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ARTIFICIAL INTELLIGENCE FOR OPTIMIZED WELL CONTROL AND MANAGEMENT IN SUBSURFACE MODELS WITH UNPREDICTABLE GEOLOGY

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SUMMARY

A comprehensive control policy structure utilizing Artificial Intelligence (AI) is presented for closed-loop management in subsurface models. Conventional Closed-Loop Optimisation (CLO) approaches entail the iterative implementation of information assimilation, past synchronization details, and effective optimizing procedures. Information assimilation is more difficult when there is uncertainty in the geological approach and the specific model conclusions. Closed-Loop Reservoir Monitoring (CLRM) offers a control strategy that promptly correlates flow information obtained from wells, as typically accessible, to appropriate well stress configurations. The rule is characterized by time-based compression and gate-based converter sections. Learning is conducted during a preprocessing phase utilizing geological modeling derived from various geological settings. Illustrative instances of oil extraction using water insertion, utilizing both 2 and 3-dimensional geological designs, are shown. The AI-oriented technique demonstrates a 17.2% increase in Net Present Value (NPV) for 2D instances, an additional 31.5% for 3D cases compared to the effective optimization of previous models, and a 1-6.5% enhancement in NPV relative to standard CLRM. Based on the methods and variable configurations examined in this study, the controlling policy method yields a 71.34% reduction in processing expenses compared to conventional CLRM.

Key words: *artificial intelligence, geology, well, reservoir.*

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INTRODUCTION

Closed-loop modeling is employed for management across several sectors, such as chemical plant activities, wind farm oversight, and subsurface administration of resources [1]. The Closed-Loop Optimisation (CLO) approach often involves the modification of system parameters (decisions) at various stages in response to new information [2]. In subsurface flow programs, such as groundwater administration, CO_2 sequestration, geothermal activities, and oil/gas manufacturing, CLO analysis often entails integrating information to integrate fresh well-based information and rigorous optimization procedures.

This CLO involves identifying ideal well parameters (flow rates or tensions) that are mean over a series of realizations that reflect the uncertain underlying geology [19]. Both data integration, also known as history matchmaking, and resilient optimization methods are demanding. This is particularly applicable when the algorithms are derived from several geological situations. This applies if the research intends to examine systems with sand streams exhibiting varying introductions, sinuosity, width, etc.

This study presents a novel controlling methodology for effective CLO [4]. Unlike conventional CLO techniques, the learning of the controlling method relies solely on past geological designs rather than history-matched ones, hence eliminating the necessity for the repetitive execution of operationally intensive integration of data and efficient optimization processes [5],[10]. In realistic scenarios, including nonlinear output limitations, such as an optimal field water generation rate, conventional resilient optimization methods yield excessively conservative remedies, as these limitations must be adhered to throughout all or almost all conclusions [14]. The management policy technique overcomes this problem by adjusting well parameters in a model-specific way depending on measurements [6].

This study presents a broad and nonintrusive Artificial Intelligence (AI) based management policy technique for CLO of the flow simulation [3], [20]. The control strategy is constructed with temporal convolution and newly developed gated converter modules. The structure is trained via the CLO approach, with the training information derived from flow experiments over a collection of previous geological modeling [8]. Upon adequate training, the procedure promptly correlates observable quantities to decision factors that dictate ideal configurations for current injection and manufacturing wells. The research evaluates the framework utilizing 2D and 3D geological modeling derived from singular and numerous geological situations, focusing on issues related to generating oil by injecting water. The efficacy of the AI-based approach is evaluated against reliable optimization using previous geological simulations.

BACKGROUND

Several strategies have been proposed to alleviate the computing strain of optimizing and integrating data phases in conventional closed-loop processes. These encompass surrogate or proxy algorithms utilizing reduced-order numbers, Deep-Learning (DL) scenarios [9], and Machine-Learning (ML) algorithms [21]. A recent proposal introduced a DL surrogate utilizing Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) for CLO [11]. Although the methods have demonstrated varied effectiveness in reducing computing needs, none face up to the conservative characteristics of the solutions derived via resilient optimization. Only some of these methodologies were intended to manage several geological conditions simultaneously.

