Decision Tools for Electricity Transmission Service and Pricing:

A Dynamic Programming Approach

by

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Abstract

For a deregulated electricity industry, we consider a general electricity market structure with both long-term bilateral agreements and short-term spot market such that the system users can hedge the volatility of the real-time market. From a Transmission Service Provider's point of view, optimal transmission resource allocation between these two markets poses a very interesting decision making problem for a defined performance criteria under uncertainties. In this thesis, the decision-making is posed as a stochastic dynamic programming problem, and through simulations the strength of this method is demonstrated. This resource allocation problem is first posed as a centrally coordinated dynamic programming problem, computed by one entity at a system-wide level. This problem is shown to be, under certain assumptions, solvable in a deterministic setup. However, implementation for a large transmission system requires the algorithm to handle stochastic inputs and stochastic cost functions. It is observed that the curse of dimensionality makes this centralized optimization infeasible. Thesis offers certain remedies to the computational issues, but motivates a partially distributed setup and related optimization functions for a better decision making in large networks where the intelligent system users drive the use of network resources. Formulations are introduced to reflect mathematical and policy constraints that are crucial to distributed network operations in power systems.

Thesis Supervisor: Dr. Marija D. Ilic
Title: Senior Research Scientist

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To my family,

Meral, Sait and Sinan.

Contents

List of Figures

Chapter 1

Introduction

This thesis aims to develop decision-making tools for the participants of the newly evolving electricity transmission market where demand and supply determine the value of the transmission service. Traditionally, transmission system has been treated as a passive, static pipe-like system for transmission of energy. However, with deregulation transmission system is now treated as an individual entity. It can no longer be assumed passive and static. It is not passive because it is a scarce resource and responds to usage levels. It is dynamic because it has usage-based and reliability-based uncertainties. These realized concepts show why transmission is a service, which bundles the right to use capacity with reliability of service delivery.

Transmission capacity is a scarce resource whose pricing and allocation pose a very challenging problem. Not only is the problem itself very intriguing, but determining a solution or a solution set, is also very interesting especially when various versions of market setup are considered. This thesis will focus on two setups that form the basis for two qualitatively different ways of transmission service and pricing in the evolving energy markets: One, where there is a central decision maker and one where distributed decision making by the smart system users is allowed. Even though the setups are very different, the decision makers in both cases are faced with the same basic question of allocation of transmission capacity. Briefly, the goals are to:

- In a coordinated setup: From a Transmission Service Provider (TSP) point of view, find the optimal capacity allocation between selling long term forward contracts for delivery prices ex ante and selling delivery rights in the spot market priced ex post depending on the real time congestion levels determined by the real time demand, supply and system-related reliability constraints.
- In a distributed setup: From a system user point of view, a generator or a consumer, find the optimal combination of buying rights to transmit power through long term

contracts or by buying transmission service in the real time market price determined by other users' demand and system reliability.

The challenge of finding the right combination of long term forward contracts and the real time spot market for transmission service is parallel to the challenge observed, in the forward and spot energy markets. We assume existence of an electricity daily spot market as well as the longer-term bilateral contracts between suppliers and consumers. The scope is limited to bilateral contracts and does not include multi-lateral ones nor any arbitrage activities by intermediary trading bodies. In order for the supply/demand transactions at the energy level to be implemented, arrangements must also be made for their delivery from the supplier to the consumer at the transmission level. Although the two mechanisms seem similar, transmission service allocation is more complex due to high number of interactions as well as due to strict technical constraints of the network. And while much progress has been made in the energy trading, transmission service allocation is not as well studied and requires much work on the formulation side to lay the foundations for development of practical algorithmic tools.

In this thesis, the goal is to design the tools at a formulation level. Transmission service and its pricing to the electricity market participants are posed as a stochastic optimization problem. The uncertainties of the system stem from both market activities of other users and from the uncertain equipment status. The theory of dynamic programming is utilized extensively to structure the stochastic optimization functions.

1.1 Problem Statement

The goal is to detail the optimal allocation of transmission line capacities to maximize the objective function of the decision maker within system constraints. Since the two setups described above have different decision makers, there are two sub problems to define under the problem statement:

1.1.1 Centrally Coordinated Operation

The centrally coordinated operation can be represented as shown in Figure 1.1 where boxes define functions, and arrows define inputs. The system users submit service requests from which the decision maker chooses those that maximize his revenue and those that can be implemented without stability problems, and this forms the *U* function. *S* maps those chosen injections to line flows.

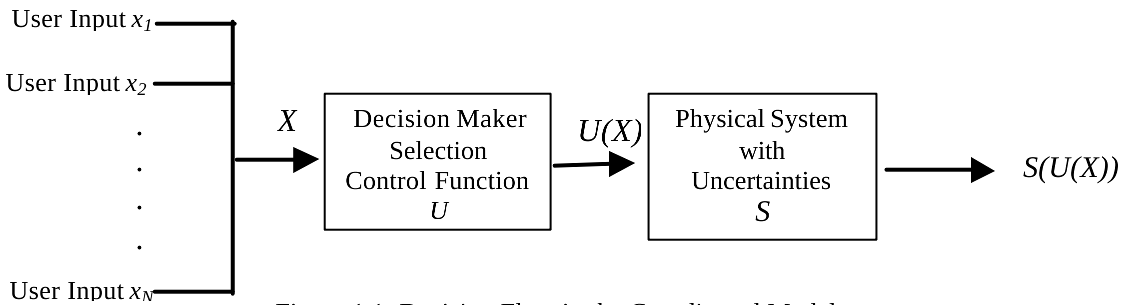


Figure 1.1: Decision Flow in the Coordinated Model.

From $S(U(X))$, the system revenue, $Revenue^{System}(f_1(S(U(X))))$ can be derived and it can also be seen that *U* has ensured that resulting line flows are within limits as well as that it tends to maximizing revenue. All components of the formula are dynamic with changing values requiring use of expected values in the above formulation. Unlike this approach, the majority of the literature for electric power transmission provision assumes a type of centralization but treats the problem as a deterministic, non-linear static optimization, as does the optimal power flow analysis [37].

1.1.2. Partially Distributed Operation

Below is the representation of the distributed decision-making. The price signal for using the transmission from a supervisor is communicated to the system users, so system user at each node *i* uses this data and expectation of the other users actions to make his decision $x_i = f_2(P,x_j)$, for all nodes *j*.

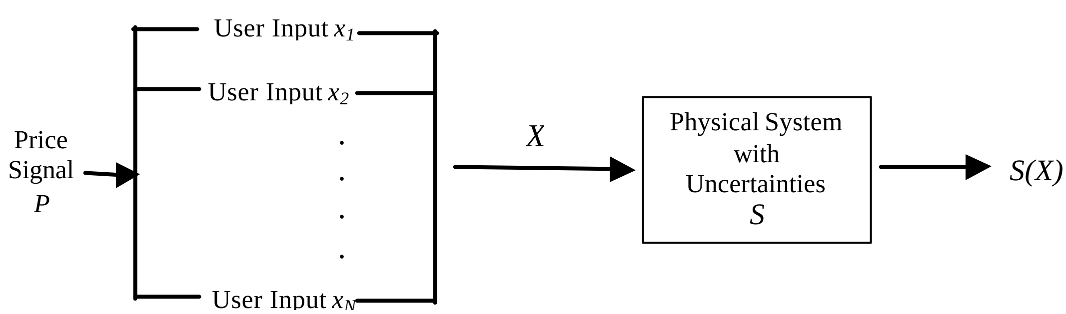


Figure 1.2: Decision Flow in the Distributed Model.

As it can be seen, that there is no central control that ensures the results of *S(X)* to be within system limits, which is the main challenge in the distributed model. The responsibility of making sure that system constraints are met is left to the price signal whose calculation is crucial. Distributed control of the transmission system is a rarely studied problem due to its complexity and high level of uncertainties. Allocation of network resources in a distributed manner between real time and forward market is a very new approach that is presented in this thesis.

1.2 Thesis Summary and Contribution

Currently, there is no tool deployed in decision making for bilateral agreements along with spot market trades. This is due to the fact that the volume of bilateral agreements is still not a major part of the electricity market. However, we believe that the use of such long-term contracts, both physical and financial will increase in the future under the deregulated regime. This evolution requires better planning and scheduling to which the dynamic programming algorithm is a solution. Besides developing decision-making tools for optimal allocation, we also intend to contribute, through this thesis, models and frameworks for both central coordination and distributed control of the transmission network. In addition, what distinguishes the problem formulation in this thesis from many other existing references is the consideration of system uncertainties in these models.

Chapter 2 provides the background for the overall setup and technical tools as well as the framework that the thesis presents. Chapter 3 formulates the basic problem of resource allocation in a centrally coordinated setup, where transmission service provider (TSP) is the decision maker. This chapter points out the computational issues faced by the implementation of the formulations and offers some approximation approaches. Chapter 4 again builds the decision-making problem for a central body, but this time factors in the physical, reliability-related, uncertainties of the system. This new version requires some background on electric power system reliability and risk in transmission networks, which is included in Chapter 4. Both Chapter 3 and Chapter 4 define the problem of resource allocation fully, but assert that in a market environment distributed decision-making might be as effective and also could alleviate the computational issues. Chapter 5 explores and formulates the distributed decision making problem. Chapter 6 demonstrates the strength of the proposed methods through simulations and Chapter 7 concludes the thesis. Appendix A has the source code for the simulations.

Chapter 2

Transmission System Design and Tools

This chapter provides the definitions and setups proposed for the transmission capacity market. It presents a set of current tools that are used to operate the market and points out the need for new tools. The chapter also provides background to the technical tools that are used in the thesis, namely dynamic programming and optimal power flow analysis.

2.1 Overview of Electricity Markets

The optimization suggested under both the coordinated and the distributed schemes is proposed in a market setup in which the TSP offers long-term bilateral contracts at a premium to enable the load and the supply to hedge against the volatility of the spot prices [35]. As mentioned before, the roles of the intermediary traders and secondary markets are excluded for this analysis and that leaves only three players to analyze, the supply, the load and the TSP. Two types of transactions will be available to the market players:

1.Long Term Bilateral Contracts: These are contracts between a supply-load pair that designate the obligation of supply to produce a certain amount of power at a negotiated price for a defined time period in the future. These energy contracts are matched with transmission right contracts to deliver the chosen quantity. The failure to provide this service will incur a penalty to the TSP. For this study, the agreements can be established only between nodes that are physically connected with a single line, and agreements between three or more parties are not permitted. And the price of any contract, in this thesis, refers to the injection price the users are willing to pay the TSP for the access to transmission service.

