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Prediction of LTE Cell Degradation Using Hidden Markov Model

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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

Long-Term Evolution (LTE) networks play a crucial role in providing high-speed wireless communication services. However, operators often have incomplete awareness of the overall state of their LTE networks due to the vast number of cells, the dynamic nature of LTE networks operations, complex interference scenarios, and huge number of key performance indicators (KPIs). This thesis presents a novel approach to predict LTE cell degradation levels using Hidden Markov Models (HMM). HMMs are a class of probabilistic models that can be used to capture the dynamic nature of LTE networks. HMMs model the sequential occurrence of cell degradation events, which provides network operators statistical insights into the future state of cells based on historical data.

To develop our prediction model, we used KPIs, such as average traffic volume, number of Reference Signal Received Power (RSRP) measurement report, and number of outgoing handover requests as observation datasets. These KPIs are clustered into six unique observation sequences, which form the basis for our model training. Then, the Baum-Welch algorithm is applied to train and obtain the HMM parameters for modeling the cell degradation. The results of the study convincingly demonstrate the performance scores of the HMM prediction model. With an average of 23 observation lengths, the HMM achieved an average accuracy of 93.12%, F1 score of 91.81% and a precision of 92.82%. These metrics illustrate the effectiveness of using the proposed HMM approach in predicting LTE cell degradation levels.

This research addresses the challenges of monitoring and analyzing LTE cell degradation events by proposing a comprehensive methodology for LTE cell degradation prediction using HMM and KPIs. The timely provision of predictions enables operators to proactively identify and address potential network issues, optimizing network performance and enhancing quality of service.

The main limitations of this study are that it was conducted on a small number of cells and only four degradation states. Future work should test the approach on a larger number of cells with various KPIs and complex states using different types of HMMs.

Keywords: *LTE cell degradation prediction, HMMs, KPIs, Baum-Welch algorithm and Accuracy*

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List of Acronyms

3GPP	3rd Generation Partnership Project
4G	Fourth-Generation
5G	Fifth Generation
CDR	Call Drop Rate
CSSR	Call Setup Success Rate
DL	Down Link
DTMC	Discrete Time Markov Chain
eNB	Evolved Node B
EPC	Evolved Packet Core
ET	ethiotelecom
EUTRAN	Evolved Universal Terrestrial Radio Access Network
GPRS	General Packet Radio Service
GW	Gateway
HetNets	Heterogeneous Networks
HMM	Hidden Markov Model
HSPA	High-speed packet access
HSS	Home Subscriber Server
inHO	Incoming Handover
IoT	Internet of Things
IP	Internet Protocol
KPI	Key Performance Indicators
KQI	Key quality Indicators
LENA	Low Energy Wireless Network Analyzer
LR	Linear Regression
LSTM	Long-Short Term Memory
LTE	Long Term Evolution
MC	Markov Chain
MIMO	Multiple Input Multiple Output
MME	Mobility Management Entity

NS-3	Network Simulator 3
OFDMA	Orthogonal Frequency-Division Multiple Access
OPEX	Operating Expenditure
OSS	Operation Subsystem
PCA	Principal Component Analysis
PDN	Packet Data Network
PRB	Physical Resource Block
QoS	Quality of Service
RAN	Radio Access Network
RNN	Recurrent Neural Network
RRC-SR	Radio Resource Controller Success Rate
RSRP	Reference signal received power
RSRQ	Reference Signal Received Quality
SAE	System Architecture Evolution
SGW	Service Gateway
SINR	Signal-to-Interference-plus-Noise Ratio
SLA	Service Level Agreement
SON	Self-Organizing Networks
SVM	Support Vector Machine
UE	User Equipment
UMTS	Universal Mobile Telecommunications System
EUTRAN	Evolved Universal Mobile Telecommunications System Terrestrial Radio Access Network.
WCSS	Within-Cluster Sum of Squares

1. Introduction

1.1. Network Performance Monitoring

Due to increasing demand for seamless connectivity and high-speed mobile data services, Long Term Evolution (LTE) has become the dominant technology for wireless communication networks. LTE is a fourth-generation (4G) standard that used extensively for applications ranging from mobile broadband to Internet of Things (IoT) across various domains and industries [1]. For example, mobile broadband can provide high data rate and low latency connectivity for IoT devices that need to stream video, audio, or other multimedia services. The number of connected devices, including IoT devices, forecasted to reach 4.1 billion by 2024 [2]. This indicates that the increasing demand for cellular services as well as the need to keep user equipment always connected to mobile networks.

However, the provision of uninterrupted user equipment connectivity within limited radio resources poses a significant challenge, as LTE cells often experience degradation due to different factors. Cell degradation refers to the condition where the cell's performance in handling traffic is significantly lower than expected. This degradation can be caused by factors such as increased user traffic, interference, hardware failures and degradation of the radio environment because of physical obstructions and users' mobility [3, 4, 5].

Self-Organizing Networks (SON) are used to manage network complexity while reducing operating expenditure (OPEX) associated with network monitoring. As part of the LTE standardization process, SON was standardized by the third Generation Partnership Project (3GPP) in Release 8 [6, 7]. The idea of SON further enhanced in Release and Release 10 with more use cases and features for High-speed Packet Access (HSPA) and LTE/LTE-Advanced networks [8, 9].

The functionalities of SON covers three main categories: self-configuration (automated configuration), self-optimization (automated update of parameters for best service) and self-healing (that includes fault detection, isolation, diagnosis) [10, 11]. The SON monitoring function continuously monitors Key Performance Indicators (KPIs) to detect problems in the network. If a KPI falls outside of its acceptable range, the monitoring function triggers an alarm. The alarm provides information on the KPI and possible causes, enabling the network operator to investigate and take corrective action. In some cases, the monitoring function can take corrective action itself [8].

Fixed thresholds of KPIs evaluates the operation quality and health state of a cellular network [9, 10] . This is a good starting point to identify potential problems within a network and to take corrective action. For instance, the availability KPI in *Table 1.1* measures the percentage of time that a network is available to users. This information can identify areas where the network is performing poorly and to take steps to improve performance.

Table 1.1: Common KPI's and thresholds for performance monitoring

KPI	Threshold	Description
Availability	>95%	This metric measures the percentage of time that a network is available for use.
Call Drop Rate (CDR)	<2%	This metric measures the percentage of calls that are dropped before they are completed.
Congestion Rate	≤2%	This metric measures the percentage of time that a network is congested.
Call Setup Success Rate (CSSR)	≥ 96%	This metric measures the percentage of times that a call is successfully set up.
Handover Success Rate (HOR)	≥ 96%	This metric measures the percentage of times that a call is successfully handed over from one cell to another.

However, there are some basic problems with these monitoring techniques:

- *Reactive approach:* By the time a degradation or outage is detected using a fixed threshold approach, it may already be too late to take corrective action.
- *Sensitivity:* Fixed threshold based monitoring is not always sensitive enough to detect minor changes in network performance. This can lead to problems going undetected until they have become serious.

- *Static metrics:* The metrics used to monitor a network are often static. The thresholds to measure the performance typically based on industry standards or best practices; they are typically set once and then not changed very often. This means that they do not take into account the dynamic changes in the network environment.

Table 1.2 presents the industry standard classification of base transceiver station (BTS) outage states in wireless networks. The states are categorized as *minor, major, critical, and crisis*, based on the number of BTSs affected and the duration of the outage. The crisis state further divided into three subcategories: *yellow, red, and black*. However, this classification results in a significant number of states that makes the analysis complex.

Table 1.2: Industry-defined outage states for Base Transceiver Stations

Affected Number of BTS	Minor State	Major State	Critical State	Crisis State		
				Yellow	Red	Black
Capital city ≥ 5 & ≤ 25 $BTSs$ @ the same time **unavailability**		0 Min to $12hrs$	12 hrs to 1 day	1 day to 2 $days$	2 $Days$ to 3 $Days$	>3 $days$
Capital City >25 & ≤ 50 $BTSs$ @ the same time **unavailability**		0 Min to $6hrs$	12 hrs to 1 day	1 day to 2 $days$	2 $Days$ to 3 $Days$	>3 $days$
Capital city >50 & ≤ 75 $BTSs$ @ the same time **unavailability**			0 Min to 1 day	6 hrs to 1 day	6 hrs to 1 day	>1 day
Capital city <75 & ≤ 100 $BTSs$ @ the same time **unavailability**			0 $Min-6$ $hrs.$	6 hrs to 12 $hrs.$	12 hrs to 18 $hr.$	>18 hrs
Capital city >100 & ≤ 200 $BTSs$ @ the same time unavailability			0 min to 4 hrs	$4hrs$ to 8 hrs	$8hrs$ to 12 hrs	>12 hrs
Capital City >200 $BTSs$ @ the same time **unavailability**				0 Min to 4 $hrs.$	4 hrs to 8 hrs	>8 hrs
Regional Main towns ≥ 10 & ≤ 50 $BTSs$ @ the same time **unavailability**		$0Min$ to 1 $Days$	1 $days$ to 3 $days$	3 $Days$ to 5 $Days$	5 $days$ to 10 $days$	>10 $Days$
Remote /road coverage >100 $BTSs$ @ the same time **unavailability**			0 min to $1day$	$1day$ to $2day$	2 $days$ to 4 $days$	>4 $days$

On other hand, various levels of cell degradation are categorized as "minor" in the industry definition, which operators do not consider this state to be manageable and therefore care less about this state. However, these levels of degradation can still have a significant impact on the network performance and user experience. For instance, a cell with reduced signal strength may not be able to support as many users, or it may experience more dropped calls. This can lead to user complaints and loss of revenue.

Therefore, determining the level of degradation and accurately predicting the future state of LTE cell condition is the most important task in monitoring cellular networks. This information can be used to take predictive (proactive) maintenance or optimization action to improve the network performance and user experience.

1.2. Hidden Markov Models for Cell Degradation Prediction

Various levels of cell degradation, excluding outages, are classified as minor in the industry definition. These levels of degradation can still affect the performance of the network and lead to outages if not addressed. One approach to assessing the health of a network even when there are no outages is to focus on a group of cell or BTS and collect related data such as reference signal received power (RSRP). This data and Machine learning algorithms such as hidden Markov models (HMMs) can be used to identify patterns that may indicate problems.

The prediction of cell degradation has been the subject of research using a variety of KPIs and machine learning algorithms. For example, in [12], accessibility degradation was predicted using a discrete-time Markov chain (MC) from historical Radio Resource Controller Success Rate (RRC-SR) data. In [13], a recurrent neural network (RNN) was used to process simulated reference signal received power (RSRP) reports to detect cells' performance degradations and complete outages. An ensemble learning-based approach, or a combination of machine learning algorithms such as random forest, decision tree, and support vector machine, has also been applied to detect anomalies in cellular networks [14].

However, these approaches have some limitations. For instance, MC is a simple model that can be used to predict cell degradation, but it is difficult to apply it when the network states are hidden or unknown. Additionally, RNN can capture long-term dependencies and complex patterns in sequential data, but it requires sufficient training data and has high computational cost [15]. Ensemble learning is a combination of multiple machine learning algorithms, which can improve accuracy but can also be computationally expensive.

The selection of a model for network state prediction and other applications should consider the specific application and the available resources. Some of the most common selection criteria include simplicity of the algorithm, prediction accuracy, memory usage, computational power and speed [16, 17]. The relative importance of these factors will vary depending on the specific application. Therefore, there is no single best approach for predicting cell degradation, and different methods may have different advantages and disadvantages depending on the data and the problem at hand.

In this thesis work, we proposed a HMM to overcome some of the limitations described above. HMMs are attractive option for real-time applications as they are simpler models than ensemble learning-based approaches and are more computationally efficient model than RNN [15].

HMMs are a type of statistical model that can be used to predict the future state of a system based on past and present states of the system. In the case of LTE cell degradation, the system is the LTE cell itself. The states in this system are the different levels of degradation that the cell can experience. These states can be defined by the average RSRP value, which is a measure of the signal strength of the cell. Therefore, HMMs are particularly well suited for predicting the degradation of LTE cells because they can model the state of the network in different ways. For example [18, 19, 20]:

- *Modeling the temporal dynamics of LTE cell degradation:* HMMs can model the probability that a cell will degrade over time. This information can be used to predict when a cell is likely to degrade, and to take steps to prevent or mitigate the degradation.

- *Modeling the spatial distribution of LTE cell degradation.* HMMs can be used to model the probability that a cell will degrade in a particular location. This information can be used to identify areas where LTE cell degradation is likely to occur, and to take steps to improve the performance of LTE networks in those areas.
- *Modeling the impact of different factors on LTE cell degradation:* HMMs can model the impact of interference, shadowing, and user traffic on LTE cell degradation. This information can be used to identify the root causes of LTE cell degradation, and to take precise corrective measures to mitigate the impact of those factors and optimize network performance.

