Periodic Control of a Reverse Osmosis Water Desalination Unit

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Abstract—Enhancement of the performance of a reverse osmosis (RO) unit through periodic control is studied. The periodic control manipulates the feed pressure and flow rate of the RO unit. To ensure the periodic behavior of the inputs, the manipulated variables (MV) are transformed into the form of sinusoidal functions. In this case, the amplitude and period of the sinusoidal functions become the surrogate MV and are thus regulated via nonlinear model predictive control algorithm. The simulation results indicated that the control system can generate cyclic inputs necessary to enhance the closed-loop performance in the sense of increasing the permeate production and lowering the salt concentration. The proposed control system can attain its objective with arbitrary set point for the controlled outputs. Successful results were also obtained in the presence of modeling errors.

Keywords—Reverse osmosis, water desalination, periodic control, model predictive control.

I. INTRODUCTION

REVERSE osmosis units are commonly used as a filtration process in sea and brackish water desalination. The membrane-based RO operation suffers from two major problems; concentration polarization [1] and membrane fouling. These factors adversely influence the RO performance by reducing the permeate flux and consequently lead to loss of productivity. It is believed that membrane fouling causes an irreversible decrease in flux. Practically, fouling is overcome by regular shut-down and membrane cleaning procedures. Concentration polarization on the other hand is characterized by reversible decline in water flux through the membrane. Usually, concentration polarization can be controlled via two main methods [2]: (i) changes in the characteristics of the membrane [2], (ii) modification of flow rates and flow regime. The latter is handled by alternating the influent of the RO process [3,4]. Examples of such approach includes backwashing and periodic operation of the module, through forcing some of the process variables [5]. The analysis of periodically forced reverse osmosis has received considerable attention in the literature [2, 5-10]. Al-Bastaki and Abbas [11] have reviewed other methods used to enhance membrane performance.

Ali et al. [12, 13] studied the performance of an RO tubular membrane module under oscillatory feed conditions using a validated rigorous dynamic model.

It is found that the performance of the RO operation in terms of higher permeate production and less salt concentration can be obtained by periodic forcing of the feed pressure and feed velocity. The previous work was based on a validated mathematical model for a tubular membrane unit [14].

To ensure the RO process operation in a periodic fashion for the sake of maximizing the performance, application of a suitable control system is required. In the previous work [12, 13] the periodic forcing was carried out in open-loop mode. In this paper we compliment the work of Ali et al [13] by incorporating a robust control algorithm such as NLMPC to achieve the desired periodic input necessary to optimize the process performance.

The nonlinear model predictive control belongs to the family of model predictive controllers (MPC). The MPC algorithms differ from the other advanced controllers in that a dynamic optimization problem is solved on-line each control execution. Review of the nonlinear MPC theory and its industrial applications has been reported in the literature [15-17]. The contribution of this paper falls into enhancing the water production and quality of RO processes through periodic operation. An NLMPC algorithm that generates the necessary periodic operation is proposed and employed.

II. PROCESS MODEL

The entire investigation is based on a dynamic model of tubular membranes that was developed and validated in an earlier study [14]. Both steady state and dynamic behavior were validated against a lab-scale experimental unit.

III. THE ON-LINE NLMPC ALGORITHM

In this work, the structure of the MPC version developed by Ali and Zafiriou [15] that utilizes directly the nonlinear model for output prediction is used. A usual MPC formulation solves the following on-line optimization problem:

$$\min_{\Delta u(t_k),....,\Delta u(t_{k+M-1})} \sum_{i=1}^{P} \left\| \Gamma(y(t_{k+i}) - R(t_{k+i})) \right\|^2 + \sum_{i=1}^{M} \left\| \Lambda \, \Delta u(t_{k+i-1}) \right\|^2 \tag{1}$$

subject to

$$A^T \Delta U(t_k) \le b \tag{2}$$

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For nonlinear MPC, the predicted output, y over the prediction horizon P is obtained by the numerical integration of the state space equation:

$$\frac{dx}{dt} = f(x,u,t) \qquad (3)$$

$$y = g(x) \qquad (4)$$

in discrete time fashion from t_k up to t_{k+P} where x and y represent the states and the output of the model, respectively. $f(.)$ is a general nonlinear function of the process states, inputs and time while g(.) is either a linear or nonlinear function that maps the states into the process measured outputs. The symbols $\| . \|$ denotes the Euclidean norm, k is the sampling instant, Γ and Λ are diagonal weight matrices and $R = [r(t_{k+1}) \cdots r(t_{k+P})]^T$ is a vector of the desired output trajectory. $\Delta U(t_k) = [\Delta u(t_k) ... \Delta u(t_{k+M-1})]^T$ is a vector of M future changes of the manipulated variable vector u that are to be determined by the on-line optimization. The control horizon (M) and the prediction horizon (P) are used to adjust the speed of the response and hence to stabilize the feedback behavior. The parameter Γ is usually used for trade-offs between different controlled outputs. The input move suppression parameter, Λ, on the other hand, is used to penalize different inputs and thus to stabilize the feedback response. The objective function (Eq. 1) is solved on-line to determine the optimum value of $\Delta U(t_k)$. Only the current value of Δu, which is the first element of $\Delta U(t_k)$, is implemented on the plant. At the next sampling instant, the whole procedure is repeated.

