A Case Study on Intelligent Operation System for Wireless Networks

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Abstract: The emerging fifth generation (5G) network has the potential to satisfy the rapidly growing traffic demand and promote the transformation of smartphone-centric networks into an Internet of Things (IoT) ecosystem. Due to the introduction of new communication technologies and the increased density of 5G cells, the complexity of operation and operational expenditure (OPEX) will become very challenging in 5G. Self-organizing network (SON) has been researched extensively since 2G, to cope with the similar challenge, however by predefined policies, rather than intelligent analysis. The requirement for better quality of experience and the complexity of 5G network demands call for an approach that is different from SON. In several recent studies, the combination of machine learning (ML) technology with SON has been investigated. In this paper, we focus on the intelligent operation of wireless network through ML algorithms. A comprehensive and flexible framework is proposed to achieve an intelligent operation system. Two use cases are also studied to use ML algorithms to automate the anomaly detection and fault diagnosis of key performance indicators (KPIs) in wireless networks. The effectiveness of the proposed ML algorithms is demonstrated by the real data experiments, thus encouraging the further research for intelligent wireless network operation.

Keywords: 5G; self-organizing network; machine learning; anomaly detection; fault diagnosis

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1 Introduction

The wireless communication technologies have experienced significant advancement over the past three decades, from the first generation (1G) system to fourth generation (4G) networks. The cellular networks successfully transform from pure telephony systems to versatile networks that can transport rich multimedia content and have a profound impact on our daily life. The rapid development of the mobile Internet generates a tremendous amount of traffic and consequently requires more bandwidth and better quality of experience. The next-generation wireless networks, i.e., the fifth generation (5G) cellular networks, which are assumed to be commercially deployed in 2020, have the potential to satisfy such a rapidly growing demand for data traffic [1].

The 5G networks mainly have three types of scenarios [2]: first, the enhanced mobile broadband (eMBB) aims to provide broadband multimedia to human-centric use cases; second, the ultra-reliable low latency service (URLLC) with strict requirements in terms of latency (ms level) and reliability (five nines and beyond) is used for remote control of robots or tactile Internet applications; third, massive machine type communications (mMTC) is mainly used to connect a very large number of devices and transmit a low load of non-delay-sensitive informa-

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tion. It is believed that 5G will significantly promote the transformation of the smartphone-centric networks into an Internet of Things (IoT) ecosystem [3] that integrates a heterogeneous mix of wireless-enabled devices ranging from smart-phones to connected vehicles, drones, wearables, sensors, and virtual reality devices. The throughput will be 1 000 times more in aggregate from 2015 to 2020 and the number of devices will grow to 500 billion [4]. In order to achieve the capacity growth, 5G cells have to be densely deployed, about 40 to 50 times as many as 4G networks. Moreover, a typical 5G node is expected to have 2 000 parameters to be configured and optimized, significantly more than a typical 2G node (500 parameters), a 3G node (1 000 parameters) and a 4G node (1 500 parameters) [5]. It is foreseen that the network operations of 5G will become an enormous challenge. As estimated in [5], there will be 53 to 67 times increase in operational complexity in 5G compared to 4G.

The operational expenditure (OPEX) is always an important issue for wireless networks. The idea of self-organizing network (SON) was evolved in 2G, 3G and 4G. However, the automation is realized by predefined policies, rather than intelligent analysis and smart decisions. It is time-consuming and expensive for 5G operators to operate and configure the network all manually by humans. In order to reduce the OPEX and facilitate the efficiency of the next generation networks, several studies have investigated the benefits of applying machine learning (ML) and big data technology in SON, showing promising results [5]–[8]. The ML engine has the potential to automate many scenarios of SON, for example, node deployment planning, advanced load balancing, resource allocation strategy, quality-of-experience (QoE)/quality-of-service (QoS) analysis, and network monitoring, paving a way to a proactive, self-aware, self-adaptive and highly efficient networking. In this paper, we focus on the intelligent operation of wireless network through applying ML technology.

This paper is organized as follows. In Section 2, the ML preliminaries are demonstrated, and a framework of intelligent operation system designed by layered scheme is proposed. Then two use cases are illustrated, which use ML algorithms to automate the anomaly detection and fault diagnosis of key performance indicators (KPIs) in wireless networks. Promising results for on-site data analyses are shown in Section 3. Finally, we draw the conclusions in Section 4.

2 Framework of the Intelligent Operation System

2.1 Machine Learning Preliminaries

ML technology has attracted wide attentions for several decades, especially with the third wave of artificial intelligence (AI) facilitated by rapid developments of deep neural networks, big data analysis and cloud computing. ML is being applied to more and more areas, for example, image processing, face recognition, speech recognition, natural language processing, computational advertising, recommendation system, and automated driving. Depending on the type of data input and output, and the type of task or problem intended to solve, there are three main categories of learning algorithms as follows:

1) Supervised Learning.

