ML and MCDM for Abnormal Cell Detection in 5G & B5G Networks

Reza Moammer Yami [1], Ali Akbar Khazaei [1]*, and Saeed Rahati Quchani [2]

***Abstract*--Self-organizing communication networks are a vital pillar in 5G and B5G technology, which operate automatically without human intervention in self-healing, self-configuring, and self-optimizing. Self-healing in these networks predicts and resolves network problems and improves performance with the following three methods in the research conducted: rule-based, algorithmic, and machine-learning approaches. This research used the TOPSIS technique as a multi-criteria decision-making method to rank and score cells after data preprocessing. Then, based on the rank of each cell, it is divided into two classes: normal and abnormal. Then, with three algorithms, decision tree, New Bayes and Random Fars, normal and abnormal cell prediction was performed independently. In the last step, using the combined method of maximum voting, the algorithm was completed and the results showed an improvement in the parameters Precisio=0.939, Recall=0.962, F-Measure=0.968, Accuracy=94.0717**.

***Index Terms*- Self-Organizing Networks, Simple Bayes, Decision Tree, Random Forest, 5G/B5G Networks, Topsis**

I. Introduction

WHIT the advancement of wireless communication technologies and the increasing use of mobile phone networks, and the penetration of this technology into the structure of human life, having a strong and intelligent infrastructure with high speed and efficiency is considered the primary requirement of the next generation networks. With the upgrade of internet speeds and the emergence of concepts such as the Internet of Things in 5G & B5G networks, the necessary infrastructures to support and provide better services to users from a hardware and software perspective have become very significant. One of the most important issues today regarding communications and introduced networks that have this capability is that they are receiving much attention. Undoubtedly, the structure and capabilities of the networks supporting this generation of mobile communications must be such that all protocols and ideas for creating it can be implemented in both hardware and software. Among the best-known structures of mobile networks using this technology, Self-Organizing Networks can be mentioned. These networks can be defined as adaptive and autonomous networks with scalability, stability, and agility to maintain the desired goals. The basic structural features of these networks began with the establishment of 3GPP Release 8. Fig. 1 shows the overall development of these networks.

Therefore, SON is considered one of the ten main study areas in 5G, as shown in Fig. 2. Self-organizing networks can self-correct their structure and improve their performance without human intervention. The main goal of creating such a capability to improve performance and correct network structure without human involvement is to reduce OPEX and CAPEX. This is achieved in three areas: 1) Self-configuration of the network structure by itself, 2) Self-optimization of network performance by itself, and 3) Self-healing of the network architecture and structure by itself.

With the capabilities designed for self-organizing networks to properly achieve the intended goals, protocols and software and hardware infrastructures are certainly needed. Among the infrastructures in these networks for self-healing and performance improvement is the proper functioning of the cells present in the network. The cells in these networks must be healthy and free from any hardware or software defects. Undoubtedly, given the very high energy consumption of the cells in these networks, their failure and defects will disrupt network efficiency. Algorithmic, rule-based, and parametric approaches [3] have been proposed to predict the efficiency and defects of these cells, each of which has its applicability under certain conditions. However, in complex conditions, algorithmic processes and rule-based processes often do not have the necessary efficiency to model the idea in mind for

1. Department of Electrical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran.
2. Department of Biomedical Engineering, Faculty of Engineering, Islamic Azad University, Central Tehran Branch, Tehran, Iran.

Corresponding author Email: khazaei@mshdiau.ac.ir

predicting cell defects.

Release	WI	Feature
Rel.8	SA5-SON concepts and requirements	SON concepts and requirements
Rel.8	SA5-Self establishment of eNBs	Self configuration
Rel.8	SA5-SON Automatic Neighbour Relation (ANR) list management	ANR, PCI
Rel.9	SA5: Study of SON related OAM Interfaces for HeNBs	SON related OAM Interfaces for HeNBs
Rel.9	SA5: Study of self-healing of SON	Self-healing management
Rel.9	SA5: SON OAM aspects: Automatic radio network configuration data preparation	Automatic radio network configuration data preparation
Rel.9	SA5:SON OAM aspects of self-organization management	Self-optimization (MRO, MLB, ICIC)
Rel.9	RAN3: Self-organizing networks	CCO, MRO, MLB, RACH opt.
Rel.10	SA5:SON self-optimization management continuation	Self-coordination, self-optimization (MRO, MLB, ICIC, RACH opt.)
Rel.10	SA5: Self-healing management	CCO, COC
Rel.10	SA5: OAM aspects of ES in radio networks	ES
Rel.10	RAN2-3: LTE SON enhancements	CCO, ES, MLB, MRO enhancements
Rel.11	SA5:ULTRAN SON management	SON management
Rel.11	SA5: LTE SON coordination management	SON coordination
Rel.11	SA5: Inter RAT ES management	OAM aspects of ES management
Rel.11	RAN3: Further SON enhancements	MRO, MDT enhancements
Rel.12	SA5: Enhanced NM centralized CCO	Enhanced NM centralized CCO
Rel.12	SA5: Multi-vendor plugs and play eNB connection to the network	Multi-vendor plug-and-play eNB connection to the network
Rel.12	SA5: Enhancements on OAM aspects of distributed MLB	OAM aspects of distributed MLB
Rel.12	SA5: Energy efficiency related performance measurements	Energy efficiency related performance measurements
Rel.12	SA5: Het-Nets management/OAM aspects of network sharing	Het-Nets/network sharing
Rel.12	RAN2-3: Next generation SON for ULTRAN/EUTRAN	SON per UE type, active antennas, small cells
Rel.12	RAN2-3: ES enhancements for EUTRAN	ES
Rel.13	RAN2-3: Enhanced Network Management centralized CCO	CCO
Rel.13	SA5: Study on Enhancements of OAM aspects of Distributed Mobility Load Balancing SON function	MLB
Rel.14	RAN: OAM (SON for Active Antenna Systems (AAS)-based deployments)	Energy efficiency

Fig. 1. Evolution of SON in 3GPP [1]

Therefore, the use of parametric processes based on learning is very important, and they also can adapt and model complex conditions. In this study, we intend to predict defective cells in 5G/B5G self-organizing networks by using a hybrid approach of rule-based processes and parametric methods based on learning.

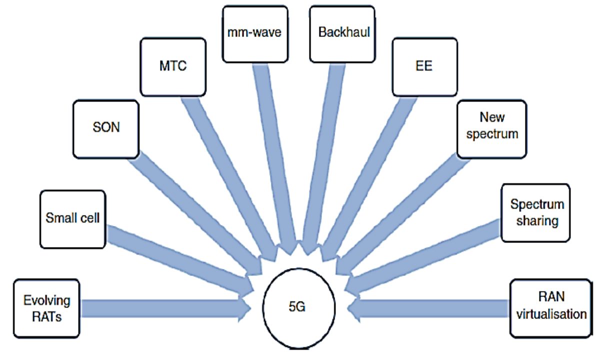

Fig. 2. 10 main study pillars of the 5G [2]

Abnormal cells include:

- A cell that does not provide service due to hardware reasons such as battery failure, etc. or software.

