PROSPECTS OF WIND POWER PREDICTION AND VARIABLE OPERATION IN OPTIMIZING WIND-POWERED REVERSE OSMOSIS OPERATION

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ABSTRACT

Reverse Osmosis (RO) is a dominant process in the desalination industry. However, concerns have been raised regarding its impact on the environment due to the dependency of commercial-scale plants on fossil fuels. Renewable Energy (RE) has been used in several studies to operate RO plants and decarbonize water production. However, the technology is either limited to small-scale plants, or large-scale plants that rely on a grid connection to meet the required water demand. This study is part of an international collaboration that aims to efficiently operate large-scale RO plants using wind energy and achieve the transition to fully sustainable RO. Variable-speed operation and modular operation are defined as strategies to operate the RO plant according to the available wind energy. As an initial step, this paper studies the combination of variable operation and wind-speed prediction in optimizing the operation of wind-powered RO. An Artificial Neural Network (ANN) was trained using a full year wind speed time-series to predict hourly average wind speed using a previously recorded 12-hour time series. The prediction exhibited high accuracy based on the regression analysis and would be implemented in the RO control system during the next stages of development. Wind speed prediction presents great potential for scheduling the startup/shutdown cycles of RO trains during modular operation. Currently, a pilot RO plant is being developed at Aston University for future testing. It is designed to deliver comparable operation to commercial RO plants by using commercial components arranged in a split feed flow configuration.

Keywords: Reverse osmosis, Renewable energy, Variable speed operation, Modular operation; Neural network.

I. INTRODUCTION

Water security is recognized as a global challenge due to the expected 50% rise in global water demand by 2030 [1]. The desalination sector has been growing constantly to keep up with the growing water demand and water security threats. Water production from desalination has increased from 66.4 million m^3/day in 2012 to 99.7 million m^3/day by 2018 [2-4]. RO dominates the field of water treatment, e.g., it provided 65% of the total desalination capacity by 2016 [5, 6]. However, concerns have been made regarding the impact of RO desalination on the environment due to their reliance on fossil fuels. The CO_2 emission from seawater RO plants ranges from 1.7 to 2.8 $kgCO_2/m^3$, which would have a noticeable impact considering the large-scale operation of RO [7].

Renewable Energy (RE) has been used in several studies to operate RO plants and decarbonize water production. However, fluctuation and intermittency are major drawbacks for the commercialization of RE driven RO, especially while considering that RO plants are favored to work under stable conditions. Several studies used energy storage to fill the gap between the fluctuating energy supply and the RO constant demand. However, the efficiency of energy storage systems is always a question of debate, as they increase the capital cost, complicate the system, require large area and regular replacement, especially when considering upscaling to commercial plants [8, 9]. In addition, using energy storage systems tends to increase water production costs, to different extent depending on plant design and location. Two studies [10, 11] compared the water production costs for a SWRO system with and without energy storage. Production costs increased from 7.8 to 8.3 €/m^3 in [10] and increased from 10 to 13 \$/m^3 in [11]. Accordingly, the technology of RE-driven RO is either limited to small-scale plants due to the inefficiency of large-scale electricity storage or large-scale plants that rely on a grid connection to meet required water demand [10, 12]. This study is within the framework of an international research collaboration between three British universities and the University of Bahrain to discuss issues on water, energy and food nexus in the Kingdom of Bahrain. The collaboration between Aston University and University of Bahrain is focused on linking commercial RO desalination plants to renewable energy sources. Bahrain is considered as a water scarce country; it lies in an very arid region and suffers a rapidly declining freshwater share per capita [13]. In 2003, 23% of Bahrain's water consumption was met by desalinated water, which increased significantly to 54.1% by 2011 [13, 14]. Today, Bahrain relies almost entirely on desalination. The independent operation of large-scale RO plants by mature renewables, such as wind and solar energy, would have a positive impact on water security in Bahrain and the Gulf region.

