Electric Power Networks Efficiency and Security, Edited by Lamine Mili and James Momoh.
ISBN 0-471-XXXXX-X

Chapter 4.2

GIS-Based Simulation Studies for Power Systems Education

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Editor's Summary: This chapter advocates the application of two educational methods, namely case studies and decision modeling, as the best way to teach design and management methods in power systems. A sample of case studies is presented, which includes public policy studies aimed at transmission and generation expansion subject to a cap on electricity prices and generation emissions. The second educational approach makes use of the structured decision modeling under multiple, conflicting performance measures; the objective is to seek a set of desirable and feasible solutions among numerous alternatives. As illustrative examples, the authors discuss several interesting case studies that deal with the selection of the right site and size of DG or of FACTS to mitigate instabilities in power systems. Furthermore, examples of simulation results are presented to illustrate the cost, spatial, and temporal relationship of the interconnection of the DG to the distribution feeders. A very comprehensive formulation of unit commitment is examined too. The chapter also includes the description of the working software package that the authors developed. Termed the Virginia Tech Electricity Grid and Market Simulator (VTEGMS), the main component of this package makes use of

object-oriented programming as a means to maximize the robustness and flexibility of the software. A good reference of available optimization methods and simulation packages are summarized in the quoted references and in a table of comparison of software.

$.1 Overview

In this chapter we prescribe computer simulation as a robust tool that should be integrated into any comprehensive educational curriculum in the field of power systems design, engineering and management. Our advocacy of computer simulation is based on the essential role that this methodology plays in two foundational elements of power systems education – case studies and decision modeling. These elements, in turn, are necessary in the education of future power-system designers, engineers and managers who need to understand the ever-expanding complexities of these systems from the points of view of their many stakeholders. Computer simulation is unique among modeling techniques to support case analysis and decision modeling for such complex systems. In conjunction with case studies, text and lecture materials computer simulation forms a flexible educational support system (ESS). In this chapter we will provide an overview of the role of case analysis and decision modeling in power-systems education and the basic elements of simulation models along with an explanation of the essential role they play in this education.

We are motivated by two concomitant features of the educational landscape. First, the important role played by power systems in the economic health, environmental quality and national security of the United States and other countries has become evident. As a consequence, operation, design and management of power systems have become disciplines that are gaining in popularity and importance. Second, the operation, design and management of power systems involve large numbers of inter-related systems that are mutually dependent in mathematically complex ways. New developments in generation technologies, market deregulation, environmental regulations, reliability standards and security concerns are aggravating the complexity and interdisciplinary nature of this topic. New and existing personnel in the fields of power-system engineering, grid operation, power plant control, energy portfolio management, public-policy and consulting demand up-to-date and holistic education in the rapidly changing power-systems discipline.

Decision making is the common foundation of all of the challenges in the fields mentioned above and we view all learners as future decision makers. Hence, our design of educational tools will revolve around decision analysis. Examples of the decision domains that our educational tool must support include,

- Public policy decision problems - environmental policy planning, market regulation planning, infrastructure planning
- Engineering decision problems – protection system design, generation and transmission technology selection
- Business decision problems –generation capacity planning, unit commitment, optimal dispatch, demand side response, trading strategy, financial risk management

For each of these decision problems the cause-effect relationship between decision alternatives and key performance indicators (KPI) such as cost, reliability, pollution, market equity, etc. must be understood and analyzed by the decision maker. For the learner, modeling the decision of a case study is the most effective method for identifying the tradeoffs inherent in the KPIs. The learning process can be brought to fruition only by quantifying these tradeoffs and experimenting with the cause-effect relationship inherent in each decision – a task that demands computer simulation.

Electric generation units, power grids and energy markets form a complex system that evolves over time through the decisions of system managers, engineers, unit operators and market participants as well as through the influence of weather, load variation, market prices, forced outages and the physical behavior of network components. Some of these influences have a random component to their variations over time making the trajectory of the power system stochastic. Computer simulation is unique among modeling techniques in its ability to capture the effects of numerous interacting influences as well as of randomness on the performance of a system. Furthermore, the raw output of a simulation in the form of the trajectory of performance measures over time can be summarized in statistically valid ways to evaluate the long-run behavior of a system over time and over a representative sample of random scenarios.

$.1.1 Case studies

A case study is a presentation of a problem in the context of realistic conditions, people and events. Unlike traditional textbook problems, a case study does not present a well-formulated problem but rather a situation of conflicting needs and desires instigated by the disparate points of view of various stakeholders. Each case presents the learner with a situation in which a decision is needed. The learning process is pursued through the learner's attempts to create a model of the decision problem and to use the model to determine the best choice of alternatives. See Bodily, 2004 [7].

Case studies are the most effective form of learning assignment for the education of professionals for several reasons (see Barnes, Christensen, and Hansen, 1994 and Wasserman, 1994):

- Students become active instead of passive learners. Students learn by doing.
- Students are forced to define questions, not just answers.
- Students must identify, respect and consider several points of view on a problem.
- Students are forced to apply theory in order to create structure for the case as opposed to applying a structured method to a well-defined, contrived problem.
- Students are forced to compromise and look for workable, feasible solutions when there are conflicting needs and constraints.
- Students acquire general problem-solving skills within a field of study instead of mere formulaic solution methods that, in real situations, must be applied with modifications and adjustments in consideration of assumptions that are not met and factors that were ignored in the development of the methods.
- Students gain maturity and confidence by facing the ambiguity of realistic cases.

In every industry the decision problems that comprise the public policy, engineering and management naturally fall into a hierarchical order. The solutions to decision problems that have long-term consequences and that are updated infrequently become parameters that influence decisions that have shorter-term consequences and that can be updated more frequently. For example, the choice of technology for a new generation unit will influence the way that this unit is committed and dispatched. Hence, a hierarchy of decisions emerges in which longer-range, less-frequent decisions are placed above shorter-range, more frequent decisions. We assert that a holistic understanding of a subject such as the design, engineering and management of power systems requires the learner to attempt to solve all of the essential decision problems associated within this subject as well as to see these decision problems in their hierarchical order. A collection of case studies in hierarchical order integrated with text and lecture material comprises a well-designed educational experience for future professionals in the field of powers systems.

The list below forms such a collection. These cases include problems of operating a conventional power system as well as problems of designing and operating power systems of the future.

<u>Level 1: Public Policy Cases</u>

- How to set the emissions limits on generation units in a given power grid
- How to limit the prices that can be cleared in a given power market
- How to limit the prices that can be charged to different consumer groups in a given power market
- Where to install new transmission lines, gas pipelines or publicly-owned generation in a given power grid

<u>Level 2: Power Systems Design Cases</u>

- How to select non-traditional generation technologies for distributed generation (DG)
- How to select the best location for DG.
- How to select the type of generation plant to add to a given power grid
- How to plan the installation of new capacity in a given power grid
- How to coordinate protective devices for a given power grid.
- How and where to change protection coordination for DG.
- How to select fast, alternating-current transmission (FACT) devices to strengthen transmission systems.

- How to coordinate protections and placement of FACT devices for voluntary islanding during catastrophic events.
- How to determine locations that are exposed to catastrophic hidden failures.

Level 3: Power Systems Management Cases

- How to set circuit breaker limits in a given power grid
- How to configure FACT controllers. See Acha, et. al., 2004.
- How to commit the generation units to a given power grid
- How to dispatch the generation units in a given power grid
- How to bid or offer energy in a wholesale energy market for a given power grid
- How to configure a portfolio of financial derivatives to support the risk management of an energy trading position within a given power market
- How to commit and dispatch generation units to a power grid that is practicing various forms of
    - DSR
    - environmental restrictions
    - market regulations
    - demand growth rates
    - fuel cost volatility
- How to encourage consumers to shape load in order to balance cost and convenience.

The educational cases have several unique characteristics that carry the learner through these decisions in a realistic manner:

- Interactive – students are able to change different aspects of a power system's elements, markets or regulatory environment in order to experiment with different scenarios for the configurations of physical assets, time series of loads and failures, location and type of generation, contractual arrangements between customers and suppliers and regulatory constraints. For each scenario entered by a student, the KPIs of the system must be computed by a computerized model.

- Realistic – the educational cases are based on prototypes of real and proposed power systems, markets and regulatory environments.
- Configurable – the development of a case-based ESS will yield not only a sample of case studies for use in courses, but also structures for the database, student interface and cases that can be modified with new data for the development of new case studies.

Clearly, a qualitative overview of the decision problems listed above does not prepare a prospective power systems engineer, manager or regulator for the real world. An understanding of the tradeoffs presented by these decision problems requires a quantitative analysis of them. Decision support systems that are more sophisticated than a collection of simple formulas are necessary. Specifically, our case analyses require decision support systems that embody mathematical decision models.

Many powerful methodologies for building and optimizing decision models have been developed over the last fifty years. The lexicon of modeling tools includes computer simulation, linear programming, integer programming, nonlinear programming, dynamic programming and many others. Momoh (2004) provides a comprehensive overview of decision models for power-system cases and their associated optimization methods. Although these methodologies have been available for several decades, they have not enjoyed rapid adoption by businesses and institutions. One reason for their slow adoption is that most people find model formulation very difficult. The computerized tools for describing and prescribing solutions can be applied only after a descriptive decision model has been created -- a task that generally is accomplished through the art and science of an operations researcher who understands the problem domain and the structure of decision models. For the practicing manager or analyst, model application is the process that delivers business performance. Therefore, our educational goal is to teach the application of models to the decision problems described earlier.

A general understanding of the structure of decision models and their application is necessary for both the learner and the teacher. We provide such an overview below.

$.1.2 Generic decision model structure

A decision model quantifies the cause-effect relationships between actions and outcomes. The outcomes of an action are expressed in terms of performance measures, which, for any decision alternative, are used by the decision maker to determine the alternative's feasibility and desirability. For example, the performance measures for the unit dispatch decision in a given time period include the total cost of generation across all dispatched units, the total grid power loss, the line load on each transmission line, the load coverage for each load bus, the reliability of the system, etc. To the challenge of quantifying these performance measures we propose the application of decision models. Models are the brains within a decision support system that transform masses of data into knowledge.

In order to specify the scope of the decision the modeler categorizes the causative factors into two sets: a set of controllable factors that are used to define the alternatives available to the decision maker and a set of uncontrollable influences on the performance measures.

The alternatives of a decision represent the choices, options or actions that a decision maker is empowered to execute within the scope of a given decision. Mathematically, we must represent these alternatives in terms of a well-defined set of data elements that we call decision variables. For example, the alternatives for the unit dispatch decision in a given time period can be represented by the set of power output values for each generation unit that is available. This vector of power output values would constitute the decision variables for this decision. Among all of the possible sets of values for the decision variables, the decision maker seeks the one that yields the most desirable, feasible performance. This solution is called the optimal solution to the decision problem for which the model is built.

The uncontrollable factors of a decision are the influences on the performance measures that cannot be chosen by the decision maker. We call these uncontrollable factors parameters. For example, the parameters of the unit dispatch decision for a given time period include the capacities of each available generation unit, the thermal capacity of each transmission line, the real and reactive load at each load bus, the coefficients of the operating cost function of each available generation unit, etc. A parameter could remain constant throughout the analysis or could be a random variable. If some parameters are random variables, then the performance measures that depend on these parameters also are random variables – a characteristic of the model that earns it the label "stochastic". Parameters, or their probability distributions, must be measured, estimated or forecasted in order to build the database for a decision model.

