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Forecasting Technology Maturity Curve of Cloud Computing with its Enabler Technologies

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Abstract: **Forecasting the technology maturity and adoption curve is important for finalizing research policy, investment plan and development plan. In the last decade many governments, enterprises and researchers showed interest in cloud computing technology. Many surveys reported cloud computing as a disruptive technology. This paper investigates technology maturity curve of cloud computing. To gain more insight, maturity curve of cloud computing is investigated with its enabler technologies using growth curve methods. The maturity of technologies is forecasted using the number of papers and patents which are obtained from U.S., European patent office, IEEE and ScienceDirect. The best fitting of logistic and Gompertz growth curve methods are calculated using MAE and RMSE error measures. The majority of the technologies follow introduction, growth, maturity and decline pattern. Results show that the growth pattern of virtualization, distributed computing and grid computing is similar to the S-shaped curve. The life cycle pattern and growth rate of each technology is different. The growth rate on paper and patent indicators are different.**

Index Terms: **Cloud computing, growth curves, technology forecasting, technology life cycle.**

I. Introduction

Today the consumer durable, industry and technology products are changing continuously and rapidly. Change in product/technology is opportunity and threat to developers and users. Product life theory proved that products follow life cycle pattern from introduction to decline and finally disappearing from the marketplace (Herbst, 2001). Investigating life cycle patterns and stages for nondurable consumer goods is dominated in literature for a long time. Product/technology life cycle theory is helpful to developers, consumers and governments for policy making, operational and investment plans etc. Technology forecasting is a systematic approach to identify the probable direction and rate of technology growth (Firat et al., 2008). In literature, wide range of methods are investigated for technology forecasting. Technology S-curve is a powerful tool to investigate the trend of technologies. Based on the literature review Schilling and Esmundo (2009) reported that S-curve methods for technological improvement are investigated for a wide range of technologies from different sectors such as automobiles, electronics and computers. Different growth curve methods are used for identifying S shaped life cycle of technologies from different domains such as energy, electronics, telecommunication technologies, IT technologies. Based on the literature review, Schilling and Esmundo (2009) reported that many technologies follow S-curve pattern for their performance improvement as an indicator. Dubaric et al. (2011) reported that wind motors and microwave heating technology follow the technology life cycle. Technology maturity curve on patent data shows S-curve pattern (Chen et al., 2011; Intepe and Koc, 2012; Madvar et al., 2019). Growth patterns of mainframes, minicomputers and personal computers reported in (Teng et al., 2002) and mainframes reported in (Steurer et al. 2012) are similar to S-curve. Whereas, Schilling and Esmundo (2009) reported that fossil fuel composite trajectory is not similar to an S-curve. In literature, numbers of investigations are done to explain technology diffusions through an S-curve.

Today, cloud computing technology is popular due to its ‘pay as you use’ concept. Scalability, dynamic resource provisioning, ease of use, on-demand self-service are characteristics of cloud computing. In recent times, this new computing model is strongly influencing IT world and enterprises. According to McKinsey Global Institute’s (MGI) reported cloud computing as economically disruptive technologies (Manyika et al., 2013). IDC

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reported that (Frank, 2012), worldwide information technology (IT) spending on cloud computing, acquisitions of software as a service (SaaS) and the number of industry-focused public cloud services platforms are increasing rapidly. According to KPMG and NASSCOM report, cloud computing technology will impact organizations and society. Cloud computing technologies have dominated Gartner's strategic technology list form year 2004 to 2014 (Gartner). The increasing interest of enterprises in cloud computing adoption creates the need for identifying the current state and life cycle of cloud computing.

For development of any technology, multiple factors are responsible (Utterback, 1994). Technology development and progress is dived by developments of its sub-technologies (Ford, 1988). In most of the research papers, life cycle of subsystems are ignored while investigating the life cycle of technology (İntepe & Koç, 2015). Cloud computing development is contributed by different technologies (Iyer & Henderson, 2010; Zhang et al., 2010). This paper aims to investigate the maturity of cloud computing technologies using patents and papers as indicators. To gain more insight, maturity curve of cloud computing is investigated using its enabler technologies. Logistic (Pearl) and Gompertz models are used in many investigations (Ryu & Byeon, 2011). This paper compare the results of logistic and Gompertz. The shape of the growth trajectory and inflection points are the main issues in life cycle forecasting.