Recent studies have tackled the difference in energy supply and demand by using 'Variable operation' to directly connect the RO plant to the RE source, where it showed adequate performance as an operation scheme for this application [15, 16]. Variable operation averts the need for energy storage, backup systems and associated costs, which is very attractive for islands, remote areas and countries with low energy availability from fossil fuels [17]. In general, variable operation of RO plants relies on two operation strategies as follows:

- **Modular operation:** An operation strategy that depends on the RO plant modularity, where the RO units/trains are connected or disconnected according to the available energy [18].
- **Variable-speed operation:** The RO plant operates with variable production rate and permeate recovery by changing feed pressure and flow rate based on the energy available. Normally, variable frequency drives are used to achieve this flexible operation mode [16].

For variable operation to be used in large-scale plants, two problems have to be addressed. Initially, the effect of pressure and flow rate should be determined on the plant's components. In addition, the startup and shutdown procedure should be simplified and scheduled to accommodate modular operation [15]. This paper introduces the role of variable operation and RE availability prediction in efficiently managing the RO plant load against wind energy variation aiming to transfer the technology to large-scale/commercial plants. Initially, the pilot RO plant designed for performing tests related to this project will be described. In addition, the proposed method for implementing variable operation and varying plant parameters is defined. Furthermore, the potential role of wind speed prediction in optimizing the plant modular operation is presented.

II. RESEARCH CONDUCTED

2.1 Pilot RO plant

A pilot RO plant is planned for commissioning at Aston University to be a test bench for optimizing the operation of renewable energy-driven RO plants. The RO test rig, presented in Fig. 2, has all the essential features of a large plant to deliver comparable performance. The plant rated production capacity is around 3 m^3/h. It includes two parallel pressure vessels, each containing three 8” RO elements in series. One pressure vessel can be shut down using an isolation valve, to enable modular operation, similar to including multiple RO trains. In addition, a pressure exchanger developed by Energy Recovery Inc. (ERI) will be included as an energy recovery device. The ERI pressure exchanger will be a unique addition to this study compared to most studies that opted to use smaller energy recovery devices (e.g., Clark pump and axial piston motor). Moreover, the control system is designed to manipulate the feed flow rate and pressure against disturbances such as changes in available power, feed concentration and feed temperature within a safe operating window.

