Supply Chain Design and Optimization with Applications in the Energy Industry

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In this chapter, we discuss a few supply chain design concepts and optimization models that have been applied in the energy sector. It is not our intention to provide a comprehensive review of the vast literature. Our goal is to provide the reader with pointers to some interesting and challenging problems, thereby triggering thoughts on the synergies between supply chain optimization and energy sustainability. To this end, we select four supply chain research areas that have seen substantial synergies with energy research. These four areas are strategic sourcing, inventory management, supply chain competition, and network design. This chapter discusses these areas and related applications in the energy industry.

1.1 ▪ Strategic Sourcing and Power System Management

Strategic sourcing in supply chain management involves understanding supply characteristics and making decisions such as supplier selection, procurement quantities, and managing supply uncertainties. When suppliers are reliable (i.e., no supply uncertainty), the sourcing strategy hinges on the trade-off between the efficiency and responsiveness of the suppliers. When some suppliers are unreliable but offer low-cost supply, one must strike a balance between the cost advantage of unreliable suppliers and the cost of mitigating supply uncertainties. Both of these trade-offs manifest themselves in power system management, which we discuss in this section.

1.1.1 ▪ Efficient and Responsive Sourcing in Power System Capacity Planning

Suppliers with short lead times allow a supply chain to quickly respond to demand fluctuations, but the speed typically means extra cost to the supply chain. To manage the trade-off between efficiency and responsiveness, a supply chain can choose to have a mixture of efficient and responsive suppliers. A well-known example is the "dual-response" manufacturing in the supply chain for Hewlett Packard inkjet printers [1]. One supplier has low production cost but long lead time; the other has short lead time but high production cost. Using both suppliers allows Hewlett Packard to serve a large portion of its demand efficiently while meeting short-term demand fluctuations responsively. Other examples of using hybrid modes of production can be seen in the fashion clothing industry [2].

Capacity planning for electric power systems also involves the trade-off between efficiency and responsiveness, but with different features. Imagine yourself making capacity investment decisions in an electric utility company. How would you plan a portfolio of power generation technologies to meet uncertain electric demand over the next twenty years? You can choose from a variety of technologies with very different cost structures and construction lead times. It may take more than ten years to undergo the approval and construction processes of a nuclear power plant, whereas gas-fired generators can be installed within two years. The responsiveness in this context pertains not to the production lead time but to the capacity construction lead time. The total cost comprises the capital, operating, and outage costs.

The above utility capacity planning problem was first studied by Gardner and Rogers [3], who extended the traditional planning methods by taking differences in technology lead times into account. They considered two groups of technologies differentiated by construction lead times. The capacity investment of long lead time technologies must be decided prior to the resolution of uncertain demand, whereas the decisions for short lead time technologies need not be made until demand realizes. The problem is formulated as a two-stage stochastic program with recourse. The solution is termed as an "act, learn, then act" solution and compared with the solutions from traditional planning methods that ignore the difference in technology lead times. One traditional approach is "act, then learn," in which the capacity mix is decided under a given demand forecast; no recourse is considered. Another traditional approach is "learn, then act," in which a capacity mix is found for each given demand realization, and then the solutions are combined, in an ad hoc fashion, to arrive at an implementable solution.

The analysis in [3] reveals that the traditional planning methods may be seriously flawed. There are circumstances where some short lead time technologies are screened out by the traditional planning methods but enter the optimal solution; there are also circumstances where some long lead time technologies are used in the traditional solutions but dropped in the optimal solution. The optimal solution tends to utilize the responsiveness provided by the short lead time technologies, and thus forgoes some cost advantage of the long lead time technologies. The paper informs the system planners that they need to examine the extent to which technology lead times can be traded off against capital and/or operating costs.

Beyond uncertain demand, the utility capacity planning problem is often complicated by many sources of uncertainty. The Fukushima tragedy has spurred reevaluation of nuclear power technology and resulted in regulatory changes in many countries. The tightened Environmental Protection Agency (EPA) regulations on emissions are pushing many coal-fired power generators toward retirement. The shale gas boom has made natural gas power generation technologies more economical, amidst regulatory and geopolitical uncertainties. Increasing uncertainties require utility planners to build more flexibility into the power systems planning process. Recognizing the value of flexibility also encourages the development of technologies with shorter construction lead time.