A supervised learning algorithm is fed with a set of data that contains both the inputs and the desired outputs. The data is known as the training data that consists of a set of training examples. Through iterative optimization of an objective function, a supervised learning algorithm aims to determine a general rule that can nicely map inputs to outputs. There are a number of popular supervised learning algorithms which have been developed and achieve successful applications, for example, regression model (RM), support vector machine (SVM), hidden Markov model (HMM), random forest (RF), and time series forecasting. In wireless networks, these models have the potential to solve a number of problems. Fox example, in massive multi-input multi-output (MIMO) systems associated with hundreds of antennas, both detection and channel estimation lead to high-dimensional search-problems, which can be addressed by these models to estimate or predict radio parameters that are associated with specific users [9]. Forecasting the trend of user equipment (UE) mobility or the traffic volume of different services is another possible application.

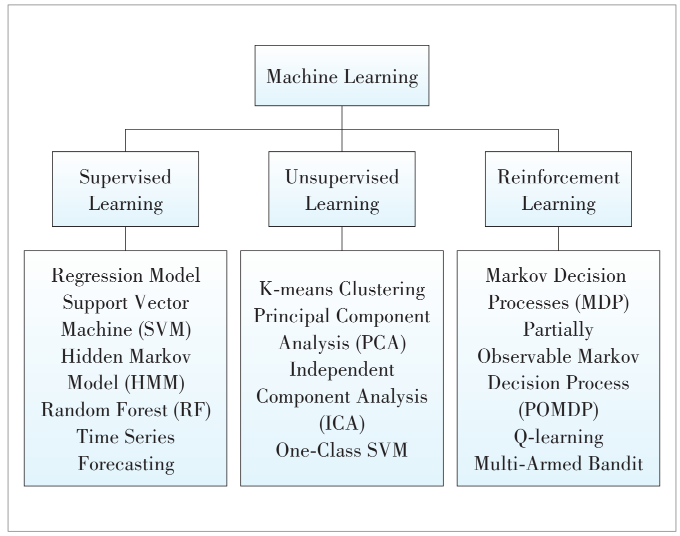
2) Unsupervised Learning.

Different from the aforementioned supervised learning, the input information for unsupervised learning does not contain priori labels. Therefore, the unsupervised learning algorithm has to rely on its own capability to find the embedded structure or pattern from its input, like grouping or clustering of data points. The typical unsupervised learning algorithms include K-means clustering, principal component analysis (PCA), independent component analysis (ICA), one-class SVM, etc. The K-means clustering was studied in [10] to partition the mesh access points (MAPs) into several groups in a hybrid optical/wireless network scenario, in order to optimize both the gateway partitioning and the virtual-channel allocation. K-means clustering can also be used to detect network anomaly. PCA and ICA are two common algorithms used for signal processing and feature dimension reduction. They can be developed for the physical layer signal dimension reduction of massive MIMO systems to reduce the computational complexity or in the area of anomaly-detection, and fault-detection problems of wireless networks with multi-performance data monitoring.

3) Reinforcement Learning.

Inspired by both control theory and behaviorist psychology, reinforcement learning is an area of machine learning regarded with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward. Many reinforcement learning algorithms use dynamic programming techniques and do not assume explicit knowledge of whether they have come close to its goal. They are used when exact models are infeasible. Due to its generality, the field is studied in many other disciplines, such as control theory, operations research, information theory, multi-agent systems, and swarm intelligence. There are several typical reinforcement learning algorithms, for example, Markov decision processes (MDP), partially observable Markov decision process (POMDP), Q-learning, and multi-armed bandit (MAB). In conjunction with MDP models, Q-learning has been extensively applied in heterogeneous networks. As in [11], the authors presented a heterogeneous fully distributed multi-objective strategy for the self-configuration/optimization of femto cells. The reinforcement learning methods can also be applied in problems like spectrum sharing for device-to-device networks and energy modeling in energy harvesting.

The three categories of machine learning algorithms and the typical methods in each category are summarized in **Fig. 1**.



