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A Methodological Approach to Assessment and Reporting of the Model Adequacy in Simulation Studies

Michael Sony, Namibia University of Science and Technology, Windhoek, Namibia
https://orcid.org/0000-0002-8003-5216

V. Marriapan, Agnel Institute of Technology and Design, Goa, India

ABSTRACT

Assessment and reporting of model adequacy is an important step in the simulation modelling process. It stipulates the levels of precision and accuracy, which are important features of the model predictions. In an academic research activity, an important step for model development is the process of the identification or accepting whether the model is wrong. The evaluation of the adequacy of developed models is not possible through a single statistical test. This paper delineates a technique to implement model adequacy. A live case is demonstrated on the proposed methodology by evaluating a simulation model which was designed by us to simulate a well-established mathematical model. A step-by-step methodological approach is delineated in this paper along with a case study of investigation of a simulation model with a mathematical model used to demonstrate this methodology. The paper concludes with an algorithm and a flow chart for performing model adequacy for assessing the adequacy of the developed model with existing models.

KEYWORDS

Anova, Case Study, Lack of Fit, Markov Model, Methodological Approach, Model Adequacy, Regression Analysis, Simulation

1.0 INTRODUCTION

Simulation Models are used to represent various mechanisms of natural phenomenon or system behaviour or an event under consideration. Models are representations of reality. These simulation models can be used as an important tool for a decision support system for various stakeholders such as the policymakers, managers, researchers, engineers and others (S Michael, Mariappan, Amonkar, & Telang, 2009; Atamturktur, Stevens, & Brown, 2017; Miao, Xie, Yang, Tai, & Hu, 2017; Fritzsche, 2018). The tasks such as validation of precision, the accuracy of proposed simulation models form an important aspect. A wrong model can lead to erroneous conclusions, which can cost the stakeholders a large sum of money(M Sony & Mariappan, 2019). Besides simulation models can be used to communicate and advance the scientific knowledge, which in turn can lead to discoveries or challenging old discoveries or theories(Mac Nally, Duncan, Thomson, & Yen, 2018). The simulation Modeling process is a methodological process. The process begins with clearly identifying the statement of objectives. The other steps in are 1) exploring assumptions about the proposed model boundaries 2) how appropriate are the available data 3) the design of the model structure 4) evaluating the models

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results from studies like simulation and 5) recommending solutions(Tedeschi, 2006; S Michael, Amonkar, Mariappan, & Kamat, 2009; Michael Sony & Naik, 2011; Sony Michael, Mariappan, & Kamat, 2011; Montgomery, 2017). A rigorous model testing of simulation methodology is recommended to prove the appropriateness of a model(Khorsan & Crawford, 2014), as no single tests to confirm its appropriateness. The tests are performed on the models to gather evidence as to its acceptance and usability(Sterman, 2002). Improved model validity enhances the credibility of the research and acceptance among other researchers. The simulation modelling process is further strengthened by the process of by identifying wrongness of the model (Melhart, Sfikas, Giannakakis, Yannakakis, & Liapis, 2018). This delineation process of identifying the weakness strengthens the process of model development in all its phases. There has been strong criticism of the concept of model validation and verification(Addiscott, Smith, & Bradbury, 1995). It is partly due to the philosophy that it is impossible to validate all components of the model(Oreskes, Shrader-Frechette, & Belitz, 1994; Saltelli, Tarantola, Campolongo, & Ratto, 2004; Foures, Albert, & Nketsa, 2016). There are formal approaches for model verification and validation. One of the most widely used methods is quantitative methods for verification and validation. However, a recent study suggests that to explore all possible behaviours of models one should take into account both qualitative and quantitative approach (Foures et al., 2016). Another point to be considered is that model is a representation of process or phenomenon. In other words, it approximates reality or phenomenon. Thus, testing a model in an absolute sense is not advisable. Nevertheless, it should be tested for the purpose for which it was designed. Before undertaking any experimentation or sensitivity analysis with the model, it should be thoroughly tested(Tedeschi, 2006; Denil, Klikovits, Mosterman, Vallecillo, & Vangheluwe, 2017). Many researchers have devoted considerable attention to the process of model verification and validation (Tedeschi, 2006; McCoach & Black, 2008; Foures et al., 2016; Denil et al., 2017; Montgomery, 2017). However, despite all these studies, there still exists a requirement of a testing procedure which considers both the quantitative and qualitative methodology(Foures et al., 2016; Denil et al., 2017). In this paper, the authors intend to develop a step by step procedure for model adequacy with the help of a practical case study on Model Adequacy for assessing the fit between the developed model using simulation with a well-established Mathematical Model (Markov model). Besides a reporting methodology is also reported in the study.

