Predicting Customers Issues Resolution Times in Mobile Terminals

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Abstract—**A factor affecting the customer satisfaction for users of a mobile terminal (MT) is how fast their possible service issues are resolved from the time they report them. As MT subscriptions have grown tremendously since the mid-eighties, the number of issues concerning the MT has grown as well. These are due to changes in factors such as technologies, applications, usability, and user interfaces. Technology changes have led to various issues that have to be resolved correctly and within a reasonable time, to keep subscribers satisfied and loyal. This paper has attempted to build a statistical model that can predict customer issue resolution times (iRT) from the moment they are reported through an inbuilt-tool for gathering Nokia product information and end user support (GENIUS). A two year (2010–2011) data bank of resolved technical issues was used to build a model to predict iRT. An initial result shows that the variable predictors selected for building the iRT model explains only 4.4% of the response variations in the model. In practice this model cannot be used in the real world and this advocates for further reaseach in the future.**

Keywords- Predicting Model, Customer Satisfaction, issue resolution time

I. INTRODUCTION

The aftermarket technical support engineers in mobile terminals are often asked to estimate or predict (forecast) the amount of time needed to resolve customers' issues from the field to keep the customer informed about their mobile phone handset. In a situation that the customer has already faced disappointment with the product, a low iRT is one of the factors that may attract customers and keep them satisfied and loyal to a company. A practical model of predicting the iRT would thus have a significant practical implication.

A. Prediction models

Prediction is the model used in this study.[1]

Although a prediction model would be useful, initial literature searches revealed that there is little work in mobile terminals (MT) that has attempted to predict how long a newly escalated customer issue will take to resolve. Predicting customer's iRT is an essential part of any business activity. However predicting iRT requires setting objectives one of which is to set iRT targets. Predicting techniques vary in complexity and data requirements. However each technique fits a situation and thus an appropriate method should be used for the appropriate situation to achieve high accuracy [2]. There are many forecasting techniques, [3], one could choose from. They are: (1) Subjective (2) Time Series Techniques and (3) Cross Section Techniques. The choice of the method depends upon the nature of the data and the objective of the forecaster [2]. In extreme cases many techniques, have to be combined to achieve the objective of the project. Some researchers, in [4], [5], and [6] suggest aggregating the forecast of several methods rather than a single method. The researchers concluded that the accuracy of combined forecasts depends on both the method being used and the number of methods. They further concluded that the larger the number of methods in aggregate increases the accuracy. This argument has support [7] as it claimed that combining two different methods can frequently improve forecasting. However, combining the forecasts from different methods cannot be better than the "true" underlying model of the process generating data [8]. Regardless of the method used, if the statistical rules of the technique are not adhered to, the results will be misleading.

B. Customer satisfaction in service incidents

Service failure is one "pushing determinate" that drives customer switching behavior [9] and successful recovery can mean the difference between customer retention and defection. Companies often take too long to respond to unhappy customers, and then respond impersonally. By responding quickly, a firm conveys a sense of urgency. Quick response demonstrates that the customer's concern is the company's concern. By responding personally, with a telephone call or a

[1] The terms "prediction" and "forecast" are two different words Predicting is about saying what happens, but it may be for the past, present and future. e.g. the model predicts that an extra year of education gives 1000 euros more of income. Prediction is the process of estimating values of dependent variables based on the knowledge of an independent variable. A review by Lewis-Beck [1] clarifies the fine difference between these two words: "Forecasting aims to tell of events before they happen. It differs from prediction in that it looks to the future, whereas prediction may not (as in a successful reconstruction of some past outcome). Further, forecasting differs from explanation, having the goal of predicting an outcome, rather than the goal of theorizing about outcomes".

visit, the firm creates an opportunity for dialogue with the customer—an opportunity to listen, ask questions, explain, apologize, and provide an appropriate remedy [10]. Speed of the response is crucial to customers [11]. Service employees need specific training to deal with dissatisfied customers and how to help customers solve a service issue. Customers judge the responsiveness, assurance, empathy and tangibles during the service delivery process; hence, these are seen as the process dimensions of the service delivery [10]. Customer satisfaction was found to be lower after service failure, even given high-recovery performance, than in the case of error-free service [12]. Research has shown that effectively handling customer complaints has a dramatic impact on customer retention and loyalty [13]. Collecting customer complaint data is common practice in many companies and has received vast research attention. Research has focused on the process to handle complaints on the customer experience and analysis of complaint data and the relationships to important business outcome [14], [15]; [16], [17], [18], [19], [20]. This paper is trying to develop a model that predicts the iRT for providing iCA i.e., service recovery for customers' issues. The prediction model is directed towards being a practical tool for managers in after-sales process, providing both a tool for managing after-sales service and being a prediction tool aiding customer work.