- A cell that only provides service to subscribers within the cell due to a loss of communication with the control center.

- Cells that have poor coverage due to problems with the antenna angle or antenna installation height.

To achieve this goal, the following steps have been taken:

1: Applying the TOPSIS technique and scoring and ranking each cell based on the received indicators (score of each cell between 0 and 1)

2: Classifying cells based on the received score into two classes: normal and abnormal

3: Using the VOTING hybrid learning algorithm and predicting completely defective cells

TABLE I
List of Acronyms

SON	Self-Organizing Networks
COD	Cell outage detection
COC	Cell outage compensation
OPEX	Operating Expenditures
CAPEX	Capital Expenditures
MLB	Mobility Load Balancing
MRO	Mobility Robustness Optimization
ANR	
OAM	Operation, Administration and Maintenance
ICIC	Inter-Cell Interference Coordination
UL	Uplink Traffic
DL	Down link Traffic
RAN	Radio Access Network
DT	Decision Trees
AD	Anomaly Detector
FQL	Fuzzy Q-Learning
KNN	K-Nearest Neighbors
KPI	Key Performance Indicator
LTE	Long Term Evolution

Sections 2 and 3 discuss previous research methods and our proposed method, while Section 4 presents the results. Section 5 summarizes the proposed methodology and activities.

II. Background Research

In 5G & B5G networks, the sharp increase in bandwidth demand, latency, coverage, functional status of domains (power, frequency spectrum, and other resources), flexibility, compatibility, quality of services that can be provided to subscribers, create great challenges. Overcoming these challenges requires new and intelligent methods. These methods will be based on artificial intelligence and its subsets, namely data mining and machine learning Different machine learning (ML) algorithms are divided into the following three main groups: supervised learning, unsupervised learning and reinforcement learning.

TABLE II
ML in Spectrum Intelligence and Adaptive Resource Management [4]

- Machine Learning for Spectrum Access and Sharing .
- Reinforcement Learning for Resource Allocation in Cognitive Radio Networks.
- Machine Learning for Spectrum Sharing in Millimeter-Wave Cellular Networks.
- Deep Learning–Based Coverage and Capacity Optimization.
- Machine Learning for Optimal Resource Allocation.
- Machine Learning in Energy Efficiency Optimization.
- Deep Learning Based Traffic and Mobility Prediction.
- Machine Learning for Resource-Efficient Data Transfer in Mobile Crowd sensing.

Intelligent methods based on machine learning have been used in the following areas to improve network performance Artificial Intelligence technology and its subsets such as machine learning and data mining to improve modeling and channel estimation in millimeter and terahertz bands, adaptive modulation in MIMO technology, front-end and RF processing, automatic interference cancellation, network optimization and radio resource management for wireless big data, critical communications are used.

TABLE III
Transmission Intelligence and Adaptive Baseband Processing [4]

- Machine Learning–Based Adaptive Modulation and Coding Design.
- Machine Learning–Based Nonlinear MIMO Detector.
- Adaptive Learning for Symbol Detection.
- Machine Learning for Joint Channel Equalization and Signal Detection.
- Neural Networks for Signal Intelligence
- Channel Coding with Deep Learning.
- Deep Learning Techniques for Decoding Polar Codes.
- Neural Network–Based Wireless Channel Prediction.

ML wireless communication technology is developing rapidly and is one of the main drivers in the next generation of wireless networks The three main groups affected by artificial intelligence and methods based on it in 5G&B5G networks are: (1) ML-based spectrum intelligence and adaptive radio resource management. (b) Intelligent transmission based on ML and adaptive baseband signal processing. and (iii) ML-based network intelligence and adaptive system-level optimization [4]. Tables II, III and IV show some areas of classification.

In general, three main approaches have been used in previous research for estimating cell failure in self-organizing networks: 1) rule-based [5-9], 2) algorithm-based [10-13], and 3) machine learning-based parametric [14-17]. Each approach has its applicability, depending on the requirements. The approaches mentioned in 1) and 2) do not show high performance given the structural complexity of self-organizing networks and cannot mathematically model failure estimation in complex network conditions. Additionally, since these approaches are often Traditional methods will not be able to solve the challenges and detect anomalies in the complex networks of the new generation of wireless communication, therefore, the use of machine learning techniques can better estimate failures in complex networks.

TABLE IV
Network Intelligence and Adaptive System Optimization [4]

- Machine Learning for Digital Front-End.
- Neural Networks for Full-Duplex Radios.
- Machine Learning for Context-Aware Cross-Layer Optimization.
- Physical-Layer Location Verification by Machine Learning.
- Deep Multi-Agent Reinforcement Learning for Cooperative Edge Caching

In rule-based approaches, based on previous work [18-21], the target objectives are usually achieved by employing filters and methods fundamentally based on statistical concepts. In fact, in this approach, proven statistical laws and empirical concepts and rules are algorithmically used to determine the effect of network parameters and perform the intended estimations regarding failures and errors in the network. For example, the decision tree statistical structure can be mentioned as one of the problem-solving methods in this approach. Another flaw of this approach is the lack of a precisely predefined benchmark for measuring performance accuracy. Therefore, the efficiency of methods performed using this approach lacks operational clarity in structurally complex conditions. Similarly, for algorithm-based approaches, as in rule-based approaches, performance evaluation metrics do not parametrically determine method accuracy and efficiency. In research using this approach [22-23], similar to rule-based methods, cell failure estimation in the network has been performed based on a theory of the problem along with its existing parameters and quantities in the form of an algorithm. A noteworthy issue with methods based on this approach is algorithmic complexity in mapping parameters to the problem solution and sometimes implementation infeasibility given the increase in this complexity in the problem, as well as incompatibility of the algorithm with parameters within the problem model. Moreover, methods in the algorithmic approach are structurally very similar to rule-based methods. In both, solving the target problem in detecting network malfunction and failure is usually performed by carrying out a sequential routine.

For machine learning-based methods to determine defective cells and generally detect errors in networks, the learning pattern must be specified based on the available data type. The working areas of ML techniques in cell fault management are shown in Fig. 3.