2.0 BACKGROUND LITERATURE

Through a landmark paper, Oreskes et al (1994) expressed that "models cannot be verified or validated in the sense of having the truth of their assumptions established with certainty, they reminded us, nor does impressive past performance by a model guarantee its future performance". A model is found to be confirmed if the output fits the observational data, however, the support provided even in such instances is partial(Parker, 2020). To confirm whether the existing simulation model fits the target is to test it in terms of particular respects and degrees(Lloyd, 2010). Another method of testing would be to test whether the model is fit for interest and it is called as the adequacy of purpose view(Parker, 2020). There are several methods available to confirm or disconfirm or falsify a model(Parker, 2020). One of the most popular methods would be to test whether a model is similar to a target model concerning degrees and respects(Weisberg, 2012). The second method would be to test particular modelling assumptions. In particular, test the truth is still in question, for example, that particular quantities in the target are related according to a certain equation(Parker, 2020). One of the other popular methods would be to test whether the model is fit for a particular purpose. In this method, the model quality is assessed relative to a purpose. Hence, the model evaluation seeks to learn whether a model is adequate or ðt for particular purposes. The US National Research Council report depicts model evaluation as "the process of deciding whether and when a model is suitable for its intended purpose"(Council, 2007). Though there are a variety of methods for evaluation of model adequacy, there still exists a requirement of a testing procedure which considers both the quantitative and qualitative methodology(Foures et al., 2016; Denil et al., 2017). Also, a step by step methodology will help the future researchers while assessing the model adequacy of the simulation model in the scientific environment.

2.0 PROBLEM ON HAND

Markov model is used widely in reliability engineering. It models independent as well as dependent failures and repair modes(Yang & Dhillon, 1995; Sony Michael & Mariappan, 2012). Stochastic process of failure interaction in transmission was developed to account for dependent failures(Alsammarae, 1989; S Michael, Mariappan, et al., 2009; M Sony & Mariappan, 2019). One of the issues in Markov models are as the number of components to be modelled increases, the complexity of Markov model increases. Hence it becomes difficult to model such systems. A Simulation becomes a pertinent technique to solve such problems. A simulation model was developed to solve the failure interaction problem(Sony Michael et al., 2011). The authors have also developed a simulation program to simulate various system performance measures. It simulates parameters 1) the probability of the stochastic system modelled being in a specific state 2) System Availability. The model incorporates features like data inputs, initialization the system, system observation criteria, evaluating summary statistics and results. Next event approach was used to model the same. The model when compared with the Markov model the error was very small for practical purposes. Design of experiments was done on the model. The control factors in this study were MTTR (mean time to repair), MTBF (mean time between failure), the interaction factor, and runs. The levels were set up after discussion with experienced Engineers working in the field. Since the study was performed on computers, full factorial design technique was used. The total number of replications was 3125 along with five replications. The simulation environment to fit in entirety has the full factorial design of experiments was conducted, which gave us $5^4 = 625$ experiments each of the experiments have 5 replications amounting to 3125. Now we have two sets of situations to investigate.

1. Responses obtained from simulation model Y, which has five different responses, for each experimentation. This is known as Y matrix
2. For each response mentions in Sr. No 1, will have corresponding 5X responses for corresponding 5Y responses.

The issue here is that there is no single technique to assess the adequacy of simulation models in this case due to the complexity of the situation and as such, it is proposed to use a combination of statistical and non-statistical testing methodology to assess the significance of the proposed model.

3.0 MODEL ADEQUACY TECHNIQUE.

A regression line is proposed between the proposed simulation model and well-established or deterministic Model (Markov Model). The regression model parameters were tested using the hypothesis. A regression line has a both slope and intercept. To test these of the proposed regression model (Accuracy line), one of the fundamental assumptions is that error components are normally distributed. In other words, errors are normally and independently distributed. In addition to it the mean zero and variance σ^2. This is usually abbreviated as NID $(0, \sigma^2)$. The values obtained by solving the model are called predicted values. The observed values are values from the deterministic model. The X-axis was denoted to the predicted values and the Y-axis to the observed values. This was done as the observed values had natural variability because it is a deterministic model with no random variation. The proposed technique suggests that the regression line becomes accuracy when the number of responses on Y and the number of responses in X becomes the same or equal. Hence it is pertinent to test the slope which should be one and intercept zero.

3.1 Accuracy Line Parameter Hypothesis Testing

From the above data, the regression line was tested, and it was found to be

Y = 1.00009 X -0.0000. The estimated parameter using a simulation study was on X-axis. The deterministic value was on Y-axis. The accuracy line should be hypothesis tested for slope and intercept. The slope should be one. Also, the intercept of the accuracy line should be zero with 95% confidence. It is pertinent therefore to test the slope and intercept of the proposed accuracy line.

a) t- test

i) Slope Parameter

Ho: b = b1 = 1

$$t_o = \left| \frac{\hat{\beta} - b1}{\sqrt{\frac{\sigma^2}{S_{xx}}}} \right|$$

Substituting the values, it is found that $t_0 = 0.22$. The t-values from the table were $_=$ 1.66 since $t_0 < t_{0.05,623}$, the null hypothesis not rejected with level of significance 5%

ii) Intercept parameter

Ho = d =0

$$t_o = \left| \frac{\hat{\beta} - d}{\sqrt{\sigma^2 \left[\frac{1}{n} + \frac{\bar{X}}{S_{xx}} \right]}} \right|$$

d = 0

σ^2 =9.20117594246353e-006

$\bar{X}$ =0.8324894

N= 625

S_{xx} = 53.7256664508996

It is found that $t_0 < t_{0.05,623,}$ hence the null hypothesis is not rejected with a level of significance 5%.

