Model Based System Design to Support Variability and Flexibility, and Early Bidding Phase of New Procurement

Abdelkrim Doufene, *Researcher, MIT*, Vivek Sakhrani, *Researcher, MIT*, Abdullah Alkhenani, *Research Assistant*, KACST**,** Bo Yang Yu**,** *Researcher, MIT, MIT,* Adnan Alsaati, *Senior Researcher, KACST,* Anas Alfaris, *Professor, KACST,* and Olivier de Weck, *Professor, MIT*

***Abstract* - A generic design of a complex industrial system allows the reduction in engineering cost and time to market because of the ability to adapt a technical solution given a particular context. We present in this study a model-based design approach that allows managing variability and flexibility in design to support both near- and long-term decisions. A case study addressing a solar desalination combination problem illustrates this approach. The produced models are organized in an open-web decision support system, which governs access to an integrated suite of models. This suite includes computational models for the operation of three desalination and two solar technologies and a life-cycle investment model, first developed as stand-alone applications and then modularized with the web platform to provide a set of linked models. In addition, to assist a collaborative design of solar desalination plants, a possible application of this work is to support a new e-bidding process.**

***Index Terms*— system architecture; multidisciplinary optimization; flexibility; variability; e-bidding; solar desalination**

I. Introduction

THE diversity of solutions available to meet the needs of clients is increasing and makes the reuse of each solution in the appropriate context of its use difficult. The design of systems that can fulfill varying customer requirements or specifications while maintaining optimal performance at low cost is a complex challenge. Management of design variants requires rigorous approaches that can allow for an adaptive bridge between the client`s high-level needs with technical solutions. An architectural design framework coupled with multiobjective and multidisciplinary optimization models can help in structuring, organizing, and identifying common platforms that can be used cost effectively for different requirements. Thus, we can quickly develop new system solutions by reusing existing designs. A model-based design approach helps in structuring and organizing the views that enable a complete and justified design of a complex industrial system. It is useful for managing trade-offs and decisions when we often seek to meet several multidisciplinary expectations, given several design constraints and variables stemming from the system environment. The resulting models can serve as a baseline for managing variability and uncertainty, adapting the technical design to different contexts of use and associated business models while reducing engineering costs by reusing models and reducing the time to market.

The utility and benefits of a model-based system design have been discussed in many research works [1][3]. The aim of this study is to describe a design approach that could be used to deal with variability and flexibility, as well as on how it could be extended in order to support an early e-bidding process.

To illustrate our approach, we present in this study a library of models for solar desalination design. Coupling of the desalination process with solar technology is a complex problem. These types of plants are still relatively new, and their design should be generic in order to support variability (different potential locations, etc.) and flexibility (external parameters and capacity changes over time, etc.). As various types of desalination processes and solar technologies have been developed, the selection of the best combination requires several design criteria. Capital costs, operation, and maintenance costs, plant site, salinity of seawater, environmental impacts, and water quality requirements are examples of design criteria involved in selecting a suitable desalination process. Furthermore, the selection of a suitable solar system is governed by a number of factors such as plant configuration, energy, location, solar irradiance, dust, and working fluids. Moreover, when integrating the solar technology and desalination processes, several requirements and constraints arise. A generic design of a solar desalination plant will reduce the cost of engineering studies and the time to market owing to the reuse of existing designs.

In the following sections, we report related works, introduce the design approach, and discuss a case study and its results and research perspectives.

Abdelkrim Doufene[1,*], Vivek Sakhrani[1], Abdullah Alkhenani[2], Bo Yang Yu[1], Adnan Alsaati[2], Anas Alfaris[2], and Olivier de Weck[1]

[1]*Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA 02139, USA*
[2]*King Abdulaziz City for Science and Technology, King Faisal Rd, Riyadh, Saudi Arabia*
[*]Contact: doufene@mit.edu

II. Related works

A model-based design approach provides guidance and rules for structuring, classifying, and organizing different architectures [4]. A design framework serves as a reference to organize all the elements of the architecture of a system with several views [5]. The principle of views was first discussed in [6]. As discussed in [1], model-based approaches are very useful and helpful for risk reduction, enhancing team communication, discovering system issues, performing trade studies, early detection of errors, integration, as well as traceability [7][9].

Furthermore, in industrial practice, to design a complex system, there are several multidisciplinary objectives and constraints. Conducting the analysis, defining the right criteria, and evaluating alternatives are difficult tasks. This difficulty is, particularly, owing to the fact that the separation between the problem definition and the solution design is often unclear [11]. Multiobjective optimization is performed and used as a basis for trade-off analysis and decision-making.

Research works have been conducted using Pareto modeling in the context of system architecture [11]–[14]. Refs. [15],[16] introduce the concept of fuzzy Pareto optimality. They recommend to keep some optimal solutions (near Pareto frontier solutions) when designing a system. In case of uncertainty, they advocate to take into account, in addition to the Pareto optimal solutions, some other alternatives to anticipate the unintended exclusion of viable solutions and perhaps even desirable ones, particularly because of unforeseen or unpredictable external influences in an uncertain environment. In this regard, in the context of system of systems, [17] discusses a design process beginning with a global goal of constructing a multi-criteria decision process in order to create a set of alternatives representing different choices. Ref. [18] discusses a scenario planning tool in order to perform “what if” scenarios that can be used to evaluate the effects of different planning policies and to select the most suitable one.

