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Uncertainty and Complexity Considerations in Food-Energy-Water Nexus Problems

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ABSTRACT

The food-energy-water nexus (FEWN) has been receiving increasing interest in the open literature as a framework to address the widening gap between natural resource availability and demand, towards more sustainable and cost-competitive solutions. The FEWN aims at holistically integrating the three interconnected subsystems of food, energy and water, into a single representative network. However, such an integration poses formidable challenges due to the complexity and multi-scale nature of the three subsystems and their respective interconnections. Additionally, the significant input data uncertainty and variability, such as energy prices and demands, or the evaluation of emerging technologies, contribute to the system's inherent complexity. In this work, we revisit the FEWN problem in an attempt to elucidate and address in a systematic way issues related to its multi-scale complexity, uncertainty and variability. In particular, we provide a classification of the sources of data and technology uncertainty from historic data, forecasting and process parameters, and propose ways to quantify their impact on the integrated system analysis. To effectively tame the FEWN's multi-scale complexity, we distinguish between the introduced error of approximation and optimization of employed surrogate models. In turn, it is possible to characterize their impact on optimal FEWN decision-making based on the quantification of the introduced errors at all levels. Thus, we present strategies to systematically characterize FEWN process systems modeling and optimization. Ultimately, this facilitates translating obtained solutions into actionable knowledge by quantifying the level of confidence one can have in the derived process model and optimal results.

Keywords: Food & Agricultural Processes, Energy, Water, Design Under Uncertainty, Surrogate Model, Environment

INTRODUCTION

The food-energy-water nexus (FEWN) has been identified in the open literature as an effective methodology to address the increasing disparity between natural food, energy and water resource availability and the respective resource demands sustainably. Based on a detailed analysis of the interconnections of the food, energy, and water subsystems, the FEWN aims to facilitate synergies among the three resource network subsystems, whereas competition is to be avoided to ultimately uncover trade-off solution strategies [1]. This proposed sustainable systems integration approach poses formidable challenges from a process systems engineering (PSE) perspective, including but not limited to multi-scale uncertainty, appropriate system boundary definition, together with multiple and often conflicting stakeholder perspectives [2]. Furthermore, it has been shown that FEWN research does not produce sufficient actionable knowledge [3], meaning that obtained PSE FEWN frameworks and results are not translated into real world impact. In turn, the achievable synergy level of obtained optimal FEWN solutions is not only limited by the data availability, but also by the utilized modeling and complexity reduction techniques due to the introduced uncertainties and errors [4, 5].

Therefore, this work revisits the FEWN problem statement to systematically address its multi-scale complexity and uncertainty. More specifically, the scope of this work is to present methods to quantify introduced errors across all scales stemming from the necessity to overcome uncertainty, modeling, and computational complexity. While characterizing data uncertainty is well established in the literature, this work presents a novel distinction among the errors of approximation and optimization to fully characterize modeling complexity based on a representative surrogate energy-water supply model. Bridging the computational complexity of the surrogate model is evaluated via clustering of operational decisions of the water supply system. In turn, this work presents a framework to characterize introduced errors at all levels to provide decisionmakers, such as stakeholder or policymakers, with a quantifiable level of confidence one can have in the derived process model and optimal results.

The similarities among data uncertainty and complexity mitigation strategies are a central narrative of this work, the basis of which is elucidated via a representative energy-water supply system in the section FEWN Modeling. For impactful FEWN system modeling and optimization relevant system parameters have to be defined according to historic data which inherently introduces errors due to data uncertainty. Regarding data uncertainty the major challenges can be identified as (i) data variability, (ii) data aggregation, and (iii) data forecasting. All of this is discussed as part of the FEWN Modeling section. Due to the multi-scale complexity of the FEWN an interconnected system model cannot be optimized directly. In turn, modeling complexity mitigation via surrogate modeling, such as feedforward artificial neural networks (ANNs) or linear regression, and computational complexity reduction via algorithmic strategies, such as clustering or rolling horizon approaches, are discussed in the section System Complexity. It is important to note that the observations discussed in this work can readily be extended from FEWN approaches to general PSE problem statements tackling interconnected process systems and are essential for deriving actionable knowledge by quantifying the introduced errors stemming from data uncertainty and variability, as well as from the selected approximation and optimization methods.

