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Application of Reliability Prediction Model Adapted for the Analysis of the ERP System

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Abstract**—**This paper presents the possibilities of using Weibull statistical distribution in modeling the distribution of defects in ERP systems. There follows a case study, which examines helpdesk records of defects that were reported as the result of one ERP subsystem upgrade. The result of the applied modeling is in modeling the reliability of the ERP system from a user perspective with estimated parameters like expected maximum number of defects in one day or predicted minimum of defects between two upgrades. Applied measurement-based analysis framework is proved to be suitable in predicting future states of the reliability of the observed ERP subsystems.

Keywords**—**ERP, reliability, Weibull

I. Introduction

TODAY, ERP systems have become a very important part of overall operations in companies, but also introduced new risks into the business because a malfunction of any part of the ERP system may cause downtime in business. Defects that arise as a result of an ERP software module change unfortunately cannot be avoided, but it is only possible to make some effort to decrease the number of defects. Modeling the reliability of the installed ERP system from the user perspective can help identify the risks of using such systems and assess the impact of possible consequences on overall business. Upgrades and customization of ERP systems are very frequent cause of new defects in the system. Constant change of an existing ERP system is unavoidable for different reasons like user requirements, technology change and development process. In this paper, a reliability modeling from a user perspective is presented for one part of an ERP system deployed at one telecom provider. Presented case study illustrates analysis of help desk data collected during one year of observed ERP subsystem usage. The user was interested to find out the critical parameters of system maintenance resulting from the regular monthly upgrades such as the expected number of new defects and boundaries in which they will appear. The proposed model is an improvement of the initial research, described in more details at [1], in which the impact of ERP upgrades was modeled in time domain.

That is a very common case of software reliability modeling in general, when the probability of occurrence of defects in the system is function of time, e.g. after ERP upgrade a certain number of new defects will be discovered in the ERP system with elapsed time probability. In this paper, the paradigm of presented case study is different because the numbers of recorded defects are not indexed in time. This approach is actually much more common in the statistical analysis, when patterns are grouped and sorted by the number of occurrences within a range of values and compared with assumed theoretical statistic distribution. In this paper, Weibull distribution is confirmed as a best fit model that describes number of defects distribution for every period between two subsequent upgrades. Applied measurement-based analysis framework is proved in prediction of Weibull distribution parameters.

II. Basic Definitions

There are no generally accepted definitions for software *error*, *fault* or *failure* but according to [2] next definitions can be used for any software system:

- software error is error due to a mistake made by the software developer during the programming process
- software fault is a manifestation of a software error
- software failure occurs when a fault prevents software from performing its required function within specified limits

When an ERP user has a problem experienced with a product it might be due to a software failure caused by a fault. More often (sometimes 80 to 90 percent [7]) a customer calls experiencing difficulties due to poor procedures, unclear documentation, poor user interfaces, etc. The product actually works good but poorly designed and much to the dissatisfaction of the user. In that case problem can be addressed with wider definition as *defect* [2] as something that requires necessary change in ERP system. According to definition of software reliability [2], ERP system reliability can be defined as the probability of defect-free software operation in a specified environment for a specified period of time.

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III. MODELING

Modeling the appearance of defects in the observed ERP subsystem comes down from Figure 1.

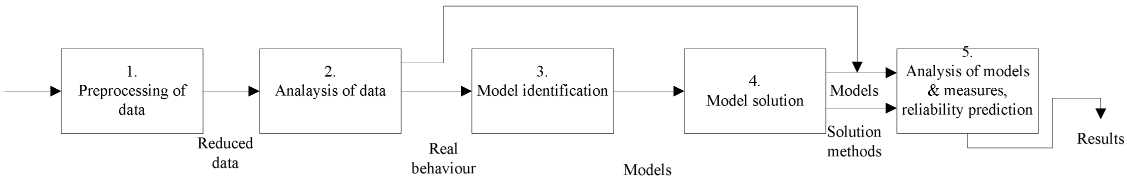

Fig. 1 Measurement-based analysis framework of ERP system reliability

In the step 1 from Figure 1, defects were grouped in samples by days for every period between upgrades. As an example, grouped defects for the 7th month for one ERP subsystem named as Module1 are shown at Table I.