This study introduces a model-based design approach combining system architecture and multiobjective optimization to help decision makers in addressing flexibility and variability. It also introduces the concept of e-bidding process. The approach is illustrated through a case study on solar desalination systems.

III. Design approach

A first draft of the approach was presented in [19]. An adapted and completed version is presented in Figure 1. The starting point of designing a system is the definition of its boundary and main operations. This first step allows the identification of stakeholders, enabling systems, their expectations, and constraints over the life cycle of the system of interest [11],[14]. This step considers particular aspects such as the market, end-user, regulations, technology availability, and natural environment.

Once the main functional and non-functional requirements are identified, the system architecture organizes the different views allowing to achieve a comprehensive system modeling. This step clarifies the relationship between design constraints and design variables, functions, components, and interfaces, and yields design concepts that could be modeled and simulated.

Simulation is used to verify and validate the design. It reduces the cost and time of engineering studies through the use of models. The connection and traceability between simulation models with associated architectural design facilitate the change propagation analysis; they maximize the reuse to save time and cost. The link between system architecture and simulation is iterative and incremental. Indeed, simulation models are detailed increasingly following the progress in the design process.

Many decisions are made at this stage of the design process to generate the initial guidelines for choosing system designs and levels of maturity and to achieve quality, reliability, security, flexibility, robustness, sustainability, and scalability of the system life cycle [20]. However, the multitude of multidisciplinary objectives and constraints makes trade-off analysis difficult. Therefore, multidisciplinary design optimization is performed in order to identify the optimal design in a particular environment and at a particular time.

Once an optimal design is identified, changing the temporal dimension by infusing uncertainties and future scenarios of use could yield potential future designs. Thus, this first optimal design could be used as a basis for addressing flexibility in design (designing for changeability.)

Similarly, changing the spatial dimension could yield different designs that are optimal in other locations. This variety of design could be captured in a commonality platform. Thus, this first optimal design could be used as a basis for addressing variability in design (designing for commonality.)

Following the design approach as summarized in Figure 1, we present a case study in the context of solar desalination.

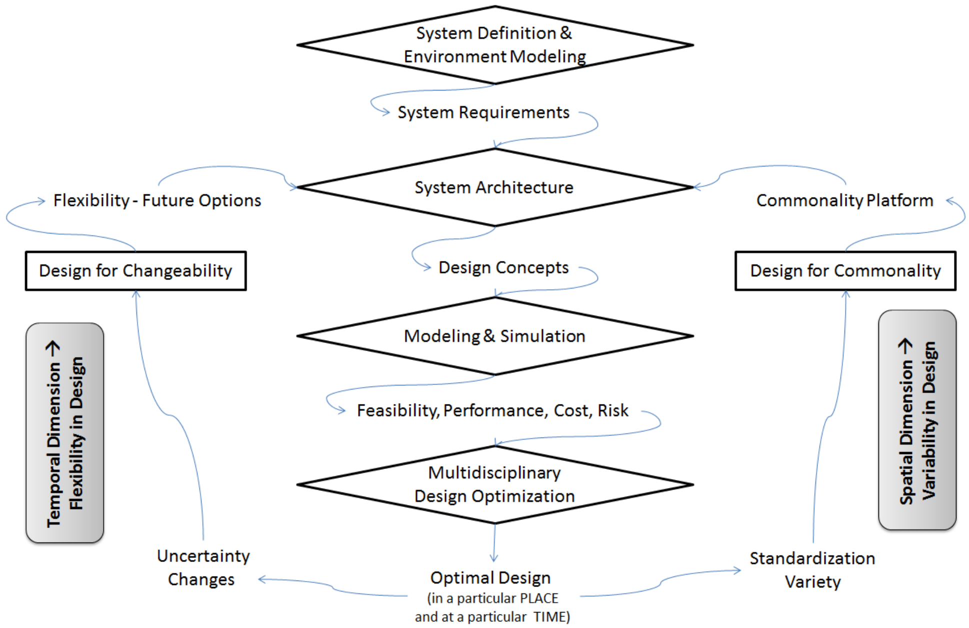

Figure 1. Design approach adapted from [19]

IV. Background of the Case Study

The desalination of seawater has been the most expensive method of producing potable water at a commercial scale, mainly owing to the high capital and energy costs [22]. Nevertheless, it represents a viable option to meeting the water demand of the perpetually increasing world population. It is indeed projected that close to 70% of the world's population will face water shortage issues by 2025, while approximately 50% of the world's population lives within 200 km of the seacoast [22].

The ever-increasing energy demand is also leading toward economic problems if the matter is not tackled in an optimal manner. Fortunately, many countries have been bestowed with abundant renewable energy such as solar and wind, thus setting the stage for a more sustainable source of energy. When combined with desalination technology, the possibilities for more sustainable water systems are endless. However, planning the efficient deployment of a renewable energy-based desalination system is constrained by several key performance attributes, such as sustainability, optimality, strategic security, and robustness as well as the ideal phasing and deployment of facilities.

