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Predicting Service Reliability - Using Survival Analysis of Customer Fuzzy Satisfaction

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Abstract. *It had been known that the main objective of adding service was creating value to improve customer satisfaction. Therefore, if customer satisfaction was plotted in time series variable, service reliability function was reflected. The benefits obtained from understanding the service reliability function were knowing the trend of service life cycle and analyzing the time to react for service in order that the company could offer service innovation before the service became unfavorable. This research was aimed to analyze service reliability function by using the definition concept of product reliability function which was called survival analysis. To reduce bias data because of linguistic variable such as customer satisfaction, fuzzy logic was used in this research. The data was collected by doing a survey to 100 SAMSAT customers about their satisfaction. SAMSAT is a public unit giving service in tax. Then, fuzzied customer satisfaction was plotted in time series to describe the survival analysis of service. In other words, the plotting result was used to determine the right time for innovating service. So, the conclusion was drawn that survival analysis implemented in service field could help the managerial level in terms of innovation management. In addition, fuzzy logic used could bold the bias definition of customer satisfaction. Furthermore, this framework would be able to be used in mobile application development for future research in terms of supporting a company to define the right moment of service innovation based on asimple customer satisfaction survey.*

Keyword: *Service reliability, survival analysis for service, fuzzy logic in service, fuzzy satisfaction, technology as support*

1. Introduction

In business atmosphere, every company competed with each other to offer valuable products to customers. Consequently, innovation should be urgent when a product got into decline phase to protract product life cycle so that company paid attention to product life cycle regarding to appropriate time to market for some innovation (Chen, Reilly, & Lynn, 2012). In this case, product reliability function was helpfully used to [illegible] (Bose, Ghosh, Manda, Sau, & Kunar, 2013). If the product offered by a company was a tangible product, then it would be easy to model its reliability function. However, if the product offered by company was a service which was an intangible product, it would be difficult to describe its reliability function. Nevertheless, the similarities between reliability function of a tangible product and that of an intangible product were found (Wahyudi & Hadiyat, 2013). On a tangible product, it could be known that the product carried its function well when it was new, but naturally it would decrease along with product age. Likewise the service, a new service contributed to customer satisfaction since it was considered as value added and innovative, but the satisfaction level would be different at the first experience and at the next experience. In the long term, the impression of service as value added would [illegible] which should [illegible] for customer. This phenomenon reflected that reliability function for service was analog with reliability function for tangible product. Therefore, companies were able to determine the right time to launch their service innovation before customer satisfaction decreased by doing analysis for their service reliability function.

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Even though the reliability function of both service and product were identical, they still had differences. Establishing reliability function for product was relatively easier than that for service since related data to the function were product failure which was measureable. Whereas, customer satisfaction as response variable in reliability function for service was difficult to measure, ambiguous and every customer had different assessment standard of satisfaction (Meng, Jiang, He, & Guo, 2015). Thus, there would be two main problems in this research i.e., assessment standard of satisfaction between customer and determination of critical time to innovate the service.

Considering the importance of solving those problems, we needed to integrate fuzzy logic to solve the difference of satisfaction standard by converting customer satisfaction into fuzzy satisfaction. Then, the fuzzy satisfaction would become input data for reliability function. Furthermore, reliability function could be used to find critical moment to provide service innovation. Based on this back ground, this paper was aimed to analyze the reliability function of service by adopting the concept of survival analysis which was usually used for reliability function of product and by using fuzzy logic to bold customer satisfaction level.

2. Literature Study

In the early 2000s, there was interfusion of product and service in industry (Lovelock, & Wirtz, 2007). Service had dominated the economy and had grown rapidly over the past decade (Snyder, Witell, Gustafsson, Fombelle, & Kristensson, 2016). In the same reference, it was explained that service contributed the national economy as well as manufacturer that made tangible products. Based on the contribution, many manufacturers engineered the product planning and development. The product was produced by considering the voice of customer, and then the durability would be monitored and evaluated through reliability function. Thus, the company could predict product life cycle and prepare product innovation. Furthermore, company that made tangible products could maximize the contribution of product to economy (Snyder et al., 2016). Therefore, service should be managed as well as managing the product. It could be conducted by offering service innovation periodically, so company could control the customers' emotional aspect and make bonding with it (Lovelock & Wirtz, 2007).

