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IMPROVING SOFTWARE RELIABILITY GROWTH MODEL SELECTION RANKING USING PARTICLE SWARM OPTIMIZATION

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ABSTRACT

Reliability of software always related to software failures and a number of software reliability growth models (SRGMs) have been proposed past few decades to predict software reliability. Different characteristics of SRGM leading to the study and practices of SRGM selection for different domains. Appropriate model must be chosen for suitable domain in order to predict the occurrence of the software failures accurately then help to estimate the overall cost of the project and delivery time. In this paper, particle swarm optimization (PSO) method is used to optimize a parameter estimation and distance based approach (DBA) is used to produce SRGM model selection ranking. The study concluded that the use of PSO for optimizing the SRGM's parameter has provided more accurate reliability prediction and improved model selection rankings. The model selection ranking methodology can facilitate a software developer to concentrate and analyze in making a decision to select suitable SRGM during testing phases.

Keywords: *Software Reliability Prediction, Model Selection, Parameter Estimation, Particle Swarm Optimization, Distance Based Approach, Software Reliability Growth Model (SRGM)*

1. INTRODUCTION

As rapid technological development contributed to the increasing size and complexity of software system, software quality has become more critical to deliver good software. Software quality is defined as the standard to which a system, component or process meets designated requirements, user needs or expectations [1]. Among many quality attributes, software reliability is one of the highest concern by developers and project managers with the considerations of business profitability, user safety and preservation of the environment. It is an important factor to consider in the software development life cycle because unreliable software has high probability of containing some errors or bugs that may cause system failure to occur if those problems is not handled properly. Some examples of critical system failures have shown unfavorable impact on the environment, caused economic loss, or even harmful to the human lives. Thus, software reliability prediction (SRP) has become crucial activities in software development process in order to produce reliable and good quality software.

Among all the prediction models, SRGMs have been widely used in many different software domains, such as telecommunications, embedded systems, military, banking and industrial control systems [2][3]. However, some studies showed that different families of models have specified characteristics that will perform better than others [4]. Accordingly, some researchers had attempted to propose a new model for discovering the best model for every specific application by comparing the existing different models [5]. Although the idea of selecting reliability model during development phase is good, but it has been found that it is a difficult task due to the characteristics of software failures [6].

During the process of model selection to obtain best reliability model, there is some concerns in getting the prediction result from the reliability model, especially SRGMs. In order to obtain accurate and reliable ranking or model selection, the reliability prediction must also be as accurate as possible as compared to the real data obtained. Therefore, the parameter estimation process of SRGMs must also be enhanced to improve the reliability prediction.

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Therefore, in this paper, the software reliability prediction model selection methodology is studied and discussed along with the application of PSO in parameter estimation and DBA in model selection ranking process. The model selection methodology is important to the project manager, developer or software engineering practitioner to have a detailed description or guideline in order to let them select and implement the suitable software reliability model during or before the testing phase providing little or no data on the current project.

The DBA ranking process can provide insights on which model is the most suitable among the listed models by using the comparison of prediction quality of each models. On the other side, the reliability prediction accuracy of the models also be improved by implementing the PSO that can optimizes the parameters of the reliability models. The better reliability prediction helps to detect or predict the errors or faults that may occurred during the testing phase accurately, thus also assists the practitioners like project manager to allocate sufficient time and cost for the testing purposes.

This paper is divided into five section, namely: introduction, related works, software reliability model selection ranking methodology, experimental results and discussions, and conclusion or future works.

2. RELATED WORKS

This section describes the problems or motivation that leading to model selection of SRGMs and explains about the PSO implementation in parameter estimation of the models.

SRGMs are classified as the black box models and are used for removal of faults [7]. These models use failure data obtained during the testing period of software development [7] to determine the growth behavior and hence derive reliability prediction. Various types of SRGMs have been developed and implemented in many different industry sectors since the 1970s [8]. These models are further classified into two types, namely: failure rate models, and failure intensity models or as known as non-homogeneous Poisson process (NHPP) models.

Error counting process is modeled to represent the software testing and debugging process, and NHPP models has a counting process $\{N(t), t \geq 0\}$ with the intensity function $\lambda(t)$, which behaves like a Poisson distribution with the mean function $m(t)$ represented the expected number of errors detected within time $(0, t)$ [9][10].