A. *Solar desalination technologies integration*

Conventional combinations of solar technologies with desalination processes are discussed in [22]. There are two types of desalination processes. First is the reverse osmosis (RO) process, which requires electricity for operation and can be coupled with a photovoltaic solar system that converts solar radiation into direct current electricity. Second is the thermal desalination process, which is derived using thermal energy and can be coupled with solar thermal systems that use thermal collectors to capture and absorb the solar radiation and then convert it into heat. Given the fact that desalination systems and solar systems are developed independently and then integrated together, the analysis for each system would be carried out separately. In this study, we focus on the main solar technologies: the photovoltaic (PV) and concentrated solar power (CSP) as well as the main desalination technologies, i.e., multistage flash (MSF), multiple effect desalination (MED), and RO.

B. *Energy requirements for solar desalination systems*

Selecting the best solar desalination system for specific conditions requires a good understanding of the energy requirements associated with desalination. Energy requirements vary from one desalination process to another based on the desalination technique as well as other desalination-related systems such as seawater intake pumping, pretreatment, and post treatment. Table 1 shows the typical energy requirements for industrial desalination techniques. It can be observed in Table 1 that the RO desalination technique is more efficient in terms of energy than the thermal desalination techniques. However, thermal desalination techniques are still attractive as they can handle seawater with high salt concentration.

TABLE I
DIFFERENT ENERGY REQUIREMENTS FOR INDUSTRIAL DESALINATION TECHNIQUES [23]

Technique	Heat requirements (Thermal) kWh/m^3	Electricity requirements (Pumping) kWh/m^3	Combined energy demand kWh/m^3
RO	-	4–6	4–6
MSF	40–120 (thermal)	2.5–5	21–58
MED	30–120 (thermal)	2–2.5	15–58

C. Cost considerations for solar desalination systems

Cost reduction is the key driver in considering solar desalination. However, estimation of the solar desalination system cost is affected by many factors, such as location, solar irradiance, energy efficiency of the desalination system, salinity of the feed seawater, material and labor cost by geographical areas, and financing packages. Table 2 provides the desalination cost per unit of water produced for some desalination techniques coupled with conventional or solar energy sources. Moreover, the water cost is directly affected by the solar desalination system's capacity [22].

TABLE II
DESALINATED WATER COST FOR VARIOUS COMBINATIONS OF DESALINATION PROCESSES POWERED BY CONVENTIONAL OR SOLAR ENERGY [24]

Desalination system powered by energy source	Cost ($/m^3)
Conventional energy + RO, ED, MSF, MED, & VC	0.5–3.5
Solar thermal + MED	1.25–6.25
Photovoltaic energy + RO	4–11

Even if solar-assisted desalination appears to be not competitive yet with conventional fossil fuel desalination in terms of unit product cost of fresh water, the continuing research activity in solar and desalination technologies can significantly enhance such technology to become an attractive choice for fulfilling the future global desalination requirements.

V. APPLICATION TO SOLAR DESALINATION

This section summarizes the different models developed following our design approach as part of the Strategic Sustainable Desalination Network (SSDN) project [25]. The aim of this project is to develop a decision support platform for planning the efficient deployment of a sustainable desalination network at a country level.

A. Environment models

Following our design approach, the aim of first tasks in designing the coupled desalination–solar energy facility is to clearly identify the system boundaries and their external interfaces with the environment. It is important to delimit the system(s) of interest from the external environment with which they interact to understand the dynamics of the overall system behavior. This boundary setting exercise allows the clearest possible view of external interfaces of the systems of interest before proceeding into the optimization of its internal interfaces. We thus depict the desalination plant and the solar plant as the bounded subsystems of interest, as shown in Figures 2 and 3, which together form the solar desalination system.

The desalination and solar subsystems both show a relationship with physical site features and locational attributes such as weather conditions and water quality characteristics. They also depend on infrastructure components such as energy transmission lines and water distribution lines. The owners and manufacturers of equipment are important stakeholders in the design of these subsystems because the choice of technologies sets up the business and competitive dynamics. Furthermore, design decisions take place in different regulatory and standard environments. Thus, the external interfaces either influence or place constraints on the design of the subsystems.

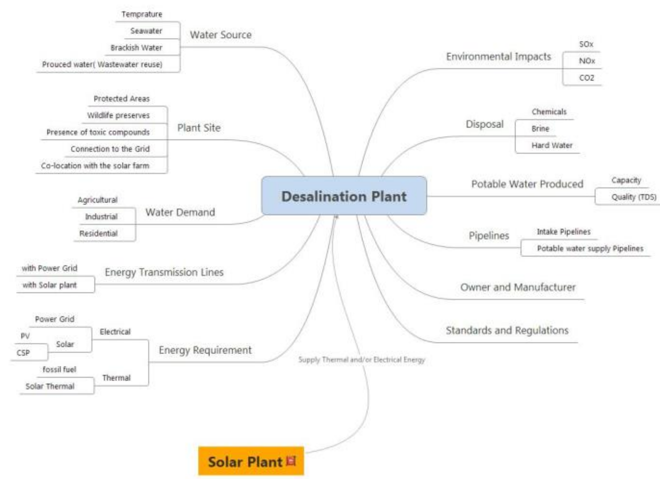

Figure 2. Desalination plant as a black box with its external dependencies and linkage to the solar plant

