The Optimization of Bank Branches Efficiency by Means of Response Surface Method and Data Envelopment Analysis: A Case of Iran

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Abstract

In this paper the DRC model is presented for solving multi objective problem. The proposed model is a combination of data envelopment analysis, Cuckoo algorithm and the response surface method. Due to reasons like costs, time and irreversible damages, it is not possible to analyze each and every one of the proposed models in practice, so the simulation is used. Since the number of experiments for simulation process is high then the optimization has gone to practice and directs the simulation process. The response surface method is used as one of the approaches of simulation optimization. Furthermore, data envelopment analysis is used to consider several response surfaces as efficiency response surface. Then this efficiency response surface is solved by Cuckoo algorithms. The main advantage of DRC model is to make one efficiency response surface function instate of multi surface function for every output and also using the advantages of Cuckoo algorithms. In order to demonstrate the effectiveness of the proposed approach, the branches of Refah bank in Mashhad is analyzed and the results are presented.

Keywords: Simulation, Optimization, Response Surface Method, Data Envelopment Analysis, Cuckoo Algorithm.

JEL Classification Codes: M1, C9, C6.

1. Introduction

Multi response problem is often difficult due to different factors should be taken into account during problem solving. Then

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optimizing multiple responses is of main concern among decision makers. Response surface methodology (RSM) is usually get the optimum parameter following analysis of variance (ANOVA) for distinctive factors. Through RSM, an equation (determining the relationship between a single output and inputs) can be established based on experimental data. A contour plot is employed to determine the surface graphical and characterize the optimal inputs. Once several responses are recognizing, the optimal parameter is determined by visualizing overlay contour plots. As a result, RSM creates response surfaces for each output; the overlay contour plots are complicated once several responses are existed. In this situation, recognizing the optimum parameter setting is complicated. traditional means of optimizing several responses in DOE is to develop a multi-response problem as a constrained optimization problem (Myers at al., 2004). Another method is the Derringer-Suich method (1980) via a desirability function. Koksoy (2005) utilized the Derringer Such approach to optimize dual responses. Allen and Yu (2002) extended RSM with novel low-cost response surface methods (LCRSMs). Candioti et al. (2014) presented methods and application of RSM when several responses have to be simultaneously optimized and classified methods to two category, graphical optimization and Desirability function. For more information about graphical optimization refer to (Myers and Montgomery (2009) and Bezerra at al. (2008) and for other refer to Sarabia at al. (2009) and Candioti et al. (2008). Jambeswar et al. (2013) proposed a DEA approach for optimization of multiple responses in electrical discharge machining of AISI D2 steel and presented an equivalent single response capable of representing all individual responses.

Díaz-Garcíaand et al. (2014) modeled the multi response surface problem as a multi objective stochastic optimization, and diverse solutions. Liet al. (2015) proposed a multiple response-surface method for slope reliability analysis. The number of surfaces will increase with an increasing number of outputs. The optimizations of several responses are complicated. So, recognizing optimal inputs for a multi-response model is difficult once several outputs should be optimized simultaneously. Tsai et al. (2010) presented a new optimization method that incorporates data envelopment analysis (DEA) with RSM to optimize multiple responses problem. As DEA is an efficient tool of analyzing data with several inputs and outputs, their method an-

alyzes the designed experimental data with several outputs by utilizing DEA. Several responses are analyzed via DEA to achieve relative efficiency for each experimental run. Then RSM is used to construct the optimal parameter-setting based on the relative efficiencies. Finally, multi-responses problem can be easily transformed in a single surface through the combination of DEA and RSM. Therefore, complexities related to the simultaneous tradeoff between several surfaces can be overcome.

The presented model in this paper is just like the one presented by Tsai et al. (2010), by this difference that the optimization COA module has been added to this model which can improve the proposed approach and concern for the detention of the problem has been resolved. By the way, DRC model is used to the design of new decisions making unit (DMU) on data envelopment analysis in the branches of Refah Bank in Mashhad and each DMU (branch) can be considered as an experiment, while the Tsai model was developed to determine product specifications. In DRC approach, multi responses are optimized simultaneously. First, a proper model would be selected for the experiment, then RSM and DEA models are used to analyze the experimental data. Finally, by the Cuckoo algorithm (COA) and the obtained equation from RSM and DEA the determination of the input parameters goes on in order to have the most outputs of the system. The related outputs can be obtained by considering the amount of inputs using RSMs for each output. The following, whole process of DRC approach is described and the data from Refah Bank branches in Mashhad would be discussed.