From the t-test it can be safely proved slope is 1 and intercept are zero, hence proposed simulation model is accurate. However, this is subject to the condition that validity is subject to statistical significance on the accuracy line.

3.2 F-test for Significance

The accuracy line/regression line should be tested for significant for linearity. An F-test is proposed to test the significance of accuracy line. Analysis of variance (ANOVA) procedure is used. The technique separates the variability of the deterministic model(Markov) into two parts. The analysis of variance with its two components is given in Equation 1

$$\sum_{j=1}^{n}\left(y_j-\overline{y}\right)^2=\sum_{j=1}^{n}\left(\hat{y}_j-\overline{y}\right)^2+\sum_{j=1}^{n}\left(y_j-\hat{y}_j\right)^2 \tag{1}$$

There are two components of the equation 1. The first measures the amount of variability in Y_i, which are accounted for by the accuracy line. The second component measures the residual variation, which was remaining unexplained by the accuracy line (Regression line). The model error sum square it denoted as $SS_E = \sum_{j=1}^{n}\left(y_j-\hat{y}_j\right)^2$

The Sum Square of residuals is modelled as $SS_R = \sum_{j=1}^{n}\left(\hat{y}_j-\overline{y}\right)^2$ Thus, the equation 1 can be rewritten as equation 2.

$$S_{syy} = SS_{residuals} + SS_{error} \tag{2}$$

In the equation 2 $S_{syy} = \sum_{i=1}^{n}\left(y_j-\overline{y}\right)^2$ is the total is corrected sum of squares of Y. It was further observed that $SS_E = S_{syy} - \hat{\beta}_1 S_{xy}$. Thus, $S_{syy} = \hat{\beta}_1 S_{xy} + SS_E$ To calculate the sum of squares (regression) as given in the Equation 3

$$SS_{(Reg)} = \hat{\beta}_1 S_{xy} \tag{3}$$

The sum of squares (total) S_{syy} has n-1 dof (degree of freedom). SS_{Reg} and SS_E have 1 and n-2 dof. Thus, $E(SS_E/(n\text{-}2) = \sigma^2 + \beta_1^2 S_{xx}$

It may be noted that SS_E / σ^2 is independent chi-square random variable with n-2 dof. Similarly, SS_{Reg} / σ^2 also independent chi-square random variables with 1 dof .

The null hypothesis Ho: $\beta_1=0$. If the null hypothesis is true, the statistic follows the

$F_{1,n-2}$ distribution. Thus, it is pertinent to reject the Ho if $f_0 > f_{\alpha,n-2}$ .The quantities $MS_{Reg} = SS_{Reg}/1$. In similar parlance $MS_{Error} = SS_E/n\text{-}2$. These are called mean squares regression and mean square error. Therefore, mean β_1^2 is calculated as sum of squares divided by the degrees of freedom. The results should be formatted as given in the table 1.

Ho: Slope = 0 in other words it means there is no linear relationship between Proposed and Deterministic Model.

Table 1. F-test

Source SS dof MS Fovalue
Regression 52.72 1 52.72 5859577
Residual 0.0057 623 0.000009
Total 52.74 624

Ss =sum of squares dof = degree of freedom MS = mean squares

The estimated value from the table1, it is seen Fo is greater than $f_{0.05,1,62.,}$ Hence the H_0 is rejected. Thus, it is proved a linear association.

This test proves a linear relationship between the proposed model and deterministic. However, there is an academic debate about the usage of regression models to judge the accuracy of proposed models, A sequence of analysis is usually recommended between model-predicted and observed values. The three criteria for model validation between the predicted and observed values are 1) identical means 2) identical variances and 3) positive correlation. A model used for practical purposes rarely meets these assumptions. Using linear regression as model adequacy has also been a subject of critique as the assumptions in practical circumstances are rarely satisfied. Thus, the hypothesis tests are subject to scatter data and regression line lacks sensitivity.

The academic community is divided on the usage of the regression line as an accuracy line between the proposed model and deterministic model(Kleijnen, Bettonvil, & Van Groenendaal, 1998). The residuals between the proposed and deterministic models should be subjected to the number of statistical analysis. Besides, the regression model or accuracy line should be tested for stringent assumptions. These assumptions when tested in real life are hardly met. The violation of the assumption of linear regression questions its usage as an accuracy line(Eubank & Spiegelman, 1990; Harrison, 1990; Mitchell, 1997). Besides, if the assumptions are violated null hypothesis tests give unclear results depending on the fact relating to the degree of scattering of the data. The proposed accuracy line or regression line will also lack sensitivity. It is since the regression or accuracy line will fail to distinguish between data points.

