The Modular Design of Photovoltaic Reverse Osmosis Systems – Making Technology Accessible to Non-Experts

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Abstract

Photovoltaic reverse osmosis (PVRO) systems can provide water to many underserved communities. These systems need to be custom tailored for the water demand, solar insolation and water characteristics of a specific location. Systems can be constructed from modular components to be cost effective. Designing a custom system composed of modular components is not a simple task. For a given modular inventory, a large number of possible system configurations exist. Determining the best system configuration is a daunting task for a small community without expertise. This paper presents a computer-based modular design method that can enable non-experts to configure such a system for their community from an inventory of modular components. The method employs fundamental engineering principles to reduce the number of possible configurations and optimization methods to configure a system. Example cases for a range of communities demonstrate the power of this approach.

Keywords: Photovoltaic Reverse Osmosis, System Design, Optimization

1 Introduction

1.1 Motivation

Access to safe drinking water is a critical problem for many isolated communities. They often have access to seawater or brackish groundwater, making desalination a possible solution. However, desalination is an energy intensive process. Power is often a critical issue for remote communities that are off the electrical grid. Diesel generators can be used, but they pollute the environment and fuel is expensive. It has been shown that photovoltaic powered reverse osmosis (PVRO) desalination systems can provide water for these locations and can be cost effective for well designed systems in terms of water produced over the system lifetime [1].

Each remote community has different seasonal solar characteristics, water chemistry and water demand and for best performance, a PVRO system needs to be custom configured to meet the individual needs of the community. Systems assembled from inventories of mass-produced commercial components are most cost-effective. Unfortunately, choosing the system configuration from an inventory of available modular components to meet the individual needs of a location is not a simple task. For a given modular inventory, there are a very large number of possible system configurations. An experienced designer could select the best components and architecture. However, for remote areas without experts, determining the best system configuration is difficult.

This paper presents a computer-based modular design method that will enable non-experts to configure the best custom PVRO system from an inventory of available components. This algorithm applies design filters to a component inventory to limit the size of the design space for a given application and location. An optimization is then conducted over this reduced design space to determine the best system configuration.

1.2 Background

Researchers have developed methods to optimize reverse osmosis desalination systems [2-6]. Initial research developed a generalized reverse osmosis system representation which was used in a mixed-integer non-linear program (MINLP) to determine the two-stage reverse osmosis system that would satisfy a required water production [2]. Researchers have also simplified this approach to eliminate some of the integer design variables [3-5]. Other system representations based on graph-theory have also been developed to optimize the configuration of a PVRO system [6]. The models used in these methods make the simplifying assumption that water flows through the network can be determined arbitrarily, when these rely on valve positions and pump operating points. Also, these methods lack the ability to incorporate modules from a given inventory, which is essential for small remote communities.

Modular design methods have also been developed for other applications, such as robotic systems. Researchers considered inventories of different robotic links, end effectors, robot bases, and power systems. Genetic algorithms were employed to optimize these discrete systems [7-10]. Researchers developed methods to reduce the size of the design space to limit the computational effort required in system optimization [7, 8]. These methods are domain specific and can't be directly applied to PVRO systems. Also, these cases considered simple cases and the associated models were not complex, making the large design space easy to manage.

Modular design methods have been used to design of analog and digital electronic circuits. Again, genetic algorithms were used to design circuits such as analog filters [11-14] and transistor based amplifiers [13]. These methods are not applicable to the design of modular PVRO systems as the methods didn't consider inventories of potential modules, and used relatively simple system models.

Automated network synthesis has also been applied in the design of heat exchanger, mass exchanger, and chemical processing networks. These problems were commonly solved using genetic algorithms [15-17]. These methods provided insight for the modular design problem, but are not directly applicable. All of these approaches had limited system topology optimization, and did not incorporate different module types into the problem. A new method is needed to automatically design PVRO systems for an individual application and location.

1.3 Approach

This paper presents a computer-based modular design method that will enable non-experts to configure the best PVRO system for a particular community from an inventory of potential system components, as shown in Figure 1. The inventory consists of different motors, pumps, reverse osmosis membranes, energy recovery devices and PV panels. Even for small inventory, there are many possible system configurations, or in other words, a large design space. The approach first prunes the size of the design space using filters based on fundamental engineering principles to make the problem tractable. The algorithm then performs an optimization on the reduced design space using a genetic algorithm. The optimization routine employs a new experimentally-validated graph-based modeling approach to evaluate different system configurations. This approach is demonstrated using several sample cases with various system scales and locations.

