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SHORT TERM AND LONG TERM FORECASTING OF CLOUD COMPUTING USING MULTIPLE INDICATORS

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ABSTRACT

In recent times, the cloud computing model is strongly influencing IT world and enterprises. The increasing interest of enterprises, technology developers and Governments in cloud computing creates a need to investigate the potential direction and rate of technological change. This paper presents short term and long term forecasting of cloud computing with the workload, data traffic, revenue and number of service providers as an indicator. Genetic algorithms and particle swarm optimization (PSO) are designed for short term forecasting. The results are compared with double exponential smoothing method. Results of GA and PSO are close to the best but fine tuning is necessary. Cloud adoption curve and industry life cycle are identified using best-fitted growth curve from logistics, gompertz, log logistic and mono molecular. These growth curves are implemented using autoregressive regression that further improved using genetic algorithms. Logistic growth curve is best fitted to all datasets except PaaS providers. The results show that cloud computing technologies show "S shaped" growth pattern for all the selected indicators with very fast growth rate. Cloud computing technologies have crossed the inflection point in between the year 2011 and year 2014 for all selected datasets. Use of multiple methods and multiple indicators validates the growth pattern of cloud computing. Results show that the growth of Software as a Service cloud provider's revenue is very fast as compared to Infrastructure as a Service and Platform as a Service. The growth in the number of platform as a service cloud providers is very slow as compared to infrastructure as a service and software as a service.

Keywords: Cloud computing, technology life cycle, technology forecasting, growth curve, multiple indicators, evolutionary algorithms.

INTRODUCTION

Every product or technology follows a life cycle pattern from introduction to decline. The Product Life Cycle (PLC) concept was developed in the 1950s. Since then, it is important part of marketing theory [19]. One of the important purposes of the PLC concept is to identify the current stage of product in its life cycle pattern and accordingly select the best strategy for sales, cost, profit, competitor etc. [19]. Since the mid 1980's, several authors has noted that technological development follows certain patterns [31]. Life cycle pattern of technology consists of several distinct stages. Generally, the stages are introduction, growth, maturity and decline [5, 14, 24]. Sales, revenue, cost, competitors etc. shows different behavior during different phases of the product life cycle and technology life cycle.

In the literature, a wide range of technologies are analyzed/forecasted such as biotechnology, optical storage, RFID, 3D TV, programming languages, operating systems, supercomputers, semiconductors, vacuum tubes, steam engines etc. In the last few years, cloud computing is a buzzword in the technology industry. According to McKinsey Global Institute [29], KPMG and NASSCOM [33], IDC [16], Gartner [37] and many other firms cloud computing is a disruptive technology that will make a huge impact on enterprises, communities and societies. There is a need for sensitizing various players about to be judicious in investing heavily on technology systems as it undergoes the inevitable life cycle and informing them at what stage of technology life cycle they are entering. Selection of appropriate indicators and methods is important for accurate forecasting of values/trends. In the literature, different indicators are used to measure technologies. Generally, direct measures such as sales data, revenue and market share are frequently used for forecasting. A large number of methods have evolved for technology forecasting. Forecasting methods are divided into quantitative techniques and qualitative methods. Proper selection and application of methods to the problem is an important issue [14, 20, 30].

The subject of this study is the application of the technological forecasting methods to the process of life cycle analysis of cloud computing. The primary objective of this paper is to forecast the direction and rate of growth of cloud computing technologies. The main objective is divided into three sub-objectives.

1. To identify the technology indicators for cloud computing forecasting.
2. To identify necessary and suitable technology forecasting methods.
3. To compare the performance of statistical and evolutionary methods such as genetic algorithms and particle swarm optimization.

Paper presents short term and long term forecasting of cloud computing using multiple indicators. Time series data of workload, data traffic, revenue and number of providers are used as an indicator. In literature, it is observed that long term forecasting of many technologies follows a trend that is similar to an S-shaped curve [1, 3, 6, 13]. Diffusion curve shows the penetration of the technology in the market. Time series data of workload, data traffic and revenue are used to identify cloud adoption curve. The industry life cycle model hss emerged from the PLC concept and the diffusion models [25]. ILC model characterizes an ideal evolution of an industry over time. Management of technology [35] and concepts from “supply-side” microeconomics and evolutionary economics [18] supports industry life cycle theory. Number of providers is used as an indicator for industry life cycle model.

