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Random Forest Algorithm-Based Lightweight Comprehensive Evaluation for Wireless User Perception

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ABSTRACT The quality of wireless user perception for cells in a particular scenario is reflected on a set of indicators. Comprehensive evaluation of those cells is the base of network optimization for operators. Traditional methods use weighted sum of all indicators as the evaluation result. However, these indicators include some ineffective ones, which leads to an unconvincing evaluation result. To achieve a convincing and accurate result, we propose a lightweight comprehensive evaluation method. Firstly, indicator selection is implemented via random forest algorithm. Secondly, those selected indicators are weighted via entropy method. Finally, we compute the score of all cells with the weights. Experiment results are given to show that the cells with higher score perform better on all indicators, which is coincide with the actual situation. Hence, our proposed method is not only lightweight but also obtain more accurate result.

INDEX TERMS Comprehensive evaluation methods, wireless user perception, indicator selection, random forest (RF).

I. INTRODUCTION

With the development of wireless communications [1]–[14] and internet of things (IoT) [15]–[18], terminal users put forward higher requirements for the quality of wireless user perception. In order to improve network performance as well as users experience, operators always try to do more optimization works. Key quality indicators (KQIs) are viewed as important factors to optimize networks. In a single cell scenario, there are many KQIs covering different fields such as webs, videos and games. Hence, it has become an urgent problem to comprehensively evaluate the quality of wireless user perception.

Traditional methods such as deviation evaluation method [19] and mean square deviation evaluation method [20] often resort to the distribution of all indicator values. However, some unimportant indicators probably have an impact on other important indicators, which leads to an unconvincing evaluation result. In terms of comprehensive evaluation, for creating a more effective evaluation system, many experts and scholars dedicate to obtain a comprehensive evaluation result with few indicators. Wenjie *et al.* [21] employ analytic hierarchy process (AHP) and the Criteria Importance Though Intercrieria Correlation (CRITIC) method to calculate a comprehensive weight to realize multi-indicators evaluation. This method contains of an evaluation matrix which is based on a lot of experience of engineers. Hence, this method gives a subjective result in terms of the evaluation of wireless user perception. Xie [22] introduce a comprehensive evaluation method for multivariate based on principle composition analysis (PCA) and back propagation (BP) neural network [23]. They convert all indicators into

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some principle components and obtain the comprehensive result with these principle components. PCA depends on the linear relationship among indicators. The principle components have no credibility when there is no linear relationship between indicators. To solve the drawbacks of PCA, it is natural way to analyze nonlinear problem in comprehensive evaluation with multiple indicators. Lin and Zhu use kernel principle composition analysis (KPCA) to evaluate regional economic and social development [24]. KPCA considers the nonlinear relationship among indicators. For indicators of KQI data, there is almost no linear or nonlinear relationships. Hence, either PCA or KPCA performs poorly in the comprehensive evaluation based on KQI data.

As for a kind of machine learning algorithms, random forest (RF) is used to solve pattern recognition problems. Rogez *et al.* use RF for human pose detection due to the fact that RF can perform very well in pattern recognition [25]. As an ensemble method, RF builds many trees as weak classifiers and aggregate them to predict. Training many different trees from a single data set requires random sampling from the data set. Therefore, there are a variety of random forests according to how trees are built. One of the most popular RFs is that of which building trees based on classification and regression trees (CART) procedure [26]. During the process of building trees, Gini index is used to calculate the contribution of each feature, which is applied on feature selection. RF is a state-of-the-art method on feature selection. Considering the high dimension feature vectors which need time and memory to be handled, Gharsalli *et al.* apply feature selection on the wide feature set based on feature importance score computed by RF [27].

In order to make the evaluation results more objective and eliminate the adverse impact among indicators, we propose a lightweight comprehensive evaluation method. Different from the traditional comprehensive evaluation methods, our proposed method provides an indicator pre-selection for KQI data with plenty of indicators, making the indicator set more efficient. More precisely, we train a RF network with a labeled data set [28]. Then the contribution of each indicator is calculated and converted into the importance score of all the indicators. The indicators with high importance score are selected and those with low score are eliminated according to a threshold. Finally, we weight all selected indicators using entropy method [29] and calculate the final score of each cell in a particular scenario with these weights and order them. We select ten cells including top five and bottom five to analyze concretely. Experiment results show that our proposed method gives a reasonable comprehensive evaluation of wireless user perception which is coincide with actual situation.