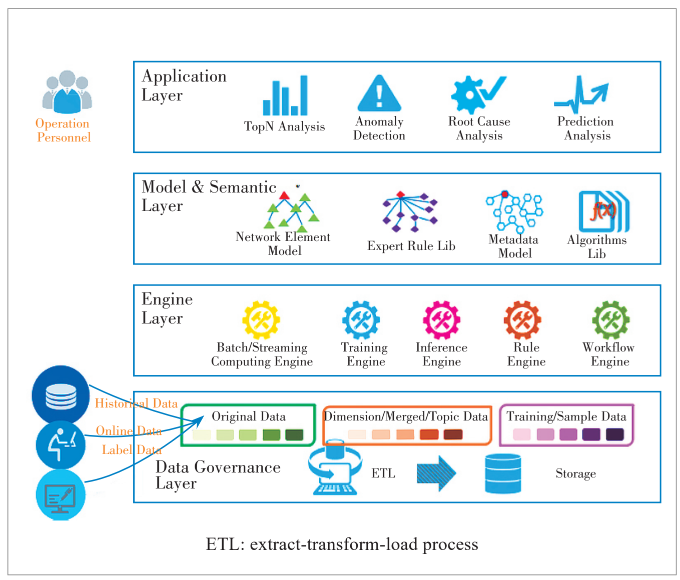
▲Figure 1. Three categories of machine learning algorithms and typical methods in each category.

2.2 Intelligent Operation System Design

Although ML can be applied in a number of aspects in SON, this paper focuses on the application of ML technology in the intelligent operation and maintenance (O&M) of wireless networks. **Fig. 2** demonstrates a possible implementation for the framework of intelligent operation system. The system is designed in such a layered manner as to maximize the flexibility, scalability, and manageability. The system consists of four layers: the data governance layer, engine layer, model & semantic layer, and application layer. Detailed description of each layer is demonstrated as follows.

1) Data Governance Layer.

The original data are collected, screened and transformed in this layer. Data is the fundamental ingredient for successful implementation of ML. In the wireless network system, diverse kinds of and large amount of data are produced from individual modules, which contain valued information for network maintenance. Examples of data include KPI data, key quality indicator (KQI) data, alarm data, configuration data, log data, etc. The data could be collected in three ways. Historical data are collected from a wide range in the history, mainly used for model training. Online data are collected automatically in real-time, which are used for online application of the trained model, such as anomaly detection of KPIs. Label data are collected by labeling tools and used to train supervised machine learning algorithms or improve the algorithm performance. For example, the operation expert can label each data point of a KPI whether anomalous. Then, these label data can be used to train an anomaly detection model. The collected original data are managed with an extract-transform-load (ETL) process, producing the dimensional data, merged data, topic data or training data. Dimensional data are produced from original data according to different perspectives, for example, KPIs could be classified into accessibility indicators, retainability indicators,



▲Figure 2. A general overview of intelligent operation system.

mobility indicators, etc. The original data could be merged spatially or temporally, for example, the cell-level KPIs are merged into sub-network level. Original data could be organized into topic data according to application scenario, for example, traffic flow data are used to network traffic monitoring. Training data are the final processed data that are able to calibrate the ML algorithms.

2) Engine Layer.

The engine layer provides a number of common engine modules for the upper application layer. The batch computing engine processes the off-line and high volumes of data, and the data often spread a wide period of time. A famous technology used for batch computing is the Hadoop Map/Reduce. The streaming computing engine is suitable for processing data in real-time, usually used for the computing of online ML models after they have been trained off-line. The training engine supplies a framework with training ML models. It defines several standard steps to train a ML model, such as data normalization, feature extraction, feature selection, model training, and post-processing. The rule engine and inference engine can be used to build expert systems, which are essentially composed of two sub-systems: the knowledge base and the inference engine. Both forward chaining and backward chaining reasoning modes are available in such a engine. The workflow engine provides tools for managing the processes of developing a ML application. It facilitates the organization of such modules as the data reading module, data preprocess module, training module, and online testing module. The engine layer can include other engine types, which are not showed here.

3) Model & Semantic Layer.

The model & semantic layer provides several abstract models and basic libraries to fulfill an end ML application. The network element (NE) model defines several explicit mathematical models of individual wireless network modules, for example, the communication model in physical layer, the device parameters of some physical components, the exact relationship between some KPIs, and the network topology of different elements. The metadata model is adopted to define some general concepts when a set of objects share the same attributes, operations, relations, and semantics. For example, a time series metadata model is formulated to represent all those data (KPIs/KQIs) of time series nature. The metadata model should define several common attributes: sampling frequency, time-range, period, sampling value, time-stamps, and etc. The expert rule library collects a number of rules defined by O&M experts. These rules can be used as input to ML algorithms or to improve the performance of the algorithm. For example, the experts can define the correlation of some alarms, for instance, one KPI is the root cause of another KPI. The algorithm library collects plenty of ML algorithm modules used for developing ML applications. As mentioned above, the ML algorithms include SVM, HMM, RF, ICA, PCA, K-means clustering, and so on.

4) Application Layer.

