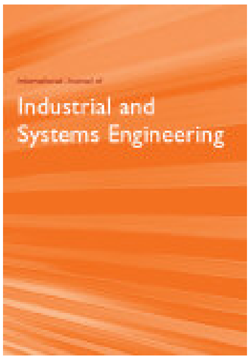

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A new hybrid method for optimising multi-surface problems: DSM method (power plants of Iran)

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A new hybrid method for optimising multi-surface problems: DSM method (power plants of Iran)

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Abstract: In this paper, a new hybrid method is proposed for optimising multi-response surfaces simultaneously which is a combination of data envelopment analysis and the response surface method. For this reason, the proposed method is called the DSM method. This method not only investigates optimising multi-response surfaces but also considers the efficiency maximisation of decision-making units (DMUs). As a result, the outcome of this method is an optimised set of inputs and outputs with high efficiency of DMUs. DMS considers each DMU as an experiment in the design of the experiment and multi-response surfaces are transformed into a single-response surface, and instead of different response surfaces, an efficiency surface is replaced. Due to the high importance of the electricity industry and energy production, power plants, which are responsible for a very important part of electricity generation, have to increase the efficiency of their activities in order to make better use of resources. In this regard, the proposed method is implemented to account for the efficiencies of the power plan of Iran, and determine the optimum factors for the construction of a new one.

Keywords: data envelopment analysis; DEA; response surface method; RSM; efficiency; optimisation; power plant.

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1 Introduction

Optimisation problems are very important in most branches of science and their goal is to find the best possible solution to a problem. Most real-world problems involve several incompatible objectives. Achieving one goal may lead you away from another. It is difficult to identify the optimal inputs for a multi-objectives (surfaces) model when multiple outputs have to be optimised simultaneously. Many of these problems can be solved by converting all objectives into one objective or constraints (Zhang et al., 2021). The first step in the optimisation process is to estimate the relationship between system input and output variables. In this context, experimental design methods are used to investigate the causal relationship between one or more control factors and a response variable (Kutner et al., 2005). One of the most practical of these methods is the response surface method (RSM), which was first introduced by Box and Wilson (1951), which is a set of mathematical methods for analysing and modelling different problems in which a desired response is affected by several factors (Montgomery, 2017).

The main goal in RSM is discovering the input variables that make the output variables maximised or minimised. In other words, the RSM method includes a collection of statistical and mathematical techniques, which use to modelling and solving optimisation problems. Using the RSM, the equation of the relationship between output and inputs can be determined based on experimental data (Fakhri et al., 2018). A surface is used to determine the level of optimal inputs. When multiple responses are detected, the optimal parameter is determined by visualising the surfaces. In this case, identifying the optimal parameter is very complicated (Myers et al., 2004). Allen and Yu developed the RSM with new low-cost RSMs that include graphical optimisation and utility function (Allen and Yu, 2002). In order to optimise problems with multiple response surfaces, there are various methods that can be referred to Hejazi et al. (2012), Akçay and Anagün (2013) and Park and Kim (2005). There are many hybrid methods in this field that will be fully explored in the next section. One of the methods for evaluating the performance is the data envelopment analysis (DEA) method (Zhu et al., 2020), which is a non-parametric and applicable to many problems. The purpose of DEA is to determine the efficiency of a decision-making unit (DMU) through the process of how inputs are converted to outputs (Amin and Hajjami, 2020). This method is rarely combined with the RSM method in the literature. So far, the combination of these two methods has not been used for optimisation problems. Determining the optimal inputs for multi-response surface problems is complex. In this paper, a combination of two methods DEA and RSM, a hybrid method to optimise the multi- response surface problems is presented. Depending on the efficiency of the units, an efficiency surface is created and replaces the response surfaces. By optimising this surface, in addition to determining the optimal parameters, the efficiency value is also maximised at the same time. In this paper, control variables and independent variables refer to problem inputs. Also, response variables mean problem outputs.

In order to implement and evaluate the proposed method of the paper, which is called DSM due to the combination of DEA and RSM methods, the problem of optimising the performance of power plants has been considered. The electricity industry, as an infrastructure industry, has a valuable and fundamental role in the process of economic development of the country and the creation of development infrastructure and provides the necessary bases for the dynamism and growth of the country in various economic, industrial, cultural and social fields (Zheng et al., 2021). Therefore, measuring the efficiency of power plants is of great importance. The power industry is one of the major industries in energy production. It can be divided into three categories of production, transmission, and distribution (Jindal and Nilakantan, 2021). Meanwhile, the electricity generation section in power plants is very important. The main function of the power plants is to convert energy from other forms to electrical energy. Therefore, increasing efficiency and productivity in this industry is very important. Standardisation of power plant construction has many benefits such as ease of designing and building new power plants, reducing costs and improving the time required to build new power plants (Eash-Gates et al., 2020). Therefore, with the help of the proposed DSM model, a power plant with maximum efficiency will be designed, which has many advantages.

The following is a review of the paper related to hybrid RSM methods and research conducted in the field of power plants. Then the research gap is presented. In the next section, the process of the proposed DSM model is described and interpreted. In the fifth section, 14 power plants in Iran are considered to study the application of the proposed method. In the sixth part of the paper, the model validation is done through the method of optimisation of response surfaces, goal planning and goal attainment method and the conclusion will be presented at the end.

2 Literature review

Table 1 is presented in order to review the papers related to the hybrid methods. As can be seen, the RSM method is combined with various tools such as neural network, genetic algorithm, PSO, NSGA-II and etc. Despite the practicality of both DEA and RSM tools, few methods have been proposed in the field of combining these two methods. Also, according to Table 2, the RSM method has been used in various fields such as Facility location, supply chain system, bank branches efficiency and etc.