The rest of this paper is organized as follows. In Section II, we introduce the source of the dataset in this evaluation system. Section III gives the details of our evaluation system. We analyze the performance of this system in Section IV. Finally, the paper is concluded in section V.

TABLE 1. The relationship between I_i and 12 indicators.

I_i	Features Name
I_1	Page response success rate (%)
I_2	Page response delay (ms)
I_3	Page display success rate (%)
I_4	Page display delay (ms)
I_5	Page download rate (kbps)
I_6	Video play success rate (%)
I_7	Cache time delay (ms)
I_8	Stream media rate (kbps)
I_9	Instant communication response success rate (%)
I_{10}	Instant communication response delay (%)
I_{11}	Mobile game response success rate (%)
I_{12}	Mobile game response delay (ms)

TABLE 2. Labeled dataset for training RF.

	I_1	I_2	I_3	...	I_{10}	I_{11}	I_{12}	Label
Cell 1	100	160	100	...	70	100	49	0
Cell 2	91.52	342	86.44	...	80	100	59	1
Cell 3	100	191	100	...	53	100	59	0
Cell 4	85.00	317	80.00	...	65	100	71	1
Cell 5	93.75	133	87.50	...	89	60	97	1
...	...	...	...	...	...	...	...	...
Cell n	82.50	254	77.50	...	51	100	49	1

II. SOURCE OF DATASET

KQIs are business quality parameters based on different services. KQIs are mostly close to the life of users. Different business categories are covered in these KQIs including webs, videos, instant communications and games. For the sake of simple description, I_i $(i = 1, 2, \cdots, 12)$ is used to refer to i-th indicator. The relationship between I_i and 12 indicators is listed in Table 1. We can obtain the quality of experience (QoE) [30] by analyzing the KQI data of wireless user perception of a cell. In this evaluation system, a random forest is trained by a dataset which is labeled according to actual measurement to train a random forest. We take Table 2 as an example of the labeled dataset. At last, we evaluate all cells in a specific high-rise scenario to verify the performance of our proposed method. There are 287 cells in this scenario. Table 3 is taken as an example of the validation dataset.

III. SYSTEM DESIGN

In this section, we introduce the design of this proposed system. Firstly, we give an overview of system structure, and then introduce the detail of each step.

A. OVERVIEW OF SYSTEM STRUCTURE

As shown in Figure 1, we first build a labeled dataset. A RF network is trained with this dataset. Each tree node in this RF corresponds to an indicator. The importance of these indicators is scored by calculating their contribution to

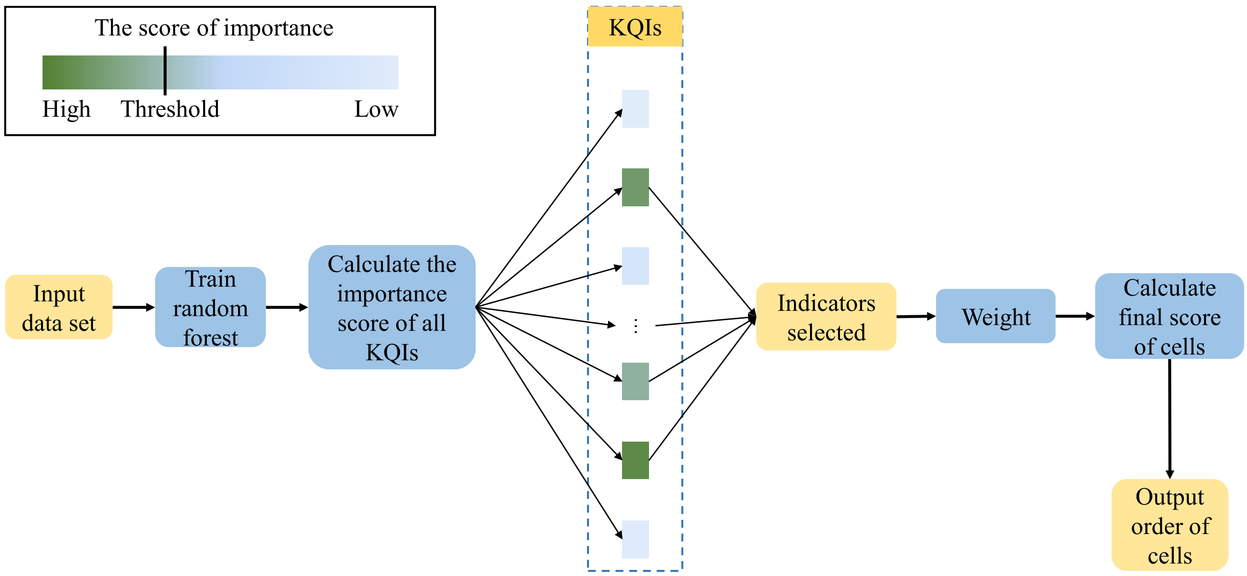

FIGURE 1. The structure of the comprehensive evaluation system.

