Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Anomaly Detection of LTE Cells using KNN Algorithms:

The Case of Addis Ababa

By

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Approval by Board of Examiners

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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This thesis has been submitted for examination with my approval as a university advisor.

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Abstract

For mobile operators, delivering quality service to their customers is very important as service quality significantly affects their business. To achieve a consistent quality service delivery, they need to continuously monitor and analyze their network performance and timely address any obtained performance drops. Performance drops in mobile networks can be observed in key performance indicators (KPIs) of spatially distributed cells with different magnitude and at different time periods. As it is practically difficult to address all performance drops simultaneously, it is preferable to make prioritized corrective actions starting from cells with critical drops, also called anomaly cells. To detect anomaly cells, different automated methodologies have been proposed and analyzed.

Yet, ethio telecom still applies manual and subjective anomaly detection method where measured KPI values are manually compared with fixed thresholds to determine if the measured values are within defined required ranges or not. Cells with KPI values out of the required range are analyzed for identifying performance drop root causes and taking corrective actions. The manual and subjective anomaly detection method is prone to detection errors and is maintenance time, manpower and then cost inefficient. These challenges of manual and subjective detection can be improved by applying advanced automatic methods based on machine learning algorithms.

In this thesis work, KNN based anomaly detection algorithms such as KNN classification, local outlier factor (LOF) and connectivity outlier factor (COF) anomaly detection models is implemented, and their comparative evaluation are made for Addis Ababa LTE cells. The comparison is made based on type of output, complexity and their true positive rate (TPR) for time series and cell level detections. Unlike KNN classification, LOF and COF do not need heavy data set training and are able to provide anomaly scores instead of two-class labels. Experimentation results show that COF provides slightly better performance than the other models with negligible performance difference. For instance, the performance of COF with respect to TPR for RRC setup success rate in the experimentation is 97.91% for cell level detection and 88% for time series detection.

Key words: Anomaly detection, Connectivity outlier factor, Local outlier factor, KNN classification, Machine Learning, KPI, Alarm, LTE

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List of Acronyms

3GPP	3rd generation partnership project
AUC	Area under ROC curve
COF	Connectivity outlier factor
EPC	Evolved packet core
E-RAB	Evolved radio access bearer
EWMA	Exponentially weighted moving average
FPR	False positive rate
FNR	False negative rate
HSPA	High speed packet access
HSS	Home subscription server
IS	Information system
KNN	K nearest neighbours
KPI	Key performance indicator
LOF	Local outlier factor
LTE	Long term evolution
MME	Mobility management entity
MNO	Mobile network operator
NMS	Network management system
PCC	Policy and charging control
PCRF	Policy and charging resource function
P-GW	Packet data network gateway
PRB	Physical resource block
PRS	Performance record system
PS	Packet switch
QoS	Quality of service
RAN	Radio access network
ROC	Region of convergence
RRC	Radio resource control

RRU	Radio resource unit
SAE	System architecture evolution
SDR	Service drop rate
S-GW	Serving gateway
SLA	Service level agreement
SMC	Service management center
SON	Self-organized networks
SPC	Statistical process control
TS	Time series
TNR	True negative rate
TPR	True positive rate
UE	User equipment
VoIP	Voice over internet protocol

1. Introduction

1.1 Background and Motivation

Today, where subscribers need seamless connectivity anywhere and anytime, increasing base stations for providing adequate capacity and coverage is not enough. Thus, mobile operators need to timely monitor their network and work on quality of service assurance for providing granted quality of service to customers. However, the changing dynamics of radio network features and metrics pose challenges for operators in terms of optimizing and maximizing network efficiency while reducing operational expenditure [1]. According to [2] radio access network (RAN) organizations are always in need of quick answers to the following questions:

- Is there an easier way of sensing the performance and quality of a RAN network?
- Is there a more efficient way to detect and compensate for service performance drops?

Globally, competition in the liberalized telecommunications markets and the requirements of customers for more complex services are leading to a greater emphasis on quality of service automation [1]. To prevent fault and outage early before they possibly occur it is important that the detection and localization of anomaly cells should be as fast as possible. The efficiency of anomaly detection determines the quality of taking corrective actions for performance drop recovery. To realize network monitoring automation operators are moving towards self-organized networks (SON) self-healing functionalities to detect and fix network faults [3-5].

In ethio telecom network monitoring is done on equally spaced time intervals (monthly, weekly, daily and hourly) for all cells as shown in Figure 1-1. The performance values queried from performance recording systems (PRS) mostly depend on the configuration quality in the U2000 server and the quality of configuration depends on the detection and analysis quality of the quarried performance values. Performance values of several cells in Addis Ababa do not fulfill the requirement value range, and priority for taking corrective actions to bring into the requirement range is given to cells with significant performance drop also called anomaly cells in this thesis work. Anomaly cells mostly occur in LTE network as the network features are dynamic and more complex than the other technologies.

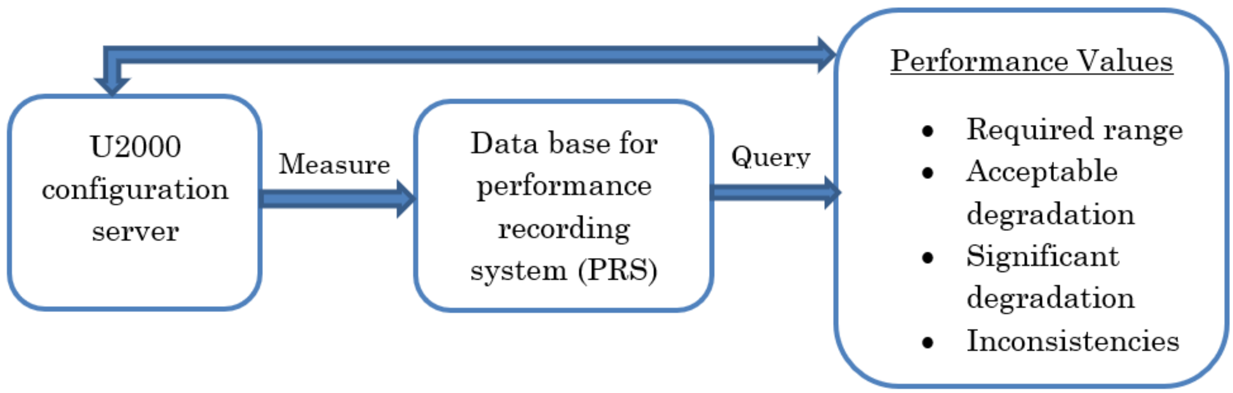


Figure 1-1 LTE Cells KPI Monitoring Architecture

Currently, ethio telecom applies a fixed KPI requirement threshold to determine if cells fulfill the required range or not. For cells that do not fulfill the requirement, detection of anomaly cells is done on manual and subjective bases without considering the severity of performance drop. With the manual and subjective detection, it is practically difficult to routinely detect anomaly cells from hundreds of diverse KPI measured values. Thus, a mechanism to automatically detect anomaly cells in every KPI metrics needs to be implemented. As discussed in [6] in operational cellular networks cell level and time series anomaly detection mechanisms are feasible.

As explained in [7] machine learning significantly improves the efficiency of routine activities as it provides systems the ability to automatically learn and improve from experience. As there are several automatic anomaly detection models, it is important to have their comparative evaluation to select the best model for Addis Ababa LTE cells.

1.2 Statement of the Problem

The manual and subjective anomaly detection method in ethio telecom consumes maintenance time and manpower and, hence, is cost inefficient. As the performance of several cells in different KPI metrics do not meet the fixed requirement threshold and it is practically difficult to fix all the cells in all metrics simultaneously, the manual and subjective detection faces difficulty in prioritizing cells for corrective actions. Thus, anomalies remain unfixed for a longer time and they become a cause for anomalies of higher magnitude and complete network outages. The manual detection process is prone to errors, thus detected anomalies raise questions of credibility in different regions of the company and sometimes become a source of conflict between departments.

In summary, the main problems are,

- The hard and fixed KPIs threshold does not consider the dynamic nature of cells as it is fixed.
- The current manual detection is done based on current performance values and faces difficulty to include history performance values.
- The manual anomaly detection is maintenance time, manpower and then cost inefficient.
- The manual anomaly detection method is prone to errors, thus it may lead to wrong analysis and let anomalies to remain unfixed.

1.3 Objectives

1.3.1 General Objective

The general objective of this thesis work is to present performance comparison and implementation of machine learning algorithms for automatic detection of anomaly cells for Addis Ababa LTE network.

1.3.2 Specific Objectives

The specific objectives of the thesis are

- Undertake performance comparison of anomaly detection algorithms for Addis Ababa LTE cells.
- Select and implement most suitable machine learning algorithms for cell level and time series anomaly detection of LTE cells in Addis Ababa.
- Present the most anomaly cells for selected KPIs along with their anomaly score and occurrence time.

1.4 Methodology

The applied methodology for this thesis work is depicted in Figure 1-2.

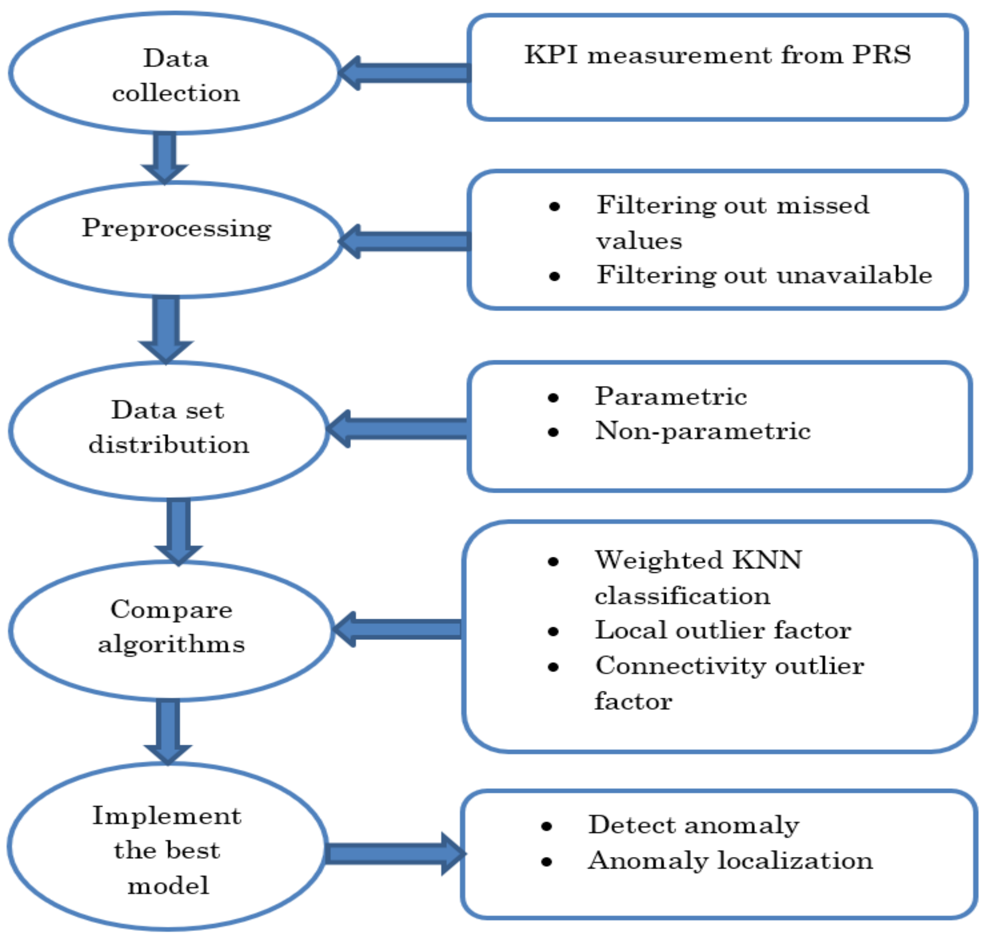


Figure 1-2 General Methodology of the Thesis

The detection work starts with collection of LTE cells performance data. Because it is practically difficult to have experimentation for all KPIs RRC setup success rate, E-RAB setup success rate and service drop rate KPI metrics are collected as a sample raw data.

After collecting the data, preprocessing work is done to filter out inconsistent values. The algorithms that can be applied accept numeric values only and missed values should be filtered out. Because performance drops due to power outage, alarms and transmission cut should not be considered as anomalies, performance values of cells with alarms and unavailable cells are also filtered out.

For there are several anomaly detections models, model comparison is done considering different criteria and the best model is accordingly selected. Implementation of different algorithms that are based on the best model, performance evaluation and comparison of the algorithms is done using Matlab as a tool.

1.5 Related Work

Performance anomalies in LTE cells occur due to several reasons. One of the main causes of an anomaly in mobile networks is an error in feature configuration and parameter change.

In [1] a configuration management assessment method for a SON in mobile networks using a two-sample Kolmogorov-Smirnov test is explained. The authors in [1] collected RRC setup success rate, E-RAB setup success rate, inter eNodeB handover success rate and cell availability of 1230 eNodeBs from a network management system (NMS) as a raw data. The authors noted that not all configuration changes bring a positive result and some configuration changes can lead even to a worse performance drop. Their focus is to give recommendations to undo or accept the corresponding configuration changes. However, the methodology the authors followed shows a two class (normal or anomaly) labeled result, and hence it is difficult to have the degree of anomaly and evaluate the severity of performance drops with the corresponding KPI metrics.

There are several types of anomaly detection algorithms that are applied to different data set types. These algorithms are different for different services (voice, data, image) and for different data set distribution types (parametric and non-parametric). In [9] comparison of different anomaly detection algorithms is clearly explained and recommends the preferred anomaly detection model for different data set types and purposes. The focus of [9] is to compare unsupervised anomaly detection algorithms for different services. The paper clearly explained and compared KNN-based, clustering-based, statistical-based, subspace-based and classifier-based anomaly detection algorithms, but none of them is implemented for LTE KPIs data.

In [6][10] it is explained that no single model can accurately detect all anomalies in mobile network performance. The papers focus on the problem of cell anomaly detection, addressing partial and complete degradations in cell-service performance, and they implemented an adaptive ensemble method framework for modeling cell behavior. The framework uses key performance indicators (KPIs) to determine cell-performance status and control legitimate system configuration changes.

In [11] cell outage detection via handover success rate anomaly detection in UMTS networks is discussed. The author applied density-based local outlier factor for the anomaly detection and percentile-based threshold setting by preparing a reference value at first. The paper has not explained the degree of the service outage and could not indicate if the outages are performance drop or complete failures. The author has not also explained how exactly the initial reference threshold values are set.

Several other related works are done. However, to the best of my knowledge cell level and time series anomaly detection algorithm that considers spatial and temporal proximity and is more suitable for Addis Ababa LTE network KPIs is not studied and selected, while demonstrating the feasibility of operational deployment.

1.6 Scope and Limitation of the Thesis

The scope of the thesis is to compare and implement KNN-based anomaly detection methods for Addis Ababa LTE cells for cell level and time series scenarios.

The limitation of the thesis is that anomaly detection experimentation is done for selected KPI metrics and not for all. Thus, anomaly detection of cells from KPIs that can be measured with a driving test is not included in both scenarios.

1.7 Contribution of the Thesis

This research work presents the following two major contributions:

- It provides comparative analysis of KNN algorithms for anomaly detection in the context of Addis Ababa LTE network and can supports operators to select the most appropriate anomaly detection model for their network.
- It provides the directions and methodologies for automating the current manual anomaly detection approach. This automation can help operators to enhances service quality and revenue by saving maintenance time, manpower and then cost. Furthermore, it presents better data insights and avoids human errors and thus bring better credibility in reporting.

