Digital transformation of packaged reverse osmosis plants for industrial and sewer mining applications

Claudio Kohn[1], Hung Cong Duong[1,2], Ngoc Bich Hoang[3], and Long Duc Nghiem[1,3,*]

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[1] Centre for Technology in Water and Wastewater, University of Technology Sydney, Ultimo NSW 2007, Australia

[2] School of Environmental Engineering, Le Quy Don Technical University, 236 Hoang Quoc Viet, Co Nhue, Bac Tu Liem, Ha Noi, Viet Nam

[3] Institute of Environmental Sciences, Nguyen Tat Thanh University, Ho Chi Minh City, Viet Nam

* Corresponding author:

Long D. Nghiem: Centre for Technology in Water and Wastewater, School of Civil and Environmental Engineering, University of Technology Sydney, NSW 2007, Australia

Phone: +61 2 95142625   E-mail: duclong.nghiem@uts.edu.au

Abstract

Purpose of Review: Packaged reverse osmosis (RO) systems are often synonymous with industrial water supply and high quality water reuse. These RO systems can satisfy specific industries with stringent water quality specifications. They are also compact for deployment in basement of commercial buildings for sewer mining. Increasing applications of packaged RO systems opens the door for digital transformation of their design, operation, and maintenance for a quantum leap in system performance (energy consumption, treatment efficiency, and cost). This review summarises opportunities and challenges associated with the digitalisation of packaged RO systems and guide the industry to take advantage of these opportunities.

Recent Findings: Digital connectivity and machine learning offer a game changing capability to packaged RO systems. With digital capability, it is more cost effective to design, operate, and manage these RO systems. Performance can be optimised via a range of approaches that are not possible with traditional human intervention. For example, hybrid systems that require sophistication control and prediction can benefit from big data analytics. On the other hand, other system that needs less intervention can work autonomously with little human intervention.

Summary: Automatic high-quality water treatment systems have attracted significant attention in recent years. This review identified a gap in understanding variable possibilities that machine learning and prediction can be successfully utilized by RO systems. This review confirms that artificial intelligence and machine learning can improve the way these systems work. Future research should strive to achieve a better way to apply these applications in packaged RO systems.

Keywords: packaged reverse osmosis (RO) systems; digital transformation; machine learning; sewer mining; industrial water supply.

Introduction

RO has a long history of development, started in the 1960s by Sidney Loeb and Srinivasa Sourirajan, who pioneered the fabrication of thin film composite membranes with salt removal capability and excellent water permeability (Loeb & Sourirajan, 1963). The industrialisation of the process allowed expansion of water treatment to the industry and provided a cost-effective way for seawater and brackish water desalination (Joo & Tansel, 2015). As of Jan 2022, RO has accounted for over 50% of the global desalinated water volume or 22.4 million m^3/d (Lattemann et al., 2010). As such, it is perhaps not a surprise that much of the focus on RO has been given toward large scale operations. In fact, recent literature has largely ignored opportunities for significant performance gain and cost reduction in packaged RO plants that are numerous and widespread in the industry and small scale water use operations.

Packaged RO systems are widely used for industrial water supply and small scale water reuse. Most industrial processes have very specific water quality requirements beyond potable water standards. As a result, it is not possible to comply with these requirements without additional treatment to further purify tap water. For example, ultrapure water for electronic manufacturing must have much lower content of dissolved salts and free of any suspended particles. Over the last few decades, the demand for high-quality water has significantly increased (Zhang et al., 2021). There is also an emerging trend to supply high quality water to remote operations (such as fishing vessels and remote mining operations) where traditional water sources do not exist. Water must be obtained from compromised sources (e.g. seawater, brackish groundwater, storm water run-off, and even wastewater) to support these activities, especially in remote locations. It is becoming increasingly pertinent to find solutions to produce the highest quality water from these compromised sources. Reverse osmosis (RO) has become the primary solution for industrial water supply since it can reliably provide high-quality water supplied from almost any sources.

