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A multi-stage optimization model for flexibility in engineering design

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Abstract

Engineered systems often operate in uncertain environments. Understanding different environments under which a system will operate is important in engineering design. Thus, there is a need to design systems with the capability to respond to future changes. This research explores designing a hybrid renewable energy system while taking into account long-range uncertainties of 20 years. The objective is to minimize the expected cost of the hybrid renewable energy system over the next 20 years. A design solution may be flexible, which means that the design can be adapted or modified to meet different scenarios in the future. The value of flexibility can be measured by comparing the expected cost without flexibility and expected cost with flexibility. The results show that a flexible design for hybrid renewable systems can decrease the expected cost by approximately 30%.

Keywords
Engineering design, hybrid renewable energy system, flexibility, Monte Carlo simulation, Bayesian optimization.

1. Introduction
Traditional engineering design assumes that engineered systems will operate in stable environments in which the regulations, technologies, and usage patterns will not change [1]. In reality, designs may not succeed because the operating conditions or demand for a product may change. Since engineered systems constantly face changes and unpredictability in their operating environments, these systems should be designed with the capability to respond to the future changes [2]. Flexibility in design enables the designers to review the initial design of a system in the future and provides them with the option to take actions to modify the system. Therefore, designers should consider the future uncertainties in the initial design of the system. A flexible design gives designers the ability to easily modify the design in order to respond to changing circumstances such as increasing or decreasing demand [2]. Engineered system design can be viewed as a decision-making process, but complexity and uncertainty make decision making for systems design challenging [3, 4]. Designers need to understand the costs and benefits of designing a flexible system in order to determine if they should pursue a flexible design. Engineering economics can help designers evaluate those costs and benefits.

Engineered systems, especially large-scale infrastructure, may operate for a long time. A framework is needed to incorporate both long-range uncertainties and computationally expensive simulations, which are used to evaluate engineering designs. This paper optimizes the design of a hybrid renewable energy system (HRES) when the objective function is evaluated using Monte Carlo simulation that incorporates uncertainties over a 20-year lifespan. Two models are developed to optimize the system design. The first model uses a simulation optimization algorithm that considers 10,000 possible future scenarios, and the design variables are selected that minimize the expected discounted cost. In this model, the initial design of the HRES will be fixed and unchanged during the planning horizon. The second model allows the decision makers to review the initial design in the future and modify the design depending on how the uncertainty is realized.

The uniqueness of this paper is to measure the value of flexibility in the complex engineered systems which require computationally expensive simulations to evaluate the objective function and develop a model to optimize the design of engineered system under highly uncertain parameters. This is the first study that uses a simulation optimization technique for the flexible design of HRES. The mathematical model is modified to identify the flexible design by considering multiple stages of decision making to minimize the expected cost of design. The optimization algorithm measures the value of flexibility by comparing the value of the design with and without flexibility.

2. Decision Making Framework

The high cost and uncertainty with the sources of the renewable energy technologies are the main challenges of renewable energy usage. To overcome these challenges, renewable energy sources can be integrated to meet energy demand. The HRES under consideration consists of solar panels, wind turbines, a battery, an electrolyzer, a hydrogen tank, and fuel cells. The mathematical model for the HRES comes from [5, 6]. The solar panel and wind turbine work to generate electricity. If solar and wind generation exceeds demand, then the surplus amount of energy is stored in the battery for future use. The battery is used if wind and solar generation is less than demand. If battery's capacity is exceeded, any excess energy is converted to hydrogen by the electrolyzer and stored in the hydrogen tank. Energy storage systems are included in the model to overcome the mismatch between the electricity demand and supply [7]. If the wind, solar, and battery sources of energy cannot fulfill demand, the fuel cell can convert the stored hydrogen to electricity. If the combination of all these sources cannot satisfy demand, diesel fuel can be purchased to satisfy the remaining demand. Figure 1 depicts the energy flow inside the HRES.

