A COMPARATIVE APPLICATION OF TELECOMMUNICATION TRAFFIC FORECASTING METHODS TO A BACKBONE LINK IN TANZANIA

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*I*n this paper various mathematical models to characterize and forecast telecommunication traffic time series traffic have been applied, and the ranges of validity of the models are determined by comparing them with measured traffic data using the measurement errors criteria method which resulted into the superior model. Based on this model (the ARIMA (0,2,1) model for smoothed data), the traffic forecast findings show that by the year 2006, the traffic demand will exceed the current installed capacity of 140 Mbps in the Tanzania Telecommunications Company Limited (TTCL) network along the major link between the Dar es Salaam and Dodoma backbone route. The traffic forecast findings necessitate the migration from the current plesiochronous digital hierarchy (PDH) system to a higher capacity system so as to meet the growing needs of telecommunication services on the route. The traffic forecasting techniques are portable and can be applied by other telecommunication network operators like TTCL or by TTCL itself to other backbone links in its network.

Keywords: autoregressive integrated moving average, Statlets, time series, plesiochronous digital hierarchy, digital wavelength division multiplexing.

INTRODUCTION

A telecommunication backbone network is a huge capacity transmission link, which carries information signals grouped into larger aggregate signals from lower capacity transmission tributaries that interconnect with it and where local, regional or zonal networks connect to it for long-distance communication. The connection points are known as network nodes or telecommunication switching nodes. In such networks, high capacity transmission equipment must be used to transport such demands more efficiently. In the Tanzania Telecommunications Company Limited (TTCL) network, such networks are based on traditional microwave radio plesiochronous digital hierarchy (PDH) technology as shown in Figure 1.

For a system like PDH, which is not synchronous and uses digital time division multiplexing (TDM) technology, the following issues are specific to its applicability in the backbone networks of such systems:

(i) There are no standards for higher capacity transmission rates above 140 Mbps.

(ii) Insertion or removal of lower transmission rate tributaries to or from a backbone link requires that full hierarchy of multiplexing or demultiplexing be performed at each switching node. This necessitates deployment of large equipment volumes, which leads to higher capital equipment and maintenance costs.

(iii) Electronic regenerators that are costly and expensive to install and maintain are required at every 40-50 kms to overcome signal attenuation and extend the backbone network coverage. This assumption is valid if one assumes that the earth is a perfect sphere and antenna heights are about 50 metres. Placement of repeater stations on high hills or

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mountains extends the distance between repeaters but may necessitate the use of diversity reception techniques at repeater stations to overcome fading effects.

(iv) Error detection and correction or automatic request for retransmission (ARQ) hardware and software is usually required at every repeater station.
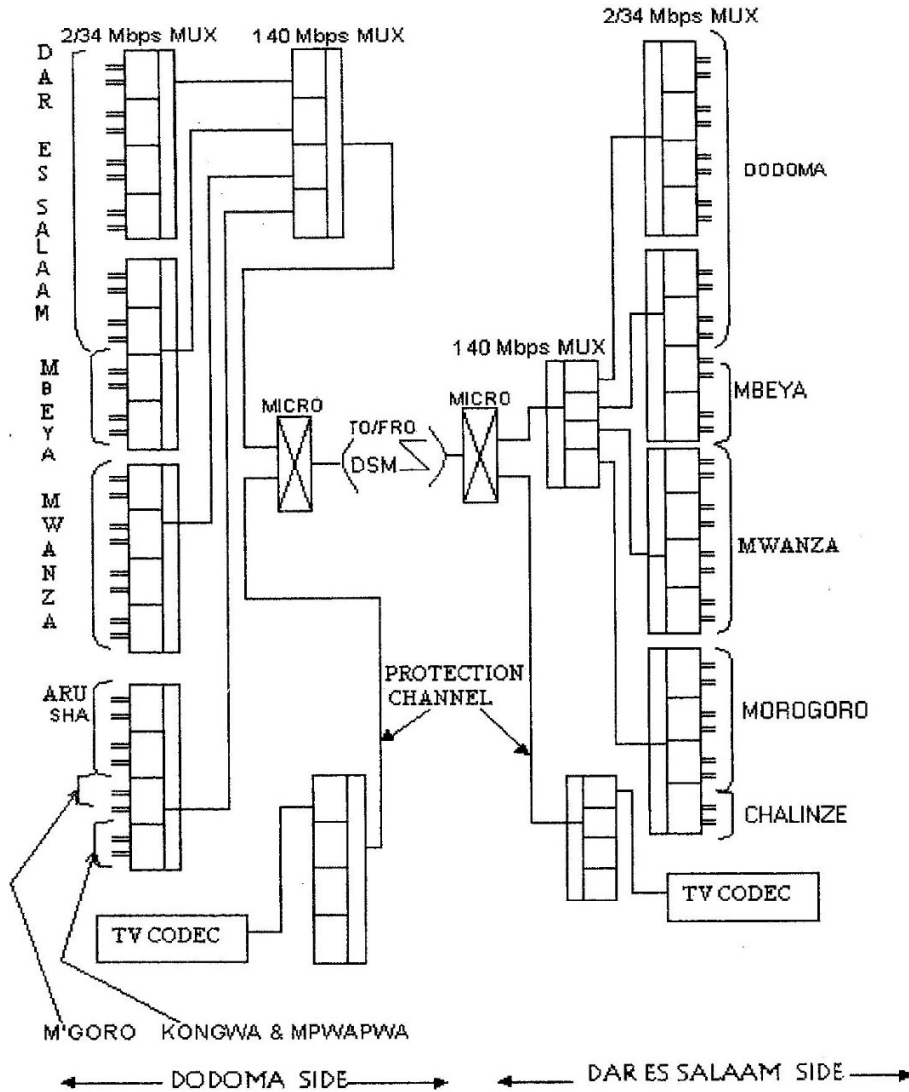