The remainder of this paper is organized as follows: In section 2, we explain how and where the data was gathered and the descriptive statistics of the data is also displayed. We explain how the customer issues are escalated and the predicting model block diagram is provided with explanation. Section 3 explains the statistical procedure method. Section 4, the predicting model results and testing are tabulated and explained. In section 5, a discussion and conclusion are provided.

II. CASE AND DATA GATHERING

Nokia is one of the biggest mobile phones manufacturers in the world. Millions of phones are sold by the company. The authorized service vendors (ASV) provide services for Nokia products. The customers in this paper are the ASV's who are in turn in contact with end users or consumers. It is important for the ASV to have an estimate of time for when a customer issue will be resolved. By knowing the iRT the ASV can for example, decide to give a loan or swap the MT to keep the customer satisfied. A two year (2010-2011) data bank of resolved technical issues is gathered and analyzed using suitable statistical methods to predict the iRT for service recovery. The following describes the after sales service issue escalation chain [21] and data gathered from the process.

A. High level customer issue escalation process

The customer issue escalation process is shown in Figure 1 below where:

- SL Service Level
- SL1 Authorized Service Vendor (ASV)
- SL2 Country Sales Area - Care (CSAC)
- SL3 Region Sales Area - Care (RSAC)
- SL4 Care Product Mangers (CPM)
- SL5 Product Designers (R&D)

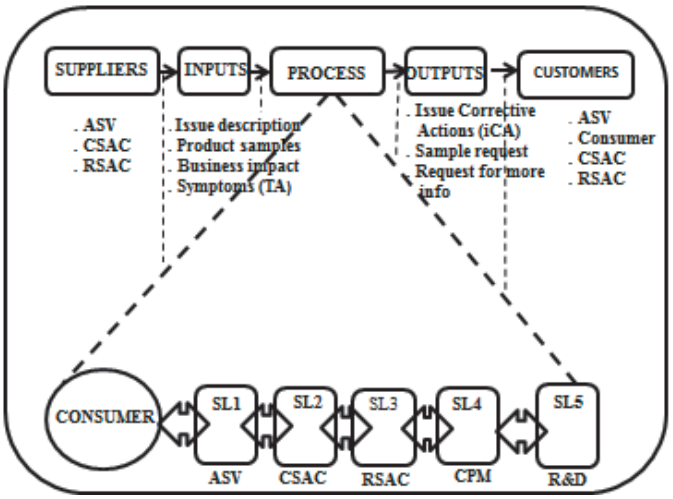

Figure 1. SIPOC diagram of the customer issues escalation

The main suppliers in the SIPOC (Supplier, Input, Process, Output, and Customer) diagram are the mobile terminals authorized service vendors (ASV), and less frequently is the manufacturer using the country sales area technical support engineers (CSAC) and the manufacturers region sales technical support engineers (RSAC). The inputs are the customers' issues raised by the ASV (called SL1 in the service chain network) including the product specifications like software, variant software, product samples, issue symptoms (TA), business impact (iBI) due to the issue etc. The process is described as follows: When a customer X approaches an ASV with an issue Y with his/her mobile terminal (MT), the ASV tries to find a solution for the Y issue and resolve the issue and gives back the MT to the customer X. However if the issue Y can't be resolved by the AVS, the issue is documented into an in-house tool called GENIUS and escalated to the sales area (SA) technical support (referred as SL2 in the service chain), who then resolves the issue and returns it back to SL1 or otherwise they escalate the issue to regional sales area technical support engineers (RSAC) i.e. SL3. The process goes as described before until the issue resolution is found. The issue correction action (iCA) is the output in the SIPOC chain. The customers are mainly the ASV and indirectly the consumers i.e. end users of the MT.

