IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received November 12, 2019, accepted November 25, 2019, date of publication November 27, 2019, date of current version December 13, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2956285

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

KAIXUAN ZHANG[1], (Student Member, IEEE), JUAN WANG[1], (Student Member, IEEE), WEI ZHANG[2], (Member, IEEE), KE WANG[3], JUN ZENG[1], GUANGHUI FAN[1], AND GUAN GUI[1,3] (Senior Member, IEEE)

[1]College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
[2]School of Computer Science, Nanjing University of Posts and Telecommunications, Nanjing 210023, China
[3]School of Electronic and Information, Yangtze University, Jingzhou 434023, China

Corresponding authors: Wei Zhang (zhangw@njupt.edu.cn) and Guan Gui (guiguan@njupt.edu.cn)

This work was supported in part by the Project Funded by the National Science and Technology Major Project of the Ministry of Science and Technology of China under Grant TC190A3WZ-2, in part by the National Natural Science Foundation of China under Grant 61672297, in part by the Jiangsu Specially Appointed Professor under Grant RK002STP16001, in part by the Innovation and Entrepreneurship of Jiangsu High-Level Talent under Grant CZ0010617002, in part by the Summit of the Six Top Talents Program of Jiangsu under Grant XYDXX-010, and in part by the 1311 Talent Plan of Nanjing University of Posts and Telecommunications.

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

The associate editor coordinating the review of this manuscript and approving it for publication was Xuxun Liu.

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

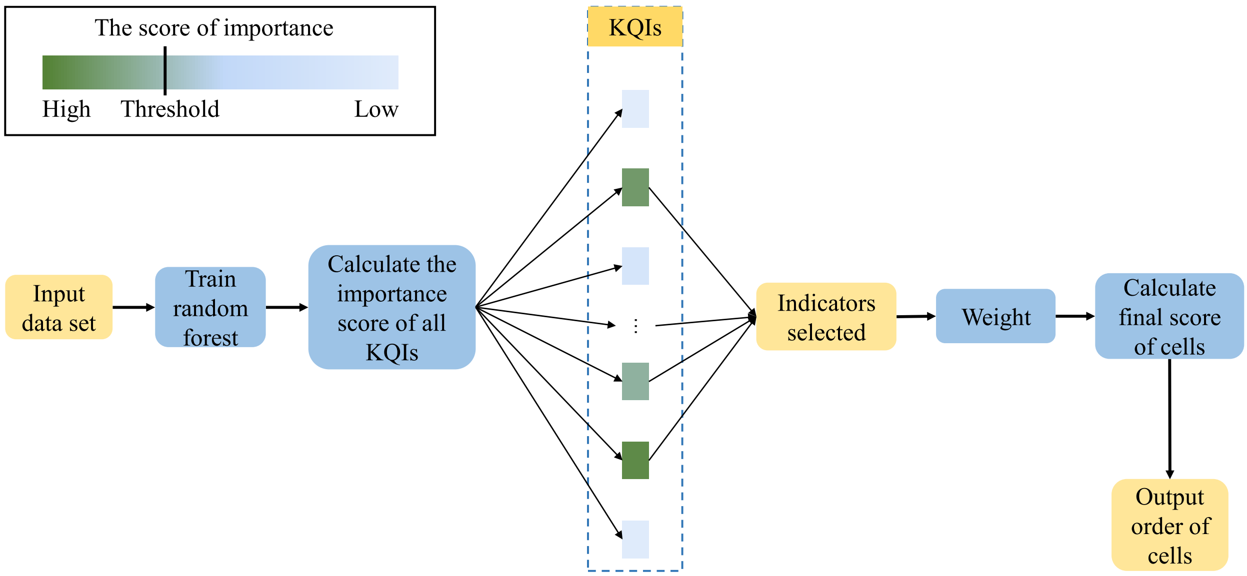

FIGURE 1. The structure of the comprehensive evaluation system.