1.1.2 ▪ Random Capacity and Volume Flexibility in Power System Operations

In a typical power system, resources are coordinated by unit commitment and economic dispatch programs. The unit commitment program is run every day to determine which generators (i.e., units) are committed to power generation for each hour of the next day, and the economic dispatch program is run in real time to determine the output levels of the committed generators. These programs involve sophisticated system modeling and optimization techniques and thus present great opportunities for applying operations research and analytics.[1] Although these programs reflect high granularity of the reality, they do not directly serve the purpose of designing energy policies.

For policy design, models need (at least initially) to be simpler than reality but complicated enough to capture the essential trade-offs in reality. Such models will allow various stakeholders to understand the mechanisms by which certain policies affect key trade-offs and system performance. Large system models can then be used to simulate the system performance and estimate the impact of certain policies.

In supply chain research, there has been a significant amount of work devoted to managing supply uncertainties. We refer the reader to [5], [6], [7], and the references therein. Below, we provide a perspective of thinking about power generation systems that is useful for policy research. This perspective will lead to models that share some features with the supply chain literature, yet present unique characteristics.

Power generators can be categorized based on capacity certainty and volume flexibility:

1. Random capacity, very low marginal cost;
2. Certain capacity, volume inflexible, low marginal cost;
3. Certain capacity, volume flexible, high marginal cost.

Type 1 capacity refers to intermittent generation from renewable sources, such as wind and solar power. Their marginal cost of production is nearly zero, but they have inherent uncertainties. Type 2 capacity includes nuclear power generators, which have low marginal cost and are typically designed to run at a constant power output level. Type 3 capacity consists of generators with varying degrees of flexibility. They are more flexible than type 2 but also more costly to run. Coal-fired generators have a higher marginal cost than nuclear power generators, but they can adjust their output at a certain rate (known as the ramp rate). A higher ramp rate means a shorter lead time for changing the output level. The most flexible generators are oil- and natural gas-fired combustion turbines, which can meet demand fluctuations from minute to minute, but these generators have high operating cost

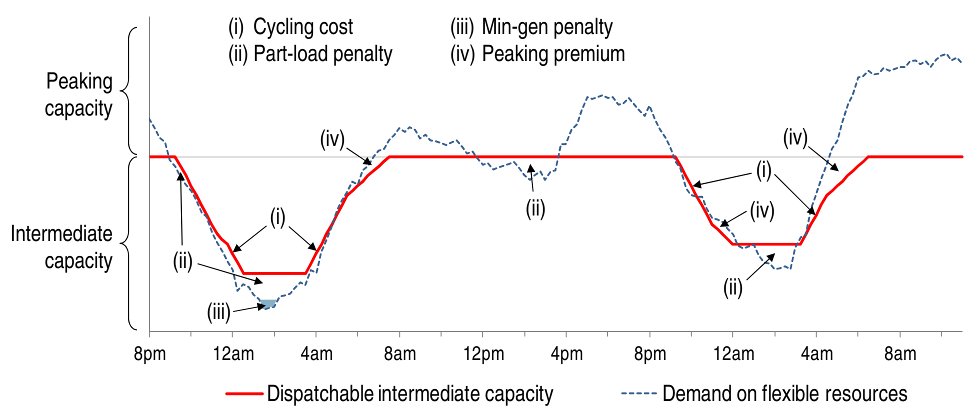
[1] For example, the Midcontinent Independent System Operator (formerly named Midwest ISO) won the 2011 INFORMS Edelman Award [4] for using operations research to improve reliability and efficiencies of the region's power plants and transmission assets.

and thus are known as peaking generators. There are also gas-fired combined-cycle generators whose flexibility is in between coal-fired generators and peaking generators. In terms of marginal cost, combined-cycle generators have become competitive to coal-fired generators due to the lower price of natural gas in recent years.