FEWN MODELING

The assumed system boundary inherently influences the FEWN system's modeling and solution generation. Accordingly, it has to be identified based on the defined research goals for impactful decision-making of FEWN frameworks [6]. This work investigates the quantification of complexity and data uncertainty mitigation errors across all scales of FEWN systems for the derivation of actionable knowledge. Accordingly, a representative FEWN process system, based on benchmark resource supply systems, is selected as the relevant system boundary.

A renewable energy supply system for the identification of the cost-optimal mix of renewable energy generation and storage system has been selected as a representative energy supply system due to its reduced greenhouse gas emissions and therefore key role in the energy transition [7].

$$P_D(t) \leq \sum_t (P(t) - EC(t) + \sum_{t,k}[P_{rel,k}(t) - P_{stor,k}(t)]) \quad (1)$$

$$P(t) = \sum_{Tech} n_{Tech} \cdot p_{Tech}(t) \quad (2)$$

$$P_k^{bat}(t) = P_k^{bat}(t-1) + P_{stor,k}(t) - P_{rel,k}(t) \; \forall k \in K \quad (3)$$

The governing equations of the energy supply system are summarized for evert time point $t \in T$ from Eq. (1) to (3). The energy demand $P_D(t)$ has to be satisfied by generating renewable energy from different technologies such as biomass, wind turbines, single axis tracking or fixed angle solar panels (see Eq. (2)) or releasing energy from available energy storage systems ($P_{rel,k}(t)\ k \in K$). In turn, a surplus of renewable energy availability can be used to store energy ($P_{stor,k}(t)\ k \in K$) or satisfy the energy consumption of the water supply system ($EC(t)$).

Reverse osmosis (RO) desalination water supply systems have already been identified as benchmark water supply systems in the literature and are accordingly selected for this study [8].

$$SEC(t) = \frac{1}{WR^{sys}(t)} \cdot \Big(\frac{1}{4 \cdot \eta_1} \sum_{j=1}^{4} P_{f,1,j}(t) + \dots \frac{(1-WR_1(t)) \cdot (1-WR_2(t))}{\eta_1} \Big[\frac{1}{2} \sum_{j=1}^{2} P_{f,3,j}(t) - \frac{1}{4} \sum_{j=1}^{4} P_{r,2,j}(t) \Big] - \dots \frac{(1-WR_1(t)) \cdot (1-WR_2(t)) \cdot (1-WR_3(t)) \cdot \eta_2}{2} \sum_{j=1}^{2} \Delta P_{ERD,j}(t) \Big) \quad (4)$$

$$EC(t) = SEC(t) \cdot Q_p(t) \quad (5)$$

$$Q_p(t) = WR^{sys}(t) \cdot Q_f(t) \quad (6)$$

$$WR^{sys}(t) = WR_1(t) + (1 - WR_1(t)) \cdot WR_2(t) + (1 - \dots WR_1(t)) \cdot (1 - WR_2(t)) \cdot WR_3(t) \quad (7)$$

Eq. (4) to (7) summarize the governing RO desalination system equations. The specific energy consumption can be calculated based on the feed pressures ($P_{f,i,j}(t)$) of every stage (i) and parallel flow (j), as well as water recoveries per stage ($WR_i(t)$) and of the overall system ($WR^{sys}(t)$), together with the pressure difference across the energy recovery device ($\Delta P_{ERD,j}(t)$). The remainder of the RO system is characterized by the system's energy consumption ($EC(t)$), together with its produced permeate ($Q_p(t)$) and required feed flow ($Q_f(t)$). $Q_p(t)$ can then be used to satisfy the municipal water demand and the water demand for biomass farming of the renewable energy supply system. In addition, a water storage balance analogous to Eq. (3) can be added to the RO desalination system.

