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Optimal Decision Guidance for the Electricity Supply Chain Integration With Renewable Energy: Aligning Smart Cities Research With Sustainable Development Goals

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ABSTRACT The evolution of the smart cities' research and the relevant discussion on well-being is challenging the design of policies, information systems, and computational methods toward the alignment to Sustainable Development Goals (SDG) of the United Nations. Sustainable GOAL 7—Affordable and Clean Energy—is the focus of this paper. The requirement to integrate certain levels of renewable energy sources into the electricity grids to meet sustainability measures creates unfavorable variability in the entire electricity supply chain and delays the integration of renewable energy sources into the energy systems. This paper introduces a methodology and an optimization model for the electricity supply chain that allows reducing the variability of the renewable energy sources supply by optimal planning of the supply chain operations. The methodology supports electricity decision makers to identify the optimal operation of the electricity supply chain, taking into account multiple objectives and supply chain designs, including innovative architectures. The multi-objective linearized optimization model allows regulating the flow rates of energy and water for the electricity supply chain. The methodology was evaluated, considering three possible integration architectures for the loads and real-time electricity pricing. For each of the studied architectures, the analysis showed the optimal dispatching to reduce the energy variation due to the increasing renewable energy penetration into the grid. The results show how the methodology can present decision makers with optimal operation of the supply chain, such that a minimum energy variation is achieved at a minimum cost. The key contribution of this paper to the agenda of the special section entitled ''Urban Computing & Well-being in Smart Cities: Services, Applications, Policymaking Considerations'' is multifold: It sets a scientific framework for the promotion of the SDG #7 and innovates in the design and deliverable of a fully functional eco-system for the optimization of the electricity supply chain. It also defines well-being as an affordable and clean energy primer.

INDEX TERMS Electricity supply industry, decision making, optimization, renewable energy sources, power-generation economics, power grids.

I. INTRODUCTION

Integrating renewable energy sources into the electricity grid provides immense opportunity to address many vital energy-related issues including increasing climate change and greenhouse gas emissions, reliance on fossil fuels, as well as the volatility of energy prices because of highly variable fossil fuel prices. However, due to the variability of renewable energy sources, the increased adaption of renewable energy comes at the expense of adding significant variability to the electricity grid leading to generation concerns, increased operational costs and many other challenges facing electricity supply chain [1].

The energy supply from renewables can be typically predicted given the installed systems capacity, efficiency levels,

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and the natural and climate characteristics of the geographical sites such as temperature, Direct Normal Irradiance (DNI), and wind speed. The variation of the supply significantly affects the operations of the electricity utilities, particularly as the portfolio of renewable energy sources increases. For example, California Publicly Owned Utilities (POUs) required to participate in the country's largest renewable energy purchase program. The POUs are required since early 2000s to source 33% of their electricity from renewables by 2020. This mandate was increased recently to reach 50% [2]. This level of adoption creates a major impact on electricity supply chain operating costs. To lessen the impact of renewables integration several control measures and techniques involving additional costs are employed. Some of the most commonly techniques include energy storage systems, operational balancing techniques, and many innovative approaches including water desalination and electrical vehicles [3].

This paper proposes an optimization modeling approach to support decision making in the electricity supply chain. The optimization model allows for identifying efficient operations to absorb the variability of the supply from the renewable energy sources and thus allowing optimum integration of renewables into the electricity grid. The main goal is to optimize the operations such that the net load variations caused by renewable energy over time is minimized. To prove the concept of this approach, the paper investigates various integration levels of renewables into the electricity supply chain. In addition, the paper investigates various supply chain design options (i.e., architectures) traditional and innovative non-traditional solutions proposed in the literature to lessen the impact of the integration of the renewables on the electricity grid. These design options are investigated with various integration control measures and techniques. These design options vary from incorporating simple water desalination system (i.e., reverse osmosis), to those with integrated energy storage (i.e., batteries), to a reverse osmosis desalination integrated with pumped hydro system. The proposed model is unique in providing means to incorporate innovative and non-traditional architectures, which are specifically important for the electricity grid adaption to renewable energy sources. The optimization results can be used to show that for a certain penetration level of renewable sources, a range of load variation reduction can be achieved for the range of design options of the electricity supply chain.

Specifically, the main contributions of the current work include. First, a methodology that supports electricity decision makers to identify the optimal operation of the electricity supply chain taking into account multiple objectives and supply chain designs including innovative architectures. Second, a multi-objective linearized optimization model that allows regulating the flow rates of energy and water for the design components of the electricity supply chain.

The remaining sections of the paper are organized as follows. Section II provides a background discussion including the techniques used to lessen the renewable energy impact on the electricity grids. Section III discusses research questions. Section IV provides details on the investigated architectures. Section V discusses the proposed methodology to evaluate the performance of the electricity supply chain. Section VI proposes the mathematical model. Section VII presents a real world case and its results. Section VIII concludes the paper with discussion and future directions.

II. BACKGROUND

Renewable energy power plants generate electricity only when the natural source is available unlike the conventional power plants which are turned on and off by operators at will. The direct relationship between renewable power generation and weather conditions is inevitable. Control measures are required to allow renewables full integration with the electricity grid and to lessen the impact of this integration on the grid.

A. INTEGRATION TECHNIQUES

Some of the techniques commonly used to lessen the impact of renewable energy integration on the electricity grid include Energy Storage Systems, Operational balancing methods, and a variety of innovative solutions.