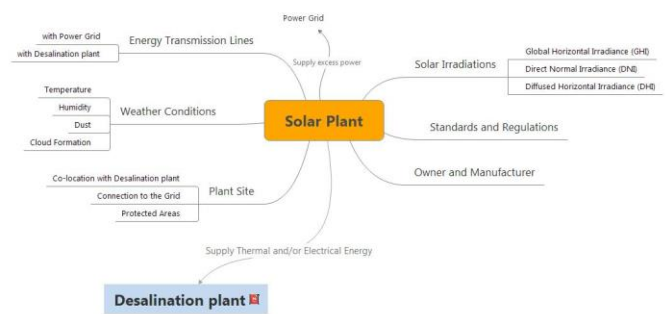

Figure 3. Solar plant as a black box with its external dependencies and linkage to the desalination plant

B. Model library

Figure 4 depicts the model library. As part of the SSDN project, we developed two solar models (PV and CSP) and three desalination models (MSF, MED, and RO). Data organized in a geographic information system (GIS) database are important components. They contain site-specific data on locational attributes pertaining to weather (temperature, density, dust, cloud formation, and insolation) and seawater conditions (seawater temperature, salinity distribution, and other characteristics). The investment tradespace model (ITM) is a multiobjective screening model that takes site-specific data from the GIS database and empirical values for plant design parameters, and investigates the interaction of contractual structures with plant designs. The ITM reduces a very large design space to a set of feasible design configurations, which have the potential to maximize the economic value of the plant under uncertainty.

The integrator module (IM) is central. It receives locational information from the GIS database and other models. Based on a set of rules for connectivity and integration, it should allow synthesizing technically feasible and valid architectures (with different combinations of models). The resulting architectures should then be simulated and evaluated given a set of evaluation criteria. The evaluation criteria to find the optimal design are metrics selected depending on the stakeholders. Some of these include water cost, water quality, energy consumption, modularity, and adaptability. Pareto frontiers could be produced base on these criteria.

The interdependencies across the dimensions of the solar desalination problem make the integration within the IM a key challenge. For example, the design of the solar plant depends critically on the design of the desalination facility, and a number of design configurations may emerge. In some cases, constraints on solar plant design may also limit the design space by imposing constraints on the design of the desalination facility, primarily through the energy available for power desalination. Finally, this framework simulates iteratively the design performance to meet the multiple objectives of minimizing water cost, water shortages, and environmental impacts, and maximizing economic asset values of the single solar desalination plant. We describe in detail the models in the following paragraphs. The models were developed with the intention of simulating design processes and understanding how designers make trade-offs. Therefore, very precise predictions of plant performances over a wide range of operating parameters were not necessary, thereby making these models adequate for their purpose.

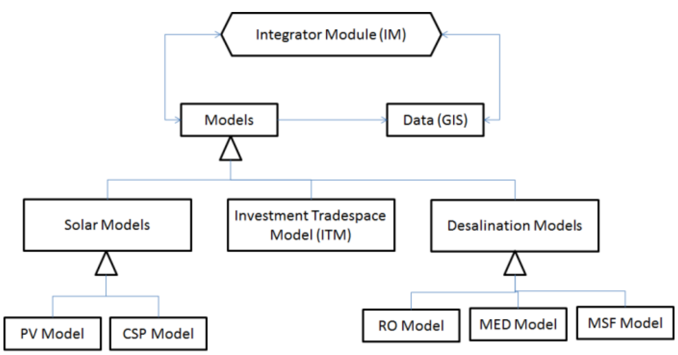

Figure 4. Model library

1) Desalination Models

In the SSDN project, we addressed the two main types of desalination processes (membrane and thermal). We described MSF more generally, and studied MED and RO processes in detail. These processes were implemented in Matlab.

The MSF model, as developed, includes three main components: feedwater/brine heating sections, multistage recovery sections, and multistage rejection sections. Exhaust heat recovery boilers provide the energy requirement for the evaporation process, which is later recovered in the condensation process. The model expects the following user defined inputs: number of simulation runs, number of stages, distillate flow rate, feedwater salinity, final stage temperature, top brine temperature, feedwater temperature, brine flow rate per stage width, and vapor velocity. Upon the completion of each simulation, the model outputs the following data: performance parameters, individual stage parameters, heat transfer areas, and stage flow rates. The performance parameters that the single MSF desalination plant focuses on are the performance ratio and the specific heat transfer area. The model calculates the heat transfer areas for both the condenser and evaporator. The width, length, gate height, and pool height for each stage is also calculated. Finally, the model produces the feedwater, brine, distillate, and steam flow rates for each stage [25].

The MED model as developed is a thermoeconomic model of MED desalination system with a thermal vapor compressor (TVC), which is based on the energy and exergy analysis in combination with economic principles. Basically, thermoeconomics includes the associated costs of the thermodynamic inefficiencies in the total product cost of an energy system. The proposed model considers five decision variables: motive steam temperature and flow rate, number of effects, last effect temperature, and condenser minimum temperature difference. Other independent variables that are related to the location of the site intake such as the seawater temperature, salinity, and ambient temperature are considered as parameters. The outputs of the model in which some can be optimized are the operating data for each effect (such as temperature, pressure, and flow rates), capacity, gain output ratio, exergy destructions of different units in the MED–TVC system, electrical power required, heat transfer areas, and unit product cost [30].

