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Research article

An intelligent decision support system for groundwater supply management and electromechanical infrastructure controls

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ABSTRACT

This study presents an intelligent Decision Support System (DSS) aimed at bridging the theoretical-practical gap in groundwater management. The ongoing demand for sophisticated systems capable of interpreting extensive data to inform sustainable groundwater decision-making underscores the critical nature of this research. To meet this challenge, telemetry data from six randomly selected wells were used to establish a comprehensive database of groundwater pumping parameters, including flow rate, pressure, and current intensity. Statistical analysis of these parameters led to the determination of threshold values for critical factors such as water pressure and electrical current. Additionally, a soft sensor was developed using a Random Forest (RF) machine learning algorithm, enabling real-time forecasting of key variables. This was achieved by continuously comparing live telemetry data to pump design specifications and results from regular field testing. The proposed machine learning model ensures robust empirical monitoring of well and pump health. Furthermore, expert operational knowledge from water management professionals, gathered through a Classical Delphi (CD) technique, was seamlessly integrated. This collective expertise culminated in a data-driven framework for sustainable groundwater facilities monitoring. In conclusion, this innovative DSS not only addresses the theory-application gap but also leverages the power of data analytics and expert knowledge to provide high-precision online insights, thereby optimizing groundwater management practices.

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1. Introduction

Sustainability has emerged as a critical imperative, a sentiment echoed by global initiatives such as the Belt and Road Initiative (BRI), which underscore the importance of harmonizing economic growth, community well-being, and environmental protection (Wang et al. [1]; Al-Sulaiti et al. [2]). In response to the escalating challenges faced by the environment and nature, there is a global push for a sustainable way of life, reflecting heightened expectations worldwide (Balsalobre-Lorente et al. [3]). Central to fostering urbanization, industrialization, and an enhanced quality of life is the pivotal role played by the management of water resources and supply (Fathollahi-Fard et al. [4]). Addressing these management challenges necessitates the integration of managerial approaches, technology, and industry practices (Abbas et al. [5]; Al-Sulaiti et al. [6]).

Regrettably, historical patterns of imprudent and unsustainable groundwater abstraction, driven by escalating water demands, have posed significant threats to both human well-being and the natural environment (Mojtahedi et al. [7]; Tian et al. [8]). Consequently, there is an urgent need for efficient and intelligent management of water withdrawal from these finite groundwater resources, emerging as a top priority for stakeholders and water users alike (Fathollahi-Fard et al. [9]). This imperative is rooted in the collective desire to achieve sustainable water demand and supply management while safeguarding the integrity of our limited water resources (Ingildsen and Olsson [10]).

The first step of smart water resources management, e.g., groundwater systems, is to provide required water withdrawal data, including flow rate, hydraulic and electric parameters of wells and pumps (Eggimann et al. [11]). Supervisory Control and Data Acquisition (SCADA) systems can manage all this favoring a large variety of sensors widely used in water systems (Candelieri et al. [12]). The SCADA systems gather and analyze real-time data for monitoring the performance of the water supply systems, including their equipment such as pumps. The data collected needs to properly be analysed and interpreted as meaningful information for decision-makers (Ingildsen and Olsson [10]). Various data-driven models and tools can conduct data analytics in water systems (Ali et al. [13]). Nowadays, machine learning (ML) is one of the popular tools due to its ability to predict the future with high levels of precision (Xenochristou et al. [14]). Many researchers have employed ML models to successfully forecast water systems' performance. Some examples include Random Forest (RF) (Chen et al. [15]), Support Vector Machines (SVM) (Rodriguez-Galiano et al. [16]), artificial neural networks (ANN) (Ostad-Ali-Askari et al. [17]; Montazeri et al. [18]), and boosted regression trees (BRT) (Knierim et al. [19]; Ransom et al. [20]).

The RF model is an ensemble ML method for regression and classification that operates by building a huge number of decision trees (Breiman [21]) using a random vector independently sampled from the input vector. Bagging is a method to produce a training dataset where a randomly selected part of the predictor variables is applied to construct each model's individual tree (Fathollahi-Fard et al. [9, 22]). The trees are grown to the maximum depth of the new training dataset using variables without pruning. This is one of the major merits of the RF regression over other tree methods such as the M5 model tree (Quinlan [23]). Moreover, the RF is a suitable method for indicating the nonlinear influence of variables and can handle complex interactions between variables, and is not influenced by multi-collinearity (Breiman [24]). Band et al. [25] showed that the RF models in forecasting nitrate concentration in groundwater are more accurate than other ML algorithms such as Cubist, SVM, and Bayesian ANN. Singh et al. [26] investigated the potential of the M5P model tree, ANN and RF for predicting the effects of impurities such as ash and organic manure on soil infiltration rate in various geometries. The performance evaluation parameters have proved that the RF approach performs extremely accurately compared to the M5 model tree and ANN considered models for this dataset. Ouedraogo et al. [27] demonstrated that the prediction correlation of the RF algorithm for modeling groundwater nitrate pollution is much better than the multiple linear regression (MLR) method.

According to the IDC report (Fig. 1), the spent financial resources for smart cities will be increased from 2018 to 2023. Also, this fact leads to an increase on the costs through smart systems and facilities. Plus, as per Fig. 2, the most spent finance is related to the implementation of smart infrastructures, and it illustrates that this section of facilities needs enhancement from automation and smartening aspects. In addition, Fig. 3 demonstrated that environmental smart monitoring through the smart city plan is divided into 16 % connectivity, 9 % software, 39 % hardware, and 37 % services. Therefore, increasing the software systems instead of hardware substructures makes the cost of smart city operations optimized.

ML algorithms can serve as predictive models, effectively integrated with decision-making frameworks to address intricate systems (Abbasi et al., [28]; Abbasi et al. [29]). Classical Delphi (CD) is one of the management techniques used for prediction based on the outputs of some rounds of questionnaires anonymously answered by a group of experts. The responses in each round are aggregated

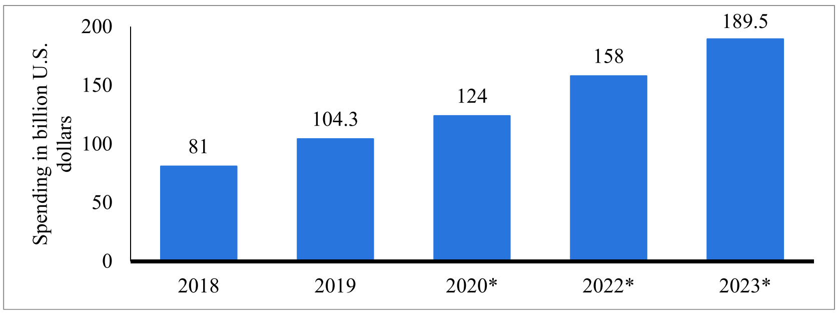


Fig. 1. Technology spending on smart city initiatives worldwide from 2018 to 2023 (in billion U.S. dollars), Source: IDC; ID 884092.

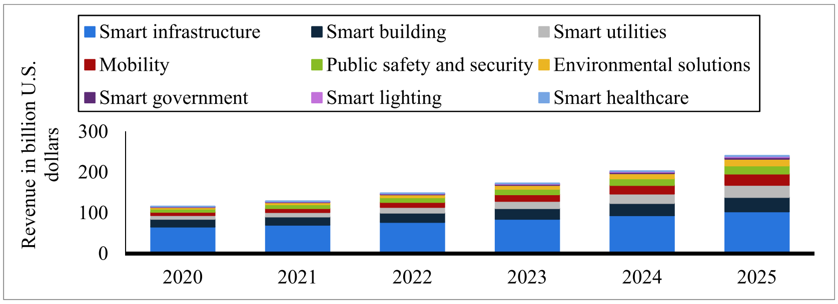


Fig. 2. Projected revenue of the smart city market worldwide from 2020 to 2025, by segment (in billion U.S. dollars), Source: Statista; ID 1111642.

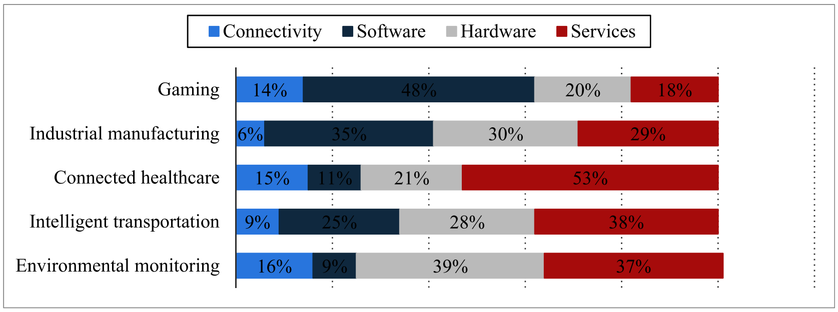


Fig. 3. 5G edge computing ecosystem market revenue share forecast worldwide in 2023, by segment/key industry, Source(s): KPMG; IDC; ID 1176665.

and shared with the experts. They can change their responses according to the previous round results. Ultimately, the information acknowledged by more than 60 % of the experts is integrated and presented as the final outputs. This method is extensively employed when there are controversial opinions about a managerial problem (Chouhan et al. [30]).

A large volume of water demands in warm and dry climates is supplied from groundwater abstraction as the main water resources via pumping stations (Drake [31]; Lonergan [32]). Smart management of water supply requires the key parameters of pumping facilities are collected and analysed. These parameters in pump systems include hydraulic (water flow rate, pressure head and etc.), electrical (amperage, voltage and etc.), and mechanical (energy functions, electromotor problems, etc.) considerations (Speed [33]).

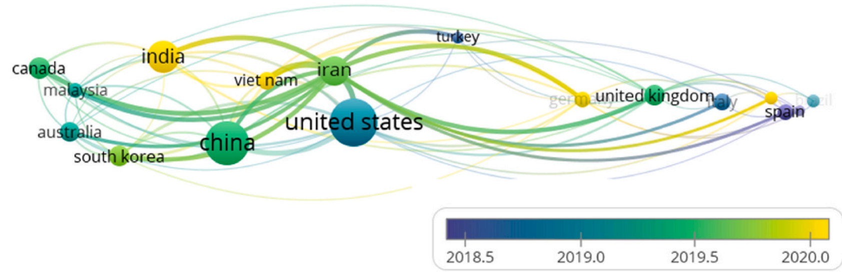
The evaluation of pump performance should extend to a comparison with specific standard tables designed for real-time equipment health monitoring, as outlined by McGhee and Steel [34]. While current control systems in water resource management facilities offer valuable management insights for optimal pump system operation (Gandon [35]; Hoffman [36]; Mezher et al. [37]), these systems often involve physical sensors and incur substantial electrical, mechanical, and structural costs, imposing financial burdens on water resource management organizations (Hanswal et al. [38]). In addressing this challenge, scientists have conducted an analysis of the economic impacts of investments in the water sector on public health. Due to the financial strain associated with the capital cost and maintenance of physical sensors and other facilities in water resource management, the deployment of economic computerized telemetry tools becomes a viable option, particularly in industrial sectors such as water and wastewater companies (Ma and Wang [39]).

In the realm of pumping system parameters, the prediction of flow rate, pressure head, and water demand using ML techniques has become a common practice. From a comprehensive literature review, various methodologies, including ANNs, SVMs, fuzzy logic, hybrid models, and RF, have been employed to forecast water demands and demonstrate diverse applications (Chen et al. [40]; Pacchin et al. [41]; Peña-Guzmán et al. [42]; Sampathirao et al. [43]; Amini et al., [44]; Sun et al. [45]; Afrin and Yodo [46]; Yang et al. [47]).

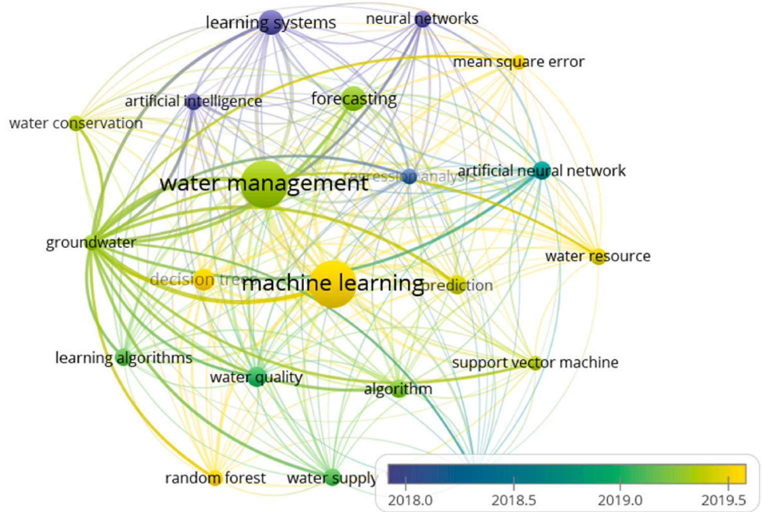
To determine this research area's importance, the library evaluation is done based on data mining of Scopus databank through the VOSviewer software. Due to creating the databank, smart systems' application in water management issues are extracted from Scopus datacentre. According to Fig. 4-a, it is clear that the United States and China had the most publications in the mentioned issues, and also, Iran increased its activities in the using smart system in the water management research area. Likewise, based on Fig. 4-b, integration of machine learning and water management systems is in trend and expanding this investigation area attracted both academia and industrial practitioners.

1.1. *Monitoring groundwater resources*

Zhou [48] presented a method for monitoring of groundwater by sampling frequency data analysis. Plus, in this study, just the level of groundwater is evaluated, but this investigation is assumed as a frontier of groundwater management by soft computing. Plus,



(a)



(b)

Fig. 4. The outputs of bibliography through this study as per (a) country distribution and (b) keywords occurrences.