In order to compensate for modeling errors and eliminate steady state offset, a regular feedback is incorporated on the output predictions, $y(t_{k+1})$ through an additive disturbance term [15].

IV. CONTROL OBJECTIVES AND IMPLEMENTATION

The control objective here is to maximize the RO performance by operating in cyclic mode via forcing the input to be in the form of periodic function. In this case, the controlled outputs are the permeate (q) and the salt concentration (C_p) while the manipulated variables (MV) are the feed pressure (P_f) and the feed flow rate in terms of its velocity (u_f). Standard NLMPC regulates the manipulated variables in optimal fashion according to the control law given in Eq. 1. The generated control signals may not be necessarily periodic. Therefore, the NLMPC algorithm should be modified to generate periodic behavior for the MV. for this purpose, the process inputs, are transformed into sinusoidal function in discrete time fashion as follows:

$$P_f(t_k) = P_{f_{ss}} + A_{m1}\sin(\beta) \qquad (6)$$

$$u_f(t_k) = u_{f_{ss}} + A_{m2}\sin(\beta) \qquad (7)$$

Where A_m is the period amplitude, t_k is the sampling instant and β is the argument of the *sin* function that includes the cycle period p as follows:

$$\beta = \frac{2\pi t_k}{p} \qquad (8)$$

The cycle period is defined as function of the sampling instant (T_s) as follows:

$$p = \alpha T_s \qquad (9)$$

The period of the cyclic function will be considered identical for both variables. According to Equations (6,7), the primary MVs are defined by surrogate three manipulated variables, which comprise the amplitude for each input and the unified cycle period. Therefore, NLMPC will manipulate the feed pressure and flow rate indirectly through regulating their input characteristics, i.e. the amplitude and period of oscillation. Note that the new formulation can be easily reset to the standard formulation by setting β to a constant value of $\pi/2$.

The controlled outputs embedded in Eq. 1 include the permeate production and salt concentration as a point values at specific sampling instants. However, because the operation will be periodic, the point value will be replaced by the time-average value of the controlled variables. Furthermore, the averaged value is normalized by their corresponding steady state values. In standard application, NLMPC will derive the normalized averaged value of q and c_p to their desired set points. It should be noted the entire simulation including the numerical integration of the model and the optimization of the NLMPC objective function is carried out using MATLAB software.

V. RESULTS AND DISCUSSION

Implementation of the proposed NLMPC algorithm for servo problem is shown in Fig. 1. The objective here is to maximize the ratio of the average permeate production to its steady state value and to minimize the ratio of the average salt concentration to its steady state value. Arbitrary set point is chosen for both controlled outputs. Specifically, $(q/q_{ss})^{sp}$ is set to 1.25 and $(Cp/Cp_{ss})^{sp}$ to 0.95. This means that 25% increase in the permeate production and 5% reduction in the salt concentration are sought. The set points are considered arbitrary because the objective is not to meet the specific set points but rather to increase q and decrease C_p by some amount. The signal amplitude for feed pressure is bounded by ± 30 bar, and that for feed velocity by ± 30 cm/s. The period per sampling time (α) is constrained between 3 and 10. Note that 3 is the minimum value that allows for complete periodic behavior within the given sampling time and simulation interval. A sampling time of 1 sec is used in the simulation. The MLPC parameter values are M = 1, P = 1, Λ = [0 0 0] and Γ = [1 1]. In the entire simulations, both controlled outputs are

given the same weight by setting Γ to one (or any other equal values). Fig. 1 shows the raw values of the permeate production and the salt concentration. In addition, the figure illustrates the normalized average values for the same outputs. The latter is the actual variables used as the controlled output in the NLMPC algorithm. The generated periodic inputs are also shown in the same figure.