RO has many advantages compared to other treatment technologies (Wenten & Khoiruddin, 2016). RO systems are compact and modular. Thanks to early inventions to produce thin-film composite membranes and modulised them in spiral wound modules, a large membrane surface area can be packed in to a small volume For example, an 8 inch membrane module with volume of less than 40 L can hold 85 m^2 in membrane surface area. Through modulisation and standardisation, capacity of a packaged RO system can be increased by simply adding more membrane modules. RO membrane is operated under a hydraulic pressure, this feature makes the system easy to control, and they produce high-quality water without complicated engineering operation. Another significant advantage of RO is the possibility to build the system on a skid that can be relocated and installed in different locations. These skids can be installed in shipping containers, making it possible to transport the plant and make it mobile (plug and play).

Packaged RO systems are frequently installed in confined space (such as shipping containers or basement of a building) where operator's access is limited or restricted. Thus, remote operation and maintenance are particularly useful and sometime a critical feature of these systems (Rezk et al., 2019). Digital transformation in the last few years has improved these features to enable better automaticity, whilst maintaining high levels of water quality. For example, today's systems can be controlled remotely via a central Human Machine Interface (HMI) that connects to the plant by broadband mobile communications. The operators do not need to be on the site and can manage multiple systems at the same time. Fully automated RO systems have capability for remote control, operation, and monitoring as well as verifying the actual state of the membranes and all relevant water quality parameters. Parameters are controlled to achieve water quality by optimising the work mode of the system. In some cases, water quality is the most critical parameter. In other cases, parameters such as plant energy consumption are more important. Many parameters can affect the efficiency of system such as water quality, temperature, and energy consumption.

Water treatment by RO is energy intensive. Thus, energy efficiency has been a major driver of many recent development in RO technology (Kim et al., 2019; Pan et al., 2020; Park et al., 2020). Digitial capability can also be applied to improve energy efficiency, especially for packaged RO systems. These RO systems can be powered exclusive by renewable energy and synchronisation between intermittent availability of solar and wind energy and RO operation system can be supported by the digital infrastructure (Khan et al., 2018). Computerised program can match RO operation with real time energy availability to reduce the energy cost (Ghaithan et al., 2021).

In packaged RO systems, in addition to energy, other considerations such as production rate, feed and product water quality, physical footprint, and membrane lifetime are also significant. In some RO plants, computerised program is also used to decide when water is produced and the best time to stop the plant for maintenance (Durán et al., 2021). Using data analytics and artificial intelligence where all the data is processed makes it the most cost-effective way to define the mode of work for the plant.

Despite the increasingly widespread use of packaged RO systems, there have been very few attempts to discuss and analyse the potential of digital transformation for improving their design, operation and monitoring. This article provides possible the first systematic review to show how digital capability can be integrated to packages RO plants and discuss the roadmap for future work. This review focuses on two dominant applications of packaged RO plants namely industrial water supply and sewer mining. The overarching architecture for advanced digital transformation is also delineated.

Packaged RO systems for industrial applications and sewer mining

Packaged RO systems are widely used for industrial applications and small scale water reuse. They are usually skid mounted and very compact to satisfy space requirement. Examples of these packaged RO systems are shown in Figure 1.

