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Response Surface Methodology for Modelling and Optimizing Efficiency in Deep Well Pumping Systems

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A B S T R A C T

This study presents research on modelling the efficiency and flow rate of deep well pumping facilities using the response surface method, evaluating the models, and assessing optimization based on target flow rate. Regression and variance analysis techniques have been successfully employed to evaluate the relationship between input factors (input pressure and power drawn from the grid) and responses (system efficiency and flow rate). ANOVA analysis has been used to examine the effects of linear and quadratic terms, and the results have shown that pressure and power drawn from the grid have a significant effect on pump system efficiency. Additionally, the performance of the regression models has been evaluated using error metrics such as R^2 value, RMSE, and MAPE. These values for the pumping facility system efficiency model were found to be 0.9993, 0.292%, and 0.71%, respectively, and for the flow rate model, they were 0.9997, 0.69 m^3h^{-1}, and 1.07%. The results obtained demonstrate that the model operates with high accuracy and explains a large part of the variance in the response variables. An optimization study was conducted to maximize pump system efficiency by maintaining the flow rate at a certain target value. According to the experimental results obtained, the target flow rate was predicted with an error rate of 1.49%, and the pump system efficiency was predicted with an error rate of 2.14%. This study highlights the effective use of various analytical and experimental methods to improve the efficiency of pump systems. Future researchers are encouraged to conduct similar analyses on a larger scale and under different operating conditions. Furthermore, evaluating different optimization strategies to improve the energy efficiency of pump systems, which can lead to significant energy savings in industrial applications, is recommended.

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Introduction

Deep well pumps are indispensable devices employed for the extraction of water and other fluids from significant depths, playing a crucial role in various industrial, agricultural, and environmental applications. These pumps are meticulously designed to function efficiently under challenging conditions, where the depth of the water source necessitates specialized extraction equipment. Deep well pumps are characterized by their ability to reach depths that exceed those achievable by standard pumps. They are suitable for applications where the water sources are deep underground (Michael & Voss, 2008). The design and performance of deep well pumps are critical in ensuring a reliable water supply and fluid extraction. Frequently exposed to high pressures and demanding operating conditions, these pumps require robust construction and efficient hydraulic performance. Optimizing the design of deep well pumps is essential to enhance their efficiency, durability, and overall performance (Gao et al., 2023).

The optimization of pump designs is of paramount importance in improving the efficiency and performance of various pump types. One effective method for achieving such optimization is the application of the Response Surface Method (RSM). RSM, a statistical technique, is utilized to model and analyze the relationship between input factors and output responses, thereby facilitating the identification of optimal operating conditions (Alawadhi et al., 2021). By integrating RSM with advanced simulation techniques such as 3D-RANS simulations, researchers can compute objective functions that are used to optimize pump geometries. This approach has proven particularly beneficial in designing centrifugal pumps for slurry transport and multistage pump impellers, with an emphasis on analyzing the relationship between structural parameters and performance (Alawadhi et al., 2021; Peng et al., 2021).

Moreover, the application of RSM in pump design has extended to the cooperative optimization of components such as impellers in multiphase pumps (Peng et al., 2021). By creating development of surrogate models based on numerical results using RSM, researchers have enhanced the hydraulic performance of high-speed magnetic drive pumps and achieved performance improvements in centrifugal slurry pumps (Abdolahnejad et al., 2022; Xu et al., 2022). Additionally, RSM has facilitated the optimization of sweep and blade lean for diffusers to suppress hub corner vortex in multistage pumps, demonstrating its versatility in addressing complex flow dynamics (Ning et al., 2021).

In conclusion, the integration of RSM in pump applications has proven to be a valuable tool for optimizing pump designs, improving performance, and reducing computational costs. By leveraging RSM alongside advanced simulation techniques, researchers have made significant advancements in pump technology, resulting in more efficient and reliable pump systems. However, while previous studies have predominantly focused on optimizing pump design parameters, there is a notable gap in research regarding the modeling and optimization of operational parameters in pumping plants (Alawadhi et al., 2021; Peng et al., 2021; Cheng et al., 2024). This study aims to fill this gap by modeling the efficiency of the pumping system and flow rate based on the pump outlet pressure and power drawn from the network using RSM. This approach is unique as it seeks to determine the most suitable operating conditions through regression analysis and optimization techniques, thereby enhancing the overall efficiency of pumping systems. This study distinguishes itself from existing literature by focusing not only on the design parameters but also on the operational parameters, providing a more comprehensive optimization strategy for pumping systems.