Figure1: Current Dar es Salaam-Dodoma 140 Mbps PDH system configuration.

One of such a backbone network in the TTCL network is layered along the Dar es Salaam-Dodoma link. It has been learnt that this link is currently facing operational incapacity that makes it a problem for network interconnection to, for example, mobile cellular telephone service providers. This can be said to have been driven by an increase in traffic arising from provision of mobile cellular services through a liberalized telecommunications sector. A recent quantitative statistical investigation for the above-mentioned link shows that by the year 2006 the projected traffic will exceed the current installed capacity of 140 Mbps. By 2015, forecast traffic demand will be above 622 Mbps. This projection was done based on the actual traffic data collected from the link and estimated using the Auto-Regressive Integrated Moving Average (ARIMA) method.

Given the traffic growth rate, the challenge is to design an appropriate and cost-effective system that will replace the existing PDH system in the TTCL network. This is because the PDH system is in practice not totally adequate for higher capacity upgrades above 140 Mbps to meet forecast traffic demand of more than 622 Mbps by the year 2015. The methodology of traffic analysis and system design proposed should be portable and applicable to other links in the TTCL network.

At present, there are two possible options for TTCL to increase its backbone transmission capacity: using digital time division multiplexing (TDM) technology, or optical technology using digital wavelength division multiplexing (DWDM) technology. A recent study [5, 13] justifies the economics of using DWDM technology in a telephone company. The analysis shows that a capital cost saving of 33% is achieved for using DWDM technology over non-DWDM technologies. To upgrade the system transmission for more capacity utilization, the DWDM solution's upgrade cost is the least with the upgrade cost of the digital TDM technology solution not that far behind.

The main research results reported here are two-fold:

(i) Telecommunications traffic time series traffic forecast methods suitable for Tanzania are identified and a method for comparing them to get a "best" forecasting method is found. The forecasting method is portable and can be applied to forecast traffic data for other links in the TTCL backbone network.

(ii) A technological platform that will serve as an evolutionally long-term solution to meet the growing needs of the major telephone link between the proposed capital of Tanzania, Dodoma, and its major commercial centre, Dar es Salaam, is proposed.

FORECASTING OF TIME SERIES DATA

Formal approaches to forecasting of time-series data began in the 1940's and became quite widespread in business and government in the 1950's. Since then, business, government and non-governmental organizations have used such approaches for strategic planning and forecasting. In the past few years, there have been a number of techniques developed in the field of statistics to analyse time series data and improve forecasting accuracy. Telecommunications researchers have applied many of these time series analysis techniques to telephone traffic projections.

The classes of models for forecasting time series data discussed in the sequel are: the linear model, the exponential model, the quadratic model, the constant mean model, the autoregressive (AR) model, the moving average (MA) model and the auto-regressive integrated moving average (ARIMA) model. Of all the models, the ARIMA model is the most widely discussed and highly cited work in forecasting. Theoretically, researchers and practitioners believe that it is the most accurate approach [2, 3, 9, 12, 19, 21].

Researchers from the past 25 years suggest that relatively simple methods are adequate for extrapolation such that the combination of forecasts from two or more extrapolation methods will reduce error significantly [2]. In this paper, a comparison of the six models has been conducted using the **Statlets** software package. The superior model is identified and forecast results are analysed based on the best-selected model.

Univariate and Multivariate Time Series

A time series is a sequence of observations on a variable of interest recorded over that time. Essentially, it is assumed that the measurements are obtained at equally spaced time points to provide a sample $X_1, X_2, X_3, \bullet \bullet \bullet, X_N$ of length n. In this paper, a univariate data analysis of the time series data is performed [4].

Data acquisition

In general, traffic measurements along a telecommunication network link include several items such as, the offered traffic (in erlangs), carried traffic, call attempts, successful calls, number of calls overflow, etc. In most cases, the offered traffic data on a link of interest is normally collected for further analysis because the link channel capacity is dimensioned from the knowledge/estimate of the offered traffic load and the grade of service (GoS), which is determined by the telecommunications network operator or the regulator.

In this study, measurements were done during busy hour periods from 10:00-11:00 Hrs on working days (Monday to Friday) in a week. 36 time series of offered traffic data points were collected on monthly basis for this work from January 1998 to December 2000. The link of interest was a PDH microwave radio system between Dar es Salaam and Dodoma in TTCL network. The 36 data points consist of a sum of incoming and outgoing traffic along the

existing spur routes supported by the link shown in Figure 1.