1.8 Thesis Structure

The thesis is organized as follows:

Chapter two presents a theoretical background on LTE networks, LTE KPIs and anomalies. Chapter three presents basics of anomaly detection methods and anomaly detection classification aspects. Chapter four discusses anomaly detection in the case of Addis Ababa LTE network and the limitations of the current detection mechanism applied in ethio telecom. Chapter five is about KNN-based anomaly detection methods and their mathematical models. Experimentation of data sets and result analysis along with performance evaluation of the algorithms are discussed in Chapter six. Finally, Chapter seven deals with conclusion and future work.

2 LTE KPIs and Performance Anomaly

According to [13] LTE is defined as a new packet-only wideband radio with flat architecture technology developed to get enhanced capacity, reduced service latency, increased data rate and lower cost data delivery than previously developed GSM and UMTS services. The initial assumption during development was that LTE will have a peak downlink data rate of 100Mbps and uplink data rate of 50Mbps with a round trip time (RTT) latency of 10ms. LTE uses orthogonal frequency division multiple access (OFDMA) in downlink and single carrier frequency division multiple access (SC-FDMA) in uplink as multiple access. Resource allocation in the frequency domain takes place with a resolution of 180 kHz resource blocks called physical resource blocks (PRB) both in uplink and in downlink. Resources are allocated based on different scheduling techniques.

The work towards LTE started in 2004 and is continuously evolving [13][14]. LTE standards are delivered in rolling versions or releases. The first LTE standard is Release 8, that could deliver a downlink data rate of 150Mbps and uplink data rate of 75Mbps which is higher than the target set. According to [13] 3GPP standardized LTE network versions as shown in Table 2-1.

Table 2-1 LTE Standard Versions

Release	Release 8	Release 10	Release 11	Release 12	Release 13	Release 14	Release 15
Freeze date	2009	2010			2016		2018
Comment	LTE	LTE-A			LTE-A Pro		

In Addis Ababa LTE Release 8 technology is installed. Thus, the LTE technology in this paper refers to "LTE Release 8". All the LTE cells in Addis Ababa are installed with the same capacity but configured with different network parameter values.

2.1 LTE Network Architecture

The service quality delivered is determined by different network elements and interfaces between them. The fact that KPI as a measure of service quality needs to be end to end (from the mobile user equipment to the core elements), it is important to see how the different network components are linked and interconnected. According to [13] the LTE network architecture that includes the network elements along with the interfaces looks as shown in Figure 2-1.

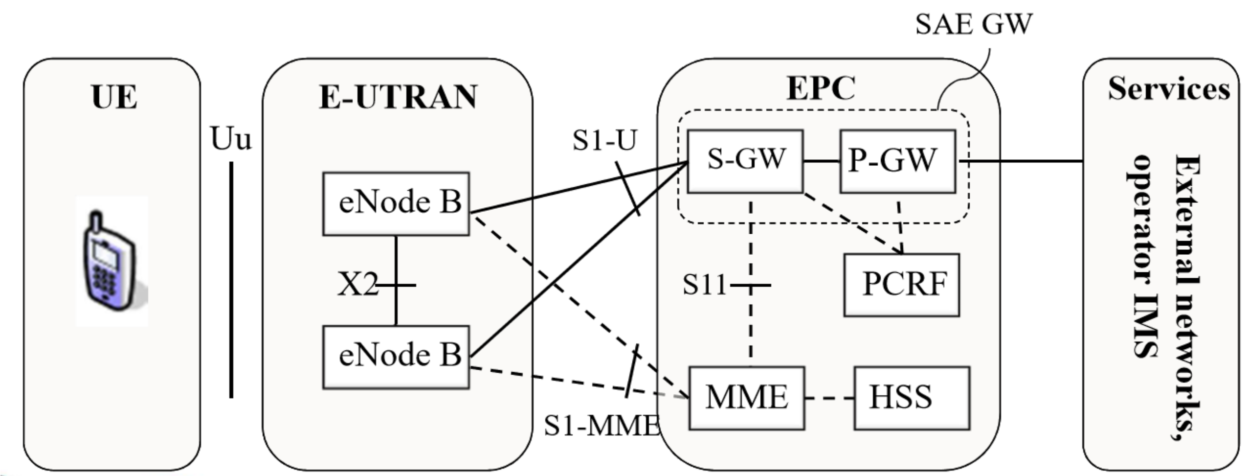


Figure 2-1 LTE Network Architecture[13]

As can be seen in Figure 2-1 there are several LTE network elements and components. By referring to books in [13] and [14] the description of LTE components is explained as,

I. User Equipment

The user equipment (UE) is the device that the end user uses for communication. Typically, it is a handheld device such as a smart phone or a data card or it could be embedded, e.g. to a laptop. UE also contains the universal subscriber identity module (USIM) which is a separate module from the rest of the UE, which is often called the Terminal equipment (TE). USIM is used to identify and authenticate the user and to derive security keys for protecting the radio interface transmission. Functionalities that include mobility management functions such as handovers and reporting the terminal's location are supported by the user equipment.

II. E-UTRAN Node B

E-UTRAN NodeB (eNodeB) is a radio base station that is in control of all radio related functions in the fixed part of the system. eNodeBs are typically distributed throughout the network's coverage area, each eNodeB residing near the actual radio antennas. Functionally eNodeBs acts as a layer 2 bridge between UE and evolved packet core (EPC), by being the termination point of all the radio protocols towards the UE. In this role, the eNodeB performs ciphering and deciphering of data, IP header compression and decompression, which means avoiding repeatedly sending the same or sequential data in an IP header. The eNodeB is responsible for and has an important role in radio resource management, mobility management, bearer handling, user plane data delivery, securing and optimizing radio interface delivery.

III. Mobility Management Entity

Mobility management entity (MME) is the main control element in the EPC. Typically, the MME would be a server in a secure location in the operator's premises. It operates only in the control plane and is not involved in the path of user plane data. The main MME functions include authentication and security, mobility management, managing subscription profile and service connectivity.

IV. Serving Gateway

Serving gateway (S-GW) is part of the network infrastructure maintained centrally in operation premises for user plane tunnel management and switching. The S-GW has a very minor role in control functions. It is only responsible for its own resources, and it allocates them based on requests from MME, P-GW or PCRF, which in turn are acting on the need to set up, modify or clear bearers for the UE.

V. Packet Data Network Gateway

Packet data network gateway (P-GW) is the edge router between the EPC and external packet data networks. It is the highest-level mobility anchor in the system, and usually it acts as the IP point of attachment for the UE. It performs traffic gating and filtering functions as required by the service in question. As to the S-GW, the P-GWs are maintained in operator premises in a centralized location. P-GW is the highest-level mobility anchor in the system. When a UE moves from one S-GW to another, the bearers must be switched in the P-GW. The P-GW will receive an indication to switch the flows from the new S-GW.

VI. Policy and Charging Resource Function

Policy and charging resource function (PCRF) is the network element that is responsible for policy and charging control (PCC). It makes decisions on how to handle the services in terms of QoS and provides information to P-GW.

VII. Home Subscription Server

Home subscription server (HSS) is the subscription data repository for all permanent user data. It also records the location of the user in the level of visited network control node, such as MME. It is a database server maintained centrally in the home operator's premises. There are several interfaces in LTE network, some of the commonly known standard interfaces are listed below [13][14].

- Uu interface is an interface for the control plane and user plane between UE and eNode B.
- X2 interface is an interface for control plane and user plane between two eNodeBs.
- S1-u interface is an interface for the user plane between eNodeBs and S-GW.
- S11 interface is an interface for the control plane between MME and S-GW.
- S1-MME interface is an interface for the control plane between eNodeBs and MME.

2.2 LTE KPIs

KPIs are primary metrics to evaluate process performance as indicators of quantitative management, and to measure progress towards operator's goals [17][18]. A KPI is a measurable value that demonstrates how effectively a network is serving the user. KPIs describe the fitness level of a network, and this fitness level is measured with different metrics. KPIs are specified through definition and measurement of key parameters of internal network system [17][18].

Because several factors affect KPIs of networks, the measurement and the monitoring process are dynamic and must be done continuously till the KPI values meet the requirements [1][17][18]. LTE network KPIs are usually measured at network infrastructure level and service level. A good KPI value of the infrastructure is required for a good service level KPI, and a good service level KPI is required for a good quality of experience of users. 3GPP specification puts definition and categorization of KPIs. Accordingly, LTE KPIs are categorized in to 6 groups listed in Table 2-2.

Table 2-2 LTE RAN KPIs Categorization According to 3GPP [14][19].

No	KPI category	Meaning and example of indicators
1	Accessibility	Accessibility KPIs are used to measure whether services requested by users can be accessed in a given condition. This also refers to the quality of being available when users needed the service.
		Example • RRC setup success rate • E-RAB setup success rate • Call setup success rate(data)
2	Retainability	Retainability KPIs are a measure of how users keep the networks possession or able to hold and provide the services.
		Example • Service drop rate • Call drop rate (VOIP)
3	Availability	Availability KPIs are a measure of how ready the network is to deliver service for users.

		Example • Cell availability rate
4	Mobility	Mobility KPIs are a measure of the capability of the networks service continuity during user's movement.
		Example • Intra frequency handover success rate • Inter frequency handover success rate • IRAT handover success rate
5	Integrity	Integrity KPIs are a measure of the networks character or honesty to its users.
		Example: • Throughput per cell • Throughput per user • Latency
6	Utilization	Utilization KPIs are a measure of utilization of the maximum capacity of the network for a specified resource.
		Example: • UL PRB utilization • DL PRB utilization • Power utilization

According to 3GPP there are several other KPIs that are not included in the list in each category. In this thesis work experimentation is done for RRC setup success rate, E-RAB setup success rate and service drop rate.

I. RRC Setup Success Rate

RRC is the major part of the control signaling between UE and the network. RRC messages control all procedures related to establishment and release of connection including paging. Configuration measurements and reporting for handovers are also controlled by RRC messages. The main and possible reasons that can be listed for RRC failure are RRC setup failure due to no response from eNodeB, RRC setup failure due to eNodeB rejection and failure due to no response from UE after getting a response from eNodeB. RRC setup success rate is calculated based on the counter at the eNodeB when the eNodeB received the RRC connection request from UE. Complete RRC connection setup can be illustrated by the diagram in Figure 2-2.

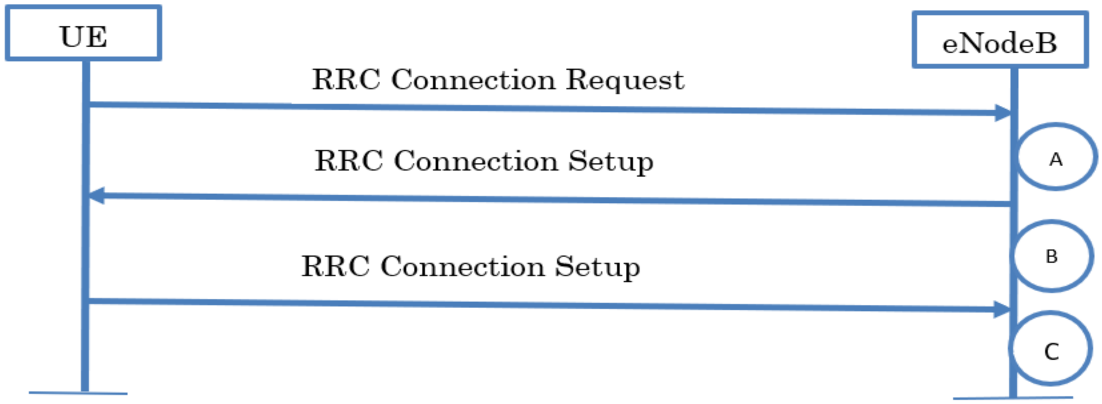


Figure 2-2 RRC Connection Setup Process [19]

Number of RRC connection attempt is collected by the eNodeB at point A, and the number of successful RRC connection is calculated at point C.

$$RRC\ setup\ success\ rate = \frac{RRC\ \text{Connection Setup Complete}}{\text{RRC Connection Request}} * 100\% = \frac{C}{A} * 100\% \qquad (2\text{-}1)$$

II. E-RAB Setup Success Rate

E-RAB is a protocol to establish a fixed communication path between UE and core network. It is within a radio access bearer that the network builds up the end-to-end QoS connection. Bearers in LTE cells are granted or rejected by admission control algorithm in the E-RAB. E-RAB setup responses can be sent after RRC connection reconfiguration setup is successful.

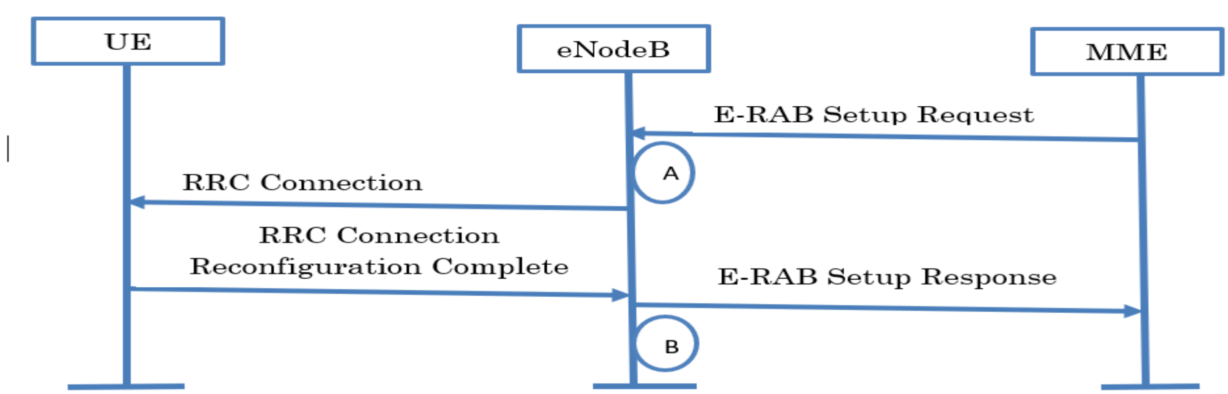


Figure 2-3 E-RAB Setup Success Process[19]

E-RAB setup success rate KPI shows the probability of success ERAB to access all services including VoIP in a cell or radio network. The complete ERAB setup can be illustrated by the process diagram in Figure 2-3. KPI is calculated based on counter ERAB connection setup attempt at point A and successful ERAB setup counter at point B.

III. Service Drop Rate

Service drop rate as KPI indicates the drop rate of all the services in a cell or radio network, including call drop rate in VoIP service. This KPI measures abnormal releases at the eNodeB and is equivalent to call drop rate in voice services. The main causes for performance anomaly in service drop rate are,

- Abnormal E-RAB release due to eNodeB
- Abnormal E-RAB release due to transmission
- Abnormal E-RAB release due to network congestion
- Abnormal E-RAB release due to EPC

$$\text{Service Drop Rate} = \frac{ERAB\ Abnormal\ \mathrm{Re}lease\ \text{Counter}}{ERAB\ \text{Normal Release + ERAB Abnormal Release}} * 100\% \qquad (2\text{-}2)$$

2.2.1 LTE KPI Parameters

The quality of configuration of LTE parameters is critical to bring quality of service. There are several LTE performance parameters that determine the degree of service quality. With the dynamic nature of LTE network, the parameters need to be configured/reconfigured timely to recover any obtained performance drops. However, the reconfiguration may not always bring a positive result and sometimes a worse performance in the configured/reconfigured cell can be observed. Thus, quality of parameter configuration is usually the source of cell performance anomaly with respect to KPIs that are directly associated or dependent on the parameter to be configured or reconfigured. Certain configuration in one cell may bring cell performance anomaly in another cell. Some of the common LTE performance parameters are listed below.