TABLE 3. Validation dataset.

Cell name	I_1	I_2	I_3	...	I_{10}	I_{11}	I_{12}
Cell 1	94.01	101	91.45	...	53	100	50
Cell 2	100	112	100	...	46	100	65
Cell 3	85.49	292	83.2	...	204	100	56
Cell 4	98.18	257	98.18	...	56	100	47
Cell 5	96.63	80	94.95	...	110	100	37
...	...	...	...	...	...	...	...
Cell n-2	91.47	585	87.5	...	61	100	113
Cell n-1	91.06	649	88.56	...	113	100	52
Cell n	86.25	1521	81.32	...	842	98.76	403

the classification. We set the threshold based on the distribution of importance scores and then we select the indicators whose importance scores are above the threshold. Finally, we weight these indicators using entropy method and calculate the final weighted score of each cell as the evaluation result.

B. INDICATOR SELECTION BY RF

Indicator selection [31] is the basis of the evaluation method. For KQI data, the indicator system contains plenty of indicators, which makes the evaluation system become sluggish. In order to minimize those indicators and select the most effective ones for comprehensive evaluation, we use indicator importance-based technique. Various methods in machine learning compute indicator importance scores. We choose RF in variable selection problem when multivariate are handled. RF is an efficient method which contains few parameters to set. It is used usually for multi-class classification and multi-variate regression problems. It is also successfully used in many computer vision applications such as 2D and 3D face analysis [32], action recognition [33] and facial expression recognition.

RF is a kind of bootstrap aggregating (Bagging) algorithm, which is an integration technique to train the k weak classifiers by selecting k new datasets from the original dataset through sampling with replacement randomly. By combining several weak classifiers, the final results can be obtained by voting or taking mean, so that the results of the overall model have higher accuracy and generalization performance. The use of the Out-Of-Bag (OOB) error estimation is one of the most important characteristics of RF. The OOB is a sample set not used in the training of the current tree. So, this internal estimation of the generalization error enhances the accuracy of tree classification. It is also crucial for feature importance quantification. The weak classifiers work with CART, which selects features based on Gini coefficient index. Since it is a combination of binary trees, Gini coefficient can be defined by

$$G_m(p) = 2p_m(1 - p_m) \tag{1}$$

in which p_m is the probability that the sample belongs to one class in node m. We measure the degradation of impurity with the score of Gini coefficient, which is defined by

$$IM_{jm}^{(Gini)} = G_m - G_l - G_r \tag{2}$$

where G_l and G_r represent the Gini coefficient of two new nodes after the node m branching. The importance of j-th indicator in i-th tree is given by

$$IM_{ij}^{Gini} = \sum_{m \epsilon M} IM_{im}^{Gini} \tag{3}$$

where M represents the node set that j-th indicator shows up in i-th tree. Assuming that there are n trees in RF, the importance score for the j-th indicator is defined by

$$IM_j^{Gini} = \sum_{i=1}^{n} IM_{im}^{Gini} \tag{4}$$

Finally, we normalize the score of all indicators and sort them. We select the indicators whose importance score accounts for more than half of the total score as the representative to evaluate the quality of wireless user perception, which eliminates the impact of some unimportant indicators.

C. CONSTRUCTION OF MULTI-INDICATOR COMPREHENSIVE INDEX

The selected indicators are integrated to a score according to comprehensive evaluation method for multi-indicator [34] in order to make a comprehensive evaluation for wireless user perception. Normalization and weight need to be performed when constructing comprehensive evaluation index.

1) NORMALIZATION

As we can see from Table 2, all the indicators show with different dimensions, which might have an impact on comprehensive evaluation. On the other hand, the indicators can be divided into cost indicators like page response delay (ms) and benefit indicators like page response rate (%). The smaller the value of cost indicators is, the better the result is. The bigger the value of benefit indicators is, the better the result is. In order to eliminate the influence of dimensions, we normalize these two kinds of indicators respectively. The normalization of indicators can be defined as follows.