Table 1 A review of previous papers on hybrid RSM methods and its applications

No.	*Author (year)*	*Problem*	*Method*
1	Giddings et al. (2001)	Facility location problems	RSM
2	Anjum et al. (1997)	Optimise the parameters of a process	Neural Network and RSM
3	Yahya et al. (2020)	Optimisation of hydrogen production	ANN coupled GA and RSM
4	Anarghya et al. (2018)	Thrust and torque force analysis	RSM and MLPNN-GA
5	Li et al. (2019)	Multi-objective optimisation of the fibre-reinforced composite injection moulding process	Taguchi method, RSM, and NSGA-II
6	Chau et al. (2019)	Multi-objective optimisation design for a compliant rotary joint for upper limb assistive device	FEA-based RSM and PSO algorithm
7	Gansterer et al. (2014)	Setting production planning parameters	VNS with RSM
8	Kim et al. (2002)	Modelling and optimisation of a GMA welding process	GA and RSM
9	Ghazali et al. (2018)	Optimisation of crystal violet adsorption onto date palm leaves	RSM and ACO
10	Eswari et al. (2016)	Optimum culture medium composition	RSM and ACO
11	Tsai et al. (2010)	Optimisation of multiple responses	DEA and RSM

Table 1 A review of previous papers on hybrid RSM methods and its applications (continued)

No.	*Author (year)*	*Problem*	*Method*
12	Yousefzadeh et al. (2020)	Comparative analysis of hydrometallurgical methods for the recovery of Cu from circuit boards	fuzzy AHP-TOPSIS and RSM
13	Santhanakumar et al. (2017)	Optimising the micro WEDM parameters	TOPSIS and RSM
14	Wang et al. (2015)	MCDM problems with interval numbers	TOPSIS and RSM
15	Gok (2015)	Surface roughness and cutting force	fuzzy TOPSIS, multi-objective grey design and RSA
16	Bagal et al. (2019)	MCDM optimisation of parameters for wire-EDM machined stainless steel	RSM-TOPSIS, genetic algorithm and simulated annealing
17	Shang et al. (2004)	Operational design of a supply chain system	Taguchi method, response surface methodology, simulation, and optimisation
18	Anjum et al. (1997)	Multi-objective problems	COA and DEA
19	Akbarzadeh and Shadkam (2015)	Production planning problem	COA and DEA
20	Akbarzadeh and Shadkam (2015)	The optimisation of bank branches efficiency	RSM and DEA
21	Gorjestani et al. (2015)	Multi-objective problems	COA and DEA
22	Shadkam and Bijari (2017)	Selection and determination of order quantity in supplier selection problem under uncertainty and quality criteria	GDEA, RSM, COA and simulation
23	Borhanifar and Shadkam (2016)	Multi-objective problems	COA and SAW
24	Shadkam and Jahani (2015)	Multi-objective problems	COA and ε constraint
25	Shadkam (2014)	Portfolio selection of Tehran's stock market	Factor analysis and clustering
26	Reddy et al. (2020)	Mathematical modelling for prediction of tube hydroforming process	RSM and ANN
27	Singh et al. (2012)	Modelling and optimisation of electro-discharge diamond face grinding	Taguchi methodology, RSM and with material removal rate (MRR)
28	Kumar et al. (2018)	WEDM of Nimonic-90: a nickel-based super alloy	GA-based optimisation using RSM
29	Naghiha et al. (2019)	Evaluation and ranking of production methods in industrial environments	An integrated AHP-DEA methodology

Various researches have been done in the field of RSM use. The paper of Moslemi and Shafiee (2020), in order to model a multistage problem, the global criterion (GC) method is used to optimise the estimated response surfaces by a robust approach in the optimisation phase. In this paper, Wang et al. (2020), a new Bayesian model and optimisation for multi-response surfaces are proposed. Also, it has been shown that Bayesian SUR models can provide a more flexible and accurate model than standard multivariate regression models. In the paper of Moslemi and Shafiee (2020) examined the use of RSM in a multi-step process, which is one of the most efficient statistical approaches to this type of problem. However, it is necessary to optimise each answer in all steps to find the best solution for achieving the whole problem and robust optimisation can be very useful here.

Table 2 Papers related to the efficiency of power plants

NO.	*Author (year)*	*Problem*	*Method*
1	Cook and Green (2005)	Evaluating power plant efficiency	DEA and hierarchical model
2	Cook and Zhu (2007)	An analysis of power plant efficiency	Group common weights in DEA
3	Nwaoha et al. (2018)	Process simulation and parametric sensitivity study	MEA–DEA blend
4	Khanjarpanah et al. (2018)	Sustainable location optimisation of hybrid wind-photovoltaic power plant	multi-period double frontier network DEA
5	Sueyoshi and Goto (2015)	nuclear power plant	DEA
6	Şeyma et al. (2019)	Efficiency Assessment of Hydroelectric Power Plant	DEA
7	Tsolas (2020)	Procurement and Construction (EPC) Power Plant Projects	Series Two-Stage DEA
8	Sueyoshi and Goto (2011)	Assessment of Japanese fossil fuel power generation	DEA
9	Liu et al. (2010)	Evaluation of thermal power plant operational performance	DEA

To evaluate efficiency, variables are needed that can provide the correct result of the performance of DMUs. The selection of input and output variables is one of the most important steps in evaluating the efficiency of power plants by DEA. If the required variables are not selected correctly, the evaluation results are invalid (Amin and Hajjami, 2020). For this purpose, various papers on the efficiency of power plants have been reviewed, the results of which are shown in Table 2. There are many papers on the efficiency of power plants. In the paper of Khodadadipour et al. (2021), the performance of 32 thermal power plants is evaluated using a proposed model. The proposed model is based on input-oriented DEA model with undesirable outputs and is called the Expected Ranking Criterion.