2.Real Time Spot Market: This is the traditional regulated spot market where demand meets supply and market clears at a spot price determined by demand and supply curves. The price depends on the cost functions as well as on the demand elasticity functions of the loads. The spot transmission service market matches the energy spot market to provide the capacity. Like in any market environment, the level of demand, which is stochastic, determines the demand for the price of the transmission service.

The load and supply can choose which type of transactions they would like to participate in between the deterministic risk-free bilateral agreements at a premium and the risky spot market at the market clearing price. In other words, the generators generally produce for both the spot market and the bilateral agreements, similarly the loads buy their electricity through both types of setups. They do this in a fashion to maximize their individual welfare functions. Under the coordinated setup, the TSP also makes decisions to determine whether to allocate its resources, line capacity, to the bilateral agreements requests or to the spot market participants again to maximize its revenues.

2.2 Time Frames and Event Characteristics

The decisions of the players belong to either one of the time frames, season-ahead or the near real-time. Season-ahead decisions are made using forecasts of market behavior that also include the uncertainties of the physical system. They are either concerned with provision of a service or with the risk hedging for the future. Season-ahead decisions by the transmission system owner dictate how its lines will be allocated between the forward market and the spot market as well as which long term contracts to choose among all requests. The system users make a set of similar decisions. The loads decide from whom to obtain their power and how much they are willing to pay for it. The generators decide to whom they should sell their power to, at what price and for how long. Both users also determine their priorities for the transmission service in light of the uncertainties. In this thesis, season ahead planning is considered long term; whereas, long-term decision-making has been traditionally thought of as investment level decision making for long horizon projects. The incentive for investment or recovery of investment in transmission system is not studied in this thesis. Moreover, since the long-term in the thesis is about three months, a season, discounting of the costs and revenues are ignored.

Near real-time decisions are modifications made to long-term decisions as more current information becomes available in addition to the spot market. With more information, load and supply may decide to call off a bilateral agreement or establish one, similarly the TSP can decide to curtail an agreement it had accepted before or respond near real-time to near real-time decisions made by the other players. Most of the actions taken by the TSP in the short run will be to deal with congestion appearing in the system, and calculating profit through congestion charges and ensuring reliable service. For example, if a load believes that spot prices will be high in the next period, it may choose to strike a bilateral agreement and the supply side might find this acceptable, as it will itself hedge against the risk of elastic load. In another setting, the TSP can decide to curtail a bilateral agreement with the expectation of making higher profits in the spot market even after paying a penalty.

The motivation for the players to operate in these two different dimensions is a result of the volatility of the spot market. It is an attempt to avoid congestion ahead of time or be at least prepared for it. Not only does the existence of two options make it harder for the users to plan cleverly, but it also makes any system optimization hard. Including these two different time frames in the same optimization function, each having different characteristic, is very challenging. As there are different times frames to consider, looking at it more closely, it can be seen that spot market and long term bilateral market inputs have very dissimilar characteristics in the way they evolve in time. The bilateral agreements can be treated as asynchronous discrete events that start and end at certain times; whereas, the spot market is a continually evolving continuous time input. These two market inputs come together in terms of continuous flows in real time, but in analysis they present a hybrid system model that lends way to a discrete event dynamic system (DEDS) formulation. In this context, the control for discrete inputs to the system is determined by the current state of both continuous and the discrete elements [12]. Looking at these more closely:

Time Driven Spot Market:

F_{ij} = Continuous flow between nodes i and j.

f_1 determines the flows $F_{ij}(t) = f_1(P_D(t), P_G(t), u(t), T(t))$

$P_D(t)$ is the total system demand

$P_G(t)$ is the total system generation

$u(t)$ is the control of bilateral agreements at time t

$T(t)$ is the state of the physical topology

Event Driven Bilateral Agreements:

$BA(t)$ defines the bilateral agreement vector that is implemented at time t;

$BA(t) = f_2(BA(t-1), BA^{new}(t), u(t))$

f_2 determines the control $u(t)$ based on the pervios time period and applies it to the incoming events to determine the current state.

Total System Control:

Optimal control for this hybrid system maximizes the system revenue over the total control space U.

$$R^{system}(t) = \max_{U} f_3(BA(t), u(t))$$

with respect to the system constraints

1. $\sum P_D(t) = \sum P_G(t)$
2. $|F_{ij}(t)| =< F_{ij}^{max}$ for all ij.

While the above expressions define a complex problem, when looked into the function f_3, it is observed that the available computational tools to calculate system revenue of the real time flows, cannot handle a hybrid market definition. Rather total system dispatch control uses a discretized version of the continually-evolving real time spot market. (This refers to the optimal power flow analysis that uses a snapshot of the system to determine optimal operational dispatch, thus highest profits. Please see later Section 2.3.2.) Moreover, function f_1 is also hard to use due to the non-linearity it exhibits with the distribution factors. This is the main motivation behind abandoning a DEDS formulation of a hybrid system. We prefer to use discrete models for all inputs and the system to make use of the optimal power flow analysis for revenue calculations of the spot market. Our model treats the bilateral agreements the same as the hybrid model, but instead of a continuous treatment of the spot market, it takes snapshots of the spot market at fixed time intervals and combines it with the bilateral discrete inputs to develop a dynamic programming approach.

2.3 Reliability and Uncertainties

There are two kinds of reliability that are considered in the thesis. One is the reliability issues arising from physical uncertainties, second is the reliability issues related to the usage of the system determined by system inputs, which can be at normal operating conditions or lead to network congestion.

2.3.1 Physical System Uncertainty

In both the centrally coordinated and the distributed modes of operation, TSP needs to model its system accurately to insure system reliability and incorporate risk of its system into his objective functions. In the coordinated scheme, as the decision maker, TSP, has to know the uncertainties inherent to the system, i.e. equipment outages, in order to make sound long-term decisions. Similarly, in the partially distributed set-up TSP is responsible for sending the right price signals, which have the incorporated information about the system conditions. Uncertainties inherent in the grid are numerous, but this thesis will focus on line outages as a subset of equipment uncertainties only. Methods developed in this sub-case can be extended to substation, generation outages and their likes. We consider the line outage problem to be the most complex because the effect of any outage event effects the system topology, i.e. it determines how well the system can absorb and cover up for that outage. A line outage could be viewed as a high impact, low probability uncertain event and cannot be ignored as TSP develops his decision tools for serving electricity market participants, studied in Chapter 4. In [19] it is shown how due to a line outage, the topology of a transmission network can change so drastically that some isolated parts of the network can be formed where some generations units can exert market power and become monopolies even in a competitive energy environment. This is a perfect example why transmission reliability is a big issue. Chapter 4 will go into detail about line outages and their incorporation into the decision-making process.

The concept of reliability is a big topic in itself and a revisit to the current reliability tools is necessary due to the unbundling of the reliability services in the industry. The currently practiced (N-1) reliability test requires that the grid be used under normal conditions (prior to any equipment outages) somewhat conservatively; the reliability test requires sufficient generation and transmission reserve capacity in a stand-by mode in order to supply the consumer in an uninterrupted way in case any single equipment outage takes place. The regulated industry approach to reliability treated transmission system and generation systems as a single unit and collected the work under bulk system reliability analysis. Under the vertically integrated utility, this makes sense because then, if one line of the transmission system owned by utility A were to fail, then utility A would re-dispatch its own generator units in the area to make sure that all the loads were served. Since this was possible, they used a conservative method to run their system: the (N-1) security criteria. This method suggests that the maximum operation be bounded by the limits imposed on the system derived from cases where there is loss of a major component of the bulk system, mainly lines and generators. [20] analyzes some of these issues in depth. Chapter 4 suggests a less conservative reliability analysis.

2.3.2 Market Input Uncertainty

Market uncertainties can be grouped in two classes:

1) Spot Market Uncertainties
2) Bilateral Agreement Uncertainties

Spot market uncertainties capture the volatility of the real-time operations. Changing demand and changing supply result in a rapidly varying behavior. Figure 2.1 shows the load diagram for a week in May in New England [33].

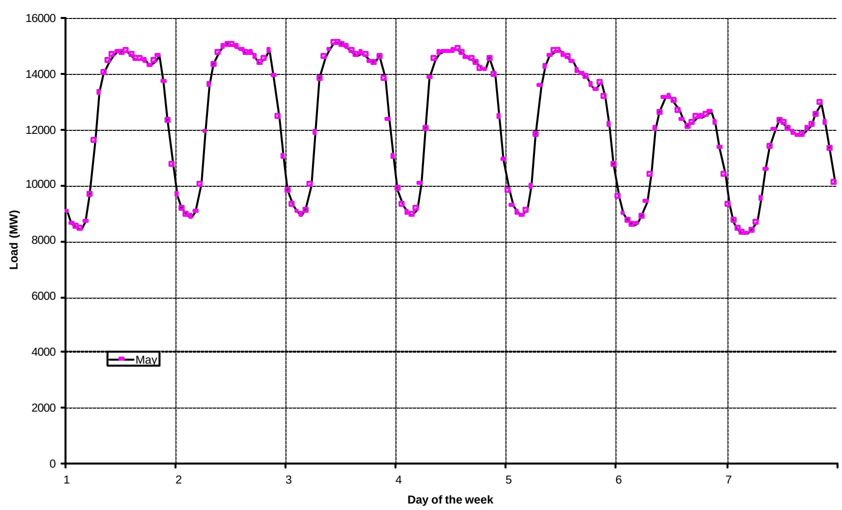


Figure 2.1: Load diagram for a week in May, New England

And Figure 2.2 shows a plot of average 24-hour load patterns for each month in New England [33].

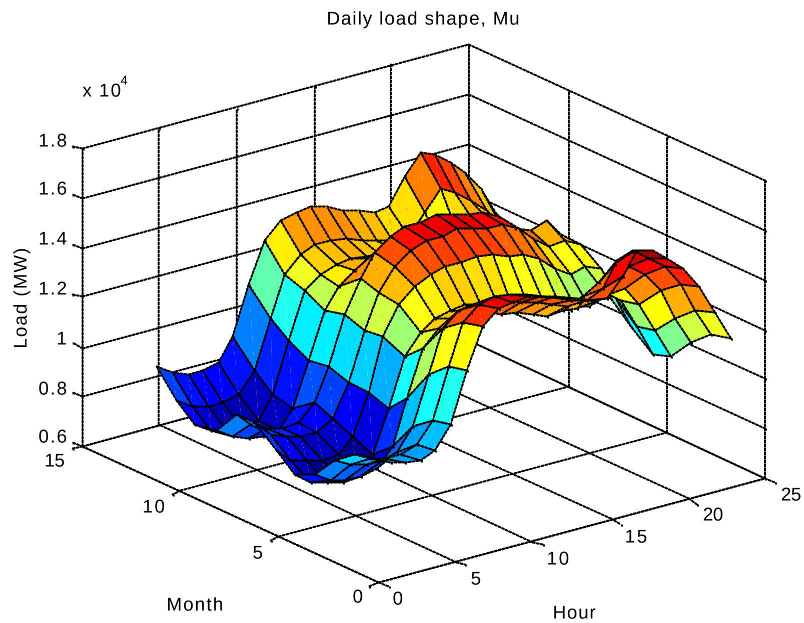


Figure 2.2: Average monthly patterns of daily load, New England

Bilateral uncertainties refer to the possible quantity, price and duration parameters that any BA can take. In addition, the unknown arrival time of the agreements is another element of uncertainty.

