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REAL DATA APPLICATION AND ANALYSIS FOR EVALUATING SEVERAL SUB-MODELS OF GENERALIZED JELINSKI-MORANDA FORMULA

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ABSTRACT

The generalized Jelinski-Moranda (GJ-M) model were suggested by Al turk and Alsolami (2016a) to offer several sub-models with different failure rate behavior that can suit more different software development projects. The effectiveness of this suggested general formula was checked through a simulation study [see; Al turk and Alsolami (2016b)]. In this paper the GJ-M model will be checked subjectively and objectively through five actual software reliability data. Three methods of estimation and four evaluation criteria will be used in our application. Both subjective and objective evaluation results show the applicability and flexibility of the suggested general formula as it can produce several sub-models with different failure rate trends.

1. INTRODUCTION

Software reliability models in an important approach to assess the reliability of any manufactured software. Finding the best fit model for different software projects is a very critical issue as until now and although with the huge number of the exists software growth models in the literature still not being able to standardize one single reliability growth model to capture with all software failure behaviors. The fault detection rate has three possible trends as the testing time progresses; increasing, decreasing, or constant which need to be considered when choosing reliability growth model. Validating the software project using the Generalized Jelinski-Moranda (GJ-M) model will help finding the best fit case easier because of its ability to cope with all possible trends of failure detection rate through its sub-models. By varying the shape parameter β of our suggested general formula (see; Al turk and Alsolami (Lutfiah Ismail, 2016a)), six different sum-models are generated for our real framework in this paper including the very well known Jelinski-Moranda (J-M) (Jelinski and Moranda, 1972) and Schick and Wolverton (S-W) (Schick and Wolverton, 1978), models.

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Furthermore, applying several estimation methods (see e.g. Kapur *et al.* (1999), Pham (Pham, 2000) and Xie (1991) can be another mechanism that may help at choosing the best performance estimators that increases the predictive capability of the best fit growth model. In this paper the maximum likelihood estimation (MLE),non-linear least-square estimation (NLSE), and Weighted non-linear least-square estimation (WNLSE) methods will be used to obtain the best performance estimators for our suggested sub-models. The models are evaluated subjectively and objectively using four goodness-of-fit tests.The rest of this paper is arranged as follows: Section 2 gives brief description of estimation methods for the GJ-M model. Section 3 illustrates the evaluation techniques that will be used in our real application. Real application will be presented in Sections 4. Eventually, the application is concluded in Section 5.

2. GENERLIZEDJELINSKI-MORANDA (GJ-M) MODEL ESTIMATION

The probability density function (pdf) of the GJ-M [Al turk and Alsolami (2016a)] is defined as follows:

$$f(t_i) = \varphi[N - (i - 1)]\beta t_i^{\beta-1} e^{-\varphi[N-(i-1)]t_i^{\beta}} \qquad (1)$$

Where

i : is the fault index, φ: is a proportionality constant, N: is the number of initial faults present in system, β: is the shape parameter, t_i: is the ith time interval between detection of $(i-1)^{st}$ and i^{th} faults. The mean time to failure can be represented by the following expression:

$$E(t_i) = \frac{\Gamma(\frac{1}{\beta}+1)}{[\varphi(N-i+1)]^{\frac{1}{\beta}}} \qquad (2)$$

More characteristics of the GJ-M model can be found in [Al turk and Alsolami (2016b)]

2.1. Brief review of maximum likelihood estimation (MLE) method

Using the MLE method and the failure time data with size $n; \{t_1, t_2, \ldots, t_n; n > 0\}$, the likelihood function of the GJ-M model will be defined as follows:

$$L(N, \varphi, \beta) = \beta^n \varphi^n \prod_{i=1}^n [N-(i-1)] t_i^{\beta-1} e^{-\varphi \sum [N-(i-1)]t_i^\beta} \qquad (3)$$