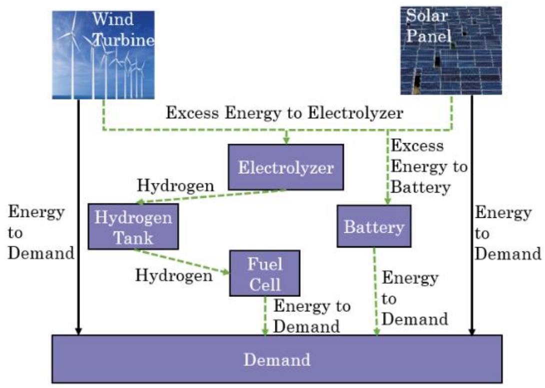

Figure 1: The energy flow of hybrid renewable energy system [6].

$$Min\ cost = \sum_{i=1}^{I} c_i^{inv} cap_i + \sum_{i=1}^{I} c_i^{om} \frac{(1+\lambda)^T - 1}{\lambda(1+\lambda)^T} cap_i + \sum_{i=1}^{I}\sum_{r=1}^{R_i} c_i^{rep} \frac{1}{(1+\lambda)^{L\times r}} cap_i + c_f \sum_{t=1}^{T} p_t \tag{1}$$

Subject to:

$$E_{pv} = 0.15 A_{pv} S \tag{2}$$

$$E_{wg} = \begin{cases} 0.36 A_{wg} u^3 & \text{if } 3.5 < u < 14 \\ 1000 A_{wg} & \text{if } 14 < u < 25 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$E_{fc} = \begin{cases} 0.6 min(D - (E_{wg} + E_{pv} + Ebat_t), 0.95 Etank_t) & \text{if } D < E_{wg} + E_{pv} + Ebat \ \& \ Sbat = Sbat_{\min} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$E_{el} = \begin{cases} 0.6(E_{wg} + E_{pv} + Ebat - D) & \text{if } D > E_{wg} + E_{pv} + Ebat \ \& \ Sbat = Sbat_{max} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$Etank_t = Etank_{t-1} + E_{el} - E_{fc} \tag{6}$$

$$Sbat_t = Sbat_{t-1} + 0.8(Ebat_t - Dbat_t) / Batcap \tag{7}$$

$$Sbat_{min} < Sbat_t < Sbat_{max} \tag{8}$$

$$E_{i,t} \le cap_i \quad \forall i = 1,\dots,I,\ t = 1,\dots,T \tag{9}$$

$$0 \le cap_i \le cap_i^{max} \quad \forall i = 1,\dots,I \tag{10}$$

The decision variables for designing the HRES are the capacity of the PV panel, the wind turbine, the battery, the electrolyzer, the hydrogen tank, and the fuel cell. The decision maker should choose the capacity of each component that minimizes the expected discounted life-cycle cost of the HRES. The cost function consists of four parts: investment, operations and maintenance, replacement, and diesel fuel costs. The parameters c^{inv}, c^{om}, and c^{rep} are the investment, operations and maintenance, and replacement cost of the design components. The number of times the i^{th} component will be replaced is R_i. L_i is lifetime of the *ith* component. The planning-time horizon has T total periods, and λ represents the interest rate. The parameter c_f is the diesel fuel cost and p_t is the amount of fuel purchased at period t. Since several of these parameters are uncertain, Monte Carlo simulation is used to calculate the cost function. The expected cost of design is calculated as the average after N different simulations.

Eq. (2) shows the output power of the PV panel. S indicates the solar irradiation on the surface of the panel, and A_{pv} represents the area of the solar panel. Eq. (3) shows the output power of the wind turbine where A_{wg} is the area of the rotor and u is the wind velocity. Eq. (4) shows the amount of energy generated by the fuel cell. The amount of energy generated by electrolyzer to be stored in the hydrogen tank is calculated with Eq. (5). The amount of energy in the tank at time t is calculated with Eq. (6). Eq. (7) shows the battery charge at time. *Batcap* depicts the capacity of the battery. Eq. (8) states that the level of battery charge should be between $Sbat_{min}$ and $Sbat_{max}$. The energy generated by each component at time t must not exceed the chosen capacity for each component cap_i. Each component also has a maximum capacity, cap^{max}.

The simulation optimization models can be solved with the Bayesian optimization algorithm. The Bayesian optimization algorithm considers the objective function as a random variable that follows a Gaussian distribution. The objective function is simulated for a selected set of design alternatives, which are used to update the probability distribution over the objective function. After calculating the posterior mean and variance for the objective function, Bayesian optimization selects the next decision variable for which to simulate the objective function. The algorithm continues until there is enough confidence that the optimal decision variable has been selected [8]. This paper uses the Random Embedding Bayesian Optimization (REMBO) developed by Wang et al. [9] to implement the Bayesian optimization algorithm.

3. Application

In this section, the design of HRES is optimized to deliver electricity for the state of California under highly uncertain demand. The planning horizon is the next 20 years (from 2017 to 2036) and the period of decision making is 1 month. The investment and replacement cost parameters follow triangular distribution function. Table 1 shows the value of the investment, maintenance and replacement cost parameters along with the lifetime of the components of the HRES. It is assumed that the hourly solar irradiation is normally distributed with the mean of 0.5 kwh/m2 and the standard deviation of 0.1. It is assumed that the wind velocity is normally distributed with the mean of 5 m/h and standard deviation of 1. The interest rate, λ, is 2% per year.

