IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 13, 2019, accepted December 28, 2019, date of publication January 29, 2020, date of current version February 6, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2970224

Capacity and Frequency Optimization of Wireless Backhaul Network Using Traffic Forecasting

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This work was supported by the University of Malaya under Grant BK032-2018.

ABSTRACT Telecom operators are aiming to provide high-grade data, multimedia applications and low latency videos for smart devices. As today's mobile data is experiencing rapid growth and the usage of smart devices are fabricating unparalleled challenges for telecom operators to meet the global bandwidth requirement. From the first generation to fourth generation, the technology evolution is predominantly governed by the hardware side but now it is moving towards the concept of cognitive network management, resource orchestration and machine learning-based solutions. In this paper, we propose the adaptive capacity and frequency optimization (ACFO) method for adaptive optimization based on time series forecasting approach. The daily capacity utilization of microwave (MW) links is analyzed to use forecasted demand. Based on the projected demand, the capacity and frequency optimization will be executed. The two main forecasting models 1) SARIMA and 2) MLP are used and for performance evaluation, we used RMSE and MAPE criterion. The analytic outcomes show that MLP with two layers and six hidden nodes (6/6) are good enough to achieve the desired results. In some cases, we need to exceed the hidden nodes up to fifteen (15/15). By using the forecasting approach, the reactive optimization will successfully shift to the predicted/ proactive optimization, will balance the resource distribution and can condense the wastage of resources. The outcome of the study will be a contribution to the dynamic resource optimization in wireless backhaul network.

INDEX TERMS Time series forecasting, capacity planning, dynamic resource optimization, wireless backhaul optimization.

I. INTRODUCTION

It has been observed that the cellular network is growing speedily for the last two decades and undergone a succeeding evolution. This evolution makes life easy for communication and survival in both social and business worlds. Therefore, the demand of wireless devices and technology is increasing rapidly and the requirement of high data rates and mobility has also increased. The cellular network has transformed from simple voice network to a network that can convey rich multimedia contents over generations [1]. However, there are still number of wireless devices connects to broadband network on daily basis. The mobile traffic will be experiencing the exponential growth in the next decade as shown by the predictions (Shown in Figure 1) [2], [3].

In the 4G era of cellular networks, the cellular backhaul network, that is used to offer the bridge between radio network (base stations) to core network is anticipated to undergone the deep stress as capacity requirements are increased to accommodate the latest broadband services [4]. The main technology of wireless backhaul network is point-to-point microwave links and it is swiftly growing to cater rising

The associate editor coordinating the review of this manuscript and approving it for publication was Young Jin Chun.

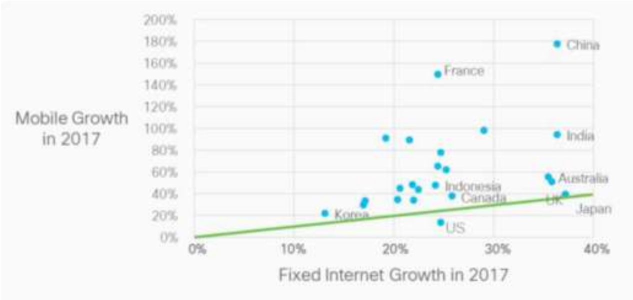

FIGURE 1. Fixed and mobile internet growth rate 2017 (source: [3]).

capacity demand, enhance network proficiency, and allow operators to cut down the network operational cost. More than 50% of cellular base stations of world are connected through microwave links [4]. Microwave links for backhaul are the first choice because they are more secure than cable networks, easy to manage and cheap. They also take benefits of already deployed infrastructure for the base stations [5].

In 5G wireless backhaul network, one of the challenging and interesting issue is smart management and optimal deployment. In [43], two-scale cost efficiency optimization is proposed over most frequently using shortest path (SP) and Bellman-Ford (BF). The full-duplex (FD) communication in wireless backhaul network is made possible by self-interference (SI) cancelation technology. In [44], they proposed the QoS-aware FD concurrent scheduling algorithm to maximize the number of flows with their QoS requirement. Massive multiple-input multiple-output (MIMO) technology for wireless backhaul network has increased the bandwidth and has potential. Many researchers are working on this. In [45], they worked on link selection method in which only certain access points will be activated and only certain users will use wireless backhaul links and power analysis between transmit power and median downlink rate. In the view point of QoS requirement of 5G network services, they introduced C-RoFN architecture using software defined networking for multi-stratum resources optimization which can allow the multi-layer vertical integration of radio and elastic spectrum resources, and cross-stratum horizontal merging of optical network [46]. In order to support the bandwidth-hungry services and applications, the cloud radio over fiber network (C-RoFN) technology enhances the resource utilization and the quality of services. In [47], they worked on wavelength selective switch (RWSS) architecture and routing radio wavelength assignment (RRWA) algorithm in the context of C-RoFN for resource utilization rate, blocking probability and provisioning latency.

In [48] the authors provided the comprehensive literature on options for future mobile fronthaul and backhaul (MFH & MBF). They stated that in term of offering low-latency and high-capacity connection the optical add drop multiplexing (OADM) ring technology technology will play important role.

The evolution of microwave transmission has powerful advancements to the backhaul network to carry new

TABLE 1. Evolution in Microwave Technology (source: [2], [3]).

TIME FRAME	BEFORE 1999	1999	2002	2005	2009	2010	EXPECTED 2020
Nominal Generation	1G	2G	3G	3G	3G	3G+/4G	5G
Standard	GSM HSCSD	EDGE	WCDMA	HSPDA	HSPA+	LTE, LTE-A	Multi-RAT
Peak Data Rate	10 kbps	200 kbps	384 kbps	3-21 Mbps	42 Mbps	>60 Mbps	Upto 1 Gbps
Conventional Backhaul	TDM	TDM	ATM	ATM/SDH	ATM / IP	IP, Hybrid	IP, Hybrid, Millimeter-wave

IP interfaces from traditional TDM as shown in Table 1. Overall, IP delivers a low-cost communication solution in term of Mbps cost, that helps to reduce the bandwidth requirement using more efficient and advance multiplexing in Ethernet switches. In fourth generation, many new data-hungry services have been introduced such as interactive gaming and mobile TV, these services effect the performance of the whole cellular network. In result, the consumers experience a low-quality network and increase in churn rate, impacting the revenues and becoming a limitation for innovative services. To deal with this situation the mobile network operators will need the radio access technologies that permit the smooth delivery of end to end (E2E) services, bringing high performance with maintaining the minimal latency levels. In wireless network resources are limited as compared to wired solutions, therefore proper analysis and optimization is required to ensure the optimization and minimum operational latency.

