Recurrent Neural Network-based Base Transceiver Station Power Supply System Failure Prediction

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***Abstract*—In mobile telecom networks, Base Transceiver Station (BTS) is a key infrastructure that connects customers with the mobile network. BTSs are geographically scattered across the networks service area and thousands of fault indicating alarms are generated by a typical BTS on a daily basis. Thus, proactively maintaining the BTS before faults happen is beneficial to guarantee proper operation of the network and reduce operational costs. In the mobile networks installed in the city of Addis Ababa, Ethiopia, failure in power supply system of BTSs takes the biggest share for mobile services interruption. This work investigates the early prediction of BTS failures due to power system and environmental abnormalities using recurrent neural networks (RNN) with long short term memory (LSTM) and gated recurrent unit (GRU) cells. Eleven power-supply system related features and alarms were collected from a real-time power and environmental monitoring system installed in each BTS. Moreover, the experiments were performed on five BTS sites with sixteen weeks of observations. The experimental results show that GRU using sigmoid activation function with feature reduction achieves better performance than using LSTM with the different configurations investigated. Unlike the prevailing practice in the network operator, which is taking corrective actions in response to alarms, the results in this experimental provide a new insight to the mobile operator to exploit patterns inherent in the daily measured data and predict the well-being of its infrastructure.**

***Index Terms*—Base Transceiver Station, Gated Recurrent Unit, Long Short Term Memory, Recurrent Neural Network, Prediction.**

I. Introduction

Driven by high data demand growth, mobile network operators are expanding their network infrastructures to cope with this increase [1]. Uninterrupted operation of its network is the main focus of any telecom operator to guarantee quality of service (QoS) and ensure customer satisfaction. However, as network infrastructures expand, the likelihood of failure occurrence and services interruption increases and sometimes finding failures is a tough and time taking task.

Nowadays, the trend is towards proactive maintenance, that prevents failure before happening, by using predictive maintenance approaches [2]. Proactive maintenance will reduce service downtime [2] [3], protect expensive equipments from damage [4] [5], guarantee QoS and thereby increase revenue. In mobile networks, the cost of downtime is very high if the failures are on critical components, critical sites, (e.g., a hub site whose failure may be the cause for other sites disruption) and during pick-hours. Predicting imminent failure requires availability of historical failure information and measurement data to set a better proactive maintenance strategies [6].

In mobile networks, BTS is one key infrastructure element that is performing the task of connecting customer equipment with the cellular network. BTSs are installed in geographically scattered service areas, including remote countryside and sides of roads. BTS services may be interrupted due to many reasons like power supply system failure, transmission system failure, backbone optical fiber cut, improper ventilation, natural disaster or many more. BTS power supply system is comprised of alternating current (AC) and direct current (DC) parts, where each has a primary and secondary (or backup) options. Voltage fluctuations, power failure and other faults often occurs; thus the BTS power supply capacity and quality of power supply cannot be guaranteed, which cause great difficulties to the BTS equipment maintenance. Having a regulated and uninterrupted power supply depends on the quality of AC power from electric utility grid, availability of power backup options, environmental conditions, and proper maintenance and operation of the power supply system. Modern BTSs have smart power and environmental condition monitoring system (e.g., NetEco provided by HUAWEI) installed to record events and generates fault indicating alarms. These monitoring systems collect real-time measurements, generate system alarms and are capable of keeping history log data. All network components in a BTS are supplied from a common power system, but with different sets of priorities. Services with the highest priority are connected

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on separate distribution units (but from a common source) and services with the lowest priority are connected to another distribution unit. The main reason behind connecting the loads on different distribution units is to easily disconnect them on different orders when faced with different scenarios.

Since power systems are critical elements in any communication system [7], their failure may cause an interruption to the complete services or failure of other subsystems. In the case of BTSs installed in Addis Ababa city, Ethiopia, power system failure takes the biggest portion as the root cause of failure. A one-month BTS report obtained from the operator indicates that around 2067 BTS failure registered for April 2019, of which 54% of the failures are due to power system, 33% are attributed to commercial power outage (in this case the service by the Electric Power utility), 9% is due to transmission and fiber cut, and the remaining 4% of the failure causes are unknown. Therefore, predicting BTS power system failure is a vital issue to enhance the performance of the power systems, thereby improving provisioning of the overall service.