For cost indicators:

$$z_{ij} = \frac{max\left\{x_{1j}, \ldots, x_{nj}\right\} - x_{ij}}{max\left\{x_{1j}, \ldots, x_{nj}\right\} - min\left\{x_{1j}, \ldots, x_{nj}\right\}} \tag{5}$$

For benefit indicators:

$$z_{ij} = \frac{x_{ij} - max\left\{x_{1j}, \ldots, x_{nj}\right\}}{max\left\{x_{1j}, \ldots, x_{nj}\right\} - min\left\{x_{1j}, \ldots, x_{nj}\right\}} \tag{6}$$

In both of the two equations, $max\left\{x_{1j}, \ldots, x_{nj}\right\}$ and $min\left\{x_{1j}, \ldots, x_{nj}\right\}$ represent the maximum value and minimum value, respectively under j-th indicator.

2) WEIGHTING

For comprehensive evaluation method in multi-indicator, weighting plays an important role. There are a lot of methods to obtain weight including subjective and objective methods [35]. Subjective weighting [36] works based on the experience of some experts. On the contrary, objective weighting [37] obtains the weight by mathematical or statistical analysis of the raw indicator information. In this paper, we use entropy method, a kind of objective weighting, to weight all the indicators selected.

First, we need to calculate the probability p_{ij} of i-th sample x_{ij} in j-th indicator, which is given by

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{7}$$

where n equals the number of samples. Then, the entropy e_j of j-th indicator can be calculated by

$$e_j = -k \sum_{i=1}^{n} p_{ij} ln p_{ij} \tag{8}$$

where $k = \frac{1}{ln(n)} > 0$, hence $e_j > 0$. After that, we calculate the redundancy of entropy by

$$d_j = 1 - e_j \tag{9}$$

where d_j equals the entropy redundancy of j-th indicator. Finally, the weight of j-th indicator w_j can be defined as by

$$C_i = \sum_{j=1}^{m} x_{ij} w_j, \quad i = 1, 2, \ldots, n \tag{10}$$

where x_{ij} represents the value of i-th cell in j-th indicator after normalization. w_j is the weight of j-th indicator and m equals the number of indicators selected in a particular scenario.

IV. ALGORITHM EVALUATION

In order to evaluate the performance of this proposed comprehensive evaluation method, we opt for high-rise scenario to verify the performance of this method. In this scenario, there are 287 cells. We use proposed comprehensive evaluation method, mean square deviation (MSD) method and weights from expert experience to score all cells in this scenario. It is worth noting that MSD methods have been also applied in many fields [38]–[52].

A. PROPOSED COMPREHENSIVE EVALUATION METHOD

We build a labeled dataset by measuring a number of history data manually. Then we train the RF with labeled dataset and calculate the importance of all indicators. The order of all indicators according to the importance score is show in Fig. 2. The sum score of top five indicators accounts for more than half of total score. So we select these five indicators as the representative of wireless user perception in this scenario. We weight these indicators selected using entropy method and calculate the final scores of all cells in Table 4.

According to the order of evaluation result, we pick the top five and the bottom five cells to analyze the indicators concretely. The final scores of them are shown in Table 4. We analyze all indicators of these cells with the threshold of each indicator. These thresholds come from experience in business. We count the number of poor indicators as shown in Fig. 3. Poor indicators refer to the value of which is greater than threshold for cost indicators and less than threshold for benefit indicators. We can see from Fig. 3, the top five cells barely have poor indicators, while the bottom cells tend to have more poor indicators. So the result of our proposed method is in line with actual situation.

B. MSD METHOD

MSD method reflects the degree of dispersion of a data set [20]. Generally, the larger the MSD of an indicator is,

TABLE 4. Final score by proposed method.