Table 3 An overview of the inputs and outputs considered in power plant research

NO.	*Author (year)*	*Problem*	*Input (x)*	*Output (y)*
1	Wang et al. (2019)	Chinese coal-fired power plants	1 Capital 2 Fuel 3 Labour	1. Electricity generation
2	Wu et al. (2019)	Energy and environmental efficiency measurement	1 Capital 2 Labour 3 Coal 4 Oil 5 Gas	1 Volatile hydroxy-benzene 2 Cyanide 3 COD 4 Petroleum 5 Ammonia-nitrogen 6 Gross industrial output value
3	Mahmoudi et al. (2019)	Performance evaluation of thermal power plants considering CO_2 emission	1 Generation capacity 2 The total hours of operation 3 The internal consuming 4 The fuel consumption 5 The number of non-operational employees 6 The number of operational employees 7 The cost of generated power 8 The total cost of training	1 The total revenue 2 The total amount of electricity generated 3 CO_2 emission
4	Khalili-Damghani et al. (2015)	Combined cycle power plant performance assessment	1 Fuel	1 Electricity power 2 NO_x 3 SO_2 4 CO_2 5 SO_3
5	Sueyoshi and Goto (2011)	Unified efficiency measurement	1 Generation capacity 2 Number of employees 3 Coal 4 Oil 5 LNG	1 Generation 2 CO_2 emission

Also, various papers in terms of inputs and outputs to calculate the efficiency are presented in Table 3, which these inputs and outputs will be used according to the opinions of power plant engineers and available information to implement the proposed method.

3 Research gap

As mentioned in the previous sections, optimising problems with several response surfaces are very complex and difficult, and several methods have been proposed in the field of optimising such problems that have advantages and disadvantages. In this paper, the combined DSM method, which is a combination of two DEA and RSM methods, is presented to solve these problems. In the proposed method, due to the use of only one surface instead of the output response surfaces, optimisation is done easily and there is no need to use multi-objective problem solving methods and after creating an efficiency surface, the problem can be solved with single-objective optimisation methods.

As shown in Table 1, so far limited methods of combining DEA and RSM have been developed, while both of these methods are among the most practical and desirable optimisation tools. On the other hand, in the limited methods that are made from the combination of these two tools, so far it has not been used to solve problems with several response surfaces. Therefore, in the proposed approach, it simultaneously uses the advantages of both of these methods to optimise multi-surface response problems. Another advantage of the proposed method is the maximisation of efficiency in addition to the optimisation of problem parameters, which is not used in any of the multi-response optimisation methods. That is, the parameters of the system are determined in such a way that in addition to the optimality of the system will also lead to its high efficiency.

Given that the electricity industry is very vital and fundamental in a country, the use of appropriate methods in the field of power plant design is strongly felt. Therefore, in this paper, the proposed method is used to design an ideal power plant and the power plant parameters are determined in such a way that the power plant has maximum efficiency. It is worth mentioning that so far, the two methods of RSM and DEA have not been used in combination to evaluate the performance of power plants.

4 The proposed DSM method

In this research, the DSM hybrid method is presented to solve multi-surfaces optimisation problems. The proposed model is a combination of DEA and RSM. The main advantage of the DSM is that it creates a single response surface instead of optimising multiple surfaces for each of the output or objective functions. And that in addition to optimising the problem, efficiency is maximised simultaneously. The general process for the proposed DSM algorithm is shown in Figure 1. Also, the pseudo-code of this method is shown in Figure 2.

Figure 1 The process of the proposed DSM method

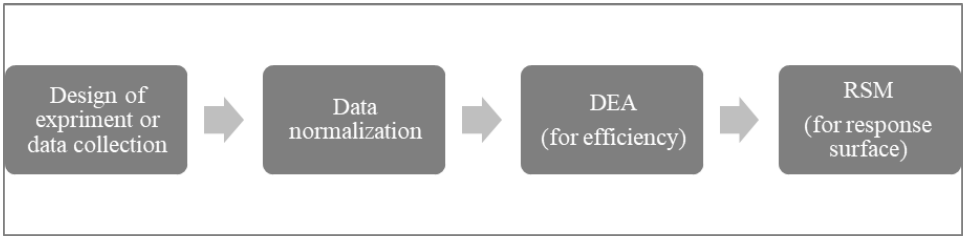


Figure 2 The pseudo-code for DSM method

1. Design of experiment or data collection: Control factors and response variables of problem are determined.

2. Data normalization: To reduce the effect of different scales on the data, the collected data have been normalized.

3. Determination of efficiency for each experiment by DEA: Using the input and output values of the step 2, the efficiency value of each experiment is calculated.

4. Making efficiency surface by RSM: using the input values of step 2 and the efficiency values obtained from step 3, an efficient surface is created using the RSM.

5. Calculate optimal inputs: The optimal values of input variables or control factors are obtained.

6. Calculate optimal outputs: The optimal values of outputs variables or responses are obtained.

Control factors and response variables are determined by previous research and expert opinion for DMUs. Each DMU considers as an experiment. Depending on the type of data, it can also be collected through the design of experiments. To reduce the effect of different scales on the data, the collected data have been normalised. In this study, the Euclidean norm in equation (1) is used.