With the above taxonomy, it is possible to look at power system operations from the supply chain optimization angle. The combination of types 2 and 3 resources is similar to the dual-response manufacturing discussed previously, with type 2 capacity serving the baseload and type 3 capacity meeting demand fluctuations. There are two key differences. First, the trade-off between efficiency and responsiveness in power system operations occurs in a much shorter time frame, and power generation and consumption must be constantly balanced. Second, the cost structures of power generators have their unique features, which we elaborate below.

Wu and Kapuscinski [8] model two subgroups within type 3 generators: fully flexible generators (peaking generators) and intermediate generators. Fully flexible generators can adjust their output almost instantaneously, whereas intermediate generators have limited flexibility reflected by the four cost components illustrated in Figure 1.1: (i) *Cycling cost.* Cycling an intermediate generator increases the wear and tear cost and requires extra fuel during the startup process. The dispatchable intermediate capacity (solid curve) represents the intermediate capacity that is started and can be dispatched to produce energy. (ii) *Part-load penalty.* Intermediate generators are most efficient when producing at full load (i.e., all dispatchable capacity is utilized). Operating at any lower load increases the average production cost; this extra cost is the part-load penalty. (iii) *Min-gen penalty.* In normal operating conditions, the part load should stay above a minimum generation level (e.g., 50% of the dispatchable capacity); otherwise a min-gen penalty will be incurred. (iv) *Peaking premium.* The dispatchable intermediate capacity cannot be adjusted instantaneously and thus peaking generators may be needed even if the load on flexible resources is below the total intermediate capacity, which occurs in the areas labeled as (iv) in Figure 1.1.

Figure 1.1. *Costs of balancing electrical systems: An example*



The system operator aims to minimize total operating cost, which entails continuously balancing the above cost components, whether or not intermittent generation is present. The growth of intermittent generation resources (type 1) poses increasing management challenges. If we meet 20% of energy demand from renewable sources (mandated by the renewable portfolio standards in many states), the actual percentage of demand met from renewable sources can vary wildly from 0% to 100%, depending on the weather. These fluctuations introduce additional variability into power systems, which complicates the trade-off among the aforementioned cost components.

Wu and Kapuscinski [8] model the above cost components and study the policies for using intermittent renewable energy. When intermittent generation was introduced into most countries and regions, it was given priority to be used; this policy is referred to as the *priority dispatch* policy. Implementing such a policy requires little change to the system optimization programs because intermittent generation is simply subtracted from the demand before the programs are run. With the rapid growth in renewable energy penetration, the intermittency began to challenge the systems' ability to balance supply with demand. Curtailment thus became necessary when excessive energy from intermittent resources threatened system reliability. In some circumstances, although curtailment is not absolutely necessary, it provides the system operator with an additional lever to manage variability, thereby reducing system operating costs. Such curtailment is allowed under the *economic curtailment* policy, but not under the priority dispatch policy.

In [8], the authors compare the two policies and identify the sources of the operational benefits of the economic curtailment policy. Among the four cost components discussed above, economic curtailment policy significantly reduces cycling cost and peaking premium. Curtailing intermittent generation during low-demand periods helps reduce the need for cycling intermediate generators (i.e., reduces the depth of the valleys in the dispatchable intermediate capacity in Figure 1.1). Curtailment also allows more intermediate generators to start up earlier in the morning (i.e., shifts the increasing part of the dispatchable intermediate capacity in Figure 1.1 toward the left), reducing the peaking premium that would otherwise be incurred to meet the rising morning demand. In addition to these operational benefits, economic curtailment also increases the utilization of cheaper inflexible generators.

It is worth noting that the model in [8] is a stochastic dynamic programming model. The value of economic curtailment is higher under the deterministic optimization programs used prevalently in practice. This is because curtailment serves as a recourse for the decisions generated by deterministic optimization programs, but this recourse is not as valuable under stochastic dynamic programs because the decisions are already adjusted in response to the weather and demand fluctuations.

The recent work by Al-Gwaiz et al. [9] is another example of utilizing the taxonomy introduced earlier to study energy policies. This work focuses on modeling and analyzing the power market competition, which features supply function competition (i.e., each firm submits a supply function that specifies the amount of power it is willing to produce at each price). Different from the classical supply function equilibrium literature which studies the competition involving only generators of type 3, the authors study the supply function competition between inflexible and flexible generators. Furthermore, the authors introduce intermittent generation into the model and analyze how it affects the competitive behavior of the other generators. This research opens a promising avenue for analyzing how random capacity and volume flexibility impact power market competition.