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

$$IM_j^{Gini} = \sum_{i=1}^{n} IM_{im}^{Gini} \quad (4)$$

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:

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

For benefit indicators:

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

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

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \quad (7)$$

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

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

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

$$d_j = 1 - e_j \quad (9)$$

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

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

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

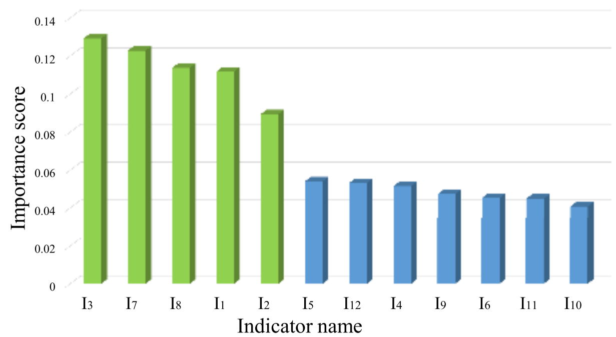

FIGURE 2. The importance of all indicators in high-rise scenario.

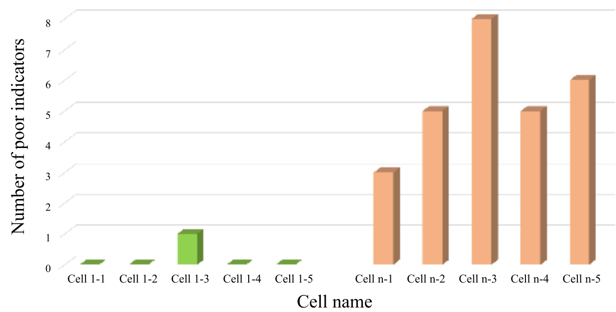

FIGURE 3. The number of poor indicators in the ten cells.

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

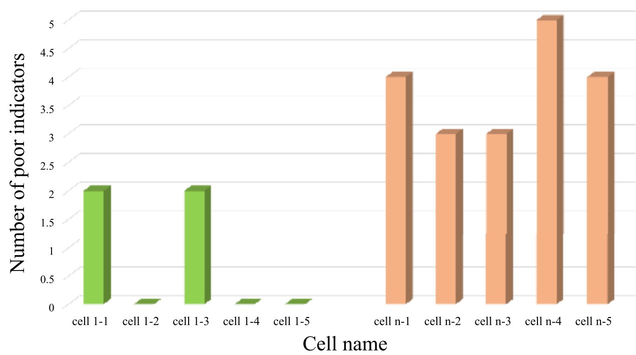

FIGURE 4. The number of poor indicators by MSD method.

(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

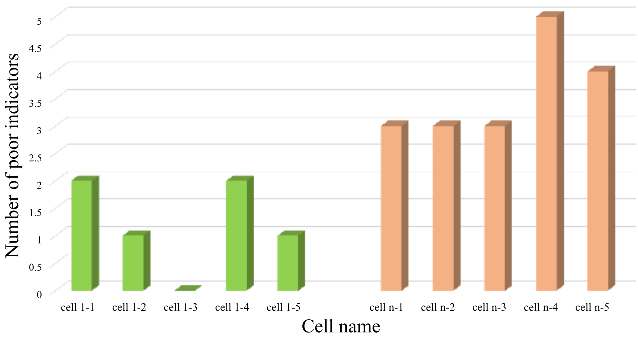

FIGURE 5. The number of poor indicators by subjective evaluation method.

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.

ACKNOWLEDGMENT

The authors would like to express their thanks to the BOCO Inter-Telecom for their KQI data.

REFERENCES

[1] Z. Na, Y. Wang, X. Li, J. Xia, X. Liu, M. Xiong, and W. Lu, "Subcarrier allocation based simultaneous wireless information and power transfer algorithm in 5G cooperative OFDM communication systems," *Phys. Commun.*, vol. 29, pp. 164–170, Aug. 2018.

[2] Q. Li, A. Liu, T. Wang, M. Xie, and N. N. Xiong, "Pipeline slot based fast rerouting scheme for delay optimization in duty cycle based M2M communications," *Peer-Peer Netw. Appl.*, vol. 12, no. 6, pp. 1673–1704, 2019, doi: 10.1007/s12083-019-00753-z.