However, Lovelock and Wirtz (2007) also explained about service recovery that service offers could be ineffective and inefficient when service delivered was not meeting the needs and was not at the right time. It was ineffective when customer still felt satisfied with the current service offered. It meant that the company did not need to give service innovation because the customer felt that the current service was still suitable with their need. Thus, it was not the right time to offer service innovation. Another ineffective situation was when the customer needed more time to experience the service intensively because the service offered was still in introduction phase. In the case of the service was still in introduction phase, company needed more time to build customer awareness of the current service so it was not necessary to provide service innovation. The consequence of ineffective offers was inefficient efforts.

The trend of research in service field

In the recent decade, service science evolved to study on how service could be well managed so that customer satisfaction as the main goal could be improved. It was reflected by many studies that discussed the role of service engineering tools in achieving customer satisfaction such as researches about Kano, SERVQUAL, Kansei Engineering, Quality Function Deployment (QFD), SEE Methodology, etc. Kano was used to categorize service attribute based on the impact of service improvement to customer satisfaction (Lee, Hu, Yen, & Tsai, 2009). SERVQUAL was used to evaluate service performance through the analysis of the gap between perceived service and expected service (AbuKhalifeh, & Som, 2012). Kansei engineering was used to improve service by using customers' emotional approach (Hartono, Suryani, & Ongkowijoyo, 2013). QFD was used to translate the voice of customer into service or product characteristics (Bergquist, & Abeysekera, 1996). SEE Methodology was used to innovate the service by using three stages (Corallo, Latino, & Neglia, 2013). However, those topics were corrective action to improve service. It needed customers' feedback first, then company did the evaluation and improvement. There were few researches that discussed how to predict the right moment when a company innovated the service particularly by approaching the service life cycle (Hadiyat, Wahyudi, & Sari, 2017).

Those researches (Kano, SERVQUAL, Kansei Engineering, Quality Function Deployment, SEE Methodology) conveyed that the effort to predict the moment of service phase in satisfying the customers became an interesting topic. For an instance, there was a discussion that Kano's categories could be changed as timewent by (Raharjo, 2007). At first, certain innovative service might belong to "Attractive" category, but in the long term, it could change into "Must be" category because of several factors such as customers' taste. Capturing this phenomenon, researchers used several tools to ensure the Kano's categories by using Analytic Hierarchy Process (Momani, Al-Hawari, Al-Shebami, & Al-Araidah, 2014). The other research concerning the use of service performance to retain the customer applied Markov Chain to estimate the probability of customer switching to competitors (Adebiyi, Oyatoye, & Mojekwu, 2015). When the customer switched to a competitor, it reflected that the service was entering decline stage. However, predicting service life cycle as an analysis of service reliability was still necessary to explore.

Service life cycle based on reliability function

The urgency of this topic research was conveyed by the importance of time to react for either certain service or product in market. Knowing the time to react for either service or product would give many benefits for a company particularly in innovation, product quality and marketing strategy (McNally, Calantone, & Akdeniz, 2011). In purpose of exploring the time to react, a company could use reliability function of either service or product. In manufacturing field, product reliability is the probability that product works well, as well as its main function (Bose et al., 2013). For an instance, the main function of Air Conditioning is to cool the room, then the probability that Air Conditioning works to cool the room at certain temperature in time series is called Reliability function of Air Conditioning. By adopting the definition of reliability function for product, reliability function for service could be built by plotting the main function of service, which was the customer satisfaction in time series (Wahyudi, & Hadiyat, 2013).

Based on reliability function, survival analysis could be done. Survival analysis was the interpretation result of reliability function. Survival analysis is a branch of statistics which analyzes the time of events, such as death in biological organisms and failure in mechanical systems (Mohammed, 2014). He explained more that this topic was called reliability theory or reliability analysis in engineering, and duration analysis or duration modeling in event history analysis in sociology.

Likewise, the research conducted by Wahyudi, & Hadiyat (2013), the weakness of research in service field was involving the relatively subjective assessment for service performance reflected by customer satisfaction. Thus, fuzzy logic was purposed to reduce bias data because of various definitions regarding qualitative answer from customers such as expectation and satisfaction (Wahyudi, 2017).

