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Time series forecasting model of future spectrum demands for mobile broadband networks in Malaysia, Turkey, and Oman

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5G network planning;
6G network planning

Abstract Mobile broadband (MBB) services are rapidly growing, causing a massive increase in mobile data traffic growth. This surge in data traffic is due to several factors (such as the massive increase of subscribers, mobile applications, etc.) which have led to the need for more bandwidth. Mobile service providers are constantly improving their network efficiency by upgrading current networks and investing in newer mobile network generations. However, these improvements will not be enough to accommodate the future spectrum demands. This paper proposes a time series forecasting model to analyze future spectrum demands based on the spectrum efficiency growth of MBB networks. This model depends on two key input data: the average spectrum efficiency per site and the number of sites per technology. The model is used to predict the spectrum efficiency growth of three countries (Turkey, Malaysia, and Oman) from 2015 to 2025. The proposed model is compared with various traditional statistical models such as the Moving Average (MA), Auto-Regression (AR), Autoregressive–Moving-Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA). The forecasted results indicate that the average spectrum efficiency and growth will continue to rise multiple times by 2025 compared to 2015. The data from this prediction model can be used as input data to forecast the required spectrum needed in future for any specific country. This study further contributes to the network planning of future mobile networks for Fifth Generation (5G) and Sixth Generation (6G) technology. The proposed model obtains higher accuracy (by 90%) compared to other models. The proposed model is also applicable to any country,

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especially when new wireless communication technologies emerge in future. It is customizable and scalable since spectrum regulators can add additional metrics that positively contribute towards accurately estimating future spectrum efficiency growth.

1. Introduction

Spectrum efficiency is a significant performance metric that has been continuously enhanced and upgraded to almost double its past figure with every new arrival of wireless technology [1–3]. The latest technology usually enhances the Modulation and Coding Scheme (MCS), increases the Sectors Number (SN), and employs Multiple-Input and Multiple-Output (MIMO) techniques [4–7]. To achieve better spectral efficiency, operators are continuously upgrading current wireless technology to newer generations. For instance, the Second Generation (2G) and Third Generation (3G) have been upgraded to the Fourth Generation (4G) and 5G based on the Long-Term Evolution (LTE) and LTE-Advanced technology [8,9]. According to several studies [8–11], many operators worldwide have already upgraded the 2G and 3G sites to LTE and LTE-Advanced sites. This upgrade is deemed necessary to fulfill the expected surge in data demands and enhance network coverage [12,13]. The innovative solutions and diverse applications offered by the latest radio technology have been of great benefit.

Several works [14–16] have presented spectrum sharing based on licensed and unlicensed spectrums to address the issue of limited resources. In [17–19], a handoff technique that utilize licensed and unlicensed spectrums was presented for cognitive radio networks. Such enhancements will help resolve the contradiction of providing large data exchanges with enhanced spectrum efficiency, thus reducing future spectrum demands. Based on several prediction studies which focused on network coverage for various technologies (e.g., 2G, 3G, and 4G+) [3,8,9], the 3G network still proves to be the dominant network while 4G is the less deployed counterpart [120–22]. In future, the popularity of 4G, 4G+, 5G, and 6G mobile networks will increase while the utilization of the 2G and 3G networks will decrease. However, there is a need to formulate a prediction model to forecast the future spectrum growth of MBB networks.

From the brief review, it can be concluded that spectrum efficiency will continue to grow in the near future. Although it is difficult to determine the growth rate, it can be predicted using a developed forecasting model. Predicting future spectrum efficiency growth which will offer valuable insight regarding the general trends of MBB development. Forecasting spectrum efficiency growth is a significant tool that can be directly employed by regulators and mobile operators to help determine the relevant strategies for tackling future spectrum demands as well as the deployment of potential mobile networks. Spectrum efficiency growth is the main input metric for predicting future spectrum demands [1,23–25]. Several developed models consider spectrum efficiency growth as the main metric for that purpose, such as the United States regulator, the Federal Communications Commission (FCC) [23], Pyramid Research [24], and Wireless Communication Center (WCC) [25]. Although the FCC and Pyramid Research [23,24] consider spectrum efficiency growth as an input metric for their forecasting, they have not explained how the estimation is conducted. Based on our review, it is difficult to obtain or assess spectrum efficiency. A forecast is deemed necessary to determine the required enhancements for predicting the future spectrum needed to fulfill potential mobile data demands [26]. It is essential to develop a competent model that can project an accurate spectrum efficiency measure.

This work proposes a novel model to estimate the forthcoming spectrum efficiency growth. This model is a function of the average spectral efficiency for each site per technology and the number of sites per technology. The average spectrum efficiency is calculated as the average value over all spectrum efficiencies for all network types belonging to the same technology, while the number of sites is assessed as the summation of all equivalent site numbers over the total network types belonging to one technology. The developed model is then used to predict the spectrum efficiency and spectrum efficiency growth for years 2015 to 2025 in Malaysia, Turkey, and Oman. Mobile Telecommunication Operators (MTOs) in the considered countries are labelled with different names for privacy and confidentiality of the dataset, as shown in Table 1. This research forecasts the spectrum efficiency growth of each country, regardless of the MTO names since they are not a necessary benchmark for the analysis. For Malaysia, the estimation is performed based on the input market data of four main MTOs: M1, M2, M3, and M4. The results indicate that by 2025, the average spectrum efficiency growth will increase by around 2.43 times more as compared to that of 2015. For Turkey, the estimation is performed based on the input market data of three main MTOs: T1, T2, and T3. The input data is analyzed based on the data collected from the operators' annual reports, Analysys Mason, and other online sources. For Oman, the estimation is performed based on the input market data of two main MTOs: O1 and O2. The input data is assessed based on the data collected from the operators' annual reports, the Ministry of Technology and Communications (MTC), and other online sources. However, all input data for the considered countries do not reflect on the actual spectrum efficiency growth for any operator since this is an estimation study. The results indicate that by 2025, the average spectrum efficiency growth may increase by around 5.5, 2.4, and 2.9 times more than that of 2015 based on the estimated input market data in Turkey, Malaysia, and Oman, respectively. This increase will contribute towards forecasting and fulfilling mobile data demands in future. This paper is a continuation of our previous works that have been published in Ref. [1] and [27]. However, this paper only focuses on spectrum efficiency growth, which is one input metric for forecasting the

Table 1 National MTOs labeling in Malaysia, Turkey, and Oman.

Country	National MTOs			
	First	Second	Third	Fourth
Malaysia	M1	M2	M3	M4
Turkey	T1	T2	T3	
Oman	O1	O2		

Table 2 List of abbreviations.

Abbreviation	**Definition**
2G	Second Generation
3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
ANNs	Artificial Neural Networks
AR	Auto-Regression
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive–Moving-Average
ASE	Average spectrum efficiency
BPNN	Back-Propagation Neural Network
DNN	Dynamic Neural Network
EDGE	Enhanced Data for Global Evolution
FCC	Federal Communications Commission
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GPRS	General Packet Radio Service
GRU	Gated Recurrent Unit
GSM	Global System for Mobile
GSMA	GSM Association
HSDPA	High Speed Downlink Packet Access
HSPA	High-Speed Packet Access
LSTM	Long Short-Term Memory
LTE	Long-Term Evolution
MA	Moving Average
MAE	Mean Absolute Error
MBB	Mobile Broadband
MCMC	Malaysian Communications and Multimedia Commission
MCS	Modulation and Coding Scheme
MIMO	Multiple-Input and Multiple-Output
MSE	Mean Squared Error
MTC	Ministry of Technology and Communications
MTOs	Mobile Telecommunication Operators
NMAE	Normalized MAE
NRMSE	Normalized RMSE
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SEG	Spectrum Efficiency Growth
SN	Sectors Number
SVR	Support Vector Regression
WCC	Wireless Communication Center

spectrum gap of future mobile networks. Table 2 summarizes all abbreviations used in this paper.

The rest of this paper is organized as follows: Section 2 provides a background of the forecasting models. Section 3 explains the details of our proposed model. Section 4 presents the spectrum efficiency analysis. Section 5 discusses the interconnected directions to accommodate high data demands. Finally, Section 6 concludes this paper.