Table 1: The cost (in millions of $ per 1 MW) and lifetime parameters of the components of the HRES [9].

Component	L (years)			$c^{inv}(\times 10^3)$			$c^{rep}(\times 10^3)$			c^{om}
	lower limit	mode	upper limit	lower limit	mode	upper limit	lower limit	mode	Upper limit	-
Wind	10	25	30	5	7	9	5	6	7.5	20
Solar	10	20	25	1.5	2.5	3	1.2	2	2.5	75
Battery	1	5	7	1.5	2	2.2	1.3	1.5	2.1	20
Electrolyzer	5	10	13	1	2	3	0.9	1.5	2	25
Fuel Tank	10	20	25	0.8	1.3	1.5	0.8	1.2	1.3	15
Fuel Cell	0.7	1.7	2.7	1	3	4	1.9	2.5	3	172

3.1 Demand Forecast

Renewable energy systems are designed for long-term usage. It is necessary to establish those sources of electricity generation considering possible future scenarios. Demand for the electricity is serially autocorrelated and time series analysis models autocorrelated data. The arima function in MATLAB software [10] is used to forecast the electricity demand using historical monthly demand data for electricity for California from 2001 to 2016 [11]. Monte Carlo simulation method is used to generate 10,000 paths for demand through sampling from ε (with the mean of 0 and the variance of 20,000) and applying it into the *arima* model. Figure 2 shows the generated scenarios for the demand for electricity for the next 20 years of simulation.

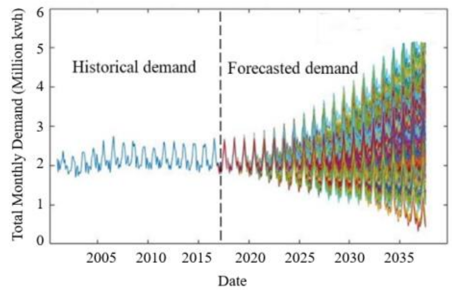

Figure 2: Simulation of electricity demand for California, 2017-2036.

3.2 Design without flexibility

The simulation optimization model (Eqs. (1-10)) has been solved considering 10,000 demand future scenarios of the next 240 months (i.e., 2017-2036), those generated with the arima model. The Bayesian optimization algorithm finds the design variables (i.e., capacity of the components of the HRES) that minimizes the expected discounted cost. In the design without flexibility, the system is designed once at the beginning of the system operation (i.e., 2017) and the design will not be modified in the future.

Table 2 shows the optimal result for design without flexibility. The results show that 78% of the demand during the 10,000 simulations from 2017-2036 are fulfilled with the solar panels and wind turbines. Since the amount of energy generated by these two sources exceed the demand for many time periods, the surplus amount of energy will be conserved in the battery and hydrogen tank for future use. The results show that the battery and fuel cell satisfy 17% and 4% of the demand, respectively. The HRES requires diesel to meet approximately 1% of the demand. This optimal design has an expected discounted cost of $40.66 trillion, with $9.56 trillion investment cost, $21.66 trillion operation and maintenance cost, and $9.4 trillion replacement cost.

Table 2: The optimal design of the HRES for design without flexibility.

Plant	Optimal Capacity (Giga watt)	Percentage (%)
Solar panel	392	78
Wind turbine	146	
Battery	89	17
Electrolyzer	1041	-
Hydrogen tank	3221	-
Fuel cell	138	4

Figure 3 shows a random simulation out of 10,000 demand simulations to illustrate how demand is fulfilled with different sources of energy in a random simulation. In this simulation the capacity of solar panel and wind turbine cannot fulfill the raising demand after 2020 so the battery and fuel cell will be utilized to supply the electricity to the demand.

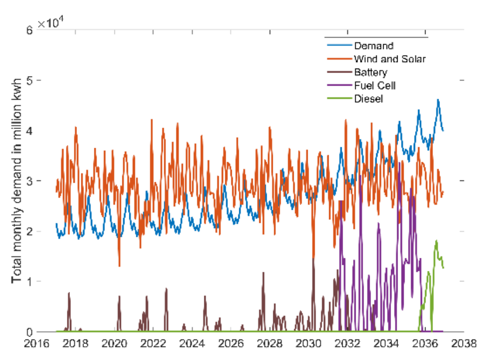

Figure 3: Demand fulfillment for a random demand scenario.

