Order Priority Evaluation Based on Kriging Model Under Supply Chain Environment

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ABSTRACT How to tackle the order production priority in production scheduling is a key issue for make-to-order enterprises. Some approaches of determining the order production priority have been proposed from different angles such as linear programming, entropy weight and analytic hierarchy process. Nevertheless, under the supply chain environment, the determination of order production priority becomes a complex problem, and traditional approaches have their limitations. Hence, in this paper, a new evaluation index system of order production priority is established under supply chain environment, and then an evaluation model of order priority based on Kriging model is proposed to determine the order production priority. The performance of proposed model is demonstrated by simulation experiments. The results show that the proposed model is suitable for the problems of small samples and it is a feasible, effective evaluation model for order priority. Compared to other models, the proposed model has improved the evaluation precision of order priority. Meanwhile, the proposed model performs more reliable and stable and it augments the methods for order production priority.

INDEX TERMS Order production priority, supply chain, make-to-order, Kriging model.

I. INTRODUCTION

For make-to-order enterprises, how to deal with orders is a key issue in production scheduling. Order processing with good speed and accuracy can not only offer better service to hold clients, but also save floating capital and decrease cost. Slotnick [1], Esmaeilbeigi et al. [2] and Zhen et al. [3] explored order acceptance and scheduling problem in make-to-order industries. Reasonably, in today’s marketplace characterized by globalization, flourishing customers’ customized demands and severe competitive pressure, manufacturing firms must select and maintain the orders from core suppliers to survive and succeed. More and more scholars have also done a lot of research work on order processing in supply chain environment [4]–[6]. Therefore, it is necessary to determine which orders should be accepted and in what sequence to process them, while how to determine order production priority is a crucial step for order processing [7]. On the other hand, the problem of order priority is a complex and crucial process as a consequence of possibly conflicting multi-criteria. As a result, various methods and techniques consisting of theoretical, practical and modeling approaches have been utilized in different researches to address the issue of determining the order priority.

Many approaches are used to investigate the problem of order evaluation. Su [8] used mixed integer linear programming (MILP) and various heuristics, including a genetic algorithm, to solve an order acceptance problem. Wen et al. [9] presented a mixed integer programming formulation and used numerical analysis to study simultaneous pricing, order acceptance, scheduling, and lead-time decisions. Vasko et al. [10] appraised buyer order using multiple attribute expert support systems with analytic hierarchy process (AHP). Xiao [11] introduced a novel evidential fuzzy multi-criteria decision making method (EFMCDM) by integrating Dempster-Shafer theory with belief entropy to determine the optimal alternative. Cheng et al. [12] proposed Atanassov type intuitionistic fuzzy sets to determine
the supply selection and ranking. Xiao [13] proposed an AHP method for order priority using fuzzy number. Xu and Sun [14] proposed an integrated approach combining production strategy and production scheduling which took the production strategy, theory of constraints and linear programming into account. These approaches discuss order priority in view of different points which can help manufactures effectively solve multi-criteria decision making problem in supplier ranking. Linear programming assumes that there is a linear relationship between order priority and its influential factor. Actually, the evaluation model of order priority is affected by many factors and cannot be generalized nonlinearly. AHP has the merit of providing a structured yet relatively simple solution to the decision-making problems, but it depends heavily on human judgments on knowledge and experience [15]. In recent years, machine-learning [16]–[18] such as the neural network model and support vector machine (SVM) has been widely used because it can deal with complexity and uncertainty compared to traditional approaches. Oh et al. [19], [20] used SVM to deal with quality monitoring and control, quality assessment. However, Oh also pointed out traditional SVM failed to consider explicit defective types and warranty expenses. Moreover, the generalization ability of SVR largely depends on the selection of parameters, and it costs a lot of calculation to select parameters [21]. Tang and Cai [22] proposed a non-linear evaluation model for order priority based on radial basis function (RBF) neural network, the results showed the evaluation model grounded on RBF network improved the evaluation accuracy. The main merit of this method is that it does not need the complicated process decision making, but only depends on historical data. However, RBF neural network model is a kind of machine learning algorithms based on empirical risk minimization principle and the theory of “large sample”. So it is not suitable to deal with the problem of order priority because order history data is a kind of small sample problems. Moreover, RBF model has a complex network structure and is easy to over-fit [23], [24].