3. Methodology

The data in this research were obtained from research regarding service quality improvement in public service (Maulani, Hartono, & Hadiyat, 2017). The obtained data were satisfaction level for service delivered by SAMSAT public service and duration of being SAMSAT customers. Survival analysis was also discussed in that research without considering fuzzy at satisfaction level. However, customer satisfaction was linguistic and relatively ambiguous. Every customer might have different definition or standard of satisfaction. The methodology of this research was presented by Figure 1.

The collected data in this research was customer satisfaction toward certain service considering the duration of being a customer. There were several methods to conduct this research. First, the method could be conducted by observing customer satisfaction toward the service for the same customer periodically time by time. Then, the relationship between satisfaction and time would form a pattern of service life cycle.

Based on that pattern, the moment of decreased satisfaction could be analyzed as a signal to offer service innovation. By assuming that service was delivered in the same way by a company to customers who were homogeneous, then the observation of customer satisfaction periodically time by time could be represented by any customer. Thus, the second method to collect the data for this research was observing customer satisfaction toward service periodically time by time without assigning certain customers. Based on those methods, observing periodically time by time could be more efficient by clustering the customers into several categories based on the duration of being a customer. Then, each category represented a certain phase of customer satisfaction toward the same service.

The obtained data of customer satisfaction and duration of being a customer would be tested for their correlation. Correlation test was necessary to ensure that both variables had a relationship, so it would help analyzing the result of service reliability.

Further data processing was converting customer satisfaction into fuzzy customer satisfaction consisting of several steps, i.e. membership determination, fuzzification and defuzzification. The last data processing of this research was establishing service reliability function by using the concept of survival analysis. Based on fuzzy satisfaction, the phase when the service started declining was identified. Then, establishing probability density function of duration of being a customer who felt unsatisfied by using survival analysis could be done. This survival analysis would be used to predict service reliability. The methodology of this research was presented by Figure 1.