By taking the natural logarithm of both sides of Equation (3), then finding the first partial derivative with respect to the unknown three parameters and setting the obtained equations to zero the maximal likelihood estimates of N, φ, and β are the solutions of the following three equations:

$$\hat{\varphi} = \frac{n}{\sum_{i=1}^n [N-(i-1)]t_i^\beta} \qquad (4)$$

$$\frac{n\sum_{i=1}^n t_i^\beta}{\sum_{i=1}^n [N-(i-1)]t_i^\beta} = \sum_{i=1}^n \frac{1}{[N-(i-1)]} \qquad (5)$$

$$\frac{n}{\beta} + \sum_{i=1}^n \ln t_i = \frac{n\sum_{i=1}^n (N-(i-1))t_i^\beta \ln t_i}{\sum_{i=1}^n [N-(i-1)]t_i^\beta} \qquad (6)$$

2.2. Brief review of nonlinear least squares estimation (NLSE) method

The nonlinear least squares NLS estimates can be obtained by solving the following two equations:

$$\sum_{i=1}^n \frac{t_i}{(N-i+1)^{\frac{1}{\beta}+1}} = \frac{\Gamma(\frac{1}{\beta}+1)}{\hat{\varphi}^{\frac{1}{\beta}}} \sum_{i=1}^n \frac{1}{(N-i+1)^{\frac{2}{\beta}+1}} \qquad (7)$$

$$\Gamma'\left(\frac{1}{\beta}+1\right)\left\{\sum_{i=1}^n \frac{t_i}{(N-i+1)^{\frac{1}{\beta}}} - \frac{\Gamma\left(\frac{1}{\beta}+1\right)}{\hat{\varphi}^{\frac{1}{\beta}}} \sum_{i=1}^n \frac{1}{(N-i+1)^{\frac{2}{\beta}}}\right\} =$$

$$\frac{-\Gamma(\frac{1}{\beta}+1)}{\beta^2}\left\{\sum_{i=1}^n \frac{t_i[\ln\hat{\varphi}+\ln(N-i+1)]}{(N-i+1)^{\frac{1}{\beta}}} - \frac{\Gamma(\frac{1}{\beta}+1)}{\hat{\varphi}^{\frac{1}{\beta}}}\sum_{i=1}^n \frac{[\ln\hat{\varphi}+\ln(N-i+1)]}{(N-i+1)^{\frac{2}{\beta}}}\right\} \qquad (8)$$

Where $\Gamma'(z) = \int_0^\infty dt(\ln t) t^{z-1} e^{-t}$

Then substituting the obtained estimated values of N and β into the following equation we get the NLS estimate of φ.

$$\hat{\varphi} = \left[\Gamma\left(\frac{1}{\beta}+1\right)\sum_{i=1}^n \frac{1}{[(N-i+1)]^{\frac{2}{\beta}}} \Big/ \sum_{i=1}^n \frac{t_i}{[(N-i+1)]^{\frac{1}{\beta}}}\right]^\beta \qquad (9)$$

2.3. Brief review of weighted nonlinear least squares estimation (WNLSE) method

The WNLS estimates $\hat{N}$ and $\hat{\beta}$ will be obtained by finding the solution of the following two equations:

$$\sum_{i=1}^n \frac{w_i t_i}{(N-i+1)^{\frac{1}{\beta}+1}} = \frac{\Gamma(\frac{1}{\beta}+1)}{\hat{\varphi}^{\frac{1}{\beta}}} \sum_{i=1}^n \frac{w_i}{(N-i+1)^{\frac{2}{\beta}+1}} \qquad (10)$$

$$\Gamma'\left(\frac{1}{\beta}+1\right)\left\{\sum_{i=1}^n \frac{w_i t_i}{(N-i+1)^{\frac{1}{\beta}}} - \frac{\Gamma\left(\frac{1}{\beta}+1\right)}{\hat{\varphi}^{\frac{1}{\beta}}} \sum_{i=1}^n \frac{w_i}{(N-i+1)^{\frac{2}{\beta}}}\right\} =$$