The application layer includes a number ML applications developed for facilitating the intelligent O&M of wireless network. These applications are produced by utilizing the components from the lower layers. They are usually developed case by case, to solve practical O&M problems and should be easily used by operation personnel. TopN analysis application would automatically show the top-n cells whose QoS are poor, such as with a high drop call rate, low connection rate, and low paging success rate. The TopN analysis is one of the most common functions for network maintenance. Its automation can significantly reduce the load of an O&M engineer. The anomaly detection application is used for automating the process of fault detecting in the network. Fox example, whether abnormal in each point of a KPI can be detected depends on dynamic threshold technology. Comparing with the static threshold configured by manner, a ML-directed dynamic threshold has the potential to improve detection accuracy and efficiency. Root cause analysis could be used for automatic association or correlation analysis between different events and detect the root cause, like an alarm or a detected KPI anomaly. The root cause analysis is critical for fault diagnosis and fault recovery. Prediction analysis is useful for QoS/QoE or other variable prediction according to historical and current state of the network. It is a critical step toward proactive operation of the system with possible applications like fault prediction, load balance, and capacity plan, consequently reducing the fault rate and increasing the resource utilization. It is worth noting that here only a few examples are enumerated and many other applications would be developed according to different requirements.

3 Use Cases

The aforementioned framework illustrates a unified solution for implementing an O&M operation system. In this section, two use cases will be described in detail, domestrating the ML algorithms developed for anomaly detection and anomaly diagnosis with KPIs. They are the example functions of the anomaly detection application and root cause analysis application in Fig. 2.

3.1 Anomaly Detection with KPIs

The KPI anomaly detection is quite important for network maintenance. Due to the complexity of a 5G network that contains numerous radio nodes and other components, there are a huge amount of KPI data to be monitored, which may be time consuming, error-prone and even impossible. An ML-based anomaly detection method is proposed in this paper, as shown in **Fig. 3**. It is essentially composed of three modules: anomaly detection, anomaly scoring, and feedback modules. The anomaly detection model and scoring model are trained with off-line data, using the batch computing engine and training engine in Fig. 2. Then, the KPIs data are detected online based on the streaming computing engine. The KPI data point whose anomaly score is higher than a predefined threshold will be noticed to the O&M engineer and the engineer can label it whether abnormal, providing feedback to the training module to improve the algorithm performance.

The KPIs represent varied characteristics because of the diverse characteristics of network modules. For example, some KPIs show periodicity while others do not; some KPIs have trend, while the other KPIs are stable. A two-stage modeling method is proposed in this paper to deal with the huge challenge for comprehensive modeling of all kinds of KPIs. As shown in **Fig. 4**, the first stage is the classification stage, where a time series clustering algorithm is formulated to classify the KPIs based on their structure characteristics. In the second stage, the module selects an appropriate time series model for each KPI category, predicting the normal baseline at each time point for a KPI. Avalue would be denoted as anomaly if it exceeds the baseline of the online detection.

The time series clustering method based on structural features has been introduced in [12], which proposed a hierarchical scheme to reduce the complexity of clustering. Firstly, the time series are classified into two main categories: the significant periodicity and non-significant periodicity, based on Fourier transformation. Secondly, the k-means algorithm is used to cluster the time series in each main category base on seven features extracted from the KPI series. In the first stage, the frequency amplitude spectrum of a KPI is calculated by discrete Fourier transformation (DFT) as follows:

$$\left|F[k]\right| = \left|\sum_{n=0}^{N-1} x(n) e^{-j\frac{2\pi}{N}kn}\right|, 0 \leqslant k \leqslant N-1. \tag{1}$$

We denote the maximum, mean and standard deviation of the amplitude spectrum as $|F|_{\max}$, $|F|_{\text{mean}}$, and $|F|_{\text{std}}$. If satisfying $|F|_{\max} > |F|_{\text{mean}} + c \cdot |F|_{\text{std}}$, where c is a predefined coefficient larger than 3, the KPI would be classified as significant periodicity, otherwise non-significant periodicity. Please refer to [12] for the more detailed descriptions of the clustering process.

When a KPI is classified, a suitable time series model will be selected according to its characteristic. There are a number of candidate models available, such as density estimation, Olympic model, regression model, Holt-Winters model, and auto-regressive integrated moving average (ARIMA) [13]. Fox example, if a KPI contains trend and periodicity, the Holt-Winters model is able to model it as following:

$$\begin{aligned} l_t &= \alpha^*(x_t - s_{t-m}) + (1-\alpha^*)(l_{t-1} + b_{t-1}) \\ b_t &= \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \\ s_t &= \gamma^*(x_t - l_{t-1} - b_{t-1}) + (1-\gamma^*)s_{t-m} \end{aligned}, \tag{2}$$

where l_t, b_t, and s_t are the level component, trend component and seasonal component respectively, and m is the period of time series. The forecasting value at h step would be:

$$\hat{x}_{t+h|t} = l_t + hb_t + s_{t-m+h_m^+}, \tag{3}$$

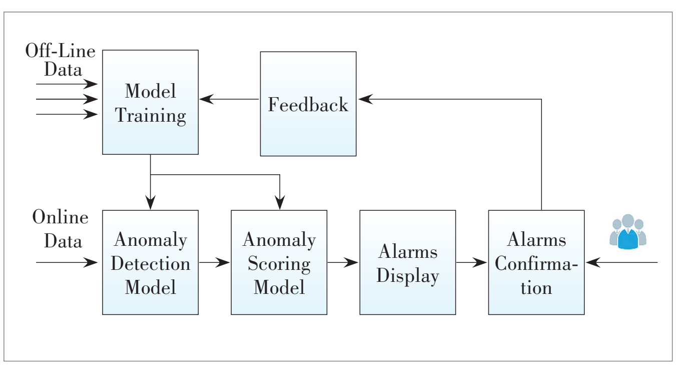
where $h_m^+ = \lfloor (h-1) \bmod m \rfloor + 1$. When the prediction value and fitting errors in historical data are calculated, the normal baseline could be formulated as:

$$\begin{aligned} \hat{x}_{t+h}^L &= \hat{x}_{t+h|t} - z_{1-\alpha/2}\sigma_H \\ \hat{x}_{t+h}^U &= \hat{x}_{t+h|t} + z_{1-\alpha/2}\sigma_H \end{aligned}, \tag{4}$$

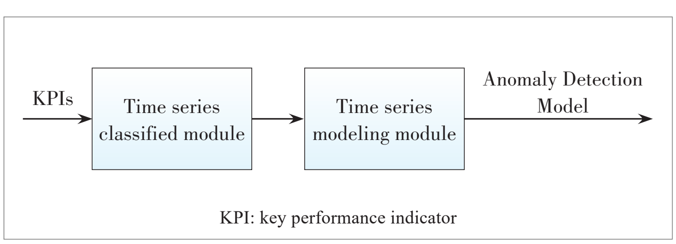
where $z_{1-\alpha/2}$ is the $1-\alpha/2$ percentile of standard Gaussian distribution and α_H is the standard deviation of fitting errors in historical data. A common used value for α is 0.003. **Fig. 5** is an illustration of the computed thresholds for a KPI.

The other types of KPI can be modeled by other time series models. For example, the data with significant randomness could be modeled by density estimation, rather than the Holt-Winter model.

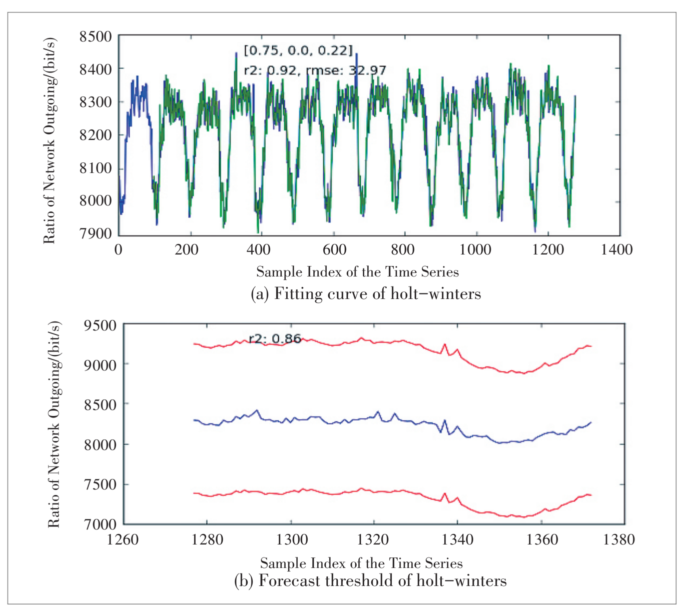
The anomaly scoring model is critical for reducing the false alarm and can facilitate the O&M engineer to focus on important events. The detailed algorithm would not be demonstrated



▲Figure 3. An illustration of machine learning (ML)-based anomaly detection method.



▲Figure 4. A demonstration of two-stage time series modeling method.



▲Figure 5. An illustration of time series modeling by Holt-Winters: (a) represents the true value (blue curve) and fitting value (green curve) in historical data; (b) represents the true value (blue curve) and the predicted thresholds (red curve) in the following day.

in the paper for the sake of space limit is a planning research topic in the future.

3.2 Anomaly Diagnosis with KPIs

When a KPI anomaly is detected, it is quite worthy to define the root causes for rapid fault recover. **Fig. 6** depicts the anomaly diagnosis method developed in this paper, which combines a rule-based diagnosis module and a ML-based diagnosis module to handle a wide range of scenarios.