1.2 ▪ Inventory Management for Energy Storage Facilities

Energy storage is to grids as inventory is to manufacturing firms. Energy storage is used to buffer against predictable variability (e.g., diurnal demand cycles) and unpredictable variability (supply or demand shocks) to smooth conventional resources' power output. Smoothing production reduces cost because the power generation cost function is highly convex: the marginal cost of nuclear power is below \$5 per MWh whereas that of a peaking unit can be \$80 per MWh. The classic inventory optimization theory discussed in Chapter 33 focuses on minimizing inventory-related costs under linear production/purchasing cost. Convex production cost has also been considered in the literature, pioneered by Modigliani and Hohn [10], who examine the optimal production schedule for meeting demand over a planning horizon. However, energy storage operations involve different cost structures and thus present opportunities to develop inventory theory for energy storage applications.

Electricity per se cannot be stored; to be stored, electricity must be converted into other forms of energy, such as potential or chemical energy. This conversion process involves energy loss, known as the *conversion loss*. The other closely related measure is *storage efficiency*, which is equal to $1-$conversion loss rate. For example, the storage efficiency of a lithium-ion battery ranges from 80% to 90%. The stored energy does slowly decrease over time (similar to inventory holding cost), but this type of energy loss is often negligible compared to the conversion loss, because energy storage typically operates on daily cycles or more frequently.

The cost model represented in Figure 1.1 has been extended in [8] to include costs of storage operations. It is interesting to study how storage operations impact emissions. First, storage allows more clean intermittent energy to be used (instead of being curtailed) and thus reduces emissions. Second, storage reduces the peaking cost while increasing the use of intermediate capacity, which leads to more or less emissions depending on types of fuels. Third, energy conversion losses during storage operations increase emissions. The net effect of storage on emissions depends on the relative strengths of these three factors and is detailed in [8].

Secomandi [11] develops a model for natural gas storage facilities, which can also be applied to energy storage for power systems, as the model incorporates injection and withdrawal loss factors (mathematically equivalent to conversion loss) and holding cost. The author also considers a constraint on the rate at which energy can be injected and withdrawn—important for both natural gas storage and energy storage. The problem is formulated as a stochastic dynamic program, and structural properties of the optimal policy are derived. The optimal policy is characterized by two stage- and price-dependent base-stock targets: if inventory falls between the two targets, it is optimal not to do anything; otherwise the firm should inject or withdraw to bring the inventory as close as possible to the closer target.

Wu et al. [12] focus on understanding the types of real options in energy storage operations and how one should trade off among these options. The authors analyze a heuristic policy commonly used in practice (the rolling intrinsic policy, which solves a deterministic problem every period using up-to-date price information) and point out that this heuristic policy does not attempt to capture the options' extrinsic values that arise from the stochastic evolution of the prices. The authors then design a new heuristic policy, in which the prices are adjusted to approximate the extrinsic values before applying the traditional policy. This simple idea turns out to be very effective: in a three-period setting, the new policy is optimal, and in multiperiod settings, numerical results for natural gas storage show that the new policy recovers a significant portion of the value loss of the traditional policy.

It is important to note that many electricity markets include not only an energy market but also an operating reserve market (also known as an ancillary services market). Operating reserve is the reserved capacity that allows the system operator to manage supply-demand imbalances caused by normal fluctuations or unexpected disruptions. Energy storage can serve as an operating reserve, and thus the storage value needs to incorporate the values derived from both energy and operating reserve markets. Drury et al. [13] quantify the value of compressed-air energy storage (CAES) derived from both markets. They find that the value from the energy market alone (i.e., the energy arbitrage value) cannot support CAES investment in most locations, but the addition of the revenues from providing operating reserves can support CAES investment in several locations.

A promising research avenue is to construct rigorous models for valuing energy storage participating in both the energy and operating reserve markets. The allocation of storage capacity to each market is nontrivial. As discovered in [13], the optimal allocation of storage capacity to provide operating reserves and energy arbitrage has seasonal trends, and can shift significantly based on market conditions. Energy storage capacity needs to be dynamically allocated to maximize its market value.