Some examples of the NHPP models including Goel-Okumoto (GO) Model, a NHPP with an exponentially decaying rate function that considering failure detection, Gompertz Growth Curve Model (S-shaped) that adopted by many Japanese computer manufactures and software houses, Logistic Growth Curve Model, Generalized Goel NHPP model, and Yamada delayed S-Shaped Model.

There are many SRGMs has been proposed or developed. Most of them are designed with their own limitations, assumptions and unique characteristics. Each model suited and produced good result for certain data set, but no model is good enough for all data sets from different domains [5]. The generalization problem of SRGM has further complicates model selection for reliability prediction process.

Following the effort of Adbel-Ghaly et al. [11] in model selection, there are more researches and studies aimed to obtain optimal model selection approach. The studies includes DBA proposed by Sharma et. al. [5], Goodness of Fit (GOF) methods by Miglani [12] and Ullah et. al.[13], and also weighted-criteria method by Hung-cuong [14]. However, these studies are using numerical methods like least square estimation (LSE) and nonlinear regression (NLR) as the SRGM parameter estimation methods which can be improved by computational intelligence (CI) method such as PSO.

PSO is an evolutionary computation and gradient based global optimization technique which mimics the movement behavior, and intelligence of fishes and birds. It initiates with a population of random particles that explores the solution search space. Each particle is represented by coordinates vector string and a randomized velocity. In each iteration, velocity of each particle has been update depends on its previous velocity, the location at which it reached the best fitness (pbest), and the location of neighbor at which it reached the best fitness in a neighborhood (gbest), and then update the position of the particle in the problem space.

Optimal model selection using PSO has been proposed by Malhotra and Negi [15] to solve the

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SRGM parameter estimation problem. The proposed method has been validated using sixteen project data and compared to the genetic algorithm (GA) which is also an evolutionary algorithm. The comparison results showed that PSO have high predictive ability and better than GA. The authors also highlighted PSO may provide much better results if the constraint handling mechanism is improved.

As the reliability of the software is important to deliver good quality software, therefore software development practices such as reliability prediction needed to be carry out. Thus, model selection approach is essential in order to choose suitable reliability model to predict the reliability of the software during development and testing phases. Besides that, the parameters of the reliability model, especially SRGMs must be optimized in order to produce more accurate reliability prediction and these can be done by implementing CI methods such as PSO in parameter estimation process.

3. SOFTWARE RELIABILITY MODEL SELECTION RANKING METHODOLOGY

This section presents the model selection approach by using PSO parameter estimation. The primary goal of this approach is to obtain more accurate reliability prediction by selecting optimal model based on the data set domains. Figure 1 shows the overall process.

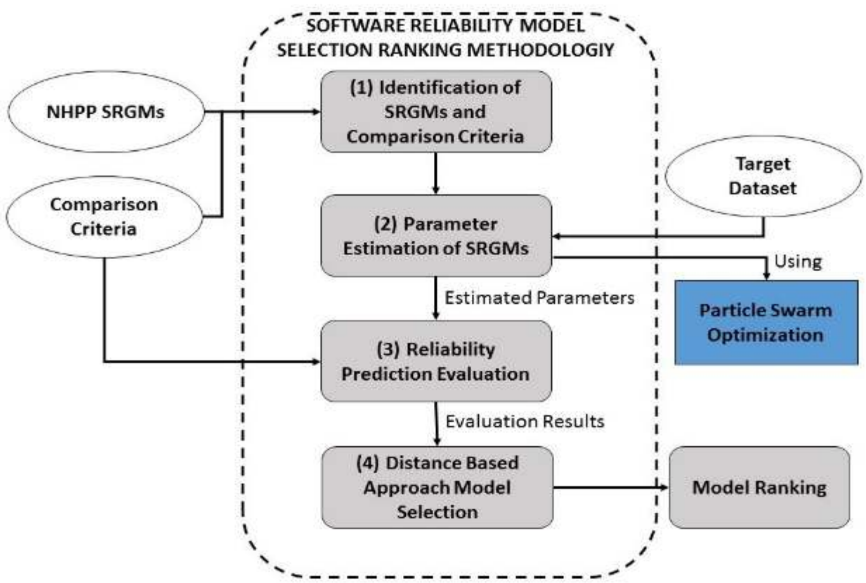

Figure 1: Software Reliability Model Selection Ranking Methodology

3.1 Identification of SRGMs and Comparison Criteria

The NHPP SRGMs used to predict the software reliability and comparison criteria that used to evaluate prediction accuracy involved needed to be identify in order to carry out model selection. In this study, the NHPP SRGMs used are limited not exceeding three parameters in their mean value function. These SRGMs are as listed in Table 1.