2. Forecasting models

This section provides several time-series forecasting models that use past series values to predict current values. Various statistical models and Artificial Neural Networks (ANNs) are utilized to forecast future data in many areas including social, economic, finance, engineering, foreign exchange, business, and stocks. The time series statistical forecasting models such as Moving Average (MA), Auto-Regression (AR), Autoregressive–Moving-Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), etc., are very suitable for time series data with linear processes and they work well for small or large data. The ANNs or deep learning models (e.g., Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)) are extremely efficient in solving nonlinear problems in the real world, however, they require sufficient big data to provide competitive results to various statistical time series forecasting models. For instance, in [28], the authors used two deep Recurrent Neural Network (RNN) variants, (LSTM-RNN) and (GRU), to predict link quality in wireless community networks with huge data. The results demonstrated that these models yield higher accuracy compared to other models. Similarly, [29] analyzed univariate time-series forecasting data using several models such as Dynamic Neural Network (DNN), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and ARIMA. The outcomes revealed that all neural network-based and traditional statistical models work well if sufficient amounts of big data are available. However, in some cases, the neural network-based model has higher accuracy compared to traditional models. In [30], the authors evaluated the performance of linear and nonlinear models such as Back-Propagation Neural Network (BPNN), Support Vector Regression (SVR) LSTM, GRU, and ARIMA for short-term forecasting of tropical storms. The performance evaluation results indicate that the ARIMA model provides better forecasting accuracy than other models. The errors in the ARIMA model are slight, offering an overall stable forecasting throughout several forecasting steps. In contrast, some related works such as [31,32] used statistical models for forecasting future trends in the telecommunication industry. From pervious works, it can be seen that the forecasting accuracy depends on various factors such as application, size, and pattern of the dataset. It is recommended to use traditional statistical forecasting models since only small datasets are available in this sector. In our work, traditional statistical forecasting models (such as MA, AR, ARMA, and ARIMA) are applied as a benchmark due to the limited dataset. The mathematical representations of these forecasting models are discussed as follows:

Moving Average (MA) Model, also known as the moving-average process, refers to past forecasting errors in a time series model. The output variables depend on the current and past values, given as:

$$X_t = \mu + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} + \varepsilon_t \quad (1)$$

where μ is an expectation of X_t, $\theta_1, \theta_2, \cdots, \theta_q$ are the model parameters of order MA(q), and ε_t is the white noise error. The MA assumes that the current value of a random variable depends on q past errors which depend on the errors at $\varepsilon_{t-1}, \varepsilon_{t-2}, \cdots, \varepsilon_{t-q}$. For example, the MA (1) process is given as $X_t = c + \varepsilon_t + \theta_1\varepsilon_{t-1}$, where c is constant. Another MA model uses the mean of past values to forecast the current value. This type of model is called Simple MA. The running or rolling average model calculates the average over a set number of periods with a sliding window or interval. For instance, the MA for a series of data $d = d_1 + d_2, \cdots, d_n$ can have a sequence of n values given as:

$$X_t = \frac{d_n + d_{n-1}, \cdots\cdots d_{S-(n-1)}}{S} \quad (2)$$

$$X_t = \frac{1}{S}\sum_{i=0}^{n-1} d_{S-i} \quad (3)$$

where S represents the sliding window or the period of selected past values. The chosen period of the sliding window depends on the type of interest movement: short-term, medium-term, or long-term.

Auto-Regression (AR) Model is a linear combination of the variable's historical values that predicts the variable of interest. The AR model forms stochastic difference equations where its output variable is linearly dependent on its own historical values and stochastic term. The AR model of order p at the current value can be defined as follows:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \quad (4)$$

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t \quad (5)$$

where c is constant, $\varphi_1, \varphi_2, \cdots, \varphi_p$ are the model parameters, and ε_t is the white noise. The AR model is flexible since it handles a wide range of various time series patterns depending on the model parameters. The ε_t only affects the scale of the series but not the pattern. For instance, the processes of the AR(p) model are not stationary when p = 1 with $\varphi_1 > 1$. However, the AR model is normally limited to stationary data with $-1 < \varphi_1 < 1$ and $-1 < \varphi_1 < 1, \varphi_1 + \varphi_2 < 1, \varphi_2 - \varphi_1 < 1$ for AR(1) and AR(2), respectively. The restrictions become much more complicated if $p \geq 3$. Simplifying the AR(p) to low order processes is given as follows:

$$Y_p = \begin{cases} \varphi_1 Y_0, if p = 1 \\ \varphi_1 Y_1 + \varphi_2 Y_0, if p = 2 \end{cases} \quad (6)$$

Autoregressive–Moving-Average (ARMA) Model is a combination of MA and AR, represented by a notation ARMA (p, q). The p and q denote the order of the AR and MA models, respectively:

$$Z_t = \mu + c + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta\varepsilon_{t-q} + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \quad (7)$$

$$Z_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i\varepsilon_{t-i} + \varepsilon_t \quad (8)$$

where μ and c are the expectations of Z_t and constant, respectively. The autoregressive integrated moving average (ARIMA) model is a generalization of the ARMA model, represented by the notation ARIMA(p,d,q). The only difference between ARMA and ARIMA is the added parameter d which refers to the degree of the first differentiation involved. All previously discussed models are special cases of the ARIMA model, as summarized in Table 3.

Two types of ARIMA are present: seasonal and nonseasonal. The seasonal ARIMA depends on seasonal lags and differences to fit the seasonal pattern, usually represented as ARIMA(P,D,Q). It requires time series data (i.e., systematic, calendar-related influences) which consist of a value for each month of a calendar year. However, nonseasonal ARIMA is almost similar to a trend pattern which consists of a time series data without calendar-related influences and irregular effects, usually represented as ARIMA(p,d,q).

3. Proposed model

A novel mathematical model is proposed to project future spectrum efficiency as well as spectrum efficiency growth. The proposed spectrum efficiency model is mainly evaluated as a function of the average spectrum efficiency per site and the number of sites per technology, as illustrated in Fig. 1. The spectrum efficiency growth is computed as a ratio between the spectrum efficiency of a corresponding year to that of a random previous year. For instance, the spectrum efficiency growth $\left(\xi_{Y_F}\right)$ for the future year Y_F(e.g., the year 2025) can be evaluated as a ratio between the spectrum efficiency of the year Y_F to the spectrum efficiency of the corresponding year Y_C (e.g., 2015). This is mathematically expressed in Eq. (9) as:

$$\xi_{Y_F} = \frac{\bar{\eta}_{Y_F}}{\bar{\eta}_{Y_C}}, \quad (9)$$

Table 3 Special cases of the ARIMA model.

ARIMA Case	Description
ARIMA(0,0,0)	White noise
ARIMA(0,0,q)	Case of MA
ARIMA(p,0,0)	Case of AR
ARIMA(p,0,q)	Case of ARMA
ARIMA(p,1,q)	ARIMA with degree of first differencing

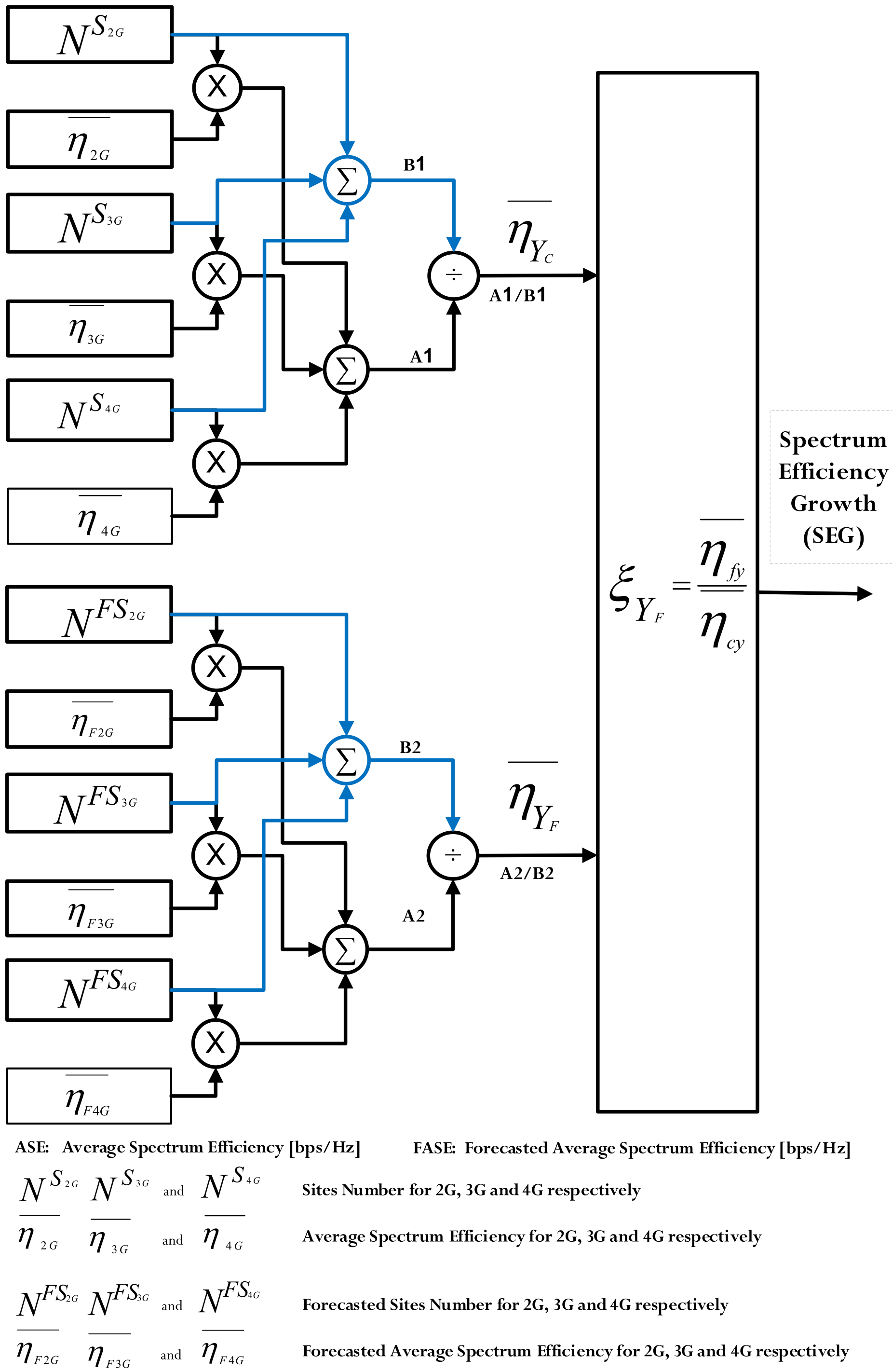

Fig. 1 Proposed spectrum efficiency growth model.

where $\bar{\eta}_{Y_F}$ and $\bar{\eta}_{Y_C}$ represent the average spectrum efficiencies per site over all technologies for years "Y_F" (i.e., 2025) and the current year "Y_C" (i.e., 2015), respectively.