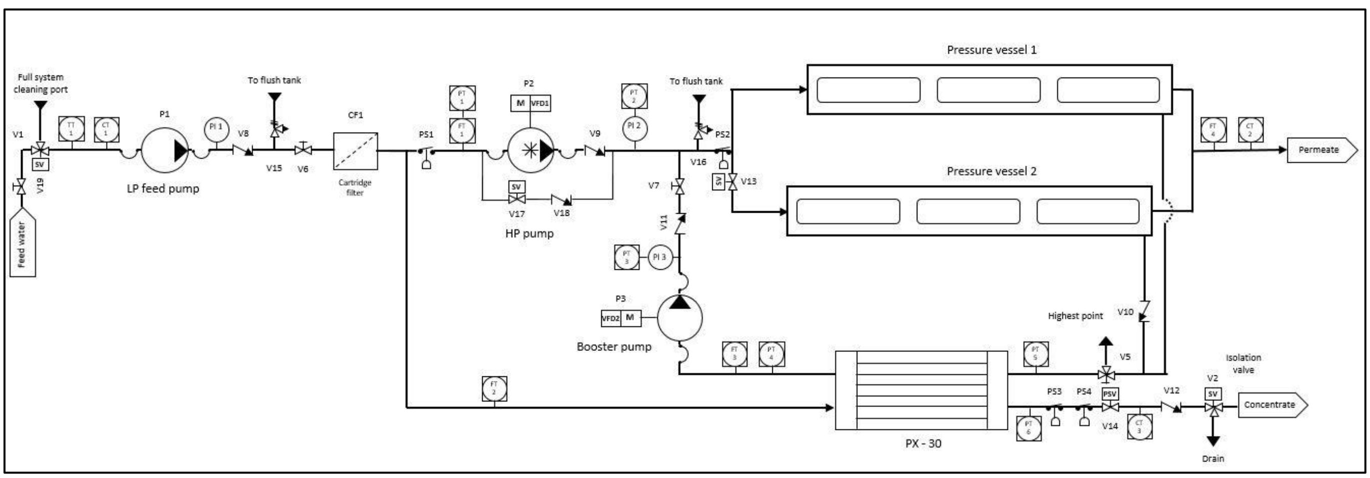


Fig. 1. Pilot RO plant.

2.2 Variable-speed operation and operation limits

Variable-speed operation depends on operating the plant at varying power consumption points depending on the available energy. The plant’s power consumption is varied by changing the feed pressure and flow rate, which changes the plant production rate and permeate recovery respectively [15]. Operating a RO plant using variable-speed operation requires two procedures. Initially, an operation strategy is selected to optimally change the operation parameter with available energy. Pohl et al. [19] presented an investigation of different operation strategies to operate RO plants, concluding that operation at constant recovery ratio offered the best performance regarding the specific energy consumption, permeate quality and wide operation range. The second procedure is defining a safe operation window to set the boundaries of acceptable change in operating parameters. Several studies [19-21] presented design specific operation window, however, the same general concept is used by varying the feed pressure and flow rate according to the hydraulic limitations of the RO membrane. The hydraulic limitations of the RO membranes are described as follows [19-22]:

a) Maximum feed pressure that the membrane can withstand
b) Maximum allowed feed flow based on the membrane mechanical loading
c) Maximum permeate flow per element and the maximum recovery per element which could lead to excessive concentration polarization.
d) Minimum concentrate flow to avoid salt precipitation and membrane fouling.

The operation boundaries are defined by simulating the membrane performance against changes in feed pressure and feed flow rate while holding specific parameters constant.

2.3 Modular operation and wind speed prediction

RO plants consist of multiple identical units called RO trains. In modular operation, RO trains are switched on/off to match the RO plant load to the available RE. In commercial RO plants, standard startup/shutdown procedures are recommended by membrane manufacturers to prevent excessive membrane fouling, prevent membrane damage due to excessive loading and ensure the water quality and productivity are as claimed [23, 24]. RO trains start-up procedure include purging the air out of the membranes using low-pressure water before gradually increasing at a rate of 0.7 bar per second until reaching the set point [23]. The permeate is discarded during this process until it reaches the desired quality [24]. During shutdown, the RO membranes are flushed using low pressure permeate water to prevent scaling or salt deposition. Membrane flushing takes place until the concentrate conductivity reaches the feed conductivity. Startup/shutdown procedures are consuming of clean water to flush the membranes, energy to operate the flushing pumps and time wasted that the plant could be producing permeate - all of which are finite in the case of RE powered RO. The time, energy and clean water required for startup and shutdown are subject to the capacity and design of the RO trains.
While operating using RE, startup and shutdown of RO trains will more frequent than in case of constant operation. Scheduling the startup and shutdown procedure for solar-photovoltaic operated RO plants is achievable by using the solar irradiance distribution curve. For wind-powered RO, it is more challenging to schedule the RO trains startup/shutdown procedure due to the fluctuation and intermittency of wind speed, wherein a single day there might be several start-up and shutdown cycles for a specific RO train [17]. RE forecasting is a promising technique to improve the possibility of plant scheduling for wind-powered RO plants and achieve similar operation scheme as solar powered RO plant.

