Decision Guidance Approach to Power Network Analysis and Optimization

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Abstract: This paper focuses on developing an approach and technology for actionable recommendations on the operation of electric power network components. The overall direction of this research is to model the major components of a Hybrid Renewable Energy System (HRES), including power generation, transmission/distribution, power storage, energy markets, and end customer demand. First, we propose a conceptual diagram notation for power network topology, to allow the representation of an arbitrary complex power system. Second, we develop a formal mathematical model that describes the HRES optimization framework, consisting of the different network components, their respective costs, and associated constraints. Third, we implement the HRES optimization problem solution through a mixed-integer linear programming (MILP) model by leveraging IBM Optimization Programming Language (OPL) CPLEX Studio. Lastly, we demonstrate the model through an example of a simulated network, showing the ability to support sensitivity / what-if analysis, to determine the behavior of the network under different configurations.

1 INTRODUCTION

We have seen in recent years several trends, which are significantly transforming the existing mechanisms for supplying energy to satisfy electricity demand. At the forefront, environmental concerns are driving a surge in motivation to integrate renewable energy sources into the power grid. Political factors exacerbate this trend, as there is a significant push for reducing dependency on imported fossil fuels. Economic aspects take into consideration the financial viability of operating those solutions, as well as the need to maintain a reliable source of supply.

This last factor represents a potential problem for the effective deployment of some of the most promising renewable sources, such as wind and solar, stemming from the uncertain nature of their generation, which could drive volatility of the energy supply.

Several complementary elements come into place to address these issues. 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. As a specialization of these smart grids, we see the development of Hybrid Renewable Energy Systems (HRES), or Integrated Renewable Energy Systems (IRES), both of which denote an elaborated energy grid that relies on multiple sources - in general, renewable ones such as solar, wind, and hydro, combined with traditional sources such as diesel, and the placement of storage technology at key locations on the grid, to establish a reliable, cleaner and stable flow of supply.

A key problem facing decision makers is to find the most efficient way to operate such grids, which are becoming increasingly more complex, including different types of generation facilities, electricity storage equipment deployed throughout the network, transmission and distribution facilities, sources of demand scattered through a region, and markets for buying/selling energy and/or capacity. The question of electricity storage is a particularly important one, involving the options of placing the right storage technology at key locations to address multiple needs: balancing power supply to compensate for potential fuel shortages and the stochastic nature of renewable sources; deferring costly upgrades of the transmission/distribution infrastructure by placing storage technology next to the end consumer location;

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allowing frequency regulation; and creating opportunity for revenue generation through secondary markets.

This paper focuses on the problem of determining the optimal operation of the network in the short term, taking into account the components of power generation, storage placement, transmission, external markets, and consumption. The underlying decisions relate to the optimal flows and mode of operation of each component of the smart grid. Most of the current research in the area exhibits several limitations: it focuses on more specific aspects of the network, as opposed to an integrated view; is based on mostly simulation engines or heuristics, not on mathematical programming optimization; and much is focused on micro-grids, rather than largely distributed networks.

Addressing those limitations is exactly the focus of the present research, proposing and implementing a decision guidance framework for optimal operation of power networks with renewable resources and storage. We propose a conceptual diagram notation for power network topology, to represent Hybrid Renewable Energy Systems (HRES). We develop a formal mathematical model that describes the HRES optimization framework, consisting of the different network components, their respective costs, and associated constraints. We implement the HRES optimization problem solution through a mixed-integer linear programming (MILP) model by leveraging IBM Optimization Programming Language (OPL) and CPLEX Studio. Lastly, we demonstrate the model through an example of a simulated network, showing also the ability to support sensitivity and what-if analysis to determine the behavior of the network under different configurations.

