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Time Series Predictive Models for Social Networking Media Usage Data: The Pragmatics and Projections

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Authors' contributions

This work was carried out in collaboration among all authors. Author MAJ came up with the novel idea, designed the analytical experiments, guided the coauthors and wrote the manuscript. Authors GJ and RR acquired the requisite data by referential studies and from public domain data bases, conducted series of computational analytical experiments needed to develop time series based prediction models and also evaluated the best fit. All the three authors read and approved the final manuscript.

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ABSTRACT

Aims: We have set forth three main objectives in the work presented in this paper, they are namely, to study how social networking media usage is surging over the time for three social media networks viz., Facebook, Twitter and LinkedIn, ii.to develop best fitting time series predictive models for predicting future usage of three network media and, iii. to make a comparative analysis to herald the ups and downs noticed in the usage across three network media considered.
Study Design: Application of time series techniques for the analysis of social network user's data. The main research question addressed by this work is to see how time series models augurs for time dependent data such as the one chosen in this research.
Place and Duration of Study: Research Center, Department of Master of Computer Applications, Siddaganga Institute of Technology, Tumakuru, Karnataka, India, between January 2020- April 2020.
Methodology: The work delved on collection three social network users (Facebook, LinkedIn, and

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Twitter) data for a span of nine years i.e., for the tenure 2011-2019. One dimensional, two dimensional and three dimensional visual analytics is made prior to time series analysis. Time series predictive analytics involved development of best fits for prediction. To select the best fits among linear, polynomial, exponential, power function and logarithmic models, mean absolute error and root mean square error metrics were used.

Results: Linear, polynomial function trend lines proved to be the best for Facebook, LinkedIn and Twitter respectively with low values of MAE and RMSE and high values of regression coefficients as compared with other kinds of models. Apart from the error metrics, the Theil's U-statistic values of 0.928, 1.008 and 1.21 for Facebook, Twitter and LinkedIn also heralded the fact that these functions are superior models when compared with other naïve models. It is also projected that by 2025, Facebook will see 10,000 billion, followed by LinkedIn at 1500 billion while Twitter would see 750 billion people if same kind of surge trend prevails in user numbers across three networks considered in this research.

Conclusion: This paper presented a unique work which is supposedly deemed to be the first of its kind to the best of the knowledge of authors. The models come with a limitation that, they can provide accurate projection if the same trend prevails in the pattern of upheavals in usage.

Keywords: Social media networks; Facebook; Linkedin; Twitter; time series models; trend analysis.

1. INTRODUCTION

A more generic definition of social media found when glided over a huge repository of referrals in literature is that it is a mode or vehicle for computer mediated communication where people set up their profiles and generate the information pool of themselves, intermix and watch or see their pals or other users online in a predictably regular way [1]. Basically it is Internet based persistent channels meant for mass personal communication enabling people to establish deciphering of perceptions and establishing interactions. Social media networks are deriving value from user generated contents [1]. Three predominant systemic characteristics of social networking are [2,3];

- The people will possess uniquely identifiable profiles, encompassing user supplied, other users contributions and also the gist of data provided by the system.
- People can articulate connections publicly, thus enabling the others to be viewed and traversed across.
- People can refer, create, and/or interact with vast pool of user garnered content availed or provided by their peers on the site.

It is reported that [4], 67% of all American adults and 75% of the Internet users use one or more social media networks. People in the age group of 18-29 years (supposedly young population) have found to have adapted to social media scaling the highest rate of 99% [5]. Among different social networks Facebook has the coveted distinction of being exceeded the number of citizens in the world's largest country. Twitter is widely popular, and relatively newer social media such as Snapchat and Instagram have been consistently raising the ladder of popularity. Younger generation is reported to having been migrated to Snapchat and Instagram by abandoning Facebook [6,7,8]. In a recent study, it has been reported that, the Internet users spent an average time 2 hours every day on some social network and messaging services this span is around one third of their daily computer time [9]. Researchers in this area have heralded many lucrative benefits that these social networks bring to the fore. Much to the delight of individuals and enterprises [10,11,12]. Some have touted it as the bright side and continue their rhetorical as networks being democratizer of consumers [13]. Justifiably so, the firms are being benefited in terms of improved marketing, customer services, public relations, product development, decision making and exchange of information related to business activities. However, the flip side of social networks was also showcased by some. It is echoed that some of the tools are ripping apart the social fabric of how the society works [14]. The enormous presence of social media networks is instrumental in undermining the freedom and wellbeing of the individuals and communities specifically with reference to cyberbullying, trolling, privacy invasions, and spreading of fake news.

This paper however, does not attempt to glide through the brownie issues, censures, and hypes on use of social media networks. The case in point is development of time series models on social network usage for a long span stretching over 9 years. The rest of the paper is organized as follows, section II elaborates the usage trends of Facebook, Twitter and Instagram. Section III delves on methodology adopted in this work, the evaluation and validation of various time series models are enunciated in section IV. The results and discussions are presented in section V, finally the paper concludes in section VI.

2. RELATED RESEARCH

Going by the enormity of the utility of social media and also its social relevance to multitudes of stakeholders, different fields such as information systems, health care, and social network related crimes have drawn substantial attention by researchers [15]. The social networks such as Facebook, Instagram, LinkedIn, Pinterest, WhatsApp, YouTube and the like are more sustained by user generated content. According to a report published in 2017, Facebook was found to be in an exalted position of being the leader in the world of social networks with 1.97 billion monthly users [16]. It was also reported that Twitter was used to an extent of 88% for the marketing purposes [17]. The literature survey indicated that a huge number of publications are related to exploration and examination of the facets and many sides of social networks. These studies are overwhelmingly done by academicians and practitioners. The major conclusion seems to be that the usage of social media has had the goal of garnering feedback from stakeholders [18]. In a very recent study involving finding of overall popularity of social media network over the Internet [19], following facts have emerged:

- During the beginning of 2020, the number of Internet users has exceeded a mammoth figure of that has crossed 4.5 billion.
- The active social media users have crossed 3.8 billion mark, a 9% i.e., 321 million new users have been added since 2019 till April 2020.
- It is found through an analysis restricting regional use, that the world wide variation in active penetration of people as high as 71% in Eastern Asia, followed by 69% in North America, 67% in Southern America , 67% in Northern Europe, 59% in Western Europe, 39% in Northern Africa and Middle Africa capped at 7%.

Interestingly enough. In another report, it is highlighted that there is a continuing decline of Facebook use by younger age group [12-15 years] with a decrease in Facebook profile generation has gone down to 31% in 2018 from 40% in 2017. While Instagram saw an increased trend from 14% to 23% in the same period. Snapchat stood stand still at 31%. Further, the report has also spelt out that the spending rate was an average of 2 hours and 24 minutes per day by so called digital consumers, particularly affixed to messaging applications on social networks [20].