Storage location choice is another important research direction. Denholm and Sioshansi [14] consider the trade-off between colocating storage with a wind farm and locating storage closer to the load. When storage is colocated with a remote wind farm, the main advantage is the downsized transmission line and increased utilization of the transmission line. However, being remote to the load, storage is not as valuable as if it were closer to the load. The paper investigates whether the reduced transmission costs exceed the costs associated with locating energy storage away from the load.

1.3 ▪ Competitive Feedstock Procurement for Biofuel Production

The biofuel supply chain resembles any other multi-echelon chain in that it involves a number of stages for biomass harvesting, storage, processing, and transportation, and those for biofuel manufacturing, transportation, and blending. The design problem could be considered as an extension of the ones discussed in Chapter 33. A unique feature of the biofuel supply chain, however, is that the increasing demand for bioenergy crops leads to intensive competition for agricultural land—an already scarce resource worldwide—among uses for energy production, food production, and environmental conservation [16]. While traditional inventory management theories normally consider resource competition among similar vendors, the feature of biofuel supply chains leads to two direct consequences. First, ill-planned biofuel industry growth may result in suboptimal land use, significantly reducing food supply; in turn, this will lead to higher food prices, higher greenhouse-gas emissions, and reduced biodiversity. This probably explains why U.S. corn prices have increased dramatically since 2006 to record high in recent years [17]. Second, desirable economic returns from biofuel production have renewed farmers' interest in reclaiming idle marginal lands as substitutes for regular farmland. Marginal land has long served as a source of environmental conservation (e.g., CO_2 sequestration, habitat preservation, soil productivity restoration); however, since 2007, two million hectares of conserved land in the U.S. has been reclaimed, causing significant environmental hazards, such as soil erosion and pollution from fertilizer runoff. These issues directly involve intriguing organizational, operational, and infrastructure interdependencies among multiple industry sectors (e.g., energy, environment, agriculture) that are difficult for any single industry stakeholder to handle. Such issues often require holistic government intervention and policy regulations, which could be designed using game-theoretic modeling techniques such as those discussed in Chapter 33.

For example, the biofuel production goals (as specified by the U.S. government) have raised a number of pressing questions: Are strategic changes in agricultural land use and feedstock production (e.g., mix of feedstocks) required? How will government regulations and climate control policies affect industry development? What is the optimal size and locational distribution of biofuel refinery plants, how should the feedstock supply contracts be priced, and to what extent is there a divergence between the privately profitable and the socially optimal designs? In particular, the government faces a difficult food-energy-environment trilemma: how to stimulate the growth of the biofuel industry while, at the same time, protecting food security and environmental sustainability?

Addressing these challenges requires a comprehensive analysis that holistically addresses the biofuel industry, the food sector, the environmental sector, and the involved farmland markets. Integrating multiple layers of decisions into one overarching modeling framework is challenging because such decisions are often planned and managed by different stakeholders, who often have independent, if not conflicting, objectives—this generally results in extremely complicated dynamic interactions and requires novel solution methods. These types of problems seem to be related to the earlier research on spatial location equilibrium, as first proposed by [18], where a firm determines the location and production level of its facilities, knowing that these decisions will have direct impacts on the sales prices of products in spatially distributed markets. The concept was later extended to a plethora of supply chain network equilibrium models, originating in [19], to address Nash or Stackelberg types of competitions among decision-makers in multi-echelon supply chain networks.

In the biofuel supply chain setting, the emerging industry (e.g., biofuel sector) penetrates into an existing business (e.g., food sector) and competes for feedstock/farmland supply through existing or new spatially distributed sources (or markets). The emerging industry seeks the best strategic design configuration (e.g., refinery location and capacity, supply pricing and procurement, and transportation logistics) to maximize its own profit. Meanwhile, the existing business sector reacts to the new business by rearranging its supply chain operations (e.g., adjusting production level and alternating supply allocation), and each party looks for ways to maximize its benefit under the changing business world. The introduction of the emerging industry often involves spatial equilibrium of commodity flow, market demand, and resource supply.

