

A Multiperiod Generalized Network Flow Model of the U.S. Integrated Energy System

Part I – *Model Description*

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Abstract—This paper is the first of a two-part paper presenting a multiperiod generalized network flow model of the integrated energy system in the United States. Part I describes the modeling approach used to evaluate the economic efficiencies of the system-wide energy flows, from the coal and natural gas suppliers to the electric load centers. Under the proposed problem formulation, fuel supply and electricity demand nodes are connected via a transportation network, and the model is solved for the most efficient allocation of quantities and corresponding prices. The methodology includes physical, economic, and environmental aspects that characterize the different networks. Part II of this paper provides numerical results that demonstrate the application of the model.

Index Terms— **Generalized network flow model, integrated energy networks, nodal prices, optimization.**

I. NOMENCLATURE

The main symbols and terms used in this paper are described below for quick reference.

A. Sets

- L_{ij} Set of linearization segments on the energy flowing from node i to node j .
 M Set of arcs.
 N Set of nodes.
 T Set of time periods.
 G Set of arcs representing electricity generation ($G \subset M$).

B. Parameters

- $c_{ij}(l, t)$ Per unit cost of the energy flowing from node i to node j , corresponding to the l th linearization segment, during time t .

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- $b_j(t)$ Supply (if positive) or negative of the demand (if negative) at node j , during time t .
 $e_{ij,max}$ Upper bound on the energy flowing from node i to node j .
 $e_{ij,min}$ Lower bound on the energy flowing from node i to node j .
 $\eta_{ij}(l)$ Efficiency parameter associated with the arc connecting node i to node j , in the l th linearization segment.
 $SO2_i(t)$ Sulphur dioxide emissions rate associated with the fuel consumed by power plant i , during time t .
 α_i Removal efficiency of the pollution control equipment installed at power plant i . If no pollution equipment exists at power plant i , then $\alpha_i = 0$.
 $NSO2$ National SO_2 limit.

C. Variables

- $e_{ij}(l, t)$ Energy flowing from node i to node j , corresponding to the l th linearization segment, during time t .

D. Definition

Integrated Energy System: The production, transportation, storage, and conversion system that moves energy from its fuel sources to the electric distribution subsystem.

II. INTRODUCTION

THE movement towards deregulation and competition has led to an increased level of decentralization in energy-related decision making. As a result, electric power systems are planned and operated without the conscious awareness of implications in other energy subsystems, namely the consideration of the integrated dynamics with the fuel markets and infrastructures. This has been partly due to the difficulty of formulating models capable of analyzing the large-scale, complex, time-dependent, and highly interconnected behavior of the integrated energy networks, while accounting for characteristics unique to each energy subsystem (e.g., coal, natural gas, and electric power). Consequently, each subsystem supports specific procedures and strategies according to its own value system (i.e., economic, technical, political, and environmental context), which may not be consistent with procedures and strategies necessary for an efficient overall operation.

Today's industry climate motivates a more integrated study

of the energy system. First, as the electric power industry becomes more competitive, economic performance of electricity delivery is intensely scrutinized from a national perspective, with electricity delivery price as a key metric. Customers and regulators are questioning electricity markets in which prices are significantly higher than those in other parts of the country, resulting in heavy pressure to identify means to gain economic efficiencies (lower prices) without seriously diminishing the reliability of the system. Second, the percentage of fuel purchased on the spot market has been increasing with a corresponding decrease in the percentage of fuel purchased under long term contracts. In addition, long term contracts have become shorter in duration, as electric power generators try to pass market risks on to primary energy suppliers (producers and carriers). This fact increases concern on the part of generation owners that they may be more vulnerable to short or medium term contingencies in fuel supply. Third, there exists increasing awareness of the environmental problems caused by pollution emitted by the electric energy sector, which leads to increased pressure to internalize externalities associated with electric power generation. In particular, the passage of the Clean Air Act Amendments (CAAA) of 1990 forced electric generators to reduce their emissions of sulfur dioxide (SO₂) through the implementation of an innovative tradable permit system. Utilities are endowed with considerable operational flexibility since it is the total quantity of emissions that matters and a utility can achieve its target level through emission controls, fuel switching, conservation programs, or by buying allowances. Depending on the compliance strategies adopted, the impacts of the SO₂ regulations can go beyond the electric power subsystem and affect the energy flows of the fuel networks. For example, if a utility that owns coal-fired power plants decides to comply with the program by switching to natural gas, this will have implications on the fuel networks, decreasing the coal flows and increasing the gas flows into the affected plants. Finally, the perception has grown that the national economy relies on a complex, multi-scale, distributed, and increasingly vulnerable and interconnected energy infrastructure [1]. The interconnected and interdependent nature of these infrastructures makes them vulnerable to cascading failures, i.e., the propagation of disruption from one system to the other, with possible catastrophic consequences.

