PLANT PERFORMANCE OPTIMIZATION USING SMARTOPS^{TM}

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ABSTRACT

The implementation of machine learning (ML) leads to the capability of identifying the non-linear relationship of input and output data. The growing availability and frequency of data collection has resulted in the widespread implementation of ML techniques for predictive modelling. The SmartOps^{TM} approach aims at providing 'early warning' in feedwater variations and optimizing the cleaning schedules using ML. This study was conducted at a water treatment plant, situated beside a main industrial plant in Malaysia. Taking the source from the pond water, the treatment plant is equipped with ultrafiltration (UF) and reverse osmosis (RO) membranes, and the product water was sent to the main plant for manufacturing purpose. The SmartOps^{TM} model outperforms other ML model in the prediction of pond water quality. The SmartOps^{TM} model shows relatively high r^2 values at 0.97 in the prediction of the conductivity as compared to other ML model (r^2 = 0.80). The process optimization using the SmartOps^{TM} is expected to save and minimize the operational costs, which include the chemical and electrical consumption of the treatment plant. The methodology offers a great potential for implementation in the operations of treatment plant, which could improve energy consumption and hence, making the plant more capable and optimized over time.

I. INTRODUCTION

Membrane processes have been widely used in the water treatment industry for decades. However, membrane fouling is a significant barrier which could limit the efficiency of reverse osmosis (RO) process. Differential pressure (DP), transmembrane pressure (TMP), permeate flowrate/flux and salt rejection could be used to monitor RO membrane performance. There are several factors which could affect the membrane performance and these include feed water characteristics, operating parameters and membrane properties [1]. There are different approaches in the analysis of membrane performance and these include physics-based, data driven and hybrid models [2]. In physics-based model for RO membrane, solution-diffusion transport mechanism described using Fick's law, osmotic pressure in terms of Van't Hoff or Pitzer equations and concentration polarization model based on film theory model could be employed as physical models [3]. However, it is challenging to predict the whole systems using classical mathematical models due to the complexity of membrane and fouling processes. Hence, it is crucial to explore other advanced methods to address the limitations of classical models for the predictions of membrane process performance.

Data-driven and predictive modelling have attracted a lot of attention in the water treatment industry in the recent years due the shortcomings of physics-based models. The higher frequency and availability of data collection has resulted in the broader implementations of machine learning (ML) techniques in predictive modelling. ML could be denoted as the use of algorithms to learn from data, obtain hidden knowledge and make predictions in the related field. In recent years, there is also a growing number of studies of the applications of ML in the field of water treatment for (1) optimization of the operation of water treatment plant and (2) evaluating the effect of changing feed water quality on the capacity and efficiency of treatment [4].

Supervised ML is categorized under ML and artificial intelligence (AI) and it is defined by the use of labeled datasets to train algorithms in order to classify data and predict outcomes accurately. Artificial neural networks (ANNs) are one of the most commonly used supervised ML algorithm in the field of membrane applications [5], [6]. In a recent study by Odabaşı et al., ANNs were used to predict pressure difference across the membrane and it was found to outperform random forest and multiple linear regression models [1]. Roehl et al. has used ANN models to quantify the cause of membrane fouling in the first stage of a full-scale RO system [7]. The simulated model run has indicated that adjustments of chlorine dosing following incoming foulant concentrations could reduce fouling rate.

Random forest is one of the most common tree-ensemble algorithms for supervised ML problems. The random forest model is gaining more attention due to its high accuracy, robustness against outliers and the ability for generalization. Other than these models, there are other ML models which were employed for the RO process, for example, support vector regression, gradient boosting tree model, fuzzy logic, and genetic programming [8].

SmartOps™ is an integrated digital solution for asset management, plant performance, predictive maintenance and remote monitoring and control. The key benefits of SmartOps™ include (1) early detection of deteriorating membrane performance and feedwater variations using ML, (2) access real time data for trending and reporting of key performance indicators, (3) predict the cleaning schedule of membranes and (4) operation optimization to minimize operational costs.

As the influent water quality could pose a large impact on the operating conditions and cleaning frequency, water quality prediction is essential in water treatment plant management. Currently, plant operators are using sensors/probes to monitor the changes in feed water quality, but they are unable to do predictions on this parameter. Nevertheless, these monitoring data serve as a basis for data-driven models for predictive analysis. Water quality predictions can provide a framework for the plant operators to act as a ‘preemptive warning’ so that the most appropriate counter measures could be implemented.