Data Smoothing

In most cases imperfections with real-world data are not noticed until the data analysis starts. To discover and generate new knowledge for building a reliable and comprehensive knowledge base, some form of smoothing is usually required before analysing the data. In so doing random variations, irrelevant or missing attributes in the data set can be reduced or cancelled in order to prepare the data for a more efficient and effective data analysis.

Some of the available smoothing methods include: the Random method, the Random walk method, the moving average (MA) method, the Holt's method, the Winter's method and the exponentially weighted moving average (EWMA) method. Of all the methods, the MA method and the EWMA method are the most commonly used techniques in industry [17, 20]. The above two smoothing options are the ones that have been applied in this work for smoothing the actual collected data for the Dar es Salaam to Dodoma route and are also included in the software package used here. In MA smoothing the weights that are assigned to the observations are the same and equal to I/N, where N is the number of observations. Exponential smoothing is similar to a moving average, but it places more weight on the most recent data. The weight on early periods drops off exponentially so that the older the data, the less their influence.

In the collected data, smoothing factors were selected based on a judgmental approach using a computerized search by varying their values. This procedure was repeated a number of times until the magnitude of the mean error (ME) was lowest. The value of the smoothing constant, α, [20] that results into lowest magnitude of mean error was selected for further analysis to produce smoothed data series shown in Figure 2(a). In this case it is the simple moving average with 5 terms and

α =0.1. The number of five terms was used for smoothing purpose, but when varied could not give any significant improvement in reducing the ME. Figure 2(b) shows a time sequence plot of the actual collected busy hour traffic for the Dar es Salaam to Dodoma link from January 1998 to December 2000.
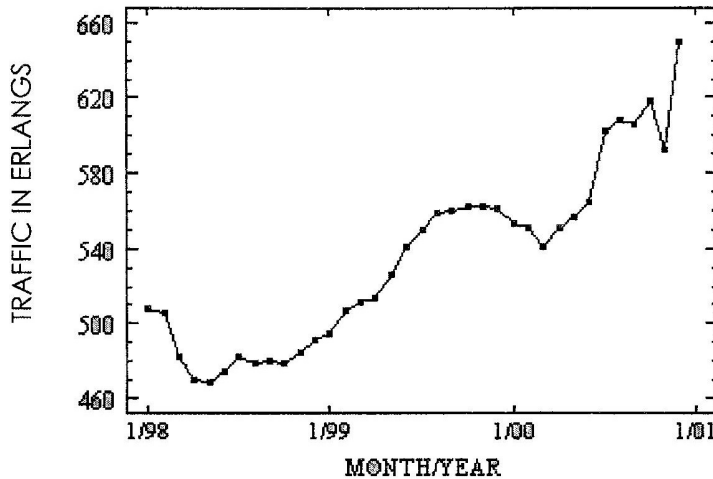

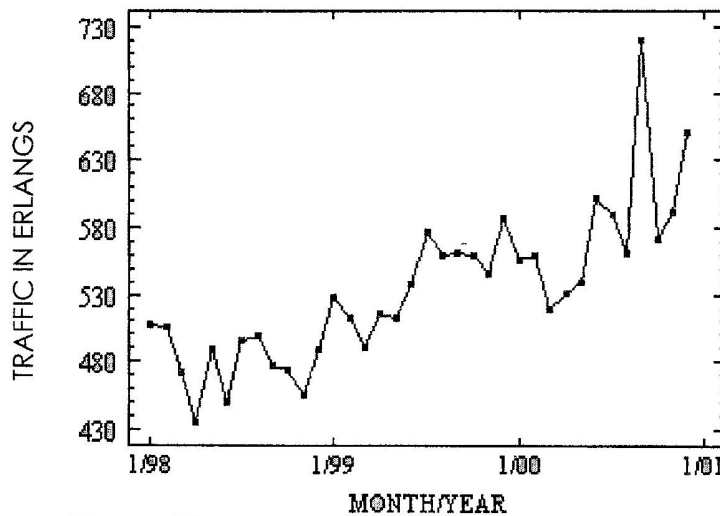Figure 2(a): Smoothed traffic data time sequence plot.

Figure 2(b): Actual traffic data time sequence plot.

MODEL FITTING AND COMPARISON

Mathematical models readily available from the literature [2, 4, 10, 20] were used to forecast traffic data using the linear model, the exponential model, the quadratic model and the constant mean model. Since this work has found the use of the Moving Average model and especially the Autoregressive Integrated Moving Average model to be especially accurate, this paper will explicitly reproduce these two models.

The Moving Average (MA) Model

The MA model forecasts future values based on a weighted average of past values. Mathematically, it can be written as [20]:

$$X_t = \overline{X} + A_t - \phi_1 A_{t-1} - \phi_2 A_{t-2} - \bullet\bullet\bullet - \phi_q A_{t-q} \qquad (1)$$

where X_t is the time series, $\overline{X}$ is the mean of the series, A_{t-1} are the variance (some times called "shocks") of the series which is new or uncorrelated with the past, and $\phi_1, \bullet\bullet\bullet, \phi_q$ are the parameters of the model. The value of q is called the order of the MA model (e.g., MA (q).).