Rather than trying to detect faults manually, currently Artificial Neural Networks (ANN) can be used to classify, predict and diagnose faults of individual components or failure of a subsystem. ANN can learn patterns and capture information automatically from the data. To the best of our knowledge, there is no prior work that applies ANN techniques to predict BTS failure. Some of the prior works done in a related area are on power plant fault analysis, power system transformer failure, and power grid connected photovoltaic system failure. In [14], diagonisis of common faults in power plant is conducted using Artificial Neural Networks (ANN). The work done in [15] used ANN to predict power grid failure. 10 years of grid system data (generation, load, transmission, and distribution) and features like drought, hurricane, load growth, generation reserve, and proper control system operation rate were used as an input for the prediction. Another work in [16] recommends predicting transformer failure using ANN. They demonstrated that predicting the fault occurrence time has a greater advantage to develop reliable service provisioning. ANN based model was also used in [17] to predict power generation of a grid which is connected to a photovoltaic plant. The input variables for training include solar radiation, ambient temperature, and power measurements were taken for 14 hours and they applied Mean Absolute Bias Error (MABE) and Root Mean Square Error (RMSE) as a performance measurement. They conclude power prediction generated power from the grid performs well and they found RMSE of 9.86% and the MABE of 7.16%. Due to the nonlinear behavior of most of the time-series data and limitation of ANNs with capturing long-term information, predicting the failure accurately is challenging. To deal with this problem Long-short-term memory (LSTM), a variant of Recurrent Neural Network (RNN) was introduced in [18]. It was demonstrated that LSTM is capability of predicting both long term and short term faults.

This work investigates prediction of BTS failures due to power system and environmental abnormalities using recurrent neural networks (RNN). Eleven features related to power supply system and environmental conditions were collected from a real-time power and environmental monitoring system installed on each BTS. The main contributions of the paper are as follow,

1) The prevailing practice in the network operator is to take corrective actions in response to alarms. This work proposes having a smarter BTS system that exploit patterns inherent in recorded historic data and predict the well-being of its infrastructure.
2) Given that tens of thousands of BTSs are geographically scattered and operate in different environmental conditions and unreliable power grid system, the prediction can help the operator implement efficient maintenance plans and procedures.

The remaining part of the paper is organized as follows. Section 2 discusses the architecture and main components of a BTS power system. Sections 3 focuses on BTS power system failure and how to detect it. Section 4 is about recurrent neural networks, which is the main algorithm used to build the predictive models. In section 5, the methodology followed for this research work is discussed in detail. Section 6 discusses the experimental setup. Finally, in section 7 and 8 the results obtained are analyzed and a conclusion of the work is given.

II. Base Transceiver Station Power System

BTS systems are composed of different components like mobile system equipment, transmission equipment, and power equipment. BTS power system is responsible for supplying the required electrical power to the BTS subsystems and it is composed of different power sources, protection devices, switches, fuses, and circuit breakers. One way of broadly categorizing the BTS power system is into the AC distribution unit and DC distribution unit. Fig. 1 shows a typical BTS power supply system and below is a brief description of each subsystem [7].

1) *AC distribution unit (ACDU)* - gets AC power from the commercial power system, generator, renewable energy sources or any combination of the three. Factors to consider while choosing the AC power sources include: whether the site is indoor or outdoor, estimated traffic load, whether the site only gives mobile services or hub sites (which is used as backbone link for other BTSs or exchange), service supported, site access (transport to and from the site), operation and maintenance constraints and location (available spaces at the site and site geographical conditions) [8] [9]. When the commercial power source is interrupted (i.e., totally turned off, phase lost or below the expected threshold), automatic transfer switch (ATS) control module will send start signal to the secondary AC source.
2) *DC distribution unit (DCDU)* - includes rectifiers, battery banks, Load Low Voltage Disconnect (LLVD) distribution, Battery Low Voltage Disconnect (BLVD) distribution, and surge arrester fuses and different contactors. Rectified 48VDC is supplied to both DC loads and