The research we review has typically employed classification methods to determine network malfunction and failure based on the labeled structure of the data. For example, in a study by Babalola and Balian [24], the Support Vector Machine classifier [25] and the Hidden Markov Model algorithm [26] were used to estimate cell failure. The results showed an accuracy of 97.02% for the applied method. In the work of Verma et al. [27], which was aimed at determining user power in predicting parameters of the LTE network, the K-Nearest Neighbor [28], SVM, and Naive Bayes [29] algorithms were implemented to achieve the goal. In the results obtained from their study, the SVM algorithm performed better than the other methods. Its accuracy was 96.17% for Downlink and 96.10% for Uplink. Wang et al. [30] in their work employed a hybrid learning approach to address the challenge of imbalanced labeled data in detecting errors in 5G self-organizing networks. The results demonstrated high efficiency for the proposed algorithm by Wang et al. Wit [31] utilized the Random Forest algorithm [32] in his study to identify several possible errors in SON networks. The main goal of Wit's work was to recognize error types with higher identification ability by learning models. To prevent overfitting, cross-validation was employed during model training. Wit's results showed F1 scores of 0.58, 0.92, and 0.52 for the network's optical interface, temperature alarm, and VSWR alarm errors, respectively.

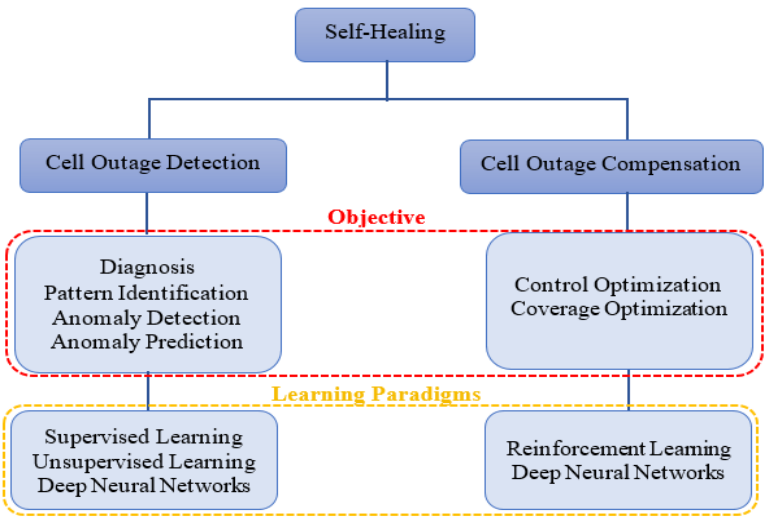

Fig. 3. Working areas of ML techniques in cell error management [3]

This technology focuses on identifying and repairing faulty cells for optimal network performance. The following three approaches have been used by the research community in previous work. These approaches, with their advantages and disadvantages, are:

Machine Learning in Wireless Communication		
Reinforcement Learning	**Unsupervised Learning**	**Supervised Learning**
Policy interaction [48]	K means [33],[34]	K nearest neighbor [40]
Value interaction [49],[50]	Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [35],[36],[37]	Decision tree [41]
Temporal difference [51]	Gaussian mixture [38]	Random forest [42]
State–action–reward–state–action [52]	Autoencoder [39]	Logistic regression [43]
Q-learning [53],[54],[55]	**Fault definition**	Multilayer perceptron [44],[45],[46]
Q-value function [56],[57]		Support Vector Machine [47]
Parameter estimation		**Fault definition**

Fig. 4. Machine learning by learning patterns in wireless communication

1. Role-based approaches Based on empirical rules:

- Suitable for small network structures**-**

- Lack of accuracy

-Increase error

- Very complex formulation

2. Algorithm-based approaches Based on statistical theories:

- Suitable for small network structures
- Low flexibility for complex structures
- High operational complexity
- Fairly accurate

3. Parametric-based approaches Based on machine learning:

- Suitable for large network structures High

-flexibility for complex structures

- Operational simplicity and transparency
- Based on data type and quality

The above summarizes a small part of machine learning efficacy regarding mobile communication network technology in SON networks. In general, there are typically three overall learning approaches in machine learning-based methods, clearly differentiated in Fig. 4. Work based on each includes

[33-39] for unsupervised learning, [40-47] for supervised learning, and [48-57] for different algorithms in reinforcement learning. The general theme of each is using machine learning-based methods for error detection and determining system parameters and efficiency in networks. Regarding error detection via reinforcement learning in SON networks [58] and deep learning, a more recent branch of machine learning has been performed [59-60]. Given our different approaches, we will not review these studies. Our proposed algorithm will be explained below. The research is presented in a general classification based on areas of work in Fig. 4.

III. Proposed Method

In this section, the proposed algorithm is presented. This algorithm is designed in five steps and is shown in Fig. 5, where each step is discussed in detail below.

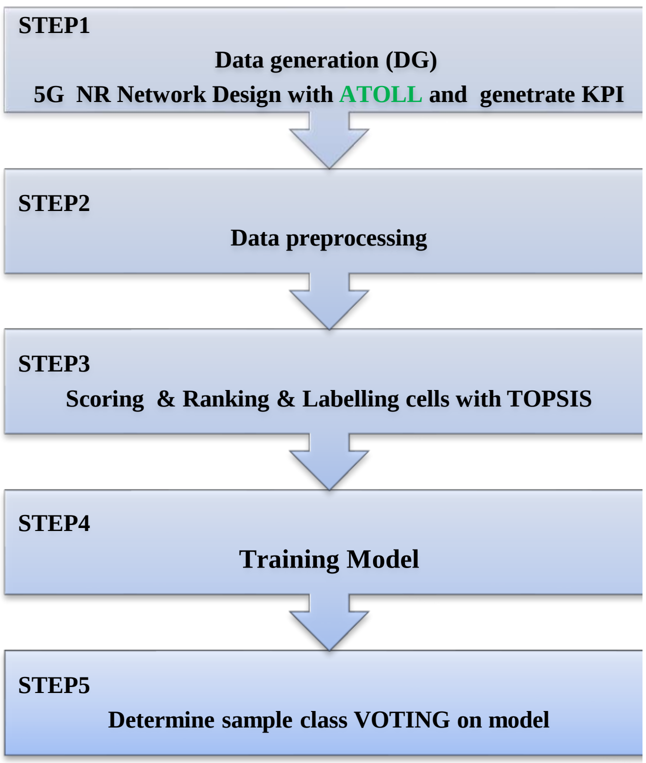

Fig. 5. Diagram of the proposed method

STEP1

A. Data Generation

(Data generation 5G NR Network Design with ATOLL)

In the first step, a cellular network design was carried out using ATOLL software. From the received indicators, three types of indicators were selected to analyze and examine the signaling, voice, and data conditions of each cell. The following is a brief explanation of the ATOLL software and the modules used. The following is a discussion of the types of data and definitions of each.

