ORIGINAL SCIENTIFIC PAPER OPEN ACCESS

Multi-criteria optimization of sucker rod pump operation using AHP–TOPSIS based decision analysis for predictive paraffin control

Borivoj Novaković[1], Stevica Jankov[2], Milan Nikolić[1], Luka Đorđević[1*]

[1]University of Novi Sad, Technical faculty "Mihajlo Pupin", Zrenjanin, Serbia

[2]Naftagas – Oil Services LLC, Novi Sad, Serbia

ARTICLE INFO

* **Correspondence:** luka.djordjevic@uns.ac.rs

DOI: 10.5937/engtoday2500011N

UDC: 621(497.11) **ISSN:** 2812-9474

Article history: Received 9 October 2025; Revised 11 November 2025; Accepted 15 November 2025

ABSTRACT

This study presents an integrated methodological framework for optimizing the operation of sucker rod pumps affected by paraffin deposition through the application of multi-criteria decision-making techniques. Predictive maintenance (PdM) data collected from five production wells were analyzed to evaluate performance indicators before and after implementation of paraffin control procedures. The Analytic Hierarchy Process (AHP) was used to determine the relative importance of key performance criteria (post-PdM downtime, reduction percentage, and post-maintenance operational stability) and the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) ranked the wells according to their overall efficiency and reliability. Results indicated that well K-3 had the highest overall performance, with minimal downtime and low operational variability; wells K-1 and K-5 followed in the ranking. The combined AHP-TOPSIS approach provided a systematic decision support tool for prioritizing investments in automation, monitoring and maintenance strategies within oil production systems. The findings indicate that integrating MCDM methods with predictive maintenance data improves the accuracy of decision making and supports operational optimization in petroleum production environments.

KEYWORDS

Multi-Criteria Analysis, AHP, TOPSIS, Sucker Rod Pump, Operational Reliability.

1. INTRODUCTION

The growing demand for production efficiency and continuous operation has increased the significance of system maintenance in industrial environments. Conventional maintenance practices, including reactive and planned maintenance, are progressively being replaced with methods that allow proactive identification and prevention of potential failures. Predictive maintenance applies analytical tools to anticipate failures and enables timely interventions that decrease downtime and repair expenses [1,2]. The development of affordable sensors and real-time monitoring systems has made it possible to collect extensive operational datasets. When integrated with analytical algorithms and engineering expertise, these data sources support further advancement of PdM. Current research is focused on building multivariate models and computational algorithms that can improve predictive accuracy and optimize maintenance costs [3]. The introduction of artificial intelligence into PdM contributes to both cost reduction and improvements in operational safety and performance. Researchers continue to develop AI-based models that improve the autonomy and adaptability of robotic systems working in complex production conditions [4].

A practical example of PdM application involves an algorithmic system designed to detect and predict paraffin accumulation through analysis of load variations in sucker rod strings and motor electrical parameters. This method shows that indicators commonly used for failure diagnostics can be effectively applied for predictive purposes, improving the overall reliability of the pumping system. Experimental testing on five production wells enabled quantitative evaluation of PdM efficiency under real operating conditions and provided the basis for developing guidelines to reduce downtime and maintenance costs in oil production [5]. The concept of predictive maintenance offers a wide range of possibilities through the use of modern tools for system condition monitoring, including vibration analysis and fluid diagnostics. Timely diagnostics can prevent the occurrence of more significant technical failures [6].

Integrating artificial intelligence into PdM frameworks has led to the development of explainable AI models that increase transparency and reliability in maintenance-related decisions. Such models assist in identifying the fundamental causes of component degradation, supporting more accurate planning of maintenance interventions [7]. Nevertheless, several practical challenges remain. Data integrity, sensor calibration, and the need for qualified personnel can influence the effectiveness of PdM implementation. Addressing these aspects requires collaboration between specialists in data analysis, mechanical engineering, and field operations to establish stable and efficient predictive maintenance systems [8].

Industrial sectors that adopted PdM have reported a decline in unplanned downtime, longer equipment service life, and improved utilization of maintenance resources. These results indicate higher operational efficiency and a more sustainable approach to managing industrial assets [9]. Predictive maintenance represents a shift in maintenance management, where data analytics, artificial intelligence, and continuous monitoring allow early detection of irregularities and proactive control of equipment health. This results in higher reliability, reduced operational costs, and improved workplace safety. As technology advances, PdM is expected to become increasingly important across industrial sectors, transforming maintenance management practices [10].