- Resource allocation (uplink and downlink)
- Inter-cell interference coordination (ICIC)
- Mobility control (Including cell reselection parameters)
- Load control (including admission control and random-access control)
- Power control (uplink and downlink)

2.2.2 Impact of Alarms in LTE Cells KPI

According to [20] LTE cells need to monitor the status of their hardware and software. If software or hardware faults are detected by the cell alarms are generated. This hardware or software faults are usually a cause for significant drops and complete outages. The hardware and software faults may include faults in radio resource unit (RRU), baseband processing board (BBP), common public radio interface (CPRI) port, feeder, power supply system, and transport link. There are several types of alarms, in [21] alarms are classified in to critical, major, minor and warning according to their severity. In [21] the alarm categories are defined as,

- Critical alarms are the most serious alarms that can interrupt the services and causes the NE to break down. Critical alarms need to be handled immediately.
- Major alarms have minor impacts on certain NEs or system functions and needs to be handled as soon as possible before they become a cause to disable important features. This type of alarms can not be a cause for complete system break down. Cells with major alarms are expected to be with significant performance drops in the metrics related to the affected features.
- Minor alarms indicate for invents that do not have any impact on the Network elements, but they are an indication that the system detects a potential or imminent event that may affect services. Their aim is to inform the maintenance team for future faults.

- Warning alarms indicate an event that has no impact on the system functions and services. However, the event may have potential impacts on future service quality of NEs or resources.

2.3 Anomaly in LTE KPIs

According to [4] “an anomaly is an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism”.

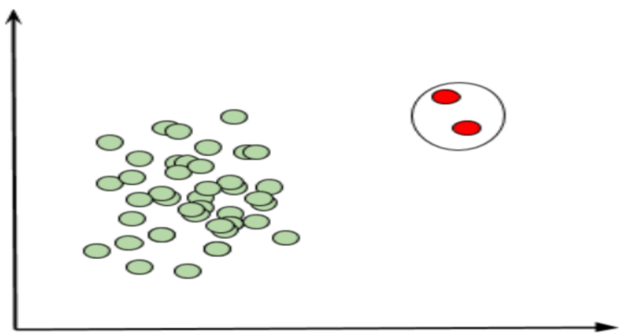


Figure 2-4 Definition of Anomaly [22]

In [3] anomaly is defined as an observation that is well outside of the expected range of values in a study or experiment. From both definitions one can understand that anomaly values are different from most of the values and their root causes are expected to be generated by a different mechanism. The definition of anomaly can be easily describes as shown in Figure 2-4. The figure shows that the red points are different from the other samples and thus they are anomalies. In this paper the anomaly concept refers to unexpected performance value in a specific KPI metrics that is below the requirement and that can be listed among the top least values.

2.3.1 Types of Anomaly

The nature of the desired anomalies is not always the same. Anomaly types are different in different application domain and even with in the same domain. According to their nature there are 3 types of anomalies[9].

I. Point Anomalies

If an individual data sample is anomaly in relation to other data sets the data sample is considered as point anomaly [22]. For example, in hourly call drop rate data of a single cell for 24 hours, the call drop rate is recorded less than 1% for 23 hours, but 5% for the remaining 1 hour, the hour with call drop rate of 5% is a point anomaly as it is with a significantly different value than the other hours.

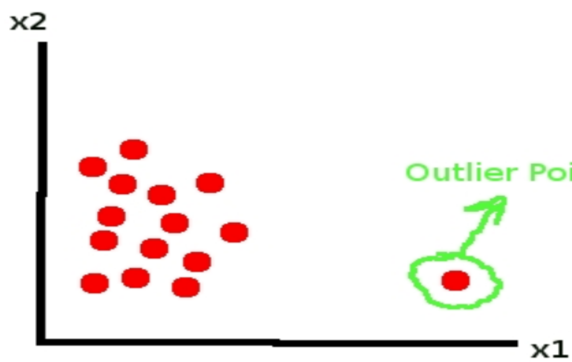


Figure 2-5 Point Anomaly [22]

In Figure 2-5 the encircled point is a point anomaly. The encircled red point individually compared with the other samples is anomaly as the point is far from the other points.

II. Contextual Anomalies

If a data sample is anomalous in a specific context, then it is termed as a contextual anomaly also called conditional anomaly [23]. Contextual anomalies are defined in terms of contextual attributes and behavioral attributes. Availability of power, time, health status and congestion status of network elements are some of the contextual attributes. The KPI metrics such as call setup success rate, call drop rate and RRC setup success rate are the behavioral attributes.

For example, a call setup success rate of 95% during high congestion busy hour is not anomaly, but it is anomaly when network is not congested. Similarly, if a cell is 80%

available in the existence of a major alarm it is not anomaly, however a cell with similar availability in the absence of an alarm can be considered as anomaly. A similar example can be taken from a monthly temperature measurement in a year. A temperature of 25^0 c in January in Ethiopia is normal but a similar temperature in august can be anomaly.

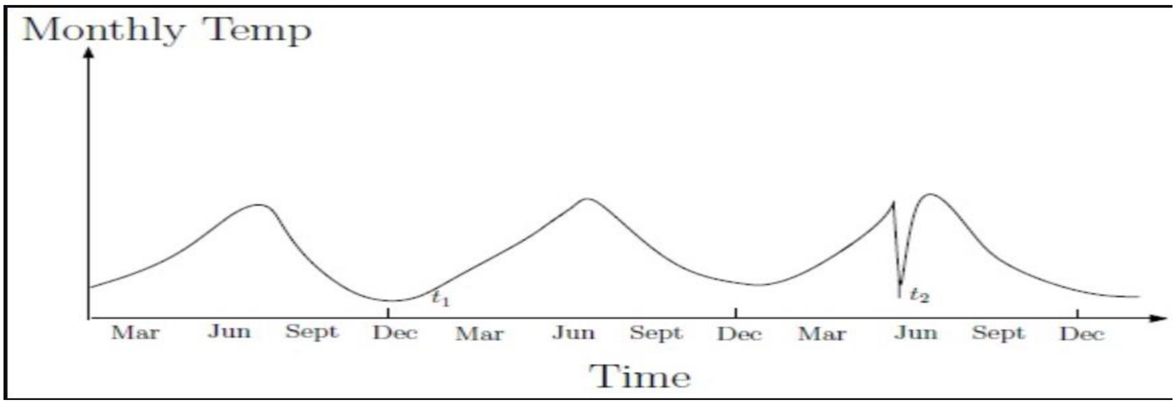


Figure 2-6 Contextual Anomaly[23]

In Figure 2-6 t2 is normal relative to the temperature of all months. But it is contextually anomaly. In June a temperature value of t2 is anomaly but normal in other months.

III. Collective Anomalies

If a collection of related data samples is anomalous with respect to other data sets it is termed as collective anomaly [24]. In collective anomaly the individual data sets themselves may or may not be anomalies. For example, a cell that is 100% available but that do not carry enough traffic is a collective anomaly. Cells in the same cluster showing significant performance drops from the remaining clusters can be considered as a collective anomaly. A single cell performing in the required range with specified KPIs, but the combination of the KPIs is not in the required range can also be a collective anomaly.

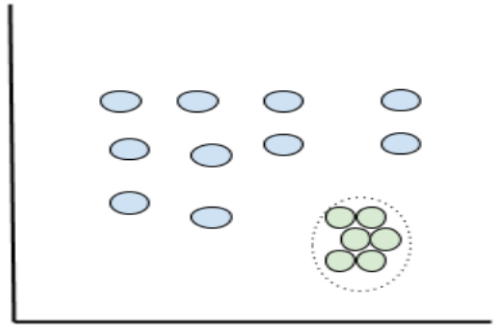


Figure 2-7 Collective Anomaly[24]

Figure 2-7 shows that the encircled points are collective anomalies.

2.3.2 Root Causes of Performance Anomaly

There are several causes of performance anomalies. Some of the causes are visible and displayed as an alarm, while others are not visible and need deep root cause analysis and investigation. Though the sources of anomalies vary from KPI metrics to other KPI metrics, they can be generally grouped into common causes and Special causes.

I. Common Causes

Common causes are the source of anomaly in any type of feature KPIs. These type of causes commonly occur in the network infrastructure, thus detecting and fixing the problem is not complex as they do not need deep analysis and their effect is visible right after their occurrence. These causes affect the overall performance of the network and there will not be a KPI that can escape the impact of this type of causes. This type of causes mostly occur due to incidents and system changes on the infrastructure of the network. For example: power outage, transmission media cut, and higher-level network element failure such as core network failure.

II. Special Causes

Special causes are those that are specific to the feature KPI. They affect service level KPIs and the occurrence of anomaly in one KPI may affect other KPIs and can be a cause for anomaly in another feature KPI too. These kinds of causes include configuration problem, feature activation or deactivation and parameter changes. This type of causes usually occur due to human errors for lack of knowledge or common mistakes. Because performance drops are expected on cells having visible problem due to common causes, the focus of this thesis work is on anomalies that occur due to special causes that are not visible and need deep analysis.

3 Anomaly Detection Methods

Authors Erich Schubert and Arthur Zimek defined anomaly detection as "the identification of rare items, events or observations which raise suspicions by differing significantly from majority of the data". In [3] anomaly detection is defined as the identification of data points, items, observations or events that do not conform to the expected pattern of a given group. In this paper anomaly detection is a process of automatically detecting worst performance cells in specific metrics in a specified time.

3.1 Classification of Anomaly Detection Methods

There are several anomaly detections types. Anomaly detection mechanisms can be classified considering the following main aspects [25][26].

- Nature of input data
- Availability of supervision
- Type of output
- Type of anomaly
- Input data set distribution

3.1.1 Nature of Input Data

According to the nature of input data anomaly detection mechanisms can be classified as univariate and multivariate anomaly detection techniques. The input data sets can be of numeric, image, text or any other type.

Univariate anomaly detection is a process of detecting anomalies taking a single variable as an input. The single variable may have several dimensions. For example, in LTE network service drop rate anomaly detection, the service drop rate may have day, hour and cell as dimensions, but the target is to find the anomaly value in service drop rate which is a single variable. In multivariate anomaly detection the detection of anomalies is from among or a combination of several variables taken as an input. For example, in LTE network anomaly detection from a cell with KPI metric of service drop rate and E-RAB setup success rate at the same time is multivariate anomaly detection. A combination of normal values of univariate anomaly detection for multiple variables may also create anomaly combination.

Anomaly detection mechanisms based on nature of input data and relationship among data instances can also be classified as temporal, spatial and spatio-temporal. In this thesis temporal and spatial anomaly detection are discussed to find the time of anomaly occurrence and the cell with anomaly performance in a specified metrics.

3.1.2 Outputs of Anomaly Detection

The anomaly detection results of different models are not all the same. Anomaly results can be either a label (anomaly/not anomaly) or score based. Score based anomaly results show the degree of abnormality of a sample. For the labeling type anomaly detection supervised machine learning algorithms with two class classification are preferred but for the score-based results unsupervised machine learning, that are based on rank, order or percentile are preferred.

3.1.3 Distribution of Input Data Sets

According to the distribution of input data sets anomaly detection mechanisms are classified as parametric and nonparametric. Parametric anomaly detection is applied for anomaly detection of a data with defined probability distribution (normal, poison, exponential...). With this type of anomaly detection, the anomaly values are those that are less probable to occur. If p (data sample) $< \varepsilon$, the sample is classified as an anomaly otherwise it is classified as normal value. Such kind of detection algorithms are suitable for data labeling type of detection and are not good for detection with anomaly score [9]. Nonparametric anomaly detection is applied for data set types that do not rely on data belonging to any parametric family of probability distributions. Nonparametric distribution do not mean that the data sets are without distribution but the parameters of the distribution are unspecified [9].

3.1.4 Availability of Supervision

Anomaly detection can be performed manually via statistical analysis. However, for better accuracy and automation machine learning can be applied. In machine learning the system is trained with the data sets behavior. According to the availability of supervision of data labels in the detection process anomaly detection algorithms are classified as supervised, semi-supervised and unsupervised anomaly detection.

I. Supervised Anomaly Detection

According to [9][27] a supervised machine learning algorithm is one that relies on labeled input data to learn a function that produces an appropriate output when given new unlabeled data. In supervised machine learning a labeled data for normal and anomaly class is available and the model is trained. The challenge of supervised anomaly detection is that the proportion of normal to anomaly samples is high and needs over sampling. KNN classification, regression, support vector machine and decision trees are the most common supervised anomaly detection algorithms.

II. Semi Supervised Anomaly Detection

According to [9][27] semi supervised anomaly detection is used for a data set with a known class label for normal data values. The model is trained for a single class and data samples out of the class are detected as anomalies. When training and testing data sets are selected for cross validation the combined data set is modeled using unsupervised anomaly detection. The main problem with this type of detection is that unseen but legitimate normal values can be classified as anomaly and false negatives can be generated.

III. Unsupervised Anomaly Detection

According to [9][27] unsupervised anomaly detection algorithms are applied for data sets that do not have defined class labels. Thus, this model does not need training and learn the behavior of the data sets by themselves. The unsupervised models assume the proportion of normal to anomaly values is high. The problem with these models is that they can detect many small clusters that are not necessarily anomaly.

Figure 3-1 clearly shows that the supervised anomaly detection techniques need a labeled training data set and gives a two-class label as an output and a semi supervised needs a training data set for the normal points and gives a label of anomaly and normal as an output. In the case of unsupervised learning unlabeled data set is given to the model and the model by itself identifies the data sets and produces anomaly score in different degrees of anomality.