2. Proposed DRC Model

Since the proposed model includes three modules DEA, RSM, COA, it is called as DRC approach. The suggested model chart is as the Fig 1. The steps of DRC are discussed below.
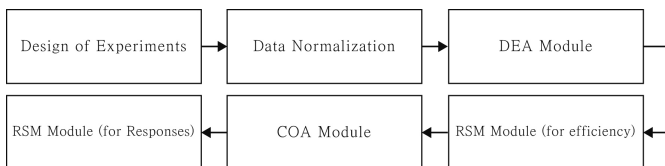
<Figure 1> The Chart of DRC Model

Step 1. Design of Experiments

Control factors, response variables and quality features of response variables are determined by the researcher experience and his/her options. So a proper plan would be used for the experiment. There are different experiments plans to prepare the design, refer to (Montgomery, 2012). After the experiment was done, the amount of relative responses for each experiment has been registered.

Step 2. Data Normalization

To decrease the effect of different data scale in DEA, the experimental data have been normalized. In this approach Euclidean norm is used in the form of (1). Other norms also can be used.

$$y'_{ij} = \frac{y_{ij}}{\sqrt{\Sigma_j^n y_{ij}^2}} \tag{1}$$

Step 3 Determination of Efficiency for Each Test by DEA

DEA is a nonparametric method in operations research. It is used to empirically measure efficiency of DMUs. Efficiency measurement has always been of interest of researchers since of its importance in operation inspections in companies and organizations. Farrell (1957) pioneered the efficiency measurement in engineering discussions of companies.

The case that Farrell considered for measurement included one input and one output. Charnes, Cooper and Rhodes (1978) expanded Farrell's point of view and presented a sample which was able to measure the efficiency by various inputs and outputs. This sample was called as data envelopment analyses.

CCR approach is as a basis model in DEA and is presented as (2). This approach has been presented in two forms of input and output oriented.

$$max E_u = \frac{\Sigma_x u_y o_{ty}}{\Sigma_x v_x I_{tx}}$$
$$s.t. \frac{\Sigma_y u_y o_{wy}}{\Sigma_x v_x I_{wx}} \le 1, \; w = 1, \cdots, L \tag{2}$$
$$u_y \ge 0, \; v_x \ge 0$$

where E_u is relative efficiency of DMUt, u_y the output weight of y, v_x the input weight of x, and o_{wy} and I_{wx} are output of y and input of x, respectively. The reason of selecting input or output oriented approach for a DMU approach in relative efficiency analyses is that in some cases the management does not have any control on amount of output and its amount is specified and fixed previously, power plants are an instance of varying inputs in which input oriented approach is used, though in some cases the input is fixed and the output oriented approach is in practice. Finally choosing input or output oriented model depends on manager's control on each of the inputs and outputs.

Step 4. Making Efficiency Response Surface by Means of RSM

The goal of this method is to determine the best amount of input variables of a system which affect the output variable (either maximize or minimize it). On the other hand response surface methodology includes a group of statistical and mathematical techniques for modeling and solving the optimization of

simulation. In some models the main factors are identified to make a meta-model to understand how inputs (factors) are changed to output responses. This Meta-Model, often like a first or second order regression can be used to predict the amount of responses of interesting combinations from factor levels. This is because of the point that simulation costs per each combination can be so high. Meta-models can also be used for finding the combinational factors which regulate the optimized output (minimized or maximized).