Turner [49] evaluated groundwater resource interactions with surface water and sewage dynamically in littoral zone. Whereas, Turner's study was one of the basically research projects in the mentioned subject. Laier [50] surveyed the groundwater monitoring procedure which are located above the natural gas resources in Denmark. In this study, simple frequent analyses are utilized for smart monitoring of the declared resources. Shamsudduha et al. [51] assessed the performance of Gravity Recovery and Climate Experiment (GRACE) for groundwater resource management in the Bengal Basin. In the investigation, validity and verification of GRACE are evaluated by probable statistical analysis. Next, Jahromi et al. [52] changed the trend of study in this field and presented a novel approach for groundwater metering and management by Meter Data Management (MDM) with concentration on energy and water issues. Finally, Parra et al. [53] presented a novel method for scheduling the groundwater resources in smart cities by conductivity sensors. As per Fig. 5 which is provided by Fishbone method, all researches contributed some novelties to smart monitoring of groundwater resources, but, the present research focuses on a Decision Support System (DSS) for monitoring of the mentioned resources. It is clear that if evaluation of groundwater subject lonely is old title and in the following, integration of groundwater and pumping process monitoring and prediction are argued.

1.2. Prediction models for groundwater resources

Coppola et al. [54] presented a method based on Artificial Neural Network (ANN) for monitoring and forecasting groundwater and pumping process consideration to climate changes. The mentioned research is done in Tampa Bay, Florida, USA. Then, Emamgholizadeh et al. [55] developed an integrated computational method based on ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS). The declared research is concentrated on Groundwater Level (GWL) as a response of estimation procedure. Mahmoudpour et al. [56]

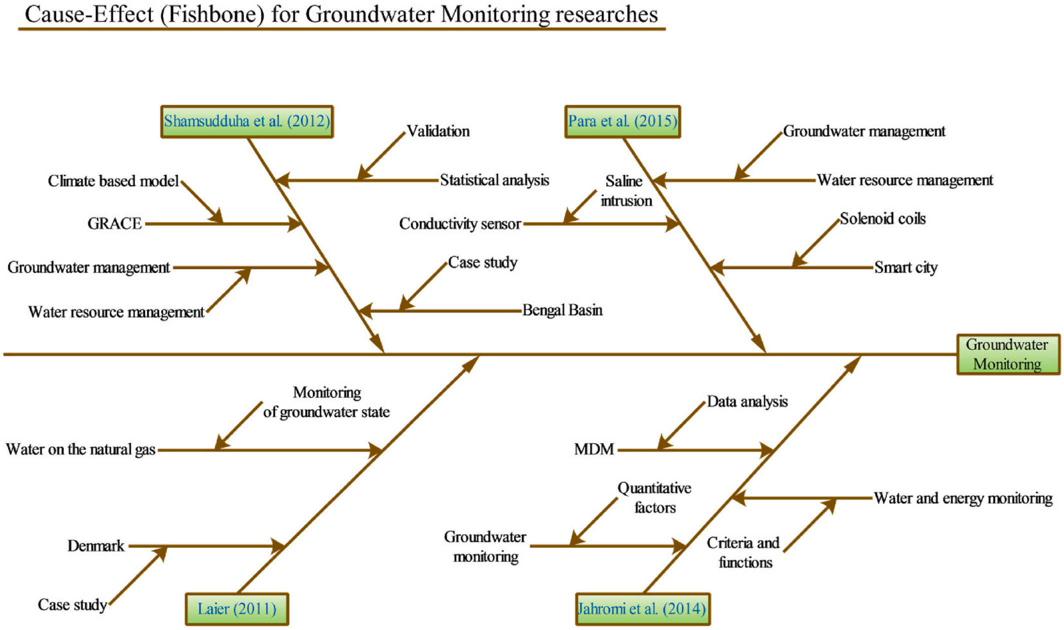


Fig. 5. The historical analysis of groundwater monitoring studies by Fishbone structure.

simulated the groundwater resources PMWIN (MODFLOW for Windows) in the south of Tehran. In the declared investigation, land subsidence and trends of groundwater are appraised in the case study. Yin et al. [57] developed Bayesian based machine learning computations for evaluation of storage change in the groundwater resources as per uncertainty concept. Clark [58] presented a

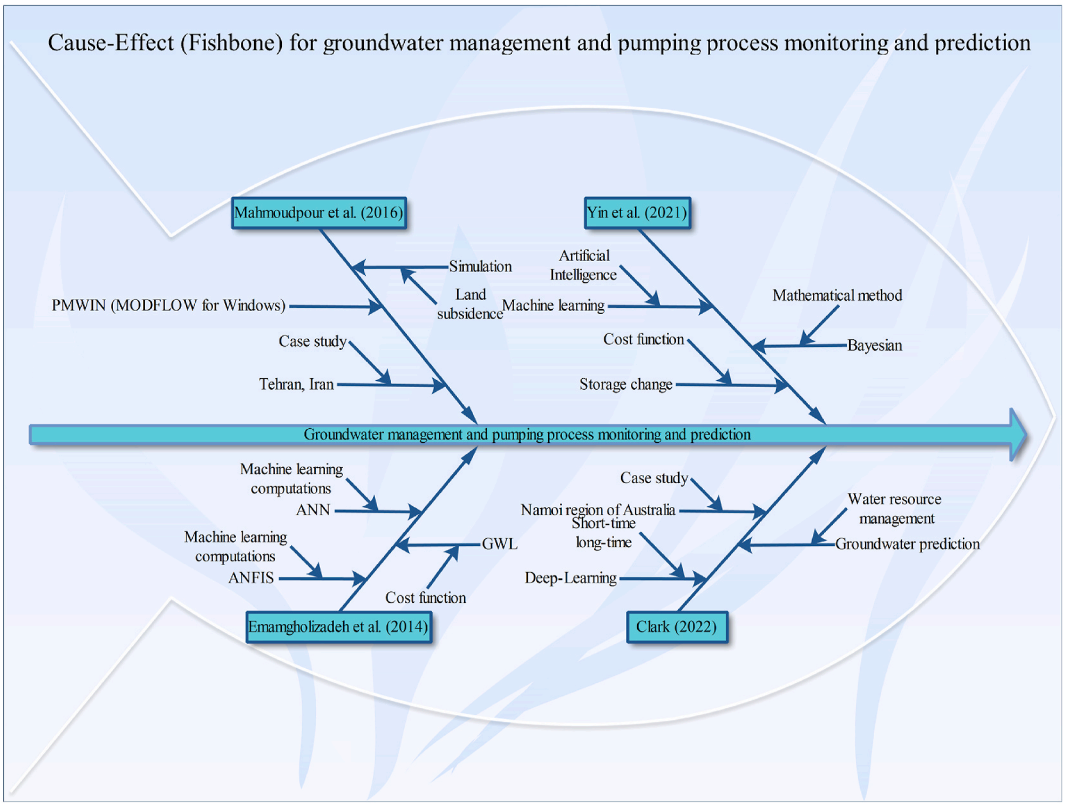


Fig. 6. The historical analysis of groundwater prediction studies by Fishbone structure.

numerical system according to Deep-Learning (DL) calculation in Namoi, Australia. In this study both short-term and long-term aspects of forecasting performance are scrutinized. Considering to Fig. 6, it is clear that the reviewed studies are concentrated on prediction aspect and the present investigation are emphasized on monitoring, prediction and control stages in the same time.

1.3. Controlling the groundwater resources

Rifai et al. [59] developed a decision support tool for real-time management of pump processing with three different sections contain simulator, global and site-specific modules. The declared system covered monitoring, prediction and control aspects of pumping in the case study. Likewise, Fredericks et al. [60] presented a decision system as smart controller of groundwater resources. In this basic study, MODFLOW, Geographical Information System (GIS), and U.S. Geological Survey (USGS) are utilized. Finally, for discussion of the mentioned research's outcomes, Stream Depletion Factor (SDF) are operated. Chen et al. [61] created a real-time decision framework for agricultural water scheduling. In this study, three aspects of water resource management contain soil specification, water data analysis, and DSS are programmed. Perea et al. [62] evaluated the application of Genetic Algorithm (GA) as controller of groundwater resources in daily periods. In the declared research both water and energy are entered as variables which are computed by Water User Associations (WUAs). Finally, a novel system which is named Model to Optimize Water Extraction (MOPWE) is presented as a result of the study. In the other research, Agarwal et al. [63] industrialized a method for smart groundwater resource management in the irrigation usages. Last but not least, Zippe et al. [64] reviewed different aspects of decision support approaches in the groundwater resource management.

While examining the body of literature in Fig. 7, it becomes evident that all the reviewed studies have focused on machine learning techniques for predicting various groundwater and pump specifications. In line with these research endeavors, our current study also employs artificial intelligence computations to assess our smart DSS.

This study endeavours to introduce an innovative data-mining decision-making framework, leveraging real-time data collected from pumps in wells and incorporating expert experience. The methodology is exemplified through a practical case study in Mashhad, Iran. Initially, the study assesses the performance and accuracy of the RF algorithm in forecasting critical parameters such as flow rate, current intensity, and water pressure head, as well as conducting time series and spatial analyses of energy consumption for pumps, i.e., particularly noteworthy in the absence of hard sensors.

Subsequently, empirical knowledge from experts at the water and wastewater company of Mashhad, Iran is systematically gathered and scrutinized to define alarm logics and allowed thresholds for operating parameters, contributing to the enhancement of pump performance. The culminating output is a user-friendly software tool, serving as a DSS, tailored for the monitoring and decision-making processes associated with pump performance and operation.

To encapsulate the primary research contributions:

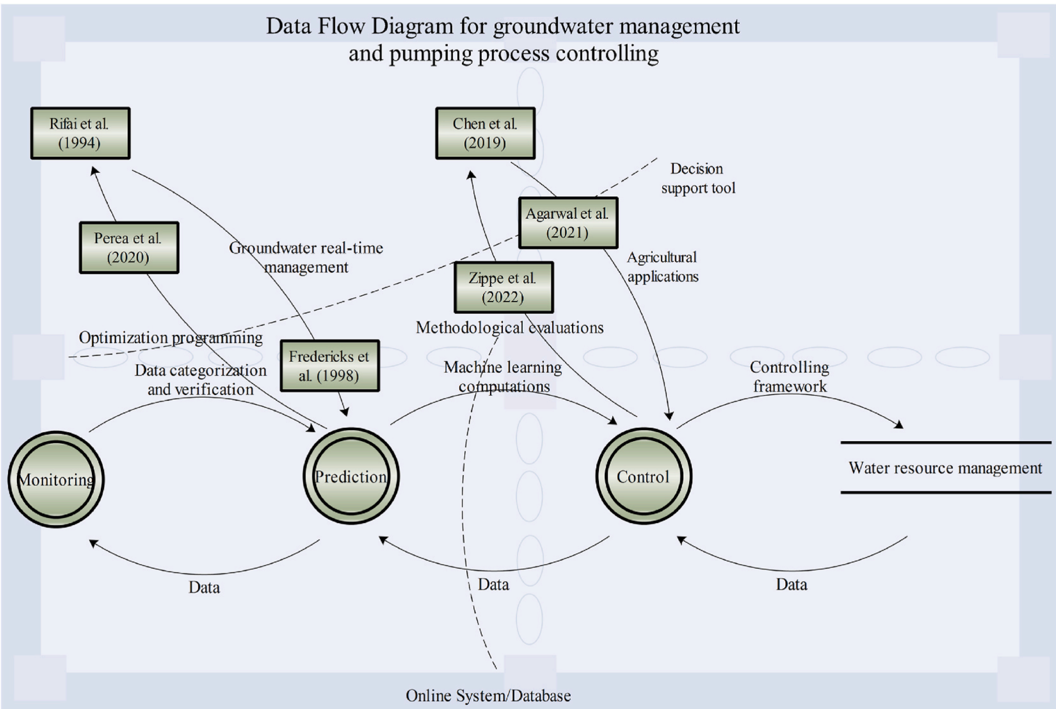


Fig. 7. The historical analysis of groundwater control studies by Trend-flow structure.

- Creation of an intelligent DSS, effectively bridging the gap between theoretical groundwater management research and its practical application.
- Establishment of a comprehensive database encompassing groundwater pumping parameters through the collection of telemetry data from six randomly selected wells, including flow rate, pressure, and current intensity.
- Conducting statistical analyses to set threshold values for critical factors such as water pressure and electrical current, informed by the collected telemetry data.
- Development of a soft sensor utilizing the RF machine learning algorithm for real-time forecasting of key variables through continuous comparison with pump design specifications.
- Integration of expert operational knowledge from water management professionals using the CD technique, enriching the DSS with practical insights.
- Provision of high-precision online insights, optimizing groundwater management practices and underscoring the practical application of data analytics and expert knowledge.

In the following sections, we assess mathematical and statistical models in Section 2, and present the modeling results in Section 3 with a particular focus on the concept of knowledge management. Section 4 delineates the implementation of the DSS for groundwater facilities management and its alignment with Sustainable Development Goals within this study. Section 5 highlights the main research limitations, implications, and policy recommendations from our results. Ultimately, in Section 6, we provide an evaluation of the key findings and offer insights into future research directions.

2. Methodology

In this section, we delve into the statistical evaluations, data mining, computational methods, and the implementation of our intelligent DSS algorithm, both offline and online. The development of a smart decision support system for sustainable groundwater management in this study involves a nuanced approach, incorporating quantitative data analysis, machine learning forecasting, expert knowledge elicitation, and integrative modeling to craft an intelligent management framework.

The proposed methodology employs operational data from sensors and telemetry systems to statistically model the normal behaviour and thresholds for parameters like flow rate and pressure, establishing a baseline for monitoring well performance. Additionally, machine learning predictive modeling contributes to forecasting key variables, even in instances where physical sensors may fail, ensuring enhanced monitoring continuity. The RF algorithm is particularly adept at handling complex variable interactions and large telemetry datasets, commonly encountered in water systems management. The CD expert elicitation method systematically synthesizes the knowledge and experience of groundwater professionals to develop data-driven actionable insights for decision support. Using the advantages of aforementioned methods, this study provides a more comprehensive approach using the integration of statistical evaluations, predictive models, expert logic, and real-time monitoring capabilities into a unified management framework.

