $= \frac{TP}{(P)}$
6	Sensitivity	Recall
7	F-measure	$\frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$
8	Accuracy	$\frac{\text{TP + TN}}{(\text{P + N})}$
9	MCC (Mathew's correlation coefficient)	$\frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$
10	ROC (Receiver Operating Characteristics) Area	In (ROC) Curves TP rate is plotted on Y axis while FP rate is plotted on X axis. ROC graphs are two dimensional graphs in nature
11	PRC (Precision-Recall) Area	The values of precision for corresponding values of sensitivity is captured in the PRC plot

Table II defines the parameters for evaluation of the detailed accuracy of classification [9] – [17]

III. DESIGN AND IMPLEMENTATION

The block diagram for Vertical Handover Decision Algorithm is captured in detail in the figure 2.
Figure 3 shows the flowchart and Figure 4 captures the algorithm for vertical handover.

IV. SIMULATION AND RESULTS

The simulation has been done in WEKA (Waikato Environment for Knowledge Analysis) workbench.
Table III captures the Universe of Discourse for all the input parameters.
Figure 5 and 6 give the QoS and Handover decisions, using Random Forest Decision Tree for the indicated input parameter values.
Basis the values of the parameters, it is implied that the network does not have the suitable parameters for handover. Figure 7 shows the decision tree for QoS using Random Forest approach.
Similarly, decision tree for Handover has been developed using Random Forest Decision Tree.
The dataset is divided into K mutually exclusive subsets (folds) and cross-validation implemented for K = 5, 10 and 15 for both QoS and handover.

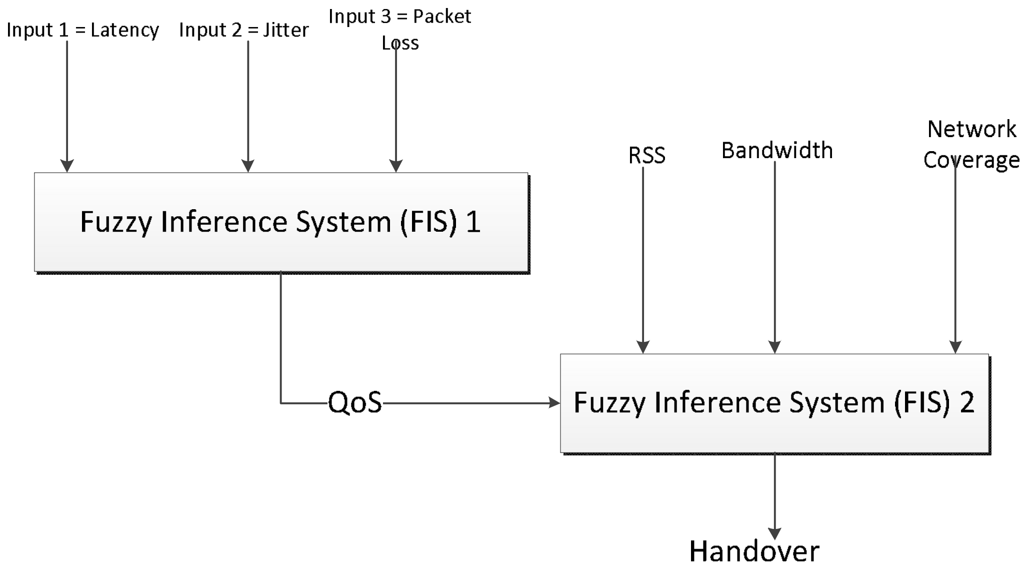

Figure 2 Block Diagram for VHDA

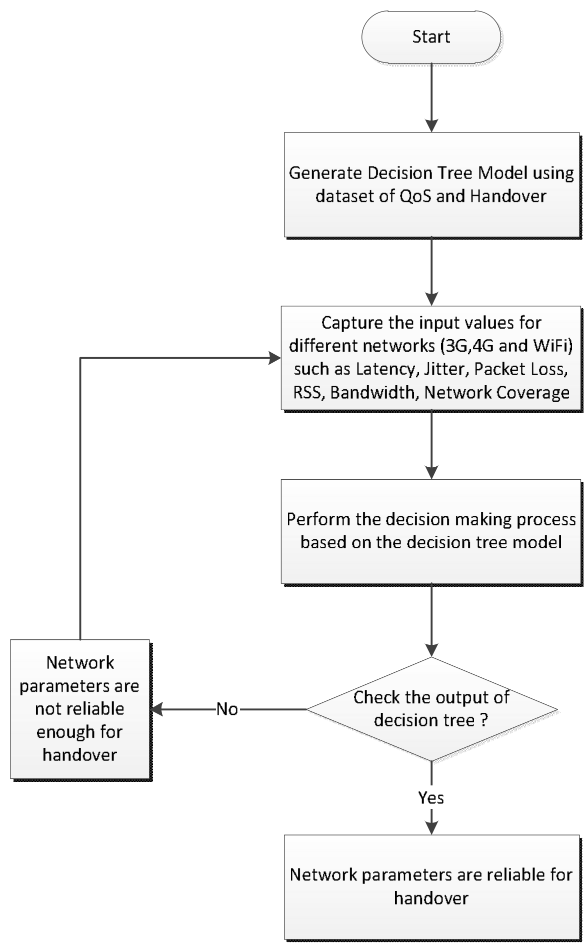

Figure 3. Flowchart for Vertical Handover

Aim of Algorithm :

