Decision Guidance Framework for a Hybrid Renewable Energy System Investment Model

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Keywords: Hybrid Renewable Energy System, Mixed Integer Linear Programming, Optimization, Power Networks, Investment Decision Guidance.

Abstract: This paper focuses on making optimal investment and operational recommendations for a Hybrid Renewable Energy System (HRES). For this purpose we develop a modular composite analytic performance model for HRES investment, which is based on an extensible library of atomic component models, including renewable sources such as solar and wind, power storage, power contracts, and programmable customer loads' switches. The performance model formally expresses feasibility constraints and key performance indicators, including total tost of ownership, environment impact, and infrastructure resilience, as a function of investment and operational decision variables. Based on the performance model, we design and develop a decision guidance system to enable actionable investment recommendations that optimize key performance indicators subject to the operational constraints associated with the network. Finally, we demonstrate the model in a case study based on a real world example for a municipal electric utility.

1 INTRODUCTION

1.1 Drivers for Renewable Energy Networks and Key Trends

The focus of this paper is to provide a flexible framework that allows for modelling and optimizing the investment in resources for a Hybrid Renewable Energy System (HRES).

The planning and management of power had undergone a significant transformation in the past few years. Developments in the technological and political-economic landscape have been driving significant changes and complexity to electric power networks, transforming the existing mechanisms for supplying energy to satisfy electricity demand. At the forefront, environmental concerns are causing a surge in motivation to integrate renewable energy sources into the power grid. Political factors intensify this trend, as there is a significant push for reducing dependency on imported fossil fuels (understanding that these considerations will vary between countries, as the sources of energy may be more or less abundant within a particular geography). Economic aspects take into account the financial viability of operating those solutions, as well as the need to maintain a reliable source of supply. Concerns with long-term resilience of the infrastructure reflect the incidence of natural disasters as well as potential terrorist threats. Finally, the technology allows the expansion of alternative sources of energy (such as solar and wind) at a lower cost (in some cases even cheaper than traditional generation methods), even operated by the end consumers, combined with more efficient energy storage mechanisms. Control of power networks becomes more sophisticated through the development of smart grids.

The combined effect of environmental concerns with geo-political factors regarding the dependency on fossil fuels, is driving the establishment of power networks that are resilient, reliable, and economically efficient, and that have a reduced impact on the environment. In this context, several complementary developments come in place to address these needs. First, the establishment of smart grids, which expand the more traditional power grids, by using two-way flows of electricity and information to create an automated and distributed advanced energy delivery network. Figure 1 (U.S. Energy Information Administration, 2014), depicts a typical network configuration for a power grid, which we will expand later on, with a more detailed explanation of the different components' role.

Second, as a specialization of these smart grids, we see the development of Hybrid Renewable Energy

Levy, R. and Brodsky, A.
Decision Guidance Framework for a Hybrid Renewable Energy System Investment Model.
DOI: 10.5220/0010231203380346
In *Proceedings of the 10th International Conference on Operations Research and Enterprise Systems (ICORES 2021)*, pages 338-346
ISBN: 978-989-758-485-5

System (HRES) (sometimes also called Integrated Renewable Energy Systems). HRES denotes an elaborate energy grid that relies on multiple sources – most prevalent of which are renewable sources such as solar, wind, and hydro, combined with more traditional sources such as fossil-fired power generators, as well as with storage technology at key locations of the grid, to establish a reliable, cleaner and stable flow of supply. In this context, the role of electricity storage is particularly important in order to address multiple needs: balancing power supply (uncertain due to potential fuel shortages and the stochastic nature of renewable sources), deferring costly upgrades of the transmission/distribution infrastructure, allowing frequency regulation, and creating opportunity for revenue generation through secondary markets.