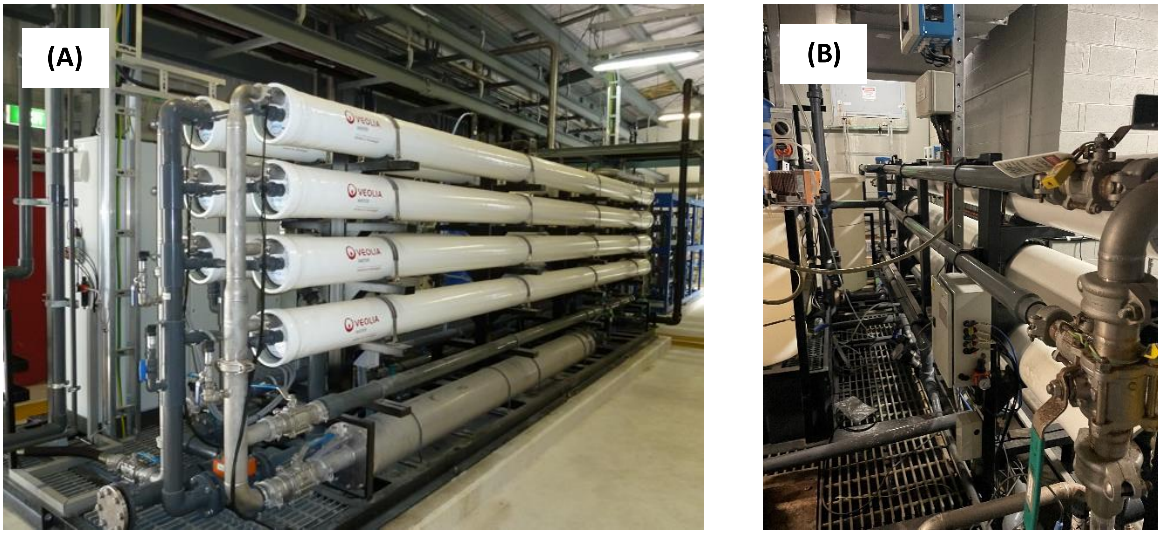

Figure 1: (A) A typical off the shelf packaged RO system for industrial application, and (B) The packaged RO system for sewer mining at Darling Quarter (Sydney, Australia).

Individual industrial processes are unique and can have very specific requirements beyond potable water standards. For example, RO can be used to enrich ammonium and nitrate for subsequent recovery during NH_4NO_3 production as industrial explosive and fertilizer (Duong et al., 2021). In addition, it is not always possible to comply with industrial water supply requirements with tap water, unless additional treatment is provided. For example, ultrapure water for electronic manufacturing must have much lower content of dissolved salts and free of any suspended particles. Over the last few decades, the demand for high-quality water has significantly increased (Zhang et al., 2021). There is also an emerging trend to supply high quality water to remote operations (such as fishing vessels and remote mining operations) where traditional water sources do not exist. Water must be obtained from compromised sources (e.g. seawater, brackish groundwater, storm water run-off, and even wastewater) to support these activities, especially in remote locations. It is becoming increasingly pertinent to find solutions to produce the highest quality water from these compromised sources. Reverse osmosis (RO) has become the primary solution for industrial water supply since it can reliably provide high-quality water supplied from almost any sources.

The concept of sewer mining was first proposed in the early 1990s (Butler & MacCormick, 1996) but has only been applied to a larger scale in recent years. Although RO technology is already capable of reclaiming wastewater for reuse, its application has only become cost-effective in recent years due to advancement in data engineering and the ability to remotely operate and maintain packaged RO systems.

The traditional urban water management approach is to collect and transfer wastewater to a centralised location for treatment then discharge or beneficial reuse. This traditional approach requires extensive infrastructure for long distance water transfer while ignoring opportunities for on-site non-potable water reuse, especially in commercial buildings or densely populated apartments with large water demand for non-potable consumption such as irrigation, cooling, and toilet flushing. Sewer mining is an innovative approach that can significant reduce water consumption and cost of water management in the urban environment (Arias et al., 2020).

The infrastructure to store and move wastewater across the city to a centralised plant is tremendous and includes pipes, pumps, and underground tanks (Zhang et al., 2018). Most of these assets can be in compromised conditions, compared to the visible asset like bridges or streets (Rehan et al., 2014), since they are located under the surface, and people cannot see them. If a wastewater pipe is leaking and contaminating the soil under the surface, it might be difficult to repair because in many cases the problem cannot be seen and difficult to repair

In most cases, sewer mining can be defined as the extraction of wastewater from a sewer main for purification to suitable standard for non-potable reuse. The waste stream from sewer mining is returned to the sewer for subsequent treatment at an existing centralised wastewater treatment plant. Since sewer mining is accomplished via small plants along the sewer line, there is adequate redundancy and their operation does not affect the overall network. Sewer mining can add value to urban water management since reclaimed water is used for non-potable applications, such as toilet flushing, cooling, and irrigation on site (Sotelo et al., 2021). Potable water consumption can be reduced and the need for long distance water transfer can be eliminated.

