Decision guidance approach to power network analysis:
Developing an optimization technology solution to support management and operations of electric power components

Roberto Levy[1], Alexander Brodsky[1] and Juan Luo[2]
[1] *Computer Science Department, George Mason University, Fairfax, VA, 22030, USA*
[2] *Information Tecnology Unit, George Mason University, Fairfax, VA, 22030, USA*

Technical Report GMU-CS-TR-2015-14

Keywords: decision support; decision guidance; optimization, HRES; electric power network.

Abstract: This paper focuses on developing an approach and technology for actionable recommendations on the operation of components of an electric power network. 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 (residential and commercial). 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 also 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 a series of trends, which are significantly transforming the existing mechanisms for supplying energy to satisfy electricity demand. At the forefront, environmental concerns with climate change and other impacts are driving a surge in motivation to integrate renewable energy sources into the power grid. Political factors exacerbate the trend, as there is a significant push for reducing dependency of 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. This stems from the uncertain nature of their generation, which could drive volatility of the energy supply, if we are to depend on these sources as a bigger share of our energy consumption.

In this context, several complementary elements come in place to address these issues. 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, for 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 what has been called Hybrid Renewable Energy Systems (HRES), or in other instances Integrated Renewable Energy Systems (IRES), both of which denote an elaborated energy grid that rely on multiple sources - in general renewable ones such as solar, wind, and hydro, combined with more traditional sources such as diesel, and the placement of storage technology at key locations of the grid, to establish a reliable, cleaner and stable flow of supply.

A key problem facing decision makers today 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 different options of placing the right storage technology at key locations, to address multiple needs: balancing power supply, deriving from 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); allowing frequency regulation; and finally, creating opportunity for revenue generation through secondary markets.

This paper places a closer focus on the problem of determining the optimal operation of the network in the short term, taking into account the components of power generation, distribution/transmission, storage placement, external markets, and consumption. The underlying decisions relate to the optimal flows and mode of operation of each component of the smart grid.

As we discuss in Section 2, extensive research has been developed to support optimization of hybrid energy systems. However, there are several limitations that characterize most of the work. First, a significant portion of the research has been, due to the inherent complexity of such problems, focused on more specific aspects to be addressed (see for example (Katsigiannis et al., 2010), (Courtecuisse et al., 2010), (Yokohama and Wakui, 2009), and (Ekonomou, 2010). Although these works provide valuable insights into different aspects of the grid, they do not convey an integrated view of the network, therefore, not addressing the issue of optimization of the grid as a whole.

Second, the body of work that effectively addressed a more holistic and integrated view, including all the different aspects of the network (for example HOMER (Lambert et al., 2006) and other similar packages), was primarily driven by simulation engines, with the purpose of arriving as the best option among the simulated scenarios. Other similar research also recurred to different heuristics methods, rather the using optimization tools, based on mathematical programming.

Finally, much of the work was more focused on micro-grids, rather than a largely distributed network see (Bernal-Augustin and Dufo-Lopez, 2009) or (Cormio et al., 2003)). Therefore the issue of optimizing distribution of energy, and the location of the different components (in which we focus in the present work) were not a part of those models. We describe related work in more detail on section 2.

Addressing those limitations is exactly what we focus on the present research. In this paper, we propose and implement a decision guidance framework for optimal operation of power networks with renewable resources and storage. More specifically, the contributions of this paper are as follows.

First, we propose a conceptual diagram notation for power network topology, to allow the representation of Hybrid Renewable Energy Systems (HRES). 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) 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 possibly growing demand, by allowing the planning and simulation of placement of components (including storage solutions) in different key locations of 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 usage of storage. Third, we can profitably leverage existing energy market, to be able to sell excess capacity in certain periods of time 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.