The paper contents are organized as follows. Section II is about background concepts and growth curve methods. Section III presents the growth curve forecasted results. Finally, Section IV is conclusions.

II. Background and Methods

This section presents the concept of technology S-curve and growth curve methods.

A. Technology S-curve

From last three decades, many authors reported that technology development follows specific patterns (Nyberg & Palmgren, 2011). Diffusion models fit to specific shapes and forms of diffusion patterns. The exponential pattern fit to innovations that diffuse very rapidly. S-curve tool found better to investigate growth pattern of many technologies (Kauffman & Techatassanasoontorn, 2006). Nieto et al. (1998) reported that among all technology life cycle models, S-curve is the one the best tool that shows the evolution of technology. S-curve shows the evolution of product or service or technology with respect to time. A number of users of the product or technology plotted over time show an S-shaped technology adoption or substitution curve. S-curves are beneficial to understand product/technology evolutions and opportunities for growth. The technology growth rate varies with technologies. The growth rate of high technology products is higher than low technology consumer products (Kaplan). Understanding of technology or product current status on the life cycle curve is beneficial to the strategic planner to extend life and leverage performance/adoption of technology (Kaplan).

Foster (1986) introduced one of the well-known theory, S-curve. The S-curve is model of plot technology development. Asthana (1995) reported that technology progress trajectory is similar to S-curve for many cases. Researchers for plotting technology/product life cycle used many technology indicators. Technology indicators are indices for direct characterization and evaluation of technology (Chang, 2008). The common indicators are research publications and patents (Porter & Cunningham, 2004; Chang, 2008). The technology life cycle is influenced by effort in research and development or time. In the early stage, technology progress is slow. Then it shows rapid growth followed by a decline. In literature, it is observed that many technologies follow a trend that is similar to an S-curve (Christensen, 1993; Ayres, 1994; Andersen, 1999; Ernst, 1997).

Technology life cycle is divided into different stages. Generally, technology life cycle has introduction, growth, maturity and decline phases (Firat et al., 2008; Chen et al., 2011, Çetindamar et al., 2016, Jamali et al., 2016; Aslani et al., 2018). Introduction phase: The technology is just beginning to emerge. Growth phase: Technology shows rapid growth. Maturity phase: In this stage, technology shows a reduction in growth rate. Decline phase: There is a decline in the performance of technology.

B. Growth Curves

Trend projection belongs to extrapolation technological forecasting methods. It uses historical data to identify the direction and rate of technology growth. Any single technology is limited in its ultimate performance by its principle of operation. Once technology reached its upper limit, it is replaced by another technology that uses a different principle of operation. Growth curves forecast about how and when technology will reach its upper limit. Growth curves are also helpful to predict the progress of technology through different phases of life cycle (Firat et al., 2008). There are many growth curve methods are available for examining the technology progress. Logistic curve and Gompertz curve are popular growth curves.

The formula for logistic (Pearl) curve is,

$$y_t = \frac{L}{1+ae^{-bt}} \tag{1}$$

where 'y_t' is the value of interest that is growth variable, 'L' is the upper limit value of 'y_t', 'e' the base of the natural logarithms, 'a' describes the location of the curve, 'b' controls the shape of the curve and 't' is time (Bengisu & Nekhili, 2006).

Characteristics of logistic curve is symmetric nature of curve. 'b' indicates the rate of adoption.

The inflection point of this curve occurs at t = (In a)/b. When y_t = L/2, the maximum growth rate is L*b/4.

The formula for Gompertz growth curve is,

$$y_t = Le^{-ae^{-bt}} \qquad (2)$$

where 'y_t' is the value of interest that is growth variable, 'L' is the upper limit value of 'y_t', 'e' the base of the natural logarithms, 'a' describes the location of the curve, 'b' controls the shape of the curve and 't' is time (Bengisu & Nekhili, 2006).