B. Data gathered for the model

A two year (2010-2011) data bank of more than 10 000 resolved technical issues was gathered from the in-house database for building an iRT prediction model. The parameters which were deemed suitable for building the predicting model were:

- Entity types of mobile terminal, i.e. the business unit (BU)

- The software platform, (SWP) i.e. for example Symbian, Windows 7, Linux tablet, Maemo, CDMA, MeeGo and Mango
- Program centers (PC) where the MT design was done
- Sales area (SA)
- Symptoms of the reported issues (iTA)
- Business impact of the reported issue (iBI)

The interrelation of the above variables is shown in Figure 2. The authorized service vendor (ASV) in SA originates an issue provided by a customer owning a mobile terminal (MT). The issue is documented and described in the inbuilt house tool called GENIUS. The ASV defines the iBI and symptom of the issue (TA). The AVS provides also the product type of the MT, SWP and other supplementary information like the name of the operator, error screenshot, availability of the MT samples for verifications if needed, etc. The ASV is known as level one (L1) when reporting the issues in the GENIUS tool. The Program Center (PC) is the research and development department where the MT was designed. The PC is provided by the care technical support personnel, known as level 2 (SL2) in the SA to the issue database tool, in this case GENIUS. The TA, iBI, SA, SWP, BU and PC are variables that are fed into the iRT predicting model under study. The SWP, BU and PC are interdependent. The SWP is the software version in the MT; BU is the category of the MT e.g. smart MT, mobiles MT.

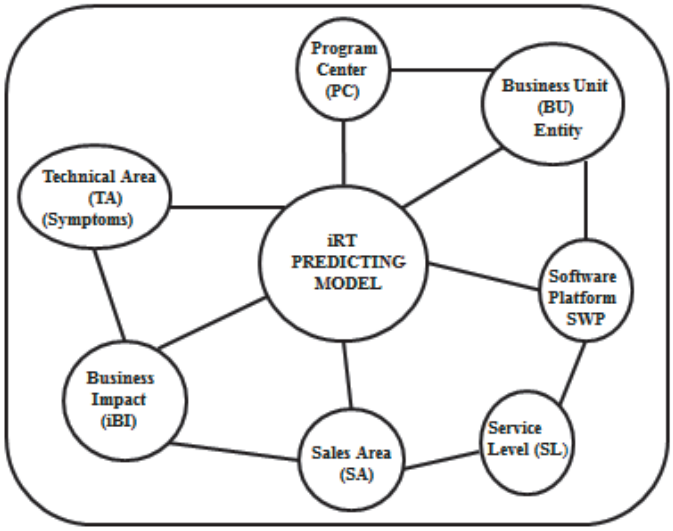

Figure 2. Block diagram of the variables for predicting iRT

Figure 3 displays the iRT predicting model.

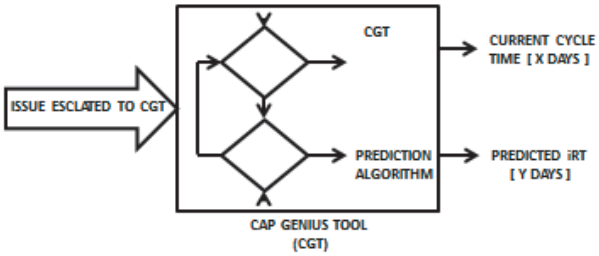

Figure 3. The iRT Predicting Model Diagram

The model displays two outputs at the same time, one which is the current time, i.e. how long has an issue been open (X days) and the second is the predicted time (Y days) for resolving the issue.

The descriptive statistics of the variables gathered are summarized in Annex I.

III. STATISTICAL PROCEDURE METHODS

A statistical model was fitted to the two year (2010–2011) data bank in order to obtain an estimation model that can be used to predict the iRT's for future customers. The statistical model used was a linear model. The iRT values were first Box Cox transformed in order for the model to meet the assumption of normality. Other model assumptions were also checked. Several candidate variables were proposed to be included in the model as explanatory variables and the model was then reduced by removing a non-significant variable in service level (SL). The final model for each level is provided in the results section. Some values of the different explanatory variables were excluded from the modeling, due to limited number of observations. All the candidate variables were chosen so that they could later be used for the actual or absolute (aiRT) prediction and so the information would have to be available when the customer brings the device for maintenance. The model yields the predictions on Box Cox transformed scale, (the Minitab simply finds an optimal power transformation) so that before building the model in Excel, coefficients need to be transformed back to the original scale of measurement. The statistical models for different levels were fitted using the Minitab version 16.1. The model was built and tested with Excel.