Cell degradation condition can be considered as a dynamic process because the state of the cell changes over time due to factors like interference, traffic load, environmental conditions or user location. Therefore, HMM is used in this thesis for modeling the temporal dynamics of LTE cell degradation.

1.3. Statement of Problem

Despite the significant advancements in cellular network technology, the issue of cell degradation remains a challenging problem that is often overlooked in favor of cell outage [21, 22]. Traditional methods, such as those based on KPIs or alarm correlation [23], have proven to be inadequate in detecting or predicting cell degradation [24], creating a gap in maintaining optimal network performance. Because, this is time-consuming and labor-intensive process and as a result, it is difficult to ensure that all cells are inspected regularly, which means that some cells may be neglected and allowed to stay in a degraded state.

Furthermore, most existing literature on this subject has relied on simulated datasets or datasets that do not accurately represent real-world LTE network conditions [24] . This lack of real-world applicability limits the effectiveness of these studies in addressing the issue of cell degradation in practical scenarios. Additionally, the majority of the literature has only considered three levels of degradation: *normal, medium, and high* [23]. This classification may not be sufficient to capture the complexity and variability of cell degradation in real-world networks.

To address the problem of cell degradation in cellular networks, it is essential to conduct research using real-world LTE network datasets and consider a more nuanced classification of degradation levels. This approach should not only include normal, medium, and high levels but also critical levels of degradation. HMM can be used to model the degradation process and detect the degradation level of cells. By using HMM, it is possible to predict the future state of a cell based on its past states and observations. This approach could potentially lead to more accurate detection and prediction methods, ultimately improving the performance and reliability of cellular networks.

1.4. Literature Review

In [25], an algorithm for predicting accessibility performance on an LTE/SAE network using historical KPI data was proposed. The algorithm uses a Discrete Time Markov Chain (DTMC) model to predict future network conditions based on the state sequence obtained from the historical data. The article explains the use of Markov processes to model network performance and discusses the identification of three accessibility states. The proposed method was tested on a real LTE/SAE network for one month, and the probability that a certain cell will be in one of the three states (*high, acceptable, or low/degraded*) in future time was calculated. These results were used for root cause analysis, degradation detection, and scheduling preventive measures. The article provides a detailed explanation of the proposed algorithm and its potential applications in network management.

In [11], the authors proposed a HMM for efficient cell outage detection in 5G heterogeneous networks (HetNets). The HMM was used to probabilistically estimate a cell outage based on the current states of the base stations, which were classified into four categories (*healthy, degraded, crippled, and catatonic*) based on the base station transmission power. The measured values of RSRP and RSRQ were used to define or label the observation symbols. The prediction algorithm was based on the Forward-Backward algorithm. The proposed algorithm was evaluated on the NS3 LENA 1 platform (tool), with the parameters modified to imitate a 5G HetNets. Simulation results demonstrated that the proposed strategy could detect cell outage with 95% accuracy and correctly predict the other cell states 80% of the time. However, the proposed method might not be able to identify all cell outages, such as those caused by hardware malfunctions or power outages. Overall, the authors present a promising approach for efficient cell outage detection in 5G HetNets using HMM.

In [26], the authors proposed a correlation-based cell degradation detection method for LTE networks. The method uses inter-cell analysis to detect sleeping cells and other network issues by comparing KPIs of one cell with corresponding KPIs of other cells. The correlation coefficient between cell pairs used as a means for degradation detection. The authors selected three comparing cells for each target cell based on their correlation with the target cell. A predefined threshold level and usage percentage of downlink physical resource block (DL PRB) for 24 hours’ time window collected from a live LTE network was used to evaluate the proposed approach. The proposed method correctly classified 72% of the degradation samples and only produced 13% false positives. The authors concluded that the proposed method could easily modified to improve detection accuracy in more complicated scenarios.

In [27], the authors proposed a framework for cell outage detection and degradation classification in SONs using a combination of alarms, KPIs, and machine learning algorithms. The framework uses expert analysis and correlation-based feature selection techniques to select KPIs that indicate cell degradation. The selected KPIs are CDR, CSSR, and Incoming Handover (inHO) Success Rate. The fixed thresholds of these KPIs are used to define three classes of degradation: *normal, medium, and critical*. The framework also checks a set of selected KPIs to make cell outage detection after the specified outage alarms are checked. The authors also discussed various methods for detecting and managing cell outages in cellular networks, including data analysis, neighbor cell list reports, handover statistics, and machine learning algorithms. The document provides valuable insights into the use of machine learning techniques for cell outage detection and degradation classification with 99% accuracy for both cell outage detection and cell degradation classification using random forest algorithm. Therefore, the use of these methods can improve network performance and reduce downtime.

In [28], the authors propose a method for predicting the state of a wireless network using MC and HMM. The method first analyzes the traffic load at an access point with respect to time to generate a sequence of states of the access point. The authors then use MC and HMM to predict the future load of the access point. The proposed approach considers the observed traffic (in Byte) as the observation sequence and access point state sequence as the hidden states. The state of an access point classified as low, mid, or high based on the number of active connections. Both HMM and MC can accurately predict future load on wireless access points, and the accuracy improves as the training data size increases. The results show that the MC can predict with an accuracy of 95.55% for the next 50 days if the initial transition matrix is calculated directly.

In these research articles, various methods for predicting and detecting network performance degradation and cell outages in wireless networks are proposed. The article in [25] introduces an algorithm that uses historical data and a DTMC model to predict future network conditions, which can be used for root cause analysis and preventive measures. The article in [11] presents a HMM for efficient cell outage detection in 5G HetNets, achieving high accuracy in detecting cell outages. The article in [26] proposes a correlation-based method for detecting cell degradation in LTE networks, using inter-cell analysis and correlation coefficients. The article in [27] introduces a framework for cell outage detection and degradation classification in SONs, using expert analysis, KPIs, and machine learning algorithms. The article in [28] presents a method that uses MC and HMM to predict the state of a wireless network based on traffic load, achieving high accuracy in load prediction. Overall, these methods offer promising approaches for improving network management and performance.

In our research, we have selected HMM for LTE cell degradation prediction. HMMs are statistical models that can effectively model temporal dependencies between events. Our approach differs from previous works in in the following ways:

- We focus on cell degradation rather than cell outage, recognizing that degradation is a more subtle condition that can be challenging to detect or predict using traditional methods.
- The dataset used for evaluating the HMM is more representative of real-world LTE networks compared to the datasets used in previous research.
- Unlike other literature that considered only three degradation levels, we have included four possible degradation levels: *normal, medium, high, and critical*.

1.5. Objectives

1.5.1. General Objective

The general objective of this thesis work is to develop a HMM-based model for predicting the degradation severity of LTE cells.

1.5.2. Specific Objectives

To achieve our general objective, the specific objectives of the thesis are:

- Reviewing relevant literature and existing methodologies for predicting LTE cell degradation severity.
- Collecting and analyzing relevant data on LTE cell performance and degradation.
- Identifying and selecting appropriate features and parameters for modeling LTE cell degradation.
- Developing an HMM-based model for predicting LTE cell degradation sequences and discussion results obtained by the model.
- Validating and evaluating the performance of the HMM-based model using real-world LTE cell data.
- Discussing the limitations and potential future directions for further research in the field of LTE cell degradation prediction.

1.6. Scope and Limitations

The scope of this thesis is to develop a method for predicting the degradation of LTE cells using HMMs. The thesis aims to focus on predicting four different hidden states of cell degradation: normal, medium, high, and critical. These states will be determined based on average RSRP values. The thesis plans to train the HMM using various parameters such as average traffic volume, outgoing handover request time, and the number of RSRP measurement reports. The ultimate goal is to use the trained HMM to predict the future state of cell degeneration severity, which will be represented by a hidden state sequence inferred statistically from the HMM. It should be noted that this thesis is limited to predicting cell degradation solely based on the aforementioned parameters and does not consider other potential factors that may influence the degradation process.

1.7. Methodology

After the problem has been identified and the objective has been determined, the methodology used in this thesis is presented using a workflow diagram shown in *Figure 1.1*. The study concept used in this thesis mainly requires observation dataset. This observation dataset was collected from Operation Subsystem (OSS) of ethio telecom network. The collected data is then passed through preparation process, which includes cleaning the data, feature selection, and transforming the data into a format that is compatible with our model. Features for observation sequence was selected based on techniques called principal component analysis (PCA) and domain knowledge. Using the average RSRP values, we define four hidden states that our model can predict. The four hidden states represents the degradation severity of a cell. The preprocessed observation dataset and the defined number of hidden states were used as an input to train HMM model. We used the Baum-Welch algorithm to train our model and estimate the HMM parameters, namely the initial probability, the transition probabilities and the emission probabilities. Once the HMM is trained and parameters are obtained, we used to predict the future degradation state and the sequence of the degradation state over the time.

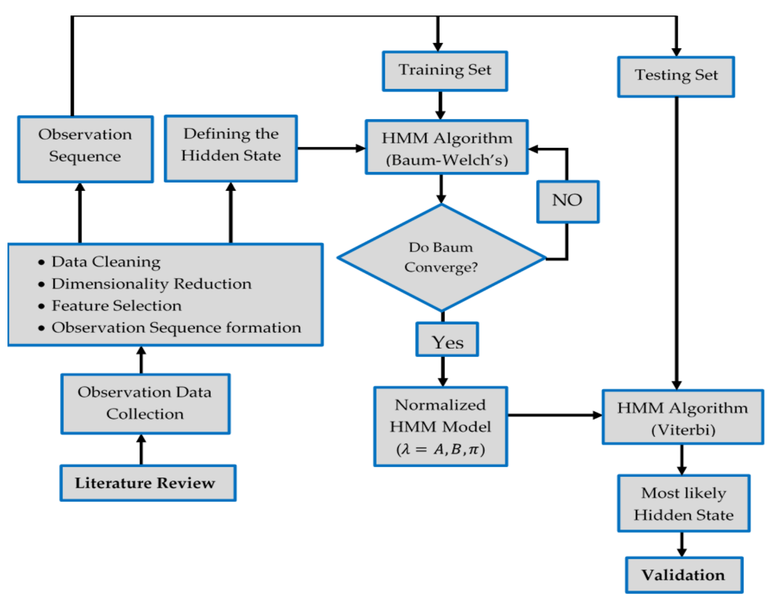

Figure 1.1: System model for prediction of cell degradation.

1.8. Contributions

This work will have the potential to make significant contributions to the field of cellular networks monitoring. One of its expected contributions is the prediction model for LTE cell degradation. In addition, the study may also provide the following:

- *Improved decision-making:* The result from HMM-based prediction model can be used to improve decision-making by providing network operators with more accurate information about the state of the cellular network.
- *Earlier identification of problems:* By predicting the sequence of degradation severity, network operators can identify problems earlier than they would be able to by simply monitoring the current state of the LTE cells. This can help to prevent outages and improve the quality of service for users.

1.9. Thesis Outline

The remaining parts of the thesis document is organized as follows: Second section gives an overview of LTE network and its architecture with more emphasis on the components of an LTE network, such as eNB, EPC and the concepts of radio interfaces and functions will be discussed. Third section provides introduction of HMM including background knowledge, the notations and assumptions used in HMM. The three basic problems of HMM with their solution will also discussed briefly. In fourth section, the detail experimental processes and steps of the proposed approach will be discussed. Fifth section contains result and discussion including model evaluation. The last section provides a conclusion of the overall study and considerations for future work.

2. Overview of LTE Network

Long-Term Evolution (LTE) started with the third Generation Partnership Project (3GPP) Release 8 and continued in Release 10 with the objective of meeting the increasing performance requirements of mobile broadband. Some key features of Release 8 include high spectral efficiency, very low latency, support of variable bandwidth, simple protocol architecture, and support for SON operation. Release 10, also referred to as LTE Advanced, which is a 4G specification that offers enhanced peak data rates to support advanced services and applications (100 Mb/s for high mobility and 1 Gb/s for low mobility) [29]. LTE uses a number of different technologies to achieve its high performance, including [30]:

- *Orthogonal Frequency-Division Multiple Access (OFDMA):* a modulation scheme that allows multiple users to share the same radio channel.
- *Multiple Input Multiple Output (MIMO):* multiple antennas that allows LTE networks to transmit and receive data over the same radio channel.
- *Carrier Aggregation*: which allows LTE networks to combine multiple frequency bands to achieve even higher data rates.