TABLE I
GROUPED DEFECTS BY WORKING DAYS, FOR THE 7TH MONTH, MODULE1

working day	defects
1	15
2	2
3	3
4	20
5	17
6	14
7	10
8	8
9	9
10	4
11	18
12	22
13	17
14	8
15	17
16	8
17	12
18	26
19	14
20	7
21	5
22	0

The samples from Table I must be grouped in specific interval of number of defects. There is no optimal choice for the number of bins (*k*), but there are several formulas which can be used to calculate number of bins based on the sample size (*N*) [4].

As described in [3], MathWave EasyFit application has been used for statistical analysis and that software is using empirical formula:

$$k = 1 + log_2 N \tag{1}$$

Number of samples in Table 1 is N=22 and from (1) number of bins is calculated as $k \approx 6$.

According to Table I, maximum number of defects D_{max} in one day is 26. The width of interval that includes the number of reported defects from Table I in separate bins can be calculated as:

$$\Delta = D_{max} \ \% \ k \quad = 5 \tag{2}$$

In the step 2, as a result of (1) and (2), defects from Table I are sorted at Table II as empirical distribution of number of defects from Table I.

TABLE II
EMPIRICAL DISTRIBUTION OF NUMBER OF DEFECTS FROM TABLE 1

number of defects per one day	[0,5>	[5-10>	[10,15>	[15,20>	[20,25>	[25,+∞>
number of samples	4	6	4	5	2	1

In the step 3 and 4, analysis of data has resulted in Weibull distribution [6] of number of defects for every period between two subsequent upgrades. As an example, theoretical best fit Weibull distribution for empirical distribution from Table 2 is calculated with EasyFit [3] with parameters α=1,9797, β=13,752. Parameters of best fit Weibull distribution can be calculated with different algorithms like method of moments (*MOM*) [4], maximum likelihood estimates (*MLE*) [4] or least squares estimates (*LSE*) [4]. In presented application [3] Weibull distribution parameters are calculated with MLE algorithm. According to [2], parameters are calculated from (3) and (4):

$$\frac{n}{\alpha} + \sum_{i=1}^{n} lnX_i - \frac{n\sum_{i=1}^{n} {X_i}^{\alpha} lnX_i}{\sum_{i=1}^{n} {X_i}^{\alpha}} = 0 \tag{3}$$

$$\beta = \left(\frac{\sum_{i=1}^{n} x_i^{\alpha}}{n}\right)^{\frac{1}{\alpha}} \quad (4)$$

As an example, comparison of empirical distribution from Table II and theoretical best fit Weibull distribution is displayed at Fig. 2. Theoretical Weibull distribution is calculated with:

$$P(n) = 1 - e^{-(\frac{n}{\beta})^{\alpha}} \quad (5)$$

In formula (5) n is number of defects, and $P(n)$ is cumulative probability for number of defects that will be distributed in interval [0,n]. For example, the cumulative probability that number of defects will be distributed in interval [0,25] with estimated Weibull parameters (α=1,9797, β=13,752) is 98%.

