An End-to-End Framework for AI Integration in Desalination Systems

Qusai Khaled¹ \bullet , Uzay Kaymak¹ \bullet , and Laura Genga²

¹ Jheronimus Academy of Data Science, Eindhoven University of Technology, Eindhoven, The Netherlands

q.k.h.abo.shama@tue.nl, U.Kaymak@ieee.org

² School of Industrial Engineering, Eindhoven University of Technology, Eindhoven,

The Netherlands

l.genga@tue.nl

Abstract. In the context of population growth, urbanization, and industrial expansion, water scarcity emerges as a significant concern, with projections indicating that around two billion individuals may face this challenge by 2050. Hence, the increased pressure on existing water resources calls for new water supply solutions in light of the growing demand. Desalination emerges as a promising alternative solution, particularly in regions confronting limited water resources. The sector has experienced remarkable growth, witnessing a 41% capacity increase over the past decade, with projections hinting at a twofold expansion by 2030. Such expansion requires integrating cutting-edge modeling techniques to ensure efficacy and cost-effectiveness. Artificial intelligence (AI) shows potential to revolutionize desalination and water treatment practices, yet its implementation remains limited. Delayed integration is believed to stem from the lack of trust among domain experts, knowledge gaps between water professionals and data scientists, and untapped potential within the field. This paper proposes The Integrated System Perspective for AI-based Desalination (ISP); an End-to-End Framework for AI in desalination. ISP-AID facilitates identifying AI applications across various project stages, from design to maintenance, uncovering opportunities for cost reduction and efficiency improvement. It adopts a structured data science perspective, integrating the Cross-Industry Standard Process for Data Mining (CRISP-DM) to guide AI algorithm selection and deployment. Spanning project cycle, process design, and data science levels, the framework aims to instill trust, foster collaborative problem understanding, and highlight untapped potential. This positions domain experts to actively develop data-driven solutions and enhancing confidence in innovative methodologies. By facilitating collaboration and exploring AI applications, the framework could expedite adopting efficient desalination solutions, thereby addressing global water scarcity challenges.

Keywords: Desalination · Reverse Osmosis · Artificial Intelligence · Machine learning.

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1 Introduction

Desalination is considered a potential solution to fresh water scarcity, particularly in countries with poor water resources [\[4\]](#page-4-0)[\[11\]](#page-4-1). While it plays a crucial role in meeting the freshwater needs of 330 million people across the globe [\[15\]](#page-4-2), it is often not prioritized due to several challenges; like high capital costs, high energy requirements, and environmental and political concerns [\[4\]](#page-4-0). To produce 1 $m³$ of drinking water, seawater desalination can consume more than three times the energy needed in surface water treatment [\[11\]](#page-4-1).

Artificial Intelligence (AI) has the potential of revolutionizing the desalination and water treatment industry [\[12\]](#page-4-3). Previous studies have shown promising results in utilizing AI for reducing operational expenses and enhancing overall efficiency [\[7\]](#page-4-4). Furthermore, researchers investigated how to leverage common machine learning algorithms such as artificial neural networks [\[14\]](#page-4-5), genetic algorithms [\[6\]](#page-4-6), particle swarm optimization [\[16\]](#page-4-7), support vector machines and decision trees [\[10\]](#page-4-8), for modeling and optimizing various desalination processes, leading to improved efficiency, reduced energy consumption and lower operation costs.

Despite the significant strides made in artificial intelligence research, its implementation within the desalination industry remains limited [\[5\]](#page-4-9)[\[8\]](#page-4-10) [\[12\]](#page-4-3). Several factors contribute to this limitation, including a lack of trust in AI models compared to knowledge-based models [\[13\]](#page-4-11), a knowledge gap between domain experts in the water sector and data scientists [\[12\]](#page-4-3), and the existence of largely unexplored potential at the intersection of AI and desalination [\[2\]](#page-4-12). Consequently, the aim of this research is to help overcome these challenges through end-to-end data driven framework. The proposed framework, namely The Integrated System Perspective for AI-based Desalination (ISP), could help instill trust, foster collaborative problem understanding and highlight untapped potential on the intersection of AI and desalination.