In addition, LTE networks are more efficient than previous cellular technologies, using less power to transmit and receive data. This makes them more environmentally friendly and allows for longer battery life on mobile devices. However, the advantages of LTE make the complexity of the system increased, in terms of optimizing, operating and managing the system. Therefore, network operators need a more efficient way to manage networks by reducing manual involvements.

2.1. Network Architecture of LTE

LTE network architecture can be divided into two main sub networks: The Radio Access Network (RAN) and Core Network [31] as shown in *Figure 2.1*. Each sub-network contains different network elements that have different functions.

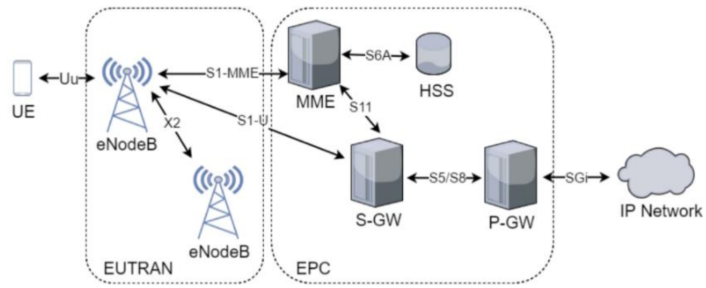

Figure 2.1: LTE network architecture, main components and interfaces [4]

2.1.1. Radio Access Network for LTE

The radio access network (RAN) is used for wireless radio connection between the mobile phones and antennas from the mobile operator. The radio access network is also called Evolved Universal Mobile Telecommunications System Terrestrial Radio Access Network (E-UTRAN). RAN infrastructure is formed of the following nodes:

- *LTE mobile terminals:* are mobile handsets and other devices that support the LTE standard carried by end users and used to connect subscribers to the Evolved Node B (eNB) via Uu interface.
- *Radio Interface:* Radio interface is a wireless connection between the LTE mobile terminals and eNB. It is a wireless signal that form the mobile cells.
- *eNBs:* The E-UTRAN allows connectivity between a UE and the EPC via the S1 interfaces. E-UTRAN is a mesh network that contains a set of eNB, which is the main component that allows users to connect to the network. Each eNBs are connected to each other through the X2 interface.

2.1.2. Core Network for LTE

The LTE core network is called Evolved Packet Core (EPC). The EPC is the 4th generation 3GPP core network architecture. When developing the 4G systems, the 3GPP community decided to have an all IP network with packet switching architecture [32]. In addition, fewer number of network nodes are used for the handling of user traffic. For these reasons, the EPC is considered as a flat architecture compared to that of General Packet Radio Service (GPRS) and Universal Mobile Telecommunications System (UMTS) core network [32].

The EPC is composed of four network elements: Mobility Management Entity (MME), Service Gateway (SGW) and Packet Data Network Gateway (PDN-GW) [33].

- *Mobility Management Entity (MME):* is the key control node of the LTE core network that deals with the control plane. It takes care of the signaling related to security and mobility for the E-UTRAN. It is also the node responsible for tracking the user devices in the network and paging in case of any new data for the devices.
- *Serving Gateway (SGW):* is the interconnection point between the radio side of the network and the EPC. It routes incoming and outgoing user plane IP packets towards the UE.
- *Packet Data Network Gateway (PDN-GW):* is the interconnection point between the EPC and the external IP networks. It routes the user plane IP packets to and from the external IP networks. It also performs the functions of IP address or prefix allocation to the UEs and policy control and charging.
- *Home Subscriber Server (HSS):* is a database that stores the various user-related and subscription-related information. In coordination with the MME, the HSS performs the functions of mobility management and user authentication.

2.2. Standardized LTE Network Interfaces

In the third Generation Partnership Project (3GPP), Release 8, standardized signaling interfaces have been implemented to facilitate end-to-end communication between the E-UTRAN and core network elements. These interfaces, including the X2 interface and the S1 interface, play a crucial role in enabling connectivity within the EPC and between eNodeBs and the core.

For instance, the X2 interface facilitates messaging and control plane procedures, such as mobility management, between eNBs. On the other hand, the S1 interface is primarily used for transporting user data. Together, these interfaces help reduce latency in communications by allowing high throughputs, quick switching times, and low power consumption. Their standardization not only enhances communication efficiency but also ensures seamless interoperability between network elements.

2.3. Key Performance Indicators of LTE Network

Competition in the liberalized telecommunications markets and customer requirements for more complex services are leading to a greater emphasis on the provision of efficient customer service. To achieve this goal, telecommunication operators have found the Service Level Agreement (SLA) solution. In the performance management hierarchy, Key Quality Indicator (KQI) supports SLA; KPIs supports KQI; and KPI is supported by network performance data from network elements [34].

The most crucial steps for the mobile operator are the performance of cellular networks and the evaluation of quality of service (QoS) because they are related to profits and subscribers' satisfaction. Thus, the QoS for the cellular network is an important factor in the competition for subscribers and can be accomplished when the network is properly optimized to meet SLA. However, due to the continuously increasing number of users, it is hard to optimize the cellular network and needs evaluation of network performance.

As a result, mobile network statistics must be determined in order to maximize the performance of LTE networks in a particular area [35].

LTE KPIs can be divided into two broad categories, namely user perceived experience and radio network KPI as shown in *Figure 2.2*. The user perceived experience is generally carried out directly with a drive test (outdoor area) or walk test (indoor area) [36]. The radio network KPIs commonly called Evolved RAN KPIs.

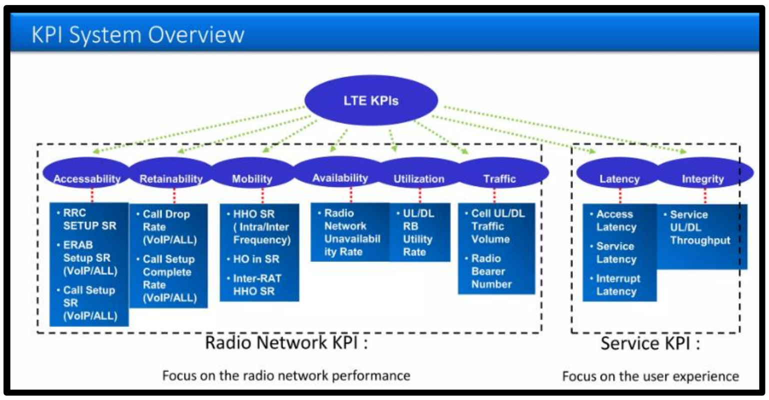

Figure 2.2: Classifications of LTE KPI [35]

KPIs, or key performance indicators, vary based on the services. The download and uplink throughput, as well as the strength and quality of the signal, are KPIs that have an impact on the network's capacity and coverage. KPIs also serve as indicators of whether a piece of technology or equipment satisfies requirements for deployment readiness.

In this thesis, we have been focused on the KPIs that affect the network directly, such as RSRP and its number of report within the usable RSRP range, traffic volume across the cell and number of handover request time. RSRP is a measure of the signal strength of the reference signal from the cell.

A low RSRP value indicates that the signal is weak, which can lead to problems such as dropped calls and poor data speeds. The number of reports within the usable RSRP range is a measure of how often the signal is strong enough to maintain a good connection.

Traffic volume across the cell is a measure of the amount of data that is being transferred across the cell. A high traffic volume can lead to congestion, which can degrade the performance of the network. *Number of handover request time* is a measure of how often the network has to hand over a connection from one cell to another. A high number of handover requests can indicate that the network is congested or that there is interference

2.4. The Challenges of Cell Degradation in LTE Networks

Cell degradation in LTE networks is a problem that arises when a cell or a site fails to provide the users with the required level of service or performance. The factors that contribute to the degradation of LTE cells can be classified into two categories: internal and external. Internal factors are related to the equipment malfunction or configuration errors of the cell or the site, such as hardware failure, software bugs, misalignment of antennas, etc. External factors are related to the environmental conditions or user behavior that affect the cell or the site, such as interference, signal attenuation, weather changes, user load, mobility patterns, etc. [37, 38, 39].

The types or categories of cell degradation can be defined based on the impact of the degradation on the network performance or service quality. Some common types are:

- *Signal quality degradation:* This type of degradation affects the signal-to-interference-plus-noise ratio (SINR) of the cell, which is a key indicator of the quality of the radio link. Signal quality degradation can result in lower data rates, higher error rates, and higher retransmission rates for the users [39, 38].
- *Throughput degradation:* This type of degradation affects the data rate or capacity of the cell, which is a key indicator of the efficiency of the radio resource utilization. Throughput degradation can result in lower user satisfaction, lower network revenue, and higher network congestion for the operator [37, 38].
- *Coverage degradation:* This type of degradation affects the coverage area or reachability of the cell, which is a key indicator of the availability of the network

service. Coverage degradation can result in lower signal strength, higher handover failure rates, and higher call drop rates for the users [39, 38].

- *Service disruption:* This type of degradation affects the functionality or accessibility of the cell, which is a key indicator of the reliability of the network service. Service disruption can result in complete loss of network service, higher user complaints, and higher operational costs for the operator [39, 38].

The effects of cell degradation are primarily related to the decrease in network efficiency and service level, which may have an impact on both users and the operator. Some possible consequences are [37, 38, 39]:

- *Reduced user experience*: Cell degradation can cause lower data rates, higher error rates, lower signal strength, higher handover failure rates, higher call drop rates, and complete loss of network service for the users. These can reduce the user satisfaction, trust, and retention for the operator.
- *Increased operational costs:* Cell degradation can cause lower network revenue, higher network congestion, higher user complaints, and higher maintenance costs for the operator. These can reduce the profitability and competitiveness of the operator.

Overall, cell degradation poses significant challenges for LTE networks, affecting signal quality, throughput, coverage, and overall service. Addressing these degradation level and factors for ensuring efficient network optimization and maintenance are crucial for delivering a reliable and high-quality cellular experience to users.

3. Introduction to Hidden Markov Models

HMM is a probabilistic machine-learning model, which used in many disciplines to perform classification tasks. HMM provides solution of three problems: evaluation, decoding and learning to find most likelihood classification. This section starts with description of Markov chain and then it follows elaboration of HMM, which is based on Markov chain. Discussion of all algorithms used to solve the three basic problem of evaluation, decoding and learning is included.

3.1. Markov Chain

Markov models or Markov chains (MC), named after Andrey Andreyevich Markov (1856–1922) [40, 41] are stochastic model describing a sequence of observable or visible states. The basics of Markov models is that *the current state depends only on the most recent state,* which is known as the first order Markov property [42]. It is to mean *that only the current state is relevant to define the future state.* This property is an important assumption we are making when using the HMM. Mathematically, we can say the probability of being in a certain state $\boldsymbol{S}$ at a certain time $\boldsymbol{t}$ only depends on time step $\boldsymbol{t-1}$.

$$P\left(q_{t+1} = S_j | q_t = S_i\right) \tag{3.1}$$

The easiest ways to understand these concepts is to visualize a Markov model with two states connected by four transitions:

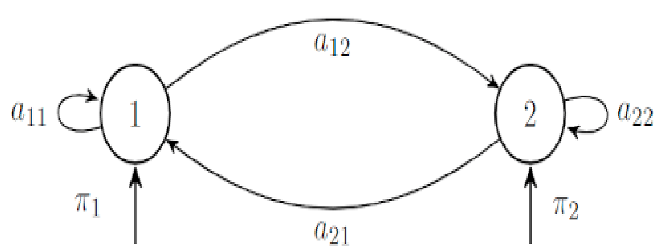

Figure 3.1: An example of Discrete-time Markov Chain.