The integration of PdM with multi-criteria decision-making methods such as the AHP and the TOPSIS enables structured evaluation of factors that affect sucker rod pump performance and paraffin control efficiency [11]. Through AHP, the relative weights of selected criteria are determined, while TOPSIS provides ranking of alternatives based on their proximity to an ideal solution. The combined use of these approaches allows an integrated assessment that includes technical, operational, and economic parameters relevant to SRP decision-making [12]. This methodological framework supports optimization of SRP performance under diverse and variable operating conditions. Recent research confirms that applying AHP-TOPSIS techniques improves pump efficiency. For instance, using dynamometer card data together with machine learning models enables accurate diagnostics and prediction of SRP malfunctions, leading to reduced downtime and higher production [13]. The introduction of digital twin concepts further allows real-time simulation and optimization of SRP operation, contributing to improved performance and operational reliability.

2. MATERIALS AND METHODS

The research was conducted to quantitatively evaluate the efficiency of predictive maintenance systems applied to production wells equipped with sucker rod pumps affected by paraffin deposition. The analysis was based on operational data collected from five production wells, labeled K-1 to K-5. The primary goal was to determine investment priorities for automation and monitoring based on quantitative indicators of operational performance following the implementation of paraffin control procedures.

2.1. Data characteristics and source

The experimental material consisted of annual operational indicators from five production wells, which included the following parameters:

- Downtime_pre_PdM (days/year): average downtime prior to predictive maintenance implementation,
- Downtime_post_PdM (days/year): average downtime after PdM implementation,
- Reduction (%): percentage reduction in downtime achieved through PdM,
- Std_dev_post: standard deviation of post-PdM downtime, representing operational stability.

The data were derived from real production records and processed without additional extrapolation, except for normalization required for multi-criteria analysis. This ensured representativeness of the sample and comparability of results across the analyzed wells.

2.2. Methodological Framework

The systematic assessment of PdM efficiency was performed using a combination of the AHP and the TOPSIS, both belonging to the class of MCDM methods. This combination was selected to provide a transparent and numerically consistent assessment framework, integrating expert judgment with objective operational indicators. The AHP method was applied to determine the relative weights of the evaluation criteria through expert-based pairwise comparison. This allowed the integration of technical, operational, and economic aspects into a unified decision-making structure. The criteria were defined as follows:

- Downtime_post_PdM (cost type – lower values indicate better performance);
- Reduction (%) (benefit type – higher values indicate better performance);
- Std_dev_post (cost type – lower values indicate better performance).

The normalized weights obtained from AHP were, with a consistency ratio 1, confirming the logical consistency of expert evaluations. The TOPSIS method was subsequently used to rank the wells according to their overall performance. The procedure involved:

1. normalization of the decision matrix using the vector norm,
2. multiplication of normalized values by the AHP weights,
3. determination of ideal (best) and anti-ideal (worst) solutions,
4. calculation of the Euclidean distance of each alternative from both solutions,
5. computation of the closeness coefficient used for final ranking.

3. RESULTS AND DISCUSSION

Based on the available quantitative data, including downtime before and after the implementation of PdM, the percentage reduction in downtime, and the standard deviation of operational parameters following PdM, this study applies an advanced MCDM framework aimed at objectively evaluating and optimizing the performance of production wells. An integrated approach combining AHP and TOPSIS was adopted to simultaneously incorporate expert judgment and quantitative indicators into the decision-making process, ensuring a balanced and transparent analytical structure. The AHP method was employed to determine the relative weights of the evaluation criteria and to quantify their influence on overall system efficiency through pairwise comparisons based on expert assessments. This process enabled the integration of technical, economic, and operational criteria within a unified hierarchical evaluation framework, providing a rational basis for subsequent quantitative analysis. The derived weights established the relative importance of each criterion, ensuring methodological consistency and decision transparency.

Subsequently, TOPSIS was applied to rank the analyzed wells according to their similarity to the ideal solution, reflecting their overall operational suitability and performance after PdM implementation. This method enables the precise identification of wells that achieve the most favorable combination of minimal downtime, maximum reduction in inefficiencies, and stable operational behavior. The obtained ranking provides a robust foundation for strategic decision-making regarding investment prioritization in automation, monitoring, and system optimization, as well as for the rational allocation of technical and financial resources.