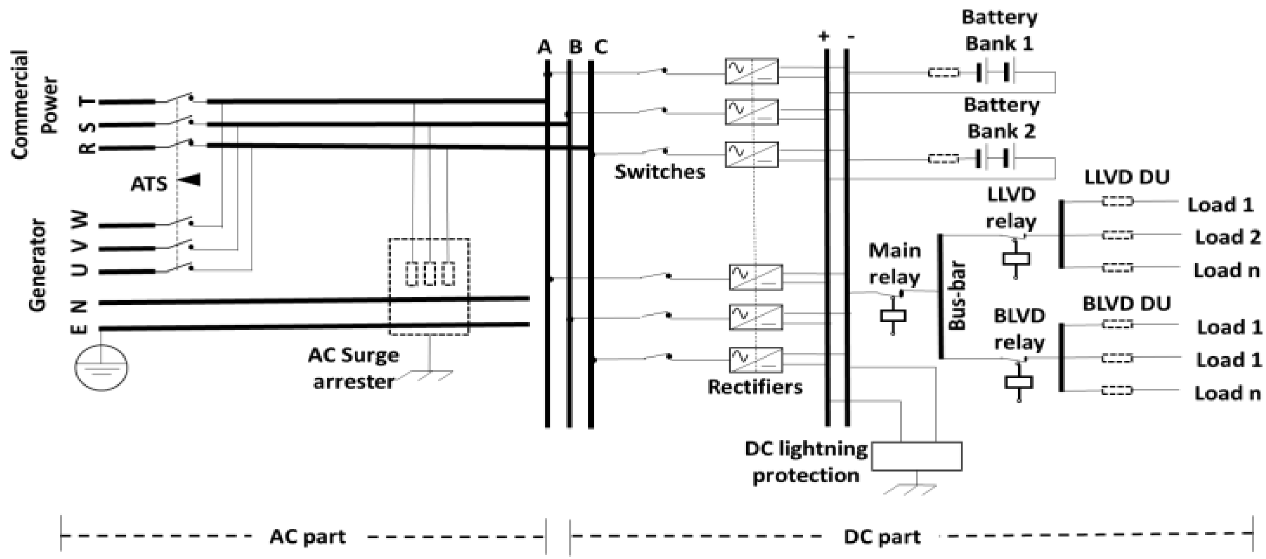

Fig. 1. BTS power system.

battery banks in parallel. LLVD and BLVD functions are used to serve the loads with different priorities. When the battery voltage becomes below the configured threshold, the system will automatically disconnect less prior equipment by tripping off the LLVD contactor. The purpose of disconnecting less prior services is to keep active the critical loads until the battery bank exhaust its stored power (gets to the minimum configured voltage level) .

3) *Rectifier* - The rectifier is used to convert the 220V AC voltage received from commercial power or generator to 48VDC voltage which is used to power the DC loads and charge the battery bank constantly. In addition, the rectifier is responsible for regulating or smoothing the voltage which will be supplied to the loads, protect over or under voltage, DC-to-DC conversion, filtering harmonics and current equalizations. The rectifiers in the BTS used can operate on a wide range of phase voltage (from 80VAC to 300VAC with a frequency range from 45Hz to 65Hz).
4) *Battery bank* - The battery bank is responsible to give power to the equipment at the sites when commercial power (generator and solar, depending on the configuration) fails to supply power to the site so the battery banks serve until it exhausts (minimum configured voltage level) its stored power. In addition, even-though it is for small duration the battery bank supplies DC power during the transition of the loads from commercial power to the generator and vice versa. The configuration of the battery banks in the BTS power system is as shown in Fig. 2.
5) *Auxiliary units* - BTS power system encompasses different types of components including environmental equipment's (air conditioner and fan), surge protection, AC or DC fuses, circuit breaker, relay and lightning arrester.