Telecom operators usually function through group of employees that uses their accumulated experiences and knowledge to manage the network operations and services. However due to the rapid increase in their business and the innovation in technology, the telecom operators are facing issues because of which they have to struggle in keeping their work up and to deliver new services. The usage of big data, delivering practical solution and advance data analysis forms the basis for the smart decision-making in business world. Forecasting the amount of data traffic with great accuracy that how much mobile users will utilize has become very essential for precise traffic engineering and resource allocation demand.

The aim of this study is to develop an intelligent automated capacity optimization method along with frequency suggestions in order to optimize frequency using forecasting algorithms. The intelligent method is a future capacity forecasting system based on the real-time capacity utilization of the microwave (MW) links. Based on the capacity demand, the optimization of network resources like capacity and frequency channel will be done. The proposed method

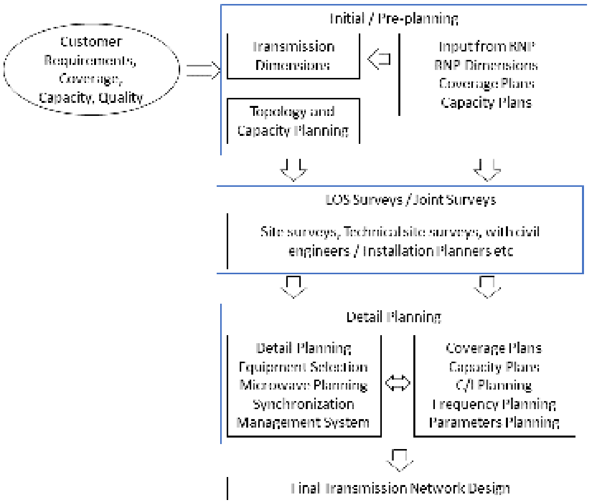

FIGURE 2. **Transmission Planning Process.**

will enable the telecom companies to efficiently interpret the network demand over each channel and facilitate the planning and optimization of the network resources with greater precision.

Section II of the paper provides the brief overview of conventional network planning and optimization processes; in section III the shortcomings of conventional approach are discussed. Section IV discusses the proposed method based on forecasting approach, Section V is about methodology, results and the conclusion.

II. CONVENTIONAL CELLULAR NETWORK PLANNING and OPTIMIZATION

The transport network planning procedure involves the sequence of linked activities that are used to produce the cost effective and high-quality network with an immense volume of standby capacity. It is responsibility of every planner to put their maximum effort to maintain the stability among quality, capacity and cost. The process has three main phases before reaching to the final stage as show in Figure 2. Generally, the process looks simple but practically it is more difficult because there are many repetitions at every step before reaching to a final plan.

The first step starts with data gathering along with the prerequisites of quality and capacity that form the basis of the whole planning procedure. In pre-planning, the main points that come from the input of radio planning engineers, the input about the number of base stations and backhaul capacity requirements. Once the number of radio base stations and their basic requirements are acknowledged, it helps transport/transmission planning engineer to define the capacity and quality goals for the network. The transmission equipment varies operator to operator like microwave radios, antennas, equipment threshold, frequency and information on the media. Based on product availability, a nominal network topology, transmission equipment, quality targets, capacity, and link budget calculations are done. The pre-planning stage emphasizes on the dimensioning features of the transport/transmission network. the transport/transmission network. In the second step of planning process, a site/joint survey with other teams such as radio and civil planners is conducted to assure visibility on both ends. The visibility criteria are based on Fresnel zone concept has to be fulfilled. It leads to the formation of path profile.

During the third step, the decision has been made regarding the type of equipment required to deploy the network; This decision further leads to a detailed calculation of link budget and topology planning. As mentioned earlier, the transmission equipment varies from operator to operator which means in some networks, the number of frequency bands are less while there are more in some therefore frequency planning needs special care during bandwidth planning. Poor frequency planning might be the reason for decline in the network quality and later might result in a fall in revenue for the service provider. The frequency planning is based on the concept of microwave network, which operates under an interference free environment to assure that the 'carrier' signal reaches its destination without getting any other 'interfering' signal. The level of interference is higher if two signals are closer in terms of frequency and signal strength. There are different types of interference; some of which are intra-system interference, co-channel interference, inter-channel, inter-hop, and external interference and each kind needs proper planning to build interference free network.

The parameter that is used to calculate the level of interference is called carrier-to-interference (C/I) ratio. To execute the synchronizations plans is an important aspect of detail transmission planning, because now network is consisting of mixed technologies like (SDH, PDH, IP and Hybrid) and they required proper synchronization and clock setting. The microwave network is collection of wireless point-to-point links therefore they need good take care of propagation phenomena during link budgeting. In detail the propagation deals with the factors such as free space loss, weather conditions, rain rate, train profile, multipath fading and received signal level (RSL) etc. Before proceed to the final plan the important step is performance measure, that defines the error performance objective and parameters need to be measured against specific standard values. The link availability is characterized on the basis of the error performance parameters. This stretches a pretty good idea on where the network planning should be commencing. After the execution of whole process in detail the final plan might be different from the one drawn up at initial stage. The complete process is generally an iterative one at different points as the transmission planners try to ensure a balance amid network capacity, quality and costs [5]–[8].

A. BACKHAUL NETWORK OPERATIONS AND MANAGEMENT

After deploying network, the core objective of network operations, administration and management is to backed up cellular services by achieving effective and consistent working in both scenarios. In the first case the network experiences the pressure due to overload or failure, in the second case when there is any change due to new equipment, or any upgrades in equipment or services. Another aim of network management is to provide quality of services; therefore, the network management is a repeated practice. Because the network is growing increasingly to fulfill the higher capacity demands the recursive process has become speedier. The ISO telecommunications management network model describes five functions of network management: fault, configuration, accounting (or administration), performance, and security (FCAPS) (International Telecommunication Union—Telecommunication Standardization Sector (ITU-T), 2000b)

B. OTHER RECOMMENDATIONS

Network optimization is an expertise that are used to improve the network performance according to the particular environment. The need of precise network optimization is increased because information communication technology (ICT) is expanding rapidly with business users consuming great volume of network bandwidths. If proper and timely steps are not in placed, this steady development can increase stress to the network infrastructure. The core motive of any optimization perform in network is to make sure the optimal network design at lowest cost, precise use of system resources, free flow of data and removing the given set of network's constraints. The network optimization is equally important for individual links up to the entire network.

There are two common problems which trigger the transmission network optimization, first one is difference between required and allocated capacity second one quality standards (see Figure 3). Once the core problem has been acknowledged, the rectification process started as per the decided key performance indicators (KPIs). The important KPIs in a transport/transmission network are linked to the quality standards of microwave links such as propagation fade margins, bit error rate, congestion control, Packet drop etc.