In *Figure 3.1*, the states are represented by circles numbered in it. The probabilities of getting from one state to the other are called *transition probabilities*. For example, the transition probabilities between states in the above figure are assigned by $\boldsymbol{a_{ij}}$**.** The general transition probability matrix for $\boldsymbol{N}$ hidden states would be:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}_{N\times N} \tag{3.2}$$

Where $\boldsymbol{N}$ is an integer that found in $\boldsymbol{1 \leq n \leq N}$ and it represents the size of transition matrix, which is the maximum number of states under the study. Each elements ($\boldsymbol{a_{ij}}$) in the above probability matrix tells us the probabilities of staying in state $\boldsymbol{i}$ at time $\boldsymbol{t}$ or the transition probabilities from state $\boldsymbol{i\ to\ j}$ at a time $\boldsymbol{t+1}$. Moreover, the transition probabilities for a given state $\boldsymbol{S_i}$ should satisfy one condition:

$$\sum_{j=0}^{N} a_{ij} = 1 \tag{3.3}$$

The variable $\boldsymbol{\pi_i}$ in the Figure 3.1 represents the probability of starting at state $\boldsymbol{i}$**.** The general representation of the initial distribution of Markov chain for $\boldsymbol{N}$ state would be [42]:

$$\pi = \begin{bmatrix} \pi_1 = P(q_1 = 1) \\ \pi_2 = P(q_2 = 2) \\ \vdots \\ \pi_N = P(q_{nb} = N) \end{bmatrix}_{N\times 1} \tag{3.4}$$

Where $\boldsymbol{N}$ is number of the states under the study. The requirement that the total probabilities of starting states must satisfy a condition:

$$\sum_{i=0}^{N} \pi_i = 1 \tag{3.5}$$

Lastly, if all states $\boldsymbol{q_t}$ are known or observable the output will be the sequence of the states from an initial to a final state, and we will call this sequence observation sequence $\boldsymbol{O}$. The calculation for probability of observed sequence would be:

$$P(O = Q|A, \pi) = P(q_1) \prod_{t=2}^{T} P(q_t|q_{t-1}) = \pi_{q_1} a_{q_1 q_2} \ldots a_{q_{T-1} q_T} \tag{3.6}$$

Where $\boldsymbol{\pi}$ represents the sum of initial probabilities and $\boldsymbol{A}$ is the vector of transition probabilities. $\boldsymbol{\pi_{q_1}}$ represents the probability of start at state $\boldsymbol{q_1}$. While $\boldsymbol{a_{q_1 q_2}}$ represents the probability of reaching state $\boldsymbol{q_2}$ from $\boldsymbol{q_1}$. Equations (3.1) to (3.6) describes the properties of first order Markov process, hence $\boldsymbol{A}$ *and* $\boldsymbol{\pi}$ are typical parameters that describe MC.

3.2. Hidden Markov Models

As it has been discussed earlier, all states in MC were visible, so we call them observable. Hence, MC comes to model the changes of the states through time. In some cases, the true states of what we wish to explore are not directly observable, but they may have possible effects that are visible or observable. Such a system can be described as HMM and is defined by the parameters in the following definition:

Definition: HMM is a generative probabilistic model, which consists of N not directly observable states and M distinct observation symbols or symptoms per state [43, 42]. M represents the size of the emission probability that will be discussed next.

3.2.1. Components of HMM Parameter

The components of a discrete-time hidden Markov model are summarized as follows.

1. A finite set of hidden states:

   $$S = \{q_1, q_2, q_3, \ldots, q_N\} \tag{3.7}$$

   Where, $\boldsymbol{N}$ is the number of hidden states (S).

2. A state transition probability matrix (A) of $\boldsymbol{N} \times \boldsymbol{N}$:

   $$A = \{a_{ij}\} \tag{3.8a}$$

$$a_{ij} = P\left(q_{t+1} = s_j \middle| q_t = s_i\right),\ a_{ij} \geq 0,\ 1 \leq i,\ j \leq N \tag{3.8b}$$

$$\sum_{j=1}^{N} a_{ij} = 1;\ \ 1 \leq i \leq N \tag{3.8c}$$

3. An initial state probability distribution $\boldsymbol{\pi} = \{\boldsymbol{\pi}_\mathbf{i}\}$ where, $\boldsymbol{\pi}_\mathbf{i} = \mathbf{P}(\mathbf{q}_\mathbf{t} = \boldsymbol{s_i})$, **and**

$$\sum_{j=1}^{N} \pi_\mathrm{i} = 1\ ;\ 1 \leq i \leq N. \tag{3.9}$$

4. An observation sequence measured at regular time intervals,

$$O = \{o_1, o_2, o_3, \dots, o_M\} \tag{3.10}$$

Where, $\boldsymbol{M} =$ the length of the observation sequence

5. An observation probability (Emission probability) distribution related to the hidden states:

$$\mathrm{B}\ = \left\{\mathrm{b_j(k)}\right\} \tag{3.11a}$$

$$\sum_{k=1}^{T} b_j(k) = 1; \tag{3.11b}$$

Where, $\mathrm{b_j(k)} \geq 0; 1 \leq \mathrm{j} \leq \mathrm{N};\ 1 \leq \mathrm{k} \leq \mathrm{T}$

Thus $N, M, A, B\ and\ \pi$ are the five crucial components of HMM. The compact form of the five HMM elements, which is a standardized and widely used HMM parameter, is denoted by:

$$\boldsymbol{\lambda} = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi}\ ) \tag{3.12}$$

These parameters define the underlying probabilistic structure of HMM. By computing these parameters from a set of training data, we can observe how the system operates and use it to make predictions or decisions in various applications. The illustration in *Figure 3.2* describes the structure of HMM that contains all the components listed above.

The observation probability also known as the emission probability $\boldsymbol{B}$ usually represented as a matrix specifying the probability of observing a particular symbol or output given a certain hidden state.

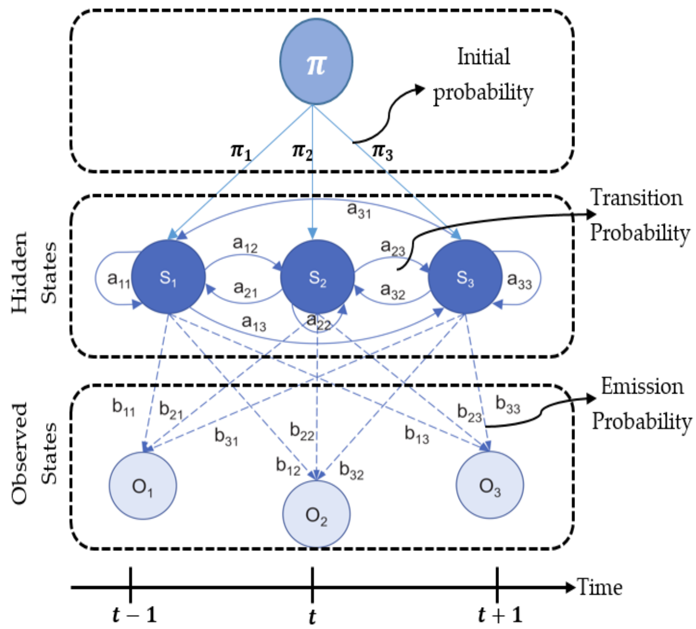

Figure 3.2: HMM with three hidden states and three observations.

The rows in the matrix shows the number of hidden states and the columns of the matrix shows observation symbols. Here is the general emission matrix:

$$B = \begin{bmatrix} b_{11} & b_{12} \dots & b_{1m} \\ b_{21} & b_{22} \dots & b_{2m} \\ \vdots & \vdots \quad \ddots & \vdots \\ b_{N1} & b_{N2\dots} & b_{nm} \end{bmatrix}_{N\times M} \tag{3.13}$$

Where, $\boldsymbol{N}$ represents the maximum number of hidden states and $\boldsymbol{M}$ represents the maximum length of observation symbols. Hence, $\boldsymbol{N\ and\ M}$ determines the size of emission probability matrix.

3.2.2. HMM Assumptions

Markov Assumption: A first-order HMM instantiates two simplifying assumptions. As in case of first-order Markov chain, the probability of a particular state is dependent only on the immediate previous state:

$$P(q_i|q_1 \dots q_{i-1}) = P(q_i|q_{i-1}) \tag{3.14}$$

Independent Assumption: The probability of an output observation O_i is dependent only on the state that produced the observation q_i , and not on any other state or any other observations:

$$P(O_i|q_1 \dots q_i, \dots, q_n, O_1, \dots, O_i, \dots O_n) = P(O_i|q_i) \tag{3.15}$$

The Stationary Assumption: Here it is assumed that state transition probabilities are independent of the actual time at which the transitions take place. Mathematically,

$$P(q_{t1+1} = j|q_{t1} = i) = P(q_{t2+1} = j|q_{t2} = i),\ \text{For } t_1 \& t_2 \tag{3.16}$$

3.3. The Three Basic Problems in HMM

There are three well-known problems, which could be solved by HMM for real world applications [44]. In this sub-section, we briefly describe these three problems and the next sub-section will describe the efficient algorithms used to solve the three problems. The three basic problems in HMM are described as follows:

The Evaluation Problem: Given the model $\lambda = (A, B, \pi)$ and a sequence of observations $O = (O_1,\ O_2, \dots, O_T)$, what is $P(O|\lambda)$? here, we want to determine the probability of the observed sequence O with respect to the given model $\boldsymbol{\lambda}$.

Decoding Problem: Given $\lambda\ =\ (A, B, \pi)$ and an observation sequence O, *how do we find an optimal hidden state sequence* for the underlying Markov process. In other words, we want to uncover the hidden part of the HMM.

Learning Problem: Given an observation sequence O and the dimensions N *and* M, *what is the optimal model parameter* $\lambda\ =\ (A, B, \pi)$ *that maximizes the probability of observation sequence* $P(O|\lambda)$? This can be viewed as training a model that best fit the observed data.

3.4. Solutions for HMM Problems

Once the problems in HMM described, it will be logical to introduce the algorithms for computing the solution for them. There are four important algorithms when dealing with

HMM problems. The main objective of the algorithms is to reduce the computational complexity while computing the solution of HMM problems.

3.4.1. The forward algorithm

Given $\boldsymbol{O} = (\boldsymbol{o_1}, \boldsymbol{o_2}, \dots, \boldsymbol{o_T})$ $\boldsymbol{and}$ the model $\boldsymbol{\lambda} = (\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\pi})$, the probability of the observation sequence $\boldsymbol{O} = (\boldsymbol{o_1}, \boldsymbol{o_2}, \dots, \boldsymbol{o_T})$ generated by a state sequence $\boldsymbol{q}$ can be calculated by:

$$P(O|q, B) = b_{q1}(o_1) * b_{q2}(o_1) * \dots * b_{qT}(o_T) \tag{3.17}$$

On the other hand, the probability of the state sequence $\boldsymbol{q}$ can be found as:

$$P(q|A, \pi) = \pi_{q1} * a_{q1q2} * a_{q2q3} * \dots * a_{qT-1qT} \tag{3.18}$$

The probability that $\boldsymbol{O}$ and $\boldsymbol{q}$ occur simultaneously, is the product of (3.17) and (3.18):

$$P(O, q|\lambda) = P(O|q, B) * P(q|A, \pi) \tag{3.19}$$

⇨ $P(O, q|\lambda) = \pi_{q1} b_{q1}(o_1) \prod_{t=2}^{T} a_{qT-1qT}\, b_{qT}(o_T)$

⇨ $P(O|\lambda) = \sum_{all\ q} P(O|q, B) * P(q|A, \pi)$

Therefore, re-arranging the above equation,

$$P(O|\lambda) = \sum_{q1,q2,\dots,qT} \pi_{q1} b_{q1}(o_1) \prod_{t=2}^{T} a_{qt-1qt}\, b_{qt}(o_t) \tag{3.20}$$

The interpretation of the computations in the above equations is that: at time $\boldsymbol{t} = \boldsymbol{1}$, the process starts by jumping to state q_1 with the probability $\boldsymbol{\pi_{q_1}}$. In this state, the observation symbol $\boldsymbol{o_1}$ is generated with probability $\boldsymbol{b_{q_1}(o_1)}$. The clock advances from $\boldsymbol{t}$ $\boldsymbol{to}$ $\boldsymbol{t+1}$ and a transition from $state$ 1 $(\boldsymbol{q_1})$ to $state$ 2 $(\boldsymbol{q_2})$ will occur with the probability $\boldsymbol{a_{q_1q_2}}$. The symbol $\boldsymbol{o_2}$ will be generated with the probability $\boldsymbol{b_{q_2}(o_2)}$. The process continues in the same manner until the last transition is made (at time $\boldsymbol{T}$), i.e. a transition from $\boldsymbol{q_{T-1}}$ to $\boldsymbol{q_T}$ will occur with the probability $\boldsymbol{a_{q_{T-1}q_T}}$, and the symbol $\boldsymbol{o_T}$ will be generated with the probability $\boldsymbol{b_{q_T}(o_T)}$.

The drawback of this direct computation is the infeasibility due to the exponential growth of computations as a function of sequence length $\boldsymbol{T}$. It requires $[\boldsymbol{2T-1}]\boldsymbol{N^T}$ Multiplications and $[\boldsymbol{N^T - 1}]$ additions. Therefore, to address such type of problem, *the forward algorithm* [42] is more efficient to reduce the computational cost to linear, in relation to T.

