Comparison of Metamodel Performances on an Electronic Circuit Problem

Muzaffer Balaban

Turkish Statistical Institute, 06100, Ankara, Turkey.

Author’s contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

Article Information

DOI: 10.9734/AJPAS/2021/v11i230261

Editor(s): (1) Dr. Manuel Alberto M. Ferreira, Lisbon University, Portugal.

Reviewers: (1) Abdulhaq Hadi Abedali, Mustansiriya University, Iraq.

(2) Dawit Yeshiwas Mekuria, Debre Markos University, Ethiopia.

Complete Peer review History: http://www.sdiarticle.com/review-history/65584

Received: 20 December 2020
Accepted: 12 February 2021
Published: 01 March 2021

Abstract

Aims: Investigation of building and validation of metamodels which of linear regression, simple kriging, ordinary kriging and radial basis function for an electronic circuit problem are the main aim of this study.

Study Design: An electronic circuit problem was considered to compare the performances of the metamodels. Latin hypercube design was used for experimental design of five input variables of the considered problem.

Methodology: A training data set consisting of 45 experiments and a validation data set consisting of 500 experiments were obtained using Latin hypercube design. Input variables were used by coded to calculate the spatial distances between observation points more consistently. Then using training data set linear regression, simple kriging, ordinary kriging and radial basis function metamodels were built. And, performance measures were calculated for the validation data set.

Results: It has been shown that simple kriging which are applied to outputs the differences from the mean, and ordinary kriging metamodels, produce superior solutions compared to the linear regression and radial basis function metamodels for the electronic circuit problem considered in this study. Prediction superiority of SK and OK than RBF on five-dimensional problem is another important result of the study.

Conclusion: Kriging metamodels are considered to be strong alternatives to the other metamodels for the problems that are considered in this study and have a similar nature. Since the superiority of metamodel methods to each other may vary from problem to problem, it is another important issue to compare their performance by considering more than one method in problem solving stage.

*Corresponding author: E-mail: balabanmuzaffer@gmail.com;
Keywords: Metamodel; simple kriging; ordinary kriging; linear regression; radial basis functions; Latin hypercube design.

1 Introduction

Researchers use the simulation model instead of the real system since the experiments cannot be performed on the real system due to cost or other constraints [1]. These models also can be quite complex, and simpler models of these models are built [2]. Kleijnen [3] defined these models as the model of the model or metamodel. A metamodel is a function that uses some simulation parameters as inputs and predicts some characteristics of the simulation output [4]. Generally, response surface methods using linear and quadratic regression models were used as metamodels [2,5,6]. Artificial neural network (ANN) [7], radial basis function (RBF) [8] and kriging [9] are other methods frequently used metamodels in the literature.

In this study, the model-building and validation stages of linear regression (LR), simple kriging (SK), ordinary kriging (OK) and RBF metamodels are explained and shown how to apply them using on the electronic circuit problem and how to choose the appropriate kriging metamodel. SK and OK metamodels used in this study are the original form in geo-statistics, and extended from two-dimensional case to five-dimensional case. SK metamodel has been applied to both output variable data and the differences from the mean. Gaussian and multi-quadratic functions were used as RBF metamodels. According to the results of the study, it is seen that SK that applied to the differences from the mean and OK metamodels make better predictions by a small margin than the LR and RBF metamodels. Additionally, Superiority of SK and OK than RBF is shown on five-dimensional problem for linear prediction. It is evaluated that kriging metamodels are strong predictors for problems of similar structure. Since the superiority of metamodel methods to each other can vary from problem to problem, it is another important issue to compare their success by taking into account more than one method in problem solutions.

Remaining parts of the article as follows. In the section 2, the technical structure of metamodel methods is summarized. Section 3 discusses experiment design and metamodel validation methods. In the section 4, metamodels are developed on an electronic circuit problem and the performance criteria are calculated. In section 5, conclusion is presented.

2 Metamodel Methods

The metamodel is a general method, especially when input/output relationships are unknown, and it specifies a mathematical approach that models the behavior of another model [4]. The aim is to determine the metamodel form that best suits the input/output relationship.