III. SHORTCOMING FROM CONVENTIONAL APPROACH

Due to increase in network the manual KPI monitoring system is harder task for optimizers. The swift growth of information communication technology industry has promoted to progressively more dynamic, heterogenous and complex networks. Such a large-scale and complex network provoke many challenges with operations, administration and maintenance of network [9]. Additionally, many packet-switched networks are undergoing intense development in data traffic due to the growing demand of wireless devices usage, social networking services and application.

Network Capacity planning and optimization is equivalently important. For seamless coverage and user's connectivity to the network the suitable network capacity is very important. It is essential for cost effective and efficient infrastructure solution; the accurate capacity should be in desired location. The present network strategies are not enough to cater the frequently changing network condition commencing

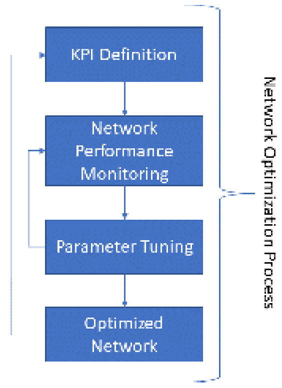

FIGURE 3. Network Optimization.

from the explosive traffic expansion [10]. Therefore, Capacity and frequency optimization are complicated and time taking as the complexity of the cellular backhaul network is increasing [10], [11], [12]. Dynamic resource allocation becomes and essential technique for resource planning and deploy them optimally, it also helps to increase the primary and secondary network throughput [13]. Predicting the future is the key for optimal optimization and resource allocation, and forecasting has a proven success in different area of communication network for better network optimization and management [14].

A. FORECASTING NETWORK ACTIVITIES FOR BETTER NETWORK MANAGEMENT

Cellular network has experienced a magnificent development in the information communication technology traffic in recent years, in results network operators regularly voiced concern about declining profits, network quality and management issues. It is the perfectly right moment to rethink again how to improve and innovate the control on network traffic. So, the quality of service (QoS) and quality of experience (QoE) is ensured by amalgamating intelligence into network control system. The traffic prediction can be very effective for smart network management and cut down the vagueness in supply and demand of network resources. The traffic prediction can also be helpful in reducing the capital and operational expenditures, accommodating the upcoming traffic variation with less resources [15], [16]. The precise traffic anticipation is indispensable for network planning optimization in both scenarios long and short term [17]–[19].

There are numerous studies have been performed on data and mobile network traffic forecasting. The forecasting models such as ARIMA, GARCH, FARIMA and Holt-Winter has been studied and their performance on internet traffic data is performed by [17]. The data analysis and forecast the future requirement using SARIMA/GARCH is done on EVN telecom dataset [20]. The study done by [18] used both ARIMA and FARIMA models for 3G network traffic forecasting. The traffic forecasting application is presented by [21], based on AR, NN and GP algorithms and they used both voice and data traffic of 2G, 3G and 4G. The forecasting of TCH mobile

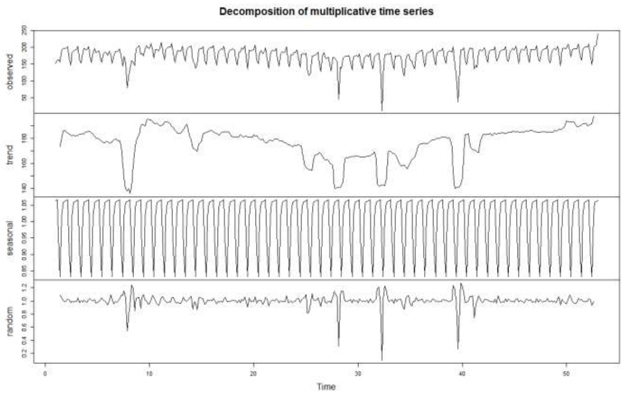

FIGURE 4. Charactertics of recorded dataset network Optimization.

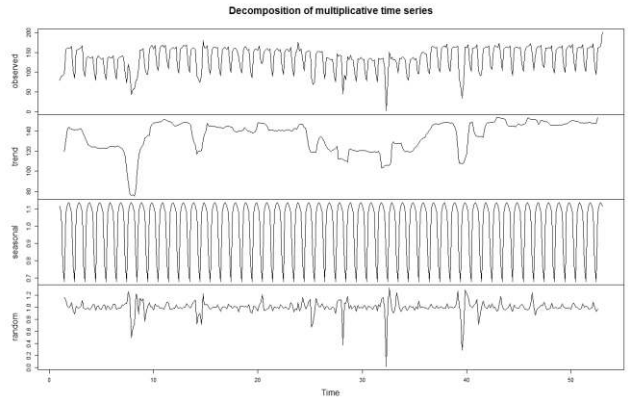

FIGURE 5. Charactertics of recorded dataset network Optimization.

traffic and daily traffic of mobile network are done using multiplicative seasonal ARIMA by [22] and [23] respectively. The seasonal GARCH model is used by [24] for internet traffic forecasting. Holt-Winter and Neural network ensemble methods were used at different scales to forecast the network traffic [25]. In [26] the wireless prediction method has developed using Gaussian Process (GP) using real 4G traffic traces. For future 5G cellular networks the forecasting approach will be helpful, including radio resource management, mobility management, general management and orchestration, and service provisioning management [27]. The historical traffic traces of radio base stations are used to develop the hybrid traffic prediction model that is used to predict the workload and power requirement [28].

In summary, there are number of network traffic modeling and prediction techniques have been established to cater the rising requirements of information communication technology (ICT) industry. These techniques are involve in many disciplines such as traffic prediction [15], [29] congestion control [30], [31], admission control [32], Network planning and optimization [33], [34], [19], [35], network management [36]–[38], improving the QoS for users [15], [36], [39], power management system [28] and traffic pattern analysis [40], [41].

IV. PROPOSED METHOD FOR CAPACITY AND FREQUENCY OPTIMIZATION

Mobile network operators usually collect a vast number of KPIs, that are differ from operator to operator. We collected real network's capacity utilization traces from one the cellular operator in Pakistan. Due to the privacy of data they did not allow to public their data so we generate the synthetic data based on these traces and hide identify and important information. We produce the synthetic data with keeping in mind that the basic components of time series like, trend, seasonality and random variable is not affected. As illustrated in Figure 4 & 5, that collected data is a collection of many microwave links and every links has their own characteristics. The x-axis represents the time in days and y-axis represent the trend, seasonality and random components, and that are

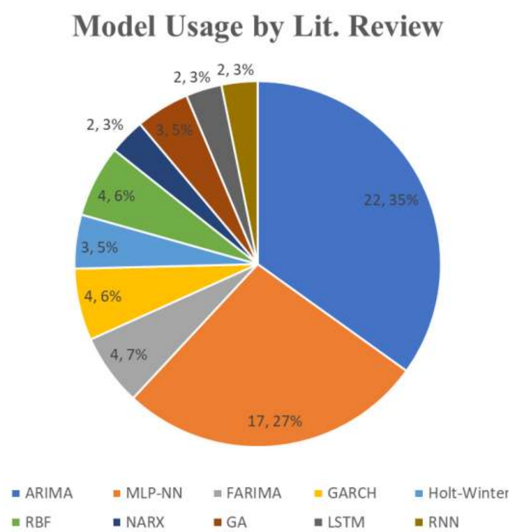

FIGURE 6. Model Selection (Lit. Review in ICT).

different from each other and we may experience stationary and non-stationary, linear and non-linear data in this model. Therefore, the most common and successful models such as SARIMA and MLP-NN are chosen to deal with this type of totally independent multiple time series data.