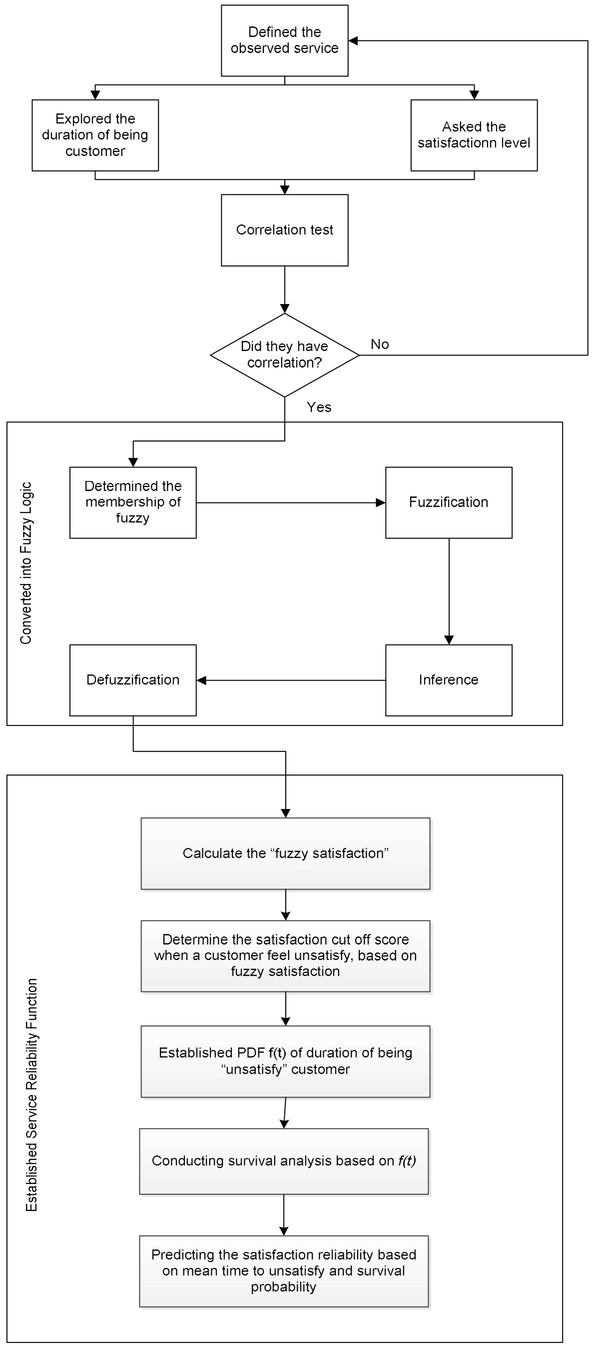

Figure 1.
Research Framework

4. Findings and Discussion

In accordance with figure 1, the first step conducted in this research was computing the correlation coefficient of *r* to ascertain the relationship between satisfaction level and duration of being customers. By using Minitab®, the correlation coefficient of *r* for both variables was -0.6. This number conveyed that the relationship between satisfaction level and duration of being customer was relatively strong and inversely proportional. It also supported the background of research. Based on the obtained data, there was a pattern showing that the longer a person became a customer, the satisfaction level decreased. It meant that service had life cycle or service had reliability function, which was necessary to be analyzed. In this research, the first variable was duration of being a customer in years and the second variable was satisfaction level in likert scale of 1 to 10 (the greater, the better). For further data processing, satisfaction level would be converted into fuzzy satisfaction through several stages, i.e. defined membership function, fuzzification, defined rules or inference and defuzzification. In defining membership function, crisp input set was firstly defined. Supposed that the data processed were represented by set A where A was the data set of satisfaction level in likert scale of 1 to 10, then the crisp input set could be written as $A = \{x|1 < x < 10\}$.

Therefore, the membership function could be written as follows.

$$X_A(x) = \begin{cases} 1, if x is member of A \\ 0, if x is not member of A \end{cases} \quad (1)$$

Based on the membership function, satisfaction level that was in linguistic scale could be converted into fuzzy satisfaction level. Facilitating the conversion process was conducted by visualizing the membership function into graph. The membership function graph was adopted from Chen and Hwang (1992). The scale of crisp set used in Chen and Hwang was 0.1 to 1, while in this research the scale would be 1 to 10. Figure 2 presented the membership function graph.

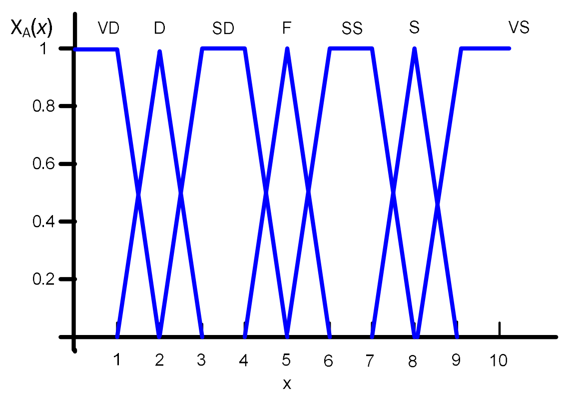

Figure 2.
Membership Function

Notation information:

- VD stands for Very Dissatisfied
- D stands for Dissatisfied
- SD stands for Slightly Dissatisfied
- F stands for Fair
- SS stands for Slightly Satisfied
- S stands for Satisfied
- VS stands for Very Satisfied
- $X_A(x)$ and x referred to equation 1

If a customer gave 8.5 for satisfaction level, it meant that the customer experienced the ambiguous feeling between Satisfied and Very Satisfied because according to figure 2, the number of 8.5 intersected the membership area between Satisfied and Very Satisfied. By using fuzzy, this situation could be reinforced that 8.5 covered satisfied scale of 0.5 and Very Satisfied scale of 0.5. The value of 0.5 could be obtained from the axis of $X_A(x)$ when x was equal to 8.5. Therefore, customer satisfaction level contained ambiguous feeling because different satisfaction standard between customers could be reduced since an answer from customer would represent relevant membership area with certain proportion. Furthermore, the value of satisfaction level split by relevant membership area was defuzzified into crisp output. Then, crisp output would be the response variable for survival analysis. Many methods were probably used to obtain crisp output such as centroid method, height method, first or last of maxima, mean-max method, and weighted average. In this research, weighted average was used to obtain crisp output. We used weighted average because the data of satisfaction was not ratio scale but likert scale. The result of this weighted average would be called fuzzy satisfaction. However, it was necessary to determine inference or rules to obtain fuzzy satisfaction. The inference or rules used in this stage were the expected value of each linguistic scale that was calculated from its geometric mean of fuzzy triangle number. The result was presented in Table 1. Meanwhile, crisp output calculated by using weighted average was presented in Table 2.