In the past two decades, as commonly used in computer experiments, Kriging model has enormous capabilities for complexity and is a nonlinear functional approximator [25]. It has attracted widespread interest in engineering, statistics and supply chain management. Dellino et al. [26] developed a robust method using Kriging model, and illustrated the validation of the methodology through classic Economic Order Quantity (EOQ) inventory model. Parnianifard et al. [27] approximated the simulation model of an (s, S) inventory system using Kriging model and demonstrated that Kriging model had the capabilities as a simulation tool. Compared to out-dated methods, Kriging model can deal with complexity, uncertainty and nonlinearity [28], [29].

The main contribution of this paper is emphasized in three folds. Firstly, Kriging model has not been applied to order priority under supply chain environment up to now. Kriging meta-modelling technique is introduced to establish the model of order priority determination in supply chain. Secondly, our proposed method is compared with RBF model which is often used to deal with order processing, the comparison results show that our method is more effective and has more advantages. What’s more, the results based on our method are closer to the actual situation. Lastly, our method provides a new research idea and broadens the research of order priority determination in supply chain environment.

The rest of this paper is organized as follows. In Section 2, a brief survey of RBF and Kriging models are introduced. In Section 3, a hierarchical structure of a more systematic and comprehensive evaluation index systems is given for the order priority under supply chain environment, then the proposed method for order priority based on Kriging model is presented. In Section 4, the comparative results for order priority based on RBF and Kriging meta-modeling techniques are obtained. Finally, some conclusions are drawn in Section 5.

II. AN OVERVIEW OF METAMODELING METHODS
A. RADIAL BASIS FUNCTION
The RBF meta-model was originally proposed by Hardy for fitting irregular topographic contours of geographical data [30]. The general form of RBF approximation function can be given in equation (1).

\[ \hat{y} = \hat{f}(x) = \sum_{i=1}^{m} \beta_i \phi(\|x - x_i\|) \] (1)

where the term \( \hat{f}(x) \) is an RBF approximation function to the true response, \( \beta_i \) are unknown coefficients to be determined, \( m \) is the size of the sample data, \( \|x - x_i\| \) is the Euclidean norm, \( \phi \) is the basis function. \( \beta_i \) can be determined through solving the following linear equation:

\[ A \beta = Y \] (2)

Then

\[ \beta = A^{-1}Y \] (3)

where \( A \) is the design matrix, \( A_{ij} = \phi(\|x_i - x_j\|), Y = [y_1, y_2, \ldots, y_m]^T \).

In addition, the most commonly used basis functions include cubic, linear, thin-plate spline, multi-quadric, Gaussian and inverse multi-quadric functions [31]. For a given sample data, the selection of basis function has greatly influence on the precision of RBF model. Given that the radial functions of RBF are not to be positive definite in some cases, an augmented RBF is developed by adding a linear polynomial which is given as equation (4).

\[ \hat{y} = \hat{f}(x) = \sum_{i=1}^{m} \beta_i \phi(\|x - x_i\|) + \sum_{j=1}^{p} \delta_j b_j(x) \] (4)

where \( b_j(x) \) is a linear polynomial function, \( \delta_j \) is the unknown coefficient. As equation (4) is underdetermined, the orthogonality condition is further imposed on coefficients \( \delta_i(i = 1, 2, \ldots, p) \), so that

\[ \sum_{i=1}^{m} \beta_i b_j(x_i) = 0 \quad j = 1, 2, \ldots, p \] (5)

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\[ \sum_{i=1}^{m} \beta_i b_j(x_i) = 0 \quad j = 1, 2, \ldots, p \] (5)
Combining equation (4) and equation (5), the coefficients \( \beta \) and \( \delta \) can be obtained by the following equations:

\[
\begin{pmatrix}
A \\
B \\
0
\end{pmatrix}
\begin{pmatrix}
\beta \\
\delta
\end{pmatrix} =
\begin{pmatrix}
Y \\
0
\end{pmatrix}
\]

(6)

where \( B_{ij} = b_j(x^i) \).