Contrary to common belief, the presence of random parameters does not preclude the application of decision models. In fact, the ability to model decision-making under conditions of uncertainty can be considered the highest form of the modeler's science. In order to construct a stochastic model we must make use of the probability distributions of the random parameters. Doing so requires specification of these probability distributions as, for example, the estimates of the mean and the standard deviation define the probability distribution of a normally distributed parameter and the coefficients and volatility of a mean-reversion forecasting formula define the probability distribution of a future commodity price.

Performance measures that cannot be predicted with certainty introduce the element of risk into the decision. In these cases, the distributions of random performance measures must be summarized over all scenarios into measures that capture both risk and reward. For example, for the unit dispatch decision in a given time period the total cost of generation is a random variable because the total load is not known with certainty in advance. Variations in the load from its forecasted value are handled by automatic dispatch of reserve power. Consequently, the actual total cost of power generated during the given time period can be predicted by a decision model only up to the probability distribution of this cost. Summarizing this probability distribution over all possible load scenarios in terms several summary measures such as the distribution's mean and its upper and lower quartile points gives the decision maker a representation of expected financial cost as well as the risk associated with this cost.

Most decision alternatives associated with the design and management of a power system have ramifications that extend over long time horizons. The trajectory of a performance measure over a time horizon can exhibit various kinds of cyclic, trended or memory-influenced behavior. In order to provide useful indicators of the performance of an alternative, a decision model must summarize these trajectories over a time horizon that is long enough to capture all of the time-varying behavior of the performance measures. For example, for the unit dispatch decision over *multiple* time periods the total cost of generation will exhibit fluctuations and memory due to load variation over time, load momentum, generator startup costs and ramping constraints. Summarizing the time series of generation cost in terms of its time average provides the decision maker with a useful indicator of overall cost performance. When a model summarizes performance measures over random scenarios and over time, as necessary, the resulting measures are called key performance indicators (KPI) as they are used directly to evaluate the feasibility and desirability of each alternative.

In order to specify the feasibility and desirability of performance, the decision maker imposes a decision criterion on each KPI. There are two possible forms for each criterion: a KPI can be constrained from above or below in order to impose bounds on performance or a KPI can be maximized or minimized in order to pursue performance to its greatest possible extent.

The cause-effect relationships from decision variables and parameters to KPI's form a descriptive decision model. The qualifier "descriptive" indicates that the model's value is to predict or describe the performance of a system for a hypothetical set of inputs to that system. Hence, a computerized descriptive model provides the decision maker with an efficient means to test any proposed alternative and a trial-and-error capability for searching for the best alternative. Given enough time, the decision maker can arrive at an alternative that yields optimal or near-optimal, feasible performance.

Some decision models can also help select the best course of action from among an overwhelmingly large set of alternatives. An extension of a descriptive model engages a computerized search algorithm that, in effect, automatically performs an, intelligent trial-and-error procedure for the decision maker. Such an extended model is called a prescriptive model. Prescriptive models provide dramatically enhanced decision support when a decision involves so many feasible alternatives that manual trial-and-error is impractical.

The first step in building a decision model is to define data elements and to derive the mathematical relationships that constitute the descriptive model. The categories of data elements are:

- Decision variables
- Parameters
- Performance measures
- KPI’s
- Criteria

$-1 shows the general structure of a decision model. The most important perspective to draw from Figure $-1 is the fact that a descriptive model forms the core of a prescriptive model. Furthermore, the search routine of the prescriptive model is usually performed by a commercially available code of a search algorithm (e.g., linear programming, integer programming, etc.). However, the rest of the construction in Figure $-1, without which the search routine is useless, is the responsibility of the modeler.

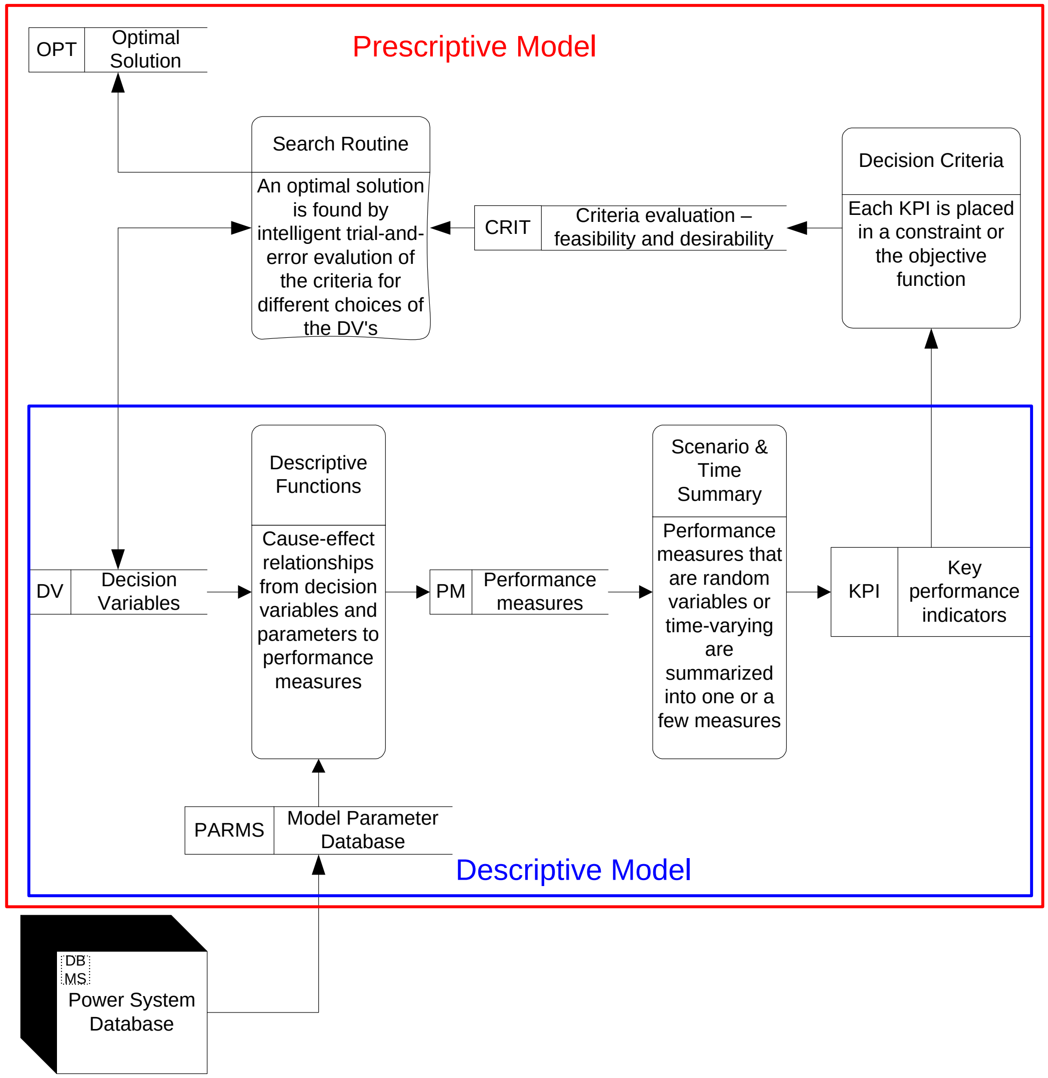


Figure $-1: The data flow of descriptive and prescriptive models

$.1.3 Simulation modeling

Decisions related to power systems have outcomes (performance measures) that play out over a long time and that can take on many scenarios due to randomness in system parameters such as loads and market prices. Furthermore, the relationship between decision variables and performance measures for power-systems decision problems is typically very complex and nonlinear. Of all of the forms of decision modeling, simulation is uniquely capable of capturing complex cause-effect relationships, time varying performance measures and stochastic effects. In fact, for many of the decision problems that the learner needs to model, simulation is the only modeling technique that can produce a reasonably accurate descriptive model. For example, simulation can be used to identify the vulnerabilities of the protection system prompted by the interconnection of DG to a distribution feeder. By comparing the total DG short-circuit contribution passing through protection devices with the pick up settings of the devices the required protection coordination changes for a specific DG location can be determined, Depablos (2004). Figure $-2 shows a simulation of a fault at bus 2 that results in a DG short-circuit contribution greater than the pick up setting of the protective device B. This will clearly result in miss-operation of unit B and unnecessary loss of load.

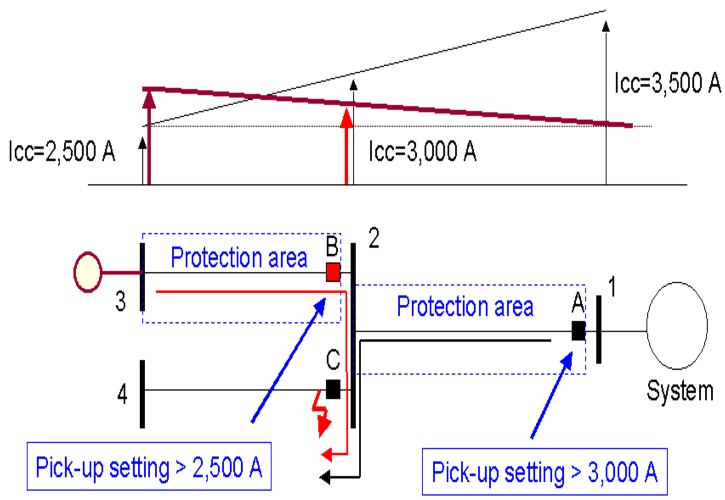


Figure $-2: Effect of DG insertion in the coordination of protective devices.

Every simulation model is a computerized description of a system. A system can often be visualized as a collection of interacting operations with flows of material, power, cash or other commodities among them. The simulation model tracks the state of the system as it evolves over time through the occurrence of events such as changes in load, outages, unit dispatching, short circuits and the passage of time. In order to do this a simulation model is created in the form of a computer program that consists of the following fundamental elements.

- Random Number Generator
- Event Scheduler

- State Transition Procedures
- System State Data Management
- Performance Measure Output

Through the creation of an artificial clock that marks simulated system time the simulation program schedules the events that cause the system to evolve. Transitions in the state of the system take place at points in time determined by the Event Scheduler. In the case of a typical simulation of a power grid, the Event Scheduler would be programmed to update the time on an hourly basis. At each of these transition times, the State Transition Procedures update the state of the simulated power system to reflect changes caused by the events that occur at the transition time. The current state of the system is represented by the System State Data. The System State Data is used by the Performance Measure Output routines to store values of performance measures over the time period that has just ended. Once the updated performance measures are filed, the simulation program returns to the Event Scheduler to process the next system-changing event.

Some of the state-changing events, such as load variations and outages may be the result of random effects. Computer simulation models are able to introduce random events into the event schedule through the use of random number generators. Through this mechanism, computer simulation models can represent realistically the performance that results from planned system interventions as well as unplanned system influences.

Events are defined by the modeler in terms of the simplest changes that can take place in the system that is modeled. By modeling the detailed interactions of system components over small intervals of time and aggregating the results of these interactions complex behavior can be described through the use of numerous, relatively simple transition procedures. In fact, computer simulation is the only modeling technique that can capture the complexity and randomness of a typical power system.