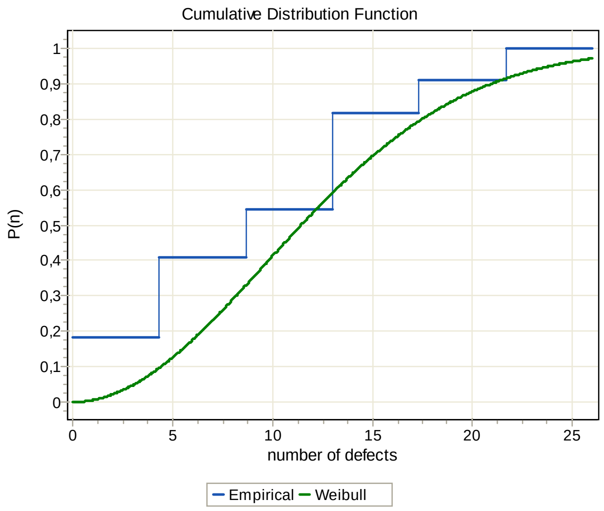

Fig. 2 Comparison – empirical and best fit Weibull distribution, Module1, 7th month

The resulting distribution is compared with empirical distributions from Table II with statistical tests like Kolmogorov-Smirnov (KS) [4] and Anderson-Darling (AD) [4]. Test results for the chosen significance level (α=0,05) are presented at Table III.

TABLE III
KS AND AD TEST FOR THE BEST FIT WEIBULL DISTRIBUTION, MODULE1, 7TH MONTH

Kolmogorov-Smirnov		Anderson-Darling	
Statistic $[D_n]$	0,11934	Statistic $[D_n]$	2,1147
Α	0,05	α	0,05
Critical Value $[D_0]$	0,28087	Critical Value $[D_0]$	2,5018
Reject?	No	Reject?	No

Described procedure must be repeated for each period after the upgrade.

In the step 5, prediction of future Weibull distribution must be tested. The whole procedure of prediction is basically reduced to the use of some known algorithms to predict future values of the theoretical distributions based on previous reports. For example, if the parameters of theoretical distributions that are describing previous six upgrades are known, then it is possible to determine the parameters of expected distribution for the seventh month. In a presented case study, two algorithms were used like Linear Regression [4](in the following text LR) and KNN [5] algorithm. Example of using the LR procedure for prediction on 7th month, using previous six pairs Weibull parameter α and β, from presented case study (Table 7) , is visible at Figure 3. Example of using the KNN algorithm ($k = 3$), for the same prediction, is presented at Table 4. For LR procedure, prediction is α=1,9933; β=11,6138 and for KNN algorithm prediction is α=1,8762; β=12,9642. Formal statistical tests are performed for both predictions and results are presented at Table 5 and Table VI. According to statistical test results (Table 5, Table VI) prediction is good.

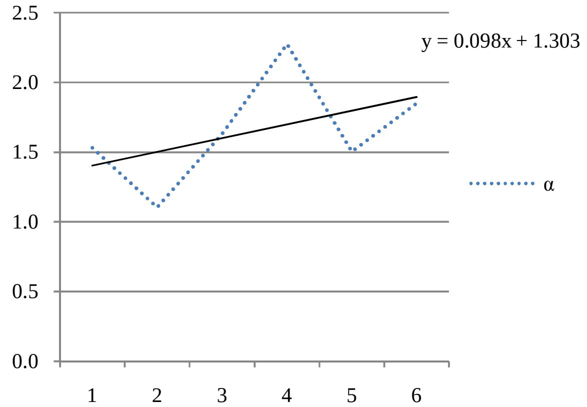

Fig. 3 LR method in prediction of Weibull α parameter, for 7th month, after Module1 upgrade

TABLE IV
KNN METHOD IN PREDICTION OF WEIBULL PARAMETER, FOR 7TH MONTH, AFTER MODULE1 UPGRADE

Month	α	Distance	Nearest neighbor for k=3
1	1,5306	6	
2	1,1038	5	
3	1,6279	4	
4	2,2743	3	2,2743
5	1,5034	2	1,5034
6	1,8509	1	1,8509
7	**1,8762**		

TABLE V
KS AND AD TEST FOR LR PREDICTION, 7TH MONTH, AFTER MODULE1 UPGRADE

Kolmogorov-Smirnov		Anderson-Darling	
Statistic $[D_n]$	0,12315	Statistic $[D_n]$	2,2242
α	0,05	α	0,05
Critical Value $[D_0]$	0,28087	Critical Value $[D_0]$	2,5018
Reject?	No	Reject?	No