Forecasting the future on a scale of time is a daunting task in many fields. Stock exchange courses and bull indices projections in the foreseeable future is one example. The prediction of likely quantum of flow of data on networks by data processing specialists is yet another example. The bone of contention is to is about analyzing the currently available trend, the trend in the past to do a prediction of the future. Many techniques exist for the approximation of the underlying process of a time series: Functions that auto regress linearly [21], nonlinearly [22], artificial neural networks [23], Kohonen's feature Maps [24], approximate reasoning based methods[25] and classifiers such as SVMs[26] just to mention a few. For several years, support vector machine have done several rounds in predictions across a vast variety of domains, which consequently led to several other reasonable alternative methods [27]. All these methods have one thing in common that they lay significant emphasis on underlying process and modeling them. The models so developed model are used with the last known values of the series to forecast the future values. The difficulty commonly faced by all these methods is the determination of adequacy and required significant information for precise prediction.

However, there exists no comprehensive study that does data analytics related tasks and related explorations on people's use of social networks in particular. Therefore, it is felt that such an endeavor will not only provide a holistic view of the extent of usage of social media across the globe , but will also provide researchers an opportunity to make comprehensive analysis of skewed uses, preferred uses, and purposeful uses. Apart from predictive analytics of foreseeing the surging of usage numbers, it is also possible to categorize users based on the kind of information that they transpire across. To fulfill this goal, this study makes a focused attempt to develop time series predictive models based on the usage data of three social networks namely, the Facebook, LinkedIn and the Twitter.

3. THE DATA AND THE PRELIMINARY ANALYTICS

The data for developing the models were availed from [28]. The worldwide uses of social networks namely, Facebook, Twitter and LinkedIn for the period 2011-2019 were tabulated in quarterly segmented manner. Initial cleansing of the data such as for typos and other mistakes were done. Missing data was noticed in LinkedIn in terms of number of users for 3 to 4 years. The missing data values were filled by method of imputation by using the value of standard deviation and mean value of available data. A section of the data is presented in Table 1.

3.1 One Dimensional Visual Analysis

The one dimensional view of the data was availed through box plots. The point in concern is just variation in number of users across 2011 to 2019. Fig. 1 shows box plot of Facebook usage numbers, Fig. 2 showcases the variation across the three networks for user data considered annually.

A careful examination of the three box plots delineated for each of the networks reveals the following:

- Facebook enjoys being highest used among all the three. In terms of central tendency, the interquartile range is 800 million users for Facebook, followed by 150 million by Twitter and LinkedIn being at the least with just 50 million users over 9 years of span.
- In a nutshell, with highest users Facebook has evidently shown highest range of user numbers from a minimum of 400 billion to 1700 billion a mammoth spurt of 76% in user numbers over a span of 11 years. This is followed by Twitter with 46% swell and LinkedIn showing a meager raise of 29% in user numbers.
- All the three of them have one thing in common, that there are no outliers.
- The difference between the box plots drawn for quarterly data and annual user data has been only in terms of median, maximum, minimum and quartile values
- One clear demarcation in case of LinkedIn has been the coincidence of median and third quartile values in both the cases.

Table 1. A cross section of the data

Quarters	Year	Twitter(in millions)	Facebook (in millions)	LinkedIn(in millions)
q1	2011	30	372	102
q2	2011	40	417	116
q3	2011	49	457	131
q4	2011	54	483	145
q1	2012	68	526	161
q2	2012	85	552	174
q3	2012	101	584	187
q4	2012	117	618	202
q1	2013	138	665	218
q2	2013	151	699	238
q3	2013	167	728	259
q4	2013	185	757	277
q1	2014	204	802	296
q2	2014	218	829	330
q3	2014	231	864	332
q4	2014	241	890	347
q1	2015	255	936	364
q2	2015	271	968	380
q3	2015	284	1007	396
q4	2015	288	1038	414
q1	2016	302	1090	433
q2	2016	304	1128	450
q3	2016	307	1179	467

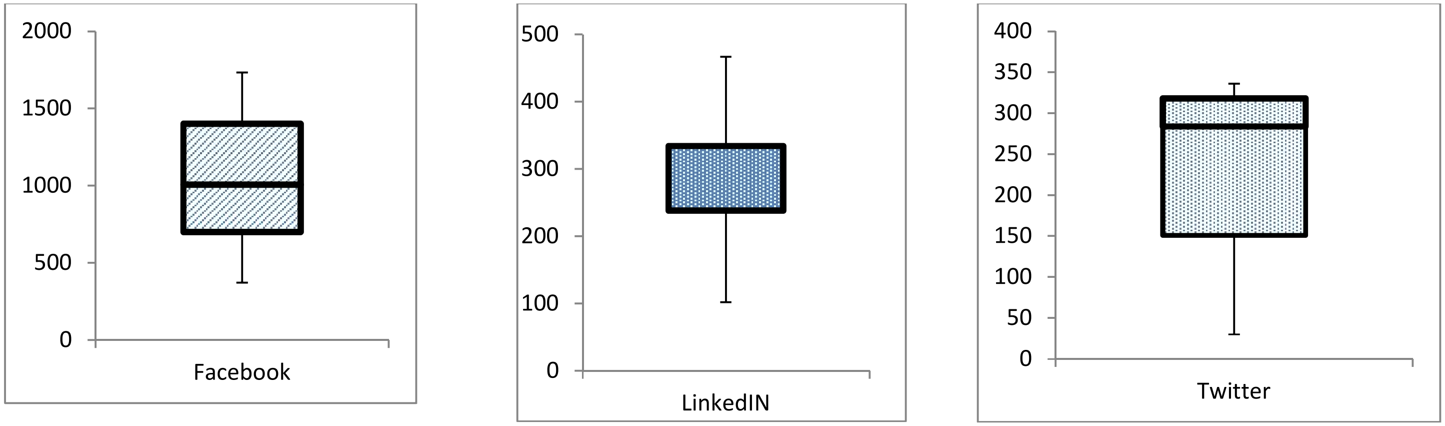

Fig. 1. Box plots of quarterly user numbers for three networks

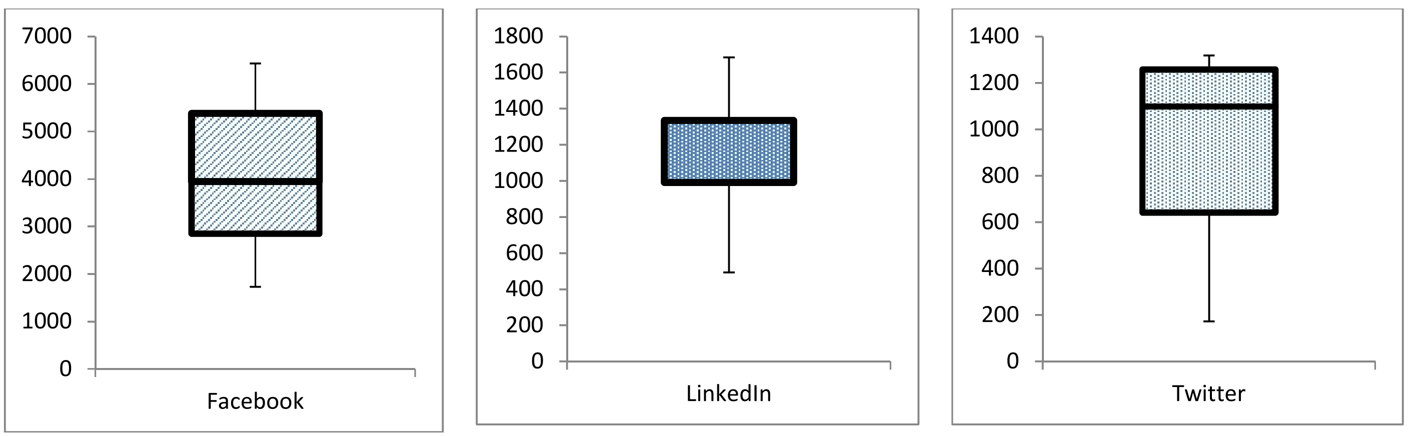

Fig. 2. Box plots of annual user numbers for three networks

The descriptive statistics of the data is presented in Table 2. A close examination of the details presented in the table reveals the following:

