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Machine Learning Based Quantitative Association Rule Mining Method for Evaluating Cellular Network Performance

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ABSTRACT Cellular network performance is often evaluated by key performance indicator (KPI) and key quality indicator (KQI). The association between KQI and KPI is the most critical step to optimize the performance of cellular network. Traditional association methods between KPI and KQI are based on the end-to-end evaluation. However, these methods require professional engineers to evaluate cellular network performance, and the man-manned evaluation is often inaccurate and labor-consuming, which cannot find out the caused factor of deterioration networks. In order to solve the problem, we propose a machine learning based quantitative association rule mining (QARM) method called SWP-RF, which consists of sliding-window partitioning (SWP) and random forest (RF), to associate KPI with KQI. Specifically, we first use SWP to discretize continuous attributes into boolean values, which is adopted to mine its association rules. The warning intervals and the warning points is obtained by SWP. Next, we use RF feature importance to measure the association between KPI and KQI. The priority of the association strength between all KPIs and each KQI can be obtained by RF. Finally, we select the warning points and the association strength priority as optimal output solution. Experiments are conducted over the actual data from telecom operators and the results confirm the feasibility and accuracy of the proposed method.

INDEX TERMS Quantitative association rule mining (QARM), machine learning, continuous attributes, sliding-window partioning (SWP), random forest (RF).

I. INTRODUCTION

With the fast fifth-generation (5G) wireless communications [1]–[14], the cellular network performance, which is often evaluated by key performance indicator (KPI) and key quality indicator (KQI) [15], has been getting more and more attention [16], [17]. On the one hand, KQI is derived from a number of sources, including the performance metrics of the service or underlying support services as KPI, and hence it can reflect the quality of user perception [18]. On the other hand, KPI is used to evaluate the network performance and corresponding operation quality [19], [20]. The association between KPI and KQI is the most critical step to optimize the performance of cellular network. The traditional association methods between KPI and KQI are based on end-to-end evaluation [21]. These methods often require professional engineers to evaluate network performance according to personal experience at multiple protocol layers and interfaces to derive network optimization strategy. However, these personal operations often cause the evaluation with inaccurate and

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labor-consuming. In 5G and beyond [22]–[26], it is urgent to develop intelligent method to associate KPI and KQI in order to evaluate the cellular network intelligently.

Usually, ARM technique is a common association method to find some interesting hidden associations between things, which is first proposed by Agrawal et al. [27]. In [27], an association rule is an expression $X \rightarrow Y$, the strength of such a rule is usually evaluated by the support and the confidence. Given two thresholds that are the minimum support (MinSupp) and the minimum confidence (MinConf), the rule is strong, when its support is greater than MinSupp and its confidence is greater than MinConf. However, conventional ARM techniques are limited to the databases comprising the categorical data. With the passage of time and the advances of technology, the data we deal with is no longer categorical alike market-basket data, thus, the concept of QARM was born.

QARM is applied to databases containing both categorical and continuous attributes. QARM techniques are mainly divided into three categories: Statistics, non-discretization, and discretization. The statistical method includes hypothesis testing, correlation analysis and so on. The non-discretization method is interested in the relationship between the entire attributes, such as the association of words in a text document. The discretization method [28]–[32] groups the adjacent values of continuous attributes to generate finite intervals. Each interval is mapped to a boolean value, and then the association rules of these boolean values are mined by using ARM techniques.

In this paper, we propose a machine learning based QARM method called SWP-RF, which consists of SWP and RF, to associate KPI with KQI. Specifically, SWP is a form of discretization method, which can effectively discretize continuous attributes into boolean values by sliding windows. And then we can mine the association rules of boolean values to obtain the interval of strongest association between continuous attributes. RF is a form of non-discretization method which trains a model by constructing continuous attributes into labels. The model extends the importance of features to the associations among features, and obtains the association strength priorities of the continuous attributes. In scenarios of network performance optimization, it usually uses the subjective experience to optimize the KPI, which is inaccurate and labor-consuming. Hence, our proposed combination method can provide guidance for network performance optimization, which is more objective and more accurate.