The order priority model involved in the paper is high-dimension nonlinear problem which is similar to that in the literature [31], [32], so an augmented RBF was used in this paper.

**B. KRIGING MODEL**

Kriging model was originated from the geo-statistics community and used by Sacks et al. to model the results achieved from computer simulations [33], [34]. The response of Kriging model is viewed as a realization of a stationary random process from a Bayesian perspective. The general form of this model is expressed as

\[
f(x) = \sum_{i=1}^{m} \beta_i f_i(x) + Z(x)
\]

(7)

where \( Z(\cdot) \) is a stationary random process with zero mean, and its covariance is commonly assumed to be Gaussian,

\[
cov(Z(x^k), Z(x^l)) = \sigma^2 R(x^k, x^l)
\]

\[
= \sigma^2 \exp[-\sum_{i=1}^{d} \theta_i (x_{i}^k - x_{i}^l)^2]
\]

(8)

where \( \sigma^2 \) is the process variance and \( R(\cdot) \) is the correlation function, \( d \) is the dimension of \( x \). The linear part of equation (7) is usually assumed to be a constant (called ordinary Kriging model), parameter \( \theta(\theta_1, \theta_2, \ldots, \theta_d) \) which is often estimated using maximum likelihood. Given the sample sets \( (x_1, \ldots, x_n) \), \( Y \) is the vector of the observations at the given sample sites. The corresponding predictor of universal Kriging model can be formulated as following,

\[
\hat{f}(x) = f^T(x) \hat{\beta} + r^T(x) R^{-1}(Y - F \hat{\beta})
\]

(9)

where

\[
r = [R(x_1, x_1), \ldots, R(x_n, x_n)]^T
\]

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

\[
F = \begin{bmatrix}
f_1(x_1) & \cdots & f_1(x_n) \\
\vdots & \cdots & \vdots \\
f_m(x_1) & \cdots & f_m(x_n)
\end{bmatrix}
\]

And \( f_i(x) \) in Equation (8) is usually defined with polynomials of orders 0, 1 and 2. More specific, \( x_j \) denotes the \( j \)th component in \( x \). \textbf{Constant}, \( p = 1 \):

\[
f_1(x) = 1
\]

(10)

\textbf{Linear}, \( p = n + 1 \):

\[
f_i(x) = 1, \quad (x) = x_1, \ldots, f_{n+1}(x) = x_n
\]

(11)

The prediction variance can be calculated in Equation (12).

\[
\hat{\sigma}^2 = \hat{\sigma}^2 [1 + u^T (F^T R^{-1} F)^{-1} u - r^T R^{-1} r]
\]

(12)

where \( u = F^T R^{-1} r - f \) and \( \sigma^2 \) is estimated in equation (13).

\[
\hat{\sigma}^2 = \frac{1}{n} (Y - F \hat{\beta})^T R^{-1} (Y - F \hat{\beta})
\]

(13)

where the generalized least-squares estimate of \( \beta \) is given in equation (14).

\[
\hat{\beta} = (F^T R^{-1} F)^{-1} F^T R^{-1} Y
\]

(14)

Kriging model provides ‘exact’ interpolation, i.e., predicted output values at inputs already observed equal the simulated output values and it often gives better global predictions than regression metamodel [35], [36]. Now, Kriging model is extensively used for computer-aided engineering in the development of airplanes, automobiles, semiconductor, computer monitor, and so on [37]–[39], but rarely used in the fields of order priority.