There are several benefits to be achieved by the development of such a model. First, in a context of uncertain and probable growing demand, by allowing the planning and simulation of placement of components (including storage solutions) in different key locations on the grid, we can make a realistic assessment of their best utilization, and consequently, defer a potentially expensive upgrade of distribution lines. Second, we can minimize overall costs associated with regular operations due to a more efficient combination of power flows and use of storage. Third, we can profitably leverage existing energy markets, to sell excess capacity at periods of low demand. And finally, as a clear trend exists for transitioning from fossil fuels to renewable sources, the model can support a realistic analysis of how best to perform this transition.

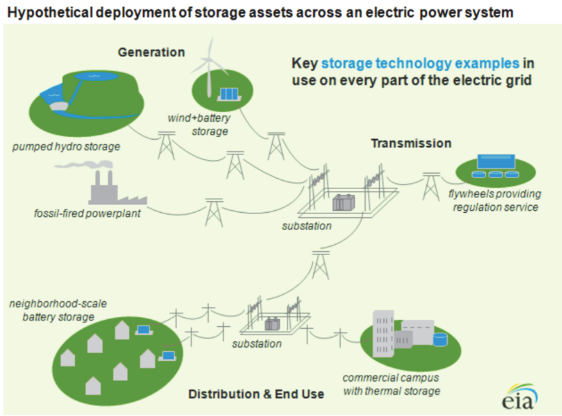

Figure 1: Distributed power system with storage technologies (Source: U.S. Energy Information Administration).

2 RELATED WORK

A significant body of research has been developed in the past few years to address the smart grid and the aspects related to its planning and operations. The first group of research surveys existing work on the topic rather than proposing new methods. Fang et al. (2011) define the smart grid as an enhancement to the traditional power grid of the 20th century, by leveraging two-way flows of electricity and information to create an automated and distributed advanced energy delivery network. They performed a survey of a large amount of work, classified into three major categories: Infrastructure System (i.e. the technologies underlying the Smart Grid for generation, information control and communications); Management System (management techniques for optimal operation of the grid); and Protection System (security). Our present work falls mainly in the second category.

Other surveys (Baños et al., 2011; Erdinc and Uzunoglu, 2012; Chauhan and Saini, 2014) provide a comprehensive review of optimization and heuristic methods applied to individual renewable sources of energy to achieve optimal sizing of components. Similarly, Deshmukh and Deshmukh (2008) provide a review of the mathematical modelling of the different components of an HRES. The methods covered include traditional methods such as Linear Programming (LP), Quadratic Programming (QP), Mixed Integer-Linear Programming (MILP), as well as heuristics and meta-heuristics approaches, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Neural Networks (ANN), and others. Although robust results were achieved in those areas, the research focuses on optimizing the size of individual sources, and does not deal with the energy flows between components involved in the operations of the combined network.

As many of the optimization models deal with multi-objective optimization, conventional methods can be used through unification of the objectives into one consolidated function, or through a Pareto-optimal set, in which a set of non-dominated solutions are selected. Alternatively, less traditional methods are proposed (Katsigiannis et al., 2010), in which a Multi-Objective Genetic Algorithm is utilized to minimize the system long term Cost of Energy (COE) as well as the amount of emission of CO_2 – equivalents, using a life-cycle approach that takes into account emission beyond the production of energy. This model, however, is designed to address the optimal combination to be utilized among the different components, but does not address the design of a flexible network from an operational perspective, as we do in our model.

Several models have been developed to explore other alternative methodologies, with the intent of deflecting the inherent difficulty of traditional optimization models. Mahor et al. (2009) provide a review of multiple papers that attempt to overcome the problem through the use of Particle Swarm Optimization (PSO), but those papers focus on the so called 'Economic Dispatch' problem, and on planning the output of given set of generating units. For this problem, the network flows did not play a role. Courtecuisse et al. (2010) propose a methodology for designing a fuzzy logic based supervision model for an HRES, based on the guidance of maximizing the usage of wind power, and minimizing the use of non-renewable power by designing a supervisor system that controls the power generation of each component, and its frequency. However, they do not attempt to optimize the functioning of the HRES for cost, environmental impact, or other objectives.