A. FORECASTING MODELS USED IN STUDY (MLP-NN and ARIMA)

By definition the MLP-NN and SARIMA model are good for linear and non-linear both type of data and by literature review is shown in Figure 6 and Table 7. The Figure 6 is derived from the literature presented in Table 7.

B. ARIMA MODEL

First, we are going to train our times series data on auto ARIMA that is the abbreviation of autoregressive integrated Moving Average. It comprises of an autoregressive (AR) term that refers to lags of differenced series and a moving average (MA) term that refers to lags of errors whereas (I) is the total number of differences used to keep the time series data stationary as shown in Equation 1 [42]. The generic formula

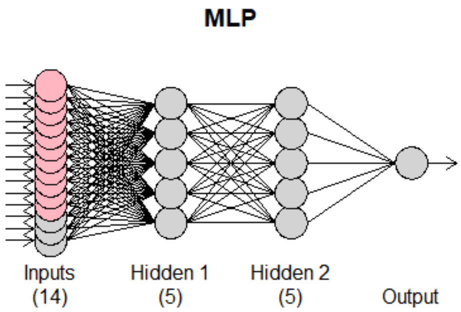

FIGURE 7. MLP model with 14 inputs and 2 hidden layers with 5 hidden neurons in each layer.

for the model is SARIMA(p,d,q)×(P,D,Q)[S], where p, d and q are non-seasonal AR term, non-seasonal differencing and non-seasonal MA respectively. Similarly, the seasonal term of differencing is D, seasonal MA term is Q and the time span of periodic seasonal pattern by S. ARIMA (p, d, q) (P, D, Q) [S] values are automatically selected as we used R function 'auto.arima' from library 'forecast' and value of S is 7 that means our data is weekly.

$$ARMA\,(p,q) = \omega_0 + \omega_1 z_{t-1} + \ldots + \omega_p z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \quad (1)$$

where non-seasonal terms are

$$AR \rightarrow \omega\,(B) = 1 - \omega_1 - \ldots - \omega_p B^p \quad (2)$$

$$MA \rightarrow \theta\,(B) = 1 + \theta_1 - \ldots - \theta_q B^q \quad (3)$$

And seasonal terms are described as follow

$$Seasonal.AR \rightarrow \omega\left(B^s\right) = 1 - \omega_1 B^s - \ldots - \omega_p B^{ps} \quad (4)$$

$$Seasonal.MA \rightarrow \theta\left(B^s\right) = 1 + \theta_1 B^s + \ldots + \theta_q B^{qs} \quad (5)$$

C. MLP-NN MODEL

To represent and capture complex and big data as an input/output, Artificial Neural Network ANN is considered as a powerful tool for data modeling. The most commonly used ANN model for machine learning is multi-layer perceptron MLP. The MLP model is a general purpose and flexible type of artificial neural network. The 'mlp' function of R from library 'nnfor' is used for MLP implementation the main parameters of the function are selection of hidden layers, number of networks to train and activation function. By default, this function uses only one hidden layer with 5 hidden modes and sigmoid activation function. The model automatically generates a network if ensembles and its training start with different initial random weights. The magenta colored input nodes are the one with deterministic inputs which is the seasonality and the grey nodes are the autoregressive inputs as shown in Figure 7.

D. EVALUATION METHOD

Performance evaluation is imperative when it comes to comparing among different models. In this, the actual data is compared with forecasts and it allows evaluating the performance or accuracy of the model. The process is not limited only to accuracy check of particular models but also it evaluates the performance of the entire process and change each step accordingly. In this study, we use root means squared error and mean absolute percentage error methods for the evaluation process.

TABLE 2. Lit. Review of RMSE and MAPE s.

Model \ Cererian	RMSE	MAPE
ARIMA	(Tran et al., 2015), (Kim, 2011), (Zhani & Elbiaze,2009), (Biernacki, 2017), (Zhuang et al., 2015a), (G. Jia et al., 2009)	(Tran et al., 2015), (Y. Yu et al., 2013), (Cortez et al., 2010), (Otoshi et al., 2015), (Tang et al., 2017), (Otoshi et al., 2015), (Tang et al., 2017), (Africon, 2017), (Y. Jia et al., 2015)
NN-MLP	(Katris & Daskalaki, 2015), (Oliveira et al., 2016), (Oliveira, Barbar, & Soares, 2014), (Biernacki, 2017), (C. Zhang & Patras, 2018)	(Katris & Daskalaki, 2015), (Hotel et al., 2014), (Alfred, 2014), (Cortez et al., 2010), (Tang et al., 2017)

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} (xa_i - \hat{xa}_i)^2} \quad (6)$$

$$MAPE = \frac{1}{n}\sum\nolimits_{i=1}^{n} \left|\frac{xa_i - \hat{xa}_i}{xa_i}\right| \quad (7)$$

where xa_i is the actual value, $\hat{xa}_i$ is the forecasted value and n is the sample size or number of observations. The MAPE and RMSE both are the most popular criterion in the context of mobile network for time series data assessment. The RMSE depends on the scale of the variable of interest, so it is appropriate for paralleling unlike models across the same time series. On the other hand, MAPE is also a widespread measure of accuracy because it is scale independent and also because it can be inferred and understood better.

V. METHODOLOGY

The process of developing the automated method for capacity and frequency optimization is explained in the following Figure 8 and implementation of that algorithm is performed using R.

In the starting steps 10 – 30, the dataset generated from network traces is fed into the model for analysis and forecasting. The complete historical data right from the beginning is imported and converted as separate time series for each MW link as described in Table 3. The dataset has more than one MW link, every MW link is treated as separate time series and differentiate on the basis of columns number in recorded data as shown in Table 3.

