



SMART CLASSIFICATION OF SUBMERSIBLE PUMPS

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ABSTRACT

Submersible pumps play a vital role in diverse industrial applications, ranging from water supply to the transfer of hazardous chemicals. Their classification, traditionally based on operational and design characteristics, often faces limitations in precision and adaptability. This study explores the integration of artificial intelligence (AI) and machine learning (ML) to enhance the classification and optimization of submersible pumps. Utilizing datasets of pump parameters, advanced ML algorithms like Random Forest and Support Vector Machines were applied, achieving significant improvements in prediction accuracy. Experimental results highlight the inverse relationship between flow rate and head, as well as the impact of pump diameter on performance. The research underscores the potential of smart systems in creating adaptive, data-driven classification models that surpass traditional methods. Future work involves refining algorithms, expanding datasets, and incorporating real-time decision-making systems to address dynamic operational challenges. This approach offers a promising direction for improving the efficiency and reliability of submersible pump systems in modern engineering.



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I. INTRODUCTION

This Submersible pumps are the most common type of machines used in our industrial life. These machines run on a very fundamental transport mechanism based on the increase of the velocity of the medium. This increased velocity creates a submersible force, enabling the conveying of the medium to the discharge point. In other words, they help transport a liquid by adding a submersible force metric to elevate the liquid. Since viscosity does not play a significant role in the rejection of the liquid flow, they are usually used for non-viscous liquids and gas [1]. Even though their name refers to a submersible mechanism, their function is mostly associated with speed and velocity, fields of fluid mechanics.

The liquid acceleration and discarding according to this are performed in a continuously varying field of slow decreases, which is due to an increase in the volume of uniformly growing radial streams surrounding the eye of the impeller into the pointed weak submersible force. This produces rising effects converting with height [2], [3]. In this modern life, submersible pumps are used in a wide area of applications, ranging from small houses that utilize water supply to industrial applications for pumping hazardous and aggressive chemicals. Their basic structure integrates an impeller, either open or radial, directly connected to a motor with a shaft. The motion generated from the motor is transmitted to the impeller to rotate it. The fluid coming from the inlet of the pump is conveyed by the impeller through the vanes when rotating.

Submersible force is imparted to the fluid by the impeller to send it at its outside rim to achieve the pump's offering. In addition to the impeller section, a volute is mounted to receive the high-speed fluid from the impeller and to convert it to an almost static column. These components have a crucial role in pump performance. Therefore, understanding the behavior of these pumps is of practical importance in modern engineering. [4], [5]. This study focuses on the important role of submersible pumps in various industries and highlights the growing application of intelligent systems in their classification. Traditional classification methods used to select pumps, although important, often lack precision and adaptability.

With artificial intelligence and machine learning to be introduced as an effective means of classifying submersible pumps, this work demonstrates the effectiveness of applying machine learning algorithms such as Random Forest to optimize pump classification and performance prediction.

II. LITERATURE REVIEW AND APPLICATIONS

It should be noted that among the successful cases where smart classification methodologies have been applied in several submersible pump applications. These case studies are reported as learned lessons while pursuing the development of efficiency-based decision-making in submersible pump classification systems, facilitating decision-making support for the classification of new designs and aiding the enhancement of existing pumps-in-series techniques used in the industry. Together, these cases illustrate the breadth of the application domain and suggest potential areas for future extension of work. This structural guidance has come from technology developers who have been characterized, tested, and verified with their techniques. These verification activities have been incorporated using a software system, service, or product in a manner that is likely to support commercialization or other applications of the system [6].

From small pumps moving water to large compressors and blowers, artificial intelligence with machine learning is proving effective for the automatic classification of submersible pumps [7]. One important conclusion from this case-based study is the need for AI techniques employing strong mathematical foundations and true machine learning, due to the fact that theoretical hydraulic limitations define the pump parameters, limiting and reducing the searches at the feature selection stage, while providing great accuracy. This work shows the growing research in submersible pump classification systems such as pumps-in-series/in-parallel using new approaches and models, often AI and machine learning, with varying result accuracies. Decision trees have enjoyed great success in the classification stage, further boosting the efficiency of the case-based reasoning system, having demonstrated practical application, now forming a decision support model for pump series classification rules in the industrial user community.