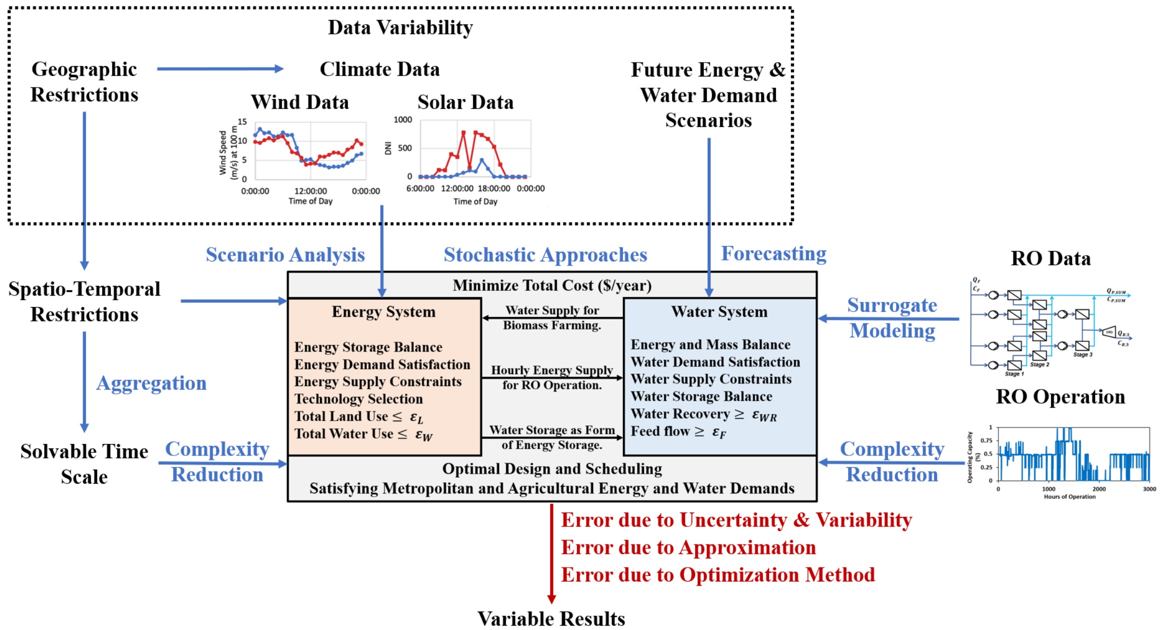

Figure 2: Representative renewable energy and RO water supply system under investigation with specified uncertainty and complexity considerations.

For semi-arid and arid water scarce regions with high temperatures and harsh external conditions, outdoor agriculture is neither a viable nor a sustainable option. Therefore, greenhouse farming systems providing a controlled environment for secure plant growth are selected as a representative food supply system [9].

To reduce the overall system complexity only the renewable energy supply system and the RO water supply system are considered in detail. The greenhouse system is considered via water and energy demand fulfillment constraints in addition to metropolitan energy and water demand constraints [10]. Accordingly, optimal solutions specify the design and operation of an interconnected renewable energy supply system and RO water supply system with energy and water storage consideration for the dynamic water and energy demand fulfillment as specified by the demands of an urban center and a greenhouse farming system.

The overall representative energy-water supply system for metropolitan and agricultural ecosystems is summarized together with all encountered data uncertainties and modeling complexities in Figure 2. The detailed mathematical model of the renewable energy supply system can be found in [7], of the RO water supply system in [8,11] and their modeled interconnections in [10]. The novelty of this work consists of revisiting the FEWN problem statement by systematically discussing mitigation strategies overcoming data uncertainty and variability, as well as system modeling and computational complexity. Dependent on the complexity mitigation strategy not only the feasible region of the optimization model, but also the obtained optimal results in the form of the objective function and optimization variable values can potentially be altered [11]. To maintain the practicability of derived FEWN frameworks and results, it is of the utmost importance to quantify the introduced errors. This represents a certified level of confidence decision-makers can have in the proposed FEWN process systems solutions.