To Generate the decision tree

Input(s) :

Dataset
List of attributes

Output:

A decision tree for QoS & Handover

Procedure

I. Basis the inputs (dataset & list of attributes), apply the method for selection of attributes
II. Find the best splitting criteria
III. Basis the splitting criteria ,Generate the decision tree
IV. End

Figure 4 Algorithm for Vertical Handover using Decision Tree

TABLE III. UNIVERSE OF DISCOURSE

S. No	Parameter (Measuring Unit)	Min. Value	Max. Value
1	Latency (in msecs)	0	6
2	Packet Loss (in %)	0	6
3	Jitter (in msecs)	0	6
4	RSS (in dBm)	-78	-66
5	QoS	0	7
6	Bandwidth (in Mbps)	1	14
7	Network Coverage (in Mtrs)	1	150

```
Enter the Latency value: 32

Enter the Packet Loss value: 0.4

Enter the Jitter value: 11
Network parameters depict bad Quality of Service
```

Figure 5 Output of QoS

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Enter the QoS value: 6

Enter the RSSI value: -78

Enter the Bandwidth value: 2

Enter the Network Coverage value: 110
Network doesn't has Handover favourable parameters
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Figure 6 Output of Handover

In Table IV, we have given the detailed accuracy parameters calculated for Random Forest Decision Tree Algorithm for QoS. In the similar way, we have the detailed accuracy table for Handover.
Table V shows the comparison of performance parameters for handover for cross-validations with K = 5, 10 and 15 using Random Forest approach.
From table V, it is observed that increase in the folds of cross-validation, improves the performance parameters.

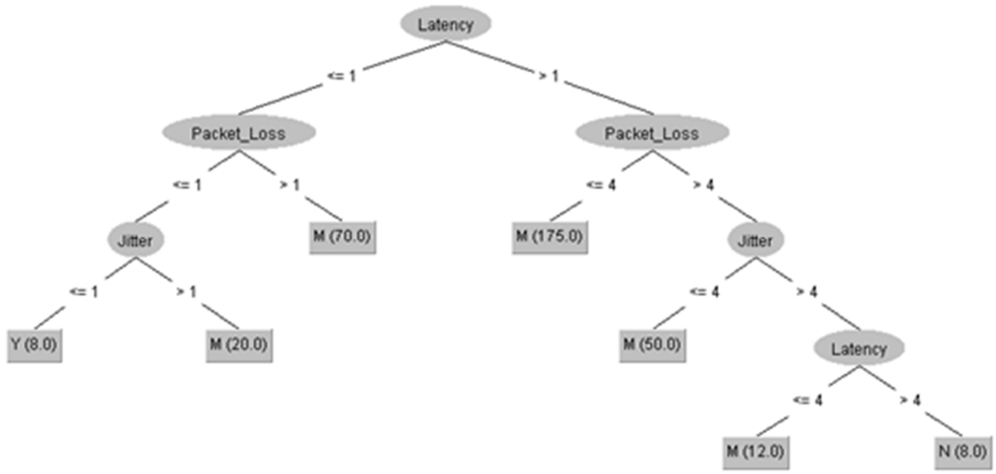

Figure 7 Decision Tree for QoS

TABLE IV. DETAILED ACCURACY FOR RANDOM FOREST DECISION TREE ALGORITHM FOR QOS WITH CROSS VALIDATIONS 5 FOLDS

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Good	1.000	0.09	0.727	1.000	0.842	0.849	1.000	1.000
Moderate	1.000	0.125	1.000	1.000	1.000	0.841	1.000	1.000
Bad	0.750	0.00	1.000	0.750	0.857	0.863	1.000	0.788
Weighted Average	0.985	0.119	0.988	0.985	0.986	0.842	1.000	0.993

TABLE V. PERFORMANCE PARAMETERS FOR VARIOUS CROSS VALIDATIONS USING RANDOM FOREST FOR HANDOVER

Points	Correctly Classified Instances	Incorrectly Classified Instances	Kappa Statistic	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error (in %)	Root Relative Squared Error (in %)	Total Number of Instances
Cross Validation 5 Folds	222887 (99.9955%)	10(0.0045%)	0.9999	0.0001	0.0057	0.0302	1.1634	222897
Cross Validation 10 Folds	222891 (99.9973%)	6 (0.0027%)	0.9999	0.0001	0.0046	0.0243	0.9329	222897
Cross Validation 15 Folds	222892 (99.9978%)	5 (0.0022%)	1	0.0001	0.0038	0.0206	0.7735	222897

Table VI shows the confusion matrix for Random Forest Decision tree.

TABLE VI. CONFUSION MATRIX FOR RANDOM FOREST DECISION TREE

		Predicted Class	
		No	Yes
Actual Class	No	129952	3
	Yes	9	92933

V. CONCLUSION

This paper captures the design and implementation of Vertical Handover Decision Algorithm based on Random Forest Decision Tree. The implementation takes into account all important parameters which decide Vertical Handover in real life scenarios. The algorithm can be easily refined to accommodate more parameters, determining the quality of reception. Similar implementation based on other decision trees and comparison of their performance parameters have shown that Random Forest Decision tree is the best suited for making Vertical Handover Decision.

Working in the same fashion, the decision tree, cross-validation results and accuracy parameters have been worked out for J48, REP Tree and Random Tree. It is observed that the best handover decision is obtained using the Random Forest Decision tree in terms of correctly classified and Incorrectly classified instances.

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