The average spectrum efficiency per site over all technologies is mainly determined by knowing MCS [33], SN, and the MIMO scheme (e.g., 4 × 4, 8 × 8, or other higher-order combinations) for each individual site. These parameter settings may vary between sites with the same technology and will definitely vary between different technologies. Since it is difficult to determine the actual system settings (e.g., MCS, SN, and MIMO types) for each individual site, a new method was derived to estimate the average spectrum efficiency per site over all technologies at any year; "Y_F" or "Y_C". Since the actual network consists of several site numbers belonging to various technologies with different spectrum efficiency levels, the proposed model is mainly calculated as a function of the average spectrum efficiency per site and the total site numbers that belong to the same technology. The actual network consists of several technologies, therefore, 2G, 3G, and 4G are considered. This is further expressed in the devised formula of Eq. (10) as:

$$\bar{\eta}_Y = \frac{\sum_{i=1}^{N_G}\left(\bar{\eta}_{iG}\, N_Y^{S_{iG}}\right)}{\sum_{i=1}^{N_G} N_Y^{S_{iG}}}, \tag{10}$$

where $\bar{\eta}_{iG}$ is the Average Spectrum Efficiency (ASE) per site belonging to technology "i", while $N_Y^{S_{iG}}$ is the number of sites belonging to technology "i" at year "Y". N_G represents the total technology number available in the network. Using Eq. (10) $(\bar{\eta}_Y)$, this model can be applied to estimate the average spectrum efficiency per site over all technologies at any year, whether "Y_F" or "Y_C".

According to the average spectrum efficiency, evaluation over all network types should belong to the same technology. This is because each technology consists of different network types. For instance, the 3G network includes HSDPA, HSUPA, HSPA, and HSPA + . Accordingly, the average spectrum efficiency per site that exists with the same technology can be mathematically evaluated by the formulated model in Eq. (11):

$$\bar{\eta}_{iG} = \frac{\sum_{j=1}^{N_{nt}^{iG}} \eta_j}{\sum_{j=1}^{N_{nt}^{iG}} N_j^{S_{iG}}}, \tag{11}$$

where $\bar{\eta}_{iG}$ represents the ASE per site belonging to technology "i"; i is the technology type which can be 2G, 3G, or 4G; j is the network type (e.g., in 3G technology, j stands for HSDPA, HSUPA, HSPA, or HSPA +); N_{nt}^{iG} is the total number of network types belonging to one technology (e.g. "i"); η_j is the spectrum efficiency for network type "j"; while $N_j^{S_{iG}}$ represents the site number of network "j" belonging to technology "iG".

The total number of sites that belongs to each technology type (such as 2G, 3G, and 4G) can be obtained from different sources; from the operators' annual reports, regulators, OpenSignal, GSMA, and other online resources. It can be estimated based on historical data, similar to what we had accomplished in our spectrum gap forecasting study (refer to Ref. [25]). Consequently, both $\bar{\eta}_{Y_F}$ and $\bar{\eta}_{Y_C}$ can be evaluated by Eq. (10). However, the input parameters should be for the corresponding year. From Eqs. (9) and (10), the spectrum efficiency growth for the year "Y_F" can be determined as a function of the average spectrum efficiency, $\bar{\eta}_{iG}$, and the sites number, N_{iG}^S, belonging to the same technology. Thus, the spectrum efficiency growth can be evaluated by the simplified mathematical model in Eq. (12).

$$\xi_{Y_F} = \left(\frac{\sum_{i=1}^{N_G}\left(\bar{\eta}_{iG}\, N_Y^{S_{iG}}\right)}{\sum_{i=1}^{N_G} N_Y^{S_{iG}}}\right)_{Y_F} \times \left(\frac{\sum_{i=1}^{N_G} N_Y^{S_{iG}}}{\sum_{i=1}^{N_G}\left(\bar{\eta}_{iG}\, N_Y^{S_{iG}}\right)}\right)_{Y_C} \tag{12}$$

Since mobile technology is rapidly changing and different factors may impact the growth of spectral efficiency, an additional variable is proposed as a multiplier to make the model more flexible for use in any country or with any technology in future. This new proposed variable is A. Thus, the spectrum efficiency growth can finally be evaluated by the simplified mathematical model in Eq. (13):

$$\xi_{Y_F} = \left(\frac{\sum_{i=1}^{N_G}\left(\bar{\eta}_{iG}\, N_Y^{S_{iG}}\right)}{\sum_{i=1}^{N_G} N_Y^{S_{iG}}}\right)_{Y_F} \times \left(\frac{\sum_{i=1}^{N_G} N_Y^{S_{iG}}}{\sum_{i=1}^{N_G}\left(\bar{\eta}_{iG}\, N_Y^{S_{iG}}\right)}\right)_{Y_C} \times \mathrm{A} \tag{13}$$

This work employs three performance metrics: the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root-Mean Squared Error (RMSE), given as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|A_i - F_i| \tag{14}$$

where the normalized MAE is given as:

$$NMAE = \frac{MAE}{\frac{1}{n}\sum_{i=1}^{n}|F_i|} \tag{15}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2 \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2} \tag{17}$$

where the normalized RMSE is given as:

$$NRMSE = \frac{RMSE}{\frac{1}{n}\sum_{i=1}^{n}|F_i|} \tag{18}$$

The A and F are actual and forecasting data, respectively. n represents the number of test data. The performance of the proposed model is evaluated by obtaining its accuracy percentage and comparing it with several forecasting models (MA, AR, ARMA, and ARIMA). The accuracy is calculated based on the available data of all MTOs and technologies.

$$F_e = \frac{|A - F|}{A} X100 \tag{19}$$

$$Accuracy = \max(0, 100\% - F_e) \tag{20}$$

F_e denotes the forecast error where the overall accuracy represents the model accuracy over all technologies for each MTO. The ratio of logarithm accuracy is used instead of the coefficient of determination R^2 to verify whether the forecast value is higher or lower than the actual value. The logarithm ratio R_{AF} is defined as the ratio of the forecast to the actual value, expressed as:

$$R_{AF} = \log\left(\frac{F}{A}\right) \tag{21}$$

The positive values of R_{AF} indicate that the forecasted value is higher than the actual value, while the negative values of R_{AF} indicate that the forecasted value is higher than the actual value.

4. Analysis of spectrum efficiency growth

This section presents the forecasted future spectrum efficiency and spectrum efficiency growth for Turkey, Malaysia, and Oman by employing the derived models formulated in Eqs. (10) and (12), respectively. This forecast has been conducted for multiple years, from 2015 to 2025. This is based on the input market data of three major MTOs in Turkey: T1, T2, and T3; four major MTOs in Malaysia: M1, M2, M3, and M4; and two major MTOs in Oman: O1 and O2. The statistical data for generating the input metrics have been obtained from prominent agencies, such as the operators' annual reports, regulators, MCMC [34], GSMA [21], Analysys Mason [22], Huawei [35], MTC [36], and Ooredoo [37]. Predictions have been executed for every individual operator. Subsequently, the total forecasted spectrum efficiency and spectrum efficiency growth are combined to present the entire expected results for the whole of Turkey, Malaysia, and Oman.

The proposed model efficiently forecasts future spectrum efficiency and spectrum efficiency growth. The model mainly utilizes the average spectrum efficiency and site number per technology as input parameters to ensure an accurate prediction. Tables 4, 5, and 6 present these input parameters, the forecasted future spectrum efficiency, and the spectrum efficiency growth of three, four, and two main MTOs in Turkey, Malaysia, and Oman, respectively. These input parameters and forecasted results are only for one year (i.e., 2025). The forecasted average spectrum efficiency is calculated for each individual MTO in Turkey, Malaysia, and Oman for the year 2025 compared to the year 2015. Similarly, the spectrum efficiency growth represents the average growth ratio for every individual MTO in 2025 over the year 2015. The results in Tables 4, 5, and 6 are presented as an indication of the collected input and forecasted data, while further insights are provided and discussed in the following results with a detailed comparison between metrics over various years. The existing 2G, 3G, and 4G networks have several versions: (GSM, GPRS, and EDGE), (HSDPA, HSUPA, HSPA, and HSPA +), and (LTE and LTE-A), respectively. The typical average spectrum efficiency for each technology is given as: 0.17 bps/Hz, 4.87 bps/Hz, and 23.16 bps/Hz for 2G, 3G, and 4G networks, respectively. In this regard, the forecasted average spectrum efficiency for all sites number is calculated by multiplying the overall sites number with the typical average spectrum efficiency for each technology.

Fig. 2 displays the predicted results of the site number and spectrum efficiency for each MTO in Turkey, Malaysia, and Oman for year 2025. It can be seen that the site number in Oman is less compared to Turkey and Malaysia due to population and area. The site number in Turkey and Oman will see an increasing trend compared to Malaysia since it has a strategy to reduce 3G networks from 2021 onwards. All targeted countries require a spectrum efficiency above 14 bps/Hz. Turkey recorded higher spectrum efficiency growth compared to Malaysia and Oman.

All forecasted results for every individual MTO are presented in Figs. 3 and 4 from 2015 to 2025. Fig. 3 displays the forecasted spectrum efficiency, while Fig. 4 displays the projected spectrum efficiency growth. Fig. 3 (a), 3 (b), and 3 (c) highlight the forecasted spectrum efficiency of three considered MTOs in Turkey, four MTOs in Malaysia, and two MTOs in Oman, respectively. The forecasted spectrum efficiency for Malaysia and Oman gradually increases, while it initially increases in Turkey until 2022 and then slightly decreases due to the forecast of low site numbers in the last three years. Fig. 5.