The identification of relevant data of reduced order compared to the historically available data remains one of the main challenges of solving FEWN problems toward practical impact. To operationalize the FEWN researchers have to not only mitigate data variability, but also derive representative data from a plethora of historical data (aggregation) and extrapolate currently available data to future trends (forecasting), as depicted in Figure 2. For all of these data uncertainty challenges, a sensitivity analysis of derived results can be leveraged as a proxy of the introduced error. One of the most direct ways to quantify the sensitivity of optimal solutions dependent on changing parameter values is multi-period or what-if scenario analysis. These approaches attempt to integrate uncertainty into policymaking through iterative exploration of possible optimal solutions [12]. Here, this can be understood as varying assumed input climate data profiles, such as solar direct normal irradiance (DNI) or wind speeds, or potential future energy and water demand profiles and prices. Other strategies to capture data variability include stochastic approaches which leverage probability distributions to approximate the variable input data [13]. In this instance, the original deterministic optimization model becomes stochastic and can be solved via either Monte Carlo simulation, chance-constrained or robust programming.

To extrapolate patterns and behavior from historic data into the future forecasting techniques are utilized. Here, the introduced error of uncertainty stems from the quality of representative data utilized for forecasting and how accurate future trends can be captured based on this training data set. While there exist long term projections of future water demands, this is not the case for future energy demands and prices. To address this challenge, Baratsas et al. [14] established a quantitative framework to evaluate the integrated price of energy, the Energy Price Index (EPIC), which, influenced by both the demand and prices of energy products, signifies the average monthly price of energy for end-use consumers. To predict the present value for the demand and price of the energy products, a rolling horizon methodology is utilized since the availability of data for the demand and prices for certain energy products is often lagged by one to three months [15].

The interested reader is advised to consult [16] for a general review of advantages, disadvantages, and novelties of time series forecasting techniques applied to the energy sector. It is important to note that the degree of uncertainty significantly increases with the projected time scale of the forecast. This is for example illustrated by the divergence of long-term projections for industry sector energy consumptions due to varying base and final year assumptions and if non-monetary drivers are used to project material demand [17]. Even if long-term projections are generated via a rolling horizon approach, the introduced uncertainty increases with every forecasted time step due to the possibility of compounding the forecasting error.

Aggregation aims at reducing comprehensive historic data into a manageable representative data set which is subsequently used to replace the original historic data. This is for example applied to hourly or daily wind speed or solar direct normal irradiance profiles for renewable energy systems optimization or available subland clusters for land-use optimization. Accordingly, an error of uncertainty is introduced in the process system due to the scale reduction. However, this scale reduction also reduces the computational complexity which simultaneously introduces an error of optimization. Here, one can appreciate the interconnectedness of complexity reduction and data uncertainty. To address the computational burden associated with hourly time discretization and extensive time horizons in optimization models, Tso et al. [18] proposed a decomposition algorithm based on agglomerative hierarchical clustering (AHC), moving away from traditional k-means clustering, to preserve the time chronology of the input data. To select the optimal number of clusters, a cut-off threshold, showing the percentage of slope decrease in within-cluster variance, is applied, which can be understood as the allowable aggregation error.

SYSTEM COMPLEXITY

The individual renewable energy supply system and the RO water supply system are highly complex to model and optimize due to their nonlinear behavior. In fact, dependent on the selected time scale the interconnected model is computationally intractable [10]. However, solely optimizing each subsystem individually is not sufficient to uncover synergies among the supply systems [1]. In turn, researchers employ surrogate models together with advanced algorithmic strategies to overcome modeling and computational complexity [19]. While these are effective approaches to reduce system complexity, these methods introduce errors due to the leveraged approximation and optimization strategies.