3.3 Design with flexibility

A flexible design may differ from the optimal design because an optimal design will be optimal for a probability-weighted combination of scenarios and the flexible design will allow for different designs, each of which depends on the realization of an individual scenario. In the design without flexibility, the decision maker designs the HRES based on all the future demand and cost simulations from the current time to the end of planning horizon. However, in the design with flexibility, the designers have the option to modify the design and decide whether to expand the capacities of the HRES, if it is needed to generate more electricity to meet increasing future demand. The design with flexibility strategy requires a smaller initial investment than the design without flexibility. This strategy defers additional costs to the future and takes advantage of the time value of money [12].

The proposed method for flexible design starts by optimizing the model (i.e., Eqs. (1-10)) during the first T_1 periods by considering all the N future scenarios in the time 0 to T_1. The optimal initial design will be used as an input in the design modifications stage. At time T_1, the decision for the capacity expansion will be made. The future scenarios from the design modification period to the end of planning (i.e., periods T_1 to T) is divided into K_2 different categories. Given the initial optimal design, the additional capacity should be found by minimizing the expected cost for each of the K_2 categories from T_1 to T. The total expected cost of the flexible design ECF has two cost items: (1) the initial expected cost and (2) the average capacity expansion costs of stage 2, discounted by the interest rate λ. ECF takes the following form:

$$ECF = E[cost^1] + \frac{1}{K_2}\frac{1}{(1+\lambda)^{T_1}}\sum_{k_2=1}^{K_2} E[cost^2] \,|\, cap^1 \tag{11}$$

In the above equation, it is assumed that demand can be in any of regions at any stage with equal probability.

In this study, one additional stage for the design modification is considered. In the stage 1, the initial design and expected discounted cost considering the uncertain demand profiles for 2017-2026 are calculated using Eqs. (1-10). The results of this first stage decision making show that the initial optimal design of the components of the HRES have less capacity than the optimal solution in the design without flexibility model (see Table 3). The initial optimal design from 2017-2026 serves as an input to decision making in stage 2, which covers 2027-2036. Given the initial optimal design, the Bayesian optimization determines whether or not additional capacity for the HRES should be constructed if demand is low, if demand is medium, and if demand is high ($K_2=3$). Stage 2 contains three different sets of design variables and three different expected discounted costs, one for each demand profile. The average expansion costs are calculated as the expected cost of additional capacity at stage 2. The total expected cost of flexible design is calculated using Eq. (11). Table 3 shows the optimal design for the HRES with flexibility assuming the design could be modified in 2027.

Table 3: The optimal design of the HRES with flexibility.

Component	Initial design	Stage 2		
		High demand	Medium Demand	Low Demand
Solar panel	263	0	0	0
Wind turbine	31	128	98	0
Battery	17	54	39	0
Electrolyzer	230	0	0	0
Hydrogen tank	616	0	0	0
Fuel cell	68	0	0	0
Expected Cost ($ trillion)	20.55	12.22	7.63	7.08

The initial expected cost in stage 1 is $20.55 trillion. Expanding the initial design to include more capacity for wind and battery in stage 2 in the medium and high demand scenarios increases the expected cost, but the expected cost of this expansion is less than if the cost was spent immediately. The design with flexibility enables the system to defer the additional cost of investment and replacement to the future and takes advantage of the time value of money. It also avoids the operation and maintenance cost for full deployment during the first 10 years of operation. The total cost of design with flexibility is $27.22 trillion. The value of flexibility is measured by subtracting the expected discounted cost of designing with flexibility from the expected discounted cost of designing without flexibility. The value of flexibility is $40.66 - $27.22 = $13.44 trillion, which represents a 33% percent reduction in the cost.

4. Conclusion

This paper provides a method to incorporate demand uncertainty into the flexible design of a HRES. The HRES is composed of six components: solar panels, wind turbines, a battery, an electrolyzer, a hydrogen tank, and a fuel cell. The optimal design of the HRES is identified considering 10,000 demand scenarios for electricity for California for the next 20 years. This optimal design without flexibility is computed with the Bayesian optimization algorithm and will not be modified in the future. However, a flexible design for the HRES allows the designers to modify the initial design in the future. The uniqueness of this paper is to measure the value of flexibility in a complex engineered system such as an HRES which requires computationally expensive simulations to evaluate the objective function. A design with flexibility is conducted where the HRES's capacity can be expanded in the future. The results show that a single design modification 10 years after the system deployment can reduce the system's expected discounted cost by 33%. For the future research, machine learning approaches (e.g., artificial neural networks [13, 14]) will be employed to make predictions on the parameters of complex engineered systems [15].

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