In a similar vein, Mezher et al. [37] developed an expert system for mechanical pump performance management, utilizing a knowledge-based approach that captured operational data trends, diagnostics, and recommendations from industry advisors. Ransom et al. [20] showcased high-accuracy nitrate concentration forecasting using boosted regression tree machine learning models, leveraging robust groundwater quality sensor datasets. Gheibi et al. [65] presented a practical risk analysis decision framework for water treatment plants, integrating failure mode effects analysis, and Shannon entropy-based Petri Net modeling, thereby synthesizing

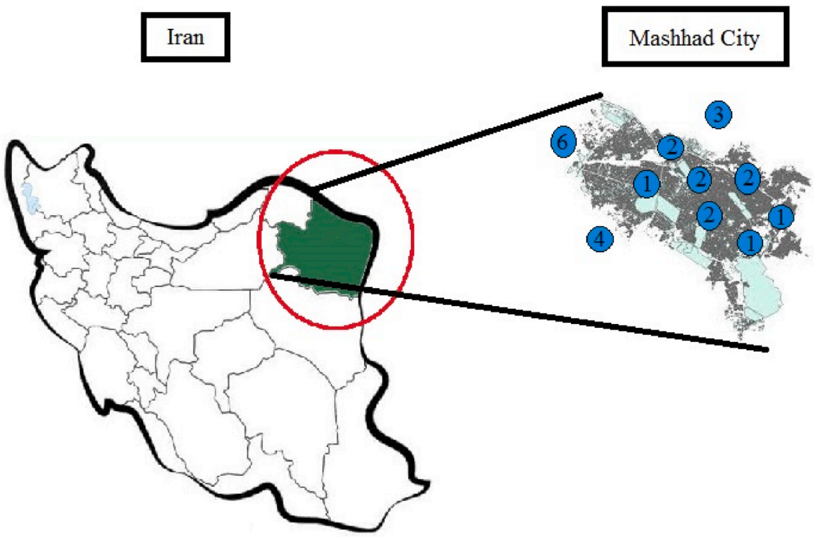


Fig. 8. Location of Mashhad, Iran and distribution of wells in the map with numbers in each region.

computational techniques with human expertise. Fathollahi-Fard et al. [9] developed an integrated optimization and learning-based decision support system for the efficient operation of water supply and wastewater collection networks, combining exact methods, adaptive mechanisms, and expert knowledge. Sun & Wang [45] designed an intelligent prediction and control system for landslide evolution state monitoring, employing multi-task machine learning models to enhance performance.

2.1. Case study

The methodology is demonstrated here on a real-world case study of Mashhad city in the east of Iran and the main tourist attraction and business centre (Shahsavar et al. [66]). The city has a population of over 3 million and an area of 351 km^2. The data collected from the telemetry systems include about 1,048,000 data records related to the hydraulic, electrical, and mechanical properties of 24 wells over a two-year period. Mashhad is a crowded city in Iran and its water systems are huge with more than 800,000 users. Therefore, for the execution of the smart city concept in the mentioned area, the application of Artificial Intelligent (AI) is crucial.

The location of wells in the case study is illustrated according to Fig. 8. According to Fig. 5, it becomes clear that the wells are distributed in different zones of Mashhad, Iran with diverse soil mechanics and water resources specifications. Also, Fig. 9 expresses the water resources characterization of case study. The mentioned scheme is related to water resources management plan of Mashhad from 2016 to 2020 and it obtained from the water management company of Khorasan province. According to Fig. 9, volume of produced water from wells as groundwater resource is considerable in Mashhad, Iran. Likewise, this trend is steady in the declared region and therefore, smart sustainable controlling of water supply facilities in this resource is crucial more than more.

2.2. Statistical analysis and data mining

Here, Fig. 10 illustrates the research framework of this study comprising four modules: statistical analysis, ML, facility health monitoring, and knowledge management (Fertier et al. [67]; Meng et al. [68]). In the statistical appraisal, descriptive analysis and histogram scrutinizing of water flow rate (Q), pressure (P), Voltage (V_1, V_2, V_3, V_{12}, V_{13}, V_{23}), current intensity (I_1, I_2, I_3), and Power (PF) are carried out by SPSS in order to determine the allowed thresholds of each parameter (Erfani et al. [69]). Then, the main core of the forecasting model for the prediction of flow rate, pressure, and an electrical current is programmed using RF algorithm (Gheibi et al. [70]) in Python environment. The algorithm with the highest level of precision is selected to design the prediction model.

These parameters were deliberately selected due to their provision of critical operational, hydraulic, electrical, and mechanical data pertaining to the wells and pumping systems. As previously highlighted, effective groundwater resource management necessitates continuous monitoring of key factors such as flow rates, pump energy usage, and efficiencies. This comprehensive approach allows for the optimization of performance and informed decision-making. The significance of each chosen parameter is noteworthy:

- Flow rate serves as a direct indicator of water demand and yield.
- Pressure signals the proper functioning of extraction.
- Electrical current and voltage characterize energy consumption.
- Power quantifies energy efficiency.

Through a process of statistical analysis and the construction of machine learning models using time-series data collected via telemetry systems on the wells, the researcher establishes robust thresholds and predicts parameters like flow rate in real-time, even in situations where physical sensors may fail. This strategic choice of parameters, coupled with the data analytics approach, empowers the decision support system to identify underperforming wells/pumps, diagnose issues, and enhance monitoring and control capabilities, thereby contributing to sustainable groundwater management.

Previous researches provide extensive evidence on the relevance of hydraulic and electrical metrics like flow, pressure and current for developing optimization solutions, predictive models and intelligent decision support approaches for efficient groundwater and pump infrastructure management. Water flow rate is widely monitored in groundwater management systems as it directly indicates

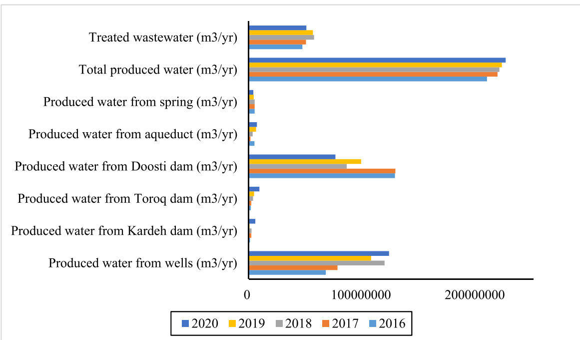


Fig. 9. Water resource management of Mashhad, Iran from 2016 to 2020.

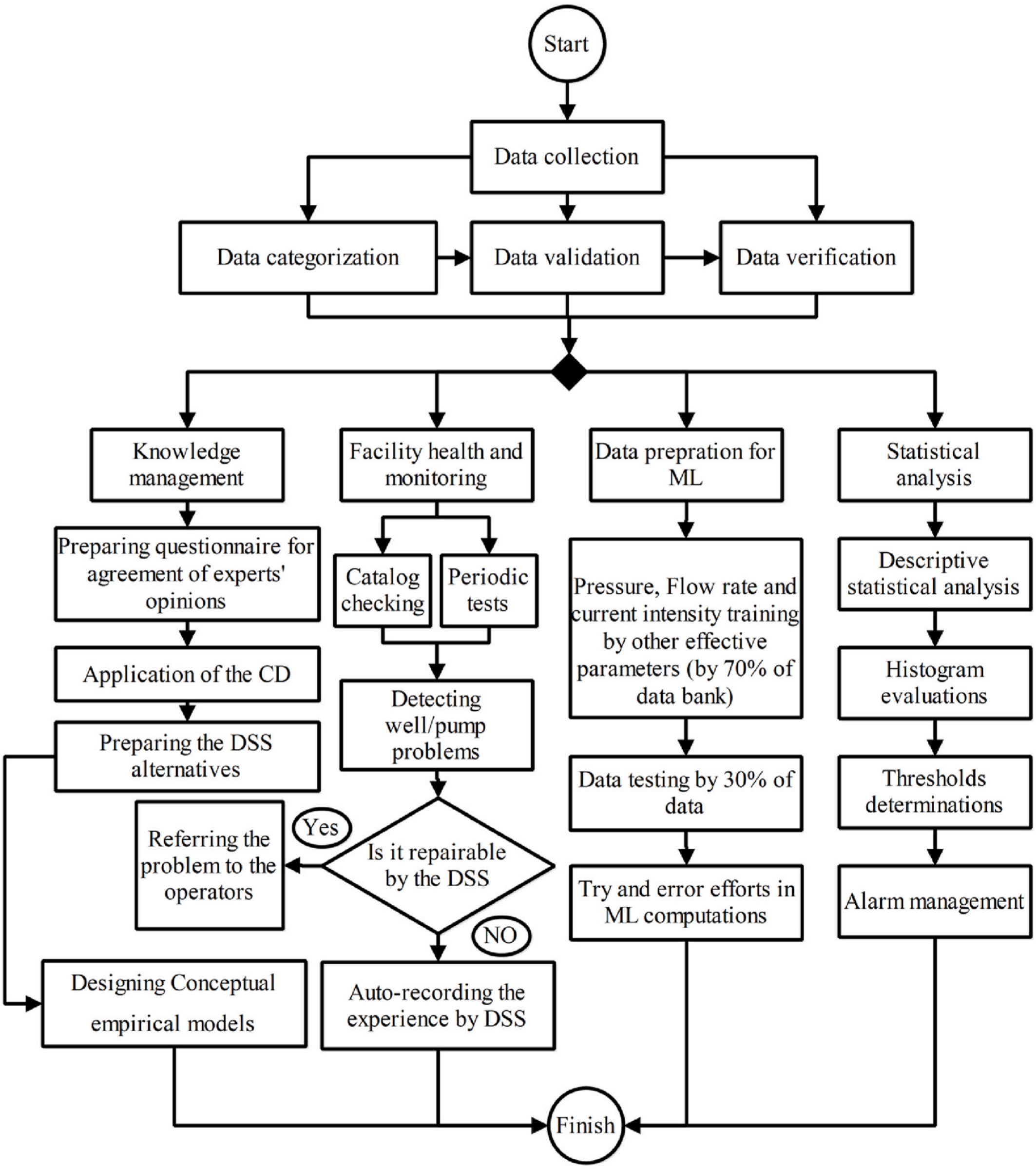


Fig. 10. Research scheme of this study.

water demand and well yield (Speed [33]; Gandon [35]). Pressure sensors provide critical insights into proper functioning of extraction (Hoffman [36]; Almeida & Ramos [71]). As pumps are major consumers of energy, current, voltage and power offer measurable characterizations of energy usage which must be optimized in operations (Ma & Wang [39]; Hanswal et al., [38]; Shah et al. [72]). Specific studies validating the importance of measuring such hydraulic and electric factors come from Mezher et al. [37] who designed an expert system for pump performance management using flow rate, pressure, current, voltage trends. Candelieri et al. [12] demonstrated high accuracy short-term water demand forecasting by training machine learning models on pump flow rate data from meter readings. Eggimann et al. [11] review various hydro-electric smart meter data types for analytical approaches in sustainable urban water management. Additionally, Coppola et al. [54], developed an artificial neural network model that predicted transient groundwater levels by learning from time-series data on related pumping rates, water usage as well as climatic variables. Conductivity sensors offered Parra et al. [53] valuable insights into managing urban groundwater resources. Thomas et al. [73] showed how pump sensor data combined with remote sensing and machine learning can support groundwater resilience planning.

The selection of parameters was meticulously based on the specific needs of the industry and the project's objectives, ensuring a comprehensive and tailored approach to groundwater management. The parameters selected for evaluation were carefully chosen to align with industry standards and the unique requirements of groundwater management. These parameters directly reflect the critical aspects of well and pump health, ensuring the relevance of our evaluation to real-world scenarios. Each parameter selected holds practical significance in the context of groundwater facilities monitoring. For instance, flow rate, pressure, and current intensity are fundamental indicators of pump and well performance, directly impacting the sustainable extraction and utilization of groundwater resources.

The telemetry data collected from six randomly selected wells encompassed a range of parameters essential for effective monitoring. These parameters were identified as crucial by industry experts, ensuring the inclusion of relevant and impactful data points in our evaluation. Additionally, the statistical analysis conducted on the telemetry data allowed us to establish threshold values for factors such as water pressure and electrical current. These thresholds are pivotal in determining the optimal functioning of groundwater systems, thereby contributing to the overall efficiency and sustainability of water resource management. Moreover, the implementation of a RF machine learning algorithm served to forecast key variables in real-time. This not only provides a predictive aspect to our evaluation but also enables continuous monitoring of variables critical to groundwater management, offering a proactive approach to system health. In addition, we integrated expert operational knowledge obtained through the CD technique, enriching our evaluation with insights from professionals in the water management industry. This ensures that our parameters are not only data-driven but also informed by the practical experiences and expertise of those actively involved in groundwater facilities management. Finally, the selected parameters collectively form a holistic approach to optimizing groundwater management. By combining statistical analysis, machine learning, and expert knowledge, our approach aims to provide high-precision online insights that contribute to the sustainable and efficient utilization of groundwater resources.

The conceptual model of the forecasting core in the ML module is demonstrated in Fig. 11. Online dynamic comparing collected data from the pumps' telemetry system with design catalogues of pumps and periodic field check-ups on the pumps' performance can create a practical framework for health monitoring of pumps and wells as a DSS (Yu et al. [74]; Irannezhad et al. [75]). In the last part of this research, a conceptual framework for empirical judgment of achieved data is created by applying the CD method (Gheibi et al. [76]). The algorithm of the CD method in the present study is demonstrated in Fig. 12.

According to pre-training and testing as well as the comparisons made between the RF data mining has appropriate efficiency in forecasting water flow rate, water pressure, and current intensity of wells and pumps based on other effective factors as per Eq. (1) (Mirabi et al. [77]; Amini et al. [44]). The RF algorithm in this study is illustrated in Eq. (1).

$$\mathrm{F(x)} = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{1}$$

RF is an ensemble of B trees $\{T_1(x)\dots T_B(x)\}$ where x is the factor aimed to be predicted. The ensemble produces B outputs $\{\hat{Y}_1 = T_1(x), \dots, \hat{Y}_B = T_B(x)\}$ where $\widehat{Y}_b$, $b = 1, 2, \dots, B$ is the prediction for each record by bth tree. Outputs of all trees are aggregated to produce one final prediction, F(x). In regression, it is the average of the individual tree predictions. The RF algorithm randomly selects 70 % of the recorded data for training while the remaining 30 % is used to evaluate the algorithm performance. The P, V_1, V_2, V_3, I_1, I_2, I_3, and PF have been considered as influencing factors, whereas Q has been assigned as the output. The last programmed system is flexible for estimation of P, Q, and current intensity (mean of all I_1, I_2, and I_3) as outcomes of the prediction system. The model performance for test data is analysed using a few statistical indicators listed in Fig. 13.

