Integration of LSTM based Model to guide short-term energy forecasting for green ICT networks in smart grids

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***Abstract*—Existing ICT networks are characterized by high level of energy consumption. In order to power up 5G base station sites, rising energy cost and high carbon emissions are major concerns that need to be dealt with. To achieve carbon neutrality, ICT sector needs to transform base station sites in a self-sustainable manner using renewable energy sources, local batteries and energy conservation techniques, even in adverse weather conditions and unexpected power outages. In this paper, short term-forecasting models are studied for accurate energy consumption and production forecast. The proposed architecture provides adaptive energy conservation technique using time series data analysis and Long Short-Term Memory for 5GNR base station site which is independent of traditional power sources and is completely powered by green energy. The accuracy analysis of this study was performed by the Mean Square Error (MSE) and Root Mean Square Error (RMSE). The results show high accuracy levels of LSTM model in guiding short-term energy forecasting for green ICT networks.**

***Index Terms*—short-term forecasting, energy-weather forecast, time-series neural networks, LSTM, ICT network, 5GNR BS, energy conservation technique, MSE, RMSE, python**

I. Introduction

The overall energy consumption of ICT sector is likely to grow upto 20% of total global energy usage by 2030 [1]. Moreover, ITU-T predicted that by 2030, ICT sector will be using 1.3 times of global energy which is 1.3 times of that in 2015 [2]. According to estimates, 5G base station (BS) is supposed to consume three to four times of the 4G BS with annual power consumption of about 2.00 - 3.38 million kWh [3]. Henceforth, like many sectors, ICT organizations are working towards lowering energy bills using various energy conservation techniques and AI tools. The fifth generation of mobile communication is not only struggling with high energy consumption and growing bills but also large CO2 emission footprints.

Besides relying on traditional power grid sources, there are alternative approaches such as renewable energy sources (RES) including solar and wind power. RES can provide green energy supply for powering on-grid and off-grid BS site. However, energy saving feature of 5GNR BS is still needed due to unnecessary large amount of energy waste which is about 1000 degrees per year, while remaining full powered [4].

Energy efficiency is one of the key factors to achieve carbon neutrality and it also helps reduce energy demand efficiently. The short-term forecasting models based on artificial intelligence and pattern recognition can contribute to energy efficiency. Thus, it is viable to effectively plan energy usage based on accurate energy predictions [5]. These short-term forecasting models based on accurate machine learning predictions will enable energy saving features and determine the optimal operation time as well as reducing overall energy consumption for developing eco-friendly and cost-effective self-sustainable BS sites. Accurate energy forecasting along with achieving energy efficiency, will have many benefits such as optimal penetration of RES, which will reduce risk of over and under generation of energy. It can also perform critical energy behaviour and site analysis to design optimal backup storage size and integrate short-term forecasting models to transform power hungry 5GNR BS sites into self-sustainable green ICT networks.

ICT sector has been left with no choice but to transform its BS sites to use energy efficiently due the ongoing worldwide economic crises, rise in global warming as well as the COVID-19 pandemic. To achieve this goal, it is vital to use forecasting tools to predict energy behaviour to meet the required demand even in adverse weather conditions while completely relying on RES. Using the proposed short-term forecasting methods, 5GNR BS site can be transformed into a carbon neutral, self-sustainable model. By predicting the energy consumption and solar photovoltaic (PV) production, this paper investigates a power saving feature and provides a proposed architecture to achieve energy efficiency while defining new roles to Distributed Service Operators (DSOs). The contributions of

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the study are as follows:

- We propose a framework for activating/deactivating power saving feature in 5GNR BS based on adaptive energy consumption technique.
- We predict the solar PV production and power consumption of the 5GNR BS site based on LSTM, a time series neural network model.
- We design an intelligent energy conservation technique using Message Queuing Telemetry Transport (MQTT) for green 5GNR BS sites.