II. SYSTEM MODEL

In this paper, the proposed SWP-RF method consists of SWP and RF. The flowchart of our system model is presented in Figure 1, which consists of data preprocessing, sliding-window partitioning (SWP) and random forest (RF). In this paper, we take the KQI data and KPI data in cellular network as the inputs to mine quantitative association rules.

Firstly, the KQI data and KPI data will be preprocessed to reduce the redundancy. Secondly, in the part of SWP, all

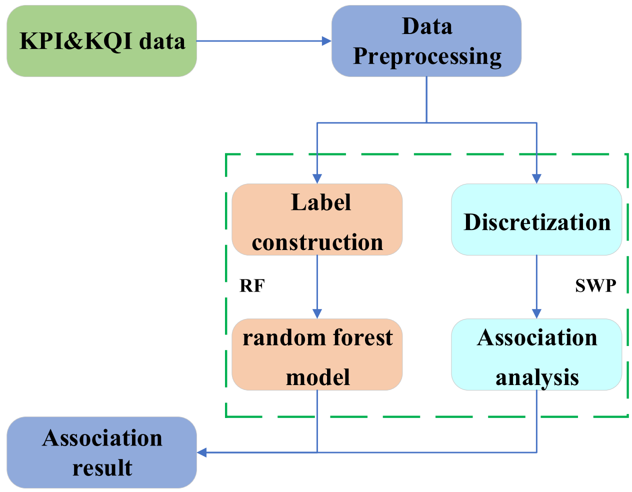

FIGURE 1. The system model.

possible discretization results of KQIs and KPIs, which are called windows, can be obtained by traversing the entire indicator through sliding windows. We aggregate the windows of an indicator into a window set, and map all windows into boolean values to mine boolean association rules. Through the obtained association results, we can get the warning intervals and warning points. In the part of RF, the main idea is to discretize KQIs to construct labels by reference thresholds and regard all KPIs as features, and then a RF model is trained by using the aforementioned features and labels. The trained model extends the importance of features to the associations among features and then the priority of the association strength between all KPIs and each KQI can be obtained. Finally, we combine the warning intervals and warning thresholds with the association strength priority to produce an association result table as the output of our proposed method.

III. OUR PROPOSED METHOD

A. DATA DESCRIPTION AND PREPROCESSING

The dataset is obtained from the telecom operators. The dataset consists of wireless perception in terms of KQIs and KPIs. Table 1 gives the first 5 rows of the data set. Each row of the table consists of time, cell name, 34 KPIs, and 4 KQIs. In Table 1, RRC Connection Reconstruction Ratio and E-RAB Average Establishment Time are two kinds of KPIs, the Instant Messaging Response Delay and the Game Response Delay are two sorts of KQIs.

At the beginning, the data needs to be preprocessed, such as correlation analysis. Correlation analysis is used to reduce the redundancy between 34 KPIs by measuring the linear correlation between KPIs. When the correlation coefficient is greater than 0.5, it indicates that the linear correlation between the two indicators is strong, and only one of them should be retained. Due to too many KQIs, Figure 2 only shows the Pearson correlation coefficient between 20 KPIs,