2.4 Technical Background

A brief background is appropriate to introduce two tools used in the thesis. Dynamic Programming is a decision making tool. The optimal power flow analysis is an optimal dispatch tool used by the transmission operators.

2.4.1 Dynamic Programming and Curse of Dimensionality

The formulations of the resource allocation problems studied in the thesis are posed as dynamic programming problems. Dynamic Programming (DP) is a very effective way to pose problems that feature discrete-time dynamic systems with additive cost over multi stages. These problems involve decision making at each stage whose outcome depends on other parameters of the future stages. Therefore, the desirability of any current decision is calculated by their current cost and expected future costs. It is important to state the notation of the DP formulations beforehand. k designates the discrete time index taking values between 0 and N. x is used to describe the state of interest, u the control or decision variable, belonging to an admissible space, that evolves x into future states. w is the random noise that introduces uncertainty. Function g calculates the per stage cost, $g(x,u,w)$. The optimization function can now be represented as [3]:

$$J\left(x_k\right) = \min_{u_k \in \mathbf{U}} e\left\{ g_N\left(x_N\right) + \sum_{i=k}^{N-1} g_i\left(x_i, u_i, w_i\right) \right\} \quad (2.1)$$

The strength of the formulation comes from the principle of optimality where optimal solutions to tail sub-problems can all together define the overall optimal solution:

$$\begin{gathered} J_N\left(x_N\right) = g_N\left(x_N\right) \\ J_k\left(x_k\right) = \min_{u_k \in \mathbf{U}} e\left\{ g_k\left(x_k, u_k, w_k\right) + J_{k+1}\left(f_k\left(x_k, u_k, w_k\right)\right) \right\} \end{gathered} \quad (2.2)$$

This is the objective function form that is used in this thesis for network allocation formulations and the algorithms for their simulations. While the expression looks compact, it is usually hard to find a closed form representation of J which leads to enumeration based methods. Computational effort can get very expensive with bigger control space and longer time periods, higher k, hindering the desirability of DP. Such cases are classified under the Curse of Dimensionality, which will be referred to in the thesis to motivate approximation methods.

Please note that the dynamic programming formulations, in this thesis, are defined in discrete time. One can think of the whole time horizon as a season and each time increment can be a day. If there are T days in a season the optimization will go from $k=1$ to $k=T$. The definitions belong to a system with N_G generators and N_L load, demand, nodes.

2.4.2 Optimal Power Flow

The use of Optimal Power Flow (OPF) has increased with deregulation where the solution of this static optimization reveals the locational-based marginal prices of electricity (LBMP) which are considered to be optimal prices under perfect market assumptions. This solution also is called the economic dispatch. The idea is to aggregate all the demand and supply bids for resources at a single node in the system to determine the market-clearing price for that node using generation cost functions. This price then in return determines the injections and withdrawals that optimize system operation and maximize social welfare. These are also called the spot market prices and quantities. Let N_L be the load nodes and N_G the supply nodes, given the demand at each load node

$P_L = \{P_{L_1}, \cdots, P_{L_{N_L}}\}^T$ the optimal generation dispatch is $P_G^* = \arg\min_{P_G} \sum_{i=1}^{N_G} c_{G_i}\left(P_{G_i}\right)$ with

subject to system constraints :

1) Load-Generation Balance $\sum_{j=1}^{N_l} P_{L_j} = \sum_{i=1}^{N_G} P_{G_i}$

2) Line Capacity Limits $\left|P_{ij}\right| \leq P_{ij}^{\max}$

Any time the thesis refers to the calculations of spot prices, spot injection, the above optimization is used. For large systems of many nodes, this optimization can also get very costly [36]. Given these tools, the specific problem formulations of interest in this thesis can be derived.

Chapter 3

Coordinated System Operation with Static Topology

This chapter formulates an approach to a centrally coordinated transmission allocation. Depending on design, the formulations differ as a function of uncertainties considered. Figure 3.1 shows the tree of uncertainties. This chapter develops the tools under the static topology assumption. Computational issues and some solutions to the above cases are discussed.

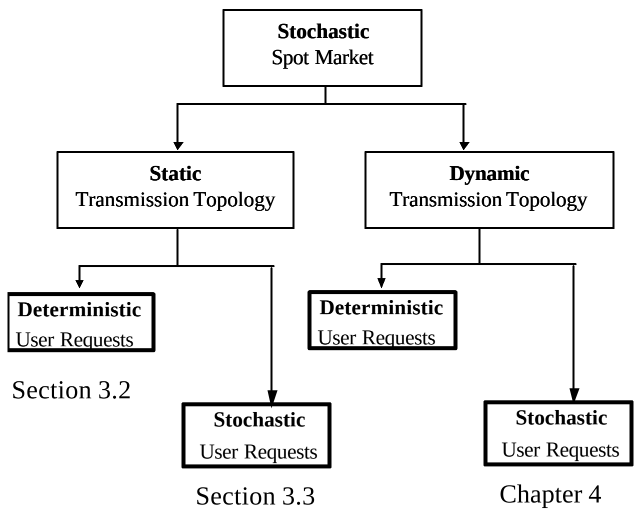


Figure 3.1: Tree of Uncertainties

3. 1 Coordinated Decision Making by the TSP

This centralized scheme is a direct extension of the TSP's role as a transmission provider in a regulated industry. The new component is the operation of bilateral agreements that allows the TSP to collect a profit other than charging the spot market users for transmission service. Bilateral and spot markets both influence the quantity of power flow on the lines, which have a certain carrying capacity. The higher the congestion on one line, the higher the price due to high demand for the line flow usage. Even though it may seem that the TSP would like to use as much of its lines as possible, thus accept any incoming bilateral and spot market requests, a different scheduling system is shown to yield higher revenue. Bilateral agreements that are accepted in one period of time, e.g. a day, might impact the line congestion levels of the next. While maximizing revenue for one period, they may decrease it for the next compared to the case where the agreement had not been accepted. Or, an agreement may take up capacity that would be more profitable to sell later to another party. This is analogous to the problem of asset allocation among investments.

In short, we are looking at a finite horizon, multi stage decision-making problem under uncertainties for the TSP. The goal is to a build a tool and a framework where the system revenue is maximized, season-ahead, by the TSP who chooses the optimal combination of the incoming bilateral agreements, implements them in addition to the spot market in consideration of limited transmission resources. Using dynamic programming tools, this near real time resource allocation problem can be solved effectively.

Figure 3.2 shows the procedure under the coordinated scheme. At time $t = -p$ with reference to the beginning of the season at time $t = 0$, system users decide on the parameters of the bilateral agreements they would like to participate in. These parameters are quantity, price to be paid as access fee to transmission network, the start and end time of the contract. Under this setup, the resource allocation optimizations carried out by the system users while determining the agreements they would like to arrange, is not discussed in detail. For centrally coordinated operation, this simplification is acceptable since TSP has the final word in deciding which agreements get implemented. Sections on priority pricing and decentralized models attempt to detail user decision-making processes in Chapter 5.

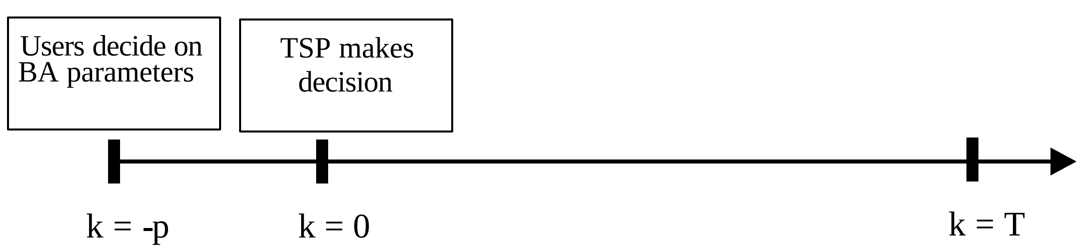


Figure 3.2: Time line of events

Under the assumption of static physical system topology, once the supply and demand units make their own allocation decisions season ahead, two variations of centrally coordinated operation can be designed:

Case 1: Users communicate their contract information to TSP between $t=-p$ and $t=0$. This is depicted by Deterministic user requests branch in Figure 3.1. (Section 3.2)

Case 2: Users do not communicate any information. This is depicted by Stochastic user requests branch in Figure 3.1. (Section 3.3)

Under both cases, rejection of an agreement prior to its start does not incur any compensation payments to the TSP; whereas, curtailment in real time requires compensation. To compensate, TSP agrees to provide the service demanded by the load from the spot market at the load bus.

3.2 Deterministic User Requests

Users inform the TSP of the agreements they would like to buy transmission service for. TSP can then go ahead and use this information combined with forecasted spot load to determine the optimal decision-control path. In a system of N_G generators and N_L loads, TSP objective function is as follows:

$u_{ij}[k]$: The control decision of accept of rejecting BAs injecting at bus i and withdrawing at bus j at time $t = k$.

$\boldsymbol{Z}[k]$: The vector of bilateral agreements whose elements are $Z_{ij}[k] = [\ Q^Z_{ij}[k], P^Z_{ij}[k], tr^Z_{ij}[k]\ ]$ which are the BAs communicated to the TSP and begin at $t = k$.

$\boldsymbol{X}[k]$: The vector of BAs, which have been accepted by TSP prior to k, and TSP has the responsibility of delivering this service whose elements are: $X_{ij}[k] = [\ Q^X_{ij}[k], P^X_{ij}[k], tr^X_{ij}[k]\ ]$.

$\boldsymbol{P^{Ws}}[k]$: The column vector of probable spot prices for all buses in the system $P^{Ws}_i[k]$. $P^{Ws}_i[k]$ is a row vector of b possible spot price values with probabilities ?: $P^{Ws}_i[k] = [\ (P^{Ws}_{i,b}[k],\ ?_{i,b}[k])\ ]$ for all b.