2 A Framework for Exploring AI-based Desalination

We introduce the Integrated System Perspective for AI-based Desalination (ISP-AID), a framework designed to provide end-to-end solutions for desalination challenges. ISP-AID serves as a versatile tool for systematically exploring the potential of data-driven solutions, as depicted in Figure [1.](#page-2-0) Before approaching the AI application selection phase of the framework, ISP-AID establishes the problem understanding part considering three levels of application; project level, process level and data science level. By adopting this holistic approach, the framework enables the identification of the suitable data driven solutions, with the assistance of knowledge experts. The key potential of the framework lies in the participatory business understanding phase, which not only uncovers previously unexplored application avenues through domain knowledge, but also fosters trust through the participatory nature the process. Therefore, ISP-AID builds the problem understanding for an AI application based on selection process design and project life cycle, while bearing in mind the data requirements,

Fig. 1. Proposed ISP-AID framework.

once an alignment is reached over the intended objective, such as predicting the performance of a pre-treatment process during project design, or optimizing the energy consumption of reverse osmosis process during project operation. the data science level is then resumed towards modelling, interpretation and evaluation. If the evaluation shows an alignment with the problem understanding, the application is deployed into the project life cycle.

3 Theoretical Experiment: ISP-AID Application

To illustrate the application of our proposed framework for AI integration in desalination, we present a theoretical experiment that demonstrates its functionality and benefits in addressing real-world challenges.

3.1 Problem Understanding

The framework begins by establishing a shared problem understanding between domain experts and data scientists. Domain experts identify a process within desalination operations with significant potential for improvement, whether due to high costs or low efficiency. This identification can occur through the application of the framework to their ongoing project phase while focusing on specific aspects of process design, such as maintenance optimization during project expansions.

For instance, There is a limited research focusing on AI applications during the design phase despite its potential for optimization and cost reduction, which underscores the need for innovation in this area. Similarly, while operational parameter optimization garners significant attention during the operation phase [\[9\]](#page-4-13),

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the unexplored territory of performance prediction using design parameters suggests untapped potential for improvement. Additionally, the maintenance stage presents an opportunity for AI integration, particularly in predictive maintenance [\[7\]](#page-4-4)[\[3\]](#page-4-14), given its substantial impact on operational expenses [\[11\]](#page-4-1). This underscores the importance of a thorough investigation of AI applications across all phases of desalination projects to identify and capitalize on opportunities for enhancing efficiency and sustainability.

3.2 Guided Progression and Continuous Improvement

Once a problem area is identified, data scientists collaborate with domain experts to initiate the data science project using the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework [\[17\]](#page-4-15). This structured approach guides the project through key phases, including business understanding, data preparation, modeling, evaluation, and deployment.

While data scientists leverage advanced AI algorithms to develop models, a key aspect of the framework is ensuring interpretability and transparency of these models. Especially that interpretability assumes a critical dimension in the framework, especially given its contribution to trust [\[1\]](#page-3-0). By maintaining a cyclical process, the framework allows for continuous feedback and refinement, ensuring that domain experts find the models as interpretable as possible.

After completing one cycle of the process, the solution is reassessed in the context of the problem understanding to evaluate its effectiveness in enhancing the desired element within desalination operations. This assessment informs further iterations of the framework, allowing for continuous improvement and refinement of AI solutions tailored to the specific needs of desalination projects.

4 Conclusion

Looking towards future research in the field of AI-driven desalination, there is ample opportunity for further investigation and expansion of the ISP-AID framework. Detailed aggregation of desalination projects and processes across various desalination technologies could enhance the framework's utility and applicability. Moreover, leveraging the framework to conduct a systematic literature review categorized through its lens could provide valuable insights into unexplored areas, By continuing to advance research in this area and leveraging frameworks such as ISP-AID, we can unlock new possibilities for data-driven solutions in desalination, ultimately driving progress towards more efficient and sustainable water treatment practices.

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