- All the statistical parameters i.e., average, standard deviation, variance, median and mode are high with reference to Facebook, with Twitter and LinkedIn following it in a decreasing order.
- High variance values in user numbers of all the three networks indicates that the quarterly numbers showed a wide palpable gap. This value is a testimony that this data deserves a look out for a detailed analytics to draw meaningful insights.
- As far as the distribution of data is concerned, Facebook usage numbers show almost normal distribution. While the negative skewness of twitter and LinkedIn is indicative of a leftward skew.
- Kurtosis value being < 3.0 in all the cases indicate that the peak is broader i.e., platykurtic, with tails of spread quite lesser than normal distribution.

3.2 Two Dimensional Visual Analysis

Two dimensional visual analytics were carried out prior to time series best fit elicitation. The trend lines are separately drawn on quarterly, yearly and half yearly basis. This was done in a bid to find the possibilities of vagaries, sudden spikes and sudden dips in the trend line. The patterns are portrayed in Figs. 3, 4 and 5 respectively in that order.

A meticulous walk on the three trend lines depicting the surges on quarterly, half yearly and yearly basis reveals the following:

- The pattern of surge seems to be almost same. With Facebook at the top with almost monotonic increase in all the three time scales
- Among Twitter and LinkedIn, LinkedIn users outnumber the Twitter users. However, the surge is capped marginally.
- Another interesting observation as with regard to Twitter and LinkedIn has been that beyond last quarter of 2016, the surge almost flattens and shows marginal difference of 8% in quarterly surge. The difference is almost 0% when half yearly and yearly surge numbers.

The third observation points to the fact that, while Facebook usage numbers went skywards, the magnitude of LinkedIn and twitter users was almost moves constantly. This may be attributed to the fact that, the Facebook engulfs all kinds of users of all age groups, while Twitter and LinkedIn have users of typical demographics. Twitter users are younger, wealthier and more educated than an average American [29]. As per the recent survey, most of the LinkedIn users happened to be graduates, and students, senior level influencers and top level executives [30]. The bar chart in Fig. 6 also clearly corroborates the observations elicited from line graphs. The monotonic rise in Facebook user numbers and undulating user numbers in case of Twitter and LinkedIn. Correlation analysis was also done in order to establish, if linear kind of a relation in user numbers is palpable among networks.

The correlation analysis was also done. The correlation matrix is presented in Table 5. With this a three dimensional analytics is administered. It is evident from the matrix that the growth pattern in number of users is almost linearly related in case of Facebook and Twitter. The user number growth is fairly linearly related in case of LinkedIn and Twitter also. However such relation is not evident in case of LinkedIn and Facebook.

Table 2. Descriptive statistics of user numbers

	Twitter	Facebook	LinkedIn
Mean	232.8108108	1035	299.8648649
Standard Deviation	103.5011642	407.8555708	93.85454531
Variance	10712.49099	166346.1667	8808.675676
Mode	330	#N/A	334
Median	284	1007	334
Skewness	-0.76042394	0.059271796	-0.572415308
Kurtosis	-0.930844291	-1.277995607	-0.329642087