ATOLL software helps 5G NR network development and provides wireless operators with design and optimization throughout the network lifecycle. ATOLL combines features for network design and optimization processes. And can design and implement a real network. ATOLL is a comprehensive radio planning and optimization platform that includes traffic models that can be used in network implementation, and this software automatically simulates and plans network cells at any scale. This software can support 2G to 5G networks. A network has been designed by ATOLL software and KPIs of the network which are stored hourly have been received from the level of each cell. The received KPIs are introduced below. KPIs received from the network level help network planning and analysis with the aim of network optimization. However, insufficient KPI data can limit efficient network planning, leading to increased operating costs, which can negatively impact both the network OPEX & and CAPEX. This dataset contains the performance status of 67,000 cells across the network level with several features that, after reviewing the dataset of interest, were prepared with 12 key indicators for each cell. These 12 indicators cover the network performance status in the areas of network signaling, radio quality of each cell, network service quality index, as well as network traffic status for UL/DL links and HANDOVER of each cell, and the number of successful and unsuccessful calls in the network. These KPIs, which can be used based on network statistics to review and improve the network status, are:

● **ERAB Success Rate**, S1 Signal E-RAB Setup Success Rate and Radio Resource Control (RRC) are key metrics to measure user access in the network and are indicative of network signaling. They indicate the probability of successfully accessing the service under various conditions. RRC requires a carrier to start service. The UE sends RRC Setup Complete to the eNB, Ih sends an S1 Initial UE Message with UE Details to the MME. If the bearer is required, the MME sends an Initial Context Setup Request to the Enb. This ERAB attempt message contains the QCI bearers and values. RRC is a layer 3 protocol used between UE and base station in UMTS, LTE and 5G. It is specified by 3GPP and transmitted via the PDCP protocol.

● **RAN_Avail_Rate**: Availability Radio Network

● **Handover** in wireless communications (LTE) is the seamless transfer of continuous sessions from one base station to another as mobile devices move through network cells. There are two types of delivery: intra-frequency and inter-frequency.

● **Call Setup Success Rate** (CSSR) measures the percentage of successful connections to dialed numbers during call attempts.

● **Call Drop Rate** (CDR) is a critical performance indicator that determines the number of times a call gets disconnected or drops before it gets completed successfully.

● **UL/DL Traffic** :UL/DL traffic is the speed difference between sending and receiving data, and the upload speed is usually lower than the download speed for Internet access.

● **Average_CQI**: CQI stands for Channel Quality Indicator, and it is an important concept in cellular communication.

● **Average_UL_Packet_Loss**: Packet loss means that data packets do not reach their destination due to network congestion and other factors.

What creates the features of a data set should maximize the information gain they provide the machine to separate the sample classes so that the samples can be distinguished from each other as much as possible based on their class with the best possible result. Also, the efficiency of the feature within the data set itself should make the data meaningful, and considering the usage of the feature, facilitate the performance of a system. In addition, the structure of the features relative to each other is also very important in terms of data correlation. Having features with less data dependency on each other can enable the learning model to generate output with greater ability and efficiency. In the dataset used for the current study, considering the internal concepts of the network, the set of features referred to as KPIs, 12 cases along with the expression of their existence nature are stated in Table V.

TABLE V
Features of Data

ERAB Success Rate
S1Signal_E-RAB_Setup_SR
RAN_avail_Rate
HandOver
InterF_HOOut_SR
IntraF_HOOut_SR
Call_Drop_Rate
Uplink and DownlinkTraffic
Call Setup Success Rate (CSSR)
Average_CQI
Radio Resource Control (RRC)
Average_UL_Packet_Loss

As shown in Table V, the 12 main KPIs are used to identify defective cells and cells with anomalies to implement the goal. To rank and classify each cell in terms of the value that each KPI has, one of the common methods is to use multivariate statistical algorithms. In this study, we used the TOPSIS method to label the data and used it in the classification process, which we explained below. By applying TOPSIS, we labeled the data generated by ATOLL software, which is mobile network design software, and used it in the classification process.

STEP2

B. Data Preprocessing

Given the values of the features present in the data, to prevent their unrealistic impact and also reduce the data dispersion, it is common to try to map the values of the data features to the same range for each of them. For this purpose, operations such as normalization are used. In the current activity, we have used this operation. Equation 2 shows the normalization [21].

$$x_{normalized} = \frac{x - min}{max} \quad (2)$$

In the above equation, max and min are the maximum and minimum values of a feature for the samples, respectively. Using this equation, the values of all features in the samples will be mapped to the range [0,1].

STEP3

C. Scoring & Ranking & Labeling Cells With TOPSIS

In this step of the proposed algorithm, each cell is ranked and scored using the TOPSIS technique. Based on the score received by each cell, two categories of normal and abnormal cells are determined. Based on the score received by each cell, which varies from 0 to 1. Abnormal cells have a score close to zero.

The TOPSIS algorithm is a rule-based method and uses the concepts of ideality and similarity to rank data. The ideal solution is unattainable in real problems, so our goal is to find a close and optimal solution. TOPSIS treats an M-criteria problem as a geometric system. The method selects the alternative with the closest distance to the ideal solution and the furthest distance from the anti-ideal solution. TOPSIS ranks the alternatives based on their similarity to the ideal solution using the distance criterion as a criterion. In general, the TOPSIS method includes the following steps:

1. Construct the decision matrix
2. Normalize the decision matrix
3. Weight the normalized decision matrix
4. Determine the positive and negative ideal solutions (PIS and NIS)
5. Calculate the distances between the positive and negative ideal solutions
6. Compute the relative closeness
7. Rank the alternatives

The mathematical nature of the TOPSIS algorithm is fully explained in [61].

STEP4

D. Training Model

Combining machine learning models is used to maximize the strengths of each algorithm. There are three approaches in this regard:

- Bagging method
- Boosting method
- Voting method

To achieve this goal, three types of supervised machine learning algorithms are used. These algorithms have been used in the form of mixed voting learning in the proposed algorithm. Below, we refer to the machine learning algorithms used, and the results of each simulation are presented separately in the results section.

1. Naive Bayes Classification Method

The naive Bayes classification method [29] is a probabilistic approach that makes simple assumptions. In this method, it is assumed that the data samples and their features are functionally independent of each other and will not affect other samples in the results obtained from using them. A mathematical relationship is expressed for this classification with the assumption that given the assumed sample x, how likely is it that the sample in question belongs to the class?

Equation 1 expresses the generality of the naive Bayes method [29].

$$p(c_j|X) = \frac{p(X|c_j) * p(c_j)}{(X)} \quad (3)$$

The data sample x is a member of the class in which the probability value P has the highest value compared to other classes. In the naive Bayes method, since in the initial assumed model, we have the assumption of independence of samples and features, we may face an increase in classification error.

Reason for using the Naive Bayes algorithm: Predicting the class of the test data set is easy and fast. If the data has a normal distribution.

The data used in this study is normally distributed.