II. System Models

This section describes the method and activities performed in this paper in order to transform power hungry ICT networks into green and sustainable 5GNR BS sites by using proposed short-term energy forecasting models. All the processes of this project and the flow of the energy and data is explained step by step. In the following subsections we start by discussing our short-term forecasting models for 5GNR BS power consumption and integration of energy-weather forecast for activating/deactivating energy saving feature, and then introduce our developed architecture and energy conservation framework. Furthermore, this paper will focus on real-time data collection and propose a novel technique to achieve carbon neutrality.

A. LSTM Basics

They key basis of the proposed system is use to use multiple short-term forecasting models to enhance energy efficiency. There are several classical machine learning algorithms which are simple, fast and mostly used with small datasets such as Autoregression (AR), Hidden Markov models (HMM) etc. Modern deep learning methods are able to handle large datasets and are optimal for time-series predictions such as weather-forecasting and energy consumption behaviours. A recurrent neural network (RNN) is considered one of the effective solutions for forecasting time series data. The study shows that RNN performs quite efficiently in predicting the next element in a sequence, but fails to carry the data if the sequence is long enough. [5].

To solve this, one way is to extend the network with explicit memory. One of the proposals of this kind is networks with long short-term memory (LSTM), which uses special hidden blocks, the natural behavior of which is to memorize input data for a long time. Since it has a feedback functionality, the memory cell units have the ability to add new information based on learning long-term dependencies. These memory cells are capable of retaining its states over time using explicit memory and gating units. These gating units will control the information flow through cell state and hence LSTM model can selectively forget using the forget gate and add new memory using the input gate [4] [5].

Extensive literature review was carried out before selecting the LSTM model as an intelligent technique to deploy the power saving feature for 5GNR BS. Many research papers were referred such as [6] [7] before finalizing this technique.

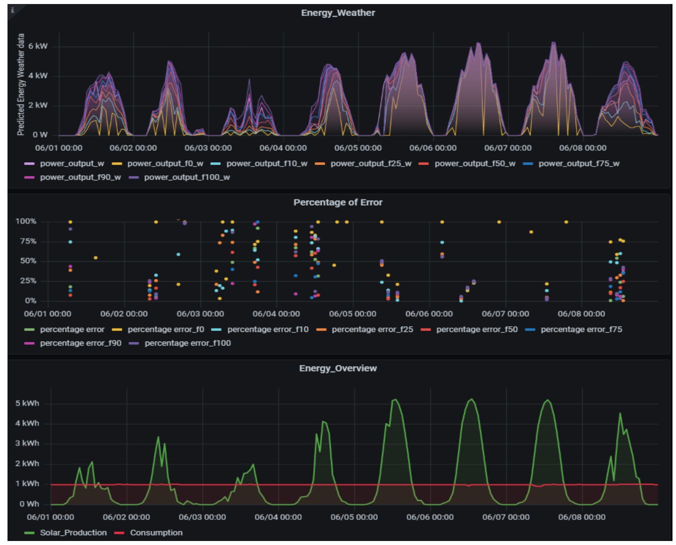

Fig. 1. Short-term live energy-weather forecast for next 66 hours

B. Forecasting Model

There are two forecasting models used to guide the energy consumption behaviour of the BS. Fig. 1, shows the first forecasting model which is based on meteorological data of the Finnish Meteorological Institute (FMI). The provided energy weather forecast converts solar radiations such as global and system specific radiations into kilowatt hours for each site-specific coordinates over the next 66 hours [8]. The forecast is based on the HIRLAM weather forecast model of the FMI which includes all weather forecasting related information such as cloud coverage, panel and air temperature, defuse and direct radiations. The site-specific local short-term predictions provided by FMI as energy-weather forecast are obtained from API call using Python code.