Materials and Methods

This study was carried out in the Deep Well Pump Test Tower (Figure 1) established within the scope of the project numbered TUBITAK 213O140 at Selçuk University, Faculty of Agriculture, Department of Agricultural Machinery and Technologies Engineering. The deep well was fed from the tank with 4" and 6" pipes from the top.

Gravel with a bulk density of 1.54 kg/m³ and a geometric diameter of 7-15 mm was placed around the 10cm wide well screen. In this way it has formed the environmental work of a deep well. Table 1 shows the technical specifications of the deep well submersible pump and submersible motor used in the present experiments. The technical specifications of the measuring instruments used in the present experiments are given in Table 2.

Software and an automated system were developed to record the measured values. A wireless communication card transmits the sensor data to a computer. The information stored in the central unit was entered into the software; under the operator's name, in the desired intervals. The recording process was designed to obtain data every second. Once 50 data points had been received from a sensor, recording was initiated after the pumping regime.

Flow rate (Q), outlet pressure (m), power drawn from the network (kW) and well drawdown (Δ) values were measured at 10 different valve openings at the optimum operating speed of the pump. Pump manometric head (Hm) value and pumping plant system efficiency (ηֽ) were calculated. All parameters were measured in triplicate at each valve opening. The EN ISO 9906 standard was used for the measurements and calculations of the pump operating characteristics.

Results and Discussion

General characteristics of the pumping plant

The average values of the general characteristic curves of the deep well pumping plant are presented in Figure 2. As the Q increased, the Hm value decreased, and the well drawdown level increased.

Table 1. Technical specifications for submersible pump and motor

Pump technical specifications	Pump	Submersible motor technical specifications	Submersible motor
Pump outside diameter (mm)	203.2	Brand	Watermot
Pump material (TSE EN 1591)	Cast iron	Volt (V)	380
Pump shaft material	Stainless steel	Amper (A)	13.6
Pump shaft diameter (mm)	30	Hz	50
Pump number of stages	1	rpm (l/min)	2780
Number of blades	6	Power (kW)	5.5
Blade thickness (mm)	5	Shaft diameter (mm)	25
Impeller outlet diameter (mm)	150	Cooling type	Water-cooler
Impeller outlet width (mm)	20	Cable cross-section	3x2.5 mm^2

Table 2. Technical specifications for measurement devices

Device	Technical specifications
Flow meter	S MAG 100 TİP, DN 125 flange connection electromagnetic flow meter, 220 V supplied digital indicator, instant flow, percent flow, total flow indicators. Adjustable 4-20 mA plus and frequency output. Measurement Range: 15-440 m³/h. Measurement error: ±0.5%.
Manometer	WİKA, 0-10 bar, Bottom installed, 4-20 mA output. Accuracy < ± 1 %
Water level meter	Hydrotechnik brand, 010 type/1,5 V, 150 m scaled cable, voice and light indicator type.
Temperature sensors	Turck brand, 10-24 VDC, -50...100 ^{0}C, 4-20mA output.
Computer	Asus intel core i7.

