Assessment of parameter uncertainty in the maintenance scheduling of reverse osmosis networks via a multistage optimal control reformulation

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Abstract

In this work, the influence of uncertain parameters on the maintenance scheduling of Reverse Osmosis Networks (RONs) is explored. Based on a foundation of successful applications in various maintenance optimization domains, this paper extends the methodology to the domain of RON regeneration actions planning, highlighting its adaptability to diverse areas of dynamic processes with planning uncertainty. Traditional approaches in membrane cleaning scheduling have predominantly relied on Mixed-Integer Nonlinear Programming (MINLP), often leading to combinatorial problems that fail to capture the dynamic nature of the system. As part of this study, a novel approach based on the Multistage Integer Nonlinear Optimal Control Problem (MSINOCP) formulation is used to automate and optimize membrane cleaning scheduling without requiring combinatorial optimization. To evaluate the consequences of parameter uncertainty, 26 scenarios are considered in which the cost of the energy unit is considered as variable based on a random distribution, and these results are compared to a scenario where a fixed cost parameter is assumed. The findings show that when the cost of energy is considered as an uncertain parameter, the optimization process requires more frequent cleaning measures.

**Keywords**: reverse osmosis networks, maintenance scheduling optimization, energy cost uncertainty, multistage optimal control.

* 1. Introduction

Reverse osmosis (RO) is recognized as a prominent desalination technology, using pressure driven membrane processes ([Wenten, 2016](https://www.sciencedirect.com/science/article/pii/S2666790821002445%22%20%5Cl%20%22bib25)). Although RO is currently used in a variety of applications including selective separation, purification, and concentration processes, as well as in the food industry ([Wenten, 2016](https://www.sciencedirect.com/science/article/pii/S2666790821002445%22%20%5Cl%20%22bib25)), water scarcity has led to the global adoption of RO for cost-effective water desalination and wastewater treatment (Ahmed et al., 2023).

However, membrane fouling is a significant issue in RO processes, diminishing membrane lifespan, permeability, and increasing operational challenges. This phenomenon negatively impacts the quality and quantity of desalinated water, posing a hurdle to the sustainable use of RO membranes due to compromised efficacy and economic aspects. Fouling results from physicochemical interactions between water pollutants and membrane materials, leading to the accumulation of foulants on membrane surfaces and inside pores (Ahmed et al., 2023).

Therefore, regular membrane cleaning is essential to maintain long-term performance in RO systems, restore system productivity, minimize overuse of instruments, reduce environmental impacts, and reduce the generation of unwanted byproducts (Mappas et al., 2022).

Various approaches, including nonlinear programming, Artificial Intelligence (AI), and Genetic Algorithms (GA), have been explored in the literature to address the long-term cleaning scheduling of RO membrane systems. The predominant focus in existing literature revolves around the Mixed-Integer Nonlinear Programming (MINLP) formulation of the problem (Guzman et al., 2022)

In this paper, the Multistage Mixed-Integer Optimal Control Problem (MSMIOCP) method is used to address the RON scheduling problem (Mappas et al., 2022). This method divides the time horizon into stages, characterizing each stage with process models represented by Differential Algebraic Equations (DAEs) and associated constraints. The decision variables, which determine the process operation, shutdowns, plant operating conditions, and product costs at each stage, are discretized over the time horizon. The "feasible path approach" is employed for the sequential solution of the DAEs using an integrator. The solution benefits from the bang-bang nature of cleaning decisions, allowing relaxation of integer restrictions, transforming the problem into a standard Nonlinear Programming (NLP) problem without the need for combinatorial optimization methods. In the following sections, the implementation of the MSMIOCP approach is extended to enable the inclusion of specific parameters, such as the unit cost of energy, as non-deterministic in order to facilitate improved decision-making for the maintenance of the RONs.

* 1. Maintenance scheduling of reverse osmosis networks

Reverse osmosis (RO) is a water purification process that uses a partially permeable membrane to remove ions, unwanted molecules, and larger particles from water. The process involves applying pressure to the water on one side of the membrane, forcing it to pass through the membrane while leaving the contaminants behind.

**Stage 1**

RO membranes

**Stage 2**

RO membranes

Pump

Fead water

RO product water

RO reject water

Figure 1: Simplified process flow diagram of a reverse osmosis network

Maintenance scheduling of RO networks refers to the planning and organization of maintenance activities for the components and systems involved in the RO water purification process. RO systems are critical for producing clean and purified water, and like any complex system, require regular maintenance to ensure optimal performance, efficiency, and longevity.