[3] X. Liu, M. Zhao, A. Liu, and K. K. L. Wong, "Adjusting forwarder nodes and duty cycle using packet aggregation routing for body sensor networks," *Inf. Fusion*, vol. 53, pp. 183–195, Jan. 2020.

[4] M. Liu, T. Song, and G. Gui, "Deep cognitive perspective: Resource allocation for NOMA based heterogeneous IoT with imperfect SIC," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2885–2894, Apr. 2019.

[5] G. Gui, H. Sari, and E. Biglieri, "A new definition of fairness for non-orthogonal multiple access," *IEEE Commun. Lett.*, vol. 23, no. 7, pp. 1267–1271, May 2019.

[6] M. Wei, S. Sezginer, G. Gui, and H. Sari, "Bridging spatial modulation with spatial multiplexing: Frequency-domain ESM," *IEEE J. Sel. Topics Signal Process.*, vol. 13, no. 6, pp. 1326–1335, Oct. 2109, doi: 10.1109/JSTSP.2019.2913131.

[7] Z. Zhou, M. Dong, K. Ota, G. Wang, and L. T. Yang, "Energy-efficient resource allocation for D2D communications underlaying cloud-RAN-based LTE-A networks," *IEEE Internet Things J.*, vol. 3, no. 3, pp. 428–438, Jun. 2016.

[8] Z. Zhou, J. Gong, Y. He, and Y. Zhang, "Software defined machine-to-machine communication for smart energy management," *IEEE Commun. Mag.*, vol. 55, no. 10, pp. 52–60, Oct. 2017.

[9] Z. Zhou, Y. Guo, Y. He, X. Zhao, and W. M. Bazzi, "Access control and resource allocation for M2M communications in industrial automation," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 3093–3103, May 2019.

[10] M. Liu, J. Yang, T. Song, J. Hu, and G. Gui, "Deep learning-inspired message passing algorithm for efficient resource allocation in cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 1, pp. 641–653, Jan. 2018.

[11] J. Wu, M. Dong, K. Ota, J. Li, and Z. Guan, "FCSS: Fog computing based content-aware filtering for security services in information centric social networks," *IEEE Trans. Emerg. Topics Comput.*, to be published, doi: 10.1109/TETC.2017.2747158.

[12] N. Zhang, P. Yang, S. Zhang, D. Chen, W. Zhuang, B. Liang, and X. S. Shen, "Software defined networking enabled wireless network virtualization: Challenges and solutions," *IEEE Netw.*, vol. 31, no. 5, pp. 42–49, May 2017.

[13] F. Tang, Z. Md Fadlullah, N. Kato, F. Ono, and R. Miura, "AC-POCA: Anti-coordination game based partially overlapping channels assignment in combined UAV and D2D based networks," *IEEE Trans Veh. Technol.*, vol. 67, no. 2, pp. 1672–1683, Feb. 2018.

[14] Y. Liu, A. Liu, X. Liu, and M. Ma, "A trust-based active detection for cyber-physical security in industrial environments," *IEEE Trans. Ind. Informat.*, to be published, doi: 10.1109/TII.2019.2931394.

[15] X. Liu, T. Wang, W. Jia, A. Liu, and K. Chi, "Quick convex hull-based rendezvous planning for delay-harsh mobile data gathering in disjoint sensor networks," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published, doi: 10.1109/TSMC.2019.2938790.

[16] X. Liu and P. Zhang, "Data drainage: A novel load balancing strategy for wireless sensor networks," *IEEE Commun. Lett.*, vol. 22, no. 1, pp. 125–128, Jan. 2018.

[17] X. Liu, "Node deployment based on extra path creation for wireless sensor networks on mountain roads," *IEEE Commun. Lett.*, vol. 21, no. 11, pp. 2376–2379, Nov. 2017.