In this study, we numerically and successfully used 47, 342, and 417 pumps in running the case-based reasoning system for standard and non-standard testing cases [8]. We illustrate a non-standard series classification that would have required approximately 2500 experiments, where energy savings and operational differences would have also gone unnoticed. We have also presented several case-based reasoning operational and design-based case studies in which the case-based reasoning system could be used. Although there is much to advance, the use of mathematics, AI, and machine learning has brought about many lessons learned, providing a good starting point for this complex application. In the future, a better understanding of these and other AI techniques could be combined and, with the assistance of an industrial expert, further developed in a SaaS, apps, and API [9].

The other most commonly notable techniques included: pumps/in-series/in-parallel, system head loss, system dynamics and pressure, general gradient flow curve nadir, industrially derived, static and dynamic, similarity metrics, data and ontologies, non-dimensional and affinity laws, complementarity, similarity, and variability, experimental and test cases. In general, our focus has been on smart classification using case-based reasoning approaches [10], [11]. Submersible pumps convert rotational energy from electric or combustion motors into the mechanical movement of a fluid. The energy is attached to the fluid dynamics of the pump. A submersible pump contains a number of key components [12]. First, an impeller increases the speed of the fluid. Following the impeller, the rotating fluid is decelerated in a restrictive volute [3].

Additional diffusers are used in multi-stage pumps to further decelerate the fluid and convert more of the now kinetic energy into pressure. Finally, the pump flange has a personnel door in the centre to access the wear rings, mechanical seal, and sealing system cooling liquid inlet and outlet ports. The physics of the flow dictates that pumps operate at an intersection between flow and pressure. However, the pump can be configured as a fluid jet that imparts high velocity to the fluid, in the case of mixed flow and axial flow pumps. This gives the pump some flexibility as to where the intersection can take place [13], [14]. In terms of fluid flow and pump design (Figure1), it is generally deemed beneficial to increase the flow rate through the pump with minimal losses at the intersection of flow and pressure. In plumbing and turbine applications, the intersection of pressure and flow is crucial.

In general, the pump should maintain the energy from the fluid jet and carry it to the outlet. For optimal energy transfer from motor to fluid and improved design, this generally means as high a flow as possible while still considering pressure requirements and limitations. This is especially true of high-pressure systems with frequent tight bends, such as in the cooling loop of a nuclear core. Energy losses will generate even more heat, and fluid can even heat up enough to boil, potentially causing rapid vapor generation and a series of undesirable events. Therefore, using the absolute minimum flow necessary for a given pressure is beneficial because any additional flow causes a loss at the intersection of the pump.[15], [16].

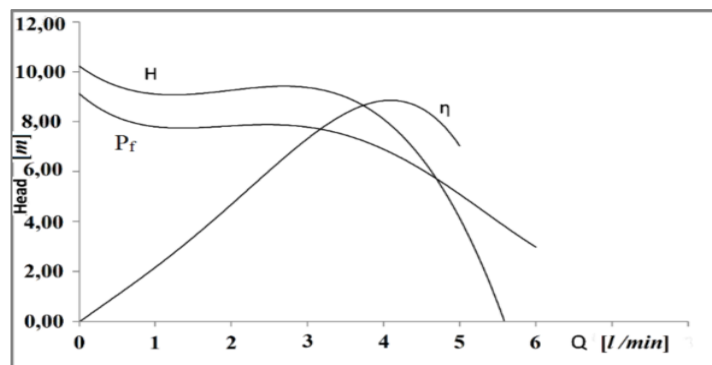


Figure 1: Typical characteristic curves of submersible pump.