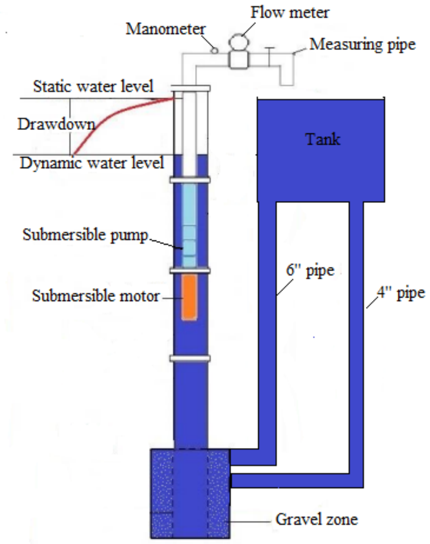

Figure 1. Deep Well Pump Test Tower

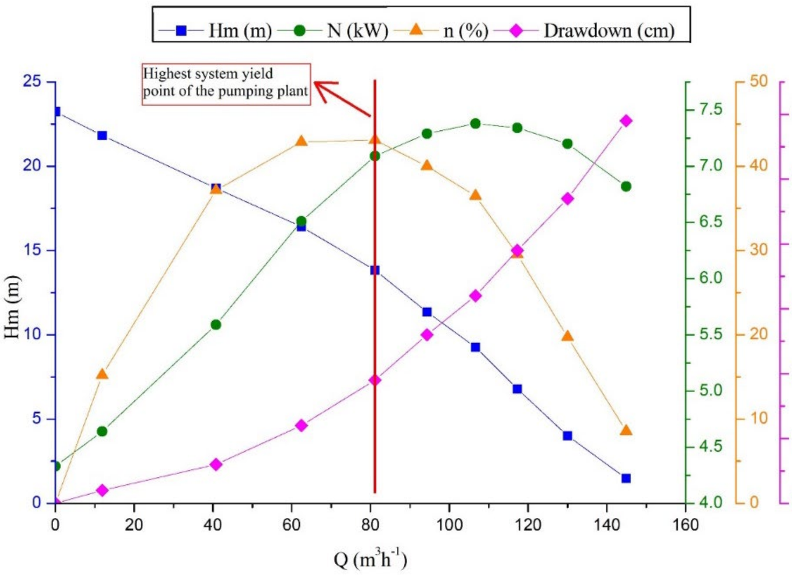

Figure 2. General characteristic curves of the pumping plant

Tablo 3. Experimental results related design table

Std Order	Run Order	Pt Type	Blocks	Pressure (bar)	Power (kW)	Pump system efficiently (%)	Flow (m^3 h^{-1})
11	1	0	1	2.05	4.66	15.21	11.88
9	2	0	1	2.02	4.62	15.29	11.88
2	3	1	1	1.51	6.51	42.87	62.45
8	4	-1	1	1.53	6.49	43.24	62.03
12	5	0	1	1.27	7.07	43.64	80.73
4	6	1	1	1.25	7.07	43.23	81.15
13	7	0	1	1.02	7.29	40.71	94.33
10	8	0	1	1.03	7.29	41.25	94.75
6	9	-1	1	0.79	7.38	36.47	106.65
3	10	1	1	0.77	7.38	35.24	105.38
1	11	1	1	0.77	7.38	35.38	105.80
5	12	-1	1	0.53	7.34	29.19	117.70
7	13	-1	1	0.53	7.34	29.19	117.70

Consequently, the power drawn from the network increased up to a flow rate of 108 m^3 h^{-1}. At the maximum efficiency point of the pumping plant, which is 43%, the Hm is 13.83 m (1.27 bar), the power drawn from the network is 7.09 kW, and the well drawdown level is 19 cm. These results are consistent with the general characteristics of pumping plants. Çalışır (2010); Doğan and Yağmur (2023); Orhan et al. (2012) reported similar results in their studies. These results show that Hm decreases with increasing Q, which is a general characteristic of the pump, and the pumping system efficiency increases up to a certain flow rate level and then decreases.

RSM Application in Pumping Plant

As a computational application for modelling and optimization, RSM is becoming increasingly popular within engineering (Uslu and Celik, 2020). The basic aim of this method is to determine the effects of various input factors on response parameters and to optimize them. RSM evaluate the relationship between input and output parameters and, optimize responses based on the input parameters. Specifically, RSM use the least squares method to evaluate significant factors, to achieving the desired results and optimize the interaction between the variables (Inayat et al., 2019; Kumar and Dinesha, 2018). This approach employs the least squares method to establish a relationship between input and output parameters, thereby optimizing the response based on the input factors.