The ARIMA Model

The ARIMA model addresses the problem of trying to estimate the state of a time series data; X_t. It is the combination of two models, that is, the MA model and Auto-Regressive (AR) model. An AR model is a linear regression of the current value of the series against one or more prior values of the series. A time series data, which needs to be differenced so as to be made stationary, is said to be "integrated". That is, ARIMA models are based on differenced data in order to simplify the structure of the time series.

The ARIMA model can thus be written as [20]:

$$W_t = \overline{X} + \frac{\phi(B)}{\Theta(B)} \alpha_t \qquad (2)$$

where t is the indexes time, B is the backshift operator $(B_{xt} = X_{t-1})$, and α_t is the independent disturbance (random errors). $\phi(B)$ is the AR operator, represented as a polynomial in the backshift operator as:

$$\phi(B) = 1 - \phi_1 B - \bullet\bullet\bullet - \phi_p B^p \qquad (3)$$

$\Theta(B)$ is the MA operator, represented as a polynomial in the backshift operator as:

$$\Theta(B) = 1 - \Theta_1 B - \bullet\bullet\bullet - \Theta_p B^q \qquad (4)$$

In ARIMA (p d q) model, the term (p d q) refers to the order of the nonseasonal AR, differencing and MA, respectively. Any number between 0 and 2 of AR, MA and differencing operators may be applied in the software package used.

Model Fitting

The historical measured busy hour monthly traffic data in Erlangs for the period of 1998-2000 between Dar es Salaam-Dodoma route was used to fit the following models: the quadratic model, the linear model, the constant mean model, the exponential model, the moving average model and the ARIMA model. Three quantitative measures were used as criteria for validation and performance comparison of the models, called performance indices, which are small when the model performs well and large when the model performs poorly. These are: the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE).

Model Comparison

Tables 1 and 2 show the results of the comparisons when the models are applied to TTCL's busy hour traffic monthly data collected for the Dar es Salaam to Dodoma link from January 1998 to December 2000.

Table 1: Measurement errors for actual data

S/N	Forecasting Model	MSE	RMSE	MAPE
1	Quadratic	1054.21	32.47	4.55
2	Exponential	1092.64	33.06	4.57
3	Linear	1113.80	33.37	4.66
4	ARIMA (2, 2, 1)	1409.47	37.54	5.44
5	MA	1569.25	39.61	4.88
6	Constant Mean	3170.61	56.31	8.16

Table 2: Measurement errors for smoothed data

S/N	Forecasting Model	MSE	RMSE	MAPE
1	ARIMA (0,2,1)	201.98	14.21	1.64
2	Quadratic	277.24	16.65	2.67
3	Exponential	325.57	18.04	2.87
4	Linear	348.95	18.68	2.92
5	MA	474.97	21.79	3.08
6	Constant Mean	2249.58	47.43	7.60

Actual collected data was used for traffic forecasting using six methods shown in Figures 3 to 8. These Figures show the forecasts for the periods immediately after the last historical data value, together with 95%-forecast limits.
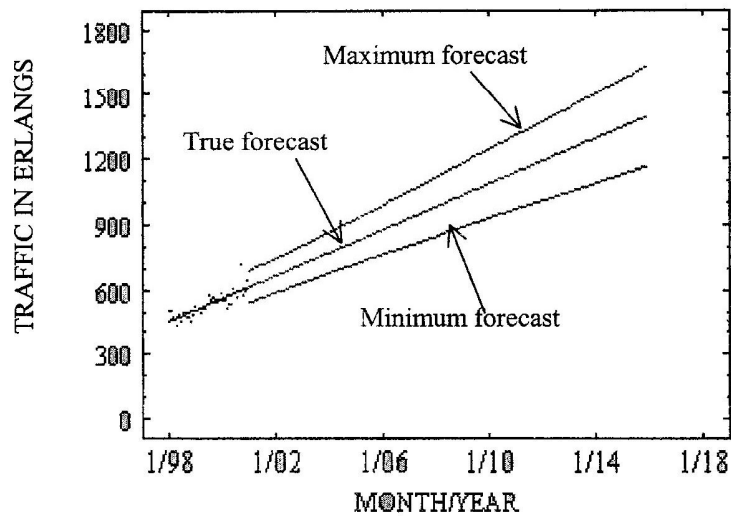