2. Decision Tree Classification Method

In this data structure, the decision tree [62] samples achieve classification based on their current class; it embodies an algorithmic nature more than a learning one. The decision tree's construction initiates from its root, culminating in leaf nodes: a strategic design that facilitates efficient analysis and prediction processes. The dataset's non-leaf nodes specify features, while each leaf node determines the class of a given sample. As for internal nodes, they possess branches correlating to potential answers; these are nothing but the current values for every feature. In terms of decision-making processes about a sample: it ultimately attains its relevant goal – this is what we refer to as its decision point. A set of questions determines the class by asking, and for this reason, we label such a structure as a decision tree; it is in this process that the sample's class gets determined. The process achieves maximum performance in most log k(n) stages if each internal node exhibits an exact branch count of k. Notably, n represents the number of internal nodes within the tree; thus, this feature underscores large data's high efficiency with decision trees. The decision tree uses the following features:

- It is suitable for classification problems- of discrete functions.
- It is resistant to noise in the input data, for example in samples where some features are valueless.
- It is represented understandably using if-then rules.
- Decision tree learning algorithms usually use greedy search.
- To build a decision tree in learning algorithms, samples must be labeled.

3. Random Forest Classification Method

Utilizing various base decision tree classifiers with distinct structures for our data separation operations yields a random forest [32]. Each independent decision tree, created through randomized feature selection at splitting nodes, contributes to the final classification of a data sample based on its unique structure. Finally, during classification. In short, Random Forest is a powerful and versatile ensemble algorithm that is becoming an essential tool in the field of machine learning. Its performance in over-reduction, handling a large number of features, and providing accurate predictions has made it a popular choice for application development. It can also be said that:

- It can perform both regression and classification tasks.
- It produces good predictions that are easy to understand.
- It can handle large data sets effectively.
- It provides a higher level of accuracy in predicting outcomes in decision-making algorithms.

STEP5

E. Determine Sample Class VOTING on Model

Using unsupervised methods means that decision-making is always based on examples. Our learning is model-less. This means that the entire dataset is needed during the decision-making process. This approach can disrupt the target operation. On the other hand, such algorithmic structures are ambiguous and, most importantly, without a mathematical model, there will be no precise criterion for evaluating the operation. Therefore, it becomes very important to design ideas to guide the process towards supervised patterns. With the labeling of the data done in the previous steps, the three classification algorithms mentioned are used, and the fourth step of these processes is carried out. In the fifth step, a hybrid model is presented to determine the class of a cell. To do this, we classify each example using all three algorithms, returning the output with the majority class as the output class.

In step 5, the proposed algorithm uses the majority vote learning model to predict defective cells. The three algorithms introduced in step 4 are trained independently and then their predictions are compared. Voting can be performed. In majority voting, the overall prediction is made based on the majority of the results of all models.

The next section analyzes the results of our proposed method.

IV. RESULTS

We compared the proposed method with basic machine learning methods as well as other similar methods using simulated data. The data used in the study consisted of 67,000 samples. Given the protocols that exist in networks, the cells present in the network had 543 defective samples according to the KPI values. In fact, this imbalance in the data is the biggest challenge that existed for decision-making in the samples. One of the reasons for using the classifiers is based on this existing parameter.

Table V compares the proposed method with each of the basic algorithms as well as several performed research.

- **Naive Bayes Classification Result**

Correctly Classified Instances	91.143 %
Incorrectly Classified Instances	4.857 %
Kappa statistic	0.1581
Mean absolute error	0.0485
Root mean squared error	0.2193
Relative absolute error	51.4057 %
Root relative squared error	100.985 %

TABLE VI

Naive Bayes Classification Result

Precision	Recall	F-Measure	Cell class
0.913	0.964	0.938	A=0
0.866	0.887	0.872	B=1

- **Decision Tree Classification Result**

Correctly Classified Instances	92.6878 %
Incorrectly Classified Instances	11.312 %
Kappa statistic	0.3023
Mean absolute error	0.1696
Root mean squared error	0.3252
Relative absolute error	83.239 %
Root relative squared error	102.589 %

TABLE VII

Decision Tree Classification Result

Precision	Recall	F-Measure	Cell class
0.904	0.914	0.900	A=0
0.923	0.985	0.953	B=1

- **Random Forest Classification Result**

Correctly Classified Instances	93.658 %
Incorrectly Classified Instances	11.312 %
Kappa statistic	0
Mean absolute error	0.1683
Root mean squared error	0.279
Relative absolute error	82.6153 %
Root relative squared error	88.022 %

TABLE VIII

Random Forest Classification Result

Precision	Recall	F-Measure	Cell class
0.936	0.949	0.944	A=0
0.897	0.900	0.899	B=1

- **Proposed Method Result**

Correctly Classified Instances:	94.0717 %
Incorrectly Classified Instances:	5.1283 %

TABLE IX

Proposed Method Result

Precision	Recall	F-Measure	Cell class
0.939	0.962	0.968	A=0
0.954	0.995	0.974	B=1

TABLE X

Comparing the Proposed Method by Basic Models and Some Related Research [63]

TAYP ML Algorithm	ALGORITHM Method	Scalability	Training Time	Response Time	Training Data	Complexity	Accuracy
Supervised Learning	Bayes	Low	Low	Low	Low	Low	Fair
	K-NN	Low	Low	Low	Low	Low	Fair
	NN	Fair	High	Low	High	High	High
	SVM	Fair	Fair	Low	High	High	High
	DT	High	Low	Low	Low	Low	Low
	CF	High	Fair	Low	High	High	High
Unsupervised Learning	K-Means	High	High	Low	Low	High	Fair
	SOM	High	Fair	Low	High	High	High
	Game Theory	Fair	---	Fair	---	Fair	Fair
	AD	Fair	Fair	Fair	High	Fair	Fair
Controllers	Feedback	High	---	Fair	---	Low	Low
	FLC	Low	---	Fair	---	Fair	Fair
Reinforcement Learning	QL	Fair	High	Fair	Low	Low	Fair
	FQL	Low	High	Fair	Fair	Fair	Fair
Markov	MC	High	Fair	Low	Fair	Low	Fair
	HMM	Fair	Fair	Low	Fair	Fair	Fair
Heuristics	Heuristics	Low	---	Fair	---	Fair	Fair
	GAs	Low	High	High	High	High	High

The comparison of the proposed algorithm with the methods in Table X based on the criteria listed is as follows:

Scalability :The purpose of feature scaling is to ensure that all features contribute equally to the learning process, regardless of their original scale. This is achieved in the proposed algorithm by considering the value of each index and assigning a weight of ten to each high-quality index in the prediction.

Training Time: Considering the three basic algorithms used, this criterion in the proposed method is fair compared to previous research.

Response Time: This criterion is fair based on the type and number of steps of the proposed algorithm. Because the proposed algorithm has a high speed in the ranking part and behaves fairly in the application of the bidding algorithms. This process is carried out in two stages for prediction. Once, three algorithms are applied independently and in the second part, majority voting is used.