Energy-weather forecast along with the historical measurement data for PV power output can also help achieve goals such as critical site analysis, sizing the optimal backup-battery and determination of the number of PV arrays required to deploy self-sustainable BS with 3GPP Next Generation NodeB (gNB) site. In the current study, actual predictions have been made using energy-weather live forecast, historical site-specific measurement data and the power consumption of 5GNR BS as shown in Fig. 1 and Fig. 2, according to expected energy availability.

The energy and data flow illustrated in Fig. 3, contains various on-site sensors like solar irradiance, ambient temperature and PV module temperature. These on-site sensors along with the energy weather live forecast are processed by the micro-controller (RP2040) and is stored in the database. Fig. 2 also shows the comparison between the energy production forecast and the real-time solar PV production using percentage error. This real-time monitoring of the energy behaviour is visualized using Grafana. The use of deep learning, in particular LSTM, is our proposed model to guide short-term energy forecasting decisions.

Fig. 2. Solar PV and 5GNR BS site-specific data for one year

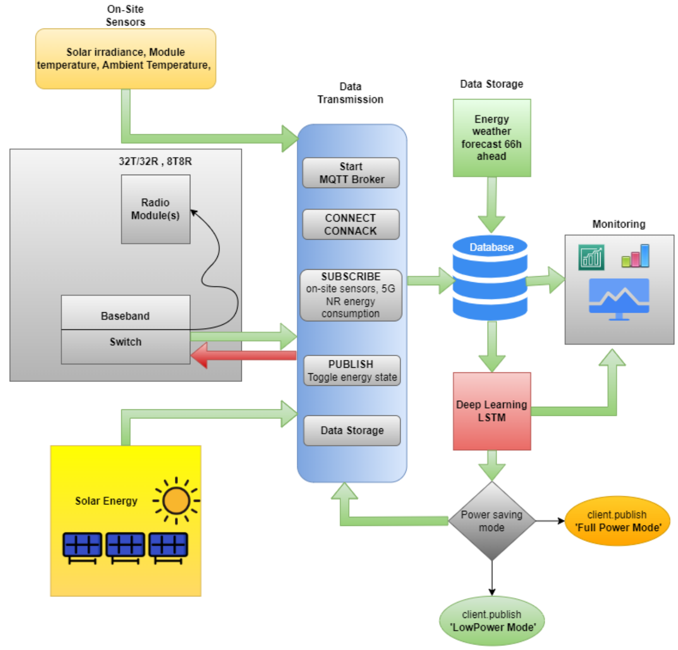

Fig. 3. Energy and Data flow of the intelligent power saving feature of 5GNR BS

C. Data collection

The datasets used in this paper were obtained from multiple sources such as real-time power consumption data from 5GNR BS and solar PV production at the rooftop of University of Oulu. The real-time power consumption data was taken from 5GNR BS which is part of the 5G Test Network (5GTN) consisting of baseband unit, switch and radio modules. The first dataset contains a total of 5009 data values which is for seven months of real-time energy consumption usage for 5GNR BS in kWh. The real-time data was collected from November 2021 to May 2022 with the interval of one hour.

The second source of the analysed dataset consists of twenty four solar panels installed at the rooftop of University of Oulu. This dataset is the real-time solar PV production in kWh at co-ordinates 65.0593° N, 25.4663° E. The data was collected from July 2021 to May 2022 with the interval of one hour containing total of 8230 data values. Both the datasets are then finally organized into dataframes using Python packages such as pandas.

D. Energy and data flow structure

Here we analyse the energy and data flow of the proposed architecture. As demonstrated in Fig. 3, 5GNR BS site with distributed antenna based cellular network powered by solar panels has multiple on-site sensors. These on-site sensors along with both solar PV and 5GNR BS energy data is sent using simple messaging protocol suitable for IoT devices i.e. MQTT [9]. Using the ***publish*** and ***subscribe*** system, MQTT client will connect to MQTT broker over the network as indicated in Fig. 3.