Table 1.
Fuzzy Triangle Number and Expected Value of Linguistic Scale

No	Linguistic scale	Fuzzy Triangle Number			Expected Value
1	Very Dissatisfied	0	1	2	0
2	Dissatisfied	1	2	3	1,82
3	Slightly Dissatisfied	2	3,5	5	3,27
4	Fair	4	5	6	4,93
5	Slightly Satisfied	5	6,5	8	6,38
6	Satisfied	7	8	9	7,96
7	Very Satisfied	8	9	10	8,96

Table 1 was used to determine the weight of each linguistic scale. The weight would be used to obtained crisp output. For an instance, linguistic scale of very dissatisfied customers had fuzzy triangle number of 0, 1, 2 based on figure 2, so the expected value which was geomean of the triangle number would be 0. Thus, the weight of very dissatisfied customers was 0. Once the weight of each linguistic scale was determined, customer satisfaction was collected from 100 customers and we considered the duration of being a customer. The sample number of 100 was obtained from data adequacy calculation. Meanwhile, questionnaire was tested for its validity and reliability. The obtained data was in likert scale of 1-10 where the greater the value, the more satisfied the customers were. However, it was difficult to determine the limit between satisfied and dissatisfied. Therefore, we needed to convert the customers' response into fuzzy value that was shown on Table 2. Based on the raw data at a glance, it could be described that satisfaction tended to decrease in line with the duration of being a customer. Based on the obtained data, there was a pattern showing that the longer a person became a customer, the more decreasing the satisfaction level was.

Table 2.
Satisfaction Level Conversion

Customer	Duration of being customer	Satisfaction Level	VD	D	SD	F	SS	S	VS	Fuzzy Satisfaction
	(years)	(1-10)	0	1,82	3,27	4,93	6,38	7,96	8,96	
1	3	4		1	0					0,098
2	5	4		1	0					0,098
3	4	4		1	0					0,098
4	6	3	0	1						0,098
5	4	5		0	1	0				0,148
6	7	3	0	1						0,098
7	6	5		0	1	0				0,148
9	7	4		1	0					0,098
11	8	5		0	1	0				0,148
12	3	5		0	1	0				0,148
13	6	4		1	0					0,098
14	3	5		0	1	0				0,148
15	5	4		1	0					0,098
16	3	3	0	1						0,098
17	8	3	0	1						0,098
18	3	5		0	1	0				0,148
23	6	4		1	0					0,098
25	5	5		0	1	0				0,148
27	8	5		0	1	0				0,148
28	5	5		0	1	0				0,148
29	6	4		1	0					0,098
30	7	4		1	0					0,098
33	7	3	0	1						0,098
34	7	3	0	1						0,098
35	7	3	0	1						0,098
36	4	5		0	1	0				0,148
37	5	5		0	1	0				0,148
38	6	4		1	0					0,098
39	7	4		1	0					0,098
41	4	5		0	1	0				0,148
42	7	3	0	1						0,098
43	7	3	0	1						0,098
44	7	3	0	1						0,098
45	7	4		1	0					0,098
46	5	6			0	1				0,191

Table 2. (Continued)
Satisfaction Level Conversion

Customer	Duration of being customer	Satisfaction Level	VD	D	SD	F	SS	S	VS	Fuzzy Satisfaction
	(years)	(1-10)	0	1,82	3,27	4,93	6,38	7,96	8,96	
47	8	5		0	1	0				0,148
48	3	5		0	1	0				0,148
49	6	4		1	0					0,098
50	3	5		0	1	0				0,148
51	5	4		1	0					0,098
52	3	5		0	1	0				0,148
53	7	3	0	1						0,098
54	7	4		1	0					0,098
56	8	3	0	1						0,098
57	3	5		0	1	0				0,148
58	6	4		1	0					0,098
59	3	5		0	1	0				0,148
60	6	4		1	0					0,098
61	3	5		0	1	0				0,148
62	5	4		1	0					0,098
63	3	4		1	0					0,098
64	5	4		1	0					0,098
65	4	4		1	0					0,098
66	6	4		1	0					0,098
67	3	5		0	1	0				0,148
68	6	4		1	0					0,098
69	3	5		0	1	0				0,148
70	5	4		1	0					0,098
71	3	5		0	1	0				0,148
72	6	4		1	0					0,098
73	3	5		0	1	0				0,148
74	3	5		0	1	0				0,148
75	6	4		1	0					0,098
76	3	5		0	1	0				0,148
77	3	5		0	1	0				0,148
78	6	4		1	0					0,098
79	8	3	0	1						0,098
80	3	5		0	1	0				0,148
84	7	4		1	0					0,098
86	8	5		0	1	0				0,148