Data-driven modelling techniques take advantages of large datasets obtained from the monitoring tools with advanced statistical analysis. Studies have shown the use of various ML techniques, including supervised machine learning in environmental studies associated to water treatment plant and membrane technology [9] [10] [11]. Various supervised ML models are used to train the data in this study and physics-based models are used to keep the prediction within physical reality. The objective of this study is to show the application of SmartOps™ in predicting the variations in source water quality and optimization of process parameters so that the operational costs could be minimized.

II. RESEARCH CONDUCTED

2.1 Treatment plant feed water and process

The study was conducted in a water treatment plant equipped with ultrafiltration (UF) and RO Infinity^{TM} (ROI^{TM}), located at Taiping, Malaysia. The process flow diagram (PFD) of the treatment plant is shown in Figure 1. The treatment plant is situated beside a main industrial plant and it uses the surface pond water as the source. The plant is equipped with four trains of conventional UF as the pre-treatment and integrated with Gradiant's RO Infinity^{TM} process (four trains) to produce RO permeate with low TDS (<30 mg/L). With ROI technology, the water recovery could be increased and RO membrane lifetime could be prolonged. In this study, there are only three UF and ROI trains in operation. Feed water from the open pond water intake is fed to the UF to remove any suspended impurity before treatment with ROI. Sodium bisulfite (SBS) and anti-scalant are dosed prior to ROI to protect the membranes from fouling and scaling. The product water is sent to the main plant for manufacturing purposes. The treatment plant is equipped with full supervisory control and data acquisition (SCADA) system and feed water quality are recorded in real time. The RO permeate lines are equipped with conductivity meters to monitor the permeate quality being generated. The measured feed water parameters were summarized in Table 1.

Table 1: Water quality of water source (pond water)

Parameter	Unit	Results
pH @ 25ºC	-	7.84
Conductivity	µS/cm	633
Turbidity	NTU	3.29
Total dissolved solids (TDS)	mg/L	317
Nitrate, NO_3^-	mg/L	5.31
Phosphate, PO_4^{3-}	mg/L	17.64

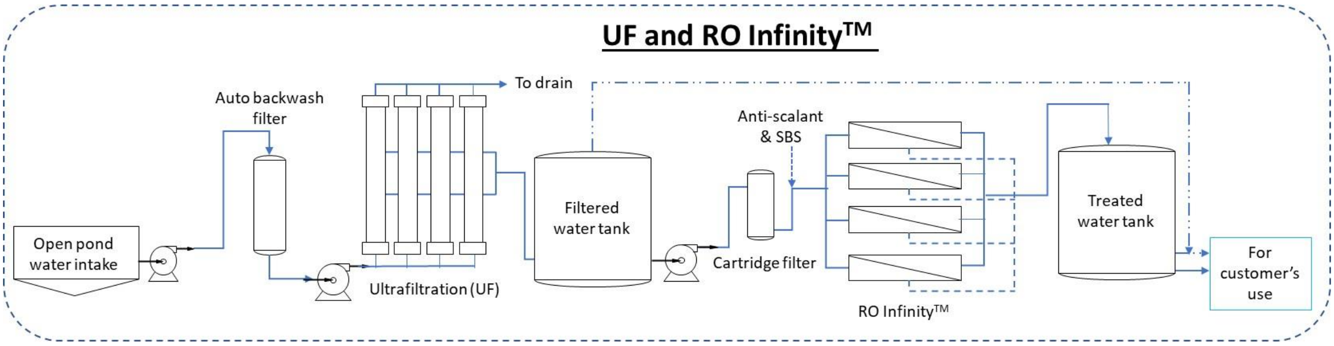


Figure 1: Process flow diagram for the treatment plant

2.2 SmartOps^{TM} digital solutions

Figure 2 shows the process workflow for SmartOps^{TM} digital solutions. In summary, SCADA collects data from the monitoring sensors in the treatment plant. The data is pre-processed and cleaned in preparation to train the ML model. The data is separated into training and testing set for the evaluation of the ML model. The trained model is then used for predictions and the setpoints are changed based on the optimized model.