In a simulation model of a power system, the power flows through each network element and the cash flows associated with the power flows can be modeled for each hour of each day. From hour to hour, the simulation program updates the status of each generation unit, load and network element and stores this status in computer memory. The performance measures of the power system are computed and the results filed.

Another simple example of simulation modeling is found in the case of the unit dispatch decision. The simulation model for this decision would compute, for any given dispatching plan and for any given scenario of loads, the total generation cost as well as other performance measures. $-3 portrays a time series of generation costs over a 24-hour period for one scenario of loads. This time series would be summarized most appropriately in terms of its average. A simulation model could generate this time series if the scenario of loads was provided as input parameters. We call the computation of performance measures over a time horizon for one scenario of parameters a "replication" of the simulation model.

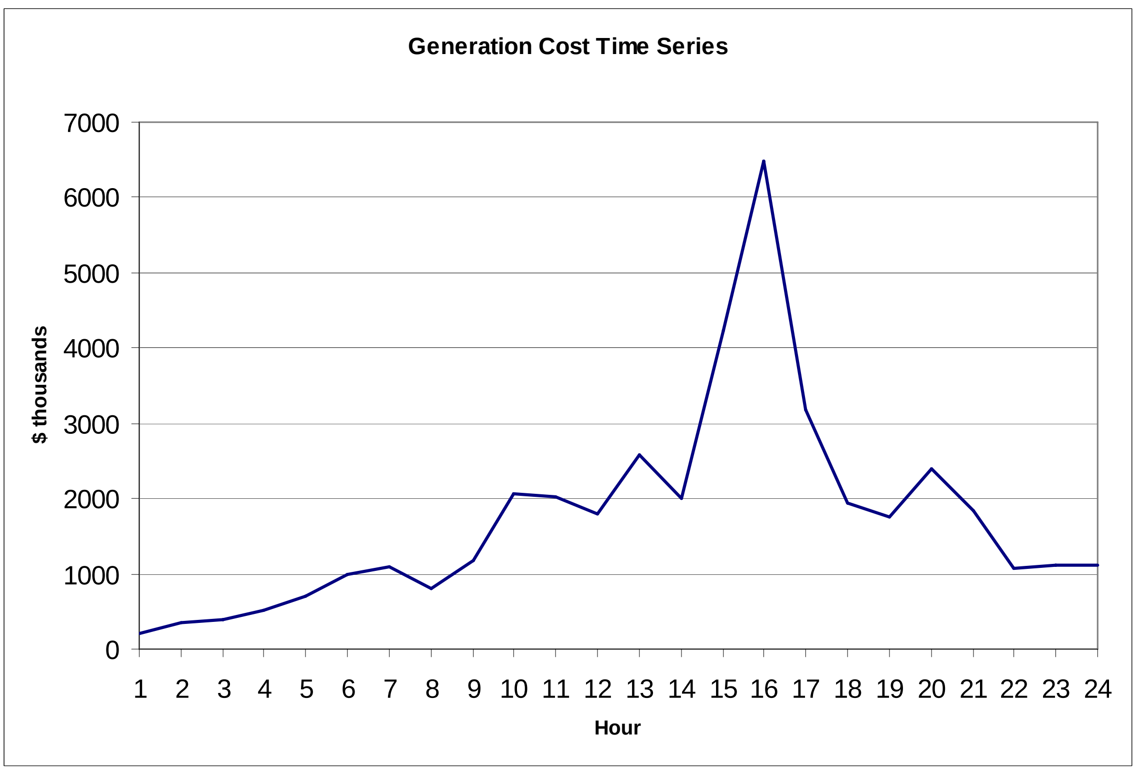


Figure $-3: Generation cost time series example

In order to assess the KPI's of risk and expected cost of a dispatching plan, we would like to compute the generation cost over many 24-hour time horizons, each one of which represents one possible scenario. In this way we obtain a representative sample of system performance from the population of all possible scenarios. Figure $-4 shows a sample of scenarios of the time series of generation cost. By computing the time average of each of these time series we obtain an overall measure of performance for that scenario. Table $-1 shows these time averages and Figure $-4 shows the distribution of the sample of costs given in Table $-1. Finally, we summarize the data in Table $-1 by computing their average and the value at risk evidenced by these data. Value at risk is a measure of financial risk that is commonly used in the energy industry. In this case, we compute VAR as follows:

$$VAR = C_{90} - \mu_c$$

where $\mu_c =$ the mean cost, estimated from the sample to be 1,774 and $C_{90} =$ the cost at the 90th percentile point of the distribution of costs, estimated from the sample to be 1,850. The two measures of expected cost and VAR are KPI's for the dispatching decision model that capture the expected financial value of the dispatching plan and a measure of financial risk associated with the dispatching plan.

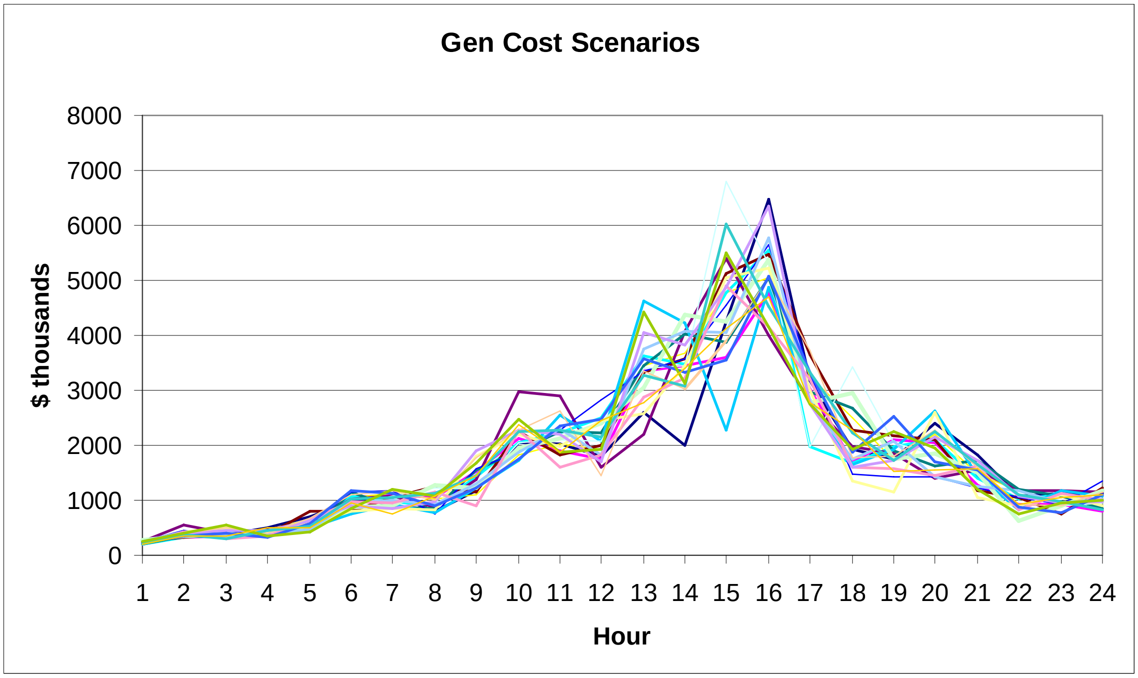


Figure $-4: Generation cost scenarios

Table $-1: Scenario Averages

Scenario	Average Cost
1	1742
2	1683
3	1807
4	1778
5	1782
6	1847
7	1791
8	1790
9	1734
10	1875
11	1799
12	1724
13	1757
14	1632
15	1875
16	1794
17	1753
18	1841
19	1793
20	1692
Average=	1774
VAR=	76

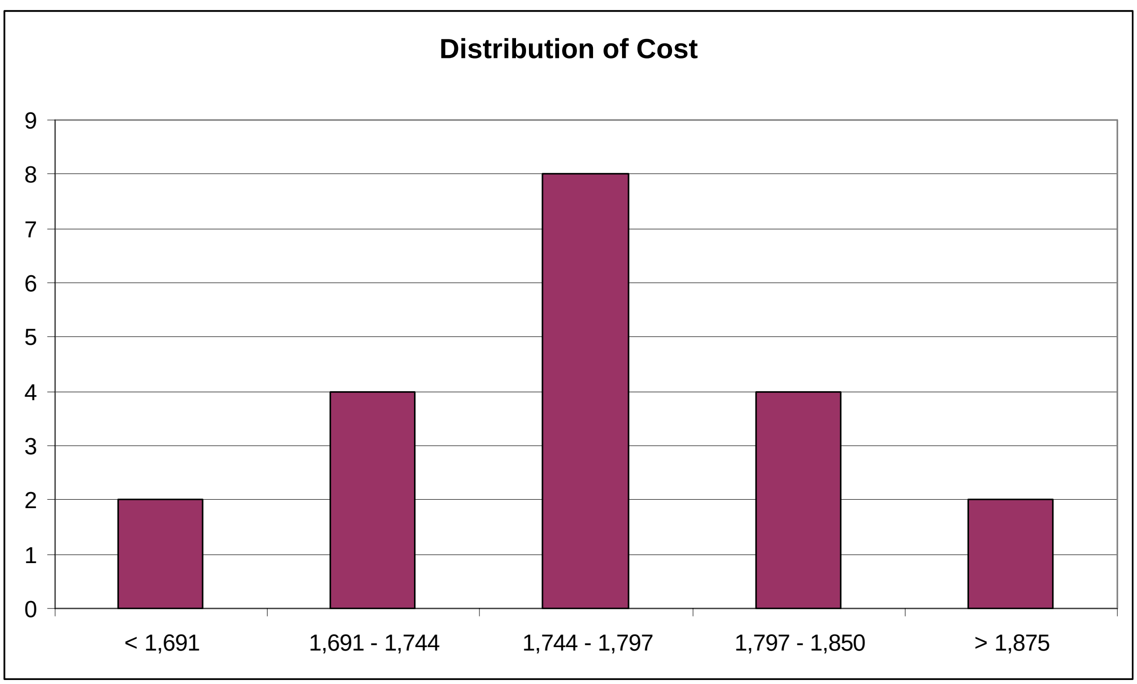


Figure $-5: Distribution of Sample of Costs

$.1.4 Interfacing

As a practical matter, a computerized educational support system is effective only if its interfaces for learners and teachers are transparent and easy to learn. To these users of a simulation program, the simulation is a tool for analyzing tradeoffs associated with decisions related to the design and management of a power system. Clearly, the underlying details of the simulation model, such as random number generators, statistical evaluation of performance measures, event scheduling should be hidden from these users. The learner’s interface to the simulation package should be designed for entry of decision variables and viewing of KPI’s that result from these settings of the decision variables. The teacher’s interface should include the ability to modify the parameter database in order to create different configurations of a power system for different sets of learners.

One of the most natural representations of the assets of a power system is that of a geographic information system (GIS). A GIS is fundamentally a database of objects, each of which can be indexed by a location in terms of an x-coordinate, a y-coordinate and elevation coupled with a graphical interface that displays these objects on a map. Generation units, power lines, transformers, substations, and buildings or other sites where loads occur can be represented in a GIS database and displayed on a computer screen so that a learner or a teacher can see clearly the components that make up the power system under study. In addition, GIS provides a connection that permits linking the physical and economic databases of the electric grid to available sociopolitical databases, opening the possibility to study the effect public policy, public perception and other sociopolitical factors that influence decision makers in real systems. Coupling the GIS system to the simulation program provides a seamless interface for the user between data entry and KPI’s. Figure $-6 shows a flow chart of the kind of ESS that we advocate in this paper.