In this study, RSM was employed to model pump system efficiency and flow as functions of outlet pressure and grid consumption across different pump system orifices. RSM begins by identifying an appropriate correlation between output and input parameters, utilizing a quadratic equation model for this correlation. The model is illustrated below (Uslu and Celik, 2020):

$$y= \beta_0 \sum_{i=1}^{k} \beta_1 x_1 + \sum_{i=1}^{k} \sum_{j\geq 1}^{k} \beta_{ij} x_i x_{j+} \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon \quad (1)$$

Where β is regression constant, k is the number of input parameters, i is the linear measurable quantity, j is the quadratic factor and ε is the random error, $X_1, X_2, \ldots\ldots, X_k$ are the input parameters and Y is the response.

Table 3 presents the design matrix along with the experimental data. In the RSM model, pressure and power were selected as input variables, while pump system efficiency and flow rate were chosen as output variables.

Table 4. Variance analysis of pump system efficiently values

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	1191.85	238.370	2231.2	0
Linear	2	225.27	112.637	1054.31	0
P	1	0.03	0.032	0.3	0.6
N	1	0.59	0.588	5.51	0.051
Square	2	1.97	0.985	9.22	0.011
P*P	1	1.85	1.848	17.29	0.004
N*N	1	1.01	1.014	9.49	0.018
2-Way Interaction	1	0.02	0.025	0.23	0.646
P*N	1	0.02	0.025	0.23	0.646
Error	7	0.75	0.107		
Lack-of-Fit	5	0.74	0.148	30.12	0.032
Pure Error	2	0.01	0.005		
Total	12	1192.6			

P: Pressure (bar), N: Power drawn from the mains (kW)

Table 5. Analysis of the variance of the flow rate values

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	15182.8	3036.57	5042.5	0
Linear	2	12288.3	6144.17	10203	0
P	1	6	5.95	9.89	0.016
N	1	3.6	3.61	5.99	0.044
Square	2	1.1	0.54	0.9	0.45
P*P	1	0.9	0.92	1.53	0.257
N*N	1	0	0.02	0.04	0.848
2-Way Interaction	1	0.2	0.15	0.26	0.628
P*N	1	0.2	0.15	0.26	0.628
Error	7	4.2	0.6		
Lack-of-Fit	5	4.1	0.83	18.72	0.051
Pure Error	2	0.1	0.04		
Total	12	15187.1			

P: Pressure (bar), N: Power drawn from the mains (kW)

ANOVA was utilized to identify significant relationships between input factors and responses. A higher F-value and a lower P-value indicate a the greater importance of each term in the proposed model for the response, with a P-value accepted as significant at 0.05 (Dana et al., 2020). As shown in Table 4, for the linear coefficients, the P-value for all variables is greater than 0.05. However, regarding the quadratic coefficients, the P-values for pressure and power drawn from the mains are less than 0.05. This indicates that pressure and power drawn from the mains have a significant impact on the efficiency of the pumping system.

In Table 5, the p-values for the linear coefficients of the pressure variable and power drawn from the mains are less than 0.05. Conversely, for the quadratic coefficients, all variables have p-values greater than 0.05. This indicates that the squared coefficients of the pressure variable and the power drawn from the grid have a significant effect on the flow rate.

RSM produces squares to estimate pump system efficiency and flow parameters based on input parameters as shown in Eqs. (2) and (3).

$$\eta_{system}=-147.2+36.3P+47.3N-17.31P\times P-3.57N\times N+1.88P\times N \quad (2)$$

$$Q=87-99.4P+4.3N+12.21P\times P+0.55N\times N+4.7P\times N \quad (3)$$

Where η_{system} is the system efficiency of the pumping plant, P is the pump outlet pressure, N is the power drawn from the grid and Q is the pump flow rate.

The model was assessed using the model the coefficient of determination R^2 value, root mean square error (RMSE), and mean absolute percentage error (MAPE). The R^2 value was employed to measure the performance of the model, as it indicates the percentage of variation in the response variable that can be explained by the independent variables (Shahhosseini et al., 2019). A stronger predictive relationship is indicated by a higher R^2 value. Conversely, RMSE and MAPE are used as error measures, with lower values indicating better model performance (Gültepe, 2019; Wang and Xu, 2004). The R^2 values of the pump system efficiency and flow rate models were calculated to be 0.9993 and 0.9997, respectively (Figure 3). The RMSE for the pump system efficiency (Figure 3a) and flow rate (Figure 3b) models were 0.29 (%) and 0.69 (m^3 h^{-1}), and the MAPE were 0.71 (%) and 1.07 (%), respectively. Considering these low error metrics, it can be concluded that the application of RSM to pump system efficiencies was highly successful.