Various criteria have been used to compare or evaluate the models in the reliability engineering domain. Each comparison criterion emphases on different model performance aspects [16] and to evaluate the fitting between a real data set and a calculated values of SRGMs [14].

In this study, we make use the most of criteria used in Sharma et al. [5] excluding some highly correlated criteria [16] that shown in Table 2.

3.2 Parameter Estimation of SRGMs

Each SRGM has their own mean value function m(t). These functions have some physical interpreted parameters that may represent

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characteristics of each models such as failure detection rate, and total number of errors [17]. For example, Goel-Okumoto (GO) model has mean value function as shown:

Mean value function, m(t)=a(1-e^(-bt))

Where a is the expected total number of faults to be detected and b represents the fault detection rate, a ≥ 0, and b ≥ 0.

These parameters, in case of GO model, parameters a and b, needed to be estimated correctly, in order to obtain accurate prediction of a SRGM [17]. Inaccurate estimation of these parameters can cause miscalculation of time and cost allocated for ongoing projects which may cause software release delay or over budget.

In this study, these parameters are estimated by using PSO methods. Figure 2 shows the overall process of the PSO. The parameters of PSO is shown in Table 3.

Table 1: List of NHPP SRGMs

SRGM	Mean Value Function
Generalized GO (GG)	$m(t) = a(1-e^{-bt^c})$
Goel-Okumoto (GO)	$m(t) = a(1-e^{-bt})$
Gompert	$m(t) = ake^{-bt}$
Inflection S-Shaped (INFS)	$m(t) = \frac{a(1-e^{-bt})}{1+\beta e^{-bt}}$
Logistic Growth (Log)	$m(t) = \frac{a}{1+ke^{-bt}}$
Musa-Okumoto (MO)	$m(t) = a\,ln(1+bt)$

The data set was saved in a data text file and used as input to estimate the parameters of SRGMs by using the developed PSO algorithms. Referring to Figure 2, each parameter of the SRGM model are represented by the swarm particles. The position and velocity of the particles in each population are randomly generated at the beginning. The fitness of particles are then determined by using MSE in order to obtain the pbest and gbest of the populations. After that, individual particle's position and velocity are updated. The process iterating until the termination condition of 1000 iteration to obtain optimized particle values. The estimated parameters of each model are recorded.

Table 2: List of Comparison Criteria

Comparison Criterion	Notation/Formula
Accuracy of Estimation (AE)	$\left\lvert \frac{\sum_{i=1}^{k} m_i - \sum_{i=1}^{k} m(t_i)}{\sum_{i=1}^{k} m_i} \right\rvert$
Mean Square Error (MSE)	$\frac{\sum_{i=1}^{k}(m_i - m(t_i))^2}{k}$
RMSE	$\sqrt{\frac{\sum_{i=1}^{k}(m_i - m(t_i))^2}{k}}$
Mean Absolute Error (MAE)	$\frac{\sum_{i=1}^{k}\lvert m_i - m(t_i)\rvert}{k}$
R^2	$1 - \frac{\sum_{i=1}^{k}(m_i - m(t_i))^2}{\sum_{i=1}^{k}(m_i - \sum_{j=1}^{k} m_j/k)^2}$
Bias	$\frac{\sum_{i=1}^{k}(m(t_i) - m_i)}{k}$
Variation	$\sqrt{\frac{1}{k-1}\sum_{i=1}^{k}(m_i - m(t_i) - Bias)^2}$
Predictive ratio risk (PRR)	$\sum_{i=1}^{k}\left[\frac{(\hat{m}(t_i) - m_i)}{\hat{m}(t_i)}\right]^2$
Sum od Squared Error (SSE)	$\sum_{i=1}^{k}(m_i - m(t_i))^2$
Theil statistic (TS)	$\sqrt{\frac{\sum_{i=1}^{k}(m_i - m(t_i))^2}{\sum_{i=1}^{k} m_i^2}}\ X\ 100\%$