Source: [17].

Pump impeller and volute designs take a range of needs into account, including allowed manufacturing costs, flow rate, fluid viscosity, power available, and the necessary lift. A variety of fluid dynamics terms are crucial to describe the flow of a pump. Most important are the flow capacity, expressed in the dimensions of volume per minute or volume per hour, and the pressure head. Flow capacity is a measure of the discharge of a pump and determines the pump's industrial classification. The efficiency of the pump describes the effectiveness of the pump in compressing the fluid. The actual efficiency of the pump is easy to determine, but the highest efficiency may arise at a flow rate that yields insufficient pressure.

Flow rate is often hidden as a parameter to approximate efficiency pump performance [18]. Thus, a working and correctly classified pump may have a performance curve in better agreement with another classification. Furthermore, the largest problem arises for volumetric and hydraulic loss coefficients when the pump characteristics are fitted directly, but the pump can be classified accurately without any knowledge of the classification of the pump or flow routed through a pump. Most importantly, however, an incorrectly classified pump system is not efficient and not a good choice. When designing or using pumps, it is crucial to be aware that different arrangements of components will function differently at different required flow rates, and different pump systems have a large range of range [19].

III. MATERIALS AND METHODS

III.1 TRADITIONAL CLASSIFICATION METHODS

Submersible pumps are inclusive in nature and fall under the category of submersible separation machinery. They are extensively deployed in various industry verticals like chemical plants, petrochemical firms, power plants, oil, and gas production segments. These pumps are classified on the basis of certain predefined conditions such as external design standards, driver-rotating means used, materials used, hydraulic performance within the pump casing, liquid type to be handled, internal design characteristics, operational characteristics, the alignment between pump mechanism and driver, casing type used, and discharge direction followed. Based on the design of the impeller and direction of the pump shaft, they are classified as horizontal or conventional pumps, vertical pumps, axial, mixed, straight, single suction, and double suction pumps. Submersible pumps have a long history and have been utilized since ancient times.

The traditional classification of submersible pumps has mainly been centred on operational characteristics, applications in which they are to be used, design features, impeller exits, and shaft disposition [20]. Date, studies have categorically investigated different forms of classification of submersible pumps. In general, two major types of classifications exist: classification based on the category of construction and end suction. Submersible pumps are classified based on the suction-end construction: first, on the basis of hydraulic performance within the pump casing, and second, based on the hydraulic relationship in pumps and their systems [21]. These classifications provide a detailed level of understanding about commercial pumps and allow for an idea of which types of pumps are available in the market. However, these approaches possess some distinct disadvantages since they are only suitable for pumps that use standard designs and do not describe pumps built following standard generic designs.

Another widely used method employs a multi-level classification of submersible pumps based on different viewpoints such as type of driver, flow within the impeller, construction, simple or compound suction, and pump speed. Such methods often lead to the categorization of submersible pumps with large granularity, irrespective of the number and connectivity used in this approach. They exhibit some advantages of being easy to understand and apply in defining the requirements for a new pump, with some disadvantages of few categories with different designs being inherently grouped in the same category, besides the regressive characteristic of the method. They generally show a limited level of accuracy, which results in difficulty in reuse when components are designed using the funnel approach. Frequent growth in the specialization and perfection of pumps has over the years led to the current use of large numbers of categories combined to achieve a reasonably wide pump design flow detail.[22], [14].

III.2 FRAMEWORK FOR CLASSIFYING SUBMERSIBLE PUMPS

Impeller Type and Number, Casing Design, Estimated Flow per Casing Pumps are usually designed in several iterative steps, of which the first is always the most crucial. During the initial pump design, the most important design aspects, such as impeller type and number, casing design, and flow orientation (radial, mixed, or axial), have to be selected. These features determine the subsequent steps of the design process as they directly affect pump performance, pump efficiency, and pump size. Even though there are various pump classifications, pump geometry is always a feature application. The classification of submersible pumps according to impeller type and flow orientation is often based on experience and historical background, describing the development of the pump types themselves. Pumps having similar designs make a useful basis for classifications, as it is easier to generalize them among each other and in comparisons with other pump designs. Within groups of similar design, comparison with measurements can lead to categorizations of designs for use in the pump design software as the pumps produce for similar service levels.