$$\frac{\Gamma(\frac{1}{\beta}+1)}{\beta^2}\left\{\sum_{i=1}^n \frac{w_i t_i[\ln\hat{\varphi}+\ln(N-i+1)]}{(N-i+1)^{\frac{1}{\beta}}} - \frac{\Gamma(\frac{1}{\beta}+1)}{\hat{\varphi}^{\frac{1}{\beta}}}\sum_{i=1}^n \frac{w_i[\ln\hat{\varphi}+\ln(N-i+1)]}{(N-i+1)^{\frac{2}{\beta}}}\right\} \qquad (11)$$

Where $\Gamma'(z) = \int_0^\infty dt(\ln t) t^{z-1} e^{-t}$

Then $\hat{\varphi}$ can be found by substituting $\hat{N}$ and $\hat{\beta}$ in Equation (12).

$$\hat{\varphi} = \left[\Gamma\left(\frac{1}{\beta}+1\right)\sum_{i=1}^n \frac{w_i}{[(N-i+1)]^{\frac{2}{\beta}}} \Big/ \sum_{i=1}^n \frac{w_i t_i}{[(N-i+1)]^{\frac{1}{\beta}}}\right]^\beta \qquad (12)$$

More details can be found in [Al turk and Alsolami (2016b)].

3. MODEL EVALUATION TECHNIQUES

Mean of square errors (MSE), root mean of square errors (RMSE), mean absolute errors (MAE) and mean absolute percentage errors (MAPE) criteria are used for the evaluation purpose in our real application. The lower the criteria value, the better model performance we get. The formulas of those four criteria are:

$$MSE = \frac{1}{n-k}\sum_{i=1}^n (y_i - \hat{y}_i)^2 \qquad (13)$$

$$MAPE = \frac{\sum_{i=1}^n \left(\frac{|y_i-\hat{y}_i|}{y_i}\right)}{n} \times 100\% \qquad (14)$$

$$RMSE = \sqrt{\frac{1}{n-k}\sum_{i=1}^n [y_i - \hat{y}_i]^2} \qquad (15)$$

$$MAE = \frac{1}{n-k}\sum_{i=1}^n |y_i - \hat{y}_i| \qquad (16)$$

Where, i : is the fault index, $\hat{y}_i$: is the predicted value, y_i: is the true value, n: the sample size of the data, k: the number of parameters [for more details see; Zhang *et al*. (2003), Gentry *et al*. (1995), Chai and Draxler (2014)].

4. REAL DATA APPLICATION

In this section, five of real data examples are given to illustrate the applicability of the GJ-M reliability model, six sub-models will be generated. For the estimation of parameters of the G-JM model the maximum likelihood (ML), the nonlinear least square (NLS) and weighted nonlinear least square (WNLS) estimation methods are used. The best sub-model will determined according to MSE, RMSE, MAE, and MAPE criteria. Useful evaluation results of these real numerical examples will be presented at the end of this section.

4.1 Data sets

Six sub-models are generated in the application by varying the value of the shape parameter β. Five real data sets with different sizes are used. Those data sets are: the NTDS data

and consists of 26 failures [see; Goel and Okumoto, (1979)], the F11-D program data which includes 15 failures [see; Moranda, (1975)], the AT&T Bell failure data and its size is 22 [see; Pham and Pham, (2000)], Philips failure data 1 and Philips failure data 2 with n=246 and 312 respectively [see; Al turk, (2007)].

4.2. Application algorithm

Step 1: Enter data set after checking the fitness between it and our studied model using ks.test() function from stats package, and testing the existence of the hetroscadisty problem using qqtest()function from lmtest package.

Step 2:Generate six sub-models as special cases of the GJ-M model by assuming that:$\beta = 0.5, 1, 1.5, 2, 2.5,$ and $3.$

Step3: Set initial values for the sub-models' parameters.