In the literature, linear and quadratic regression models were often used as metamodels. Alternatively, RBF, ANN and kriging models are also used as metamodels [2,10]. LR, SK, OK and RBF metamodels are discussed in this study.

The purpose of all metamodels is to find the best prediction of $Z(x_0)$ denoted $\hat{Z}(x_0)$ for a new point $x_0 \in D$. $Z(x)$ is the process (deterministic or random), $x \in D$ and $x = (x_1, ..., x_k)'$ the point vector, observations $Z = (z(x_1), ..., z(x_n))'$ at observation points $x_i = (x_{i1}, ..., x_{ik}) \forall i = 0, ..., n$.

2.1 Regression metamodels

Regression models originally developed for the analysis and modeling of the results of physical experiments [11]. Then they were used effectively to build descriptive models or metamodels for applications in many areas. Regression metamodels are developed to build the best of response surfaces and are the process of selecting first or second degree polynomial models fitted to the system response [2]. In this study, the LR metamodel was selected because the output of the problem is linear.
2.1.1 Linear regression

LR model with $k$ input variables is as given by Eq. (1) below \[3,10,12\].

$$Z(x) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i$$  \hspace{1cm} (1)

Model parameters, $\beta$, are estimated with the least square method as in Eq. (2) \[13\].

$$\hat{\beta} = (X'X)^{-1}X'Z$$  \hspace{1cm} (2)

Where $X$ is the design matrix of input variables at experiment points, $Z$ is shows the output variable value vector at the training points. The LR estimate for the new $x_0$ point is obtained from the product of the value vectors as given in Eq. (3).

$$\hat{Z}(x_0) = \hat{\beta} x_0$$  \hspace{1cm} (3)

2.2 Krigeing metamodels

Krigeing method has been developed for modeling and interpolation in geo-statistics [14]. In krigeing method, the prediction value is obtained as the linear combination of the experimental data and the recalculated weights using the appropriate variogram or correlogram model for each prediction point. Sacks et al. [9] applied krigeing for the first time as a metamodel to deterministic simulation outputs. Van Bevers and Kleijnen [15] used krigeing metamodel for random simulation outputs. Then Biles et al. [1] applied krigeing metamodel to constrained simulation model outputs.

Since krigeing is based on statistical relationships between observed points, it is not only a technique for creating a prediction surface, but also provides some measure of the precision and accuracy of the predictions. Among all linear estimation models, they are unbiased estimators with the smallest mean square error. Krigeing is more suitable for data obtained from large experimental areas and they are general models [6]. There are many types of krigeing used in the literature [9,14,15,16]. In this study, SK and OK metamodel were chosen considering the output structure of the problem.

2.2.1 Variogram and correlogram

Variogram and correlogram analysis are very important in the development of krigeing metamodel since they are used in the calculation of krigeing weights [17]. Variogram estimation between two observations, $Z(x_i)$ and $Z(x_i + h)$ for random process $Z(x)$ is obtained as given in Eq. (4) [18].

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (Z(x_i) - Z(x_i + h))^2$$  \hspace{1cm} (4)

Where, $h$ is distance operator between observations, $N(h)$ is the number of observation pairs of $Z(x_i)$ and $Z(x_i + h)$ [13]. Covariogram estimation between two observations, $Z(x_i)$ and $Z(x_i + h)$ is found as given in Eq. (5). The relation between variogram and covariogram is also given in Eq. (6).

$$c(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} (Z(x_i) - \mu) (Z(x_i + h) - \mu)$$  \hspace{1cm} (5)

$$\gamma(h) = c(0) - c(h)$$  \hspace{1cm} (6)

In the calculation of krigeing weights, correlogram is also used instead of a variogram. Correlogram estimation between two observations, $Z(x_i)$ and $Z(x_i + h)$ is found as given in Eq. (7).

$$\hat{c}(h) = \frac{\hat{c}(h)}{\hat{c}(0)}$$  \hspace{1cm} (7)
Where, \( F(h) \) is the correlogram estimator, and \( \sigma(0) \) is the variance of the process. Generally, correlogram is used instead of variogram or covariogram to calculate kriging weights especially in deterministic simulation. A theoretical correlogram model is used to calculate the kriging weights for each new point. The theoretical correlogram model should conform to the experimental correlogram data. The mostly used theoretical correlation models in the literature are given below Eq. (8), Eq. (9) and Eq. (10) [9,19,6].