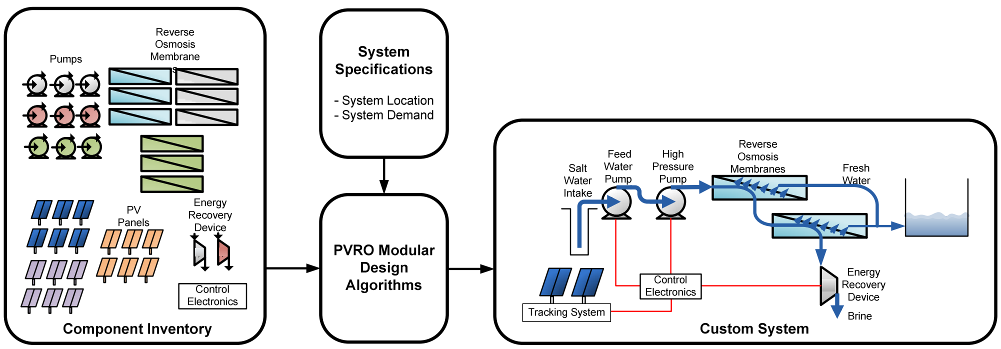


Figure 1: PVRO modular design problem.

2 Modular Design Approach

2.1 Problem Description

The problem considered is the design of a PVRO desalination system for a remote community using an inventory of modular components. It is assumed that the systems are designed to operate variably to eliminate the need for energy storage in the form of batteries. Also, it is assumed that the system requirements, such as the solar radiation, input water salinity and water demand for the community are well known. Using this information, the algorithms can be used to configure a custom system for the community which can be constructed from modular components by a non-expert.

2.2 Modular Design Approach Overview

The optimization framework to configure PVRO systems from an inventory of available modular components is shown in Figure 2. In this framework, a series of different filters are used to systematically reduce the size of the design space. The preliminary filters use computationally efficient, simple tests to eliminate inappropriate modules and subassemblies. The smaller design space is then further refined by an assembly level filter using relatively simple calculations. Finally, a high-fidelity model is used on the fully reduced design space to optimize the system and determine the final PVRO configuration.

The PVRO system configuration is represented by a series of discrete integer variables. In addition, the equations which describe the system performance are non-linear. A genetic algorithm was selected to optimize the final system configuration as they can easily encode discrete variables and incorporate non-linear equations. Genetic algorithms are often the preferred choice for topology optimization problems.

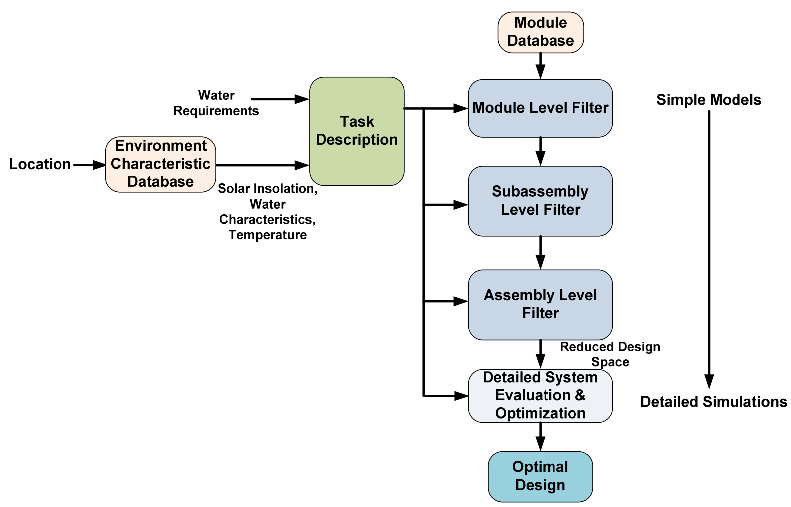


Figure 2: Modular design architecture.