As shown in Fig. 6, when the detected anomaly is a known fault that can be explicitly diagnosed by predefined expert rules, the rule-based diagnosis module could define the root causes according to related information, such as the NE model in Fig. 2, which contains the network topology, the exact mathematical function between the KPI and related counter indicators (counter indicators are more basic performance data, comparing to KPIs), and expert rule library. The rule-based module can generally output exact rule causes and provide direct execution suggestion for recovering.

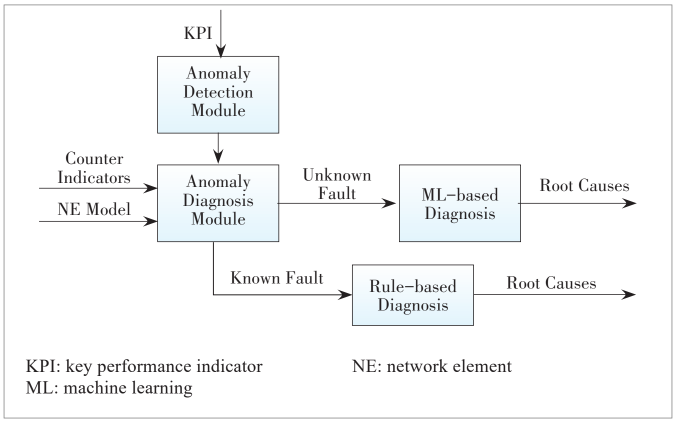
When the detected anomaly is an unknown fault, the ML-based diagnosis module would define the root causes by using the partial least squares regression (PLS) algorithm as proposed in this paper. The PLS has been used in multivariate monitoring of processing operating performance, which is almost in the same way as PCA-based monitoring [14]. Instead of only finding hyper-planes of maximum variance for independent variables, PLS finds a linear regression model by projecting the response variables and the independent variables to a new space. Compared to standard linear regression, PLS regression is particularly suitable when the dimension of response variables is more than independent variables and when there is multi-collinearity among independent variables. As illustrated in **Fig. 7**, when an abnormal KPI is detected, PLS models the KPI as a response variable and the correlated counter indicators as independent variables. Following the PLS modeling, the contribution analysis is conducted to find the top root counter indicators.

Denoting the data matrix of correlate counter indicators as $X$and the matrix of a KPI as Y, the PLS model between X and Y can be formulated as:

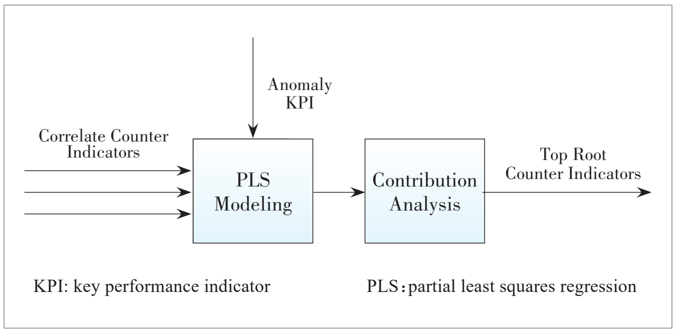
$$\begin{aligned} X &= TP^T + E \\ Y &= UQ^T + F, \end{aligned} \tag{5}$$

where T and U are projections of X (the X score, component or factor matrix) and projections of Y (the Y scores), respectively; P and Q are orthogonal loading matrices; and matrices E and F are the error terms. As the PLS model has only one response KPI, the PLS1 algorithm can be used for estimating the T, U, P and Q. And then, a T^2 statistic is used to represent the model status at each observation $\mathbf{x}$ as in [14]:

$$T^2 = \left\| \Gamma \mathbf{x} \right\|^2, \tag{6}$$



▲**Figure 6. A mixed scheme that combines the rule-based and ML-based diagnosis modules for KPI anomaly diagnosis.**