The integrated application of AHP–TOPSIS thus provides a comprehensive and data-driven assessment of predictive maintenance performance under complex production conditions, enhancing the accuracy, reliability, and transparency of decision-making in oil production management.Table 1 presents the data for the wells.

Table 1: Data for the wells

Wells	Downtime_pre_PdM (d/years)	Downtime_post_PdM (d/years)	Reduction (%)	Std_dev_post
K-1	14.200	0.800	94.400	0.400
K-2	12.500	1.000	92.000	0.500
K-3	11.800	0.600	94.900	0.200
K-4	13.000	1.100	91.500	0.600
K-5	12.200	0.900	92.600	0.300

The pairwise comparison matrix (AHP) was used to evaluate the relative importance of the selected criteria by systematically comparing each criterion with every other one in terms of their contribution to the overall objective. This matrix serves as the foundation of the AHP method, enabling the quantification of subjective expert judgments into numerical weights that reflect the hierarchical structure of decision-making. The resulting consistency ratio (CR) was subsequently calculated to verify the logical coherence of expert evaluations, ensuring methodological reliability and internal consistency within the weighting process. Table 2 presents the results of the weight evaluation matrix.

Table 2: Weight evaluation matrix

	Downtime_post (lower better)	Reduction% (higher better)	Std_dev_post (lower better)
Downtime_post (lower better)	1.000	2.000	3.000
Reduction% (higher better)	0.500	1.000	2.000
Std_dev_post (lower better)	0.333	0.500	1.000

The TOPSIS method begins with the normalization of the decision matrix using the vector norm. This step ensures that criteria with different units are made comparable. Next, the normalized values are multiplied by the weighting factors, typically determined by AHP, to reflect the relative importance of each criterion. The ideal (best) and anti-ideal (worst) solutions are then identified based on the type of criterion (benefit or cost). The distances of each alternative to these solutions are calculated, and the closeness coefficient is determined. Finally, alternatives are ranked according to their closeness coefficient, where a higher value indicates a better candidate.

Table 3: TOPSIS results (Closeness coefficient and rank)

No.	Wells	Downtime_post (d/year)	Closeness_TOPSIS	Rang
1	K-3	0.600	1.0000	1
2	K-1	0.800	0.5790	2
3	K-5	0.900	0.4746	3
4	K-2	1.000	0.2110	4
5	K-4	1.100	0.0000	5

The well with the highest closeness coefficient represents the most suitable candidate for priority investments or further automation, characterized by a combination of low downtime, high reduction, and low variability.

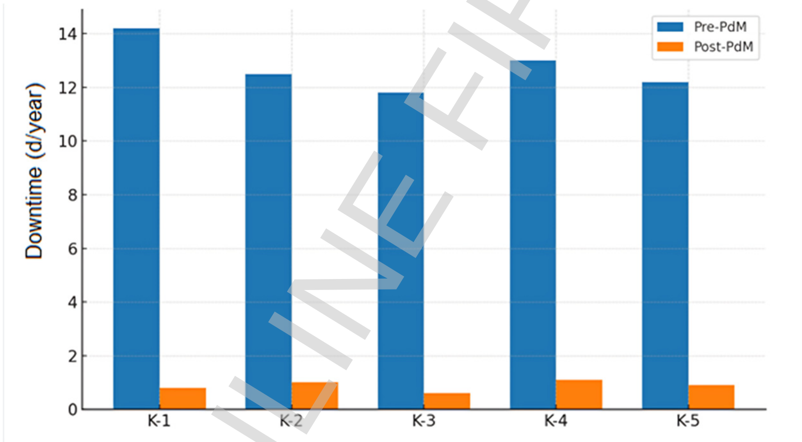

Figure 1: Downtime before and after the implementation of predictive maintenance

Figure 2 shows the TOPSIS analysis, indicating closeness to the ideal (the higher, the better) and the ranking of wells.