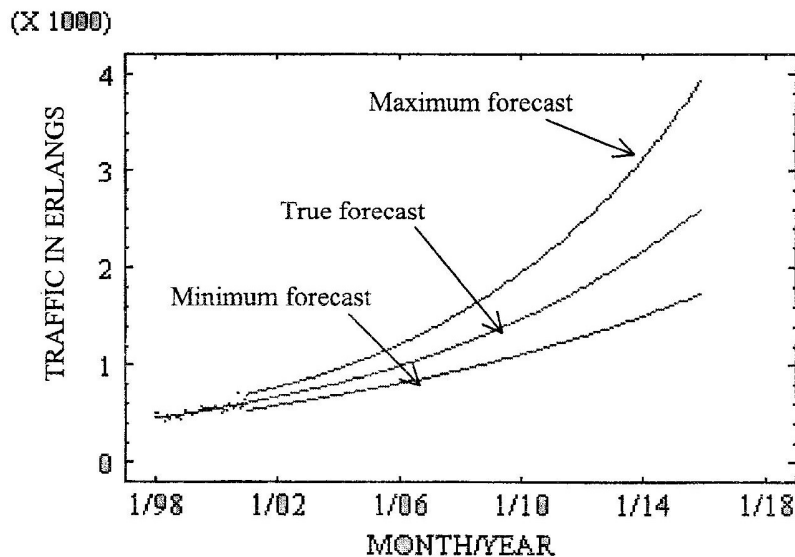Figure 3: Actual data forecast plot for linear trend model.

Figure 4: Actual data forecast plot for Exponential trend model.
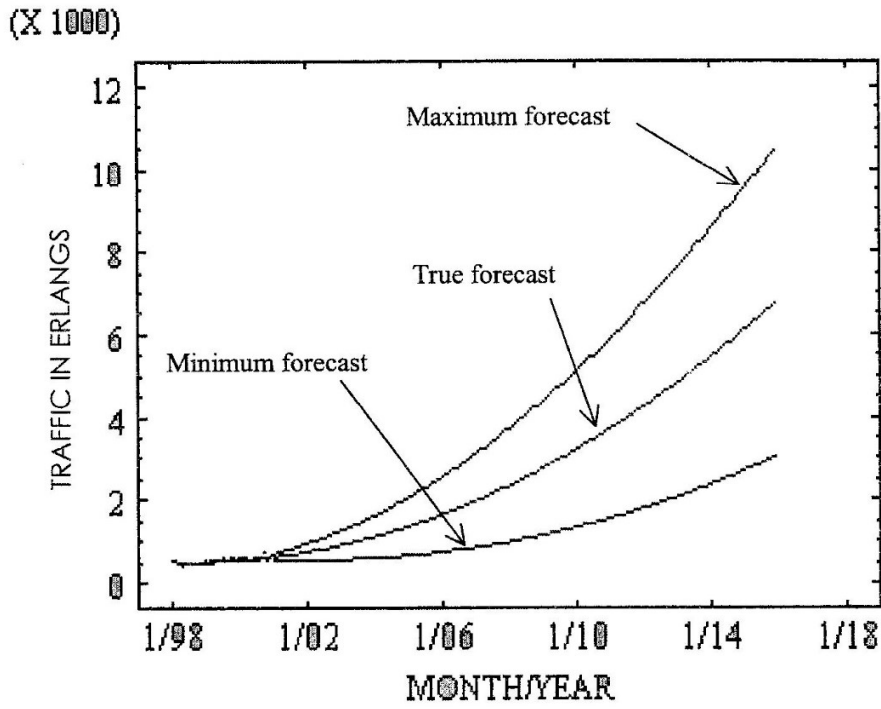
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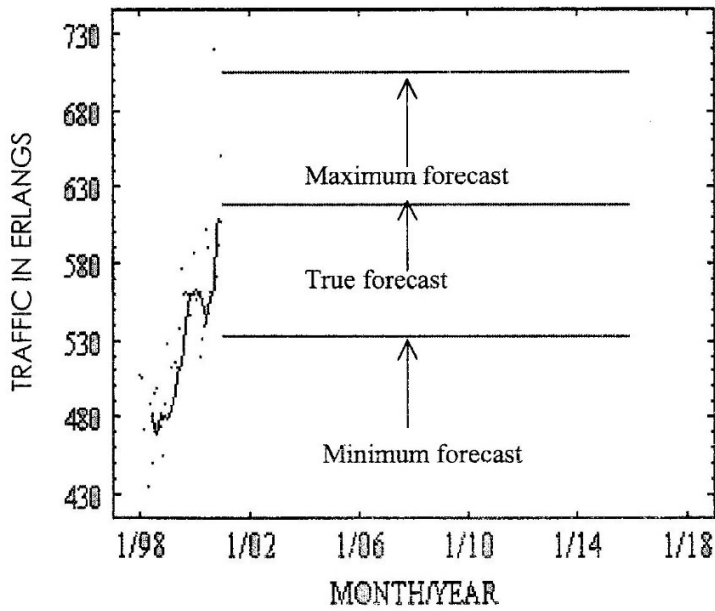Figure 5: Actual data forecast plot for ARIMA (0, 2, 2) model.