Step4: Estimate the generated models' parameters based on MLE method, to accomplish this step the nlminb package will be utilized.

Step 5: Estimate the generated models' parameters based on NLSE method, to accomplish this step theminpack.lm package will be utilized.

Step 6: Estimate the generated models' parameters based on WNLSE method, to accomplish this step the optimal weightw_i will be found by calculating the inverse of the variance where $i = 1, 2, …, n,$ and the minpack.lm package will be utilized.

Step 7: Select the best fit model among the six generated models based on four selection methods MSE, RMSE, MAE and MAPE by using their mathematical formulas in Equations (13,14,15and 16).

4.3. RESULTS AND DISCUSSION

The results of MSE, RMSE, MAE and MAPE criteria are listed in Table (1, 2, 3 and4) and drawn in Figure (1). According to the criteria's results the following points are concluded:

Based on MSE, RMSE and MAE results we can see that:

For NTDS, F11-D program and AT&T bell data sets; the best fit model is Model 2, its smallest MSE, RMSE andMAEvaluesare obtained by using the WNLSE method, noticing that Model 2 is the very common J-M model, and all in all this model performs well using the three selected estimation methods. While, For Philips data 1 and data 2; the best fit model is also the JM model but when using the MLE method, remarking that those two data sets is the larger selected ones with 246 and 312 failure times respectively and this indicates that the MLE method works properly with large data sets.

Table 1. MSE criteria for comparing some sub-models of the GJ-M formula

Model Data	Model 1 (β = 0.5) MSE_{MLE} MSE_{NLSE} MSE_{WNLSE}	Model 2 (β = 1) (JM model) MSE_{MLE} MSE_{NLSE} MSE_{WNLSE}	Model 3 (β = 1.5) MSE_{MLE} MSE_{NLSE} MSE_{WNLSE}	Model 4 (β = 2) (S-W model) MSE_{MLE} MSE_{NLSE} MSE_{WNLSE}	Model 5 (β = 2.5) MSE_{MLE} MSE_{NLSE} MSE_{WNLSE}	Model 6 (β = 3) MSE_{MLE} MSE_{NLSE} MSE_{WNLSE}
NTDS	111.34	7.31	37.88	73.30	79.49	75.39
data	98.19	7.75	65.55	139.62	173.39	187.97
(26)	98.19	7.20	92.09	155.32	180.03	188.92
F11-D	53.76	8.80	9.31	12.06	15.49	18.90
Program (15)	50.78	10.40	8.95	7.98	9.27	11.31
	50.78	4.34	5.51	8.62	11.56	13.54
AT&T Bell	83.01	6.04	4.07	12.65	20.65	29.58
Data	78.53	2.37	17.89	49.16	73.92	88.37
(22)	78.53	1.56	27.56	62.95	84.89	93.94
Philips	12955.08	1263.26	11662.95	18347.32	19444.38	19707.06
data 1	7224.53	15404.14	19634.22	20179.81	20200.85	20048.57
(246)	14263.76	1690.31	19089.24	19972.88	19944.07	19894.02
Philips	19844.71	4443.82	14041.68	21849.68	24584.68	24428.80
data 2	11091.34	28721.97	32946.15	32952.33	32952.33	32952.33
(312)	24598.31	6581.12	30234.26	32939.63	32952.33	32952.33