The flow of the system operation also consists of data analysis. As illustrated in Fig. 3, the system operation use Application Programming Interface (API) to collect energy-weather forecast which calculates the solar PV production during the next 66 hours. Here, FMI conducts eight forecast simulations at once instead of just one, with probability forecasting system as shown in Fig. 1. These MetCoOp Ensemble Prediction System are estimates on the forecast uncertainty and the spread between these forecasts (narrow or wide) depends on adverse weather conditions [8]. Fig. 2 shows the energy weather forecast for site-specific coordinates for the period of one year. The energy weather data was collected at an interval of one hour and stored in MYSQL database to be used for training the short-term energy forecasting model.

Finally, the last part of the Fig. 3 shows the flow of all the real-time collected data entered into LSTM model for iterative training. Based on the training data, the LSTM model will set the 'CUT-OFF-VALUE' which will eventually guide the 5GNR BS to toggle its energy state using MQTT client.publish feature. Real time and predicted data is visualized using Grafana as shown in Fig. 1.

E. Data Training and Test Split

The collected datasets were divided into training and test data. The first dataset used in our system model is seven months of power consumption data for 5GNR BS. The data was split into training and test set with 90% of the data values i.e. 4508 data into training set and rest of the data values i.e. 501 values into test set. Similarly, the second data set is the historical measurement data of the site-specific solar PV production. With 8065 data values for training set and rest of the 165 values were used to testing. This dataset contains energy production values for eleven months of PV production of solar panels.

The Python package sklearn.preprocessing was used to perform MInMaxScaler in order to scale the data values between zero and one. After scaling and splitting the data into training and test sets, the input data was reshaped into samples, time steps and features.

F. LSTM Model implementation

After gathering sufficient amount of data about the 5GNR BS power consumption and site-specfic solar PV production, LSTM model was used for short-term energy forecasting over the whole dataset using constant number of inputs, neurons, output, time steps, epochs e.t.c. In order to obtain high accuracy, LSTM model is fitted with best possible combinations using hit and trail method. Finally, the LSTM model performance was evaluated using the best possible configuration combination while comparing it with the actual data. Keras (version 2.3.1) a high level neural network library was used with configuration details presented in Table I.

TABLE I
LSTM Model Configuration

Model	Sequential
Hidden layers neurons	64
Loss	MSE, RSME
Optimizer	Adam
Method	linear, relu
Dense	8
model.fit	verbose 1 , epochs 100, step size 252

G. Proposed System Architecture

The disadvantage of any system that uses solar panels is a strong dependence on weather conditions. With low levels of solar radiation for an extended period of time, due to precipitation and cloud cover, there are risks of low power availability which may lead to system shutdown unless the BS site is connected with the traditional grid. As demonstrated in Fig. 4, the proposed architecture attempts to solve the traditional grid dependability and provides a solution for ICT network to completely rely on RES while simultaneously reducing the impact of weather conditions. It proposes an intelligent power saving feature for zero carbon powered 5GNR BS sites. Fig. 4 presents the architecture design based on the role of the Distributed Service Operator (DSO) and the integration of the energy weather forecast to guide the short-term demand response management.

The proposed architecture assigns new roles to DSOs as following.

- DSOs can provide peak load and demand response management using short-term forecasting models to ensure green ICT networks.
- DSOs can monitor ICT network traffic and avoid energy waste during adverse weather conditions as shown in Fig. 4.
- DSOs can integrate these proposed short-term forecasting models which provides foundation for eco-friendly, self-sustainable BS site.