The remainder of this paper is organized as following: Section 2 surveys related literature in place; Section 3 provides the framework and methodology to be utilized in the model, and how it translates a given topology and an actionable model for decision analysis; Section 4 presents the design of the formal mathematical model for the optimization. Section 5 discussed the implementation of the model through the use of IBM OPL CPLEX Studio. Section 6 examines a case study, through a simplified prototype that was developed in order to demonstrate the feasibility of the model for a power utility using realistic assumptions and a small synthetic data set, to address different conditions of generation and transmission capacity against demand, fuel costs variation, etc. Section 7 provides our conclusions and directions for further development of this research.

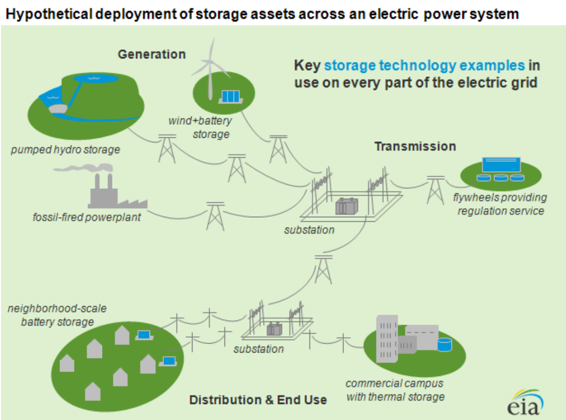

Figure 1: Distributed power system with storage technologies (Source: U.S. Energy Information Administration)

2 RELATED WORK

A significant body of research has been developed in the past few years to address the smart grid and the different aspects related to its planning and operations. The first group focuses on surveying 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 (dealing with management techniques for optimal operation of the grid); and Protection System (focusing mainly on security). Our present work falls mainly in the second category.

On 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 modeling 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 work was focused on optimizing the size of individual sources, and did not deal with the energy flows between components, involved on 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, derived through an Life-cycle approach (i.e. taking into account emission beyond the production of energy). This model also, however, is designed to address the optimal combination to be utilized among the different components, and does not address the design of a flexible network, from an operational perspective, as we do in this work.

Several models have been developed to explore other alternative methodologies, with the intent of deflecting the inherent difficulty of traditional optimization models due to the complexity of the model, and multiple local optimal solutions. (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, focus 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) proposed 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, as well as the frequency. This paper, however, does not attempt to optimize the functioning of the HRES for cost, environmental impact, or other objectives.

Much work was devoted with focus on the demand side, ranging from prediction models based on Artificial Neural networks, (Yokohama et al., 2009) and (Ekonomou, 2010), to mechanisms for Demand Side Management (DSM) Demand Regulation (DR) to counter the constraints on the energy supply in the context of multi-objective optimization of a mixed renewable system (Moura and de Almeida, 2010). Although this work can be helpful in complementing our solution, from the perspective of addressing the load and consumption projections, it does not address our area of focus.

Other research focused on simulating the HRES model (Bernal-Agustin and Dufo-Lopez, 2009), 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). Although the concept is useful to solve these complex and non-linearized problems, it focuses on stand-alone hybrid system only, not on distributed networks.

Several papers focused on optimization of hybrid models through Linear Programming approaches (Cormio et al., 2003), where the model described the energy system as a network of flows, by combining the use of multiple sources (renewable and non-renewable) to the demand for energy services, through a given planning horizon. The objective function to be minimized encompassed all fixed and variable costs (investment and operations), subject to a series of constraints, related to the demand, sources, environmental impacts, etc. The model builds on a comprehensive modeling 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 some respects: first, it is based on a simulation approach to arrive at the 'optimal' combination, among pre-selected discrete set of options, as opposed to relying on true optimization techniques for addressing a larger universe of combinations; second, it solves the problem for micro-grid planning, i.e. it does not address a larger energy distribution network, in which the location of the components play a role on the optimized operation.

3 TOPOLOGY REPRESENTATION FOR POWER NETWORKS

3.1 Electric Power System and Components

As discussed in Section 1, Figure 1 represents a typical deployment of power storage across an electric power system, depicting the delineation of the main components of an electric network, how they interconnect to satisfy demand for end use, and how they can leverage storage technology as part of the solution to optimize different aspects of delivery, and to balance potential sources of instability.