1.2 The Problem and Technical Challenges

There are key decisions to be made by stakeholders in the public and private sector, who need to determine the policies, investment and operations of an HRES for the energy and power sector, as is the focus of this paper. One involves determining the optimal investment in a balanced portfolio amongst a growing set of energy resources and providers with varying capital investment costs and constraints. Another key decision is finding the most efficient way to operate the different HRES resources. In this paper, we focus on the investment and operations decisions associated with an HRES described as a pool of electric power, fed by a variety of components to satisfy distributed sources of demand (although our work will not focus on the distribution/transmission question, functioning instead as a centralized model). Analyzing and making actionable recommendations on investment in the grid is challenging due to a number of factors:

- Highly complex interaction among different components of a power network
- Trade-offs between multiple goals and objectives, including the total cost of ownership, CO2 emissions and environmental impacts, service reliability, grid resilience and socio-economic impacts.
- Uncertain patterns of energy demand, as well as supply, especially when relying on renewable sources.

There has been extensive research to support modelling of hybrid energy systems (Chauhan and Saini, 2014) and (Erdinc, and Uzunoglu, 2012). Typically, however, the models are hard-wired for specific energy technologies and scenarios, and do

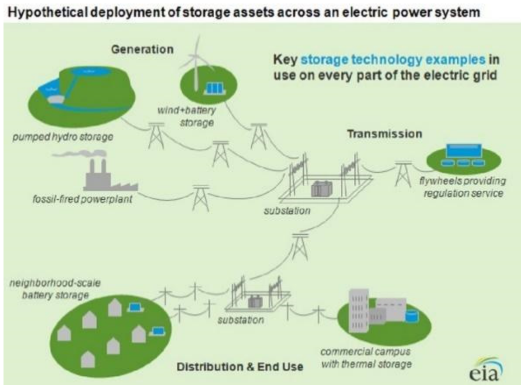

Figure 1: Distributed power system with storage technologies (Source: U.S. Energy Information Administration).

not provide a flexible framework to allow easy composition of designs of networks or microgrids for a variable combination of components such as generators, batteries, etc. There has been some work that allows a more flexible modelling framework and software implementation (see for example HOMER (Gilman et al., 2006)). Most of the research, however, is less reliant on mathematical programming (MP) and formal optimization methods, and more on heuristics or on simulation based engines. Among those works that effectively use MP, it is common to see the application of Mixed Integer Linear Programming (MILP) to investment and operations problems in power networks. For a good overview of MILP and other related integer optimization problems and approaches, see (Hoffman and Ralphs, 2012). There is a body of research that uses MILP Optimization models for power generation investment and operations decision (see (Omu et al., 2013), (Wouters et al., 2015), (Tenfen and Finardi, 2015), (Yang et al., 2015)), while others focus on Demand-Side Management (DSM) optimization (see (Barbata and Capone, 2014) for a survey). These papers, however, do not provide a way to model the network with components that can unify aspects of power supply and demand optimization in one integrated framework. Additionally, these works do not attempt to build the investment decision model from the optimal operation of the underlying day-to-day model; instead, they make simplifying assumptions regarding the operation to derive the rough-cut impact of the investment decisions. An alternative approach is the one provided by (Papavisiliou and Oren, 2013). They define the Unit Commitment Problem as a set of interconnected nodes/buses with stochastic elements reflecting supply and demand uncertainty. The proposed solution approach is based on a two-stage mixed stochastic programming, to commit generation to demand source. This approach is robust and well suited to address stochastic problems on dispatching energy. However, it is directed towards operational decisions, and does not attempt to address the investment decisions, which are key to our research.

When addressing an MILP approach for the types of applications described, it is common to recur to modelling languages that are specialized in mathematical programming and optimization problems (Hoffman and Ralphs, 2012). Powerful languages such as OPL and AMPL are in place to address those needs (Martin, 2002) and (Fourer et al., 1990). OPL and AMPL provide many advantages to make the optimization modelling easier and less error-prone. Some good examples of Power Network optimization models utilizing OPL are found in (Levy et al., 2016). However, they still require a considerable knowledge of optimization methods to properly program with them. Furthermore, they are not built for the use of reusable components between models; instead, each new model has to be created from scratch.