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

Using the input and output values, the efficiency value of each experiment is calculated. There are several models for DEA. In this research, the CCR method, which is the most basic method in this field, has been used (model 2).

$$\begin{aligned} &\max E_u = \frac{\sum_j u_y O_{ty}}{\sum_x u_x I_{tx}} \\ &\text{S.t.} \\ &\frac{\sum_y u_y O_{wy}}{\sum_x y_x I_{wx}} < 1 \\ &w = 1, \ldots, L, u_y > 0, u_x > 0 \end{aligned} \tag{2}$$

Using the input values and the efficiency values, an efficient surface is created using the RSM. One of the advantages of the proposed method is that instead of generating multiple response surfaces for the outputs separately, an efficiency surface is provided. In fact, the efficiency surface replaces the output response surfaces, and to find the optimal level of control variables, there is no need to optimise the output surfaces, and only optimising the efficiency surface is sufficient [equation (3)].

$$\max \text{ efficiency} = f(x) \tag{3}$$

According to the efficiency surface obtained, optimisation is done and the optimal values of input variables or control factors are obtained. In order to obtain the corresponding values for the optimal outputs, the response surface of each output is created and the optimal values of the inputs are placed in these equations and the values of the optimal outputs are obtained.

5 Implementation of DSM model in Iran power plants

In order to evaluate the performance of the proposed DSM method, data of 14 power plants in Iran have been collected. In order to determine the efficient power plant as well as to determine the optimal parameters (inputs and outputs) to create an ideal power plant, the proposed method is implemented according to the steps of Figure 3.

Step 1 *Design of experiment or data collection:* the selection of problem variables has been done with the help of similar previous researches and with the opinion of power plant engineers. Problem inputs include the number of generators, number of personnel, annual fuel consumption (m^3/h), and outputs include thermal efficiency, nominal power, and net electricity generation. The inputs and outputs shown in Table 4 are related to different cities in Iran, which were collected in 2020.

Step 2 Data normalisation: to reduce the effect of different scales on the data, the collected data have been normalised by Euclidean norm.

Step 3 Determination of efficiency for each experiment by DEA: each power plant has been considered as a DMU and the efficiency of each unit using the data from step 2 and the CCR model is calculated. Efficiency values are shown in the last column of Table 4.

Step 4 Making efficiency surface by RSM: in this step, a surface for efficiency is constructed using the information of Table 4. The efficiency surface is shown in Figure 4 and the objective function of model 4. Surfaces are created using Minitab software.

$$\begin{aligned}
&\max e = -0.64 - 136.049x_1 + 87.0675x_2 + 47.1746x_3 - 367.41x_1^2 + 10.0824x_2^2 \\
&\qquad + 57.1776x_3^2 + 482.74x_1x_2 + 539.83x_1x_3 - 709.644x_2x_3 \\
&0 \le 0.64 - 136.049x_1 + 87.0675x_2 + 47.1746x_3 - 367.41x_1^2 + 10.0824x_2^2 \\
&\quad + 482.74x_1x_2 + 539.83x_1x_3 - 709.644x_2x_3 \le 1 \\
&0 \le x_i \le 1, \qquad i = 1, 2, 3
\end{aligned} \tag{4}$$

In model 4, the objective function is related to the efficiency surface of Figure 4, and the first constraint states that the value of the objective function should be between zero and one, given that it is related to efficiency, and the second constraint is related to the boundaries of input variables that are in the range of zero to one due to normalisation.

Figure 3 Flowchart of the implementation of the proposed DSM method in power plants

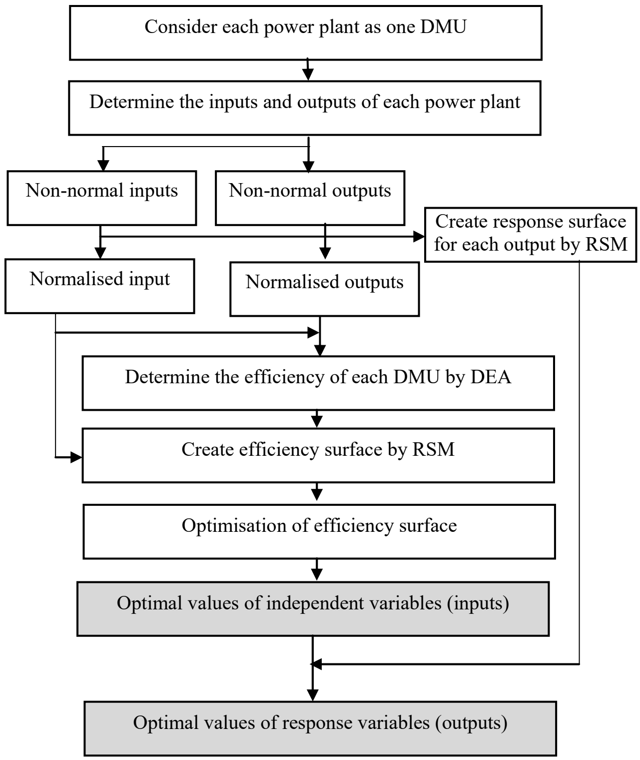
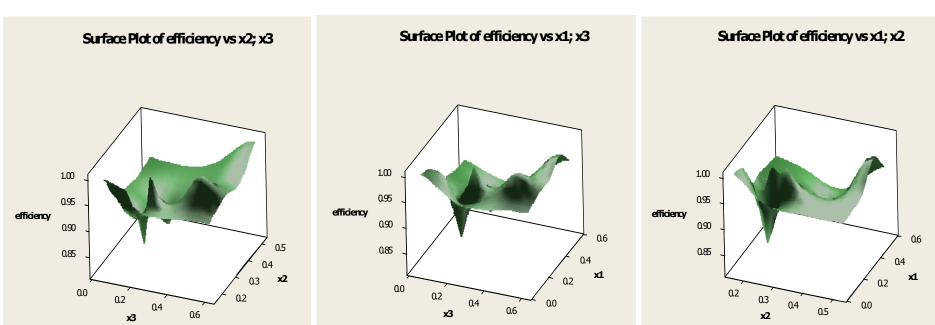