As shown in Fig. 14, the conceptual model of the data mining and ML stage forecasts flow rate, pressure, and electrical current intensity in wells and pumps. The model is developed based on the datasets for six particular wells with distinct properties in various parts of the region. A screening process has selected these wells to represent the statistical society of the studied 24 wells of Mashhad, Iran. The acquired data is received from telemetry systems in the water and wastewater company of Mashhad. The prediction model's performance has been assessed twice to confirm the highest level of performance.

2.3. Application of DSS

In this study, integrated Petri Net and Shannon Entropy (SE) models (Gheibi et al. [78,79]) have been employed to establish the DSS (Eftekhari et al. [80]), as illustrated in Fig. 15. With the application of the SE decision-making system, the situation of each role (achieved based on knowledge management, facility health monitoring and alarm management) is determined in the Petri Net model.

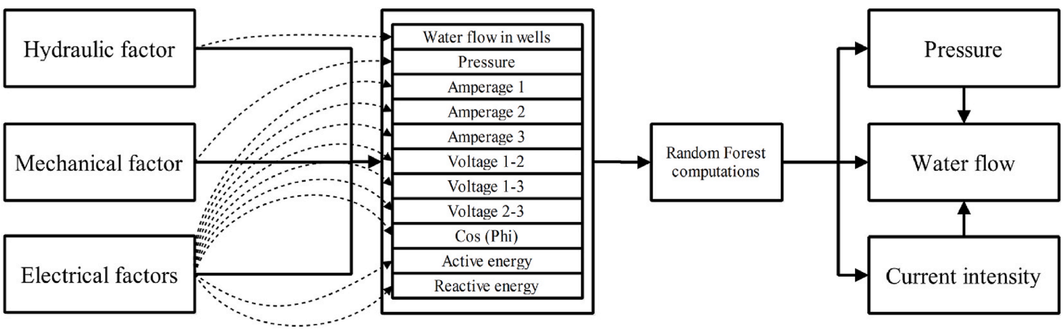


Fig. 11. Conceptual model of the forecasting core in the ML module.

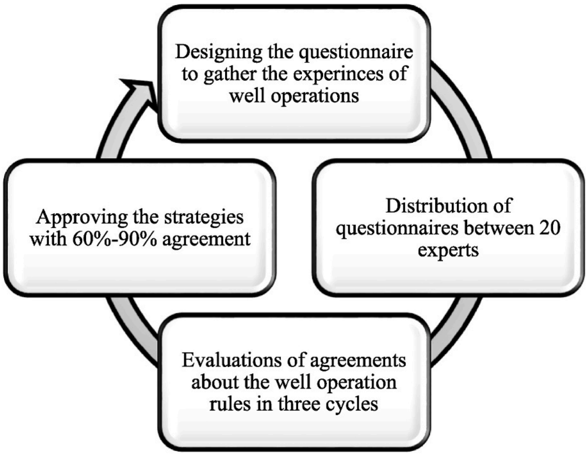


Fig. 12. The algorithm of CD method in this research.

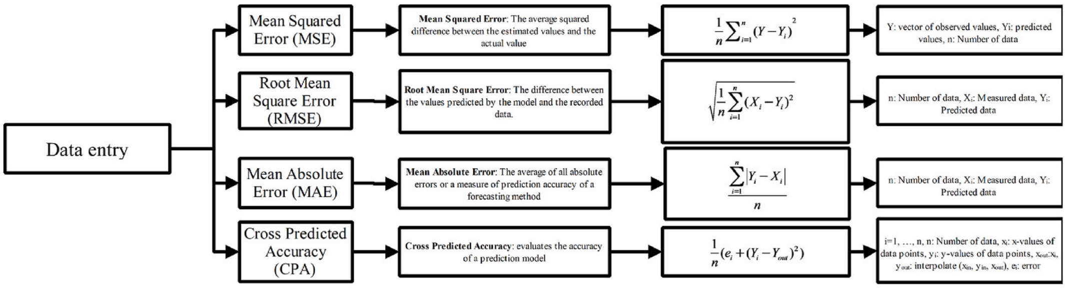


Fig. 13. Statistical Indicators' formula and description.

3. Results and discussions

In this section, statistical evaluations, data mining and ML prediction model, facility health monitoring, knowledge management by CD method, DSS in groundwater facilities management, and managerial are presented and discussed.

3.1. Statistical evaluations

The outcomes of descriptive statistical analysis and histogram diagrams are summarized in Fig. 16, respectively. As per the mentioned Table, mean values of significant parameters such as Q, P, I_1, I_2 and I_3 are equal to 0.0171 m3s-1, 346,000 Pa, 2.73e+8 A, 2.73e+8 A, and 2.73e+8 A, respectively. Moreover, in Table IS, zero and minus values reveal that the water facility is in standby condition and does not perform effectively in the operation system. The median value of Q measured 0.020 m3s-1 in each well, is interpreted as moderate water demand in each loop. The median of P, I_1, I_2 and I_3 are computed 340,000 Pa, 110.64 A, 111.81 A, and 115.68 A. Comparisons made between the mean and median values of effective factors declare the existence of several errors (wrong recorded data) in online telemetry system. Prediction process will be complicated with these data although the presence of faulty records is a common phenomenon in online telemetry industrial control systems mainly due to non-calibrated sensors, inefficiency and inappropriate functionality of electrical tools and appliances, and telecommunication infrastructures' inconsistencies. Despite these problems, our approach has endeavoured to create an accurate forecast model considering these incorrect data.

Histogram distribution concentration of effective variables Q, P, V_1, V_2, V_3, V_{12}, V_{13}, V_{23}, I_1, I_2 and I_3 are calculated in the ranges of [0.02–0.025], [(0–1) e+5 and (5–7) e+5], [$\geq$ 300], [$\geq$ 300], [> 300], [> 300], [> 300], [> 300], [0–200], [0–200] and [0–200], respectively. According to the statistical evaluations, thresholds of an alarming system for fluctuation of recorded data in the DSS are determined. If the received data is recorded beyond the critical range more than three times, The DSS alarms the operators with a warning message. It is worth noting that the critical range is defined as the allowed threshold for each parameter where 70 % of the recorded data is accumulated based on histogram diagrams. Therefore, Q, P, I_1, I_2 and I_3 parameters thresholds for possible alarms include [0.01–0.02], [1E+5-7E+5], [0–200], [0–200] and [0–200]. Also, because of the similar behaviour of current intensity values, the average of I_1, I_2, and I_3 is defined as I, which will be appraised in an alarm management system. In the DSS, the threshold determination should be flexible and adjustable by the principal's opinion and experience. Therefore, the DSS designs a flexible platform to manually define the maximum and minimum allowed recorded data of the parameter and the number of repetitions for

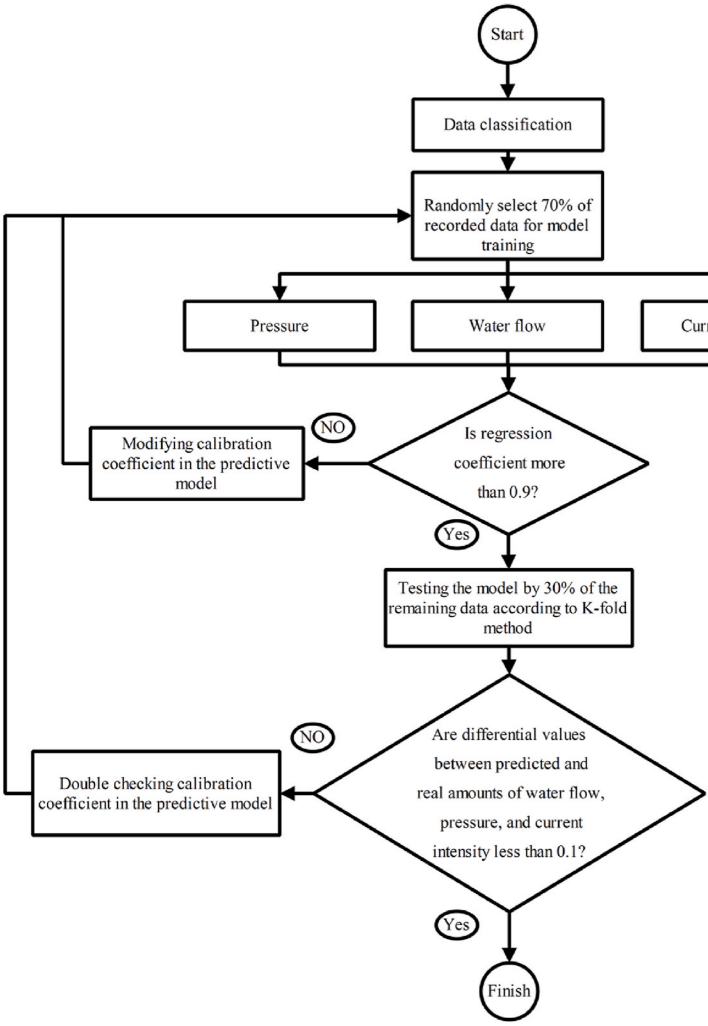


Fig. 14. Flowchart of the RF model used in this study.

exceeding the allowed thresholds in each controlling factor. Fig. 16 demonstrates statistical analysis of measured variables in pump stations as per (a) Voltage statistical indicators, (b) Kurtosis and Skewness of all electrical factors, (c) descriptive statistical parameters of current intensities and PF, and (d) full statistical specifications of Q and P.

In the following, the four main studies which are related to statistical evaluation of pumping processes data analysis are compared with results of the present research according to Fig. 17. Within this framework, our current investigation has introduced novel concepts rooted in statistical analysis, machine learning, and Knowledge-Based Systems (KBS), distinguishing our work from the existing body of prominent studies.

3.2. Data mining and ML prediction model

This section employs the RF algorithm to train the forecast model in Python. Among all computations, the RF algorithm has shown an appropriate performance The RF algorithm has been used to train a ML model in Python environment that forecasts water flow rate, water pressure, and current intensity of the wells and pumps in Mashhad, Iran. The outputs of the performance evaluation of this algorithm in the mentioned wells are illustrated in Fig. 18. In this regard, the RF algorithm prediction model exhibits the highest level of compatibility with the real data compared to the three other algorithms. The Mean Squared Error (MSE) approaches zero in all wells, except for the 2nd well, as depicted in the figure. This indicates no significant difference between the predicted parameters and the actual records by the telemetry system in 6 wells which confirms that the forecast model is of high precision. This parameter in the 2nd well is remarkably high (3.98) due to the wrong information in the dataset related to this well.

According to these outcomes, the Root Mean Squared Error (RMSE) is also close to zero in most wells, affirming the high validity of the anticipation model. However, it is relatively large in well 2, highlighting the existence of wrong observed data in its dataset. The Mean Absolute Error (MAE) is deemed acceptable in all six wells, as this parameter does not assign greater weight to larger errors.

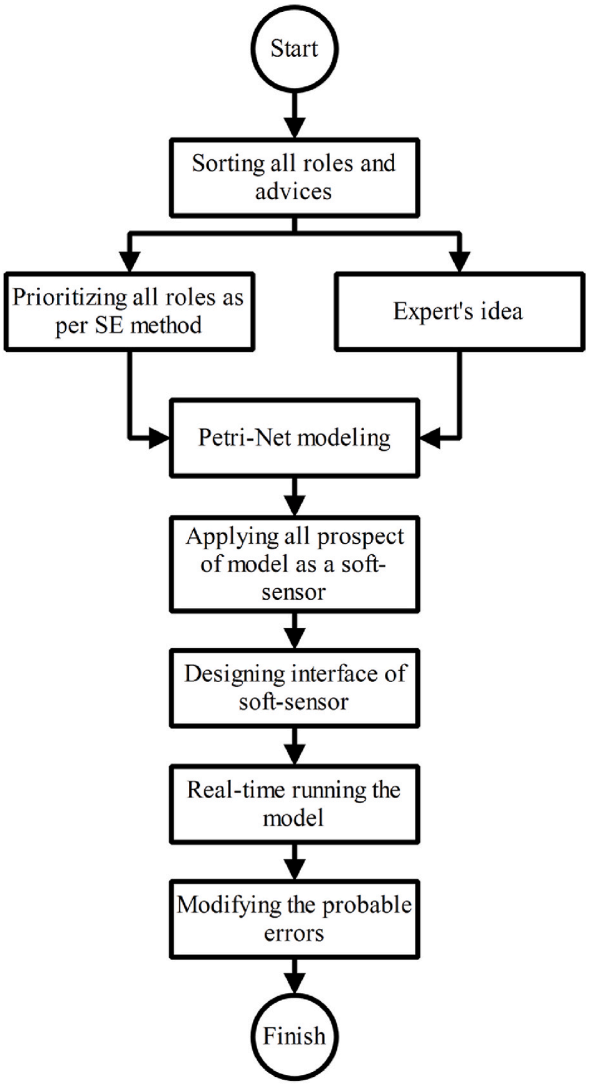


Fig. 15. Development of our DSS in the present research.

Therefore, there is an insignificant disparity between well two and other wells' MAE parameters. The Cross-Predictive Ability (CPA) evaluates the generalizability of the model to unseen data. In this regard, this parameter is equal or very close to 1 in about 90 % of the wells, which signifies great applicability of the forecast model in predicting the effective parameters in future. However, the CPA metric in well two has been reported 0.58, indicating large errors in received data from this well again.

The outcomes of the statistical evaluation of the RF algorithm applied in the ML model's training and testing demonstrate the prediction model's high precision. This confirms that RF is an appropriate algorithm for predicting wells and pumps' parameters, including water flow rate, pressure, and current intensity. The reliable performance of the RF algorithm can be due to its nonparametric characteristic, i.e., it does necessarily follow a normal distribution. Besides, it indicates a more powerful performance against outlier values than other methods, as each tree in the RF algorithm is generated from different data subsets (Amini et al. [44]).