Artificial Neural Networks (ANN) can predict future time series without a predefined mathematical model. They are widely used for prediction and function approximation of nonlinear systems due to their ability to handle noisy and incomplete data [25]. ANN was suggested by several studies and delivered adequate performance for predicting wind speed [26-28]; however, its use in RO applications was limited to modelling the RO modules or integrated into the control system. Using ANN wind speed prediction to enhance the performance of wind-driven RO was not previously introduced [15].
A two-layer feed-forward backpropagation network, presented in Fig. 1, is used in this study as it showed adequate performance for approximating different functions in previous studies regarding the convergence time, accuracy and network generalization [29]. The ANN is trained for forecasting the average wind speed for one hour ahead using data collected of the past 12 hours. Prediction accuracy will be presented using Mean Square Error (MSE) and regression analysis that estimates the relationship between the target and predicted values.

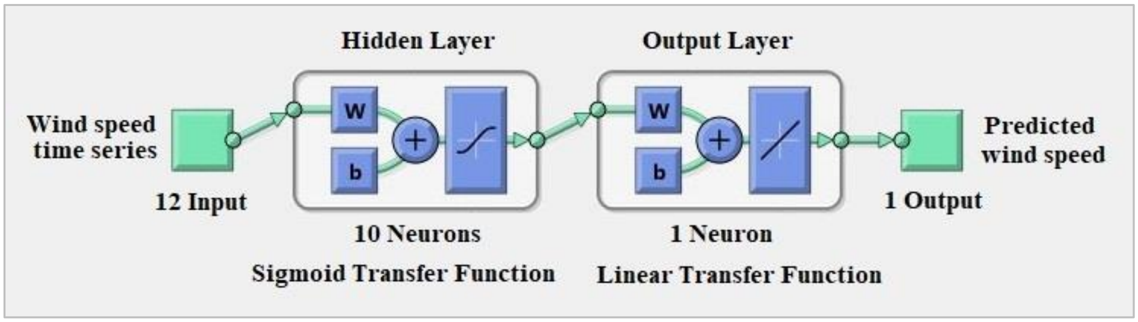


Fig. 2. Two-layer feed-forward backpropagation ANN.

III. RESULTS

3.1 Outlining the boundaries of safe operation

The safe operation window for the pilot RO plant, presented in Fig. 3, is developed to set the boundaries of parameter variation while using variable speed operation. It was defined using the Reverse Osmosis System Analysis (ROSA) software by varying the feed pressure and flow rate across the RO membrane's hydraulic limitations. Each pressure vessel was set to include three DOW-FILMTEC SW30HRLE-400 elements in series for feed water of 35000 mg/l NaCl concentration. The boundaries of operation were set by the maximum recovery per element (13%), maximum permeate flow per element (1.4 m^3/h), minimum concentrate flow (3.4 m^3/h) and maximum feed/brine flowrate (14 m^3/h) [23]. The operation window was defined for operating with one pressure vessel or two pressure vessels in parallel, each containing 3 RO modules in series.

The operation window starts with the intersection of the maximum allowable feed flow rate and the minimum permeate concentration. At this point, the plant is operating with the highest feed flowrate possible and lowest operating pressure. Note that the feed pressure is above the osmotic pressure, as the osmotic pressure will produce permeate at a concentration higher than 500 mg/l. The feed pressure is increased gradually at constant feed flow rate until a maximum permeate flow per element of 1.2 m^3/h is achieved. The feed flow rate is then reduced with increasing feed pressure (increasing recovery) while maintaining the maximum permeate flow per element. This will lead the RO plant to achieve the maximum recovery per element (13%) and thus, reach the feed pressure ceiling. The highest possible feed pressure is noted to be 62.8 bar, which is less than the 83 bar limit set by the membrane manufacturer. After the maximum pressure and maximum recovery per element are achieved, the feed pressure and flow rate are reduced while the recovery ratio per element is maintained at 13%. This will cause the concentrate flow to drop to the recommended minimum of 3.4 m^3/h, which is enough to flush the brine outside the membrane and prevent salt deposition. The feed pressure and flow rate are decreased while maintaining the concentrate flow at 3.4 m^3/h until the permeate reaches the maximum allowed concentration. The recovery ratio is then decreased while maintaining the lowest possible pressure and maximum concentrate salinity.