Gompertz curve also forms an S-curve but it is asymmetric. It's progress slows down with the adoption. The Gompertz model is usually better for consumer adoptions. For Gompertz growth curve, the point of inflection occurs at t= (ln a)/b, where y_t = L/e i.e. when the growth has reached 37% of the upper limit (Winsor, 1932; Radojičić & Marković, 2009). Steurer et al., (2012) summarized as, it is right-skewed S-curve. The growth phase is shorter than decline phase. It describes incremental technological change.

Forecasting by growth curve method works in two steps.

- Estimate the parameters of growth curve. Trappey & Hsin-Ying (2008) presented the transformation of growth curve methods into a linear function. Then simple linear regression is used for estimation of parameters of linear model.
- Identify the best-fit growth model using error measures such MAD and RMSE.

III. Results and Discussion

This section describes the results of growth curve methods applied in our study to find growth patterns of selected technologies.

This section presents the results of growth curve method for cloud computing and its enabler technologies. The identified cloud computing enabler technologies are virtualization, web 2.0, distributed computing, grid computing, service oriented architecture, utility computing and autonomic computing. The technology indicators used are patents and papers. The historical dataset of patents and papers is prepared from US patents, Espacenet patents, IEEE papers and ScienceDirect papers. The terms "cloud computing", "virtualization", "web 2.0", "distributed computing", "grid computing", "service oriented architecture", "utility computing", "autonomic computing', are used as keywords in the field of title to find out patents and papers.

Any single technology is limited in its ultimate performance by its principle of operation. The upper limit is based on the physical and chemical limits. This is applicable to technologies based on physical, chemical, mechanical operations, etc. The technologies under consideration are software technologies. These technologies are not dependent on limits imposed by nature. Therefore, upper limit identification using physical, mechanical, chemical limits is not possible. The technology indicators selected for investigation are number of papers and patents. In this investigation, upper limits are higher numbers than the last known past values. As mentioned in table I, upper limit for each technology for each selected indicator is different. The assumption is that the selected growth curve must correctly fit the historical data. If the chosen growth curve matches the dynamics of the growth of the technology then the extrapolated data matches the future behaviour of the technology. Error calculation methods, Mean Absolute Deviation or Mean Absolute Error (MAD or MAE) and Root Mean Square Error (RMSE) are used to find fitting of growth curve methods.

Table 1 shows the average error values for the selected prediction period. The prediction period starts with the year of technology start. Gompertz method is best fitted to most of the technologies on dataset of IEEE, ScienceDirect and Espacenet. Historical data of US patents is best fitted by logistic method except autonomic computing.

Table 1. Error values on prediction period for selected technologies

Cloud enabler technology	**Dataset (starting year)**	**Upper limit**	**Logistic**		**Gompertz**	
			MAE	**RMSE**	**MAE**	**RMSE**
Virtualization	IEEE (1988)	10000	461.54	682.79	**65.15**	**122.54**
	ScienceDirect (1979)	6000	279.80	452.63	**81.13**	**179.28**
	Espacenet (1997)	6000	128.95	145.48	**9.97**	**12.98**
	USPTO (1990)	15000	823.31	1435.34	445.75	1123.12
Web 2.0	IEEE (2006)	4000	138.17	162.25	**89.66**	**107.97**
	ScienceDirect (2005)	10000	164.52	200.41	127.41	147.81
	Espacenet (-)	-	NA			
	USPTO (2003)	2000	115.44	183.99	**23.74**	**40.84**
Service oriented architecture	IEEE (2003)	4000	81.31	93.25	**43.85**	**51.41**
	ScienceDirect (1999)	5000	105.74	121.35	**23.50**	**41.32**
	Espacenet (2004)	1000	15.01	19.73	**7.12**	**10.58**
	USPTO (2005)	4000	167.52	192.83	**40.08**	**80.25**