Response surface methodology is an optimization algorithm which looks for optimization responses in two phases. This method by use of semi regression models is firstly looking for determination of optimization area in first phase, and determination of optimization response in the second phase. In fact when the data have been verified by response surface method, the data would be examined by a first order regression equation as (3).

$$\hat{e}_s = y(x) = \beta_0 + \sum_{j=0}^{d} \beta_j x_j + \epsilon \epsilon \sim N(0, \sigma^2) \qquad (3)$$

If the obtained correlations are valid the model is accepted, unless it would be approximated by a second order regression equation. The amount of efficiency and arrangement of relative parameters are analyzed by RSM to determine the level of response. Response level efficiency of second order model is as (4):

$$\hat{e}_s = y(x) = \beta_0 + \Sigma_{j=1}^{d} \beta_j x_j + \Sigma_{j=1}^{d} \Sigma_{j'=j}^{d} \beta_{jj'} x_j x_{j'} + \epsilon \qquad (4)$$

The advantage of combining DEA and RSM is in fourth step in which instead of generating multi surface approach for every output it is available to present one surface approach for the already calculated optimization, so e replaces ys.

Steps 5. Determining Optimized Input by COA Algorithms

Optimized parameter can be obtained by (5) based on obtained efficiency response surface in step 4.

$$\max \hat{e}_s = f(x) \quad x \in \Omega \qquad (5)$$

Here Ω is the acceptable area. Since the obtained function from RSM and DEA is a nonlinear model so efficient algorithms must be used, here we must use the advantages of Cuckoo algorithms which is one of the good methods in solving nonlinear issues in high dimension problem, in so doing one can get near optimized response (Shadkam & Bijari, 2014). Since the exact methods are usable for nonlinear problems in low dimensions. Then using COA, the dimensions of the problem is not important. COA obtains an optimal solution for small dimensions and good answer for high dimension. Then using COA in DRC algorithm, proposed algorithm is applicable for high dimensions problems.

Below a brief introduction to COA algorithm is presented, though for more information refer to (Rajabioun, 2011). The COA is summarized as follows and Figure 2:
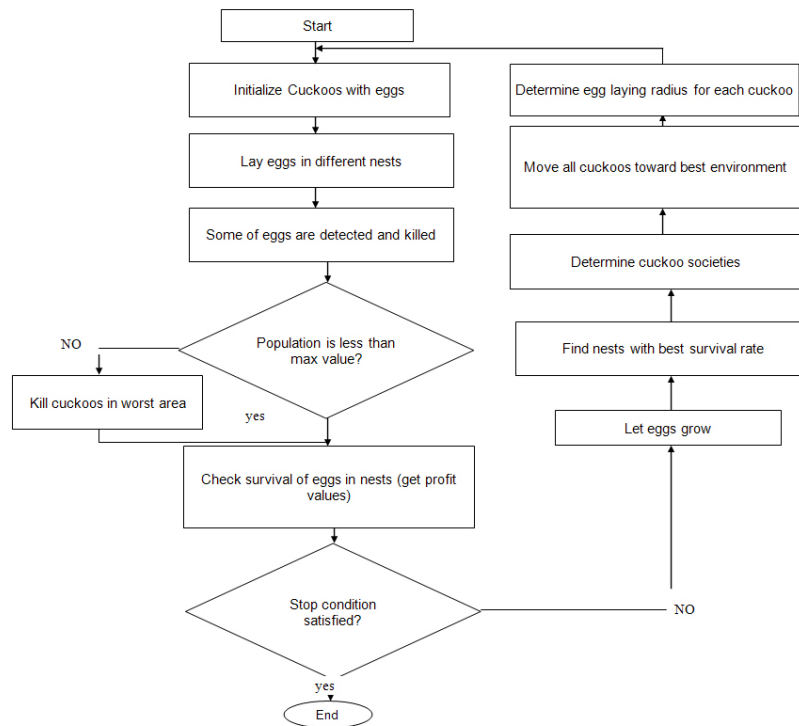
<Figure 2> Flowchart of Cuckoo Optimization Algorithm

Prepare habitats with some arbitrary solution at random;
Assign some eggs to each cuckoo;
Specify ELR for each cuckoo;
Allow cuckoos lay eggs within ELR;
Remove those eggs that are discovered by host birds;
Allow eggs hatch and chicks grow up;
Assess the habit at of each grown cuckoo;
Remove cuckoo live in worst habitats and confine maximum number of cuckoo in environment;
Cluster cuckoos and detect best place and select goal point;
Allow new cuckoo population travel toward goal point;
If stop condition is satisfied, then stop. If not, go to 2.