In robust optimization of output for oil and gas reservoirs that hold water, which entails identifying optimum controls for injecting and exploitation wells, the inherently cautious characteristics of optimization have spurred the creation of rule or controlling methodologies [7]. Zheng et al. suggested a strategy that establishes well settings and controls according to water cuts, defined as the proportion of extraction speed to the overall generation speed [12]. The policy variables in the investigation were derived by maximizing a foundational geological framework.

El Bakali et al. proposed a control strategy that allocates the overall generation and injecting rates of liquids among wells according to a priority system, with priority defined as the quantity of water cutoff [13]. The controlling strategies were depicted by a series of explicit expressions that enhance the movement modeling. Implementing this controlling strategy necessitates knowledge of the simulator's code repository. Despite their efficacy, these controlling policy techniques frequently have significant heuristic elements and fail to account for the whole array of accessible data, much of which is instrumental in policy formulation.

Progress in ML has facilitated the application of AI methods for deriving policies in sequential decision-making. AI has effectively trained AI entities capable of playing various games at human or superhuman proficiency. Given the exceptional proficiency of AI in formulating strategies for engaging in games, these methodologies are progressively being implemented in different fields. Li et al. examined the application of AI to derive active control techniques for drag decreases in turbulence [22]. Sharma et al. utilized AI for the open-loop oversight of conjugated heat transfer devices [15]. AI has been employed for form improvement in aerodynamic challenges. The application of AI in the growth and oversight of oil reserves has been extensively explored in recent research, as the study will now examine.

Nasir et al. assessed several AI methods to enhance well controls across numerous geological conclusions [16]. A full CNN correlating variables like tension at every unit to reservoir controllers embody their strategy. AI has been utilized for analogous problems where the regulation correlates the stress and boundary at every unit of specific modeling to the controllers. Salehian et al. proposed strategies for maximizing producing wells' quantity, placement, and drilling sequencing [17]. The actions are modeled using a CNN and developed via several geological scenarios with different financial scenarios. In research for subsurface flow issues, reservoir modeling is established, and state variables, such as tension and oversupply, are accessible [18]. These numbers are unclear, and only manufacturing or injection statistics are recorded. The premises underpinning several current solutions are valid in (open-loop) mechanistic contexts.

PROPOSED AI-BASED WELL CONTROL AND MANAGEMENT

The rule and value variables must be specified to implement the proposed method. The research denotes the policy (π) and valuation (V) variables using the neural network structure illustrated in Figure. 1. This design consists of a temporal convolutional unit and a gated converter component.