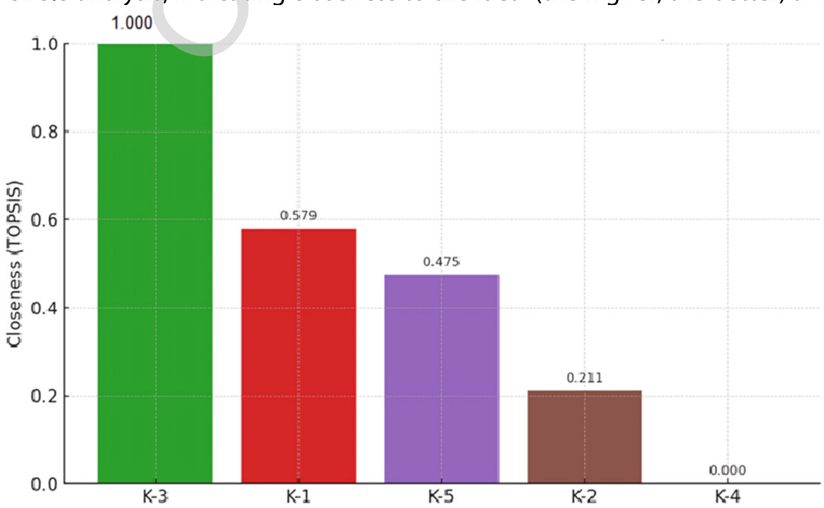

Figure 2: TOPSIS analysis, indicating closeness to the ideal (the higher, the better) and the ranking of wells

The radar chart in Figure 3 presents the normalized criteria values used for evaluating the performance of production wells after the application of predictive maintenance and paraffin control measures.

Each axis represents one of the selected criteria: post-maintenance downtime, reduction percentage, and post-maintenance standard deviation. The closer a line is to the outer boundary of the diagram, the better the corresponding performance. Well K-3 shows the most favorable overall characteristics, combining the lowest post-maintenance downtime and variability with the highest reduction percentage. Wells K-1 and K-5 also demonstrate relatively balanced performance, while wells K-2 and K-4 exhibit lower normalized values across most criteria. This graphical comparison supports the numerical TOPSIS ranking, confirming that well K-3 achieved the most stable and efficient operation following the implementation of predictive maintenance procedures.

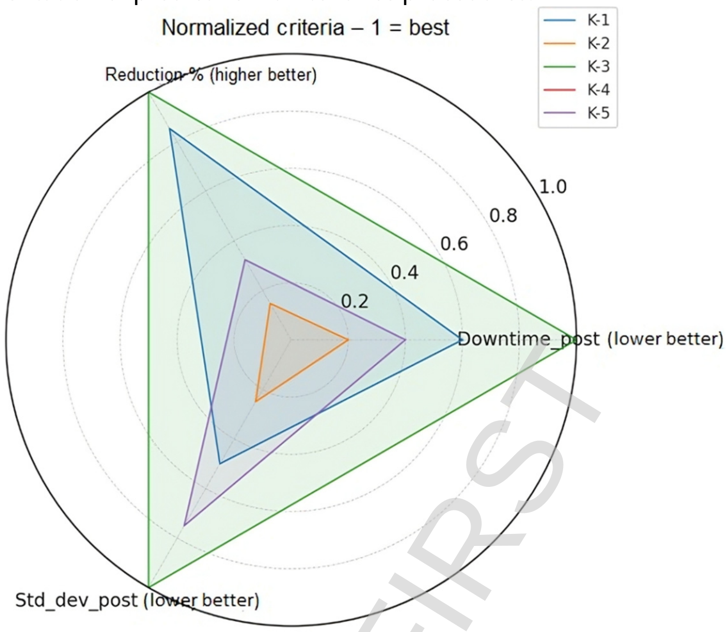

Figure 3: TOPSIS closeness coefficients and ranking of production wells

4. CONCLUSION

The results of this study confirm that integrating predictive maintenance with multi-criteria decision-making methods significantly enhances the operational efficiency of pumping systems in the oil industry. The analysis conducted on five production wells demonstrated that combining objective operational indicators with expert evaluations through the AHP–TOPSIS framework enables reliable and transparent performance assessment. Notably, well K-3 achieved the highest similarity coefficient to the ideal solution, which reflects its minimal downtime, the highest percentage of downtime reduction, and stable operating conditions following the implementation of the PdM strategy.

The application of multi-criteria analysis enabled the clear identification of priorities for automation and modernization of maintenance systems, ensuring optimal allocation of technical and financial resources. The results confirm that this approach provides a more accurate decision-making basis than conventional single-criterion methods, as it integrates technical, economic, and operational aspects.

Furthermore, the integrated AHP–TOPSIS framework can be applied to other areas of the oil and process industries where optimization of maintenance and management of complex technical systems is required. The methodology demonstrates a high level of adaptability and can be further enhanced by incorporating digital twin technology and artificial intelligence to improve prediction accuracy and automate decision-making processes.