3. Implementation of DRC Model in Branches of Mashhad Refah Bank

To implement DRC model and its validation, the data from 40 active branches of Refah Bank in Mashhad is used. 5steps mentioned are followed thoroughly.

Step 1. Gathering Data and Design of Experiment

In this step by gathering the data from 40 active Refah Bank branches in Mashhad, in 2010, DRC model is implemented. The data from 40 active Refah Bank branches in Mashhad are formed in 5 inputs and 3 outputs. The inputs include: The number of staffs, the number of ATM+ POS+ Pin Pad devices for each branch, rental estimates, number of cash funds, and the sum of staffs'expenses in Rials. Outputs include: the sum of current accounts, the number of issued cards in 2010, and transactions of ATM + POS + Pin Pad. It is necessary to mention that in order to design of experiments for bank efficiency; each branch is considered as a experiment.

Step 2. Normalizing the Data

The normal value of bank branches data is calculated by Euclidean norm.

Step 3. Determining Efficiency

Efficiency of each branches have been obtained by lingo 8.0 software based on normalized data in step 2. Efficiency is calculated based on CCR models (Table 1).

Step 4. Efficiency Response Surface Function

In this step based on the obtained efficiencies in step 3 we can have response surface function, i.e. instead of three surfaces for each output (Ys) just one surface is obtained for efficiency which would be used for design of new branches in future. In this step response surface is calculated by Minitab 16.0 software. Table 2 shows the obtained results of the analysis of variance for the response surface.

<Table 1> Efficiency of Bank Branches

Branch	e	Branch	e	Branch	e	Branch	e
1	0.3247	11	0.7729	21	0.7430	31	0.5835
2	0.6658	12	0.4637	22	1	32	0.5340
3	0.9492	13	1	23	0.6595	33	1
4	0.3982	14	0.4102	24	0.9653	34	0.4178
5	1	15	1	25	0.8077	35	0.8323
6	0.8146	16	1	26	0.4182	36	0.8709
7	1	17	1	27	0.7888	37	0.7893
8	1	18	0.5955	28	0.9767	38	0.5756
9	0.8558	19	0.7184	29	1	39	0.3340
10	1	20	1	30	0.7031	40	0.2829

<Table 2> Analysis of Variance for Efficiency

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.2823	0.2823	0.0313	1.73	0.314
Linear	3	0.2082	0.0346	0.0115	0.64	0.629
Square	3	0.0570	0.0354	0.0118	0.65	0.622
Interaction	3	0.0170	0.0170	0.0056	0.31	0.816
Residual Error	4	0.0725	0.0725	0.0181		
Total	13	0.3549				

Obtained surface for CCR efficiency are as (6):

e
$= -22.9329x_1 + 2.41647x_2 - 12.1895x_3 + 15.0993x_4 + 25.6021x_5$
$+171.596x_1^2 + 0.274773x_2^2 - 11.0827x_3^2 - 69.1348x_4^2 - 52.8781x_5^2$
$+11.3138x_1x_2 - 43.7122x_1x_3 - 59.1991x_1x_4 - 135.263x_1x_5$
$+19.5884x_2x_3 - 11.5824x_2x_4 - 23.7760x_2x_5 + 62.7006x_3x_4$
$+43.8978x_3x_5 + 104.571x_4x_5 - 0.700887$ (6)

Step 5. Determining the optimization inputs by COA

In this step the developed model from pervious steps (models 6) is solved by COA algorithms and the following answers are obtained for inputs (Xs), we can construct new branches with maximum efficiency by using these results. The results are shown in Table 3.

The parameter of COA algorithm is as follow:

Initial Cuckoo population = 5, the minimum number of eggs = 2, the maximum number of eggs = 5, the number of clusters = 2, Motion coef = 0.3, maximum number of Cuckoo=50.