Energy Storage is mainly a controlled reservation of energy in some form that can be released when needed. Electrical energy can be converted into other forms of energy for storage. Modern Storage Technologies can be grouped into six main categories according to storage medium. The most developed energy storage systems include Pumped Hydro Storage, Compressed Air Energy Storage, Flywheels, Lead-acid and Lithium-ion Batteries, High Temperature Batteries, and Flow Batteries [4]–[6]. The design options discussed in this paper incorporate two of these systems, Pumped Hydro Storage (PHS) and the traditional Lithium-ion Batteries (LiB). In the PHS, the electrical energy is used to pump water to a higher elevation reservoir. Natural force of gravity is used to allow water to flow back to a lower elevation water reservoir passing through turbines to generate power. In spite of the high initial costs of the PHS, it can achieve an efficiency of about 78% with low operating and maintenance costs in addition to its long economic life span of about 50 years. The LiB falls under the highly mature technology (over 150 years) and stores electricity as a chemical potential to be released later when needed as electricity [4]–[6].

It is very critical for the electricity grid operators to forecast renewable energy variabilities in order to maintain an adequate electricity availability to end user and to maintain a certain required balance to the electricity grid. Several physical and statistical forecasting methods for weather conditions are implemented to determine the amount of renewable electricity generated that will be injected into the electricity grid. Operational practices also contribute to controlling the variable generation of renewables. These practices are different from one country to another due to differences in renewable energy development, grid structure, market and institutional environments. Some of these practices include giving priority to renewable energy generation to be injected into the grid and enforcing upper limits on renewables generation [7], [8].

As more renewable energy penetrates the electricity grid, improved stability and reliability of electricity supply becomes more critical. More flexibility needed to be introduced to the electricity supply chain in order to provide the necessary balance between supply and demand of electricity. This may include developing advanced renewable energy generating units, having a centralized renewable energy generators control, and renewable energy modeling improvement. Moreover, the fact that flexibility of renewable energy systems is not mature yet and still under development, increasing the flexibility in conventional power plants (i.e. Hydro, crude oil, natural gas, coal, and nuclear) allows finding the adequate capacity and the flexibility for the electricity grid. In addition, large-scale transmission network expansions reduce the forecast errors for flexibility of renewable energy and enhance the balance between interconnected areas. Penetrating the electricity grid with large amounts of renewable energy creates sharp peaks that can be smoothened by load shifting giving better opportunity for grid control [8]. Many of the demand side loads can be used as a deferrable load such as water heating and desalination [9]–[11], electrical vehicles and manufacturing systems battery charging [12]–[14]. The current work assumes that a combination of storage systems and innovative techniques are being used to address the variability issues. Specifically, the optimization model assumes incorporating batteries, pumped hydro storage, and water desalination solutions. The following subsection describes the optimization modeling approaches used in the literature.

B. OPTIMIZATION MODELLING

Many researchers focused on optimizing the system design of the electricity supply chain when integrating renewable energy sources. Connolly *et al.* [15] provides a review of 37 computer-based tools for analyzing the integration of renewable energy into various energy systems with different objectives. Only a small number of these tools are focused on optimizing energy system operations to accommodate fluctuations of renewable energy generation mostly using deterministic models, linear network models, and simulation models. These tools are Energy plan [16], MesapPlaNet [17], H2RES [18], and SimREN [19].

Many researchers developed optimization models to optimize the system design. This requires taking into account existing power sources, renewable sources, and energy storage systems. These researchers primarily used nonlinear models to solve sizing problems while the energy system was modeled as a finite state machine. These models mainly employ Genetic and Evolutionary algorithms and use Pareto fronts to explore the possible solutions [20]–[22]. The other approach focuses on optimizing operating conditions of the system for each time step by modeling them as decision space variables and use in addition to Evolutionary and Genetic algorithms Linear and Mixed Integer Linear Programming in a two-level problem solving [23]–[26]. The later approach can be used to solve for small-scale problems or for global large size problems. The first approach requires precisely defining the operating conditions for the electricity plants and the storage. In addition, the number of the system states increases exponentially with the number of the system components. The second approach has its limitations as well specially when solving a problem with a large number of decision space variables, which is reflected on the time requirement. This paper addresses the issues in the current approaches in the literature by providing a linearized model with three decision variables that capture the flow rates between the system components.

The approach followed in this paper optimizes the operating conditions specifically when both traditional and innovative non-traditional solutions are employed as part of the system design. These innovative solutions include desalination systems and pump hydro systems. The linearized multi-objective model used in this paper employs three decision variables to represent the flow rates from and to system components. The objective function minimizes the undesirable variation of the load caused by the renewable generation over time and the annualized costs associated with the system design. Pareto efficiency is used to generate optimal solutions capturing the multiple objectives of the decision makers (beneficiaries) utilities. A Pareto frontier is composed by multiple optimization runs evaluating the two objectives in which each of the runs provides a Pareto efficient solution. A value (i.e., alpha) is used to allow the users to vary the weight of the two objectives according to his/her priorities.

III. RESEARCH QUESTIONS

Within the overall context of smart cities and well-being research, the issue or Energy Consumption & Optimization towards affordable and clean energy for social inclusive economic growth has a central position. The purpose of this research study is to analyze the issue of Electricity Supply Chains as a Well-Being primer. Towards this direction, the following are the key questions:

Research Question 1: How advanced computing methods can promote optimization techniques towards Sustainable GOAL 7: Affordable and Clean Energy?

Research Question 2: Which are the components of a methodological framework and an optimization model for the electricity supply chain that allow reducing the variability of the renewable energy sources supply by optimal planning of the supply chain operations?

Research Question 3: Which are the implications for Smart Cities Research and well-being? It also defines well-being as an Affordable and Clean energy primer. In our future research, we are targeting the exploitation of machine learning computational intelligence for the improvement of the performance.