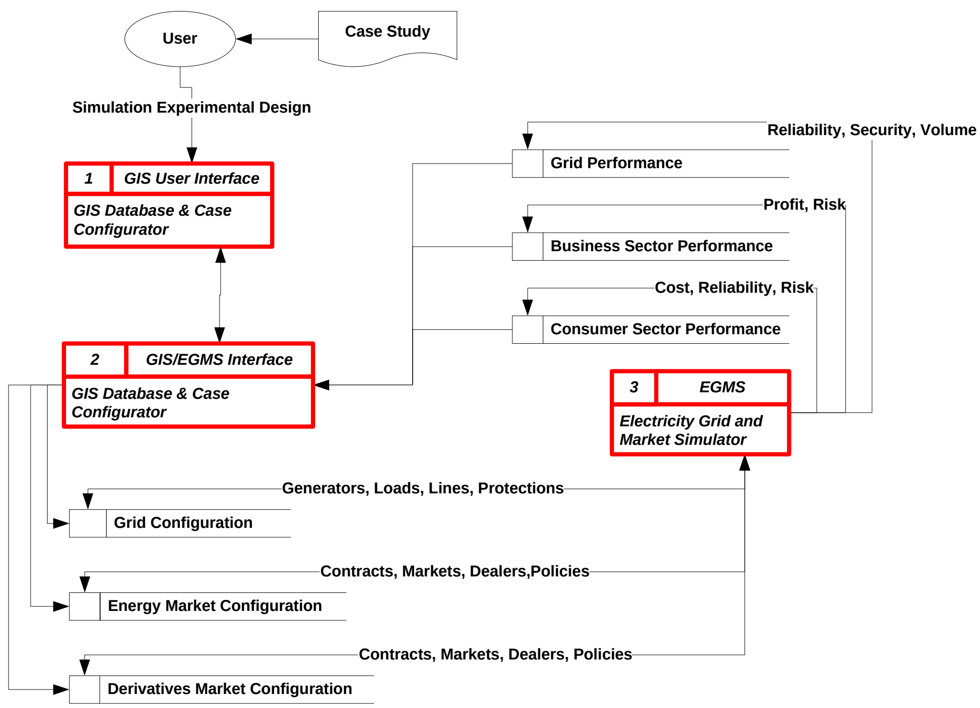


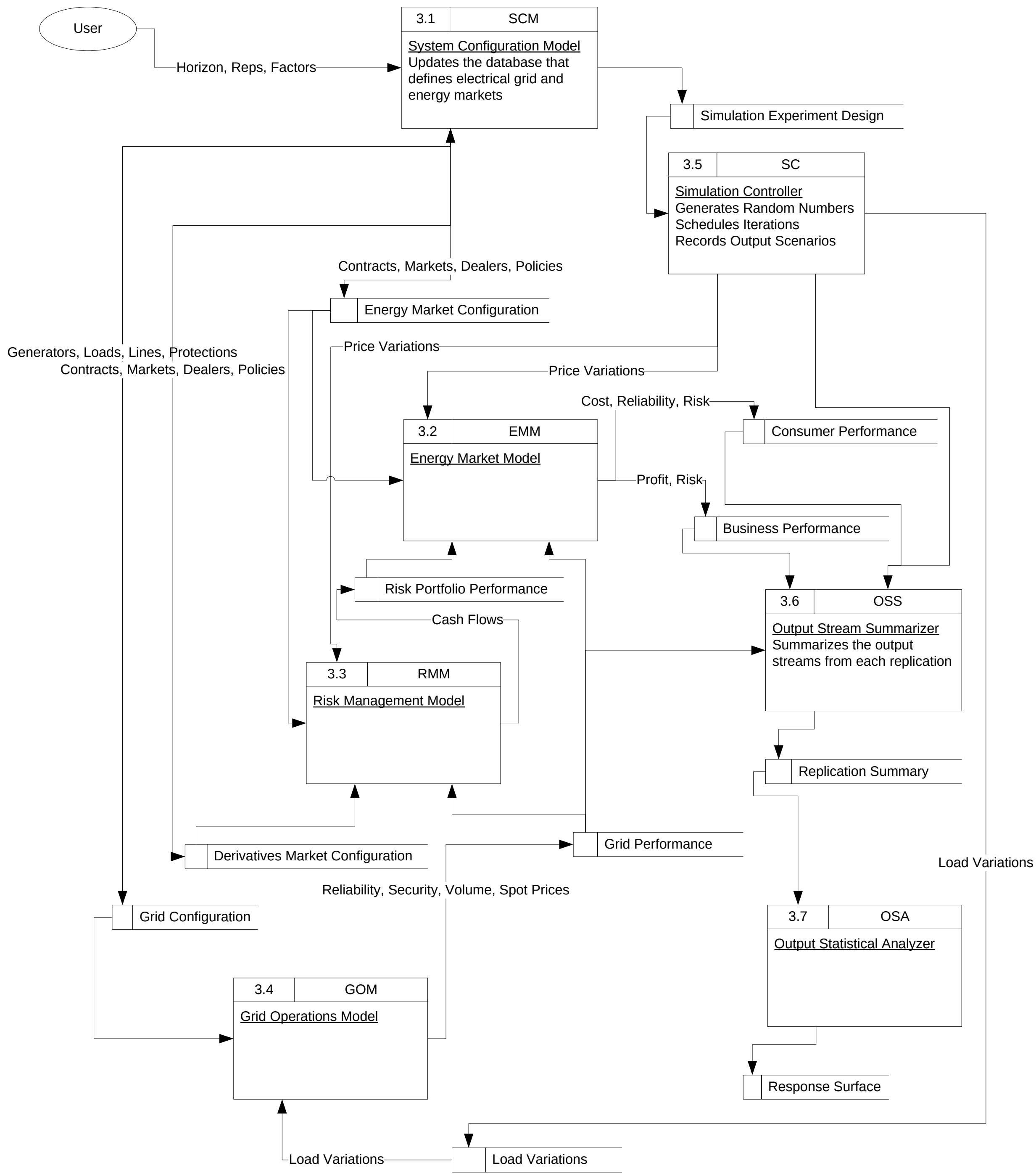
Figure $-6: Data Flow Diagram of ESS

The Electricity Grid and Market Simulator (EGMS) is a crucial part of the simulation program. Because of the modular nature of the components in an energy grid, object oriented programming (OOP) is a good choice of coding paradigm for EGMS. In OOP, the computer program consists of *objects*. An object packages data (or *properties*) and data processing functions (or *methods*) into one unit. For example, a Time object may contain hour, minute, and second as its properties. The methods of Time object may include assigning values to these properties and printing them in different time formats. The way an object-oriented program works is that the objects communicate with one another by sending and receiving messages among them. A message that an object receives can be an inquiry for a property of the object or a request for the object to perform one of its methods. After receiving messages from other objects, an object will process the data, and send the result to other objects. OOP has been widely-used in large-scale software development for years because of the modularity, expandability, and reusability of the code. Unlike the traditional programming, keeping the OOP code up-to-date is relatively easy and cost-effective. These advantages are so compelling that we cannot imagine coding an EGMS without OOP.

In order to program EGMS using OOP, we define the following main objects:

1. **Grid Operations Model (GOM)** is an object that simulates planning, scheduling, dispatching and controlling an electrical grid.
2. **Risk Management Model (RMM)** is an object that assesses the financial risk and develops strategies to manage it.
3. **Energy Market Model (EMM)** is an object that evaluates market performance.
4. **System Configuration Model (SCM), Simulation Controller (SC), Output Stream Summarizer (OSS), Output Statistical Analyzer (OSA)** are objects for the management of the simulation program, data entry and output reporting.

Figure $-7 depicts the relationships among these objects. When the simulator runs, GOM reads the grid configuration, simulates the electricity flows, and updates the grid performance. RMM reads the grid performance and derivatives market configuration, performs risk analysis, and updates the risk portfolio performance. EMM reads the risk portfolio performance as well as the market configuration and grid performance and outputs the consumer sector performance and business-sector performance. All of these events are executed for each time interval of the simulation.



DFD level 2

Figure $-7: Data flow diagram of EGMS

To simulate the power flows with GOM, we need to solve a set of power-flow optimization problems (see Momoh 2001). Solving such optimization problems is the most computationally intensive part of the simulator. Since the flows must be updated for every simulated time interval, the speed of the simulator could become a problem if the code for solving the optimization problems is not efficient. Writing an efficient optimization routine from scratch could be very time-consuming. Fortunately, some proprietary software packages, such as CPLEX and IMSL, provide routines for these purposes. With years of research and development invested in these software packages, their routines are proven to be efficient and reliable. Consequently, the construction of EGMS should be integrated with these routines.

$.2 Concepts for modeling power system management and control

The determination of optimal power flow in a grid over a sequence of time periods can be modeled as a set of decisions and actions that execute the workings of the energy markets and the technical control of the electricity grid. In the operation of real energy markets and grids as well as in a simulation of these systems, the operational decisions are supported by computerized models. These models manifest several challenging features of mathematical modeling and optimization, which we describe below in a constructive sequence.

$.2.1 Large-scale optimization and hierarchical planning

The control of markets and electricity grids requires coordinated decision-making across five decision domains.

1. Configuring: installed generation capacity, grid configuration, market regulations
2. Planning: bi-lateral contracts, wholesale bids & offers, unit availability
3. Scheduling: unit commitment, ancillary service contracts, reserve requirements
4. Dispatching: unit dispatch, demand management, regulation
5. Controlling: voltage control, frequency control, circuit protection

The large number of variables that these decisions encompass classifies this collection of decisions as a large-scale optimization problem. There is no practical decision-support system that can simultaneously optimize all of these decisions. Consequently, power grid and market management is carried out through the application of some conventional heuristic approaches.

A heuristic approach that is often used is one that is based on a hierarchical sequence of decisions that lead, through successive levels of detail, to a final solution. The basic idea behind hierarchical planning is that the solution to a rough-cut representation of a decision in terms of aggregated decision variables can serve as a set of guidelines and constraints for a refined decision in terms of detailed decision variables. In other words, the final solution to a problem can be achieved by first "coarse-tuning" the solution and then "fine-tuning" the solution.

In the case of energy grid management, the conventional hierarchy of decision making conforms to the ordered list shown earlier. For example, the problems of determining the unit availability, unit commitment and unit dispatch are all related through performance measures such as profit and service level, which depend on all of these three decisions. Rather than attempt to find solutions to all three decisions simultaneously so that a globally optimal solution is obtained, a hierarchical planning approach would specify three separate decisions to be solved in stages. The determination of unit availability, based on approximate representations of total demand over the upcoming week, provides capacity constraints on the commitment and dispatching decisions. The commitment decision, based on a forecast of load variations over the next 36 hours for which real-time dispatching will be needed, consumes the bulk of the generation capacity and leaves a judicious amount of capacity for support of the imbalance dispatching decisions.