[18] L. Hu, A. Liu, M. Xie, and T. Wang, "UAVs joint vehicles as data mules for fast codes dissemination for edge networking in smart city," *Peer-Peer Netw. Appl.*, vol. 12, no. 6, pp. 1550–1574, 2019, doi: 10.1007/s12083-019-00752-0.

[19] W. Chen, X. Hao, and J. Lin, "An improved Fuzzy Comprehensive evaluation method using expanded least deviations algorithm," in *Proc. IEEE Conf. Cybern. Intell. Syst.*, Sep. 2008, pp. 1087–1091.

[20] F. Ai-Ying, Z. Qing-Wei, X. Zhi-Hai, and D. Geng-Sheng, "Binary image scrambling evaluation method based on the mean square deviation and the bipartite graph," in *Proc. Int. Symp. Comput., Commun., Control Automat. (CA)*, May 2010, pp. 237–239.

[21] F. Wenjie, X. Xiangning, and T. Shun, "A multi-index evaluation method of voltage sag based on the comprehensive weight," in *Proc. China Int. Conf. Electr. Distrib.*, Sep. 2018, pp. 613–617.

[22] X. Xie, B. Xia, and J. Yu, "A comprehensive evaluation method based on PCA and BP neural network," in *Proc. 5th Int. Conf. Inf. Comput. Sci.*, Jul. 2012, pp. 71–74.

[23] H.-C. Hsin, C.-C. Li, M. Sun, and R. J. Sclabassi, "An adaptive training algorithm for back-propagation neural networks," *IEEE Trans. Syst., Man and*, vol. 25, no. 3, pp. 512–514, Mar. 1995.

[24] J. Lin and B. Zhu, "Comprehensive evaluation on regional economic and social development based on kernel principal composition analysis," in *Proc. Chin. Control Conf.*, Aug. 2006, pp. 1765–1768.

[25] G. Rogez, J. Rihan, S. Ramalingam, C. Orrite, and P. H. S. Torr, "Randomized trees for human pose detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2008, pp. 1–8.

[26] P. A. Chou, "Optimal partitioning for classification and regression trees," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 4, pp. 340–354, Apr. 1991.

[27] S. Gharsalli, B. Emile, H. Laurent, X. Desquesnes, and D. Vivet, "Random forest-based feature selection for emotion recognition," in *Proc. Int. Conf. Image Process. Theory, Tools Appl. (IPTA)*, Nov. 2015, pp. 268–272.

[28] M. G. Tsipouras, D. C. Tsouros, P. N. Smyrlis, N. Giannakeas, and A. T. Tzallas, "Random forests with stochastic induction of decision trees," in *Proc. IEEE Int. Conf. Tools Artif. Intell. (ICTAI)*, Nov. 2018, pp. 527–531.

[29] M. Liyi, X. Wanxin, and G. Jian, "Entropy method for decision-making of fuzzy information," in *Proc. IEEE Int. Conf. Softw. Eng. Service Sci.*, Jul. 2010, pp. 467–470.

[30] J. Wang and W. Cheng, "Heterogeneous quality of experience guarantees over wireless networks," *China Commun.*, vol. 15, no. 10, pp. 51–59, Oct. 2018.

[31] J. Ding, G. Si, B. Li, J. Yang, and Y. Zhang, "Construction of composite indicator system based on simulation data mining," *J. Syst. Eng. Electron.*, vol. 28, no. 1, pp. 81–87, Feb. 2017.

[32] X. Zhao, T.-K. Kim, and W. Luo, "Unified face analysis by iterative multi-output random forests," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 1765–1772.

[33] A. Yao, J. Gall, and L. Van Gool, "A Hough transform-based voting framework for action recognition," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, Jun. 2010, pp. 2061–2068.

[34] Y. Liping, P. Yuntao, Y. Chun, and W. Yishan, "Study on peer review and multi-indicators evaluation in scientific and technological assessment," in *Proc. Int. Symp. Knowl. Acquisition Modeling*, Dec. 2008, pp. 794–798.