The error of approximation is well studied in the literature and can readily be quantified based on the coefficient of determination (R^2) or the mean squared error (MSE). On the contrary, the introduced error due to the selected optimization method can be understood as the introduced change in objective function value and degrees of freedom (DOF) due to the utilization of a surrogate model or advanced algorithmic strategy. The variation of DOF and objective value (Err_{opt}) can be quantified by calculating the R^2 (or MSE) of the "original" optimization model (x_i) and the surrogate model optimization results ($\widehat{x_i}$), as shown in Eq. (8). In this case, R^2 can be understood as the amount of original model variability explained by the surrogate model and optimization method which should ideally be one. To summarize all introduced errors, R^2 for each approximation or optimization approach can be calculated and subsequently be multiplied to obtain a final value for the introduced error due to the necessity of system complexity mitigation.

$$Err_{opt} = 1 - R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (8)$$

$$Err_{obj} = 1 - \frac{\hat{y}}{y} \qquad \hat{y}, y \geq 0 \quad (9)$$

Further, the change in objective function value can be quantified based on Eq. (9), where Err_{obj} denotes the introduced error based on the derived objective function values. In this case, $\hat{y}$ denotes the optimal solution obtained via the surrogate optimization model, whereas y represents the originally obtained optimal solution. Based on this definition we can conclude that if

- $Err_{obj} > 0$, then $\hat{y}$ is a lower bound for y.
- $Err_{obj} < 0$, then $\hat{y}$ is an upper bound for y.

This deduction is only valid if the objective function values are positive. For negative objective function values, the reversible observations are applicable.

Modeling Complexity

As previously mentioned, the RO water supply system is selected to illustrate the influence of surrogate modeling on optimal decision-making. We selected simple linear regression, first-order Taylor approximation, multiple linear regression, and feedforward artificial neural networks (ANNs) with rectified linear units (ReLUs) as activation functions as potential surrogate models. Shallow ANNs with a limited number of neurons utilizing ReLUs can be interpreted as a multiple variable piecewise linear regression. If one of these models, in the presented sequence, satisfied a set quality of approximation criterion ($R^2 \geq 0.95$) the corresponding model has been selected to balance simplicity and accuracy.

Here, the specific energy consumption (R^2=0.99) and the energy consumption (R^2=0.99) of the RO plant can both be calculated based on individual shallow ANNs utilizing ReLUs as activation functions. The RO plant's overall permeate flow (R^2=0.98) and water recovery (R^2=0.98) can be approximated via first-order Taylor expansions. In this instance, the surrogate model explains approximately 94% of the observed variability of the original model and thus we can certify the introduced error due to approximation to be 6%. Accordingly, the original mixed-integer nonlinear programming (MINLP) problem can be successfully approximated by a mixed-integer linear programming problem (MILP) [11].

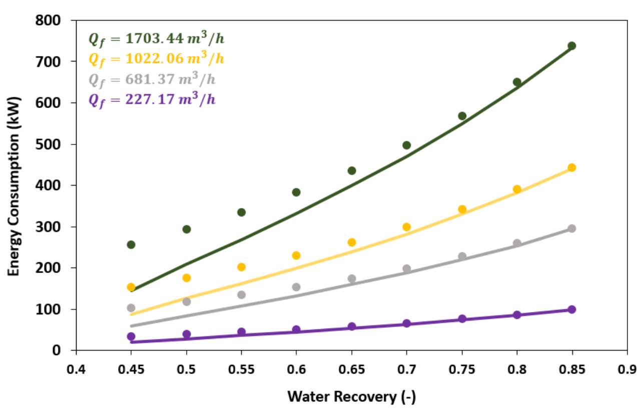

Figure 3: Results of RO modeling and optimization. Lines: Original MINLP model; Points: MILP Surrogate model.

In turn, the error of optimization can be quantified by optimizing both the MINLP and MILP for the same set of constraints. The optimization models have been solved in GAMS with the Gurobi solver for the MILP problem and the BARON solver for the MINLP problem. Results of this analysis in terms of a direct comparison between the optimal energy consumption of the RO plant for changing feed flows and efficiencies of the MINLP and MILP problem are displayed in Figure 3. Here, we can appreciate how the differences in minimized energy consumption between the MILP and MINLP model shrink with increasing water recovery and decreasing feed flow. The difference between the two optimization approaches results in R^2=0.98, meaning that solely based on the optimization approach an additional error of 2% is introduced in the objective function values. This change in objective function value can also be quantified by calculating Err_{obj} (Eq. (3)) for every pair of feedflow and water recovery. Interestingly, the error of objective function value does not change significantly with changes in feed flow, which is exemplified by a maximum standard deviation of 0.0026 across all values.