Table 3: Parameters of PSO

Parameter	Value
Population size	30
Acceleration factors, c1 and c2	2.05
Inertia constant, w	0.7298
Fitness function	MSE
Termination condition	1000 iterations

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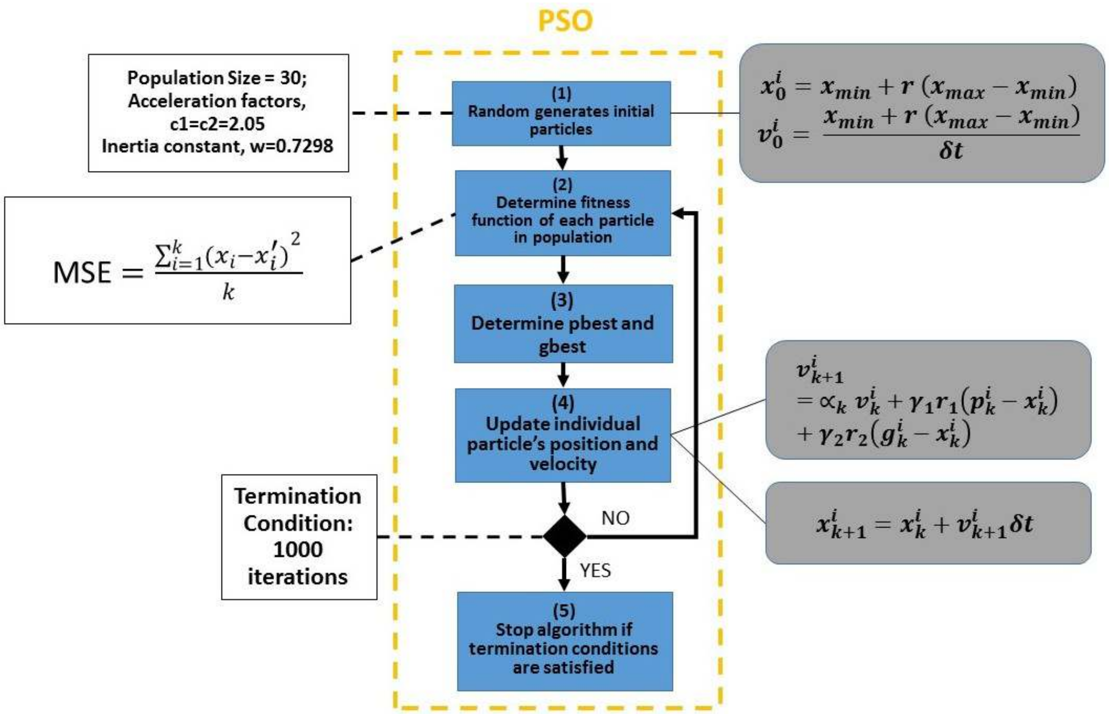

Figure 2: Overall Process of PSO

3.3 Reliability Prediction Evaluation

The estimated parameters that obtained using PSO algorithm in the previous section are used as inputs in the developed algorithm to carry out reliability prediction. The parameters are substituting in the mean value function m(t) of each SRGM model. The values of m(t) then are calculated by using the week instances in the data set. The estimated m(t) values are recorded. After that, the prediction evaluation are done by comparison of the estimated values of m(t) and actual data values in the data set, using all the comparison criteria listed in Table 2.

3.4 Distance Based Approach Model Selection

DBA method that proposed by Sharma et al., [5] were used for model selection and ranking of NHPP SRGMs with the comparison criteria listed. DBA method has the capability to solve complicated multi-attributes decision problems, integrating both qualitative and quantitative fact by the application of simple mathematical formula and operation of direct matrixes [5]. The overall DBA process is shown in Figure 3.