1.3 Key Contributions

Bridging these gaps is exactly the focus of this paper. More specifically, the contributions of the paper are as follows: First, we develop a modular composite analytic performance model (PM) for investment decisions in the HRES, which is based on an extensible library of atomic models for HRES components, such as diesel generators, renewable sources such as solar and wind, power storage, contractual agreements with third parties, and programmable switches. The performance model expresses metrics of interest and feasibility constraints as a function of investment and operation decision variables. Decision variables include all investment choices and system operational controls over the time horizon, such as (1) power flows in the network as a whole, (2) specific controls for each physical network component, and (3) financial instruments such as contracts with external power providers. Feasibility constraints include capacity limitation of physical resources, power flow equilibrium, contractual terms, and satisfying power demand over the planning horizon. Metrics of interest include net present value of investment and operation over the planning horizon, or the amount of carbon dioxide emissions, or a combined measure of financial and environmental impact. Second, we develop an HRES Decision Guidance System (DGS) based on the performance model. The HRES DGS is unique in that it allows extensibility of a model component library similar to simulation systems, yet achieves the quality of optimization results and computational time of mathematical programming solvers. This is achieved by using the Decision Guidance Analytics Language (DGAL) and Management System (Brodsky and Wang, 2008), (Brodsky and Luo, 2015), (Nachawati et al., 2017). The HRES DGS performs simulation, optimization, and trade-off analysis to support investment decisions, based on an extensible Knowledge Base (KB) of reusable component models. Finally, we provide a case study based on a real world example for a microgrid application, utilizing real data documented for a municipal electric utility, to demonstrate the applicability of the model and to derive actionable recommendations on investments on selected technologies, and the operations of the same technologies.

The remainder of this paper is organized as follows: Section 2 describes an application example for an electric utility, to be used as a basis for the formalization; Section 3 presents the design of the formal mathematical model to be used for optimization; Section 4 discusses the implementation of the model through the use of the DGS; Section 5 examines a microgrid case study, using a combination of real data and realistic assumptions applicable to a municipal utility. Section 6 provides our conclusions and directions for further development of this research.

2 MUNICIPAL ELECTRIC UTILITY EXAMPLE

2.1 Overview

To better visualize the application of the formal model, we will refer to a case study that constitutes a practical implementation of the approach. This case study was developed as part of a joint initiative between the Department of Computer Science and the School of Public Policy of George Mason University. The effort was driven towards identifying relevant planning problems of a municipal utility, and developing a solution model to address them. We believe this to be a good initial ground for developing our framework, which could be further expanded to allow variability and complexity, and better illustrate the flexibility of the model.

Different municipalities in Virginia are associated in a central organization, which has a contract with a third party power generation company, to purchase electric power. This contract is based on separate metering for each municipality, and drives charges on different elements, mainly peak power demand and actual energy consumption. A typical electric supply for a municipality is composed of a number of substations for its residential customers, and separate substations serving industrial customers. The municipality may own diesel generators located in these substations that are bid into the capacity pool. If the generation provider needs additional generation to meet their peak demand, it may dispatch the additional generation capacity, for a cost (if a unit is not available when dispatched, a penalty may be incurred). The generator capacity will not affect the peak demand for billing calculation.

The peak demand charge is based on coincidental demand, i.e. the demand at the municipality level occurring at the time the generation provider identifies and communicates an overall peak that occurs for the month. Other peak demand times (non-coincidental) are also observed, so if a non-coincidental peak demand is above a certain ratio to the coincidental peak demand, the charge is adjusted to account for the non-coincidental peak demand. This way the municipal utility is not incentivized to shift the demand artificially to reduce the coincidental peak, and therefore reduce the overall cost.