**III. PROPOSED METHOD FOR ORDER PRIORITY BASED ON KRIGING MODEL**

**A. ESTABLISHING THE EVALUATION INDICES UNDER SUPPLY CHAIN ENVIRONMENT ABBREVIATIONS AND ACRONYMS**

The key step in constructing the evaluation model of order priority is to build a scientific and reasonable evaluation index system. As order priority is affected by many factors, such as processing capability, order profit, customer order trend. Also, information sharing plays a very important role under supply chain environment. The evaluation index for order priority becomes more complicated. Through systematic analysis and expert interview, relevant factors affecting order priority can be roughly divided into three categories. The first criterion is order terms, mainly including delivery time, order profits and order amounts, the second criterion is the aspects of production, which is composed of production costs, products quality and processing capacity, the third criterion is customer terms considering information sharing including customer order trend, order urgency capacity, period of cooperation between clients and so on [40], [41]. Information sharing in supply chain is an important determinant of supply chain coordination and performance. The degree of information sharing determines the degree of supply chain coordination to a great extent, and the coordination of supply chain is one of the key factors that affect the performance of supply chain and its nodes. Through information sharing, each node enterprise can fully know supply, inventory, production and demand of the upstream and downstream enterprise. The sales planning, production planning, purchase planning can be made in the shortest time. Thus, the supply time can be shortened maximally, the cost of the supply chain operation is minimized, and customer satisfaction is improved [22]. And the index of order urgency degree is used to measure supply chain information sharing, which is determined by marketing information, inventory and customer’s orders from...
downstream companies. The hierarchical structure is presented in Figure 1.

**B. THE FRAME OF ORDER PRIORITY MODEL BASED ON KRIGING**

The evaluation of order priority is a dynamic, nonlinear decision-making process. There are many factors influencing the evaluation of order priority. Different factors have different effects on the evaluation result. And it is difficult to establish a reasonable, precise mathematical analytical formula to expose the nonlinear relationship between the input and output of the evaluation model for order priority. Supposed \((x_1, x_2, \ldots, x_n)\) as order priority evaluation index, the mathematical model of order priority is

\[
y = f(x_1, x_2, \ldots, x_n)
\]  

(15)

where \(f(\cdot)\) represents evaluation function, and \(y\) represents the evaluation value of order priority.

The essential nature for establishing the evaluation model of order priority is to find a most suitable function \(f(\cdot)\) which can describe accurately the complex, nonlinear relationship between the input and output of the evaluation model. Hence, we use Kriging model to substitute the evaluation function \(f(\cdot)\), then equation (15) can be replaced as

\[
\hat{y} = \hat{f}(x_1, x_2, \ldots, x_n)
\]  

(16)

where \(\hat{f}(\cdot)\) represents Kriging model, \(\hat{y}\) represents the predictor value from Kriging model.

The optimal Kriging parameter is obtained through the method proposed by the literature [42], thus the evaluation model of order priority based on Kriging model is set up, and the performance is tested by test sample.

**C. IMPLEMENTING STEPS OF OUR PROPOSED METHOD**

A concrete implementation step of our proposed method is as follows:

**Step 1:** Quantifying the index values. According to the index system of order priority, we firstly normalize the index values of sample orders linearly. When the index is qualitative, we put it into a quantitative index by experts scoring, and then the quantitative indices can be obtained by the pretreatment of the actual data. These quantitative indices are used as the input variable (or vector) \(x\).

**Step 2:** Collecting the data set \((x, y)\). The expected overall evaluation \(y\) is given by experts according to their comprehensive analysis on the evaluation index system for order priority. The value of \(y\) is also given after quantitative process. The larger overall evaluation \(y\) means a higher priority, where \(y \in (0, 1)\). Then the samples which are used to construct order priority model are given. To eliminate the adverse effects of index dimensional differences, the order priority evaluation samples \((x, y)\) are normalized.

**Step 3:** Building order priority model based on Kriging model. The data set acquired from **Step 2** is divided into two subsets, namely the training data set and test data set. Using the training samples, the optimal Kriging parameters \(\theta\) are obtained through the estimation method named leave-one-out cross-validation which adopted by the literature [42]. The optimal initial estimator of \(\theta\), the lower and the upper bounds
of the hyper-parameter $\theta$ are identified using cross-validation such that they minimize the prediction mean square error ($MSE$) on the base of training set, at the same time, the suitable regression model and the correlation model are selected. Thus the order priority evaluation model based on Kriging model is established.