In the following, for verification of RF performance in this study, the created ML-based model is evaluated according to data of 10 different wells which five of them are related to Shandiz city -which is demonstrated through Fig. 19-a, and other ones are connected to Torbat-Hydariyeh city in Fig. 19-b. The outcomes of statistical computations are demonstrated in Fig. 19. The outcomes show that error values are insignificant publicly and it is acceptable from operational aspects. Likewise, it is worth noting that the homogeneity of errors in both Shandiz and Torbat-Hydariyeh cities are more than in Mashhad's case study. Therefore, it proves that the mechanical of well No. 2 in the Mashhad's case study is abnormal, and the created model has enough reliability for predicting water demand, pressure, or current intensity.

According to Fig. 20, in data mining of wells facilities issues and groundwater management subject, some different studies are done. But, difference of the present research with them is related to combination of machine learning and KBS as a DSS.

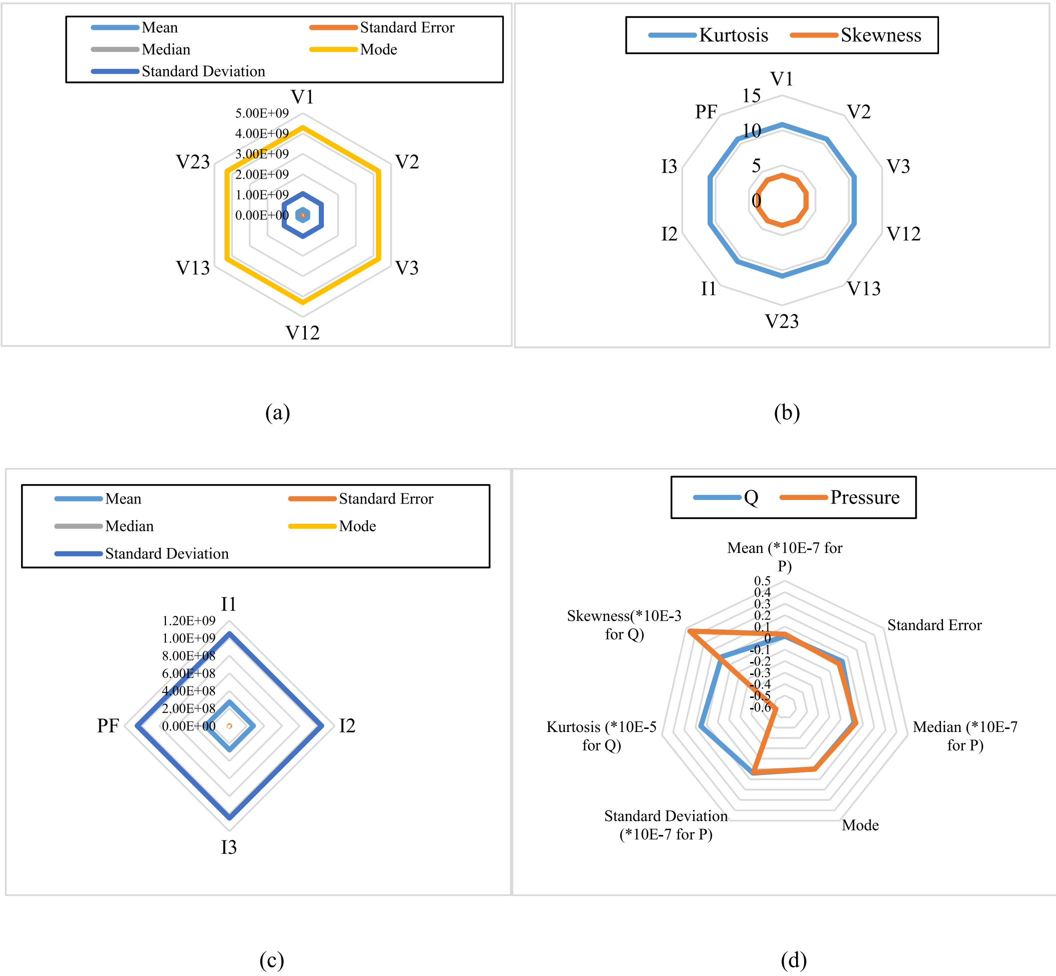


Fig. 16. Statistical analysis of measured variables in pump stations as per (a) Voltage statistical indicators, (b) Kurtosis and Skewness of all electrical factors, (c) descriptive statistical parameters of current intensities and PF, and (d) full statistical specifications of Q and P.

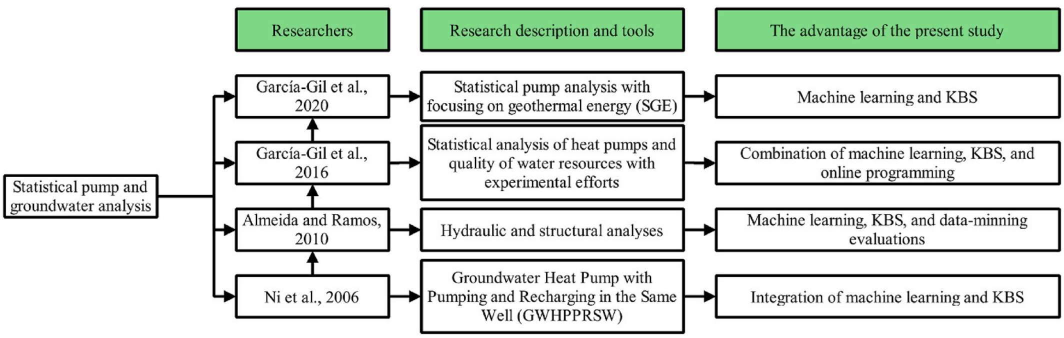


Fig. 17. Schematic plan of groundwater facilities' statistical data analysis researches with comparisons to the present research.

3.3. Facility health monitoring

The main objective of the pump's health monitoring is to integrate the empirical knowledge and experience with the design tables, catalogues, and the pump characteristic curves. This comprehensive information has been then interpreted to meaningful statements and commands implemented in the smart management framework through ML methods. The output algorithm is demonstrated in Fig. 21. According to this figure, the pumps Health Monitoring commences with the pumps' simultaneous operational, energy

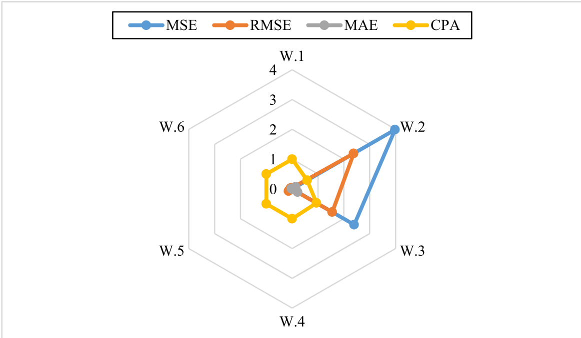
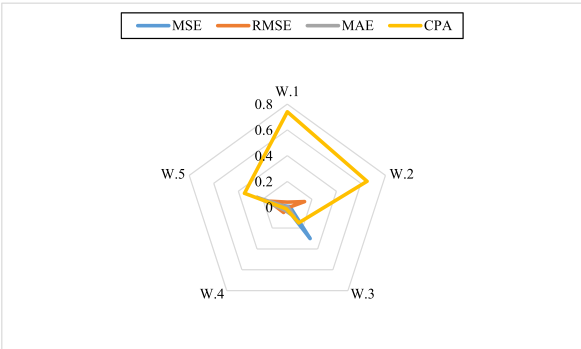
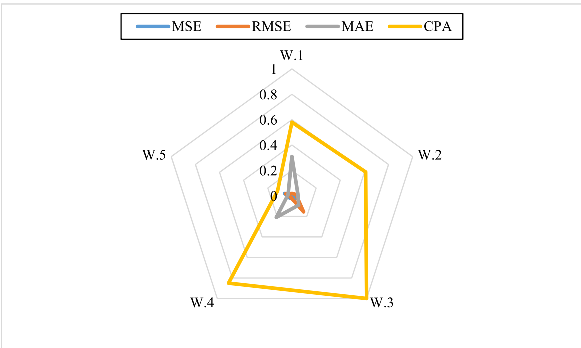


Fig. 18. Performance evaluation parameters of RF algorithm in data mining.



(a)



(b)

Fig. 19. The outputs of verification the RF performance through 5 different wells from (a) Shandiz and (b) Torbat-Hydariyeh cities.

intensity, and efficiency monitoring. In operational control, the primary goal is to establish a permanent condition in the water flow extracted from the wells. The system inspects the water flow rate constantly and any unusual record will be reported to the operator to take the proper measure. In case of any unexpected situation, the administrator is asked whether pump's shutdown is necessary or not. A healthy pump will be substituted for the current one if the operator decides to turn off the present pump. The allowed threshold defined for energy intensity and efficiency are extracted from the investigations in the catalogues and characteristic curves of the pumps as well as interviews with water management experts and professionals. The standard thresholds for energy intensity and efficiency in the pumps of Mashhad are determined [0.5–1.5] and [55–75] %, respectively. In case of recording water flow rate beyond these allowed limits, the operator will be warned to examine hydraulic and electrical parameters, water flow rate, and dynamic and static water levels in wells and apply the appropriate solution to the problem.

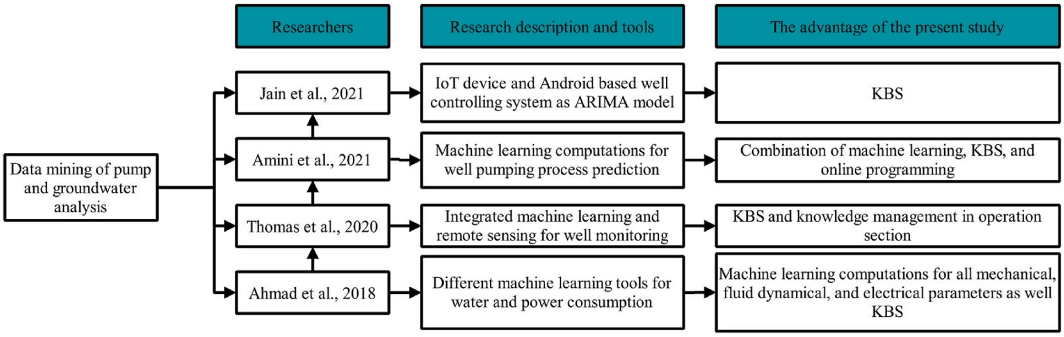


Fig. 20. Schematic plan of data-mining in groundwater subject researches with comparisons to the present research.

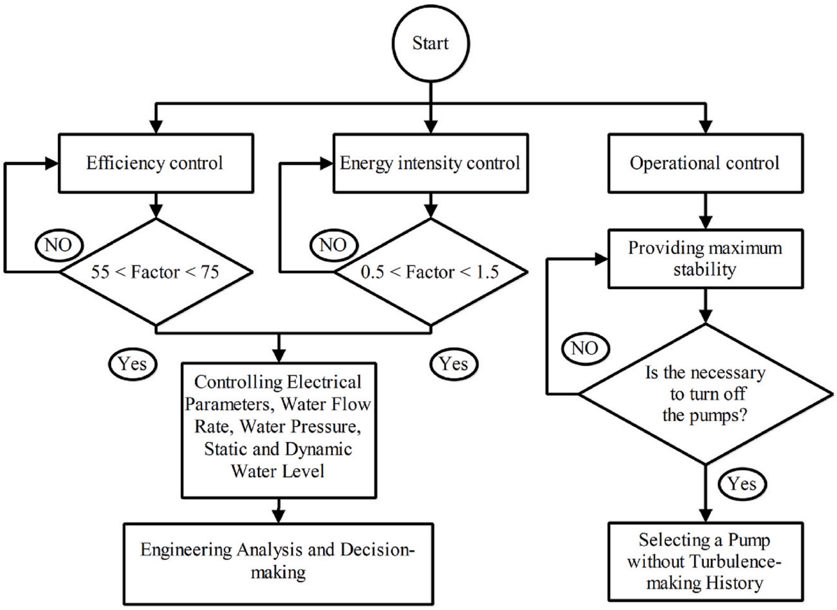


Fig. 21. The operational algorithm of pumps Health Monitoring in this study.

3.4. Knowledge management by CD method

The expertise of the professionals in Mashhad Water and Wastewater Company has been gathered, analysed, and integrated using CD Method according to Fig. 12. The empirical knowledge of the operators and administrators in well and pump facility management departments and declared technical information in pumps catalogues and design tables are integrated and presented as computerized algorithms to be employed in a smart management framework. This DSS is important in industrial fields as it atomizes the wells and pumps monitoring and management process. The ultimate results of CD method after three rounds of interviews with the experts in the water and wastewater company of Mashhad, analysis and evaluation of their responses, and creating a conceptual model extracted from these interviews are declared in 2 main algorithms illustrated in Fig. 23 and 24. A pre-interview round has also been conducted to provide the general understanding and an overall algorithm that explains the pumps' operation and the possible errors that may disrupt their optimum performance. The outputs of this pre-interview are also demonstrated in Fig. 22.

At first, the selected group of experts are pre-interviewed to determine the most effective parameters on wells behaviour and pumps performance and the acceptable threshold for these parameters. According to the pre-interview outputs indicated in Fig. 22 and pumps' characteristic curves, most wells in Mashhad supply 30 L s^{-1} water flow rate with a pressure head of about 200 m. Therefore, a desirable range which is determined for all the wells in Mashhad, Iran based on the experts' opinion has been defined 8–30 L s^{-1}. It is worth mentioning that the flow rate has been seldom recorded below 1 or over 45 L s^{-1}, so those records are neglected in defining the critical range in this research. The allowed threshold for water pressure has also been described between 1 and 5 atm. The voltage in most of the pumps has been reported between 380 and 410v, and current intensity is determined almost twice as much as the power in these pumps. It has also been concluded that significant differences between the three voltages and current intensities signify the existence of an error or breakdown in the pump accurate operation.