The intuitive appeal of this approach is found in the selection of decision variables for each level of the hierarchical planning process. The first level generally, involves strategic decisions that have long-term effects such as unit availability. The second level involves decision variables that describe how the available assets are to be committed. The third level involves decision variables that describe how committed assets are to be dispatched. The fourth level and fifth levels involve decision variables that describe how dispatched assets are to be controlled. Under the hierarchical scheme, long-range, strategic decisions are made first. These decisions then impose constraints on the shorter-range, more detailed decisions that follow. At each level the plan for the entire system is developed in more detail.

The approximation inherent in hierarchical planning is introduced in the modeling of the performance of lower-level solutions at any stage in the hierarchy. In order to simplify each stage's problem, the effects of the lower-level decision variables on the current stage's constraints and the objective function are approximated. In turn, the solution to a higher-level problem specifies constraints on the next lower-level problem, and so on.

Using the "hat" notation to indicate approximations, the hierarchical planning approach is described as follows:

Suppose we have four sets of decision variables x_1, x_2, x_3, x_4 for the following decision model,

$$\max f(x_1, x_2, x_3, x_4)$$

subject to:

$$\begin{aligned} &g_1(x_1, x_2, x_3, x_4) \le 0 \\ &g_2(x_1, x_2, x_3, x_4) \le 0 \\ &\dots \\ &g_n(x_1, x_2, x_3, x_4) \le 0 \end{aligned}$$

By approximating the effects of variables x_2, x_3, x_4 we construct the following aggregate planning problem.

$$\hat{f}_1(x_1) \approx f(x_1, x_2, x_3, x_4)$$

$$\hat{g}_{1j}(x_1) \approx g_j(x_1, x_2, x_3, x_4) \quad \text{for } j = 1,\dots,n$$

The first optimization in the hierarchy is,

$$\max_{x_1} \hat{f}(x_1)$$

subject to:

$$\begin{aligned} &\hat{g}_{11}(x_1) \le 0 \\ &\hat{g}_{12}(x_1) \le 0 \\ &\dots \\ &\hat{g}_{1n}(x_1) \le 0 \end{aligned}$$

Resulting in a solution, x_1^*, which becomes a parameter in for all of the succeeding problems. The second approximate decision model is,

$$\hat{f}_2(x_2) \approx f(x_1^*, x_2, x_3, x_4)$$

$$\hat{g}_{2j}(x_2) \approx g_j(x_1^*, x_2, x_3, x_4)$$

$$\max_{x_2} \hat{f}(x_1^*, x_2)$$

subject to:

$$\begin{aligned} &\hat{g}_{21}(x_1^*, x_2) \le 0 \\ &\hat{g}_{22}(x_1^*, x_2) \le 0 \\ &\dots \\ &\hat{g}_{2n}(x_1^*, x_2) \le 0 \end{aligned}$$

The remaining optimization problems are formulated in a similar manner.

$.2.2 Sequential decision processes and adaptation

The control of markets and electricity grids must be done on a continuous basis, which necessitates ongoing decision-making regarding the supply availability, demand management, unit commitment, dispatching, ancillary services and regulation. For practical reasons, the planning horizon is divided into discrete time periods and the planning decisions are expressed and solved in terms of actions for each period. Of course this discrete representation of the time scale for a process that changes continuously introduces an approximation. However, the notion of developing a plan in finer and finer detail as each level of hierarchical planning is executed applies to the time scale as well. Higher-level, more strategic decisions are given a longer planning horizon and longer planning periods. By their nature these decisions can be made more crudely than tactical or operational decisions. As one moves down the hierarchy of decisions, the planning horizons and the planning periods are made shorter. Table $-2 shows the basic scope and definition of the five levels of hierarchical planning that make up our model of power grid management.

Table $-2: Planning horizons and periods

Decision Domain	**Planning Horizon (typical)**	**Planning Period (typical)**
Configuring	> 1 year	> 1 month
Planning	1 day - 1 year	1 day
Scheduling	36 hours	1 hour
Dispatching	1 hour	5 minutes
Controlling	0.5 hour	< 5 seconds

A sequential decision process (SDP) is sequence of decisions made over time in a way that each decision can adapt to the effects of all previous decisions and adapt to the outcomes of uncontrollable influences on the performance measures. A general methodology for optimizing SDP's is known as decomposition or dynamic programming.

Dynamic programming decomposes an optimization by segregating the decision variables into subsets and creates a group of nested optimization problems. For example, suppose we have four sets of decision variables x_1, x_2, x_3, x_4 representing the actions that can be taken at each of four time periods that make up the planning horizon and p_1, p_2, p_3, p_4 are the probability distributions of the random variables that influence the performance measures of the system that is to be controlled. Each performance measure may be expressed in terms of some measure of risk with respect to these random influences. The decision model for optimizing the plan can be stated,

$$\max f(x_1, x_2, x_3, x_4; p_1, p_2, p_3, p_4)$$

subject to:

$$g_1(x_1, x_2, x_3, x_4; p_1, p_2, p_3, p_4) \leq 0$$
$$g_2(x_1, x_2, x_3, x_4; p_1, p_2, p_3, p_4) \leq 0$$
$$\ldots$$
$$g_n(x_1, x_2, x_3, x_4; p_1, p_2, p_3, p_4) \leq 0$$

The dynamic programming methodology transforms this optimization into a nested sequence of optimization problems with the decisions of later time periods nested with the decisions of earlier time periods. The optimization procedure starts with the innermost nested problem (last time period) and works in stages to the outermost problem (first time period). A dynamic programming formulation of the problem described above is built from the following nested set of optimizations,

$$\max_{x_1}\left(\max_{x_2}\left(\max_{x_3}\left(\max_{x_4} f(x_1, x_2, x_3, x_4; p_1, p_2, p_3, p_4)\right)\right)\right)$$

At each stage, the optimization procedure derives optimal decision rules as opposed to optimal decisions. A decision rule is a set of contingency-based decisions. In this case, the contingencies at any stage are the combined effects of all outer decisions (not yet determined by the optimization procedure) as well as the range of uncontrollable influences on the performance measures over the time periods prior to the stage's decision. Through this methodology we can explicitly express the decision rule for each time period in terms of the outcomes of the random variables of all previous periods. Such a representation of the decision rule accurately portrays the real situation that is faced by the decision maker in each time period.

The correct solution to a stochastic, sequential decision process consists of the state-contingent decision rules generated by the dynamic programming solution. However, the derivation of the large number of such decision rules that would be necessary for a problem as complex as that of unit commitment and dispatch precludes the use of dynamic programming. Instead, planning for stochastic load and generation levels is achieved through the use of a control heuristic known as rolling horizon and adaptation. This procedure is used commonly in the commitment and dispatching of generation units.

Rolling horizon and adaptive control is executed through the combination of three planning techniques:

- Rolling the plan: Plans are updated at regular intervals. The time between updates is called the planning interval.
- Planning over a horizon: Each plan extends over a number of future time periods. The time over which a plan is derived called the planning horizon.
- Adapting the plan: At each update of the plan, the plan is adjusted within limits that are determined by the system's constraints on the rates at which resource flows can change. The planning horizon for each plan consists of a horizon over which the plan must be "frozen" followed by a horizon over which adjustments are allowed. The boundary between the fixed portion of a plan and the adjustable portion of a plan is called the planning "fence".

In the case of electricity scheduling and dispatch there are four adaptation options. Table $-3 defines these options. Each option is constrained to be exercised within the capacities that are set by the capacity reservation decisions made at a higher level of the decision-making hierarchy (see previous section). The update intervals, planning horizons and time fences given in Table $-3 are typical values in the operation of a large power grid.

Table $-3a: Capacity and demand constraints on scheduling options

Scheduling option	Capacity constraint	Demand constraint
Day-ahead unit commitment	Day ahead offers	Day-ahead bids
Imbalance commitment	Imbalance offers	Imbalance bids
Regulation reserve commitment	Regulation reserves offers	Regulation forecast
Spinning reserve commitment	Spinning reserves offers	Control error forecast

Table $-3b: Scheduling option parameters

Scheduling option	Update interval	Planning horizon	Time fence
Day-ahead unit commitment	24 hours	36 hours	12 hours
Imbalance commitment	24 hours	30 hour	6 hours
Regulation reserves	8, 16 hours	9, 17 hours	1 hour
Spinning reserves	8, 16 hours	9, 17 hours	1 hour

Table $-3c: Capacity and demand constraints on dispatching options

Dispatch/Control option	Capacity constraint	Demand constraint
Day-ahead dispatch	Day-ahead commitments	Day-ahead commitments
Real-time dispatch	Imbalance commitments	Demand forecast
Ancillary service regulation	Regulation reserve commitments	Regulation error
Voltage/frequency control	Spinning reserve commitments	Control error feedback

Table $-3d: Dispatching option parameters

Dispatch/control option	Update interval	Planning horizon	Time fence
Day-ahead unit commitment	8, 16 hours	9, 17 hours	1 hour
Real-time dispatch	1 hour	1.5 hours	30 minutes
Ancillary service regulation	5 minutes	30 minutes	5 minutes
Voltage/frequency control	4 seconds	30 seconds	4 seconds

The approximation that is inherent in a rolling horizon and adaptation procedure stems from the use of a deterministic forecast for each plan update. The accuracy of this forecast increases as the forecast horizon decreases. Consequently, the adaptation options with the shortest time fences enjoy the most accurate forecasts and can be viewed as “fine tuning” actions with respect to the “coarse tuning” of the plans produced by the longer-fence options.

$.2.3 Stochastic decisions and risk modeling

Demand for electricity and, to a lesser degree, supply, are not known with complete certainty, a priori. For this reason, decisions regarding supply availability, demand management, unit commitment, dispatching, ancillary services and regulation involve some risk. Such decisions are labeled stochastic. There are several approaches to coping with risk, all of which incorporate some combination of buffering and adaptation.

In our model we use a measure of financial risk known as value-at-risk (*VAR*). For every business decision, the decision maker has some desired level of financial performance that is considered satisfactory. However, due to the uncertainties of the real world, the financial performance of any decision is a random variable that can take on a range of values with probabilities given by a distribution that is known through the modeling of the decision. Ranking all of the scenarios for this random variable according to their associated financial performances, the decision maker can apply his/her own perspective on risk by specifying a probability that identifies the portion of these scenarios that constitute the “downside” risk of the decision. For example, a decision maker could consider the lowest-performing 10% of scenarios as the downside potential of a decision. Once this probability is set, the minimum financial loss that the downside scenarios can generate, measured relative to the pre-defined satisfactory level of return, is called the value-at-risk. *VAR* is typically computed over a risk horizon of one day and suffices to represent the exposure of a portfolio of contracts to downside risk from falling prices or falling demand. Figure $-8 illustrates the concept of *VAR*.