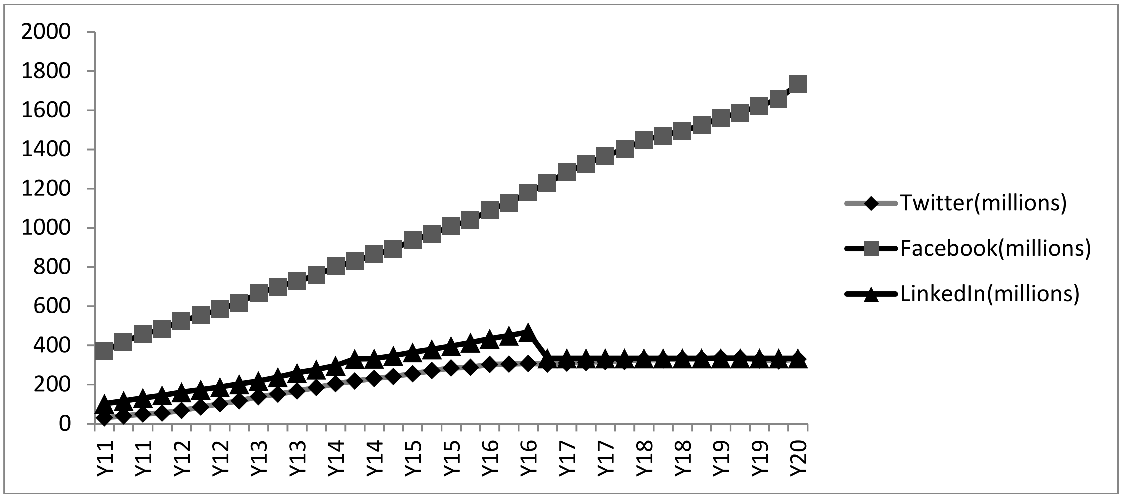

Fig. 3. User numbers quarterly surge trend line

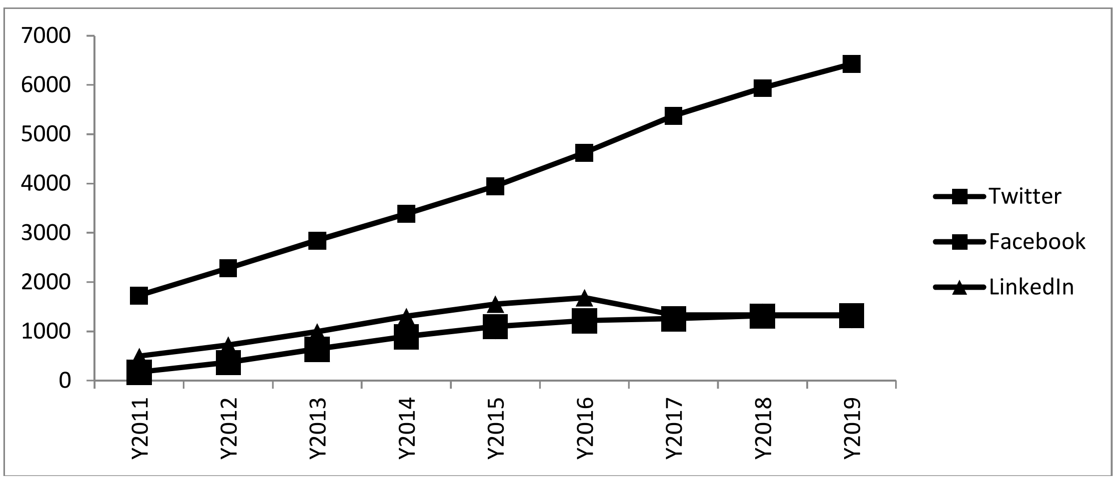

Fig. 4. Yearly surge trend in user numbers

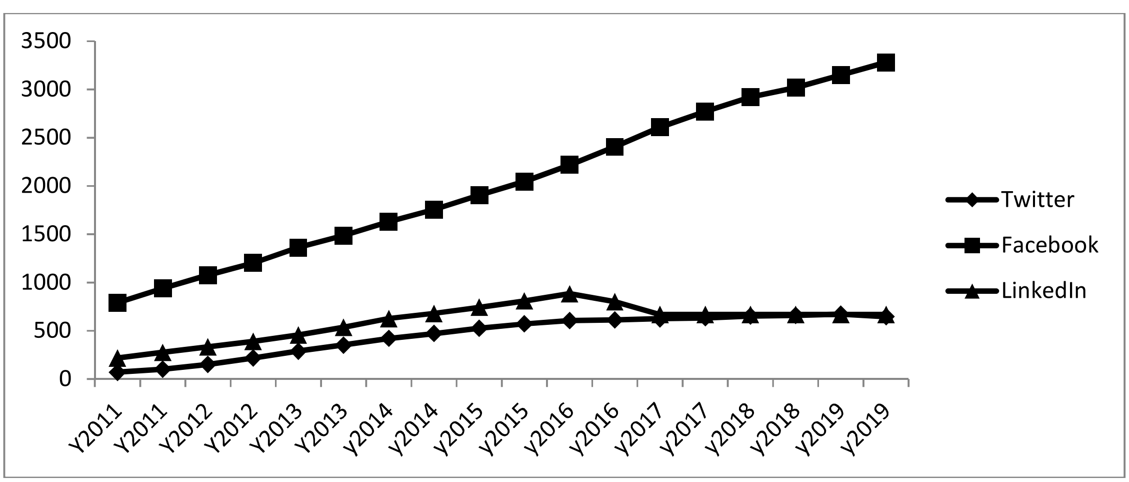

Fig. 5. Half yearly trend in user numbers surge

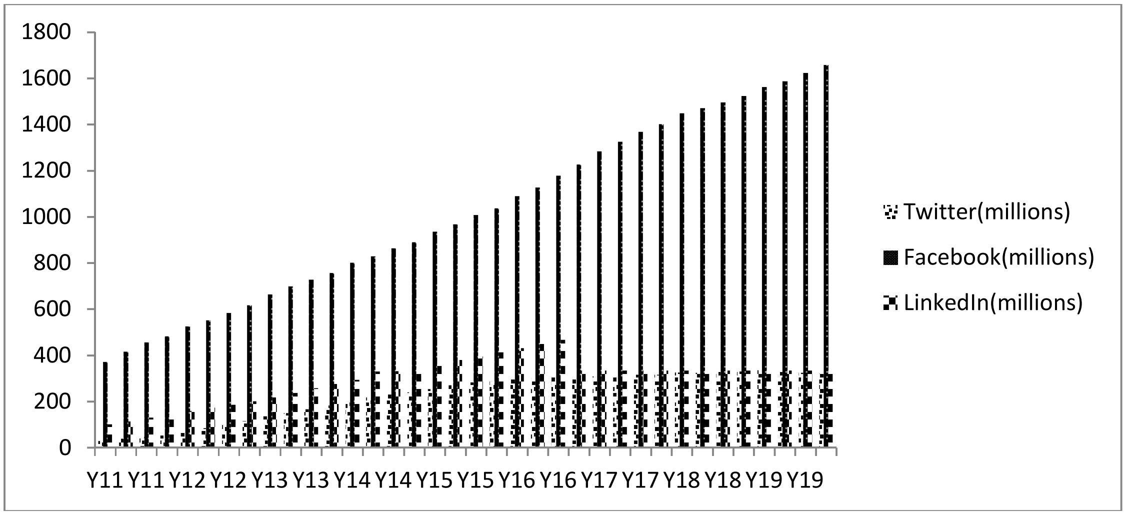

Fig. 6. Bar chart depicting the quarterly user numbers across networks

Table 3. Correlation matrix

	Twitter	Facebook	LinkedIn
Twitter	1		
Facebook	0.932555	1	
LinkedIn	0.885902	0.687131	1

4. TIME SERIES MODELS

The data as presented in various sequels were modeled and functions are fitted. The curve fitting exercise was done using R. Time plot is one of the most clear graphical representation for the time series in which the data is plotted against time. Time series forecasting is the use of a model to predict future values based on previously observed values. While regression analysis is often employed in such a way as to test theories that the current values of one or more independent time series affect the current value of another time series, this type of analysis of time series is not called "time series analysis", which focuses on comparing values of a single time series or multiple dependent time series at different points in time. Curve Fitting is the process of constructing a mathematical function or a curve is the curve fitting. That has the best fit to a series of data points, possibly subject to restraints. Either Interpolation or smoothing is involved in curve fitting where an exact fit to the data is required, or in which a "smooth" function is constructed that approximately fits the data respectively. A related topic is regression analysis and statistically inference. Regression analysis targets more on questions and in statistical inference observation of how much uncertainty present in a curve that is fitted to data with random errors is done. To ascertain values of a function where no data are applicable, Fitted curves can be used as an assistance for data visualization and to compile the relationships among two or more variables. The use of a fitted curve beyond the range of the actual data, and is subject to a degree of uncertainty refers to extrapolation, since it may reflect the method used to construct the curve as much as it reflects the actual data.

Fig. 7 (a)-(d) shows the four types of lines of fits for Twitter user data on quarterly basis while Fig. 8(a) – (d) displays the four types of lines of fit for annual user data. In both the cases, polynomial fits seems to augur well with its high regression coefficient almost equal to 1.

In the same token, among the yearly user data trend lines of Twitter, polynomial seemed to be best with highest regression coefficient, followed by linear and logarithmic lines of fit. So far as LinkedIn is concerned, the quarterly data seemed to be unwieldy due to sudden fall at 25th month and flattening from thereupon. These observations are clearly visible in Fig. 9(a) –(d). With this flutter, still the polynomial regression line has almost aligned with the data points and also has shown adequate regression coefficient of 0.87.