### TABLE 1. Training and test data in Kriging model.

| No. | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | ... | $x_{14}$ | $y$ |
|-----|-------|-------|-------|-------|-------|-----|---------|-----|
| 1   | 0.0318| 0.0627| 0.8689| 0.9459| 0.016 |     | 0.9757  | 0.256|
| 2   | 0.0026| 0.0299| 0.7459| 0.973  | 0.0001|     | 0.9999  | 0.402|
| 3   | 0.1281| 0.1971| 0.4016| 0.9189 | 0.0687|     | 0.9028  | 0.378|
| 4   | 0.0252| 0.0602| 0.9918| 0.9459 | 0.0124|     | 0.9824  | 0.316|
| 5   | 0.0408| 0.112 | 0.8689| 0.9459 | 0.0209|     | 0.9788  | 0.698|
| 6   | 0.0089| 0.008 | 0.7869| 0.973  | 0.0035|     | 0.9868  | 0.295|
| 7   | 0.0188| 0.0065| 0.8689| 0.973  | 0.3505|     | 0.9752  | 0.831|
| 8   | 0.0099| 0.0314| 0.8689| 0.9459 | 0.0269|     | 0.992   | 0.199|
| 9   | 0.0358| 0.0443| 0.459 | 0.9189 | 0.0685|     | 0.9661  | 0.165|
| 10  | 0.3245| 0.1926| 0.8689| 0.7027 | 0.176 |     | 0.6786  | 0.792|
| 11  | 0.0224| 0.0239| 0.7459| 0.9459 | 0.0109|     | 0.9758  | 0.676|
| 12  | 0.0001| 0.0005| 0.8689| 0.973  | 0.2707|     | 0.9947  | 0.526|
| 13  | 0.9999| 0.5172| 0.8689| 0.027  | 0.5451|     | 0.0001  | 0.453|
| 14  | 0.1541| 0.0816| 0.6639| 0.8649 | 0.1329|     | 0.842   | 0.718|
| 15  | 0.0374| 0.0214| 0.8689| 0.9459 | 0.0191|     | 0.9581  | 0.782|
| 16  | 0.2365| 0.1498| 0.8689| 0.7838 | 0.1279|     | 0.7669  | 0.269|
| 17  | 0.1956| 0.3021| 0.8689| 0.8919 | 0.1055|     | 0.8547  | 0.928|
| 18  | 0.1148| 0.0538| 0.8689| 0.8919 | 0.0614|     | 0.879   | 0.482|
| 19  | 0.1544| 0.115 | 0.8689| 0.8378 | 0.083 |     | 0.8507  | 0.434|
| 20  | 0.8902| 0.9995| 0.9098| 0.2703 | 0.4852|     | 0.2555  | 0.852|
| 32  | 0.2923| 0.1722| 0.8689| 0.7297 | 0.1584| 0.88 | 0.7097  | 0.793|
| 33  | 0.3795| 0.1963| 0.8689| 0.5135 | 0.206 | 0.21 | 0.6172  | 0.293|

**FIGURE 3.** Comparison between actual scoring, RBF and Kriging for different test points.
Step 4: Obtaining output predictor. According to the test data and established Kriging model given by Step 3, we obtain the predictor value $\hat{y}$ of the overall evaluation $y$.

Step 5: Determining ranking order. The order priority is determined by the value of $\hat{y}$ according to the results from Step 4.

As a result, the basic flowchart of order priority model based on Kriging model is shown in Figure 2.

IV. SIMULATION EXPERIMENT

For make-to-order enterprises, the order priority becomes one of the most critical activities due to the key role of order acceptance on cost, quality, delivery and service in achieving the objectives of a supply chain, especially suffering from backlogged orders. In fact, the order priority for the company is regarded as a complex decision making problem which is affected by various conflicting factors. In this section, the following enterprise which takes the mechanical and electrical products is studied by our proposed method.

A. DATA SET

To test the effectiveness of the proposed model, a real set of performance rating of buyer orders in electrical enterprise is collected. According the actual needs of enterprises, ten indexes are selected as following: Order amount($x_1$), Order profits($x_2$), Delivery time($x_3$), Product quantity ($x_4$), Total transaction amount($x_5$), Customer credit rating($x_6$), customer order trend($x_7$), Period of cooperation between client($x_8$), Order urgency degree ($x_9$), Production costs($x_{10}$). At the same time, expert scoring ($y$) are given based on historical data. The data are preprocessed by adopting linear normalization and listed in Table 1 which gives training and test data. A larger experts scoring means the order has a higher priority.