The RO model as developed is capable of simulating in detail the main physical processes necessary to describe the operation of an RO plant, and has been validated with data from both commercial software and real data from a commercial RO plant. The model also includes a simple financial module to assess the capital and operational costs. The model simulates the operation of the RO system describing the process in every membrane inside each pressure vessel, the operation of the pressure vessels, and the operation of the several RO trains. The model is based on solution diffusion models published in the literature, which have been applied successfully to simulate not only desalination processes with RO but also the transport in dialysis or gas permeation. Membranes from different manufacturers have different performances, and this model addresses such differences by making use of a database with individual specifications provided by different membrane manufacturers. The model characterizes the operation at steady state for design conditions, and it has recently been adapted for the simulation in part load operation assuming that individual RO trains can operate either at full capacity or would be shut off. The model currently can be run using two types of strategies: either the user sets the amount of feedwater that will be entering the plant, or the user sets the total production of water required from the plant. The model was also built with a basic financial analysis tool based on data available in the literature so that currently it is possible to not only evaluate the physical performance of the RO plant but also obtain relevant economic metrics. The financial module accounts for the total capital costs of the pumps and energy recovery devices. The costs of piping are neglected in this version of the model but can be easily included in a future iteration. The capital cost, operational cost, and energy consumption of the intake and pre-treatment system depends on the combination of the intake and pre-treatment choices, as well as the intake seawater flow rate. The model was calibrated using design data from a large commercial plant in the northeastern coast of Saudi Arabia on the Persian Gulf. The validation process was performed using a commercial software used as reference in this industry, the RO system analysis (ROSA) from Dow Chemical Company, which has been validated in other studies [28][29]. The RO model validation is presented in Appendix 1.

2) Solar Models

The solar plant components of the SSDN project are employed to assess the use of CSP and PV technologies in combination with desalination processes at various locations [25]. The assessment will consider electricity, heat output, efficiencies, associated capital investments, operation and maintenance costs, and possibilities for storage. The solar models developed are less sophisticated than the desalination models. We aim to use the system advisor model (SAM) developed by the US National Renewable Energy Laboratory (NREL) in the future. SAM models describe the performance characteristics of physical equipment in the system and project costs. Renewable energy options in the current version of SAM (2014.1.14) include wind, solar (PV and CSP), geothermal, biomass, and generic or custom formulations. The SAM tool would be used to simulate the electricity and thermal energy (heat) production and to assess other performance measures for a variety of design configurations at various time scales while supplying the desalination plants.

In addition, one of the main models developed as part of the SSDN project that we do not report in this study is the dust mitigation model presented in [31]. The ultimate objective of this model is to study the potential impact of incorporating dust mitigation technologies into PV and CSP, taking into account their effects on performance and cost. The developed Matlab model focuses currently on the dust impact on PV, which will be adapted to CSP later. The model consists of two physical performance components and a financial component. The first layer calculates the amount of radiation reaching the panel surface for the chosen location set by the user, simulating the dust impact and the performance of each of the dust mitigating technologies. The second layer calculates the PV panel performance knowing the amount of irradiation actually reaching the panel: the model allows for a choice from a number of solar modules based on different PV technologies. The third layer calculates the financial performance, including estimates of capital investment, operation, and management costs for each year. The dust mitigating technologies being assessed for dust mitigation performance are electrodynamic screens, air-blowing mechanisms, and superhydrophobic nanocoatings. The model is tested using Saudi-specific data. To validate the model, the results were compared with those obtained from the European Solar Test Installation's Photovoltaic GIS [31].

3) GIS Module

Because one of the main objectives of the SSDN project is to provide a decision support system platform to evaluate and refine complex scenarios addressing the location, timing, and technology of solar and desalination investments, a GIS is created and currently being populated with real data for that purpose. All the data related to water salinity, solar irradiance, and dust as well as water demand are collected. The geospatial aspect is emphasized to support the argument that understanding and attempting to solve solar desalination systems issues must be performed on a level that exposes the spatial cross-dependencies of such systems. Details of this GIS are described in [32].

4) Investment Tradespace Model

ITM is a multiobjective screening model that reduces a very large design space—a set of many feasible plant designs—to a much smaller set of "attractive" designs that meet the key objectives or design criteria. A tradespace model is a high-level (low-fidelity) model that relates the attributes of conceptual designs to their expected performance outcomes along multiple dimensions. The ITM developed here takes as inputs locational water quality attributes and information on water demand and energy price uncertainty, and investigates how these economic factors and contract structures interact with technical design features under uncertainty. The screening model attempts to simultaneously relate the economic asset value (for the agent) to the social value (value to the principal) inclusive of costs and losses owing to water shortages. It also produces risk profiles along these value dimensions, and technical system-level outcomes such as reliability of meeting demand under water demand uncertainty. Many stakeholders in the water industry inquire whether a tradespace model could be useful in the front-end conceptual design phase and early bidding phase for new desalination plant procurements. This trend is consistent with a recent movement in systems engineering in which bidders submit their design models in response to tenders instead of paper-based documents. A version of the ITM with a user interface was tested in a series of pilot experiments for both independent and collaborative design. After model refinement, the ITM was deployed at scale in design exercises with a large number of collaborators. Between October and December 2014, approximately 140 designers at MIT participated in a design exercise using the ITM. Some of them used the model independently, i.e., they designed desalination facilities on their own. Other designers used the model collaboratively. In these cases, collaborating designers played the role of stakeholders and exchanged information about designs, or communicated with each other to identify designs that met their different competing objectives. The design exercises were controlled. This enabled the results of independent designs to be compared with collaborative designs using the ITM [26][27].