There has been significant work in scheduling fuel deliveries in order to optimize electric energy production [2]. The common denominator of all published fuel scheduling approaches is that they view the fuel system only in terms of delivered prices and associated penalties for possible violations of contracts. In other words, there has been little effort to optimize the electric power system operations with consideration of the integrated dynamics of the fuel markets and infrastructures, accounting for the fuel production, storage, and transportation costs and capabilities.

A number of energy models have been developed for policy analysis, forecasting, and to support global or local energy planning. Reference [3] provides an overview of some of the

most important ones. Other energy models include the National Energy Modeling System (an energy policy model used by the U.S. Department of Energy) and the Integrated Planning Model (an environmental policy model used by the U.S. Environmental Protection Agency, i.e., EPA). An important consideration regarding many of the existing energy models is that they typically tend to be highly resource intensive, both in terms of expertise requirements to develop the model and support the underlying data, and in terms of execution time and other computational resource requirements, reflecting the highly complex algorithmic and programming routines. Although many of these models integrate different energy systems in a modular form, they are not typically designed to illustrate the effects of alternative energy transportation modes. These models typically focus on a long term planning horizon (more than 10 years) and their methodology usually follows a top-down approach that evaluates a broad equilibrium framework from aggregated economic variables. In contrast, the bottom-up model presented in this paper addresses a medium term operational horizon (several months to 2-3 years) and follows an optimization methodology that captures the physical and environmental restriction of the coal, natural gas, and electricity flows in an engineering sense. In addition, few of these models are available to the research community. Consequently, many opportunities exist to enrich the rather limited technical literature and information available in the public domain.

In this two-part paper, we propose a generalized network flow model of the national integrated energy system that incorporates the production, storage (where applicable), and transportation of coal, natural gas, and electricity in a single mathematical framework, for a medium term analysis. Fig. 1 depicts the different components that comprise the integrated energy system, as defined in this paper.

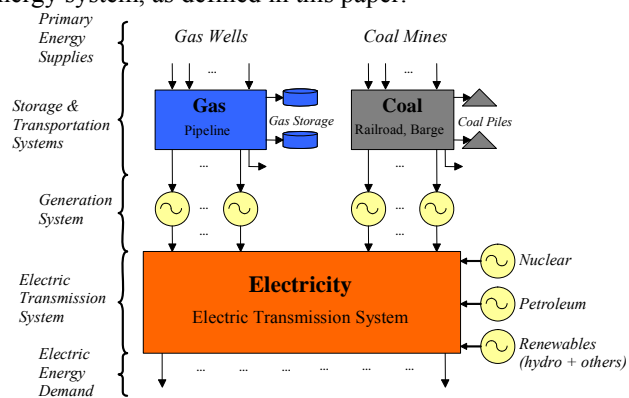


Fig. 1. The integrated energy system.

In general, the model can be used to foster a better understanding of the integral role that the coal and natural gas production and transportation industries play with respect to the entire electric energy sector of the U.S. economy. The model represents the major fossil fuel markets for electricity generation (coal and natural gas) and solves for the optimal solution that satisfies electricity demand, deriving flows and prices of energy. Each energy subsystem considers the factors

relevant to that particular subsystem, for example, coal transportation costs, or gas transmission capacities. The modeling framework presented integrates the cost-minimizing solution with environmental compliance options to produce the least-cost solution that satisfies electricity demand and restricts emissions to be within specified limits. Despite the relative importance of electricity generation from nuclear energy (roughly 20%), it is exogenously given because of its slow dynamics, which are assumed not to influence the medium term analysis intended. The schedules of electricity generated from renewable energies are also represented as direct inputs into the electric transmission system, due in part by their relatively small contribution to the generation mix and the lack of emissions restrictions. In addition, most of them cannot be transported as a raw fuel (e.g., wind and sunlight) and therefore represent no energy movement alternative to electric transmission in the way that coal and natural gas do. Water, however, could be endogenously included in the model and formulated with the network flow techniques presented in this paper, as long as data characterizing the hydraulic networks (e.g., reservoir capacities) were available. The model could also accommodate possible energy transportation futures which could include, for example, widespread use of DC links and/or hydrogen networks.

