COMPRATIVE STUDY ON PRE-MATURE SOFTWARE RELIABILITY METHODS

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Abstract
Software industry suffers many challenges in developing a high quality reliable software. Many factors affect their development such as the schedule, limited resources, uncertainty in the developing environment and inaccurate requirement specification. Software Reliability Growth Models (SRGM) were significantly used to help in solving these problems by accurately predicting the number of faults in the software during both development and testing processes. The issue of building growth models was the subject of many research works. In this paper, we explore the use of fuzzy logic to build a SRGM. The proposed fuzzy model consists of a collection of linear sub-models joined together smoothly using fuzzy membership functions to represent the fuzzy model.

Keywords: SRM(Software Reliability Methods, SCP (Soft Computing Principles)

I. INTRODUCTION

Machine Learning (ML) and Soft Computing techniques, such as Genetic Algorithms (GAs), Genetic Programming (GP), Evolutionary strategies (ESs), Artificial Neural Networks (ANN), Fuzzy Logic (FL), and Particle Swarm Optimization (POS), to solve software engineering problems expanded in the recent years. Estimation of the COCOMO model parameters using Genetic Algorithms (GAs) for NASA Software Projects were provided in [2]. Parameter Estimation of Hyper-Geometric Distribution Software Reliability Growth Model by Genetic Algorithms was presented in [3]. Predicting accumulated faults during the software testing process using parametric and non-parametric models were explored in many articles [4]–[6]. In [7], author provided a strategic solution for estimating software defect fix effort using self-organizing neural network. Genetic programming (GP) was successfully used to find a model that fits the given data points without making any assumptions about the model structure [8], [9]. GP found to be a powerful technique in developing software reliability growth modeling. In this paper, we explore the use of fuzzy logic to predict faults during the software testing process using software historical faults data. In section II, we provide an overview of various SRGM. An introduction on fuzzy modeling technique is presented in section III. The proposed fuzzy model structure is presented in section IV. Detailed information about the data set and the experiments developed are provided in sections V, VII.

II. SOFTWARE RELIABILITY GROWTH MODELS

In the past three decades, hundreds of models were introduced to estimate the reliability of software systems [10][12]. The issue of building growth models was the subject of many research work [13], [14] which helps in estimating the reliability of a software system before its release to the market. Serious application such as weapon systems and NASA space shuttle applications were explored [15][17]. Faults may be encounter in market released software. This is a challenge for software companies. It might affect their reputation and finance. Software reliability growth models were significantly used to help in computing the number of faults which is still resides in the software [18]. Thus, specifying the effort required to fix faults, the time required before software can be released and the cost of repair. Software reliability growth models employ system experimental data for testing to predict the number of defects remaining in the software. Software reliability models can be classified to two types of models according to prediction style either from:
• the design parameters thus called "defect density" models
• the test data thus "software reliability growth" models.

Some known SRGM are Logarithmic, Exponential, Power, S-Shaped and Inverse Polynomial models [19], [20]. They are typical analytical models. They normally describe the fault process as a function of execution time (or calendar time) and a set of unknown parameters. The model parameters normally estimated using least-square estimation or maximum likelihood techniques [13].

III. FUZZY MODELING

Fuzzy logic have been successfully used to solve variety of problems in system identification, signal processing and control [21][24]. Fuzzy modeling has been regarded as one of the key problems in fuzzy systems research [25][26]. In the past years, research focused on the development of fuzzy systems from both theoretical and applications oriented prospective were presented in [27][29]. A fuzzy model structure can be represented by a set of fuzzy If Then rules [30]. A fuzzy rule has two parts the antecedent and the consequence. The antecedent variables reflect information about the process operating conditions. Modified by evaluating the total average cost and software reliability simultaneously. The total cost in this model was minimized within the constraint of software reliability. Models assessing the effects of reliability and cumulative costs of software testing have demonstrated that expected average costs of software testing can be reduced by restricting the scope of testing procedures. The consequent of the rule is usually a linear regression model which is valid around the given operating condition [31][35]. Consider a dynamical system with a set on inputs $x_1, x_2, \ldots, x_n$ variables and y single output variable. The relationship between these variables can be represented as:

$$y = f(x_1, x_2, \ldots, x_n) \quad (1)$$

Our objective is to develop a fuzzy model structure which describe the function f between the inputs x_i, $i = 1, \ldots, n$ and the output y.

Knowing that the inputs and outputs are measured at the sample time t; $t = 1, 2, \ldots, N$.