$\boldsymbol{Q^{Ws}}[k]$: The vector of probable spot demands for all buses in the system $Q^{Ws}_{ij}[k]$, injected from bus i to bus j at $t = k$ in the spot market. $Q^{Ws}_{ij}[k]$ is a row vector of c possible values with probabilities f : $Q^{Ws}_{ij}[k] = [\ (Q^{Ws}_{ij,c}[k],\ f_{ij,c}[k])]$ for all c.

$W_s[k]$: Vectors that capture the randomness in $\boldsymbol{P}^{Ws}[k]$ and $\boldsymbol{Q}^{Ws}[k]$.

The performance to be maximized is the revenue collected by the system. The revenue has two flows: One from the execution of the agreements, and the other from the spot market at that time period. These two elements need to be related since the transmission capacity used up by the bilateral agreements has an influence on the spot prices and therefore the revenue. Optimal power flow calculation is used to calculate the spot market revenue taking into consideration the line capacities altered by acceptance of the bilateral agreement. The seasonal revenue is maximized over the decision space U. The decision space contains the decisions TSP makes as to whether to accept or reject BAs. The first line in the expression defines the revenue collected from the agreements that are accepted at time $t = k$. The second line defines the revenue collected from agreements already being implemented and last line defines the expected revenue collected from the spot market as a product of nodal price differences between the injection and the withdrawal bus and the expected quantity carried between them:

$$
\begin{aligned}
&R^{season} = \sum_k \left(R^{BA}[k] + R^S[k] \right) \\
&\arg\max_U \underset{W_s}{e}\left\{ R^{season} \right\} = \underset{W_s}{e}\left\{ \sum_k \left[\begin{array}{l} \sum_{ij} u_{ij}[k] P_{ij}^Z[k] Q_{ij}^Z[k] + \\ \sum_{ij} P_{ij}^X[k] Q_{ij}^X[k] + \\ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k] \right) Q_{ij}^{W_S}[k] \end{array} \right] \right\} \qquad (3.1) \\
&\text{subject to } \left| Flow_{ij}[k] \right| \le F_{ij}^{\max} \\
&\forall i.j \in \left\{ N_G, N_L \right\}, i \ne j
\end{aligned}
$$

Given the above cost function, the detailed dynamic programming algorithm is as follows (3.2):

Current State:

$$X_{ij}[k] = [Q_{ij}^{X}[k]\ P_{ij}^{X}[k]\ t_{ij}^{X}[k]]$$

Expected Incoming BA:

$$Z_{ij}[k] = [Q_{ij}^{Z}[k]\ P_{ij}^{Z}[k]\ t_{ij}^{Z}[k]]$$

State evolution function f:

$$f(\mathbf{X}[k], \mathbf{u}[k], Z[k]) = T(\mathbf{X}[k]) + T(\mathbf{u}[k] * Z[k]) = \mathbf{X}[k+1]$$

where T terminates an agreement or update the commitment:

$$T(\mathbf{X}[k]) = \begin{cases} tr_{ij}[k] \le 1 \rightarrow Q_{ij}[k] = P_{ij}[k] = t_{ij}[k] = 0 \\ tr_{ij}[k] > 1 \rightarrow tr_{ij}[k+1] = tr_{ij}[k] - 1 \end{cases}$$

The cost function becomes:

$$\underset{W_S}{e}\left\{g\left(\mathbf{X}[k], \mathbf{u}[k], Z[k], \mathbf{W_S}[k]\right)\right\} = \underset{W_S}{e}\left\{\left[\begin{array}{l} \sum_{ij} u_{ij}[k] P_{ij}^{Z}[k] Q_{ij}^{Z}[k] + \\ \sum_{ij} P_{ij}^{X}[k] Q_{ij}^{X}[k] + \\ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k]\right) Q_{ij}^{W_S}[k] \end{array}\right]\right\}$$

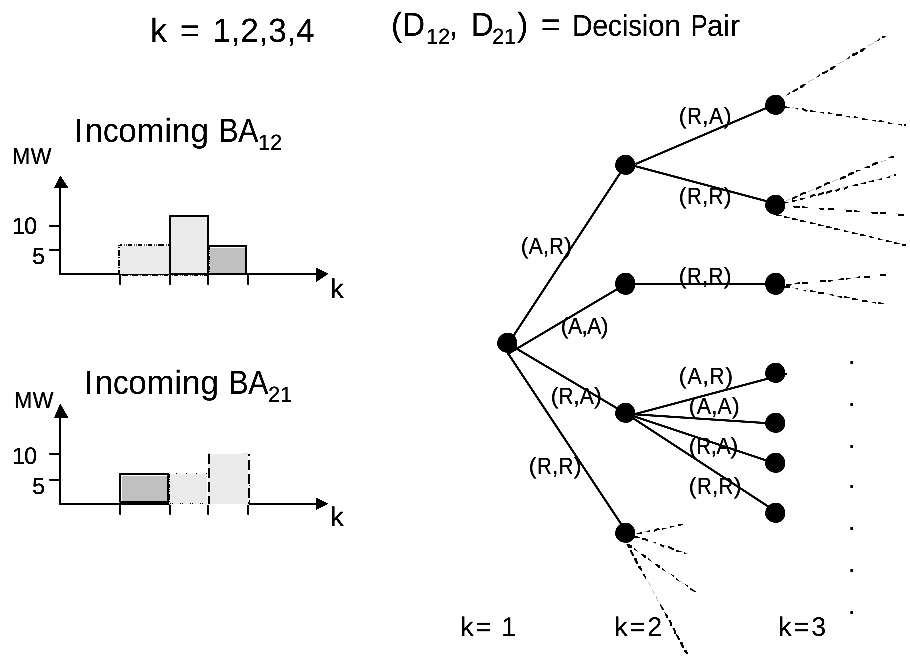
Putting the cost functions together to determine cost-to-go expression and combining it with Bellman's equality:

$$J_N(\mathbf{X}_N) = g_N(\mathbf{X}_N)$$

$$J_k(\mathbf{X}[k]) = \arg\max_{u[k]} \underset{W_S}{e}\left\{g_k\left(\mathbf{X}[k], \mathbf{u}[k], Z[k], \mathbf{W_S}[k]\right) + J_{k+1}\left(f\left(\mathbf{X}[k], \mathbf{u}[k], Z[k], \mathbf{W_S}[k]\right)\right)\right\}$$

The above expression does not explicitly show the optimal power flow analysis that determines the spot prices and quantities for the purpose of compactly expressing the algorithm. (Note: This particular definition partially violates the elements of the disturbance matrix to be independent from one another since it is well studied that spot market behavior of consecutive time periods are related. This will be corrected in Section 3.4.4 under the discussion for state augmentation.)

The uncertainty in the spot market requires the decision to be done over the expectation space for the spot market parameters. (The physical system uncertainties were



3.3: DP Tree for a 2-Bus system

not included in the formulation, which is relaxed in Chapter 4.) Effectively under this version, TSP solves an optimization function over the decision space to develop a simplified tree similar to one shown in Figure 3.3 for a 2-Bus system.

The tree structure in Figure 3.3 shows how the size of the dynamic programming tree grows exponentially with the number of nodes in a system and linearly with the number of time periods. Not only are there a high number of nodes, but also while building the DP tree, each revenue calculation at each node requires probabilistic optimal power flow analysis, which involves iterations of the non-linear OPF optimization for all probable values. This introduces high level of complexity to which solutions such as ordinal optimization, approximate dynamic programming and perturbation analysis are being considered as a remedy. For practical purposes, assume that the black nodes in Figure 3.3 are the expected revenues over $\boldsymbol{W_s}$. Once the dynamic programming tree is completed, the algorithm does the backward walk from the leaves of the tree to the root to determine the possible maximum accumulated revenue, and chooses the associated optimal decision vector. It is important to expand the tree in Figure 3.3 to really show the branching without the aggregation of expected values at each node. The detailed dynamic programming tree depicting the uncertainties in the spot market for a 2-Bus system is shown in Figure 3.4. This is for a situation where there are 3 possible load levels each with probability P_{Li} and 2 possible supply levels P_{Sj}. The triangle states depict the state changes due to different controls, and the circle states depict the probabilistic states due to the uncertainty in the state parameters. To attach more meaning, the triangle states would describe the 'accept' or 'reject' decisions of the bilateral agreements whereas the circles would be different spot revenues for a given control branch. Note the timing of these branching, control branches evolve the state from time *t* to *t+1*, but the state uncertainty branches do not involve a decision but rather can be thought of as happening in the same time period.

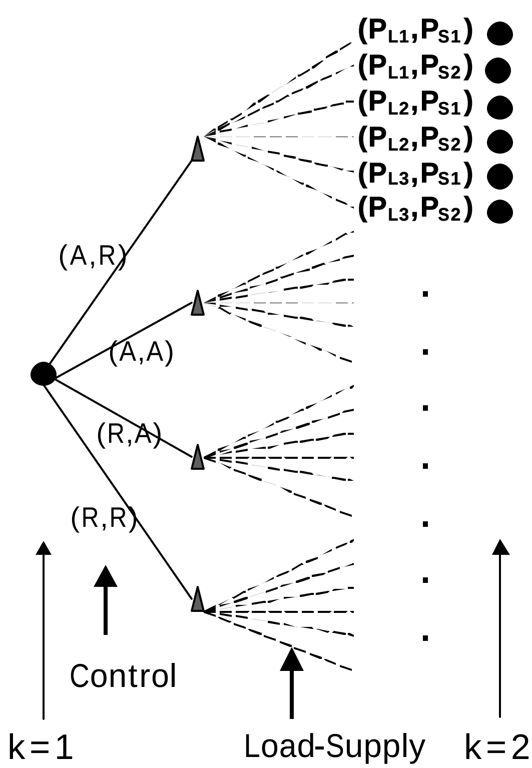


Figure 3.4: Detailed DP Tree

Please note that both trees are constructed by the same amount of computation. For the 1st tree, probabilistic OPF simply samples the probability distributions and runs OPF for each sample and brings the results together at the end to form a result distribution; thus the expected values can be readily calculated. The second tree, instead, runs OPF for all possible values without creating distributions. The thesis will refer to the second tree with individual trajectories for the purpose of pictorially describing the computational issues.