Part I of this paper describes the theoretical underpinnings of the modeling approach adopted, the mathematical formulation, and the modeling assumptions. Part II provides numerical results and identifies directions for future work and possible applications of the model.

III. MODELING APPROACH

A. Network Flow Model

The integrated energy system is readily recognized as a network defined by a collection of nodes and arcs with energy flowing from node to node along paths in the network. Such a structure lends itself nicely to the network flow programming modeling technique. When a situation can be entirely modeled as a network, very efficient algorithms exist for the solution of the optimization problem, many times more efficient than ordinary linear programming in the utilization of computer time and space resources. The network flow problem formulated in this paper falls into the category of generalized minimum cost flow problem and can be solved by applying the generalized network simplex algorithm [4].

The solution of the generalized minimum cost flow problem is to satisfy electric energy demands with available fossil fuel supplies at the minimum total cost, without violating the bound constraints. The costs considered are the fossil fuel production, transportation, and storage costs, the operation and maintenance costs associated with electricity generating units operations, and the electric power transmission costs. Although the emission constraint does not comply with the network structure (see Section IV.B), the problem still can be solved very efficiently when it is included.

B. Tie Line Representation

A tie line is an undirected arc, because the energy can flow in both directions. Since the network flow model requires directed arcs, the transformation in Fig. 2, shows an equivalent model with an undirected arc replaced by an oppositely directed pair of arcs. If the flow in either direction has a lower bound of zero and the arc cost is nonnegative, the solution algorithm finds an optimal non-overlapping solution, in which one of the flows in the directed arcs is zero.



Fig. 2. Representation of transmission lines.

C. Elimination of Nonzero Lower Bounds

A network flow model with directed arcs having nonzero lower bounds can be replaced by an equivalent model with zero lower bounds. The left side of Fig. 3 shows an arc with lower bound e_{min} , upper bound e_{max} , cost c , and multiplier η . An equivalent representation of the arc with zero lower bound is shown on the right side of Fig. 3. Making this transformation requires an adjustment of the supply at both ends of the arc, i.e., b_i and b_j . This transformation also changes the objective function by a constant equal to $c \times e_{min}$ that can be recorded separately and then ignored when solving the problem. In the specific case when an arc has equal upper and lower bounds, i.e., when the flow is fixed, application of this procedure results in its elimination from the equivalent network because the upper bound on its flow becomes zero.

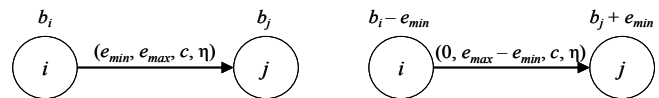


Fig. 3. Removing nonzero lower bounds.

D. Node Transformation

A standard network flow model associates only supply or demand with each node. Yet, in the integrated energy system, there are certain node-like facilities (fuel production facilities, power plants, and storage facilities) for which it is important to associate costs, capacities, and efficiencies. The transformation into a standard network flow model is done by replacing each of these nodes into a pair of nodes with an arc connecting them. The parameters of this arc dictate the restrictions on the flow that passes through the respective facility. Fig. 4 illustrates this transformation.

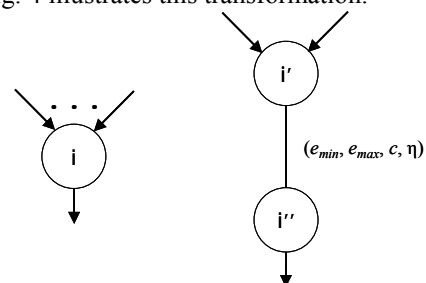


Fig. 4. Node transformation.