Much work is focused on the demand side, ranging from prediction models based on Artificial Neural networks (Yokoyama et al., 2009; Ekonomou, 2010), to learning consumer behavior through piecewise regression (Luo et al., 2012; Luo and Brodsky, 2010), and to mechanisms for Demand Side Management (DSM) and Demand Regulation (DR) to counter the constraints on the renewable energy supply (Moura and de Almeida, 2010). This line of work complements our solution, in terms of load and consumption projections, but it does not address our main area of focus.

Other research focuses on simulating the HRES model, and on developing optimization strategy to minimize Net Present Cost (investment costs plus the discounted present value of all future costs) or the 'Levelized' Cost of Energy (total cost of the entire hybrid system divided by the energy supplied by the same) (Bernal-Agustin and Dufo-Lopez, 2009). Although the concept is useful in solving complex and non-linearized problems, it focuses on stand-alone hybrid system, not on distributed networks.

Several papers focus on optimization of hybrid models through Linear Programming approaches (Cormio et al., 2003), where the model describes the energy system as a network of flows, by combining the use of multiple sources (renewable and non-renewable) of energy services, through a given planning horizon. The objective function to be minimized encompasses all fixed and variable costs (investment and operations), subject to a series of constraints related to demand, sources, environmental impacts, etc. The model builds on a comprehensive modelling of the different elements/components for generation and consumption, however, it does not support a modular approach for adding components located in different parts of the network, with considerations of distribution flows among possibly segregated regions.

In the realm of software solution packages, many comprehensive models were also developed, one of the best known being HOMER (Lambert et al., 2006), which provides a robust framework for planning and simulating an HRES model for a micro-grid, and driving the identification of the optimal model through the simulation of discrete number of scenarios. A good number of packages were developed in the same vein. HOMER (as well as other similar packages), offers a user-friendly framework that allows the flexibility to incorporate the elements as required, by establishing options for each component, amount, and sizing, together with the determination of patterns for the grid load, and external factors such as wind, sunlight, etc. that affect the behavior of the components. Their framework, however, does not address the problem which is the focus of our research in two respects: it is based on a simulation approach as opposed to relying on true optimization techniques, and it solves the problem for micro-grid planning but does not address a larger energy distribution network.

3 TOPOLOGY REPRESENTATION FOR POWER NETWORKS

Based on the power network depiction in Figure 1, we generate a topology diagram (Figure 2), which maps every physical facility in the picture to a corresponding component in the diagram below, Orange circles represent *generators*, blue circles represent *aggregators*, yellow circles represent *market*, green circles represent *storage (*for the purpose of this exercise, we don't differentiate between different storage technologies, purple circles represent *transmissions*, lines represent *power flows*, small ovals represent the *power flow identifiers*, and red rectangles represent *demand* (both residential and commercial).

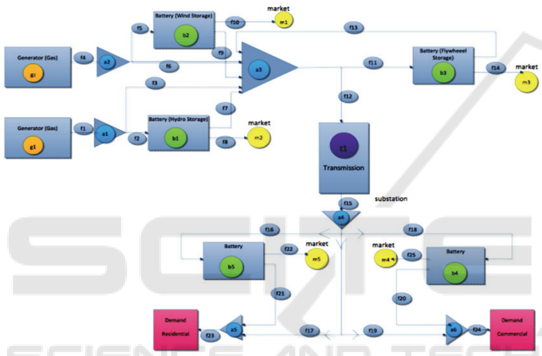

Figure 2: Topology Diagram.

This diagram can serve as the basis for establishing the formal model in the next section, as well as the case study subsequently, as it provides a modular view for the components to be assembled in distinct forms to reflect different network configurations.

The topology diagram can be used for two interrelated decision problems:

1. Operational (short term) – for every hourly interval, determine the optimal power flows across multiple components to satisfy projected demand during a given time horizon, while optimizing an objective function (e.g. cost optimization, emissions, or a combination of factors). A decision to be made at the beginning of each hourly interval, as a rolling time horizon.
2. Planning/Investment (mid to long term) – based on expected demand growth, decide on preferred investments on network improvements. This problem normally involves decision on policy, when evaluating larger scales networks.