Starting with generation, as we mentioned before, fossil-fuel generation plants represent the more traditional source of generation, with a stable/predictable supply, but also a major cause of carbon emissions (as other pollutants), and for that reason being a less attractive source. Renewable sources on the other hand, such as wind and solar, are an attractive alternative to eliminate/reduce emissions, but in general are less stable as a source, therefore requiring mechanism for balancing supply.

From the point of view of transmission and distribution, we usually see the placement of substations upstream (i.e. close to the generation/supply source), which distributes electric power to other substations downstream (i.e. near end consumers). Although this subsystem can be considered stable and predictable, the concern is normally scalability, as the demand grows with time, driving the need to upgrade lines and substation, which can represent considerable expense.

As for the end demand, we have residential, commercial and industrial customers, with considerable variability throughout the day, as well as seasonal and other effects, driving stochastic behavior. Here again, storage mechanisms can be used to attenuate the effects on this variability.

Electricity storage can be deployed throughout an electric power system—functioning as generation, transmission, distribution, or end-use assets — an advantage when it comes to providing local solutions to a variety of issues. Sometimes, placing the right storage technology at a key location can alleviate a supply shortage situation, relieve congestion, defer transmission additions or substation upgrades, or postpone the need for new capacity.

Different types of storage technology are depicted, and can attend different functions based on the nature of the technology and the physical location of the solution. Pump hydro storage, for example, is a mature and well proven technology based on pumping water from a low to a high reservoir, through a turbine powered by the grid, and then releasing the water back to the lower reservoir, releasing energy, when needed. Their downside is the cost, and the potential environmental impact they may create.

Batteries on the other hand, can provide a possible solution to compensate for variability of a renewable source, such as the wind-battery example depicted. Such an integrated wind-storage system could create a stable supply of energy, but at the same time, increase significantly the cost of the solution. Similar structure is also proposed for a combined solar-battery solution. On its most basic level, a battery is a device consisting of one or more electrochemical cells that convert stored chemical energy into electrical energy. Advances in technology and materials have greatly increased the reliability and output of modern battery systems, and economies of scale have dramatically reduced the associated cost, allowing them to be applied to larger energy generation solution at an acceptable cost, and a much longer lifespan.

A flywheel is a rotating mechanical device that is used to store rotational energy. It is able to capture energy from intermittent energy sources over time, and deliver a continuous supply of uninterrupted power to the grid. Flywheels also are able to respond to grid signals instantly, delivering frequency regulation and electricity quality improvements.

Other storage solutions can operate on the end users side, helping address the demand variability, therefore stabilizing the load in the short term, and avoiding transmission infrastructure upgrades in the long term. Some of these solutions include the thermal storage situated in a commercial campus. Thermal energy storage is very economical, and is usually placed at the site of electricity consumption. Thermal storage lowers a building's electricity costs by shifting the time of day when the building runs its cooling system. Other consumption level solutions may involve the use of batteries to regulate demand on a residential neighborhood.

3.2 Conceptual Diagram for Power Network Topology

Based on the prior picture, we generate a topology diagram, which maps every physical facility in the picture to a corresponding component in the diagram below, as follows. In the diagram, 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* and the small ovals represent the *power flow identifiers*. Red rectangles represent *demand* (both residential and commercial).