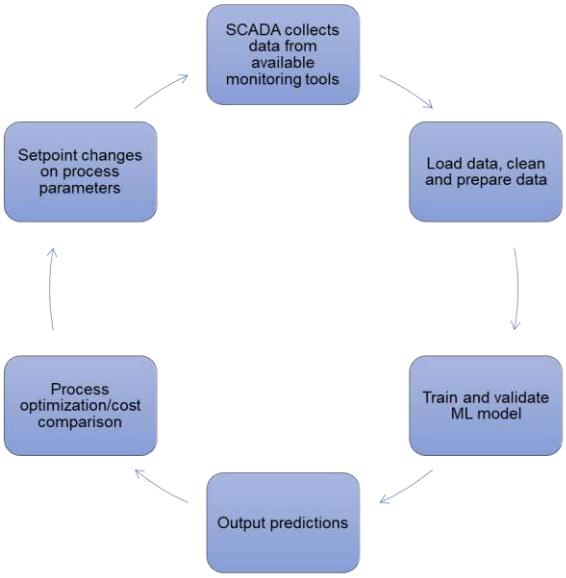


Figure 2: Process workflow for SmartOps^{TM} digital solutions

2.3 Model design

Influent conductivity is one of the most important variables in the membrane process as it affects the permeate flux and rejections [12]. The conductivity of the source water is susceptible to change, depending on weather and the surrounding conditions. Due to this reason, the current work focuses on the predictive analysis of feed conductivity (from an open pond water intake) using weather data and the surrounding conditions as the inputs. Figure 3 presents the flowchart of the model design for the data-driven modelling. It started with data collection and followed by variable characterization and correlation. After the inputs to the model are fixed, the data is split into training, validation and testing datasets. Various models are tested in order to select the best model with highest r^2 value.

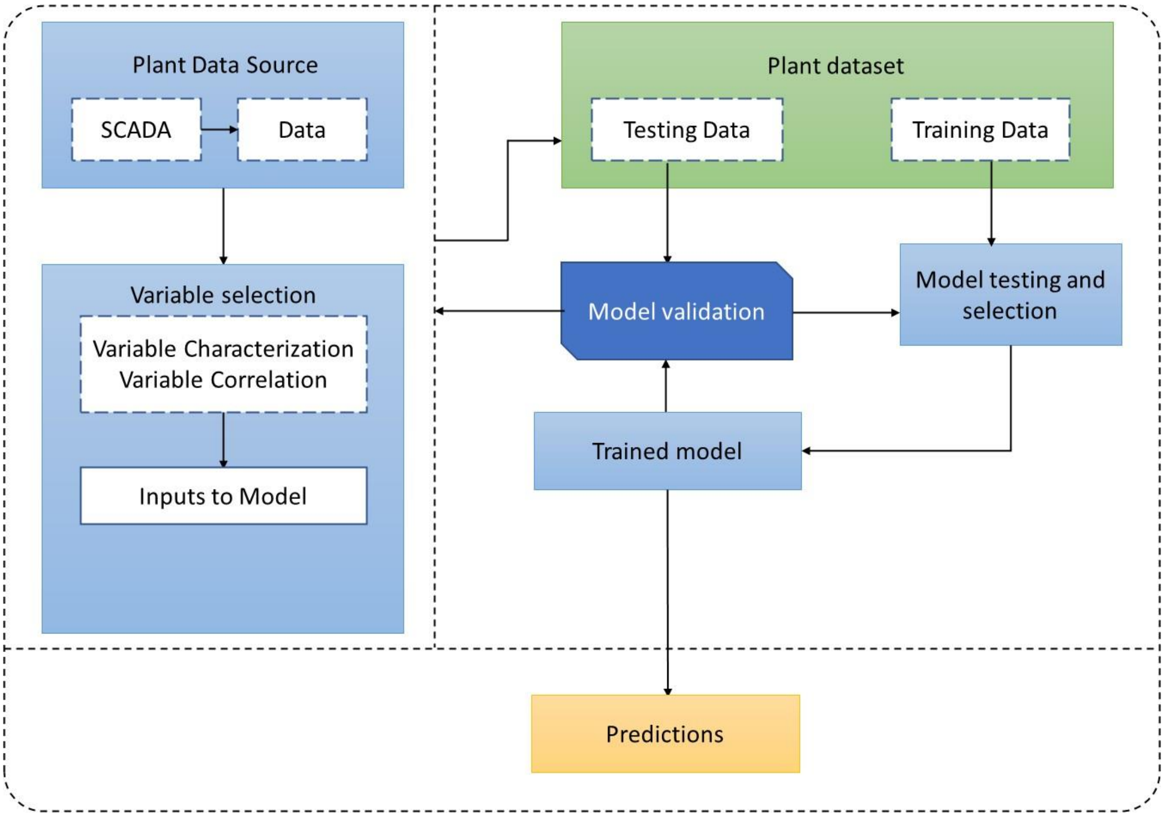


Figure 3: Model design structure diagram.