Gaussian Model: \( r(h) = \exp \left( -\left(\frac{h}{\theta}\right)^2 \right) \)  \hspace{1cm} (8)

Exponential Model: \( r(h) = \exp \left( -\frac{h}{\theta} \right) \)  \hspace{1cm} (9)

Linear Model: \( r(h) = \max(1 - \theta h, 0) \)  \hspace{1cm} (10)

2.2.2 Simple kriging

SK refers to the stationary states where the mean is known and constant, and variogram and covariogram functions are known. SK is used in modeling of spatial statistics [14]. It is the most widely used kriging metamodel method for deterministic simulation outputs after detrended [9]. Model assumption of \( Z(x) \) is given in Eq. (11).

\[
Z(x) = \mu + \epsilon(x) \quad (11)
\]

\( \mathbb{E}[\epsilon(x)] = 0 \).

Two different prediction model for SK are given in equations (12) and (13).

\[
\hat{Z}(x_0) = \sum^p_{i=1} \lambda_i Z(x_i) \quad (12)
\]

\[
\hat{Z}(x_0) = \mu + \sum^p_{i=1} \lambda_i (Z(x_i) - \mu) \quad (13)
\]

Prediction weights are obtained by Eq. (14).

\[
\lambda = R^{-1} r \quad (14)
\]

Where,

\[
R = \begin{bmatrix}
1 & r(x_1, x_2) & \cdots & r(x_1, x_n) \\
r(x_2, x_1) & 1 & \cdots & r(x_2, x_n) \\
\vdots & \vdots & \ddots & \vdots \\
r(x_n, x_1) & r(x_n, x_2) & \cdots & 1
\end{bmatrix},
\]

\[
r = (r(x_1, x_0), r(x_2, x_0), \ldots, r(x_n, x_0))',
\]

\[
\lambda = (\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n)'.
\]

SK prediction for a new \( x_0 \) point is obtained from multiplying the vectors as given in (15).

\[
\hat{Z}(x_0) = \lambda' Z \quad (15)
\]

2.2.3 Ordinary kriging

OK refers to situations where the mean of the process is constant and unknown and the variogram function is known. OK is mostly used in modeling of spatial statistics [14]. It was used by Van Beers and Kleijnen [15] to model the random simulation outputs. Balaban [20] examined its validity on some test problems.
The OK predictor for the point $\mathbf{x}_0$ is obtained as follows given in Eq. (16).

$$Z(\mathbf{x}_0) = \sum_{i} \lambda_i Z(\mathbf{x}_i)$$ \hspace{1cm} (16)

$$\sum_{i} \lambda_i = 1$$ \hspace{1cm} (17)

The weights are obtained as in Eq. (18).

$$\lambda_a = R^{-1}r_o$$ \hspace{1cm} (18)

Where,

$$R_o = \begin{bmatrix} R & 1 \\ 1 & 0 \end{bmatrix},$$
$$r_o = (r(\mathbf{x}_1, \mathbf{x}_0), r(\mathbf{x}_2, \mathbf{x}_0), \ldots, r(\mathbf{x}_n, \mathbf{x}_0), 1)^T,$$
$$\lambda_o = (\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_m)^T,$$
$$1 = (1, \ldots, 1)^T.$$

The OK prediction for a new point $\mathbf{x}_0$ is obtained from the multiplying of the vectors as given in Eq. (19).

$$\hat{Z}(\mathbf{x}_0) = \lambda^T Z$$ \hspace{1cm} (19)

2.3 Radial based functions

RBF was developed by Hardy [8] for interpolation of scattered multivariate data. This method uses linear combinations of a symmetric radial function based on Euclidean distance or a similar metric to create a metamodel. RBF equations are defined as shown in Eq. (20) [12,21].