This paper focuses on problem 1 – although it can support the analysis on problem 2, by allowing what-if analysis on the operations under each option being evaluated.

In the next section, we will introduce a formal description of the model, addressing the key considerations for each component, as well as the main variables involved.

4 FORMAL MODEL

4.1 HRES Optimization Framework

We define an optimization framework as a tuple:

HRES:

$(T, F, A, AIF, AOF, CMP, CIF, COF, DS, GS, BS, TS)$

Where:

- $T = \{1,2,3 \ldots N\}$ *is the Time Horizon with fixed intervals 1, 2,..., N (each with duration IntervalLength)*
- F *is the set of flow ids between the components of the network*
- *A is the set of aggregator ids*
- *AIF:* $A \rightarrow 2^F$ *is an Aggregator Input Flow function that, for each aggregator* $a \in A$, *gives a set of its input flows AIF(a)*
- *AOF:* $A \rightarrow 2^F$ *is an Aggregator Output Flow function that, for each aggregator* $a \in A$, *gives a set of its output flows AOF(a)*
- *CMP is the set of component ids, including generators, transmission/distribution, batteries, demand sources*
- *CIF:* $CMP \rightarrow F \cup \{\Lambda\}$, *where* $\Lambda \notin F$, *is a function that, for every component* $c \in CMP$, *gives:*

$(1)\ its\ input\ flow\ CIF(c)\ \in F$

OR

$(2)\ CIF(c) =$

$\Lambda\ to\ indicate\ that\ component\ c\ does\ not\ have\ an\ input flow$

- *COF:* $CMP \rightarrow F \cup \{\Lambda\}$, *where* $\Lambda \notin F$, *is a function that, for every component* $c \in CMP$, *gives:*

  $(1)\ its\ output\ flow\ COF(c)\ \in F$

  OR

  $(2)\ COF(c) =$

$\Lambda\ to\ indicate\ that\ component\ c\ does\ not\ have\ an\ input flow$

- *DS = (D, dF), is the Demand Structure tuple, where:*

$D \subseteq CMP$ is a set of demand source IDs; We require that demand source IDs do not have output flows, i.e. $(\forall d \in D)\ COF(d) = \Lambda$

dF: $D \times T \to \mathbb{R}^{+}$ is the demand function that, for each demand source d and time interval t, gives the predicted demand dF[d,t] in kw.

- *GS = (G, fPr, gCap, gEff) is the Generators Structure tuple, where:*
  - *$G \subseteq CMP$ is the set of generator ids; we require that generators do not have input flows, i.e.*
    - $(\forall g \in G)\ CIF(g) = \Lambda$
  - *fPr: $G \times T \to \mathbb{R}^{+}$ is the price function that for each generator g and time interval t, gives the expected fuel price fPr[g,t] in \$/Btu*
  - *$gCap$: $G \to \mathbb{R}^{+}$ is a function that gives for each generator g, the maximal capacity of generation gCap(g) in kw*
  - *$gEff$: $G \to \mathbb{R}^{+}$ is the function that gives for each generator g, the efficiency gEff(g) in Btu/kw.*
- $TS = (TD, LR, TMC, tCap)$ *is the Transmission/Distribution Structure tuple, where:*
  - *$TD \subseteq CMP$ is the set of Transmission/Distribution ids*
  - *$LR: TD \to [0,1]$ is the Loss Ratio of each Transmission/Distribution id*
  - *TMC: $TD \to \mathbb{R}^{+}$ is the annual maintenance cost for each Transmission/Distribution id*
  - *tCap: $TD \to \mathbb{R}^{+}$ is the maximal capacity of transmission in kw for each Transmission/Distribution id*
- *BS = (B, NBC, BLC, BMC, bcF, BIE, M, bmP, ppC) is the Battery Structure tuple, where:*
  - *$B \subseteq CMP$ is the set of Battery ids*
  - *NBC: $B \to \mathbb{R}^{+}$ is the new battery cost (for replacing each battery id)*
  - *BLC: $B \to \mathbb{R}^{+}$ is the Battery Lifecycle Parameter, for each battery id*
  - *BMC: $B \to \mathbb{R}^{+}$ is the annual maintenance cost for each Battery id*
  - *bcF: $B \times T \to \mathbb{R}^{+}$ is the battery capacity function that for each battery b and time interval t, gives the expected energy storage capacity bcF(b,t) in kwh*
  - *BIE: $B \to \mathbb{R}^{+}$ is the battery initial energy level at t = 0*
  - *M is set of market ids being served by batteries*
  - *bmP: $B \times M \to bmP[b,m]$ are all battery-market pairs, for $\forall b \in B$ and $\forall m \in M$*
  - *ppC: B M $\to \mathbb{R}^{+}$ is the price that each market is willing to pay for committed capacity (in \$/kw)*