Training Data: Due to the imbalance of normal and abnormal cells, it shows high quality based on the segmentation performed.

Complexity :This criterion is low in terms of accuracy, precision, and accuracy results. The reason for this is the use of the TOPSIS technique as a rule-based approach to overcome the challenge of the complexity of the problem data.

Accuracy: Based on the results, it is considered a highly accurate method.

Research conducted in the field of self-healing to detect defective cells is based on three principles:

1.Receiving the desired indicators from the network level

2.Not receiving indicators from the network level

3.Changes in some indicators in neighboring cells and determining cell failure based on behavioral changes in neighboring cells.

Unbalanced data: According to the results and research conducted on this topic, one of the most challenging issues is unbalanced data.

Most of the activities carried out in this section have been half-hearted. The reason for this is the number of failures per cell, which is a real working network is very low, and to overcome this challenge, new approaches must be achieved that have a very high ability to predict a low number of defective cells in the real network.

In the proposed algorithm, a new principle has been added to the previous approaches, which is:

The simultaneous receipt and non-reception of network level indicators are considered to detect cell failure.

This approach allows the cell performance status to be determined more accurately by weighting each indicator and considering positive and negative scores for the indicators.

In this proposed method, there is no restriction on considering the indicator to determine the quality of cell performance.

Also, in the innovative part of this algorithm, it can be noted that the status and quality of work of each cell are examined in three parts:

- Cell signaling status: A cell can, despite the ability to send voice, but if there is a problem in cell signaling, it is not able to serve the subscriber and vice versa

In previous research, most researchers' approach is focused on the normality or abnormality of the uplink and downlink links to determine the cell's operating status. Also, the indicators used in this research have been obtained from three levels: user, cell, and network. While in other research, most of the work has been done on data received from one area.

The algorithm used in this study provided favorable results The algorithm used in this study has provided favorable results considering the type of unbalanced data. However, in [24], this study due to the use of linear SVM algorithms and dimensionality reduction, has a good solution as long as the data set is not large. This method does not perform well for large data sets due to the complexity of the data due to the nature of the algorithms used. But the positive point of this is the reduction of the data dimensions, which increases the complexity of the algorithm and increases the response time, while in our proposed method the computational complexity of the data is eliminated with the TOPSIS technique and there is no need for dimensionality reduction.

V. CONCLUSION

Self-organizing communication networks (SON) automatically correct network structures to enhance operational efficiency by reducing OPEX and CAPEX. Identifying defective cells within the network using key performance indicators (KPIs) is crucial for maintaining network efficiency. Machine learning-based approaches are increasingly preferred over traditional methods for identifying problematic cells. A hybrid learning method combining rule-based labeling with ensemble supervised learning accurately predicts and differentiates defective cells. The TOPSIS algorithm categorizes data effectively, and a mix of naive Bayes, decision trees, and random forests improves classification accuracy. This approach addresses challenges with imbalanced datasets and mitigates model bias by using multiple algorithms. An iterative approach with multi-criteria decision-making algorithms like TOPSIS improves accuracy and sensitivity in identifying defective cells within the network. The algorithm used showed the following results: Precisio=0.939, Recall=0.962, F-Measure=0.968, Accuracy=94.0717.

VI. Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

VII. Conflict of Interests

All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

References

[1] J. Moysen and L. Giupponi, “From 4G to 5G: Self organized network management meets machine learning,” Computer Communications, vol. 129, pp. 248–268, Sep. 2018, doi: 10.1016/j.comcom.2018.07.015.

[2] J. Rodriguez, Fundamentals of 5G Mobile Networks. John Wiley & Sons, 2015.

[3] D. Mulvey, C. H. Foh, M. A. Imran, and R. Tafazolli, “Cell Fault Management Using Machine Learning Techniques,” IEEE Access, vol. 7, pp. 124514–124539, 2019, doi: 10.1109/access.2019.2938410.

[4] F.-L. Luo, Machine Learning for Future Wireless Communications. John Wiley & Sons, 2020.

[5] M. Amirijoo et al., “Cell outage management in LTE networks,” in 2009 6th International Symposium on Wireless Communication Systems, Sep. 2009. Accessed: Aug. 02, 2024. [Online]. Available: http://dx.doi.org/10.1109/iswcs.2009.5285232

[6] Q. Liao, M. Wiczanowski, and S. Stanczak, “Toward cell outage detection with composite hypothesis testing,” in 2012 IEEE International Conference on Communications (ICC), Jun. 2012. Accessed: Aug. 02, 2024. [Online]. Available: http://dx.doi.org/10.1109/icc.2012.6364384

[7] A. Karatepe and E. Zeydan, "Anomaly Detection In Cellular Network Data Using Big Data Analytics," European Wireless 2014; 20th European Wireless Conference, Barcelona, Spain, 2014, pp. 1-5.

[8] S. Novaczki and P. Szilagyi, “Radio Channel Degradation Detection and Diagnosis Based on Statistical Analysis,” in 2011 IEEE 73rd Vehicular Technology Conference (VTC Spring), May 2011. Accessed: Aug. 02, 2024. [Online]. Available: http://dx.doi.org/10.1109/vetecs.2011.5956417

[9] P. Kumpulainen, M. Särkioja, M. Kylväjä, and K. Hätönen, “Analysing 3G radio network performance with fuzzy methods,” Neurocomputing, vol. 107, pp. 49–58, May 2013, doi: 10.1016/j.neucom.2012.07.033.

[10] H. Yan, L. Breslau, Z. Ge, D. Massey, D. Pei, and J. Yates, “G-RCA,” in Proceedings of the 6th International Conference, Nov. 2010. Accessed: Aug. 02, 2024. [Online]. Available: http://dx.doi.org/10.1145/1921168.1921175

[11] R. N. Cronk, P. H. Callahan, and L. Bernstein, “Rule-based expert systems for network management and operations: an introduction,” IEEE Network, vol. 2, no. 5, pp. 7–21, Sep. 1988, doi: 10.1109/65.17975.

[12] G. Jakobson and M. Weissman, “Alarm correlation,” IEEE Network, vol. 7, no. 6, pp. 52–59, Nov. 1993, doi: 10.1109/65.244794.