2.3 Design Space Example

To show the effectiveness of this approach, a design space study for a modular PVRO inventory was performed. For the simple inventory shown in Figure 3, a series of filters were applied to reduce the size of the design space. To determine the initial design space, it is assumed that each system must contain at least one PV panel, one pump and motor, one RO membrane, and one energy recovery device or pressure control valve. It is also assumed that the required pressure vessels, connecting components and power control electronics are readily available.

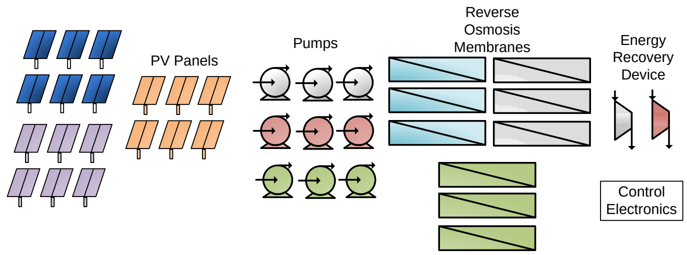


Figure 3: Inventory used in modular design space analysis.

Full presentation of combinatorics and the design filters is beyond the scope of this paper, but the reduction in the design space is shown in Table 1. The size of the initial design space is approximately 10^{108}. By applying simple physical principles and constraints, the size of this design space is reduced to 10^{7}, a design space size that is readily handled by an optimization routine.

Table 1: Design space reduction by modular design algorithm.

Filter Level	Design Space Size
Component Library	$\sim 10^{108}$
Module Level Filter	$\sim 10^{48}$
Subassembly Level Filter	$\sim 10^{42}$
Assembly Level Filter	$\sim 10^{7}$

2.4 System Optimization

The final step in the modular design algorithm is to optimize the PVRO system over the reduced design space. The system is represented by binary and integer variables, making the optimization difficult. This particular configuration can be easily incorporated into a genetic algorithm, which is used here.

The optimization routine is coupled to a detailed system model, described below, to determine the most cost-effective configuration that satisfies the water requirements of a location. The design variables for this problem consist of the component connections (binary variables), number of components (integer variables), and component types (integer variables).

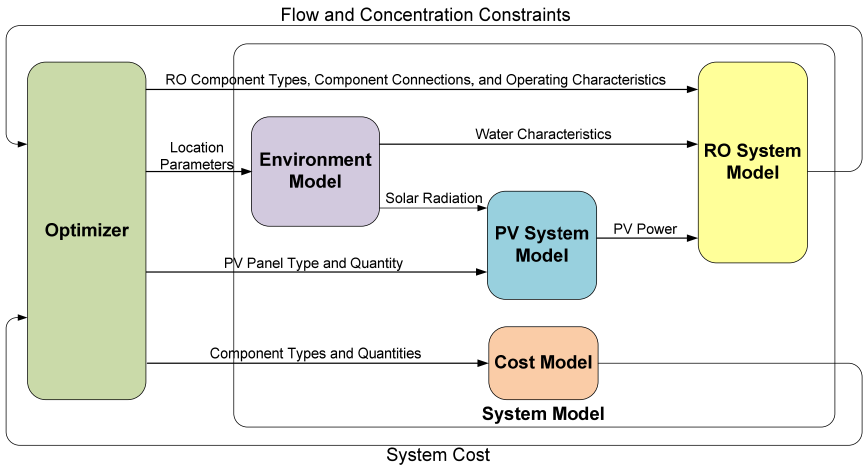


Figure 4: Optimization and model setup.

3 System Modeling

The final step in the modular design algorithm requires a detailed system evaluation tool to implement a genetic algorithm optimization. In this model structure, historical environmental data for the water salinity and solar radiation for a given location are used [18, 19]. This data is used by models of the PV and RO components to determine the system performance. The PV and RO components coupled via the system power.

3.1 Environment Modeling

Knowledge of the local water conditions and solar conditions are required to design a PVRO system for a small community. During a design, the water salinity and composition are determined using a water assay. For the sample cases conducted here, the water salinity and temperature is determined from the World Ocean Database [19]. Average yearly values are used for all sites.