E. Linearization of Costs and Efficiencies

A typical input-output characteristic of a steam turbine generator can be represented by a convex curve [2]. When

multiplied by the fuel cost, we obtain the generating unit cost as a convex function of the flow. Total cost functions can then be approximated by piecewise linear functions, which leads to step incremental cost functions. In a network flow representation, each linearization segment is modeled by an arc, with the number of arcs determining the accuracy of the approximation. To illustrate this idea let us consider an arc that carries flow between nodes i and node j . The cost associated with the flow in this arc is a convex function and can be fitted by a piecewise linear cost function. This cost function tells us that the first 20 units of flow have a unit cost of \$2.5, the next 10 units of flow have a unit cost of \$5, and any additional amount has a unit cost of \$10, up to the capacity of 40 units of flow. As shown in Fig. 5, this situation is modeled using a set of arcs, each one representing a segment of the piecewise linear cost function. Because the unit costs are increasing, the flow in a given arc will only be positive if all the other arcs with smaller unit costs have reached their capacity limits, which guarantees that the solution is physically possible.

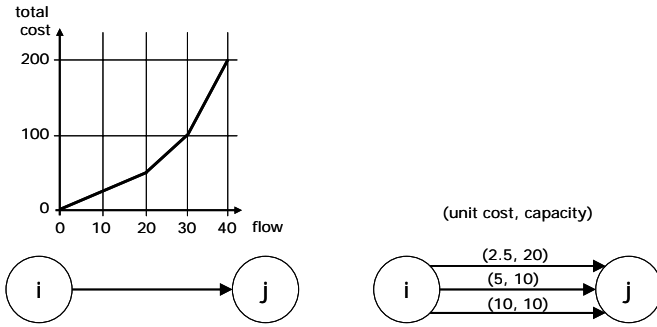


Fig. 5. Representation of convex cost functions.

Nonconvex cost functions, in particular those associated with the input-output characteristics of combined cycle gas turbines, cannot be addressed exactly with network flow programming techniques, and are therefore approximated by linear or piecewise linear convex functions. Although optimization techniques capable of dealing with nonconvexities are available [5], the cost in modeling complexity outweighs the improvement in model fidelity, considering the level of aggregation intended.

Efficiency parameters may also be modeled using piecewise linear functions of the flow and can be represented by the multiple arc transformation illustrated above for convex cost functions. For example, power losses along the transmission lines are proportional to the square of the flow, and efficiency can therefore be approximated by a piecewise linear function where the slopes decrease with the flow. In this situation, it is guaranteed that the arcs with the higher efficiency parameters (lower losses) will be filled up first, since they require the smallest amount of flow, and thus the smallest cost, for the same energy demanded at the destination node.

F. Dynamics of the Model

Static models have no underlying temporal dimension. However, in the case of the integrated energy model, we want to account for the evolution of the system over time, as

inventory is carried over from one time period to another.

Multiperiod network flow models may be viewed as a composition of multiple copies of a network, one for each period, with arcs for the temporal linkages in the system. With this construction, the size of the network is proportional to the number of periods.

If a single time step is chosen to apply to the entire model, it must be small enough to capture the fastest dynamics of the integrated energy system, which are imposed by the electric energy subsystem. However, this results in unnecessary and counterproductive computations that take place for slower energy subsystems. Alternatively, one can capture the fact that the integrated energy system is composed of different energy subsystems with distinct dynamics, and define a different time step for each one, thus eliminating the burden of redundant simulation. As a result, different simulation time steps can be used for different energy subsystems [8].

IV. MATHEMATICAL FORMULATION

A. Generalized Network Flow Model

Mathematically, the multiperiod generalized minimum cost flow problem is an optimization model that can be formulated as follows:

$$\text{Minimize } z = \sum_{t \in T} \sum_{(i,j) \in M} \sum_{l \in L_{ij}} c_{ij}(l) e_{ij}(l,t) \quad (1a)$$

subject to:

$$\sum_{\forall k} \sum_{l \in L_{jk}} e_{jk}(l,t) - \sum_{\forall i} \sum_{l \in L_{ij}} \eta_{ij}(l) e_{ij}(l,t) = b_j(t), \forall j \in N, \forall t \in T \quad (1b)$$

$$e_{ij,\min} \leq e_{ij}(t) \leq e_{ij,\max} \quad \forall (i,j) \in M, \forall t \in T. \quad (1c)$$

The objective function z in (1a) represents the total costs associated with the energy flows from the fossil fuel production sites to the electricity end users and non-electric natural gas consumers. These total costs are defined as the sum of the fuel production costs, fuel transportation costs, fuel storage costs, electricity generation costs (operation and maintenance costs), and electricity transmission costs. The constraints in (1b) and (1c) represent the energy balance constraints for all nodes the flow bound constraints for all arcs, respectively.