In addition, each municipality operates a program involving switches for water heaters and HVAC, which can control the consumers' demand and therefore affect peak billing. When water heater switches are activated they delay the corresponding demand for a different time period. HVAC demand locks a certain temperature for a period of time. The municipality provides a monetary incentive (or a corresponding free service) for customers that agree to install the switches in their households.

Some municipalities are examining different problems related to the investment and operation of some of the technologies. Regarding the generation, they have to decide whether to invest in additional diesel generators, to replace any of the existing ones either with new generators, or possibly to consider other technologies such as batteries or solar power instead, and determine the best schedule for dispatching those sources (above and beyond the requirements from the external generation provider).

Regarding the switches, decisions are to be made as to the number of additional switches to install at its customers' locations, and how best to operate them.

We use some of these problems as a basis for our case study, and to provide a starting point for the development of our formal model.

Our initial problem formulation is to recommend an optimal portfolio of investments between diesel generators, batteries, solar and household switches, as well as optimal operations within a given time horizon to minimize total costs of ownership (TCO) at present value.

2.2 Problem Statement and Illustration

We present here the problem statement and an intuitive description of a simple instantiation based on the formal model. The problem is stated as recommending an optimal portfolio of investments between different local technologies (e.g. diesel generators, batteries, and renewable sources) and household switches, as well as optimal operations to satisfy demand within a given time horizon to minimize total costs of ownership (TCO) at present value.

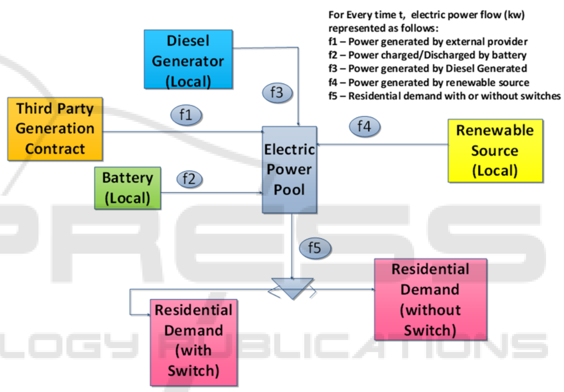

Figure 2: Simplified HRES Problem Schematic.

Based on this model, we developed an initial framework and component library to reflect the performance model for each of the components: generator, battery, households, and power generation contract. Each component generates metrics including the daily cash flows corresponding to operations and investment costs, and the power generated/consumed by time interval. A separate performance model consolidates the cash flows and the power for the microgrid across the individual components. The investment decision variables include buying/installing a diesel generator, buying/installing a battery, buying/installing a solar generation unit, and the number of new switches to be installed at the households. The operations decision variables include, for each time interval, the amount of energy generated by the diesel generator, the amount of charge/discharge of the battery, and the state of activation of the switches. The objective function is the minimization of the net present value of the investment and operational costs for all components for the time horizon.

3 FORMAL MODEL

3.1 Notation for Optimization Problem Formulation

We consider HRES investment optimization problems of the form:

$$minimize/maximize\ IO(P,V)$$
$$\textit{subject to: } \mathrm{IC(P,V)} \qquad (1)$$

where:

- P is a vector of parameters to the problem that range over a domain Dp
- V is a vector of investment and operation decision variables that range over a domain Dv
- $IO: Dp \times Dv \rightarrow R$ is the investment objective function (such as net present cost) that gives a value in R for for any instance of (P,V) in the domain $Dp \times Dv$
- $IC: Dp \times Dv \rightarrow \{T, F\}$ is the investment constraint, expressed as a Boolean function, that gives, for any instance of (P,V) in the domain $Dp \times Dv$, T (true) if the constraint is met, or F (false) otherwise

To support a range of HRES optimization problem for different objective functions IO and reusability of model components, we define an HRES *analytic performance model* as a tuple *(P, V, Cmp, M, C)*

where:

- P, V are defined above
- Cmp is a computation procedure that computes, given an input (P,V):
- a vector of metrics M = (M_1,...,M_k) that contains the investment objective IO(P,V), i.e., IO(P,V) = M_i for $1 \leq i \leq k$.
- the investment constraint C, i.e., IC(P,V) = C

the HRES optimization problem is defined by the HRES analytic performance model *(P, V, Cmp, M, C)* and a metric $M_i$in M designated as the optimization objective.