Fig. 4 (a), 4 (b), and 4 (c) show the predicted spectrum efficiency growth of three, four, and two considered MTOs in Turkey, Malaysia, and Oman, respectively. The results represent the predicted output for the eleven years, from 2015 to 2025. The results in both figures indicate that the spectrum efficiency and growth ratio will radically increase within the coming years. The average predicted spectrum efficiency per site for all operators in 2025 may reach up to 13.96 bps/Hz, 16.37 bps/Hz, and 15.62 bps/Hz in Turkey, Malaysia, and Oman, respectively. Compared to 2015, the average predicted growth ratios for all operators in 2025 may increase up to 5.5, 2.75, and 1.92 times in Turkey, Malaysia, and Oman, respectively. This increase is due to the outcome of continuous migration and upgrade from old to newer technology for mobile cellular systems.

The forecasts performed for Turkey, Malaysia, and Oman are based on the combined input data of all considered MTOs. Tables 7, 8, and 9 present the combined input parameters as well as the forecasted future spectrum efficiency and spectrum efficiency growth of the main MTOs in Turkey, Malaysia, and Oman, respectively. These input parameters and estimated future results are for years 2015 to 2025. All forecasted results are displayed in Figs. 5, 6, and 7.

Fig. 5 exhibits the predicted growth of the number of sites for all technology types: 2G, 3G, and 4G. In Fig. 5 (a), the number of forecasted sites is estimated based on the historical data collected from the operators' annual reports, Analysys Mason, and other online sources for each individual technology in Turkey. In Fig. 5 (b), the number of forecasted sites is estimated based on the historical data collected from the Malaysian Communications and Multimedia Commission (MCMC), and then distributed among operators based on their capabilities. Fig. 5 (c) displays the estimated number of forecasted sites according to several published data in the annual reports of the Ministry of Technology and Communication (MTC) in Oman and a published report by Ooredoo. The capability of each MTO is assessed based on the mobile connection number reported by GSMA [21] for each individual technology in Malaysia. The results indicate that the number of sites will continue to radically increase for 4G technology and slightly increase for 3G technology. It will not noticeably grow for the 2G technology. The reason is that

Table 4 Input parameters and spectrum efficiency results for three MTOs in Turkey for 2025.

Operator	SN/T			Typical ASE/T [bps/Hz]			Forecasted ASE [bps/Hz]	SEG
	2G	3G	4G	2G	3G	4G		
T1	5808	83,647	82,932	0.17	4.87	23.16	13.51	5.4
T2	0	74,748	76,690	0.17	4.87	23.16	14.13	5.5
T3	0	70,263	75,156	0.17	4.87	23.16	14.32	5.6
Average	1936	76,220	78,260	0.17	4.87	23.16	13.96	5.5

SN/T : *Sites number per technology*; *ASE* : *Average spectrum efficiency*
ASE/T : *Average spectrum efficiency per technology*; *SEG* : *Spectrum efficiency growth (2015 – 2025)*

Table 5 Input parameters and spectrum efficiency results for four MTOs in Malaysia for 2025.

Operator	SN/T			Typical ASE/T [bps/Hz]			Forecasted ASE [bps/Hz]	SEG
	2G	3G	4G	2G	3G	4G		
M1	16,345	23,985	85,927	0.17	4.87	23.16	16.71	2.34
M2	6306	42,166	121,041	0.17	4.87	23.16	17.755	3.57
M3	14,237	33,337	82,471	0.17	4.87	23.16	15.954	2.64
M4	0	40,798	51,146	0.17	4.87	23.16	15.044	2.66
Average	**36,888**	**140,286**	**340,585**	**0.17**	**4.87**	**23.16**	**16.37**	**2.75**

Table 6 Input parameters and spectrum efficiency results for two MTOs in Oman for 2025.

Operator	SN/T			Typical ASE/T [bps/Hz]			Forecasted ASE [bps/Hz]	SEG
	2G	3G	4G	2G	3G	4G		
O1	2488	5371	12,177	0.170	4.870	23.160	15.40	1.80
O2	2626	3503	10,844	0.170	4.870	23.160	15.83	2.04
Average	**2557**	**4437**	**11,511**	**0.170**	**4.870**	**23.160**	**15.62**	**1.92**

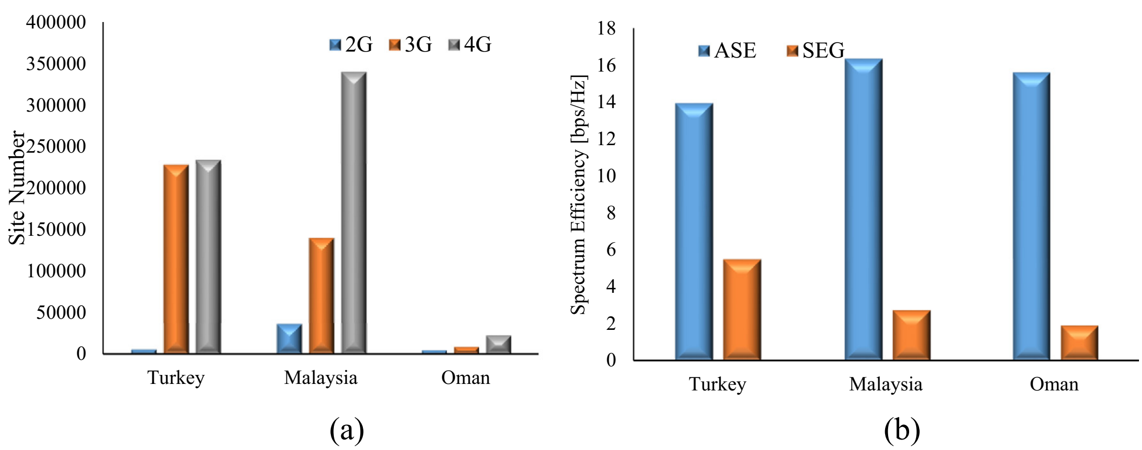

Fig. 2 Predicted results in 2025 of (a) site number and (b) spectrum efficiency for the targeted countries.

operators normally upgrade 2G and 3G networks to newer technology that continue to enhance coverage and system capacity, therefore, the preference is to only install more advanced technology such as the 4G.

From the results in Figs. 5, 3G is the dominant network while 4G is less deployed in the years 2015 to 2018 in Turkey and Malaysia, and the years between 2016 and 2020 in Oman. However, the predicted number of sites for 4G will be exponentially higher by 2025 for all considered countries. Fig. 5 (a) further illustrates that the 2G network will gradually decrease, while Fig. 5 (b) and 5 (c) recorded no significant increase or decrease between 2015 and 2025.

The 4G deployment in 2025 will reach up to 64.5% from the total networks established, while 2G and 3G will reduce to 7.6% and 27.9%, respectively. The 5G network is not mentioned here since the first commercial 5G system has only been deployed in 2020. In fact, the deployment of 5G networks in Turkey, Malaysia, and Oman may take another two to three years after standardization. The first anticipated phase of 5G deployment will not be broad and thus was not considered in our prediction. The increase in the predicted number of 4G and 4G + sites will offer additional data exchanges with enhanced spectrum efficiency, which will further reduce spectrum demands. The reasons behind such improvements are normally due to the increase of sector numbers, the implementation of massive MIMO, and higher modulation schemes such as 64-QAM and 254-QAM. These technological solutions are continuously enhanced to cope with the rapid advancement of radio MBB technology.

The increase in the number of sites contributes to the future extension of the 4G network coverage, further leading to spectrum efficiency enhancements. Fig. 6 displays the average spectrum efficiency from 2015 to 2025 for Turkey, Malaysia, and Oman. The predicted enhancement in spectrum efficiency,