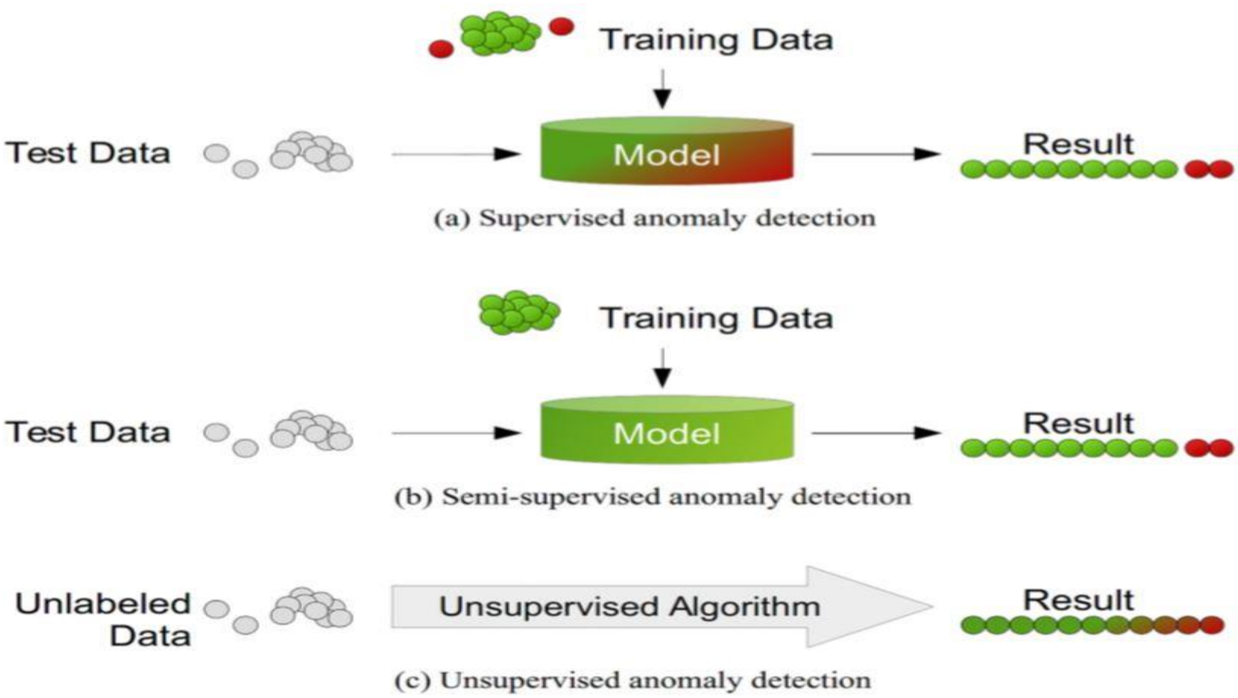


Figure 3-1 Modes of Anomaly Detection on Availability of Labeled Data Set[9]

3.2 Challenges of Anomaly Detection

There are several challenges in detection of anomaly. The most common challenges are [28]

- Defining the normal behavior baseline that usually requires domain expertise. The fact that normal behavior evolves over time is also a challenge for setting a baseline.
- Availability of labelled data for training and validation
- The boundary line between normal and anomaly behavior is not precise
- Notion of anomaly depends on context

3.3 Application Areas of Anomaly Detection

Anomaly detection is applicable in several fields of study and operational activities[9]. Some of the areas are,

- Performance monitoring
- Fraud detection
- Healthcare systems
- Fault management
- Intrusion detection

4 Anomaly Detection in Addis Ababa LTE KPIs

Ever since LTE network is installed in Addis Ababa in 2015 [29] and the service became on air ethio telecom is working hard to deliver enhanced service quality to its customers. LTE KPI monitoring is the systematic process of measuring, analyzing and using information to track network performance towards reaching the KPI requirements[17]. KPI monitoring is done to bring cells to a fixed and required performance value in all KPI metrics[30]. For monitoring purpose, the requirement for all LTE KPIs is set between ethio telecom and Huawei Tech.co.Ltd. Some of the LTE KPI requirements set are listed in Table 3. KPI monitoring is not a one-step task, but a process consisting of measuring KPI values, detecting performance drops, analyzing and fixing obtained problems.

Table 4-1 Sample KPI Requirement Range in ethio telecom

NO	KPI metrics name	Required value range
1	RRC setup success rate	≥ 98.5%
2	ERAB setup success rate	≥ 99%
3	Service drop rate	≤ 1%
4	LTE HO success rate	≥ 98%
5	UE context setup success rate	≥ 99%
6	Cell availability	≥ 99%
7	Attach time	≤ 800ms
8	CSFB duration	≤ 5S
9	Call setup success rate	≥ 98%

4.1 LTE KPI Measurement

William Edwards Deming (1900-1993) an American statistician professor and author quoted "if you can not measure it, you can not manage it". According to Edwards performance measurement is the key to deliver quality of service. Performance measurement is done with defined metrics called key performance indicators (KPI). KPI measurement is not a one-step task, it is a continuous process that is performed 24X7X365.

LTE KPI measurement is continuously done, and the measurement values are stored in a database called performance recording system for next action. The measured values are calculated with a predefined configured logical formula from measured counter values. Some KPIs that cannot be measured and calculated with defined formulas from counters such as latency are measured via drive test. KPI measurement values are calculated from defined and standard formulas. There are two types of formulas in KPI measurement called physical and logical formulas [16][19].

I. Physical Formula

In physical formula, KPI value is expressed in terms of the details of counter values. For example:

$$RRC \text{ Setup Success Rate} = \frac{\text{RRC Connection Success Counter}}{RRC \text{ Connection Success Counter} + \text{RRC Connection Failure Counter}} \qquad (4\text{-}1)$$

II. Logical Formula

In logical formula, KPI formula is expressed in terms of other KPIs.
For example:

$$ERAB\ Establishment \text{ Success Rate} = \frac{Number \text{ of Successfull ERAB Esatblishments}}{Number \text{ of Received ERAB Establishment Attempts}} \qquad (4\text{-}2)$$

Measured KPIs can be expressed in terms of mean, ratio, cumulative or combined[18][19].

- Mean reflects a mean measurement value based on several sample results. For For example: average throughput, average traffic
- Ratio reflects the percentage of a specific case occurrence to all the cases. For For example: RRC setup success rate, service drop rate (SDR)
- Cumulative reflects a cumulative measurement which is always increasing. For example: counters, total traffic volume

Percentage, second, erlang and Kbits/sec are some of the units of KPI measurement. The values that we get from the formulas are the KPI values that are recorded in PRS. In LTE network the performance measurement takes place in cell level, site level and overall in the evolved packet core side. For better network management and effective network QoS monitoring, measurement is mostly done on cell level bases. In ethio telecom monitoring is done on weekly time intervals by taking daily busy hour data for analysis as it is practically difficult to manually monitor performance of cells on daily and hourly time intervals.

4.2 LTE Worst Performing Cells Selection & Analysis

KPI analysis is a process of filtering and identifying cells that do not meet the KPI requirement, selection of worst performing cells and identification of fault root causes. In ethio telecom educated guess type of analysis is done manually to select worst performing cells by considering only the current measured KPI values. In the case of root cause analysis there are measured counters and alarms that support the analysis process in the system. Such activities are mostly done with employees that have higher experience (experts) in the area. The most important part of LTE KPI analysis is worst performing cell selection process.

Considering the threshold values shown in Table 4-1, ethio telecom uses two scale (above and below the requirement) fixed threshold in all KPIs metrics and all the time for network monitoring. This fixed threshold does not vary with the dynamic nature of LTE network performance. During performance comparison of cells with the requirement with defined metrics several cells do not meet the target values even when the average performance value of the cell with respect to the defined metrics is greater than the minimum required KPI value. In the current KPI monitoring process of Addis Ababa LTE network, no effort is done to farther improve the performance value if the value is within the required range. For example, the required value range for RRC setup success rate is ≥ 98.5%, if the measured value of the metrics is 98.5 the analyst and radio expert will not try to improve it to 100% even when there is a possibility. It is because ethio telecom is using fixed threshold and the recorded value has meet the requirement.

For cells that are with KPI values less than the requirement a corrective action to recover or compensate the performance drop needs to be taken. Because the performance recovery or compensation can not be done for all the cells at the same time prioritization of the cells for corrective actions is important. Thus, the cells with lower performance value are given priority after observing their current performance value. This method is not efficient as it is not able to check back the performance history of the cells in the specified metrics.

After having the measurement detail investigation of all the cells is done and cells with the required performance range and those with a performance drop are manually filtered. The manual filtering mechanism more focuses on current values and lacks accuracy to include the history performance of each cell. However, in machine learning based anomaly detection, worst cell selection can consider both the current values and the performance history as shown in Figure 4-1.

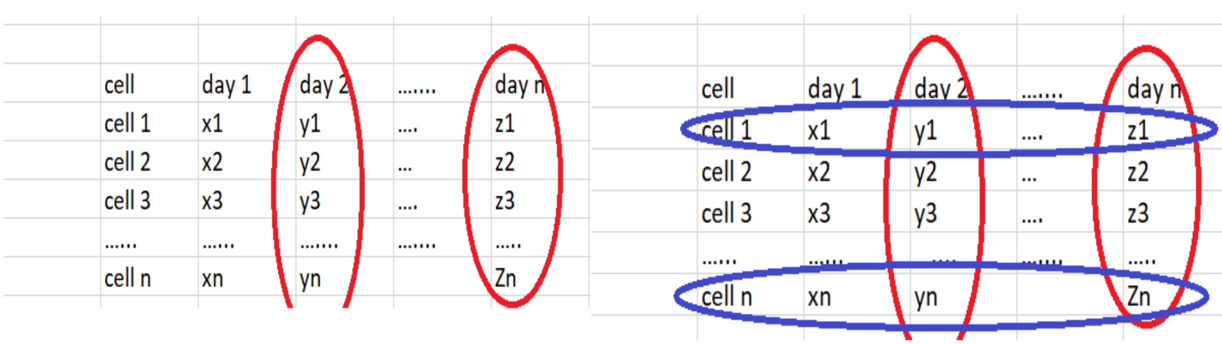


Figure 4-1 Manual Worst Cell Selection vs Automatic Anomaly Detection

In Figure 4-1 it is clearly seen that in manual worst cell selection of a single KPI metrics column wise value comparison is done for daily data and is difficult to consider the performance history, but in automated anomaly detection worst cell selection, considering the current value as well as the history performance is possible. The manual anomaly detection becomes more complex for detecting anomaly cells with multiple KPI metrics simultaneously.

There are several KPIs for each cell and manual worst performing cell selection is time consuming and sometimes difficult to do it on time. When the selected worst performing cell list are prepared as a report to different zones of Addis Ababa there is a problem of not accepting the report. Complaints on reports to different departments and zones brings a question of credibility. These less credible reports are observed to lead for wrong decisions that do not bring a performance improvement and sometimes for worse performance. The manual worst performing cells selection is routine and tiresome for employees and this creates employee dissatisfaction in the work and lets employees to work extra hours from the normal working hours. For this reason, ethio telecom pays additional payment as an incentive for employees involved in the work.

5 KNN-based Anomaly Detection Techniques

KNN-based anomaly detection algorithms classify datasets based on similarity of their neighbors. These algorithms use the relative distance and relative density to find top N neighbors. The key assumption with nearest neighbor algorithms is that normal points have close neighbours while anomalies are located far from other points. KNN classification, local outlier factor and connectivity outlier factor are among the KNN-based anomaly detection algorithms discussed. Though, there are several anomaly detection methods, there is no significant difference in detection process and modeling for most anomaly detection mechanisms [41]. Figure 5-1 shows the general framework of anomaly detection mechanisms.

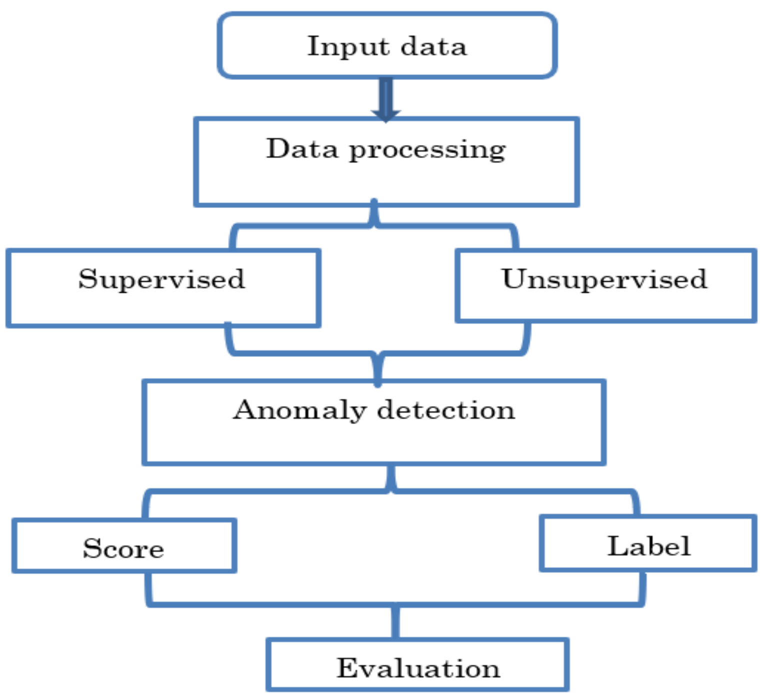


Figure 5-1 General Framework of Anomaly Detection [41]

In this thesis work the data collection and preprocessing stages are common steps for all models to be compared and implemented. The detection process followed for the experimentation of the models is separately explained.

5.1 Assumptions

Though measurement errors are expected, it is assumed that the errors made by the measuring system is negligible. Thus, recorded performance drops are assumed to be due to configuration change, parameter change and unexpected incidents. If critical or major alarm is not observed in the specified time, performance drop of cells is expected to occur due to configuration/ reconfiguration problems and not due to common anomaly causes.

5.2 KNN Classification System Model

KNN classification is a supervised machine learning model used to classify data sets in to two labels based on the label of majority of its neighbors. The KNN algorithm assumes that similar things exist in proximity. The quote "birds of the same feather flock together" better explains the KNN classification. It is a nonparametric classification method that classifies data sets based on learning from training data sets. The process model of KNN classification implemented in this thesis work is shown in Figure 5-2.

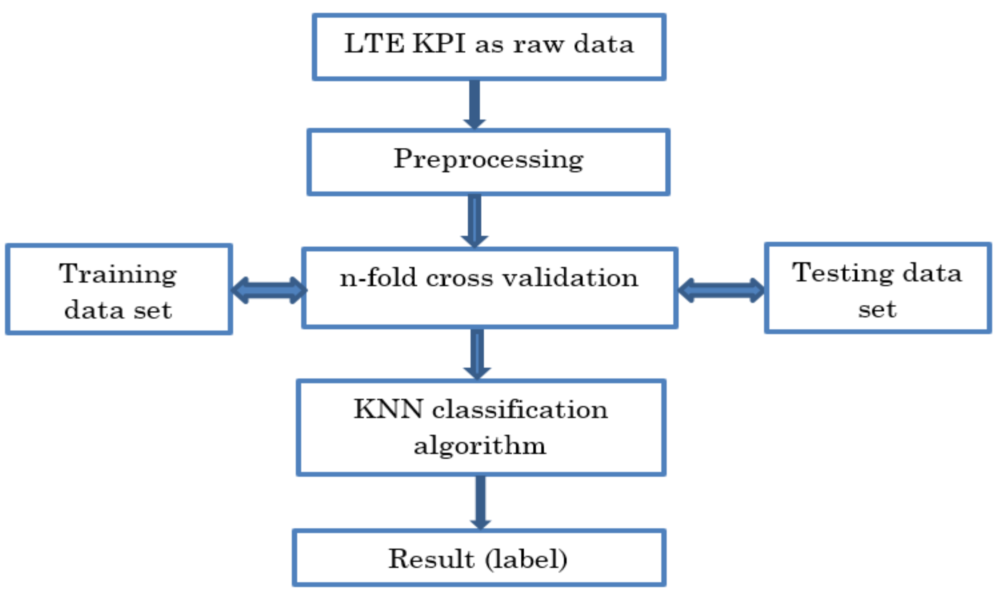


Figure 5-2 KNN Classification Process Model

5.2.1 Mathematics of KNN Classification

Once enough data has been acquired, the next step is to label individual data samples. As explained in the definition of anomaly, the anomaly values significantly deviate from the requirement. Thus, labeling the anomaly requires setting a threshold that is certain confidence interval far from the requirement. According to [3] a KPI data sample that deviates one standard deviation (δ) from the average KPI value is 68.2% anomaly, and data sample that deviates 3*δ from the average is 99.7% anomaly. In this thesis work KPI data samples that are 3*δ away from the average KPIs values will be labeled as anomalies. As the collected data sets are for cell level and time series scenarios, finding the 3*δ variation from the average will not be the same for these two types of data sets.