$$Z(\mathbf{x}) = \sum_{i=1}^{n} w_i \Phi(||\mathbf{x} - \mathbf{x}_i||)$$ \hspace{1cm} (20)

Where, $n$ is the number of sampling points, $w_i$ is the weight determined by the least square method and $\Phi(||\mathbf{x} - \mathbf{x}_i||)$ is the base function defined for the observation point $i$. There is a wide variety of symmetric RBF in the literature [22]. In this study, multi-quadratic and Gaussian functions were used as RBF in metamodel creation and verification stages. These basis functions are given in Eq. (21) and Eq. (22), respectively. Where, $h$ is the distance value, and $c$ is the scaling parameter equal to 1.

$$\Phi(h) = \sqrt{h^2 + c^2}$$ \hspace{1cm} (21)

$$\Phi(h) = e^{-ch^2}$$ \hspace{1cm} (22)

3 Experimental Design and Validation of Metamodels

Experimental design is one of important stages of metamodeling studies both establishing and validation. It determines which input variable combinations will be run for simulation model. For kriging, spade filling methods such as the Latin hypercube design (LHD) are often used. Since experimental data are expensive in simulation studies (especially in random simulation), it is also very important to work with a reasonable number of experiments [23,24].
3.1 Latin hypercube design

In order to establish a metamodel with the kriging method in accordance with the simulation results, an experimental design method that can provide homogeneous distribution on the response surface from gap filling methods such as LHD should be done in fact or intervals. LHD was developed by Mc Kay et al. [25] for the computer experiments design. The level of value each factor will take is included in the design once. All factors have the same number of levels. Experiments are designed as many as the number of levels. In this design, the permutation of the levels is determined randomly. Kleijnen [6] states that LHD is the most suitable design for kriging. The data obtained by LHD are also suitable for establishing a quadratic regression metamodel since they contain many levels of the input variable [24].

3.2 Validation of metamodels

Before using metamodels for processes requiring precise computation instead of the model, its validity must be demonstrated with performance criteria. This stage is a necessary step in choosing which meta-model to use instead of the model.

The validity of a metamodel can be evaluated in two ways. First, performance criteria are calculated for the training points used while building the model. The second is done by calculating the performance criteria that show the prediction accuracy for the new data set that are not used while building the model [26]. Simpson [27] suggested the use of an independent data set determined randomly for the validation of the model since it gives zero error estimation for all experimental points used in the kriging model. In his study, the second approach is preferred. The most commonly used three performance evaluation criteria are given in Eq. (23), Eq. (24) and Eq. (25). Where, \( Z(x_i) \) is output value of the experiment at point \( x_i \), \( \hat{Z}(x_i) \) is the prediction value at point \( x_i \) and \( \bar{Z} \) is average of outputs.

Mean Square Errors (MSE):

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (Z(x_i) - \hat{Z}(x_i))^2
\]  

(23)

Root MSE (RMSE):

\[
RMSE = \sqrt{MSE}
\]  

(24)

\( R^2 \) measure:

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (Z(x_i) - \hat{Z}(x_i))^2}{\sum_{i=1}^{n} (Z(x_i) - \bar{Z})^2}
\]  

(25)

It is expected that MSE and RMSE should be minimum among all metamodels and \( R^2 \) should be near to 1 for performance comparison. In the literature to reduce the number of parameters for the regression models \( R^2 \) adjusted are recommended. Because such as kriging and RBF metamodels have different structure than regression, the use of \( R^2 \) adjusted is meaningless.