Table 2. RMSEcriteria for comparing some sub-models of the GJ-M formula

Model Data	Model 1 (β = 0.5) $RMSE_{MLE}$ $RMSE_{NLSE}$ $RMSE_{WNLSE}$	Model 2 (β = 1) (JM model) $RMSE_{MLE}$ $RMSE_{NLSE}$ $RMSE_{WNLSE}$	Model 3 (β = 1.5) $RMSE_{MLE}$ $RMSE_{NLSE}$ $RMSE_{WNLSE}$	Model 4 (β = 2) (S-W model) $RMSE_{MLE}$ $RMSE_{NLSE}$ $RMSE_{WNLSE}$	Model 5 (β = 2.5) $RMSE_{MLE}$ $RMSE_{NLSE}$ $RMSE_{WNLSE}$	Model 6 (β = 3) $RMSE_{MLE}$ $RMSE_{NLSE}$ $RMSE_{WNLSE}$
NTDS	10.55	2.70	6.15	8.56	8.92	8.68
data	9.91	2.78	8.10	11.82	13.17	13.71
(26)	9.91	2.68	9.60	12.46	13.42	13.74
F11-D	7.33	2.97	3.05	3.47	3.94	4.35
Program	7.13	3.22	2.99	2.82	3.05	3.36
(15)	7.13	2.08	2.35	2.94	3.40	3.68
AT&T Bell	9.11	2.46	2.02	3.51	4.54	5.44
Data	8.86	1.54	4.23	7.01	8.60	9.40
(22)	8.86	1.25	5.25	7.93	9.21	9.69
Philips	113.82	35.54	108.00	135.45	139.44	140.38
data 1	85.00	124.11	140.12	142.06	142.13	141.59
(246)	119.43	41.11	138.16	141.33	141.22	141.05
Philips	140.87	66.66	118.50	147.82	156.80	156.30
data 2	105.32	169.48	181.51	181.53	181.53	181.53
(312)	156.84	81.12	173.88	181.49	181.53	181.53

Table 3. MAE criteria for comparing some sub-models of the GJ-M formula

Model Data	Model 1 ($\beta = 0.5$) MAE_{MLE} MAE_{NLSE} MAE_{WNLSE}	Model 2 ($\beta = 1$) (JM model) MAE_{MLE} MAE_{NLSE} MAE_{WNLSE}	Model 3 ($\beta = 1.5$) MAE_{MLE} MAE_{NLSE} MAE_{WNLSE}	Model 4 ($\beta = 2$) (S-W model) MAE_{MLE} MAE_{NLSE} MAE_{WNLSE}	Model 5 ($\beta = 2.5$) MAE_{MLE} MAE_{NLSE} MAE_{WNLSE}	Model 6 ($\beta = 3$) MAE_{MLE} MAE_{NLSE} MAE_{WNLSE}
NTDS	9.23	2.54	5.88	8.00	8.18	7.80
data	8.62	2.51	7.99	11.14	12.09	12.41
(26)	8.62	2.45	9.18	11.47	12.14	12.36
F11-D	7.36	2.96	3.00	3.40	3.83	4.21
Program (15)	7.16	3.17	3.01	2.59	2.94	3.27
	7.16	1.99	2.21	2.89	3.36	3.61
AT&T Bell	8.33	2.33	1.78	3.33	4.22	4.97
Data	8.08	1.34	4.25	6.60	7.78	8.30
(22)	8.08	1.10	5.10	7.28	8.17	8.45
Philips	95.89	30.71	96.82	118.66	121.38	121.98
data 1	70.83	109.78	122.46	123.77	123.68	123.00
(246)	101.20	30.99	121.09	122.85	122.58	122.37
Philips	114.82	58.33	98.64	126.60	136.59	135.66
data 2	84.85	149.78	158.11	158.12	158.12	158.12
(312)	131.55	68.05	153.03	158.10	158.12	158.12