IV. ARCHITECTURES

The paper assumes three different design options or architectures of the supply chain. These architectures are among the most recommended innovative solutions to lessen the impact of renewable energy integrations into the grid. They vary from electricity grid with integrated simple Reverse Osmosis (RO) desalination, to RO desalination integrated energy storage (i.e., batteries), and an RO desalination integrated Pumped Hydro. All three architecture operated by electricity grid that is assumed to have various penetration levels of renewable energy generated from solar photovoltaic fields. Figures 1 to 3 provide simple block diagrams to describe the three architectures. The oval shapes are used for the energy source, rectangle shapes for the mechanical components of the architecture, and rounded rectangle shapes for the energy storage components. The decisions on optimal energy resource dispatching, and water and energy flow rates for each of these architectures can then be used to demonstrate the optimal performance for each architecture.

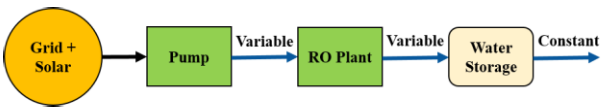

FIGURE 1. Electricity supply chain with solar source and simple RO desalination (Architecture 1).

A. INTEGRATION USING SIMPLE RO DESALINATION

This architecture incorporates a simple RO desalination plant used as a control measure to manage the energy flow. The RO desalination system consists of three main parts, conventional pumps, desalination unit (RO pre-treatment, membrane, post treatment), and water tanks for operational storage. The plant operated using electricity directly from the grid. The water flow rates to pumps and RO desalination units are variable depending on the operational decisions. This variability of water flow rates is used to compensate for the variability in the solar generation to the electricity grid. Fig. 1 below shows a simple block diagram of this architecture.

B. INTEGRATION USING RO DESALINATION AND ENERGY STORAGE SYSTEM

The second architecture also incorporate a simple RO desalination plant operated using electricity directly from the grid. However, this architecture employs an energy storage system. The system consists of four main parts, conventional pumps, desalination unit (RO pre-treatment, membrane, and post treatment), water tanks for operational storage, in addition to Lithium-Ion batteries as the energy storage system. The water flow rates to pumps and RO desalination units are variable depending on the operational decisions. The variability of water flow rates and the energy storage levels are both used to compensate for the variable generation of

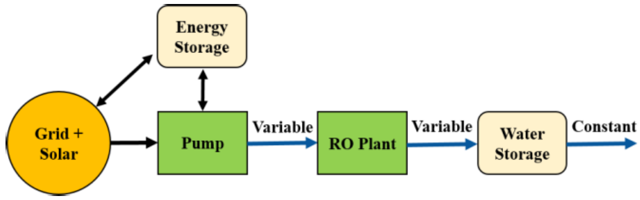

FIGURE 2. Electricity supply chain with solar source, simple RO desalination, and energy storage (Architecture 2).

solar energy. Fig. 2 below shows a simple block diagram of this architecture.

C. INTEGRATION USING RO DESALINATION AND PUMPED HYDRO STORAGE

The third architecture assumes an RO desalination plant integrated with Pumped Hydro System. The RO plant is operated using power directly from the grid. The system consists of three main parts, pumps, two water reservoirs on two elevations (high and low), and RO desalination unit. While the water flow rate to RO unit is constant, the water flow rates to pumps and water reservoirs are variable and depend on the operational decisions to compensate for the variability of solar generation. The constant flow rate to desalination plant provides the advantages of steady operation and lower operation and maintenance costs. Fig. 3 below describes the architecture components.

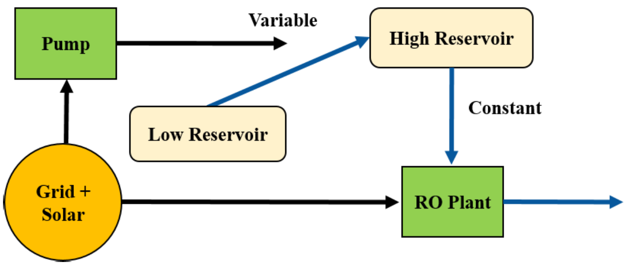

FIGURE 3. Electricity supply chain with solar source and integrated RO desalination and pumped hydro system (Architecture 3).

V. METHODOLOGY

The proposed methodology supports decision makers to identify the optimal performance of the electricity supply chain taking into account multiple objectives and supply chain designs (i.e., architectures). The next five sub-sections describe the methodology in details.

A. DESCRIPTION OF METHODOLOGY AND PARETO OPTIMAL SOLUTIONS

The proposed methodology addresses two objectives. The first objective minimizes the variation of the load caused by the renewable generation over time. This objective addresses the net load variability by using the flexibility inherent to water desalination process. The flexibility is employed to obtain smoother net load profiles. The second objective minimizes the annualized costs associated with the solution. The amount of variation reduction of each architecture is calculated from the historical load profiles and solar generation versus operation with optimal planning of desalination load. The details on how variation reduction is calculated are provided in the next sub-section. The cost of the solution of each architecture is calculated based on the solution annualized costs including its operational costs. The optimization runs are used to generate the points of the Pareto front. The users can use a small value to vary the weight of the objectives in the objective function according to the user priorities. The following describes the methodology in steps from the user's (i.e., the decision maker) point of view.

Given a certain set of architectures, we vary a small value (α), solar energy penetration rate (P), and the size of the desalination capacity (S).

- α ranges from 0 to 1 to represent the weight factor of the two main optimization objectives, the variation and the overall costs.
- P ranges from 0 to 100%, representing the percentage of solar generation in respect to the overall load.
- S vary between medium, large, or very large with the actual capacity depends on the location being investigated.