Example of results from the ITM

The tradespace analysis provides some intuition regarding risk and performance. Regression analyses of the “reference class” dataset suggest that economies of scale exist for very small plant capacities (up to 10,000 m^3/day of potable water) but are exhausted for mid-scale plants (20,000–30,000 m^3/day). Modular plants with mid-size units can therefore be most profitable because there are no returns to scale from increasing size upfront, when faced with uncertain water demand, while allowing for capacity expansions. This insight is consistent with other empirical observations in the literature, and gives rise to an experimental hypothesis that after observing the net present value (NPV) performance in the training round, the agent will initially propose mid-size plants under water demand uncertainty and fixed price concessions. The tradespace model also shows that for mid-size plants, a fixed-price concession allocates the water demand risk to the agent. It will therefore under-invest initially and then exercise capacity addition options in a way that lags demand. The minimum revenue guarantee allocates some of this demand risk to the principal; therefore, the agent should initially over-invest, but also enable and exercise capacity options to take advantage of the upside when water demand is high. Under a revenue collar, the upside for the agent is truncated by the ceiling of the collar; hence, the agent will over-invest initially, but limit capacity expansion options because their revenue is capped.

Results from the current version of the tradespace model do in fact reveal design trade-offs. Figure 5 shows the Pareto trade-offs in two different settings. The chart on the left shows a situation where the agent firm is investing in a monolithic (non-modular) desalination facility of a chosen technology (RO here) under a fixed price water purchase contract ($/$m^3$ delivered), and the firm can vary the production capacity of the plant as an independent variable. The horizontal axis shows the project’s profitability (NPV) for the firm, whereas the vertical axis denotes the social losses (unserved demand) as a consequence of the selected level of capacity. The chart has three different curves for differing degrees of volatility (0%, 5%, and 10%) in the water demand from the plant. In general, points on the top left of the chart indicate levels of capacity that minimize social losses, and points on the bottom right suggest those that maximize the firm’s NPV. The analysis suggests that as NPV increases, the social losses also increase because of the trade-off between the two objectives. We observe this result irrespective of the degree of volatility in demand; however, for higher levels of volatility, there are many levels of capacity that meet one objective but not the other.

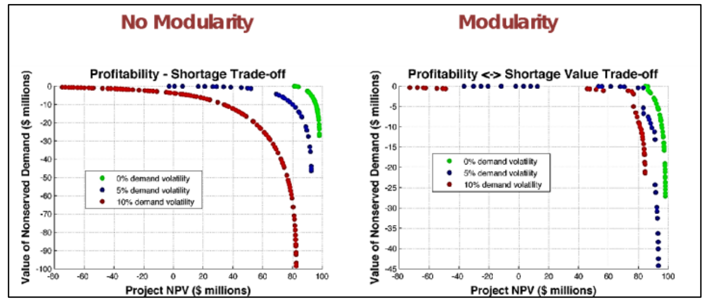

Figure 5. Pareto trade-offs in monolithic/non-modular (left) and modular (right) plant designs, with modular presenting knee points that simultaneously maximize project NPV and minimize the social losses of unserved demand

4) Integrator Module

Desalination technologies can be supplied with solar energy in various combinations that are shown to be technically feasible. We started integrating desalinization models with solar models described previously. The resulting architectures are simulated and evaluated under given evaluation criteria and comparison methods. Pareto frontiers could be produced in order to show the different design alternatives. Among different possible combinations of desalination processes driven by solar energy, PV–RO is a promising combination as well as an MED process coupled with a solar thermal heat source. The aim is to assess hybrid combinations; however, we started by first considering the MED–CSP and PV–RO combinations.

In order to assess the MED–CSP combination, we conducted a thermoeconomic and performance analysis for an MED–TVC process driven by CSP. A solar steam generation system is introduced to provide the required thermal energy in the form of steam to two steam ejectors in series of the MED system using a boiler heat exchanger. This combined solar desalination system is built based on the CSP and MED models using Matlab. Effects of variations in parameters, such as compressed steam temperature and number of effects on unit product cost, specific heat transfer area, gain output ratio, the specific flow rate of the cooling water, exergy destruction, and solar field area were investigated. Moreover, a case study is performed to evaluate the unit product cost of desalinated water along the Red Sea coast of Saudi Arabia taking into account the variation of location-sensitive parameters, namely ambient temperature, solar radiation, seawater salinity, and seawater temperature along the Red Sea coast during wintertime [30].