At this point of the discussion, it should be emphasized once again that OPF is a simulation-based tool. (It simulates static optimization of the system without considering any temporal components.) It lacks control and learning mechanisms. But among all the drawbacks, the most significant disadvantage is that it is based on simulation rather than working with closed-form functions or distributions. This is because the optimization of OPF is nonlinear. When OPF uses the load and supply curves it does not use them on a functional basis but rather samples them. The answers are represented similarly where the resulting sample points are interpolated to form the resulting flow distributions most of the time after a series of refining linearizations. However, it is accurate to add that this method works well since rarely any load or supply curve can be represented as an explicit function with a distribution. Therefore extending the OPF to a probabilistic version leads to similar issues. Even if the probabilistic load and supply could be expressed in a compact distribution form, OPF would still sample this distribution and make simulations to get the resulting flows.

This section only considered the spot market uncertainty, assuming that the players would communicate their forward contract requests ahead of time. However, it is more realistic to assume that the system users will communicate the information about the agreements to the TSP at the time they would like to start it any arbitrary point in the season rather than the beginning of the season. This motivates the development of the model for stochastic inputs.

3.3 Stochastic User Requests

Relaxing the deterministic assumption, TSP now also needs to handle the random disturbance of bilateral agreements. The coordinator TSP still has the control to accept or reject the agreements as they come in, but season-ahead, TSP now tries to accurately forecast the disturbance for two purposes:

1. To achieve season-ahead planning so that TSP knows how to behave in response to requests for service overall.

2. Each day can be treated as the 1st day of a season that allows the TSP to make decisions about an agreement by looking at its impact on the system for a season-long window of time.

Before introducing some solutions and extension to the above formulations, it is important to visit the assumption behind TSP's generation of possible bilateral agreements. For this case when TSP needs to develop its own forecast for the BA arrival process, he can use two methods:

1) Historical Cost Methods: TSP can refer to the past values for the bilateral agreements it served, or

2) Monte Carlo Projections: TSP can refer to tools that have been developed to study bilateral contracts and how the transmission company needs to do static tests to ensure that the operational security is not jeopardized. [13] presents a method of creating sample, random bilateral agreements vectors using Monte Carlo methods to evaluate the bounds of safe operation. [14] offers a mechanism to evaluate the impact of bilateral agreements on the system through sensitivity analysis. Monte Carlo simulations are used to create bilateral agreements. Linear programming and sensitivity analysis tools are used to measure if any agreement or set of agreements poses a threat to system security. Moreover, the transmission service provider can use these very tools not only to test situations but also to develop bounds and constraints as well as general rules for the operation of the bilateral contracts. This is very valuable for the TSP however, it is crucial to see that the mentioned approaches treat the bilateral agreements as being separate from the spot market and overlook their impact on real time flows with changing spot market characteristics which dynamic programming with stochastic spot market disturbance considers. That is why, this thesis motivates stochastic dynamic programming and gradual temporal learning from a tool, which couples real time and forward markets which can be developed by the below formulations:

Because TSP has control over the agreements, the disturbance from this input is treated differently than the spot market disturbance, $W_s[k]$. And the stochasticity in the BA requests is considered in the control function. In addition to the notation defined in Section 3.2, let

$\boldsymbol{Y}[k]$: The expected incoming bilateral agreements at time $t = k$, $\boldsymbol{Y}[k]$ is a column vector of all $\boldsymbol{Y}_{ij}[k]$.

$\boldsymbol{Y}_{ij}[k]$ is a row vector of all n possible bilateral agreements from ij at k with their associated probabilities ?:

$\boldsymbol{Y}_{ij}[k] = [\ (\boldsymbol{Y}_{ij,n}[k], ?_{ij,n}[k])\ ]$ such that

$(\boldsymbol{Y}_{ij,n}[k], ?_{ij,n}[k]) = (\ [\ Q^{Y}{}_{ij,n}[k], P^{Y}{}_{ij,n}[k], tr^{Y}{}_{ij,n}[k]\ ], ?_{ij,n}[k])$.

The optimization of the TSP now becomes an expectation both over random W_s and and over controllable Y:

$$R^{season} = \sum_{k}\left(R^{BA}[k] + R^{S}[k]\right)$$

$$\arg\max_{U} e_{Y,W_s}\left\{R^{season}\right\} = e_{Y,W_s}\left\{\sum_{k}\begin{bmatrix}\sum_{ij} u_{ij}[k]P_{ij}^{Y}[k]Q_{ij}^{Y}[k] + \\ \sum_{ij} P_{ij}^{X}[k]Q_{ij}^{X}[k] + \\ \sum_{ij}\left(P_{i}^{W_S}[k] - P_{j}^{W_S}[k]\right)Q_{ij}^{W_S}[k]\end{bmatrix}\right\} \tag{3.3}$$

Control decision function µ depends on both X and controllable Y.

$$u_{ij}[k] = m_{ij}\left(X_{ij}[k], Y_{ij}[k]\right)$$

$$\text{subject to} \left|Flow_{ij}[k]\right| \leq F_{ij}^{\max}$$

$$\forall i.j \in \left\{N_G, N_L\right\}, i \neq j$$

With this updated cost function, the detailed DP algorithm becomes (3.4):

Current State:

$$X_{ij}[k] = [Q_{ij}^X[k]\, P_{ij}^X[k]\, tr_{ij}^X[k]]$$

Expected Incoming BA:

$$Y_{ij}[k] = [Q_{ij}^Y[k]\, P_{ij}^Y[k]\, tr_{ij}^Y[k]]$$

State evolution function f:

$$f(\mathbf{X}[k], \mathbf{u}[k], \mathbf{Y}[k]) = T(\mathbf{X}[k]) + T(\mathbf{u}[k] * \mathbf{Y}[k]) = \mathbf{X}[k+1]$$

where T terminates an agreement or update the commitment:

$$T(\mathbf{X}[k]) = \left\{ \begin{array}{l} tr_{ij}[k] \le 1 \rightarrow Q_{ij}[k] = P_{ij}[k] = tr_{ij}[k] = 0 \\ tr_{ij}[k] > 1 \rightarrow tr_{ij}[k+1] = tr_{ij}[k] - 1 \end{array} \right\}$$

The cost function becomes:

$$\underset{Y,W_S}{e}\left\{ g\left(\mathbf{X}[k], \mathbf{u}[k], \mathbf{Y}[k], \mathbf{W_S}[k]\right)\right\} =$$

$$= \underset{Y,W_S}{e}\left\{\left[\begin{array}{l} \sum_{ij} u_{ij}[k] P_{ij}^Y[k] Q_{ij}^Y[k] + \\ \sum_{ij} P_{ij}^X[k] Q_{ij}^X[k] + \\ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k]\right) Q_{ij}^{W_S}[k] \end{array}\right]\right\}$$

Putting the cost functions together to determine cost-to-go expression and combining it with Bellman's equality:

$$J_N(\mathbf{X}_N) = g_N(\mathbf{X}_N)$$

$$J_k(\mathbf{X}[k]) =$$

$$= \underset{u[k] W_S, Y}{\arg\max}\; e \left\{ g_k\left(\mathbf{X}[k], \mathbf{u}[k], \mathbf{Y}[k], \mathbf{W_S}[k]\right) + J_{k+1}\left(f\left(\mathbf{X}[k], \mathbf{u}[k], \mathbf{Y}[k], \mathbf{W_S}[k]\right)\right)\right\}$$

As seen above, DP formulation was able to capture all market uncertainties in the system. Control parameters partially handled the stochasticity in the bilateral market; and the random system disturbance described the spot market uncertainty. As more uncertainty is included in the model, the size of the decision space becomes combinatorial which requires approximate solutions for a feasible implementation. This is the problem of curse of dimensionality.

3.4 Possible Approaches to the Curse of Dimensionality Problem

In general, there are two main obstacles in the application of DP. First is the size of the solution space, and the second is the complexity of the objective function J.

As seen from the above formulations and the growth order of the DP trees, determining the solution to the original DP problem leads to a computationally intractable problem classified as being NP-hard. An NP-hard algorithm is defined as a problem requiring the enumeration of some nontrivial parts of feasible solutions, which cannot be accomplished in polynomial time [18]. Thus, new approaches are needed to solve our optimization problem which becomes NP-hard even in finite horizon. Not only does the problem involve many computations increasing in time, but also this is a stochastic dynamic programming or stochastic shortest path, problem where controller does not deterministically define the next state with probability 1. Under the stochastic case, [4] probability of transition from state i to j with control u is given by a probability expression defined by the control and the previous state only; $p_{ij}(u) = P(x_{k+1} = j \mid x_k = i , u_k = u)$. Using this probability, one can also update the cost function being used to $g(i,u,j)$ such that cost is now also based on the next state. This is the essence of stochastic dynamic programming and developing Markov decision models. In TSP's formulation, the transitions between states depend on Y as well as W_s in the current definition. Since control aims to maximize revenue with respect to these uncertain disturbances, well-defined transition probabilities might be hard to obtain. In cases where clear patterns of probability of state transitions cannot be obtained, simulation based methods are used both building on the original well-defined cost functions and the approximate ones.[4]

This section first introduces Markov decision processes that from the basics for explaining approximation methods. Next simulation-based tools such as rollout algorithms are visited introducing different heuristics that replace the original control and cost functions and aim to reduce computation. Lastly, the basic issue of the complexity of the objective function itself is discussed offering approximate methods, neuro-dynamic programming (NDP), to calculate J.

3.4.1 Application of Markov Decision Processes

Consider the case where the spot market is included in the formulation but is assumed to be constant. (This is a pretty valid assumption when operations over fixed periods like seasons are considered.) In this case, the control decision varies only with the arrival of the BAs and their parameter in a static physical system.

This setup lends itself very well to exploiting theories developed for Markov decision processes in stochastic DP problems. Markov decision problems rely on obtaining the following information [4]:

$$p(i,u,j) = \text{Probability of going from state } i \text{ state } j \text{ given control } u.$$

In the problem of TSP's decision making, assuming $\boldsymbol{W_S}$ is known and slowly varying, $p(X[k],u,X[k+1])$ can be treated as having two components that influence the probability. Recall the state evolution expression:

$$\begin{aligned}
&\text{State evolution function } f: \\
&f(\mathbf{X}[k],\mathbf{u}[k],\mathbf{Y}[k]) = T(\mathbf{X}[k]) + T(\mathbf{u}[k] * \mathbf{Y}[k]) = \mathbf{X}[k+1] \\
&\text{where T terminates an agreement or update the commitment:} \\
&T(\mathbf{X}[k]) = \begin{Bmatrix} tr_{ij}[k] \le 1 \rightarrow Q_{ij}[k] = P_{ij}[k] = tr_{ij}[k] = 0 \\ tr_{ij}[k] > 1 \rightarrow tr_{ij}[k+1] = tr_{ij}[k] - 1 \end{Bmatrix}
\end{aligned}$$

The first part of the evolution of updating the current system commitment is deterministic; however, the second part with the control depends of the incoming agreements. Therefore $p(X[k],u,X[k+1])$ can be associated with the probability on getting a certain incoming request vectors *Y[k]* and *Y[k+1]* and feeding them to the controller *u[k]*: $p(X[k],u,X[k+1]) = h(X[k],u[k],Y[k],Y[k+1])$. We assume that probabilities of *Y[k]* can be well defined using historic data and exploiting auction theory where depending on a certain *u[k]*, the decision maker can attach probabilities to *Y[k+1]* he expects to get from the system users. (Probability of bidding higher, probability of asking for less quantity, etc.)

