Asian Journal of Probability and Statistics

11(2): 1-11, 2021; Article no.AJPAS.65584

ISSN: 2582-0230

Comparison of Metamodel Performances on an Electronic Circuit Problem

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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, Mustansiriyah University, Iraq.

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

Complete Peer review History: http://www.sdiarticle4.com/review-history/65584

Original Research Article

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.

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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 $\mathrm{Z}(\mathbf{x_0})$ denoted $\hat{\mathrm{Z}}(\mathbf{x_0})$ for a new point $\mathbf{x_0} \in \mathrm{D}$. $\mathrm{Z}(\mathbf{x})$ is the process (deterministic or random), $\mathbf{x} \in \mathrm{D}$ and $\mathbf{x} = (\mathrm{x}_1, \dots, \mathrm{x}_\mathrm{k})'$ the point vector, observations $\mathbf{Z} = (\mathrm{z}(\mathbf{x_1}), \dots, \mathrm{z}(\mathbf{x_n}))'$ at observation points $\mathbf{x_i} = (\mathrm{x}_{1\mathrm{i}}, \dots, \mathrm{x}_{\mathrm{ki}})'$ $\forall\, \mathrm{i} = 0, \dots, \mathrm{n}$.

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].

$$\mathrm{Z}(\mathbf{x}) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \tag{1}$$

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

$$\widehat{\boldsymbol{\beta}} = (X'X)^{-1}X'\mathbf{Z} \tag{2}$$

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

$$\hat{Z}(\mathbf{x_0}) = \widehat{\boldsymbol{\beta}}\, \mathbf{x_0} \tag{3}$$

2.2 Kriging metamodels

Kriging method has been developed for modeling and interpolation in geo-statistics [14]. In kriging 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 kriging for the first time as a metamodel to deterministic simulation outputs. Van Beers and Kleijnen [15] used kriging metamodel for random simulation outputs. Then Biles et al. [1] applied kriging metamodel to constrained simulation model outputs.

Since kriging 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. Kriging is more suitable for data obtained from large experimental areas and they are general models [6]. There are many types of kriging 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 kriging metamodel since they are used in the calculation of kriging weights [17]. Variogram estimation between two observations, $Z(\boldsymbol{x_i})$ and $Z(\boldsymbol{x_i} + h)$ for random process $\mathrm{Z}(\mathbf{x})$ is obtained as given in Eq. (4) [18].

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

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

$$\hat{c}(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} (Z(\mathbf{x_i}) - \mu)\,(Z(\mathbf{x_i} + h) - \mu) \tag{5}$$

$$\hat{\gamma}(h) = \hat{c}(0) - \hat{c}(h) \tag{6}$$

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

$$\hat{r}(h) = {\hat{c}(h)}\big/{\hat{c}(0)} \tag{7}$$

Where, $\hat{r}(h)$ is the correlogram estimator, and $\hat{c}(0)$ 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].

$$\text{Gaussian Model: } r(h) = \exp\left(-\left(h/\theta\right)^2\right) \tag{8}$$

$$\text{Exponential Model: } r(h) = \exp\left(-h/\theta\right) \tag{9}$$

$$\text{Linear Model: } r(h) = \max\,(1-\theta h, 0) \tag{10}$$

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 $Z(\mathbf{x})$ is given in Eq. (11).

$$Z(\mathbf{x}) = \mu + \varepsilon(\mathbf{x}) \tag{11}$$

$$E[\varepsilon(\mathbf{x})] = 0.$$

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

$$\hat{Z}(\mathbf{x_0}) = \sum_i^n \lambda_i Z(\mathbf{x_i}) \tag{12}$$

$$\hat{Z}(\mathbf{x_0}) = \mu + \sum_i^n \lambda_i (Z(\mathbf{x_i}) - \mu) \tag{13}$$

Prediction weights are obtained by Eq. (14).

$$\boldsymbol{\lambda} = R^{-1}\mathbf{r} \tag{14}$$

Where,

$$R = \begin{bmatrix} 1 & r(\mathbf{x_1},\mathbf{x_2}) & \cdots & r(\mathbf{x_1},\mathbf{x_n}) \\ r(\mathbf{x_2},\mathbf{x_1}) & 1 & \cdots & r(\mathbf{x_2},\mathbf{x_n}) \\ \vdots & \vdots & \vdots & \vdots \\ r(\mathbf{x_n},\mathbf{x_1}) & r(\mathbf{x_n},\mathbf{x_2}) & \cdots & 1 \end{bmatrix},$$

$\mathbf{r} = (r(\mathbf{x_1},\mathbf{x_o}), r(\mathbf{x_2},\mathbf{x_o}), \ldots, r(\mathbf{x_n},\mathbf{x_o}))'$ and

$\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n)'$.