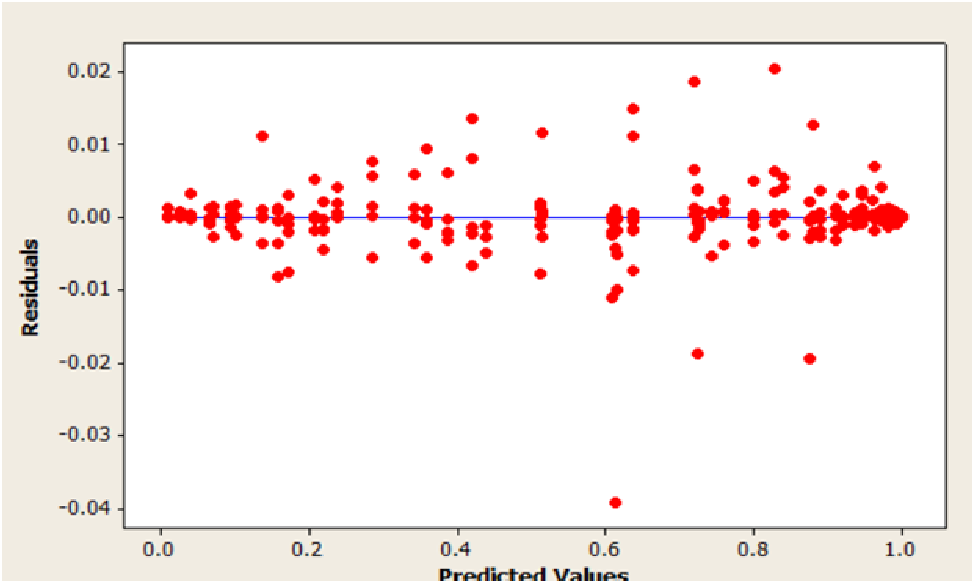
Another important factor to consider is the slope parameter of regression analysis tests. If the residual error is small, it can reject a reasonably good agreement(Tedeschi, 2006). Hence the conclusion of model fit using regression analysis must be done with caution and further, the assumptions of regression analysis should be tested. Thus, from the slope and intercept hypothesis testing it can reasonably conclude that parameters hold true with the assumption that residuals follow a normal distribution with mean `0` and standard deviation σ^2.

3.3 Assessing the Assumptions of Regression(Accuracy) Line

The proposed regression line estimation requires the assumption to be tested to confirm the applicability in model adequacy. The regression line parameters to be estimated, that errors should be uncorrelated with mean zero and constant variance. A slight apprehension of violation of assumptions of accuracy line should be dealt with by conducting the proposed tests. Three methods for assessing the accuracy of the proposed model is suggested.

a) Analyzing the Residuals
b) Analyzing the R^2
c) Lack of test

Figure 1. Plot of residuals versus predicted values from the proposed simulation model



a) Analyzing the Residual

The residuals from the proposed regression model are $e_{res} = y_i - \hat{y}_i$, where i =1,2,3…….n. y_i denotes the actual observations. $\hat{y}_i$ is the value fitted from the computed regression model? The residual is calculated and plotted to determine any pattern in the proposed regression model. In the instance case, the plot exhibits no pattern in terms of trends, oscillation etc. It is further noted that fifty per cent of data points above zero. Also, the other fifty per cent below zero in an almost equal manner. The graph is given in Figure 1. From Figure 1, it can be inferred that there is an equal distribution of error on both on positive and negative sides. To test the normality of residuals, a normal probability plot is carried out. Figure 2 is the normal probability plot of the residuals and it is used to ascertain whether residuals follow normality. In figure 2 a vertical line passing through zero residuals. The vertical line proves that the one can reasonably assume that parameter which is mean is zero and the standard deviation is zero.

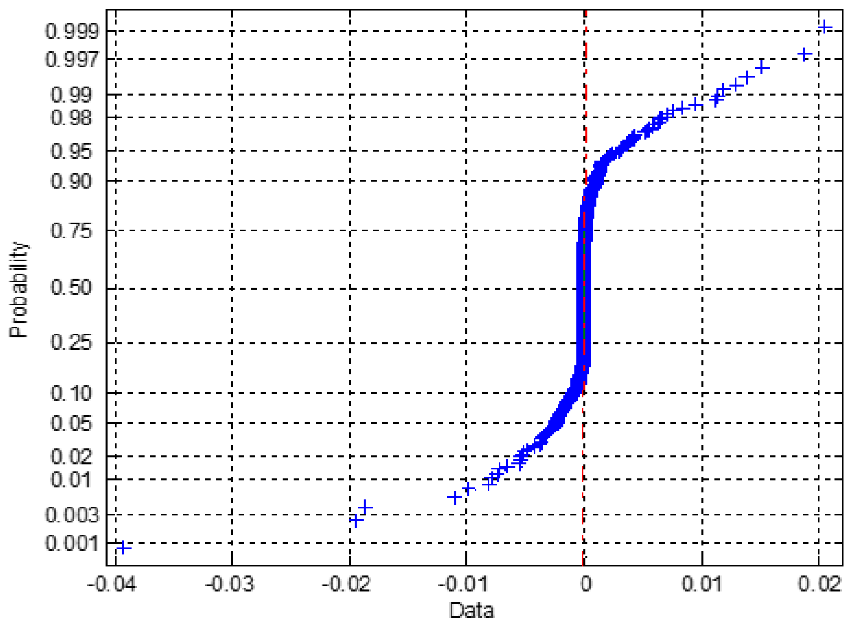
b) Analyzing the R^2

To ascertain the adequacy of the regression model, the coefficient of determination is the most widely used method. R^2 is a very widely used regression model statistic. It explains the amount of variability in the data by the regression model. The range R^2 lies between 0 and 1. *'1'* suggest a good fit. The quantity as given in Equation 4