For each architecture,

a) Set all user parameters but α (i.e., P and S) and run first two runs with α set to 0 then to 1 to find the value β which is a scaling factor used in the objective function to compensate for the value variation in the two objectives.

b) Use β value to run the optimization problem over the full range of user parameters to find values of Variation-Cost pairs.

c) Run the optimization problem for the optimal desalination operation with a single objective of cost minimization. This means that α would be set to give full weight to cost objective. Run the optimization for a range of penetration rate values to find optimal annualized cost for steady hourly RO desalination production. The additional cost encountered to achieve the variation reduction is then calculated by comparing the costs for optimal desalination steady operation versus the costs in step (b) above. The percentage of variation reduction achieved and the cost of each unit of reduction is calculated by comparing the variation levels for optimal desalination steady operation versus the variation in step (b).

B. ENERGY VARIATION REDUCTION

The impact of solar energy variability and various mitigation strategies on the electricity grid was quantified by calculating the degree to which the net load varied over a 24-hour period. This difference, MAD, is defined as the net energy demand deviation from the daily mean. MAD denotes the mean absolute deviation i.e., the total deviation of F from the average

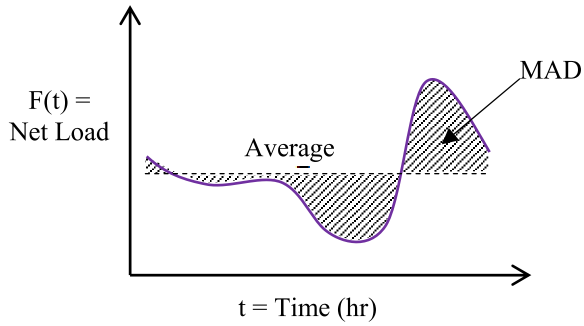

FIGURE 4. Net load variation over time.

$\overline{F}$ as shown in (1).

$$\overline{F} = \frac{1}{24}\int_{0}^{24} F(t)dt \tag{1}$$

$$MAD = \frac{1}{24}\int_{0}^{24} \left|F(t) - \overline{F}\right| dt \tag{2}$$

This is shown graphically in Fig. 4, where the function $F(t)$ represents the net load over time and the shaded area is equal to MAD according to (2).

Mitigation techniques, including deferring desalination operation, will be evaluated in part on their ability to reduce MAD, thereby reducing the impact on the utility. Quantifying the energy demand variation in this manner allows the impact of desalination plant operation to be demonstrated in one number and simply incorporated into a multi-objective cost function.

C. SOLAR ENERGY GENERATION CALCULATION

One of the goals of this work is to consider the impact of ever increasing renewable penetration on the grid, where penetration is defined as the fraction of yearly electricity load met by renewable generation, i.e., solar generation in this work. As such, solar penetration, P, is a variable input into the model allowing various scenarios to be considered. Yearly solar generation, G_y, for a given scenario, is calculated as P multiplied by the yearly load demand, L_y. Hourly solar generation, G_h, can then be calculated using hourly solar insolation values, S_h, and the total yearly insolation, S_y by the following equation:

$$G_h = G_y \cdot \frac{S_h}{S_y} = P \cdot L_y \cdot \frac{S_h}{S_y} \tag{3}$$

Using (3), all that is needed to determine the amount of solar generation in a given hour is (a) hourly solar insolation data, (b) the total yearly load and (c) the degree of solar penetration

D. AVERGING TECHNIQUES

Optimizing operation over an entire year on an hourly basis, while possible, is computationally expensive. However, capturing solar variation throughout the year is essential in determining the annual cost of operation. To this end, the model input data is comprised of hourly data that has been averaged over a given month. The model then considers 12 "days" of activity, where each "day" demonstrates the average hourly behavior for a month of the year. For instance, on the day representing January, the data used at 1am would be the average behavior at 1am taken over the entire month of January. While this averaging method does not account for daily variation in solar generation, loads and pricing, it does capture the more variable monthly variation and is appropriate as a proof of concept for this approach.

E. COST MODEL

The cost model breaks down the cost by major system components for each of the three architectures examined in this work. The system total cost is defined as the annualized costs of all system components in addition to the annual energy consumption by each architecture. Table 1 shows the major components considered in the model.

TABLE 1. Major architecture components.

Component	Architecture	Replacement Rates
Pump	1, 2, 3	0.1 [27]
RO Treatment	1, 2, 3	0.2 [27]
Tank	1, 2	0.05 [27]
Batteries	2	Calculated. (See next text)
PHS	3	0 (lifespan longer than system lifespan)

Annuity factor is used in the model to adjust the value of the capital investment to the present value. The total system costs exclude the revenues of the system product, which is the desalinated water. Water revenues are calculated from the amounts of the water produced multiplied by the water selling price. The hourly flow rate of each system component determines the operational costs of the component. The operational costs are defined as the specific operational costs of a system component multiplied by the flow rates in addition to the replacement and maintenance costs. The specific capital and operational costs for RO were estimated at \$1320.86 and \$0.5 per cubic meter according to ADC low estimates for RO in California [28]. These values were divided between system components according the table below. The specific energy consumption was estimated at 2.642 kWh per cubic meter of water produced in California [28].

TABLE 2. RO Desalination cost and energy consumption breakdown [29].