The calculation of the comparison criteria has resulted the foundation of the overall objectives and states which is contribute to a good attribute in a prediction process. The optimum model, the OPTIMAL represented the optimal state of the objective and optimal good value for attributes is represented by the best values which exist within the range of attribute values.

Supposedly, the SRGM that has all the best attribute values or as known as comparison criteria is selected as the OPTIMAL, but it is less possibly that single SRGM has all the best attribute values. Therefore, in order to solve this problem, alternatives may be used to stimulate the optimal state and become a reference to find a feasible solution. The efficiency of alternatives to achieve the optimal state of the objective function are represented by the numerical difference obtained from the comparison between alternatives and OPTIMAL.

The prediction result obtained using the estimated parameters are evaluated using a set of comparison criteria. The whole set of SRGM alternatives and the values of selection attributes (comparison criteria) are represented by the matrix with the OPTIMAL included in the last row.

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Result Alternatives Matrix,

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nm} \\ opt_1 & opt_2 & opt_3 & \cdots & opt_m \end{bmatrix} \quad (1)$$

The matrix then is standardized to ease the process and to eliminate the effects of measurement of different units using following formulae.

$$Z_{ij} = \frac{a_{ij} - \bar{a}_j}{S_j}, \quad (3)$$

$$\bar{a}_j = \frac{1}{n} \sum_{i=1}^{n} a_{ij}, \quad (4)$$

$$S_j = [\frac{1}{n} \sum_{i=1}^{n} (a_{ij} - \bar{a}_j)^2]^{\frac{1}{2}}, \quad (5)$$

Where i=1, 2, 3, …, n comparison criteria, and j=1, 2, 3, …, m SRGM models

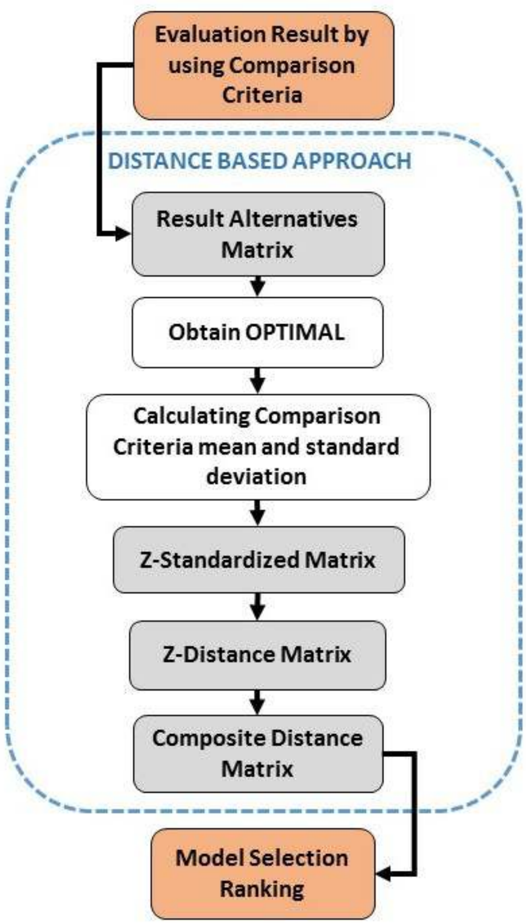

Figure 3: Overall Process of DBA

Z-Standardized Matrix,

$$\begin{bmatrix} Z_{11} & Z_{12} & Z_{13} & \cdots & Z_{1m} \\ Z_{21} & Z_{22} & Z_{23} & \cdots & Z_{2m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Z_{n1} & Z_{n2} & Z_{n3} & \cdots & Z_{nm} \\ Zopt_1 & Zopt_2 & Zopt_3 & \cdots & Zopt_m \end{bmatrix} \quad (2)$$

The difference from each SRGM alternative to the OPTIMAL were obtained by deducting each element of the optimal set by a matching element in the alternative set.