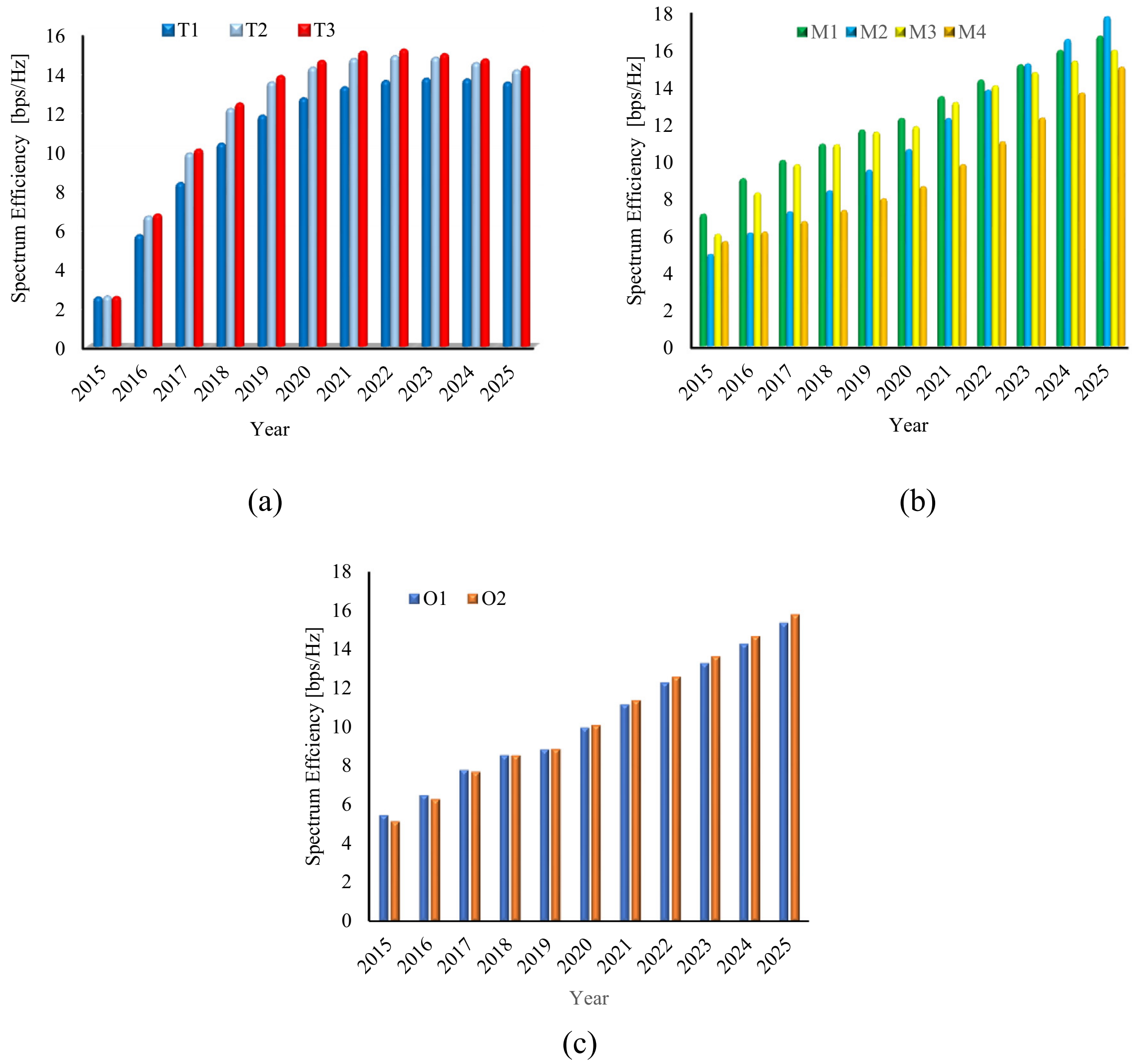

Fig. 3 Spectrum efficiency for different MTOs in (a) Turkey, (b) Malaysia, and (c) Oman.

which can be estimated by applying the formulated models in Eq. (10), is evaluated as a function of the number of sites. The predicted spectrum efficiency by 2025 is 13.99 bps/Hz, 16.31 bps/Hz, and 15.62 bps/Hz for Turkey, Malaysia, and Oman, respectively. It can be seen that Turkey's spectrum efficiency slightly decreases by 3.92% for the predicted years of 2022 to 2025 due to a significant increase in 3G network utilization compared to Malaysia and Oman. The difference in the percentage of spectrum efficiency from 2015 to 2025 is 138.33%, 83.40%, and 98.23% for Turkey, Malaysia, and Oman, respectively. Turkey's spectrum efficiency is 2.55 in 2015, which is half the spectrum efficiency in Malaysia and Oman.

These enhancements are usually performed by upgrading current networks (2G and 3G networks) to newer technology such as the 4G. Based on our forecasts and other predicted studies, [21,22,25,35], all MTOs in Turkey and Malaysia will continue to upgrade 2G and 3G networks to 4G sites. Moreover, they will progressively install new 4G and 4G + sites to fulfill the surge of future data demands. These new upgrades and installations will offer more data and higher spectrum efficiency, which will contribute to the reduction of the required spectrum in future. The proposed model's forecast demonstrates that spectrum efficiency will slightly grow over time, as illustrated in Fig. 7. This figure represents the average compound annual growth rate of spectrum efficiency over a time interval longer than one year (2 to 10 years). The average compound annual growth rate considers the most accurate and efficient method to calculate and determine the spectrum efficiency growth, which can increase or decrease over time. The figure displays an approximate compound annual growth rate of 10%, 5%, and 6% for the interval of two years compared to 14%, 8%, and 10% for the interval of ten years (from 2015 to 2025) for Turkey, Malaysia, and Oman, respectively. Over several time intervals, the spectrum efficiency growth in Turkey is high compared to Malaysia and Oman due to the annual gap in the number of sites.

Fig. 8 illustrates the average annual spectrum efficiency growth for all time intervals (2015 to 2025) for Turkey, Malaysia, and Oman. The average annual growth rates are determined by taking the average rate of each annual growth in a given period for each country. Fig. 8 demonstrates how the average annual spectrum efficiency in Turkey is higher than

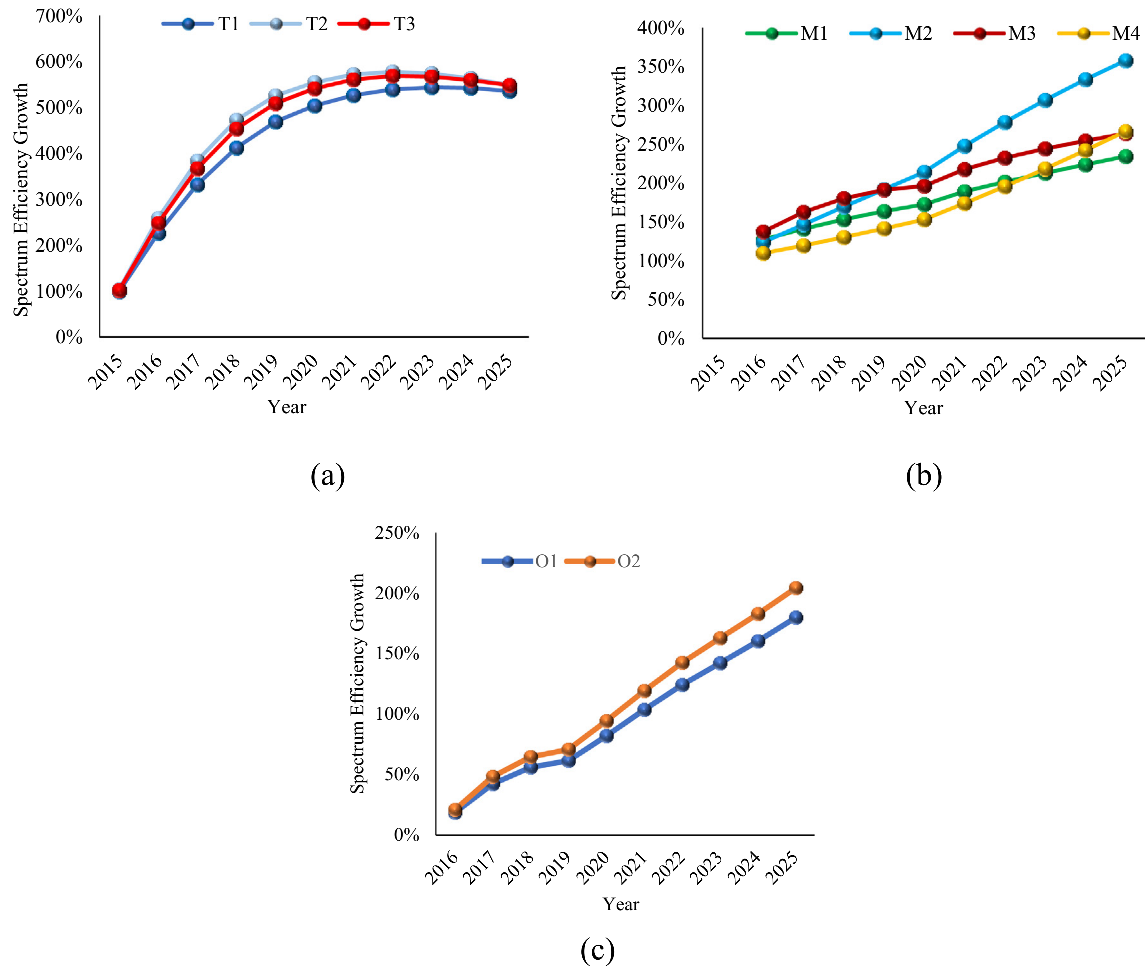

Fig. 4 Spectrum efficiency growth ratio for MTOs in (a) Turkey, (b) Malaysia, and (c) Oman.

Malaysia and Oman. The average annual rate of spectrum efficiency acquired by Turkey, Malaysia, and Oman is 24%, 9%, and 11%, respectively. Fig. 9 displays the spectrum efficiency growth rate in 2016 (with respect to 2015) and the expected growth rate in 2025. The expected growth rate in 2025 is approximately 447.45%, 143.07%, and 193.06% for Turkey, Malaysia, and Oman, respectively. It can be seen that the expected growth rate in 2025 increases by 3, 6, and 9 times compared to the growth rate in 2015 for Turkey, Malaysia, and Oman, respectively. This increase serves as an indicator for regulators and mobile operators so as to address the spectrum gap that may occur due to limited licensed spectrum bands.