For the PV–RO combination, an initial analysis is performed using a PV model developed at NREL. This PV model is being integrated with the RO model. The PV model as developed by NREL is one of the references used for the pre-design assessment of PV parks. The work being conducted currently considers many sizing options such as that the user sets the size of the RO and then the model tries to match the size of the PV plant according the nominal RO consumption, or the user sizes the PV plant, and then the model tries to match the size of the RO plant accordingly, or the user sets the size of PV and the size of RO independently. The current version of the model considers steady-state operation at each time step for 8760 h of the year off-grid operation, no storage option, and no minimum startup or shutdown periods. Knowing the installed capacities, the model is run for every hour of the year, calculating how many RO trains can be operated at each time step. At the end of the simulations, an aggregation of the outputs is computed to obtain relevant metrics (e.g., total production of freshwater and electricity, capacity factors, production profile for a typical winter and summer day, and number of startups).

VI. Early Bidding Phase of New Desalination Plant Procurements

By building up the solar desalination platform presented in this study, we envision a new model-based bidding process for the efficient procurement of solar desalination plants, in which bidder-contractors submit detailed reference designs for consideration instead of paper-based documents. Stakeholders of the system, the procurement agency, and bidders in this case, can compare the performance outcomes of their designs in a common tradespace as early as the front-end conceptual design phase. This collaborative design approach minimizes significant design evaluation cycles. Eventually, this approach can establish a movement in systems engineering in which bidders submit their design models in response to tenders, instead of documents.

We developed a decision support interface as an open web platform, which governs access to the integrated suite of models described earlier. The models were first developed as stand-alone applications and then modularized with the web platform to provide a set of linked models. This open web platform was implemented utilizing the SAFFRON framework [35]. As shown in Figure 6, users start first by selecting the technology of interest, whether it is a desalination technology, a solar technology, or an investment model. Each of these models has it is own set of design inputs that must be entered. As a result of these entered inputs, the outputs will be visualized. The variables include capital costs, operation and maintenance costs, water quality, water quantity, cost of produced water, solar irradiance, seawater salinity, and energy consumption.

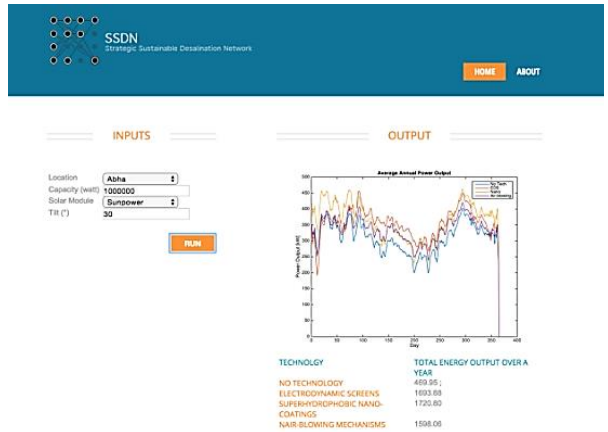

Figure 6. Single plant model web interface

VII. Discussion and Perspectives

In this study, we discussed a model-based design approach that allows the development and reuse of generic designs. The associated models can serve as a baseline for managing variability and flexibility by adapting the technical design to different contexts of use and associated business models while reducing engineering costs by reusing models and reducing the time to market.

Following this design approach, we developed a library of models to support stakeholders in comparing technologies and systems at the facility level, including, for the time being, the role of solar–thermal and solar–electrical energy requirements based upon technology choices. A key strategic issue is the degree to which solar plants are dedicated and/or co-located with specific desalination plants, including impacts on operational performance and flexibility versus solar plants that may be located elsewhere. This model library addresses the design of solar-powered desalination plants by evaluating different combinations of solar technologies with desalination processes. The objective is to select the optimal output capacity, technology, and sub-system design specifications for a single desalination facility in a certain location with its associated technical and environmental conditions. The solar plants could either be connected directly to the national power grid or function as dedicated installations to supply electricity or heat only to desalination plants. An investment model investigates the interaction of contractual structures with plant designs. This investment model reduces a very large design space to a set of feasible design configurations, which have the potential to maximize the economic value of the plant under uncertainty. Detailed process models then work within the reduced design space and draw information from a geospatial database with detailed data on locational characteristics such as site-specific attributes like feedwater salinity, temperature, and weather, which may significantly affect solar desalination design requirements, and therefore, both capital costs and operations and maintenance costs as well as environmental impacts. The models run iteratively to identify solar-powered desalination facility designs that are optimal along a number of dimensions. Another objective of this model library is to assess hybrid desalination technologies. Indeed, the best solutions in the future may not be a single technology (e.g., MED–CSP or RO–PV), but hybrid plants that combine multiple technologies such as MED/RO–PV–CSP. Moreover, it aims at studying the effect of climate change and the impacts of changing weather conditions (long-term trends for dust and sandstorms) on PV and CSP performance over the long term. All these models are compressed in a one-web platform allowing open access to many stakeholders. The purpose of this open platform is also to support a new e-bidding process, where potential contractors would submit their reference designs not on paper but as models that could be evaluated and compared directly to support benchmarking. This trend is consistent with the recent movement in systems engineering in which bidders submit their design models in response to tenders, instead of paper-based documents.

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APPENDIX 1.

RO model validation

In this section, we present the RO model verification, which was performed on two levels. First, we verify the solution-diffusion model used to simulate the RO membranes by comparing it against a commercial software package. Then, we verify the system level model by comparing the design data obtained from an existing RO plant to the model output.