IV. ANALYSIS RESULTS

To begin with, we had a large number of variable predictors (SA, iTA, PC, iBI, SWP, BU) and service level (SL) which would be used for predicting iRT at each service level. Significant variable predictors were screened for each SL as will be displayed in the next four sub chapters. It was found that not all variables were significant for building the iRT predicting model

TABLE I. GENERAL LINEAR MODEL: SL1 TIME^ 0.09

Factor	Type	Levels	Value
SA	Fixed	4	SA1, SA2, SA4, SA5
iTA	Fixed	17	iTA1, iTA2, iTA3, iTA4, iTA5, iTA6, iTA7 iTA8, iTA9, iTA10, iTA11, iTA12, iTA14, iTA15, iTA16, iTA19
iBI	Fixed	3	iBI1, iBI2, iBI3

From Table I it can be seen that SA, iTA and iBI variables were suitable for building the prediction model at SL 1

TABLE II. ANALYSIS OF VARIANCE SL1 TIME^ 0.09 USING SSADJ FOR TESTS

Source	DF	Seq SS	Adj SS	Adj MS	F	P
SA	3	5,096	3,383	1,128	25,88	0,000
iTA	16	2,102	1,948	0,122	2,79	0,000
iBI	2	0,319	0,319	0,160	3,66	0,000
Error	1035	45,105	45,105	0,044		
Total	1056	52,623				
S = 0,209, R^2 = 14,29% R^2_{adj} = 12,55%						

For SL1, significant predictor variables for the model were found to be the SA, iTA and iBI. From the above results (see Table II) for SL1 R^2_{adj} = 12,55% which means only 12,55% of the response variables variation is explained by the predictor variables.

From Fig 6, Annex II, it can be observed that the residual histogram figure is binomial but fullfills the normality condition.

TABLE III. GENERAL LINEAR MODEL: L2 TIME^ 0.13

Factor	Type	Levels	Value
SA	Fixed	4	SA1, SA2, SA4, SA5
iTA	Fixed	16	iTA1, iTA2, iTA3, iTA4, iTA5, iTA6, iTA7 iTA8, iTA9, iTA10, iTA11, iTA12, iTA14, iTA15, iTA16,
Input SL	Fixed	2	L1, L2

From Table III it can be seen that SA, iTA and input SL variables were suitable for building the prediction model at SL2.

TABLE IV. ANALYSIS OF VARIANCE SL2 TIME^ 0.13, USING ADJUSTED SSADJ FOR TESTS

Source	DF	Seq SS	Adj SS	Adj MS	F	P
SA	3	17,553	16,582	5,527	93,33	0,000
iTA	15	2, 585	2,559	0,171	2,88	0,000
Input SL	1	1,787	1,787	1,787	30,17	0,000
Error	1680	99,400	99,500	0,059		
Total	1699	121,424				
S = 0,243363, R^2 = 18,06% R^2_{adj} = 17,13%						

For SL2, significant predictor variables for the model were found to be the SA, iTA and input SL. From the above results (see Table IV) for SL2, R^2_{adj} = 17,13% which means only 17,13% of the response variables variation is explained by the predictor variables.

From Figure 7, Annex II, it can be observed that the normal probability plot fits the regression curve most of the part. residual histogram figure fullfills the normality condition.

TABLE V. GENERAL LINEAR MODEL: SL3 TIME^ 0.16

Factor	Type	Levels	Values
SA	Fixed	3	SA2, SA4, SA5
Input SL	Fixed	3	L1, L2, L3

From Table V it can be seen that SA, and input SL variables were suitable for building the prediction model at SL 3.

TABLE VI. ANALYSIS OF VARIANCE FOR SL3 TIME^0.16 USING ADJASTED SS FOR TESTS

Source	DF	Seq SS	Adj SS	Adj MS	F	P
SA	2	2,054	2,546	1,273	17,64	0,000
Input SL	2	2,216	2,216	1,108	15,35	0,000
Error	896	64,669	64,669	0,072		
Total	900	68,939				
S = 0,269, R^2 = 6,19% R^2_{adj} = 5,78%						

For SL3, 2 variables among the 7 initial variables were suitable for building the predicting model at this level. However still the $R^2_{adj.}$ was found to be very small. Only 5,78% of the response variation is explained by the predictor variables, i.e., SA and SL as indicated in Table VI.