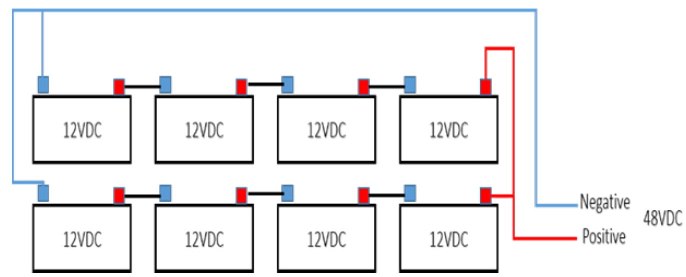

Fig. 2. 48VDC battery bank configuration (two-battery bank)

6) *Busbar* - The busbar is a copper strip or bar, where DC loads, battery bank, and the rectifier output are connected in parallel. The measurements taken from the busbar of a power system are busbar voltage, DC load current, and DC load power.
7) *Real-time monitoring unit* - Current BTS power system encompasses different measuring tools and sensors (such as temperature, humidity, voltage and power, battery status, and even door contact, smoke detector, and camera switches). Readings from the sensors are used as an input by the monitoring system and configurable alarms are generated based on the different system conditions. The real-time monitoring system used in this work takes eleven measurements related to batter status (battery charge and discharge current, battery voltage, battery temperature, batter charging cycle, and battery total discharge power), environmental parameters (temperature and humidity) and AC current. Moreover, from the load side the system measures busbar voltage, DC load current and DC load power.

III. BTS Power System Failure

BTS power system failure is an event when BTS power gets below the configured threshold or a total power blackout occurs. Based on the power system layout shown in Fig. 1, BTS power system failure can be attributed to failures from the AC main and secondary supply (under and over voltages), DC power supply system (from the rectifier), the battery system, the environmental condition in which the BTS is housed (like temperature and humidity levels), and any component failure from the communication side (from the transmission or optical system in which the power system is connected). Failures in the BTS power system can be detected from the busbar voltage, which captures relatively higher information than that of DC load current and power. Table I summarizes the various busbar voltage levels and the corresponding alarms.

In normal operation conditions, the busbar DC voltage is expected to be above 48.2 Volts. When the voltage level gets below 48.2VDC it is termed as busbar under voltage (BBUV) and is a pre-warning of LLVD failure. The duration until the apparent failure depends on the battery load carrying capabilities. When the voltage level falls below 46.2VDC, LLVD loads will be disconnected and the LLVD alarm is generated. In addition, when the voltage level gets below 45.2VDC, the BLVD loads will be disconnected and all the services at the BTS sites interrupted except the communication between the monitoring system and the site. Disconnecting the loads at the BLVD voltage level is used to protect the battery banks from deep discharging that may otherwise damage the battery elements permanently. The above stated voltage levels are default values used by the operator but they can be reconfigured based on different site conditions and operational scenarios.

IV. Recurrent Neural Network

Machine learning algorithms are playing an important part in predicting failure in various areas like power distribution, hydro-power generation plants, solar power generation plants, high voltage transmission grid and many more [11]. Recurrent Neural Networks (RNN) are one type of ANNs, which has a memory to store information at every recurrent unit to remember things from the past. RNN feeds the outputs from neurons to other adjacent neurons, to themselves, or to neurons on preceding network layers and this capability makes RNN better to model complex works which is difficult to handle by a standard ANN [12].

A traditional feed-forward neural network is not well suited to handle sequential data because it uses a fixed input sequence for learning the data. Because sequential data may have important information in the past sequence which may be used to represent the future and may be used to understand the entire data, storing this information and using it when required determine the efficiency of the algorithm. RNN solves the problem that arise to time-series and sequence data that suffer from capturing long-term information [12]. Sequence modeling mechanisms have their own criteria to be fulfilled. These are:

- It should support variable-length input;
- It should have the capabilities of tracking long term dependencies (information);
- It should have the capabilities to maintaining information order;
- It should have the capability to share parameters across the sequence.

A. Long Short-Term Memory

The LSTM is one variant of RNN that has feedback connections with itself and other neurons. It has the capability of considering the entire sequences of data. LSTM cell contains three essential parts which determine the output of every recurrent cell. These are forget, update and output gates. These gates decide what to store, erase, and output at every computation by opening and closing the information flow as shown in Fig. 3 [13].