Table 2. (Continued)
Satisfaction Level Conversion

Customer	Duration of being customer	Satisfaction Level	VD	D	SD	F	SS	S	VS	Fuzzy Satisfaction
	(years)	(1-10)	0	1,82	3,27	4,93	6,38	7,96	8,96	
87	3	5			0	1	0			0,148
88	6	5			0	1	0			0,148
90	7	4			1	0				0,098
91	5	4			1	0				0,098
92	3	5			0	1	0			0,148
93	7	3		0	1					0,098
94	7	3		0	1					0,098
95	9	3		0	1					0,098
97	8	3		0	1					0,098
98	6	5			0	1	0			0,148
100	7	4			1	0				0,098

Table 2 was a display showing the conversion process of customer response to be fuzzy satisfaction. In accordance with the previous explanation, the conversion was conducted by using weighted average. Conversion example was the calculation for the 100th customer who had satisfaction level of 4. Based on figure 2, satisfaction level of 4 would cross SD curve at point 1 and F curve at point 0. By considering the weight of SD (3,27) and F (4,93), the crisp output was 0,098.

The cut-off point to bold the phase where a customer started feeling unsatisfied was determined by rating the area of Slightly Dissatisfied, Dissatisfied and Very Dissatisfied as 1, so the value of 0.153 as the cut-off point was obtained. Therefore, unsatisfaction condition occurred when the fuzzy satisfaction value was less than 0.153. Figure 3 presented the probability density function of duration of a customer starting feeling unsatisfied. The y axis represented the relative frequency (density) i.e. how many customers felt unsatisfied, and x axis showed duration (in years) when a customer started feeling unsatisfied. Figure 3 became the base in capturing the statistical probability density function used for predicting how long a customer would fall into unsatisfied condition. The best probability distribution was then fitted into this figure, and stated as f(t).

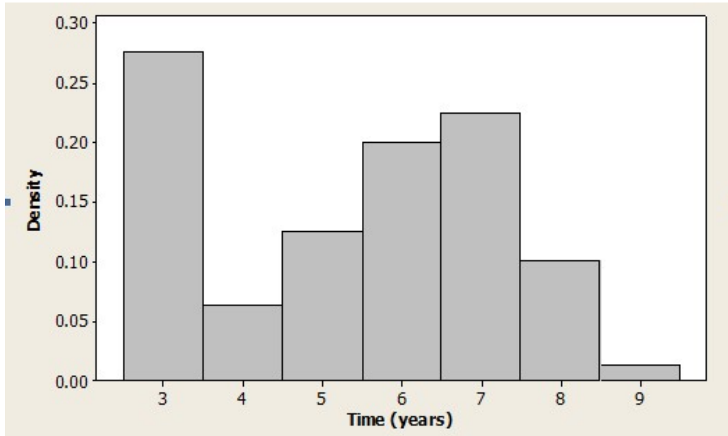

Figure 3.
The Probability Density Function of Duration of A Customer Felt Unsatisfied

Fuzzy unsatisfaction level was used as the main data in survival analysis. In this case, the aims of survival analysis were to determine the average of duration conveying how long customers felt unsatisfied; and to calculate the survival of service, for instance, the probability of a custom service would still satisfy the customer at a certain time t. The survival analysis was started by capturing the probability density function of this duration using a common distribution fitting method. The goodness of fit test was presented by Figure 4.