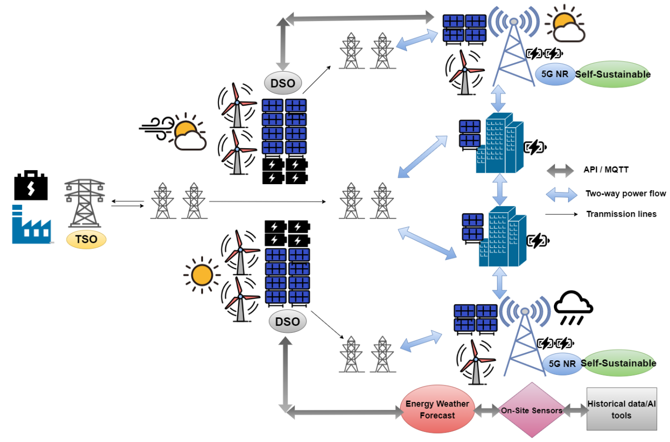

Fig. 4. Framework of the proposed architecture based on short-term forecasting models

- DSOs can store energy based on information flow and energy-weather forecast and allows BS to only wake up when the communication is expected.

III. Simulation Results and Discussions

In this section we will inspect the results which are obtained after performing data analysis. The real-time data values are compared with predicted values using the proposed forecasting model and the accuracy of the predicted results are presented. The simulations were performed in Python 3.7 using Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz and 16 GB of RAM memory.

A. Raw Data

The raw data of this study is obtained from real-time data collected at 5GTN BS site located in University of Oulu. The raw data is then fed into the LSTM model. The principle idea behind collecting raw data is to determine whether it shows any pattern. Fig. 5 represents the 5GNR BS real-time energy consumption in kWh while Fig. 6 shows the seasonal data for solar PV production in kWh. The collected raw data clearly exhibits defined patterns, useful for LSTM model configuration such as seasonal patterns for solar PV production and 5GNR BS daily power consumption. Fig. 5 shows the waveform between 01 November 2021 to 31 May 2022 for 5GNR BS power consumption. Similarly, Fig. 6 shows the waveform between 01 July 2021 to 31 May 2022 for solar PV production.

B. Actual and Predicted data value comparison

Fig. 7 shows that LSTM model can predict the actual 5GNR BS power consumption accurately for up to twenty days ahead. As Fig. 7 depicts the orange plot i.e. the predicted values coincides precisely to the blue plot which is the real-time consumption. Similarly, Fig. 8 shows predictions of seven days ahead for site-specific solar PV production which are indicated as orange plot. Fig. 8, clearly show that even on partly cloudy day, performance of the model remained coherent. Both Fig. 7

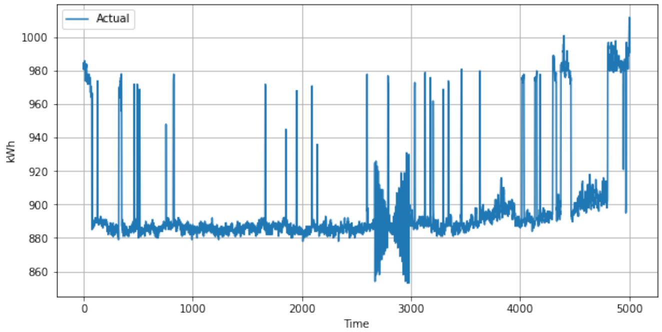

Fig. 5. 5GNR BS real-time energy consumption

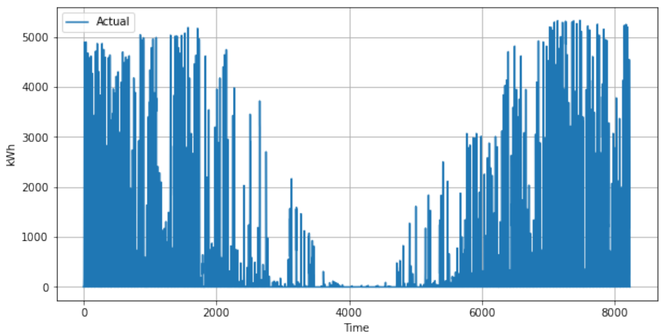

Fig. 6. Solar PV energy production

and Fig. 8 clearly show that LSTM model performs efficiently using the trained datasets to predict the time series future values for short-term energy forecasting. Table II shows the used configuration parameters for LSTM model to predict real-time data used in this study.