Distributed computing	IEEE (1948)	50000	3902.09	5345.13	1091.51	2634.07
	ScienceDirect (1972)	30000	993.37	1199.66	**344.51**	685.66
	IEEE (1988)	3000	86.18	105.26	**25.12**	41.24
	ScienceDirect (1979)	50000	3784.64	5399.13	1036.36	2370.35
Utility computing	IEEE (2002)	500	6.62	10.19	**5.61**	**6.61**
	ScienceDirect (2003)	600	**4.79**	**7.53**	10.57	14.73
	Espacenet (2005)	100	3.82	4.80	3.17	4.05
	USPTO (2001)	1500	73.01	142.12	8.72	15.59
Grid computing	IEEE (1996)	20000	553.40	830.75	**254.46**	**350.06**
	ScienceDirect (1996)	10000	296.11	354.25	**41.20**	**52.15**
	Espacenet (2003)	500	17.91	22.04	**14.32**	**17.65**
	USPTO (2003)	5000	**46.77**	**66.88**	57.54	113.32
Autonomic computing	IEEE (2002)	2000	71.79	97.09	**47.72**	**58.72**
	ScienceDirect (2002)	2000	**15.38**	**21.08**	**15.71**	**20.25**
	Espacenet (2004)	100	3.97	5.17	**3.47**	**4.38**
	USPTO (2005)	2000	30.23	35.60	**8.95**	**12.87**
Cloud computing	IEEE (2008)	30000	336.38	418.05	**150.04**	**218.44**
	ScienceDirect (2005)	6000	373.19	448.72	**67.30**	**180.02**
	Espacenet (2009)	4000	49.60	62.45	**13.85**	**23.91**
	USPTO (2009)	8000	386.55	463.40	90.05	174.45

Figures in bold indicate best values.
NA indicates not applicable.

Figure 1 shows forecasted results on IEEE papers with best-fitted growth curve method. Distributed computing is oldest technology in the selected list. The upper limit of distributed computing is very high. Though cloud computing and grid computing are new technologies the number and rate of IEEE papers publications is high. In early stage, virtualization, web 2.0, SOA and autonomic computing shows rapid growth in IEEE publications. Technology maturity curve of grid computing, distributed computing, virtualization and autonomic computing is similar to S-shaped curve.

Figure 2 shows forecasted results on ScienceDirect papers with best-fitted growth curve method. Similar to number of IEEE paper published, number of ScienceDirect papers of distributed computing is very high. Grid computing and web 2.0 shows high number of ScienceDirect papers than cloud computing. Cloud computing, SOA, web 2.0 and utility computing shows fast growth in the early years. Technology maturity curve of technologies except cloud computing and web 2.0 is similar to S-shaped curve.