In matrix form, the problem can be represented as follows:

$$\text{Minimize } z = \underline{c}' \underline{e} \quad (2a)$$

subject to:

$$\underline{A} \underline{e} = \underline{b}, \quad (2b)$$

$$\underline{e}_{\min} \leq \underline{e} \leq \underline{e}_{\max}. \quad (2c)$$

In this formulation, \underline{A} is an $n \times m$ matrix, where n is the number of nodes and m is the number of arcs. \underline{A} is called the node-arc incidence matrix. Each column of \underline{A} is associated with a decision variable, and each row is associated with a node. The column A_{ij} has a +1 in the i th row, a -1 or a $-\eta_{ij}$ in the j th row, and the rest of its entries are zero. An illustrative example of the formulation of the node-arc incidence matrix for a simple integrated energy system is presented in [6].

B. Side Constraint

The overall objective of this optimization problem is to determine the energy flows that meet the demand for electricity at the minimum operating costs, subject to physical and environmental constraints. Although all forms of electricity generation involve some adverse environmental effects, most of these impacts remain unaccounted for in the cost of power generation, as they are excluded from the prevailing U.S. regulatory framework. A notorious exception is the SO₂ tradable permit system, which is by far the most significant and well defined area covered by the regulatory treatment of environmental externalities concerning electricity generation from fossil fuels, at the national level. As a result, the only environmental restriction presently modeled in the integrated energy system is the SO₂ emissions constraint imposed by the CAAA. The potential impacts of pending or proposed legislation, regulations, and standards are not incorporated.

The mathematical formulation presented above is suitable to address the physical constraints of the integrated energy system. However, it is not sufficient to guarantee that the SO₂ emissions constraint imposed by the CAAA is satisfied. In addition to the energy balance constraints at all nodes and the flow bound constraints for all arcs, another constraint must be incorporated to impose a national-level limit on emissions. According to the CAAA, the allowances for SO₂ emissions are traded nationwide so the corresponding limit on emissions is national rather than regional or unit-level. This national limit is determined by the sum of the allowances allocated to power plants (as defined by the CAAA) and adjusted to capture the exogenously given emissions banking effects. The amount of emissions produced depends on the fuel used, the pollution control devices installed, and the amount of electricity produced. This additional constraint may be represented as follows:

$$\sum_{t \in T} \sum_{(i,j) \in G} SO2_i(t) \cdot (1 - \alpha_i) \cdot \sum_{l \in L_{ij}} e_{ij}(l,t) \leq NSO2, \quad (1d)$$

All compliance strategies that can be implemented in an operational time frame – fuel switching (e.g., use low sulfur content coal or natural gas instead of high sulfur content coal), utilization of emissions control devices or abatement technologies (e.g., scrubbers, particulate collectors), revising the dispatch order to utilize capacity types with lower emission rates more intensively, and allowance trading – are now effectively captured by the mathematical model described by equations (1a)-(1d).

The inequality constraint (1d) can be transformed into an equality constraint and incorporated in the matrix equation (2b). This transformation is done by introducing a nonnegative slack variable in the left-hand side of the equation. With the addition of constraint (1d) to equation (2b), some of the columns of the matrix A have more than two non-zero entries, which makes it no longer a node-arc incidence matrix, but instead a more general constraint coefficient matrix. In linear programming terminology, the constraint (1d)

is called a bundle, complicating, or side constraint, which specifies a flow relationship between several of the arcs in the network flow model. The integrated energy system can also be interpreted as a multicommodity flow problem, where energy and emissions are the commodities that flow along the arcs of the network. The complicating constraint ties together these two commodities.