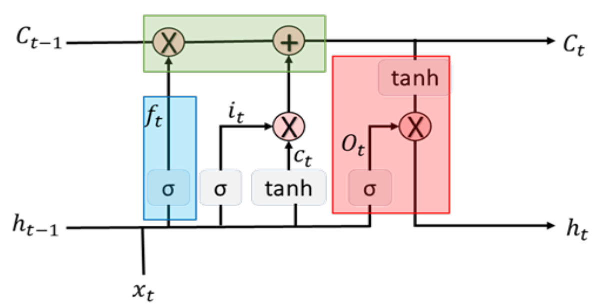

Fig. 3. LSTM internal structure.

B. Gated Recurrent Unit

GRU is another variant of RNN that is inspired by the LSTM unit but is simpler than that of LSTM from computational perspective because it is implemented with a simple internal structure. GRU consists of an update and a reset gate. The update gate defines how much previous memory to keep and the reset gate defines how to combine the new input with the previous memory and decide how much past information to forget and the update gate decide what information to add or remove as shown in Fig. 4 [13].

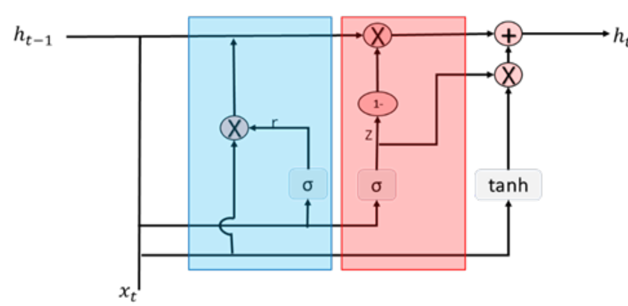

Fig. 4. GRU internal structure.

TABLE I
SUMMARY OF BUSBAR VOLTAGE LEVELS AND THE CORRESPONDING ALARM.

Busbar Voltage (V_{busbar})	**Operational Status**	**Alarm type**
$48.2 \leq V_{busbar} < 58.2$	Normal voltage level	
$46.2 \leq V_{busbar} < 48.2$	Warning for partial failure	Warning alarm
$45.2 \leq V_{busbar} < 46.2$	Partial failure	LLVD alarm and LLVD load disconnected
$V_{busbar} < 45.2$	Total failure	BLVD alarm BLVD loads disconnected

V. METHODOLOGY

To have a good predictive system of power system failures in BTSs, this research work has followed through phases of data collection, data preprocessing, detailed review of BTS power system architecture, and applicability of different machine learning approaches. The methodology followed is:

- The data is collected from the NetEco power monitoring system that contains both normal and failure events.
- After data collection, feature analysis was performed where the models built are tested with and without dimensionality reduction. To reduce the number of features from the original 11 input features, a selection was made by analyzing the relationship and correlation between the selected failures (BBUV, LLVD, and BLVD) and all the features. Therefore, busbar voltage, DC load current, and DC load power are found to have a high correlation with the actual failure. However, the busbar voltage is selected as a target feature because of BBUV and LLVD failures are well reflected on it as shown in Fig. 5.

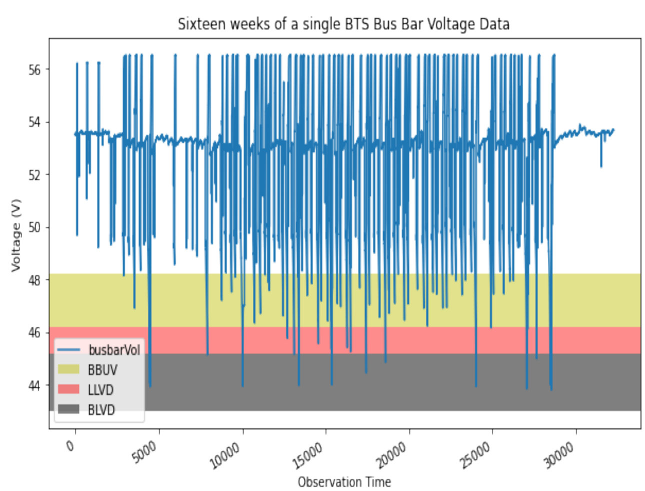

Fig. 5. Busbar voltage observation of a sample site.