Capital	41%	Operational	25%	Energy Consumption	34%
Pumps, steel	22%	Membrane replacement	12%	Pump at 0.8 efficiency [30]	90%
Materials	21%				
Civil Engineering	18%	Labor	20%	RO treatment 2-stage at 0.6 recovery rate [31]	5%
		Consumables	20%		
Other services	17%	Others	28%		
Pretreatment	8%	Maintenance	20%		
Intake, outfall	7%			Tank	5%
Membrane, vessels	7%				

The system cost of a specific architecture C_A is defined as the annualized costs of all system components, $C(m)$, in addition to the annual energy consumption of the system, $C_E(m)$, and excluding the revenues of the desalinated water. Water revenues are calculated from the amount of the water produced, W_P, multiplied by the water selling price, P_W.

$$C_A = \sum\nolimits_{m\in M} [C(m) + C_E(m)] + W_P \cdot P_W \tag{4}$$

The amount of water produced W_P depends on the flow rates of the last system component in each hour during the system operation, depending on the architecture. The monthly cost of the system energy consumption is defined as the total hourly energy consumption of the system by energy hourly price in addition to the monthly demand cost. Demand costs are calculated from specific utility defined demand charge (\$/kWh) multiplied by the maximum load occurred that month.

When batteries are used, the system cost would also include battery cost C_B. Battery cost depends on Battery capital costs A_B, battery capacity I_B, battery usage U_B and battery lifespan capacity L_B as follows.

$$C_B = \frac{A_B \cdot I_B \cdot U_B}{L_B} \tag{5}$$

where battery lifespan capacity L_B depends on battery capacity I_B and number of cycles to failure of battery at 80% depth of discharge F_B and assuming 90% efficiency this value is multiplied by 90%

$$L_B = 0.9 I_B \cdot F_B \tag{6}$$

The annualized costs of a system component combine the investment and the operational costs. The investment costs of a system component m depends on the cost of purchasing or acquiring this component, $N(m)$, which depends in return on the maximum desalination capacity for the specific location, D_{max}, adjusted to the Annuity Factor f. The operational costs of a system component m depend on the specific operational cost of this component $Hoc(m, h, t)$ and the number of days in month t. Then the annualized costs of a system component is defined as

$$C(m) = N(m).D_{max}/f + \sum\nolimits_{t\in T} [Hoc(m, h, t).d_t] \tag{7}$$

where the Annuity Factor depends on the interest rate i and the time periods in the time horizon h. Then f is defined as

$$f = \frac{1}{i}\left[1 - \frac{1}{(1+i)^h}\right] \tag{8}$$

The hourly operational costs of a system component at a specific time period, Hoc, is defined as the specific operational costs of a system component $SC(m)$ multiplied by the flow rates V of this system component at the specified time period in addition to the hourly replacement and maintenance costs and defined as $N(m).D_{max}.R(m)$. Then the hourly operational costs of a system component is defined as

$$Hoc(m, h, t) = SC(m).V(m, h, t) + N(m) \cdot D_{max} \cdot R(m) \tag{9}$$

The cost of the energy consumption of the system depends on the hourly consumption *Hec* and the price of energy at the specific time period. The hourly energy consumption of a system component at a specific time period, *Hec* defined as the specific energy consumption of the system component $S_E(m)$ multiplied by the flowrate of this system component at the specific time period $V(m, h, t)$ divided by the energy efficiency of the system component, $n(m)$.

$$Hec(m, h, t) = \frac{S_E(m) \cdot V(m, h, t)}{n(m)} \tag{10}$$

When batteries are used, the hourly energy consumption $Hec(m, h, t)$ is adjusted by adding the battery current at the specific time period $CH(h, t)$ to reflect the actual energy used from the grid as follows.

$$Hec(m, h, t) = \frac{S_E(m) \cdot V(m, h, t)}{n(m)} + CH(h, t) \tag{11}$$

VI. MATHMATICAL MODEL

Consider a set of architectures **A** such that each architecture defines a subset of system components from the component set **M** =*{Pump, RO, Tank, Battery, PHS}*. The set **T** represents sample days each representing a month of the year. **T** = *{1, 2, ...12}* and the set **H** represents the hours of that sample day **H** = *{1, 2, ..., 24}*. The next sub-sections describe the optimization model variables, objective functions, and constraints.

A. DECISION VARIABLES

The following are the decision variables related to the flow rates of system components:

$V(m, h, t)$: the water flow rate of system component m in hour h at sample day of the month t $\forall m \in M, h \in H, t \in T$

The model also defines two decision variables related to battery operations:

$S_o(h, t)$: the battery state of charge at the beginning of hour h sample day of the month t $\forall h \in H, t \in T$

C H(h, t): the battery current resulting from charge / discharge at the beginning of hour h at sample day of the month t $\forall h \in H, t \in T$

B. MULTI-OBJECTIVE MODELLING

The model considers two objectives both are minimized. The total net variation in the load and the total investment and annualized costs of an architecture. The parameter α is used to allow the decision maker to provide preference towards one objective over the other. In case of $\alpha = 0$ or $\alpha = 1$ the following objective function is used.

$$\min Obj = (1 - \alpha) \cdot C_A + \alpha \cdot N_{var} \tag{12}$$

The β is used as a scaler for the two objectives in the case of $0.1 \leq \alpha \leq 0.9$. This parameter is needed to normalize the values of the two objectives and its value is determined by running the optimization for the extreme case of each objective. The objective function is adjusted to

$$\min Obj = \frac{1-\alpha}{\beta} \cdot \left(C_A - C_{A,\alpha=0}\right) + \alpha \cdot \left(N_{Var} - N_{Var,\alpha=1}\right) \tag{13}$$