Table 4. MAPE criteria for comparing some sub-models of the GJ-M formula

| Model Data	Model 1 ($\beta = 0.5$) $MAPE_{MLE}$ $MAPE_{NLSE}$ $MAPE_{WNLSE}$	Model 2 ($\beta = 1$) (JM model) $MAPE_{MLE}$ $MAPE_{NLSE}$ $MAPE_{WNLSE}$	Model 3 ($\beta = 1.5$) $MAPE_{MLE}$ $MAPE_{NLSE}$ $MAPE_{WNLSE}$	Model 4 ($\beta = 2$) (S-W model) $MAPE_{MLE}$ $MAPE_{NLSE}$ $MAPE_{WNLSE}$	Model 5 ($\beta = 2.5$) $MAPE_{MLE}$ $MAPE_{NLSE}$ $MAPE_{WNLSE}$	Model 6 ($\beta = 3$) $MAPE_{MLE}$ $MAPE_{NLSE}$ $MAPE_{WNLSE}$
NTDS	54.14	29.04	62.85	78.46	76.31	68.45
data	51.89	38.39	82.16	122.86	146.47	160.27
(26)	51.89	37.05	104.91	143.39	163.15	173.36
F11-D	75.77	46.57	49.46	53.97	58.25	61.75
Program (15	73.99	48.94	49.04	45.68	48.51	51.44
)	73.99	36.56	40.12	46.89	51.80	54.66
AT&T Bell	57.51	24.12	23.53	36.11	43.43	50.16
Data	55.38	20.35	45.97	73.26	90.76	100.39
(22)	55.38	17.96	56.19	83.30	97.93	103.90
Philips	75.75	93.56	240.54	322.00	352.02	363.80
data 1	80.39	314.39	367.06	394.61	407.63	409.19
(246)	77.22	110.92	350.81	398.99	408.01	407.84
Philips	74.52	97.49	157.02	177.21	220.44	206.13
data 2	89.64	398.99	533.76	534.41	534.41	534.41
(312)	79.41	139.08	418.90	533.00	534.41	534.41
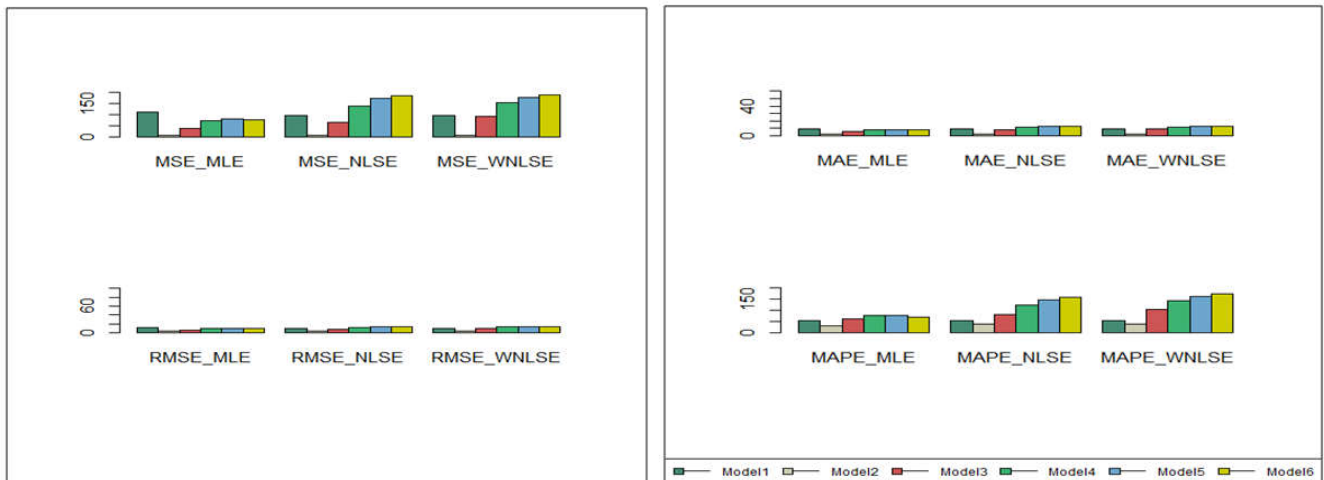
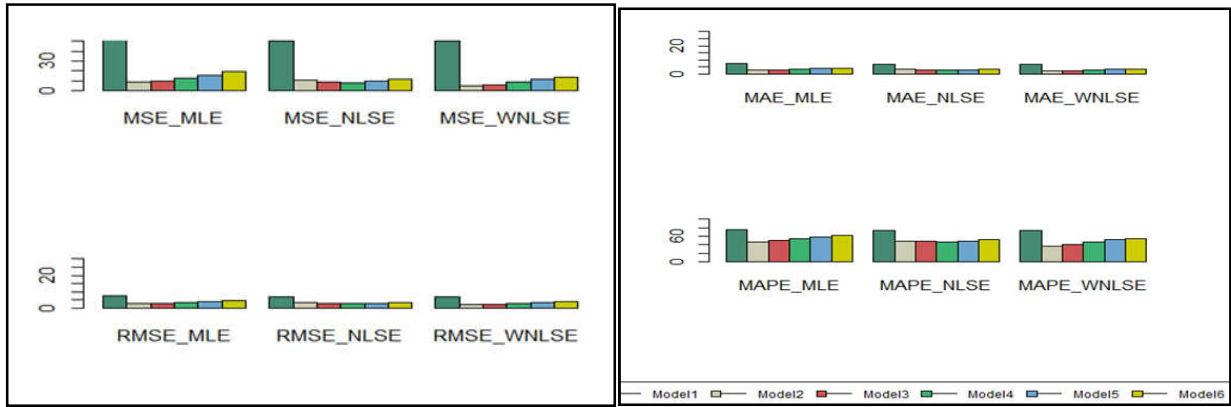
Figure 1.a. NTDS data