So given such a strong structure to the problem, optimal policies, both stationary and non-stationary can be determined using transition probabilities. Stationary policy is an admissible policy where the control policy is of the form $p = \{m\ ,m\ ,\cdots\}$ unlike the non-stationary policy $p = \{m_0, m_1, \cdots\}$ where the policy depends on time. Objective functions can be re-expressed using transition probabilities and taking expected values of the possible future trajectories. Here is the basic DP algorithm:

$$J(i) = \max_u \left[g(i, m_i(i)) + \sum_{\forall j} p(i, m_i(i), j) \cdot J(j) \right]$$

$$\text{where the greedy policy yields :} \qquad (3.5)$$

$$m_i(i) = \arg\max_u \left[g(i, m_i(i)) + \sum_{\forall j} p(i, m_i(i), j) \cdot J(j) \right]$$

These two definitions are important because they define the two qualitatively different ways to approach approximate dynamic programming:

1) Value Iteration: Tries to find the optimal value for cost-to-go function J at all k.
2) Policy Iteration: Tries to find the optimal policy μ. Rollout algorithms that are explained in the section are single step versions of policy iteration.

3.4.2 Rollout Algorithms

Rollout algorithms aim to overcome the computational problems of stochastic control problems with combinatorial decision spaces [6]. The goal is to use certain heuristics to approximate the optimal dynamic programming solution. This section introduces concepts in rollout algorithms and apply them to our centralized TSP decision-making problem under uncertainty of the market parameters. From the basic definition of DP,

$$x_{k+1} = f(x_k, u_k, w_k) \qquad k = 0,1,\ldots,T-1$$

for a T-stage problem. u_k is the control determined by the base policy $p = \{m_0, m_1, \cdots, m_{T-1}\}$ where $u_k = m_k(x_k)$. With the base policy, cost-to-go function starting at k is

$$J_k(x_k) = e\left\{\sum_{i=k}^{T-1} g_i(x_i, m_i(x_i), w_i)\right\} \tag{3.6}$$

Under base policy, the cost-to-go function satisfies the basic DP algorithm:

$$J_k(x) = e\{g(x, m_k(x), w) + J_{k+1}(f(x, m_k(x), w))\} \text{given} \quad J_T(x) = 0 \tag{3.7}$$

But when it is hard to determine the base policy p, rollout algorithm is used to determine the rollout policy $\bar{p}$ based on p. Determining the elements of $\bar{p} = \{\bar{m}_0, \bar{m}_1, \cdots, \bar{m}_{T-1}\}$ from the below expression, yields the one-step look-ahead policy:

$$\bar{m}_k = \arg\min_u e\{g(x, u, w) + J_{k+1}(f(x, u, w))\} \quad \forall x. \tag{3.8}$$

In cases when J_k is not in closed form or is hard to calculate, the one step look-ahead policy should be used with the best approximation available to ensure accuracy. To find $\bar{p}$, one needs all Q-factors under different policies [8]:

$$Q_k(x,u) = e\{g(x,u,w) + J_{k+1}(f(x,u,w))\} \tag{3.9}$$

For any time k, all the Q-factors for all possible values of $f(x,u,w)$ need to be determined. Applying the one-step look ahead policy to TSP's optimization problem:

$$Q_k(\mathbf{X,U}) = e\{g(\mathbf{X, U, Y, W_s}) + J_{k+1}(f(\mathbf{X, U, Y, W_s}))\} \tag{3.10}$$

However, it is observed that we have two different unknowns $\boldsymbol{Y}$ and $\boldsymbol{W_s}$. Thus, two Q-factors should be defined in two-dimensional state space, namely

$$Q_k^{\mathbf{Y, W_s}}(\mathbf{X,U}) = e\{g(\mathbf{X,U,Y,W_s}) + J_{k+1}(f(\mathbf{X,U,Y,W_s}))\} \quad \forall\{\mathbf{Y, W_s}\} \tag{3.11}$$

From this expression and using the probabilistic values for all the pairs, the optimal rollout policy can be determined by minimizing the expected value of the Q-factor over decision space u:

$$\overline{m}_k(\mathbf{X}) = \arg\min_u \hat{Q}_k^{\mathbf{Y},\mathbf{W}_S}(\mathbf{X},\mathbf{U}) \tag{3.12}$$

Once these structuring definitions are formed, rollout algorithms look for heuristics to produce different p trajectories for different policies. Here are a few heuristics for TSP's problem:

1) Certainty Equivalence: Fixes the disturbances ***Y*** and $\boldsymbol{W_s}$ to ***Y`*** and $\boldsymbol{W_s}$` and run the

$$\overline{m}_k = \arg\min_u e\left\{g(x,u,w') + \tilde{J}_{k+1}\left(f(x,u,w')\right)\right\} \tag{3.13}$$

2) Scenario Based Solutions: Relaxes the certainty equivalence method by creating a certain number of pair of ***Y*** and $\boldsymbol{W_s}$ to fix the number of trajectories simulated.

$$\begin{aligned}&\text{Create M sequences for } \mathbf{W_S} : W_S^m = \left[w_{s,k}^m, \cdots, w_{s,T-1}^m\right] \ \forall \mathrm{m} = \{1, \cdots, \mathrm{M}\}\\ &\text{Create V sequences for } \mathbf{Y} : Y^v = \left[y_k^v, \cdots, y_{T-1}^v\right] \ \forall \mathrm{v} = \{1, \cdots, \mathrm{V}\}\end{aligned}$$

The result is a trajectory set of (*MxV*) elements each of which should be weighted by its probability of occurrence to get the approximate $\tilde{J}_k$. The weighting function here is another optimization function where the error between the original and the approximated problem should be minimized by calibrating the weights. Moreover, with time, weights can be adjusted through learning algorithms. More will be discusses on learning in Section 3.4.4.

3) Pick the highest revenue BAs: Be selective in the Y space and fix Y to simplify the DP uncertainty from spot market.
4) Pick the shortest duration BAs: Be selective in the Y space.
5) Use expected values for the inputs at the expense of not being accurate.

To determine the best heuristic to use, all these methods should be compared to the original solution in test cases.

3.4.3 Conservative Dynamic Programming

Another approach to simplifying the curse of dimensionality, introduced by Asuman Özdaglar Köksal[1], is simplifying the multi stage problem to a single stage problem. This is a conservative DP heuristic, where a new cost function to the decision maker is introduced. The idea is to allocate the resources for the current period without looking ahead in time but with a virtual internal cost function such that the cost of allocation of resource increases with the allocation amount. The motivation is to allocate some resources at the current period and leave some free for use in the next period blindly. (This is a perfect situation for learning algorithms to be applied, to determine the optimal allocation for the future periods based on expectations.)

For the TSP, a cost function is introduced to capture the opportunities forgone in the future by making the current decision:

$$h = \text{An aggregate metric for line capacities}, \ 0 \le h \le h^{\max}$$
$$t[k,h] = \text{Cost of using h amount of resource at time k.}$$
$$t[k,h] = a^2[k]\cdot h, \text{ a a quadratic cost function}$$

Given this internal cost, the per stage optimization can be augmented to:

$$\underset{Y,W_S}{e}\left\{g\left(\mathbf{X}[k],\mathbf{u}[k],\mathbf{Y}[k],\mathbf{W_S}[k],t[k]\right)\right\}=$$
$$= \underset{Y,W_S}{e}\left\{\left[\begin{array}{l} \sum_{ij} u_{ij}[k] P_{ij}^{Y}[k] Q_{ij}^{Y}[k] + \\ \sum_{ij} P_{ij}^{X}[k] Q_{ij}^{X}[k] + \\ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k]\right) Q_{ij}^{W_S}[k] + \\ -t\left[k,h\right] \end{array}\right]\right\} \quad (3.14)$$

[1] Work in Progress. Asuman Koksal is working with Prof. Bertsekas at LIDS, MIT.

Using such a method, the TSP can develop a database of historic data to characterize system users, and cyclic requests to make this virtual cost function to be very clever. Learning algorithms are also very useful to perfect the cost function.

3.4.4 Neuro-Dynamic Programming

Neuro-dynamic programming seeks sub optimal solutions to the original dynamic programming algorithm in situations where either the objective function is not well defined or is very complex. In these cases, $J_k(x_k)$ is approximated by a scoring function $\tilde{J}_k(x_k, r_k)$ where r represents a set of parameters, weights, that approximates the original function. Given this approximation the policy can be written as [7]:

$$\tilde{m}_k(x_k) = \arg\max_u e\left[g(x_k, m_k(x), w_k) + \tilde{J}_{k+1}(f(x_k, m_k(x), w_k), r_{k+1})\right] \quad (3.15)$$

The success of the neuro-dynamic programming is determined by how well it approximates the original function, and how simple the parameter vector is. If the original function is known, r can be engineered to minimize the least squares error. If it is not known, then learning algorithms can be used to determine the parameter vector with time. The function fitting is what gives this practice the name neuro-dynamic programming, as the fitting of the sample trajectories to function parameters require feature extraction by neural networks.[5] Feature extraction method captures the main elements that describe the majority of the state evolution and the cost function without incorporating all the details of the main function.

In any sort of neuro-dynamic programming, temporal difference learning can be used to make adjustments to the approximation functions. The learning algorithm uses the difference between the actual J and the approximated $\tilde{J}$ and tries to decrease it.

$$d_k = g(x_k, u_k, w_k, x_{k+1}) + \tilde{J}_k(x_{k+1}, r_{k+1}) - \tilde{J}_k(x_k, r_k) \quad (3.16)$$

In TSP's coordinated optimization function, the main obstacle is running the optimal power flow analysis for each revenue calculation. Thus, neuro-dynamic programming can be utilized to simplify this calculation. A possible approach is to model the spot market input as varying around an average and use the parameter set to model the real-time variances.