$$R2 = \frac{SS_R}{S_{yy}} = 1\text{-}\ \frac{SS_R}{S_{yy}} \tag{4}$$

$SS_E = 0.0057323$
$SS_y = 53.73635$

Figure 2. Normal probability of residuals of the proposed simulation model



In the current study, it is estimated to be 0.999.

The criticism of R^2 is that it does not measure the value of the slope of the regression model or accuracy line in this case. Moreover, it cannot always be presumed that a larger value of R^2 means slope is steep. Besides, there is a growing debate of R^2 based on the discipline of study. Social sciences consider smaller values of R^2 compared to Engineering models. Another fact to point out is that R^2 does not measure the suitability of the proposed model. It is because R^2 can be artificially inflated if we add polynomials for higher-order while modelling. Even if y and x are related in a non-linear manner, the R^2 can be reasonably big(Tedeschi, 2006)

c) Lack of Fittest

The lack of fit of the regression model is ascertained by using this test. The simulation environment is carried out as a full factorial design of experiments(DOE). The factors affecting the simulation model was 5. MTBF line 1 & 2. MTTR line 1 & 2 ad number of runs. Hence it gave us $5^4 = 625$ experiments each of the experiments have 5 replications amounting to 3125. Now we have two sets of situations to investigate.

1. Responses obtained from simulation model Y, which has five different responses, for each experimentation. This is known as Y matrix
2. For each response mentions in Sr. No 1, will have corresponding 5X responses for corresponding 5Y responses. This is known as the X matrix

Therefore, classical lack of fit test can be constructed in this case also,
Ho: The linear regression or accuracy line is correct
H1: The linear regression or accuracy line is not correct

The lack of fit test involves partitioning the error or residual sum of squares. The two components in the partitioning are the sum of squares attributable to pure error and lack of fit error. This is shown in equation 5.

$$SS_{Error} = SS_{pureerror} + SS_{lackoffit} \tag{5}$$

$SS_{pureerror}$ is the sum of is squares attributable to the pure error. It is the sum of squares attributable to the lack of fit of the model. The $SS_{pureerror}$ is calculated on repeated observations on the response Y. This is calculated for at least one level of x. Hence the total observations are such that,

y11, y12 …………..y1, n1 The repeated observations at x1

y21,y22……………y2n_2 at x2

Ym_1, ym_2…………ym_n The repeated observations at x_m

The actual responses Y will have its own SSE (calculated from 625 x 5 responses)

$SS_E = \sum_{1}^{n} e_i = \sum_{i=1}^{n}\left(y_i - \overset{=}{y}\right)^2$ Where y_i is the response and $\overset{=}{y}$ is the grand mean of Y.

For this purpose, the SS_{Ey} will be SS_{Ex} if, the regression line is true (Y=X).

Therefore, in the parlance of ANOVA, this SSE can be portioned in two errors as described earlier. SSLOF can be computed effectively by squaring the difference between, averaged corresponding experimentation in matrices x and Y. Sum of these squares will represent SSLOF. The following equations (6) to (9) can be used for the above purposes.

$$SSPE = SSE - SSLOF \tag{6}$$

$$MSLOF = \frac{SSLOF}{m-2} \tag{7}$$

$$MSPE = \frac{SSPE}{N-m} \tag{8}$$

$$F = \frac{MSLOF}{MSPE} \tag{9}$$

Where m = number of levels or treatments. n = number of replications,

N = Total observations m x n.

Compare with standard value $f_{\alpha, m-2,N-m}$. If $F < f_{\alpha, m-2,N-m}$. If $F < f_{\alpha,m-2,N-m}$ Ho is failed to reject $F < f_{\alpha,m-2,N-m}$ Ho is rejected.

As the lack of fit test involves a procedure a stepwise procedure is suggested

Step A: Ho: The linear regression (Accuracy) model is accurate

H1: The linear regression(Accuracy) model is not accurate

Step B: Obtain the parameters of the regression model. In the instant case it was

y = 1.00009 .X- 0.00005

Step C: Using the regression line the data points for y are calculated from the x matrix.

Step D: Compute SSE(y) for y matrix is calculated and it is found to be = 267.77.
Step E *& F*: Compute SSLOF and it is found to be = 9.55e-007
Step G: SSPE = 267.77
Step H: DOF (SSLOF) = 623
DOF SSPE = 625x 5 – 625 = 2500
Step I: MSLOF = 1.55 x 10^{-9}
MSPE = 0.11
Step J: F = 1.4417x 10^{-8}
Step K: f value $_{0.05,\ 623,\ 2500}$ = 1.01 (F- table)
Step L: $F < f_{\alpha,m-2,N-m}$ thus the null hypothesis is failed to reject

The output of this test suggests that the accuracy line is correct. In model adequacy terminology, it suggests that there is no lack of fit for the accuracy line.