4. Example Application: An Electronic Circuit Problem

The regulated power supply optimization problem is considered as a test problem for the comparison of metamodels performance in this study [28]. The 5v operating voltage is commonly used by computer digital circuits. Its accuracy is 5±1%. According to the design requirements, the series linear regulator circuit is used. The value of output voltage is computed from Eq. (26). It is expected that output voltage is 5±0.05v and output current 1 A.

\[
V = \left(1 + \frac{R_3}{R_2}\right) \left(\frac{R_4}{R_3 + R_2}\right) V_E - \left(\frac{R_2 + R_4}{AR_2}\right) V_{BE}
\]  

(26)
Where $V_B$ is regulated value of voltage regulator tube and equal to 6.02 v, $V_{BE}$ is base and emitter voltage of compound triode and equal to 0.7 v, $A$ is magnification of operational amplifier, $R_1, R_2, R_3, R_4$ are value of resistances. Table 1 presents a range of input variables values.

| Input variables | Ranges of variables |
|-----------------|---------------------|
| $R_1$           | 30–130 $\Omega$    |
| $R_2$           | 680–1500 $\Omega$  |
| $R_3$           | 680–1500 $\Omega$  |
| $R_4$           | 2700–3900 $\Omega$ |
| $A$             | 2000–10000          |

Input variables were used by coded to calculate the spatial distances between observation points more consistently. The coding was obtained by dividing the lower and upper limit values for each variable (Table 1) by the upper value. Thus, all input variables values, $x = (x_1, x_2, x_3, x_4, x_5)$, are obtained between $[0, 100]$. There is no common idea for the optimal number of experiments for kriging in the literature. However, some applications are as follows. Simpson [27] used 25 experiments for a 3-dimensional problem. Martin and Simpson [26] used 40 experiments for a five-dimensional problem and Sacs et al. [9] used 32 experiments for a six-dimensional problem as training data set. In order to obtain the data used while building the model, a training data set consisting of 45 experiments was obtained using LHD. Since kriging models are the best unbiased linear estimators, in order to test the validity of the models, a validation data set consisting of 500 experiments independent of the data we used when building the model was obtained by LHD as discussed in 3.1. Training data set is given in Table 2. The column $d_1$ to $d_5$ shows design levels of the input variables.

The LR prediction model as given shown is found suitable for the training data set. Parameter estimation was obtained with the least square estimator. As a result of the variance analysis given in Table 3, the contribution of input variable $x_5$ to the model was found statistically insignificant.

The LR model is given in Eq. (27).

$$Z(x) = 5.616 + 0.005x_1 - 0.006x_2 - 0.051x_3 + 0.041x_4$$ (27)

For the kriging metamodels, the Gaussian correlogram model was chosen as the most suitable model and the model parameter was estimated as $\theta = 84.4$. My own C++ source code is driven for SK, OK and RBF metamodels. I have used statistical software for LR metamodel.

The MSE, RMSE and $R^2$ performance criteria for all metamodels were calculated using the validation data set and are given in Table 4. SK (a) and SK (b) in the table are the SK metamodels given by Eq. (12) and Eq. (13), respectively. RBF (c) and RBF (d) show multi-quadratic and Gaussian RBF metamodels given by Eq. (21) and Eq. (22), respectively.

| No | $d_1$ | $d_2$ | $d_3$ | $d_4$ | $d_5$ | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $Z$ |
|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| 1  | 16    | 15    | 44    | 34    | 7     | 49.301| 62.727| 98.758| 92.308| 30.909| 4.355|
| 2  | 44    | 44    | 17    | 31    | 21    | 98.252| 98.758| 65.212| 90.21  | 56.364| 5.796|
| 3  | 5     | 24    | 30    | 11    | 5     | 30.07 | 73.909| 81.364| 76.224| 27.273| 4.258|
| 4  | 8     | 20    | 19    | 41    | 42    | 35.315| 68.939| 67.697| 97.203| 94.546| 5.758|
| 5  | 39    | 22    | 4     | 16    | 38    | 89.511| 71.424| 49.061| 79.72  | 87.273| 6.522|
| 6  | 18    | 12    | 1     | 26    | 4     | 52.797| 59    | 45.333| 86.713| 25.455| 7.029|
| 7  | 15    | 45    | 26    | 43    | 33    | 47.552| 100   | 76.394| 98.601| 78.182| 5.356|
| 8  | 45    | 42    | 6     | 19    | 17    | 100   | 96.273| 51.546| 81.818| 49.091| 6.344|