At line 40, the count of every MW links will be checked and according to the number of observations the next step will be taken. There will be two checks at this stage; either

```
10    Start
20    Import Dataset as DS1
30    Convert DS1 into Time Series Object as TS_Data with weakly seasonality
40    If TS_Data < 30 (Observation count is less than 30)

      40.1  Train SMA Model with TS_Data as Model1
      40.2  Fit and Forecast one step ahead using Model1 as FS1
      40.3  Train MLP Model with TS_Data as Model2
      40.4  Fit and Forecast one step ahead using Model2 as FS2
      40.5  Find the accuracy of FS1 and FS2
      40.6  Choose between FS1 and FS2 with minimum accuracy RMSE
      40.7        If accuracy MAPE <= 10 of chosen FS1 or FS2
                        FS1 or FS2 (refereed step 40.6) = XF (forecasted capacity)
                        Suggest the optimized capacity based on forecasted capacity
                        XP = XF (S* XF/100)
                        Based on optimized capacity the proper frequency channel will be
                        select.
                  Else
                  goto step 40.1 and retrain the models with different parameters

      Else (when observation count is greater than 30 or equal to 30)

      50.1  Train SARIMA Model with TS_Data as Model3
      50.2  Fit and Forecast one step ahead using Model3 as FS3
      50.3  Train MLP Model with TS_Data as Model4
      50.4  Fit and Forecast one step ahead using Model4 as FS4
      50.5  Find the accuracy of FS3 and FS4
      50.6  Choose between FS3 and FS4 with minimum accuracy RMSE
      50.7        If accuracy MAPE <= 10 of chosen FS3 or FS4
                        FS3 or FS4 (refereed step 50.6) = XF (forecasted capacity)
                        Suggest the optimized capacity based on forecasted capacity
                        XP = XF (S* XF/100)
                        Based on optimized capacity the proper frequency channel will be
                        select.
                  Else
                  goto step 50.1 and retain the models with different parameters

50    Record daily observations as DailyDS
60    Merge DailyDS at below of the Dataset file as DS2
70    DS1 = DS2
80    Convert DS1 into Time Series Object as TS_Data with weakly seasonality
90    goto step 40
100   End
```

FIGURE 8. Proposed adaptive method.

TABLE 3. MW-Links Capacity Utilization Data (Mbps-absolute values).

Links / Date	MW-1	MW-2	MW-3	…	MW-N
T	51	93	167	…	127
t-1	48	97	185	…	119
t-2	44	101	184	…	119
⋮	⋮	⋮	⋮		⋮
t-N	76	204	461		257

the number of observations is <30 or $\geq$ 30. We divide our dataset on weekly seasonality therefore 30 is the base factor.

If the number of observations is <30 than Simple Moving Average (SMA) and MLP forecasting model are applied on dataset and evaluation criterion are RMSE and MAPE. The minimum RMSE and MAPE will be selected. If the MAPE value is $\leq$ 10 then it will be further processed otherwise we will retrain the model with some modifications and repeat the process until the desired forecast is achieved.

The else statement of line 40, if the number of observations is $\geq$ 30 then Seasonal Autoregressive Integrated Moving Average (SARIMA) and Multilayer Perceptron Neural Network (MLP-NN) forecasting model applied on dataset and evaluation criterion are RMSE and MAPE. The minimum RMSE and MAPE will be selected. If the MAPE value is $\leq$ 10 then it will be further processed otherwise we will retain the model with some modifications and repeat the process until the desired forecast is achieved.

The optimization is done, If the MAPE values are $\leq$ 10 then it will be good enough to replace the allocated/planned capacity as the optimization criteria $XP = XF + (S * XF/100)$ will be used. In this, if $S = 20$ means 20% safety margin will be added into the forecasted value and then the allocated/planned capacity will be replaced. The error can be negative or positive as described in Table 4. In this scenario, we can eliminate the < 70 % usage category and planned capacity will be more accurate and capacity planning will be more precise as explained in Table 4. XA is the actual capacity usage of a particular MW links, XF is the forecasted and XP is the planned/allocated capacity as illustrated in Equation 8, 9 & 10 respectively.

$$XA = \left\{xa_t, xa_{t-1}, xa_{t-2}, \ldots, xa_{(\text{t-n})}\right\} \quad (8)$$

$$XF = \left\{xa_{(t)+1}, xa_{(t+1)+1}, \ldots, xa_{(t+n)+1}\right\} \quad (9)$$

$$XP = \{x_{t-n}, \ldots, x_{t-2}, x_{t-1}, x_t, x_{t+1}, x_{t+2}, \ldots, x_{t+n}\} \quad (10)$$

$$XP = XF + (S * XF/100)\} \quad (11)$$

Based on the suggested optimized capacity, the appropriate frequency channel will be selected form the available list such as shown in Table 5; different cellular operators have their own licensed frequency channels. From the available list of a particular cellular operator, the appropriate frequency channel will be proposed. In this model, the appropriate channel based on channel spacing will be suggested as illustrated in Table 5, and after the interference calculation, the appropriate channel with proper channel spacing is applied. For instance, the suggested capacity is in between 43 Mbps to 88 Mbps then the good choice is 14MHz channel. Further the channel in 14MHz category that is appropriate will be selected after proper interference calculation. After the allocation of appropriate frequency channel according to the optimized forecasted capacity, the frequency and capacity suggestion will be generated for the optimization document.

As the optimization is a continuous process for betterment of network so at line 50 to 100, the daily observations of MW links will be added at the end of the previous latest used dataset and repeat the process of analysis and optimization.

A. ANALYSIS OF DATASET

For our study, we have generated the synthetic data based on real network usage, the dataset is a collection of capacity utilization of microwave links.

$$XA_t = \{xa_{t-1}, xa_{t-2}, xa_{t-3}, \ldots, xa_{t-N}\}$$

TABLE 4. Optimization criteria and MAPE values.

MAPE	Positive Error	Negative Error	(S = 20) Replaced Planned Capacity	If S = 10
MAPE = 10	+10 + 20 = 30	-10 + 20 = 10	Range = 70 to 90 %	80 to 100 %
MAPE = 8	+8 + 20 = 28	-8 + 20 = 12	Range = 72 to 88 %	82 to 98 %
MAPE = 5	+5 + 20 = 25	-5 + 20 = 15	Range = 75 to 85 %	85 to 95 %
MAPE = 2	+2 + 20 = 22	-2 + 20 = 18	Range = 78 to 82 %	88 to 92 %

TABLE 5. Example of frequency channels (38G frequency in GHz- 28MHz channel spacing in MHz).

Frequency-Channel BW	Channel No	Capacity at 16 QAM	Capacity at 256 QAM
38G-28MHz	CH-1	90 Mbps	180 Mbps
38G-28MHz	CH-2	90 Mbps	180 Mbps
38G-14MHz	CH-8	43 Mbps	88 Mbps
38G-14MHz	CH-15	43 Mbps	88 Mbps
38G-7MHz	CH-16	21 Mbps	42 Mbps
38G-7MHz	CH-33	21 Mbps	42 Mbps

TABLE 6. Example of dataset.