▲**Figure 7. Root cause analysis with PLS model when a KPI is abnormal.**

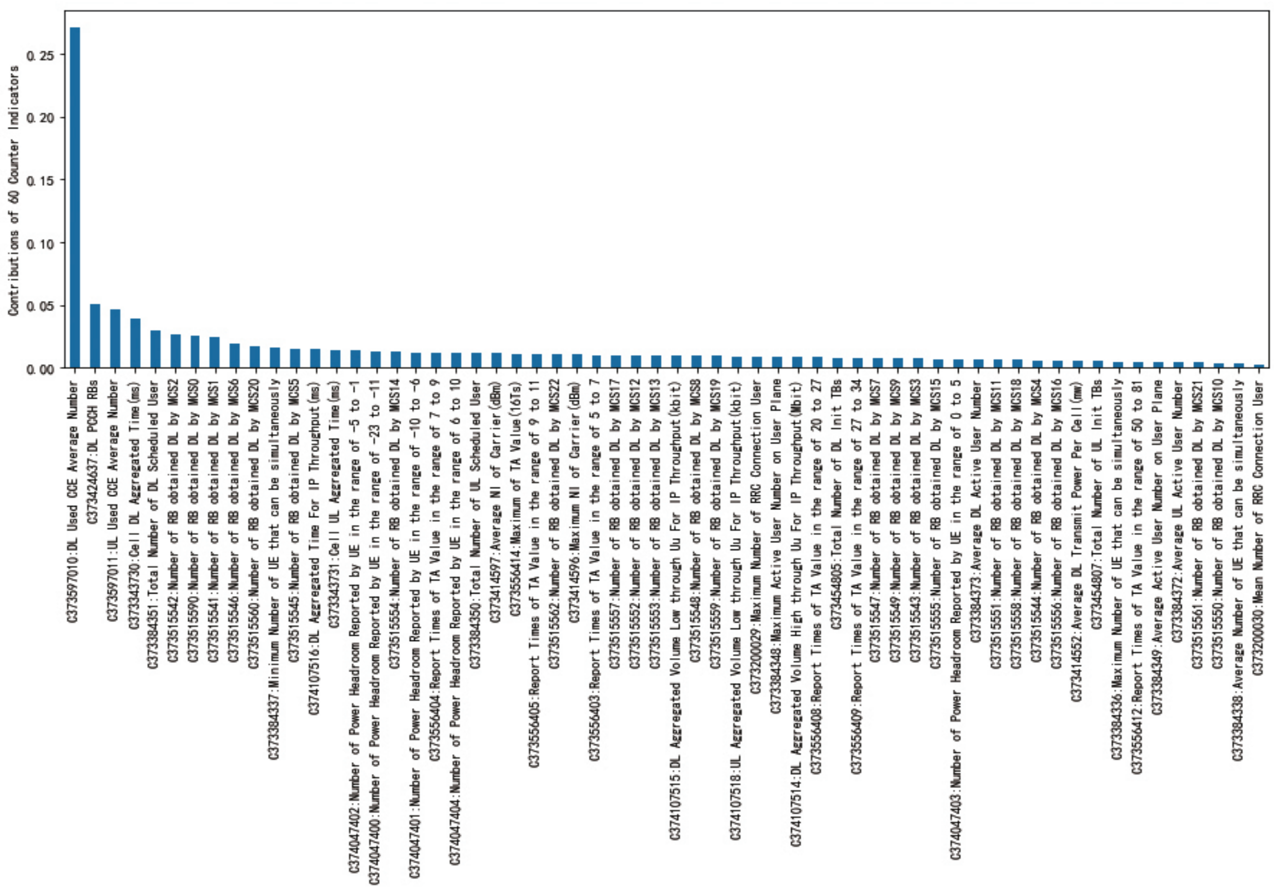
where $\Gamma = (R\Lambda^{-1}R^T)^{1/2}$, $\Lambda = \frac{1}{n-1}T^T T$ and R is the rotation matrix for X. The contribution of the i-th independent variable, i. e. counter indicator, to the T^2 statistic is calculated as:

$$C(T^2, i) = \left\| \gamma_i \mathbf{x}^2 \right\|, \tag{7}$$

where γ_i is the i-th row of Γ. The total contribution of the i-th counter indicator to the variation of the KPI can be calculated as the sum of $C(T^2, i)$ from n observations. The contributions of all counter indicators are sorted, and the top-n counter indicators are output as the root causes of the anomaly KPI. **Fig. 8** shows an experimental example, illustrating the contributions of 60 counter indicators to an anomaly KPI, downlink (DL) IP Throughput. The O&M expert confirms that the top counter indicator, C373597010:DL Used Control Channel Element (CCE) Average Number, is useful for the anomaly diagnosis, demonstrating the effectiveness of the proposed algorithm.

4 Conclusions

The research of intelligent O&M has attracted extensive in-



CCE: control channel element
DL: downlink
MCS: modulation coding scheme
NI: noise interference
PCCH: paging control channel
RB: resource block
RRC: radio resource control
TA: timing advance
UE: user equipment
UL: uplink

▲Figure 8. An experimental example of partial least squares regression (PLS) method for root cause analysis.

terest for IT system in recent years, which is known as AIOps [15]. However, this topic is relatively less discussed in wireless networks. As the evolution of wireless networks and the emerging of 5G, the networks become more complicated, emphasizing the disadvantage of manual operation and the desire to automate O&M process with intelligent analysis to handle such a challenge. In this paper, we try to formulate an intelligent operation system based on the layering concept, resulting in a flexible, scaling and manageable framework. And then, two practical use cases, the anomaly detection with KPIs data and the anomaly diagnosis of KPIs data, are studied based on the framework. A two-stage time series modeling method is proposed to construct the anomaly detection model, and a mixed scheme is proposed to the anomaly diagnosis. The real data experiments demonstrate the effectiveness of the proposed method, thus encouraging the further research for intelligent operation with ML technology. In the future, we would develop more use cases to resolve other operation issues in wireless network, for example the top-n cells analysis, the automated log analysis, the prediction analysis, and the optimal parameters configuration.