Based on the conducted analysis, it can be concluded that combining predictive maintenance with multi-criteria decision-making not only reduces downtime and maintenance costs but also improves the reliability and stability of production systems. Future research should focus on integrating such methodological frameworks with real-time monitoring systems and adaptive algorithms to achieve greater autonomy and efficiency of technical systems under operational conditions.

REFERENCES

[1] A. Abbas, “AI for Predictive Maintenance in Industrial Systems”, International Journal of Advanced Engineering Technologies and Innovations, Vol. 1(1), pp. 31–51, (2024)

[2] J. Dalzochio, R. Kunst, E. Pignaton, A. Binotto, S. Sanyal, J. Favilla, and J. Barbosa, “Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges”, Computers in Industry, Vol. 123, p. 103298, https://doi.org/10.1016/j.compind.2020.103298, (2020)

[3] W. Li and T. Li, "Comparison of deep learning models for predictive maintenance in industrial manufacturing systems using sensor data", Scientific Reports, Vol. 15(1), p. 23545, https://doi.org/10.1038/s41598-025-08515-z, (2025)

[4] M. A. Rahman, M. F. Shahrior, K. Iqbal, and A. A. Abushaiba, "Enabling intelligent industrial automation: A Review of machine learning applications with digital twin and edge AI Integration", Autom. 2025, Vol. 6(3), p. 37, https://doi.org/10.3390/automation6030037, (2025)

[5] J. Li, B. Liang, C. Li, M. Yan, and J. Yu, "Calculation methods for the gas pipeline failure rate", Journal of Petroleum Science and Engineering, Vol. 174, pp. 229–234, https://doi.org/10.1016/j.petrol.2018.11.020, (2019)

[6] B. Z. Novaković, L. Djordjević, M. Đurđev, Lj. Radovanović, N. Zuber, E. Desnica, and M. Bakator, "Effect of changes in hydraulic parameters and tank capacity of the hydraulic press system on the heating of the hydraulic oil", Eksploatacja i Niezawodność – Maintenance and Reliability, Vol. 26(4), https://doi.org/10.17531/ein/190826, (2024)

[7] A. Ucar, M. Karakose, and N. Kırımça, "Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends", Appl. Sci. 2024, Vol. 14(2), p. 898, https://doi.org/10.3390/app14020898, (2024)

[8] I. Ul Hassan, K. Panduru, and J. Walsh, "Predictive maintenance in Industry 4.0: A review of data processing methods", Procedia Computer Science, Vol. 257, pp. 896–903, https://doi.org/10.1016/j.procs.2025.03.115, (2025)

[9] M. Belim, T. Meireles, G. Gonçalves, and R. Pinto, "Forecasting models analysis for predictive maintenance", Frontiers in Manufacturing Technology, Vol. 4, p. 1475078, https://doi.org/10.3389/fmtec.2024.1475078, (2024)

[10] A. Shamayleh, M. Awad, and J. Farhat, "IoT based predictive maintenance management of medical equipment", Journal of Medical Systems, Vol. 44(4), 72, https://doi.org/10.1007/s10916-020-1534-8, (2020)

[11] J. H. Ccatamayo-Barrios, Y. L. Huamán-Romaní, M. V. Seminario-Morales, M. M. Flores-Castillo, E. Gutiérrez-Gómez, L. K. Carrillo-De la cruz, K. A. de la Cruz-Girón, "Comparative analysis of AHP and TOPSIS multi-criteria decision-making methods for mining method selection", Mathematical Modelling of Engineering Problems, Vol. 10(5), pp. 1665–1674, https://doi.org/10.18280/mmep.100516, (2023)

[12] S. Hussain, J. H. Chen, and T. Hussain, "Decision-making framework for improving bank performance in emerging markets: The analysis of AHP-TOPSIS and AHP-GRA models", Journal of Central Banking Theory and Practice, Vol. 13(3), pp. 191–218, https://doi.org/10.2478/jcbtp-2024-0027, (2024)

[13] M. Alemi, H. Jalalifar, G. Kamali, M. Kalbasi, "A prediction to the best artificial lift method selection on the basis of TOPSIS model", Journal of Petroleum and Gas Engineering, Vol. 1(1), pp. 009-015, (2010)