Solar radiation varies greatly over the course of the year due to changing seasons and local weather. To account for these variations, an average sunny day and an average cloudy day is simulated for each of the four seasons. The solar profile for the average days are determined from typical year data from the software Meteonorm [18]. The number of these typical days is determined from the solar insolation using the following relationship:

$$H = \frac{n_{sun}}{n_{total}} H_{sun} + \left(1 - \frac{n_{sun}}{n_{total}}\right) H_{cloud} \tag{1}$$

where H is the average solar insolation in the season, H_{sun} is the solar insolation on sunny day during the season, H_{cloud} is the solar radiation on a cloudy day, n_{sun} is the number of sunny days in the season, and n_{total} is the total number of days in the season. The average water production in each year can be determined by taking a weighted average of those values.

3.2 PV System Modeling

The PV system model determines the power output for a given solar profile, panel type, and number of modules. The PV modules are assumed to be identical. Manufacturer's data is used to describe the panel's dimensions, efficiency, and thermal properties. Using these properties, the power produced by the PV system is:

$$P_{Solar} = n_{panel} \left[\eta_{PV} \eta_{elec} G A_{PV} (1 + \alpha (T_{cell} - 25)) \right] \tag{2}$$

where P_{solar} is the power produced by the PV system, n_{panel} is the number of PV panels, η_{PV} panel efficiency of the model considered, η_{elec} is the efficiency of the control electronics, G is the solar radiation, A_{PV} is the PV panel area, α is the temperature coefficient of the panel and T_{cell} is the cell temperature. The cell temperature can be estimated using the following relationship:

$$T_{cell} = T_{amb} + \frac{G(NOCT - 20)}{800} \tag{3}$$

where T_{amb} is the ambient temperature and $NOCT$ is the normal operating cell temperature of the model being considered.

3.3 RO System Modeling

The RO system model must determine the water output flow rate and water quality for a given component selection, system topology, pressure operating point, power input, and input water salinity. A graph is used to represent and analyze the reverse osmosis system. The RO system components and connecting pipes are graph edges. Each edge has a type based on the component it represents and associated equations which govern the pressure, flow and water concentrations. An example system and its graph representation can be seen in Figure 5.

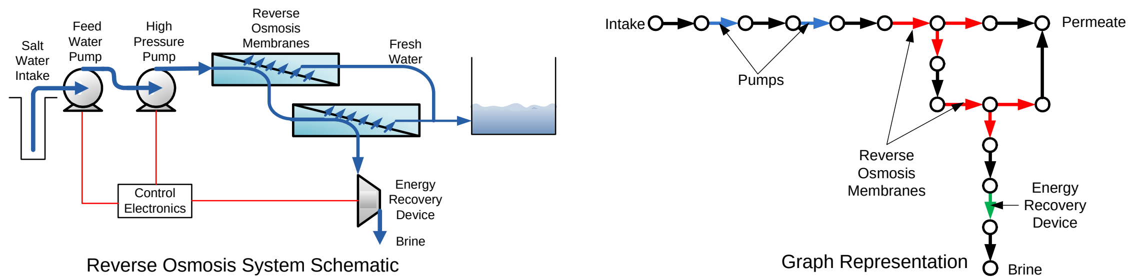


Figure 5: Reverse osmosis system and graph representation.

This approach has two advantages. It can easily capture any reverse osmosis system configuration using a node adjacency matrix of zeros and ones and a vector representing the system components, which is easily implemented in a genetic algorithm optimization. It also allows the system equations to be decoupled that allows for an iterative solution approach.

The time required to compute the water output for a single power setting takes on the order of seconds. To compute the water output using a varying power input for an average year would take many minutes, making this approach infeasible for optimization. Fortunately, the resulting system of equations, while non-linear, can be accurately approximated by interpolating between evaluated function points. The resulting water production for a sample PVRO system is shown in Figure 6. To determine the water production of a system, the graph model is generated and evaluated at 8 different power inputs, and the function evaluations form a surrogate RO system model. This surrogate model is then used for the solar profiles to determine the water production of the combined PVRO system.

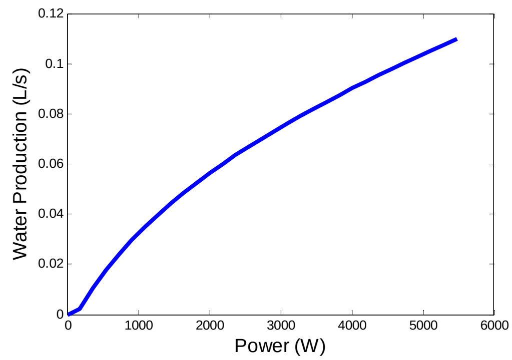


Figure 6: RO system water output for different power inputs.