The authors in [3] used basic approach statistical process control (SPC) to calculate the 3*δ variation for the cell level KPIs as the collected KPI values are recorded at the same time but from different cells. For the time series data N-period moving average and exponentially weighted moving average (EWMA) is applied as the data sets are collected in different time events and the system needs to know the data set history.

Basic approach SPC is a way of finding anomaly by using the average(mean) and the standard deviation. A confidence interval is set by multiplying the standard deviation by a certain number usually three. In other industries it may range up to six standard deviation. The threshold for anomaly labeling is given by,

$$\text{Threshold} = \mu \pm 3*\delta \quad \text{and} \quad \delta = \frac{\sqrt{\sum_{i=1}^{k}(x-\mu)2}}{k-1} \qquad (5\text{-}1)$$

Where x = performance value, k= number of samples and μ = average performance value

This basic approach SPC is a fixed threshold labeling when data sets are measured at the same time and dynamic threshold for daily changes [3]. According to [31] moving average SPC is a way of finding anomaly by using moving average and moving standard deviation. With moving average SPC dynamic threshold is set for anomaly labeling and samples are given equal weight regardless of the time occurrence. This type of labeling is more comfortable for time series data set labeling. The threshold for anomaly labeling is given by,

$$Threshold = \overline{y} \pm 3 * \partial n \quad \text{and,} \quad \partial n = \frac{\sqrt{\sum_{K-m+1}^{K} (yi - \overline{y})^2}}{m-1} \quad \textit{where M is window size} \tag{5-2}$$

The moving average also called M-point moving average, is calculated in fixed points of window size.

EWMA based SPC is a way finding anomalies by using moving average and moving standard deviation. With EWMA samples are with different weights and the weight exponentially increases from the oldest data sample to the recent data samples. The threshold for anomaly labeling is given by,

$$Threshold = EWMAt \pm 3 * \partial EWMAt \quad \text{where,} \quad EWMAt = \lambda Yt + (1-\lambda) EWMAt - 1 \tag{5-3}$$

where, λ = waiting factor

The EWMA standard deviation is calculated in relation to the moving average standard deviation by,

$$\partial EWMA = (\lambda / (2-\lambda) * \partial n2) \tag{5-4}$$

The next step in KNN classification is setting the value of K. According to [32] there is no standard mechanism to determine optimal value of K, however K should not be too small and too large, usually recommended to be odd, less or equal to the squared root of number of training data samples.

There are several mechanisms to find distance of a data sample to all other data samples. According to [33] Euclidian distance is more suitable for finding the distance between two KPI data set points. The Euclidian distance is given by the formula,

$$D(X,Y) = \sqrt{\sum_{i=1}^{n} (xi - yi)2} \tag{5-5}$$

After sorting the calculated Euclidian distance top K nearest data samples are selected as KNN. Authors in [32] explained that all samples in the KNN do not have equal contribution in labeling a data sample. The first neighbor has higher weight and the k^{th} neighbor is with the least weight. The next step in KNN classification is to find the total number of neighbors N1 and N2 in each class and determine the sum of their inverted distances with formulas, [32]

$$S1(x) = \frac{\sum_{i=1(c=1)}^{N} 1/i}{N1} \quad \text{and} \quad S2(x) = \frac{\sum_{i=1(c=2)}^{N} 1/i}{N2}, \quad i = 1,2,3.....K \qquad (5\text{-}6)$$

Finally find probability of a point X belongs to each class is calculated by the formulas below.

$$P(c=1|X) = \frac{S1(x)}{S1(x)+S2(x)} \quad \text{and} \quad P(c=2|X) = \frac{S2(x)}{S1(x)+S2(x)} \qquad (5\text{-}7)$$

Then, data is in class 1 if $P(c=1|X) > 0.5$ and in class 2 if $P(c=2|X) > 0.5$.

Prepared and labeled training data sets may not be enough for the model to enable new data set classification and may lead to model underfitting. According to [45] a technique called N-fold cross validation can be used as a remedy by removing a part of the training data and using it to get predictions from the model trained on rest of the data. This mechanism is called holdout. In N-fold cross validation, the data is divided into n subsets. Now the holdout method is repeated N times, such that each time, one of the N subsets is used as the test set/ validation set and the other N-1 subsets are put together to form a training set. Higher value of N leads to model overfitting and lower value of N leads to model underfitting. Thus, optimal value of N should be selected to give more accurate prediction result. Though, there is no clear selection criteria of N, the mostly applied 5 to 10-fold cross validation [46] is implemented in this thesis work.

5.3 Density-based Local Outlier Factor

As discussed in [34] by comparing the local density of an object to the local densities of its neighbors, one can identify regions of similar density and points that have a substantially lower density than their neighbors. In 2000 authors called Markus M. Breunig, Hans-Peter Kriegel and Jörg Sander identified a mechanism of finding anomalous data points by measuring the local deviation of a given data point with respect to its neighbors. These authors named this algorithm LOF.

LOF is unsupervised machine learning anomaly detection model that investigates the density of an object and its neighbors. According to [22] an object is identified as an anomaly if its density is relatively much lower than that of its neighbors. The basic idea that differentiates LOF from the classification models is that being anomaly is not a binary property, instead, to each object an outlier factor is assigned, which is the degree the object is being outlying [34]. The challenge with ordinary local outlier factor is finding K-nearest neighbors in the presence of duplicate data samples. Several LTE KPIs are with the same performance values and these duplicate values are confusing and complex for the LOF algorithm to determine the fixed K neighbors for each data sample. Thus, it is recommended that local outlier factor given duplicates should be implemented for LTE cells anomaly detection [35].

5.3.1 System Model of Local Outlier Factor

Unsupervised learning algorithms do not need training data sets and the algorithms by themselves learn the data set behavior. As LOF is unsupervised machine learning algorithm, preparation of training data is not important for experimentation, but the labeled data sets are used for performance evaluation. As COF is a modified version of LOF there is no difference in the general process model. The process model for LOF and COF in this thesis work is shown in Figure 5-3.

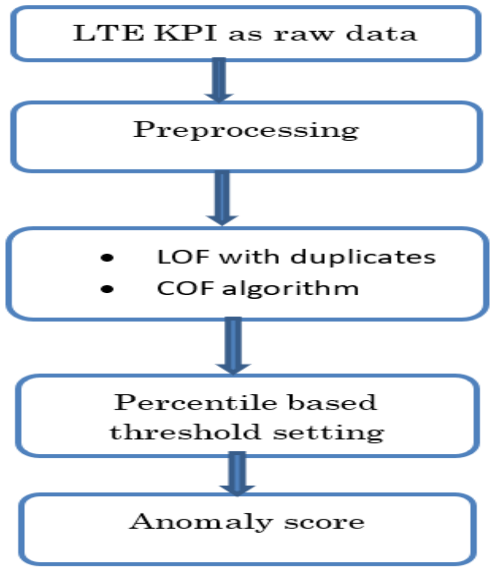


Figure 5-3 Process Model of LOF and COF

5.3.2 Mathematics of Local Outlier Factor

Local outlier factor detects the outlier by calculating the density of points based on their proximity to their neighbors. According to [34][35] local outlier factor follows the listed mathematical procedures to find the relative density of every sample point p.

I. Finding K-distance of every Point p

The K-distance of a point P represented by $dist_k(p)$ is the distance between p and its k^{th} nearest neighbor. For example, let us assume k=3, having the 6 points in Figure 5-4 the k-distance of point O is the distance between points O and point 3 as point 3 is the third nearest neighbor.

$Dist_k(o) = dist(o, 3)$, where k = 3.

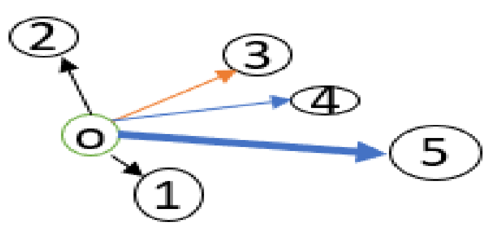


Figure 5-4 K-distance of a Point

II. K-distance Neighborhood of P

k-distance neighborhood of p represented by $N_k(p)$ is the number of objects (a set of objects) that are a distance D less or equal to $dist_k(p)$ away from point p. The k-distance neighborhood of p contains set of points whose distance from p is not greater than the k-distance. Nk (p) could be bigger than K since multiple objects may have an identical distance to point P.

$$Nk\left(p\right) = \left\{p' \mid p' \text{ in } D, dist\left(p, p'\right) \le distk\left(p\right)\right\} \quad (5\text{-}8)$$

III. Reachability Distance of Point P

The reachability distance represented by $reachdist_k$ (P←P') is the maximum of the reachability distance of point p and reachability distance of p's k-nearest neighbors.

$$reachdist_k\left(p \leftarrow p'\right) = max\left\{dist_k\left(p\right), dist\left(p, p'\right)\right\} \quad (5\text{-}9)$$

LOF uses reachability distance to find nearest neighbors unlike Euclidean distance in KNN classification. Finding reachability distance reduces the statistical fluctuation of finding distances dist(p,p').

IV. Local Reachability Density of Point p.

Local reachability density of P represented by $lrd_k(P)$ is the ratio of k-distance neighborhood of p to sum of reachability distance from P' to P. it can also be defined as the inverse of the average reachability distance.

$$lrdk(P) = \frac{\| Nk(P) \|}{\sum_{P' \in Nk(P)} reachdistk(P' \leftarrow P)} \quad (5\text{-}10)$$

V. Local Outlier Factor of Point p.

Local outlier factor represented by $LOF_k(p)$ is the average of the ratio of local reachability of p and those of p's k-nearest neighbors and is given by,

$$LOFk(P) = \frac{\sum_{P' \in Nk(p)} \frac{(lrdk(p'))}{lrdk(p)}}{\| Nk(p) \|} \quad \text{5-11)}$$

The formula shows that lower local reachability density of p and higher local reachability density of the nearest neighbors of p gives higher local outlier factor and higher degree of abnormality. Higher values of LOF indicate anomaly data whereas, lower values indicate for normal data. The normal data set are usually with a LOF value of close to 1.

5.4 Connectivity Outlier Factor

According to [36] the connectivity-based outlier factor (COF) first introduced by Tang et al. (2002) was proposed in order to handle outliers deviating from density patterns, for example straight lines. In[36] COF is described as a modified version of LOF with a difference in computing the nearest neighbors. LOF could not perform well when outliers are in areas with data samples of various distributed densities. The points in Figure 5-5 clearly explain the difference between LOF and COF in finding the neighbors.

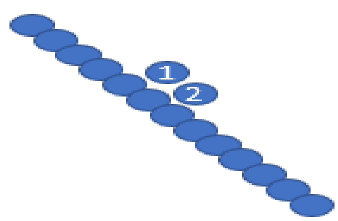


Figure 5-5 Difference between COF and LOF

In the above points p_1 and p_2 are anomaly with COF but normal with LOF. All the points other than p_1 and p_2 are easy to connect with COF but LOF measures the relative density and the points are relatively close to most of the points.

In COF, the neighborhood is computed in an incremental mode. At first, the closest object to the given object is added to the neighborhood set. The next object added is the one with its distance to the existing neighborhood to be minimum among all remaining objects. The distance between an object and a set of objects is defined as the minimum distance between the given object and any object belonging to the given set. In this fashion the neighborhood continues until it reaches size K.

5.4.1 Mathematics of Connectivity Outlier Factor

Connectivity outlier factor detects the outlier by calculating the density of points based on their proximity to their neighbors considering least cost and shortest path. According to [36][37] the mathematical procedures in calculating the values of COF are,

I. Set of k-nearest Neighbors of Point p

The set of k-nearest neighbors represented by Nk(P) is a list of all nearest neighbors to point p.

$$N_K\left(P\right) = \left\{p_{1,} p_5,\ p_3 \ldots .\ Pk\right\} \tag{5-12}$$

II. Set-based Nearest Trial

Set-based nearest trial is a set of all possible combination of nearest paths. Set based nearest trail of data point P is set of points , such that for all $1 \leq i \leq k - 1$, pi+1 is the nearest neighbor point of set $\{p_1, \cdots, p_i\}$ in set $\{p_{i+1}, \cdots, p_k\}$. where i is the index of the nearest neighbors. where i = 1,2,3…. k.

III. Set-based Nearest Path

Set-based nearest path of point p is the set of neighbor points in the order of their proximity to point p. The set based nearest path can be given in set-based sequence of edges as,

$$SBN\ edges = \left\{e_1, e_5, e_7, \ldots\ldots e_K\right\} \tag{5-13}$$

IV. Cost of Set-based Nearest Trial

The cost of set-based nearest trial is a set of distance between two nearest neighbors in the set of $N_k(P)$. for example, for k=5 the set can be given as SBN cost = {5,4,3,2,1,1}.

V. Average Chaining Distance of Point p

Average chaining distance can be expressed as the average of the weighted distances in the cost description of the SBN-trail. The average chaining distance is given by,

$$ac - distNk(p) \cup p(P) = \sum_{i=1}^{K} \frac{2(k+1-1)}{k(k+1)} * dist(ei) \qquad (5\text{-}14)$$

where dist(ei) is the sum of cost to reach all nearest neighbors.

VI. Connectivity Outlier Factor

COF is the ratio of the average chaining distance from data record p to Nk(p) and the averaged average chaining distances at the record's neighborhood. The COF value is calculated by the formula,

$$COF(p) = \frac{ac - distNk(p) \cup p(P)}{\sum_{0 \in Nk(p)} ac - distNk(o) \cup o(o) \Big/ k} \qquad (5\text{-}15)$$

The calculated value of COF is finally the anomaly score of the model.

5.5 Performance Evaluation Mechanisms of Anomaly Detection

To compare and get the most accurate anomaly detection model requires performance evaluation of the models. The outputs of the training and learning of the algorithm need to be assessed and analyzed carefully and the result needs to be interpreted to evaluate the algorithm [33][38]. The performance of anomaly detection algorithms is usually measured by their detection accuracy. But accuracy alone is not enough metric for evaluation. Thus, standard measures for evaluating anomaly detection performance are [38][39].

- Recall (true positive rate) is the ratio between the number of correctly detected anomalies and the total number of anomalies and is given by.

$$\mathrm{Re}\,call = \frac{True\ \text{posetive}}{True\ \text{posetive} + \text{False negative}} \tag{5-16}$$

- Precision (false positive rate) is the ratio of the number of data records from the normal class that are misclassified as anomalies and the total number of data records in normal class and is given by,

$$\text{Precision} = \frac{True\ \text{posetive}}{True\ \text{posetive} + \text{False posetive}} \tag{5-17}$$

- ROC curve is a trade-off between recall and precision rate. It tells how much a model is capable of distinguishing between classes. The ROC curve is usually plotted with TPR on y-axis and FPR on the x-axis.

- Area under the ROC curve (AUC) is the area under the graphical plot of the true positive rate against the false positive rate, where the true (false) positive rate represents the proportion of detected anomalies among the top n potential anomalies. Higher AUC values indicate better prediction capability of models and better detection accuracy.

As the anomaly detection model has to catch as many outliers as possible and is expected to not mislabel normal objects as anomalies, recall is more important than accuracy[40]. According to [38] for high proportion of one class to the other precision recall curves are preferred among the available measures.

6 Experimentation and Result Analysis

6.1 Data Collection and Preprocessing

LTE KPI measurements are collected from performance recording systems. According to [42] performance monitoring is better done when the KPI spacing is on hourly and daily granularity. Thus, for experimentation of this thesis work ten days (04/01/2019 to 04/10/2019) daily RRC setup success rate, E-RAB setup success rate and service drop rate of all LTE cells in Addis Ababa is collected for the cell level detection scenario and one month hourly RRC setup success rate, E-RAB setup success rate and service drop rate of all LTE cells is collected for April 2019.