Cell name	I_1	I_2	I_3	...	I_{10}	I_{11}	I_{12}	Score
Cell 1-1	94.01	101	91.45	...	53	100	50	0.74
Cell 1-2	100	112	100	...	46	100	65	0.71
Cell 1-3	85.49	292	83.2	...	204	100	56	0.69
Cell 1-4	98.18	257	98.18	...	56	100	47	0.65
Cell 1-5	96.63	80	94.95	...	110	100	37	0.61
...	...	...	...	...	...	...	...	...
Cell n-1	91.47	585	87.5	...	61	100	113	0.09
Cell n-2	91.06	649	88.56	...	113	100	52	0.09
Cell n-3	86.25	1521	81.32	...	842	98.76	403	0.084
Cell n-4	79.41	224	74.26	...	56	100	53	0.083
Cell n-5	91.55	552	87.4	...	174	100	80	0.082

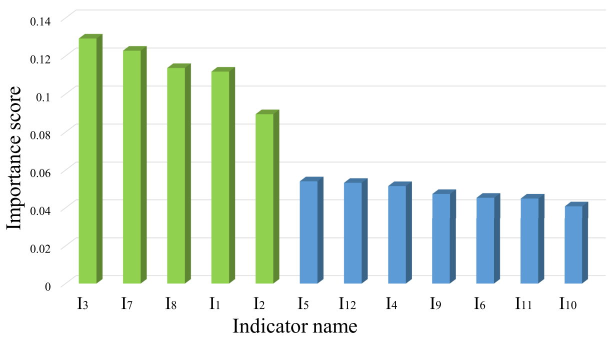

FIGURE 2. The importance of all indicators in high-rise scenario.

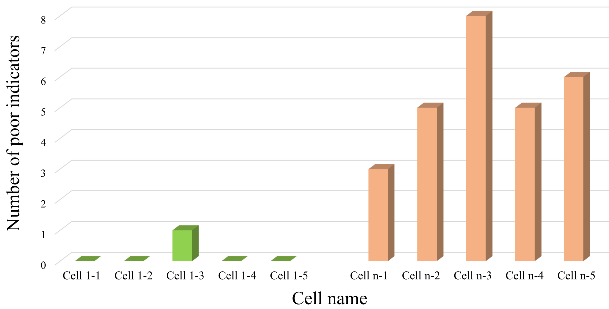

FIGURE 3. The number of poor indicators in the ten cells.

the greater impact this indicator has for comprehensive evaluation. In this situation, this indicator should have larger weight. On the contrary, the indicators with smaller MSD should have small weight. We view each indicator as a random variable. The dimensionless attribute value of each cell C_i under indicator I_j is the value of the random variable. Firstly, we need to calculate the MSD of each indicator and normalize these MSD as the final weight of each indicator. The calculation steps of this method are as follows:

(1) Calculate the means of each random variable:

$$E(I_j) = \frac{1}{n}\sum_{i=1}^{n} z_{ij} \tag{11}$$

in which z_{ij} represents the value of cell C_i under indicator I_j.

TABLE 5. Final score by MSD method.

Cell name	I_1	I_2	I_3	...	I_{10}	I_{11}	I_{12}	Score
Cell 1-1	98.36	430	90.16	...	137	100	29	0.627
Cell 1-2	94.01	101	91.45	...	53	100	50	0.614
Cell 1-3	100	264	100	...	70	100	35	0.610
Cell 1-4	96.63	80	94.95	...	110	100	37	0.609
Cell 1-5	100	112	100	...	46	100	65	0.606
...	...	...	...	...	...	...	...	...
Cell n-1	77.52	178	65.13	...	58	100	40	0.360
Cell n-2	92.15	112	90.19	...	64	0	42	0.323
Cell n-3	80.12	88	78.84	...	49	97.72	39	0.322
Cell n-4	76.95	301	69.14	...	49	100	42	0.282
Cell n-5	26.25	146	22.34	...	60	90	33	0.195

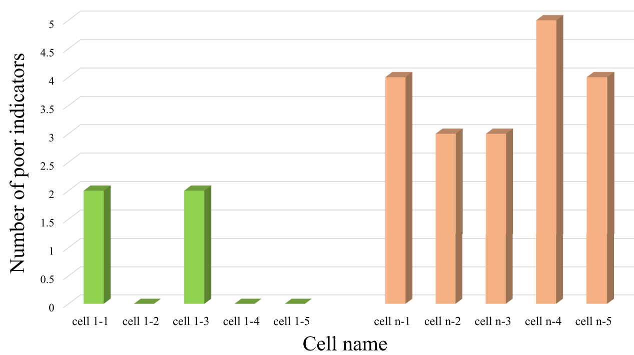

FIGURE 4. The number of poor indicators by MSD method.