3.4 RO System Equations

The equations to determine the pressures, flows and concentrations in the RO network are written by observing the flow of water through the network must be conserved. Therefore, at each node:

$$\sum_{input\_edges} Q_i = \sum_{output\_edges} Q_i \tag{4}$$

where Q_i is the flow along edge i.

The salt must also be conserved throughout the network. The salt conservation is applied at each node as follows:

$$\sum_{input\_edges} Q_i C_i = \sum_{output\_edges} Q_i C_i \tag{5}$$

where C_i is concentration of the water flowing along edge i.

The changes in pressure and concentration throughout the network are governed by the individual components. Full presentation of these equations is beyond the scope of this paper. The RO component equations can be found in [20].

3.5 Model Verification

The PVRO system modeling approach was verified using data from the MIT Experimental PVRO System, shown in Figure 7. The system schematic and model representation are shown in Figure 8. It is composed of a tracking PV panel, custom control electronics, parallel DC pumps, a Clark pump energy recovery system, reverse osmosis membrane within a pressure vessel, and plastic water tanks. The system is equipped with custom control electronics and designed to operate variably to eliminate the need for batteries. The system is fully instrumented and computer controlled to optimize the system water output, and is designed to produce approximately 350 L of fresh water per day in Boston on a sunny summer day. A full description of the system and component characteristics can be found in [20].

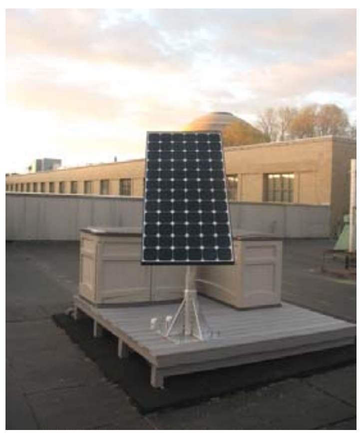


Figure 7: MIT experimental PVRO system.

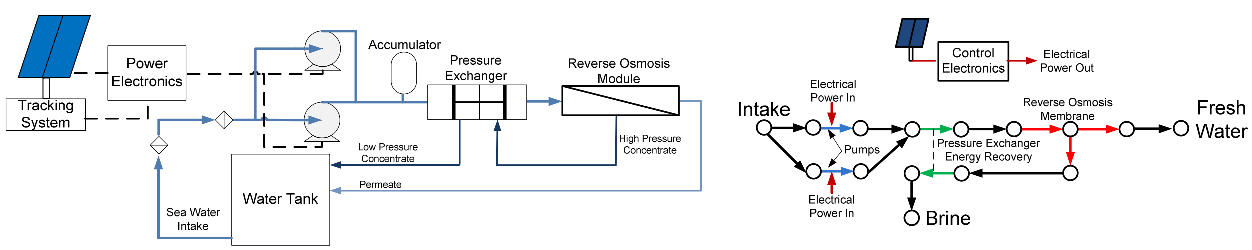


Figure 8: MIT experimental PVRO system schematic (left) and model representation (right).

Data from a partly cloudy summer day was used to validate the modeling approach. The solar profile used as an input to the model is shown in Figure 9 and the water produced by the experimental system and the model prediction is shown in Figure 10. There is a very good agreement between the data and model values, with an error of less than 8%. This shows that the graph modeling approach and the simplified analysis method accurately predict system performance. These models are appropriate for use with the modular design approach.

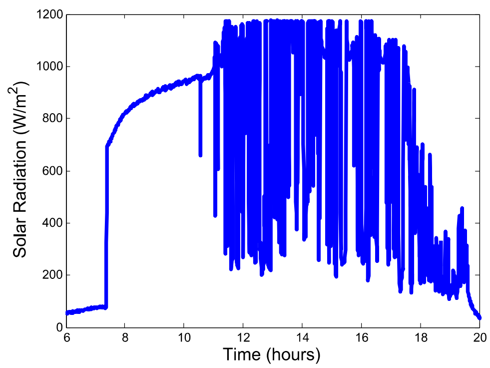


Figure 9: Solar input for model validation.