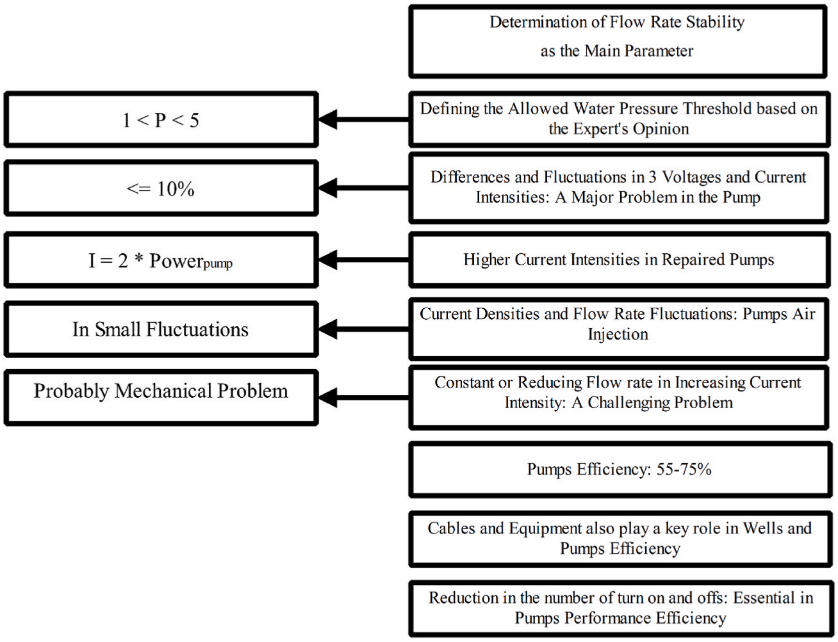


Fig. 22. The pre-interview round outcomes of the Classical Delphi method.

Furthermore, it is essential to regulate the heightened current intensity in repaired pumps to address potential efficiency drop issues. The allowed threshold for this increase is 10 % of the pump's nominal current intensity. One of the most important observed a is the fluctuation in current intensity, which notifies the air injection problem of pumps. This should be closely monitored as it can cause serious damage to pump, equipment, and well flow. Occasionally, 2 distinct parameters can jointly affect the well and pump health and should be considered simultaneously. For instance, the normal behaviour of the water flow rate and current intensity indicates the pump health, while a constant flow rate with growing current intensity implies a major problem in the pump. In addition, an extraordinary high-efficiency rate for pump operation should also be suspected as it is generally reported 65–80 %, and higher efficiency percentages should be monitored. It is worth mentioning that cables and other gadgets and equipment of the pumps are not renewed with installing a new pump. This can also make several problems and should be considered in the pump error-detection process.

According to the viewpoints of the experts in the water and wastewater company of Mashhad, it is concluded that stability in the main parameters involving water flow rate, water pressure, current intensity, voltage, and pumps' operating hours all together lead to the optimum performance of the well and pump facilities. This confirms the pump's health in electrical and mechanical aspects and protects the good health as the fluctuation in water flow rate may damage the wells' walls.

In this part of the research, the acquired concept and understanding of the pump's performance, possible errors in its operation, and probable reasons for these errors are clarified in 2 computerized algorithms applicable in ML models. As depicted in Fig. 23, water flow rate is the most prominent parameter that indicates the pump's healthy performance. As a result, the first step in monitoring pumps performance is to examine the stability of the water flow rate. However, it closely corresponds to electrical current intensity and water pressure. Therefore, these parameters should also be carefully examined for any further error. The fluctuating current intensity with water flow rate signs the air injection problem in the pump whereas growing current intensity alarms the necessity for water network pressure control. Constant water pressure may declare the existence of a problem in the pump. Otherwise, the situation should be reported to the operator for engineering analysis.

According to Delphi method outcomes for electrical parameters assessments illustrated in Fig. 24, current intensity and voltage are two of the main parameters which should be inspected concurrently. The machine first examines the unacceptable average of current intensity and is reported to the operator for engineering evaluations. The increasing average of current intensity may be due to installing a new pump. In a new pump, while an increasing average of current intensity with steady flow rate may be a sign of an unknown problem in the pump, a fluctuating average of current intensity with flow rate is caused by air injection problem in the pump. Moreover, the algorithm also scrutinizes the stability of the 3 current intensities and voltages. Impermanent current intensities indicate a problem in the pumps, whereas unsteady voltages should be notified to the administrators for subsequent assessments of technical issues.

In addition, the Petri Net method has been employed to elaborately model the logic and stages of the whole investigation in different processes, analyses, and evaluations. This Petri Net model is presented in Fig. 25.

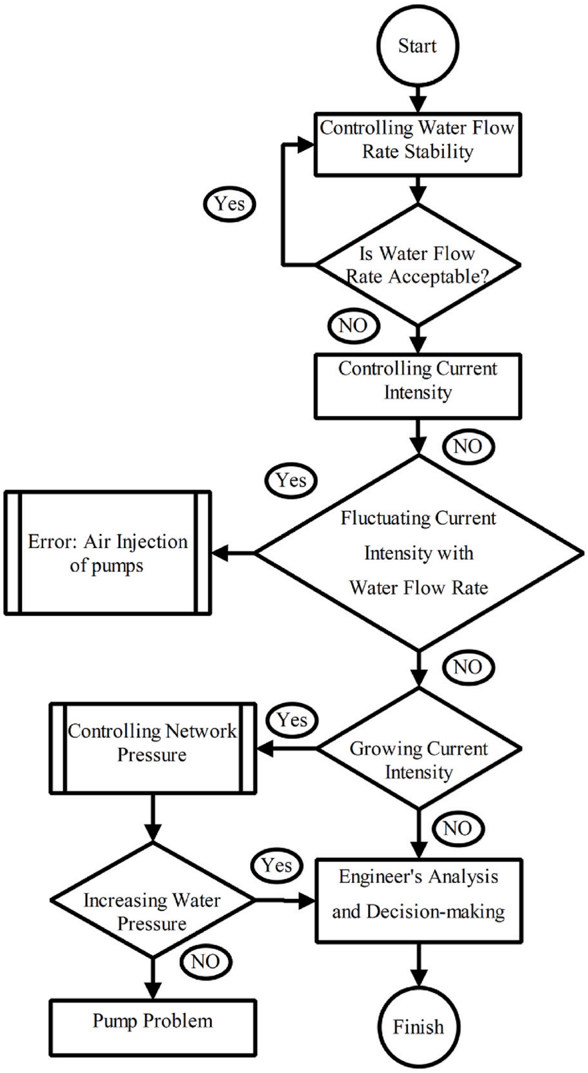


Fig. 23. Water flow rate monitoring algorithm base on Classical Delphi method.

4. Our DSS for the groundwater facilities management

The DSS is then designed and presented as shown in Fig. 26. Different parts and toolbars of the DSS are demonstrated in this figure. The most prominent part of this user-friendly smart management framework is the administration dashboard where the officials conduct the efficiency control and operation management. This toolbar enables the operator to monitor, analyze, control, and report the performance of the whole groundwater management system, every single well, and its facilities in each selected period. Moreover, as all toolbars and parts are modifiable by the user, this dashboard allows the administrators and operators' empirical knowledge and immediate decisions to be executed in this DSS. The user can also observe the parameters on diagrams and monitor the system's performance under adjustable conditions. It also provides this opportunity to select more than one parameter in each well or pump and compare their behaviour and alterations concurrently.

According to Fig. 26, "EslamAbad 02″ well has been selected in the DSS platform during the first four months of 2019. In the controlling toolbar, Q and predicted Q (Q_p) are opted to be demonstrated in comparison to each other in the diagram during this period. It is worth mentioning that other operating parameters are also possible to be chosen and compared with each other. The operator can modify the limits and thresholds for the selected parameters based on specific conditions and individual experience and knowledge in the threshold settings and alarm management toolbar. For instance, in Fig. 26, the allowed Q received from sensor is determined 14 L s^{-1}. The fluctuation range is adjusted 3, which indicates that the recorded Q can vary in the range of [11–17] L.s^{-1}. Otherwise, the operator is notified by a warning message in case of any recording of Q out of this allowed threshold more than three times. The minimum and maximum Q values illustrated on the diagram are also modifiable in this toolbar.

For example, the graph in Fig. 27 indicates the recorded Q from sensors compared to the predicted Q_p for "EslamAbad 02″ well

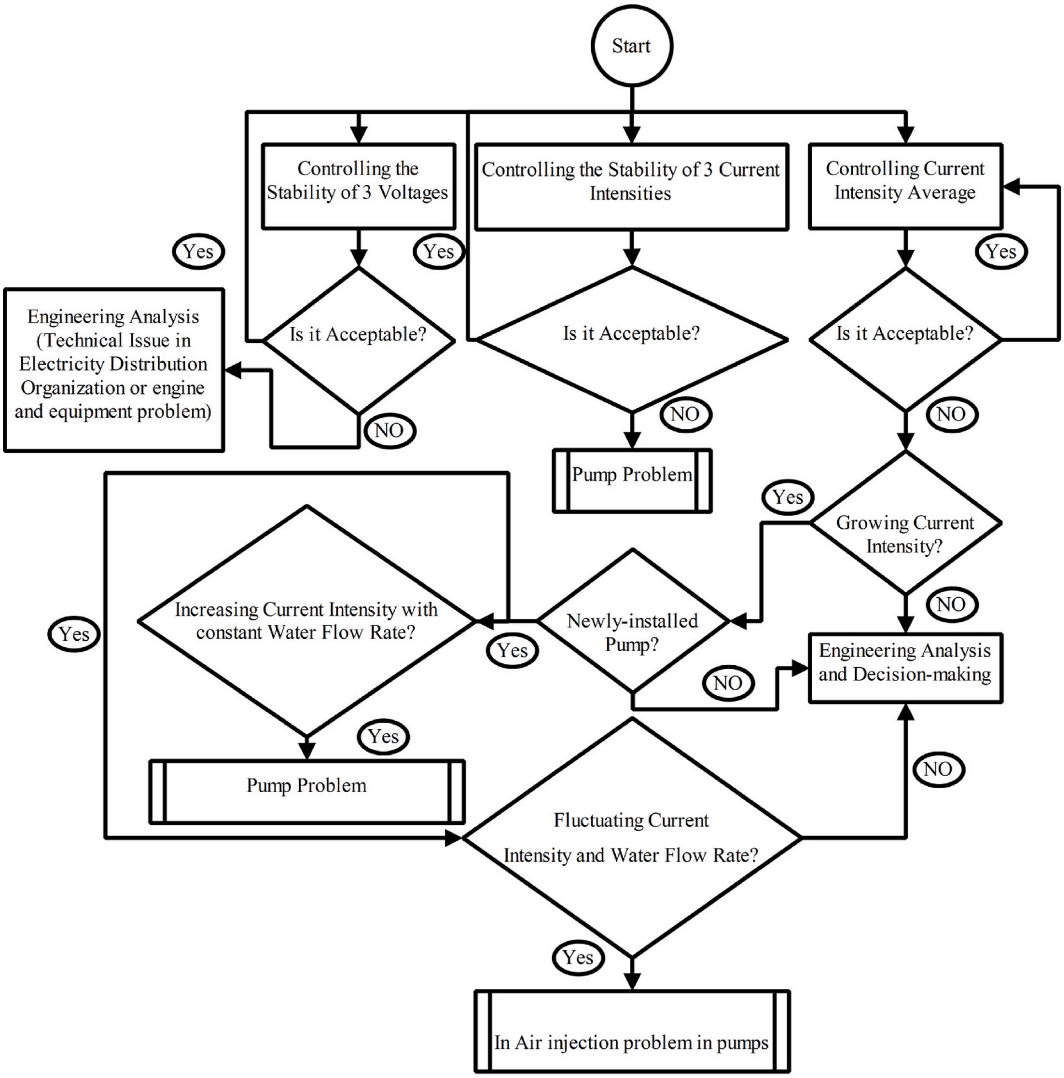


Fig. 24. Electrical Parameters monitoring algorithm base on Classical Delphi method.

during the first four months of 2019. As per the mentioned Fig, the orange box marks the allowed range of fluctuations in the recorded Q ([11–17] L.s^{-1}). While the yellow line indicates the predicted Q, the red line signs the received Q from the sensors. As evident in this figure, the yellow line is mainly in the allowed range, whereas the red line has experienced enormous variations. This can be concluded that the DSS has presented a forecast model with the highest possible precision level despite a great deal of inaccurate data recorded by the sensors. This DSS not only predicts the Q, P, I, or other well and pump parameters and detects the values of these parameters beyond the allowed thresholds but also evaluates the optimum operation condition and acceptable performance. This is achievable by online and in-situ reporting of effective parameters such as efficiency and current intensity and the possibility to determine the threshold for all hydraulic and electrical parameters.

The authorities and operators can monitor water pressure and current intensity by considering the effects of water flow rate as the most important parameter in managing wells and pumps. Figs. 28 and 29 show water pressure and current intensity compared to water flow rate, respectively. The operator can monitor the health of the pump performance by observing any unexpected change in these graphs. As per Fig. 29, the fluctuating current intensity with the water flow rate warns against the air injection problem in the pump. The acceptable water flow rate in case of fluctuating or increasing water pressure also shows a problem in the pump. This managerial DSS easily detects all these problems.

According to Fig. 30, there are also some parts in the executive dashboard that the manufacturer of pumps, pumps' properties, and standards are inserted. Then, these pumps are allocated to each well. This will enable the operators and managers to evaluate the performance and efficiency of different brands of pumps over time.