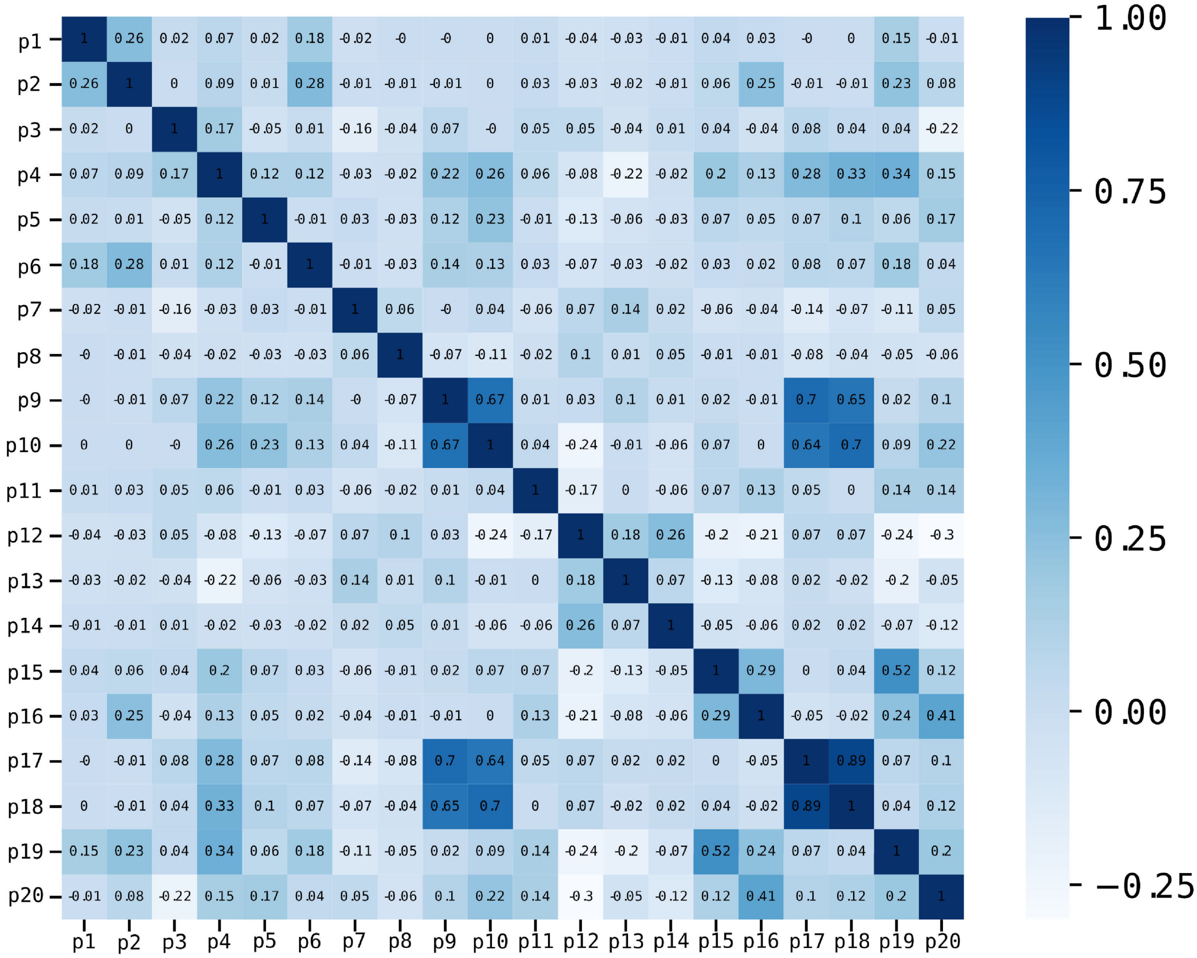

FIGURE 2. The correlations between 20 KPIs.

TABLE 1. The head of the data set.

Time (year/month/day)	Cell name	RRC Connection Reconstruction Ratio	...	Instant communication response delay(ms)
2019/3/12	Cell 1	0.001879	...	108.708
2019/3/12	Cell 2	0.002326	...	236.195
2019/3/12	Cell 3	0.002148	...	52.598
2019/3/12	Cell 4	0.053719	...	113.665
2019/3/12	Cell 5	0.011111	...	105.188

and P_i $(i = 1, 2, \cdots, 20)$ represents the i-th KPI. We can observe that the linear correlations between the 9_{th}, 10_{th}, 17_{th} and 18_{th} indicators of 20 indicators are strong.

B. THE PROPOSED METHOD: SWP-RF

In this paper, we propose a machine learning based QARM method called SWP-RF, which consists of SWP and RF. In this section, we use two parts to introduce SWP-RF.