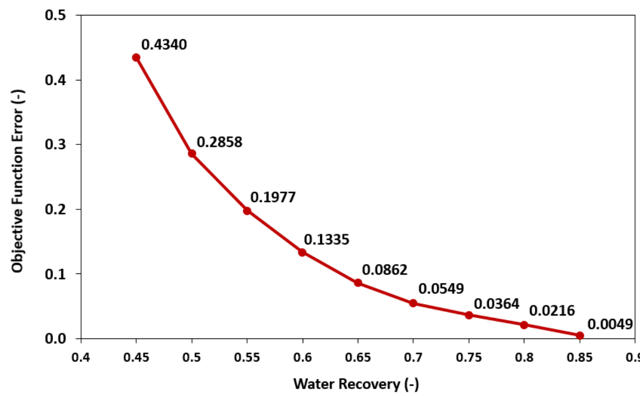

Figure 4: Results of RO modeling and optimization. Introduced error due to the selected optimization method.

Accordingly, the average Err_{obj} for each water recovery has been calculated which is depicted in Figure 4. On first glance we can postulate that the MILP problem provides in all cases a lower bound to the true optimal solution ($Err_{obj} > 0$). It is interesting to see how the error of optimization decreases with increasing water recovery, i.e. system efficiency. For water recoveries higher than 0.6, the introduced error in the objective function value is less than 0.133. Besides the change in objective function value, the utilization of surrogate models can also influence the obtained values of optimization variables.

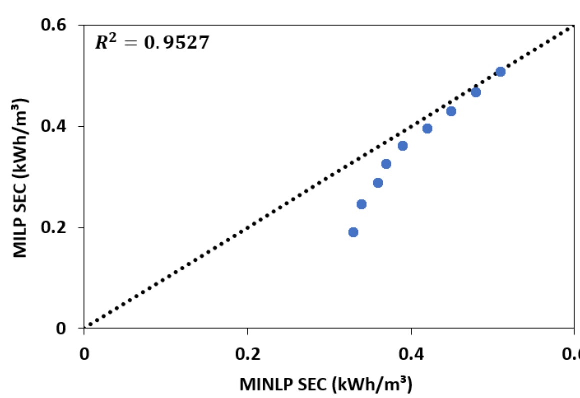

Figure 5: Results of RO optimization. Comparison of the SEC of system solutions for the MINLP and MILP case.

For RO systems, key performance indicators besides the plant's energy consumption are the system's overall water recovery, overall permeate output and specific energy consumption. Both, the MINLP and MILP optimization problem, result in the same system water recovery and permeate output, meaning that the RO systems operate at the same efficiency and output level.

Interestingly, the SEC consumption of both models differ due to the selection of different operational pressures and water recoveries per stage across the plant (see Eq. (4) and (7)). This is possible since the same water recovery of the system can be achieved with different water recoveries per stage and since the same water recovery per stage can be achieved with different pressures per stage and parallel flow across the plant. To measure this difference in operational decisions the SEC for the MINLP and MILP case are visualized in Figure 5. It is important to note that it has been shown that the SEC is only dependent on the water recovery [8] explaining the reduction in data points between Figures 3 and 5, similar to the observation regarding Figures 3 and 4. Ideally, the data points would follow a straight line of slope one indicating that the SEC results of the respective models are identical. Since this is not the case, we can appreciate the introduced optimization method error as departures from said line, which can be quantified as $R^2=0.95$. In turn, this represents an introduced error of 5% in terms of decision variable values.

Taking into account this additional error, the optimization model can only capture 88% of the original model's behavior, instead of the initial 94%. Arguably, the error due to the selected approximation approach is approximately the same as the error introduced stemming from the selected optimization approach (both 6%). This observation indeed underlines the importance of quantifying the quality of obtained surrogate model optimization results, although this is a difficult task which might not always be possible because of the potential non-solvability of the underlying physics-based models.