Figure 4 Efficiency surfaces for the power plant problem, (a) the number of personnel (x_2) and the amount of annual fuel consumption (x_3) (b) the number of generators (x_1) and annual fuel consumption (x_3) (c) the variables number of generators (x_1) and number of personnel (x_2) (see online version for colours)



(a) (b) (c)

Table 4 Inputs and outputs of power plants

Number of power plant	*City*	*Input*			*Output*			*Efficiency*
		Number of generators	*Number of personnel*	*Annual fuel consumption (m^3/h)*	*Thermal efficiency*	*Nominal power*	*Net electricity generation*	
1	Kerman	4	6	15,600,000	0.48	1,940	46,800,000	0.8188921
2	Mazandaran	5	6	19,500,000	0.48	1,940	62,400,000	1
3	Tehran	3	4	5,850,000	0.85	1,166	19,890,000	1
4	Yazd	3	4	11,700,000	0.48	1,948	39,780,000	1
5	Tehran	7	6	13,650,000	0.65	1,166	49,140,000	0.9250875
6	Saveh	5	7	39,000,000	0.75	4,000	124,800,000	1
7	Mashhad	2	4	5,850,000	0.53	1,948	21,060,000	1
8	Gonabad	1	4	3,900,000	0.48	2,000	12,480,000	1
9	Tehran	6	5	11,700,000	0.7	1,025	37,440,000	0.8983169
10	Tehran	6	5	11,700,000	0.7	1,025	39,780,000	0.9402765
11	Tehran	10	9	19,500,000	0.66	1,025	66,300,000	0.8596844
12	Tehran	10	13	48,750,000	0.75	1,025	175,500,000	1
13	Tehran	13	9	25,350,000	0.75	1,025	86,190,000	0.8921030
14	Tehran	2	4	5,850,000	0.53	1,948	19,890,000	0.99999998

Step 5 *Calculate optimal input:* to find the optimal power plant parameters, model 4 is optimised using Lingo software. The results obtained from optimising model 4 are shown in Table 5. Since the solutions are normal, they are converted to non-normal data in order to generate real solutions. According to the non-normal data, in order to create an ideal power plant, the maximum number of generators is 11, the maximum number of personnel is 12. Also, 35905193.65 (m3/h) of annual fuel has been consumed.

Table 5 The optimal values of power plant inputs

Independent variables	*Optimal value (normal)*	*Optimal value (non-normal)*
X_1	0.463614	11.19414065
X_2	0.510146	12.68201613
X_3	0.453845	35,905,193.65

Step 6 *Calculate optimal outputs:* to determine the optimal output values for the ideal power plant, a surface must be created for each output. Then enter the values of the inputs calculated in the previous step in these surfaces. Output surfaces, such as Step 4, are created with the Minitab software, except that the data used is non-normal. The response surfaces of each output are determined according to equations (5), (6), and (7) for Y_1, Y_2 and Y_3, respectively. These response surfaces are plotted in Figures 5, 6, and 7. As can be seen, the relevant surfaces have a complex shape and due to the existence of multiple local solutions, it is very difficult to optimise and find the optimal solutions for these surfaces.

$$\begin{aligned} Y_1 = & -0.669262 - 0.0347364x_1 + 0.165617x_2 - 5.43169\times10^{-15}x_3 \\ & -3.13729\times10^{-4}x_1^2 + 0.00536442x_2^2 + 5.86903\times10^{-31}x_3^2 + 0.00309932x_1x_2 \\ & -1.08497\times10^{-16}x_1x_3 + 2.37742\times10^{-16}x_2x_3 \end{aligned} \tag{5}$$

$$\begin{aligned} Y_2 = & 814.751 - 139.670x_1 + 160.006x_2 - 5.16092\times10^{-12}x_3 + 0.914678x_1^2 \\ & -3.68395x_2^2 + 1.85939\times10^{-27}x_3^2 + 2.16228x_1x_2 - 1.78126\times10^{-13}x_1x_3 \\ & +9.21560\times10^{-14}x_2x_3 \end{aligned} \tag{6}$$

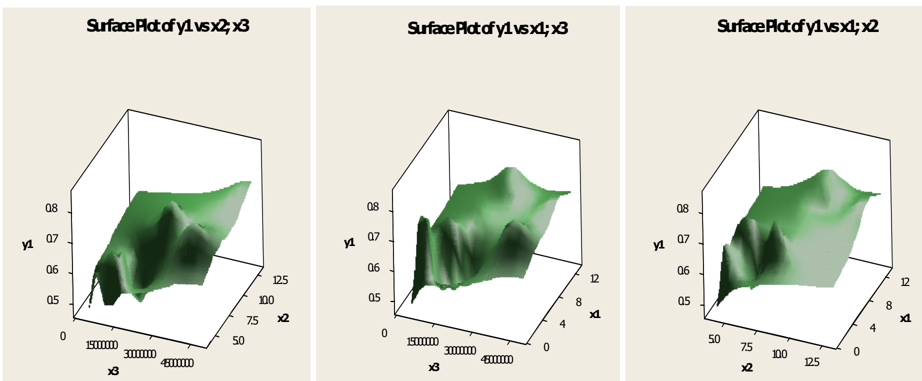
$$\begin{aligned} Y_3 = & 5{,}867{,}973 - 45{,}119x_1 + 936{,}437x_2 + 7.54920\times10^{-8}x_3 - 14{,}718.2x_1^2 \\ & -56{,}639.0x_2^2 - 6.02936\times10^{-24}x_3^2 + 52{,}509.8x_1x_2 + 4.87881\times10^{-12}x_1x_3 \\ & +1.99248\times10^{-9}x_2x_3 \end{aligned} \tag{7}$$

The values of the inputs obtained from step 5 are placed in the response surfaces (5, 6 and 7), and the optimal values of the outputs are calculated according to Table 6. To have an ideal power plant, the value of thermal efficiency is 0.58, the nominal power is 1,109 and the net electricity generation is 9,194,294.