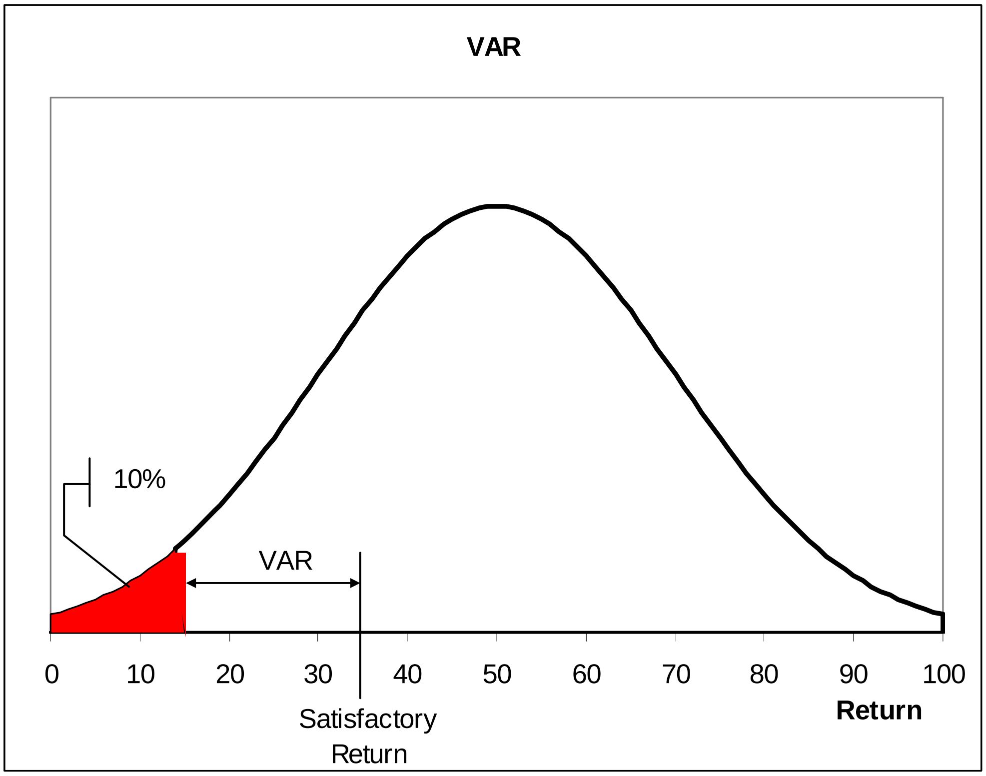


Figure $-8: Value-at-Risk Example

Mathematically, pursuing the minimization of VAR or constraining VAR below some tolerable limit is equivalent to adopting the key performance indicator of the cumulative probability of returns as we prove below.

$V =$ satisfactory return

$C =$ actual cash flow

$V - C =$ financial loss

$\alpha =$ risk level

$L =$ tolerable loss

$F_C =$ cumulative distribution of cash flow

$V - F_C^{-1}(\alpha) =$ value at risk

The constraint on *VAR* is,

$$V - F_C^{-1}(\alpha) \leq L$$

which can be expressed more simply as,

$$F_c(V - L) \leq \alpha$$

Risk measures have received much research attention over the last several decades and this brief discussion of *VAR* does not do justice to the depth of understanding of the nature of risk that this research has revealed. The interested reader is referred to Smithson (1998).

$.2.4 Group decision making and markets

In a regulated power industry, the reservation, commitment and dispatching decisions are made by a single authorized manager of the power grid. In the case of a single decision-making authority a decision can be modeled with a single objective function and accompanying constraints. However, in the case of partially regulated power grid, supply-availability decisions and demand-management decisions involve numerous decision makers, each pursuing his/her own self interests. Hence, markets are born and the decision models that describe the choices of market participants must recognize the different objectives and constraints of each market participant.

We model each market with a hierarchy of decision models in which capacity reservations are achieved in the form of bids and offers that are entered into each market by load-serving entities and suppliers of electricity, respectively. The grid operator then executes the commitment and dispatching decisions by clearing the markets, which sets the market clearing prices at each basis point in such a way that all demand constraints are met and the total cost of power to the entire grid is minimized. Table $-4 lists the markets that typically drive the management of the grid.

Table $-4a: Wholesale Markets

Market	**Transaction**	**Price**	**Buyer**	**Seller**	**Delivery Node**
LTC	Bi-lateral contract Bi-lateral contract	Bi-lateral Bi-lateral	ISO/DSO LSE	IOU/SA ISO/DSO	Gen bus Load bus
Day-ahead	Unit commitment Load commitment	LMP LMP	ISO/DSO LSE	IOU/SA ISO/DSO	Gen bus Load bus
Imbalance	Unit dispatch Load dispatch	Real-time LMP	ISO/DSO LSE	IOU/SA ISO/DSO	Gen bus Load bus
Regulation AS	Operating reserves Ancillary service	Real-time LMP	ISO/DSO LSE	IOU/SA ISO/DSO	Gen bus Load bus
Spinning AS	Reserve allocation Ancillary service	Reserve LMP	ISO/DSO LSE	IOU/SA ISO/DSO	Gen bus Load bus

Table $-4b: Retail Markets

Market	**Transaction**	**Price**	**Buyer**	**Seller**	**Delivery Node**
Bi-lateral, Regulated	Long-term contract	Bi-lateral	Consumer	LSE	Load bus

AS = ancillary services

DSO = distribution service operator, distribution grid manager

IOU = investor owned utility

ISO = independent service operator, grid manager

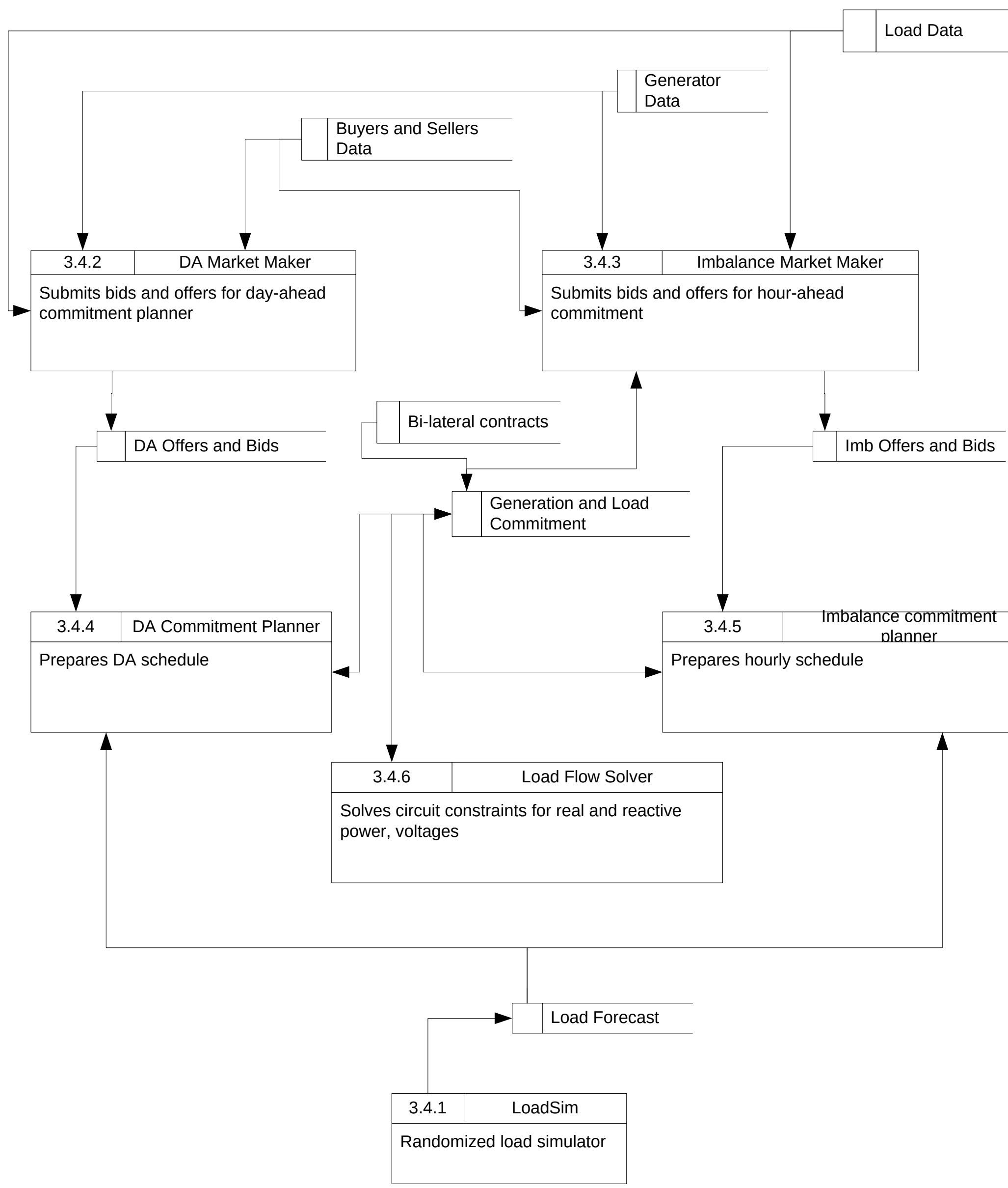
LMP = locational marginal price

LSE = load serving entity or load aggregator

SA = supply aggregator

$.2.5 Power system simulation objects

A simulation of a power system, which portrays the behavior of the system hour-by-hour over a period of many days, must mimic the behavior of the power grid's hardware as well as the decision-making of the customers, suppliers and grid operators who collectively manage the power system. In order to execute the simulated actions of market bidding/offering, unit commitment and unit dispatch in the same sequence with which these actions take place in the real system, a computer simulation of must contain software objects that behave as the decision-making agents and the grid controllers. In this section we describe the objects that form the building blocks of a typical power-grid simulation. Specifically, we present the design of a simulation package called the Virginia Tech Electricity Grid and Market Simulator (VTEGMS). Figure $-9 shows a flow chart of the interactions of these objects within VTEGMS.



VTEGMS DFD level 3

Figure $-9: Simulation of grid-driving decisions

$.3 Grid operation models and methods

In this section we describe the models and optimization methods that are used in VTEGMS, which are also typical of any EGMS. The reader should refer to Figure $-9 to see how each of the each of the models described in this section is integrated into the EGMS.

$.3.1 Randomized load simulator

A time series of demand as well as a time series of demand forecasts initiates the decisions of market bidding and offering. As we stated earlier, random parameters and random events are represented in a computer simulation through the use of random number generators (RNG). A simple example of the need for random numbers in a simulation is the requirement to represent randomly varying load over the time horizon modeled by the simulation. Formulas (1) – (3), adapted from Soares and Medeiros, 2005, shows a typical load forecasting formula that would be used to represent load for hour, *h*, of day, *d*, of a simulated horizon.

$$L_{h,d} = L^P_{h,d} + L^S_{h,d} \qquad (1)$$

where,

$$L^P_{h,d} = \alpha_0 + \rho d + \sum_{r=1}^{H} \alpha_r \cos(\omega r d + \theta_r) + \sum_{i=1}^{K} \mu_i \delta_i \qquad (2)$$

$$L^S_{h,d} = \phi_0 + \sum_{i=1}^{p} \phi_i z_{h,d} + \varepsilon_{h,d} \qquad (3)$$

$L_{h,d} =$ total load

$L^P_{h,d} =$ potential load

$L^S_{h,d} =$ irregular load

$\alpha_0 =$ initial base load

$\rho d =$ trend component of load

$\sum_{r=1}^{H} \alpha_r \cos(\omega r d + \theta_r) =$ cyclical variations in load represented by *H* harmonics of an annual cycle.

$\sum_{i=1}^{K} \mu_i \delta_i =$ load adjustments for the day of the week, holidays, etc.