- In all the experiments, a $70\%/20\%/10\%$ split is performed on the data to obtain the training, validation and testing instances which are going to be used as an input to the model.
- For predicting the impending failure of the BTS power system, an RNN (based on LSTM and GRU) model is built using standard feature normalization with sigmoid and relu activation functions. In addition, the performance of the model is checked with and without feature reduction techniques applied in the input space. The feature reduction is performed by analyzing the correlation of features using Pearson's correlation.
- To measure performance of the model, mean squared error (MSE) and the number of the epoch are used. MSE fundamentally measures an average squared error between the predicted and the actual values. The number of epochs is a parameter that defines the times that the learning algorithm will work through the entire training dataset.

VI. EXPERIMENT SETUP

This section presents the experimental setup followed in this research work. The main tasks performed are:

A. Data Collection

The data set used for this research is BTS power system measurement information obtained from NetEco power monitoring system. Totally, data is collected for five BTS sites for sixteen weeks (from April to July 2019). The data set contains eleven features with five minute sampling period. Thus, every site data set has an equal number of observations with a similar time-stamp.

B. Algorithm Selection and Implementation

The algorithm selected for this failure prediction task is RNN. The experimental implementation applied LSTM and GRU cells, with a sigmoid and relu activation functions. RNN is capable of remembering important information through the whole dataset. This characteristic makes it well suited for time-series prediction, because of its capabilities to predict the feature based on previous experience. The experiments are performed in two different arrangements: Single site and multiple site fault prediction.

The first set of experiments are implemented on a single site by varying the input data size (starting from 10 weeks through to 16 weeks). Then for the multi-site experiments, a combination of sites are used starting from a single site and progressing to include all the 5 sites by using the whole 16 weeks of observation. The main reason behind using different data sizes is to check the impact on the performance on LSTM and GRU which is dependent on the amount of past history data to predict future BTS power system failure.

C. Model Hyperparameters Tuning

Hyperparameters setup is an important stage in any machine learning algorithm, which can make significant difference in its performance. In this work, a number of repetitive experiments were performed to obtain a set of optimal RNN hyperparameters. Table II shows the optimal hyperparameters values.

TABLE II
HYPERPARAMETERS SETUP.

Hyperparameters	Values	Remarks
Number of recurrent units	64/32	Input layer/Hidden layer
Number of epoch	20	Early stopping (patience=5)
Step per epoch	100	
Validation steps	100	
Sequence Length	288 samples	1 day of data
Batch Size	256 samples	
Drop out	0.1	On both layers
Optimizer	Adam	
Gradient Clipping	1.0	

In addition to hyperparameter tuning, feature reduction technique is applied and the results obtained are compared with the ones without feature reduction. For the purpose of feature reduction, Pearson's correlation analysis between all features and the target feature has been done. This technique leads to a selection of 6 highly correlated features including the target value busbar voltage. From the correlation results found, working temperature, battery current, battery voltage, AC/DC current, DC load current, and DC load power have a better correlation result with the target feature busbar voltage. Furthermore, battery current and AC/DC current have a strong correlation with each other. Therefore, rather than using both of them which will become redundant, AC/DC current is selected to be part of the feature reduced data because it has a higher correlation with the target feature than battery current.

VII. RESULTS AND ANALYSIS

In this section the results obtained when performing failure prediction experiments on both a single and multiple BTS sites are discussed and presented.

A. Single site based fault prediction

The results found for a single site based fault prediction using a sigmoid activation function for both LSTM and GRU is shown in Table III. As can be observed from the results, GRU achieve comparatively better MSE values and faster convergence when compared with LSTM. Note that in all the results and discussions, AFR and BFR represents experiments performed after feature reduction and before feature reduction respectively. In addition, Table IV shows the results found by using a relu activation function for both LSTM and GRU. Similar to the earlier results, GRU achieves most of the time a slightly better results of MSE, number of epoch and wall time compared to LSTM.

Taking into consideration all the experiments, the minimum MSE achieved is 0.122 for GRU with feature reduction using 16 weeks data and a sigmoid activation function. Considering LSTM, the minimum MSE achieved is 0.114 before feature reduction, using 16 weeks of data and a sigmoid activation function. From the single site fault prediction points of view, the sigmoid activation function achieve better results compared with relu. This is due to the characteristics of relu activation function in some of the runs that led to an exploding gradients problems. Thus, it is recommended to use sigmoid activation functions in the final models. Another observation is that feature reduction technique reduces the number of epoch and wall time required to obtain the minimum MSE. This reduces the time complexity of the model in training and prediction and generally improved performance.