C. CONSTRAINTS DEFINITION

The following constraints represent the limitations on the operations of the system. The upper bound on the desalination capacity, which is the flowrate of the system component at a specific time period, V is defined as the maximum design capacity D_{max} adjusted to the desalination system capacity factor D_{CF}.

$$V(m, h, t) \leq D_{max} * D_{CF} \tag{14}$$

In addition, another two simple constraints are used to enforce the flow of water in the system. All desalinated water should be sent to the storage tanks and all the pumped water should be sent to RO unit at water recovery rate r. In order to guarantee fixed water flowrate from RO unit while considering the water losses from RO unit in the case of A = 3 these operational constraints are replaced with the following constraint.

$$V(m = R_O, h, t) = \frac{D_{\max} \cdot D_{CF}}{r(m = R_O)} \tag{15}$$

The flowing constraint is used to guarantee fixed water flowrate from PHS unit to RO unit.

$$V(m = PHS, h, t) = V(m = RO, h, t) \tag{16}$$

and to pump up a day's worth of water every day (plus considering PHS water losses) the following constraint is used

$$V(m = pump, h, t) \geq \frac{24}{r(m = PHS)} \cdot V(m = PHS, h, t) \tag{17}$$

The system energy consumption, *Hec*, should not exceed the total load $\xi(h, t)$ and the solar generation $\zeta(h, t)$.

$$Hec(m, h, t) \leq \xi(h, t) + \zeta(h, t) \tag{18}$$

The following constraints represent the limitations on the operations of the batteries when used. The rates of charging and discharging the battery *CH* are limited by the battery defined maximum charging rates *CD*

$$-CD < CH(h, t) < CD, \quad \forall h \in H, t \in T \tag{19}$$

The battery of state of charge is defined as follows.

Case 1: the start of optimization period i.e., $h = 1, t = 1$, then state of charge is always at 80% of the battery capacity.

$$S_O(h, t) = 0.8 \cdot I_B, \quad \forall h = 1 \text{ and } t = 1 \tag{20}$$

Case 2: the first hour of each sample day (except first sample day covered above) $h = 1, t \in T \backslash \{1\}$, then the state of charge S_O is equivalent to the last hour of the previous day in addition to the battery current for this period

$$S_O(h, t) = S_O(h = 24, t - 1) + CH(h, t) \text{ with } h = 1, \quad \forall t \in T \backslash \{1\} \tag{21}$$

Case 3: the very last hour of each sample day $h = 24$, $t \in T$, then battery is prepared to recharge for the first hour next period cycle

$$S_O(h, t) = S_O(h = 1, t) - CH(h, t) \text{ with } h = 24, \quad \forall t \in T \tag{22}$$

All other cases: the state of charge in a period S_O is defined as the state of charge in the previous period in addition to changes in the battery current

$$S_o(h, t) = S_O(h - 1, t) + CH(h, t), \text{ with } \forall h \in H, t \in T \tag{23}$$

The battery state of charge S_O must be always between 0 and 95% of the battery capacity I_B so that it is not degraded and it is used efficiently

$$0 \leq S_O(h, t) \leq 0.95 \cdot I_B$$

VII. CASE STUDY AND RESULTS

This section provides a real-world case from the state of California to show the proposed methodology and the implementation of the mathematical model to optimize the performance of the system against the three possible integration architectures.

A. LOADS AND PRICING INPUT DATA

The case study considers the loads of a large section of California by considering the publicly available hourly loads of the entire PG&E network in 2015 [32]. This network covers much of California going as north as Humboldt Country and as south as Santa Barbara County. Pricing data was estimated by using the real-time pricing of the ZP-26 region of CALISO [33] which includes the coastal region around Los Angeles and Santa Barbara. In addition to real-time pricing an estimated transmission and distribution charge of $16.16/MWh was applied, consistent with what could be expected for a customer attaching at 50 kV or above. As an industrial customer, the desalination plant would also be charged a demand charge, estimated as $4.50 per kW of peak demand in a given month.

B. SOLAR ENERGY GENERATION

Solar insolation values were obtained from National Solar Radiation Database for Los Angeles [34] in half hour increments for the year 2014. For this analysis solar insolation was defined as the diffuse normal irradiance. The amount of solar generation used in the model is a function of the desired level of solar penetration, where solar penetration is defined as the percentage of total load that is served by solar energy. For the purpose of this analysis it was assumed that enough area exists for solar panels to be deployed and serve this level of generation. Three levels of solar penetration were considered ranged between 10 and 30% maximum. As 30% of direct integration on renewable energy sources is considered high level and still beyond the reach of the grid in its current status [35].

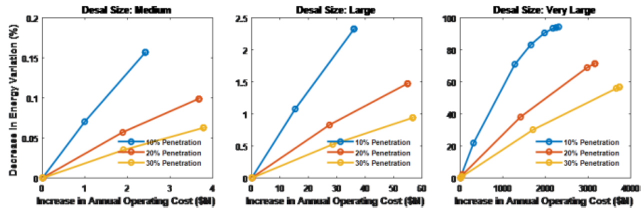

FIGURE 5. Architecture 1 results.

C. RESULTS

The results in this section organized by the integration architecture, the solar penetration rates, and the size of total installed desalination capacity. The range of the size of installed desalination capacity was set to 10,000 Acre-feet/year to represent Medium size, 150,000 Acre-feet/year to represent Large size and 1M Acre-feet/year to represent the Very Large size. For reference, the Carlsbad Desalination Plant [36] in Carlsbad, CA, which is considered medium to large size plant, generates 56,000 Acre-ft/year. The operation costs for such system were not divided into the costs for individual plants, but rather for the entire desalination network. The results obtained in this section came from applying the proposed methodology and running the optimization model with the various design options as described above. The generation of the Pareto front allows capturing both objectives of the optimization to give the decision maker a clear understanding of the trade-offs for each alternative solution.