All the collected raw data is not meaningful, instead, it contains several missed and inconsistent values. Thus, such kind of raw data need to be filtered out and the remaining data should be considered for the anomaly detection input. It is expected that if there is an alarm, performance will significantly drop. Thus, cells with critical and major alarm are also filtered out and not included in the experimentation as it is assumed that the drop is due to the alarm. Other activities such as data set labeling, distribution fitting and model training activities are performed in the preprocessing stage.

6.1.1 Distribution Fitting

Knowing the distribution from which we are going to assume the data set was generated from is not easy and fitting the data to the chosen distribution to obtain the best estimate effectively need to be done. Most KPIs are given in bounded percentages between 0% and 100%. Thus, the distribution type of the KPIs is almost the same. To make sure the distribution fitting estimation generalizes well to the population and not just the sample data fitting of three months RRC setup success rate and service drop rate to represent right and left skewed data samples is done and the result is as shown in Figures 6-1 and 6-2.

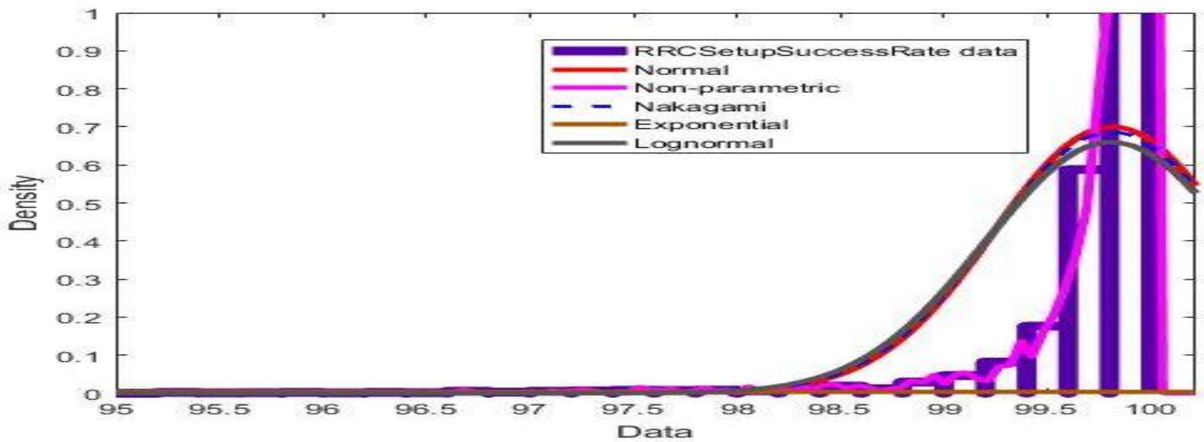


Figure 6-1 RRC Setup Success Rate Distribution Fitting

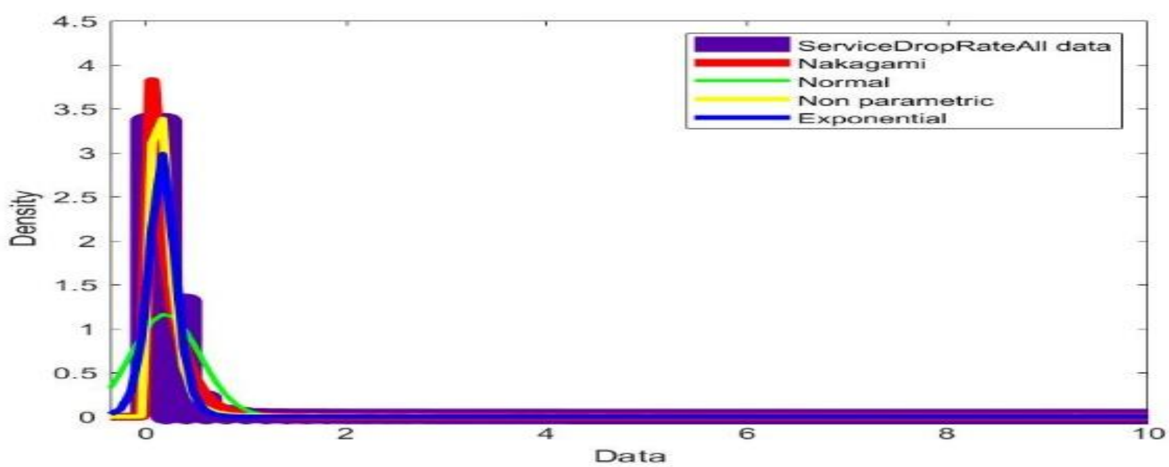


Figure 6-2 SDR Distribution Fitting

Figures 6-1 and 6-2 shows that LTE KPIs more fit to non-parametric distribution. According to [43] non-parametric distributions do not restrict themselves to any parameterized distribution, however, the data alone is considered and the distribution is modeled as an empirical distribution. According to [44] there are several non-parametric anomaly detection models, however KNN classification and density-based local outlier factor are the most common. Local outlier factor given duplicates and connectivity outlier factor are some algorithms that can be listed under local outlier factor.

6.1.2 Data Set Labeling Result

Data set labeling is used as an input for KNN classification-based anomaly detection. For LOF and COF algorithms labeling result is not used as an input for they are unsupervised machine learning techniques, but it is used as a reference for performance evaluation. The data set labeling is done with basic approach SPC for cell level KPIs and with EWMA for time series KPIs. Matlab code is implemented for labeling of the data in both scenarios. Figure 6-3 shows sample data set labeling result of RRC setup success rate for cell level detection.

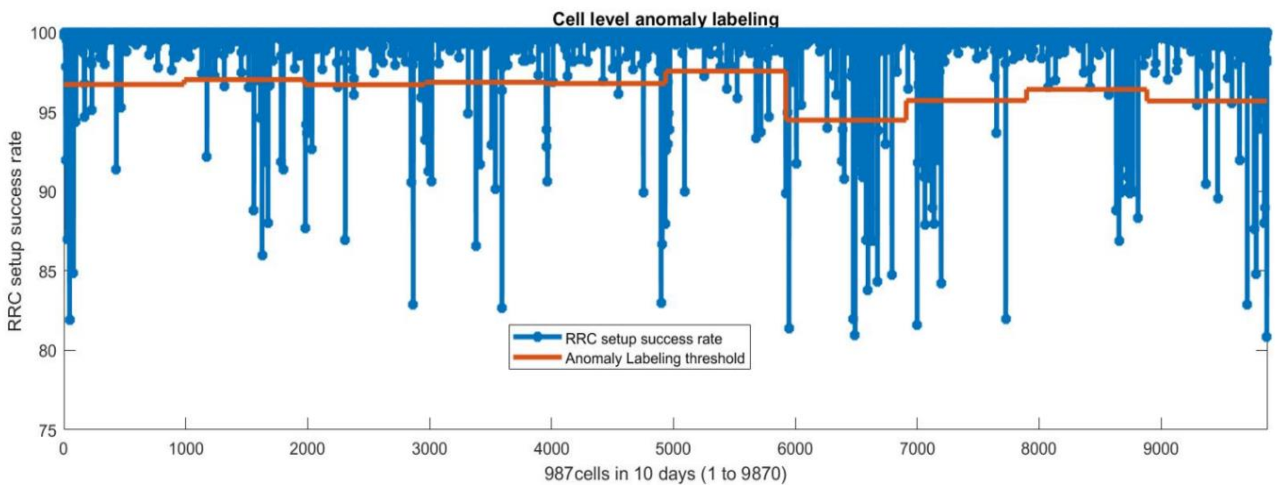


Figure 6-3 Cell Level Data Set Labeling

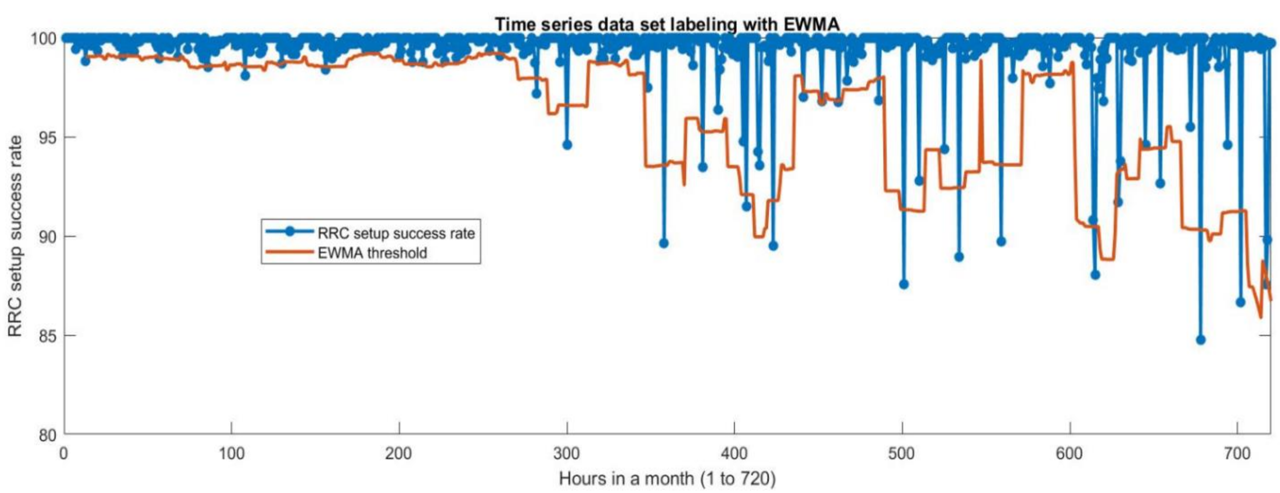


Figure 6-4 Time Series Data Set Labeling

According to Figure 6-3 cells with RRC setup success rate value less than the threshold are labeled anomalies. This is a sample data set labeling and the threshold is different for different days. Similarly, Figure 6-4 shows data set values below the red line are labeled anomalies for the data to be an input for KNN classification in time series.

6.2 Results with KNN Classification

After having the labeled and preprocessed data, a weighted KNN classification was trained with the labeled data sets. The KNN classification implementation is done for different values of K and at different values of N-fold cross validation and different proportion of training to testing data sets. The predictive result of KNN classification model at 10-fold cross validation and K=10 for cell level RRC setup success rate data is shown in Figure 6-5.

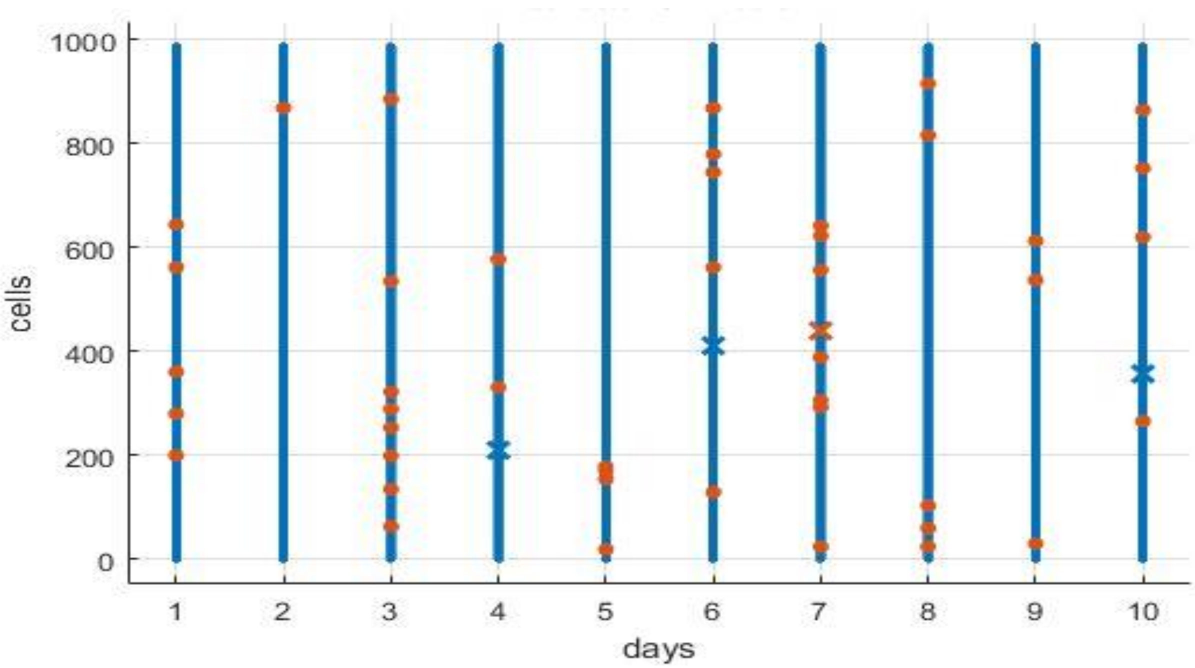


Figure 6-5 Cell Level RRC Success Anomaly Detection with KNN Classification

Figure 6-5 shows the red sample points are detected anomalies and the samples marked "X" are the wrongly classified values that are not correctly predicted by the model. All the remaining samples are normal values.

The confusion matrix of the KNN classification for trained data sets of cell level anomaly detection showed a TPR of 93% and a true negative rate of > 99% as shown in Table 4.

Table 6-1 Confusion Matrix for Cell Level KNN Classification

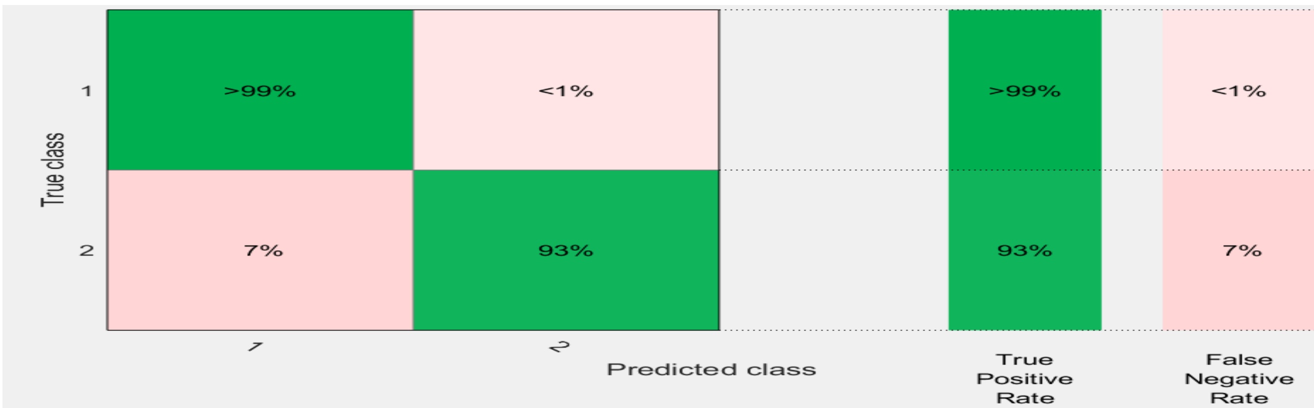
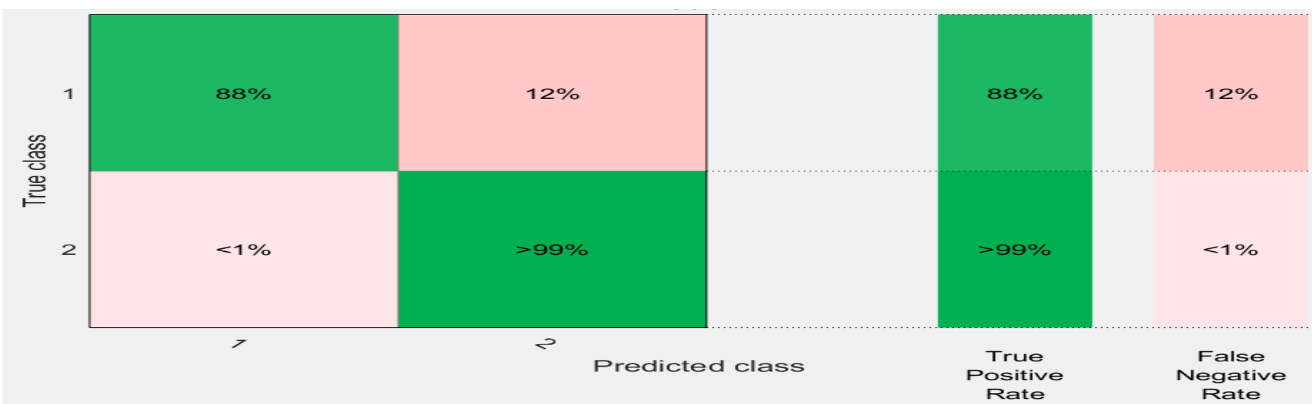


Table 6-2 Confusion Matrix of Time Series KNN Classification



Similarly, the confusion matrix for time series anomaly detection showed a TPR of 88% and a TNR of >99% as shown in Table 5. The higher value of TNR in both scenarios is due to the high proportion of normal to anomaly values.