(2) Calculate the MSD of each indicator I_j:

$$\sigma(I_j) = \sqrt{\sum_{i=1}^{n}(z_{ij} - E(I_j))^2} \tag{12}$$

(3) Calculate the weight of each indicator:

$$w_j = \frac{\sigma(I_j)}{\sum_{j=1}^{m}\sigma(I_j)} \tag{13}$$

After the calculation of weights, we need to score all cells in high-rise scenario. The result is shown in Table 5. We pick top five and bottom five cells to analyze concretely. The numbers of poor indicators in these ten cells are presented in Fig. 4.

As shown in Fig. 4, there are still two cells containing two poor indicators in top five cells, which is unsatisfied for comprehensive evaluation. On the other hand, this method involves all indicators, which make the comprehensive evaluation system sluggish and leads to an unconvincing result.

C. SUBJECTIVE EVALUATION METHOD

The subjective evaluation method [36] is an important category among variety methods of weighting. There are many subjective methods including analytic hierarchy process (AHP), binomial coefficient method, the least square

TABLE 6. The weights of all indicators.

I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}
0.080	0.087	0.105	0.079	0.079	0.092	0.074	0.075	0.088	0.095	0.072	0.075

TABLE 7. Final score by subjective evaluation method.

Cell name	I_1	I_2	I_3	...	I_{10}	I_{11}	I_{12}	Score
Cell 1-1	94.01	101	91.45	...	53	100	50	0.569
Cell 1-2	96.63	80	94.95	...	110	100	37	0.550
Cell 1-3	100	112	100	...	46	100	65	0.549
Cell 1-4	98.36	430	90.16	...	137	100	29	0.548
Cell 1-5	98.18	257	98.18	...	56	100	47	0.545
...	...	...	...	...	...	...	...	...
Cell n-1	79.36	451	77.77	...	36	98.31	45	0.349
Cell n-2	80.12	88	78.84	...	49	97.72	39	0.341
Cell n-3	92.15	112	90.19	...	64	0	42	0.328
Cell n-4	76.95	301	69.14	...	49	100	42	0.301
Cell n-5	26.25	146	22.34	...	60	90	33	0.210

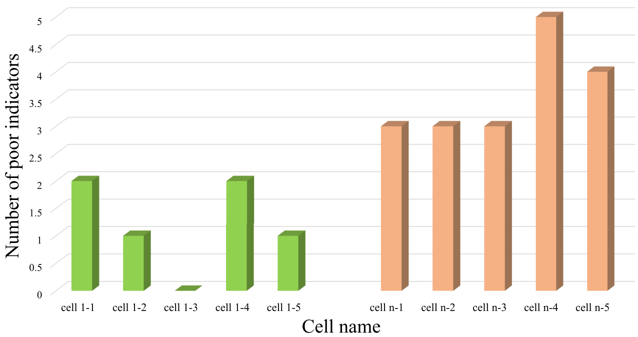

FIGURE 5. The number of poor indicators by subjective evaluation method.

method and so on. In this paper, we choose AHP to weight all indicators. The final weights are listed in Table 6.

We score all cells in high-rise scenario with these weights. The scores of all cells are shown in Table 7. As in the previous analysis, we make statistics on the number of poor indicators in ten cells, which is presented in Fig. 5. Obviously, even though in the top five cells, there are still many poor indicators. This method cannot evaluate the quality of wireless user perception in a particular scenario correctly.

Based on the above analysis, MSD method and subjective evaluation method involve all indicators, which makes the whole evaluation sluggish and the final results of them are inconsistent with actual situation. Our proposed lightweight comprehensive evaluation method involves few indicators, which makes the whole evaluation system more effective. And the final result performs well. The comprehensive evaluation result provides considerable reference for network optimization.

V. CONCLUSION

In this paper, we have proposed a lightweight multi-indicator comprehensive evaluation method based on RF and entropy method. This method can be effectively applied to multi-indicator comprehensive evaluation of wireless user perception in communities. By using this proposed method, we can obtain a relatively accurate result with few indicators. We have designed an experiment based on high-rise scenario. The result showed that lightweight evaluation result is consistent with actual situation, which means the proposed method is convincing. In terms of indicator selection, the selection of number of indicators is a fuzzy problem. Hence, it is necessary to solve this problem in future work.

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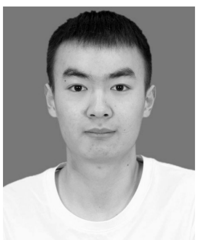

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