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Modeling and control of reverse osmosis desalination process using centralized and decentralized techniques

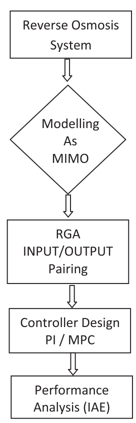
S. Sobana, Rames.C. Panda *

Senior Scientist, Chemical Engineering Department, CLRI (CSIR), Adyar, Chennai, India

HIGHLIGHTS

- Desalination of seawater using reverse osmosis has been modeled in Laplace domain.
- Two inputs and three outputs model is analyzed for RGA for input–output pairing.
- Centralized, decentralized controllers and MPC are synthesized separately.
- Decentralized–decoupled structure is satisfactory for TDS control.
- MPC controller performs well for flow rate, TDS control of permeate.

GRAPHICAL ABSTRACT



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ABSTRACT

This work implements model-based controls for the simulation of reverse osmosis (RO) desalination process for both servo and regulatory problems. Pressure from high-pressure (HP) feed pump and recycle ratio (RR) are manipulated inputs to the RO process, while permeate flow rate, concentration and pH are considered as output. Control configuration for this 2 x3 process is selected using regular interaction analysis methods. Two control strategies are adopted, namely, multiloop internal model control–proportional integral controller (IMC-PI) under centralized scheme and multivariable PI controller with decoupler under decentralized scheme. The non-square model for synthesizing the model-based control purpose is formulated using the mass balance continuity equation and model parameters are estimated. In both the cases, satisfactory results are obtained by reducing the fluctuation in the controlled parameters in the closed loop control systems. The performances of the two controllers are compared using the integral of absolute error (IAE) performance index criteria. Results with MPC are encouraging for implementation on desalination process.

1. Introduction

Potable water has become scarce as consumption has increased due to the increase in population and higher standards of living. Most of the world's water resources exist as salt water in the ocean and seas in addition to brackish water. Desalination is a process to convert high TDS seawater into low TDS portable water so that water can be used for

* Corresponding author at: Chemical Engineering Department, Curtin University of Technology, Perth, WA, Australia.
E-mail address: panda@clri.res.in (R.C. Panda).

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the public use. At present, a number of large desalination plants were operated by semi permeable membrane techniques (electrodialysis and reverse osmosis). Among these desalination methods, the reverse osmosis desalination method has the advantage from the point of view of low-energy consumption. Reverse osmosis is the separation process to separate pure water and salt solution through a semi permeable membrane. The membrane rejects most of the salts, and it allows the water to pass through the membrane, which is known as natural osmosis. In natural osmosis, the pressure on the dilute side will come down and the pressure on the concentration side will shoot up. A pressure known as the driving force is applied to overcome the osmotic pressure to the saline water section, which slowdown the osmotic flow and force the water to flow from salt solution into the water side, i.e., the direction of flow is reversed is known as reverse osmosis. In order to find a solution to the problem of growing demand for potable water, it is needed to design and install higher capacity desalination plants with proper operation control strategies.

The modeling of RO is necessary for scale up/down and optimization studies. Two types of models are available in literature for desalination process using RO. They are mechanistic model (or) membrane transport model. A detailed review on modeling RO systems has been given by Sobana and Panda [19]. The lumped parameter models converge on steady as well as transient behavior of the desalination process. After the model has been developed, it is necessary to assess the accuracy of the obtained model. Alatiqi et al. [2] used system identification techniques to estimate an MIMO **s**tructure of RO plant at Doha. Assef et al. [3], Riverol and Pilipovik [13] and Robertson et al. [14] also developed multivariable transfer function models from the plant input and output data where the model structure was obtained by fitting step response into second-order transfer function with a zero in numerator. Zilouchian and Jafar [21] identified multivariable RO desalination photovoltaic process in the form of a transfer function matrix as well as state space representation by the recursive least square techniques. Assef et al. [3] presented the model by step response data and fitting, where input and output were defined in a different way. Selvaraj et al. [10] applied fully connected multilayer feed-forward artificial neural network using the back propagation algorithm to identify the non-linear multivariable multistage flash desalination plant. Both MISO and MIMO networks have been used for the purpose of identification. Fkirin and Madhair [7] presented an optimal identification that was applied for the time-varying dynamic process based on linear combination of the recursive least square method. This scheme was applied to identify the parameters and to predict the ARMAX model of online desalination process. Saengrung [15] modeled two reverse osmosis plants using system identification and ANN tools. Riverol and Pilipovik [13] obtained the model by the identification of a discrete time model in Z domain and back transformation to S domain. Senthil Murugan and Gupta Sharad [17] formulated a model for separating solutes from aqueous system using RO system with hollow fibers and using part of the experimental results for the binary and ternary system separation. Gambier et al. [9] derived a lumped parameter dynamic MIMO model from first principle laws and used it for fault diagnosis purpose. Ahmad et al. [22] developed and simulated a membrane transport model suitable for the multiple solutes systems in RO for unsteady state condition. Chaaben and Ridha [23] developed a MIMO model by empirical transfer matrix for a small photovoltaic RO desalination process. Chaaben and Ridha [23] presented experimental data and modeling for membrane-based treatment leather plant effluent where the experimental flux data were correlated and analyzed by ANN. Most of the above models need complex computations and, hence, cannot be used directly for control purpose. Thus, it is needed to formulate simple Laplace domain models that can be used directly in control for efficient tuning of model-based controller parameters.