4.0 STEPWISE DESCRIPTION OF THE MODEL ADEQUACY PROCEDURE

As model adequacy involves many sub-modules which look similar it may cause a sort of confusion in any user. To facilitate user investigating his claim of a new model as a superior candidate over the existing established model a detailed flow chart and hence stepwise procedure are provided in table 2.

To carry out this test in an effective manner the following stepwise procedure can be adopted,

The flow chart for the same is provided in Appendix 1.

5.0 CONCLUSION

Simulation model building is an important facet in engineering and scientific applications. Assessing the adequacy of simulation models is an important step in the modelling process because it helps to understand and identify the adequacy of the proposed models in terms of its reliability and accuracy. Model adequacy is not a single step process and rather it is a complex amalgamation of several statistical tests which should be applied methodologically. Simulation model building is used by both academicians as well as a practitioner and therefore there is a need for a methodological guideline for assessment of the adequacy of the simulation model with the mathematical model. This paper delineates a methodological step by step approach for assessment of simulation models. A live case is used to demonstrate the applicability of the methodological assessment of model adequacy wherein a simulation model based on a real-life situation was compared with a well-established to compare its usage. The main findings of this paper are that model adequacy is a methodological process which consists of both statistical and non- statistical tests which should be used in a sequence to confirm the validity and reliability of the model. The methodological algorithm is depicted in Appendix 1 graphically and a step by step description of the model is delineated.

6.0 LIMITATION & FUTURE RESEARCH DIRECTION

The limitation of this assessment criteria is the extensive use of DOE and therefore it could be a time and resource-consuming process. Another limitation could be the subjective nature of pattern recognition for residual analysis. However, it is suggested that, if there is a strong pattern the algorithm rejects it, however, if the pattern is weak than statistical test for trends, oscillations, clustering may be carried out. This study was carried out by using full factorial design and future studies may explore case studies based on fractional factorial experiments. Besides, pattern recognition of residuals should also be incorporated into the assessment criteria. Another important area of research would be to incorporate this assessment methodology in a standalone software package which will help the scientific community to easily assess the simulated model methodologically. This is the first study

Table 2. Step by step algorithm for model adequacy

Step 1: Identify the model proposed and ideal one
Step 2: Perform DOE on the proposed model
Step 3: Obtain the regression equation based on the ideal established model.
Step 4: Perform t-test on slope =1 and intercept =0
Step 5: If the Ho is rejected model not accurate go to step 1 else continue
Step 6: Carry out the significance on F-test
Step 7: If Ho is not rejected model not accurate go to step 1 else continue
Step 8: If there is a pattern go to step 9 else go to step 10
Step 9: If the pattern is strong then the "model not adequate" go to step1 else go to step 10
Step 10: Calculate R^2 .
Step 11: If R^2 does not lie between 0.8 to 1 model not accurate go to step 1 else continue
Step 12: Using the regression line obtained in step 2 find the corresponding x matrix
Step 13: Calculate SS_{Ey} for Y matrix
Step 14: Find row-wise average of X and Y matrices.
Step 15: Find the sum of squares of the difference between x and y obtained in step 5. It is denoted as SSLOF.
Step 16: Calculate $SSPE = SSE - SSLOF$
Step 17: The degree freedom for SSLOF = m-2
The degree of freedom for SSPE = N-m
Step 18: Find $MSLOF = \frac{SSLOF}{m-2}$ and $MSPE = \frac{SSPE}{N-m}$
Step 19: Calculate F = $\frac{MSLOF}{MSPE}$
Step 20: Compare with Standard value $f_{\alpha,m-2,N-m}$ $f_{\alpha,m-2,N-m}$.
Step 21: If F < $f_{\alpha,m-2,N-m}$ Ho is failed to reject
F > $f_{\alpha,m-2,N-m}$ Ho is rejected.

to explicitly depict a step by step methodology which will help researchers to understand the process of model adequacy in a lucid manner.

7.0 MANAGERIAL IMPLICATIONS

The simulation model is used by the managers to test the decisions before taking out a major decision. These models will help to analyze various scenarios which can be used to cover all aspects of business decisions. The accuracy and the validity of these models are very significant as the usage of wrong models will result in wrong decisions which can cost the companies a large amount of money. This paper suggests a step by step methodological process for assessing the model adequacy of the simulation model. The developed or proposed model should be compared with the previous model using the methodology suggested in this paper. This methodology will help to assess the validity and reliability of the proposed simulation model and subsequently, it can be used to test the future business decisions. There is no single test for assessing the business decisions rather one must methodologically use these steps in its entirety. The algorithm is designed for ease in implementation and can be carried out using a spreadsheet.

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APPENDIX 1

Flowchart

Figure 3.