Most sewer mining projects utilise small scale RO often in combination with some form of pretreatment such as membrane bioreactor or ultrafiltration (Plevri et al., 2020). They are installed in an urban, commercial, or industrial area with very limited space (Figure 1B). In most cases, they are installed underground in restricted space with limit human access. Thus, it is desirable for sewer mining plants be fully automated with remote control capability. Human access to these packaged plants are limited to installation, commissioning, and major maintenance.

Traditional practice

Similar to all other treatment processes, RO systems face routine operational challenges such as unplanned shutdowns, maintenance and downtime. In addition, there can also be issues associated with membrane fouling, and long-term membrane degradation leading to variation in treated water quality. In the past, these issues were addressed by on-site operators, often in a reactive manner as they were unable to predict or anticipate these problems in advance (Eisenberg & Middlebrooks, 1984).

RO systems can be very vulnerable to changes in the working environment. This is especially significant for packaged RO plants. In many cases, these plants are installed in places where the temperature can change dramatically during day and night and the season changes. For industrial application, the water quality to packaged RO plants can vary dramatically. Therefore, the operation regime must be frequently modified to match new water quality (Wenten & Khoiruddin, 2016).

Performance of an RO system is governed by many interrelated factors. Low feed water quality may damage the membrane and gradually compromise pollutant rejection without the operators' knowledge of the problem. It is time consuming for the operator to identify the root cause, if it is possible at all (Antony et al., 2010). Operators often find it challenging to assess the actual condition of fouling or scaling and aging membranes. Therefore, in most cases, they will not attempt to predict membrane performance. In addition, there is often a lack of knowledge and adequate record keeping. In most cases, the operators would adapt a conservative solution to lower the flow production. While this is often a safe option, it dramatically increases the cost and energy footprint of RO treatment (Koutsou et al., 2020).

Overall traditional practice in the design and operation of packaged RO systems is conservative and is usually well below optimised performance.

Digital-enabled practice

Digital tools can transform the design, operation, and maintenance of packaged RO systems to achieve optimised performance (Bonny et al., 2022). Digital transformation of packaged RO systems is based on four hierarchical steps: basic computation, data normalisation, comparison and simulation, and prediction as illustrated in Figure 2.

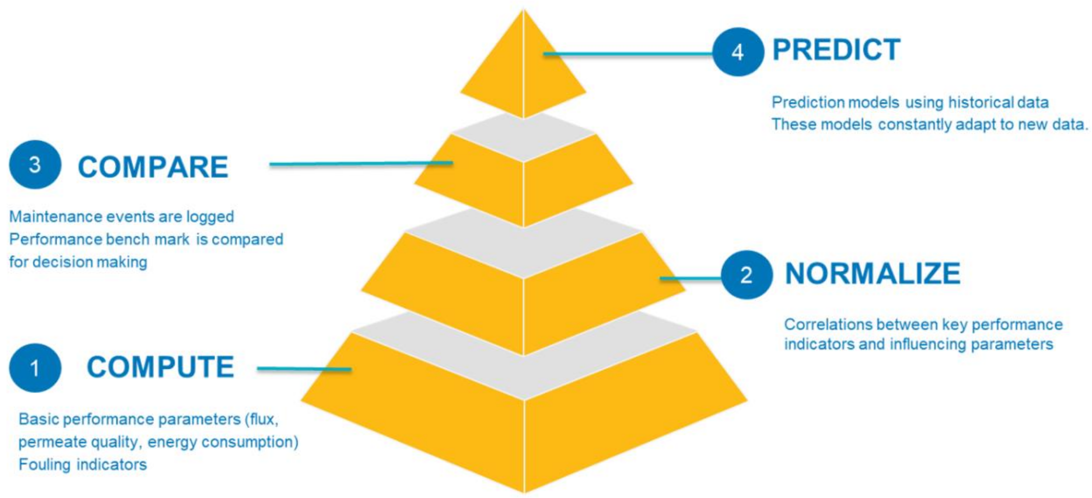

Figure 2: Digital transformation hierarchy for packaged RO systems.

The foundation for digitally transforming the design, operation and maintenance of RO systems is data acquisition and is already possible to some extent with conventional systems equipped with PLC controller and a form of data logging. The next three steps are more sophisticated and can only be realised with modern technologies. The applications of basic computation and more advanced steps in the digital transformation hierarchy are illustrated through critical analysis of the literature and experience from the Darling Quarter sewer mining facility (which is managed and operated by one of the authors).