B. Multiple sites based fault prediction

Using the parameters which achieved a better prediction accuracy for a single site prediction and applying feature reduction, prediction performance are checked for multiple sites. The experiment is done by using the five BTS power system data for training the model and making a prediction of power system failure on a single BTS. The reason behind using multiple sites' data is to analyze the prediction making capability of multiple sites for a single BTS power system failure. Table V shows the results found for multiple site test MSE results. As can be seen from the results, the minimum MSE of 0.1130 is obtained when using a single site data to make a prediction about its own power system failure. An increasing in MSE value pattern is detected when using multiple sites for prediction. The possible cause of this increase is due to the differing characteristics of the BTSs. But, this prediction approach can be used when there are BTSs with incomplete or corrupted data and new sites which doesn't have a collected data yet.

VIII. CONCLUSION

The mobile telecommunication infrastructures are increasing in number and complexity with the development of new technology and increasing demand. Thereby the maintenance, monitoring, and resource assignment of the whole system is becoming one of the main challenge for an operator. Especially trying to manage the infrastructure always with a corrective maintenance activity requires considerable effort and resources. It will also diminish the performance of the whole system which leads to poor resource utilization and loss of revenue.

A power system is a backbone of the entire communication infrastructure and its failure causes an interruption to the complete chain of services. Therefore, following good management procedures in power systems will have a big impact on the whole service provisioning and infrastructure. Nowadays, maintenance trends shift from reactive to proactive, which focus on taking actions for impending problems by using predictive techniques. This research work focused on predicting these failures before they can happen using data collected from an operators network to guarantee QoS and increase revenue. By using RNNs and building models using

TABLE III
RESULTS USING A SIGMOID ACTIVATION FUNCTION

Sigmoid Activation Function												
Number of Weeks	GRU						LSTM					
	Epoch BFR	MSE BFR	Wall Time	Epoch AFR	MSE AFR	Wall Time	Epoch BFR	MSE BFR	Wall Time	Epoch AFR	MSE AFR	Wall Time
10	8	1.354	767.4	12	1.060	1082.8	8	1.437	841.8	12	1.061	1098.5
12	14	0.925	1381.9	14	1.030	1202.3	16	0.877	1693.2	16	1.165	1680.4
14	15	1.009	1457.2	12	0.856	1157.8	10	1.008	1132.5	15	0.872	1611.0
16	7	0.122	543.2	9	0.173	677.7	7	0.114	612.1	8	0.165	708.4

TABLE IV
RESULTS USING A RELU ACTIVATION FUNCTION

Relu Activation Function												
Number of Week	GRU						LSTM					
	Epoch BFR	MSE BFR	Wall Time	Epoch AFR	MSE AFR	Wall Time	Epoch BFR	MSE BFR	Wall Time	Epoch AFR	MSE AFR	Wall Time
10	7	1.153	679.2	7	1.099	611.7	6	1.146	691.4	8	1.204	776.4
12	13	1.082	1289.8	8	1.249	753.4	7	1.097	721.4	6	1.084	631.5
14	8	1.017	771.6	10	0.822	901.3	6	1.067	640.9	9	0.776	999.9
16	6	0.502	455.7	7	0.146	517.4	6	0.733	658.5	6	0.147	520.1

TABLE V
MSE VALUES WHEN USING MULTIPLE SITES.

NO. of Sites	BTS1	BTS2	BTS3	BTS4	BTS5
1	0.1220	0.1760	0.1720	0.1130	0.1850
2	0.1332	0.1800	0.1722	0.1270	0.1840
3	0.1320	0.1800	0.1833	0.1173	0.1910
4	0.1501	0.1800	0.1711	0.1220	0.1870
5	0.1606	0.1790	0.1849	0.1250	0.1950

both LSTM and GRU, a good prediction of BTS power system failure is achieved based on the previous time serious data. Even-though, both LSTM and GRU can predict the impending failure in the BTS power system with good accuracy, GRU with sigmoid activation function achieved a minimum MSE of 0.1220 on a single site with feature reduction and using 16 weeks of BTS data.

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