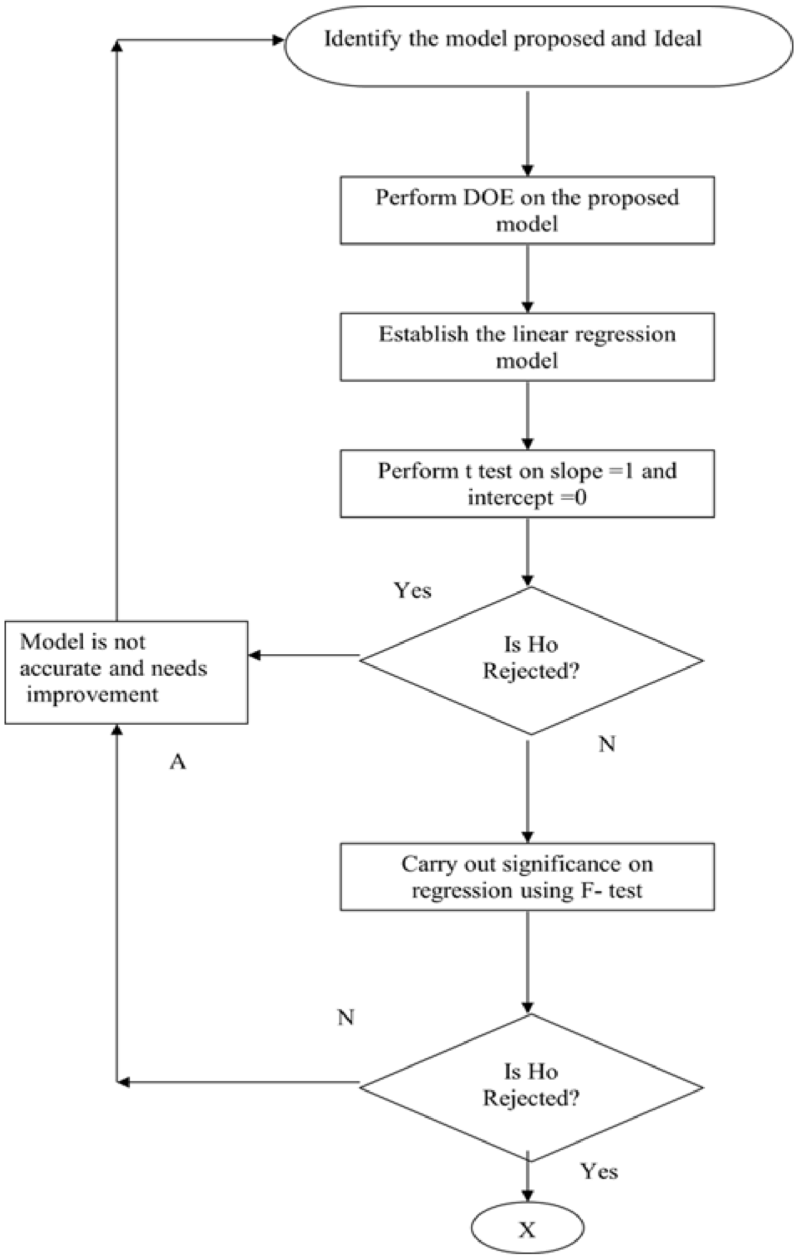


Figure 4.