Darling Quarter plant is a sewer mining plant located under the office building on the city centre of City of Sydney. The plant mines the wastewater from the main sewer line and cleans it to a level that can be reused in cooling towers top-up, toilets, irrigation, and general cleaning within the complex. At the Darling Quarter sewer mining facility, RO is integrated with many other auxiliary technologies for pretreatment (e.g. macerator, grit chamber/grease trap, clarifier), biological treatment (e.g. membrane bioreactor) and post-treatment (e.g. Ultraviolet disinfection chlorination and pH controlling, storage) before the product water and be beneficially reused.

These auxiliary components need to work in tandem with RO. Without digital capability, the operation must be conservative and is based on the rated flow. If one component is malfunction or fails to produce the required flow, the entire facility is affected. An example of more advanced computation capability is the chlorination for post-treatment of the RO permeate. Chlorination is achieved via in-line dosing. The required chlorine residue is a complex function of storage time, distance, characteristics (e.g. pH, organic content, and ammonia content) of RO permeate. Simple engineering control via PLC may not be sufficient to achieve reliable and stable chlorine residue. New digital capability can fill in the gap by adjusting for the hysteric effect between measured chlorine concentration and set point, and compensate for other variables such as flow rate and water characteristics. Artificial intelligence (AI) and machine learning capability provide an excellent solution to sophisticated problem such as this (Li et al., 2021; Nguyen et al., 2021).

Correct data normalisation is essential to ensure performance and adequate maintenance. The value of digital transformation is illustrated in Figure 3 that shows the differential pressure of a packaged RO system for industrial water treatment. Figure 3 shows a gradual increase in differential membrane pressure due to fouling as expected. Data between Dec 2020 and Feb 2021 show a slight decrease in differential pressure that could be mistaken as reduce fouling. In fact, this decrease in differential pressure was due to temperature increase. The impact of feed water temperature can be manually normalised, however, the data are very scattered. Using a computerised software to taking to account the effect of temperature and feed flow rate, a much more accurate representation of the membrane performance can be obtained as shown in Figure 3.

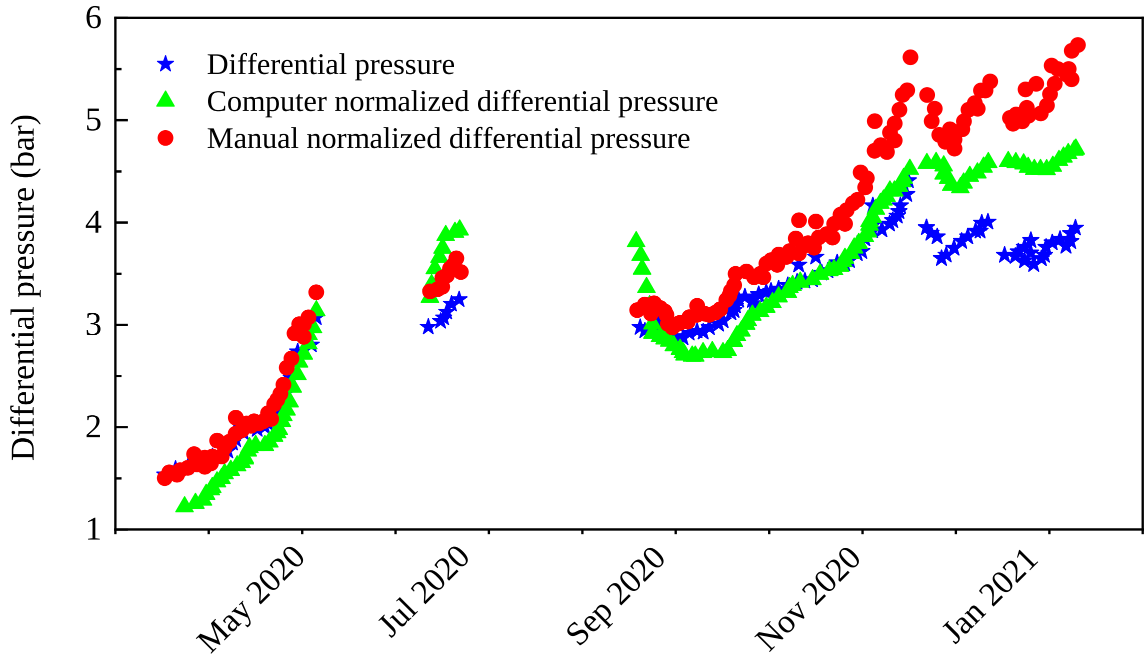

Figure 3: Smart normalisation to accurately interpret performance data.