References

[1] MITRA R N, AGRAWAL D P. 5G Mobile Technology: A Survey [J]. ICT Express, 2015, 1(3): 132 – 137. DOI: 10.1016/j.icte.2016.01.003

[2] C-LI, HAN S, XU Z, et al. New Paradigm of 5G Wireless Internet [J]. IEEE Journal on Selected Areas in Communications, 2016, 34(3): 474 – 482. DOI: 10.1109/JSAC.2016.2525739

[3] PARK T, ABUZAINAB N, SAAD W. Learning How to Communicate in the Internet of Things: Finite Resources and Heterogeneity [J]. IEEE Access, 2016, 4: 7063 – 7073. DOI; 10.1109/ACCESS.2016.2615643

[4] SOLDANI D, MANZALINI A. Horizon 2020 and Beyond: On the 5G Operating System for a True Digital Society [J]. IEEE Vehicular Technology Magazine, 2015, 10(1): 32 – 42. DOI: 10.1109/MVT.2014.2380581

[5] IMRAN A, ZOHA A, ABU-DAYYA A. Challenges in 5G: How to Empower SON

with Big Data for Enabling 5G [J]. IEEE Network, 2014, 28(6): 27 – 33. DOI: 10.1109/MNET.2014.6963801

[6] KIBRIA M G, NGUYEN K, VILLARDI G P, et al. Big Data Analytics, Machine Learning, and Artificial Intelligence in Next-Generation Wireless Networks [J]. IEEE Access, 2018, 6: 32328 – 32338. DOI: 10.1109/ACCESS.2018.2837692

[7] LONG F, LI N, WANG Y X. Autonomic Mobile Networks: the Use of Artificial Intelligence in Wireless Communications [C]//2nd International Conference on Advanced Robotics and Mechatronics (ICARM). New York, USA: IEEE, 2017: 582 – 586. DOI: 10.1109/ICARM.2017.8273227

[8] JIANG C X, ZHANG H J, REN Y, et al. Machine Learning Paradigms for Next-Generation Wireless Networks [J]. IEEE Wireless Communications, 2016, 24(2): 98 – 105. DOI: 10.1109/MWC.2016.1500356WC

[9] FENG V - S, CHANG S Y. Determination of Wireless Networks Parameters Through Parallel Hierarchical Support Vector Machines [J]. IEEE Transactions on Parallel and Distributed Systems, 2011, 23(3): 505 – 512. DOI: 10.1109/TPDS.2011.156

[10] XIA M, OWADA Y, INOUE M, et al. Optical and Wireless Hybrid Access Networks: Design and Optimization [J]. Journal of Optical Communications and Networking, 2012, 4(10): 749 – 759. DOI: 10.1364/JOCN.4.000749

[11] ALNWAIMI G, VAHID S, MOESSNER K. Dynamic Heterogeneous Learning Games for Opportunistic Access in LTE-Based Macro/Femtocell Deployments [J]. IEEE Transactions on Wireless Communications, 2014, 14(4): 2294 – 2308. DOI: 10.1109/TWC.2014.2384510

[12] MENG Z H, LIU J W, HAN J. Time Series Clustering Based on Structural Features [J]. ZTE Technology Journal, 2018, 24(03): 61 – 66. DOI: 10.3969/j.issn.1009-6868.2018.03.011

[13] LAPTEV N, AMIZADEH S, FLINT I. Generic and Scalable Framework for Automated Time-Series Anomaly Detection [C]//Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York, USA: ACM, 2015: 1939 – 1947. DOI: 10.1145/2783258.2788611

[14] LI G, QIN S-Z, JI Y-D, et al. Total PLS Based Contribution Plots for Fault Diagnosis [J]. Acta Automatica Sinica, 2009, 35(6): 759 – 765. DOI: 10.1016/S1874-1029(08)60094-4

[15] DANG Y N, LIN Q W, HUANG P. AIOps: Real-World Challenges and Research Innovations[C]//Proceedings of the 41st International Conference on Software Engineering: Companion Proceedings. New York, USA: IEEE Press, 2019: 4 – 5. DOI: 10.1109/ICSE–Companion.2019.00023

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