In the part of SWP, the sliding window contains the elements of each indicator whose values are within the range of the window. In this section, we discretize the KPIs by sliding windows. As shown in Figure 3, each black line represents the range of the values for a specific KPI, each gray box represents a sliding window. Setting a movable window on each range, which means that the minimum and maximum values of the window can change simultaneously according to the sliding stride. This window is called a sliding window. we can exhaust all possible discretization results of each KPI by controlling the extent of window sliding, the size of the window and the step size of each sliding, and then we aggregate all discretization results into a window set.

Let us take RRC Connection Reconstruction Ratio (RCR Ratio) that is a kind of KPIs as an example, RCR Ratio∈[min,max]. Assuming that the size of sliding window increases from (max-min)/50 to (max-min)/5, increasing (max-min)/50 after each traversal, the sliding stride is (max-min)/100, so we can get a window set containing about 900 windows after using sliding window partitioning to discretize the indicator. Although discretizing the indicators is time consuming, it is also acceptable. But if we discretize both of the two associated indicators by SWP, it will consume extremly high time costs. Therefore, in this paper, we discretize one of the two associated indicators by sliding

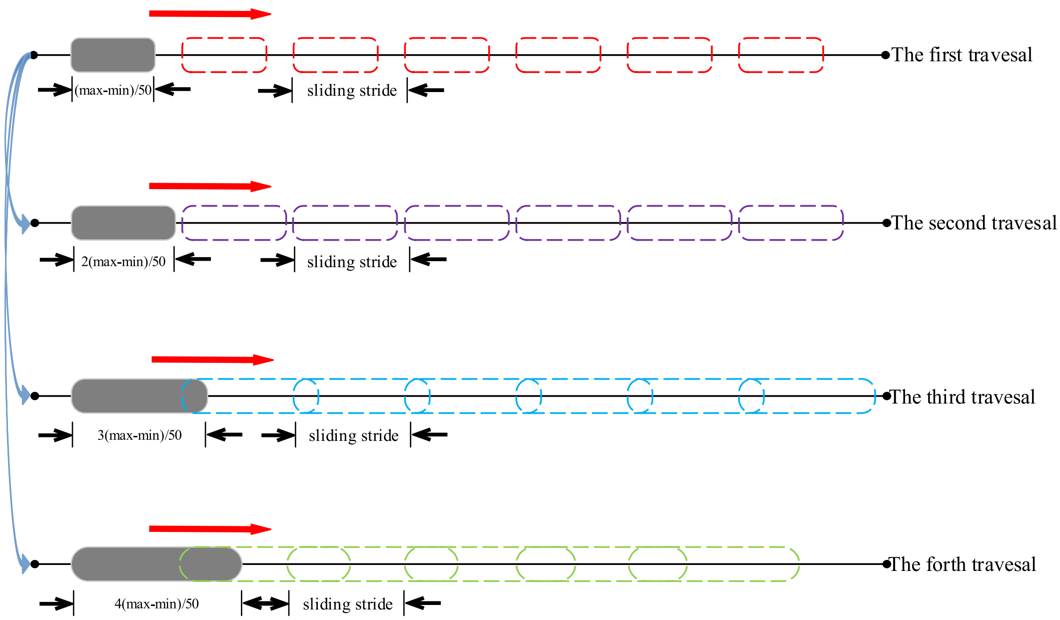

FIGURE 3. The sliding process of the windows.