6.3 Results with Local Outlier Factor

Anomaly detection results in local outlier factor are given in terms of anomaly score and not labels. Values close to 1 are close to the normal value and the higher the score the more the sample is anomaly. Anomaly score values of the data sets are calculated for different values of K. The anomaly score of all Addis Ababa LTE cells in RRC setup success rate data is shown in Figure 6-6.

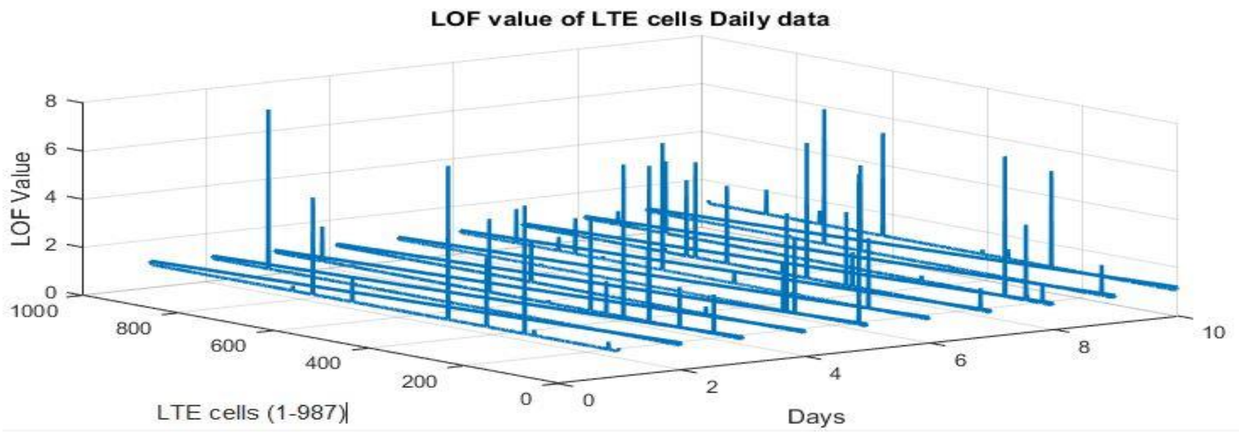


Figure 6-6 Anomaly Score of Cell Level RRC Setup Success Rate using LOF

As percentile-based threshold setting is applied to select the most anomaly cells, detection result for 0.5%, 0.75% and 1% top anomaly cells with RRC setup success rate data is shown in Figure 6-7.

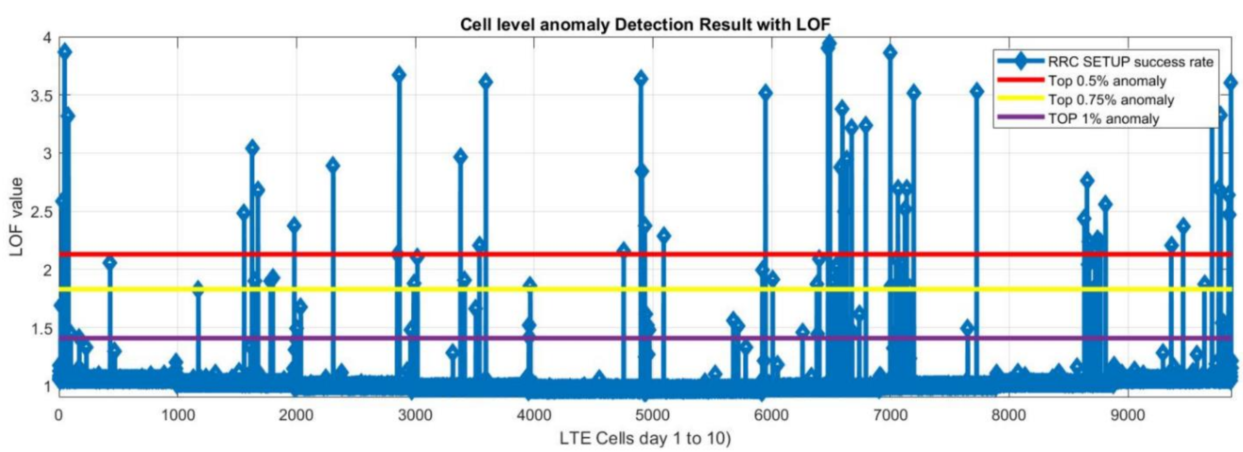


Figure 6-7 Cell Level RRC Setup Success Rate Anomaly Detection with LOF

The performance of the LOF detection algorithm at K=50 is evaluated and the TPR of the algorithm for cell level detection is 97.1%, 93.87% and 91.8% in detecting top 0.5%, 0.75% and 1% anomaly cells respectively with overall accuracy of 99.9%. As can be seen in Figure 6-7 cells with anomaly score values above 1.41, 1.83 and 2.13 are detected as top 1%,0.75% and 0.5% anomaly cells respectively.

For better analysis result and corrective action, it is important to consider and carefully analyze the performance history of cells in time series for their hourly data. Experimentation of hourly time series data taking (111176-2), located around weyra sefer as a sample for anomaly detection, the RRC setup success rate anomaly detection result at a threshold value of 1.41 for the top 1% anomaly obtained in cell level detection is shown in Figure 6-8.

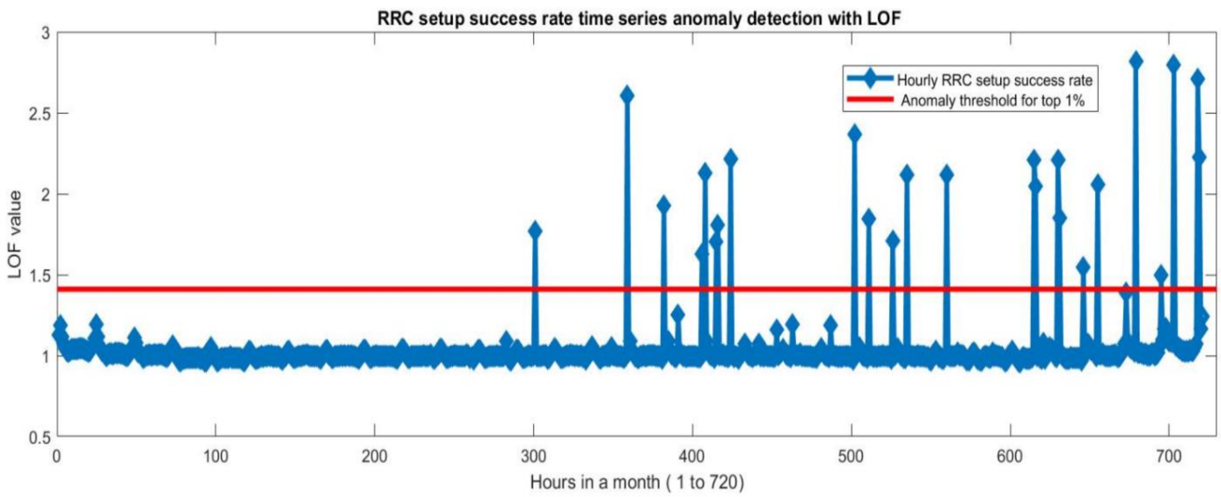


Figure 6-8 Time Series Anomaly Detection with LOF

In Figure 6-8 it is clearly observed that the performance of the cell started to significantly drop near the 300th hour and remained in fluctuation for at least 10 days. The detection result shows, the configuration/reconfiguration done around the 300th hours is not with a positive result and needs to be changed or undo. The detection performance of the time series data sets shows a TPR of 87.5% at 0.5% and 85.71% at 0.75% & 1% decision thresholds. The main reason that the time series detection is with less accuracy than cell level is that, data sets taken in hourly granularity are more dynamic than data sets in daily granularity.

6.4 Result with Connectivity Outlier Factor

Following the experimentation procedures in the process model, anomaly detection experimentation with COF for different values of K and different metrics is done. The anomaly score of all Addis Ababa LTE cells in RRC setup success rate data is shown in Figure 6-9.

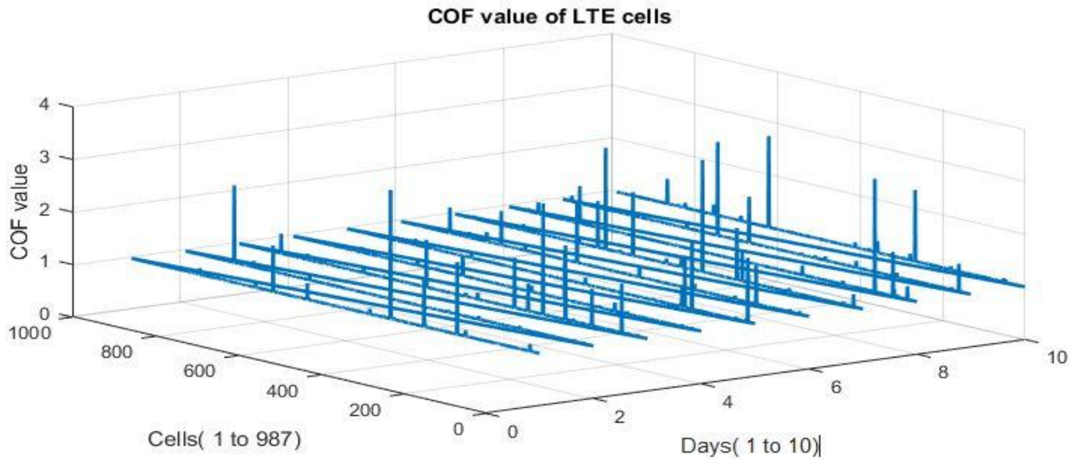


Figure 6-9 Anomaly Score of RRC Setup Success Rate with COF

As percentile-based threshold setting is applied to select the most anomaly cells, detection result of 0.5%, 0.75% and 1% top anomaly cells with RRC setup success rate data is shown in Figure 6-10.

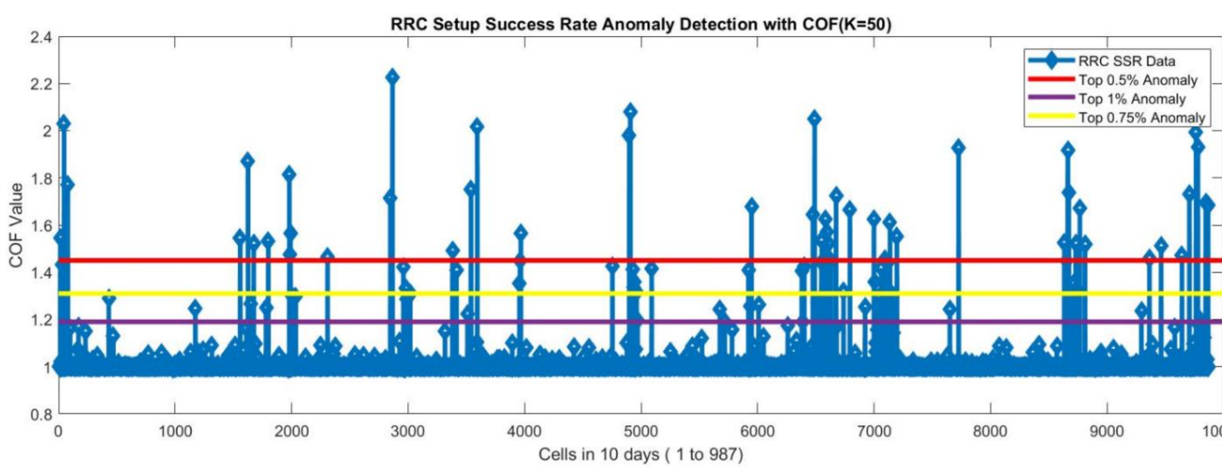


Figure 6-10 Cell Level RRC Setup Success Rate Anomaly Detection with COF

The decision thresholds are 1.19,1.31 and 1.45 for detecting top 1%, 0.75% and 0.5% anomaly cells respectively. The detection performance of COF at K=50 is evaluated and the TPR of the algorithm for cell level detection is 97.9%, 95.91% and 93.87% in detecting 0.5%, 0.75% and 1% top anomaly cells respectively with overall accuracy of 99.9%. The less performance value for high percentage thresholds is, because for higher percentage thresholds it becomes challenging to separate the normal and anomaly values as the performance of anomaly cells becomes closer to normal.

Time series anomaly detection is also done for (111176-2) as a sample. The time series anomaly detection of RRC setup success rate of the cell using COF for the 0.5% anomaly decision threshold of 1.45 is shown in Figure 6-11.

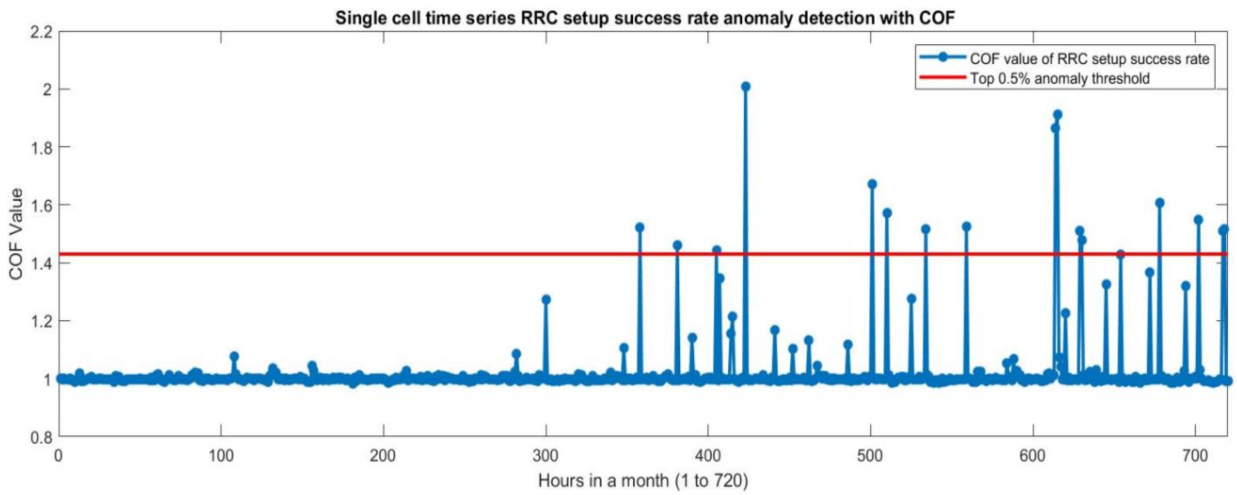


Figure 6-11 Time Series Anomaly Detection with COF for Hourly RRC Setup Success Rate

For the time series data sets a TPR of 87.5% for 0.5% & 0.75%, and 85.71% for 1% top anomaly cells in RRC setup success rate is recorded using COF. Figure 6-11 shows the experimented cell has been with a good RRC setup success rate performance for the first 350 hours of the month and anomaly performance behaviors are observed after the 350th hour and remained unfixed for the remaining hours of the month with fluctuating performance values.