As in direct computation, the aim of forward algorithm is to find the probability of the observation sequence O i.e. to find $\boldsymbol{P(O|\lambda)}$. Using the forward algorithm, a variable called $\boldsymbol{\alpha - pass}$, which represents the partial observation sequence is defined as follows: For $t = 0, 1, \ldots, T-1$ and $i = 0, 1, \ldots, N-1$; where, $\boldsymbol{t}$ is the time and $\boldsymbol{N}$ is the maximum number of hidden state under observation, then $\boldsymbol{\alpha_t(i)}$ is defined as:

$$\alpha_t(i) = P(o_0\, o_1, \ldots, o_t, q_t = q_i|\lambda) \tag{3.21}$$

Where $\boldsymbol{\alpha_t(i)}$ is the probability of the partial observation sequence up to $time$ $\boldsymbol{t}$, where the underlying Markov process is in state $\boldsymbol{q_i}$ at $time$ $\boldsymbol{t}$. Then $\boldsymbol{\alpha_t(i)}$ can be computed recursively as follows:

Let $\alpha_0(i) = \pi_i b_i(O_0)$, for $i = 0, 1, \ldots, N-1$
For $t = 1, 2, \ldots, T-1$ and $i = 0, 1, \ldots, N-1$,

$$\alpha_t(i) = \left[\sum_{j=0}^{N-1} \alpha_{t-1}(i) a_{ij}\right] b_i(O_t) \tag{3.22}$$

$$P(O|\lambda) = \sum_{i=0}^{N-1} \alpha_{t-1}(i) \tag{3.23}$$

Thus, comparing Equations (3.20) and (3.23), the forward algorithm needs only about $\boldsymbol{N^2 T}$ multiplications. It dramatically reduces the computation time.

3.4.2. Backward Algorithm

The recursion described in the forward algorithm can also be used in backwards time as well [42]. First the backward variable $\boldsymbol{\beta_t(i)}$ is defined as:

$$\beta_t(i) = P\,(\boldsymbol{o_{t+1} o_{t+2} \ldots\, o_T}\,|q_t = i, \lambda) \tag{3.24}$$

The backward variable can be interpreted as the probability of the partial observation sequence from $\boldsymbol{t+1}$ to the end ($\boldsymbol{T}$), given state $\boldsymbol{i}$ at time $\boldsymbol{t}$ and the model $\boldsymbol{\lambda}$. The definition for the forward variable is a joint probability whereas the backward probability is a conditional probability. In a similar manner (according to the forward algorithm), the backward variable can be calculated inductively. The steps in backward algorithm is:

1. **Initialization:**

   Set $t = T - 1$;

   $\beta_{\boldsymbol{T}}(i) = 1, 1 \leq i \leq N$

2. **Induction:**

$$\beta_t(i) = \sum_{j}^{N} \beta_{t+1}(i) a_{ij} b_j(O_{t+1}), 1 \leq i \leq N \tag{3.25}$$

3. **Update time:** Set $t = t - 1$;

   Return to step 2 if $t > 0$; Otherwise, terminate the algorithm.

3.4.3. Viterbi Algorithm

The Viterbi algorithm is similar to the forward algorithm [42]. The main difference is that the forward algorithm uses the sum over previous states, whereas the Viterbi algorithm uses maximization. The aim for the Viterbi algorithm is to find the best single hidden state sequence $\boldsymbol{S} = (\boldsymbol{q_1}, \boldsymbol{q_2}, \ldots, \boldsymbol{q_T})$, for the given observation sequence $\boldsymbol{O} = (\boldsymbol{o_1}, \boldsymbol{o_2}, \ldots, \boldsymbol{o_T})$ and model $\boldsymbol{\lambda}$. The probability of being in state $\boldsymbol{i}$ at time $\boldsymbol{t}$ given the observation sequence $\boldsymbol{O}$ and the model $\boldsymbol{\lambda}$ is given by [42]**:**

$$\gamma_t(i) = P(q_t = i | O, \lambda) \tag{3.26}$$

$$= \frac{P(O, q_t = i | \lambda)}{P(O|\lambda)}$$

$$= \frac{P(O, q_t = i | \lambda)}{\sum_{i=1}^{N} P(O, q_t = i | \lambda)}$$

Recalling Equations (3.21) and (3.24), $P(O, q_t = i | \lambda)$ can be found as the joint probability. Hence, the above equation can be rewritten as:

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i)\beta_t(i)} \tag{3.27}$$

The most likely state at time $\boldsymbol{t}, \boldsymbol{q_t^*}$ can be found as:

$$q_t^* = arg \max_{0 \le i \le N} [\gamma_t(i)], \; 1 \le t \le T \tag{3.28}$$

Equation (3.28) maximizes the expected number of correct states. However, since the state transition probabilities have not been taken into consideration, the given optimal path may not be valid when some state transitions have zero probability $(a_{ij} = 0)$.

3.4.4. The Baum-welch Algorithm

The Baum-Welch algorithm is a statistical algorithm used in the training of HMM. The algorithm allows us to estimate HMM parameters from raw data [45].

The estimation process is done iteratively until the parameters converge to their optimal values. The estimated parameters obtained from the algorithm used to characterize the network system and predict its future state. The algorithm efficiently re-estimates the HMM parameters. Re-estimation process is described in the following steps [46] [45]:

For $t = 0, 1, \ldots, T - 2 \; and \; i, j \in \{0, 1, \ldots, N - 1\}$, define "di-gammas" as:

$$\gamma_t(i, j) = P(\, x_t = \, q_i, x_{t+1} = q_j | \, O, \lambda) \tag{3.29}$$

Then $\gamma_t(i, j)$ is the probability of being in state q_i at time t and transiting to state q_j at time $t + 1$. The "di-gammas" can be written in terms of $\alpha, \beta, A \; and \; B$ as:

$$\gamma_t(i, j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{P(O|\lambda)} \tag{3.30}$$

For $t = 0, 1, \ldots, T - 2, \; \gamma_t(i)$ and $\gamma_t(i, j)$ are related by:

$$\gamma_t(i) = \sum_{j=0}^{N-1} \gamma_t(i, j) \tag{3.31}$$

Given the γ and "di-gamma" we verify below that the model $\lambda = (A, B, \pi)$ can be re-estimated as follows:

1. For $i = 0, 1, \ldots, N-1$, let $\pi_i = \gamma_0(i)$;
2. For $i = 0, 1, \ldots, N-1$ and $j = 0,1, \ldots, N-1$, compute:

$$a_{ij} = \sum_{t=0}^{T-2} \gamma_t(i,j) \Big/ \sum_{t=0}^{T-2} \gamma_t(i) \tag{3.32}$$

3. For $j = 0, 1, \ldots, N-1$ and $k = 0,1, \ldots, M-1$, compute:

$$b_j(k) = \sum_{t \epsilon \{0,1,\ldots,T-1; O_t = k\}} \gamma_t(j) \Big/ \sum_{t=0}^{T-1} \gamma_t(j) \tag{3.33}$$

The numerator of the re-estimated a_{ij} can be seen to give the expected number of transitions from state q_i to state q_j , while the denominator is the expected number of transitions from qi to any state. Then the ratio is the probability of transiting from state q_i to state q_j , which is the desired value of a_{ij} [46] [45].

The numerator of the re-estimated $b_j(k)$ is the expected number of times the model is in state q_j with observation k, while the denominator is the expected number of times the model is in state q_j. The ratio is the probability of observing symbol k, given that the model is in state q_j , which is the desired value of $b_j(k)$ [46] [45]. The algorithm can be summarized as follows:

1. Initialize, $\lambda = (A, B, \pi)$.
2. Compute $\alpha_t(i), \beta_t(i), \gamma_t(i,j)$ and $\gamma_t(i)$
3. Re-estimate the model λ = (A, B, π).
4. If $P(O|\lambda)$ increases, go to 2.

3.5. HMM and Other Machine Learning Models

Machine learning models such as HMM, Long-Short Term Memory (LSTM), and Logistic Regression (LR) differ from one another and have diverse uses. In contrast to LSTM, which is a form of Recurrent Neural Network (RNN) used in natural language processing, speech and gesture recognition, HMM is a statistical model used for pattern recognition and sequence modelling [47, 48]. Regression and binary classification problems, like spam filtering, are where, LR shines. The strength and the weaknesses of these algorithms are illustrated in *Table 3.1*

Table 3.1: Comparisons of HMM with Other Machine Learning Algorithms

Algorithm	Input	Output	Strengths	Weaknesses
Hidden Markov Model	Sequence of observations	Sequence of Hidden state	Captures sequential dependencies, robust to noise	difficult to train, not as good at long-term dependencies
Long Short-Term Memory	Sequence of data points	Predicted value	Can handle long-term dependencies,	Can be difficult to train, prone to overfitting
Linear Regression	Independent variables	Predicted value	Understandable & good for linear relationships	Sensitive to outliers

In conclusion, the type of algorithm to use relies on the problem's complexity, the type of data at hand, and the performance standards. HMMs are particularly helpful for simulating sequential and time-varying events and are beneficial for predicting the degradation state or conditions of LTE cell.

3.6. HMM Evaluation Techniques

To evaluate the performance of the HMM, we can compare the predicted cell states sequence with the actual hidden state sequence (if available). This can be done using common evaluation metrics for classification models, such as accuracy, precision, recall, and F1-score, can be calculated based on the predicted and actual health levels.

Accuracy: measures how often the model correctly predicts whether a given result is either true or false. It is calculated as the ratio of correctly predicted results to the total number of results evaluated.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{3.34}$$

Precision: measures how often the model correctly predicts positive results. The precision of an HMM is calculated as the ratio of true positive results to the total number of predicted positive results.

$$Precission(P) = \frac{TP}{TP + FP} \tag{3.35}$$

Recall: measures how often true positive and negative targets are correctly identified by an HMM. This is calculated by dividing the number of true positives and negatives identified by an HMM by the total number of possible outcomes that could be predicted.

$$Recall(R) = \frac{TP}{TP + FN} \tag{3.36}$$

Where TP refers to the number of predictions that the classifier correctly predicts one out of four degradation classes, FP is the total number of prediction when the classifier incorrectly predicts the classes, FN is the total number of incorrect prediction for a certain true class and TN is the total score excluding TP, FP and FN [49, 50, 51].

F1 Score: this is the harmonic mean of precision and recall, which gives an overall measure of prediction performance.

$$F1\ Score = 2 * \frac{PR}{P + R} \qquad 3.37)$$

4. Cell Degradation Modeling in LTE Networks

Cell degradation is a decrease in the performance or quality of an LTE cell. It can be caused by interference, equipment malfunction, software issues, or increased traffic load. Monitoring and managing cell degradation is crucial to ensure optimal network performance and improved user experience. Techniques such as signal strength monitoring, data throughput monitoring, and latency monitoring can be used to detect and manage cell degradation. In addition, reconfiguring the network, adding new cells, and deploying new equipment can be used to manage cell degradation. Cell degradation modeling can be used to predict the effects of cell degradation and identify areas where it is likely to occur.

This chapter provides a detailed description of the different levels of cell degradation and their effects on service quality of LTE cells, as well as the monitoring techniques used to detect and manage degradation. Finally, we try to put the relationship between the hidden and observation states.

4.1. LTE Cell Degradation Levels

The levels of cell degradation can be measured using a variety of metrics, such as the signal strength, the coverage area, KPIs. Based on the values of those metrics, there are four commonly known degradation levels.

4.1.1 . Normal Cell State

This is the level where the cell operates as expected and meets the predefined KPIs and SLAs. The signal strength and the coverage area are within the acceptable range and there are no significant issues or complaints from the user. This is the desired level of network performance, where signals are strong, coverage is extensive, and the KPIs such as throughput, latency, and packet loss are within acceptable ranges. Users can experience high-speed data connectivity and seamless connectivity.

4.1.2 . Mild Cell Degradation

Mild cell degradation represents the initial stage of degradation and typically manifests as minor issues within the LTE network. It can be characterized by reduced signal strength, slower data rates, and intermittent connectivity. Users may experience slightly slower internet speeds or occasional disruptions in their LTE service. Mild cell degradation is commonly caused by temporary interference or congestion in the network. To detect such type of cell degradation, *tracking KPIs* such as signal strength, call drop rates, data throughput, and latency provides real-time insights into the network's performance. Deviation from the defined thresholds can indicate the presence of mild cell degradation [52].

4.1.3 . Moderate Cell Degradation

Moderate degradation is a more severe level of degradation than mild degradation. It represents a more significant impact on LTE service. Dropped calls, longer call setup times, frequent disconnections, and poor voice and data quality characterize it. Users may experience degraded performance during voice calls, slower internet speeds, and intermittent connectivity issues. Moderate cell degradation can occur due to hardware faults, software glitches, or increased user demand exceeding the network's capacity.

Alarm Analysis is monitoring technique commonly used for detecting moderate cell degradation level. *Monitoring and analyzing network alarms* generated by network elements can help identify recurring issues and potential root causes of moderate cell degradation. Real-time alarm analysis can prompt immediate actions for resolving degradation events.