Paper presents the quantitative forecasting of cloud computing using statistical and evolutionary methods. Double exponential smoothing, genetic algorithms and particle swarm optimization are designed for short term forecasting. Four growth curve methods namely, logistic curve, gompertz curve, log logistic growth model and mono molecular growth model are investigated for long term growth trajectory forecasting.

The rest of the paper is organized as follows: In the next section, the forecasting methods used for cloud computing forecasting is described. Experimental details of different statistical and evolutionary methods, results and discussion are then explained in the next section. Finally, the conclusions of our study are outlined.

METHODOLOGY

This section explains forecasting methods used for investigation of the growth and trajectories of cloud computing. These methods belong to trend analysis techniques. Trend projections and growth curves are used to predict the direction and rate of change of technologies. The investigation focuses on the following two important research issues.

- In order to improve the quality of technology forecasts, multiple datasets need to be analyzed. Paper [22, 26] reported that the use of a single indicator is not reliable and suggested the use of multiple indicators in analyzing technological developments. In literature, different researchers have investigated the technology forecasting using multiple performance indicators [2, 21].
- There is no one perfect method which can serve as a one stop destination [32]. Authors suggested the use of multiple methods of technology prediction for future research [34].

Identify the Trend in the Dataset

A time series is a value of selected indicator measured over successive points in time. Historical time series data helps to understand the pattern of past behavior of technology for selected indicator. Time series methods identify the pattern in the historical data and then extrapolate it for the future. In this investigation, we have tested linear and four nonlinear trend line functions listed below. In these equations, *'y'* and *'x'* indicates the dependent and independent variables respectively. The variables *'a'*, *'b'* and *'c'* are coefficients in the equations.

Linear	$y = ax + b$
Exponential	$y = ae^{bx}$
Logarithmic	$y = a\log(x) + b$
Polynomial	$y = a + bx + cx^2$ for 2nd order $y = a + bx + cx^2 \ldots\ldots nx^n$ for nth order
Power Law	$y = ax^b$

Identifying the Appropriate Exponential Smoothing Method Based on the Existence of Trend and Seasonality

Time series data consists of a level pattern plus fluctuations caused by seasonality and randomness. The smoothing models attempt to smooth the fluctuations in time series by smoothing or averaging. Exponential smoothing is one of the statistical methods commonly used for forecasting. Double exponential smoothing (DES) is a familiar method used for trend forecasting.

In this paper, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to find suitability of methods.

$$MAE = \frac{\sum_{t=1}^{N} |E_t|}{N} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} E_t^2}{N}} \tag{2}$$

We identified the best suitable coefficients of the exponential smoothing method for each dataset. Results are forecasted using the best suitable method and coefficients.

Identifying the Best-Fitted Polynomial Trend for Short Term Forecasting Using GA and PSO

In this investigation, GA and PSO are used to find the best-fitted polynomial equation. Polynomial equation is based on two previous historical data points and polynomial equation of degree one.

$$x_t = a_1 + a_2 x_{t-1} + a_3 x_{t-2} \tag{3}$$

Genetic algorithms is population-based evolutionary Algorithm. Genetic Algorithms (GAs) is based on the natural evolutionary process [17]. Structured randomness and no need for problem-specific information is the strength of the algorithm. Algorithm 1 explains the basic steps of genetic algorithms.

i. *Random initialization of population*
ii. *Fitness calculation of each individual*
iii. *Selection of individuals for reproduction*
iv. *Crossover to produces new offspring*
v. *Mutation*
vi. *Go to step ii, and repeat until stopping criteria*

Algorithm 1: Standard Genetic Algorithms

Particle swarm optimization (PSO) is one of the popular evolutionary algorithms. PSO is a population-based algorithm. The population is called swarm and the individuals are called particles. In each iteration, current best position (pbest) and global best position (gbest) are calculated. Particles modify their position and velocity to adjust with pbest and gbest. Algorithm 2 explains the basic steps of particle swarm optimization.

i. *Random initialization of swarms*
ii. *Fitness calculation of individual particles*
iii. *Modify global best value and current best value*
iv. *Update position and velocity of each particle*
v. *Go to step ii, and repeat until stopping criteria*