3.4.5 State Augmentation

The above formulations of DP partially violate a basic assumption that the values of $\boldsymbol{W_s}$ for all time are independent [3]. The methods should be corrected to exploit the correlations between the spot market parameters, $\boldsymbol{W_s}$, namely the nodal spot prices and aggregate spot demand among buses. The elements of vector $\boldsymbol{W_s}$ are derived from optimal power flow analysis, which takes in individual demands, and supply bids of system users, determines optimal dispatch to produce the values used in revenue calculations, price and quantity of spot. Thus, one should look at the correlations among the supply and demand bids to try and model the correlations among the elements of $\boldsymbol{W_s}$. Once the underlying processes that evolve the spot market is determined, state augmentation can be used to enlarge the state space. The enlarged state space captures all the information known to the control function at time k. Previously, the formulation captured information about only the bilateral agreements in the system state definition; however, using certain models, state space can be extended to include information about the spot market at time $t=k$. The goal is to reduce the elements of $\boldsymbol{W_s}$ to the point where it can be treated it as noise.

Many studies have been done to model the spot market parameters for forecasting purposes. The following is a compact summary of the mathematical model underlying the Bid-based Stochastic Model [33]:

Spot Price Model:

Hourly price: $P_h = e^{aL_h + b_h}$

Daily 24-hour vector of prices: $\mathbf{P}_d = e^{a\mathbf{L}_d + \mathbf{b}_d}$

Load Model:

$$\mathbf{L}_d = \boldsymbol{\mu}_m^L + w_d^L \mathbf{v}_m^L,$$

$$e_{d+1}^L - e_d^L = -a^L e_d^L + s_m^L z_d^L$$

$$d_{d+1}^L - d_d^L = k^L + s^{Ld} z_d^{Ld},$$

where,

$$e_d^L = w_d^L - d_d^L .$$

Supply Model:

$$\mathbf{b}_d = \boldsymbol{\mu}_m^b + w_d^b \mathbf{v}_m^b + \sum_i p_d^i y_m^i .$$

$$e_{d+1}^b - e_d^b = -a^b e_d^b + s_m^b z_d^b$$

$$d_{d+1}^b - d_d^b = k^b + s^{bd} z_d^{bd} ,$$

where,

$$e_d^b = w_d^b - d_d^b .$$

where π_d is Markov process. Such models can be used to develop state augmentation models where the $\boldsymbol{W_s}$ disturbance becomes just the error in the estimation.

Another application of state augmentation is altering non-stationary DP problems into stationary ones by mapping non-stationary states and cost function values to stationary ones [5]. This is particularly useful to develop in order to utilize large set of DP related tools developed for stationary problems. Since the TSP optimization problem is non-stationary, with changing bilateral agreements, even after the state augmentation of the spot market, the above method might be used.

Chapter 4

Coordinated System Operation with Dynamic Topology

The formulations presented in the above section do not include uncertainties about the operation and the availability of the physical system, hence they were classified under static setup. However, relaxing that assumption shown in Figure 4.1, this section considers a dynamic physical system. It presents the probabilistic concepts behind physical system reliability. Besides the source of the risk, the chapter also discusses the approaches to who absorbs the risk in transmission service.

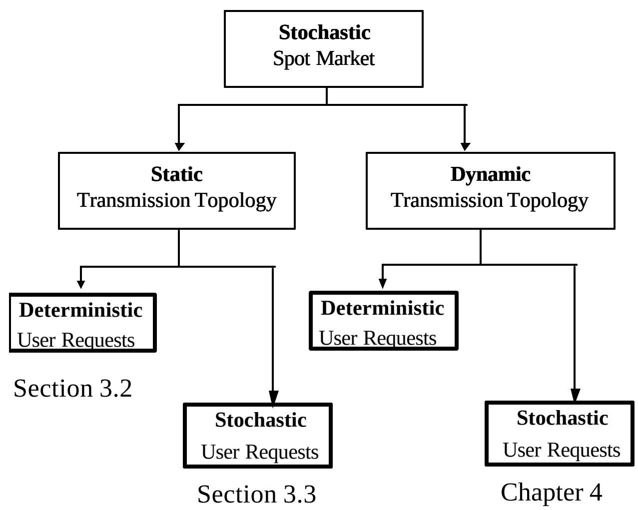


Figure 4.1: Tree of Uncertainties

4.1 TSP Objective Function

Physical system dynamics are considered to be the equipment outages in the transmission system. For simplicity, line outages are considered to be the only form of equipment outages causing reliability issues. These outages are low probability events with high impact on the operation of the system deviating it from normal conditions. Even if the isolation of nodes might not be an issue, the transmission provider suffers from congestion when one of the lines fails but the connected node still needs to be served. This may also increase congestion on other lines resulting in higher demand per line thus higher service prices. A worse case is when the line reaches its transmission limit and the nodes are not delivered the power they need. This has severe implications on the reliability of the system. That is why it is crucial for the TSP to model these events, plan and commit accordingly. Figure 4.2 shows a timeline for seasonal operation and shows the arrival of a line outage that disturbs the planned system operation.

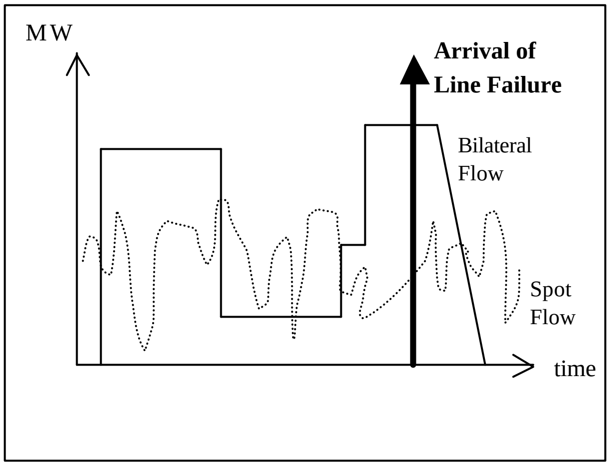


Figure 4.2: Description of Possible Events

Imagine the case in which the line which fails was the one on which a bilateral agreement was being implemented such that the re-dispatch of the generation units also leads to congestion. In this situation, the agreement be curtailed and the service provider will incur a penalty, compensating the bilateral agreement owner. This compensation charge may be high, making that agreement unprofitable even with a small probability of outage. It maybe very well be the case that profit collected from the successful part adjusted by the compensation cost might be negative in which case, not implementing the agreement would be more profitable to the TSP. (For a BA curtailed, it is assumed the power is obtained from the withdrawal node in the spot market, hence the assumption of infinite generation.) This is why it is crucial for the TSP to model these outages in order to determine if it should accept an the agreement or not. Under such circumstances, with the physical uncertainties, the TSP objective function becomes (4.1):

$$R^{season} = \sum_k \left(R^{BA}[k] + R^S[k] - Compensation[k]\right)$$

$$\arg\max_U \underset{Y,S,W_S,\Pi}{E}\{R^{season}\} =$$

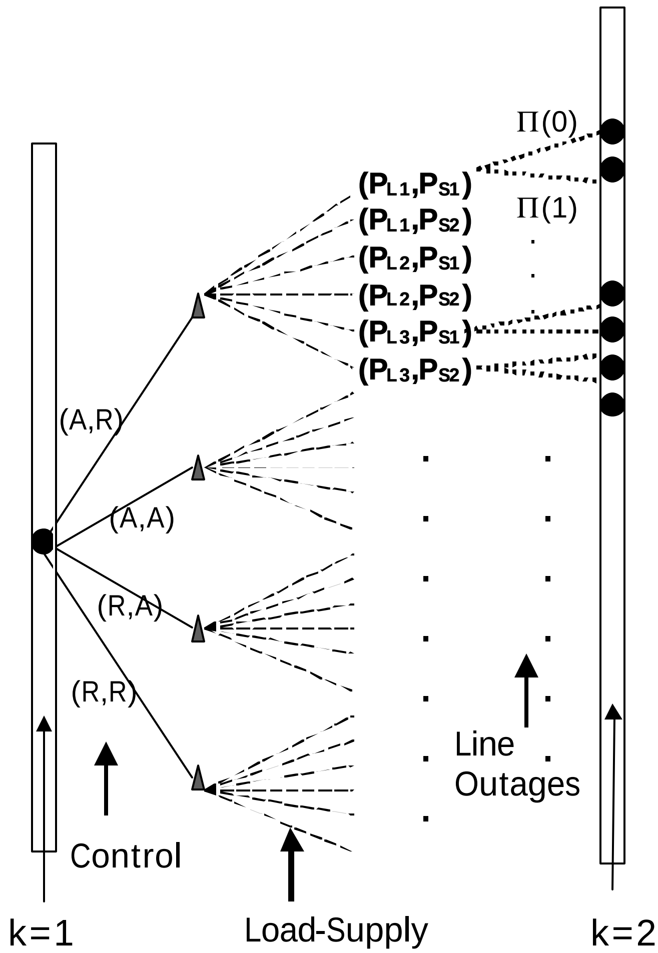
$$= \sum_k \begin{bmatrix} \underset{Y}{e}\left\{\sum_{ij} u_{ij}[k] P_{ij}^Y[k] Q_{ij}^Y[k]\right\} + \\ \sum_{ij} P_{ij}^X[k] Q_{ij}^X[k] + \\ \underset{W_S,Y,\Pi}{e}\left\{\sum_{ij}\left(P_i^{W_S}[k] - P_j^{W_S}[k]\right) Q_{ij}^{W_S}\right\} \end{bmatrix} - \sum_k \begin{bmatrix} \underset{W_S,Y,\Pi}{e}\left\{\sum_{ij}(1 - p_{ij}[k]) \bullet u_{ij}[k] P_j^S[k] Q_{ij}^Y[k]\right\} \\ \underset{W,Y,\Pi}{e}\left\{\sum_{ij}(1 - p_{ij}[k]) \bullet P_j^S[k] Q_{ij}^X[k]\right\} \end{bmatrix}$$

$$\forall i.j \in \{N_G, N_L\}, i \neq j$$

$$p_{ij}[k] = p_{ji}[k] = \begin{Bmatrix} 1 \rightarrow \text{Operational Line} \\ 0 \rightarrow \text{Failed Line} \end{Bmatrix}$$

$$Q_{Gi}[k] = \infty$$

While the formulation captures the uncertainties that TSP is interested in, it is observed that the nature of the uncertainties is quite different. The bilateral agreements are event driven and can be modeled by arrival processes with certain distributions for quantity, price and time. However, the spot market is time driven where there is a continually evolving input with small variations similar to small signal noise. Thirdly, the physical system uncertainties are modeled as low probability events with large mean times to fail and are one-time occurrences. While the first two inputs can be modeled by probability density distributions without closed forms evolving with time, for the physical uncertainties we have a different model where the only information available is the steady state probabilities of operation. As a result of the formulation above, the DP tree gets even bigger. Figure 3.4 is now extended to capture the physical uncertainties in Figure 4.3.