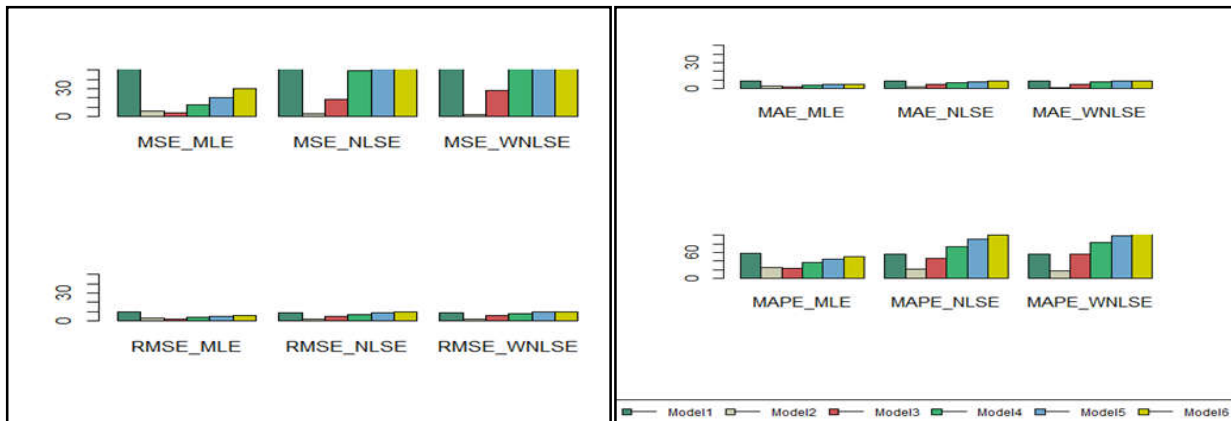**Figure 1.b. F11-D program data**
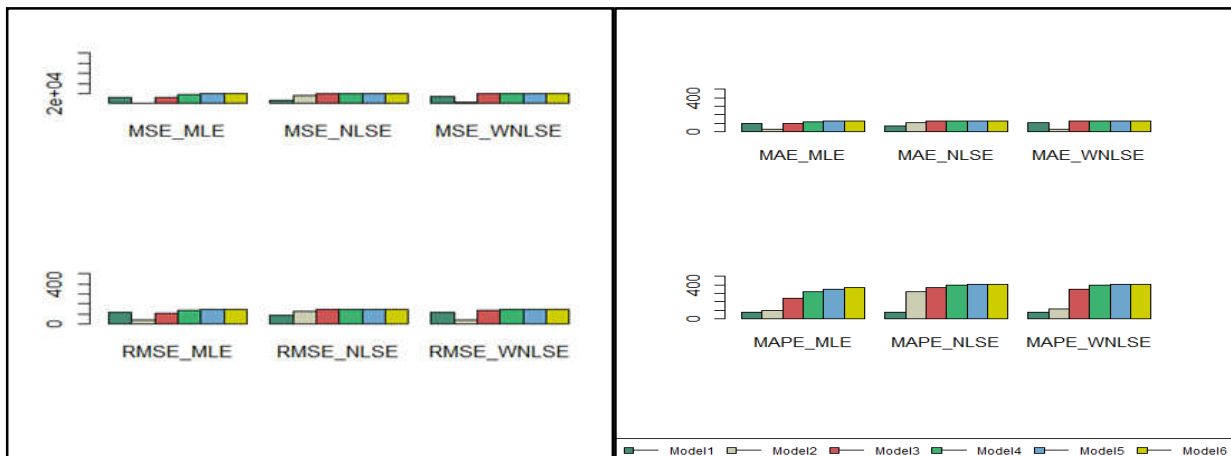