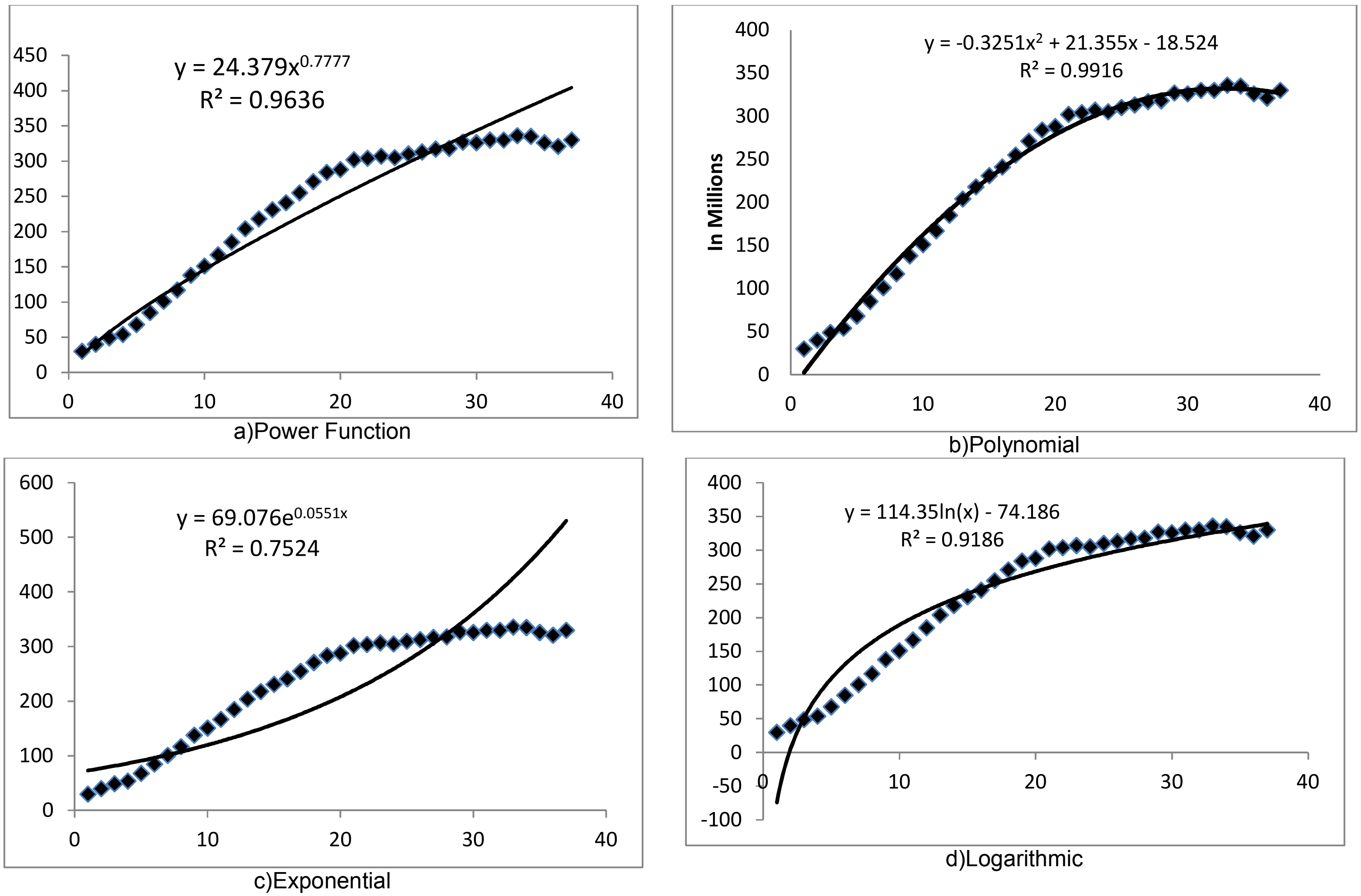

Fig. 7. Time series lines of fits quarterly data for Twitter

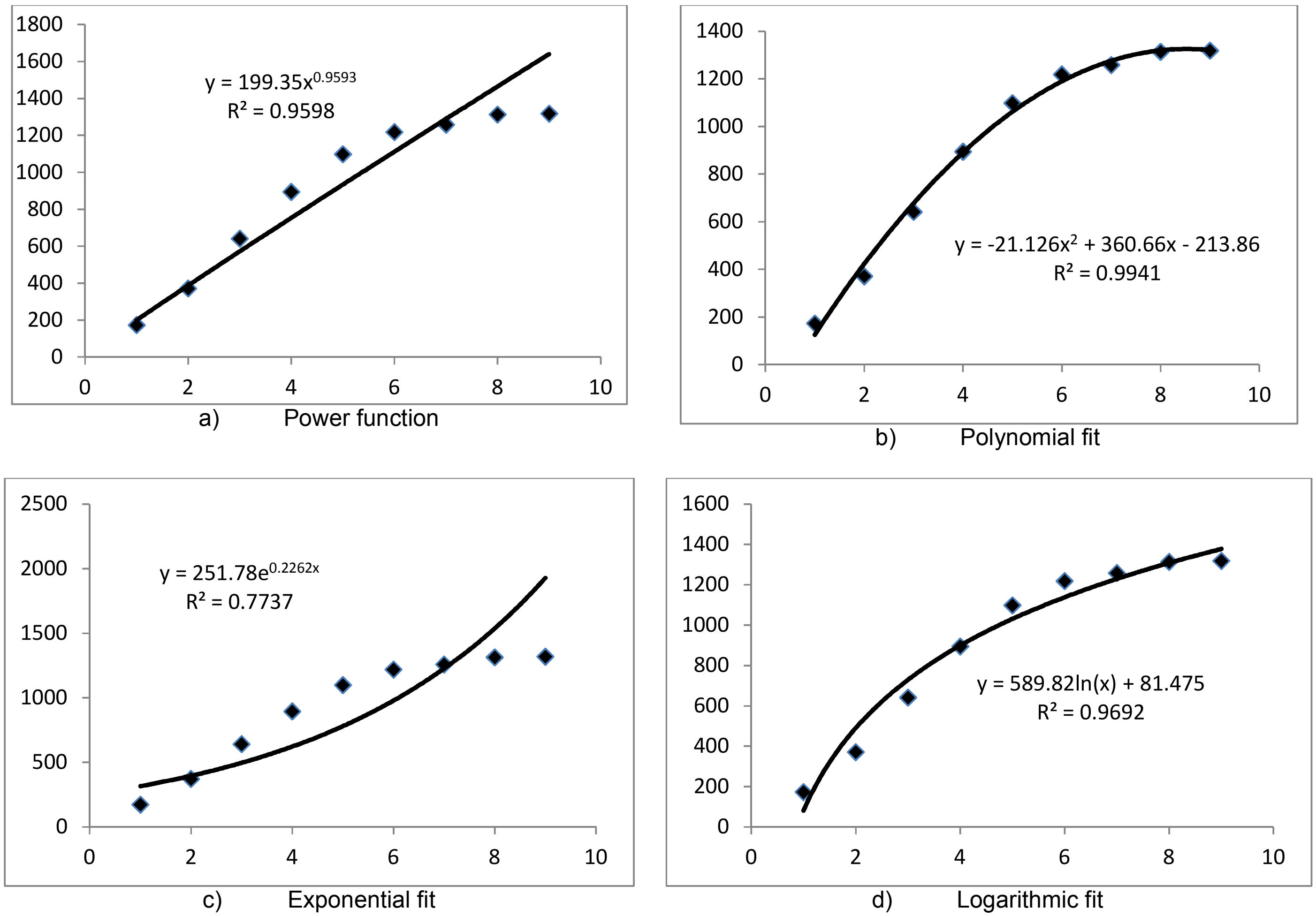

Fig. 8. Time series lines of fits yearly data for Twitter