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

$$\hat{Z}(\mathbf{x_0}) = \boldsymbol{\lambda}'\,\mathbf{Z} \tag{15}$$

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 $\boldsymbol{x_0}$ is obtained as follows given in Eq. (16).

$$\hat{Z}(\mathbf{x_0}) = \sum_{i}^{n} \lambda_i Z(\mathbf{x_i}) \tag{16}$$

$$\sum_{i}^{n} \lambda_i = 1 \tag{17}$$

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

$$\boldsymbol{\lambda_o} = R_o^{-1}\mathbf{r_o} \tag{18}$$

Where,

$$R_o = \begin{bmatrix} R & \mathbf{1} \\ \mathbf{1}' & 0 \end{bmatrix},$$

$$\mathbf{r_o} = (r(\mathbf{x_1}, \mathbf{x_o}), r(\mathbf{x_2}, \mathbf{x_o}), \ldots, r(\mathbf{x_n}, \mathbf{x_o}), 1)',$$

$$\boldsymbol{\lambda_o} = (\lambda_1, \lambda_2, \lambda_3, \ldots., \lambda_n, m)'$$

$$\mathbf{1} = (1, \ldots.,1)'.$$

The OK prediction for a new point $\boldsymbol{x_0}$ is obtained from the multiplying of the vectors as given in Eq. (19).

$$\hat{Z}(\mathbf{x_0}) = \boldsymbol{\lambda}' \, \mathbf{Z} \tag{19}$$

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].

$$Z(\mathbf{x}) = \sum_{i=1}^{n} w_i \emptyset_i(\|\mathbf{x}, x_i\|) \tag{20}$$

Where, n is the number of sampling points, w_i is the weight determined by the least square method and $\emptyset_i(\|\mathbf{x}, x_i\|)$ 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.

$$\emptyset(h) = \sqrt{h^2 + c^2} \tag{21}$$

$$\emptyset(h) = e^{-ch^2} \tag{22}$$

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 factor 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, $\mathrm{Z}(\mathbf{x_i})$ is output value of the experiment at point $\mathbf{x_i}$, $\hat{\mathrm{Z}}(\mathbf{x_i})$ is the prediction value at point $\boldsymbol{x_i}$ and $\bar{\mathrm{Z}}$ is average of outputs.
Mean Square Errors (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{Z}(\mathbf{x_i}) - \hat{\mathrm{Z}}(\mathbf{x_i}))^2 \tag{23}$$

Root MSE (RMSE):

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{24}$$

R^2 measure:

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(\mathrm{Z}(\mathbf{x_i}) - \hat{\mathrm{Z}}(\mathbf{x_i}))^2}{\sum_{i=1}^{n}(\mathrm{Z}(\mathbf{x_i}) - \bar{\mathrm{Z}})^2} \tag{25}$$

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^2adjusted are recommended. Because such as kriging and RBF metamodels have different structure than regression, the use of R^2adjusted 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.

$$\mathrm{V} = \left(1 + \frac{\mathrm{R_1}}{\mathrm{R_2}}\right)\left(\frac{\mathrm{R_4}}{\mathrm{R_3}+\mathrm{R_4}}\right)\mathrm{V_E} - \left(\frac{\mathrm{R_1}+\mathrm{R_2}}{\mathrm{AR_2}}\right)\mathrm{V_{BE}} \tag{26}$$

Where V_E 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.

Table 1. Ranges of input variables

Input variables	Ranges of variables
R_1	30~130 Ω
R_2	680~1500 Ω
R_3	680~1500 Ω
R_4	2700~3900 Ω
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, $\mathbf{x} = (x_1, x_2, x_3, x_4, x_5)'$, 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.

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).

$$Z(\mathbf{x}) = 5.616 + 0.005x_1 - 0.006x_2 - 0.051x_3 + 0.041x_4 \tag{27}$$

For the kriging metamodels, the Gaussian correlogram model was chosen as the most suitable model and the model parameter was estimated as $\hat{\theta} = 84.4$. 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.

Table 2. Experimental design and results for training data set

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	4.3555
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	4.2581
4	8	20	19	41	42	35.315	68.939	67.697	97.203	94.546	5.7587
5	39	22	4	16	38	89.511	71.424	49.061	79.72	87.273	6.5227
6	18	12	1	26	4	52.797	59	45.333	86.713	25.455	7.0298
7	15	45	26	43	33	47.552	100	76.394	98.601	78.182	5.3569
8	45	42	6	19	17	100	96.273	51.546	81.818	49.091	6.344

No	d_1	d_2	d_3	d_4	d_5	x_1	x_2	x_3	x_4	x_5	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	71.424	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	90.909	4.4567
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	5.2069
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	40.559	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	43	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

Table 3. ANOVA results for linear regression

Input variables	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
Constant	5.616	.206		27.223	.000
x_1	.005	.001	.121	6.442	.000
x_2	-.006	.001	-.101	-5.166	.000
x_3	-.051	.001	-.876	-46.558	.000
x_4	.041	.002	.396	20.213	.000
x_5	.000	.001	-.004	-.204	.839

Considering the R^2 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	R^2
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 R^2 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.

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