[35] B. Wang and S. Zhang, "A subjective and objective integration approach of determining weights for trustworthy measurement," *IEEE Access*, vol. 6, pp. 25829–25835, 2018.

[36] F. Yin, L. Lu, C. Wu, and J. Chai, "Study on subjective weighting method of multi-attribute decision making for broadcasting and TV program evaluation," in *Proc. 4th Int. Conf. Comput. Sci. Netw. Technol. (ICCSNT)*, vol. 1, Dec. 2015, pp. 462–466.

[37] L. Wei, S. Yumin, and J. Yanjiao, "Analysis of multiple objective decision methods based on entropy weight," in *Proc. IEEE Pacific–Asia Workshop Comput. Intell. Ind. Appl.*, Dec. 2008, pp. 953–956.

[38] F. Wen, X. Zhang, F. Yang, and Z. Zhang, "Direction finding in bistatic MIMO radar with unknown spatially colored noise," *Circuits, Syst., Signal Process.*, pp. 1–13, Oct. 2019, doi: 10.1007/s00034-019-01260-5.

[39] F. Wen, C. Mao, and G. Zhang, "Direction finding in MIMO radar with large antenna arrays and nonorthogonal waveforms," *Digital Signal Process.*, vol. 94, pp. 75–83, Nov. 2019.

[40] Y. Wang, M. Liu, J. Yang, and G. Gui, "Data-driven deep learning for automatic modulation recognition in cognitive radios," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 4074–4077, Apr. 2019.

[41] G. Gui, F. Liu, J. Sun, J. Yang, Z. Zhou, and D. Zhao, "Flight delay prediction based on aviation big data and machine learning," *IEEE Trans. Veh. Technol.*, to be published, doi: 10.1109/TVT.2019.2954094.

[42] H. Huang, Y. Peng, J. Yang, W. Xia, and G. Gui, "Fast beamforming design via deep learning," *IEEE Trans. Veh. Technol.*, to be published, doi: 10.1109/TVT.2019.2949122.

[43] J. Sun, W. Shi, Z. Yang, J. Yang, and G. Gui, "Behavioral modeling and linearization of wideband RF power amplifiers using BiLSTM networks for 5G wireless systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 11, pp. 10348–10356, Nov. 2019, doi: 10.1109/TVT.2019.2925562.

[44] F. Wen, "Computationally efficient DOA estimation algorithm for MIMO radar with imperfect waveforms," *IEEE Commun. Lett.*, vol. 23, no. 6, pp. 1037–1040, Jun. 2019.

[45] F. Wen, Z. Zhang, and X. Zhang, "CRBs for direction-of-departure and direction-of-arrival estimation in collocated MIMO radar in the presence of unknown spatially coloured noise," *IET Radar, Sonar Navigat.*, vol. 13, no. 4, pp. 530–537, Apr. 2019.

[46] F. Wen, Z. Zhang, K. Wang, G. Sheng, and G. Zhang, "Angle estimation and mutual coupling self-calibration for ULA-based bistatic MIMO radar," *Signal Process.*, vol. 144, pp. 61–67, Mar. 2018.

[47] J. Wang, Y. Ding, S. Bian, Y. Peng, M. Liu, and G. Gui, "UL-CSI data driven deep learning for predicting DL-CSI in cellular FDD systems," *IEEE Access*, vol. 7, pp. 96105–96112, 2019.

[48] M. Liu, J. Yang, and G. Gui, "DSF-NOMA: UAV-assisted emergency communication technology in a heterogeneous Internet of Things," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 5508–5519, Jun. 2019.

[49] Y. Xu, G. Li, Y. Yang, M. Liu, and M. Liu, "Robust resource allocation and power splitting in SWIPT enabled heterogeneous networks: A robust minimax approach," *IEEE Internet Things J.*, to be published, doi: 10.1109/JIOT.2019.2941897.

[50] N. Zhao, Q. Cao, G. Gui, Y. Cao, S. Zhang, Y. Chen, and H. Sari, "Secure transmission for interference networks: User selection and transceiver design," *IEEE Syst. J.*, vol. 13, no. 3, pp. 2839–2850, Sep. 2019, doi: 10.1109/JSYST.2019.2891641.