3.2 HRES Analytic Performance Model

We now define the elements of *(P, V, Cmp, M, C)* for the HRES formalization.

3.2.1 Parameters P

P includes generic parameters, as well as the parameters specific to each HRES component, i.e., we define P as the tuple:

$$P: (T, TotMonths, IntervalLength, Month, IR, \{P_i\}_{i=1}^{k})$$

where:

- T = is the length of the time horizon in days. We use the term time horizon TH = {1,…,T} to denote the set of days within the considered investment time horizon.
- TotMonths = {1,..,endmonth} is the set of calendar months corresponding to the contractual billing cycles, as well as other operational and leasing costs, where endmonth is the last calendar month within the time horizon.
- IntervalLength is the duration of each time interval in hours (assume a fixed number of time intervals during a day)
- Month is the set of time intervals {t_m ,…, t_n} where time t_m is the first interval of the calendar month, and t_n is the last interval of the calendar month
- We compute

$$\text{numIntervals} = \frac{T \times 24}{IntervalLength} \qquad (2)$$

- as the number of intervals in T
- $IR \in [0,1]$ is the market annual rate of return for investment
- $P_i, i = 1, \ldots k$, is the set of parameters specific to component i (see example of initial library of components in the Appendix)

3.2.2 Variables V

V includes decision variables specific to each component defined as:

$V: (\{V_i\}_{i=1}^{k})$

where:

- $V_i, i = 1, \ldots k$,is the set of decision variables specific to component i (see example in Appendix)

3.2.3 Computations Cmp

Cmp includes computations specific to each component, and general ones as defined below.

- For every component i = 1,…,k, perform computations $Cmp_i(P_i, V_i)$. Each computation $Cmp_i(P_i, V_i)$ returns (CF_i,kw_i,IC_i)

where:

- $CF_i: TH \rightarrow R$ is the cash flow of component i CF_i(d), d∈ HT gives the dollar amount spent by component I on day d (note that $CF_i(d) < 0$ represents net revenue)

- $kw_i: TH \rightarrow R$, where $kw_i(int), int = 1, \ldots, numIntervals$, is the amount of power that component i produces at time interval int (note $kw_i(int) < 0$ represents power consumption)
- $IC_i \in \{T, F\}$ is the Boolean value representing satisfaction of feasibility constraints of component i
- Compute: $HT \rightarrow R$, which is the integrated cash flow across all components. i.e.

$$CF(d) = \sum_{i=1}^{k} CF_i(d) \; \forall \, d \in TH \tag{3}$$

- Compute NPV (Net Present Value) for the HRES:

$$NPV = \sum_{d=1}^{T} \frac{CF(d)}{(1 + DailyIR)^d} \tag{4}$$

Where

$$DailyIR = (1 + IR)^{1/365} - 1 \tag{5}$$

- Compute balance flow constraint BalFlow:

$$BalFlow = (\wedge_{int=1}^{numIntervals} (\sum_{i=1}^{k} kw_i(int) = 0)) \tag{6}$$

- Compute overall feasibility constraint:

$$IC = BalFlow \wedge \; (\wedge_{i=1}^{k} IC_i) \tag{7}$$

3.2.4 Metrics M

M are the metrics computed for each component, that are defined generically as the following tuple:

$$M: (\{CF_i\}_{i=1}^{k}, \{kw_i\}_{i=1}^{k}, NPV, CF)$$

where:

CF_i, kw_i, NPV, CF are obtained as computed by Cmp as in section 3.2.3

3.2.5 Investment Constraints IC

IC includes general constraints, as well as the constraints specific to each component defined as the tuple:

$$IC: (\{IC_i\}_{i=1}^{k}, IC, BalFlow)$$

where

- IC_i, $IC, BalFlow$ are obtained as computed by Cmp as in section 3.2.3

3.2.6 Component Model

In the appendix, we demonstrate how we apply our general model to our initial library of components, constituted with initial object that supports the example described in the prior section.