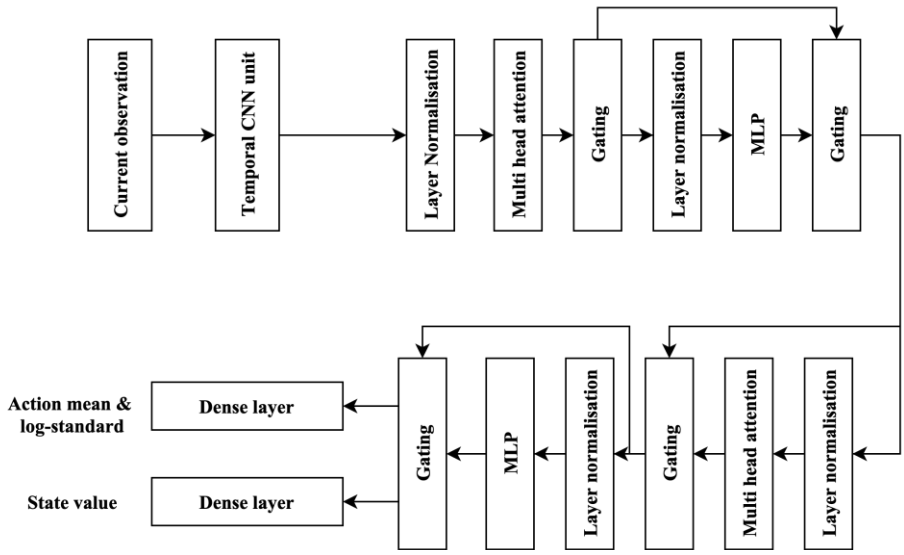

Figure 1. Time-based and two-layer conversion block for optimization

The observations d_k encompass the flow speeds and BHPs at N_d Periodic times throughout the initiation locations of controlling phases x-1 and x. This creates a subsequent temporal dimension (the controlling phases constitute the central dimension). To preserve the temporal relationships of the values in the recorded information, the research transform $d_k$into a matrix D_k. The matrix $D_k$functions as input to the time-based convolutional unit, which consists of 1D CNN levels that encapsulate the information format. The spatiotemporal unit produces a matrix e_k, serving as a concise data description. N_k to denote the dimension of the retrieved characteristics.

The gated converter unit has L levels, including Related Multihead Attentiveness (RMHA) and Multilayer Perceptron (MLP) subdivisions. Records generated at various levels of the gated converter blocks capture the agent's state. The preceding agent values for the L levels in the gated converter block and the hidden representations of the present inquiry function as sources to the gated converter blocking during the current control phase k. At the beginning of the command phase, the agent's variables are set up to zero matrices. In the final control phase, the agent perceives its position from all preceding control phases.

The RMHA submodule executes H parallel attentiveness actions on the input, comprising the prior agent statuses and embeddings from the preceding layer. The attentiveness mechanism transforms each prior memory and encoding into a feature matrix. The attention action results in a biased total of the characteristic matrices for sources, with more significant biases allocated to higher pertinent characteristics. It facilitates gathering characteristics from prior agent situations and embeddings relevant to calculating the present agent status. The outcome matrices from the H attentiveness procedures are combined through a Fully Linked Layer (FLL) to generate $\hat{y}_k$.

Recurrent Learning Unit (ReLU) signifies the gated operations functions, exemplified as a Gated Recurring Unit (GRU), utilized to enhance refinement stability. The MLP submodule comprises two FLL layers that handle the result of the subcomponent after gates. The operator condition is defined as the resultant anchoring from every layer.

An FLL handles the encoding from the last layer of the gating converter to get the activity average and activity log-standard variation for the activity distributions at controlling phase k. The CNN is designed to outcome the log deviations rather than the variance, as its result might be harmful; exponential growth will yield elevated standard deviations, as necessary. The elements of the neural network's results that determine the activity average are in a proportional dimension. Activities are selected from the event distributions during learning utilizing the activity average and standard variation. An independent FLL analyzes the agent's condition to ascertain the scalar representation of the condition.

The timed convolution unit comprises 1D CNN layers using 32 filters, with a filtering length of 2 in the initial and 3 in the subsequent levels. The initial dense level in the MLP submodule comprises 32 units, whereas the subsequent layer contains 128 units. The complete system has roughly 621k elements.