Automation, process control and cost optimization of desalination plants have become important with intensive demand for producing fresh water at a reasonable cost. To increase the throughput and also to ensure a safe operation around operating points, monitoring and control of the RO process is essential. The performance of RO plants vary to the quality of the feed and plant operating conditions. Hence, a very efficient pretreatment process was required, and an accurate control system is needed to maintain its operation close to the optimum conditions. This leads to increased productivity and prolongs the life of the membranes due to the reduction of membrane fouling. The number of publications reflects the importance of RO water desalination that has recently appeared on the subject in the literature. Several contributions have been done in the literature to process control of RO systems. The process variables are identified already and categorized under control variables (permeate salinity and permeate flow rate) and manipulated variables (feed pH and feed pump pressure). The controller for multi-input–multi-output problem can be designed using two approaches, namely, centralized and decentralized schemes. The former uses all process inputs and outputs simultaneously to find out all manipulated variables. The salient features of this control strategy are as follows: it can handle cross-loop interactions, it yields better closed loop performances and it can handle constraints on input directly. The structure can provide optimal usage of manipulated variables. However, the control algorithm and calculations may be complex and may be difficult to understand by operators. Moreover, the failure of central control system may affect all loops. The decentralized strategy uses simple control algorithm that follows standard control designs and is easy to understand by operators. Moreover, maintenance of a failed loop does not affect operations of other loops. However, it cannot handle cross-loop interactions and does not ensure optimal usage of manipulated variables and does not handle constraints on inputs efficiently. It also provides many possible control configurations.

Centralized controllers can be more sensitive to modeling errors and uncertainties than decentralized controllers, specifically in ill-conditioned processes. Decentralized control usually achieves better disturbance rejection than centralized control. Thus, sometimes the two degrees of freedom of control structures are convenient when a trade-off between tracking references and disturbance rejections is necessary. Transmission zeros of the controller are added to those of the process with the corresponding closed loop performance limitations in case of right half plane (RHP) transmission zeros. Moreover, from an industrial point of view, important practical issues as anti-windup mechanism or bumpless transfer between manual and automatic mode are generally more difficult to implement in case of decentralized schemes.

Results with conventional PI [2] and model-predictive control are available in literature. According to Alatiqi et al. [2], permeate flux and conductivity were controlled by manipulating feed pressure and pH. Open loop step response data from RO plant was used to construct a MIMO model. The best pairing of input/output control structure was formulated using system relative gain array and controllability tests. SISO PID controllers were tuned using the Zeigler–Nichols settings. The RO plant was simulated in closed loop with the biggest-log-modulus (BLT) tuning criteria. The robust characteristics of the controller and the controller performance in presence of measurement-noise or in real time are not very well understood from these theoretical results. Robertson et al. [14] developed a model-predictive control scheme (DMC) using the above process model where set point changes in the closed loop with (a) product flow rate and (b)conductivity of permeate were simulated separately with (i) DMC controller and (ii) PI controller tuned with ISE criteria, and the closed loop performance was recorded. The performances in the first case (flow rate) were in close agreement, but in the second case (conductivity), ISE results for conductivity were substantially better using DMC control; DMC control offers more flexibility in the operation of RO plant. However, real-time robust control of the RO plant is rare. Comparing the performances of constrained model-predictive control (CMPC) and PI controller was carried out by Assef et al. [4] and Reddy et al. [11], which showed the centralized control of MSF desalination plant. Burden et al. [5] and Abbas [1] concluded