Figure 1.c. AT&T Bell failure data

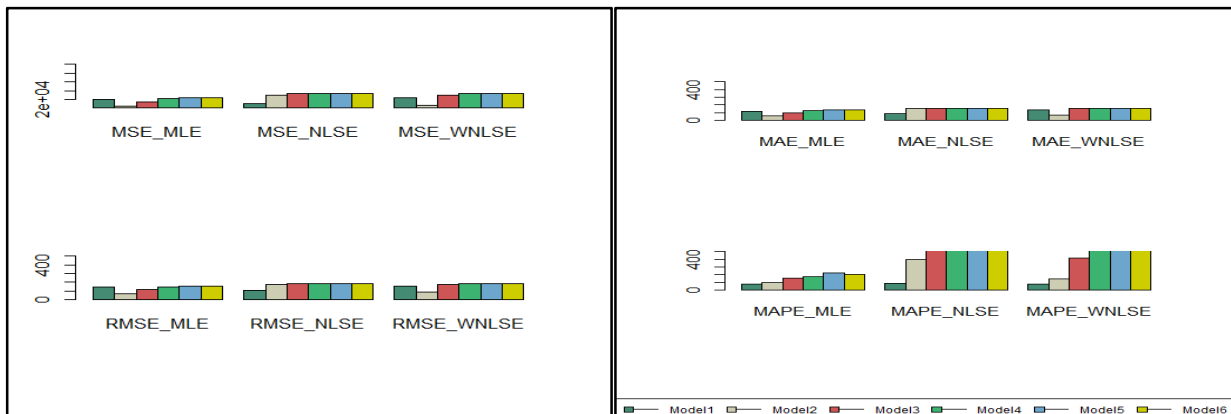**Figure 1.d. Philips failure data 1**

Figure 1.e. Philips failure data 2

Figure 1. Some criteria for comparing some sub-models of the GJ-M formula

While the results of the MAPE criteria indicate that

JM model is the best performance model for NTDS data; its smallest MAPE value is obtained by using the MLE method. In addition, the JM model gives the best predictive capability forF11-D program and AT&T bell data at WNLSE method. For Philips data 1 and data 2; The best fit model is Model 1which is obtained by supposing that the shape parameterβ = 0.5, its smallest MAPE values are gained from MLE method.

5. CONCLUDING REMARKS

According to our selected test failure data the popular and widely used J-M model has been shown to be superior compared to our other selected sub-models for most of our chosen projects based on four selected model evaluation techniques. Also and after investigating three estimation methods more reliable results have been obtained by using the WNLSE method for most of our application's cases. However, with the large real data sets the MLE method has given the more accurate prediction results. Hence, our general formula provides several sub-models to test the reliability of a wide range of software projects, and with applying different method of estimation the best appropriate descriptive model can be found with much more prediction accuracy.

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