$\phi_0 + \sum_{i=1}^{p} \phi_i z_{h,d} =$ autoregressive components of load

$\varepsilon_{h,d} =$ random component of load assumed to be normally distributed with a mean of zero and a standard deviation of $\sigma_{h,d}$

For any day, *d*, and hour, *h*, all of the terms in these formulas except $\varepsilon_{h,d}$ would be known parameters that the modeler would enter into the simulation program's database. The random component of load must be represented in the simulation program as a different value each time the load for day, *d*, and hour, *h*, is simulated. In order to do this, the simulation program generates a stream of numbers that have the properties of random drawings of numbers from a normal distribution with a mean of zero and a standard deviation of $\sigma_{h,d}$.

A RNG is a computer program that can produce a stream of numbers that appear to have come from a specified probability distribution. These streams are actually computed deterministically by a recursion formula so they are more appropriately called pseudo-random numbers. However, pseudo-random numbers have all of the statistical properties of numbers that are randomly generated from a physical process as well as some non-random properties that make them very useful for simulation studies. The essential properties of RNG's are as follows:

1. RNG's generate numbers that are uniformly distributed between 0 and 1. A uniformly distributed stream of numbers can be transformed into a stream of numbers that appear to come from any other probability distribution through standard computational techniques.
2. Each number generated in a stream of numbers should be statistically independent of all numbers generated previously and independent of all numbers to be generated afterwards. This ensures that we are not instilling unwanted memory into the behavior of the simulated system.
3. A stream of random numbers should be reproducible. This allows one to perform multiple simulations runs in the context of a simulation experiment in which all

factors, including the random influences, are controlled except those that we wish to change for the sake of the experiment.

4. The computer program that generates the random numbers should be efficient in terms of computing time and data storage requirements.

Pseudo-random numbers are not truly random. They have a "period" or "cycle length" so that a stream of pseudo-random numbers will at some point repeat itself. The pseudo-random number generators embodied in simulation models are constructed so that the length of the period is very long, alleviating concern about this property causing the numbers to be dependent on one another.

The pseudo-random numbers are generated by a deterministic formula. This makes them well-defined and also gives them the reproducibility property that we desire. The linear congruential method, which we describe in its simplest form below, is the most common method for generating pseudorandom numbers in the interval *[0,1)*. Consider a stream of numbers $x_0, x_1, ...$ such that,

$$x_{i+1} = (ax_i + b) \, mod \, c$$

$$r_{i+1} = \frac{x_{i+1}}{c}$$

$$x_0 = \text{seed}$$

a, *b*, and *c* are chosen in order to give the stream the longest period possible. For example, let *w* = the number of bits/word on the computer used to generate the random numbers. Then,

$c = 2^w$

b is relatively prime to *c*

$a = 1+4k$ where *k* is an integer

Once a stream of pseudo-random numbers in the interval *[0,1)* are generated they can be translated into a stream of numbers that appear to have been drawn from any specified probability distribution such as the normal distribution of mean *0* and standard deviation $\sigma_{h,d}$ in the load-forecasting example described earlier. Although it is beyond the scope of the treatment of simulation offered in this chapter, this transformation is straightforward and is easily coded into a simulation software package.

The interested reader is referred to Banks, et. al. (2005) for more information about the structure of simulation programs and simulation modeling. Amelin (2004) provides an overview of simulation models specifically for modeling electricity markets.

$.3.2 Market maker

Following the hierarchy of decisions, we model the planning decisions in terms of the market strategies of buyers and sellers. In the day-ahead and imbalance wholesale markets, each supply aggregator offers generation capacity in the form of a "stack", which is a list of ordered pairs of power quantities and associated offer prices. When the market clears, any power that was offered at or below the market clearing price will be sold by the supply aggregator at the market clearing price. Similarly, each load aggregator bids on power in the form of a stack in terms of power quantities and associated bid prices. When the market clears, any power that was bid at or above the market clearing price will be purchased by the load aggregator at the market clearing price.

The market maker object of the simulation applies the auction rules described above for determining the optimal offer and bid functions of each player in the market. That is, for the simulation of a power market associated with a particular power grid we construct an instance of the market for each buyer and seller of power and for each type of energy auction. In order to specify these instances, we define the following notation.

$m =$ market identification = *ltc* (long term, bi-lateral contract), *da* (day-ahead wholesale), *imb* (imbalance, wholesale), *reg* (regulation reserve), *con* (control reserve)

$M_z^m =$ market clearing price for zone z in market m

$\overline{M}_z^m =$ price cap for M_z^m

$\underline{M}_z^m =$ price floor for M_z^m

$z(k) =$ zone to which generator or load element k belongs

$B_{kj}^m = j^{th}$ bid price for power in market m from load element k

$O_{kj}^m = j^{th}$ offer price for power in market m from generator k

$S_G =$ set of all generator circuit branches

$S_A =$ set of all transmission lines

$S_S =$ set of supply aggregators

$S_L =$ set of load aggregators

$S_{Gn} =$ the set of generators marketed by supply aggregator *n*

$S_{Ln} =$ the set of loads represented by load aggregator *n*

$S_B =$ the set of all busses

$P_{kj}^m = j^{th}$ power segment bid or offered in market *m* at load or generator element *k*

P_k^m new power-commitment in market m in the planning period at load or generator element *k*

Market Model for Availability Planning (m = da, rt) for each $n \in S_S$

$$\underset{\left\{\left(O_{kj}^m, P_{kj}^m\right) k \in S_{Gn}\right\}}{Max} \sum_{k \in S_{Gn}} E[R_k]$$

Subject to:

$$Pr\,ob\left(\sum_{k \in S_{Gn}} R_k < V_n\right) < \alpha_n$$

where

$$R_k = M_{z(k)}^m P_k^m$$

$$P_k^m = \sum_{O_{kj}^m \le M_{z(k)}^m} P_{jk}^m$$

Market Model for Demand Planning (m = da, rt) for each $n \in S_L$

$$\underset{\left\{\left(B_{kj}^m, P_{kj}^m\right) k \in S_{Gn}\right\}}{Min} \sum_{k \in S_{Ln}} E[R_k]$$

Subject to:

$$Pr\,ob\left(\sum_{k \in S_{Ln}} R_k > V_n\right) < \alpha_n$$

where

$$R_k = M_{z(k)}^m P_k^m$$

$$P_k^m = \sum_{B_{kj}^m \ge M_{z(k)}^m} P_{jk}^m$$

Solution method

In this section we propose a simple, generic market model for the simulation object that represents the decision of an individual market player. This object is then instantiated in the simulation for each market participant in each market type. We assume a market for the buying and selling of power over a particular future time period that we will call the sale period.

$c_i =$ the internal capacity, or maximum volume, of an asset that the market player can offer (bid) for sale (purchase)

$c_e =$ the external capacity, or maximum volume, of the asset that the rest of the market can offer (bid) for sale (purchase) over the sale period

$m =$ the future market clearing price of the asset, a random variable at the time offers (bids) are made

$\overline{m} =$ price cap for the market

$\underline{m} =$ price floor for the market

$F_m =$ cumulative distribution function of m

$d =$ maximum demand for the asset over the sale period

The decision that the market player must make is the set of prices at which each unit of volume will be offered (bid). In effect, each market player presents a supply or demand function to the market. We define these decisions in terms of distribution functions,

$o_x(p) =$ fraction of the asset's maximum volume offered at prices $\leq p$, $x = e,i$

$b_x(p) =$ fraction of the maximum demand bid at prices $\geq p$, $x = e,i$

$0 \leq o_x(p) \leq 1$

$0 \leq b_x(p) \leq 1$

Note: $o(p)$ is right continuous and increasing and $b(p)$ is decreasing and left continuous. Conventional offer and bid mechanisms allow for the presentation of a "stack" of power to the market. The stack is a finite set of power volumes with associated prices. $\{(v_i, p_i)\}_{i=1}^{n}$. For offers, $o(p) = \sum_{p_i \leq p} v_i$ and for bids, $b(p) = \sum_{p_i \geq p} v_i$. For the purpose of this model, we assume that $o_i(p)$ is continuous and $\frac{do_i}{dp}$ is continuous except at the point of contact with the boundaries of the constraints, $0 \le o_i(p) \le 1$

In what follows we derive the decision facing an individual power supplier. The model for an individual power buyer is analogous. The market clears at a price that matches supply to demand. This condition is expressed as,

$$c_i o_i(p) + c_e o_e(p) = db(p)$$

We re-state the market-clearing condition as,

$$o_i(p) = \frac{db(p) - c_e o_e(p)}{c_i}$$

We define the right-hand side of this expression as the normalized, residual-demand random process, $\hat{d}(p)$. The market-clearing condition is then,

$$\hat{d}(p) = \frac{db(p) - c_e o_e(p)}{c_i}$$

$$o_i(p) = \hat{d}(p)$$

We note that $\hat{d}(p)$ is a random process that is decreasing and left-continuous in p and the market-clearing condition induces a market-clearing price which is a random variable. That is, the residual demand process is a function of scenarios, $\omega \in \Omega$, which implies that the market-clearing price is also a function of scenarios, $m(\omega)$. The distribution of market prices can then be expressed in terms of the distribution (forecast) of residual demand.

$$F_m(p) = F_{\hat{d}}\left(o_i(p)\right)$$

Figure $-10 shows an example of an supply function and several scenarios for residual demand. The intersections of the supply function with the residual demand functions indicate the scenarios for market-clearing prices.

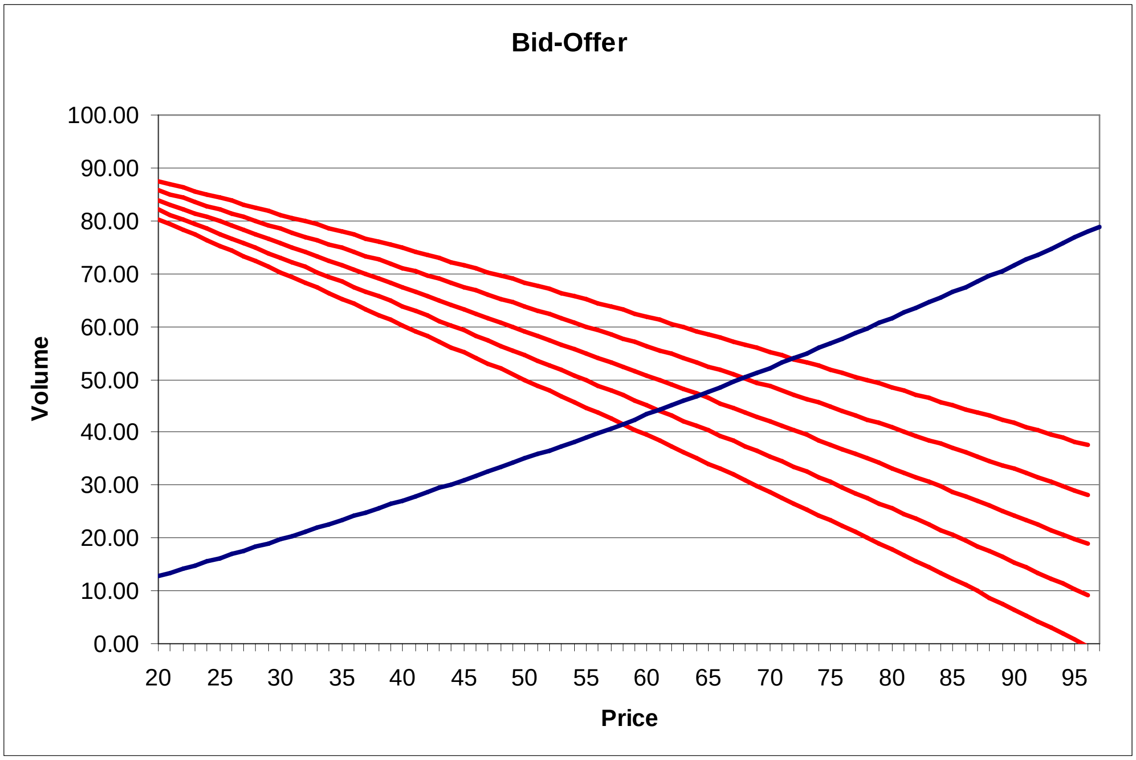


Figure $-10: Example of residual demand scenarios and offer fraction vs. price

When the market clears, the revenue (cost) that is accrued by a seller (buyer) can be evaluated as

$$r(m) = mc_i o_i(m)$$

m is a random variable, so r is a random variable.