III. RESULTS AND DISCUSSIONS

Figure 4 shows the conductivity of the open pond water intake (feed water source) of the pilot plant. To determine the variables which pose significant effect on the influent conductivity, a correlation study was carried out to reduce the dimensionality of the model. As shown in Table 2, conductivity is negatively correlated to precipitate and strongly correlated to temperature. Hence, these variables were selected as the input for the machine learning model which will be described in the following sections.

Table 2: Correlation matrix

	Precipitate	Wind speed	Air pressure	Temperature	Conductivity
Precipitate	1	-0.12	-0.15	-0.38	-0.47
Wind speed	-0.12	1	0.022	0.088	0.05
Air pressure	-0.15	0.022	1	0.14	0.3
Temperature	-0.38	0.088	0.14	1	0.75
Conductivity	-0.47	0.05	0.3	0.75	1

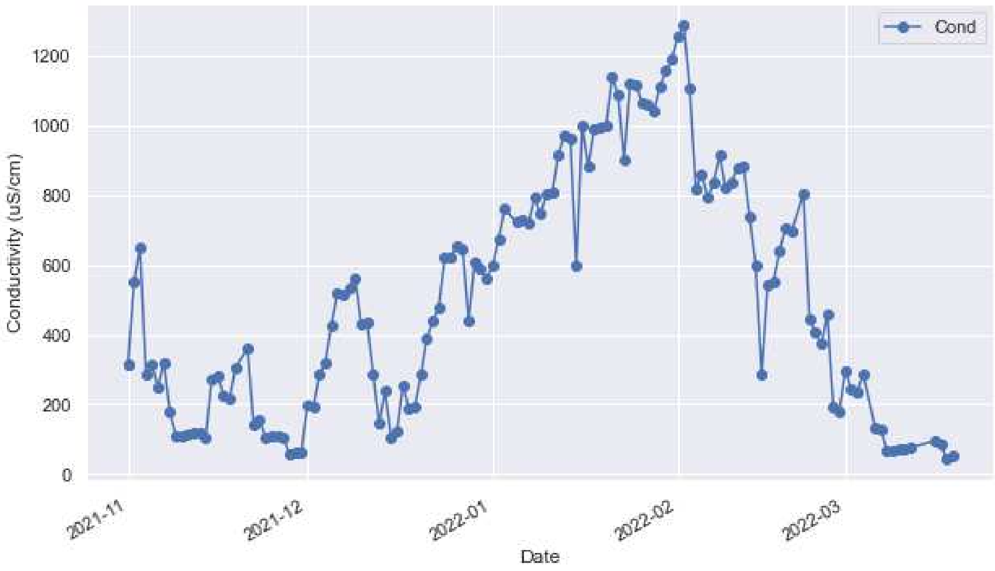
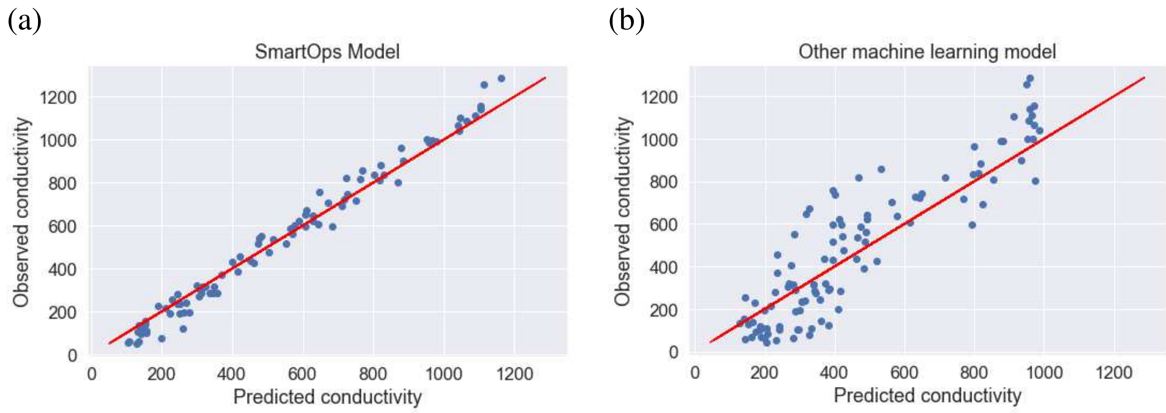


Figure 4: Conductivity of open pond water intake.