If two pressure vessels are operational, the feed flow is split between both of them and the permeate and concentrate flows are doubled, however, the same constraints still apply for the hydraulic limitation. The operation strategy could be outlined in terms of pressure or flow rate depending on the strategy used. Also, operation could be guided along the Iso-recovery lines, depending on if a constant relation between the feed pressure and flow rate is maintained.

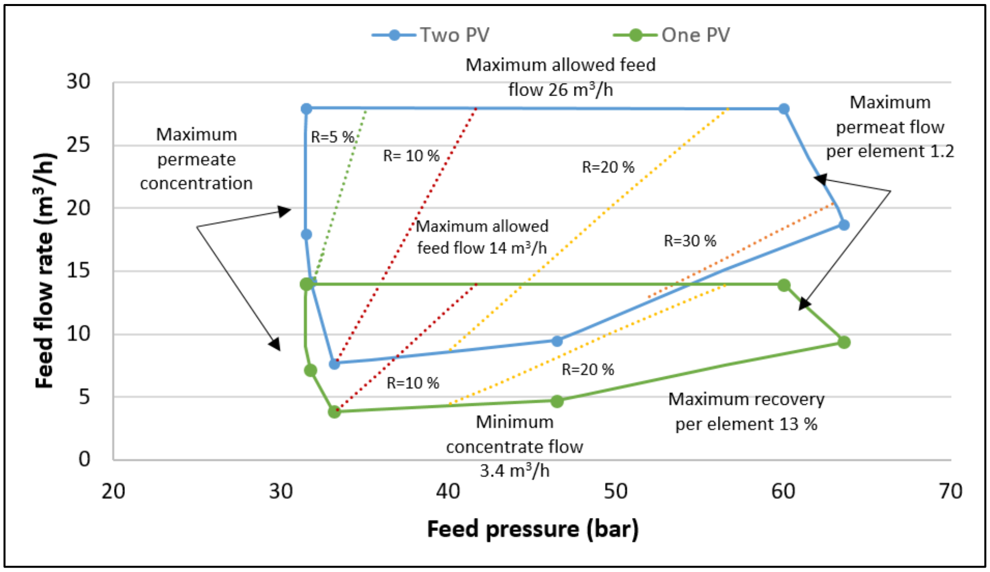


Fig. 3. Boundaries of safe operation.

3.2 Determining the accuracy of wind speed prediction

The wind speed data used in this study was collected by the Ministry of transportation and telecommunication in Bahrain and provided for this study by the University of Bahrain. The hourly wind data spans across a full year from 01 Jan 2016 to 31 Dec 2016. The wind speed was measured at Durrat Al Bahrain (Lat 25° 50' 52.96'' N Long 50° 35' 44.38'' E) at a height of 4 m. The wind data was divided to three parts: 70% of the data was used for the ANN training, 15% was used for validation and 15% was used for testing. The Artificial neural network fitting tool (NFTOOL) developed by MATLAB was used to implement this ANN. The number of neurons in the hidden layer is determined by trial-and-error analysis, such that, the training starts with a few number of neurons and increases gradually until reaching the lowest error [25]. The ANN delivered good prediction accuracy with 10 neurons in the hidden layer. For network training, the Levenberg-Marquardt backpropagation algorithm is used as a training algorithm.

Initially, 15% of the full year data was used to test the ANN overall accuracy and prediction quality by using it as target data, which is compared to the ANN prediction. The testing showed good agreement between target and predicted data, presented by a low MSE of 1.08 m/s and a high R-value of 0.913 from the regression analysis. This represents the overall quality of the wind speed prediction; however, the error might vary depending on the randomness of the wind speed, as presented in Fig. 4. In Fig. 5(a), the wind speed is predicted for each hour, while adding the actual measured wind speed at each step to the time series for forecasting the next hour. Fig. 5(b) shows the wind power perdition based on a 20 kW turbine power curve. The results show a relatively good match between predicted and target wind speed and power. In the upcoming stages of research, the ANN wind speed prediction will be coupled to a wind driven RO plant to quantify its impact on the RO plant's working hours and the water production capacity. Further improvements to the ANN prediction accuracy can be achieved by using more data for training to improve network generalization or using different techniques that are stated in previous literature. Different ranges of prediction could be used, such as predicting the wind speed for an entire day ahead; however, more wind speed data would be needed to achieve high prediction accuracy.