Closed-loop Optimization

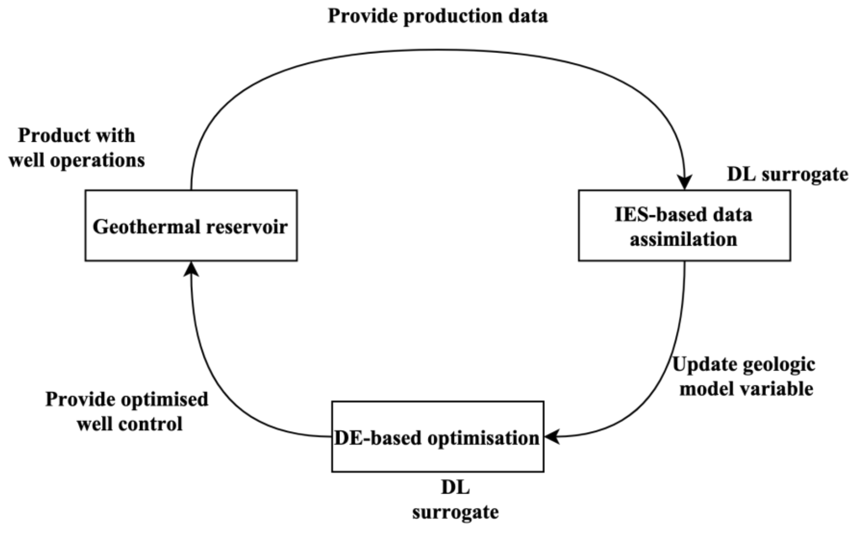

Figure 2. Closed loop optimization model

To attain effective practical CLO and information absorption in the geothermal resource manufacturing procedure, the research offers a CLO system accelerated by DL surrogates. The optimizing, data integration, and geothermal reservoirs are interconnected to create a CLO system, enabling data and data sharing to enhance the optimizing process. Figure. 2 illustrates the closed-loop process. The primary methods of the manufacturing optimizing system are outlined below:

- Gathering of historical manufacturing information: The historical manufacturing information of geothermal reservoirs, including manufacturing rate, bottom hole stress, and manufacturing temperatures, should be gathered and stored for information synthesis.
- Iterative Ensemble Smoother (IES) based information assimilation: manufacturing data is utilized to determine subsurface production characteristics (e.g., permeability, pores, etc.) using the IES method. Due to the ensemble-based nature of the IES technique, a collection of variable understandings that encapsulate the ambiguity of reservoir attributes will be changed concurrently. The revised estimations with less uncertainty are anticipated to approximate the actual values.
- Differential Evolution (DE) based productivity management: By predicting formation characteristics, well-controlled improvement for the subsequent production period is executed using the DE method. To account for reservoir characteristic uncertainty, a mean goal operator of the variable predictions is assessed and improved.
- Closed-loop process: Following the CLO procedure, the refined, well-controlling procedures are executed throughout the ensuing manufacturing phase of the geothermal reservoirs. The recently acquired production information for the next term can be employed for information integration to enhance the calibration of reservoir characteristics and diminish characteristic uncertainty. The revised reservoir characteristics optimize well control in the subsequent production phase. A CLO methodology is built, successfully combining information assimilation and manufacturing optimization processes concurrently.
- The CLO procedure identifies the best drilling practices for various control stages, and well features and productivity advances are apparent. AI substitute modeling is employed for forward calculations, substituting numerical simulation in data absorption and optimizing processes, enhancing algorithmic performance.

RESULTS

The research implements the controlling policy-based CLRM technique on two illustrative scenarios. The initial example pertains to 2D methods derived from a singular geological situation, whereas the subsequent sample pertains to 3D models distinguished by five distinct situations. The controlling method is juxtaposed with resilient optimizing based on previous geological scenarios, with predictable realization-by-realization improvement, and, in the initial instance, with conventional CLRM.

2D Methods from a Single Situation

This sample examines 2D geological systems. The training picture delineates the geological characteristics of the channelized network. The training picture, delineated on a 250 × 250 grid, encompasses an area far more significant than the understanding produced from it. Utilizing this training picture and conditioned to facial type (dirt or mud) at the well sites, the research produced 1000 conditioned discoveries with the geostatistical technique. The positions of five generators and four injectors, all situated in canal sandy, are also depicted. The porosity of mud is designated as 40 millidarcies, but the porosity of sand is established at 1650 millidarcies. The findings exhibit similarities in geological character; however, the channel placements and the connection among wells through high-permeability conduits vary.

Figure. 3(a) illustrates the progression of the anticipated NPV calculated using the geological modeling collected at the specified repetition and the well configurations established by the latest regulation. The expected NPV often rises as training advances. The variations arise from the selection of geological modeling and checking activities from the event distributed. The anticipated NPV of arbitrarily initiated method, amounting to $453 million, rises by 21.2% to $545 million over about 490 repetitions.