Goodness-of-Fit

Distribution	Anderson-Darling (adj)	Correlation Coefficient
Weibull	4.867	0.909
Lognormal	5.634	0.926
Exponential	34.172	*
Log logistic	6.767	0.907
3-Parameter Weibull	4.823	0.910
3-Parameter Lognormal	**3.850**	**0.946**
2-Parameter Exponential	153.117	*
3-Parameter Log logistic	4.813	0.929
Smallest Extreme Value	5.145	0.909
Logistic	4.808	0.929

Figure 4.
The Goodness of Fit Test Result for Unsatisfaction Level Data

Referring to figure 4, the suitable probability distribution for those data was 3-parameter lognormal where the probability density function followed formula 2

$$f(t;\mu,\sigma,\gamma) = \frac{1}{(t-\gamma)\sigma\sqrt{2\pi}} exp\left\{-\frac{[ln(t-\gamma)-\mu]^2}{2\sigma^2}\right\} \quad (2)$$

where $0 \leq \gamma < t$, $0 < t < \infty$, $\sigma > 0$. Meanwhile, μ(location), σ(scale), and γ(threshold) were the parameters of lognormal distribution. Through the set of data processing, the obtained parameters were a location equaled to 7.38463, a scale equaled to 0.0010796, and a threshold equaled to -1605.64. Figure 5 presented the set of data processing.

Estimation Method: Least Squares (failure time(X) on rank(Y))

Distribution: 3-Parameter Lognormal

Parameter Estimates

Parameter	Estimate	Standard Error	95.0% Normal CI Lower	Upper
Location	7.38463	0.239378	6.91545	7.85380
Scale	0.0010796	0.0002640	0.0006685	0.0017436
Threshold	-1605.64	385.644	-2361.49	-849.792

Log-Likelihood = -160.273

Goodness-of-Fit
Anderson-Darling (adjusted) = 3.850
Correlation Coefficient = 0.946

Characteristics of Distribution

	Estimate	Standard Error	95.0% Normal CI Lower	Upper
Mean(MTTF)	**5.38762**	0.194453	5.00650	5.76874
Standard Deviation	1.73924	0.132042	1.49878	2.01829
Median	5.38668	0.194453	5.00556	5.76780
First Quartile(Q1)	4.21401	0.213707	3.79515	4.63287
Third Quartile(Q3)	6.56021	0.214049	6.14068	6.97974
Interquartile Range (IQR)	2.34620	0.178122	2.02182	

Figure 5.
Estimating Parameter of Unsatisfaction Level Distribution

Survival analysis was conducted by calculating the reliability status following the function of R(t) and Mean Time To Failure (MTTF). The formulas of R(t) and MTTF were presented by formula (3) and (5)

$$R(t) = 1 - F(t) = \int_t^\infty f(t)dt \quad (3)$$

$$F(t) = \int_0^t f(t)dt \quad (4)$$

$$MTTF = \int_0^\infty tf(t)dt \quad (5)$$

Parameter estimation which was presented by Figure 5 informed the value of 3 parameters of lognormal distributionf(t). Thus, the cumulative distribution function of F(t) could be established. Meanwhile, the probability representing the customers feeling satisfied until certain time of t was determined by reliability function of R(t). The functions of f(t) and R(t) were shown by Figure 6 and Figure 7.

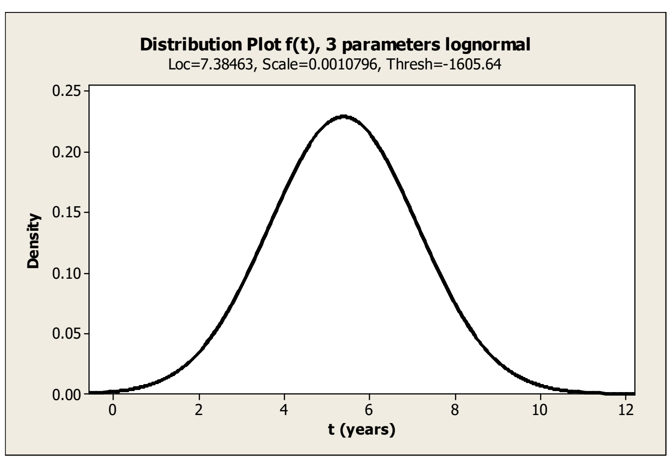

Figure 6.
Distribution Plot for Lognormal Distribution (μ=7.38463, σ=0.0010796, γ=-1605.64)