Z-Distance Matrix,

$$\begin{bmatrix} Zopt_1 - Z_{11} & Zopt_2 - Z_{12} & \cdots & Zopt_m - Z_{1m} \\ Zopt_1 - Z_{21} & Zopt_2 - Z_{22} & \cdots & Zopt_m - Z_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ Zopt_1 - Z_{n1} & Zopt_2 - Z_{n2} & \cdots & Zopt_m - Z_{nm} \end{bmatrix} \quad (6)$$

Lastly, the Euclidean composite distance (CD) between each SRGM alternative to the OPTIMAL were calculated and the SRGM with smaller CD will ranked higher.

$$CD_i = [\sum_{j=1}^{m} (Zopt_j - Z_{ij})^2]^{\frac{1}{2}} \quad (7)$$

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section describes the process and details of the experiment and their results. This section is separated into few sections, where each process in the ranking methodology was explained, and the results obtained were shown.

4.1 List of SRGMs, Comparison Criteria and Data Set

Table 1 and 2 had shown the lists of NHPP SRGMs and comparison criteria involved in this study mentioned previously in section 3 respectively. The data set used in this study is also displayed in Table 4.

The data set is the failure data of Tandem Computers Company software release that often used for software reliability studies [7][18][2][19][16][17][20]. The data are obtained from the report of defects taken from a subset of products of four separate software releases. The number of faults was normalized from 0 to 100 and the central processing unit (CPU) hours was proportionally converted into the range from 0 to 10000, in order to prevent issues occurred by confidentiality [5].

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4.2 Parameter Estimation of SRGMs

The estimated parameters using developed PSO algorithm are shown in Table 5. Besides that, the estimated parameters in the studies of using LSE [5] and Bacterial Foraging Optimization (BFO) [21] also included without manipulation for evaluation and comparison purposes.

4.3 Reliability Prediction and Evaluation Results

The aforementioned evaluation process are carried out using SRGM parameters estimated by PSO, and repeated by using the listed LSE and BFO estimated parameters. The evaluation result is recorded and tabulated. Table 6 shown the comparison criteria values of each SRGMs for PSO, LSE and BFO parameter estimation, with the best value (greyed) of the each comparison criteria for each models among the three parameter estimation methods that studied.

The best value of the comparison criteria proportionally represent the prediction quality of the model. The prediction quality of the model are better or more accurate prediction with the comparison criteria value that are smaller or closer to zero, except for the Rsquare, which showed better prediction with the value closer to one. Taking GO model as example, the RMSE value of GO-PSO is 3.408, GO-LSE is 5.609 and GO-BFO is 5.63, thus the RMSE value of GO-PSO is best value of RMSE value for GO model (GO-PSO < GO-LSE < GO-BFO), while for the Rsquare value GO-PSO is the best value (GO-PSO > GO-LSE > GO-BFO).

From the overall observation from Table 6, the evaluation results concluded that the SRGM parameters estimation by using PSO algorithm provided more accurate or better prediction quality compared to those estimated using LSE and BFO methods. This is because compared to numerical method LSE or the optimization method BFO, CI method PSO provided more optimized parameters therefore produced better or more accurate reliability prediction.

4.4 DBA Results and Model Selection Ranking

The comparison criteria values obtained during evaluation are based on the input of the DBA algorithm to produce the model selection ranking.

Table 7 shows the SRGM ranking that produced by using the parameter values of PSO, LSE and BFO parameter estimation methods. The ranking of the model will be ranks higher with the lower CD value. Taking PSO results as example, CD value for logistic growth model is zero (ranked number 1), GO model is 1.862862 (number 2), MO model is 1.979103 (number 3), number 4 and 5 are GG model and INFS model, with CD values of 3.343032 and 3.822733 respectively, and Gompert model ranked last (CD value: 9.182402).

The rankings of both three methods differed with each other's as they are changed depend on the prediction quality or accuracy and the accuracy is depended on the optimization of the SRGM parameters. On the other side, Logistic growth model is concluded as the best model to predict software reliability for this data set (Tandem Computer Software) from the comparison of the ranking produced using PSO, LSE and BFO methods, because it ranked first for all of the three method.

4.5 Discussions

PSO method shows better SRGM parameter optimization compared to LSE and BFO methods and provided better prediction quality. Compared to the numerical method LSE, PSO is the optimization techniques which is an evolutionary computation [22][23][24][15] and gradient based global optimization method, which provide more optimized parameters by obtaining optimal solution of complex nonlinear function of SRGMs [25]. PSO also does not need any assumptions on the software failure data during the implementation process.