Algorithm 2: Standard Particle Swarm Optimization Algorithm

Calculate Growth Curve Coefficients using Regression and Genetic Algorithms

Growth curve methods are quantitative and require numerical historical data. First, it fits the data and then projects the future values. Growth curves are used for forecasting the performance of technologies [12, 27] and diffusion of technology [4, 15]. In literature, different growth curve methods are investigated for technology forecasting. Paper [28] compared 17 models for the telecommunication market in 15 countries. Performance of the gompertz model and logistic model is found better than other complex models. Paper [23] presented twelve nonlinear growth models for oil palm yield growth.

Logistic model is found to be best-fitted followed by the gompertz model.

Logistic curve and gompertz curve are the most frequently referenced growth curves. In this paper, the following growth curves are investigated. Growth curves are implemented using regression method. Genetic algorithms is used to improve the fitting of growth curves.

Logistic	$y_t = \frac{L}{1+ae^{-bt}}$
Gompertz	$y_t = Le^{-ae^{-bt}}$
Log logistic	$y_t = \frac{L}{1 + a\exp(-b * log(t))}$
Mono Molecular	$y_t = L(1 - a\exp(-bt))$

EXPERIMENTAL DETAILS, RESULTS AND DISCUSSION

This section describes the experimental details and results of short and long term forecasting of cloud computing.

The workload and data traffic dataset are prepared using following reports Cisco global cloud index [7-10]. SPAMINA, Cloud email and web security [11] has published the list of cloud computing providers. We have prepared the time series dataset for Infrastructure as a Service, Platform as a Service and Software as a Service.

Table 1 shows the performance measures for trend lines on indicators of cloud computing. R-squared value indicates how close the data points are to the fitted regression line. The result indicates that the polynomial trend line of 2nd order is best-fitted to fifty percent of the cases. All the datasets show a nonlinear trend.

Results of Double Exponential Smoothing Method

Results of trend line indicate that trend is present in time series data. Hence, double exponential method is applied for forecasting. Double exponential smoothing method is tested with different smoothing values. Values of the smoothing constants are selected objectively. We search for those values, which minimizes the forecast errors.

Table 2 shows performance measures and obtained the best smoothing constants for double exponential smoothing method on adoption indicators of cloud computing. In these experiments, it is observed that the best constants of double exponential smoothing method, α and β values, are different in each case.

Table 1: Performance Measures for Trend Lines

Dataset	Trend line (R^2 Value)				
	Linear	**Exponential**	**Logarithmic**	**Polynomial**	**Power Law**
Data Traffic	0.9977	0.8591	0.9402	**0.9982**	0.9737
Workload	0.967	0.9879	0.8481	**0.9899**	0.9689
IaaS Revenue	0.9415	0.9273	0.7922	0.9666	**0.9834**
PaaS Revenue	0.7877	**0.9987**	0.5761	0.9864	0.941
SaaS Revenue	0.9346	0.9977	0.764	**0.9998**	0.9375
IaaS Providers	0.89	0.91	0.78	**0.92**	0.92
PaaS Providers	0.71	0.72	0.75	0.73	**0.84**
SaaS Providers	0.95	0.89	0.91	0.95	**0.97**

Table 2: Results of Double Exponential Smoothing Method

Dataset	Error measures		Smoothing constants	
	MAE	**RMSE**	**α**	**β**
Data Traffic	419.6	469.96	0.7	0.9
Workload	3.4	5.422	0.4	0.1
IaaS Revenue	0	0	0.5	0.4
PaaS Revenue	0	0	0.5	0.5
SaaS Revenue	0.5	1.08	0.3	0.8
IaaS Providers	19.17	22.91	0.6	0.9
PaaS Providers	4.83	6.76	0.7	0.9
SaaS Providers	16.5	19.84	0.8	0.9

Experimental Details and Results of GA and PSO for Short Term Forecasting

In this work, we have used one-dimensional solution representation where the size of the array is equal to the multiplication of number of historical data point and degree of polynomial equation. The values in the array indicate the coefficients polynomial equation. Mean absolute error (MAE) and root mean square error (RMSE) shown in Equation 1 and Equation 2 respectively are used as an objective function. Solution representation and fitness function for GA and PSO are same.