4.2 HRES Optimization Problem

The formal HRES Optimization is stated as:

$$\min_{(kw,bE,cFl,dFL,c2mFL,cC)} RevAdjCost \qquad (1)$$

Subject to Ca, Cg, Ctd, Cd, Cb

Where the decision variables, objective and constraints are given below:

Decision Variables:

- kw is the matrix of elements kw[f,t], where for every flow f ∊ F and every time interval t $\epsilon\ T$, kw[f,t] gives the the amount of kilowatts transferred between two components
- bE is the amount of energy stored in a battery at a time interval t
- cFL is the Boolean value (charge flag) that indicates if a battery is being charged at a time interval t
- dFL is the Boolean value (discharge flag) that indicates if a battery is being discharged at a time interval t.
- c2mFL is the Boolean value (commit to market flag) that indicates if a battery's capacity is committed to a market at a time interval t
- cC is the committed capacity of a battery to a market at a time interval t

Objective Function:

$$RevAdjCost = gC + tC + bC - mR \qquad (2)$$

where:

- RevAdjCost is the overall cost through the time horizon reduced by market revenue
- gC is the cost associated with operating the power generators during the time horizon (see section 4.4)
- tC is cost of maintaining the Transmission/ Distribution stations during the time horizon (see section 4.5)

- bC is the cost of operating the batteries, as well as the associated battery depreciation cost, based on usage through the time horizon (see section 4.7.1)
- mR is the revenue associated with committing batteries to market throughout the time horizon (see section 4.7.2)

Constraints:

- Ca = Aggregators' constraints (see section 4.3)
- Cg = Generators' constraints (see section 4.4)
- Ctd = Transmission/Distribution constraints (see section 4.5)
- Cd = Demand constraints (see section 4.6)
- Cb = Batteries' constraints (see section 4.7.3)

4.3 Aggregators

Power Aggregators consolidate power flows originated from m different sources, and redistribute the same flows into n different destinations. We assume no operational costs to be incurred with power aggregators.

The main constraint for each Aggregator is given by:

$$\text{Ca: } \sum_{f \,\epsilon\, AIF(a)} kw[f,t] \;=\; \sum_{f \,\epsilon AOF(a)} kw[f,t] \quad (\forall a \epsilon\ A,\ t \epsilon\ T) \tag{3}$$

4.4 Generators

We assume only output flows from the Power Generators (in the simplified case of only combustible fuel generators). The cost of operating each power generator is given by the fuel cost (Dollars per BTU), the generator efficiency (BTU per kWh), and the amount of output flow during the given time interval:

$$GenCost[g,t] = fPR[g,t] * gEff[g] * kw[f,t] * IntervalLength \quad (\forall g \epsilon\ G, t\ \epsilon\ T, f\ \epsilon\ AOF(g)) \tag{4}$$

Total operating cost for all generators across the whole time horizon is given by the sum of GenCost across Generator Ids and time intervals t, i.e.