Table 6 The optimal values of power plant outputs

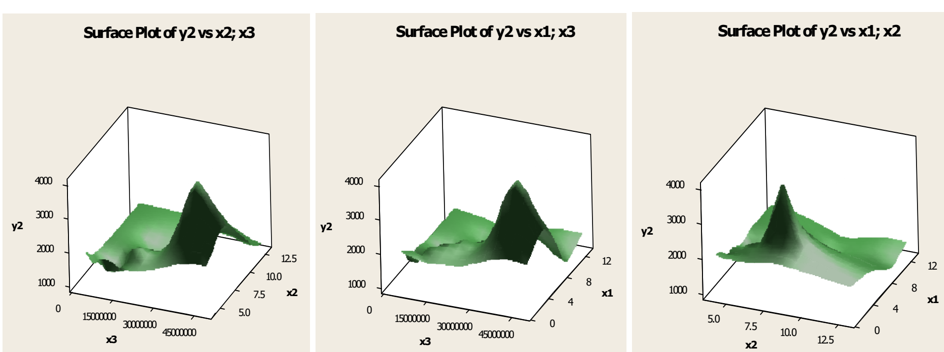
Response variables	*Optimal value*
Y_1	0.58015
Y_2	1,109.545
Y_3	9,194,294

Figure 5 First response surface (the relation between thermal efficiency and inputs), (a) the number of personnel (x_2) and the amount of annual fuel consumption (x_3) (b) the number of generators (x_1) and annual fuel consumption (x_3) (c) the number of generators (x_1) and number of personnel (x_2) (see online version for colours)



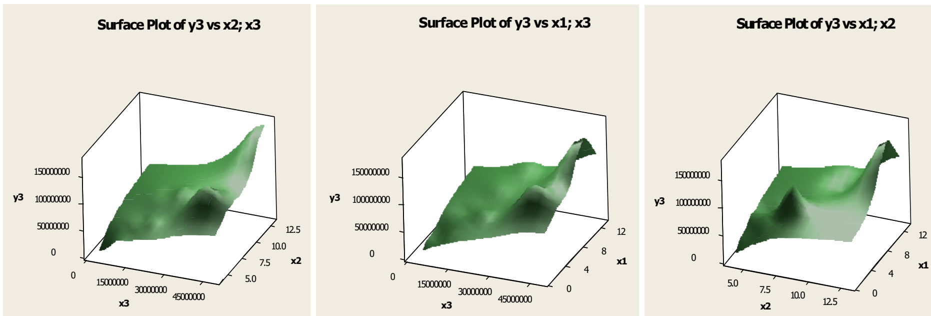
(a) (b) (c)

Figure 6 Second response surface (the relation between nominal power and inputs), (a) the number of personnel (x_2) and the amount of annual fuel consumption (x_3) (b) the number of generators (x_1) and annual fuel consumption (x_3) (c) the variables number of generators (x_1) and number of personnel (x_2) (see online version for colours)



(a) (b) (c)

Figure 7 Third response surface (the relation between net electricity generation and inputs), (a) the number of personnel (x_2) and the amount of annual fuel consumption (x_3) (b) the number of generators (x_1) and annual fuel consumption (x_3) (c) the variables number of generators (x_1) and number of personnel (x_2) (see online version for colours)



(a) (b) (c)

6 Validation of the proposed DSM model

In order to validate the DSM model, three approaches are discussed below. In the first approach, each output response surface is optimised separately. In the second approach, the goal programming method is used to optimise the data, and in the third approach, the goal attainment method is implemented.

6.1 Validation by optimising each response surfaces separately

This approach consists of three steps as follows.

6.1.1 Step 1 (optimise response surface)

In this step, the generated response surfaces for each output [equations (5), (6) and (7)[are optimised separately with the help of Lingo software and the optimal values of the independent variables are placed in the other two response surfaces. For example, after optimising the Y_1 response surface, the values X_1, X_2, X_3 are placed in the Y_2 and Y_3 response surfaces. This step is done in the same way for all three response surfaces. The purpose of this step is to find optimal input and output data for the efficient virtual power plants according to Table 7. DMUs 1, 2 and 3 are the results of the optimisation of response surfaces Y_1, Y_2 and Y_3, respectively, and DMU_4 represents the virtual power plant by the DSM method.

Table 7 The values of inputs and outputs of virtual power plant (non-normal)

DMU	*Response surface*	X_1	X_2	X_3	Y_1	Y_2	Y_3
1	Response 1 (Y_1)	0	1	0.99455	0.509009	971.0731	6,334,404
2	Response 2 (Y_2)	1	0	0.836738	–0.70431	674.9957	5,402,096
3	Response 3 (Y_3)	1	0	0.021055	–0.70431	675.9957	5,402,095
4	DSM (efficiency)	0.463614	0.510146	0.453845	0.58015	1,109.454	9,194,294

6.1.2 Step 2 (data normalisation)

As mentioned earlier, in order to reduce the effect of different data scales, the results obtained in Table 7 are converted to the normal data in Table 8. Also, all input data is normal and does not need to be normalised again. And the negative values in Table 7 mean very small values. For this reason, in order to have better results, zero is replaced by negative values.