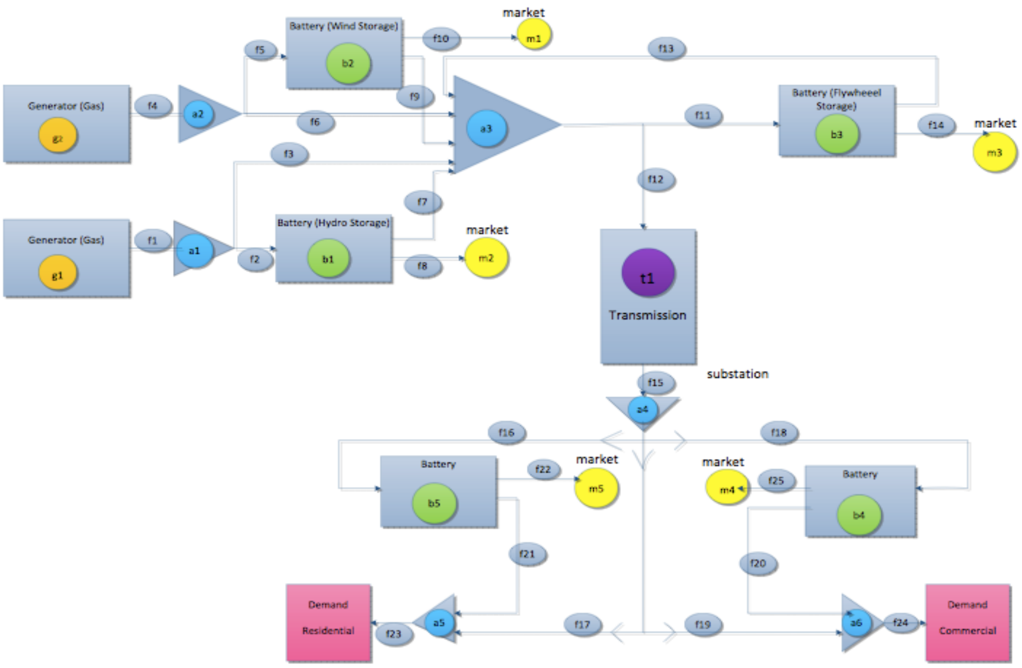

Figure 2: Topology Diagram

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 different components to be assembled in distinct forms to provide extensibility 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 to be minimized, or a combination of other factors, such as emissions). 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 the network to improve its functions. 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 us to perform what-if analysis on the operations under each option being evaluated.

In the next section, we will proceed to 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*
- *IntervalLength is the duration of each time interval*

- 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* ϵCMP, *gives:*

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

OR

(2) $CIF(c) =$ $\Lambda\ to\ indicate\ that\ component\ c\ does\ not\ have\ an\ inputflow$

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

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

  OR

  (2) $COF(c) =$ $\Lambda\ to\ indicate\ that\ component\ c\ does\ not$ $have\ an\ inputflow$

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

  D ⊆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: $D \times T \rightarrow \mathbb{R}^+$ *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 ⊆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: $G \times T \rightarrow \mathbb{R}^+$ *is the price function that for each generator g and time interval t, gives the expected fuel price fPr[g,t] in \$/Btu*
  - $gCap$: $G \rightarrow \mathbb{R}^+$ *is a function that gives for each generator g, the maximal capacity of generation gCap(g) in kw*
  - $gEff$: $G \rightarrow \mathbb{R}^+$ *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 ⊆CMP is the set of* $Transmission/Distribution\ ids$
  - LR: $TD \rightarrow [0,1]$ *is the Loss Ratio of each Transmission/* $Distribution\ id$
  - *TMC:* $TD \rightarrow \mathbb{R}^+$ *is the annual maintenance cost for each* $Transmission/Distribution\ id$
  - $tCap$: $TD \rightarrow \mathbb{R}^+$ *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: $B \rightarrow \mathbb{R}^{+}$ is the new battery cost (for replacing each battery id)*
    - *BLC: $B \rightarrow \mathbb{R}^{+}$ is the Battery Lifecycle Parameter, for each battery id*
    - *BMC: $B \rightarrow \mathbb{R}^{+}$ is the annual maintenance cost for each Battery id*
    - *bcF: $B \times T \rightarrow \mathbb{R}^{+}$ 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: $B \rightarrow \mathbb{R}^{+}$ is the battery initial energy level at t = 0*
    - *M is set of market ids being served by batteries*
    - *bmP: $B \times M \rightarrow bmP[b,m]$ are all battery-market pairs, for $\forall b \in B$ and $\forall m \in M$*
    - *ppC: $B \ M \rightarrow \mathbb{R}^{+}$ 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:

$$\min_{(kw,bE,cFl,dFL,c2mFL,cC)} RevAdjCost = gC + tC + bC - mR$$

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:

$$RevAdjCost = gC + tC + bC - mR$$

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:

Ca: $\sum_{f \in AIF(a)} kw[f,t] = \sum_{f \in AOF(a)} kw[f,t]$ $(\forall a \epsilon A, t \epsilon T)$

4.4 Generators

We assume only output flows from the Power Generators. The cost of operating each power generator (GenId0 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:

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

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 = $\sum_{t \epsilon T, g \epsilon G} \mathrm{GenCost}[g, \mathrm{t}]$

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

$Cg: kw[f,t] \leq gCap[g]$
$(\forall g \epsilon G, t \epsilon T, f \epsilon COF(g))$

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.

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

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:

$$Ca_1: kw[f_1, t] = (1.0 - LR[td]) * kw[f_2,t]$$

$$(\forall t \epsilon T, td \epsilon TD, f1 \epsilon COF(td), f2 \epsilon CIF(td))$$

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

Ca_2 kw $[f,t] \leq tCap[td]$
$(\forall t \epsilon T, td \epsilon TD, f \epsilon CIF(td))$

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:

$$Cd: kw[f,t] = dF[d,t]$$

$$(\forall t \epsilon T, d \epsilon D, f \epsilon CIF(d))$$

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] =

$$\frac{NBC[b] \ * \ cCD[b][t+1]}{BLC[b]}$$

$(\forall t \epsilon T, b \epsilon B)$

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*

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

where

cCD[b][0] = 0

For the overall Battery Costs:

batCost[b] = BMC[b] + bDep[b];

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

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]*

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 = $\sum_{t \epsilon T, b \epsilon B} ActualMarketReV[b](t)$

4.7.3 Batteries/Markets 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, $(\forall t \epsilon T, b \epsilon B, f1 \epsilon CIF(b), f2\epsilon COF(b))$:

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

Bc2: cFL[b][t] = 1 iff kw[f1, t])> 0 (0 otherwise)

Bc3: dFL[b][t] = 1 iff kw[f2, t] > 0 (0 otherwise)

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: $bE[b][1] = bE[B_i][N+1] = BIE[b]$

$bE[b][t+1] = bE[b][t] + kw[f1,t] - kw[f2,t])$ ** IntervalLength*

5 IMPLEMENTATION AS MILP

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

The model is run under a set of simplifying assumptions (we will later address how some of these assumptions could be eliminated going forward, as the model is flexible to reflect a broader set of configurations):

- This prototype is built for always satisfying the customer demand, at the established consumer rates. In other words, the pricing structure does not get affected by the decisions made in the model, nor there is an option to satisfy partial or selective demand.

- Demand in the time horizon is deterministic and known ahead of time
- Power Generation is based on fossil fuels with no restriction on fuel availability and with uniform fuel pricing across different generation facilities i.e. no wind-power or solar generation facilities for this initial model, and consequently, the power generation will also be considered deterministic.
- Power aggregators do not incur loss when redistributing power flows.
- Power loss ratios are constant and known for each Transmission/Distribution facility.
- Batteries can either be charged or discharged or committed to one specific market at any point in time. The market pays the utility by capacity committed and not by energy available (which get restored to the original value when the battery is released back).
- As a result of above assumptions, the key consideration for determining the flow of energy between the different components is the behavior of the different batteries, and the decision to charge, discharge or commit to a market each of the batteries capacity.
- Battery Capacity at any time t would be normally considered a function of the cumulative charge and discharge. For sake of simplification, we use energy capacity as a given constant for each t within the time horizon. We will also refrain from deep technical considerations in this work, regarding all the factors affecting capacity and battery utilization, using rather a simpler model to convey the concept.

6 PROOF OF CONCEPT AND CASE STUDY

In this section we propose 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 follow 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, within 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.

In order to better understand the model behavior, we first look at a highly simplified model (see Figure 3), with a minimal number of components, based on synthetic data, in order to visualize the effects.