TABLE VI
KS AND AD TEST FOR KNN PREDICTION, 7TH MONTH, AFTER MODULE1 UPGRADE

Kolmogorov-Smirnov		Anderson-Darling	
Statistic $[D_n]$	0,13953	Statistic $[D_n]$	2,0645
α	0,05	α	0,05
Critical Value $[D_0]$	0,28087	Critical Value $[D_0]$	2,5018
Reject?	No	Reject?	No

IV. CASE STUDY

Described modeling from chapter 3 was used on reliability modeling of ERP subsystem (in the following text *Module 1*) deployed at one telecom operator. For the observed ERP subsystem records of defects identified after the completion of upgrades are obtained for a period of one year. All data were reported in the internal helpdesk service, Module1 is upgraded every month so twelve empirical distributions were recorded. The first step was proving that all empirical distributions of the number of defects identified after the completion of upgrades can be described with theoretical Weibull distributions. The results are presented at Table VII.

TABLE VII
KS AND AD TEST FOR KNN PREDICTION, 7TH MONTH

Month	Best fit Weibull for empirical distribution		KS test $(\alpha = 0{,}05)$		If $(Dn < Do)$ accept Weibull
	α	β	Do	Dn	
1	1,5306	18,41	0,2941	0,1342	Yes
2	1,1038	15,149	0,2941	0,1522	Yes
3	1,6279	11,676	0,2749	0,176	Yes
4	2,2743	14,871	0,2872	0,1264	Yes
5	1,5034	13,403	0,2586	0,1432	Yes
6	1,8509	15,183	0,3014	0,1116	Yes
7	1,6279	13,364	0,2872	0,1361	Yes
8	1,4715	12,261	0,2872	0,1841	Yes
9	1,4106	13,723	0,2803	0,1999	Yes
10	2,2406	12,182	0,2941	0,1697	Yes
11	1,903	17,243	0,2872	0,1384	Yes
12	2,4272	14,995	0,2749	0,1211	Yes

According to Table 7, it is clearly shown that the Weibull distribution describes well the existing empirical distributions. The next step is supposed to explore the possibility of predicting distributions. Predictions are made for periods after 4th month and presented in Table 8. Since the KNN algorithm was used with parameter $k = 3$, there was no point in predicting earlier because that version of KNN algorithm needs a minimum of three previous samples.

TABLE VIII
LR AND KNN PREDICTION FOR WEIBULL DISTRIBUTION PARAMETERS

n	LR prediction		KS test for LR $(\alpha = 0{,}05)$		If $(Dn < Do)$ accept LR	KNN prediction		KS test for KNN $(\alpha = 0{,}05)$		If $(Dn < Do)$ accept
	α	β	Do	Dn		α	β	Do	Dn	
4	1,5183	8,344	0,2872	0,4832	Yes	1,4208	15,0783	0,2872	0,191	Yes
5	2,3229	13,8269	0,2586	0,1537	Yes	1,6687	13,8987	0,2586	0,1529	Yes
6	1,9428	11,6138	0,3014	0,2805	Yes	1,8019	13,3167	0,3014	0,1841	Yes
7	1,9933	12,9642	0,2872	0,1645	Yes	1,8762	14,4857	0,2872	0,1569	Yes
8	1,8826	12,674	0,2872	0,1975	Yes	1,6607	13,9833	0,2872	0,2223	Yes
9	1,7369	11,9909	0,2803	0,2451	Yes	1,6501	13,6027	0,2803	0,2149	Yes
10	1,6165	12,25	0,2941	0,1705	Yes	1,5033	13,116	0,2941	0,1855	Yes
11	1,8701	11,8269	0,2872	0,3647	No	1,7076	12,722	0,2872	0,221	Yes
12	1,9194	13,3982	0,2749	0,242	Yes	1,8514	14,3827	0,2749	0,2124	Yes