$$gC = \sum_{t \epsilon\ T, g\ \epsilon\ G} GenCost[g,t] \tag{5}$$

he only constraint for the output flow is given by the generator's maximal capacity:

$$Cg\!: kw[f,t] \;\leq\; gCap[g] \quad (\forall g \epsilon\ G, t \epsilon\ T, f\ \epsilon\ COF(g)) \tag{6}$$

4.5 Transmission/Distribution

The total cost associated with transmission/distribution is given by the sum of the known maintenance costs for each distribution station through the time horizon, i.e.

$$tC = \sum_{td\ \epsilon\ TD} TMC[td] \tag{7}$$

A fixed loss ratio is assumed to be known for each transmission/distribution station. Therefore, it carries a constraint of a given relationship between output and input flows based on the loss ratio:

$$Ca_1\!: kw[f_1, t] = (1.0 - LR[td]) * kw[f_2,t] \quad (\forall t\ \epsilon\ T, td\ \epsilon\ TD, f1 \epsilon\ COF(td), f2 \epsilon\ CIF(td)) \tag{8}$$

A second constraint is given by the maximal transmission capacity for the station:

$$Ca_{2:}\ kw[f,t] \;\leq\; tCap[td] \quad (\forall t\ \epsilon\ T, td\ \epsilon\ TD, f \epsilon\ CIF(td)) \tag{9}$$

4.6 Demand

Given our assumption that all end demand is satisfied, and only input flows of electric power are applicable, the main constraint is that the sum of input flows equals total demand for any end demand point for any time interval t:

$$Cd\!: kw[f,t] = dF[d,t] \quad (\forall t\ \epsilon\ T, d\ \epsilon\ D, f \epsilon\ CIF(d)) \tag{10}$$

For the same reason, revenue from end demand is not considered in the cost / Revenue optimization (as it is unchanged for a given demand load).

4.7 Energy Storage / Batteries

4.7.1 Batteries Cost

Cost of operating each battery for any time interval is given by adding the maintenance cost for the battery, and its depreciation cost. The depreciation is given by the cost of battery replacement (NBC), the cumulative charge and discharge at the end of the period (cCD) and a known battery lifecycle parameter (BLC):

$$bDep[b] = \frac{NBC[b] \, * \, cCD[b][t+1]}{BLC[b]} \quad (\forall t\ \epsilon\ T, b\ \epsilon\ B) \tag{11}$$

The accumulated amount (absolute value) that charges and discharges through a battery at the end of each time interval (t+1), is given by:

$$cCD[b,t+1] = cCD[b,t] + (kw[f1,t] + kw[f2,t]) * IntervalLength \quad (\forall t \in T, b \in B, f1 \in CIF(b), f2 \in COF(b)) \tag{12}$$

where

$$cCD[b][0] = 0 \tag{13}$$

For the overall Battery Costs:

$$batCost[b] = BMC[b] + bDep[b] \tag{14}$$

$$bC = \sum_{b \in B} batCost[b] \tag{15}$$

4.7.2 Batteries/ Market Revenue

If a battery is committed to a market for a given time interval t, additional revenue is generated, given by the price per capacity for that market and the committed capacity for the time interval (cC):

$$ActualMarketRev\ [bmP[b,m]\ ][t] = ppc[m][t]\ \ * cC[b][t] \tag{16}$$

In this model, for sake of simplicity, the capacity is treated as constant over the time horizon. Note that during the time intervals where the battery is committed to a market, the net flow of energy is zero, i.e. the energy at the end of the period is equal to that at the beginning of the same period.

The total market revenue (mR) is given by:

$$mR = \sum_{t \in T, b \in B} ActualMarketReV[b](t) \tag{17}$$

4.7.3 Batteries/ Market Constraints

At any time interval, as the following battery states are mutually exclusive:

- Charged – only input flows going into the battery.
- Discharged – only output flows going to subsequent components in the network.
- Committed to a market (i.e. using existing unused capacity at any time interval to sell it to an external market and provide revenue).