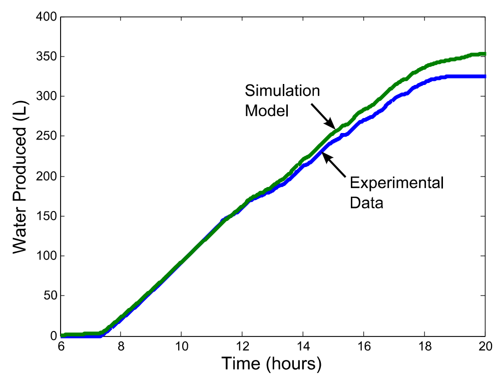


Figure 10: Experimental validation of modeling approach.

4 Optimization Examples

4.1 Economics

The objective of this design process is to minimize the net present cost of the PVRO system assuming a system life of 25 years and a 4% interest rate. Both system capital costs and maintenance costs are considered. The system assembly costs and infrastructure costs such as land, site preparation, water intake systems, brine disposal and water distribution system costs are not considered here. The component costs for the case studies are based on manufacturer's and distributor's prices. The average replacement rates shown in Table 2 are used for used to determine the lifetime system cost. A discussion of the economic analysis equations is beyond the scope of this paper, details can be found in [20].

Table 2: Component replacement rates [21].

Component	Lifetime (Years)
PV Panels	25
Control Electronics	10
Membranes	5
Pumps	10
Motors	10
Energy Recovery Units	10

4.2 Problem Description

A series of sample cases were conducted to demonstrate the approach. Systems were designed for four different locations with a seawater source and one location with a brackish water source. The location details are shown in Table 3. These locations provide a range of different water salinities and solar insolation values.

Table 3: Locations for PVRO modular design sample cases.

Location	Water Salinity (ppm)	Average Yearly Solar Insolation ($kWh/m^2/day$)
Albuquerque, NM	3000	5.79
Boston, MA	32664	4.21
Brisbane, Australia	35438	5.31
Cape Haiten, Haiti	36275	6.05
Limassol, Cyprus	39182	6.25

Systems were designed for different average water demands, ranging between 1 m^3/day and 20 m^3/day. To accommodate this wide range of systems, a large component inventory was constructed. Figure 11 shows this inventory. It consists of 6 different types of motors, 8 different types of pumps, 8 different reverse osmosis membranes, 8 different types of PV panels, 2 different hydraulic motors, 2 different generators, 5 pressure exchange energy recovery devices, and one pressure control valve. As was mentioned above, the objective of the design was to minimize the 25-year lifetime cost.

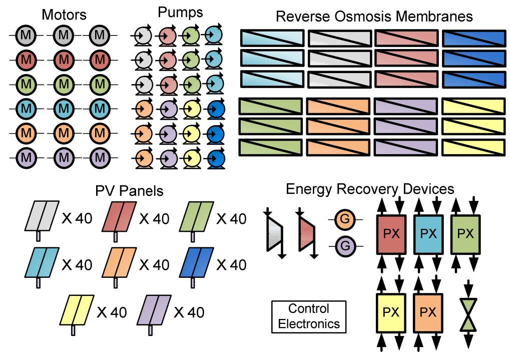
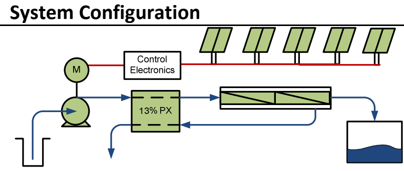
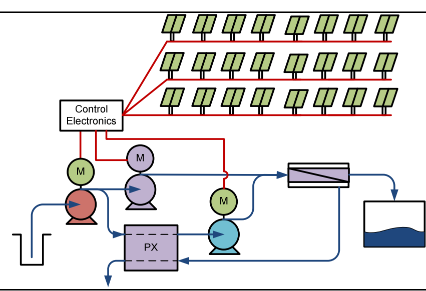
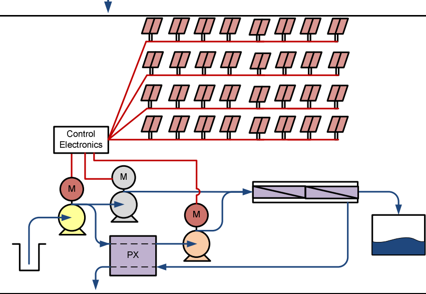


Figure 11: Component inventory used for examples.