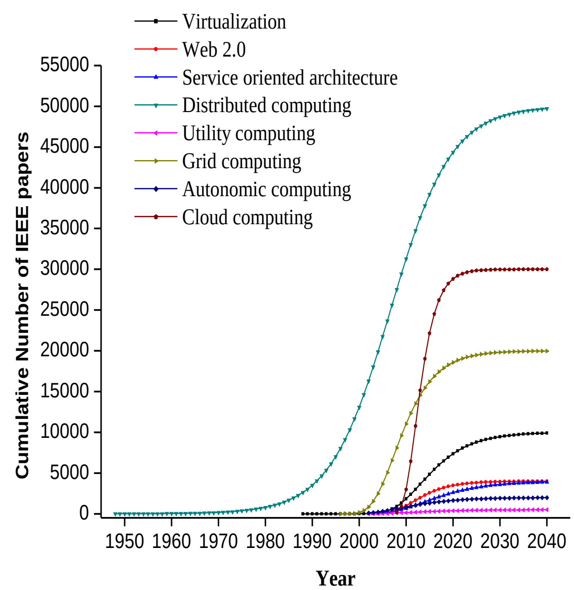

Fig. 1. Results on IEEE papers

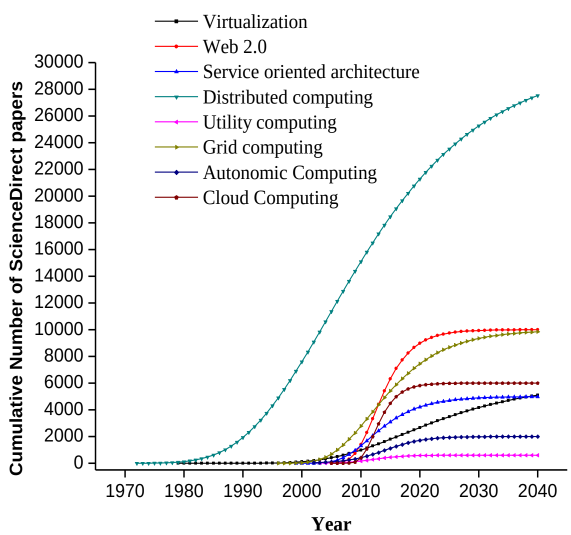

Fig. 2. Results on ScienceDirect papers

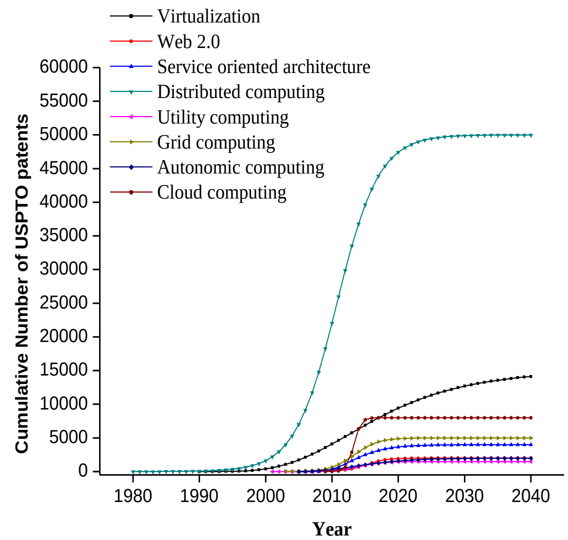

Fig. 4. Results on USPTO patents

Figure 3 shows forecasted results on Espacenet patents with best-fitted growth curve method. Virtualization and cloud computing are newer technologies as compared to distributed computing. Upper limit and growth rate of virtualization and cloud computing is higher than other technologies. Technology maturity curve of virtualization and grid computing is similar to S-shaped curve.

Figure 4 shows forecasted results on USPTO patents with best-fitted growth curve method. Compared to other technologies, distributed computing shows very high upper limit. Grid computing, autonomic computing, SOA, utility computing, web 2.0 shows fast growth in the early stage of life cycle. Technology maturity curve of distributed computing, virtualization and grid computing is similar to S-shaped curve.

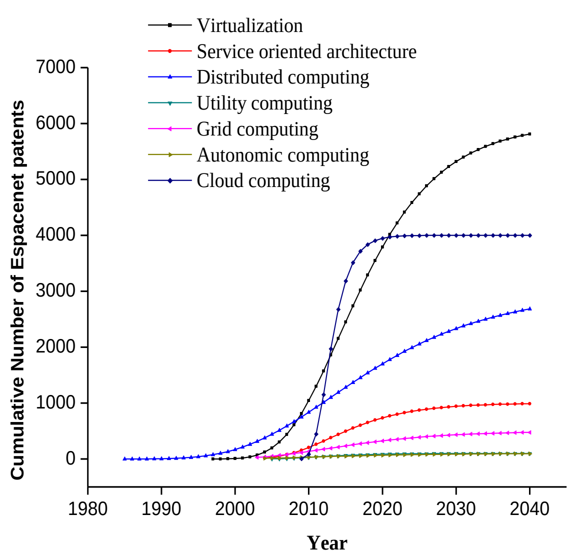

Fig. 3. Results on Espacenet patents

Table II shows year of first paper published and patent filed, obtained inflection year and age of technology at inflection year. Results show that Gompertz growth is best fitted to the majority of the datasets that indicates fast growth in the early stage of technology. Except for four cases, all these technologies have crossed their inflection point. Distributed computing and virtualization are older technologies as compared to cloud computing and it's other enabler technologies. For these two technologies, age of technology at inflection year is greater than other technologies. It is observed that for SOA, utility computing, grid computing, autonomous computing and cloud computing inflection year using research papers and patents dataset are closer. The results presented in figure 1 to 4 and table II show that technology maturity curve of distributed computing, virtualization and grid computing is similar to S-curve.