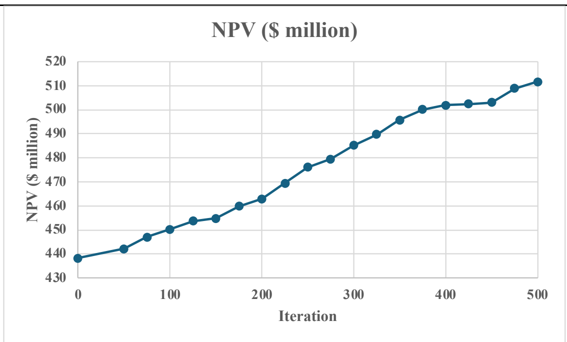

Figure 3(a). Net Present Value (NPV) prediction analysis

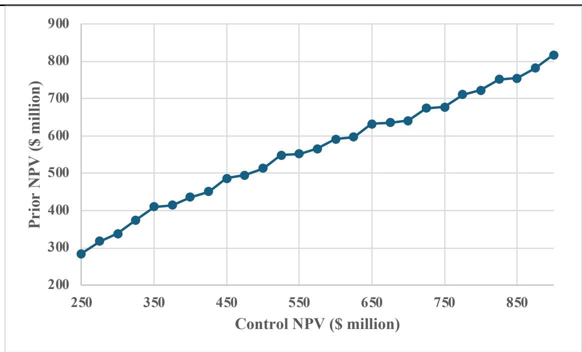

Figure 3(b). CLO result analysis

The singular group of reservoir management derived from the CLO is put into effect in every one of the 45 scenarios. The resultant NPVs were juxtaposed with those derived from the AI-oriented management scheme. Figure. 3(b) illustrates a cross-plot depicting this contrast. The chart indicates that, in 44 out of 45 designs, the AI-based controlling strategy surpasses effective optimization compared to previous methods. Compared with the last optimization, the monitoring policy has an average enhancement across all geological simulations of $65.7 million, or 15.8%. The enhancement from the AI-based strategy arises from the technique's capacity to explicitly customize the settings according to the information collected on a real-time system.

3D Methods from Many Situations

The geological modeling in the preceding example was derived from a singular geological situation. This example examines geological modeling from 5 distinct 3D situations. The geometry (form, dimensions) and direction differ across many scenarios. Conclusions are derived from every situation, with specific channel positions differing throughout discoveries.

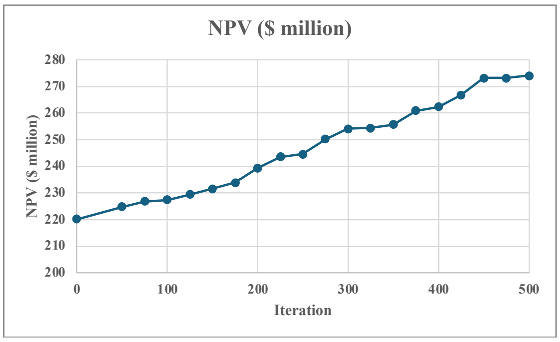

Figure 4(a). NPV prediction result analysis

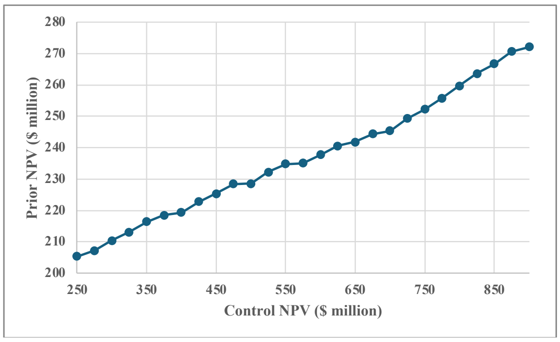

Figure 4(b). 40 test case geological method analysis

Figure. 4(a) illustrates the progression of the anticipated NPV over the training period. The predicted NPV of the stochastic starting method ($221.5 millions) rises by 31% over 450 repetitions. The 40 sample understandings are employed to assess the revised control strategies following every ten iterations. Figure. 4(b) illustrates the anticipated NPV of the controlling strategy over the 40 scenarios. Like the preceding example, the optimum controlling policy is identified as yielding the most significant predicted NPV.