4.3 Varied System Scale

In the first test, different scale systems were designed for Boston, MA. The results for systems which produce 1m^3, 5m^3 and 20m^3 of water per day are shown in Table 4. It can be seen that the system configurations becomes more complex as the system scale increases. The effect of economies of scale can be seen. For the 1m^3 system, the water cost is \$1.65/m^3. For the 20 m^3 system, the water cost decreases to \$0.85/m^3. This also demonstrates the modular design algorithm is effective at designing systems of different scales.

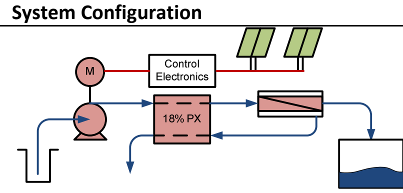
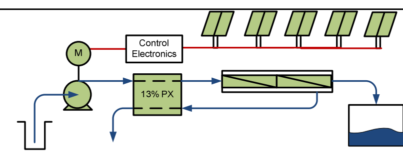
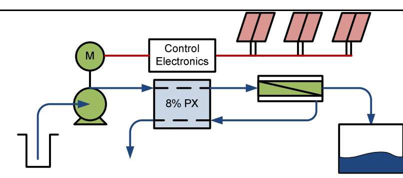
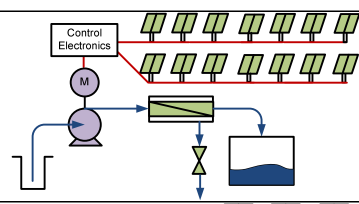
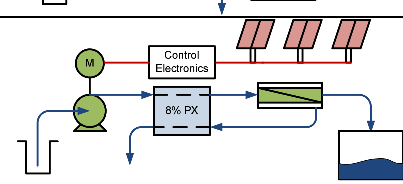
Table 4: Optimization results for varied system scale.

System Size	System Stats	System Configuration	Component Details	
1 m^3	**Lifetime Cost: \$13906** Capital Cost: \$6686 Water Cost: \$1.65/m^3		Panel Type	225 W Panels
			Motor Type	1 HP Motor
			Pump Type	300 GPH Vane Pump
			Energy Recovery Type	13% Constant Recovery Ratio Pressure Exchanger
			Membrane Type	4" Diameter, 40" long, Dow SWHRLE
5 m^3	**Lifetime Cost:\$59258** Capital Cost:\$27654 Water Cost: \$1.44/m^3		Panel Type	225 W Panels
			Motor Type	2 x 0.5HP Motor, 5 HP Motor
			Pump Type	1000 GPH Feed Pump, 450 GPH Piston Pump, 1000 GPH Boost Pump
			Energy Recovery Type	Pressure Exchanger
			Membrane Type	8" Diameter, 40" long, Dow SWHRLE
20 m^3	**Lifetime Cost:\$149568** Capital Cost:\$71794 Water Cost: \$0.85/m^3		Panel Type	295 W Panels
			Motor Type	2 x 1HP Motor, 15 HP Motor
			Pump Type	4000 GPH Feed Pump, 1320 GPH Piston Pump, 4000 GPH Boost Pump
			Energy Recovery Type	Pressure Exchanger
			Membrane Type	2 x 8" Diameter, 40" long, Dow SWHRLE

4.4 Varied System Location

Table 5 shows the results for a 1 m^3 system designed for different locations: Albuquerque, NM, Boston, MA, Brisbane, Australia, Cape Haïtien, Haiti and Limassol, Cyprus. The configurations are similar for most locations except for Limassol, Cyprus, where an energy recovery device was excluded from the design. Energy recovery devices, especially for small-scale applications, are expensive. In Cyprus, there is an abundant solar resource, making the power produced by the PV panels less expensive. As a result, the most cost effective choice is a less efficient system with more PV panels. This is not an obvious choice and it would be difficult for a non-expert to capture this subtlety.

Table 5: Optimization results for 1m^3 PVRO system in various locations.