4.1.4 . Severe Cell Degradation

Severe cell degradation represents a *critical* impact on LTE service, often resulting in a complete loss of connectivity within specific areas or for specific users. The affected cells may experience complete outage or become "*sleeping cells*" unable to provide any service [53, 54]. Severe cell degradation can occur due to equipment failures, transmission errors, or coverage limitations.

Field measurements and *Drive Tests* are commonly used techniques for detecting severe cell degradation. Performing physical field measurements and drive tests provide real-world insights into network conditions and coverage areas. These techniques can identify severe degradation problems and coverage gaps, helping in targeted resolution efforts.

The levels of degradation described above are just a general overview. The specific characteristics and effects of degradation can vary depending on the specific network and the factors that are causing the degradation.

4.2. Monitoring Techniques for Cell Degradation

In addition to the specific monitoring techniques outlined for each level of cell degradation, there are also number of different monitoring techniques that can be used to detect and measure LTE cell degradation. The techniques can be described as follows:

- *Statistical Models:* Statistical models like HMM can capture the transitions between different degradation states, allowing for proactive analysis and management of moderate degradation events. These models can aid in identifying patterns and predicting degradation states [55]. Apart from HMM, other statistical models like regression analysis, time-series analysis, and machine learning algorithms can be utilized to analyze historical data and detect degradation patterns. These models can assist in predicting degradation trends and identifying potential performance bottlenecks [56] [57].
- *Monitoring KPIs:* Continuously monitoring KPIs like signal strength, signal-to-noise ratio, and handover success rates provides a comprehensive view of network performance and highlights potential degradation issues [56] [58].

- *Fault Logs and Alarm Analysis:* Analyzing fault logs and network alarms can identify recurring or systematic issues contributing to cell degradation. This approach aids in root cause analysis and enables proactive measures for degradation management.
- *User Feedback and Complaints:* Monitoring user feedback and complaints can provide valuable information about cell degradation. Analyzing user experiences and patterns can aid in pinpointing areas experiencing severe degradation and prioritizing network improvements.

4.3. Relevance of HMM for Prediction of LTE Cell Degradation

HMMs are a type of statistical model that can be used to model the behavior of a system that is not directly observable. In the context of LTE cell degradation prediction, HMMs can be used to model the hidden states representing different degradation levels of the cells. The observed outputs can be various measurements or indicators that reflect the cell's degradation state, such as signal-strength, traffic load or error rates. The benefits of using HMMs for this purpose include:

- *Ability to handle sequential and temporal data:* HMMs are well suited for modeling time-series data, making them appropriate for analyzing LTE cell degradation levels that unfold over time.
- *Flexibility in modeling complex dependencies:* HMMs can capture the dependencies between different degradation levels, allowing for predictions that are more accurate. They can also adapt to various degradation patterns observed in different cells.
- *Incorporation of uncertainty:* HMMs provide a probabilistic framework, enabling the estimation of the likelihood of specific degradation levels. This can help in decision-making and resource allocation for LTE network management.

Overall, using HMMs for predicting LTE cell degradation levels helps network operators proactively manage and optimize their networks, resulting in improved quality of service and better resource allocation.

4.4. Modeling LTE Cell Degradation Using HMM

4.4.1. Data Collection

The study concept used in this thesis mainly requires observation dataset. We collect this observation data from ethio telecom network for a duration of one month. Three different group of KPIs that are likely to be important for LTE cell degradation were identified based on past studies on LTE cell degradation and domain knowledge of experts in the field. These groups of KPIs are related to Traffic volume, Number of handover requests and Signal strength. The dataset related to signal strength consists the average RSRP value and the report times of RSRP values in different (acceptable) ranges.

The average RSRP value of the serving cell indicates the overall signal strength of the cell, hence we used this parameter to define the hidden state of the HMM. Other KPIs were considered as an observation data. The collected data is passed through preparation process, which is most important step in any data analysis project. The preparation process includes cleaning the data, filling the null values, and transforming the data into a format that is compatible with our model, which will be discussed next.

4.4.2. Feature Selection

The raw data collected from operator network contains many features. However, not all data fields or features may be used due to several reasons. For example, two or more feature may carry the same information. This creates redundancy of information and leads to poor model accuracy. As a result, we used statistical data manipulation techniques called Principal Component Analysis (PCA) to select important features from the three identified groups of KPIs.

PCA is one of the techniques used for dimensionality reduction, and can also be used to determine feature importance. We used the following steps for feature importance calculation with PCA: First, the observation dataset was normalized. Meaning that each feature has a mean of 0 and a standard deviation 1. This is important because PCA works best on normalized data. Second, we fit the PCA model to the data. This creates a set of principal components, which are linear combinations of the original features. Thirdly, the loading scores for each principal component were calculated. The loading scores are a measure of how much each original feature contributes to a particular principal component. Finaly, we sort the loading scores by absolute value. The features with the largest loading scores are the most important features. *Figure 4.1* shows sample output of selected features with this technique.

The best feature selection method will depend on the specific data set and the goals of the analysis. However, the methods mentioned above provide a good starting point for identifying the most important features in this domain.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13
RSRP[-140to-121]	0.300172	-0.412286	0.575137	0.587853	0.222819	-0.109682	-0.037559	-0.015943	-0.013710	-0.008251	0.001880	-0.000068	-0.000606
RSRP[-120to-116]	0.541969	-0.647253	0.425309	0.086539	-0.188541	0.206932	0.113198	0.061740	0.052106	0.034264	-0.010576	-0.000648	0.000375
RSRP[-115to-111]	0.626142	-0.687176	0.204459	-0.195270	-0.185848	0.035095	-0.039645	-0.059697	-0.074316	-0.078618	0.052959	-0.018184	-0.009779
RSRP[-110to-106]	0.722032	-0.626352	0.062779	-0.224516	-0.077675	-0.085153	-0.083875	-0.042252	-0.014882	0.038626	-0.068350	0.046632	0.037139
RSRP[-105to-101]	0.808858	-0.508243	-0.113124	-0.198781	0.067084	-0.135887	-0.037309	0.023789	0.052763	0.047706	0.003958	-0.036530	-0.061924
RSRP[-100to-96]	0.892368	-0.281613	-0.256826	-0.081772	0.174169	-0.073690	0.054132	0.064883	0.042736	-0.022843	0.053091	-0.012364	0.059515
RSRP[-95to-91]	0.915113	-0.015055	-0.321726	0.057720	0.179233	0.055653	0.096344	0.023053	-0.040253	-0.055239	-0.030910	0.060133	-0.035554
RSRP[-90to-86]	0.890248	0.242654	-0.289555	0.159902	0.085220	0.125565	0.013902	-0.069333	-0.057774	0.036936	-0.035896	-0.070608	0.014211
RSRP[-85to-81]	0.814815	0.481196	-0.164330	0.201340	-0.073673	0.091259	-0.092037	-0.060938	0.037506	0.050745	0.068733	0.048456	-0.005542
RSRP[-80to-76]	0.712515	0.635598	-0.005454	0.154673	-0.191784	-0.010617	-0.104709	0.043560	0.073865	-0.082085	-0.045482	-0.020118	0.001257
RSRP[-75 to -71]	0.608401	0.723990	0.166459	0.031811	-0.191807	-0.123049	0.025574	0.109914	-0.101840	0.042115	0.013867	0.001761	-0.000301
RSRP[-70to-61]	0.483418	0.740804	0.367641	-0.162425	-0.033958	-0.121670	0.157068	-0.115633	0.044150	-0.007862	-0.002349	0.000488	-0.000089
RSRP[-60 to -43]	0.291331	0.596110	0.532618	-0.396441	0.301963	0.137735	-0.086675	0.035491	-0.006750	0.000087	0.000425	0.000149	-0.000015

(a)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
TotalDataVolume(GB)	0.928198	0.339171	0.021385	-0.136891	0.065229	2.355439e-05	-8.007500e-05
CellAvailability(%)	0.096723	0.050794	-0.989765	0.092035	-0.000215	-2.369351e-08	-2.359194e-09
ULUserThroughput(Mbps)	-0.022180	0.560629	0.105501	0.820724	0.022920	1.971551e-07	2.157984e-09
DLUserThroughput Mbps	-0.596102	0.766597	-0.022217	-0.237602	-0.009043	-7.873888e-04	-2.103714e-06
UserDLThroughput	-0.596491	0.766292	-0.022266	-0.237595	-0.009354	7.873798e-04	2.105051e-06
DLAggregatedVolumethroughUu	0.922074	0.340679	0.019131	-0.154360	0.097798	-1.968930e-05	7.070411e-05
ULAggregatedVolumethroughUu	0.932989	0.313648	0.036504	-0.004997	-0.172739	-3.645353e-06	9.788894e-06

(b)

	PC1	PC2	PC3
IntraFrequencyHandoverSR	0.085331	-0.996369	0.003610
IncomingHORequestTime	0.983566	0.053645	0.172526
OutgoingHORequestTime	0.984455	0.032768	-0.172683

(c)

Figure 4.1: (a), (b), (c): Feature selection based on loading score values.

4.4.3. Descriptions of Selected Features

According to the values of loading scores, features with the highest loading scores are considered as important feature. *Figure 4.1* (b and c), shows that Traffic volume and Number of handover requests have largest loading scores and selected for our analysis. These parameters can be described as follows:

- *Traffic volume:* Traffic volume is the amount of data that is being transmitted over the Uu interface of LTE network. A high traffic volume can put a strain on the network and lead to congestion, which can in turn lead to LTE cell degradation. Therefore, it can be used to assess the health state of LTE cell.
- *Number of handover requests:* A handover request occurs when a user's device moves from one cell to another. A high number of handover requests can indicate that the cell is degrading, as it means that the network has to work harder to keep users connected.

On the other hand, the report times of RSRP values in different ranges can tell us about the overall health state of the network. Hence, we considered all of the report times of RSRP in the acceptable range. The range of values that are acceptable for LTE network connectivity depends on the specific network. However, in general, a signal strength of -95 dBm or better is considered as good. A signal strength of -120 dBm or worse is considered as poor. Therefore, high number of report times for RSRP values in the lower ranges can indicate that the network is degrading, as it means that the signal strength of the network is often too low.

Finally, the average RSRP value is a measure of the signal strength of LTE cell and can be used to compare the signal strength of different cells. A lower RSRP value indicates a weaker signal, which can lead to degradation of the cell. The severity of the degradation depends on the specific value of the RSRP. RSRP is not included in PCA based feature selection techniques because; we used this parameter to define the hidden state of HMM.

These are just a few of the features that can be used to describe LTE cell degradation. By understanding those features, which describes LTE cell degradation, it is possible to identify cells that are at risk of degradation and take steps to improve their performance.

4.4.4. Hidden State Formation

The hidden state formation process is an important step in the development of an HMM based prediction model. In terms of LTE cell degradation, hidden state formation is a process of identifying the different states that a cell can be in and the transitions between those states. We used a multi-step process to identify the states that are most predictive of cell degradation severity. The first step is to select KPI data of LTE cells that can describe the health state and the corresponding degradation level of a cell. Based on the 3GPP, the organization responsible for developing technical specifications for cellular networks [59], descried that RSRP values, SINR and RSRQ are factors used to determine the health of an LTE cell. Although it is important to consider multiple parameters to evaluate the network's performance, ensure optimal connectivity and user experience, RSRP values are a crucial and enough for our thesis.

Therefore, the states of the cell were defined based on the usable range of RSRP values. Accordingly, the four health states and degradation level of LTE cell with corresponding range of RSRP values are described in *Table 4.1*. These thresholds are standards to set the health state of the network [60]. However, it may differ from operator to operator or from network to network. The degradation level in *Table 4.1* contains list of possible hidden states namely: *normal, medium, high and critical*.

Table 4.1: Degradation Levels of LTE Cells Based on RSRP

Health State	Usable RSRP Range (dBm)	Degradation Level
Excellent	-76 to -90	Good (Normal) degradation
Good	-91 to -103	Moderate (Medium) degradation
Moderate	-104 to -109	High degradation
Bad	-110 to -140	Severe (Critical) degradation

The four levels of cell degradation severity in *Table 4.1* are defined based on the usable range of average RSRP. The usable range of average RSRP is the range of average RSRP values that can be used by a cell to provide acceptable communication service to users. Accordingly, these levels are described as follows:

- *Good (Normal) degradation:* The cell is operating normally and there is no degradation. The usable range of average RSRP for this level is 76 to 90 dBm.
- *Moderate (Medium) degradation:* The cell is starting to degrade, but it is still operating without any major problems. The usable range of average RSRP for this level is -91 to -103 dBm.
- *High degradation:* The cell is degrading at a moderate rate. There may be some problems with call drops and data throughput. The usable range of average RSRP for this level is -104 to -109 dBm.
- *Severe (Critical) degradation:* The cell is degrading at a severe rate. There are frequent call drops and data throughput is very poor. The usable range of average RSRP for this level is -110 to -140 dBm.