In this following, a case study is conducted to evaluate the influence of parameter uncertainty on the maintenance scheduling of a reverse osmosis network (RON) with 2 stages of 3 separate RO modules in each stage, as shown in Fig. 1.

* 1. Parameter uncertainty

In the area of maintenance scheduling of RON, especially related to fouling models, it is imperative to regard certain parameters as non-deterministic or uncertain. This consideration is crucial, as the uncertainties associated with operational parameters mirror real-world variations capable of influencing the performance of the system. The influence of the uncertain parameters on the fouling process presents challenges in predicting the system behavior, measurement accuracy, or can lead to variation in fouling over time (Al Ismaili et al., 2019). Failing to incorporate them into the analysis may result in the formulation of suboptimal strategies. Thus, measures to address parameter uncertainty serve to enhance the adaptability of the model to unforeseen changes, thereby augmenting the reliability and effectiveness of the optimization process (Tang et al., 2024).

In the context of co-scheduling for seawater desalination and power generation, the inclusion of electricity prices as uncertain parameters is crucial. The variability of energy costs exerts a direct influence on the optimal operation of combined water and power (CWP) plants. Treating these uncertainties as non-deterministic parameters in the optimization model facilitates the formulation of a robust and resilient strategy that does not rely on specific probability distributions (Jabari et al., 2019).

* 1. Methodology

The proposed solution approach for addressing this issue consists of two main components. The initial part of this methodology employs a multiple scenario approach to account for parametric uncertainty. This involves generating various scenarios, each assigning specific values to uncertain parameters within predefined ranges. The scenarios created using any random sampling technique.

In the next section, these generated scenarios are used as non-deterministic parameters (energy unit cost) in the calculation of the other parameter (energy cost and income) within the Ordinary Differential Equations (ODEs) of the MSMIOCP formulation. Subsequently, the average influence of these randomly generated scenarios on the objective function is assessed. The operational efficiency of the RO membrane units is simulated through an approximate model, as presented in Mappas et al. (2022).

* + 1. Objective Function

|  |  |
| --- | --- |
| $Min Objective=Cost- Income$ | (1) |

Cost here is the sum of cleaning cost $C\_{C} $and energy cost $C\_{E}$, in euros. Based on the membrane cleaning cost per membrane unit per cleaning action $C\_{ca}$ and the total number of cleaning actions N, the cleaning cost is calculated through the following:

|  |  |
| --- | --- |
| $C\_{C}$*=* $C\_{ca}∙N$ | (2) |

The energy unit cost parameter $C\_{el} $is examined in both deterministic and non-deterministic scenarios. In the deterministic scenario, a value of 0.08 euro/kWh is considered. Thus, the energy cost is determined through two distinct approaches, one of which assumes a constant unit energy cost:

|  |  |  |
| --- | --- | --- |
| $$C\_{E}=C\_{el}\frac{\sum\_{i=1}^{6}I\_{i} ∙∆Ƥ\_{i}}{ρ}$$ | for *i* =1, 2, …, 6 | (3) |

where

|  |  |
| --- | --- |
| $I\_{i}$ = | inlet flowrate of RO module i (m3/days) |
| $ ∆Ƥ\_{i}$ = | pressure across the units (Pa) |

while the other considers it as an uncertain parameter.

In the non-deterministic setting, 26 random scenarios are defined with a normal distribution. If Eq. 3 is defined as D, and S denote the total number of energy unit cost scenarios, the energy cost for the uncertainty formulation is given by following equation:

|  |  |  |
| --- | --- | --- |
| $$C\_{E}=\frac{\sum\_{s=1}^{26}C\_{el,s}∙D}{S}$$ | for *s* = 1, 2, …, 26 | (4) |

For a permeate selling price denoted as *Pr*, in euro/m3, and a permeate flowrate of RO module i denoted as $Ƥ\_{i}$, in kg/s, the income is calculated according to the following equation:

|  |  |  |
| --- | --- | --- |
| $$Income= Pr∙\sum\_{i=1}^{6}Ƥ\_{i}$$ | for *i* =1, 2, …, 6 | (5) |

* + 1. Constraints

Simulations are conducted to demonstrate the application of the proposed framework over 26 time periods, with each lasting one week. The model constraints are given as follows:

Subject to

|  |  |  |
| --- | --- | --- |
| $$P\_{c,i}=\frac{K∙ F\_{c, i}}{ ϒ∙M\_{i}( ∆Ƥ\_{i}- ∆П\_{i})}$$ |  | (6) |
| $$∆П\_{i}= T∙\overbar{R}∙F\_{c, i}$$ |  | (7) |
| $$ ∆Ƥ\_{i}=X\_{i}(\frac{Ƥ\_{i}}{ϒ∙A∙M\_{i}}+ ∆П\_{i})$$ |  | (8) |
| $I\_{i}$=$\frac{1}{3} ∙X\_{i}$$∙F\_{T}$ |  | (9) |
| *Ij* =$\frac{1}{3} ∙X\_{i} ∙E\_{k}$ |  | (10) |
| $$Ƥ\_{i}= I\_{i}∙δ∙X\_{i}$$ |  | (11) |
| for *i* =1, 2, …, 6; *j* = 1, 2, 3; *k* = 4, 5, 6 $X\_{i}$ *= 0, 1* |

Here, $X\_{i}$ is a binary variable and equal to 1 if the RO unit is in operation and 0 if the unit is undergoing cleaning. $F\_{T}$ denotes the total rate of flow entering the RON, in m3/days, $E\_{k} $the retentate flowrate, in m3/days, and $P\_{c,i}$ the permeate concentration, in ppm, for the RO module i. The parameters utilized in the implementation of this case study are adopted from Mappas et al. (2022) and are summarised in Table 1.

Table 1: RON model parameters

|  |  |  |  |
| --- | --- | --- | --- |
| Parameters | Value | Units | Description |
| $$ρ$$ | 0.6 | - | pump energy efficiency coefficient |
| $$C\_{el}$$ | 0.08 | euro/kWh | energy unit cost |
| *K* | 4.0e-6 | kg/s m2 | solute transport |
| $$F\_{c, i}$$ | 34,800 | ppm | feed stream concentration for the RO module i |
| $$ϒ$$ | 5.0 | days | permeability constant |
| $$ M\_{i }$$ | 3.0e10 | kg/day N | membrane permeability across the units |
| *T* | 298.0 | K | operational temperature |
| $$\overbar{R}$$ | 8.31 | J/K mol | ideal gas constant  |
| *A* | 152.0 \* 1.0e0 | m2 | membrane area |
| $$δ$$ | 0.65 | - | permeate recovery ratio |

* 1. Results and discussion

The optimisation problem is implemented in Python 3.11 and run on a computer with Intel(R) Core(TM) i7-7800X CPU @ 3.50GHz, 16,0 GB RAM. The minimize solver from scipy.optimize is used. The CPU time is 140.14 minutes (64.90 and 75.24 minutes for deterministic and non-deterministic scenario, respectively).

Of the 100 multiple start cycle considered, 61 were successful. Fig. 2 illustrates the outcome of optimizing maintenance scheduling, considering the energy unit cost as a deterministic parameter (Fig. 2a-b) and as an uncertain parameter (Fig. 2c-d), respectively.

|  |  |
| --- | --- |
| Local Minima Count Graph(a)  | Local Minima Count Graph (c) |
| Cleaning schedule for the RON(b) | Cleaning schedule for the RON(d) |

Figure 2: Local minima for the successful optimization cycles and cleaning schedule graphs

As can be seen in Fig. 2b and d, when the energy unit cost parameter is considered as non-deterministic, the number of required maintenance operations increase from 15 cleaning actions to 27 cleaning actions (blue squares indicate the cleaning operations). There is also a small increase in the best value of the objective function, from €12.624 million when the energy unit cost is considered as a deterministic parameter and €12.682 million when the energy unit cost is a non-deterministic parameter. As a consequence, this increase in both the number of required maintenance operations and the value of the objective function highlights to the importance of considering uncertainty in parameters to make models more realistic and relevant to real-life situations.

* 1. Conclusions and outlook

This research focuses on evaluating the impact of parameter uncertainty on the maintenance schedule of reverse osmosis networks. It emphasizes the critical importance of incorporating non-deterministic parameters into optimization models and provides valuable insights into the complex dynamics of maintenance planning for such systems. The observed increase in the number of required maintenance actions and the value of the objective function shows the importance of considering parameter uncertainty in order to provide models more realistic and relevant to commercial applications.
For future research, investigating the interaction of multiple uncertainties simultaneously and their collective impact on maintenance planning can provide valuable insights into system resilience under different real-world scenarios.

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