System Location	System Stats	System Configuration	Component Details	
Albuquerque (Brackish Water)	**Lifetime Cost: $10074** Capital Cost: $4953 Water Cost: $1.08/m^3		Panel Type	225 W Panels
			Motor Type	0.5 HP Motor
			Pump Type	140 GPH Vane Pump
			Energy Recovery Type	18% Constant Recovery Ratio Pressure Exchanger
			Membrane Type	4" Diameter, 40" long, Applied Membranes M-B4040AHF
Boston	**Lifetime Cost: $13906** Capital Cost: $6686 Water Cost: $1.65/m^3		Panel Type	225 W Panels
			Motor Type	1 HP Motor
			Pump Type	300 GPH Vane Pump
			Energy Recovery Type	13% Constant Recovery Ratio Pressure Exchanger
			Membrane Type	4" Diameter, 40" long, Dow SWHRLE
Brisbane	**Lifetime Cost: $11954** Capital Cost: $5965 Water Cost: $1.32/m^3		Panel Type	295 W Panels
			Motor Type	1 HP Motor
			Pump Type	300 GPH Vane Pump
			Energy Recovery Type	8% Constant Recovery Ratio Pressure Exchanger
			Membrane Type	4" Diameter, 40" long, Dow SWHRLE
Limassol, Cyprus	**Lifetime Cost:$10957** Capital Cost: $7324 Water Cost: $1.24/m^3		Panel Type	225 W Panels
			Motor Type	5 HP Motor
			Pump Type	300 GPH Piston Pump
			Energy Recovery Type	None
			Membrane Type	4" Diameter, 40" long, Dow SWHRLE
Haiti	**Lifetime Cost:$11691** Capital Cost:$5623 Water Cost: $1.28/m^3		Panel Type	295 W Panels
			Motor Type	1 HP Motor
			Pump Type	300 GPH Vane Pump
			Energy Recovery Type	8% Constant Recovery Ratio Pressure Exchanger
			Membrane Type	4" Diameter, 40" long, Dow SWHRLE

4.5 Result benchmarking

To demonstrate the effectiveness of approach, the system designed to produce an average of $1m^3$ average in Haiti was simulated in Boston. The results for this system were compared to a system specifically designed for Boston. The system simulation for an average spring day is shown in Figure 12. The Boston system produces 1.09 m^3 of water on the spring day, where the system tailored for another location (Haiti) only produces 0.69 m^3 of water.

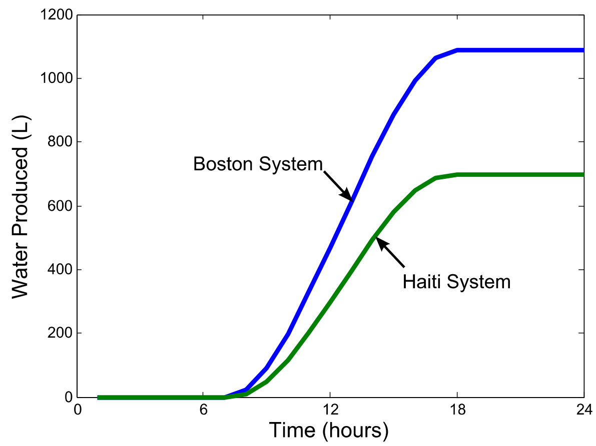


Figure 12: Comparison of two systems simulated in Boston.

Over the course of the year, the system optimized for Boston is able to produce 1.03 m^3 of water per day on average at a cost of $\$1.65/m^3$. For the system optimized for Haiti produces 0.65 m^3 of water per day on average at a cost of $\$1.97/m^3$. This suggests that the algorithm is able to design a system that is best for a location and demand.

5 Conclusions

This paper presents a design approach that can enable non-experts to configure PVRO systems for their communities from an inventory of components to meet the requirements of a particular location and water demand. The approach is able to handle the very large number of possible system configurations that exist for a given inventory. It uses a computer-based modular design algorithm to first limit the size of the design space and then performs an optimization. The optimization uses an experimentally validated system model to evaluate the system production. This algorithm is shown to be effective, discovering different system configurations are more appropriate for different locations. The method can be used in software tools to enable non-experts to configure PVRO systems for small and medium-scale applications.

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