On the other side, as compared to BFO, a non-gradient optimization method, PSO also showed has better optimization of SRGM parameters in the evaluation results. Although BFO has better convergence speed than PSO but it is not suitable in reliability prediction because of the elimination and dispersal of particles with poor foraging strategies.

Additionally, Logistic growth model ranked first and concluded as the best model for the Tandem Computer Software failure data set. This finding can be justified through the observations of SRGM parameters estimated by all the three methods (Table 5). For all the listed SRGMs, the parameter '*a*' in the mean value function represents the expected total number of faults to be detected during testing which it should be the parameter that are most crucial in reliability prediction. The parameter '*a*' of Logistic growth model in all three methods showed closer estimation or prediction to

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the actual data and among the three, parameters estimated by PSO are the best.

4.6 Limitations and Assumptions

In this study, there are some limitations and assumptions that needed to be outlined, and as stated as below:

i. Software reliability prediction is evaluated in term of prediction quality (accuracy).
ii. The SRGMs that included in the list to be test using the proposed methodology are only focused to certain NHPP SRGMs (listed in Table 1), which the parameters in their mean value functions are not exceeding three.
iii. PSO algorithm used in this study is developed using Java programming language and NetBeans IDE version 8.1, and the constant parameters of PSO are stated in Table 3.
iv. Comparison criteria used to evaluate the prediction quality of SRGMs are selected from existing literature by excluding some highly correlated criteria.
v. Only one data set is used as case study to validate and evaluate the reliability prediction, namely: Tandem Computer Software failure data.

5. CONCLUSION OR FUTURE WORKS

Reliability prediction is the important task or process in software development in order to produce good quality and reliable software. SRGMs have been widely used in many different software domains compared to all the reliability models. However, different characteristics and limitations of the SRGMs made selection of suitable model for reliability prediction difficult. Although there are existing studies or researches in model selection to choose best reliability model, the concern of prediction quality also cannot be neglected.

Therefore, in this paper, the software reliability prediction model selection methodology has been discussed. The model selection methodology consisted of four main processes, namely: identification of SRGMs and comparison criteria, parameter estimation of SRGMs, reliability prediction evaluation, and distance based approach model selection. In the parameter estimation process, PSO is used to optimize SRGM parameters. In the comparison of application of PSO in parameter estimation with the numerical method LSE and another CI method, BFO that used in the existing studies [5][21], PSO showed that the estimated SRGM parameters are more optimized than the other two methods, and provided better comparison criteria values in term of prediction quality (accuracy). The model selection is better because reliability prediction are more accurate because of the optimized SRGM parameters and that help the software developers and project managers in the decision of selecting suitable reliability model.

For the future works, the software reliability model selection methodology will be enhanced by the application of hybrid CI techniques, such as neuro-genetic, genetic swarm optimization and more. Besides that, the proposed model selection methodology will further be evaluate and validate by using varies data sets from different software domains especially for model-based reliability estimation and prediction [26][27].

Table 4: Tandem Computer Software Failure

Weeks	CPU hours	Defects found	Weeks	CPU hours	Defects found	Weeks	CPU hours	Defects found
1	519	16	8	4422	58	15	8205	96
2	968	24	9	5218	69	16	8564	98
3	1430	27	10	5823	75	17	8923	99
4	1893	33	11	6539	81	18	9282	100
5	2490	41	12	7083	86	19	9641	100
6	3058	49	13	7487	90	20	10000	100
7	3625	54	14	7846	93			

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Table 5: Parameter Estimation of SRGMs

Model Name	PSO	LSE	BFO
Goel-Okumoto	a=130.2015, b=0.083166	a=169.635, b=0.057	a=169.7149, b=0.057
Musa-Okumoto	a=72.30906, b=0.171847	a=119.538, b=0.085	a=119.8456, b=0.00848
Gompert	a=167.316, k=-0.06167, b=0205838	a=151.328, k=0.085, b=0.125	a=140.2308, k=0.0867, b=0.1352
Generalised Goel	a=118.562, b=0.076513, c=1.109731	a=68.554, b=0.007934, c=0.45	a=735.0386, b=0.016, c=0.8183
Logistic Growth	a=103.8627, b=0.284911, k=6.61957	a=107.818, b=0.269, k=6.535	a=110.2914, b=0.2622, k=6.5366
Inflection S-Shaped	a=110.8287, b=0.172062, β=1.204645	a=168.717, b=0.057, β=0.0001024	a=166.2069, b=0.0585, β=0.00091607