TABLE VII. GENERAL LINEAR MODEL: SL 4 TIME^ 0.19

Factor	Type	Levels	Value
PC	Fixed	6	PC1, PC2, PC3, PC4, PC5, PC6
SA	Fixed	4	SA1, SA2, SA4, SA5
iTA	Fixed	17	iTA1, iTA2, iTA3, iTA4, iTA5, iTA6, iTA7 iTA8, iTA9, iTA10, iTA11, iTA12, iTA14, iTA15, iTA16, iTA19
iBI	Fixed	3	iBI1, iBI2, iBI3
Input SL		3	L1, L2, L3

From Table VII it can be seen that PC, SA, iTA, iBI and input SL variables were suitable for building the prediction model at SL4.

TABLE VIII. ANALYSIS OF VARIANCE FOR SL4 TIME^0,19, USING $SS_{ADJ.}$ FOR TESTS

Source	DF	Seq SS	Adj SS	Adj MS	F	P
PC	5	44,866		8,767	42,87	0,000
SA	3	16,264	3,383	2,458	12,02	0,000
iTA	16	5,977	1,948	0,363	2,79	0,029
iBI	2	1,015	0,319	0,160	1,77	0,066
Input SL	2	6,730		0,558	2,73	0,000
Error	1728	353,369	45,105	3,365	16,46	
Total	1756	428,220		0,205		
S = 0,4522, R^2 = 17,48% R^2_{adj} = 16,14%						

For SL4, significant predictor variables for the model were found to be the PC, SA, iTA, iBI and input SL. From the above results (see Table VIII) for SL4, $R^2_{adj.}$ = 16,14% which means only 16,14% of the response variables variation is explained by the predictor variables.

From Fig 9, annex II, it can be observed that the normal probability plot fits the regression curve most of the part. residual histogram figure fulfills the normality condition.

1) Model evaluation

To evaluate the predicting models for the whole chain i.e., from SL1 – SL4, the rest of the 5000 issue cases from the 10000 instances collected in two years were used for testing the iRT predicted for the whole service chain, i.e., from SL1 to SL4 and the results are displayed in Fig 4 below. The predicted resolution time for the reported issue is obtained by the simulated model equation:

$$iRTPredicted = \sum (mSL1, mSL2, mSL3, mSL4)$$

Where mSL1, 2, 3 and 4 are predictions calculated for individual Service Levels by using GLM coefficients.

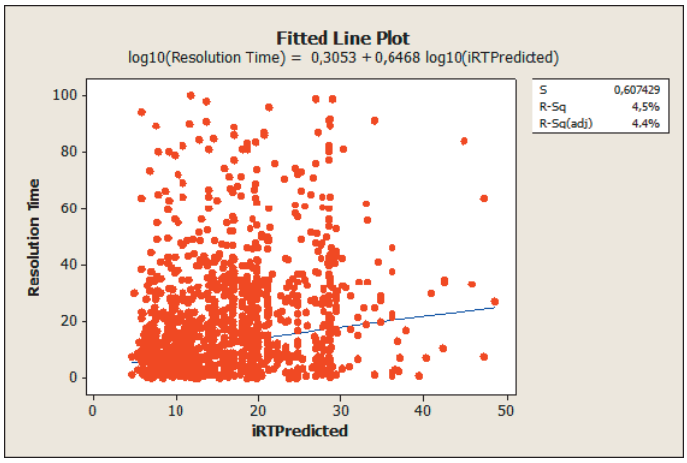

Figure 4. iRTPredicted versus actual or absolute issue resolution time (aiRT)

Regression Analysis: Resolution Time versus iRTPredicted

The regression equation is

log10(ResolutionTime) = 0,3053 + 0,6468log10(iRTPredicted)

S = 0,607429 R-Sq = 4,5% R-Sq(adj) = 4,4%

2) Analysis of variance

TABLE IX. ANALYSIS OF VARIANCE

Source	DF	SS	MS	F	P
Regression	1	21,262	21,2620	57,63	0,00
Error	1224	451,619	0,3690		
Total	1225	472,881			

From the prediction results displayed in Fig. 4, the model explains only 4.4% of the test population variation. Even though there is strong evidence against the null hypothesis (see P-value for regression in Table IX) in favor of the alternative, there is no practical significance (R-Sq and graphical analysis).