Table 10 displays the quantified forecasting errors for each model with respect to country. From the table, it is apparent that the proposed model achieved lower NMAE and NRMSE compared to other models in Turkey and Malaysia. For Turkey, the MA and ARIMA models obtained higher MAE and RMSE compared to the AR and ARMA models. For Malaysia, the ARIMA model acquired lower NRMSE (0.09) while MA, AR, and ARMA obtained 0.31, 0.21, and 0.63, respectively. For Oman, the ARIMA model achieved lower NMAE and NRMSE compared to MA, AR, ARMA and proposed models. The MA and AR models provided the worst forecasting outcomes among the five models for all three countries. However, the ARIMA model performed well for Malaysia and Oman, while the ARMA model outperformed the ARIMA model for Turkey. It can be seen that the ARMA and ARIMA models provide the most accurate forecasting results from a global perspective. The proposed model outperformed all other models by obtaining the lowest NRMSE of 0.12, 0.05, and 0.11 for Turkey and Malaysia, respectively. However, the ARIMA model outperformed all models for Oman due to smothly growth of sites number. The forecasting error of traditional statistical models (MA, AR, ARMA, and ARIMA) is affected by the pattern of time series data, whereas the proposed model examines the pattern trend, significantly influencing the prediction of accurate spectral efficiency for each independent technology.

Fig. 10 demonstrates the logarithmic function of each model with respect to country. The logarithmic function determines whether the forecast value is higher or lower than the actual value, represented by positive or negative values of the logarithmic ratio. The proposed model can be seen to have low R_{AF} and positive values for all countries. This signifies that the proposed model predicted higher values compared to actual values. The MA and ARMA models have negative R_{AF} values, indicating that the forecasted values are lower than the actual values for all three countries. MA and ARMA recorded negative R_{AF} values in all compared countries, while

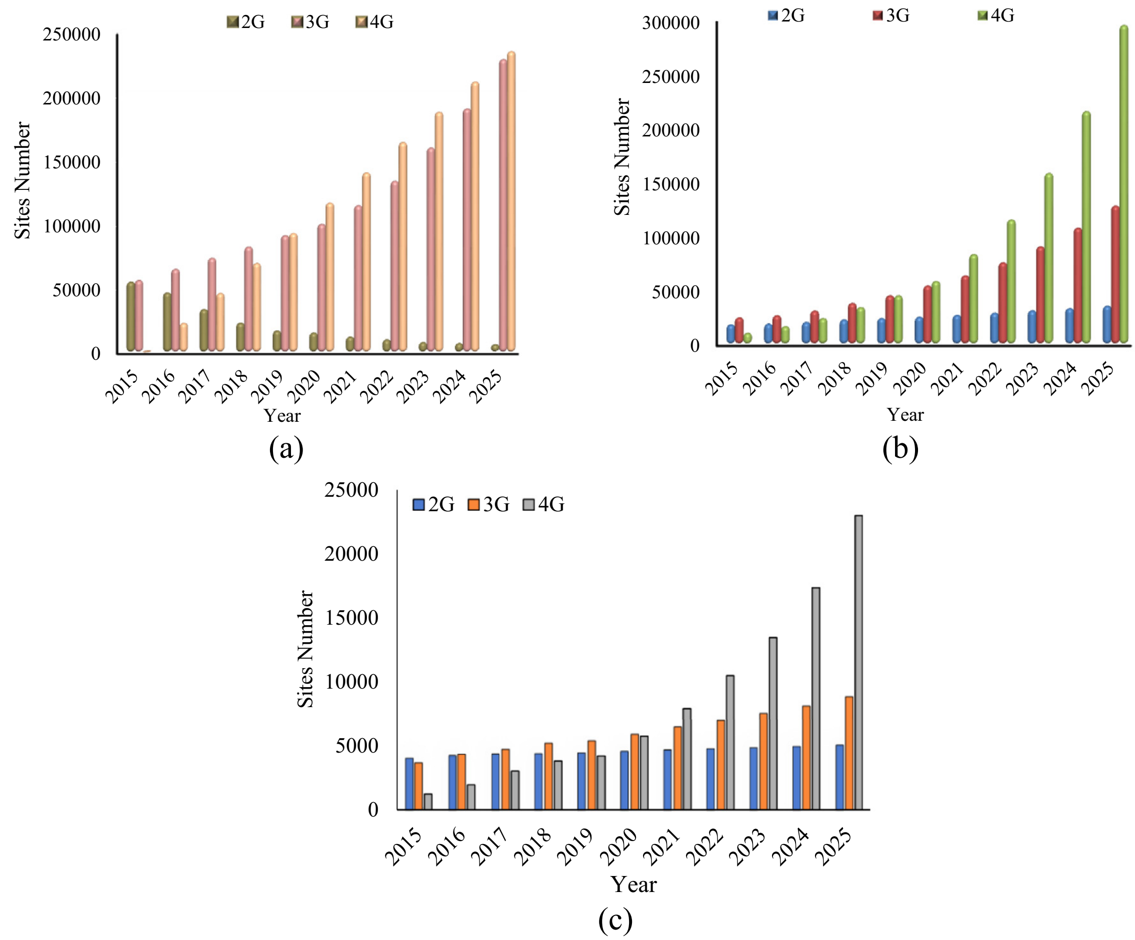

Fig. 5 The combined forecasted sites number growth for MTOs in (a) Turkey, (b) Malaysia, and (c) Oman.

Table 7 The combined input parameters and predicted spectrum efficiency in Turkey.

Year	Sites Number Per Technology			ASE over all Technology [bps/Hz]	SFG Ratio over all Technology
	2G	3G	4G		
2015	54,939	56,238	0	2.55	
2016	46,506	65,044	22,519	6.31	2.5
2017	33,483	73,851	46,103	9.34	3.7
2018	22,676	82,657	69,688	11.54	4.5
2019	16,559	91,464	93,272	12.96	5.1
2020	14,955	100,270	116,857	13.78	5.4
2021	11,755	114,875	140,441	14.28	5.6
2022	9486	133,886	164,025	14.48	5.7
2023	7484	159,803	187,610	14.44	5.7
2024	6717	190,227	211,194	14.26	5.6
2025	5808	228,659	234,779	13.96	5.5

higher R_{AF} values were observed in the AR and ARMA model for Oman and Malaysia, respectively. This indicates that AR and ARMA achieved relatively lower forecasting compared to other models Hence, AR provides the worst forecasting among all five models for Oman.

Fig. 11 presents the surface plot of the proposed model's accuracy percentage in comparison with other models (MA, AR, ARMA, and ARIMA) for Turkey, Malaysia, and Oman. Regarding the data for Turkey, the accuracy percentage is 89%, 67%, 69%, 84%, and 77% for the proposed model, MA, AR, ARMA, and ARIMA models, respectively. Generally, the proposed model and the ARIMA model both obtained higher forecasting accuracy compared to other models (MA, AR, and ARMA models). For Malaysia's data, the

Table 8 The combined input parameters and predicted spectrum efficiency in Malaysia.

Year	Sites Number Per Technology			ASE over all Technology [bps/Hz]	SEG Ratio over all Technology
	2G	3G	4G		
2015	17,717	24,107	9753	6.71	
2016	18,369	26,021	16,054	8.30	1.24
2017	19,870	30,442	23,362	9.40	1.40
2018	22,175	37,487	33,589	10.34	1.54
2019	23,419	44,522	44,488	11.13	1.66
2020	24,746	53,543	57,676	11.77	1.75
2021	26,464	62,870	82,592	12.93	1.93
2022	28,475	75,014	114,735	13.87	2.07
2023	30,606	89,853	157,872	14.73	2.19
2024	32,645	107,024	215,276	15.53	2.31
2025	34,888	127,548	295,238	16.31	2.43

Table 9 The combined input parameters and predicted spectrum efficiency in Oman.

Year	Sites Number Per Technology			ASE over all Technology [bps/Hz]	SEG Ratio over all Technology
	2G	3G	4G		
2015	4083	3745	1285	5.33	
2016	4279	4403	2008	6.41	1.20
2017	4396	4805	3086	7.78	1.46
2018	4426	5226	3881	8.58	1.61
2019	4498	5399	4270	8.89	1.67
2020	4609	5923	5826	10.06	1.89
2021	4722	6498	7949	11.31	2.12
2022	4816	7025	10,530	12.48	2.34
2023	4904	7581	13,502	13.5	2.53
2024	5006	8169	17,380	14.52	2.72
2025	5114	8874	23,021	15.62	2.93

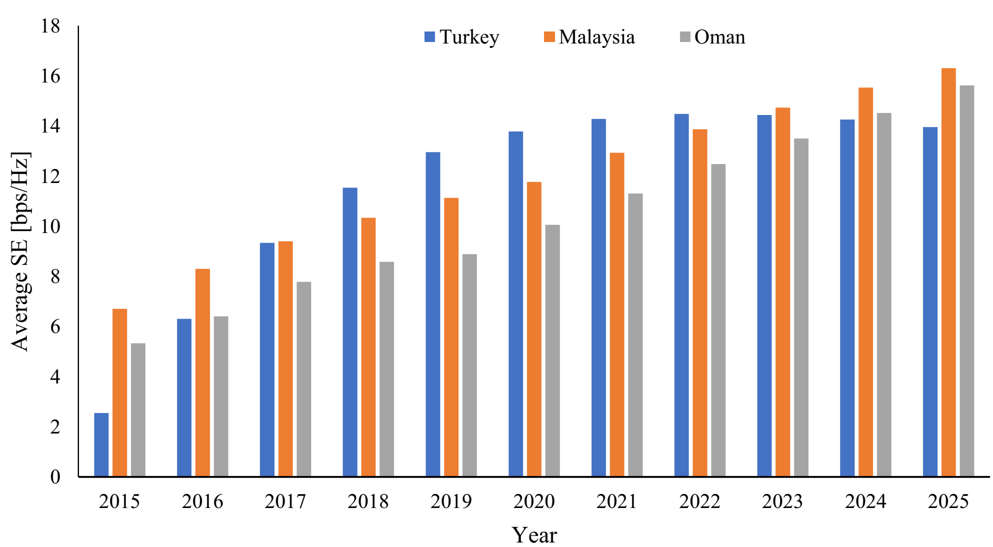

Fig. 6 Average spectrum efficiency for 2015–2025.

proposed model outperformed the other models with an accuracy of 94% compared to 78%, 71%, 70%, and 90% for MA, AR, ARMA, and ARIMA, respectively. For Oman, however, the proposed model and the MA model both obtained a similar accuracy value of 88% and 87%, receptively, while the accuracy of AR and ARMA remained below 70%. In addition, the ARIMA model achieved the highest accuracy of 95% compared to other models.