The computing expense of the monitoring policy technique is solely attributed to the preprocessing (learning) phase. Upon completion of training, the controlling strategy may promptly deliver ideal well parameters without any delay. This contrasts with typical CLRM, which needs around 170k further simulated runs (utilizing the variables from Example 1) at every controlling phase.

CONCLUSION

This study presents a comprehensive, nonintrusive controlling system utilizing AI for the CLO of subsurface flow activities. The control regulations, expressed through temporal compression and gated converter blocks, are taught using a proximate policy optimization technique. This involves solving a singular optimizing issue encompassing preceding geological scenarios. This contrasts with conventional CLRM methods requiring iterative data integration implementation and rigorous optimization procedures. Accurate representations of the geological modeling are recreated during every policy training repetition, and the governing policy variables are modified using AI. At every decision point in the live well controlling procedure, a learned controlling policy promptly correlates observed data with the ideal output and injecting well configurations.

The control strategy development necessitated 140k total flow models, comparable to 500 sequential computations in a fully distributed environment. This constitutes just 25% of the models necessary for conventional CLRM, utilizing the techniques and variable settings examined in the work. The AI-oriented method demonstrated the ability to yield solutions comparable to those obtained from the stochastic optimization of specific geological conclusions. This discovery is substantial, as predictable optimizing is impractical due to the inherent geological uncertainty. The findings unequivocally illustrated the benefits of the control policy methodology compared to solid optimizations based on previous geological modeling and the conventional CLRM strategy. The controlled policy technique yielded an average enhancement of 17.2% in NPV compared with robust (previous) optimizing and a rise of 1 to 6.5% relative to conventional CLRM.

Numerous avenues for further research exist in this domain. Applying AI might expedite the calculations necessary for training or flow network surrogate designs, and exploring these methodologies warrants investigation. The integration of realistic limitations, such as restrictions on the variations in well parameters between control phases, should be included. The methods might be broadly applied to aquifer administration, CO_2 preservation, and geothermal-producing activities in subsurface movement.

REFERENCES

[1] Doekemeijer BM, van der Hoek D, van Wingerden JW. Closed-loop model-based wind farm control using FLORIS under time-varying inflow conditions. Renewable Energy. 2020 Aug 1;156:719-730.

[2] Attia PM, Grover A, Jin N, Severson KA, Markov TM, Liao YH, Chen MH, Cheong B, Perkins N, Yang Z, Herring PK. Closed-loop optimization of fast-charging protocols for batteries with machine learning. Nature. 2020 Feb 20;578(7795):397-402.

[3] Mumtaj Begum H. Scientometric Analysis of the Research Paper Output on Artificial Intelligence: A Study. Indian Journal of Information Sources and Services. 2022;12(1):52–58.

[4] Zhang X, Li Q, Qi G. Decision-Making of a Dual-Channel Closed-Loop Supply Chain in the Context Government Policy: A Dynamic Game Theory. Discrete Dynamics in Nature and Society. 2020;2020(1):2313698. https://doi.org/10.1155/2020/2313698

[5] Castiñeira D, Darabi H, Zhai X, Benhallam W. Smart reservoir management in the oil and gas industry. InSmart Manufacturing 2020 Jan 1;107-141. Elsevier.

[6] Elshall AS, Ye M, Finkel M. Evaluating two multi-model simulation–optimization approaches for managing groundwater contaminant plumes. Journal of Hydrology. 2020 Nov 1;590:125427. https://doi.org/10.1016/j.jhydrol.2020.125427

[7] Bozkurt A. Investigation of Groundwater Zooplankton Fauna from Water Wells in Kilis Province from Türkiye. Natural and Engineering Sciences. 2023 Aug 1;8(2):86-105.