4 DGS IMPLEMENTATION USING DGAL

An initial version of this model was developed using the language JSoniq, a data manipulation language over the JSON data format. To perform optimization, we use Unity DGMS and DGAL, which machine-generate an MILP optimization problem formulation in the AMPL equational language and invoke the Bonmin solver. For this version, we utilized our initial library of components, as described in the appendix, to develop the applicable routines. Figure 3 illustrates the high-level DGMS/ DGAL framework.

A separate module was designed for each component: diesel generator, battery, solar, household demand (with or without water heater switches), and generation contract for energy provision. Each module is independent of the others, and includes the calculation of the relevant metrics for each component for the planning time horizon (i.e. power consumed/produced by time interval, and cash flows for operations costs, investment amount), and the binary variable of constraint, indicating if the constraints for the component were met. An investment/integration model consolidates the metrics, validating for example that all power supplies and demands match for each time interval, and calculating the aggregated cash flows, the aggregated investment values, and the net present value for the overall network.

The code is designed so that the future addition of new components (e.g. solar panels to be installed at the households, different generator models, wind farms, etc.) will not affect the individual components already defined.

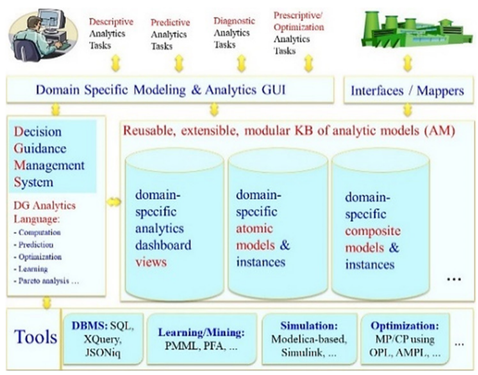

Figure 3: DGAL Framework.

5 CASE STUDY APPLICATION

For the initial, simplified scenario in our case study, we follow the example described in Section 2, utilizing a combination of real data from a municipality in Virginia (for example daily energy consumption during a calendar year and peak demand events), and realistic synthetic data (for elements not currently in place such as investment and maintenance costs for batteries and renewable sources) for twelve months of operation to recommend optimal combination of investments and operations of a diesel generator, a battery, a solar source, and water heater switches. Our initial test focuses on daily demand data for an entire year in one particular area, based on the billing and historical consumption data gathered.

The investment and operational costs associated with each technology were based on studies by third party companies as evaluation of possible replacement of current generators in place. Other data such as fuel costs and efficiency were based on available market data. Information for generation prices were obtained from billing and contractual data.

The core methodology for this application consisted in collecting the data for each of the parameters over the time horizon, based on the time interval being used, and transforming the data in a spreadsheet to the format required by the model. The data is then consolidated in a JSON format that is used as the input file for the model.

The model had a total of 1100 decision variables, including the purchase decisions of each component, the power per day generated or consumed by component for the twelve months, the status of the switches, and the upper bounds of peak power and transmission. For this size, it took a little over 8 minutes to achieve the optimal values for each variable for minimizing the Total Cost of Ownership (TCO) including investment and operations for the whole system, when running on a Toshiba Satellite S55 Laptop, with an Intel i7 2.40 GHz processor and 12 GB RAM.