According to Table VIII, used prediction algorithms are very good in one month (upgrade) prediction. There is a key question of how to use the the prediction of Weibull parameters. One possible application is to use formula (5). If the n from (5) is defined as expected maximum number of defects, $P(n)$ will be defined as probability that all samples will be from range of $[0, n]$ defects. The main problem is how to choose the value for $P(n)$. It is evident from (5) that if the $P(n)$ value is 1, then n will be ∞. In other words, in the practical application n is a maximum expected value of number of defects, but according to the formula (5) obviously cannot be the 1. It this case study, it was found that the best results in prediction of expected maximum number of defects is for $P(n)$=0,99. After substituting the predicted values for Weibull parameters from the Table 8 and $P(n)$=0,99 in (5) it is necessary to numerically solve (6).

$$e^{-\left(\frac{n}{\beta}\right)^{\alpha}} \approx 0{,}01 \qquad (6)$$

For an example, in 10th month, for LR prediction from Table 8 (α=1,6165; β=12,25), n is 21 and for the KNN prediction (α=1,5033; β=13,116), n is 37. It would be logical to choose a higher value for n that is wider interval of the expected range of number of defects per day as [0,37]. At Table 9 prediction is made for all months and compared with real data. Better results were recorded for KNN algorithm, although it may not be the rule. It would be a good to use both algorithms and choose the larger of the two calculated ranges.

TABLE IX
PREDICTED RANGES FOR THE NUMBER OF DEFECTS

	Expected range of number of defects			
month after upgrade	LR	Success of prediction [%]	KNN	Success of prediction [%]
4	[0,23]	95,00%	[0,28]	100,00%
5	[0,27]	95,00%	[0,23]	90,00%
6	[0,23]	90,00%	[0,32]	95,00%
7	[0,27]	100,00%	[0,32]	100,00%
8	[0,21]	90,00%	[0,24]	100,00%
9	[0,28]	95,00%	[0,35]	100,00%
10	[0,21]	95,00%	[0,37]	100,00%
11	[0,27]	100,00%	[0,32]	100,00%
12	[0,30]	100,00%	[0,33]	100,00%

Another application of the described distribution predictions is possible using the display like at Table 10.

TABLE X
PREDICTED DISTRIBUTION FOR THE NUMBER OF DEFECTS RANGE IN 7TH MONTH FOR MODULE1

interval	[0,5>	[5-10>	[10,15>	[15,20>	[20,25>	[25,+∞>
predicted number of samples	3	6	5	5	2	1

Predicted number of samples is calculated from (5) and KNN prediction of the Weibull distribution for the 7th month (α=1,5033; β=13,116). From the Table 10, for an example it is possible to calculate minimum of expected total number of defects for the 7th month, after upgrade, as the product of lower interval bound and predicted number of samples:

$$N_{min}=3*0+6*5+5*10+5*15+2*20+1*25=220 \qquad (7)$$

It is not possible to calculate maximum of expected total number of defects because upper bound in the last interval from Table 10 is ∞. Complete prediction for the minimum of total number of defects is displayed in Table 11.

TABLE XI
PREDICTED MINIMUM OF TOTAL NUMBER OF DEFECTS FOR THE MODULE1

month after upgrade	measured	prediction
4	284	>205
5	251	>179
6	328	>170
7	256	>220
8	234	>191
9	272	>170
10	237	>156
11	327	>156
12	318	>170

V. CONCLUSION

The presented case study has confirmed that the distribution of number of defects, which are the result of upgrading of an existing ERP subsystem, is stochastic process and Weibull distribution can be used as a good modeling tool. Algorithms used to predict future distributions (Linear regression and K-Nearest Neighbor) have given equally good results in set limits of statistical significance. Proposed measurement-based reliability parameters like expected range of number of defects or predicted minimum of total number of defects.

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