Table 8 The values of inputs and outputs of virtual power plant (normal) by approach 1

DMU	X_1	X_2	X_3	Y_1	Y_2	Y_3	*Efficiency*
1	0	1	0.99455	0.509009	0.552741	0.468221	0.8648×10^{-7}
2	1	0	0.836738	0	0.384212	0.399307	0.5676×10^{-7}
3	1	0	0.021055	0	0.384781	0.399307	0.5683×10^{-7}
4	0.463614	0.510146	0.453845	0.58015	0.631508	0.679615	1

6.1.3 Step 3 (calculate efficiency with DEA)

The efficiency values of the four virtual power plant units created from Table 8 are calculated using the CCR model with Lingo software according to the last column of Table 8. As shown, the three virtual power plants created by the first validation approach are inefficient. While the power plant by DSM method has maximum efficiency.

6.2 Validation using the goal programming

The goal planning method is one of the famous and practical methods in the field of multi-objective problems. This method has been used in various problems and has shown its superiority (Kumar and Srinivas, 2021; Akbari et al., 2020; Uddin et al., 2021). For more information about this method, you can refer to Romero (2014).

The power plant problem is modelled as a three-objective (surface) model 8. The objective functions are related to the response surface of each problem outputs [equations (5), (6) and (7)]. Boundary constraints are also created with respect to the minimum and maximum values of the problem inputs.

$$\begin{aligned}
&\max\{Y_1, Y_2, Y_3\} \\
&\text{s.t.} \\
&0 \le X_1 \le 13 \\
&0 \le X_2 \le 13 \\
&0 \le X_3 \le 48{,}750{,}000
\end{aligned} \tag{8}$$

After implementing the goal programming approach on model 8, model 9 is created. The objective function includes deviant variables (positive and negative) of the ideal values. Constraints are also created according to the goal programming approach. The first three constraints are related to the goal values of the three objective functions of the problem, and the goal values are extracted from Table 4 with respect to the maximum output values (0.85, 4,000 and 175,500,000). This model is solved with Lingo software and the results are shown in Table 9.

$$\begin{aligned}
&\min = d_1^- + d_2^- + d_3^- + d_4^+ + d_5^+ + d_6^+ \\
&\text{s.t.} \\
&-0.669262 - 0.0347364x_1 + 0.165617x_2 - 5.43169\times10^{-15}x_3 - 3.13729\times10^{-4}x_1^2 \\
&\quad + 0.00536442x_2^2 + 5.86903\times10^{-31}x_3^2 + 0.00309932x_1x_2 - 1.08497\times10^{-16}x_1x_3 \\
&\quad + 2.37742\times10^{-16}x_2x_3 - d_1^+ + d_1^- = 0.85 \\
&814.751 - 139.670x_1 + 160.006x_2 - 5.16092\times10^{-12}x_3 + 0.914678x_1^2 - 3.68395x_2^2 \\
&\quad + 1.85939\times10^{-27}x_3^2 + 2.16228x_1x_2 - 1.78126\times10^{-13}x_1x_3 + 9.21560\times10^{-14}x_2x_3 \\
&\quad - d_2^+ + d_2^- = 4{,}000 \\
&5{,}867{,}973 - 451{,}159x_1 + 936{,}437x_2 + 7.54920\times10^{-8}x_3 - 14{,}718.2x_1^2 - 56{,}639.0x_2^2 \\
&\quad - 6.02936\times10^{-24}x_3^2 + 52{,}509.8x_1x_2 + 4.87881\times10^{-12}x_1x_3 + 1.99248\times10^{-9}x_2x_3 \\
&\quad - d_3^+ + d_3^- = 175{,}500{,}000 \\
&x_1 + d_4^- - d_4^+ = 13 \\
&x_2 + d_5^- - d_5^+ = 13 \\
&x_3 + d_6^- - d_6^+ = 48{,}750{,}000 \\
&d_i^- \ge 0,\ d_i^+ \ge 0, \qquad i = 1, \ldots, 6
\end{aligned} \tag{9}$$

Table 9 The values of inputs and outputs of virtual power plant by approach 2

No.	*Input*	*X*	*Output*	*Y*
1	Number of generators	0	Thermal efficiency	0.3332
2	Number of staff	8.267591	Nominal power	1,885.806
3	Annual fuel consumption	48,750,000	Net electricity generation	9,738,607

6.3 Validation using the goal attainment method

The goal attainment method is one of the basic methods of multi-criteria decision making that has been used in different problems (Rahmani and Amjady, 2019; Krasny-Pacini et al., 2017; van Blijswijk et al., 2021) and can refer to Kiresuk et al. (2014) for more information about this method. Formulation of the goal attainment method for power plant data is done as model 10, and is optimised with Lingo software. In this model, λ represents the deviation variable that must be minimised. Given that all three objective functions are of equal importance to the decision-maker, the deviation coefficients from the goal value are 0.3, 0.3, and 0.4 for the first, second and third objective functions, respectively, in the constraints. Also, the values of 0.85, 4,000 and 175,500,000 in the right side of the first three constraints represent the goal values for the objective functions of the problem, which were determined according to the maximum values of the problem outputs. The values 13, 13 and 48,750,000 on the right side of the last three constraints of the problem are also the maximum values of the problem inputs, which are extracted from Table 4. Table 10 shows the results of model 10 optimisation.