1) ARCHITECTURE 1 OPTIMAL PERFORMANCE

Architecture 1 is the simplest architecture investigated, using a desalination plant to defer load in an attempt to decrease energy variation. Fig. 5 shows the result of the multi-objective optimization of the yearlong dispatching for this architecture. At each of the solar penetration levels investigated (i.e., 10, 20 and 30%) the optimized points were similar, with the 10% penetration results yielding slightly better energy variation reduction. The cost of reducing energy variation was between $130-240/MWh. The Pareto fronts generated for Architecture 1 considering the various solar penetration levels, give the decision maker an understanding of the trade-off between the energy variation reduction that can be achieved in return of the increase in the operating costs. The highest reduction with lowest cost increase is achieved with the Very Large desalination capacity at 10% penetration level. However, the decision maker might decide to go to higher penetration levels or lower desalination capacities given the strategic directions.

The impact of a medium sized desalination capacity is minimal as it is only able to reduce energy variation by a fraction of a percent. However, a Very Large desalination capacity, equivalent to 18 Carlsbad Desalination plants, is capable of completely reducing the energy variation due to 10% solar penetration. The hourly dispatching of Architecture 1 during an average day in July under 10% penetration is shown in Fig. 6. Architecture 1 dispatching in July under

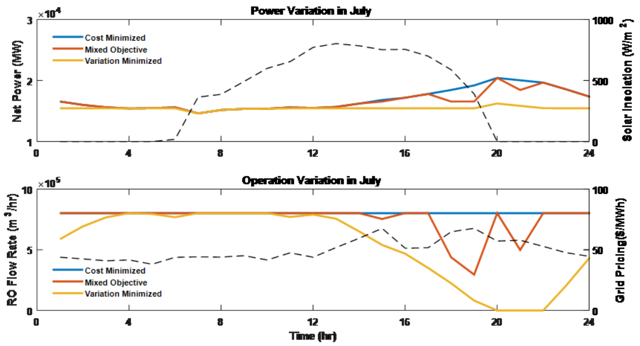

FIGURE 6. Architecture 1 dispatching in july under 10% solar penetration.

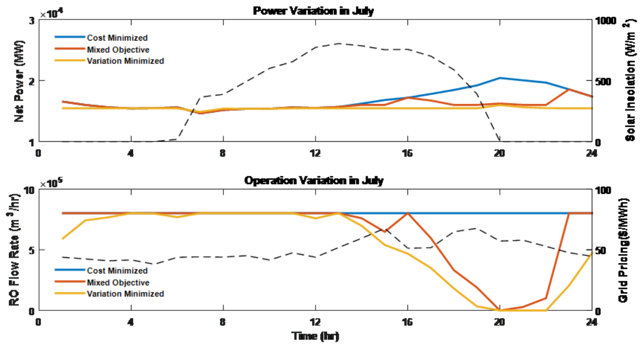

FIGURE 8. Architecture 2 dispatching in july under 10% solar penetration.

10% solar penetration. The results show that when variation is minimized the desalination flow rate goes to zero during the period of high load and low solar generation (i.e., what is known as the "neck" of the duck curve).

2) ARCHITECTURE 2 OPTIMAL PERFORMANCE

In Architecture 2, a 500MW battery farm was added and made available as an additional source for load deferment. This large battery farm was required to see any appreciable difference from Architecture 1, with smaller batteries having little to no impact in comparison with deferring desalination production. The addition of a battery farm this size allowed for greater ability to defer load and to reduce net energy variation as shown in Fig.7, and potentially a cheaper energy variation reduction costs at a minimum of $106/MWh. The Pareto fronts generated for Architecture 2 show that the highest reduction with lowest cost is achieved with the Very Large desalination capacity at 10% penetration level. The Pareto fronts show the decision maker the trade-offs if he/she decides to go to higher penetration levels or lower desalination capacities.

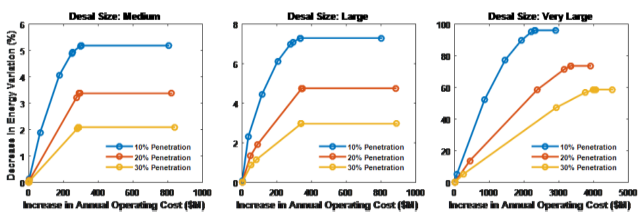

FIGURE 7. Architecture 2 results.

Once again, when energy variation is minimized, the desalination plant flow rate goes to zero during the period of high load/low solar generation as shown in Fig. 8.

3) ARCHITECTURE 3 OPTIMAL PERFORMANCE

In Architecture 3, water is no longer pumped directly to the desalination plant, but released from a Pumped Hydro Storage system at a fixed rate, allowing the desalination plant to run optimally at all times under all optimization conditions. In this case, load deferment is achieved solely via the Pumped

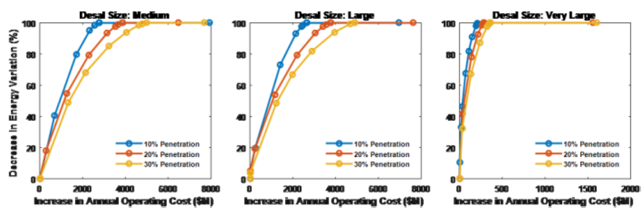

FIGURE 9. Architecture 3 results.