In standard section, the H-Q graphs of the pumps can be inserted from catalogues, experiments, monthly and annual field check-ups. It enables the user to compare each log with the optimum condition or other time periods' performance. The standard section is

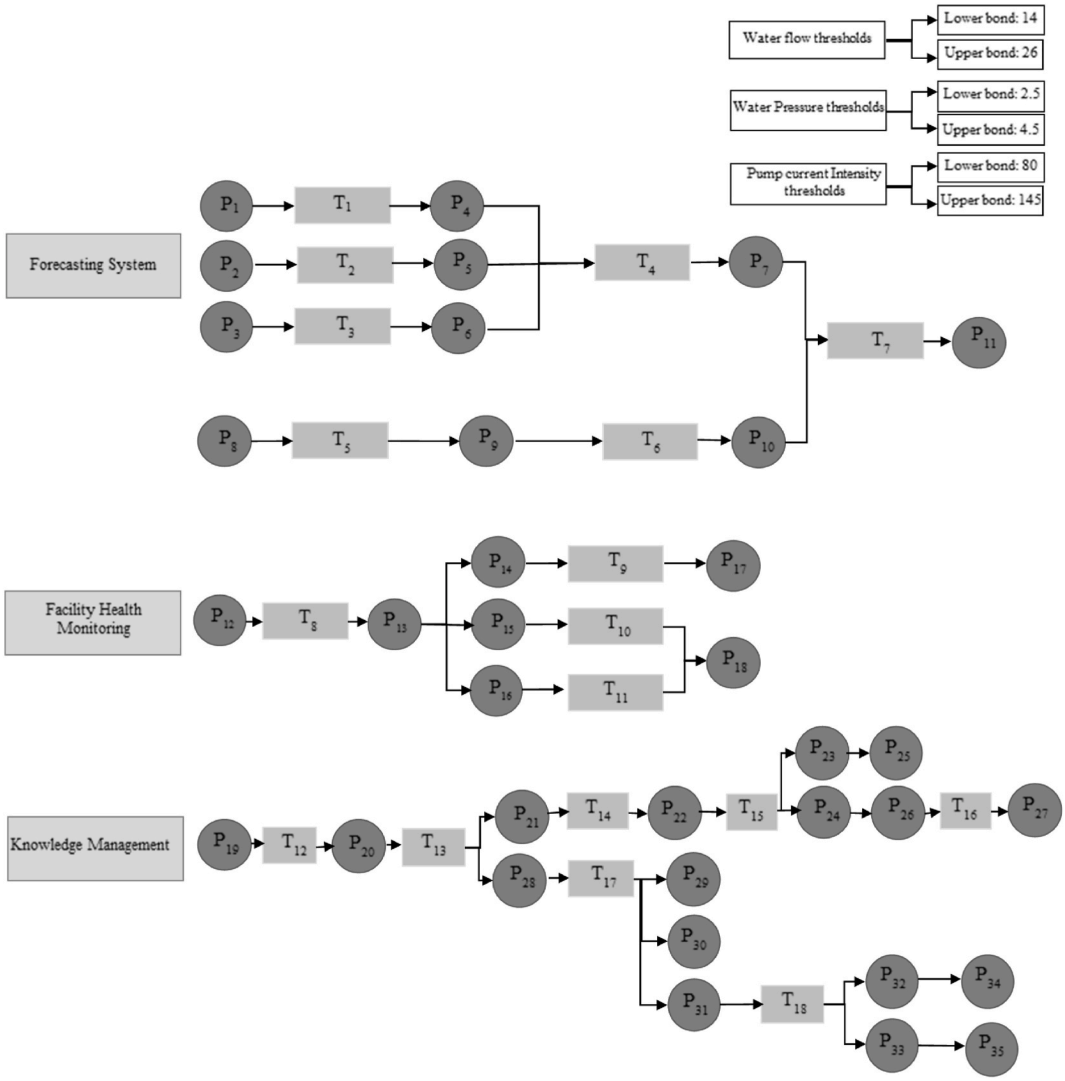


Fig. 25. The Petri Net conceptual model of the designed Decision Support System.

indicated in Fig. 31 and the H-Q curve of the pumps is also illustrated in Fig. 32. Based on Fig. 32, different fluctuations of Head (H)-Q in various tests and supervisory records are illustrated. The mentioned tests outcomes demonstrated that H and Q have a specific relationship together, and this association can be useful for controlling the pump health monitoring. For example, in this study, Q and H are set equal to 14 and 193 according to manager's opinion and the alarm management are operated as per the declared thresholds.

Fig. 33 illustrates the cost breakdown of our study, focusing on both investment and operational expenditures. Notably, 75 % of the total costs are earmarked for investments, with the remaining 25 % allocated for operational aspects. It's important to recognize that implementing this smart infrastructure for sustainable groundwater management entails substantial expenses. In alignment with the Sustainable Development Goals (SDGs), the deployment of our soft-sensor technology in Mashhad, Iran for groundwater management advances the SDG related to Sustainable Cities and Communities (Chouhan et al. [30]). Previous studies have also highlighted the potential of smart infrastructures in megacities for effective groundwater management (Qureshi et al. [81]).

Collin and Melloul [82] demonstrated that intelligent, sustainable groundwater management practices can fulfill certain aspects of the SDGs. Aarnoudse et al. [83] introduced an innovative method for smart groundwater resource monitoring in northwest China using smart card machines. Their findings indicated increased water management efficiency through the operation of semi-soft systems. In contrast, our study employs a fully soft-system approach, offering promise for addressing water stress challenges in developing countries within the context of the smart city concept.

The performance results of the RF machine learning model align with previous studies that have demonstrated the capabilities of ensemble methods like RF for prediction tasks in water systems management. For instance, Band et al. [25] found that RF outperformed SVM, Cubist and other techniques in accurately estimating groundwater nitrate levels using complex sensor parameters.

P_1: The online telemetry data of (flow rate) is received
P_2: The online telemetry data of (pressure) is received
P_3: The online telemetry data of (pump's current intensity) is received
P_4: Showing **insignificant** issue as an instant issue for Q (flow rate) equipment/well
P_5: Showing **insignificant** issue as an instant issue for P (pressure) equipment/well
P_6: Showing **insignificant** issue as an instant issue for I (current intensity) equipment/well
P_7: Indicating **significant** issues in pumps and well equipment and facilities as **1st order problem**
P_8: Forecasting Q (flow rate) with the application of novel and creative soft-sensor
P_9: Showing error reports for checking and investigating the standards, the regime of hydraulics, and physical health of pumps
P_{10}: Indicating **significant** issues in pumps and well equipment and facilities as **2nd order problem**
P_{11}: Showing the 2nd order (According to the forecasts) issues
P_{12}: **Health Monitoring of the Pumps**
P_{13}: Allocating the same priority and importance weight to the operational, energy intensity, and efficiency controls
P_{14}: Operational Control of the pump to provide the maximum stability
P_{15}: Energy Intensity Control
P_{16}: Efficiency Control
P_{17}: Substituting a pump with no turbulence history
P_{18}: Reporting to the operator for controlling water flow rate, electrical, and hydraulic parameters and engineering analysis
P_{19}: **Knowledge management and designing the integrated alarm management system**
P_{20}: Acquiring a general understanding and overall algorithm of the possible errors which may take place in pumps management
P_{21}: Flow rate Monitoring
P_{22}: Reporting unacceptable and unstable water flow rates
P_{23}: Fluctuating Current Intensity and Flow rate
P_{24}: Growing Current Intensity
P_{25}: Air Injection Problem in the pump
P_{26}: Pressure Monitoring
P_{27}: Reporting a problem in pump in case of not increasing pressure
P_{28}: Electrical Parameters Monitoring
P_{29}: Reporting unacceptable 3 Voltages records for technical analysis
P_{30}: Reporting unacceptable 3 Current Intensities for engineering analysis
P_{31}: Increasing Current Intensity average
P_{32}: Increasing Current Intensity with constant flow rate in a replaced pump
P_{33}: Increasing Current Intensity with fluctuating flow rate in a replaced pump
P_{34}: Pump problem
P_{35}: Air Injection Problem in the pump
T_1: Investigating for the records beyond the Min and Max determined limits of Q (flow rate) factor
T_2: Investigating for the records beyond the Min and Max determined limits of P (pressure) factor
T_3: Investigating for the records beyond the Min and Max determined limits of I (current intensity) factor
T_4: Exceeding the number of out-of-desirable-threshold records from 3 times per hour
T_5: Considering the disparity between forecast and real recorded flow rate data higher than 15 % as insignificant
T_6: Considering a more than 30% difference between the predicted and real flow rate factor per day as significant
T_7: Determining the subscribed issues in 1st and 2nd order groups
T_8: Application of Shannon Entropy model to prioritize each effective parameter in health monitoring of the pump
T_9: Checking the necessity of the pump shutdown
T_{10}: Checking Energy Intensity to be in the allowed range [0.5-1.5]
T_{11}: Checking Efficiency of the pumps to be in the allowed range [55-75] %
T_{12}: Application of CD method to integrate and analyze the expertise of the officials in wells and pumps management in Water and Wastewater Company-Pre-interview round
T_{13}: 3 rounds of Interviews with the pumps operators and administrators to obtain knowledge about electrical and hydraulic parameters in pumps based on the information acquired in the pre-interview round and creating 2 main algorithms from the outputs
T_{14}: Checking Water flow rate stability
T_{15}: Controlling Current Intensity
T_{16}: Checking Increasing Pressure
T_{17}: Comparing Electrical parameters including, 3 Voltages, 3 Current intensities, and the average of current intensities with allowed thresholds

Fig. 25. (*continued*).

Similarly, Ouedraogo et al. [27] showed superior groundwater pollution forecasting accuracy with Random Forest over basic multiple linear regression. The high accuracies and model generalization achieved despite imperfect real-world SCADA data highlight the Random Forest algorithm's effectiveness when dealing with unbalanced, noisy dataset characteristics prevalent in industrial water telemetry systems. Moreover, the practical integration of data-driven analytics with structured expert knowledge for decision support connects with previous efforts where pairing computational intelligence and human perspectives has enhanced sustainable water stewardship. Furthermore, Raffensperger et al. [84] evaluated a groundwater management model based on MODFLOW and GWM computations. However, their system relies on commercial platforms and offers limited flexibility compared to the computational capabilities demonstrated in our study.

Moreover, achieving balance between development needs and environmental sustainability during global crises aligns with wider

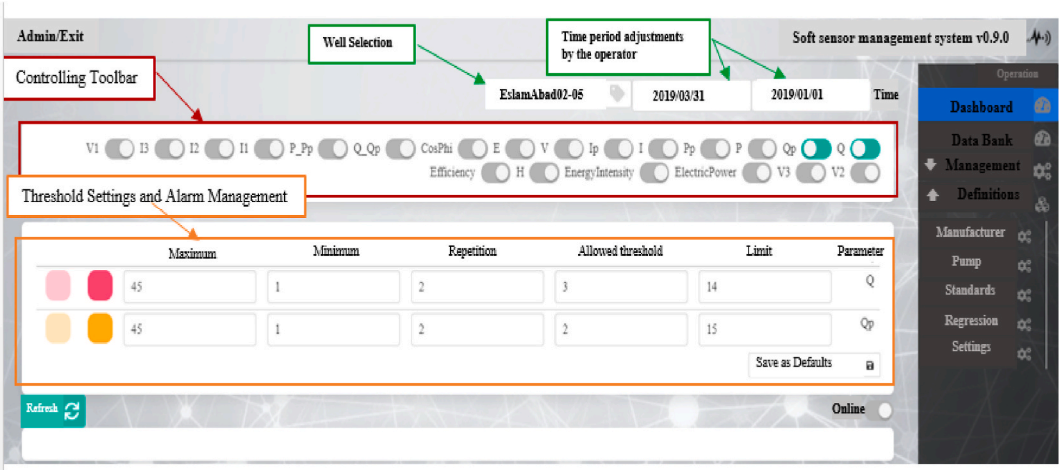


Fig. 26. The Decision Support System environment and options.

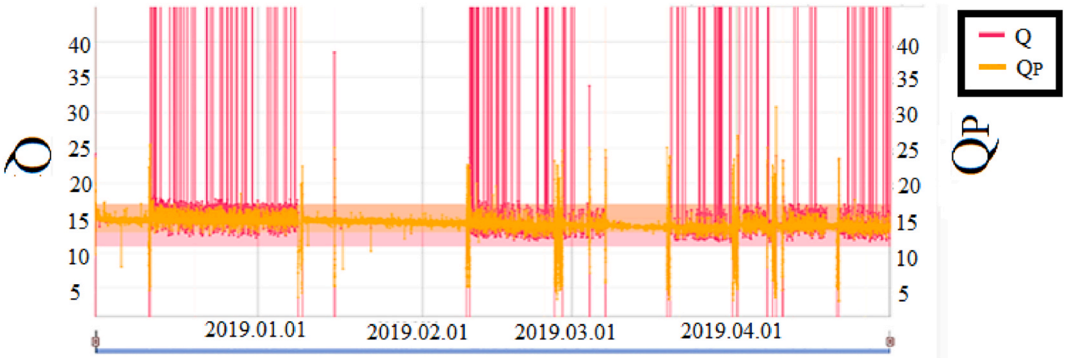


Fig. 27. The predicted Q in comparison to the recorded Q in “EslamAbad 02″ well in 2019.

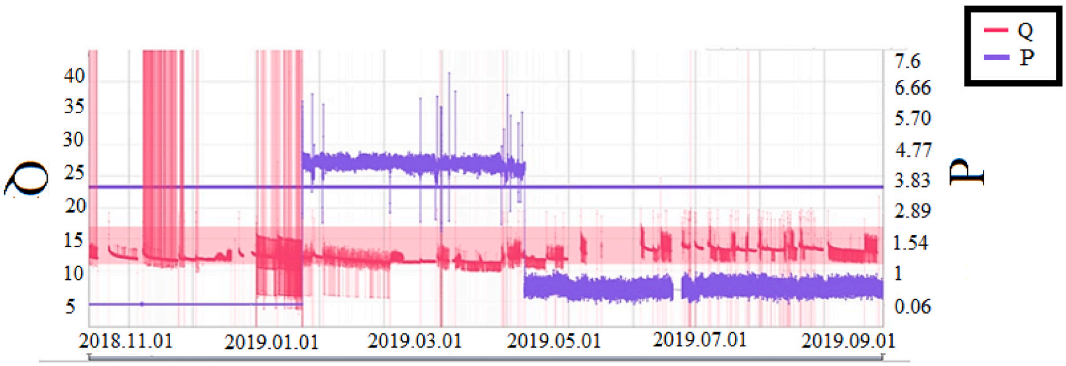


Fig. 28. The water flow rate and water pressure comparisons in “EslamAbad 02″ well in 2018–2019.

research into land, energy and food supply considerations. Simultaneously enhancing pandemic preparedness worldwide through health investments also facilitates resilience. Furthermore, managing the technological tools and infrastructures that enable social functioning allows targeted policies for sustainability, whether via urban development (Shah et al. [72]) or the intelligent water systems proposed here. Therefore, this study’s integrated data and domain expertise approach to optimize groundwater management resonates with the growing imperative across domains for systems thinking-based transitions. Embedding interdisciplinary perspectives into decision frameworks drives contextual responses, rather than reactive conventions alone. The methodological innovation coupled with practical application focus hereby propels more holistic governances.