C. Accuracy Analysis

The performance analysis of the proposed model was evaluated by measuring the accuracy of the prediction for each iteration. Fig. 9 represents the MSE curve for the trained and test data. Fig. 9 illustrates that with each iteration, the short-term power consumption predictions for 5GNR BS improves significantly. Similarly, Fig. 10 also shows the LSTM model performance evaluation for site-specific solar PV production.

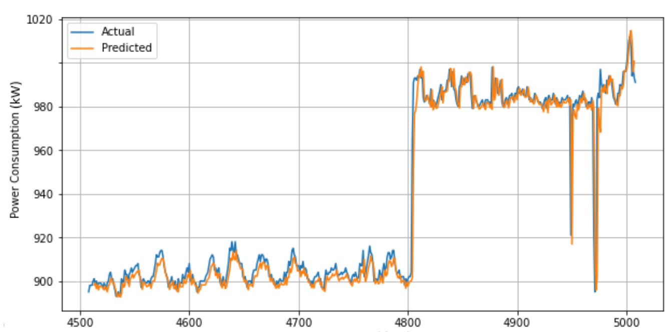

Fig. 7. 5GNR BS real-time energy consumption, actual vs predicted values

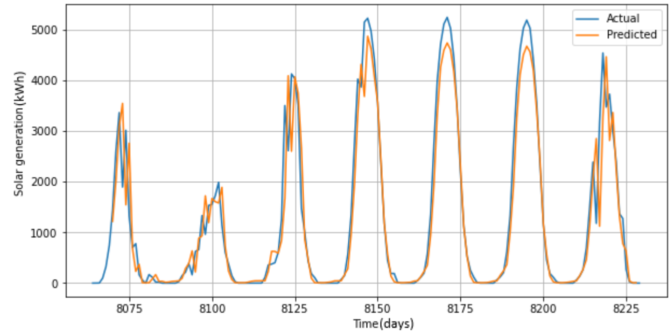

Fig. 8. Real-time solar PV production, actual vs predicted values

TABLE II
CONFIGURATION PARAMETERS FOR LSTM

Parameter	**Value**
Number of inputs	1
Number of neurons	64
Number of Outputs	1
Learning rate	0.0001
Time Steps	252

The loss curve is relatively less coherent in Fig. 10 than in Fig. 9 due to inevitable unpredictable weather conditions.

Table III represents the performance evaluation of LSTM model used for short-term energy forecasting for both datasets. Table III shows that the LSTM model performed very well when evaluated using accuracy metrics such as MSE and RMSE. Therefore, the LSTM was able to predict the future energy behavior, both for 5GNR BS power consumption and for solar PV production. The testing accuracy values as shown in Table III, represent that the LSTM model performed more accurately especially for 5GNR BS power consumption.

TABLE III
PERFORMANCE EVALUATION OF LSTM MODEL

Model Forecast	MSE	RMSE	Val. MSE	Val. RMSE
5GNR BS Consumption	0.0030	0.0551	0.0024	0.0492
Solar PV Forecast	0.0042	0.0649	0.0085	0.0924