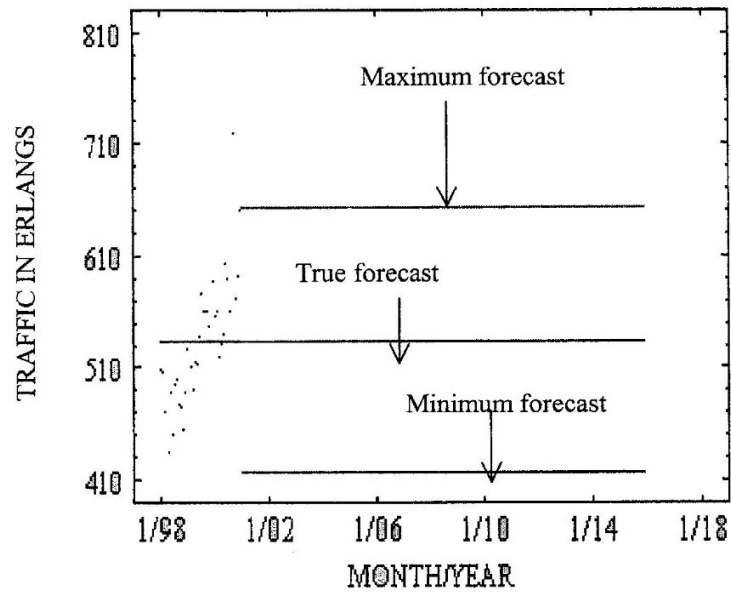Figure 6: Actual data forecast plot for MA (5) model.

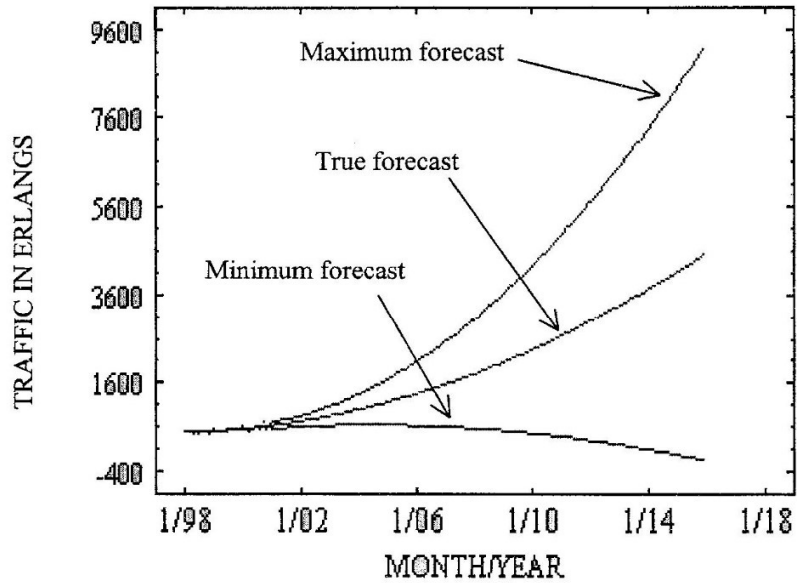Figure 7: Actual data forecast plot for Mean model.

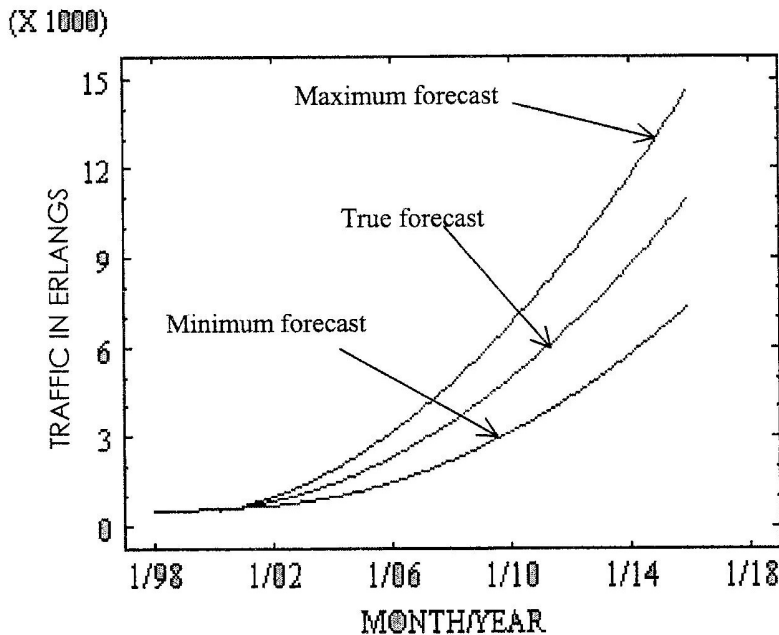Figure 8(a): Actual data forecast plot for Quadratic trend model.

Figure 8(b): Smoothed data forecast plot for ARIMA (0, 2, 1) model.

The forecast limits provide intervals in which there are two-sided lower and upper confidence interval values where the true forecast values (the middle curve) will fall assuming that the future events behave in a similar manner to the past. The other curves below and above the middle curve show the minimum and maximum forecast values respectively. The dots and plots in Figures 3 to 8 between 1998 - 2000 are the data used to fit each respective model and the data beyond 2000 is the forecast data. For the actual data, the quadratic model is the best in "forecasting" historical data for the period of 1998-2000 because it had the minimum value of the MAPE, which is 4.6 % on average, and the MSE and RMSE points of 1054 and 32 respectively. This suggests that the quadratic model may be the most useful model if smoothing is not applied to the actual collected data.