After the hidden states has been defined, the transition probabilities between the states can be estimated using historical data. For example, we can count the number of times a cell has changed from the "Normal" state to the “Medium” state, from the "Medium" state to the "Critical" state, and so on. However, in this thesis, we used a Python package called “*mchmm*” [61], which imbed the four HMM algorithms that gives a solution to HMM problems that discussed in section *3.4*. The package is used for implementing MC and HMMs then estimates all HMM parameters. It can also visualize the Markovian process of cell degradation states with their transition probabilities. For example, we used historical data of RSRP values to visualize the Markovian pattern of the hidden states that would represent the four LTE cell degradation sequence as shown in *Figure 4.2*.

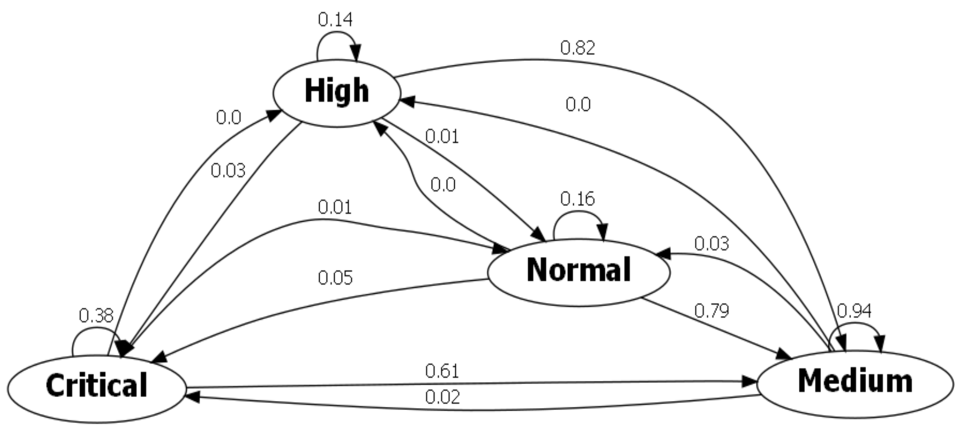

Figure 4.2: Sequence of cell degradation severity and transition probabilities

4.4.5. Observation Sequence Formation

In HMM-based prediction, the observed data must first be transformed into a sequence of symbols (labels). Then, the observation sequences are used to train the HMM and make predictions. There are two main methods for creating observation sequences:

- *Direct observation:* In this approach, the observation sequence is simply the sequence of observed or measured values.
- *Feature extraction:* In this method, the observation sequence is created by extracting features from the observed values.

In this thesis work, after important observation features are selected using PCA loadings, we used feature extraction method to transform the raw data into more relevant number of sequence of symbols. We did this because feature extraction can also lead to *better performance by reducing computational complexity* of HMM and improve model accuracy. This can be done using a variety of methods. In this thesis, clustering is used to extract features by grouping similar data points together. This will also *help us to group cell with similar properties* into group of clusters. We used K-means clustering algorithm to create new feature (column) that represent the observation sequence. K-means clustering is a popular, simple and efficient algorithm for grouping data points into clusters [62, 63]. It works by iteratively assigning data points to the cluster with the nearest mean, or centroid. The centroids are then recomputed based on the assigned data points, and the process is repeated until the centroids no longer change.

Before applying the K-means clustering, we used the elbow method to determine the optimum number of clusters. The elbow method [64] is a visual method that works by calculating the Within-Cluster Sum of Squares (WCSS). The goal of using WCSS is to obtain an appropriate number of clusters and improve the quality of clustering. The WCSS is the sum of the squared distances between each data point and the centroid of its cluster [65]. The optimal number of clusters is the point at which the WCSS curve starts to flatten out as it is shown in figure below.

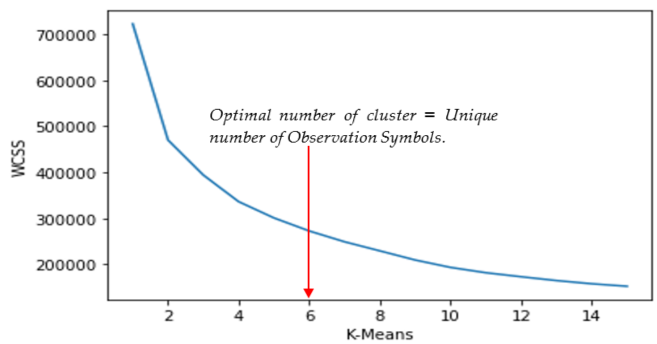

Figure 4.3: Optimal number of clusters using elbow method

As we can observe from the above figure, the elbow method suggests that the optimum number of clusters are six. Hence, the normalized feature of observation data is grouped into six (6) unique observation sequence of symbols using K-means clustering as shown in *Table 4.2*.

Table 4.2: Formation of unique number of observation symbols

Index	TotalDataVolume(GB)	OutgoingHORequestTime	RSRP[-140 to-121]	RSRP[-120 to-116]	RSRP[-115 to-111]	RSRP[-110 to-106]	RSRP[-105 to-101]	RSRP[-100 to-96]	RSRP[-95 to-91]	RSRP[-90 to-86]	RSRP[-85 to-81]	RSRP[-80 to-76]	Cluster
0	0.890716	-0.503346	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	3
1	0.301998	-0.362343	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	3
2	-0.04632	-0.341648	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	3
3	-1.230527	-0.470866	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	3
4	-1.013439	-0.288419	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
60235	-0.040168	-0.63642	-0.274645	-0.326588	-0.548744	-0.32248	-0.45164	-0.488473	0.053677	-0.156487	0.512824	0.320693	3
60236	0.017359	-0.180602	-0.149014	-0.44867	-0.732957	-0.787964	-0.961373	-0.740189	-0.023046	0.273444	0.063988	-0.089342	3
60237	-0.071882	-0.16963	-0.083782	1.40669	-0.015473	-0.388524	-0.760454	-1.074646	-0.660302	-0.82955	-0.346367	0.080838	3
60238	3.176448	4.383715	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	1
60239	3.388928	-0.6368	-0.175589	-0.222706	-0.232378	-0.204765	-0.182498	-0.152985	-0.149906	-0.1949	-0.210767	-0.209517	3

The "$\boldsymbol{Cluster}$" column in the above table contains six unique clusters labeled from $0\ to\ 5$. This can be mapped to the sequential observation symbols, and it is typically discrete. The sample output of sequential observation looks like: $array([[2],[3],[3],\ldots,[2],[1],[0]])$. Each number in the NumPy array represents the sequence of all observation symbols.

4.4.6. The Relationship of Hidden and Observable States

The emission probabilities of a HMM describe or model the relationship between the degradation states and the observation states. The degradation states are the hidden states, and the observation states are the normalized and cluster values of the average traffic volume, the number of outgoing handover requests, and the number of RSRP measurement reports. The HMM uses a transition matrix to model the probability of transitioning from one state to another.

When the hidden states make a transition, the observation states will also change. For example, when the serving cell degrades from the normal degradation state to the medium degradation state, users may experience poorer signal quality or performance. This can lead to an increase in the average traffic volume. Therefore, the number of outgoing handover requests from the serving cell is also likely to increase, as users try to connect to neighboring cells with better signal quality. Similarly, when the cell transitions from the medium degradation state to the high degradation state, the number of outgoing handover requests is likely to increase significantly. This indicates that as the degree of cell degradation increases, users may experience poorer signal quality or performance, leading them to seek alternative cells with better signal strength through handover requests.

Table 4.3 summarizes the changes in the observation states as the degradation states transition. It is important to consider the specific network conditions when interpreting the table. Accordingly, the table is based on the assumption that the cell is operating normally at the start.

Table 4.3: Modeling Cell Degradation with HMMs

Degradation States (RSRP Classification)	**Observation Emitted by Hidden State**		
	Average Traffic Volume	**Number of Outgoing Handover Requests**	**Number of RSRP Measurement Reports**
Normal	Moderate or steady	Within reasonable limits	Consistent and reflects typical user behavior
Medium	Slight increase compared to normal	Slightly increase	May increase slightly as users actively search for better signal quality
High	Significantly higher	Significant number of handover requests	Significantly higher as users continuously monitor the signal strength
Critical	At its peak or overloaded	Very high	Extremely high, indicating extensive signal quality issues and users' efforts to find a better connection

The described relationship between degradation state transitions and the corresponding changes in observation states aligns with the typical behavior and expectations within cellular network performance and user experience. Therefore, the table can be used to track the degree of cell degradation in LTE network and predict degradation sequence.

5. Results and Discussions

5.1. Training the Model

Learning in HMMs involves estimating the state transition probabilities A and the output emission probabilities B that make an observed sequence most likely. Once the list of possible hidden states and sequence of observation symbols obtained, there are two techniques to create HMMs in Python. The first technique uses the $from\_seq(\,)$ method, which takes an observation sequence and a state sequence as input. Both observation sequence and hidden state sequence should have the same length. The second technique uses $from\_baum\_welch(\,)$ method, which takes an observation sequence and a list of possible states as input.

The $from\_seq(\,)$ method is a simple way to create an HMM if both observation sequence and hidden state sequence are available. However, it is not always the best way to do so. Because, this method simply assumes that the observation sequence and the state sequence are independent. The $from\_baum\_welch(\,)$ method is more complex, but it can often produce better results. This is because the $from\_baum\_welch(\,)$ method uses an iterative Baum Welch algorithm to fit the model to the data.

In this thesis, we used the second training technique, which follows the Baum-Welch algorithm. The Baum-Welch algorithm is an iterative algorithm that is used to train or estimate the parameters of an HMM. The algorithm starts with initial estimates of the parameters, and then iteratively updates the estimates until they converge. The "$thres$" argument specifies the threshold for convergence of the iteration. This argument is the minimum change in the model's parameters (log-likelihood of the model) that is required before the algorithm terminates. We set the value of "$thres$" to be 0.00001.

If the change in the log-likelihood is less than "*thres = 0.00001*", then the algorithm is considered to have converged.

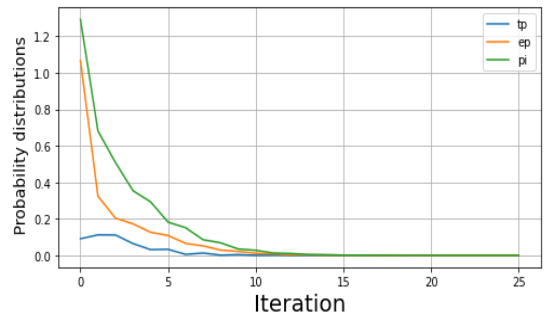

Figure 5.1: Convergence of the Baum Welch's model

The final output of the Baum-Welch algorithm is the optimized HMM parameters, which are the transition probabilities, prior (or initial) probabilities, and emission probabilities. Those are crucial parameters used to predict the future state of LTE cell and describe the HMM in terms of probability.

5.1.1 . Transition Probability Matrix

The transition probability matrix is a square matrix that describes the probability of transitioning from one degradation state to another. The row index corresponds to the current degradation state, and the column index corresponds to the next degradation state. For example, in *Table 5.1*, the value 0.83972 on the first row and second column in the matrix shows us that there is a 83.972% chance that a LTE cell in the Normal state will make transition to the Medium state in the next $\boldsymbol{t+2}$ time step. This means that the system is more likely to transit to the Medium state than staying in Normal state. However, there is also a small probability of transitioning to the High or Critical state from Normal state.

Table 5.1: The transition Matrix

	Normal	Medium	High	Critical
Normal	0.00972	0.83972	0.13309	0.01747
Medium	0.00041	0.96892	0.03060	0.00008
High	0.00062	0.99301	0.00459	0.00178
Critical	0.00184	0.96912	0.01522	0.01382

The values in the matrix also show us that there is a high probability (0.96912 and 0.99301) of transitioning from the Critical and High state to the Medium state respectively. In general, the values in the second column in the matrix show us that the system is more likely to stay in a Medium state or recover from a Critical or High degradation level than transitioning to a more severe state. This is good news but not excellent, as it means that the system is likely to remain stable and functional for a long period, of time showing a medium health state.