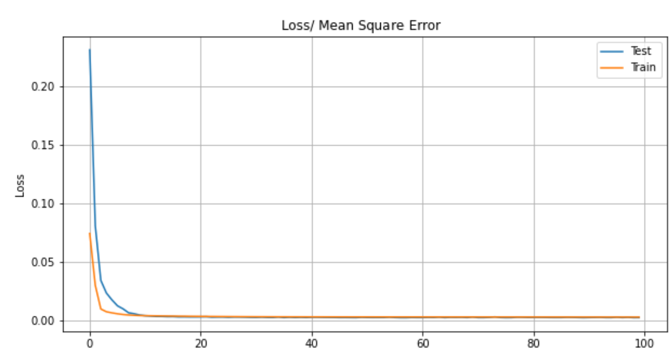

Fig. 9. Model Evaluation with '"Mean Square Error"' loss function for 5GNR BS

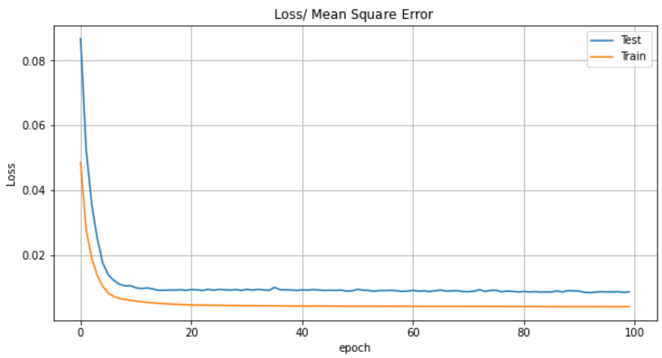

Fig. 10. Model Evaluation with ”'Mean Square Error”' loss function for SOlar PV

```python
import paho.mqtt.client as mqtt
client = mqtt.Client()
client.on_message = on_message
client.on_subscribe = on_subscribe
client.connect("127.0.0.1", 1883, 60)

def on_message(client, userdata, msg):
    print("Received message, topic:" + msg.topic + "payload:" + str(msg.payload))
    global gv
    gv = msg.payload

    if float(msg.payload) > CUT_OFF_VALUE:
        client.publish("device/relay/0/command", payload="on\off")
```

Fig. 11. Power saving feature using MQTT coding

D. Power saving feature using MQTT

After analysing the accuracy of the predicted results, Fig. 11 illustrates the steps to be taken to activate/deactivate power saving feature inside 5GNR BS power unit. LSTM model will update the 'CUT-OFF-VALUE' accordingly to the short-term energy forecast. The total of amount of predicted available energy is compared with the real-time 5GNR BS power consumption. If the available energy is less than the real-time usage, MQTT will publish the energy saving feature message to the broker. Similarly, it will deactivate the power saving feature after the solar PV production increases above the threshold. Coding for triggering the power saving feature is written in Fig. 11. The MQTT client connects to Mosquitto broker which acts as a bridge to communicate between source and destination.

IV. Conclusion

In this paper, an autonomous energy conservation technique is proposed which is used to guide the ICT networks to power up the 5GNR BS sites without relying on traditional power grids. Using the obtained data, LSTM based short-term energy forecasting models were proposed and integrated into the proposed system model. The main focus of the study was to tackle the massive carbon emission problem linked with the ICT sector and to achieve carbon neutrality and self-sustainability. Initially, LSTM model was trained to predict the overall energy behaviour associated with 5GNR BS site. Using LSTM, the output of the power consumed by the BS and energy produced by solar PV was predicted. The model performance was evaluated using accuracy metrics which shows encouraging results, highly accurate predictions and low MSE and RMSE values. The use of the proposed system model allows to design the green ICT network with DSOs playing a vital role in serving the 5GNR BS sites operating at full power. The power saving feature of 5GNR BS is enabled if the LSTM model predicts that the short-term energy availability is less than future power consumption. Therefore, LSTM model sets the 'CUT-OFF-VALUE' which eventually will be used to activate and deactivate the power saving feature using MQTT. Simulation results in comparison to real-time data from 5GNR BS and solar panels shows a high level of stability in short-term energy forecasting models with the increase in number of iterations.

The use of the proposed system allows us to deploy the 5GNR BS fully reliable on RES as a self-sustainable zero carbon solution. Further research will be aimed at improving the algorithm while also integrating short-term local gNB predictions, traffic predictions and introducing internal communication using the BS intelligent power unit for controlling each component individually. Also, it is planned to investigate the proposed architecture and implement power saving feature in real conditions.

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