C. Nodal Prices

The Karush-Kuhn-Tucker conditions associated with the constrained linear optimization problem defined above yield the so called Lagrangian multipliers or dual variables. In economic terms, the Lagrangian multipliers are explained as the shadow prices related to each active constraint at the optimal solution of the decision variables, and they represent the marginal costs of enforcing the constraints. In a network flow formulation, the shadow prices are also referred to as nodal prices, because each node of the network structure has a Lagrangian multiplier associated with it, as a result of the balance constraints defined for the nodes.

Without loss of generality, assume that the cost and efficiency parameters associated with each arc are constant functions. This permits the elimination of the parameter l , for notational simplicity. The Lagrangian function for (1a)-(1d) is given by (3), where $\lambda_j(t)$ is the Lagrangian multiplier (or nodal price) associated with the energy balance constraint at node j for time t . $\delta_{ij}(t)$ and $\mu_{ij}(t)$ are the Lagrangian multipliers associated with the lower and upper bound constraints, respectively, on the energy flowing from node i to node j , during period t . Finally, γ is the Lagrangian multiplier associated with the emissions limit constraint.

$$\begin{aligned} L = & \sum_{t \in T} \sum_{(i,j) \in M} c_{ij}(t) e_{ij}(t) + \\ & + \sum_{t \in T} \sum_{j \in N} \lambda_j(t) \left[\sum_{\forall k} e_{jk}(t) - \sum_{\forall i} \eta_{ij} e_{ij}(t) - b_j(t) \right] + \\ & + \sum_{t \in T} \sum_{(i,j) \in M} \delta_{ij}(t) [e_{ij,\min} - e_{ij}(t)] + \sum_{t \in T} \sum_{(i,j) \in M} \mu_{ij}(t) [e_{ij}(t) - e_{ij,\max}] + \\ & + \gamma \left[\sum_{t \in T} \sum_{(i,j) \in G} SO2_i(t) \cdot (1 - \alpha_i) \cdot e_{ij}(t) - NSO2 \right] \end{aligned} \quad (3)$$

For optimality, in a given time period t , the relationship between the nodal prices of two linked nodes i and j , is given by one of the following equations. If $(i, j) \notin G$, that is (i, j) does not represent electricity generation, then:

$$\frac{\partial L}{\partial e_{ij}(t)} = c_{ij}(t) + \lambda_i(t) - \lambda_j(t) \eta_{ij} - \delta_{ij}(t) + \mu_{ij}(t) = 0 \quad (4a)$$

Otherwise, if $(i, j) \in G$, that is (i, j) is an arc representing electricity generation, then:

$$\begin{aligned} \frac{\partial L}{\partial e_{ij}(t)} = & c_{ij}(t) + \lambda_i(t) - \lambda_j(t) \eta_{ij} - \delta_{ij}(t) + \mu_{ij}(t) + \\ & + \gamma SO2_i(t) (1 - \alpha_i) = 0 \end{aligned} \quad (4b)$$

If the inequality constraints are slack, i.e., not binding or

not active, the corresponding Lagrangian multipliers are zero. Therefore, from equation (4a) we conclude that if the flow bound constraints are not binding, the cost is zero ($c_{ij}(t) = 0$), and there are no losses ($\eta_{ij} = 1$), then the nodal prices of two linked nodes are the same ($\lambda_i(t) = \lambda_j(t)$). Likewise, from equation (4b) we conclude that the nodal price at a power plant node i is the same as the nodal price at the corresponding electricity demand node j if and only if the flow bound constraints are not binding, the arc cost is zero, there are no transmission losses, and the emissions limit constraint is also not binding. Note that flow bound constraints being binding is equivalent to congestion in the associated arc.

The concept of nodal prices has recently become very familiar, as several electricity markets have used the information from nodal prices to improve the efficient usage of the power grid, to perform congestion management, and also to design a pricing structure for the power system [7]. In the power industry terminology, nodal prices are often referred to as locational marginal prices, or LMPs. In 2002, the Federal Energy Regulatory Commission (FERC) proposed a standard market design that incorporates a locational marginal pricing mechanism to induce efficient electric power markets. In contrast to a single price mechanism, under a nodal pricing market, clearing prices are calculated for a number of locations on the transmission grids called nodes. Prices vary from node to node because of transmission line congestion and losses. At each node, the price represents the locational value of electric energy, including the cost of energy and the cost of delivering it, i.e., losses and congestion. In other words, the nodal price is the cost of serving the next megawatt of load at a given location. Therefore, LMP can be used to determine the value of transmission rights and to provide economic signals for generation and transmission investments.