[51] L. Yunyi, D. Fei, C. Xiefeng, X. Li, and G. Guan, "Multiple-prespecified-dictionary sparse representation for compressive sensing image reconstruction with nonconvex regularization," *J. Franklin Inst.*, vol. 356, no. 4, pp. 2353–2371, Mar. 2019.

[52] B. Wang, F. Gao, S. Jin, H. Lin, and G. Y. Li, "Spatial- and frequency-wideband effects in millimeter-wave massive MIMO systems," *IEEE Trans. Signal Process.*, vol. 66, no. 13, pp. 3393–3406, Jul. 2018.

KAIXUAN ZHANG (S'18) is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interest includes machine learning for wireless communications.

JUAN WANG (S'19) is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. Her research interest includes machine learning for wireless communications.

WEI ZHANG (M'19) received the Dr.Eng. degree in computer science from Soochow University, Suzhou, China, in 2008. From 2008 to 2011, he was a Postdoctoral Research Fellow with the Nanjing University of Posts and Telecommunications, Nanjing, China. From March to September 2016, he was a Visiting Scholar with Purdue University. Since January 2012, he has been a Professor with the School of Computer Science, Nanjing University of Posts and Telecommunications. His current research interests include computer version and machine learning.

KE WANG was born in Hubei, China, in 1988. He received the B.S. degree in automation engineering from the Hubei University of Technology, Wuhan, China, in 2010, the master's degree with the College of Electronic Information and Control Engineering, Beijing University of Technology, China, in 2016, and the Ph.D. degree with the Beijing University of Technology, in 2016. Since 2016, he has been with the Electronic and Information School, Yangtze University, China, where he is currently a Lecturer. His research interests include mobile robot and computer vision.

JUN ZENG is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interest includes machine learning for wireless communications.

GUANGHUI FAN is currently pursuing the master's degree in communication and information engineering with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interest includes machine learning for wireless communications.

GUAN GUI (M'11–SM'17) received the Dr.Eng. degree in information and communication engineering from the University of Electronic Science and Technology of China, Chengdu, China, in 2012.

From October 2009 to March 2012, with the financial supported from the China Scholarship Council (CSC) and the Global Center of Education (ECOE) of Tohoku University, he joined the Department of Communications Engineering, Graduate School of Engineering, Tohoku University, as a Research Assistant and a Postdoctoral Research Fellow, respectively, where he was also a Postdoctoral Research Fellow supported by the Japan Society for the Promotion of Science (JSPS) Fellowship, from September 2012 to March 2014. From April 2014 to October 2015, he was an Assistant Professor with the Department of Electronics and Information System, Akita Prefectural University. Since November 2015, he has been a Professor with the Nanjing University of Posts and Telecommunications, Nanjing, China, and also with Yangtze University, Jiangzhou, China. He has published more than 200 international peer-reviewed journal/conference papers. He is currently engaged in research of deep learning, compressive sensing, and advanced wireless techniques. He received the Member and Global Activities Contributions Award by the IEEE ComSoc and the eight Best Paper Awards, such as ICEICT 2019, CSPS 2019, ADHIP 2018, CSPS 2018, ICNC 2018, ICC 2017, ICC 2014, and VTC 2014-Spring. He was also selected as for Jiangsu Specially-Appointed Professor, in 2016, Jiangsu High-level Innovation and Entrepreneurial Talent, in 2016, Jiangsu Six Top Talent, in 2018, and Nanjing Youth Award, in 2018. He was an Editor of *Security and Communication Networks,* from 2012 to 2016. He has been an Editor of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, since 2017, IEEE ACCESS, since 2018, *KSII Transactions on Internet and Information Systems,* since 2017, and *Journal of Communications*, since 2019, He has been the Editor-in-Chief of EAI TRANSACTIONS ON ARTIFICIAL INTELLIGENCE, since 2018.