To summarize, the values in the transition probability matrix indicates that our model is trained from the collected data according to values described in the above transition matrix. Hence, we can use this transition probability matrix to track the degradation of a LTE cell over time. By tracking the state of the LTE cell at each time step, we can see how the probability of the LTE cell transitioning to a different state changes over time. This information can be used to predict the future state of the LTE cell and to take steps to prevent the LTE cell from degrading to a critical state.

5.1.2 . Emission Probability Matrix

The emission probability is the probability of emitting a particular observation given a hidden state. The emission probability matrix shows us the likelihood of observing a particular value given a specific state. For example, the illustration in *Table 5.2* shows the emission probability of the four-state degradation level with six cluster of cells $(0, 1, 2, 3, 4, and\ 5)$, which is unique observation symbols.

The first row of the emission probability matrix shows us the probability of observing each of the six unique symbols $(0, 1, 2, 3, 4, and\ 5)$ in the LTE cell degradation severity while the state of LTE cell is considered to be in a Normal state. For example, the value of 0.645342 in the first column of the row means that there is a 64.5342% chance of observing the cluster **0** if the hidden state is "Normal". Similarly, the value of 0.08489 in the second column of the row means that there is an 8.489% chance of observing the cluster **1** if the hidden state is "Normal" and so on.

Table 5.2: The Emission Probability Matrix

	0	1	2	3	4	5
Normal	0.645342	0.08489	0.020273	0.00994	0.077752	0.161803
Medium	0.645342	0.08489	0.020273	0.00994	0.077752	0.161803
High	0.645342	0.084891	0.020273	0.00994	0.077752	0.161802
Critical	0.645342	0.084891	0.020273	0.00994	0.077752	0.161802

The other rows of the emission probability matrix show the probabilities of observing each of the symbols given the other hidden states. For example, the second row of the matrix shows the probabilities of observing each of the symbols (cluster) given that the hidden state is Medium and so on.

5.1.3 . The Initial Probability Matrix

The initial probability ($\boldsymbol{\pi}$) is the probability of starting in a particular state. For example, the initial probability matrix in *Table 5.3* shows us the probability that the HMM will start in each of the four degradation state. The value of 0.262891 for the Normal state means that there is a 26.2891% chance that the system will start in the Normal state. Similarly, the value of 0.25605 for the "Critical" state means that there is a 25.605% chance that the system will start in the "Critical" state and so on.

Table 5.3: The Initial probability matrix

	Normal	Medium	High	Critical
0	0. 262891	0. 255794	0. 225265	0. 25605

The initial probability (π) of each state is used to initialize the state distribution of the HMM. The state distribution is a probability distribution over the states of the HMM, and it is used to calculate the probability of a particular sequence of observations.

The result obtained from our model indicates that the initial probability distribution is uniform, which means that each of the four states is equally likely to be the initial state. This means that the system is equally likely to start in any of the four degradation states. However, the initial probability distribution can be changed to reflect different assumptions about the network system. For example, if we know that the system is more likely to start in the Normal state than in the other states, then we can change the initial probability distribution to reflect this.

5.2. Hidden State Prediction and Model Evaluation

5.2.1 . Hidden State Prediction

The prediction of the most likely sequence of hidden states is a common task in HMM based prediction model. We accomplished this task using the Viterbi algorithm. The Viterbi algorithm is a dynamic programming algorithm that finds the most likely sequence of hidden states given a sequence of observed data of known length. The algorithm recursively calculates the probability of each hidden state at each time step based on the previous observations and hidden states. The most likely sequence of states is the one with the highest probability.

Once the HMM has been trained, it can be used to do prediction of the hidden state sequence, which reflects the health state of an LTE cell over time. To do predictions, we generate some observable sequence and the corresponding true hidden state using the developed HMM. We give specific observation length for the model. However, the emission probability and the transition probability decides the sequence of observation symbols. This is because of that the probability of a particular sequence of hidden states depends on the model parameters ($\lambda = A, B, \pi$), which obtained from model training.

The model uses function named $HiddenMarkovChain\_Uncover(A, B, \pi\ )$ to create HMM. Then, the $observed\_sequence, latent\_sequence\ =\ hmm.run(\ length = 4)$ function runs the HMM for a specified number of observation length. The observed_sequence and latent_sequence are variables that respectively contains the observation sequence and the actual hidden states, which emits the observation sequence. Both sequences are generated randomly with length of $\mathbf{1 + N}$ observation sequence. Where, $\boldsymbol{N} = \mathbf{4}$ is the observation length selected for evaluation of our model.

Finaly, the $y_{predicted} = hmm.uncover(\,observed\_sequence)$ function takes the observed sequence as input and uses the *hmm* model to predict the most likely sequence of hidden states that generated the observed sequence. The function uses the Viterbi algorithm to find the most likely sequence of hidden states. The result obtained through these methods summarized in the following table:

Table 5.4: Prediction output and Model performance

	Initial Probability				Length of Observation	Observation Sequence	True Hidden State Sequence	Predicted Hidden State Sequence	Performance of the Model			
	Normal	Medium	High	Critical					Precision(%)	Recall(%)	F-1 (%)	Accuracy(%)
Assumptions	[1	0	0	0]	5	['0', '5', '0', '1', '5']	['Normal', 'Medium', 'Medium', 'Medium', 'Medium']	['Normal', 'Medium', 'Medium', 'Medium', 'Medium']	100.00	100.00	100.00	100.00
	[0	1	0	0]	5	['2', '5', '1', '0', '2']	['Medium', 'Medium', 'Medium', 'Medium', 'Medium']	['Medium', 'Medium', 'Medium', 'Medium', 'Medium']	100.00	100.00	100.00	100.00
	[0	0	1	0]	5	['0', '0', '0', '0', '0']	['High', 'Medium', 'Medium', 'High', 'Medium']	['High', 'Medium', 'Medium', 'Medium', 'Medium']	85.00	80.00	78.09	80.00
	[0	0	0	1]	5	['1', '0', '0', '0', '0']	['Critical', 'Medium', 'Medium', 'Medium', 'Medium']	['Critical', 'Medium', 'Medium', 'Medium', 'Medium']	100.00	100.00	100.00	100.00
Modeled	0.262891	0.255794	0.225265	0.25605	5	['0', '4', '5', '0', '4']	['High', 'Medium', 'Medium', 'Medium', 'Medium']	['Medium', 'Medium', 'Medium', 'Medium', 'Medium']	86.67	80.00	78.67	80.00
					10	**Observation Sequence:** ['4', '1', '0', '5', '0', '4', '0', '1', '0', '5', '0'] **True Hidden Sequence**: ['High', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium'] **Predicted Hidden State Sequence:** ['Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium', 'Medium']			82.64	90.91	86.58	90.91
					50	**Observation Sequence:** ['0', '5', '0', '4', '0', '0', '0', '5', '0', '0', '5', '0', '0', '5', '0', '0', '0', '0', '0', '0', '0', '0', '0', '0', '0', '0', '0', '0', '2', '0', '0', '0', '0', '4', '0', '4', '0', '0', '0', '0', '5', '0', '0', '4', '5', '0', '0', '0', '0', '1', '0'] **True Hidden Sequence:** *['Medium', 'High', 'Medium']* ***Predicted Hidden State Sequence:*** *['Medium', 'Medium']*			96.12	98.04	97.07	98.04
					100				92.16	96.00	94.05	96.00
Average Observation Length					23			Average performance	92.82	93.12	91.81	93.12

In the above table, for a given observation sequence, the output indicates the predicted hidden state sequence is the same as the true hidden state sequence, which means that the HMM was able to accurately predict the hidden states. This is a good sign that the HMM is well trained and can be used to make accurate predictions about hidden sequences. Here is a more detailed interpretation of the output in *Table 5.4*:

- *Initial Probability:* This is the probability that the HMM is in the normal state at the beginning of the sequence. In this case, the Initial Probability: [1 0 0 0] suggests that the initial state of the HMM was in the *normal* state with a probability of 1. Which indicates the assumption that the LTE cell is working in normal condition.
- *Observation sequence:* is the sequence of cluster numbers that was observed. In this case, the observation sequence is [0, 5, 0, 1, 5]. Each numbers in the observation sequence represent a group of the LTE cell.
- *True hidden state sequence:* The true hidden state sequence represents the actual degradation levels of the LTE cells that actually generated the observation sequence at each time step. In this case, the true hidden state sequence is: [*'Normal', 'Medium', 'Medium', 'Medium', 'Medium'*].
- *Predicted Hidden State Sequence:* This is the sequence of hidden states that the HMM predicted from generated observation sequence. In this case, the predicted hidden state sequence is also [*'Normal', 'Medium', 'Medium', 'Medium', 'Medium'*]. The HMM was able to accurately predict the hidden states, which means that it is likely that the LTE cell is in a medium state of degradation

In addition, we used the initial probability generated by the Baum-Welch algorithm to predict the hidden state sequence. In this case, the initial probability is a vector: *[0.262891, 0.255794, 0.225265, 0.25605].* This probability vector indicate the likelihood of the cell being in each of the *'Normal', 'Medium', 'High', and 'Critical'* states at the beginning of the sequence. The highest probability is for '*Normal*' state, followed by *'Critical'*, *'Medium', and High.* This implies that the model predicts the LTE cell to be in a normal state initially. The predicted hidden state sequence generated by the HMM model is *['Medium', 'Medium', 'Medium', 'Medium', 'Medium'],* suggesting that the model predicts the degradation level to be consistently at the 'Medium' state throughout the observation sequence. It looks that the model might not be adequately representing the exact degrees of degradation.

5.2.2 . Model Evaluation

Based on the outputs provided in *Table 5.4*, the HMM model achieves a good performance in predicting LTE cell degradation. Here is a more detailed interpretation of the output:

- *Accuracy:* The average accuracy of 93.12% indicates that the model correctly predicts the hidden state (cell degradation level) for the LTE cells with nearly 93% accuracy. This suggests that the model is effective in classifying the cell degradation levels.
- *Precision:* The precision of 92.82% reflects that among all the predicted instances of a particular degradation level (e.g., 'Critical'), 92.82% of them are actually true positives. This performance metric indicates a low false positive rate, meaning that when the model predicts a certain cell degradation level, it is quite likely to be correct.
- *Recall:* The recall of 93.12% shows that the model captures 93.12% of all the instances of a degradation level (e.g., 'Critical'). It indicates that the model is effective in detecting instances of cell degradation, as it has a relatively low false negative rate.
- *F1 Score:* The F1 score of 91.81% is the harmonic mean of precision and recall and provides an overall assessment of the model's performance. It suggests that the model's predictions are accurate and balanced, as it considers both false positives and false negatives.

Overall, the accuracy, precision, recall, and F1 score are all very good, which means that the HMM model can be used to make reliable predictions about the degradation level of LTE cells. The model can be relied upon for accurate classification of cell degradation levels, with a relatively low rate of false positives and false negatives.

6. Conclusions and Future Work

6.1. Conclusions

This thesis proposes the use of HMMs to monitor different levels of cell degradation in cellular networks. The goal is to improve LTE network performance, reduce operational costs, and enhance the user experience by proactively addressing potential cell degradation problems. The study uses historical data collected from a telecom network to train an HMM model. The Viterbi and Baum-Welch algorithms are used in the HMM framework. The output of the trained model consists of the estimated HMM parameters, which can be used to understand how the LTE cell behave. The study also shows how to find the most likely hidden state sequence given the observation sequence and its length.

The results show that the HMM model can accurately predict the hidden states of LTE cell degradation. The average accuracy of 93.12% indicates that the model correctly predicts the hidden state in the majority of cases. The precision, recall, and F1 score are also high, which indicates that the model is able to accurately predict the degradation level of LTE cells. This shows that HMMs can be used to assess LTE cell degradation levels by modeling and analyzing the temporal behavior of the monitored KPIs. In addition to the data pre-processing steps, the prediction result indicates that the factors that can affect the performance of the HMM model, includes the choice of initial probabilities and the length of observation sequence.

The prediction result help us to conclude that HMMs can be a promising tool for the prediction of LTE cell degradation and sequence of degradation severity. The model has shown to be able to achieve good performance, and it has the potential to contribute to the prevention, mitigation, and real time monitoring of LTE cell degradation.

6.2. Future Work

The industry-defined outage states for BTS are complex and difficult to monitor due to the large number of possible states and the fact that these states can change over time and locations. In the future, it would be interesting to explore the application of different types of HMMs to model these complex states. This could include multi-state HMMs, continuous-time HMMs, hidden semi-Markov models, and switched HMMs. By exploring different types of HMMs, we can learn more about the complex states of BTS outages and how they can be monitored. This can help us to improve the performance of network monitoring systems and to reduce the impact of cell outages or degradation on user experience.

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Appendix: Publishable Manuscript