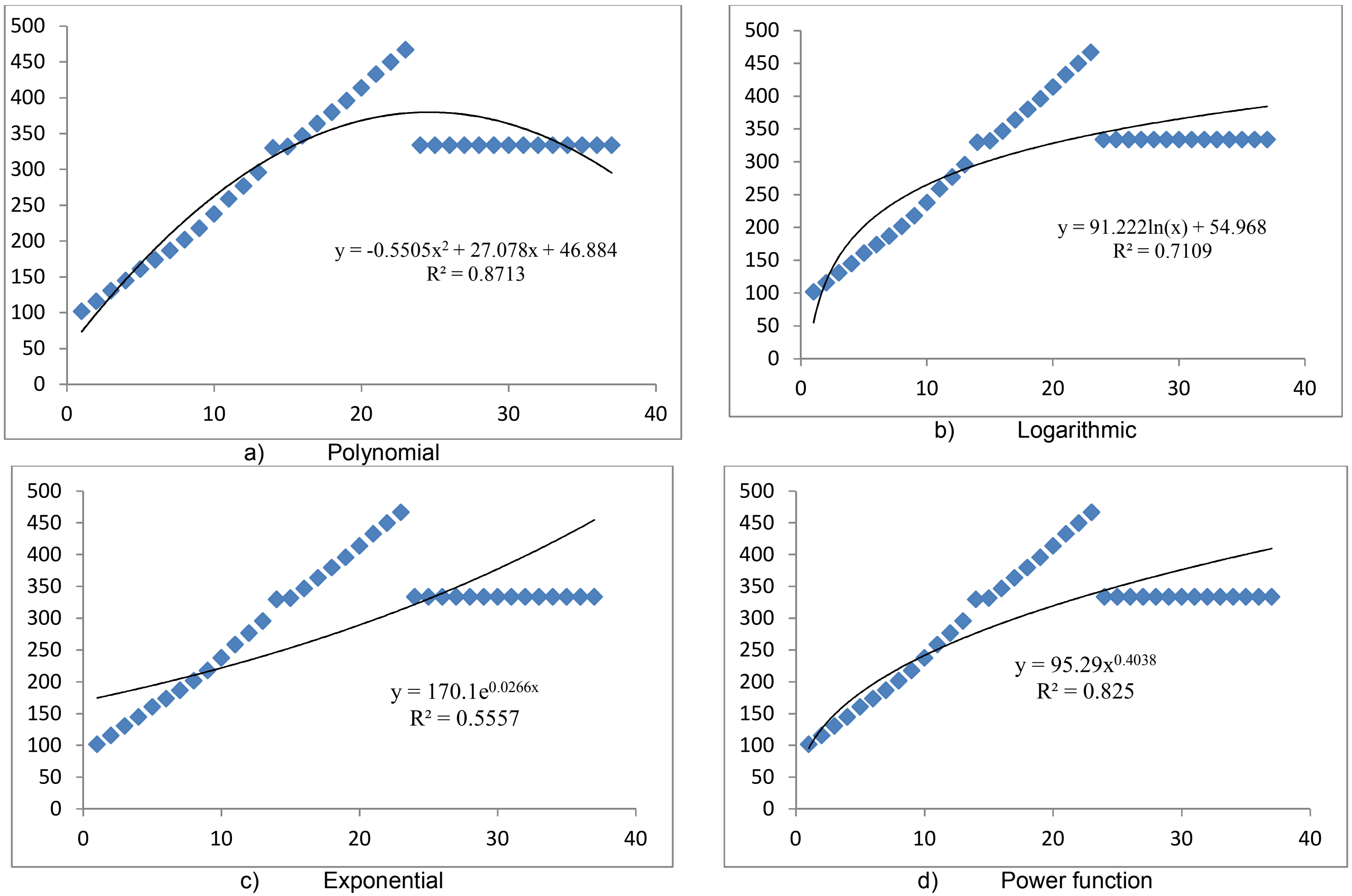

Fig. 9. Various lines of fit for Quarterly use (LinkedIn)

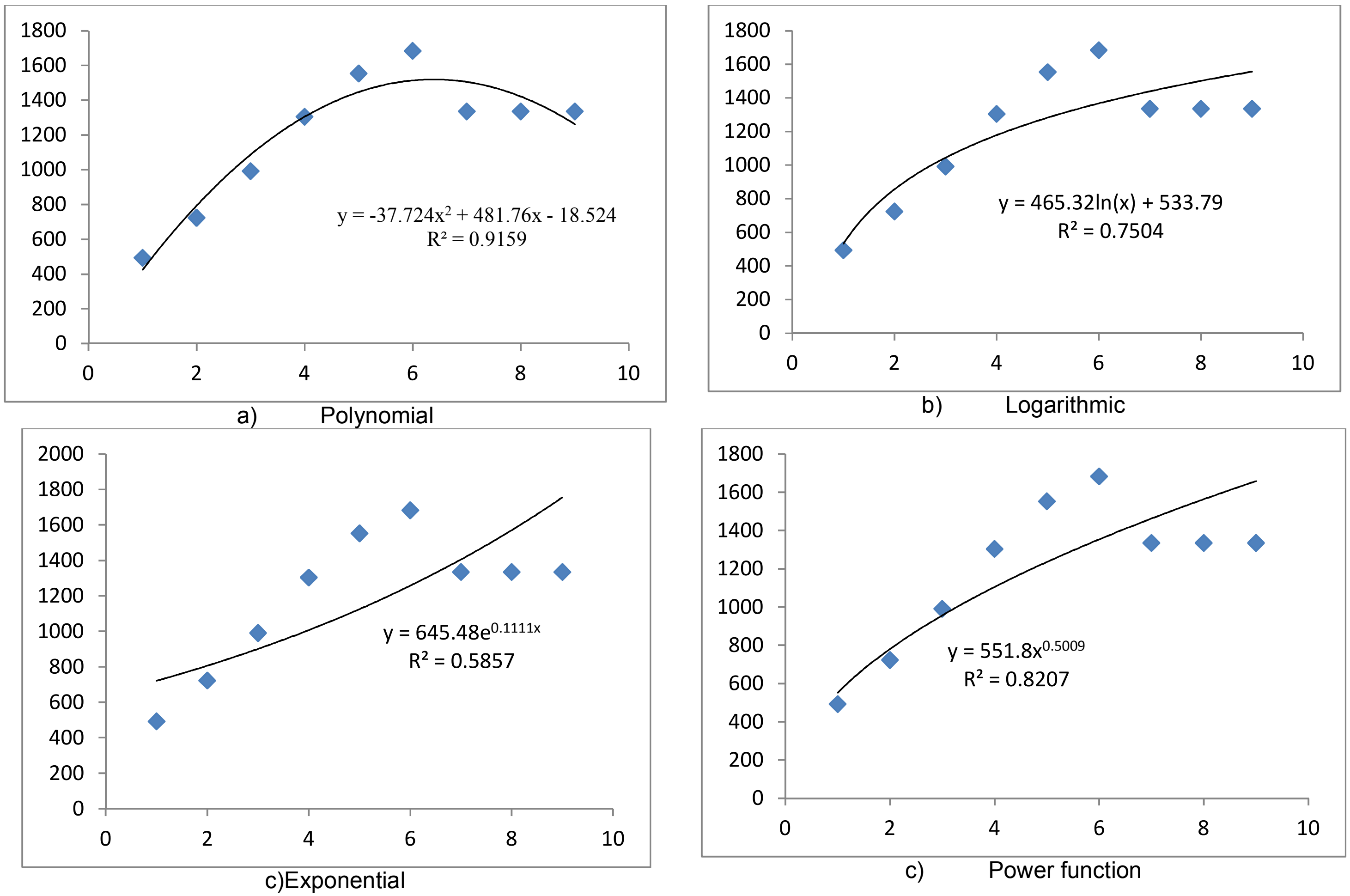

Fig. 10. Various lines of fit for yearly users data (LinkedIn)