A fuzzy model of a dynamic system for a multi-input single-output (MISO) system has a set of rules of the following format:

R_k : If x_1 is A_{k1} and . . . and x_n is A_{kn} then

$$y_k = a_{k1}x_1 + a_{k2}x_2 + \cdot \cdot \cdot + a_{kn}x_n + k_0 \quad (2)$$

where k is the rule number. For example, if we want to model a three input $n = 3$ single output system using two rules $i = 1, 2$.

The system can be represented as follows:

R_1 : If x_1 is A_{11} and x_2 is A_{12} and x_3 is A_{13} then $y_1 = a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + a_{10}$ R_2 :

If x_1 is A_{21} and x_2 is A_{22} and x_3 is A_{23} then $y_2 = a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + a_{20}$ where y_1 is the output corresponding to the region of values, in the input domain, of the variables x_1, x_2, x_3 based a set of membership function A_{11}, A_{12} and A_{13}.

The inner-product space for the fuzzy set A_i, which defines the fuzzy region in the antecedent space, can be described as:

$$A_i = N \_ j=1 \; A_{ij} = A_{i1} \times A_{i2} \times \ldots A_{in} \quad (3)$$

Thus, the degree of fulfillment is given by:

$$\beta_i = \mu A_{i1}(x_1) \wedge \mu A_{i2}(x_2) \wedge \ldots \mu A_{i1}(x_n) \quad (4)$$

Other operator can be used to develop β_i. The antecedent part of the rule divide the input domain of x into a set of fuzzy sub-domains. Each domain is corresponding to a fuzzy set. The number of rules M can be computed as:

$$M = N \_ i=1 \; T_i \quad (5)$$

where n is the dimension of the input space (i.e. the number of inputs) as described earlier and T_i is the number of terms in the ith antecedent variables.

IV. PROPOSED FUZZY MODEL STRUCTURE

Our objective is to approximation the dynamics of the fault measurements during the testing process and instead of representing it in a single nonlinear model we can extend it by a set of local linear models. Each local model should be able to represents the relationship between the historical faults

$y(k-1), y(k-2), y(k-3), y(k-4)$ and the current fault $y(k)$ in a certain range of operating conditions. Such a proposed fuzzy model structure can be successfully represented by means of fuzzy If-Then rules. The proposed model equation is given as follows:

$$y(k) = FM(y(k-1), y(k-2), y(k-3), y(k-4)) \quad (6)$$

Using membership functions and the antecedent of the rule we can define the fuzzy region in the product space. The antecedent variables gives the condition of the process status now. The consequent of the rule is typically a local linear regression model which relates $y(k)$ with $y(k-1)$, $y(k-2), y(k-3), y(k-4)$.

A rule-based fuzzy model requires the identification of the following: 1) the antecedent 2) the consequent structure, 3)

the type of the membership functions for different operating regions and 4) the estimation of the consequent parameters.

The developed fuzzy models implemented based the Takagi- Sugeno technique [31], [32]. The proposed technique does not require any a prior knowledge about the operating regimes. If a sufficiently number of measurements are collected which reflects the operating ranges of interest, the developed fuzzy model will be an efficient one.

V. THE SOFTWARE RELIABILITY DATA

John Musa of Bell Telephone Laboratories compiled a software reliability database [1]. His objective was to collect fault interval data to assist software managers in monitoring test status, predicting schedules and to assist software researchers in validating software reliability models. These models are applied in the discipline of software reliability engineering. The dataset consists of software fault data on 16 projects. Careful controls were employed during data collection to ensure that the data would be of high quality. The data was collected throughout the mid 1970s. It represents projects from a variety of applications including real time command and control, word processing, commercial, and military applications. The routines of the toolbox contain the Gustanfson-Kessel (GK) clustering algorithm, whose implementation is given in [37].

VI. VALIDATION CRITERIA

In order to check the performance of the developed model, we compute the Variance-Accounted-For (VAF) performance criterion to measure how close the measured values to the values developed using the fuzzy models. The VAF is computed as:

$$V\,AF = \_1 - var(y - \hat{y})\,var(y)\_ \times 100\%\ (7)$$

where y, $\hat{y}$ are the real actual output and the fuzzy model estimated output, respectively

VII. CONCLUSION

In this paper we identify the various soft computing technique used in Software Reliability testing. Proceeding of this paper in further we will elaborate the concepts of Pre-mature software reliability using the concepts of Soft Computing

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