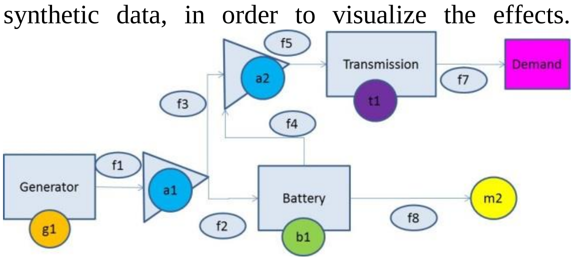

Figure 3: Simplified Topology Diagram

We populated a simple set of parameters for the components depicted and observed the behavior of changing specific values, and examining the impact on the decision variables and the objective function. As described before, given that the infrastructure is fixed for the time horizon, and the demand is assumed as known for that time period, the key variable to be regulated would be the battery, to address possible imbalance between energy supply and demand:

- When the energy from the generator(s) is sufficient to satisfy the demand, the batteries will not be utilized in the network, and will be fully committed to an external market to generate revenue.
- For any points in time when demand exceed the generator(s) capacity (also accounting for efficiencies, and possible losses in transmission), the batteries would be activated (discharged), and subsequently

re-charged in order to return to the original energy level.

- If for economic reason, it becomes more cost effective to utilize batteries for period of time (therefore saving on generators' operation), the batteries would be activated (discharged), and subsequently re-charged in order to return to the original energy level.
- If a transmission 'glut' occurs (i.e. transmission/distribution lines are not sufficient to handle remote demand, downstream batteries (located next to the demand centers) would be leveraged during those times.

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.

Summary results: Model recommended 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.

Summary results: Model recommended discharging batteries at that time.

Scenario 3: The generators capacity cannot satisfy some peak demand (for some hours of operation).

Summary results: model recommended using batteries for these periods.

Scenario 4: The transmission capacity is limited, so that it is not sufficient during some hours of peak demand.

Summary results: model recommended using the batteries downstream (at the distribution areas), to offset lack of power from upstream.

7 CONCLUSIONS AND FUTURE DIRECTIONS

In this work, we were able to demonstrate 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.

This work opens multiple avenues to be explored in the future, which can be focused on different directions: operations optimization (i.e. keeping the existing objectives for the short term, but expanding the complexity of the model to address more realistic scenarios); investment planning / policy (addressing the mid to long term decisions, from the perspective of the investment in the network, and the public/private policy determination decisions); and the technology aspects of the solution.

Regarding operations optimization, the model can be refined in several ways. First, given that one of the key overarching goals in to support a hybrid network, introducing energy generation through wind and solar power, to as alternate source to the fuel based generators. Second, we could add stochastic elements, considering the more realistic the need to incorporate demand variability (and possibly supply too, especially with renewable sources, and occasional failures of conventional ones), adding forecasting elements and/or stochastic optimization into the model. Third, we should collect and refine real data (possibly with collaboration with utility/power companies) to relax some of the simplifying assumptions and increase the applicability of the model.

In the real of long term planning, the framework could be expanded, to support decisions that go beyond the operations of the network, and to include infrastructure/ capital investment recommendations to achieve long term goals. On a broader sense, we would define multiple objectives, translated into Key Performance Indicators (KPIs), which would in turn address other goals beyond cost optimization (including environmental impact, regional employment, system reliability, etc.). This process would possibly involve multiple stakeholders / decision-makers, in the public and private sectors, which could also drive policy decisions that address those goals. What-if scenarios could provide the sensitivity analysis to the model, to 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, although a good initial model could be built directly within OPL, we could invest in more flexible tools to be developed, to allow a more intuitive modeling (i.e. driven by business rules), and reusability, therefore overcoming some of the obstacles of modeling directly in the optimization tool. This could also allow for incorporating other features such as learning and improving the model based on real data, integrating prediction mechanisms, and supporting more intuitive what-if analysis capabilities.

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.

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., and Almeida, A., 2010. Multi-objective optimization of a mixed renewable system with demand-side management, Renewable and Sustainable Energy Reviews 14, 1461–1468.