Link ID	Planned Mbps (XP)	Actual (XA)	% Utilization	Forecasted (XF)
MW-1	65.7390	25.39597788	38.63152448	
MW-2	26.3070	3.607406862	13.71272613	
MW-3	37.0240	19.47658399	52.60529384	
MW-4	31.6790	18.36380233	57.96837757	
MW-5	26.3990	5.041085982	19.09574598	
⋮				
MW-N	26.3070	5.478444107	20.82504317	

Planned Capacity (XP): Planned/allocated capacity of particular at the time of planning (input from RAN), Utilized/Actual Capacity (XA): Historical data of actual usage by a particular link and Forecasted Capacity (XF): Predicted future capacity using forecasting algorithm. The sample of data file is shown in Table 6.

As illustrated in Figure 4 & 5, the collected dataset is collection of different Microwave links, so every link has their own characteristics, like series trends, seasonality and random components. That mean we are dealing with linear and nonlinear both types of data.

VI. RESULTS AND DISCUSSION

The x-axis represents the time series daily observations of capacity utilization and y-axis denotes the capacity usage in Mbps. The green solid lines signify the original data, blue dashes represent the fitted data and highlighted area is the forecast.

The construction of the models was executed using suitable routines from R. For ARIMA, the package projection was used. We used 'nnfor' package for multilayer perceptron neural network. The training was done with 2 hidden layers with three preferences 1) with each hidden layer 6 nodes, 2) with each layer 8 nodes and 3) maximum hidden nodes used in each hidden layer are 15. The sigmoid activation function was used with backpropagation method. The details of the model's parameters together with settings and the result after applying the fitting process on the training set of each dataset are explained in Table 8. The models used for multi-step-ahead forecasting and their performance according to the RMSE and MAPE criterion are displayed in Table 8.

Referred to Table 8, the bold and underlined values are the best and accepted forecasted results as per the set measures, whereas, the bold values (only) are also acceptable. The MLP method with sigmoid activation function provides the optimal result but when equated with the convergence times, it takes more as compared to SMA and ARIMA.

Let's start our discussion with the first experiment having MW-4 (link ID). The dataset MW-4 has less than 30 observations, so in line with the methodology, we used SMA and MLP models for forecasting and analysis. The achieved MAPE using SMA(4) is 3.59 and using MLP with 2 hidden layers with each hidden layer has 6 nodes (6,6) and sigmoid activation function is 1.77 which is less than 10 as per the set benchmarks. If MAPE value is $\leq$ 10 then the next step is replacing the planned / allocated capacity with forecasted capacity. The MAPE value is 1.77 and according to suggested optimization criteria explained in Figure with safety margin (S=10), the optimized capacity range will be 88.23 to 91.77%. By this approach, the reactive capacity optimization effectually shifted to predicted optimization and the wastage of resources was more precise and well-adjusted.

Likewise, the dataset MW-5 has more than 30 observations, so as per the methodology, we used ARIMA and MLP models for forecasting. The achieved MAPE using SARMA (1, 0, 0) (2, 1, 2) [7] is 9.83, and with MLP having (6, 6) configuration is 1.57 which is less than 10 and is better than SARIMA. If MAPE value is $\leq$ 10 then the next step is replacing the planned / allocated capacity with foretold capacity. The MAPE value is 1.57 and according to criteria, the optimized capacity range will be 88.43 to 91.57.

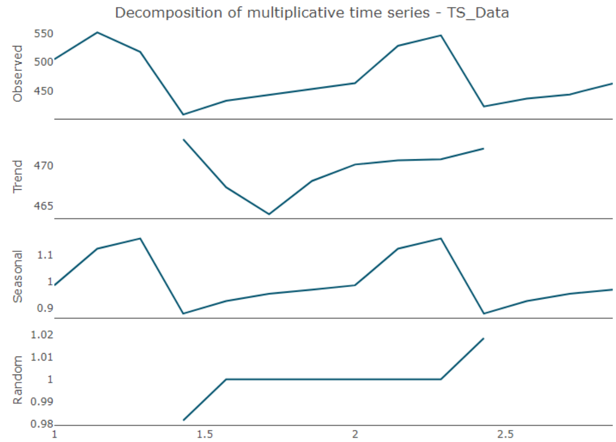

FIGURE 9. TS Component of MW-4.

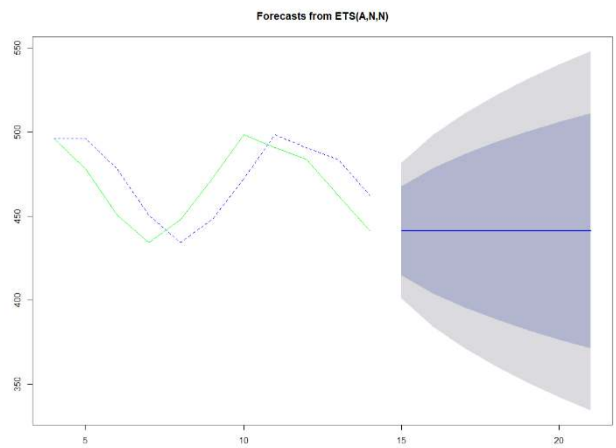

FIGURE 10. Forecasting using SMA(4) of MW-4.

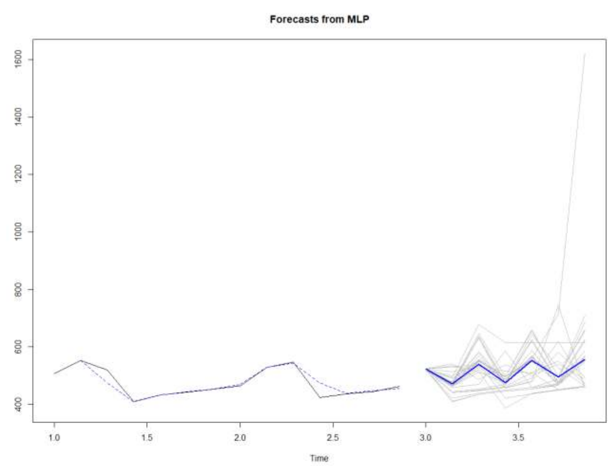

FIGURE 11. Forecasting using MLP(6,6) of MW-4.

A. EXPERIMENTS GRAPHS

Figure 9 illustrates the 14 days traces of MW-4, and also presents the main components of series. The x-axis represents the time series daily observations of

TABLE 7. Reference literature that are described in Figure 6.