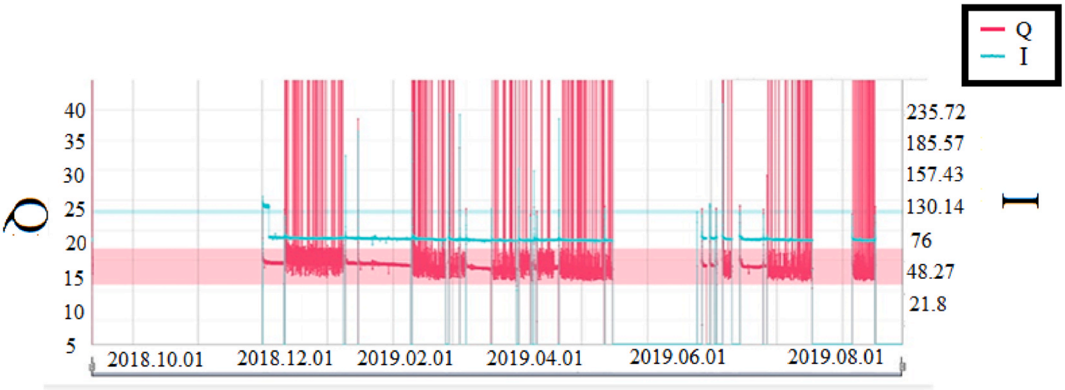


Fig. 29. The water flow rate and current intensity comparisons in "EslamAbad 02″ well in 2019.

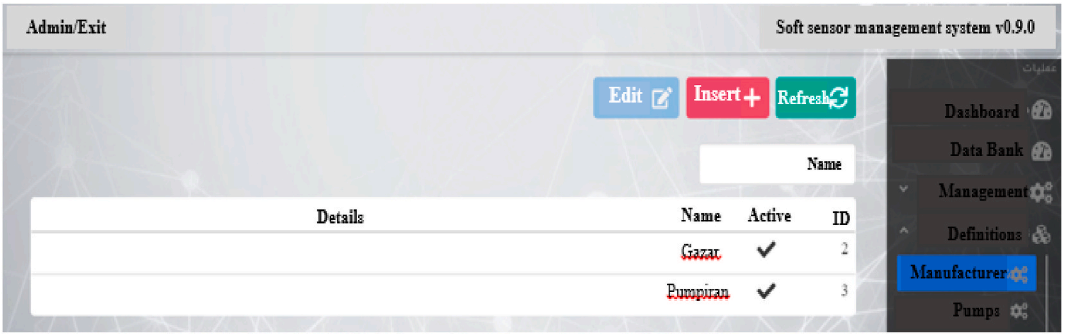


Fig. 30. Inserting the Pumps' brands in the Decision Support System.

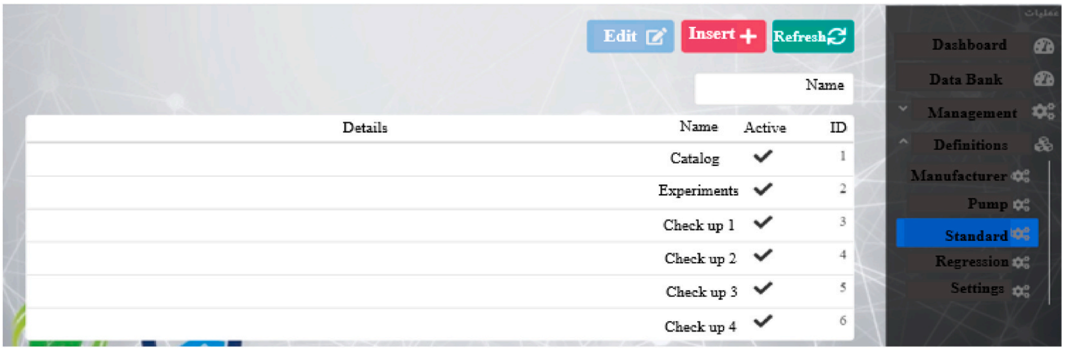


Fig. 31. Standard catalogues, experiments, and field tests.

Finally, our research has shed light on the challenges and opportunities in sustainable groundwater management, particularly through the utilization of intelligent systems like the soft sensor discussed in this study. While we have underscored the substantial costs associated with implementing such systems, it is apparent that they present a promising pathway toward achieving SDGs, especially those pertaining to Sustainable Cities and Communities (Fathollahi-Fard et al. [85]). Moreover, our study distinguishes itself by incorporating advanced computational techniques, KBS, and machine learning to address the complex task of groundwater prediction and management (Zhang et al. [86]; Mamoudan et al. [87]). In comparison to previous research, our approach showcases greater flexibility and potential for enhancing water resource management efficiency.

In conclusion, this research contributes a ground-breaking decision framework that integrates data analytics, prediction, and expertise for effective groundwater stewardship. However, delving into under-explored dimensions can further bridge the gap between theory and application. Several avenues for knowledge generation, marked by larger samples, spatiotemporal dynamics, computational advancements, parameter breadth, climate scenarios, and stakeholder preferences, present opportunities for extending methodological novelty to practical contributions across diverse sustainability contexts. Key aspects representing opportunities for

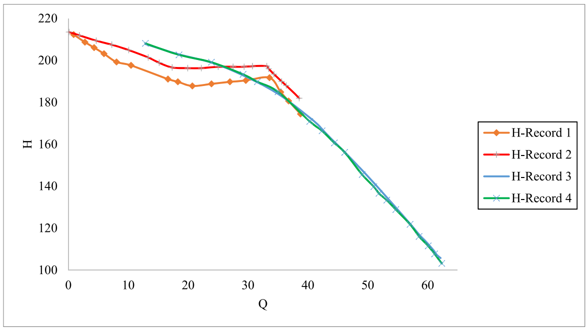


Fig. 32. Last log in H-Q curve in the present study.

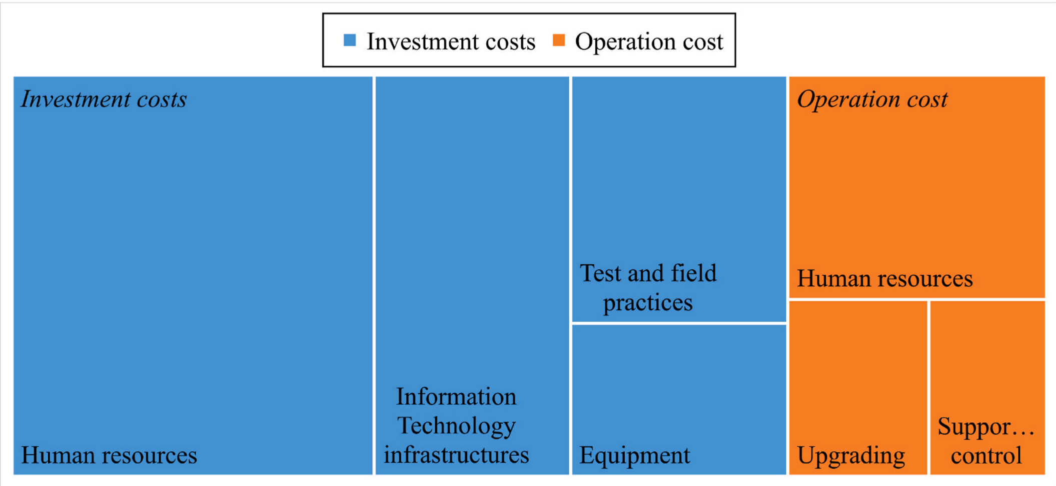


Fig. 33. An economic evaluation of soft-sensor in the present study.

additional research in this domain include:

- The current study establishes a proof-of-concept using data from six wells. Extending this approach to encompass more extensive telemetry records from pumps and wells can further validate the generalizability of the model.
- Assessing model performance when applied across different locations and over longer durations can unveil inter-site and seasonal influences on prediction robustness.
- Comparative insights into technique suitability can be gained by comparing emerging methods like deep learning, Bayesian neural networks, etc., against the RF algorithm.
- Enriching monitoring capabilities can be achieved by supplementing existing operational indicators with additional variables such as water chemistry, microbiological factors, and soil moisture.
- Evaluating model resilience for projections under climate variability can aid in assessing adaptation needs.
- Enhancing decision support can be achieved by incorporating optimization programming to recommend energy efficiency interventions alongside diagnostic abilities.
- Iteratively refining DSS functionalities to user needs and technology comfort levels can be accomplished through surveys with industry practitioners.

5. Limitations, implications, and policy recommendations

In this section, drawing from our contributions, methodologies, results, and findings, we delineate and elucidate the primary research limitations, implications, and potential policy recommendations for industrial practitioners.

5.1. Limitations

In an era marked by escalating water scarcity and the repercussions of climate change, the adoption of smart infrastructure and innovative methodologies becomes imperative. This research contributes to the ongoing conversation on sustainable water resource management, providing insights that can aid decision-makers and practitioners in addressing the global challenges of groundwater sustainability and responsible water usage. Therefore, the primary limitations of this study include:

- Absence of soil mechanics specifications in the groundwater prediction modeling.
- Limited assessment of the long-term performance of the soft-computing system, particularly about its applicability under changing climate conditions and in situations of water scarcity.
- Omission of evaluations involving high-performance machine learning systems, such as deep learning, within the scope of this study.
- This paper does not explore the application of metaheuristic algorithms for error minimization in extended, in-depth analysis.

5.2. Implications

The intelligent monitoring system developed in this study holds multifaceted implications for optimizing the sustainability of groundwater management practices across planning, operations, responsiveness and development scopes. The high-accuracy predictive capabilities facilitate informed infrastructure planning aligned to growth projections for demand, electricity pricing and climate impacts. Smoothed operations via adopting preventative approaches towards maintenance prioritization benefit service continuity risks mitigation. Quick diagnosis of emerging issues enhances rapid mobilization of targeted interventions minimizing disruptions. Structured digitization roadmaps focused on user preparedness improves receptiveness when incrementally transitioning traditional programs, avoiding change resistance.

Open environmental data sharing forms collaborative decision-spaces between public and private players to deliberate localized responses accounting for distributional disparities. Interdisciplinary skill development propagates creative problem-restructuring attitudes beyond siloed engineering conventions alone. Responsible and resilient management paradigms manifest by enabling such multidimensional techno-socio-economic implications holistically across planning insights, operational continuity, rapid responsiveness, receptive modernization, collaborative inclusiveness and creative competence. Hence, pathways from data to wisdom have the potential to responsibly balance groundwater usage sustainability by institutionalizing systemic thinking, transforming raw telemetry data into actionable intelligence.

5.3. Policy recommendations

Achieving sustainable groundwater management necessitates policy efforts across capacities, transparency, skills, incremental digitization, preventative mindsets and adaptive outlooks. Specifically, governments must fund the development of smart monitoring infrastructures that can optimize operations using data analytics and modeling demonstrated here. Regulators should promote open data availability through incentives to enable collaborative decision-making. Interdisciplinary training exposure will propagate responsible and innovative management mentalities. Structured technology integration roadmaps focused on user preparedness will ease digitized transitions supporting field practices. Standards must also mainstream preventative approaches like maintenance prioritization alongside mandating monitoring of projected climate change impacts. By enabling such multidimensional policies holistically, the foundations for data-driven, resilient and efficient groundwater management can be mainstreamed locally and globally. Institutionalizing pathways that translate raw operational data into actionable intelligence allows responsibly navigating lingering uncertainties. Thereby integrated policy efforts potentiate sustainable stewardship manifesting across technological capabilities, transparency norms, multidisciplinary competencies, digitization sequences, prevention-first mentalities and climate adaptation outlooks.

6. Conclusions and future research

In summary, the urgent global need for efficient water management in the face of escalating water scarcity concerns has led to the widespread adoption of smart water management telemetry systems. Despite the existing automation of water management and the wealth of data recorded through telemetry systems, there is a critical imperative to enhance data analysis for informed decision-making. Recognizing this, the development of an intelligent DSS has gained prominence for intelligent water resource management.

This study specifically focuses on the design and implementation of a DSS tailored for managing the groundwater resources of Mashhad, Iran. Rigorous statistical and analytical methods were applied to a substantial dataset encompassing the effective parameters of 24 wells and pumps. The outcomes of these analyses established crucial thresholds and limits for influencing parameters. The RF algorithm, identified as the most superior among various algorithms, was then employed to create a robust forecast model in Python, accurately predicting water flow rate, water pressure, and current intensity in Mashhad city's wells and pumps.

Validation of the model's accuracy, assessed through four descriptive statistical indexes, revealed values close to zero for MSE, RMSE, and MAE, with CPA approaching one, indicating a high level of precision in the soft-sensor. Subsequent steps involved field experiments, periodic check-ups, and the integration of empirical knowledge and operator expertise using the CD method. Delphi method outcomes were distilled into two algorithms, and the SE method was employed for the classification and ranking of information on pump performance and errors.

The key findings of this study highlight the versatility and efficiency of the developed DSS:

- Demonstrating effectiveness in predicting water parameters even when physical sensors are non-functional, the DSS facilitates precise monitoring and error detection in well and pump operations.
- The smart prediction model eliminates the need for costly physical sensors and flow meters, providing accurate forecasts of effective parameters.
- The smart management system amalgamates scientific knowledge, field test results, and operator expertise to function as a cost-effective professional operator.
- Applicable in rural areas with limited management facilities, the system addresses resource management challenges.
- The RF algorithm's precision, especially in managing large datasets, underscores its superiority for water management issues.
- The developed management system is versatile, applicable in diverse water studies such as surface water management, dam control, and water demand analysis.

In conclusion, a key recommendation for future investigations from this study pertains to the utilization of intelligent metaheuristic computations for optimizing the performance of water distribution networks. Additionally, exploring the feasibility and benefits of an integrated solar renewable energy system to power the pumping process represents a compelling avenue for further research.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Parisa Ataei: Writing – original draft, Investigation, Data curation, Conceptualization. **Amir Takhtravan:** Writing – original draft, Software, Methodology, Formal analysis. **Mohammad Gheibi:** Writing – original draft, Visualization, Validation, Software, Investigation. **Benyamin Chahkandi:** Writing – review & editing, Visualization, Conceptualization. **Mahdieh G. Faramarz:** Writing – original draft, Visualization, Software. **Stanisław Wacławek:** Writing – review & editing, Supervision, Funding acquisition. **Amir M. Fathollahi-Fard:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Kourosh Behzadian:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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