[13] P. Frohlich, W. Nejdl, K. Jobmann, and H. Wietgrefe, “Model-based alarm correlation in cellular phone networks,” in Proceedings Fifth International Symposium on Modeling, Analysis, and Simulation of Computer and Telecommunication Systems. Accessed: Aug. 02, 2024. [Online]. Available: http://dx.doi.org/10.1109/mascot.1997.567613

[14] G. F. Ciocarlie et al., “Anomaly Detection and Diagnosis for Automatic Radio Network Verification,” in Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, Cham: Springer International Publishing, 2015, pp. 163–176. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-16292-8_12

[15] J. B. Porch, C. Heng Foh, H. Farooq, and A. Imran, “Machine Learning Approach for Automatic Fault Detection and Diagnosis in Cellular Networks,” in 2020 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom), May 2020. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/blackseacom48709.2020.9234962

[16] L. Alho, A. Burian, J. Helenius, and J. Pajarinen, “Machine Learning Based Mobile Network Throughput Classification,” in 2021 IEEE Wireless Communications and Networking Conference (WCNC), Mar. 2021. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/wcnc49053.2021.9417365

[17] P.-C. Lin, “Large-Scale and High-Dimensional Cell Outage Detection in 5G Self-Organizing Networks,” in 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Nov. 2019. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/apsipaasc47483.2019.9023348

[18] W. Li, P. Yu, M. Yin, and L. Meng, “A distributed cell outage compensation mechanism based on RS power adjustment in LTE networks,” China Communications, vol. 11, no. 13, pp. 40–47, 2014, doi: 10.1109/cc.2014.7022524.

[19] W. Wang, J. Zhang, and Q. Zhang, “Cooperative cell outage detection in Self-Organizing femtocell networks,” in 2013 Proceedings IEEE INFOCOM, Apr. 2013. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/infcom.2013.6566865

[20] L. Kayili and E. Sousa, “Cell outage compensation for irregular cellular networks,” in 2014 IEEE Wireless Communications and Networking Conference (WCNC), Apr. 2014. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/wcnc.2014.6952531

[21] de la Bandera, P. Munoz, I. Serrano, and R. Barco, “Adaptive Cell Outage Compensation in Self-Organizing Networks,” IEEE Transactions on Vehicular Technology, vol. 67, no. 6, pp. 5231–5244, Jun. 2018, doi: 10.1109/tvt.2018.2792406.

[22] W. Li, P. Yu, M. Yin, and L. Meng, “A distributed cell outage compensation mechanism based on RS power adjustment in LTE networks,” China Communications, vol. 11, no. 13, pp. 40–47, 2014, doi: 10.1109/cc.2014.7022524.

[23] B.-K. Yeo and Y. Lu, “Fast array failure correction using improved particle swarm optimization,” in 2009 Asia Pacific Microwave Conference, Dec. 2009. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/apmc.2009.5384420

[24] O. P. Babalola and V. Balyan, “Cell Outage Detection in 5G Self-organizing Networks Based on FDA-HMM,” in Proceedings of Fourth International Conference on Computing, Communications, and Cyber-Security, Singapore: Springer Nature Singapore, 2023, pp. 119–130. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1007/978-981-99-1479-1_9

[25] Kecman, “Support Vector Machines – An Introduction,” in Support Vector Machines: Theory and Applications, Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 1–47. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1007/10984697_1

[26] S. R. Eddy, “Hidden Markov models,” Current Opinion in Structural Biology, vol. 6, no. 3, pp. 361–365, Jun. 1996, doi: 10.1016/s0959-440x (96)80056-x.

[27] D. Verma, H. Saraf, and S. H. Gupta, “Prediction of user throughput from Network Parameters of LTE Network using machine learning,” Mobile Networks and Applications, vol. 28, no. 1, pp. 244–253, Mar. 2022, doi: 10.1007/s11036-022-01934-6.

[28] Z. Zhang, “Introduction to machine learning: k-nearest neighbors,” Annals of Translational Medicine, vol. 4, no. 11, pp. 218–218, Jun. 2016, doi: 10.21037/atm.2016.03.37.

[29] K. M. Al-Aidaroos, A. A. Bakar, and Z. Othman, “Naï ve bayes variants in classification learning,” in 2010 International Conference on Information Retrieval & Knowledge Management (CAMP), Mar. 2010. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/infrkm.2010.5466902

[30] Y. Wang, K. Zhu, M. Sun, and Y. Deng, “An Ensemble Learning Approach for Fault Diagnosis in Self-Organizing Heterogeneous Networks,” IEEE Access, vol. 7, pp. 125662–125675, 2019, doi: 10.1109/access.2019.2925566.

[31] Nguyen, V. “Anomaly detection in self-organizing network.” (2019).

[32] Y. Liu, Y. Wang, and J. Zhang, “New Machine Learning Algorithm: Random Forest,” in Information Computing and Applications, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 246–252. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-34062-8_32

[33] Y.-C. Tseng, Y.-C. Wang, K.-Y. Cheng, and Y.-Y. Hsieh, “iMouse: An Integrated Mobile Surveillance and Wireless Sensor System,” Computer, vol. 40, no. 6, pp. 60–66, Jun. 2007, doi: 10.1109/mc.2007.211.

[34] M. Xia, Y. Owada, M. Inoue, and H. Harai, “Optical and Wireless Hybrid Access Networks: Design and Optimization,” Journal of Optical Communications and Networking, vol. 4, no. 10, p. 749, Sep. 2012, doi: 10.1364/jocn.4.000749.

[35] B. S. Faiçal et al., “The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides,” Journal of Systems Architecture, vol. 60, no. 4, pp. 393–404, Apr. 2014, doi: 10.1016/j.sysarc.2014.01.004.

[36] S. Shamshirband, A. Amini, N. B. Anuar, M. L. Mat Kiah, Y. W. Teh, and S. Furnell, “D-FICCA: A density-based fuzzy imperialist competitive clustering algorithm for intrusion detection in wireless sensor networks,” Measurement, vol. 55, pp. 212–226, Sep. 2014, doi: 10.1016/j.measurement.2014.04.034.

[37] Abid, A. Kachouri, and A. Mahfoudhi, “Outlier detection for wireless sensor networks using density-based clustering approach,” IET Wireless Sensor Systems, vol. 7, no. 4, pp. 83–90, Aug. 2017, doi: 10.1049/iet-wss.2016.0044.

[38] P. K. Wali, M. N. A. Prasad, N. C. Shreyas, N. C. Chaithanya, and P. K. Kuttaiah, “Gaussian mixture model-expectation maximization-based signal strength prediction for seamless connectivity in hybrid wireless networks,” in Proceedings of the 7th International Conference on Advances in Mobile Computing and Multimedia, Dec. 2009. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1145/1821748.1821842

[39] Q. Feng, Y. Zhang, C. Li, Z. Dou, and J. Wang, “Anomaly detection of spectrum in wireless communication via deep auto-encoders,” The Journal of Supercomputing, vol. 73, no. 7, pp. 3161–3178, Mar. 2017, doi: 10.1007/s11227-017-2017-7.

[40] S. Z. Erdogan and T. T. Bilgin, “A data mining approach for fall detection by using k-nearest neighbour algorithm on wireless sensor network data,” IET Communications, vol. 6, no. 18, pp. 3281–3287, Dec. 2012, doi: 10.1049/iet-com.2011.0228.