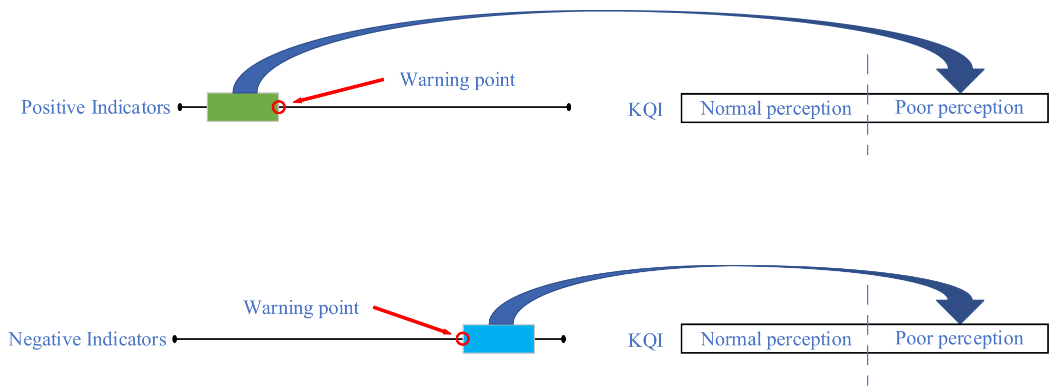

FIGURE 4. The position of the warning point.

window, and discretize another by the reference threshold offered by the telecom operators.

In order to find out the sliding window that has the strongest association with the poor perception interval of KQI, we associate each sliding window in the window set with the poor perception interval of the KQI. The sliding window having the strongest association with the poor perception interval is the warning interval of the KPI, which means that KQI is deteriorating when the KPI falls in this warning interval. In network performance optimization, it is essential to ensure the KPIs not falling in the warning interval, which means the worst user perception. Therefore, it is very important to find out a warning point before the KPIs deteriorates to the warning interval. So we define a warning point through the left or right endpoint of the warning interval.

As shown in Figure 4, the KPIs are divided into positive indicators and negative indicators. The bigger value of the positive indicators means the better performance, and the smaller value of the negative indicators means the better performance. When the value of positive indicator decreases to the right endpoint of the warning interval, the KQI falls in the poor perception interval with the highest confidence. And if the KPI continues to get smaller, it causes the KQI getting worse performance. Therefore, the right endpoint of the warning interval of positive KPI is the warning point, while the left endpoint of the warning interval of negative KPI is the warning point.

In the part of RF, we measure the priority of the association strength between KPI and KQI by RF. Firstly, we regard KPIs as the features and discretize each KQI to construct the labels. Then we use the features and the labels to train a model to evaluate the importance of the features. Finally, we use the feature importance to measure the association between KPIs and KQIs.

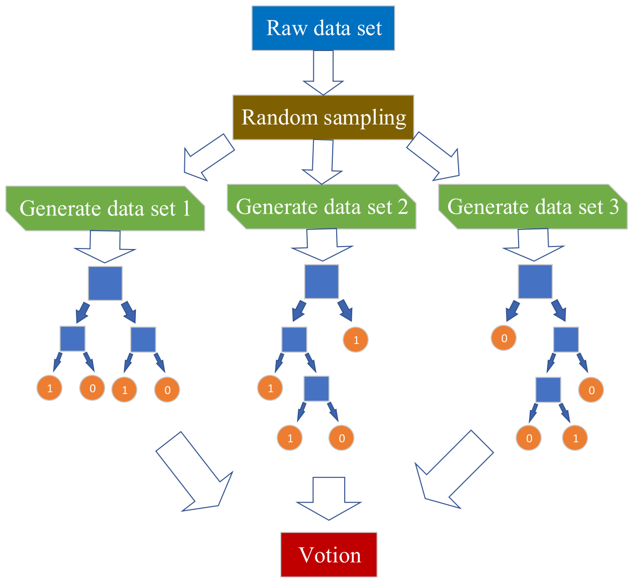

FIGURE 5. Interpretation of a random forest.

Figure 5 shows an example of a random forest. Three data sets are generated by random sampling of the original data set. Each data set generates a decision tree and the three decision trees generate a forest. Blue squares in each decision tree represent the random selected features. 0 and 1 are the labels of forests and indicate the results of classification.