Anomaly detection of SDR cell level data at k=50 using COF is as explained in Figure 6-12. The performance result is 95.91% for detecting 0.5% & 0.75%, and 93.87% for 1% top anomaly cells.

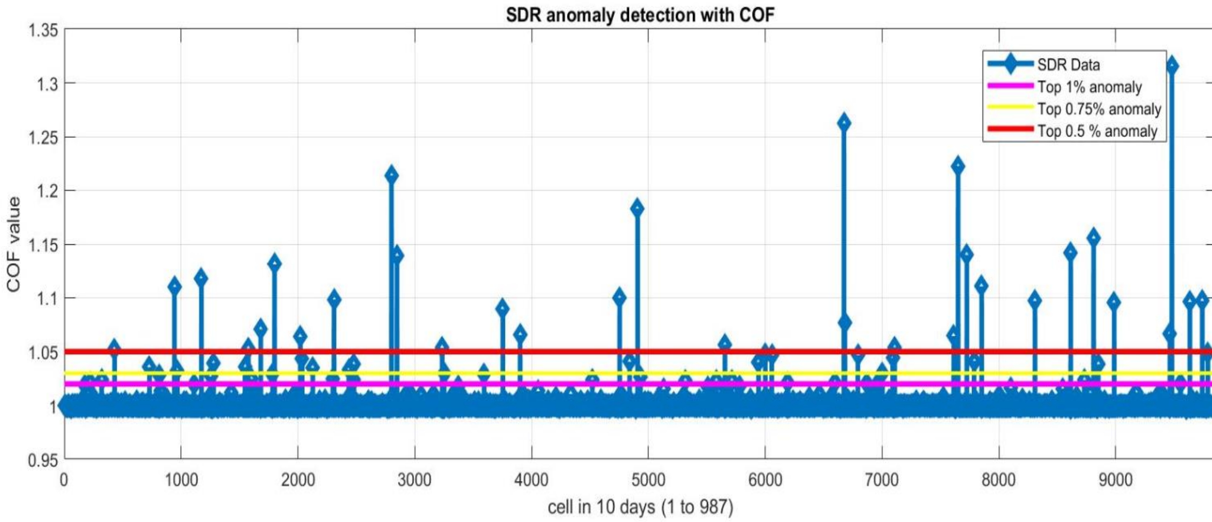


Figure 6-12 Cell Level SDR Anomaly Detection with COF

Anomaly detection experimentation for E-RAB setup success rate is also done following the same procedures with that of RRC setup success rate & SDR. The detection result at K=50 is shown in Figure 6-13. The decision thresholds are 1.17, 1.31 and 1.41 for detecting 1%, 0.75% and 0.5% top anomaly cells. The performance of detecting top 0.5%, 0.75% and 1% anomaly cells is 96%, 94.74%, 94.11% respectively.

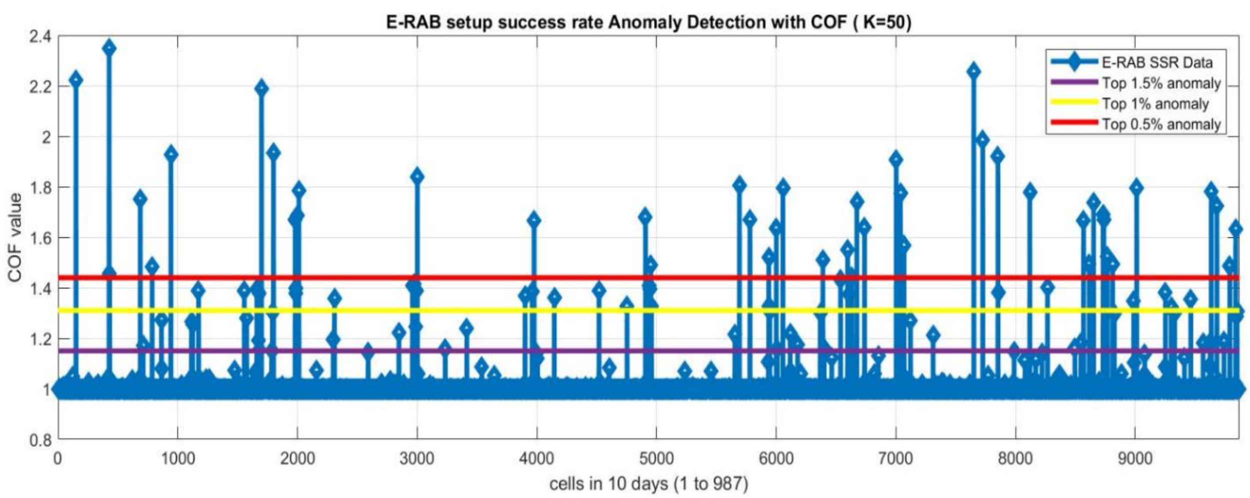


Figure 6-13 Cell Level E-RAB Setup Anomaly Detection with COF

Performance anomaly in one KPI is the cause for anomaly in several other KPIs. In this case deep root cause analysis for the performance anomalies needs to be done. The experimentation with COF is also done for time series anomaly detection. Figure 6-14 shows the existence of performance anomaly in one or two of KPI metrics can be a cause for performance anomaly in other KPI metrics.

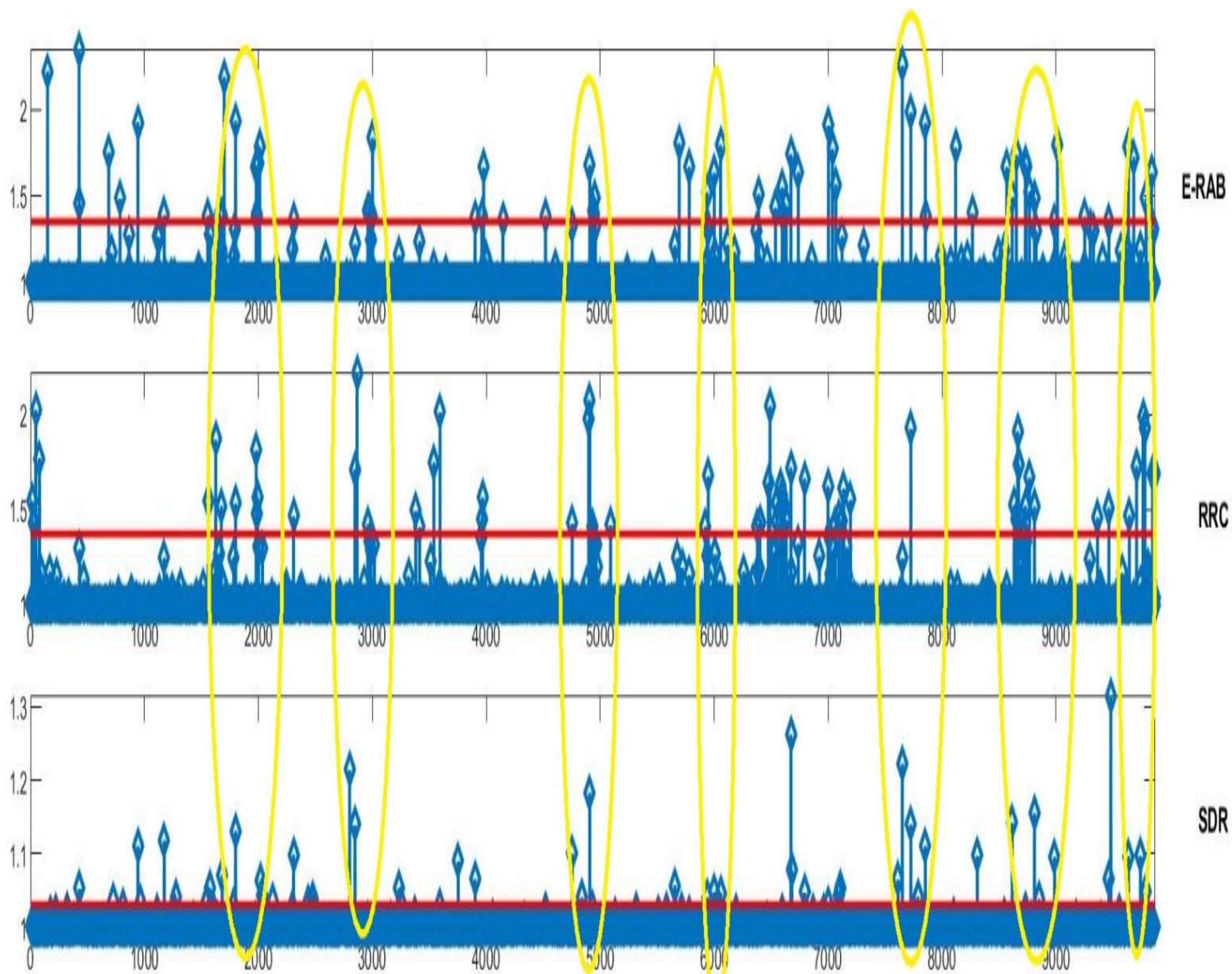


Figure 6-14 Anomaly Interdependence among Different KPI Metrices

6.5 Performance Comparison and Discussion

Anomaly detection algorithms can be compared in different aspects. The type of output, complexity and result accuracy are some of the comparison criterions considered in this thesis work. In this regard LOF and COF that can provide outputs as anomaly score are better than KNN classification that outputs two-class labels as the goal of anomaly detection is to select topmost anomaly cells. Regarding complexity, though KNN classification requires heavy training it is less complex than LOF & COF, as finding the relative density of sample data sets needs deep calculation. COF is more complex than LOF in finding cost and shortest path by calculating SBN trials and SBN edges.

The individual performance evaluation of the algorithms showed that better results are achieved at K=10 with KNN classification, at K=50 and k=25 with LOF, at K=50 and k=25 with COF for the cell level and time series detection respectively. Performance comparison of the algorithms at their best performance condition with respect to their TPR is shown in Figure 6-15.

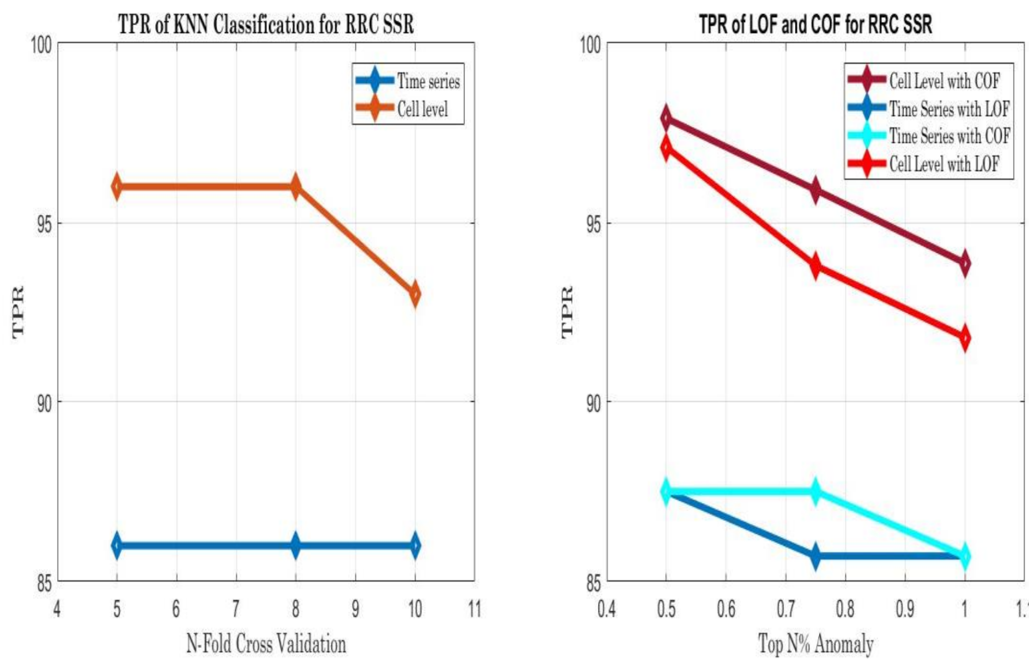


Figure 6-15 Performance Comparison of KNN-based Anomaly Detection Algorithms

The experimentation result shows that, accuracy of all the algorithms is similar and no significant difference is observed. As can be clearly seen in Figure 6-15 the TPR of the specified algorithms is almost the same but the COF seems to have better detection for a larger percentile range. The Figure shows a decreasing TPR of detecting anomalies for higher percentile-based thresholds. But for the KNN classification the TPR is not percentile dependent as it outputs two-class labels. The time series anomaly detection of the KNN classification remained the same at 5 to 10-fold cross validation.

The high accuracy in TNR for both scenarios is due to high proportion of normal to anomaly samples, and the lower TPR in time series detection than cell level detection is due to higher dynamic nature of KPIs in hourly granularity than in daily granularity. Thus, the more the nature of data samples is dynamic the more it becomes difficult for the algorithm to predict the output. Detection accuracy also becomes less when considering higher percentage of anomaly thresholds in LOF and COF as the performance value of anomaly cells become close to normal and then difficult for the algorithms to predict.

7 Conclusion and Future Work

7.1 Conclusion

Anomaly detection is one common operational task of mobile operators so that network problems are timely identified, and corrective actions are taken. The Ethiopian sole operator, ethio telecom is currently applying manual and subjective anomaly detection method, which is maintenance time, manpower and then cost inefficient. To address this problem automatic anomaly cell detection method using machine learning algorithms has been proposed, implemented and evaluated in this thesis work. Anomaly cells can be detected by the measured value of different KPI metrics from network management system. Anomaly cell with respect to one KPI metrics can be normal when measured with respect to another KPIs. Considering type of data sets, distribution type of data sets, required type of output and availability of supervision KNN-based anomaly detection methods are found to be more suitable for cell anomaly detection of Addis Ababa LTE networks.

KNN classification, LOF and COF algorithms are implemented and compared for cell level and time series scenarios. Considering type of output and availability of supervision the KNN classification is less preferable than LOF and COF as it outputs two-class labels and needs heavy training. Comparison result of anomaly detection capability of the algorithms shows that three of them are with negligible performance difference while COF showing slightly better TPR. Though COF is with better detection capability it is more complex than KNN classification and LOF in finding the shortest path for connectivity.

7.2 Future Work

In the future this anomaly detection algorithms can be done for detection of anomaly cells using multivariate KPIs. It can also be done for fault prediction, fault root cause detection and outage detection. Anomaly detection for other Technologies such as FL NGN and IP networks can also be part of the future work.

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