The concept of nodal prices widely used in the electric power arena is herein expanded to the integrated energy system, by optimizing the energy flows in a generalized network flow model that explicitly represents the electric subsystem together with the various fossil fuel networks in a single mathematical framework [8]. The nodal prices obtained as a by-product of the optimization procedure provide a means to identify the interdependencies between the fuel subsystems and the electric subsystem. In addition, because nodal prices monetize congestion costs, they provide clear economic signals that indicate where infrastructure improvements should take place to relieve constraints, thus promoting efficient investment decisions.

V. MODELING ASSUMPTIONS

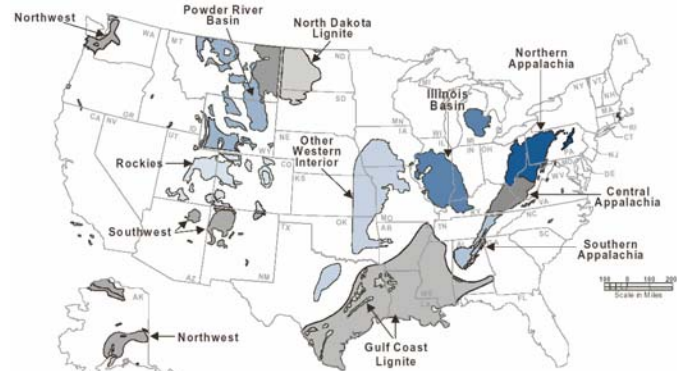
A. Coal Network

The coal network model proposed is defined based on the supply regions depicted in Fig. 6. For each coal supply region a coal production node is defined and characterized by its associated productive capacity, average heat value, average sulfur content, and average minemouth price. Because coal

exports and imports represent a very small percentage of the U.S. coal production and consumption, respectively, international coal trade is not considered. Coal consumption by non-electric consumers is also neglected.

Precise modeling of the thousands of individual transportation routes used to transport coal from mines to electric power plants would require an enormously detailed and very complex model, using large quantities of data that are not in the public domain. As a result, a simplified approach is adopted, where an arc is established between each coal supply node and all represented coal-fired power plants. A transportation link is not included when it represents an either economically or physically impractical route, based on historical data gathered by FERC Form 423. Arcs connecting coal production nodes with coal-fired plants are characterized by a lower bound that represents existing contractual agreements and a transportation cost.

Coal data are gathered from the Energy Information Administration (EIA), the Mine Safety and Health Administration of the Department of Labor, and FERC.



Source: Energy Information Administration

Fig. 6. Coal supply regions.

B. Natural Gas Network

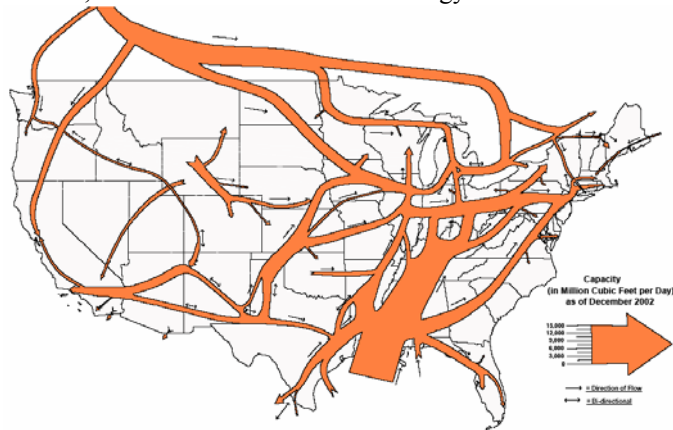
Natural gas production nodes are defined taking into account the geographical distribution of natural gas reserves and production and data availability. Natural gas production nodes are characterized by their effective productive capacity, average wellhead price, and an efficiency parameter that accounts for extraction losses.