In this paper, the original data set consists of KPIs and KQIs. The KPIs are regarded as the features. According to the reference thresholds, the KQIs are constructed into the label 0 and 1. The labels 0 refers to the normal perception interval and the label 1 refers to the poor perception interval of KQIs. The features and corresponding labels are combined into samples. The above samples are used to train a random forest model to obtain the importance of the features. What is obtained here is the importance of the features for the samples classified as label 0 and label 1, which means the importance of the KPIs for each KQI to fall in the normal or poor perception interval. The importance of the features is measured by the contributions. The greater contribution indicates that the KPI has a stronger association with the KQI in poor perception interval. Finally, we obtain the priority of association strength between KPI and KQI.

C. ASSOCIATION RESULT TABLE

The association result is shown in Table 2. In the column of the association strength priority, the smaller number represents the higher priority of the association strength. Therefore, the KPI with high priority should be optimized first when the network performance deteriorates. Since the KPIs are divided into the positive indicators or negative indicators, which is shown in the column of the attribution, we can get the warning point from the warning interval. The warning point we obtain can provide a threshold to the network optimizer for optimizing the KPI, which means that the KPI must be optimized before it deteriorates to the warning point.

TABLE 2. Association result table.

KPI	Association strength priority	Warning interval	Attribution	Warning point
KPI_A	1	$[A_{left}, A_{right}]$	Negative	A_{left}
KPI_B	2	$[B_{left}, B_{right}]$	Positive	B_{right}
KPI_C	3	$[C_{left}, C_{right}]$	Negative	C_{left}
KPI_D	4	$[D_{left}, D_{right}]$	Positive	D_{right}

TABLE 3. Association result.

KPI	Association strength priority	Warning interval	Attribution	Warning point
Downlink Physical Resource Block Average Utilization Rate	1	[0.57,0.62]	Negative	0.57
Average Number of Accepted Users	2	[30.0,36.0]	Negative	30
Uplink Service Information PRB Occupancy Rate	3	[0.25,0.31]	Negative	0.25
Downlink Users Average Rate	4	[0.85,1.4]	Positive	1.4
Uplink Physical Resource Block Average Utilization Rate	5	[0.44,0.61]	Negative	0.44

IV. EXPERIMENTAL RESULTS

A. ASSOCIATION RESULTS

In this section, we associate all KPIs with Page Display Delay (PDD) which is one kind of the KQIs. The first five rows of the association results are shown in Table 3. The association priority between all KPIs and PDD is obtained by RF. From Table 3, it can be seen that Downlink Physical Resource Block Average Utilization Rate (DPRBUR) has the strongest association with PDD, thus, the optimization priority of DPRBUR is the highest. That is to say, the DPRBUR should be optimized first when the network performance deteriorates. The warning interval, which has strongest association with poor perception interval of PDD, and the warning point which is equal to 0.57 are obtained by SWP, which means that KPI should be optimized before it deteriorates to 0.57.

B. COMPARISON OF RESULTS OBTAINED BY SWP WITH DIFFERENT MINSUPPS

We use the SWP to discretize the KPIs, and use the reference threshold offered by the telecom operators to discretize each KQI. The main control parameter is MinSupp, which defines the lower limit of the number of samples that the rule needs to cover. In addition, due to the existence of outliers in the KPIs, in order to improve efficiency, the sliding window does not traverse the interval in which the outliers are located. The results with different MinSupps are listed in Table 4.

It can be seen from Table 4, with the decrease of MinSupp, the obtained warning interval is getting narrower and the confidence is getting higher. This is because MinSupp defines the lower limit of the sample number should be covered by

TABLE 4. Results with different MinSupps.

KPI value range	Sliding range	Warning interval	Warning point	Confidence	Min-Supp
[0,0.987]	[0,0.779]	[0.57, 0.62]	0.57	0.8095	0.01
		[0.45, 0.5]	0.45	0.7992	0.02
		[0.57, 0.77]	0.57	0.7792	0.03
		[0.45, 0.77]	0.45	0.7592	0.04
		[0.45, 0.77]	0.45	0.7592	0.05

TABLE 5. The warning intervals and the warning points obtained by proposed method.