Figure 4(a) presents the surface plot of pumping system efficiency as a function of pump pressure and power drawn from the grid. The efficiency of the pumping system increased up to a certain point with rising pump outlet pressure and power.

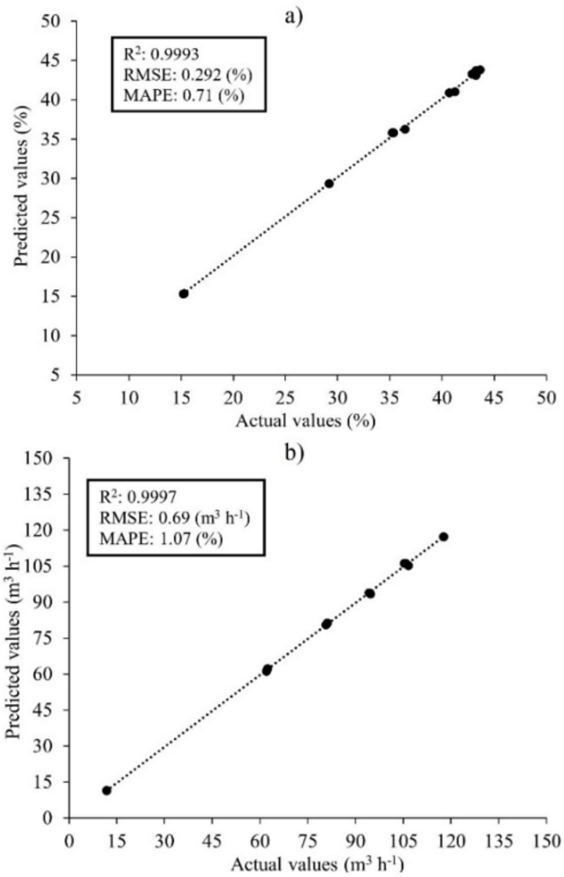

Figure 3. Comparison of actual and predicted values of pump system efficiency (a) and flow rate (b)

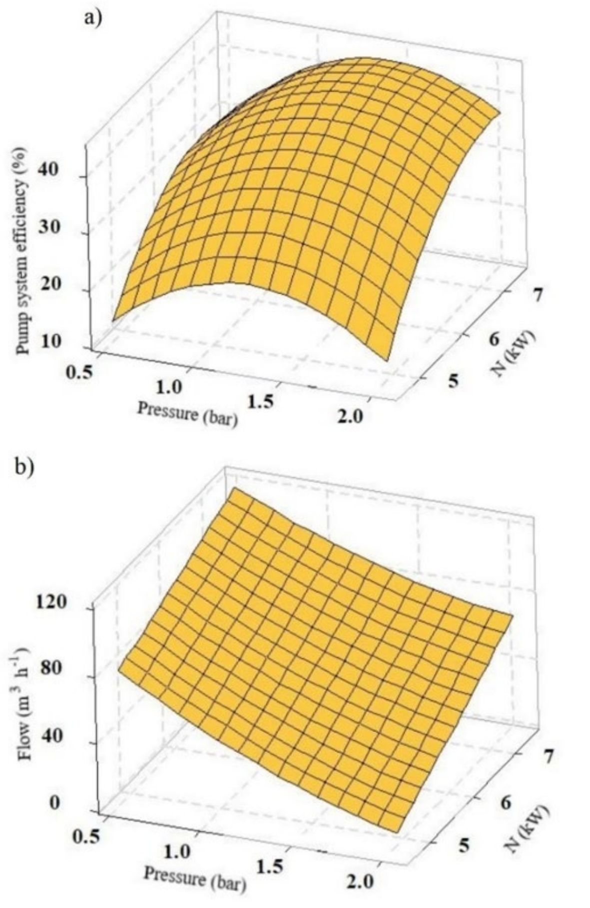

Figure 4. Effect of outlet pressure and power drawn from the mains on pump system efficiency (a) and flow (b)

Beyond this point, further increases resulted in a decrease in pump system efficiency. These trends, depicted in Figure 4(a) and Figure 4(b), are consistent with the general characteristics of pumps (Çalışır, 2010; Doğan and Yağmur, 2023; Korkmaz, 2015; Orhan et al., 2012).