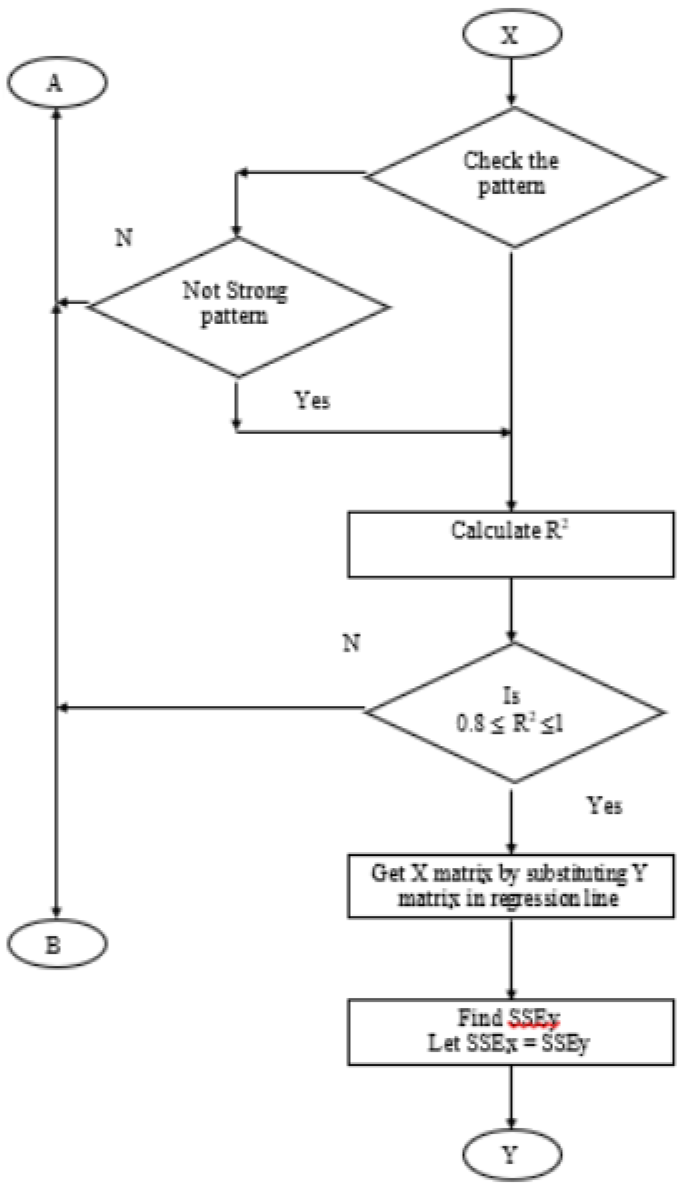
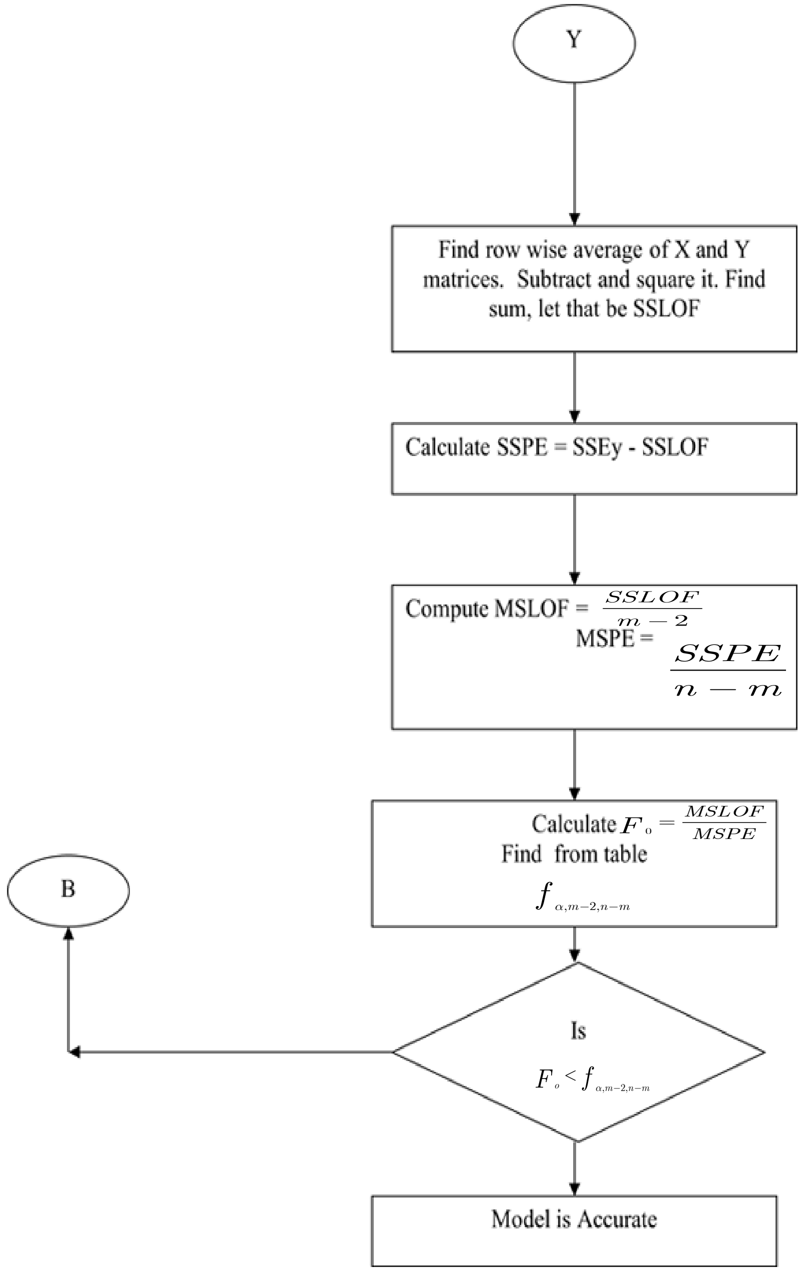

X
A
Check the pattern
N
Not Strong pattern
Yes
Calculate R²
N
Is 0.8 ≤ R² ≤1
Yes
Get X matrix by substituting Y matrix in regression line
B
Find SSEx
Let SSEx = SSEy
Y

Figure 5.


Y
Find row wise average of X and Y matrices. Subtract and square it. Find sum, let that be SSLOF
Calculate SSPE = SSEy - SSLOF
Compute MSLOF = $\frac{SSLOF}{m-2}$
MSPE = $\frac{SSPE}{n-m}$
Calculate $F_o = \frac{MSLOF}{MSPE}$
Find from table
$f_{\alpha,m-2,n-m}$
B
Is
$F_o < f_{\alpha,m-2,n-m}$
Model is Accurate