Table 2. Experimental design and results for training data set
Table 3. ANOVA results for linear regression

| No | d₁ | d₂ | d₃ | d₄ | d₅ | x₁ | x₂ | x₃ | x₄ | x₅ | Z |
|----|----|----|----|----|----|----|----|----|----|----|---|
| 9  | 10 | 33 | 16 | 32 | 20 | 38.811 | 85.091 | 63.97 | 90.909 | 54.546 | 5.6997 |
| 10 | 19 | 8  | 2  | 5  | 41 | 54.546 | 54.03 | 46.576 | 72.028 | 92.727 | 6.2304 |
| 11 | 36 | 30 | 24 | 7  | 14 | 84.266 | 81.364 | 73.909 | 73.427 | 43.636 | 4.6258 |
| 12 | 28 | 40 | 14 | 10 | 18 | 70.28 | 93.788 | 61.485 | 75.525 | 50.909 | 5.2728 |
| 13 | 30 | 7  | 12 | 25 | 19 | 73.776 | 52.788 | 59 | 86.014 | 52.727 | 6.1471 |
| 14 | 4  | 43 | 10 | 30 | 22 | 28.322 | 97.515 | 56.515 | 89.511 | 58.182 | 6.0398 |
| 15 | 41 | 34 | 22 | 39 | 25 | 93.007 | 86.333 | 71.842 | 95.804 | 63.636 | 5.7092 |
| 16 | 38 | 41 | 41 | 20 | 35 | 87.762 | 95.03 | 95.03 | 82.518 | 81.818 | 4.1598 |
| 17 | 32 | 11 | 33 | 12 | 45 | 77.273 | 57.758 | 85.091 | 76.923 | 100 | 4.3982 |
| 18 | 27 | 13 | 45 | 17 | 37 | 68.532 | 60.242 | 100 | 80.42 | 85.455 | 3.9779 |
| 19 | 3  | 6  | 34 | 6  | 39 | 26.573 | 51.546 | 86.333 | 72.727 | 89.091 | 3.9618 |
| 20 | 29 | 18 | 28 | 4  | 11 | 72.028 | 66.455 | 78.879 | 71.329 | 38.182 | 4.3307 |
| 21 | 21 | 21 | 9  | 21 | 8  | 58.042 | 70.182 | 55.273 | 83.217 | 32.727 | 6.056 |
| 22 | 22 | 29 | 3  | 28 | 32 | 59.79 | 80.121 | 47.818 | 88.112 | 76.364 | 6.8147 |
| 23 | 7  | 36 | 27 | 13 | 40 | 33.566 | 88.818 | 77.636 | 77.622 | 99.909 | 4.5457 |
| 24 | 26 | 26 | 38 | 3  | 3  | 66.783 | 76.394 | 91.303 | 70.629 | 23.636 | 3.7979 |
| 25 | 17 | 32 | 29 | 42 | 1  | 51.049 | 83.849 | 80.121 | 97.902 | 20 | 5.0269 |
| 26 | 23 | 25 | 35 | 44 | 13 | 61.539 | 75.152 | 87.576 | 99.301 | 41.818 | 5.0124 |
| 27 | 14 | 2  | 40 | 2  | 24 | 45.804 | 46.576 | 93.788 | 69.93 | 61.818 | 3.7169 |
| 28 | 34 | 4  | 39 | 23 | 16 | 80.769 | 49.061 | 92.546 | 84.615 | 47.273 | 4.5189 |
| 29 | 42 | 17 | 15 | 27 | 10 | 94.755 | 65.212 | 62.727 | 87.413 | 36.364 | 5.9906 |
| 30 | 35 | 1  | 31 | 1  | 36 | 82.518 | 45.333 | 82.606 | 69.231 | 83.636 | 4.2783 |
| 31 | 9  | 14 | 7  | 45 | 34 | 37.063 | 61.485 | 52.788 | 100 | 80 | 6.8623 |
| 32 | 40 | 10 | 11 | 35 | 26 | 91.259 | 56.515 | 57.758 | 93.007 | 65.455 | 6.6307 |
| 33 | 11 | 39 | 32 | 18 | 28 | 40.509 | 92.546 | 83.849 | 81.119 | 69.091 | 4.3685 |
| 34 | 37 | 27 | 21 | 36 | 31 | 86.014 | 77.636 | 70.182 | 93.706 | 74.546 | 5.7028 |
| 35 | 25 | 3  | 8  | 9  | 6  | 65.035 | 47.818 | 54.03 | 74.825 | 29.091 | 5.9325 |
| 36 | 13 | 37 | 23 | 22 | 44 | 44.056 | 90.061 | 72.667 | 83.916 | 98.182 | 4.9708 |
| 37 | 33 | 38 | 43 | 29 | 15 | 79.021 | 91.303 | 97.515 | 88.811 | 45.455 | 4.2945 |
| 38 | 1  | 31 | 36 | 38 | 23 | 23.077 | 82.606 | 88.818 | 95.105 | 60 | 4.6507 |
| 39 | 6  | 16 | 18 | 24 | 29 | 31.818 | 63.97 | 66.455 | 85.315 | 70.909 | 5.3453 |
| 40 | 43 | 5  | 42 | 37 | 30 | 96.504 | 50.303 | 96.273 | 94.406 | 72.727 | 4.8347 |
| 41 | 12 | 35 | 5  | 33 | 12 | 42.308 | 87.576 | 50.303 | 91.608 | 40 | 6.6548 |
| 42 | 2  | 28 | 25 | 15 | 9  | 24.825 | 78.879 | 75.152 | 79.021 | 34.546 | 4.6015 |
| 43 | 24 | 9  | 13 | 14 | 2 | 63.287 | 55.273 | 60.242 | 78.322 | 21.818 | 5.6156 |
| 44 | 20 | 19 | 20 | 40 | 40 | 56.294 | 67.697 | 68.939 | 96.504 | 96.364 | 5.7814 |
| 45 | 31 | 23 | 37 | 8  | 27 | 75.525 | 72.667 | 90.061 | 74.126 | 67.273 | 4.0241 |