KPI	Range of indicator	Warning interval	Warning point	Min-Supp
Uplink Physical Resource Block Average Utilization Rate	[0,0.984]	[0.436,0.607]	0.436	0.05
Downlink Physical Resource Block Average Utilization Rate	[0,0.987]	[0.57,0.62]	0.57	0.01
RRC Connection Reconstruction Rate	[0,0.704]	[0.032,0.052]	0.032	0.05
User Plane Downlink Average Delay	[0,47000]	[66.0,83.0]	66.0	0.03
Downlink 64QAM Coding Rate	[0,0.999]	[0.055,0.145]	0.145	0.05
MAC Layer Downlink Error Block Rate	[0,0.057]	[0.0018,0.0029]	0.0018	0.025

frequent itemsets. With the decrease of MinSupp, the narrow interval is more likely to be frequent item. So the rule that contains the narrow interval is generated and its confidence is always high. Due to the low MinSupp, the rules are not always frequent. That is to say, some rules with high confidence but not frequent will be obtained when MinSupp is low, and such rules are meaningless. Therefore, it is important to select MinSupp carefully when mining quantitative association rules.

C. COMPARISON BETWEEN THE WARNING POINTS OBTAINED BY SWP AND HUMAN EXPERIENCE

In this section, we use 7 KPIs to associate with the PDD. Table 5 shows the range of KPIs, the location of the warning intervals, the warning points and the MinSupp. The telecom operators employ a large amount of manpower to obtain the empirical results, which are shown in Table 6. Comparing the results between Table 5 and Table 6, it can be seen that the results obtained by the SWP are close to the empirical results. It is feasible to discretize the continuous attributes by using SWP.

The warning points derived from human experience require a lot of manpower and are not applicable to various independent scenarios. On the contrary, QARM based on SWP has two prominent advantages. Firstly, the results are based on the actual engineering data, which is totally practical and reliable.

TABLE 6. Human experience.

KPI	Attribution	threshold
Uplink Physical Resource Block Average Utilization Rate	Negative	0.5
Downlink Physical Resource Block Average Utilization Rate	Negative	0.5
RRC Connection Reconstruction Rate	Negative	0.05
User Plane Downlink Average Delay	Negative	100(ms)
Downlink 64QAM Coding Rate	Negative	0.12
MAC Layer Downlink Error Block Rate	Positive	0.003

TABLE 7. Results of clustering partitioning.

Number of clusters	Warning interval	Warning point	Optimal confidence	Min-Supp
5	[0.6426,0.9869]	0.6426	0.8601	0.025
10	[0.4265,0.5249]	0.4265	0.7461	
15	[0.4362,0.5072]	0.4362	0.7625	
20	[0.2671,0.3056]	0.2671	0.6399	
5	[0.4023,0.6358]	0.4023	0.7343	0.05
10	[0.2576,0.3406]	0.2576	0.6349	
15	[0.1668,0.2152]	0.1668	0.5804	
20	[0.0958,0.124]	0.0958	0.5254	

Secondly, MinSupp is defined artificially, we can consider items that support exceeds 0.1 or even 0.01 as frequent items, so we can freely define what rules are acceptable. Therefore, the SWP is better than the human experience.

D. COMPARISON BETWEEN SWP AND CLUSTERING PARTITIONING

In this section, we comparison the performance of the SWP with K-means clustering partitioning. The main parameters are the clustering number K and the MinSupp. As shown in Table 7, the results of different clustering number K are very different. With the increase of clustering clusters, warning interval is finer, but the warning interval and optimal confidence have no regular patterns. Comparing Table 4 and 7, the results obtained by SWP are closer to the empirical results, and the results are more regular than the empirical results. In fact, all the possibilities based on discretization are included in the results obtained by SWP, whether using clustering method or others.