Table 2. Results of best fitted growth curve method

Technology	Dataset (starting year)	Inflection Year	Age at Inflection (in year)
Virtualization	IEEE (1988)	2014	26
	ScienceDirect (1979)	1996	39
	Espacenet (1997)	2015	18
	USPTO (1990)	2013	23
Web 2.0	IEEE (2006)	2012	6
	ScienceDirect (2005)	2013	8
	Espacenet	NA	NA
	USPTO (2003)	2015	12
Service oriented architecture	IEEE (2003)	2014	11
	ScienceDirect (1999)	2012	13

	Espacenet (2004)	2013	9
	USPTO (2005)	2013	8
Distributed computing	IEEE (1948)	2007	59
	ScienceDirect (1972)	2005	33
	Espacenet (1985)	2014	29
	USPTO (1980)	2011	31
Utility computing	IEEE (2002)	2012	10
	ScienceDirect (2003)	2013	10
	Espacenet (2005)	2011	6
	USPTO (2001)	2015	14
Grid computing	IEEE (1996)	2008	12
	ScienceDirect (1996)	2012	16
	Espacenet (2003)	2013	10
	USPTO (2003)	2014	11
Autonomic computing	IEEE (2002)	2010	8
	ScienceDirect (2002)	2015	13
	Espacenet (2004)	2012	8
	USPTO (2005)	2014	9
Cloud computing	IEEE (2008)	2013	5
	ScienceDirect (2005)	2013	8
	Espacenet (2009)	2013	4
	USPTO (2009)	2014	5

To verify the inflection point and growth rate of cloud computing we have experimented with different upper limits. Figure 5 and 6 shows the growth rate of cloud computing with different upper limits (L) for best-fitted growth curve method. Growth rate of cloud computing is very fast. Results indicate that the growth pattern and inflection points obtained for cloud computing with variation in upper limits are similar.

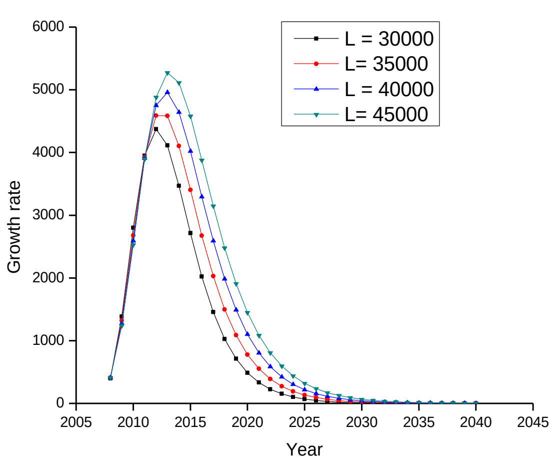

Figure 5. Growth rate results on ScienceDirect papers

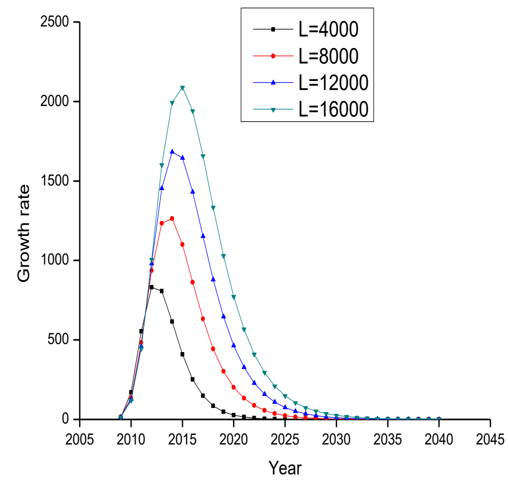

Figure 6. Growth rate results on Espacenet patents

Figure 7 to 9 presents the time series data of papers and patents up to year 2020 for selected cloud enabler technologies. Figure 7 presents the actual IEEE papers numbers for selected technologies. These values validates the results of inflection year calculated with best-fitted growth curve method presented in table II for 50% technologies. There is rapid growth in number of IEEE papers for cloud computing, distributed computing, virtualization and utility computing.

Figure 8 presents the actual Espacenet patent numbers for selected technologies. All technologies except autonomic computing shows increase in Espacenet patent filing after year 2014. Technology maturity curve of cloud computing, distributed computing, grid computing and utility computing is not similar to predicted by best-fitted growth curve method.