Different selection, crossover and mutation operators from genetic algorithms library- GAlib [36], are tested. The operators and parameter values, which give the best results are:

- Initialization: Ordered Initializer
- Selection operator: Tournament

- Crossover operator: Two Point
- Mutation operator: Flip
- Scaling: Sigma Truncation
- Population size = 40
- Crossover probability = 0.8
- Mutation probability = 0.1
- Overlapping population = 25%
- Termination criteria (Best value) = 0
- Termination criteria (Number of generations) = 1000

Table 3 gives details of PSO parameters used in experimentation.

Table 3: PSO Parameters

Swarm size	10+2*sqrt(D)
Maximum number of particles informed by a given one	3
Topology of the information links	randomly modified after each step if there has been no improvement
Random distribution of c	uniform distribution on [0, c]

Table 4 presents a comparison of double exponential smoothing method, best-fitted genetic algorithms and best-fitted PSO for short term forecasting. Performance of best-fitted genetic algorithms and particle swarm optimization are approximately the same. Performance of double exponential smoothing is better for many datasets.

Figure 1-4 shows the results of the best-fitted short term forecasting methods of selected cloud computing indicators. Results show that the revenue of all the cloud computing service models is increasing. The revenue value and growth rate for software as a service is very high as compared to infrastructure as a service and platform as a service. Results show that cloud computing workload and data traffic is increasing very rapidly. Forecasted results for the year 2014 to 2018 indicate that there is an increase in the number of cloud service providers. The growth in number of the PaaS cloud providers is very slow as compared to IaaS and SaaS.

Table 4: Comparison of DES, GA and PSO for Short Term Forecasting

Dataset	**Error measure**	**DES**	**Best-fitted**	**Best-fitted PSO**
Data Traffic	MAE	419.6	83.2	84.79
	RMSE	469.96	124.97	107.9
Workload	MAE	3.4	4.62	5.03
	RMSE	5.42	5.6	5.79
IaaS Revenue	MAE	0	0.76	0.74
	RMSE	0	0.84	0.79
PaaS Revenue	MAE	0	0.11	0.18
	RMSE	0	0.13	0.37
SaaS Revenue	MAE	0.5	2.32	2.28
	RMSE	1.08	2.63	2.58
IaaS Providers	MAE	19.17	14.38	14.38
	RMSE	22.91	20.45	20.44
PaaS Providers	MAE	4.83	8.08	8.65
	RMSE	6.76	11.57	10.89
SaaS Providers	MAE	16.5	7.34	8.573
	RMSE	19.84	10.21	11.01