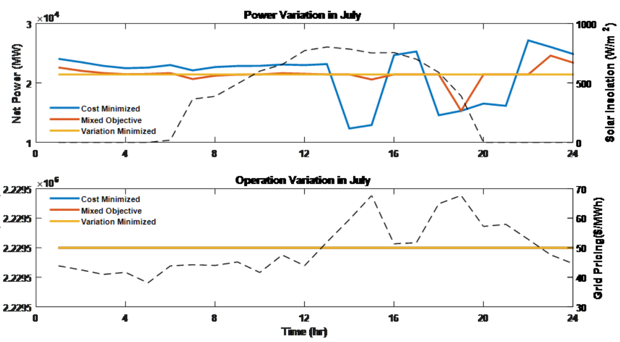

FIGURE 10. Architecture 3 dispatching in july under 10% solar penetration.

Hydro Storage. For the purpose of this case, the size is not restricted, allowing for maximum impact on energy variation reduction. This analysis does not consider the cost of creating the necessary reservoir as the price of land is highly variable depending on the location. Given the infinite size of the reservoir, 100% energy variation reduction can be achieved by any desalination plant size as shown in Fig.9. However, the effective cost ranges several orders of magnitude with the cheapest being $0.60/MWh of reduced energy variation.

The values of the objectives of the three architectures were plotted in Fig.11 to allow a comparison of their performance. Fig. 11 shows that Architecture 3 achieves the lowest cost for reduced energy variation while Architectures 1 and 2 would provide reasonable alternatives given the decision maker preferences. However, Architectures 1 and 2 are the most readily applied architectures and have a minimum energy variation cost of $100-200/MWh reduced annual energy variation. It may be possible to achieve more cost effective

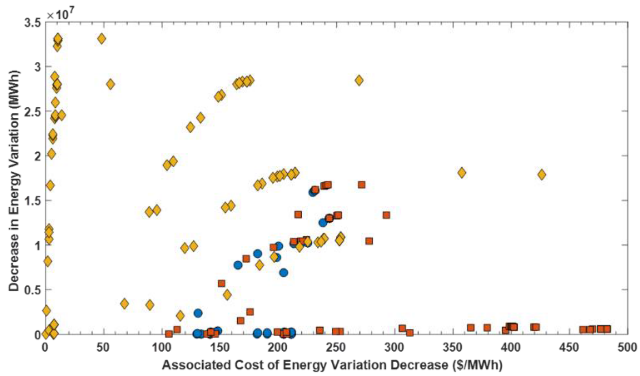

FIGURE 11. Cost of energy variation reduction.

reduction with a Pumped Hydro Storage system employed in Architecture 3 but the constraints on a Pumped Hydro Storage reservoir location added significant costs not included in this analysis.

VIII. CONCLUSION AND FUTURE WORK

This work generated a methodology and a model applying multi-objective function and considering several supply chain architectures to optimize both total cost and energy variation in the electricity grid. It was shown the degree to which the proposed methodology and model would assist the decision maker in investigating possible non-traditional alternatives for renewable integration in the electricity supply chain. For each of the three studied innovative architectures, the analysis showed the optimal dispatching to reduce energy variation due to increasing solar energy penetration into the grid. For each architecture, a family of results was generated as the value of cost over energy variation reduction was varied. By considering the trade-off between annual operating costs and energy variation reduction, the price of variation reduction was determined for the case. Through optimal planning of water and energy flow rates and energy source dispatching the minimum energy variation reduction along with the minimum associated costs were achieved for each architecture. It is very important to understand that addressing the well-being of cities' inhabitants in smart cities can be achieved only by bringing together city planners, practitioners, policymakers, and researchers and using advanced urban computation and innovative techniques such as the ones discussed in this work and discussed by other researchers who address the emerging topics in smart cities [37]–[39].

For future work, the models demonstrated in this paper can be further expanded to include the details of a proposed architecture, in addition to refining the economic model to include more specific costs. As a future work, the model can implement clustering algorithms on historical data in order to extract representative days of solar production. This allows incorporating the details of the solar profile variations instead of averaging over one month. In addition, the objective of minimum variation reduction can be enhanced by including more complicated approaches according to the electrical power system needs to provide more load flexibility. These approaches might include price signal for rewarding flexibility and allowing plant operators to bid on various electricity markets. In addition, the stochastic aspects of renewable energy production and demand can be modeled using different optimization formulations such as robust optimization, chance-constrained optimization, or stochastic optimization to include these uncertainties directly into the optimization procedure. The key implications of this research in relevance to the research objectives are provided as follows:

Research Question 1: How advanced computing methods can promote optimization techniques towards Sustainable GOAL 7: Affordable and Clean Energy?

Our unique value added contribution justifies advanced computational methods and optimization research towards a holistic ecosystem of determining factors. In a future direction, the proposed methodology and model will be supported by machine learning techniques.

Research Question 2: Which are the components of a methodological framework and an optimization model for the electricity supply chain that allow reducing the variability of the renewable energy sources supply by optimal planning of the supply chain operations?

Our unique value added contribution justifies an integrated approach: We proposed and justified with empirical testing a methodology supports electricity decision makers to identify the optimal operation of the electricity supply chain taking into account multiple objectives and supply chain designs including innovative architectures. We also integrated the methodology with a multi-objective linearized optimization model allows regulating the flow rates of energy and water for the electricity supply chain.

Research Question 3: Which are the implications for Smart Cities Research and well-being?

Our key methodological contributions defines well-being as an Affordable and Clean energy primer.

The continuation of this study will focus on the integration of our methodological framework with Business Intelligence and Analytics research, towards a fully functional Energy Supply Chains optimization dashboard. In our future research, we are targeting the exploitation of machine learning computational intelligence for the improvement of the performance.

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