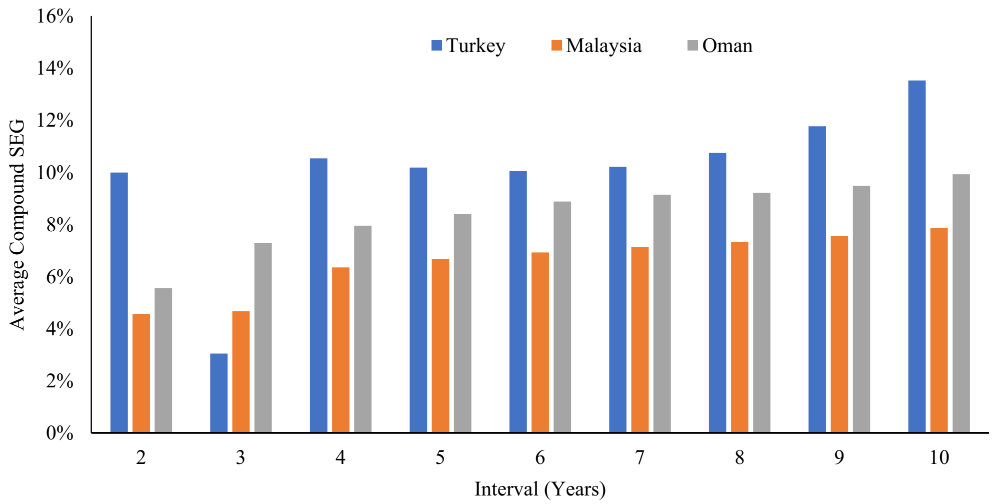

Fig. 7 Average compound spectrum efficiency growth over a 10-year time period.

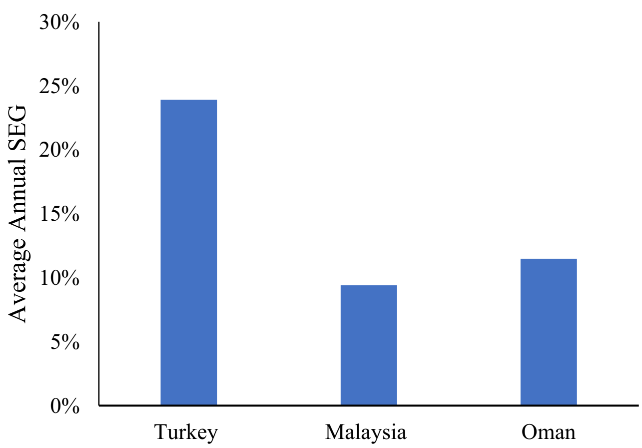

Fig. 8 Average annual spectrum efficiency growth rate.

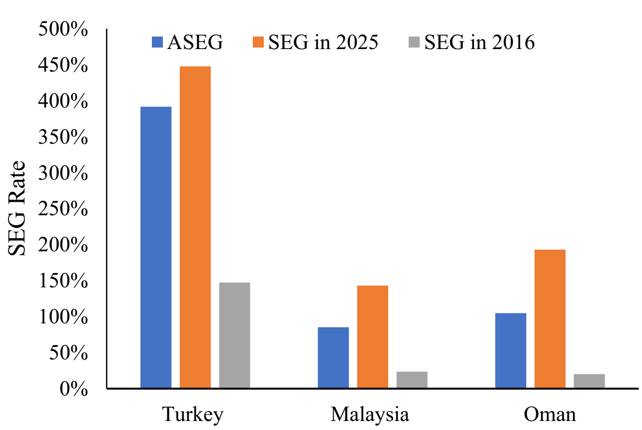

Fig. 9 Rate of spectrum efficiency growth in 2016 and 2025.

Table 11 presents a comparison of the accuracy percentage for all forecasting models. Fig. 12 displays the overall accuracy of the forecasting models. The overall accuracy of the proposed model, MA, AR, ARMA, and ARIMA is 90%, 77%, 68%, 74%, and 87%, respectively. ARIMA model achieved higher overall accuracy because it only performed well for Oman while the proposed obtained higher accuracy for Turkey and Malaysia. It can be concluded that the proposed model achieved remarkable accuracy compared to the other models. This is due to the considered parameters of the proposed model as well as the method of forecasting. The considered input parameters have a direct impact on the forecasted spectral efficiency. Hence, the number of sites from different technologies have a significant impact on independently estimating accurate spectral efficiency for each technology. The clear growth of the number of sites every year also significantly contributes to the estimation of more accurate results. Lower accuracy of traditional statistical models is probably due to the fact that these models are based on accumulated historical data which primarily capture the trend of the time-series but cannot properly characterize the different data patterns. The performance of all models also depends on the application, size, and pattern of the dataset.

Based on the above discussion, it can be concluded that the proposed model outperforms other models and has the least forecasting errors. However, the ARMA and ARIMA models provide better forecasting compared to the MA and AR models. The proposed model achieves a remarkable overall accuracy of 90% compared to the other models.

5. Recommended directions and limitations

5.1. Recommended directions

5.1.1. Current directions

The current MBB operators require to increase network capacity since mobile data traffic is dramatically increasing. Four interconnected directions are present to enhance network capacity and support the high demands of data-hungry services [38,39].

- *Network densification:* is a process of deploying more base stations to increase congested network capacity. It also helps improve mobile network coverage and availability. From the perspective of mobile operators, however, deploy-

Table 10 Comparison of accuracy percentage of forecasting models.

	Turkey			Malaysia			Oman		
	NMAE	NRMSE	R_{AF}	NMAE	NRMSE	R_{AF}	NMAE	NRMSE	R_{AF}
MA	0.335583	0.345319	−0.02427	0.306823	0.307865	−0.1132	0.158739	0.187462	−0.0626
AR	0.260691	0.26233	0.015991	0.20918	0.210305	0.105436	1.209841	1.081874	−0.27293
ARMA	0.183129	0.2002	−0.03722	0.589037	0.627341	−0.17969	0.097596	0.041546	−0.03706
ARIMA	0.329464	0.380633	−0.08776	0.084673	0.091381	0.038309	0.055140	0.059572	0.00499
Proposed	0.109328	0.12665	0.002193	0.054829	0.055234	0.017244	0.098989	0.109674	0.046922

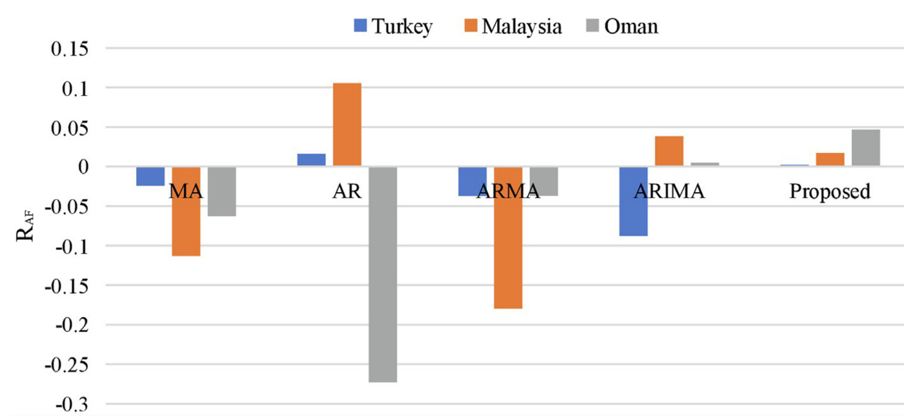

Fig. 10 Logarithmic ratio with respect to all forecasting models.

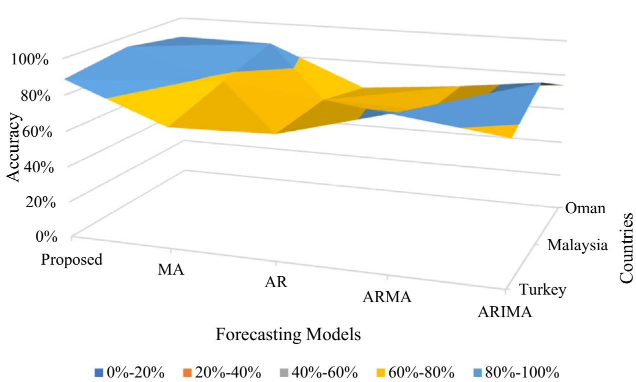

Fig. 11 Accuracy percentage of forecasting models for Turkey, Malaysia, and Oman.

ing new base stations will lead to several drawbacks: it is a time-consuming process, it is likely to increase backhauls, and it requires significant capital expenditure. This will lead to suboptimal spending for mobile networks, which will affect the price paid by end-users.