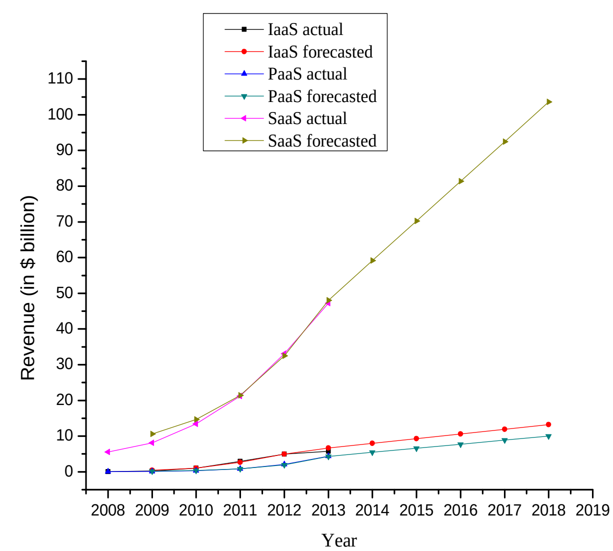

Figure 1: Forecasted Results of Best-fitted Method (DES) on Revenue

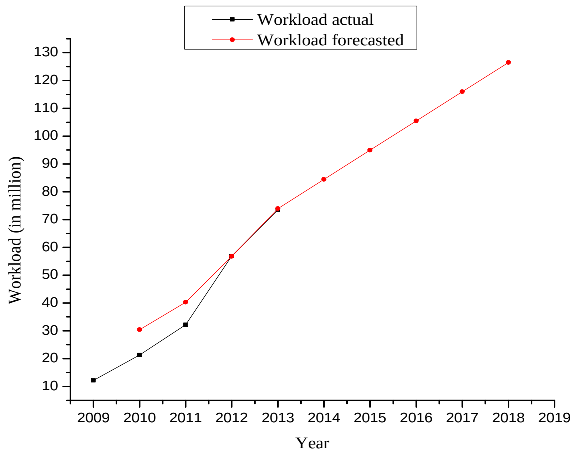

Figure 2: Forecasted Results of Best-fitted Method (DES) on Workload

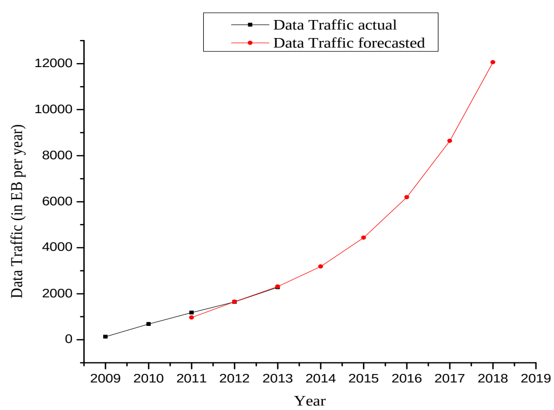

Figure 3: Forecasted Results of Best-fitted Method (Genetic Algorithms) on Data Traffic

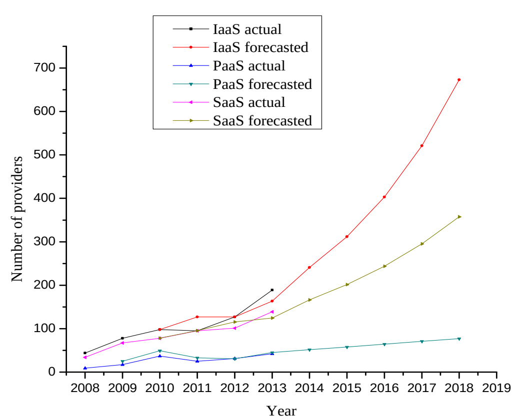

Figure 4: Forecasted Results of Best-fitted Method on Number of Providers

Cloud Computing Life Cycle Using Growth Curve

The assumption behind growth curves is that the upper limit of the technology is known. The choice of the upper limit is independent of the choice of the growth curve. The upper limit for the selected technologies based on patents and papers is unknown. The upper limits taken in this investigation are sufficiently higher values than recent historic data value. Upper limit for each technology and each dataset is different. If the chosen growth curve matches the dynamics of the growth of the technology then the extrapolated data matches the future behavior of the technology.

Autoregressive regression and genetic algorithms are used to calculate coefficients of growth curve methods.

One dimensional solution representation used in genetic algorithms. Number of coefficients in the growth curve indicates size of the solution. The coefficients are real values. Mean absolute error (MAE) and root mean square error (RMSE) shown in Equation 1 and Equation 2 respectively are used as an objective function. Different selection, crossover and mutation operators applicable to given chromosome representation are tested. Genetic algorithms are executed several times to tune the various parameters of genetic algorithms such as population size, overlapping population, probability of crossover and mutation. Genetic algorithms is tested with different seed values. The operators and parameter values which give best results are as given below:

- Initialization: OrderedInitializer
- Selection operator: GARankSelector
- Crossover operator: OnePointCrossover
- Mutation operator: GARealGaussianMutator
- Scaling: GAPowerLawScaling
- Population size = 100
- Crossover probability = 0.8
- Mutation probability = 0.2
- Overlapping population = 25%
- Termination criteria (Best value) = 0
- Termination criteria (No. of generations) = 1000

Tables 5-7 show the results of growth curve methods for selected cloud computing indicators.

Results show that genetic algorithms gives good fitting than regression method for many instances. In majority of the instances growth curve with genetic algorithms is best fitted than growth curve with regression. For a few instances genetic algorithms fail to give better fitting than regression method.