Computational Complexity

The spatial and temporal multi-scale complexity of the FEWN results in large scale optimization models, which is one of the main reasons that derived optimization frameworks are computationally intractable. It already has been shown that the full energy-water supply system cannot be solved at an hourly time scale over a one-year time horizon. To obtain an upper bound on the true optimal solution, the RO system has been restricted to a single operating point whereas the full dynamic renewable energy system is solved over a one-year time horizon [10]. In this extreme case, the RO system is effectively clustered to a single representative operating point specifying only once its constant EC, Q_p, Q_f and WR^{sys}. This is analogous to assuming that there exists only a single time period of operation of the RO system according to a "short-sighted" rolling horizon approach and can effectively be understood as introducing a different time scale for the water supply system. In turn, this inherently limits the system's flexibility and potentially its ability to adjust to the variability of the renewable energy supply system. Accordingly, altering the frequency of operational clustering corresponds to evaluating the importance of considering varying or equal time scales among the interconnected supply systems.

However, the quality of the obtained upper bound on the true optimal solution has not been quantified yet. In theory, better upper bounds to the true optimal solution can be obtained by adding more operational RO clusters to the system. This clustering of operating points can directly be compared to similar approaches for data aggregation. Alternatively, instead of solving the optimization model over a one-year time horizon, the model can only be solved for one month and then resolved 12 times to approximate the annual solution, similar to a rolling horizon strategy [20].

To evaluate the potential of operational RO clustering for complexity mitigation, this work solves the full energy-water model for two weeks at an hourly time scale

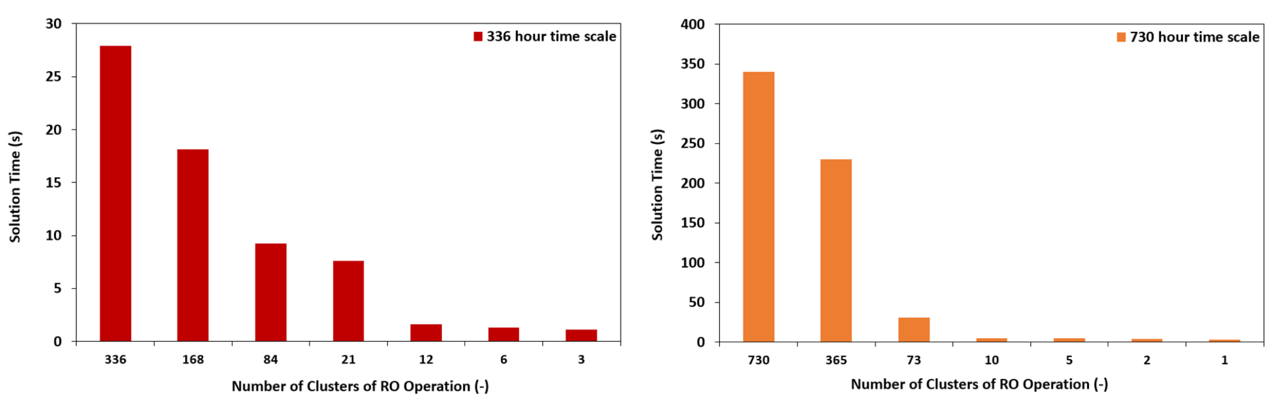

Figure 6: Impact of clustering of operational RO decisions on solution time. Left: 2 week time horizon; Right: 1 month time horizon.

(336 hours), as well as for one month at an hourly time scale (730 hours). In both instances, the RO operation is successively restricted from the full dynamic model to a single operating point. Special attention is placed on how the solution times and objective function values change with increasing operational restriction. It is expected that in all cases $Err_{obj} \leq 0$ since this clustering approach of the RO system can only provide upper bounds to the true optimal solution. For all cases an optimal solution and mixed-integer programming (MIP) gap of 0% is enforced.