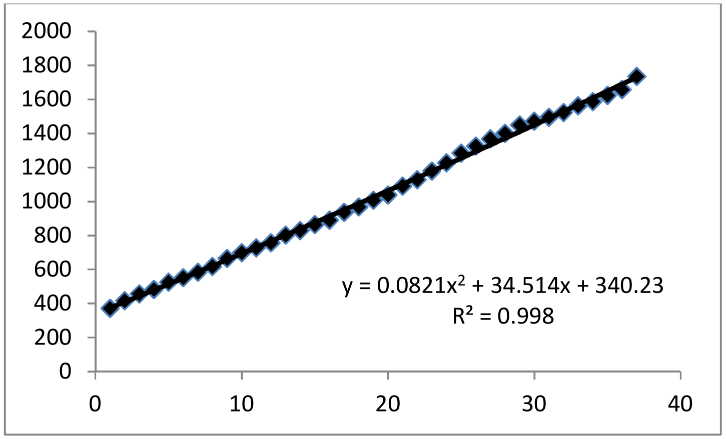

Fig. 11a. Polynomial fit

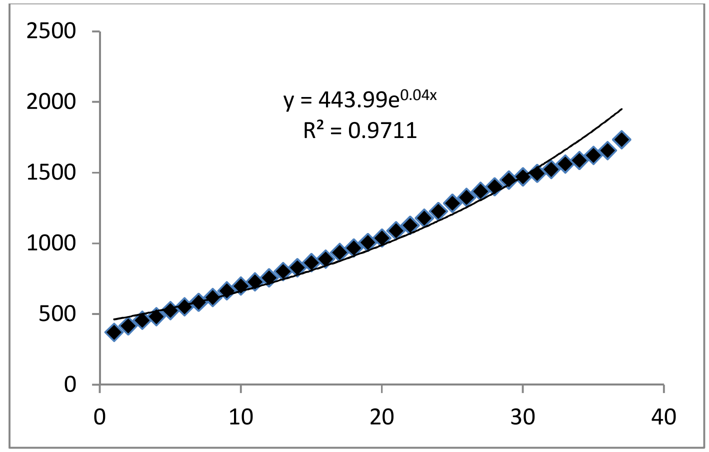

Fig. 11b. Exponential fit

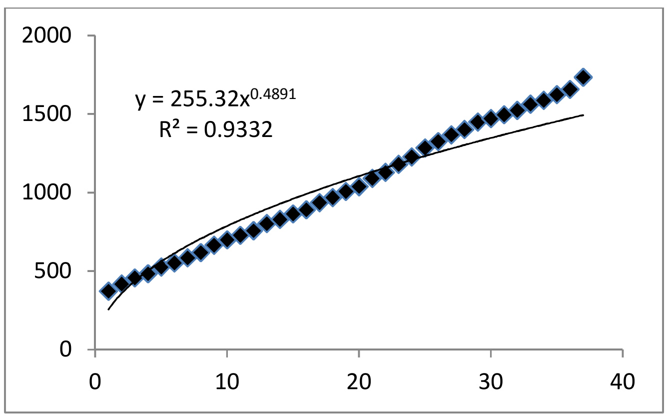

Fig. 11c. Power function

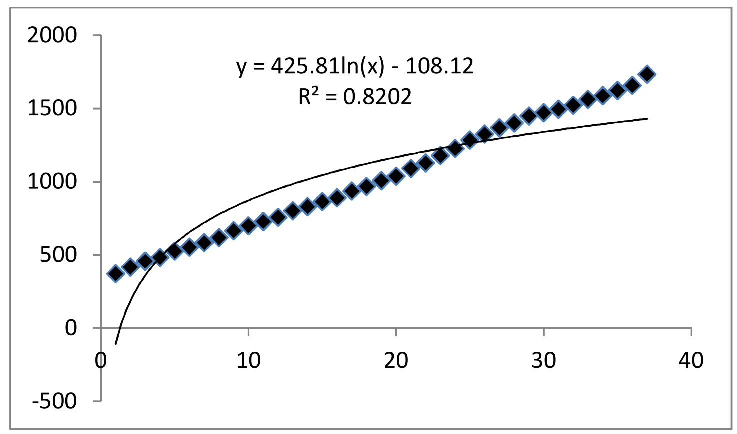

Fig. 11d. Logarithmic function

Fig. 11. Various lines of fit for quarterly data (Facebook)