[8] Sen D, Chen H, Datta-Gupta A, Kwon J, Mishra S. Machine learning based rate optimization under geologic uncertainty. Journal of Petroleum Science and Engineering. 2021 Dec 1;207:109116. https://doi.org/10.1016/j.petrol.2021.109116

[9] Franciosa P, Sokolov M, Sinha S, Sun T, Ceglarek D. Deep learning enhanced digital twin for Closed-Loop In-Process quality improvement. CIRP annals. 2020 Jan 1;69(1):369-372.

[10] Rosa C, Wayky AL, Jesús MV, Carlos MA, Alcides MO, César AF. Integrating Novel Machine Learning for Big Data Analytics and IoT Technology in Intelligent Database Management Systems. Journal of Internet Services and Information Security. 2024;14(1):206-218.

[11] Wu Z, Rincon D, Christofides PD. Process structure-based recurrent neural network modeling for model predictive control of nonlinear processes. Journal of Process Control. 2020 May 1;89:74-84.

[12] Zheng X, Junfeng SH, Gang CA, Nengyu YA, Mingyue CU, Deli JI, He LI. Progress and prospects of oil and gas production engineering technology in China. Petroleum Exploration and Development. 2022 Jun 1;49(3):644-659.

[13] El Bakali S, Ouadi H, Gheouany S. Efficient real-time cost optimization of a two-layer electric water heater system under model uncertainties. Energy Conversion and Management. 2024 Mar 15;304:118190. https://doi.org/10.1016/j.enconman.2024.118190

[14] Robles T, Alcarria R, de Andrés DM, de la Cruz MN, Calero R, Iglesias S, Lopez M. An IoT based reference architecture for smart water management processes. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications. 2015 Mar;6(1):4-23.

[15] Sharma A, Jangam A, Shen JL, Ahmad A, Arepally N, Rodriguez B, Borrello J, Bouras A, Kleinberg L, Ding K, Hadjipanayis C. Validation of a temperature-feedback controlled automated magnetic hyperthermia therapy device. Cancers. 2023 Jan 4;15(2):327. https://doi.org/10.3390/cancers15020327

[16] Nasir Y, Durlofsky LJ. Deep reinforcement learning for optimal well control in subsurface systems with uncertain geology. Journal of Computational Physics. 2023 Mar 15;477:111945. https://doi.org/10.1016/j.jcp.2023.111945

[17] Salehian M, Sefat MH, Muradov K. Robust integrated optimization of well placement and control under field production constraints. Journal of Petroleum Science and Engineering. 2021 Oct 1;205:108926. https://doi.org/10.1016/j.petrol.2021.108926

[18] Oikonomou K, Tarroja B, Kern J, Voisin N. Core process representation in power system operational models: Gaps, challenges, and opportunities for multisector dynamics research. Energy. 2022 Jan 1;238:122049. https://doi.org/10.1016/j.energy.2021.122049

[19] Zhang N, Santos RM, Šiller L. CO2 mineralisation of brines with regenerative hydrotalcites in a cyclical process. Chemical Engineering Journal. 2021 Jan 15;404:126450. https://doi.org/10.1016/j.cej.2020.126450

[20] Abdolrasol MG, Hussain SS, Ustun TS, Sarker MR, Hannan MA, Mohamed R, Ali JA, Mekhilef S, Milad A. Artificial neural networks based optimization techniques: A review. Electronics. 2021 Nov 3;10(21):2689. https://doi.org/10.3390/electronics10212689

[21] Polese M, Bonati L, D'Oro S, Basagni S, Melodia T. ColO-RAN: Developing machine learning-based xApps for open RAN closed-loop control on programmable experimental platforms. IEEE Transactions on Mobile Computing. 2022 Jul 4;22(10):5787-5800.

[22] Li Y, Chang J, Kong C, Bao W. Recent progress of machine learning in flow modeling and active flow control. Chinese Journal of Aeronautics. 2022 Apr 1;35(4):14-44.