As shown in Figure 6, the solution time decreases significantly with decreasing number of clusters for both cases. However, starting at 12 clusters for the 336 hour time scale and at 10 clusters for the 730 hour time scale no significant speed-ups in solution time can be observed. Moreover, for both cases, Err_{obj} is negligible over the complete cluster horizon as illustrated by a mean of $-1.4215 \cdot 10^{-6}$ (standard deviation of $2.3877 \cdot 10^{-7}$) and $-1.4640 \cdot 10^{-4}$ (standard deviation of $3.9754 \cdot 10^{-7}$), for the 2 week and the 1 month case study, respectively. These results suggest that there is a cluster threshold after which no speed-up in solution time and no significant changes in objective function value are expected, meaning there is an advantageous trade-off between operational flexibility (number of clusters), system solvability (solution time) and accuracy (Err_{obj}). However, we can also deduct that collapsing a bi-weekly or monthly operation in a single operating point does not result in a significant loss of information ($Err_{obj} < 1.4 \cdot 10^{-4}$). Therefore, it is suggested to evaluate how the solution of the full-time scale FEWN problem changes with increasing RO operational flexibility (yearly, monthly, bi-weekly, daily, every 12 hours). In this case the model was solved to an optimal solution and MIP gap of 0%.

Table 1: Results of solving the full-scale energy-water nexus supply model (8760 hours). Model size is specified according to the dimensions of the constraint matrix.

RO Operation	Clusters	Model Size	Err_{obj}
Yearly	1	[175331, 122778]	Basis
Monthly	12	[176310, 123801]	$3.925 \cdot 10^{-6}$ %
Bi-Weekly	24	[177378, 124917]	$7.860 \cdot 10^{-6}$ %
Daily	365	[207727, 156630]	$1.426 \cdot 10^{-5}$ %
12 hours	730	[240212, 190575]	$1.630 \cdot 10^{-5}$ %

Interestingly, the objective function value does not change for all practical purposes by allowing for more flexible operational RO decisions over one year, as shown in Table 1. In addition, the energy and water storage schedules differ only insignificantly among obtained solutions. For all intents and purposes, the obtained optimal solutions are virtually identical. The solution times on the other hand vary from 250 seconds for the yearly case to 6400 seconds (around 2 hours) and even 53,000 seconds (more than 14 hours) for the daily and every 12 hours RO operational decision strategy, respectively. For the case study presented here, the RO clustering does not seem to have an impact on the overall solution accuracy. This novel analysis overall strengthened our confidence in the harsh sounding assumption of allowing only one RO operating point over one year to obtain a valid upper bound on the true optimal solution. However, this statement can only be generalized if the solution of the full-time scale FEWN model can be obtained, i.e. via decomposition strategies. It is expected that there exists a solution drop-off with an increasing number of clusters towards the full-time scale model. The obtained results can also aid in the convergence time of the full-scale optimization model by providing valid upper bounds to the problem which potentially shrinks the solution gap significantly depending on the quality of the lower bound.

CONCLUSION

In this work, we revisited the FEWN problem statement by addressing data uncertainty and system complexity through the lens of a representative surrogate energy-water supply system. Sources of introduced data uncertainty and complexity mitigation errors have been discussed in detail. While it is difficult to quantify the introduced modeling and data uncertainty errors it is an essential task to maintain confidence in derived FEWN optimization frameworks and results. Implications of approximation and optimization methods for a RO water supply system have been discussed in detail, which has then been extended to an operational RO clustering approach to mitigate the computational complexity of the interconnected energy-water supply system optimization.

Policy makers and stakeholders are crucial in translating obtained PSE FEWN methodologies and results into real-world implementation. Being able to quantify a level of confidence one can have into proposed modeling strategies aids in this process. The proposed error quantification strategies can be leveraged to certify how much uncertainty in the obtained optimal solution is added with every data processing and modeling step. In turn, this uncertainty can be utilized to provide interpretable ranges of optimal results instead of single values, similar to confidence intervals, for transparent and effective decision-making across all levels.

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