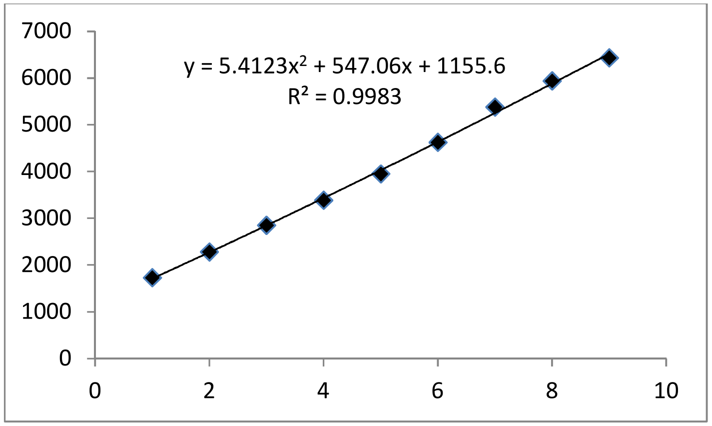

Fig. 12a. Polynomial fit

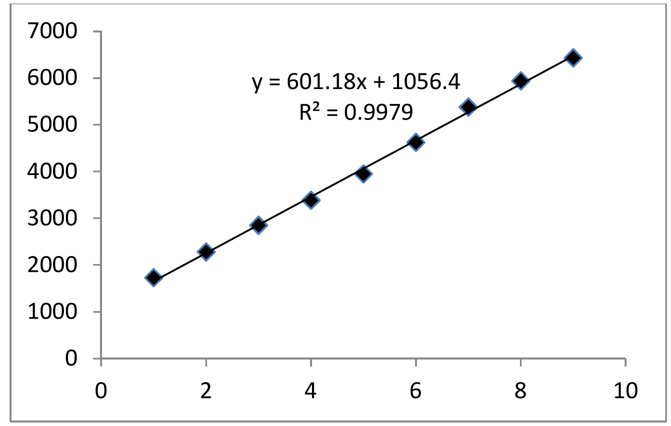

Fig. 12b. Linear fit

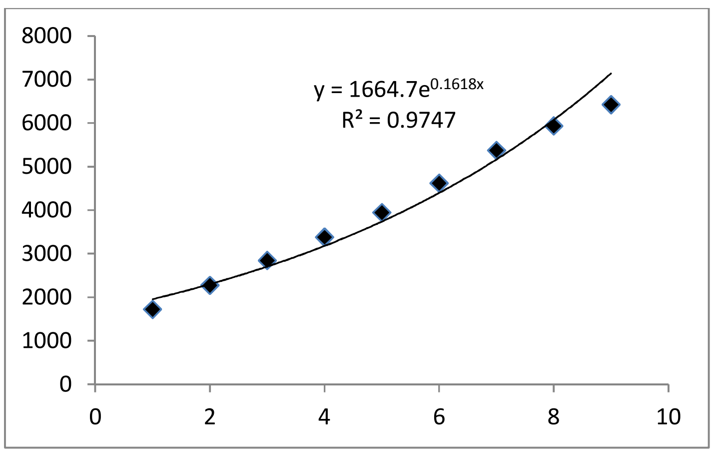

Fig. 12c. Exponential fit

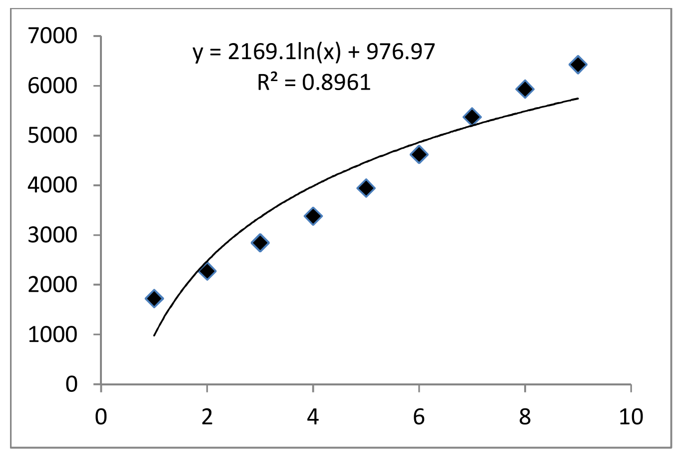

Fig. 12d. Logarithmic fit

Fig. 12. Various lines of Time series fits for annual data (Facebook)

Table 4. Models and the error metrics

Time series model	MAE	RMSE
FACE BOOK		
Linear	28.06	796.17
Polynomial	48.67	910.45
Exponential	261.16	934.7
TWITTER		
Polynomial	25.71	78.59
Power function	115.21	91.68
Logarithmic function	125.32	112.56
LINKEDIN		
Polynomial	93.29	250.01
Power function	158.22	256.78

However, when yearly data pertaining to LinkedIn is considered, the polynomial regression line seems to have fitted very well with improved regression coefficient of 0.92. In case of Facebook user number surge pattern, the swelling of numbers seemed monotonic for both quarterly as well as yearly data. This is portrayed in Figs. 11 and 12. As far as quarterly data is considered, both polynomial and exponential fits seemed to augur well with regression coefficients as high as 0.99 and 0.97 respectively. When yearly user's data is considered, polynomial and simple linear lines of fit showed high regression coefficients of almost equal to 1.

5. THE ANALYSIS AND EVALUATION OF MODELS

Apart from hinging on best fit based on high regression coefficients, the models are evaluated for the quantum of errors using mean average error (MAE) and root mean square error(RMSE). The values found for all the models considering only yearly users data is presented in Table 3. A closer examination of the lines of fit developed indicates that, for the three social networks, polynomial fitting holds fairly well with low RMSE and MAE. However, for LinkedIn, these two metrics are at a higher side. The regression coefficients in all the cases are above 0.9 which is adequate enough to consider them as best fits in the order of the coefficients.

5.1 Theil's U-Statistic

Theil's U is a statistic used to evaluate whether or not a forecasting model is superior to naive forecasting. Values less than 1 indicate the model is superior, while values greater than 1 indicate the model is worse than naive forecasting. The statistic is calculated as the square root of the ratio of the sum of the squared errors, forecasting model to naive forecasting. Mathematically, this statistic is given by [31-38],

$$U= \sqrt{\sum_{t=1}^{(n-1}(FPEt+1-APEt+1)^2/} \quad t{=}1n{-}1(APEt{+}1)2 \qquad (1)$$

Where, FPEt+1=Ft+1-Yt/Yt is the forecast relative change and the term, and APEt+1=Yt+1-Yt/Yt is the actual relative change. The statistic as computed for all the four models is tabulated in Table 4. From the Table 4, it is evident that linear model and polynomial model are superior in terms of forecasting the Facebook users data. Polynomial and power function (to a lesser extent) emerged as fair models for Twitter users data. LinkedIn data was so undulating in terms of users numbers, so much so that both polynomial and power functions showed quite higher values U- statistic (> 1.0). However, they were retained as the other time series fits showed lesser values of regression coefficients.

Table 5. The Theil's U-statistic values for the models

Model	Value
Facebook	
Linear	0.928
Polynomial	1.002
Exponential	1.213
Twitter	
Polynomial	1.08
Power function	1.15
Logarithmic	1.45
LinkedIn	
Polynomial	1.21
Power function	1.68

6. DISCUSSIONS AND FUTURE PROJECTION

From the foregone presentations of trends in social network user's progressive surge in numbers, as well as the associated models developed in this work, following analysis is recorded.

- There is a continuous increase in users in multiples for all the three social networks are considered in general and huge surges for Facebook in particular.
- The increase in users numbers is incremental as far as LinkedIn is considered (though the numbers are in billions) relative to other two networks.
- Thiel's-U Statistic being slightly more than one indicates that the time series models are excellent particularly linear and polynomial model in case of Facebook. Polynomial time series models emerged to be the best for Twitter and LinkedIn though they are marginally higher than the notional value of 1.
- The descriptive statistical features of the user number data indicate that there is a greater variation in the yearly use. The distribution of the data is skewed and the shape of the distribution is almost bell shaped (leptokurtic) which is indicated by kurtosis.
- A rough projection of future user numbers by 2025 for Facebook, Twitter and LinkedIn using the top best fitting models is slated to be projected as 10,000+ billion, 750 billion, and 1500 billion respectively. However, the caveat is that the same kind of increasing trend should prevail.

7. CONCLUSION

This paper presented a unique work which is supposedly deemed to be the first of its kind to the best of the knowledge of authors. With social media becoming ubiquitous with surging usage numbers year after year, reasonable mathematical models that will help to foresee the near future trend is of dire need. It is exactly here, that this paper meets the significance. The time series models that are developed in this work is of immense use to predict the possible spike in the number of users trimester wise and annually. Such future projections can be utilized in proper planning and evolving, articulating new user friendly approach oriented design of network interfaces and also controlling unruly behavior of users if at all they crop up. However, the models come with a limitation that, they can provide accurate projection if the same trend prevails in the pattern of upheavals in usage. Finally, the outcomes of this paper may be listed as follows:

- Establishment of amenability of social media network user's numbers and its growth on a time scale to be the candidate research problem for time series trend analysis.
- Development of various time series models for three potential social networks namely, the Facebook, LinkedIn and the Twitter.
- Projection of approximate numbers of users in the near future using the robust model among the models so developed.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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