One significant advance of digital transformation is the ability to create digital twins for comparison and simulation (Figure 4). Digital twin is defined as a digitally reconstructed version of the physical system (van Rooij et al., 2021). At a very basic level, this allows for a 3D representation of the packaged RO system. As discussed previously, packaged RO systems are usually installed in very confined space (Figure 1B). The produced 3D representation can be compared to the available space and check for suitable access for maintenance and equipment servicing. At a higher level, the digital version can be used to simulate a range of operation conditions and maintenance scenarios. It can also be used for training and for remote maintenance (Lian et al., 2022).

Predictive analytics is arguably the most significant advantage of the digital transformation of packaged RO operation. The ability to predict membrane scaling/fouling and separation performance is essential for performance optimisation and cost reduction. In fact, membrane scaling/fouling is inherent and unavoidable in all membrane filtration processes. When membrane scaling/fouling occurs, in most cases, the main result is a lower permeability, lower permeability, and higher energy consumption (Matin et al., 2019; Tong et al., 2019).

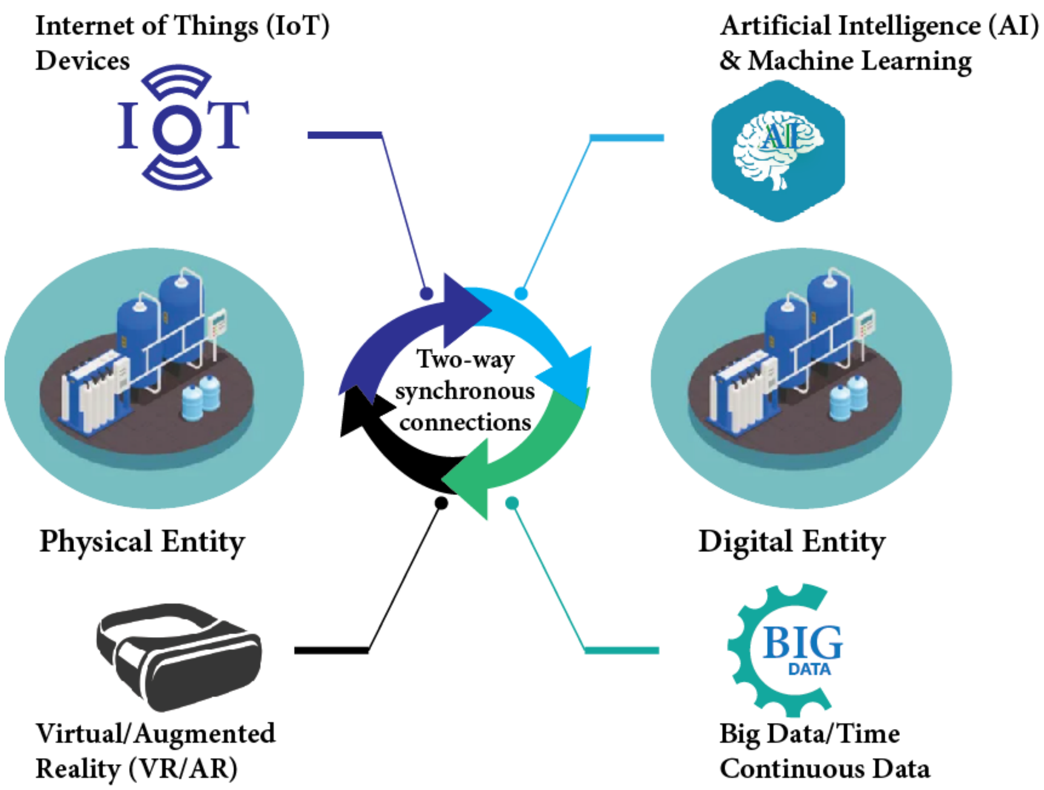

Figure 4: Digital twin for comparison and simulation.