Supervised ML uses data set as the training set to teach models to provide the desired output. The training data set should contain the correct inputs and outputs, so that the model could learn over time. Several supervised ML models were compared and the best model was selected as the SmartOps model. As shown in Figure 5(a), SmartOps model demonstrates higher r^2 value in the prediction of influent water conductivity in comparison to other ML model. This result indicates that the SmartOps model is promising in the predictive modelling of feed water quality. By having the future trend of the feed water quality and process optimization based on the SmartOps model, plant operators could have implemented more effective countermeasures, such as optimizing the chemical dosage in order to operate the plant in its optimal conditions without compromising production.



$R^2 = 0.97$

$R^2 = 0.80$

Figure 5: Prediction using (a) SmartOps model and (b) other ML model.

The energy consumption of the treatment plant was analyzed and it is shown in Figure 6. With SmartOps^{TM} digital solutions, the energy consumption of the treatment plant is expected to reduce and the results will be presented during the conference.

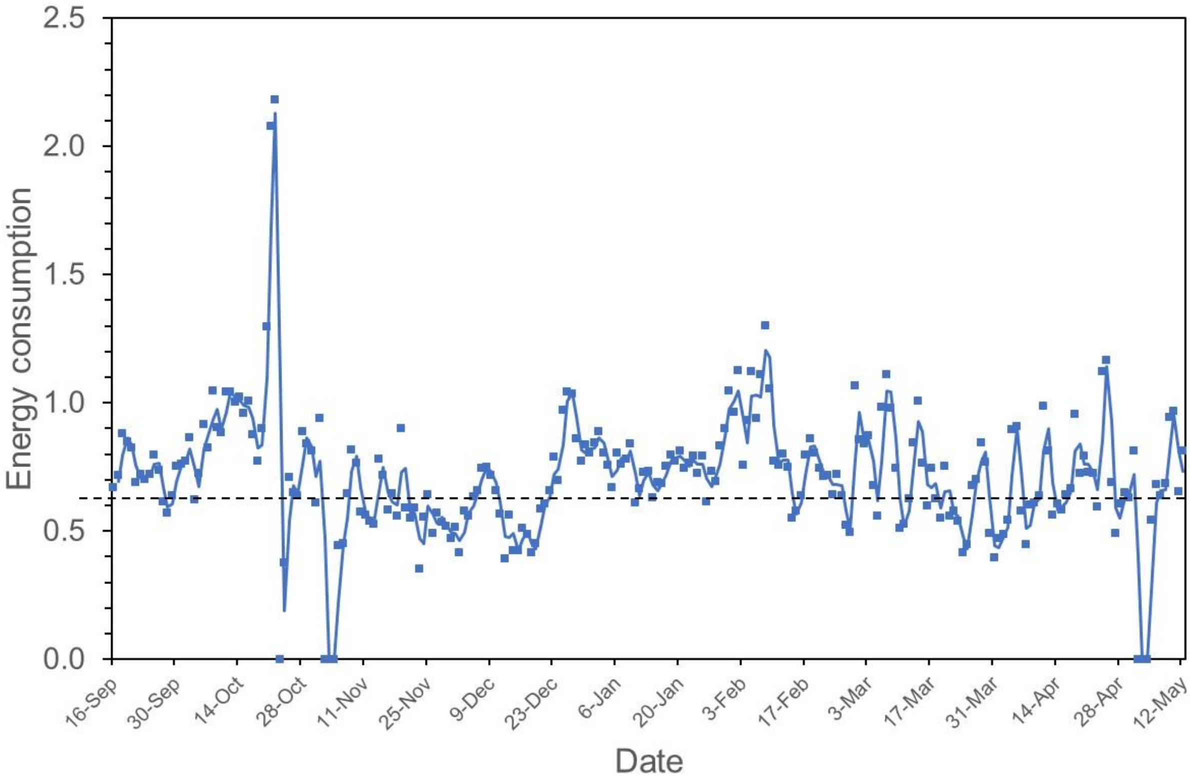


Figure 6. Energy consumption of the treatment plant.

IV. CONCLUSIONS

This study proposes the use of supervised machine learning model for the feed water quality prediction and optimization of process parameters using SmartOps^{TM} in a water treatment plant. The predictive ability of the SmartOps^{TM} model is promising with the r^2 values at ~0.9. With the SmartOps^{TM} prediction model, chemicals and manpower for operation/cleaning could be better prepared to minimize the logistic cost and unexpected plant downtime. The SmartOps^{TM} operation gives flexibility to operators in running the plant more efficiently and they could perform more proactively in the preventive measures.

V. REFERENCES

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