Considering the R² performance criterion, it is seen that all metamodels are suitable metamodels for this problem. Considering the MSE, it is seen that SK (b) and OK metamodels make better predictions respectively than other metamodels with a small difference.
Table 4. Prediction performance of the metamodels

| Model | MSE   | RMSE  | R²   |
|-------|-------|-------|------|
| LR    | 0.01508 | 0.12280 | 0.98 |
| SK (a) | 0.01011 | 0.10055 | 0.99 |
| SK (b) | 0.00778 | 0.08820 | 0.99 |
| OK    | 0.00792 | 0.08899 | 0.99 |
| RBF (c) | 0.04246 | 0.20606 | 0.95 |
| RBF (d) | 0.07600 | 0.27568 | 0.90 |

5 Conclusion

In this study, establishment and validation of SK, OK, LR and RBF metamodels for an electronic circuit problem is investigated. As the results of the study, according to MSE, RMSE and R² criteria, SK (b) and OK metamodels, produced superior prediction respectively with a small difference compared to LR and RBF metamodels.

Kriging metamodels are alternative models that can be used as metamodels instead of complex models, since they are general models and can determine the changes in local regions. Since the superiority of metamodel methods to each other may vary from problem to problem, another issue should be taken into consideration in problem solving by considering more than one method and comparing their performance.

In future studies, the performance of metamodel methods will be tested on similar problems using optimization algorithms.

Competing Interests

Author has declared that no competing interests exist.

References

[1] Biles WE, Kleijnen JPC, Van Beers WCM, Van Nieuwenhuyse I. Kriging metamodeling in constrained simulation optimization: An explorative study. Proceedings of the 2007 Winter Simulation Conference. 2007;355-362.

[2] Barton RR. Simulation metamodels. Proceedings of the 1998 Winter Simulation Conference. 1998;167-174.

[3] Kleijnen JPC. Regression metamodels for generalizing simulation results. IEEE Transactions on Systems, Man and Cybernetics. SMC-9. 1979;2:93-96.

[4] Barton, RR. Tutorial: simulation metamodeling. Proceedings of the 2015 Winter Simulation Conference. 2015;1765-177.