E. ASSOCIATION PRIORITY OBTAINED BY USING RF IN DIFFERENT SCENARIOS

In this section, we use RF to mine the association rules for the continuous attributes. We associate all KPIs with PDD. The data comes from five physical scenarios: indoor, outdoor, high-rise residential areas, villages, and urban roads. RF uses the contribution to measure the association strength between KPI and KQI. The results of the association priorities in five scenarios are shown in Figure 6. From Figure 6, it can be seen that the association strengths in different scenarios are slightly different. But overall, DPRBUR has the strongest association with PDD, and the assocaition strength between Cell User Plane Downlink Packet Abandonment Rate and PDD is low. It means that no matter whatever scenario we

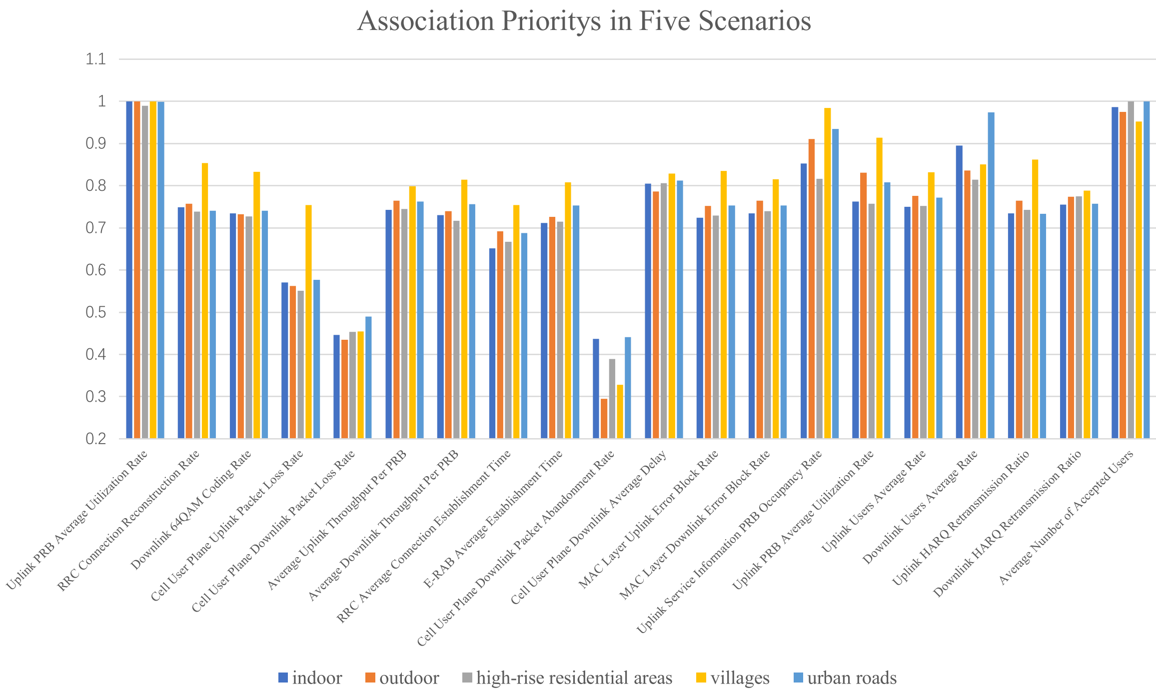

FIGURE 6. Association Prioritys in Five Scenarios.

are in, when the network performance deteriorates, DPRBUR should be the first factor to be optimized.

V. CONCLUSION

In this paper, we have proposed a machine learning based QARM method called SWP-RF to associate KPIs with KQIs. The proposed method consists of SWP and RF. The SWP outputs the warning intervals and the warning points for the KQIs. The priority of the association strength between all KPIs and each KQI can be obtained by the RF. We combine the warning intervals and the warning points with the association strength priority to produce an association result table as the output of our proposed method. The data we used comes from telecom terminal servers and the experimental results prove the feasibility and the accuracy of the proposed method.

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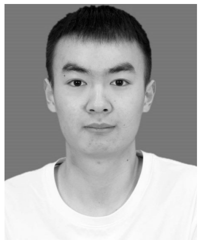

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