- *Offloading traffic:* is the process of offloading traffic data from mobile networks to complementary access network technology such as Wi-Fi and fixed networks. In this case, the load will be transferred to existing base stations. Mobile operators can provide their users with access to Wi-Fi and fixed networks and encourage them to connect to Wi-Fi hotspots available at indoor environments such as hotels, restaurants, coffee shops, and transport terminals. A related study in Malaysia [1] had stated that mobile data traffic of cellular networks does reduce by 68.47% (from 2364.47 Petabytes to 745.44 Petabytes) when mobile data traffic is off-loaded onto femtocell and Wi-Fi networks. This consequently reduces the required spectrum gap by half for 2020 relative to 2015. Although offloading to Wi-Fi hotspots which use unlicensed spectrum provides high-speed internet connection, these networks do not offer secure communication. Wi-Fi hotspots can also be very congested and may interfere with each other.
- *Improving spectral efficiency:* The spectral efficiency of mobile services increases with new mobile technology. It can be improved by increasing the number of antenna elements, radio resource management techniques, or spatial diversity multiple access. Refarming the spectrum can be applied to repurpose existing bands (i.e., 2G bands) to sup-

Table 11 Comparison of the accuracy percentage for all forecasting models.

	Proposed	MA	AR	ARMA	ARIMA
Turkey	89%	67%	69%	84%	77%
Malaysia	94%	78%	71%	70%	90%
Oman	88%	87%	64%	69%	95%
Overall	90%	77%	68%	74%	87%

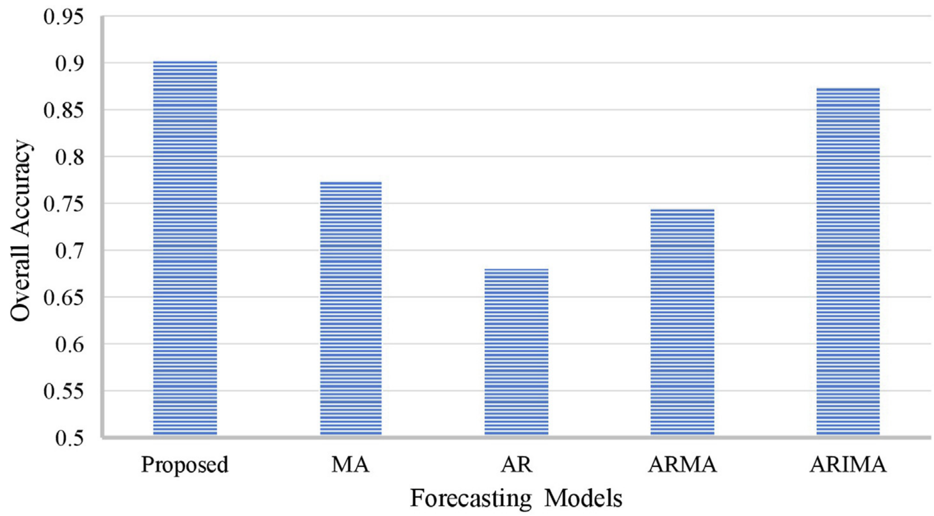

Fig. 12 Overall accuracy percentage of forecasting models.

port newer bandwidth-hungry applications. However, not all spectrums can be refarmed. Mobile operators must still continue to support some 2G connections.

- *Acquiring additional mobile spectrums*: Wireless networks face greater spectrum scarcity due to the high amounts of spectrum required. This is generated from the increasing demands for mobile internet access. Spectrum regulators must open new spectrum bands for mobile operators to accommodate the increase in network capacity. The required spectrum for each national market depends on the data population distribution, demand forecasts, and other national circumstances. According to a study [39], mobile data traffic in Malaysia will hit 2364.47 Petabytes per year from 2020, which is a significant increase from 295.72 Petabytes in 2015. Mobile data traffic is almost eight times the amount of 2015. The expected average site number and spectrum efficiency growth rates from 2015 to 2020 would be 167% and 264%, respectively. Thus, the rate of spectrum efficiency growth will increase from 264% to 417% by the year 2025. Acquiring an additional spectrum is key for fulfilling the potential data demands in future.

5.1.2. Future direction

In the 5G network, spectrum efficiency allows network operators to utilize small cells to densify their networks and reuse the spectrum more than once. This technique is becoming a common practice since it enhances capacity and allows the smooth transition from 4G to 5G. Thus, spectrum efficiency plays a crucial role in 5G network deployment due to increasing demands in data generation and processing. Several 5G trends can be summarized as follows:

- *Spectrum bands*: The spectrum bands in the new 5G radio network for MBB are divided into two categories: low bands (450 GHz to 6 GHz (sub 6 GHz)) and high bands (24.25 to 52.6 GHz millimeter wave). Both categories offer different capabilities. The low band exists in the new spectrum licensed for mobile services and 3G and 4G bands. This type of spectrum provides higher 5G network coverage with moderate capacity. The high bands support ultra-high broadband speeds envisioned for 5G, which offer higher capacity with low network coverage. The ITU-R M.2412–0 report stated that the deployment of the 5G network promises considerable increase in spectral efficiency, enabling downlink and uplink peak speeds of more than 30 bps/Hz and 15 bit/s/Hz, respectively. The recommended data rates for user experience in dense urban areas are 100 Mbit/s and 50 Mbit/s for downlink and uplink, respectively.
- *Massive MIMO and Beamforming:* The 5G network aims to improve spectral efficiency by using massive MIMO systems based on beamforming techniques. The beamforming technique is critical to 5G networks as it helps direct and adjust radio waves to target a specific receiver. Beamforming is a technique that manages radio frequencies. An access point sends out the same signal via multiple antennas to increase system capacity and performance. The serving beamforming antenna elements are installed at base stations with detector processing and coherent precoding. However, the massive beamforming systems require the use of advanced processing and complex hardware.
- *Network deployment:* The massive deployment of small cells in next-generation networks is expected to boost the overall network performance. Deploying small cells can also increase capacity and coverage, two important concerns for telecommunication operators. However, heterogeneous networks have become complex owing to the deployment of massive, small cells within macrocells. The deployment of a large number of small cells in the 5G network is expected to boost the overall system performance by enhancing coverage and improving user experience. The use of several remote radio heads and wireless relays in heterogeneous networks are needed to further boost network performance.

5.2. Study limitations

This study encountered several limitations that must be considered in future to further develop this model and acquire more accurate results. These limitations are listed as follows:

- This study forecasts future spectrum efficiency growth for MBB networks depending on the input data of existing mobile cellular networks (2G, 3G, and 4G). Emerging technology and industry trends such as the internet of things, augmented reality, artificial intelligence, drones, robotics, etc., are not considered in this study. However, forecasting future spectrum demands for these upcoming trends can be considered in future works.
- This study is limited to three countries (Malaysia, Turkey, and Oman) where the 5G MBB network is still under trial stages. The commercial 5G rollout is only expected in the next coming years. No commercial 5G base station has been deployed or opened for public use. Thus, the proposed model for forecasting spectral efficiency is applicable once the 5G data of implemented base stations are available. Accurate forecasting results depend on the size of the time series data, with long time series data providing more accurate outcomes. Hence, to forecast 5G spectrum efficiency growth, sufficient historical data is required. For our future study, 5G technology will be considered to forecast the required spectrum efficiency growth for 2030.
- Each operator/mobile service provider has a different strategy for future mobile network deployment and development. This plan is usually confidential and cannot be publicly shared, therefore, any related data cannot be easily obtained. This makes it more difficult to obtain 100% forecasting accuracy in any country. It will be challenging to acquire real data from operator/mobile service providers regarding the strategic plan for the future deployment of 5G and other mobile networks, leading to limited input data for forecasting. This subsequently leads to reduced accuracy of forecasted results.
- The deployment of the 5G mobile network has relatively begun in these three countries, with different deployment levels between them. It is certain that the 5G mobile network deployment will further increase in future. In the next five years, the 5G network is expected to become a major mobile network, contributing to further enhancements of spectrum efficiency for mobile networks. Unfortunately, we were unable to acquire data from a reliable source to implement in the 5G mobile network. The aim is to solve this issue in our future study to commence with the second phase of our forecasting.

6. Conclusion

This study proposed a new model to forecast spectrum efficiency and its growth for future mobile celluler communication networks. The model perform the forecasting based on the average spectrum efficiency per site and the number of sites per mobile communication technology. The model is applied to estimate and analyze spectrum efficiency growth in Turkey, Malaysia, and Oman according to the input data of their respective major MTOs. Major parts of the input data were collected from different sources, while other parts of the input data were estimated based on other related data collected from different sources. The spectrum efficiency and spectrum efficiency growth were presented and discussed to illustrate the radical growth between the years 2015 and 2025. Based on this study, it can be concluded that by 2025, the spectrum efficiency growth will rise up to 447.45% in Turkey, 143.07% in Malaysia, and 193.06% in Oman as compared to that of 2016. The findings will contribute to the fulfillment of future data demands and the reduction of spectrum gaps. These outcomes can be used for future spectrum planning by regulators and operators to address future spectrum gaps using one of the suggested strategies: increasing the sites number, utilizing unlicensed bands, enhancing spectrum efficiency or discovering a potential spectrum band. However, mobile network operators must also consider the cost of implementing one of the suggested strategies as well as the available resources provided by regulators in each country. The accuracy of the proposed model was compared with other forecasting models based on the input sources. The proposed model outperformed the traditional statistical models with an accuracy of 90%. The main limitation of this work is collecting data from each operator using various accurate resources. Some operators and developers are unwilling to share this type of data due to privacy and confidentiality. Forecasting spectrum efficiency growth for 5G mobile network requires sufficient historical data for at least the previous five years. For our future study, 5G technology will be considered to forecast the needed spectrum efficiency growth for 2030.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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