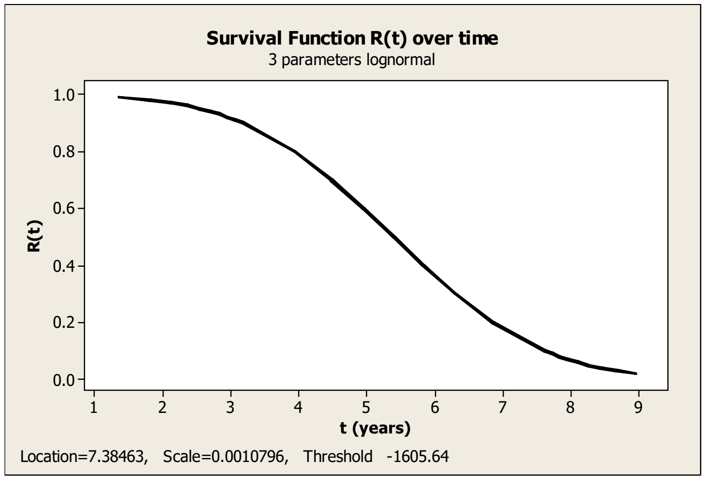

Figure 7.
Survival Function of Service Based on Fuzzy Satisfaction

Figure 6 showed the best-fitted statistical probability distribution f(t) that captured the density of duration of being an unsatisfied customer, based on data shown in Figure 3. Applying formula (3) and f(t), the reliability function R(t) had been calculated and graphed in Figure 7, where x axis represented the duration (in years) when a customer started feeling unsatisfied, and y axis showed the decreasing trend of how reliable the service was. Survival function curve of R(t) showed that the longer the customer experienced a service, the smaller the probability representing satisfied customers.

Based on the curve of R(t), the moment to innovate service could be predicted by estimating the tolerable value of R(t) and by considering the average of Mean Time To Failure (MTTF), based on equation 5. Thus, predicting service reliability was well answered. In this case, the value of R(t) which was quite high and tolerable occurred when duration of time was about 5 years. It was based on the MTTF of 5.3876 years. By considering the value of MTTF, It was recommended to SAMSAT public service to innovate their service to maintain customer satisfaction and to delay the time when the customer would feel unsatisfied. Referring to the aim of this research, the result showed that the combination of survival analysis and fuzzy had predicted the time to innovate successfully which should be taken by service provider. It was based on MTTF, about 5 years the service provider should improve their service design as a part of maintaining the level of customer satisfaction.

5. Conclusions

Based on the data processing, it could be predicted that SAMSAT as a service provider should provide service innovation once every 5 years. The prediction was made based on the survival analysis of fuzzy satisfaction. The concept of survival analysis used to be applied for tangible products could be used for service cases to recognize the life cycle of either products or services. First, the trend of customer satisfaction level was analyzed, and then probability density function of customer unsatisfaction level was established. Considering that response variable was linguistic variable and ambiguous, fuzzy logic was used to bold the definition of unsatisfaction level. The established probability density function would help doing survival analysis and determining the right moment for innovating service based on value of Mean Time To Failure (MTFF).

Thus, two main problems in this research, i.e., assessment standard of satisfaction among customers and determination of critical time to innovate the service, were solved by integrating fuzzy and survival analysis to predict service life cycle. Regarding the limitation of this research, the case study used was representing the public service the characters of which were different from the private one. In private service, the service provider was demanded to be more creative in offering the service to response the competition. It would influence the value of time to innovate. Furthermore, it affected the managerial decision to decide the time to innovate based on the type of service. Thus, predicting service life cycle was a critical point to help service providers doing survival analysis service given.

However, there were many approaches to predict life cycle of service, which was intangible product, and many possibilities to explore the use of analyzing service life cycle so that the better result of future research would be found. In this research, it would be increasingly complete if the probability of satisfaction churn was analyzed (Herowati, Ciptomulyono, Parung, & Suparno, 2014).

Furthermore, the framework to predict service life cycle based on its reliability function would be able to be developed in a software or a mobile application. Presently, another on going research is developing software that is able to display the graph of service life cycle based on simple customer satisfaction survey that is often conducted by a company. Thus, the company is able to monitor life cycle of service offered regarding whether it starts declining. In addition, technology and information system have an important role in this research. It reinforces that industry 4.0 occurs and influences multi aspects including service field development.

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