V. DISCUSSION AND CONCLUSION

This work attempted to build a time prediction model for issues presented by customers in MT of a study company. Seven different predictors (BU, SWP, SA, PC, iTA, iBI and SL) were initially choosen to build a model which would predict iRT for the customers' issue. Over 10000 issue cases from two years data stored in an in-house tool were collected for this purpose. The first 5000 pieces of data were used for building a predicting model for each individual SL. The second 5000 pieces of data were used to verify the models for the whole SL chain. The model bulding for each indivual SL showed that not every predictor was suitable for predicting, so only those predictors found by testing the significance were employed into the building process. It was found in SL $R^2_{adj.}$ to be very low which means the variable predictors could not explain well enough the response variations of the data

collected for building the models. SL2 had the highest R^2_{adj} = 17,13% and SL3 had the lowest R^2_{adj} = 5,78%. The whole SL chain i.e from SL1-SL4 had even worse R^2_{adj} = 4.4%. So it can be concluded that the variable predictors selected for building the iRT model explains only 4.4% of the response variations in the model. In practice this model cannot be used in the real world. However, the method and methodology applied to research the iRT variables can be used in future when more factors concerning the parameters explaining the variables are found. In order to improve the model predictive accuracy, further research will be done by investigating other factors and variables that will improve the prediction effectiveness. Among other things that are to be analyzed is the hardware (HW) of the products e.g. the printed wire board, as these might be of different versions at different stages of the life of the product. HW implies a circuit board where all components forming a product are surface mounted or soldered. The same goes for the software versions including the variant software which are specific for a specific customer. Another factor that might have an influence on iRT is the samples for verifying an issue. Time to receive samples for verifying an issue is not always predictable due to different custom regulations in different countries and for issue resolvers it takes a long time to receive the samples [22]. The iBI is subjective; it is likely to vary from person to person. Deeper subgrouping of the iTA would be worth investigating. Another issue that should be investigated is to find the way of working in each SL and note some practices or other work operating modes which differs from the assumed standard normal working routine.

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ANNEX I. DESCRIPTIVE STATISTICS OF THE VARIABLES GATHERED

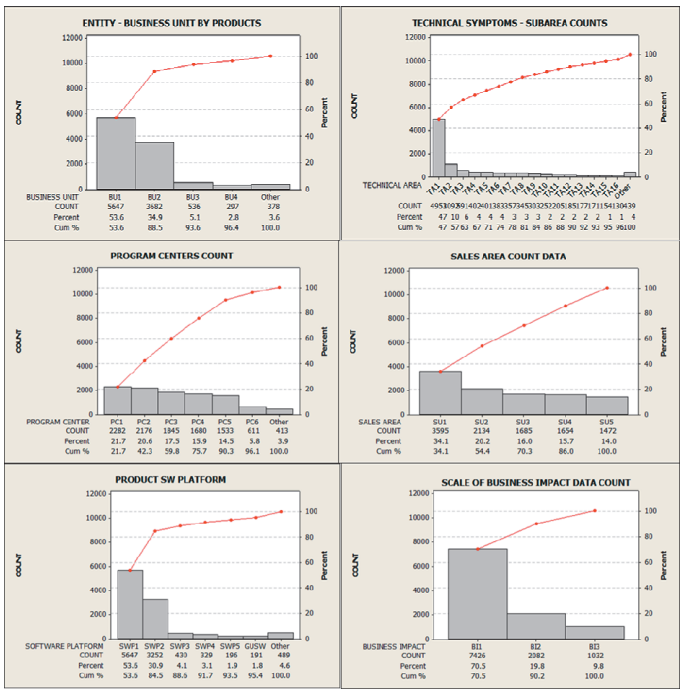

Figure 5. Pareto chart of the explanatory variables gathered for building the iRT predicting model

ANNEX II. MODEL RESIDUAL FOR DIFFERENT SERVICE LEVELS (SL)