III.3 OPERATIONAL CONTEXT

Such classifications often generalize highly varied design features and operational traits and therefore focus upon generalities. Applications focused upon operational and design efficiency often consider designs in terms of impeller efficiency alone, or for multi-stage pumps in terms of impeller casing entries, thereby neglecting suction type and geometric data. Classifications based upon these factors also express regional differences, and for overall plant sizes, component isolation has limited relevance.

The best way to categorize a problem with a pump is to assist in an early evaluation of what aspects of a pump are ensuring its lack of suitability for an application. There is no early "one-size-fits-all" approach. Differences between classifications may be minimal or irrelevant and of limited use in operational context.

III.4 ARTIFICIAL INTELLIGENCE IN PUMP CLASSIFICATION

Artificial intelligence (AI) has the potential to enhance the classification of submersible pumps significantly. It enables handling an extensive amount of data from various application fields, such as design, research, and non-technical applications. AI facilitates the classification process with greater reliability and objectivity than traditional methods, which are prone to being influenced by personal experiences, and it is employed inconsistently across different experts. An AI-empowered classifier's initial capability exceeds that of a human-centred classifier, while being capable of adapting its decision strategy over time following experts' feedback or trial-time pump operation feedback.

Discussions of potential research in AI-empowered pump classification include the development of an adjustable, undirected classification model that reorganizes itself as new data arrive and continued use of it to enhance pump classification. AI applications in classification are further discussed, and two real examples are provided to present the practicability of AI classification for pumps. The examples concern the area of engine research with the application of AI-empowered engine knock classification. Instead of using machine learning algorithms directly on the pump's models, applying them on actual pumping engines produces a new trend in classifying and characterization.[6], [4].

AI has the ability to process an extensive amount of data and develop machine learning capabilities. It enhances classifications; on some occasions, it is, in practice, better than human classifiers. There are no reported cases of AI employed in pump classification other than the initial proposition of the hierarchical classification system. Therefore, by updating and integrating AI mechanisms, a pump classification system that follows the trend of a smart system may be developed. Smart systems make decisions based on real-time data rather than a pre-designed model with a fixed strategy.

This development totally exchanges the classification methodology from a human expert system to a smart decision-making system. The data-driven decision system has many advantages, including reducing uncertainty, complexity, interpretation cost, noise, subjectivity, and variability, and would form a consistent, superlative, subjective, adapted, and cooperative system. The superiority of the proposed smart system can be easily explained. First, it is better than an expert-based classifier because it is based on historical data using intelligent methods. Second, AI is adaptive to a pump's real performance, for example, changing pump operational conditions, to reflect the pump's actual status more accurately.[2], [23], [24].

One possible classification of machine learning algorithms is into supervised learning (the output is known for a training set of "correct" input-output pairs) and unsupervised learning (only the input is known; the data is unlabeled). Clustering falls between supervised and unsupervised classification in such a way that the output of a training set is known, but it does not refer to labeled sets. Critics argue that an intelligent system should be able to enter into a dialogue with an operator, thus enabling the human to give feedback to the system in order to correct mistakes or errors by providing further training. Thus, a system based solely on unsupervised learning techniques is neither possible nor does it meet the general requirements for a smart system.