[5] Myers RH, Montgomery DC, Anderson-Cook CM. Response surface Methodology. 3. ed., New York, John Wiley and Sons, Inc; 2009.

[6] Kleijnen, JPC. 2009. Kriging metamodeling in simulation: A review. European Journal of Operational Research. 2009;192:707–716.

[7] Haykin S. Neural Networks: A Comprehensive Foundation. Pearson; 2005.
[8] Hardy RL. Multiquadric equations of Topography and other irregular surfaces. Journal of Geophysical Research. 1971;176:1905–1915.

[9] Sacks J, Welch WJ, Mitchell TJ, Wynn HP. Design and analysis of computer experiments. Statistical Science. 1989;4:409-435.

[10] Simpson T, Peplinski JD, Koch PN, Allen JK. On the use of statistics in design and the implications for deterministic computer experiments. Proceedings of DETC’97, ASME Design Engineering Technical Conferences, Sacramento, California, September. 1997;14-17.

[11] Box GEP, Wilson KB. On the experimental attainment of optimum conditions. Journal of the Royal Statistical Society. Series B (Methodological). 1951;13:1-45.

[12] Jin R, Chen W, Simpson T. Comparative studies of metamodeling techniques under multiple modeling criteria. AIAA Journal. 2000;4801:1-11.

[13] Myers DE. On variogram estimation. The frontiers of statistical scientific theory and Industrial Applications. 1991;2:261-266.

[14] Cressie, NAC. Statistics for spatial data. New York: A Wiley-Interscience Publication; 1993.

[15] Van Beers W, Kleijnen JPC. Kriging for interpolation in random simulation. Journal of the Operational Research Society. 2003;54:255-262.

[16] Balaban M, Dengiz B. Lognormal ordinary kriging metamodel in simulation optimization. Operations Research and Applications: An International Journal (ORAJ). 2018;5(1):1-9.

[17] Balaban M. Importance of correlogram analysis for kriging metamodels. International Journal of Latest Engineering Research and Applications. 2020;5(06):34–40.

[18] Matheron G. Principles of geostatistics. Economic Geology. 1963;58:1246-1266.

[19] Mitchell TJ, Morris MD. Bayesian design and analysis of computer experiments: Two examples. Statistica Sinica. 1992;2:359–379.

[20] Balaban M. Benzetimde olağan ve genel kriging meta-modelleri. Abstract book, 1st international eurasian conference on science, engineering and technology, Eurasian Sci. En. Tech, Ankara, Turkish. 2018;63.

[21] Meckesheimer M, Barton RR, Simpson T, Limayem L, Yannou B. Metamodeling of combined discrete/continuous responses. American Institute of Aeronautics and Astronautics. 2001;39 (10):1950-1959.

[22] Zhou Q, Jiang P, Shao X, Hu J, Cao L, Wan L. A variable fidelity information fusion method based on radial basis function, Advanced Engineering Informatics. 2017;32:26–39.

[23] Balaban M. Regresyon ve Kriging meta-modelleri için kullanılan deney tasarımı yöntemleri. Düzce Üniversitesi Bilim ve Teknoloji Dergis. Turkish. 2019;7(3):1444-1455.
[24] Balaban M. Benzetimde deney tasarımının önemi. Sekizinci ulusal savunma uygulamaları modelleme ve simülasyon konferansı bildiri kitabı, ODTÜ, Ankara. Turkish. 2019;106-117.

[25] Mc Kay MGD, Beckman RJ, Conover WJ. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics. 1979;21:239–245.

[26] Martin JD, Simpson T. On the use of kriging models to approximate deterministic computer models. Proceedings of DETC’04, ASME. 2004;1-12.

[27] Simpson T. Comparison of response surface and kriging models in the multidisciplinary design of an aerospike nozzle. ICASE Report NASA/CR. 1998;206935:98-16.

[28] Li Y, Lin Y, Li J. Orthogonal optimization algorithm in application to circuit design. Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE). 2013;1830-1833.

© 2021 Balaban; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar) http://www.sdiarticle4.com/review-history/65584