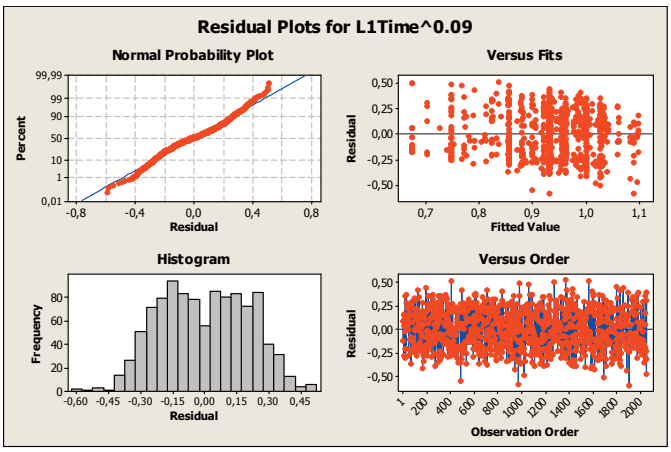

Figure 6. Model Residual for SL1

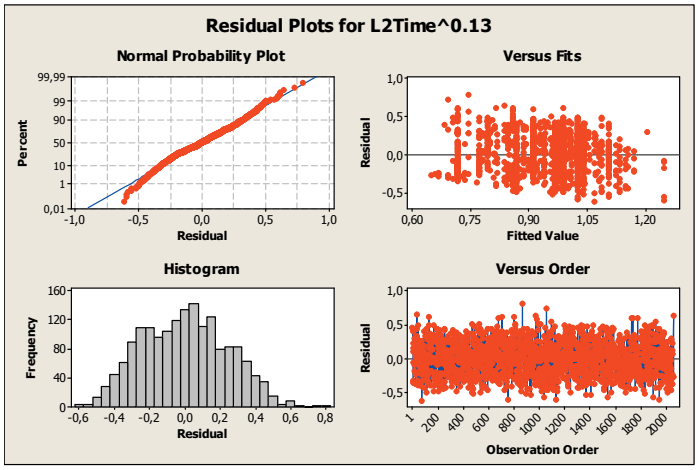

Figure 7. Model residual for SL2

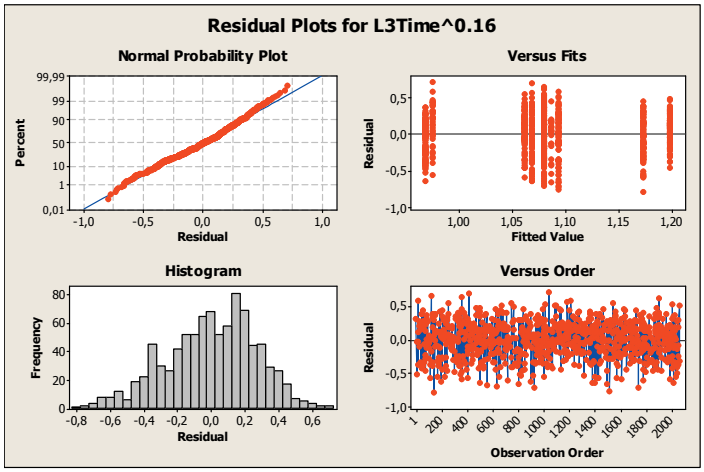

Figure 8. Model residual for SL 3

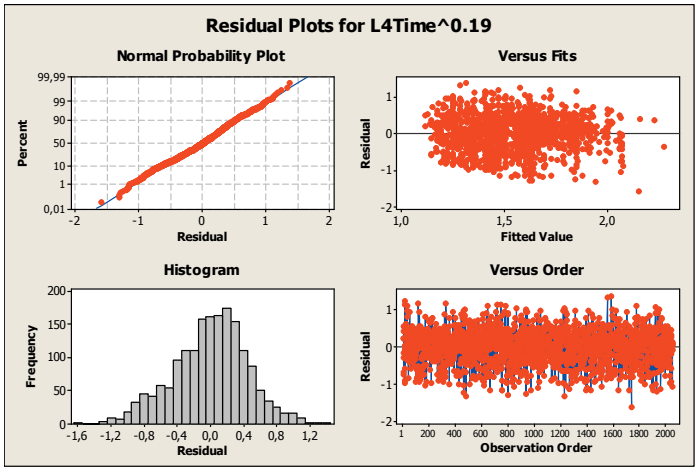

Figure 9. Model residual for SL4