B. PERFORMANCE CRITERIA

In this section, common statistical metrics, including mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), root mean squared error (RMSE) and standard deviation error (SDE), are employed to evaluate the accuracy of Kriging and RBF models. These metrics are defined by:

$$MAE = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} |y_i - \hat{y}_i|$$  \hspace{1cm} (17)

$$MSE = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (y_i - \hat{y}_i)^2$$  \hspace{1cm} (18)

$$MAPE = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$  \hspace{1cm} (19)

$$RMSE = \sqrt{\frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (y_i - \hat{y}_i)^2}$$  \hspace{1cm} (20)

$$e_i = \hat{y}_i - y_i, \quad \bar{e}_i = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} e_i$$  \hspace{1cm} (21)

$$SDE = \sqrt{\frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (e_i - \bar{e}_i)^2}$$  \hspace{1cm} (22)

where $y_i$ and $\hat{y}_i$ represent the actual and estimated values of the $ith$ data, respectively. The optimal parameters in Kriging model are identified via the estimation method in [42]. The results are shown in Table 2. “lob” and “upb” are the lower and upper bounds of $\theta$, respectively. Regploy1 denotes the first order polynomials given by equation (11), and corrgauss denotes Gaussian correlation model given by equation (8).

| Model     | Parameters | The value of the parameters |
|-----------|------------|-----------------------------|
| Kriging   | $\theta$   | 10                          |
|           | lob        | 0.1                         |
|           | upb        | 2                           |
| Regression model | regploy1    |
| Correlation model | corrgauss   |

| Sample points | model | MAE   | MAPE   | MSE    | RMSE   | SDE    |
|---------------|-------|-------|--------|--------|--------|--------|
| 15            | Kriging | 0.0358 | 0.0798 | 0.0018 | 0.0428 | 0.0418 |
|               | RBF    | 0.0715 | 0.1485 | 0.0082 | 0.0906 | 0.0887 |
| 20            | Kriging | 0.0285 | 0.0712 | 0.0011 | 0.0332 | 0.0307 |
|               | RBF    | 0.0542 | 0.1388 | 0.0049 | 0.0702 | 0.0692 |
| 25            | Kriging | 0.0353 | 0.0681 | 0.0026 | 0.0515 | 0.0505 |
|               | RBF    | 0.12   | 0.2172 | 0.0291 | 0.1707 | 0.1674 |
| 28            | Kriging | 0.0059 | 0.0111 | 0     | 0.0076 | 0.0069 |
|               | RBF    | 0.0744 | 0.1442 | 0.0134 | 0.1157 | 0.1018 |
C. COMPARATIVE RESULTS

In order to examine the performance of Kriging and RBF techniques under different sample sizes and verify the effectiveness of the proposed method sufficiently, different training points are randomly sampled from Table 1 which contains 15, 20, 25, 28 sample points separately. As the test
TABLE 4. Ranking orders based on performance rating for Kriging, RBF and actual data using 15 samples.

| Actual | Kriging | RBF |
|--------|---------|-----|
| 11     | 15      | 13  |
| 12     | 12'     | 14  |
| 14     | 11      | 12  |
| 5      | 3       | 3   |
| 8'     | 8'      | 7   |
| 6'     | 6'      | 5   |
| 17'    | 17'     | 17' |
| 2'     | 2'      | 2'  |
| 10'    | 10'     | 10' |
| 3      | 5       | 6   |
| 16'    | 16'     | 16' |
| 1'     | 1'      | 1'  |
| 9'     | 9'      | 8   |
| 13'    | 13'     | 11  |
| 7'     | 7'      | 9   |
| 18'    | 18'     | 18' |
| 4'     | 4'      | 4'  |
| 14'    | 14'     | 15  |

TABLE 5. Ranking orders based on performance rating for Kriging, RBF and actual data using 20 samples.

| Actual | Kriging | RBF |
|--------|---------|-----|
| 12     | 12'     | 12' |
| 9'     | 9'      | 10  |
| 10     | 11      | 9   |
| 13'    | 13'     | 13' |
| 3'     | 3'      | 2   |
| 5'     | 5'      | 8   |
| 7      | 6       | 5   |
| 4'     | 4'      | 3   |
| 6'     | 7       | 6'  |
| 8'     | 8'      | 7   |
| 2'     | 2'      | 4   |
| 11'    | 10      | 11' |
| 1'     | 1'      | 1'  |