<Table 3> Optimized Input for New Branch

	x_1	x_2	x_3	x_4	x_5
Normalize	0.145518	0.230198	0.00021	0.138013	0.135635
Real	7	17	2783332	3	957418311

Step 6. Determining Optimizated Outputs Corresponding to Inputs of 5th Step.

In this step it is possible to determine the corresponding outputs of inputs (Xs) from the previous step. In so doing the response surface level is used (models 7, 8 and 9).

Response surface 1 (y_1)

$y_1 = -11.5245x_1 + 0.871045x_2 - 7.10617x_3 + 3.49338x_4 + 14.1110x_5$
$+3.31300x_1^2 - 0.261779x_2^2 - 9.59654x_3^2 - 20.6481x_4^2 - 16.6984x_5^2$
$-3.25119x_1x_2 + 5.26424x_1x_3 + 68.5334x_1x_4 + 1.84470x_1x_5$
$+8.30896x_2x_3 + 0.408184x_2x_4 - 4.62097x_2x_5 + 37.1285x_3x_4$
$+9.43002x_3x_5 - 56.2101x_4x_5 - 0.297830$ (7)

Response surface 2 (y_2)

$y_2 = -32.4143x_1 + 0.900586x_2 - 9.52463x_3 + 10.6696x_4 + 28.3127x_5$
$-47.9327x_1^2 + 3.36329x_2^2 - 13.5818x_3^2 - 72.9941x_4^2 - 47.0827x_5^2$
$-5.82253x_1x_2 - 10.0812x_1x_3 + 230.016x_1x_4 + 90.4243x_1x_5$
$+17.8979x_2x_3 + 9.54116x_2x_4 - 22.8867x_2x_5 + 61.1658x_3x_4$
$+14.9263x_3x_5 - 167.061x_4x_5 - 0.382346$ (8)

Response surface 3 (y_3)

$y_3 = -10.1978x_1 + 3.19467x_2 - 0.609384x_3 + 6.11535x_4 + 2.89991x_5$
$+85.0398x_1^2 - 4.57884x_2^2 - 2.69947x_3^2 - 50.9645x_4^2 - 83.6506x_5^2$
$+3.77033x_1x_2 - 40.4870x_1x_3 - 80.4276x_1x_4 - 9.90316x_1x_5$
$+3.85195x_2x_3 + 4.34963x_2x_4 - 20.8459x_2x_5 + 4.64508x_3x_4$
$+40.1589x_3x_5 + 159.040x_4x_5 - 0.193574$ (9)

The amounts of corresponding responses to inputs of the pervious step are as Table 4.

<Table 4> Optimized Output for New Branch

	y_1	y_2	y_3
Normalized	0.14065418	0.044289072	0.131350484
Real	2830	236	39373

4. Conclusion

Optimization of simulation is an effective tool toward analysis of random systems which includes various methods. RSM is the one used in this study. RSM by means of regression equations tries to clarify the relationship between inputs and outputs of a system. If the system is a multi-response one then the number of RSM equations equals the responses, so by using these equations the optimal value of inputs of system are determined. This study by combining DEA, RSM and COA presented a combinatory algorithm called DRC in which one response surface function for efficiency is obtained instead of a multi-response surface functions for each response, this helps to determine easily the optimized inputs of system.

Here the proposed approach has been verified by using data from 40 active branches of Refah Bank in Mashhad. Each branch considered as an experiment and DRC approach is used. The obtained results can be used for designing of new branches in future with respect to the efficiency. One of the advantages of the proposed approach is to decrease the response surface. Basically instead of making various response surface (for each response), just one response surface has been used (for efficiency).The inputs of unit are determined so that not only optimized the outputs of the system, but also maximized the efficiency of the system. Thus the results of this approach can be used to design a new branch with the maximum efficiency in future. Another advantage of this approach is using Cuckoo algorithm in finding the system optimized parameters which is applicable for large scale systems.

For further research overall branches of Refah bank in the country can be analyzed. It is obvious that the obtained results by analyzing 40 branches of Refah bank are not enough. More tests and more branches bring up accurate results. Another research can be done on the newer and more efficient approaches of DEA for this module in DRC.

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