In an exploratory effort, Bai et al. [20] propose a bi-level leader-follower game model that incorporates farmers' decisions on land use and market choice into the biofuel manufacturers' supply chain design problem. The model determines the optimal number and locations of biorefineries, the required prices for these refineries to compete for feedstock resources, and farmers' land use choices between food and energy. The model is solved by transforming the mixed-integer bi-level problem into a mixed-integer quadratic program based on Karush-Kuhn-Tucker (KKT) conditions. Noncooperative and cooperative games are studied respectively to address possible business partnership scenarios (e.g., via long-term leases) between feedstock suppliers and biofuel manufacturers. Using corn as an example of feedstock crops, spatial market equilibrium is utilized to model the relationship between corn supply and demand, and the associated price variations in local grain markets. It is found that biofuel supply chain design does have a direct impact on land use choices for farms in the area. Compared with the noncooperative game scenario, cooperation among the industry and the farmers tends to save transportation cost and generate higher profit for the whole supply chain.

In a follow-up study [21], the same authors extend the framework by introducing government regulations on farmland use and an associated marginal land market into the Stackelberg game. This model better represents the problem realism with more land-use options, including the possibility of marginal land reclamation and energy/food market equilibria, thus providing more comprehensive economic insights. Noting that farmers are generally independent stakeholders, a land-use allowance concept and a cap-and-trade mechanism are introduced to provide indirect economic incentives for the farmers to comply with government restrictions. These two models are proved to achieve equivalent land use patterns at optimality, and the proposed land-use constraints are shown to be effective in balancing the amount of farmland used for food and energy production. In some cases, the proposed cap-and-trade mechanism could result in less profit for the leading biofuel manufacturers but higher social welfare for the entire system (including food, fuel, and land markets).

Wang et al. [22] further incorporate the blenders into the scope of the biofuel supply chain. The biofuel consumption mandate is enforced via the Renewable Identification Number (RIN) system, a tracking mechanism that monitors obligated parties' compliance. The biofuel manufacturers obtain an RIN for each batch of biofuel production from the EPA; RINs are then transferred to blenders (e.g., energy companies) during biofuel consumption, and they can be traded among blenders; finally, the blenders are mandated to hand in specified number of RINs to the EPA at the end of each year, or else penalties will be imposed. In this work, competition among food and biofuel industry players (including among multiple biofuel manufacturers) is addressed via Nash equilibrium models and bi-level Stackelberg leader-follower models. Based on these models, the advantages and shortcomings of the current biofuel production mandate are analyzed.

These biofuel supply chain studies generally formulate the problems into discrete mathematical programs with equilibrium constraints (MPECs), which are generally nonlinear, nonconvex, and hence quite hard to solve. Solution methods are generally based on relaxation, decomposition, and transformation. Finding efficient solution approaches for such problems remains a challenge. As a side note, some approximation schemes for large-scale discrete decisions (e.g., facility location) into differentiable continuous counterparts (e.g., facility density) have been proposed to reduce the complexity of the problems [23].

1.4 ▪ Supply Network Design under Transportation Congestion and Infrastructure Deterioration

The changes in the energy industry have created unique challenges for many critical lifeline infrastructure systems far beyond those in the energy sector. Expanding ethanol production, for example, will not only lead to the expansion of biorefinery systems but also strain existing supporting infrastructures that are already aging and degrading (see [15] for a review). In particular, the already congested local and regional transportation networks are experiencing increasing freight demands for supplying feedstocks to refineries and delivering ethanol to consumers. Due to the low energy density of feedstock biomass, transportation of the bulky feedstock (and ethanol) incurs one of the major operational costs in biofuel supply chain systems. Trucking remains the dominant mode of transportation because alternative modes would either require heavy investment or remain unsuitable for the emerging biofuel industry—for example, the current pipeline infrastructure cannot be used for ethanol transportation due to erosion concerns. Most bioenergy production facilities are designed with a very large production capacity to achieve economies of scale. As such, a large number of trucks must be added to the highway network to ship sufficient low-energy-density biomass to satisfy the enormous ethanol production requirement.