The optimization graph is shown in Figure 5. In these graphs, a target value of 100 $m^3 h^{-1}$ was set for the flow rate while maximizing the pump system efficiency. The desirability (D) value represents the effectiveness of the input factors in achieving the desired objectives in the optimization process. As the combined desirability approaches 1, it indicates a strong alignment between the input factors and the overall goals, thereby highlighting the success of the optimization process (Aydın et al., 2020). In this study, the combined desirability value was found to be 0.92. The optimal RSM setting, where the target flow rate is 100 $m^3 h^{-1}$ and the pump system efficiency is maximized, corresponds to a pump outlet pressure of 1.09 bar and a power draw of 7.38 kW from the grid. In the experimental setup, the pump outlet pressure was set to 1.09 bar. The system was operated under these conditions, and the results are presented in Table 6. The average error values of the input parameters (P, N) and output parameters (Q, η), estimated by RSM and compared with the experimental results, were calculated as 0%, 1.89%, 1.49%, and 2.14%, respectively.

Conclusion

This study employed a variety of experimental and analytical methods to enhance the efficiency of a pumping system. Regression and analysis of variance (ANOVA) techniques were successfully utilized to assess the relationship between input variables and responses. ANOVA analysis examined the impacts of linear and quadratic terms, revealing significant effects of pressure and power drawn from the grid on pumping system efficiency. Furthermore, the performance of regression models was evaluated using R-squared (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE). The results demonstrated high accuracy of the models, with the independent variables explaining a substantial portion of the variance in response variables.

Optimization efforts aimed to maintain the flow rate at a specified target value to maximize pump system efficiency. According to experimental results, the estimated error rate for the target flow rate was 1.49%, and for pumping system efficiency, it was 2.14%.

This study demonstrates that a range of analytical and experimental methods can be used effectively to improve the efficiency of pumping systems. Future researchers recommend conducting similar analyzes on a larger scale and under different operating conditions. In addition, the evaluation of different optimization strategies to improve the energy efficiency of pumping systems can lead to significant energy savings in industrial applications. It is also recommended that the methods and findings used in this study be tested in a wider scope by applying them to studies on similar systems. In this way, more effective and optimized solutions for improving the efficiency of pumping systems can potentially be developed.

Table 6. RMS predicted and experimental results and error in both results

	Output variables		Input variables	
	Q ($m^3\ h^{-1}$)	η (%)	P (bar)	N (kW)
RSM-predicted results	92.74	41.47	1.09	7.38
Experimental results	94.15	40.58	1.09	7.18
Error (%)	1.49	2.14	0	1.89

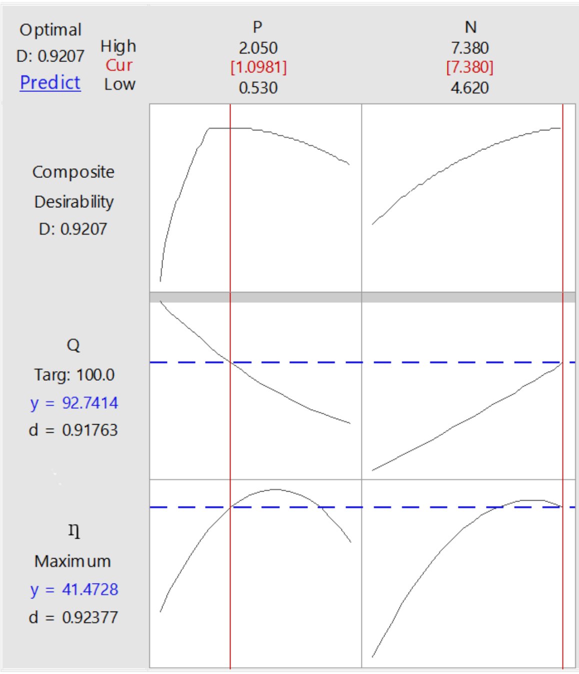

Figure 5. Optimization plot

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