Additionally, any battery can be committed to no more than one market at any given time interval.

This translates into the following constraints,

$(\forall t \in T, b \in B, f1 \in CIF(b), f2 \in COF(b))$:

$$Bc1: cFL[b][t] + dFL[b][t]\ + \sum_{Mj} c2mFL[bmP[b,m]\ ][t] \leq 1 \tag{18}$$

$$Bc2: cFL[b][t] =\ 1\ iff\ kw[f1, t]) > 0\ (0\ otherwise) \tag{19}$$

$$Bc3: dFL[b][t]\ =\ 1\ iff\ kw[f2, t] > 0\ (0\ otherwise) \tag{20}$$

Regarding the amount of energy stored in the battery at any point in time, it starts with a given amount, ends the time horizon with the same amount, and oscillates throughout the time horizon based on charges and discharges of the battery:

$$Bc4: bE[b][1] = bE[B_i][\ N + 1\ ] = BIE[b] \tag{21}$$

$$bE[b][t + 1] = bE[b][\ t] + kw[f1,\ t] - kw[f2,\ t]) * IntervalLength \tag{22}$$

5 IMPLEMENTATION AS MILP AND CASE STUDY

A simple version of this model was developed using IBM OPL CPLEX Studio.

We proposed different scenarios to provide insights into the model, and to correspond to the intuition of what to expect from its behavior for different combinations of components ads their characteristics. We also followed a given sequence of key steps that constitute the methodology: First, we depict each scenario as the topological representation, as described in section 3. Next, we capture each of the component characteristics into the variables defined by the HRES optimization framework. Lastly, we implement the MILP problem solution, by translating these variables into IBM OPL CPLEX Studio, and running the solver, to derive the solutions.

We examined scenarios in which the different parameters combinations drive distinct decision variables for the time horizon. As explained in prior section, we are examining a 24 hour time horizon, with a time unit of one hour. For each hourly interval, in essence, we are determining what would be the optimal value for power flows, battery states, commitments and costs, for the full 24-hour time frame. On real life utilization scenario, two possible operation modes could be considered: in the first, a planning engine would run based on the expected demand for the upcoming day, and after execution, the planning engine plans the subsequent day operation; another option, would be to re-evaluate dynamically the planning within a rolling time horizon, as every hour we could look at actual values, as well as adjustments on demand for upcoming 24 hours.

With these insights in mind, we proceeded to scale up the model, to reflect the topology depicted in Figure 2, and built (again recurring to synthetic data), to create the four scenarios depicted below.

- Scenario 1: Generation and transmission capacity can satisfy the demand.

  - Model recommendation: not using batteries in operation, and always committing them to market.
- Scenario 2: For some hours in the time horizon, the fuel cost is very high.
  - Model recommendation: discharging batteries at that time.
- Scenario 3: The generators capacity cannot satisfy some peak demand (for some hours of operation).
  - Model recommendation: using batteries for these periods.
- Scenario 4: The transmission capacity is limited, so that it is not sufficient during some hours of peak demand.
  - Model recommendation: using the batteries downstream (at the distribution areas), to offset lack of power from upstream.

6 CONCLUSIONS AND FUTURE DIRECTIONS

In this work, we demonstrated an approach for optimizing the operations of components of an electric power network, including power generation, transmission/distribution, power storage, energy markets, and end customer demand (residential and commercial). A prototype was developed using IBM OPL CPLEX Studio, to make recommendations for operating the network, while minimizing revenue-adjusted overall costs for a given time horizon. A simple topology was created, and different scenarios were examined to assess the basic behavior of the model, in common situations, based on realistic synthetic data. The initial results demonstrate the validity of the approach, and provide some promising directions for future development, including operations optimization, investment planning / policy, and the technology aspects of the solution.

Regarding operations optimization, the model can be refined in several ways: first, by introducing energy generation through wind and solar power, as alternate source to the fuel based generators; second, by incorporating stochasticity in demand (and possibly supply too, especially with renewable sources); Third, by introducing real data.