Scaling and fouling monitoring is particularly difficult in RO operation. RO membrane is usually modulised in spiral wound configuration. In each spiral wound module, the membrane is folded with a spacer inside that collects the water after it is filtered by the membrane. Every envelope also has a spacer from the outside (Lin, Zhang et al. 2021). This module configuration offers a very high packing density (membrane area over volume) but remove all possibility for visual inspect to monitor for scaling and fouling (Karabelas et al., 2020).

Chemical additives are usually used to control membrane scaling and fouling (Mangal et al., 2021). These additives interfere with the chemistry of specific anions and cations or act as biocides. The chemistry of these additives is complicated and will not be discussed here. However, most of the membrane manufacturers would provide a single formula for all applications regardless of the feed water chemistry. Data analytics can be used to better deploy these additives.

Until recently, the only option is to manually analyse all available process parameters of the system and the quality of the water in the inlet for an educated guess (Lilane et al., 2020). Alternative, the membrane module must be removed for visual inspection in a protocol often called ‘membrane autopsy’. Membrane autopsy has been reviewed extensively in the literature. It can provide accurate information but expensive and disruptive. The module used for autopsy cannot be reused again and given the small number of membrane modules in a packaged RO system, membrane autopsy is the last resource. The membrane needs to be taken to special laboratories with special equipment for autopsy analysis (Zheng et al., 2018). Thus, this approach is not always suitable for remote operation.

New developments in AI and big data have opened opportunities to predict and analyse for scaling/fouling without membrane autopsy. The automatic control uses process parameters that influence the performance of the membrane. Computerised programs can calculate, and correlate data gathered from the system to provide a specific solution or to predict how the plant will work in the future based on the data collected in real-time. This approach can provide information about the state of the fouling or scaling before the system performance starts deteriorating (Niu et al., 2022). Infrastructure for cloud and IoT based data analytics is now available for analytical calculation to improve the way the RO plant works (Alshehri et al., 2021).

Table 1: Machine learning and artificial intelligence models used for predicting RO. Performance.

Model	**Key findings**	**Ref**
Artificial neural network	Decision tree provides better predictive performance than ANN	(Choi et al., 2020)
Decision tree		
Support vector machines	Decision Tree yielded better results than support vector regression	(Marichal Plasencia et al., 2021)
Decision tree		
Hybridized multilayer perceptron and particle swarm optimization algorithm MLP-PSO	Modeling results are model and context dependent ML modelling can be trained and used for one plant but not for another	(Ehteram et al., 2020)
M5 model tree M5T		
Support-vector machine SVM		
Artificial neural network	ANN predict better pressure diferent than RF and MLR, Salt passage and permeate flow perform better for RF and MLR	(Odabaşı et al., 2022)
Random forest		
Multiple linear regression		
Computational Fluid Dynamics (CFD)	Promising tool to predict fouling in reverse osmosis membranes	(Najid et al., 2022)
Artificial Neural Network base on genetic algorithms	ANN base on genetic algorithms ANN models can manage the operating set-points or SWRO	(Cabrera et al., 2017)
Response surface methodology (RSM)	ANNs has higher predictive capability for forward osmosis and low pressure ultrafiltration hybrid system	(Nam et al., 2022)

Several machine learning models are available for simulating and predicting RO performance, ranging from the most basic type (such as linear regression) to sophisticated and proprietary software packages from commercial suppliers (Choi et al., 2020; Nam et al., 2022). Machine learning models and artificial intelligence algorithms recently reported in the literature are summarised in Table 1. Information corroborated from previous works in Table 1 highlight the need for more research in this area. In some cases, the predictive outcomes are dependent on the models; in other words, there is still a lack of consistency in the predictive outcomes when different machine learning models are used (Odabaşı et al., 2022). Some models appear to perform better but only in respect to a defined group of parameters. It is also noteworthy that other computerised software packages can also be used to complement machine learning capability. For example, computational fluid dynamics simulation has been successfully used to predict and simulate biofouling (Najid et al., 2022).