Fig. 7 shows the major pipeline transportation corridors. Given the complexity of this system and data availability restrictions, representation of the actual physical system is prohibitive. A simplified approach is therefore adopted, where the lower 48 states are divided into transmission regions, each region containing one transshipment node and one storage node. Transshipment nodes represent a junction point for flows coming into and out of the regions. Arcs connecting the transshipment nodes represent interregional flows. Flows are further represented by establishing arcs from the production nodes to the corresponding transshipment node. Similarly, arcs are also established between the transshipment nodes and storage nodes and from the transshipment nodes to the appropriate gas-fired power plant nodes. Imports and exports with Canada and Mexico are also represented. Natural gas

consumption by non-electric end-users is represented as an exogenously given demand in the natural gas transshipment nodes.

Natural gas transportation arcs are characterized by a capacity, a loss factor, and a transmission markup. Arcs representing natural gas storage injections are characterized by an injection capacity and arcs representing storage withdrawals are assigned withdrawal capacities and a cost parameter to account for the storage cost of service. Arcs denoting natural gas carried over between two consecutive time periods are characterized by a lower bound, which represents the cushion gas, and an upper bound, which corresponds to the total storage capacity of the region.

Natural gas network data are obtained from EIA, FERC, the Minerals Management Service of the U.S. Department of the Interior, and the Canadian National Energy Board.



Source: Energy Information Administration

Fig. 7. Major pipeline transportation corridors.

C. Electricity Network

The electric power sector is modeled at a regional level. The regions considered are the North American Electric Reliability Council (NERC) regions and subregions in the contiguous U.S., as depicted in Fig. 8. This aggregation level is based on the topology of the electrical grid and operating constraints, such as transmission bottlenecks, and is an adequate simplification of the physical and institutional complexity of the electric power industry. For each region, a transshipment node is defined and assigned a given demand, which is represented by the flow on the arc linking the transshipment node to the sink node. Arcs between the transshipment nodes are established to represent interregional transmission paths composed of one or more parallel tie lines connecting adjacent control areas in interconnected neighboring regions. These arcs are characterized by interregional total transmission capabilities, transmission costs, and loss factors. International trade with Canada is exogenously given.

Within each region, generating units with similar characteristics are clustered into equivalent power plants with a combined capacity and weighted average heat rates. Equivalent power plant nodes are differentiated by fuel type and prime mover. Coal-fired power plants are further disaggregated by the type of installed SO_2 pollution control

device, i.e., the flue gas desulfurization technology used, if any, and assigned a corresponding removal efficiency rate.

Data characterizing the electric power network are mainly obtained from EIA, FERC, NERC, and EPA.



Source: North American Electric Reliability Council

Fig. 8. NERC regions and subregions (as of December 2004).

VI. CONCLUSIONS

Although economic and physical performances of individual subsystems are well studied and understood, there has been little effort to study the integrated system's global characteristics. The study presented in this paper has been motivated by the hypothesis that the current fragmented decision making environment in which coal, natural gas, and electricity firms operate leads to potential inefficiencies. Given the critical role that these infrastructures represent and their great interdependency, it is of vital importance to keep an overall system perspective, both during planning and in all stages of operation. To the extent that traditional tools and simulation models do not allow for a comprehensive analysis capable of handling the complex dynamics of highly integrated energy systems, individual decision makers support specific procedures and strategies according to their own value system (i.e., economic, technical, organizational, political, and environmental context), which may lead to efficiency losses.

In order to address these issues, this paper has presented a multiperiod generalized network flow model of the U.S. integrated energy system. The model focuses on the economic interdependencies of the integrated system, in the sense that it represents multiple energy networks (electric, coal, and natural gas), along with a detailed characterization of their functionalities (supply, demand, storage, and transportation), within a single analytical framework that allows for their simultaneous study. The methodology includes the technological, economic, and environmental aspects of the different energy subsystems considered. The benefits of using a network flow modeling technique rather than a more general linear programming approach are associated with the fact that more efficient solution procedures can be used, which is of importance due to the high dimension that characterizes an

integrated energy system.

Reference [8] illustrates the network flow modeling approach described in this paper on a small test system. Simulation results for the U.S. integrated energy system are presented and analyzed in part II of this paper. Part II also identifies areas of further research and possible model applications.

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