In the realm of long term planning, the framework should be expanded, to include infrastructure/ capital investment recommendations to achieve long term goals. This process would possibly involve multiple stakeholders / decision-makers, in the public and private sectors, which could also drive policy decisions that address multiple goals (including environmental impact, regional employment, system reliability, etc.). The model would evaluate the effects of different policies (e.g. tax incentives, emissions regulations), as well as the prioritization of investment in network assets (such as new batteries, new distribution lines, etc.).

Finally, from a technology perspective, we could develop more flexible tools, to allow a more intuitive and reusable model, as well as incorporating other features such as learning and prediction mechanisms.

REFERENCES

U.S. Energy Information Administration, 2014. Short-term energy outlook model documentation: electricity generation and fuel consumption models. *Independent Statistics and Analysis,* U.S. Department of Energy.

Katsigiannis Y., Georgilakis P., Karapidakis E., 2010. Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables, *IET Renewable Power Generation, Vol. 4, Issue 5*, 404–419.

Courtecuisse V., Sprooten J., Robyns B., Petit M., Francois B., Deuse J., 2010. *A methodology to design a fuzzy logic based supervision of Hybrid Renewable Energy Systems, Mathematics and Computers in Simulation 81*, 208–224.

Yokoyama R., Wakui T., 2009. Prediction of energy demands using neural network with model identification by global optimization. *Energy Conversion and Management; 50*, 319-27.

Ekonomou L. 2010. Greek long-term energy consumption prediction using artificial neural networks. *Energy,; 35,* 512-7.

Luo J., Brodsky A., Li Y. 2012. An EM-based ensemble learning algorithm on piecewise surface regression problem." International *Journal of Applied Mathematics and Statistics 28, no. 4*, 59-74.

Luo J., Brodsky A. 2010. An optimal regression algorithm for piecewise functions expressed as object-oriented programs." In Machine Learning and Applications (ICMLA*), Ninth International Conference on, pp. 937-942.* IEEE, 2010.

Lambert T., Gilman P., Lilienthal P., 2006. Micropower System Modeling with HOMER, *Integration of Alternative Sources of Energy*, Farret, F, Godoy Simões, John Wiley and Sons.

Bernal-Augustin J., Dufo-Lopez R., 2009. Simulation and optimization of stand-alone hybrid renewable energy systems, *Renewable and Sustainable Energy Reviews* 13 2111–2118.

Cormio C., Dicorato M., Minoia A., Trovato M., 2003. A regional energy planning methodology including renewable energy sources and environmental constraints, *Renewable and Sustainable Energy*

Reviews 7: 99–130.
Fang X., Misra S., Xue G., Yang D., 2011. Smart Grid – The New and Improved Power Grid: *A Survey, Communications Surveys & Tutorials*, IEEE, (Volume 14, Issue: 4).
Baños R., Manzano-Agugliaro F., Montoya F., Gila C., Alcayde A., Gomez J., 2011. Optimization methods applied to renewable and sustainable energy: *A review, Renewable and Sustainable Energy Reviews 15*: 1753–1766.
Erdinc O., and Uzunoglu M., 2012. Optimum design of hybrid renewable energy systems: *Overview of different approaches, Renewable and Sustainable Energy Reviews 16*: 1412– 1425.
Chauhan A., and Saini R., 2014. A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control, *Renewable and Sustainable Energy Reviews 38*: 99–120.
Deshmukh M., and Deshmukh S., 2008. Modeling of hybrid renewable energy systems, *Renewable and Sustainable Energy Reviews ,12:* 235–249.
Mahor A., Prasad V., Rangnekar S., 2009. Economic dispatch using particle swarm optimization: *A review, Renewable and Sustainable Energy Reviews 13*: 2134–2141.
Moura P., Almeida, A., 2010. Multi-objective optimization of a mixed renewable system with demand-side management, *Renewable and Sustainable Energy Reviews 14*, 1461–1468.

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