Table 2 shows the error statistics after performing smoothing to the actual historical data for the period of 1998-2000. This Table shows that the ARIMA (0,2,1) model performs well with average forecasting errors of approximately 2% and points of 202 and 14 for

MSE and RMSE respectively. The application of smoothing has reduced the performance errors by a significant amount (compare with the performance statistics results of the best forecasting model for actual data discussed before). This implies that the ARIMA (0, 2, 1) model is the most superior model since the other models have relatively higher values for these statistics depicted in Tables 1 and 2.

For the most accurate forecasting methods, Figures 8(a) and 8(b) show the plots for the observed data and forecast values for actual data and smoothed data respectively, that is, the quadratic model for the actual data and the ARIMA (0, 2, 1) model for smoothed data. Also, included on the plots are the 95% prediction limits for the forecast.

Mathematically, the confidence limits for the forecasts are defined as [20]:

$$\overline{Y} \pm t\left(\frac{\alpha}{2}, N - 1\right)\frac{S}{\sqrt{N}} \qquad (5)$$

where $\overline{Y}$ is the desired significance level, $t\left(\frac{\alpha}{2}, N - 1\right)$ is the upper critical value of the t distribution, α is the significance level,

$N - 1$ is the degree of freedom, $\dfrac{S}{\sqrt{N}}$ is the standard error, S is the standard deviation and N is the number of data points.

With reference to Figures 8(a) and 8(b) for the most accurate forecasting methods, the quadratic model for actual data, as expected, has a wider confidence interval than the ARIMA (0, 2, 1) model for smoothed data on average. This is due to the fact that data with a larger standard deviation (unsmoothed data) has a larger confidence interval than data with a smaller standard deviation (smoothed data).

ROUTE DIMENSIONING

As previously stated in section 2.2, by using the knowledge of projected traffic estimate and grade of service (GoS), it is possible to estimate the required number of channels/ circuits of a telecommunication network link. The GoS refers to the proportion of unsuccessful calls relative to the total number of calls made over a particular time interval in a telecommunication network link especially during the busy hour. In practice, it is expressed as the proportion of calls that are allowed to fail during the busy hour owing to the limitation, for economical reasons, of the amount of installed trunk circuits in a route [6]. The GoS is any performance variable (such as congestion, delay, jitter, loss, etc.), which is perceivable by the user [8]. As such, the GoS is a parameter, which provides information on the traffic aspects of the "quality of service" [14].

Different traffic characteristic models have been proposed in the literature to empower a telecommunication network link with GoS capabilities [7, 15, 16]. The method used here in this work is based on the Erlang "loss" formula (given in equation (6)). The traffic characteristic models used to construct this method were based on the probability theory methods of telephone traffic theory [18]. The probability of call blocking, $E(n,a)$, when a

certain volume of traffic, a, is offered to a given number of circuits, n, is given by the Erlang "loss" formula (also known as Erlang B (loss) formula) expressed as [1, 11, 16, 18]:

$$E\left(n, a\right) = \frac{\dfrac{a^{n}}{n!}}{\displaystyle\sum_{i=0}^{n} \dfrac{a^{i}}{i!}} \tag{6}$$

$$, n = 0, 1, 2, \bullet \bullet \bullet, n$$

Here, a is the flow of traffic offered along a telecommunication network link expressed in Erlangs and n is the number of trunk circuits. Recursive relationships [1] are available that simplify the computation of $E(n,a)$. In practice, a grade of service of 1 to 2% has generally been adopted by the telecommunications industry, although grades of service as high as 5% on particular routes have been tolerated by some telecommunication network operators [6]. TTCL recommends the use of a grade of service of 1% for trunk circuits carrying direct route traffic. The GoS of 1% relates to call congestion within various system stages measured during the busiest hour of the day. TTCL believes that the probability of a customer not to obtain a free circuit trunk from a trunk circuit system in a direct route when attempting a call during busy hour (normally from 10:00-11:00 Hrs) is; 1 call out of 100 calls originating attempts.