As expected, the recommendations for purchase and daily operations for each component were directly affected by the comparative parameters between the components, e.g. the purchase/installation cost for each component, the maintenance costs, fuel costs (for diesel generator), billing rates for the external utility, demand patterns per month and peaks, etc. Consequently any changes in the variables associated to one of the components potentially affected the operations and the purchase decisions of all the other components as well.

Although we did not establish a direct comparison of our results to a more traditional investment model that doesn't account for the short term operations, note that, from the sensitivity analysis, the impact of short term parameters and variables have an accumulated effect on the investment decision. Therefore, this indicates (pending future detailed comparisons of results) that the integration of the short term operational decisions represent a more accurate method for investment decisions.

We also note that the solution is modular, in that we can at any point remove or add individual components/resources, without any need to modify the remainder of the model, therefore providing scalability to increase the model to address more complex scenarios with higher variability of resources. Likewise, in our simplified example we treated each component as an individual resource, not accounting for the combined value of, for example, batteries and solar/renewable sources. The model can accommodate this factor by either defining joint constraints applying to the solar generation and the battery, or alternatively creating a composite element defined by the two individual components with their combined performance characteristics.

Finally, the model can account to changes in our objective function to include different metrics such as the total emissions of the system as a whole (driven as a function of the total power generated by source/component), or a balanced combination of TCO and emission. In such a scenario, the model would favor clean energy solutions such as batteries and solar at the expense of diesel generators.

6 CONCLUSIONS AND FUTURE DIRECTIONS

In this work, we developed a formal mathematical formulation for a modular, extensible analytic performance model for investment decisions in the HRES, expressing metrics of interest and feasibility constraints as a function of investment and operation decision variables. We also developed an HRES Decision Guidance System (DGS) to support the formal performance model, relying on Decision Guidance Analytics Language (DGAL). As part of the HRES DGS, we created an extensible Knowledge Base (KB) of reusable Performance Models based on the different energy resources associated with a municipal utility example. Finally, we provided a case study based on this example for a microgrid application, utilizing a combination of real and synthetic data, to demonstrate the applicability of the model to derive actionable recommendations on investments on selected technologies.

There are several potential ways to expand the model. One promising addition is to add elements of complexity on the customer level, including stochasticity of demand, net-metering models (where customers produce solar energy for own consumption and charge back excess to utility), and dynamic pricing mechanism.

Another aspect of expansion would be to support decisions that go beyond the operations of the network, and to include infrastructure/ capital investment recommendations to achieve long term goals, based on Total Cost of Ownership.

A promising potential for the model is to define multiple stakeholders, for example adding regulators, consumers, and other utilities, each with their own specific objectives, translated into Key Performance Indicators (KPIs), which would include a variety of goals (including environmental impact, total cost of ownership, system reliability, etc.). The problem could be set as what is known as Bi-level Optimization, in which a 'leader' decision maker (in this case a regulator) who has its defined KPIs, has to define the optimal portfolio of policies (e.g. tax incentives, emissions regulations), to affect utilities and consumers behavior, which in turn optimize their own KPIs (potentially different from the leader).

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APPENDIX

Formal Model for Initial Library of Components.

To exemplify how the individual components in the library are modelled, we show here the formal model for a Diesel Generator. A similar methodology is applied to batteries, solar panels, households, and external generation contracts.

Based on our general model, we define the Fuel-Based Generators Structure tuple as:

$GS: (P_{gen}, V_{gen}, Cmp_{gen}, M_{gen}, IC_{gen})$

and we decompose each element of the tuple:

P_{gen} = (G, fPr, gCap, gEff, NGC, GLC, GMC, availG) as generators parameters
where:

- G is the set of generator ids;
- fPr: $G \times \{1, \ldots, numIntervals\} \rightarrow R^+$ is the price function that for each generator g $\epsilon\, G$ and time interval $t \in \{1, \ldots, numIntervals\}$, gives the expected fuel (Diesel) price fPr(g,t) in \$/Gallon
- $gCap$: $G \rightarrow R^+$ is a function that gives for each generator g $\epsilon\, G$, the maximal load of generation gCap(g) in kw
- $gEff$: $G \rightarrow R^+$ is the function that gives for each generator g $\epsilon\, G$, the efficiency gEff(g) in Gallon/kwh
- NGC: $G \times TH \rightarrow R^+$ is the cost cash flow function associated with a new generator (either through one-time disbursement at the beginning, or through leasing), that gives for each generator g $\epsilon\, G$ and day $d\ \epsilon\ TH$, the investment daily cost NGC(g,t)
- GLC: $G \rightarrow R^+$ is the generator Lifecycle function, that gives for each generator g $\epsilon\, G$ the expected total life GLC(g) in years
- GMC:G $\rightarrow R^+$ is the monthly maintenance cost function that gives, for each generator g $\epsilon\, G$, the estimated monthly maintenance cost GMC(g) for the time horizon
- availG: G→ {0,1} is the binary (flag) function that indicates if a diesel generator g $\epsilon\, G$ was present at the beginning of the planning horizon

V_{gen} = (iG, kw) as Generators variables,
where:

- iG: G→ {0,1} is the binary (flag) function that indicates if a new generator g $\epsilon\, G$ is being purchased
- kw: $G \times \{1, \ldots, numIntervals\} \rightarrow R^+$ is the decision variable matrix of elements kw[g, t], where for every time interval t $\epsilon \{1, \ldots, numIntervals\}$, kw[g,t] gives the amount of kilowatts generated by the diesel generator g $\epsilon\, G$

Cmp_{gen} corresponds to all the computations performed for the generator, to obtain the applicable metrics and constraints, given the parameters and variables.

The metrics are given by $M_{gen}: (kw_{gen}, CF_{gen})$ where kw_{gen} is already determined by the decision variable *kw[g, t]*.

CF_{gen} is obtained by calculating the operational and investment costs associated with the purchase and operation of the generator at each time interval, and translating into cash flow entries on a daily basis.

- We assume only output flows from a Diesel Power Generator. The cost of operating a power generator (if it was available or purchased at the start of the planning period) equals the total fuel cost and the monthly maintenance cost.
- We compute the Fuel Cost for $\forall g\epsilon\, G, t\ \epsilon\ T$, $GenFuelCost[g, t]$, based on the fuel unit cost (Dollars per Gallon), the generator efficiency (Gallon per kwh), and the amount of output flow in kwh during the given time interval:

$$GenFuelCost[g,t] = fPR[g,t] \times gEff\,[g] \times kw[g,t] \times IntervalLength \quad (8)$$

- We compute GenOpCost[g,t] , the total Operational Cost for the Power generator g at time t, as:

$$\text{GenOpCost[g,t]} = \{(GenFuelCost[g,t] + GMC[g]) \times (availG(g) + iG(g)) \quad (9)$$

- We compute the Investment cost for a new generator GenInvestmentCost[g,t] , ased on the given cash expenditures, and on the purchase decision:

$$\text{GenInvestmentCost[g,t]} = NGC(g,d) \times iG(g) \quad (10)$$

For IC_{gen}, we consider the constraints for total power output, and the condition to purchase a new generator:

- We compute the constraint for the power output based on the generator's maximal operating capacity:

$$IC_{gen1}\text{: kw[g,t]} \leq \text{gCap}[g] \quad (\forall g\epsilon\, G, t\epsilon \{1, \ldots, NumIntervals) \quad (11)$$

- We compute the constraint for the purchase of a new generator based on the consideration that we will only buy a new generator g if it was not yet available at the start of the planning horizon, i.e.

$$IC_{gen2}\text{: availB } [g] + iG[g] \leq 1 \quad (\forall g\epsilon\, G) \quad (12)$$

- We compute the overall constraint for the generator as:

$$IC_{gen} = IC_{gen1} \wedge IC_{gen2} \quad (13)$$