Most likely, the most efficient method for such purposes is to use a mix of both supervised and unsupervised learning algorithms. The classical approach to classification using belief networks is increasingly being replaced by data-driven learning methods. To achieve truly reliable classification results, the quality and quantity of data sets are essential. However, there are learning algorithms, like neural networks or fuzzy rule-based systems that can cope even with small and low-quality data sets by using a high number of features. [25-27]. The best approach to practical machine learning consists of the following steps and issues:

- **Quality of the training data sets:** Missing or irrelevant data may lead to wrong conclusions in the neural network methods. The use of collected data from open or commercial databases might bring inconsistencies to the experimentation; hence, it is more efficient to use data collected for the specific purpose of the pump classification system. Diagnostic for one class would allow users to Define the reasons for the classification decision, thereby enhancing acceptance of the predictions.[28], [29], [21].

- **Quantity of data sets:** The number of training data sets needed to achieve consistent estimates of classification results is another key issue. It is suggested that the size of the data sets should be large enough to ensure that sampling variations associated with the error in the data sets are not too large. However, due to the lack of pump performance data for both submersible and positive displacement, a small number of various pump models was used to construct the training data sets.

- **Outlining:** Even in well-established practices, the problem-solving strategies used in the analyses are vaguely described alongside the constraints associated with the problem description. It is thus important to outline the practical problems to develop an understanding of the integration with recent problem-solving tools.

- **Data pre-processing:** Before utilizing the data in a training data set, crucial issues regarding data pre-processing should be addressed. The goal of data pre-processing is to improve both the interpretability and the accuracy of the results. One possible but not exclusive approach in the data pre-processing stage is the removal of duplicate or error-ridden data and the selection of relevant features. Consequently, feature selection will reduce the dimensionality of the data while potentially improving the generalization performance of a classifier. Features such as energy efficiency and specific speed are also considered good inputs, exceptions, and allowances for the classification; however, the majority of the data that characterize one pump model are common in other pump models. Therefore, considering the predictors whose joint values are particularly.

IV. ANALYSIS STUDY

IV.1 DATA DESCRIPTION

To carry out the pump selection process using various machine learning methods, we chose tow Italian brands of pumps - SAER and PANELLI -and recorded their technical characteristics, which are as follows: Flow rate Q , Manometric head $H=f(Q)$, Pump diameter D , and Efficiency $\eta=f(Q)$

Table 1: The two brands of pumps used Table.

D" PUMP	4"	6"	8"	10"	12"
PANELLI	66	547	547	206	/
SAER	108	911	/	617	291

Source: Authors, (2026).



Figure 2: SAER and PANELLI Pumps.

Source: Authors, (2026).

IV.2 DATA PREPROCESSING

After an in-depth analysis of the pump's characteristics, a graphical representation is proposed to better understand the relationships between these parameters. Next, a correlation matrix calculation was used to evaluate the relationships between the numerical columns ("D("), "Q (m³/h)", "H (m)", and "Performance %") to identify significant correlations (see Figure 3). The correlation matrix and heat map have been successfully generated, showing the relationships between the variables. Next, we evaluated the accuracy of the pump selection process by analyzing the data further. The application of machine learning algorithms begins with data pre-processing (e.g. dealing with missing values, normalising features), followed by the implementation of three algorithms: Linear Regression, Random Forest and Support Vector Machine (SVM) to predict a target variable. The models were trained and evaluated, with Random Forest performing the best (lowest MSE and highest R²), while Support Vector Machine underperformed.

IV.3 EVALUATION METRICS DESCRIPTION

The models were trained and evaluated for classification based on quartiles of "H (m)." Logistic Regression performed the best with an accuracy of 39.85% and an F1 score of 0.3603, while Random Forest and SVM had slightly lower performance. The accuracy of the model was then improved by optimizing the parameters and using more advanced techniques. To this end, we were able to:

- Feature engineering
- Try other algorithms (XGBoost, Neural Networks)
- Collect more data - Adjust the classification categories.

Figure 4 shows the pump performance characteristics obtained.