		Information communication and technology
Statistical Model	**ARIMA & SARIMA**	(Tran, Ma, Li, Hao, & Trinh, 2015), (Y. Yu, Song, Fu, & Song, 2013), (Xue et al., 2015), (F. Xu et al., 2016), (Ntalampiras & Fiore, 2018), (Y. Jia et al., 2015), (G. Jia et al., 2009), (Africon, 2017), (Sahrani, Zan, Yassin, & Zabidi, 2017), (Alfred, Asri, & Ibrahim, 2015), (Haviluddin & Alfred, 2014), (Zhani & Elbiaze, 2009), (Cortez, Rio, Rocha, & Sousa, 2010), (Zhou, He, Sun, & Ng, 2005), (Zhuang et al., 2015), (Otoshi et al., 2015), (Rutka, 2009), (Biernacki, 2017), (Tang et al., 2017), (Szmit, Szmit, Adamus, & Bugała, 2012), (Haviluddin & Dengen, 2017), (Kim, 2011)
	FARIMA	(Y. Yu et al., 2013), (Biernacki, 2017), (Katris & Daskalaki, 2015), (Gowrishankar and P.S.Satyanarayana, 2009)
	GARCH	(Tran et al., 2015), (Zhou et al., 2005), (Kim, 2011), (Katris & Daskalaki, 2015)
	Holt-Winter	(Cortez et al., 2010), (Szmit et al., 2012), (Tikunov & Nishimura, 2007)
Machine & Deep Learning	**NN-MLP & NN**	(Xue et al., 2015), (Sahrani et al., 2017), (Alfred et al., 2015), (Cortez et al., 2010), (Biernacki, 2017), (Tang et al., 2017), (Szmit et al., 2012), (Haviluddin & Dengen, 2017), (Katris & Daskalaki, 2015), (Pilka & Oravec, 2011), (C. Zhang & Patras, 2018), (Abdullah, Abdulsalam, Daw, & Seman, 2015), (Hotel, Sulawesi, Indonesia, Science, & Mulawarman, 2014), (Alfred, 2014), (Oliveira, Barbar, & Soares, 2016), (Oliveira, Barbar, & Soares, 2014), (Karami, 2015)
	RBF	(Biernacki, 2017), (Katris & Daskalaki, 2015), (Hotel et al., 2014), (Tahyudin, 2015)
	RRBF	(Gowrishankar and P.S.Satyanarayana, 2009)
	NARX	(Haviluddin & Dengen, 2017), (Pilka & Oravec, 2011)
	ESN	(Gowrishankar and P.S.Satyanarayana, 2009)
	RNN	(Oliveira et al., 2016), (K. Zhang, Chai, & Fu, 2012)
	GP	(Le, Sinh, Tung, & Lin, 2018), (Y. Xu, Xu, Yin, Lin, & Cui, 2017)
	GA	(Alfred et al., 2015), (Karami, 2015), (Hernandez Benet, Kassler, & Zola, 2016)
	SAE	(Oliveira et al., 2016), (Oliveira et al., 2014)
	LSTM	(C. Zhang & Patras, 2018), (Fang et al., 2018)

TABLE 8. Experiments results.

Link ID	Cont. Of Observations	Figure	Performance Criterion	Models					Optimization Criteria
				SMA (n = 4)	ARIMA		MLP		XP = XF + (S * XF/100)
				Results	(p,d,q) (P,D,Q) [S]	Results	(H/O layers)	Results	If S = 10
MW-4	14 Days (14)	9 to 11	RMSE	18.63			6/6/1	18.03	88.23 – 91.77
			MAPE	**3.59**				**1.77**	
MW-15	14 Days (14)		RMSE	7.59			12/12/1	8.19	84.43 – 95.57
			MAPE	**6.19**				**5.57**	
MW-9	30 Days (30)		RMSE	NA	(1,0,0) (0,0,1) [7]	3.21	6/6/1	0.40	89.15 – 90.85
			MAPE			**8.37**		**0.85**	
MW-29	30 Days (30)		RMSE		(0,1,0) (0,1,0) [7]	13.60	6/6/1	3.75	88.63 – 91.37
			MAPE			**4.24**		**1.37**	
MW-5	181 Days (181)	12 to 14	RMSE		(1,0,0) (2,1,2) [7]	25.10	6/6/1	5.26	88.43 – 91.57
			MAPE			**9.83**		**1.57**	
MW-25	181 Days (181)		RMSE		(0,0,1) (0,0,2) [7]	2.62	6/6/1	0.49	88.54 – 91.46
			MAPE			**7.67**		**1.46**	
MW-101	365 Days (365)		RMSE		(1,0,1) (0,1,2) [7]	12.24	6/6/1	8.95	85.81 – 94.19
			MAPE			**8.79**		**4.19**	
MW-13	365 Days (365)		RMSE		(5,1,1) (2,0,0) [7]	25.87	15/15/1	4.14	84.97 – 95.03
			MAPE			71.75		**5.03**	

capacity utilization and y-axis illustrates the capacity usage in Mbps. In Figure 10 & 11, the solid green line represents the actual plot, the blue dashed lines exhibit the fitted and the highlighted area is the forecasted result.

The SMA (4) and MLP (6, 6) with sigmoid activation function are applied on 14 days traces and achieved MAPE is 3.59 and 1.77 respectively. When we compared the MLP fitted line with SMA, MLP showed very good results as can also be seen in graph that is very close fitted with real data.

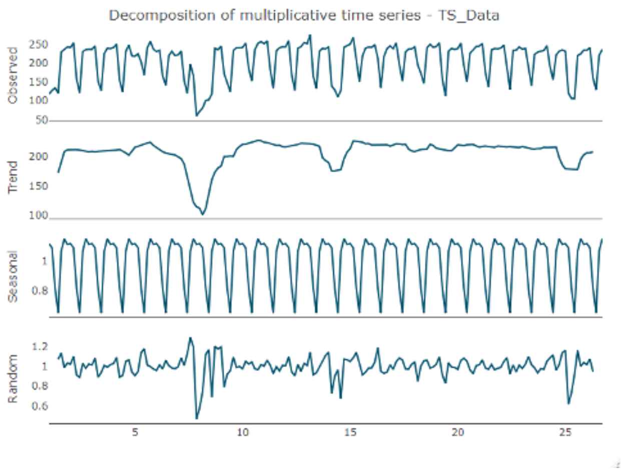

FIGURE 12. TS Component of MW-5.

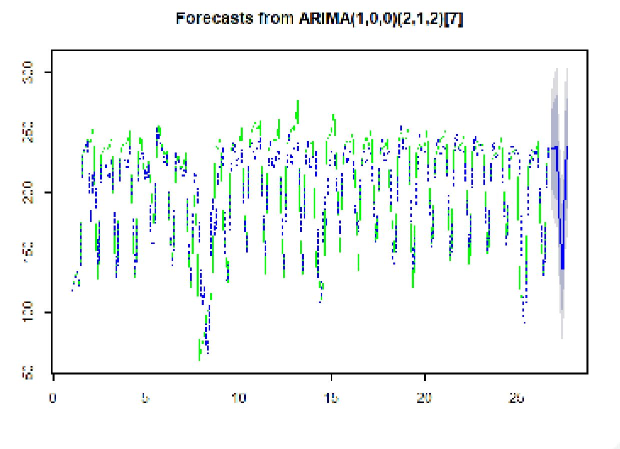

FIGURE 13. Forecasting using SARIMA of MW-5.