F_r = cumulative distribution function of the cash flow $r(m)$ over the random variable, m. Note,

$$F_r(r(p)) = F_m(p) = F_{\hat{d}}(o_i(p))$$

The market player's key performance indicators are return and risk. The former measure is evaluated as the expected cash flow,

$$E[r] = \int_0^{\infty} r dF_r = \int_{\underline{m}}^{\overline{m}} c_i m o_i(m) dF_m = \int_{\underline{m}}^{\overline{m}} c_i m o_i(m) f_{\hat{d}}(o_i(m)) \frac{do_i}{dm} dm$$

In energy markets, risk is most commonly incorporated in the market decisions in terms of a constraint on value-at-risk.

$$F_r(V-L) \le \alpha$$

or

$$\int_0^{V-L} dF_r \le \alpha$$

By the monotonicity of $o_i(m)$, for any policy, o_i, there is a well-defined market-clearing price, β, for which $r(\beta) = V - L$ or $o_i(\beta) = \frac{V-L}{\beta c_i} = \hat{d}(\beta)$. Note that β is a function of the policy o_i. Furthermore, the monotonicity of $r(m)$ implies that the risk constraint can be written equivalently as,

$$F_m(\beta) \le \alpha$$

or

$$\int_{\underline{m}}^{\beta} f_{\hat{d}}(o_i(m)) \frac{do_i}{dm} dm \le \alpha$$

The risk constraint is incorporated into an objective function with a lagrange multiplier, μ.

$$J = \int_{\underline{m}}^{\overline{m}} c_i m o_i(m) f_{\hat{d}}(o_i(m)) \frac{do_i}{dm} dm - \mu \int_{\underline{m}}^{\beta} f_{\hat{d}}(o_i(m)) \frac{do_i}{dm} dm + \mu\alpha$$

Badinelli (2006) provides an optimal solution for the supply function by using optimal control theory.

$.3.3 The commitment planner

The market maker object is used in the simulation to determine the “stacks” of generation offers and load demands for each time period. The next stage in the planning and scheduling hierarchy is that which clears the market and the selects from the generation and load stacks the power that will be supplied. However, in making this selection, the currents, voltages, generation, loads and prices must satisfy numerous constraints. Subject to these constraints, minimizing the total cost of power that is needed to cover all of the loads is a typical objective function for power pools and grid operators. See PJM (2003, 2004, 2005). Hence, we have the optimal power flow (OPF) problem that we must solve at every instance of commitment planning, which can be formulated approximately in terms of real power and capacity constraints (DC load flow model) as follows:

$\overline{P}_k =$ maximum allowed total power at load element or generator element k

$\underline{P}_k =$ minimum required total power at load element or generator element k

element k

$U_k =$ maximum upward ramp rate of generator element k

$D_k =$ maximum downward ramp rate of generator element k

$C_o^m =$ overhead cost of operating the grid for market m

$\lambda_k =$ congestion cost charged to load element k

$P_k^c =$ total currently committed power in the planning period at load or generator

$$P_k^c = \sum_{k \in S_{mk}} P_{kj} \text{ , } m = ltc$$

$$P_k^c = P_k^{ltc} + \sum_{k \in S_{mk}} P_{kj} \text{ , } m = da$$

$$P_k^c = P_k^{ltc} + P_k^{da} + \sum_{k \in S_{mk}} P_{kj} \text{ , } m = imb$$

$$P_k^c = P_k^{ltc} + P_k^{da} + P_k^{rt} + \sum_{k \in S_{mk}} P_{kj} \text{ , } m = reg$$

$$P_k^c = P_k^{ltc} + P_k^{da} + P_k^{rt} + P_k^{res} + \sum_{k \in S_{mk}} P_{kj} \text{ , } m = con$$

$\boldsymbol{I}^{bus}$ = vector of all *external* current phasors at each bus – currents injected to the grid by generators and currents drawn from the grid by loads.

$\boldsymbol{Y}^{bus}$ = bus admittance matrix constructed from the admittances of all circuit elements

$\boldsymbol{V}^{bus}$ = vector of voltages at all generator and load busses.

<u>Note:</u>

- The index *k* used in the notation for generators and loads refers to the unique circuit branch of the generator or load as opposed to the numerical identifier of the generator or load.
- Bi-lateral contracts can be modeled as bids and offers at the contract price.
- Must-serve loads (from bi-lateral contracts) can be modeled as bids at the price cap.
- Load shaping through the discretionary use of power can be modeled in terms of the bids.
- Load shaping through the use of islanded DG can be modeled in terms of the bids.
- Must-run generators (from self-scheduled generators) can be modeled as offers at the price floor.

<u>Problem: OPF (*m* = *ltc*, *da*, *imb*, *reg*, *con*)</u>

$$Min \sum_{k \in S_G} M_k^m P_k^m$$

Subject to:

<u>Constraint set 1</u>

$P_k^c \geq \underline{P}_k$ for all generators, $k \in S_G$

$P_k^c \leq \overline{P}_k$ for all generators, $k \in S_G$

$U_k \geq P_k^c - P_k^c(t-1) \geq -D_k$ for all generators, $k \in S_G$

<u>Constraint set 2</u>

$\underline{M}_z^m \leq M_z^m \leq \overline{M}_z^m$ for all zones, *z*

$P_k^m = \sum_{O_{kj}^m \leq M_{z(k)}^m} P_{kj}^m$ for all generators, $k \in S_G$

$P_k^m = \sum_{B_{kj}^m \geq M_{z(k)}^m} P_{kj}^m$ for all loads, $k \in S_L$

$$\sum_{k \in S_L} \left(M_{z(k)}^m + \lambda_k \right) P_k^m - \sum_{k \in S_G} M_{z(k)}^m P_k^m \geq C_o^m$$

<u>Constraint set 3</u>

- Emissions constraints
- Regulatory constraints
- Inventory constraints for storable power generators

<u>Constraint set 4</u>

$P_k \leq T_k$ for all lines $k \in S_A$

<u>Constraint set 5</u>

$\boldsymbol{Y}^{bus}\boldsymbol{V}^{bus} = \boldsymbol{I}^{bus}$

$Q_k^{min} \leq Q_k \leq Q_k^{max}$ for all generators, $k \in S_G$

$V_k^{min} \leq |V_k| \leq V_k^{max}$ for all busses, $k \in S_B$

$\alpha_k^{min} \leq \alpha_k \leq \alpha_k^{max}$ for all busses, $k \in S_B$

Constraint set 1, expressed in terms of real power, reflect general physical limitations of generators. Several market constraints, shown in constraint set 2, are necessary to model the behavior of the auctions that mechanize the day-ahead and imbalance markets. The last constraint in this set ensures that the power that is actually bought or sold is that which the market-clearing process selects and that revenues cover costs.

Constraint set 3 reflects special considerations of a particular power grid. Constraint set 4 consists of the thermal limits on the power lines of the grid. These constraints determine the congestion charge, λ_k , that is assigned to any load that cannot obtain power from the cheapest source of generation because of thermal limits on transmission lines that connect the load to this generation.

Finally, we must enforce the physical laws that govern real and reactive power within a circuit as well as limits on the phase and voltages of generator outputs. We assume that all voltages and currents attain their steady-state, forced-response values during each interval. We do not include transient behavior in the solution. To this end we impose Kirchoff's Current Law and Kirchoff's Voltage Law on all circuit elements, leading to constraint set 5. We also impose quality conditions on the power that is made available throughout the grid in terms of the voltage magnitude and the amount of reactive power that is allowed.

Solution method

The rather large OPF problem is traditionally solved in two stages, following the decomposition approach described earlier. The first stage consists of constraint sets (1) – (3). The optimization method can be any robust non-linear programming method. The values of real power at all generation and load busses that this stage produces are used to solve the equality constraints in constraint set 5.

Stage 2 consists of solving constraint set 5 using the Newton-Raphson Load Flow method (see Momoh 2001). The solution to the load flow problem is then checked against constraint set 4. Violations are recognized via updated congestion charges that are applied to constraint set 3. Then the two-stage process is repeated until convergence is achieved.

$.3.4 Implementation

To date, there are several versions of simulation packages for modeling power systems. Each of these packages was designed for specific purposes and exhibits particular strengths as Table $-5 indicates.

The fields of energy engineering, management and policy are burgeoning with the challenges of new technologies, business models and regulatory changes. Education of future professionals in the energy economy will require intensive exposure to realistic problems and decisions that the future holds. The breadth of this exposure, as is indicated by our hierarchical list of decision problems, is broad enough to require ESS packages of widely varying scopes – from decision models for multi-year horizons to models for hourly and minute-by-minute horizons and from decision models for broad public-policy regulations and massive capital investments to models for control of small distributed generation units. We conclude that more simulation-based ESS packages are needed.

Table $-5: Comparison of simulation packages

Package Name	Creator/Vendor	Scope	Key Features	Applications
VTGIS/EGMS	Virginia Tech (Badinelli, et.al. 2005)	Distribution grids & distributed generation	Interfaced with ESRI's ARCGIS package	Future application in university courses in electrical engineering, business, public policy
GE Maps	General Electric (GE 2005)	Regional grids	LMP computation, transmission constraints	Bid strategy, unit commitment, market studies, economic analysis
Aurora	EPIS, Inc. (EPIS 2005)	Regional grids	Nodal and zonal LMP computation, transmission constraints	Power flow computation; valuation of generation & transmission assets, FTR's, LTC's
SimRen	ISUSI (Herbergs et.al. 2005)	Multi-region grids	Dispatches wind, solar, cogen as well as conventional generation	Generation technology selection, installed capacity planning
EMCAS	CEEESA (CEESA 2002)	Adaptive systems model of regional energy markets	Agent-based modeling and simulation	Electricity trading strategies, economic analysis
STEMS	EPRI	Sort-term markets	Agent-based modeling and simulation	Energy market design, trading strategies

Finally, we emphasize the need for case studies in the education of professionals in the energy field. Computerized decision support systems alone are useful only to professionals who already understand the decision problems to which they apply these systems. However, learners must view each decision problem in a holistic, multi-disciplinary manner in order to understand fully the tradeoffs inherent in the problem. Only well-crafted case studies that are supported by companion computerized decision support systems can impose this view.

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