[41] Y. Wang, K. Wu, and L. M. Ni, “WiFall: Device-Free Fall Detection by Wireless Networks,” IEEE Transactions on Mobile Computing, vol. 16, no. 2, pp. 581–594, Feb. 2017, doi: 10.1109/tmc.2016.2557792.

[42] X. Yu, H. Chen, W. Zhao, and L. Xie, “No-Reference QoE Prediction Model for Video Streaming Service in 3G Networks,” in 2012 8th International Conference on Wireless Communications, Networking and Mobile Computing, Sep. 2012. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/wicom.2012.6478588

[43] O. Salem, A. Guerassimov, A. Mehaoua, A. Marcus, and B. Furht, “Sensor fault and patient anomaly detection and classification in medical wireless sensor networks,” in 2013 IEEE International Conference on Communications (ICC), Jun. 2013. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/icc.2013.6655254

[44] M. A. Alsheikh, S. Lin, D. Niyato, and H.-P. Tan, “Machine Learning in Wireless Sensor Networks: Algorithms, Strategies, and Applications,” IEEE Communications Surveys & Tutorials, vol. 16, no. 4, pp. 1996–2018, 2014, doi: 10.1109/comst.2014.2320099.

[45] L. L. Thing, “IEEE 802.11 Network Anomaly Detection and Attack Classification: A Deep Learning Approach,” in 2017 IEEE Wireless Communications and Networking Conference (WCNC), Mar. 2017. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/wcnc.2017.7925567

[46] Z. Yuan, Y. Lu, Z. Wang, and Y. Xue, “Droid-Sec,” in Proceedings of the 2014 ACM conference on SIGCOMM, Aug. 2014. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1145/2619239.2631434

[47] S. Kaplantzis, A. Shilton, N. Mani, and Y. A. Sekercioglu, “Detecting Selective Forwarding Attacks in Wireless Sensor Networks using Support Vector Machines,” in 2007 3rd International Conference on Intelligent Sensors, Sensor Networks and Information, 2007. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/issnip.2007.4496866

[48] P. Blasco, D. Gunduz, and M. Dohler, “A learning theoretic approach to energy harvesting communication system optimization,” in 2012 IEEE Globecom Workshops, Dec. 2012. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/glocomw.2012.6477834

[49] E. Stevens-Navarro, Yuxia Lin, and V. W. S. Wong, “An MDP-Based Vertical Handoff Decision Algorithm for Heterogeneous Wireless Networks,” IEEE Transactions on Vehicular Technology, vol. 57, no. 2, pp. 1243–1254, Mar. 2008, doi: 10.1109/tvt.2007.907072.

[50] N. Mastronarde and M. van der Schaar, “Fast Reinforcement Learning for Energy-Efficient Wireless

Communication," IEEE Transactions on Signal Processing, vol. 59, no. 12, pp. 6262–6266, Dec. 2011, doi: 10.1109/tsp.2011.2165211.

[51] C. Pandana and K. J. R. Liu, "Near-optimal reinforcement learning framework for energy-aware sensor communications," IEEE Journal on Selected Areas in Communications, vol. 23, no. 4, pp. 788–797, Apr. 2005, doi: 10.1109/jsac.2005.843547.

[52] N. Lilith and K. Dogancay, "Distributed Dynamic Call Admission Control and Channel Allocation Using SARSA," in 2005 Asia-Pacific Conference on Communications, 2005. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/apcc.2005.1554084

[53] Y. Saleem, K.-L. A. Yau, H. Mohamad, N. Ramli, M. H. Rehmani, and Q. Ni, "Clustering and Reinforcement-Learning-Based Routing for Cognitive Radio Networks," IEEE Wireless Communications, vol. 24, no. 4, pp. 146–151, Aug. 2017, doi: 10.1109/mwc.2017.1600117.

[54] L. Xiao, Y. Li, C. Dai, H. Dai, and H. V. Poor, "Reinforcement Learning-Based NOMA Power Allocation in the Presence of Smart Jamming," IEEE Transactions on Vehicular Technology, vol. 67, no. 4, pp. 3377–3389, Apr. 2018, doi: 10.1109/tvt.2017.2782726.

[55] Sadeghi, F. Sheikholeslami, and G. B. Giannakis, "Optimal and Scalable Caching for 5G Using Reinforcement Learning of Space-Time Popularities," IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 180–190, Feb. 2018, doi: 10.1109/jstsp.2017.2787979.

[56] Y. He, F. R. Yu, N. Zhao, V. C. M. Leung, and H. Yin, "Software-Defined Networks with Mobile Edge Computing and Caching for Smart Cities: A Big Data Deep Reinforcement Learning Approach," IEEE Communications Magazine, vol. 55, no. 12, pp. 31–37, Dec. 2017, doi: 10.1109/mcom.2017.1700246.

[57] J. Liu, B. Krishnamachari, S. Zhou, and Z. Niu, "DeepNap: Data-Driven Base Station Sleeping Operations Through Deep Reinforcement Learning," IEEE Internet of Things Journal, vol. 5, no. 6, pp. 4273–4282, Dec. 2018, doi: 10.1109/jiot.2018.2846694.

[58] J. Moysen and L. Giupponi, "A Reinforcement Learning Based Solution for Self-Healing in LTE Networks," in 2014 IEEE 80th Vehicular Technology Conference (VTC2014-Fall), Sep. 2014. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1109/vtcfall.2014.6965842

[59] E. Vaezpour, L. Majzoobi, M. Akbari, S. Parsaeefard, and H. Yanikomeroglu, "A Deep Learning-Based Approach for Cell Outage Compensation in NOMA Networks," IEEE Open Journal of Vehicular Technology, vol. 3, pp. 149–166, 2022, doi: 10.1109/ojvt.2022.3164685.

[60] T. Zhang, K. Zhu, and D. Niyato, "A Generative Adversarial Learning-Based Approach for Cell Outage Detection in Self-Organizing Cellular Networks," IEEE Wireless Communications Letters, vol. 9, no. 2, pp. 171–174, Feb. 2020, doi: 10.1109/lwc.2019.2947041.

[61] J. Papathanasiou and N. Ploskas, "TOPSIS," in Multiple Criteria Decision Aid, Cham: Springer International Publishing, 2018, pp. 1–30. Accessed: Aug. 03, 2024. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-91648-4_1

[62] J. Myles, R. N. Feudale, Y. Liu, N. A. Woody, and S. D. Brown, "An introduction to decision tree modeling," Journal of Chemometrics, vol. 18, no. 6, pp. 275–285, Jun. 2004, doi: 10.1002/cem.873.

[63] Klaine, P. V., Imran, M. A., Onireti, O., & Souza, R. D. (2017). A survey of machine learning techniques applied to self-organizing cellular networks. *IEEE Communications Surveys & Tutorials*, *19*(4), 2392-2431.