Framework for digital transformation

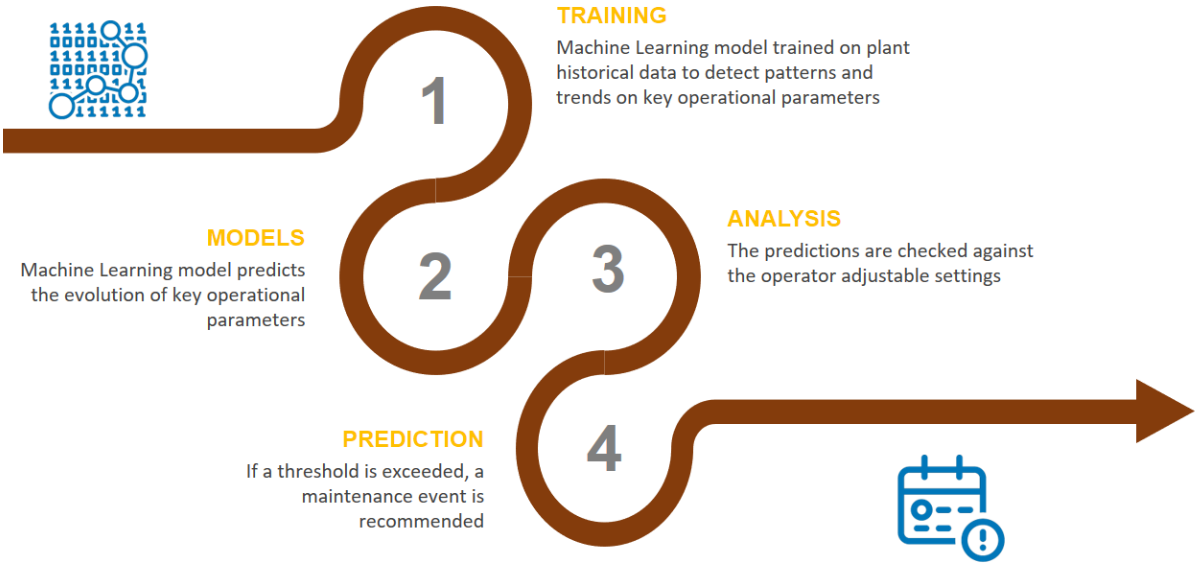

Figure 5: Four key steps for digital transformation of packaged RO systems.

Digital application to packaged RO systems is an emerging concept. It has the potential to transform the way packaged RO systems are used in the industry and for sewer mining. There have been several large scale initiatives to promote the digital transformation of packaged RO plants. Notable examples include Hubgrade from Veolia (www.veolia.com/en/solution/smart-services-smart-monitoring-solutions) and SmartOps from Gradiant (www.gradiant.com/technologies/smartops-digital/). Hubgrade and SmartOps are smart data management tools for monitoring and real-time decision making to improve water system performance including packaged RO plants. According to Hubgrade, the framework for digital transformation consists of four steps, starting from training, model development, analysis and ultimately prediction (Figure 5). Figure 5 is a useful road map for further digital transformation of packaged RO systems. Awareness of the digital capability and digital literacy are important to realise the full benefit of digital transformation of the sector.

Conclusion

Packaged reverse osmosis (RO) systems are widely used for industrial water supply and sewer mining. Digital connectivity and machine learning offer a game changing capability to these packaged RO systems. Information corroborated in this review show that with new digital capability, it is much more cost effective to design, operate, and manage these RO systems. Performance can be optimised via a range of approaches that are not possible with traditional human intervention. For example, hybrid systems that need a complicated control and prediction will require complex prediction models based on big data. On the other hand, other system that needs less intervention can work autonomously without or little human intervention. Automatic high-quality water treatment systems have attracted significant attention in recent years. This review highlights key research gaps in understanding variable possibilities that machine learning and prediction can be successfully utilized by RO systems. The review also illustrates that artificial intelligence and machine learning can significantly improve the performance of packaged RO systems.

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