1) RO membrane model

The RO membrane model was verified and compared to the ROSA program provided by Dow Water and Process Solutions.

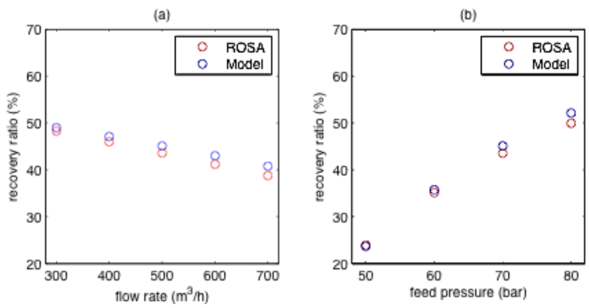

Figure 7. RO model verification: (a) varying feed flow rate; (b) varying feed pressure

Figure 7 shows comparisons of RO unit recovery ratio computed by both ROSA software and the custom-developed RO membrane model. The RO unit consisted of 65 pressure vessels with 7 membrane elements per vessel; membrane type SW30HRLE-440i was used. In Figure 7a, the feed pressure was kept constant at 70 bar, and in Figure 7b the feed flow rate was kept constant at 500 m^3/h. The results show some slight discrepancy between the ROSA and model results, but the difference is small (approximately 1% value difference in recovery ratio), and there is a consistent trend between them.

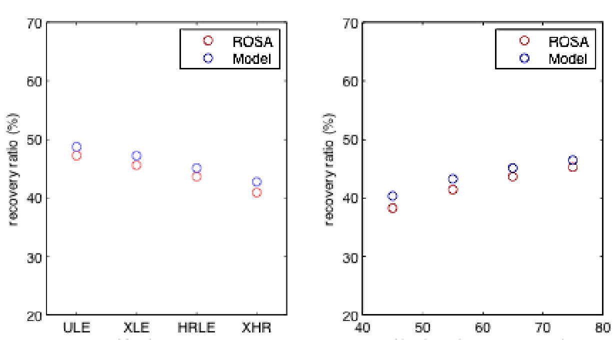

Figure 8. RO model verification: (a) different types of RO membrane element; (b) varying number

Figure 8 shows the comparison of RO unit recovery ratio computed by both ROSA software and custom-developed model. Feed pressure was kept constant at 70 bar, and feed flow rate was kept constant at 500 m^3/h. Results show consistent trends with slight variations in numerical values.

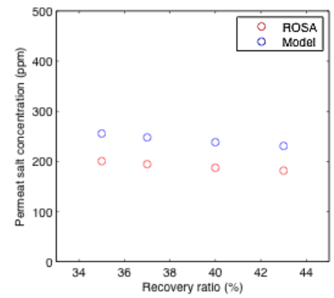

Figure 9. RO model verification, salt concentration, and recovery ratio

Figure 9 shows the permeate salt concentration predicted by ROSA versus that of the custom-developed model. Salt concentration predicted by ROSA is approximately 50 ppm lower compared to the model results, but the two results follow an identical trend. This discrepancy is mainly because of the non-availability of official permeability values, as the permeability values used by ROSA cannot be known. The consistency in the trends of the results also suggests that the differences are due to different values of constants being used. The lumped-parameter model used in the custom-built model adds another level of inconsistency compared to ROSA.

2) System level performance

A detailed design proposal for an existing RO in the Middle East was used to calibrate and verify the system level predictions of the model. Table III lists the design parameters reported in the proposal.

TABLE III

DESIGN PARAMETERS OF EXISTING RO PLANT

Parameter	Value
Feedwater flow rate	75,000 m^3/day
Intake structure	Deep open
Pre-treatment	Conventional
Number of trains	6
First pass	
Number of pressure vessels	65
Membranes/vessel	7
Feed pressure	70 bar
Second pass	
Number of pressure vessels	14
Membranes/vessel	7
Feed pressure	14 bar
Brine recirculation	100%

The plant is a 2-pass seawater RO plant. The seawater at the proposed site has a TDS of 45,000 ppm with temperatures between 15°C and 30°C, and analyses for both conditions were available. The 15°C case was used for model verification purposes. Table IV shows the comparison of the system level predictions of the model versus those of the design proposal.

TABLE IV

MODEL PREDICTION VERSUS PLANT PROPOSAL VALUES

		Design proposal	Model prediction
Water production	m^3/day	30,000	30,600
System recovery		40%	40%
Capital cost (CC)	$M	50.94	39.2
CC, intake	$M	15.4	15.6
CC, pre-treatment	$M	15.36	15.68
CC, RO train	$M	5.98	8.3
CC, other	$M	14.2	-
Energy consumption	kWh/ m^3	4.1	3
Operational cost	$/day	-	11,300

Because this proposed design was used to calibrate some of the model parameters, there is a very close agreement between the results of model prediction and those of the design proposal. The major discrepancies come from the capital costs and energy consumptions, which are not considered in the model such as post-treatment cost (approximately $1M), and civil and electrical costs (approximately $13M). The unit price of the membrane elements assumed in the model is based on online prices, which would be higher than the wholesale prices available between vendors and contractors.