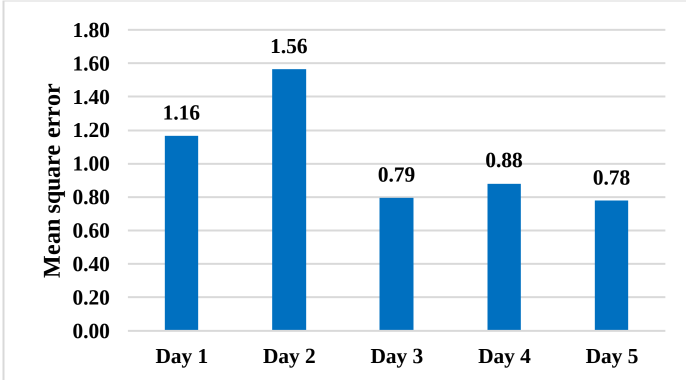
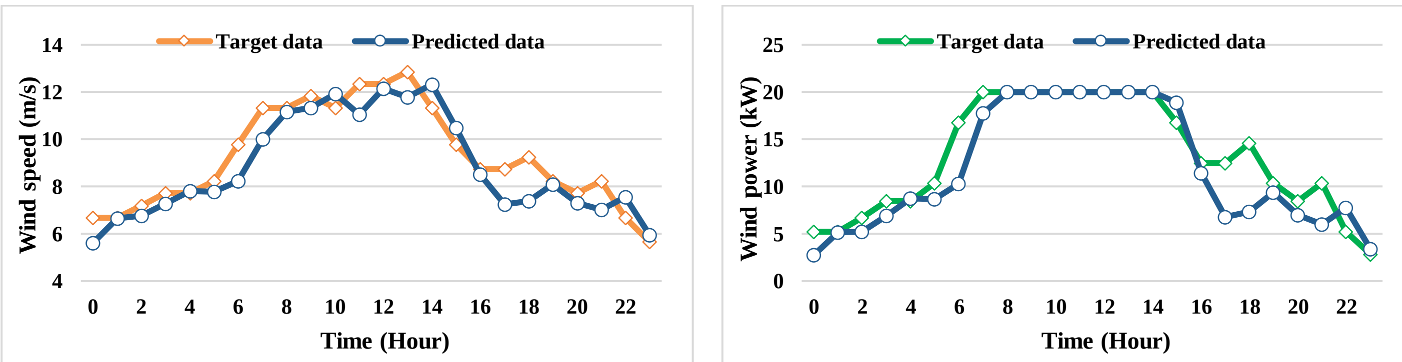


Fig. 4. Mean square error for five random days.



(a) (b)

Fig. 5. (a) Wind speed prediction, (b) Wind power prediction for a 20 kW turbine.

V. CONCLUSIONS

- The operation window is essential to define the control system trajectory towards variation in wind speed while using variable speed operation.
- Wind speed prediction is a promising technique for operation scheduling and advanced control techniques while using variable operation
- Preliminary analysis indicates that using the ANN for average hourly wind speed prediction demonstrates high accuracy according to the regression analysis (R=0.913) when compared to the random nature of wind speed.
- Future work will incorporate more details regarding the operation strategy in relation to the energy consumption, scheduling techniques based on RE forecasting and using solar-PV beside wind energy, to operate the RO plant with a more stable hybrid energy source.

VI. ACKNOWLEDGMENT

Financial support granted for this project by Aston University and University of Bahrain is greatly appreciated.

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