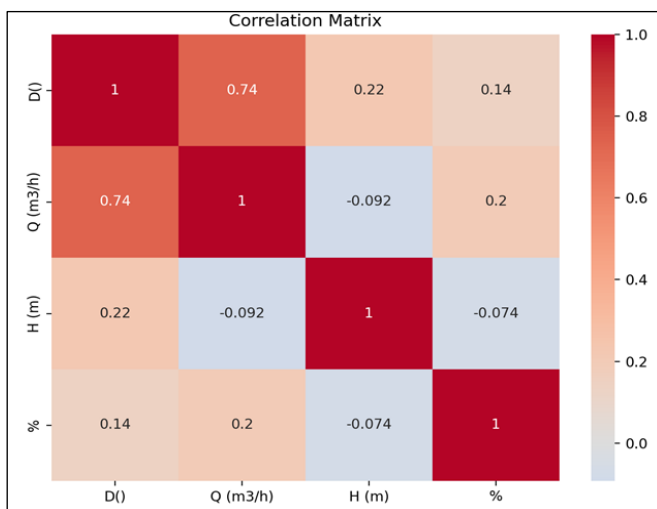


Figure 3: Correlation Matrix.

Source: Authors, (2026).

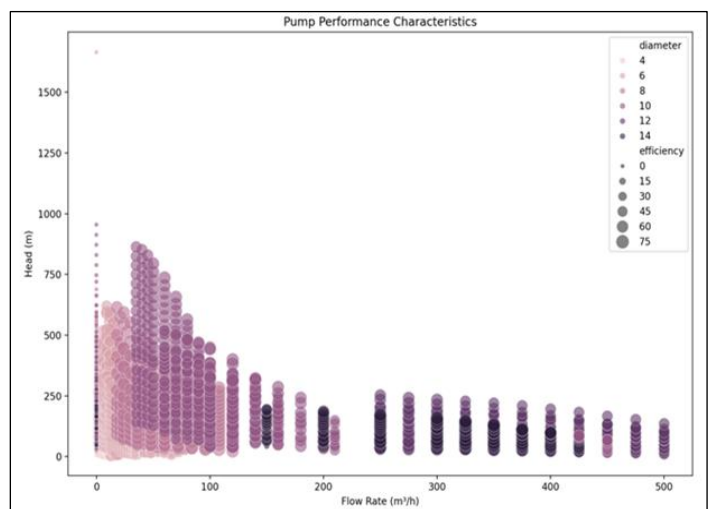


Figure 4: Pump Performance Characteristics.

Source: Authors, (2026).

The scatter plot shows the relationship between flow rate and head, with point colors indicating diameter and point sizes representing efficiency. The final cleaned dataset has (4638, 4) rows with four key parameters: diameter, flow rate, head, and efficiency. The visualization reveals several interesting patterns:

- Multiple performance curves for different pump diameters;
- A general inverse relationship between flow rate and head;
- Varying efficiency levels across operating conditions.

One of the objectives is to try to find a general formula for optimising pump performance. The first step is to analyse the relationship between these parameters and efficiency. The polynomial regression model has been successfully fitted, and the formula for efficiency has been derived. The R-squared value indicates moderate explanatory power, and the best performance point has been identified.

V. CONCLUSIONS

This study emphasizes the significant role of submersible pumps in various industries and highlights the growing application of smart systems in their classification. Traditional classification methods, though well-established, often fall short in precision and adaptability. Leveraging artificial intelligence and machine learning technologies provides a promising path to enhance the classification process, achieving greater accuracy and efficiency. Our analysis demonstrated the effectiveness of applying machine learning algorithms like Random Forest in optimizing pump classification and performance prediction. Future work should focus on expanding datasets, refining algorithms, and integrating real-time smart decision systems to address operational challenges and further improve the reliability of submersible pumps in diverse applications.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Methodology: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Investigation: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Discussion of results: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Writing – Original Draft: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Writing – Review and Editing: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Resources: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Supervision: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

Approval of the final text: Mourad Abed, Ali Bedjaoui, Abdelmoutia Telli.

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