The simulation outcome illustrated the ability of MPC to generate oscillatory response which resulted in a reasonable improvement of the process operation. The NLMPC was able to achieve the required set points. Hence, the required enhancement in the performance is attained. The interesting part is that the enhancement was achieved without additional increment in the feed conditions. In fact, the ratio of the time-average value of the feed pressure and the feed velocity to their corresponding steady state value is 0.988 and 1.007, respectively. This is the main goal after periodic operation.
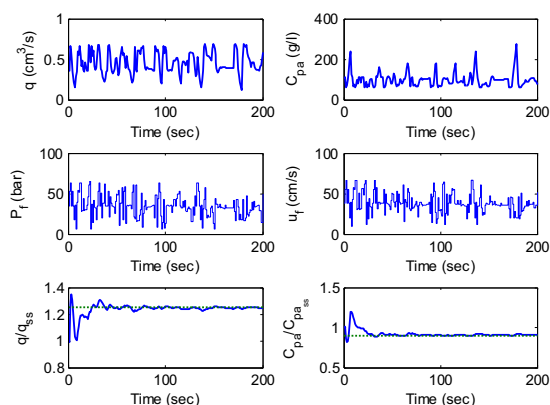

Fig. 1 Closed-loop simulation using NLMPC with T_s = 1 sec and set point: $(q/q_{ss})^{sp}$ = 1.25; $(Cp/Cp_{ss})^{sp}$ = 0.95

As mentioned earlier, the set points are arbitrary. Therefore, the simulation is repeated with different set of set poit values. Specifically, set 1: $(q/q_{ss})^{sp}$ = 1.25 and $(Cp/Cp_{ss})^{sp}$ = 0.95; set 2: $(q/q_{ss})^{sp}$ = 1.25 and $(Cp/Cp_{ss})^{sp}$ = 0.8; set 3: $(q/q_{ss})^{sp}$ = 1.43 and $(Cp/Cp_{ss})^{sp}$ = 0.8. Using the same NLMPC parameters as before, revealed that the new set points can be achieved except the second set. The new result is obtained as depicted in Fig. 2. The corresponding response of the manipulated variables for the three sets of set points is shown in Fig. 3. It is obvious that NLMPC tries to force the process into satisfying the set point for C_p. however, this is at the expense of losing the track of q. From the control objective point view, the feedback response is not reasonable. However, from the RO performance point of view, the operation is acceptable because it leads to further increase in the permeate production. It should be noted that the feasible set point for both q/q_{ss} and Cp/Cp_{ss} is not known a prior. furthermore, it may not be achievable because of the process physical limitation. Therefore, it might be interesting to implement the feedback controller without specifying set points. In this case, the controller will try to drive the process

into the best feasible extreme conditions for both q and C_p. This idea is handled in another research work.

The period of the sinusoidal function for the input variables depends on the sampling time. Therefore, similar simulation tests were carried out to study the effect of the sampling time on the controller performance. Comparison of the feedback response at different sampling times is shown in Fig. 4 and the corresponding response for the MV is illustrated in Fig. 5. The same simulation and NLMPC parameters used before is implemented here. The control objective is also the same except $(Cp/Cp_{ss})^{sp}$ is to 0.9 to cover different scenarios. It is clear from Figure 4 that acceptable controller and process performance can still be obtained. It should be noted though that small sampling instants is not desirable in real time practice. On the other hand, when the sampling time is increased, the performance degrades as demonstrated in Fig. 4. In Fact, out investigation revealed that performance deteriorate starting from a sampling time of 5 sec. The reason for performance degradation is that when the period becomes equal to half or greater than the process settling time, the periodic operation losses its effect. The idea is to rapidly alternate the process variables between different operating conditions before they reach their steady state conditions.
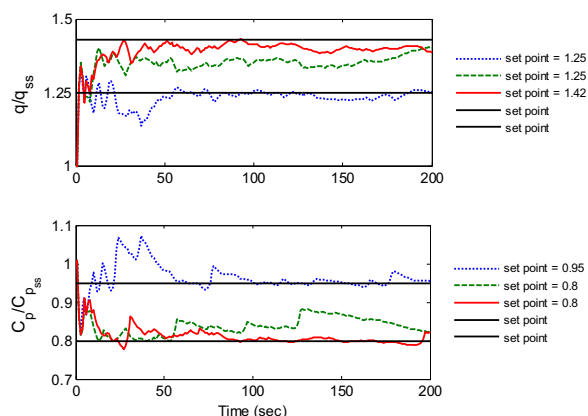

Fig. 2 Closed-loop simulation with T_s = 1 sec at different values for the set point

The previous simulation illustrated successful results for improving the process performance when perfect process model is used to represent the plant dynamics. The control objective is repeated in the presence of parametric errors in the model. Specifically, -20% errors are introduced in the value of the salt permeability and hydraulic permeability (B_i, L_p) and +20% errors are introduced in the water diffusivity (D_s). The closed-loop response under these circumstances is depicted in Fig. 6. In this case, the set point for the ratio of average q to initial steady state value is 1.25 and that for C_p is 0.95. The figure shows the row value of the process outputs for both the plant and the model to highlight the mismatch due to uncertainty. The simulation results indicate that the modified NLMPC can still track fixed set point for the controlled variables. Moreover, the transient response for the