Earlier work on the bioenergy supply chain [24] formulates a standard discrete facility location model to optimize the biofuel supply chain, where the point-to-point costs from transporting biomass, ethanol, and by-products are assumed to be exogenously given. Establishment of industry facilities, however, often induces heavy vehicle traffic that exacerbates congestion and infrastructure (e.g., bridge, pavement) deterioration in the neighboring highway network. This has been the case for the booming energy industry, especially when new production facilities are built near neighborhoods that were not originally built for heavy traffic. For instance, Iowa's growing renewable energy industries have had significant impacts on the quality of its transportation infrastructure, such that pavement repairs and maintenance costs in multiple Iowa rural counties increased significantly during and after the construction of biofuel production plants [25]. Such unintended consequences of energy production facility development increase the social cost to the general public (e.g., due to traffic delay and highway maintenance), and in turn have a negative impact on the efficiency of the freight shipments associated with these facilities.

Planning of biorefinery locations and biofuel supply chains, therefore, should be made cautiously to establish a sustainable bioenergy economy in which the investment in refinery construction and operations, the cost for biomass and ethanol transportation, and the related socio-economic impact are minimized. Bai et al. [26] develop a model to plan biofuel refinery locations where the total system cost for refinery investment, feedstock and product transportation and public travel is minimized. Shipment routing of both feedstock and product in the biofuel supply chain and the resulting traffic congestion impact are incorporated into the model to decide optimal locations of biofuel refineries. A Lagrangian relaxation based heuristic algorithm is introduced to obtain near-optimal feasible solutions efficiently. It is found through computational case studies that ignoring congestion in biofuel supply chain design could lead to much higher transportation costs for not only the biomass shipments but also the public. Hajibabai and Ouyang [27] further extend the model to allow for possible highway/railroad capacity expansion at chokepoints around the network. It is found that significant cost reductions can be achieved by simultaneously improving the capacity of the transportation network and expanding the biofuel supply chain.

Hajibabai et al. [28] present an integrated facility location model that simultaneously considers traffic routing under congestion and pavement rehabilitation under deterioration. The objective is to minimize the total cost due to facility investment, transportation cost including traffic delay, and pavement life-cycle costs.

Building upon analytical results on optimal pavement rehabilitation, the problem is formulated into a bi-level mixed-integer nonlinear program, with facility location, freight shipment routing, and pavement rehabilitation decisions in the upper level and traffic equilibrium in the lower level. This problem is then reformulated into an equivalent single-level problem based on the KKT conditions and piecewise linear approximation of traffic delay functions. Computational analysis shows that the proposed model can improve supply chain sustainability and minimize its negative societal impacts from congestion and pavement damage. In particular, significant reductions in pavement-related costs (e.g., agency cost and users' vehicle operating cost) as well as overall system-wide cost are observed, indicating that the joint optimization of the biofuel supply chain and the supporting transportation infrastructure not only results in a potential for Pareto improvement but also provides incentives for policy making and mechanism design through benefit/cost reallocation.

The supporting infrastructure is not just impacted by biofuel supply chains; similar problems are seen in a wide range of other energy industries. For example, in Pennsylvania and South Dakota, the heavy truck traffic induced by the emerging natural gas industry (e.g., for transporting water and supplies in support of the hydraulic fracturing process) has caused not only congestion to the residents in nearby towns but also severe damage to state and local roads, resulting in hundreds of millions of dollars spent on pavement repair and replacement. More generally, the development and transmission of energy can produce an array of effects at the community level, not only due to road network congestion and pavement deterioration but also including overburdened municipal services, reduced water availability for conventional uses, economic volatility, disruption of social and cultural patterns, and the stigma associated with environmental health risk and industrialization. A holistic coupled modeling approach, with embedded physical and social processes, is needed to design and analyze the energy supply networks.

1.5 ▪ Concluding Remarks

Supply chain design and optimization aim at matching supply with demand at minimum total cost, which is exactly the goal of the energy industry. With this common goal, it is not surprising that synergies exist between the two research fields. The purpose of this chapter is to highlight some of the existing synergies and provide the reader with some starting points for further reading. We hope the discussion in this chapter will foster more synergies between the two important fields in the future.

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Index