$$\begin{aligned}
&\min \lambda \\
&\text{s.t.} \\
&-0.669262 - 0.0347364 x_1 + 0.165617 x_2 - 5.43169\times 10^{-15} x_3 \\
&\quad - 3.13729\times 10^{-4} x_1^2 + 0.00536442 x_2^2 + 5.86903\times 10^{-31} x_3^2 \\
&\quad + 0.00309932 x_1 x_2 - 1.08497\times 10^{-16} x_1 x_3 \\
&\quad + 2.37742\times 10^{-16} x_2 x_3 + 0.3 \ge 0.85 \\
&814.751 - 139.670 x_1 + 160.006 x_2 - 5.16092\times 10^{-12} x_3 + 0.914678 x_1^2 \\
&\quad - 3.68395 x_2^2 + 1.85939\times 10^{-27} x_3^2 + 2.16228 x_1 x_2 - 1.78126\times 10^{-13} x_1 x_3 \\
&\quad + 9.21560\times 10^{-14} x_2 x_3 + 0.3z \ge 4{,}000 \\
&5{,}867{,}973 - 451{,}159 x_1 + 936437 x_2 + 7.54920\times 10^{-8} x_3 - 14{,}718.2 x_1^2 \\
&\quad - 56{,}639.0 x_2^2 - 6.02936\times 10^{-24} x_3^2 + 52{,}509.8 x_1 x_2 + 4.87881\times 10^{-12} x_1 x_3 \\
&\quad + 1.99248\times 10^{-9} x_2 x_3 + 0.4z \ge 175{,}500{,}000 \\
&x_1 \le 13 \\
&x_2 \le 13 \\
&x_3 \le 48{,}750{,}000 \\
&x_1, x_2, x_3, \lambda \ge 0
\end{aligned} \tag{10}$$

Table 10 The input and output of goal attainment method

No.	*Input*	*X*	*Output*	*Y*
1	Number of generators	0	Heat efficiency	0.33325
2	Number of staff	8.266716	Nominal power	1,885.72
3	Annual fuel consumption	48,750,000	Net electricity generation rate	9,738,607

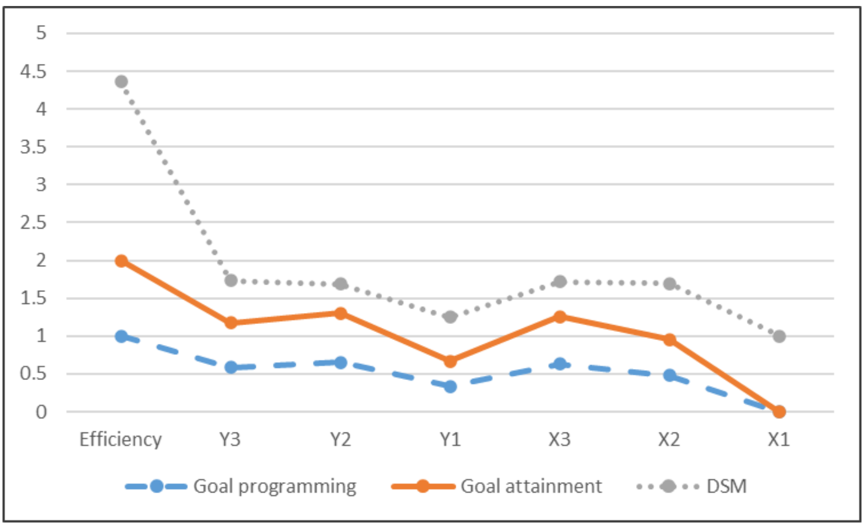
6.4 Comparison between the results of different approaches

The results of the second and third validation approaches are normalised in Table 11. The results of each approach are considered as a virtual power plant unit. It is then placed beside the data of 14 real power plants and the efficiency values for all units are calculated. The resulting efficiency values are shown in the last column of Table 11. For better ranking and separation of approaches, each unit is allowed to receive an efficiency value greater than 1. As can be seen, the DSM method has a higher efficiency than the other two approaches. Therefore, building an ideal power plant with the DSM method is more desirable than similar methods. In order to build this power plant, its design parameters are in accordance with Tables 5 and 6. For better comparison, the results obtained from the second, third and DSM approaches are plotted in Figure 8. As can be seen, the three methods are not very different in terms of resource consumption, while the efficiency of the proposed method is much higher than the other two approaches. Therefore, with the use of DSM method, the maximum output and the highest efficiency can be achieved with the minimum use of resources and inputs.

Table 11 The comparison between the results of different approaches

DMU	*Method*	X_1	X_2	X_3	Y_1	Y_2	Y_3	*Efficiency*
1	Goal programming	0	0.479311	0.627153	0.3332	0.652872	0.588099	1.000044
2	Goal attainment	0	0.47926	0.627153	0.33325	0.652843	0.588099	1.000257
3	DSM	1	0.735235	0.461908	0.58015	0.384128	0.555229	2.363679

Figure 8 The comparison between the results of three approaches (see online version for colours)



7 Conclusions

The optimisation is an effective tool in systems analysis that includes various methods. In this study, the RSM method was used. The RSM uses regression equations to determine the relationship between inputs and outputs of a system. If the system has several response variables, the number of response level equations is equal to the responses and using these equations, the optimal value of inputs is determined.

In this paper, by combining DEA and RSM, a hybrid algorithm called DSM is presented in which a surface is considered for efficiency instead of multiple response surface for each output. One of the advantages of the DSM method is reducing the number of the response surfaces, and instead of optimising multiple response surfaces for each output, only efficiency surface optimisation is considered. In addition to optimising system parameters, it also maximises efficiency simultaneously. In order to validate the

DSM method, data related to 14 power plants in Iran were considered. The DSM method was implemented to find the optimal factors needed to establish a new power plant with the highest level of efficiency.

In order to compare the performance of the proposed method with similar methods, three approaches were used. In the first approach, each response surface was optimised separately. In the second approach, the goal programming method was used and in the third, the goal attainment method was used. In each of these approaches, an ideal virtual unit is created. According to the results obtained from the efficiency of three virtual power plant units of different approaches, the efficiency of the unit obtained from the DSM method is much higher than the other two units and shows the superiority of this method over the other two methods.

Due to the similarity of multi-surface to multi-objective, the proposed approach in this paper can be used for multi-objective optimisation problems. Therefore, one of the future researches can be the generalisation of the DSM method to multi-objective problems. Also, the DSM proposed method can be used for other problems such as supplier selection, production planning, etc.

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