Table 5: Performance Measures for Growth Curves Using Regression and Genetic Algorithms on Data Traffic and Workload

Growth Curve		Data Traffic			Workload		
	Upper limit	6415	6915	7415	250	300	350
Gompertz	MAE	423.8	332.2	276.2	11.20	8.00	6.40
	RMSE	554.84	418.26	342.16	13.57	10.05	8.10
Logistic	MAE	213.8	172.4	165.8	4.40	1.40	1.20
	RMSE	321.04	225.89	196.13	5.74	2.33	1.93
Mono Molecular	MAE	1286	1042	920.2	29.00	23.80	21.40
	RMSE	1601.35	1223.06	1046.23	33.46	26.79	23.85
Log logistic	MAE	468	378	323.8	15.20	12.60	11.20
	RMSE	563.36	458.15	400.33	18.30	16.32	15.22
Gompertz with GA	MAE	267.79	240.14	215.42	9.23	7.49	6.14
	RMSE	520.73	471.38	422.80	15.22	12.55	8.06
Logistic with GA	MAE	189.92	153.2	118.53	4.09	1.64	0.91
	RMSE	274.66	198.38	192.9	7.24	2.51	1.29
Mono Molecular with GA	MAE	643.22	620.88	299.52	11.13	18.92	18.07
	RMSE	873.58	843.75	527.6	17.78	25.04	22.88
Log logistic with GA	MAE	333.63	312.71	601.77	20.08	9.66	8.77
	RMSE	595.34	557.68	824.97	27.41	14.78	13.71

Table 6: Performance Measures for Growth Curves Using Regression and Genetic Algorithms on Revenue

Growth Curve		IaaS Provider revenue			PaaS Provider revenue			SaaS Provider revenue		
	Upper limit	20	25	30	12	17	22	133	138	143
Gompertz	MAE	0.33	0.17	0.00	0.17	0.17	0.17	14.17	11.83	10.83
	RMSE	0.93	0.63	0.46	0.81	0.71	0.65	17.95	14.83	13.16
Logistic	MAE	0.00	0.17	0.50	0.00	0.00	0.00	8.33	6.83	5.50
	RMSE	0.35	0.83	1.23	0.29	0.11	0.04	12.02	9.25	7.76
Mono Molecular	MAE	2.33	2.00	1.67	1.17	0.83	0.83	36.43	29.33	26.00
	RMSE	3.28	2.75	2.53	1.75	1.54	1.47	47.52	36.91	31.90
Log logistic	MAE	0.33	0.33	0.33	0.33	0.33	0.33	14.83	13.17	12.00
	RMSE	1.19	1.09	1.01	1.16	1.17	1.17	17.87	15.80	14.88
Gompertz with GA	MAE	0.35	0.19	0.09	0.29	0.21	0.18	7.48	7.19	6.93
	RMSE	0.46	0.25	0.11	0.47	0.33	0.27	11.91	11.49	11.11
Logistic with GA	MAE	0.69	0.62	0.64	0.65	0.74	0.83	4.59	4.26	3.98
	RMSE	0.80	0.71	0.77	1.01	1.06	1.14	9.36	8.82	8.25
Mono Molecular with GA	MAE	2.19	2.03	1.94	1.12	1.08	1.06	15.72	15.50	15.27
	RMSE	2.72	2.54	2.42	1.62	1.58	1.56	22.11	21.39	20.61
Log logistic with GA	MAE	1.80	1.81	1.86	1.10	1.18	1.06	10.20	9.95	9.74
	RMSE	2.23	2.20	2.23	1.60	1.65	1.57	15.09	14.74	14.44