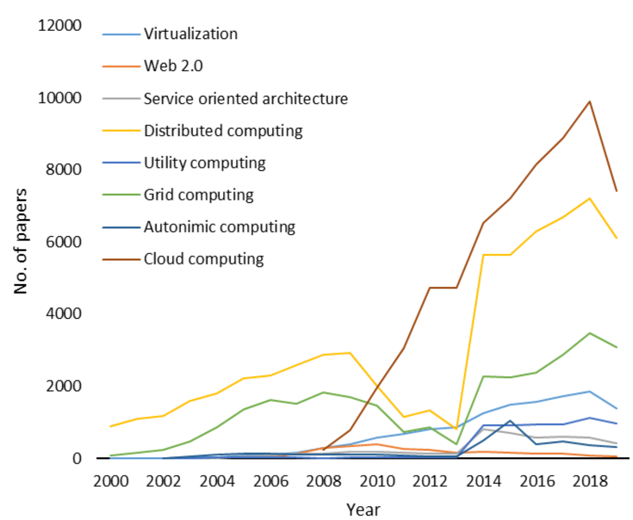

Fig. 7. Actual data of IEEE papers

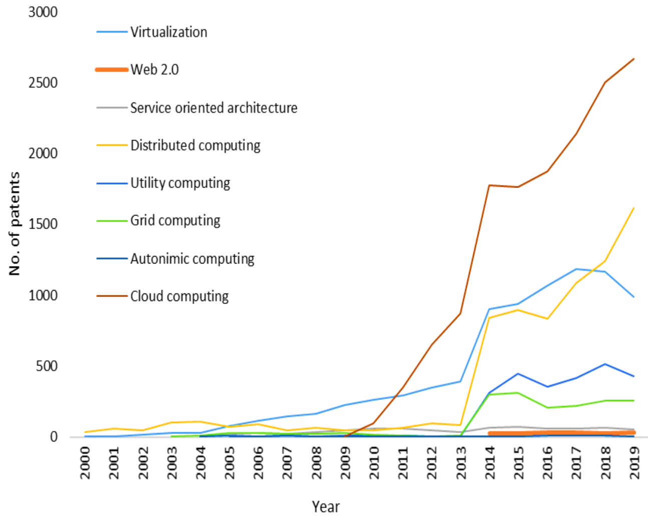

Fig. 8. Actual data of Espacenet patents

Figure 9 presents the actual USPTO values for selected technologies. These values validate the results of inflection year calculated with best-fitted growth curve method presented in table II for technologies except cloud computing, distributed computing and virtualization. These three technologies show very rapid growth after year 2014.

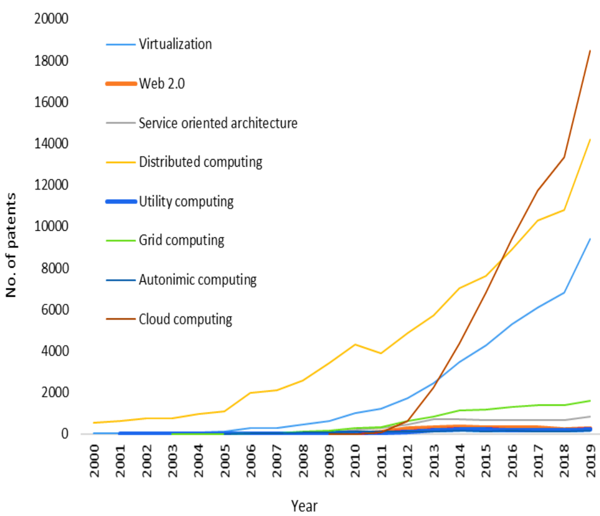

Fig. 9. Time-series data of USPTO patents

Conclusions

This research demonstrates the life cycle of cloud computing and its enabler technologies with paper and patent indicators using growth curve methods. The best-fitted method among logistic and Gompertz is identified using MAE and RMSE. The growth patterns of distributed computing, grid computing and virtualization technology are similar to S curve. The majority of cloud enabler technologies, the growth is steep and reach their peak in early stage. Growth curves of cloud computing and its enablers are crossed the inflection point. All the selected technologies showed very rapid growth.

The predicted results are compared with actual values from year 2014 to 2019. Cloud computing, distributed computing and virtualization technology shows fast growth in research papers and patents. The forecasted inflection year using best-fitted method is not accurate. There is scope to improve prediction accuracy with use of multiple technology indicators and machine learning algorithms.

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