manipulated variables and the controlled outputs differ than that shown in Figure due to the effect of the model-plant mismatch. Nevertheless, the consequence proves the effectiveness of the feedback features of NLMPC to reject the influence of the model uncertainty.
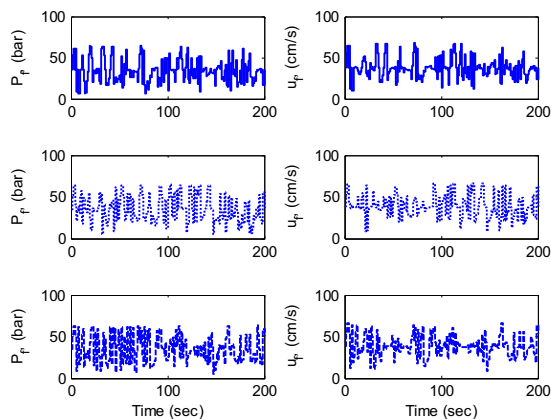
concentration. Different set point values and sampling time were also examined to study their effect on the overall performance. The promising outcome is maintained even in the presence of model uncertainty.

Fig. 3 Closed-loop response of the manipulated variables corresponding to the simulation in Fig. 2; solid: set 1, dotted: set 2, dashed: set 3
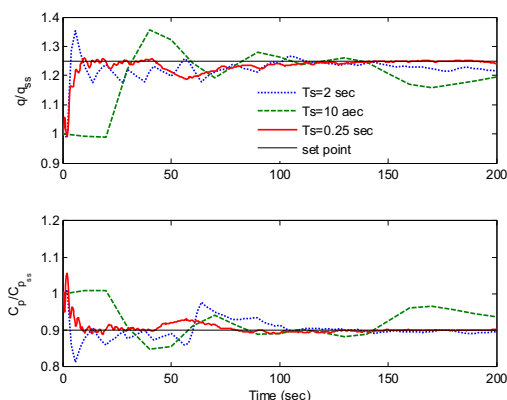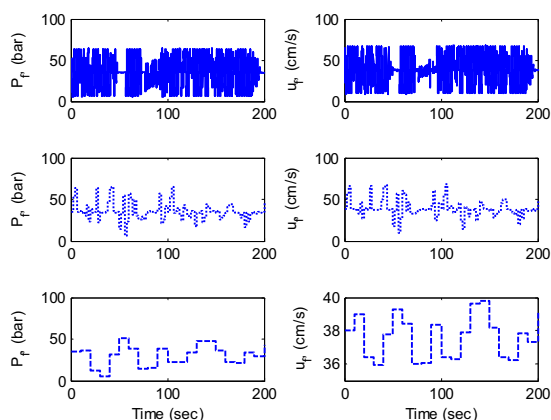

Fig. 4 Closed-loop simulation with set point: $(q/q_{ss})^{sp} = 1.25$; $(Cp/Cp_{ss})^{sp} = 0.9$ using different values for the sampling time

Fig. 5 Closed-loop response of the manipulated variables corresponding to the simulation in Fig. 4; solid: T_s=0.25 sec, dotted: T_s=2 sec, dashed: T_s=10 sec.
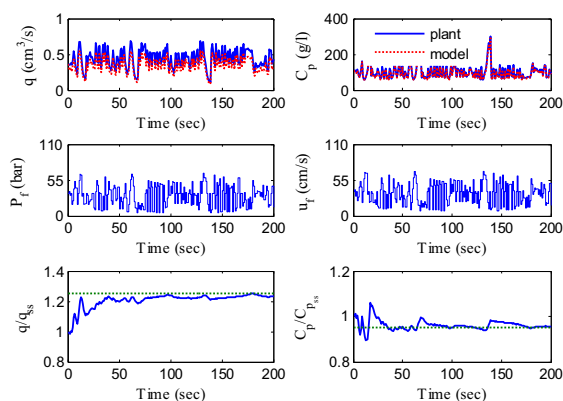

Fig. 6 Process closed-loop response in the existence of modeling errors of $B_j = -20\%$, $L_p = -20\%$, $D_s = +20\%$ using NLMPC with $T_s = 1$ sec and set point: $(q/q_{ss})^{sp} = 1.25$; $(Cp/Cp_{ss})^{sp} = 0.95$

VI. Conclusions

The performance of a tubular RO process under forced periodic inputs is studied. Feedback control system is utilized to force the input into periodic behavior. In fact, nonlinear model predictive control (NLMPC) is implemented for this purpose. NLMPC regulates the feed pressure and flow rate indirectly through manipulating their transformation parameters. The transformation parameters are the amplitude and period of the sinusoidal function that resemble the periodic behavior of the feed pressure and flow rate. The feedback simulation indicated the effectiveness of NLMPC to generate periodic input functions that managed to enhance the time-averaged value of the permeate production and salt

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