Table 7: Performance Measures for Growth Curves on Number of Providers

Growth Curve		Number of IaaS Providers			Number of PaaS Providers			Number of SaaS Providers		
	Upper limit	**650**	**680**	**710**	**190**	**220**	**250**	**544**	**574**	**604**
Gompertz	MAE	60.50	47.00	39.67	5.50	4.00	3.17	38.00	29.50	24.67
	RMSE	71.42	54.50	46.35	7.39	5.24	4.54	43.19	33.39	27.89
Logistic	MAE	38.67	29.00	25.67	4.17	5.50	6.67	21.00	17.17	14.67
	RMSE	52.32	37.97	31.46	6.84	7.51	8.77	28.73	21.13	17.53
Mono Molecular	MAE	144.17	106.67	90.33	17.33	13.33	11.33	91.00	71.33	61.33
	RMSE	192.61	133.93	110.28	21.84	15.75	13.12	118.75	88.96	74.65
Log logistic	MAE	66.33	54.33	48.67	8.17	6.00	4.67	43.67	36.50	32.50
	RMSE	76.12	62.58	56.71	10.07	7.94	6.72	50.09	42.58	38.55
Gompertz with GA	MAE	27.34	25.20	23.39	4.75	3.91	3.32	19.60	17.42	15.58
	RMSE	50.09	47.47	45.02	8.21	6.31	4.90	34.29	31.22	28.56
Logistic with GA	MAE	23.52	22.35	21.29	4.52	4.66	5.09	14.58	13.39	12.46
	RMSE	42.17	39.33	36.80	6.17	5.81	7.00	27.53	24.48	20.76
Mono Molecular with GA	MAE	53.13	51.60	50.24	11.55	9.96	8.78	42.19	40.43	38.91
	RMSE	85.84	83.77	78.67	16.96	15.50	13.66	62.40	59.83	58.27
Log logistic with GA	MAE	36.64	34.14	32.71	5.83	5.10	4.56	26.64	24.24	23.12
	RMSE	56.26	53.10	51.51	9.69	8.34	7.46	38.40	35.85	34.36

Figures 5-8 show the results of the best-fitted growth curve method for selected cloud computing indicator.

The growth of cloud data traffic is very high as compared to workload. The SaaS cloud provider's revenue is very fast as compared to IaaS and PaaS. There is domination of Software as a Service (SaaS) over Infrastructure as a Service (IaaS) and Platform as a Service (PaaS) in revenue indicator.

Figure 8 shows that there is an increase in the number of cloud service providers. The upper limit and growth rate of the selected cloud service models are different. The growth of IaaS and SaaS providers is upward. The growth in the number of PaaS cloud providers is very slow as compared to IaaS and SaaS. The growth rate of PaaS providers is reached to the peak and then declined rapidly. All three cloud service models have crossed the inflection point in the year 2011. Results show that the cloud computing industry life cycle is experiencing a low number of providers followed by an increase in the total number of providers.

The results show that cloud computing technologies show "S-shaped" growth pattern for all the selected indicators with very fast growth rate.

Table 8 shows inflections year, saturation year and best-fitted growth curve method.

Forecasted results indicate that cloud data traffic, workload and total revenue values were on the peak on the year 2011, 2012 and 2012 respectively. Forecasted results indicate that cloud computing has crossed the inflection point but there is an increase in the number of cloud service provider's revenue, workload and data traffic.