Based on the above grounds, the ARIMA (0,2,1) model with smoothed data, which is the best overall forecasting method, was, therefore, used to forecast traffic demand between Dar es Salaam and Dodoma route. The results obtained are as shown in Figure 9 and Table 3. The middle curve in Figure 9 shows the true forecast values whereas the lower and upper curves shows how much uncertainty there is from the true forecast, with the lower curve showing the minimum forecast values and the upper curve showing the maximum forecast values.
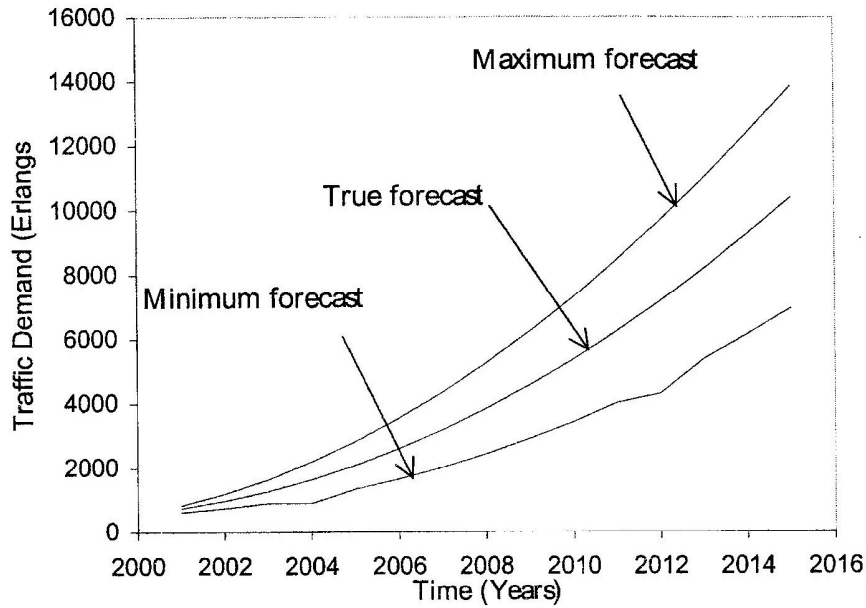
Figure 9: Traffic demand forecast in Erlangs for Dar es Salaam-Dodoma route
(up to 2015).

Table 3: Summary results of traffic demand forecast for Dar es Salaam to Dodoma route.

YEAR	AVERAGE OFFERED TRAFFIC PER ANNUM (Erlangs)			CAPACITY (Mbps)		
	Lower 95% Limits	True Forecast	Upper 95% Limits	Lower 95% Limits	True Forecast	Upper 95% Limits
1998	-	479.2	-	-	33	-
1999	-	540.5	-	-	37	-
2000	-	582.6	-	-	40	-
2001	653.8	746.2	838.5	44	50	56
2002	748.9	972.8	1196.8	50	65	79
2003	896.4	1270.5	1644.7	60	84	108
2004	905.3	1639.2	2184.5	61	107	142
2005	1340.4	2078.9	2814.4	88	135	183
2006	1646.2	2589.6	3533.1	108	168	229
2007	2003.7	3171.4	4339.0	131	206	280
2008	2417.0	3824.1	5231.2	157	247	338
2009	2886.9	4547.8	6208.8	187	294	400
2010	3414.2	5342.6	7271.0	203	345	469
2011	4000.0	6208.3	8417.1	259	400	542
2012	4280.2	7145.1	9646.7	277	460	621
2013	5346.7	8152.9	10959	345	525	705
2014	6109.4	9231.7	12354	394	594	794
2015	6932.1	10381.5	13831	447	668	889

Table 3 summarizes the overall traffic-forecast results. The average offered traffic beyond the year 2000 is the forecast results. Also included in Table 3 are the minimum and maximum forecast with 95 % confidence limits. To the extent that the 1998 – 2000 historical data used to realise this work conforms to the future behaviour, and using the best ARIMA (0, 2, 1) forecasting model for smoothed data, these limits as well as the true forecasts in, Table 3 gives a good estimate of the telephone traffic growth rate on the route.

CONCLUSION

Telecommunications traffic forecasting is a basic component for monitoring and control of telephone traffic growth patterns of future telecommunication networks. Such forecasting can provide useful information that is necessary to properly dimension a telecommunication network link and also as a basis for decisions on investments in the telecommunication networks.

In this paper, we have examined a fifteen-year ahead telephone traffic forecasts to a major link in the Tanzania Telecommunications Company Limited's network using the ARIMA (0, 2, 1) model with smoothed data. To validate our model, we have compared its performance with actual traffic data for the period 1998-2000. We have found that the ARIMA (0, 2, 1) model with smoothed data is superior to other models compared and it has yield forecasts whose accuracy is acceptable. A confidence interval for the true forecasts has generated two-sided minimum and maximum limits to the true forecasting values along Dar es Salaam to Dodoma link. These interval estimates give an indication of how much uncertainty there is in the estimate for the true forecasts.

Although the ARIMA (0, 2, 1) model with smoothed data provides relatively precise and promising forecasting results, we need to pursue the following issues for reducing performance errors:

(i)   The historical data should be extracted from a longer period of time to adjust secular trend and seasonal variations. This study used the historical data between 1998-2000 because the said link was commissioned at the end of 1997.

(ii)   The use of other forecasting models such as Kalman filtering, neural networks, etc should be explored. They may lead to better performance and definitely may be an important direction for future research.

We expect that the proposed forecasting methodology presented in this paper should be portable and applicable to other telecommunication network operators like TTCL, or by TTCL itself to other backbone links in its network.

NOMENCLATURE

AR   Autoregressive
ARIMA   Autoregressive Integrated Moving Average
ARQ   Automatic Request for Retransmission
DWDM   Digital Wavelength Division Multiplexing
EWMA   Exponentially Weighted Moving Average
GoS   Grade of Service
MA   Moving Average
MAPE   Mean Absolute Percentage Error
MSE   Mean Squared Error
PDH   Plesiochronous Digital Hierarchy
RMSE   Root Mean Squared Error
TDM   Time Division Multiplexing
TTCL   Tanzania Telecommunications Company Limited

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