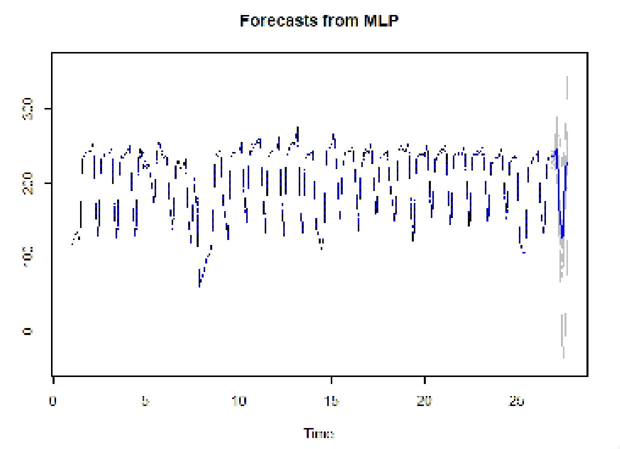

FIGURE 14. Forecasting using MLP(6,6) of MW-5.

Figure 12 illustrates the 181 days traces of MW-5, and also presents the main components of series. The x-axis represents the time series daily observations of capacity utilization

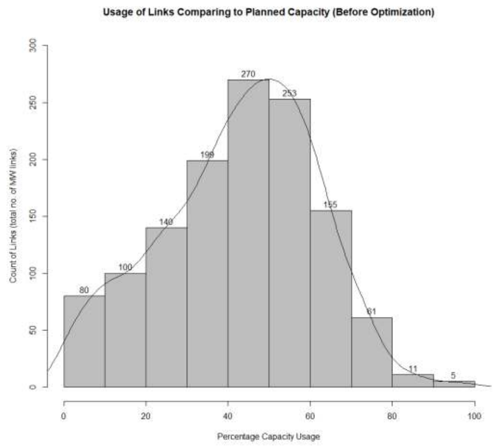

FIGURE 15. Before Optimization.

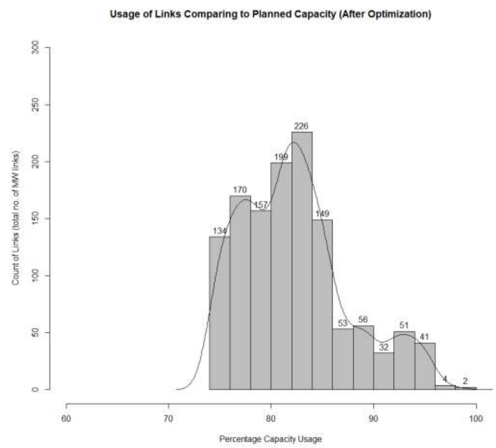

FIGURE 16. After Optimization (Predictive Optimization).

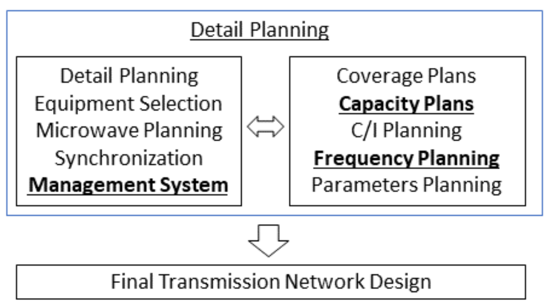

FIGURE 17. Detail Planning/Optimization Procedure.

and y-axis represents the capacity usage in Mbps. It can be observed that dataset MW-5 has nonlinear trends with cycle seasonal variations and also random components. The trend shows straight line with some dips. In Figure 13 & 14, the solid green line represents the actual plot, the blue dashed lines represent the fitted and the highlighted area is the forecasted results.

The SARIMA(1,0,0)(2,1,2) [7] and MLP(6,6) with sigmoid activation function are applied on 181 days traces and achieved MAPE is 9.83 and 1.57 respectively. When we compared the MLP fitted line with SARIMA, MLP showed very good results as can also be seen in the graph that is very close fitted with real data.

B. RESULT ACHIEVED

The results revealed that the proposed solutions are able (a) to achieve better capacity planning and optimization, (b) reactive capacity optimization shifted to predicted optimization (c) balanced resource distribution and (d) can reduce the wastage of resources.

VII. CONCLUSION

To conclude, the study and findings of the paper will be expedient to bring intelligent automation in transport/transmission optimization and planning process. The main idea behind the study is to automate the capacity optimization/planning and based on this, the frequency optimization/planning will be done. As illustrated in Figure 17, we have targeted capacity and frequency planning out of other parameters of detailed planning/optimization. Optimizing the capacity can be effective to demote or eliminate the effects of bit error rate, packet loss, congestion control and other quality parameters.

In this paper, two different forecasting model (MLP and ARIA) are mainly studied and implemented for analyzing the capacity utilization of microwave point to point links in the cellular network. The ground plan was to cash in on from the statistical attributes of the cellular network with the help of linear and non-linear forecasting models. We studied ARIMA with and without seasonal components and MLP neural network architectures as separate models to propose the automated system for capacity optimization. The RMSE and MAPE framework for evaluation is also employed for an unbiased evaluation of the models. We instituted the novel approach for capacity optimization ($XP = XF + (S* XF/100)$) and showed it using the proposed approach.

We can eliminate the <70 % usage, and the resource distribution will be more well-adjusted. In the second step, we used the optimized capacity for proper frequency channel planning. Last of all, the experimental investigation exemplified was performed using synthetic data based on real observations.

We have performed forecasting on different MW links having 14 days (14 observations), 1-month (30 observations), 6-months (181) and 1-year (365) past records of capacity utilization. The achieved MAPE values of some experiments are 1.77 (MW-4), 0.85 (MW-9), 1.57 (MW-5), and 5.03 (MW-13) with MLP configuration 6/6/1, 6/6/1, 6/6/1 and 15/15/1 respectively. Based on analytical tests and findings from the accuracy measures it reveals that in most cases the MLP with 6/6/1 configuration shows good estimation but, in few cases, we need to exceed the hidden neurons keeping the layers same as 15/15/1. Building upon the rich underpinning of the research findings described and overall understanding acquired in this paper, we have drawn certain guidelines for future research directions in this area as well as it presents the concerns that merit further research and envision that these issues may hold the aptitude in influencing the future research studies. The analysis of the selected articles uncovers that the opportunity clearly exists i.e. the forecasted capacity demand can be used for optimization of the frequency channels and the smart interference management solutions. If we are able to optimize capacity dynamically, it can lead the network with fertile frequency channel reuse planning, interference management and other parameters that are shown in Figure 17.

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