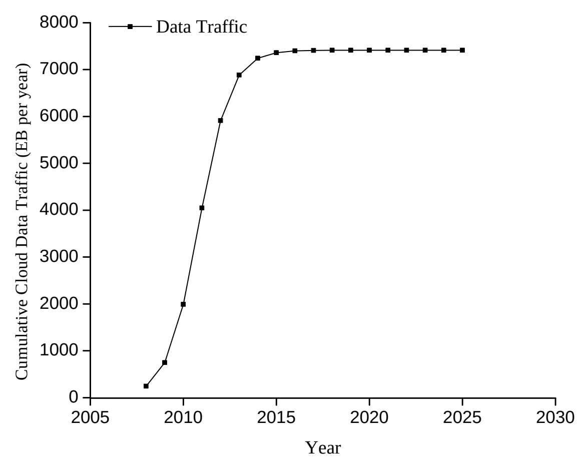

Figure 5: Forecasted Results of Best-fitted Growth Curve Method on Data Traffic

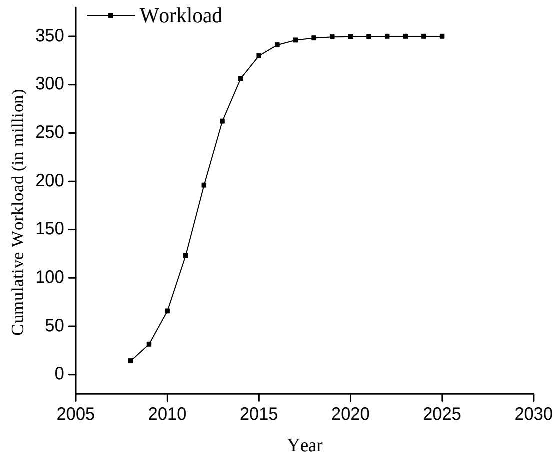

Figure 6: Forecasted Results of Best-fitted Growth Curve Method on Workload

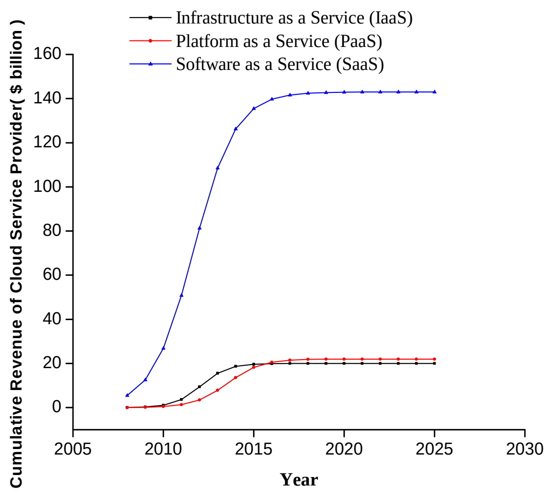

Figure 7: Forecasted Results of Best-fitted Growth Curve Method on Revenue

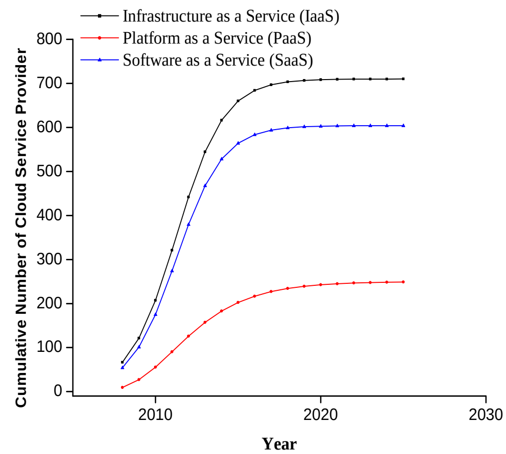

Figure 8: Results of Growth Curves on Number of Providers

Table 8: Forecasted Inflection and Saturation Year

Technology	**Inflection Year**	**Saturation Year**	**Best-fitted growth curve**
Data Traffic	2011	2023	Logistic with GA
Workload	2012	2025	Logistic with GA
IaaS	2012	2019	Logistic
PaaS revenue	2014	2022	Logistic with GA
SaaS revenue	2012	2024	Logistic with GA
IaaS Providers	2011	2025	Logistic with GA
PaaS Providers	2011	2025	Gompertz
SaaS Providers	2011	2025	Logistic with GA

CONCLUSIONS

Many researchers, business leaders and technologist reported that cloud computing is transformational technology. Many research initiatives, application developments and funding from governments are in progress. Today when the technology life cycles are becoming shorter, the knowledge generated about current state, direction and rate of growth of cloud computing technologies is helpful to governments, technology developers and customer for decision making of public policy, prioritize R&D, strategic decisions, operational decision making, adoption of technology etc.

This paper presents results of double exponential smoothing, genetic algorithms, particle swarm optimization and four growth curve methods. Genetic algorithms and particle swarm optimization methods implemented for short-term cloud forecasting with two historical data points and polynomial equation of order one. Performance of best-fitted genetic algorithms and particle swarm optimization are approximately the same. Double exponential smoothing method is found better for short term forecasting. Genetic algorithms is better suited than regression method to find coefficients of growth curve methods.

Forecasted results indicate that cloud computing has crossed the inflection year for cloud provider's revenue, workload and data traffic in between the year 2012 and 2014. Even after crossing the inflection year, cloud providers revenue, workload and data traffic are increasing. The growth of PaaS cloud providers revenue is very fast as compared to IaaS and SaaS. Forecasted results indicate that there is an increase in the number of cloud service providers. The growth in the number of PaaS cloud providers is very slow as compared to IaaS and SaaS. The industry life cycle of cloud service models namely infrastructure as a service, software as a service and platform as a service are different. All the three-cloud service models industry life cycle crossed inflection point in the year 2011. Obtained forecasted results with multiple indicators are similar.

Future scope: There is scope to improve genetic algorithms and particle swarm optimization for improving short term forecasting.

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