Table 6: Comparison Criteria Values of Each SRGM for PSO, LSE and BFO Parameter Estimation

Model Name	AE	MSE	RMSE	MAE	Bias	Rsquare	PRR	Variance	SSE	TS
GO-PSO	0.001305827	11.61710955	3.408388117	3.064774376	-0.090689664	0.99854121	0.378386691	3.500644061	232.3421911	4.539979777
GO-LSE	0.026341845	31.46687657	5.609534435	3.834256064	1.829441142	0.996048626	0.642712208	6.60999572	629.3375315	7.471911067
GO-BFO	0.026825264	31.70314348	5.630554455	3.846730448	1.863014564	0.996018957	0.641628232	6.658244851	634.0628695	7.499909777
MO-PSO	2.98E-04	15.84214879	3.980219692	3.63575781	-0.02067686	0.998010662	0.240689279	4.083784544	316.8429759	5.301660576
MO-LSE	0.036384827	44.32396603	6.657624654	4.436701909	2.526926208	0.994434129	0.559294941	8.174416716	886.4793207	8.867969332
MO-BFO	0.037299992	45.0121671	6.709110754	4.465886697	2.59048443	0.99434771	0.559440772	8.280859086	900.2433421	8.93654892
Gompert-PSO	0.008628893	124.2515182	11.1468165	9.575006653	0.599276611	0.984397426	0.893160916	11.48586846	2485.030363	14.84758184
Gompert-LSE	0.936158613	5220.610227	72.2537904	65.01621566	-65.01621566	0.344434916	35417.72494	137.2739678	104412.2045	96.24219308
Gompert-BFO	0.939560484	5253.966987	72.48425337	65.25247564	-65.25247564	0.340246224	49523.77196	137.7550218	105079.3397	96.54917022
GG-PSO	0.004578733	10.87076151	3.297083789	2.700218254	-0.317993015	0.998634931	0.830303757	3.429611024	217.4152303	4.39172219
GG-LSE	0.978789373	5409.622823	73.55013816	67.97692199	-67.97692199	0.320700131	39951.13079	142.430809	108192.4565	97.96893088
GG-BFO	0.058822637	75.02801096	8.6618711	5.498941465	4.08523216	0.990578545	0.284860422	11.47516203	1500.560219	11.5376296
Log-PSO	1.97E-04	1.623791274	1.274280689	0.917227596	-0.013664106	0.999796096	0.022392853	1.307609871	32.47582547	1.697344422
Log-LSE	0.010626344	3.633961401	1.906295203	1.417992449	0.737999572	0.999543674	0.028332749	2.354813996	72.67922802	2.539189017
Log-BFO	0.019650463	7.065925111	2.65818079	1.950642223	1.364724675	0.999112714	0.036629582	3.649563121	141.3185022	3.54070212
INFS-PSO	0.006267548	8.97921406	2.996533674	2.260430245	-0.435281222	0.998872458	0.867469442	3.170193965	179.5842812	3.991388837
INFS-LSE	0.020735912	28.93253107	5.378896826	3.728241447	1.440109091	0.99636687	0.656220888	6.0831323	578.6506214	7.164701313
INFS-BFO	0.022973022	28.4076069	5.329878695	3.687281266	1.59547636	0.996432786	0.626585537	6.159651507	568.1521381	7.099409064

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Table 7: SRGM Ranking Based on PSO, LSE and BFO

Model Name	Composite Distance (CD) Value			Rank		
	PSO	LSE	BFO	PSO	LSE	BFO
Goel-Okumoto	1.862862	0.201614	0.201299	2	3	3
Musa-Okumoto	1.979103	0.264952	0.283858	3	4	4
Gompert	9.182402	6.680736	8.648481	6	5	6
Generalised Goel	3.343032	6.9754	0.443265	4	6	5
Logistic Growth	0	0	0	1	1	1
Inflection S-Shaped	3.822733	0.185099	0.178776	5	2	2

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