TABLE 6. Ranking orders based on performance rating for Kriging, RBF and actual data using 25 samples.

| Actual | Kriging | RBF |
|--------|---------|-----|
| 6'     | 7       | 6'  |
| 7'     | 6       | 7'  |
| 4      | 3       | 2   |
| 5'     | 5'      | 4   |
| 2'     | 2'      | 1   |
| 1'     | 1'      | 5   |
| 3'     | 4       | 3'  |
| 8'     | 8'      | 8'  |

points are not less than the square root of the total sample size [43], we choose 5 test points and 28 training points in the last experiment. The results from evaluation model of order priority based on RBF model are also given simultaneously. The overall comparative results for prediction based on Kriging and RBF models in different samples are illustrated in Table 3. Table 4-Table 7 give the rankings for buyer orders based on performance rating for actual data, Kriging and RBF models. And, Figure 3 demonstrates the order rankings from Kriging and RBF models using different sample sizes.
The predicted-versus-actual values for these two techniques are shown in Figure 4.

As can be seen from Table 3, the values of the criterion SDE for Kriging model are smaller than those for RBF model, which illustrate Kriging model has great robustness in predictive accuracy in terms of SDE criterion. The sample sizes and the randomization of sample have impact on the two models which are shown in Table 3. No matter what the sample size or the sample randomization changes, Kriging model still performs better in terms of the four predictive accuracy criteria. (i.e., \(\text{MAE, MAPE, MSE, RMSE}\)). Therefore, we can conclude that Kriging model is more reliable and robust than RBF model according to the results presented in Table 3. Furthermore, and shown in Table 3, it is also noted that Kriging model yields lower SDE and lower RMSE. So we can conclude that Kriging model does not suffer from over fitting. Similar results can be concluded in Figure 3. In addition, the results also reveal that RBF model is prone to over fitting. A modest 50\% and 93\% improvement can be achieved for the small sample size (such as, 15) and the large sample size (such as, 28), respectively.

As shown in Figure 4, both Kriging and RBF models can approximately capture the correct trends. The closer the points are near to the diagonal line \((y = x)\), the more satisfactory is the performance of the technique. Hence, we can conclude that Kriging model may outperform RBF model in terms of accuracy and fitting performance.

The order rankings from RBF model, Kriging model and true ranking are also presented in Table 4-Table 7 using different sample sizes. It can be seen that the order ranking from Kriging model are closer to true ranking comparing to the order ranking from RBF model. It is also found that the prediction accuracy of Kriging model will be gradually improved with the increase of sample sizes. As shown in Table 7, when the size of sample points is enough, Kriging model can replace the actual model. In view of overall perspective, Kriging model may be a good choice as the actual evaluation model of order priority.

| Table 7. Ranking orders based on performance rating for Kriging, RBF and actual data using 28 samples. |
|---------------------------------------------------------|---------|---------|
| Actual | Kriging | RBF |
| 5' | 5' | 5' |
| 2' | 2' | 2' |
| 3' | 3' | 4 |
| 1' | 1' | 1' |
| 4' | 4' | 3 |

V. CONCLUSION

In this paper, a new method based on Kriging model is proposed to predict the order performance rating of make-to-order enterprises. Firstly, a more systematic and comprehensive evaluation index system for order production priority is constructed considering supply chain information sharing. Then, a new method of order priority in supply chain based on Kriging model is proposed. Finally, in terms of statistical metrics, including \(\text{MAE, MSE, MAPE, RMSE}\) and SDE, we compare our results with those from RBF model and actual evaluation value using different sample points. The results show that Kriging model has a better general performance and yields lower estimation error. Since the offered method has more reliable and more robust advantages than RBF model, Kriging model can be a better substitution of the actual order priority evaluation model.

Moreover, the proposed model can be easily extended to other areas of supply chain management for making appropriate decision to the managers, such as ‘Just-In-Time’ cross-docking distribution system, average travel time for traffic system. Although Kriging model has been widely used in stochastic simulation [44], [45], sometimes it can’t cope well with noise from stochastic simulation, which motivates the development of stochastic Kriging [46]. How to measure stochastic factors and adopt stochastic Kriging model to determine the order priority is our future interest.

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