4.3 Detailed DP Tree With System Uncertainties.

While the computational remedies proposed in Chapter 3 can again be used, the thesis suggests that another approach should be developed due to the significant differences in the characteristics of the physical and market uncertainties. The next section aims to describe the physical uncertainties for finite horizon operations in more detail.

4.2 Reliability Analysis for Large Transmission Systems

From a Transmission Service Provider point of view, reliability concept is usually visited during the planning stage of a transmission system. Probabilistic tools are utilized to determine the lines, connections that have the highest probability to get congested, and the transmission owner focuses on these areas for future investments in order to make sure the system is stable and achieve a stable operational network [15]. This is far from being a simple task. The probabilistic analysis that goes into robust network planning usually forces the limits of NP-hard problems. However, those decision-making problems are concerned with investment level time scales, where as the focus in this thesis is on operational time scales, which are significantly shorter, when large grid enhancements are considered [27].

Only recently has the subject of transmission reliability gotten attention by the utilities in an area other than long term planning. As a single entity, transmission owners now have the incentive to develop new reliability tools for current operations in an environment where reliability of the service provided to the customer is de-bundled as well. This means that unlike before, either the transmission provider or the system user needs to account for the risk in the system, charge for it or hedge against it. While doing this, one also has to leave the traditional bulk system reliability picture and work with a stand-alone transmission system. It is also important to note that, in the bulk system approach the focus on what the delivery of power to the distribution utility or the consumer itself. Thus the indices of reliability were developed from a consumer focus point of view: Annual Load Interrupted, Annual Unsupplied Energy, Delivery Point Interruption Severity, Load Shedding Severity [9]. However, it is important to see that TSP is not only responsible to the consumer but under the new market setup, he is also responsible to the generation units as well.

Towards operational tools, one recent work is done by Ontario Hydro, which started to use assessment techniques to learn more about the strength of their transmission system [17]. Available Transmission Capacity (ATC) is the most commonly used valuation technique that is determined by parameters like: generation dispatch, system load and its distribution, static topology and capacity limit of the transmission lines [17]. A utility would use the information gathered from the ATC of its lines to decide whether to sell firm or interruptible contracts in order to better utilize its assets, maximize revenue and minimize penalty incurred from interrupting firm contracts [25]. For large systems, determination of these parameters can be computationally expensive as it also poses a dynamic programming question under uncertainties. The study of firm vs. interruptible contracts is parallel to TSP's central decision for accepting or rejecting bilateral agreements, where bilateral agreements would be the firm contracts. Under the distributed setup developed in Chapter 5, that physical reliability needs to be factored into calculations for the price signal that the centralized operator send to the users. This signal is an aggregation of all the information about the system, which the system users then utilize to make decisions to maximize their utility.

Besides ATC methods for transmission, deregulation also lead to studies of performance based rates for distribution systems [11]. (Even though, the thesis does not focus on the distribution systems, it is important to look at developments there to see synergies.) Performance based rates is one application of probabilistic risk analysis for the physical components of the power system. Monte Carlo simulations are used to create a sample space of component failures each modeled as a Poisson process with known arrival rates. These simulations enable the utility to calculate system average interruption frequency index and system average interruption duration index to calculate ahead of time the expected level of penalties that will be faced due to interrupted service. These indices can be used for both short term operational planning, pricing, and also for long term investment planning. Combined with probabilistic risk assessment, financial impact of the physical system can also be determined in a probabilistic fashion. [11] shows a simulation for an average distribution system and also fits a lognormal distribution to the system reliability probabilities. This is very relevant work related to the reliability question the thesis would like to address, however, the drawback of using Monte Carlo simulations is the assumption of equal probability for all cases regardless of the failure characteristics of the components.

Another application of probabilistic reliability analysis is to study the loss of load probability (LOLP). These studies usually focus on probabilistic load and supply analysis, but still use static topology. LOLP calculation can show the probability of when demand at a location can exceed the supply at that location plus the inflows. [38] It is observed that this probability would be much different if the failure of a tie line is factored into the study. As these examples show a new tendency to use system reliability information more cleverly, here are a few ideas where the transmission system provider draws its motivation to factor reliability into its tools:

Reliability-Related Risk Management

Users may choose to buy financial contracts for long term risk management, they need to determine how much they would buy and what they are willing to pay depending on the risk they are facing and their risk-aversity. Trading entities might provide risk-hedging contracts for the users, but they also need similar information to price these contracts cleverly.

Clever Decision Making for Resource Allocation

This is the main subject handled in this thesis from both a service provider and system user perspective: TSP needs to use reliability information to commit to agreements, and the users need to same information to guarantee service for themselves and bid a reasonable price.

While the traditional approach to the above issues have been very conservative to bypass such questions, more liberal use of the system backed by risk management can prove to be much more optimal and efficient. Once the users manage their own risk, decentralized control also becomes more optimal as will be explained in Chapter 5.

4.2.1 Narrow Definition of Transmission Reliability

Even though the motivation behind building a smart reliability model is straight forward, the methods to actually materialize such a tool is not so obvious since the power grid is a large network of interconnections and components for which a simple system status model does not suffice. The range of situations that jeopardize acceptable levels of reliability needs to be narrowed down, in order to determine the probability of such events.

First of all, let us focus on the elements of the physical system. The physical components that make up the system range from transformer, to transmission lines, to breakers, and to generators. Since the focus of the thesis has been on the operations of the TSP, the transmission system is handled in isolation assuming that generation utility handles its own reliability issues. For a TSP, main focus would then be on transmission lines of high capacity and substations. Although both sets of elements can be treated similarly, transmission lines span a big interconnected network. Therefore, the thesis only refers to line outages and leaves the study of substations as a mere extension. Similarly, scheduled maintenance of components that interrupt services is not included since it can be treated as a deterministic event.

Although, it looks as if the above classification is an adequate narrowing down, the analysis of the transmission lines alone is very complex due to the redundancy in the system. If three lines are connecting two particular nodes, when two fail, the nodes are still connected by the last congested line in operation. This points out the need to study any transmission system individually since topology matters. However, the states of operation can be defined in a broader sense: Let the operation space be defined by three states: Normal, Alert and Emergency. Normal operation is when all the lines are in operating state and full capacity of the system is in place. Emergency is the opposite end of the spectrum where critical lines or critical capacity has been lost to dictate that the transmission system is not operation at all. The states in between define the Alert operating condition, which are the states of interest in this thesis. Emergency condition requires a totally different treatment to restore operation; whereas, alert operation calls for a new dispatch to supply the loads. While, the cutoff between Emergency and Alert is the condition defined above, namely when re-dispatch of generation is not enough to relieve the congestion; it is easier to define the cut off in more strict terms for computational purposes. Two practical definitions can be used:

1) Number of lines: Let N be the number of lines such that if N or more lines go out of service, the system enters the emergency state.
2) Capacity Lost: Let C be the amount of capacity such that if more than C MW of capacity is lost, the system enters the emergency state.

Before calculating the probability distribution for these two cases for any system, more assumptions need to be made for calculation purposes:

Assumption 1: Common Mode outage events such as weather, storms, natural catastrophes and cascaded dependent failures of components are not included. Please see [10] for extended study on common mode failures.

Assumption 2: All line failures are independent with known failure rates, such that each line operation can be modeled as a Markov chain with two discrete states and transition rates shown in Figure 4.4. From here, it can be seen that the steady state probability of being in the operating state is $\mu_n/(\mu_n+?_n)$ and the probability of being in the non-operating state is $?_n/(\mu_n+?_n)$. Since it was assumed that all lines are independent, these values can be used to determine the probability of having any combination of lines out at the same time. These combinations are referred as topologies.

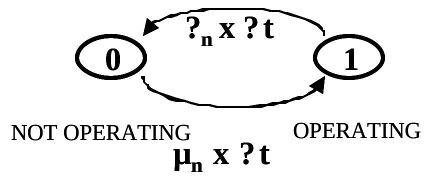


Figure 4.4: Markov Chain For Status Of a Line

For any single line, the failure and repair rates may change with age, for instance the hazard function of a component maybe a bathtub function. This is important for the reliability analysis tool to correct; however, when concerned with a time period of a season, three months compared to the lifetime of the component, it is safe to assume that the failure rate is constant.

However, even after the assumptions it is seen that for a large network, there are still a large number of cases of outages, which need to be considered while doing system reliability analysis with changing topologies. Moreover, not only are the cases so many, but the probabilities of these events are very small. We are faced with low probability high impact cases. Even determining the expected capacity of the system would require the consideration of all these low probability events, which sums up to a high number of calculations. There is some work being done to handle this computational issue. [30], for instance, tackles the problem differently: The multi-line outage cases, their probabilities as well as their impact on the remaining system flows are derived from single line outage cases and the flow sensitivities. The authors show the accuracy and the computational superiority of this approach on an N-bus M-line system.

Even when the computational problem of determining probabilities is taken care of, the problem remains. The goal is to find the expected flows on lines, expectation taken over the probability distribution of topologies calculated above. The nonlinear optimization tool, optimal power flow analysis which determines the line flows, is computational very expensive to run for so many low probability events. While the probabilistic reliability analysis with the above assumptions fulfills many of the promises that traditional methods were lacking, it is far from being extremely applicable to practical tools. Mainly because, the probabilistic analysis uses steady state probabilities of lines being in operational or non-operational states. In other words, this is equivalent to simulating the life of a particular line for time period 0 to T, as T approaches infinity. But the tools we are interested in for seasonal reliability risk analysis are not concerned with the system until infinity but rather focus on shorter periods like a season, three months. Seasonal risk management or reliability based insurance mechanisms of interest require the assessment of the reliability of the system for only a limited period of time. While the accurate way of doing these calculations call for using steady state probabilities, a main question comes up: Is it worth adding so much complexity and computational burden? If the choice is to ignore reliability concerns, then the tools will work with static topologies like traditional methods in inefficient manner. If the choice is to add the necessary probabilistic analysis, another method needs to be devised for practicality purposes.

This thesis suggests that if the status of the system is known at the beginning of the season, and if it is assumed that memoryless property holds, i.e. if ?t between observation points are small compared to the rate of transitions between states then it can be said that only one event happens in ?t, and non-overlapping time periods are independent; then instead of considering all possible states defined under the alert condition, simple markov chain can be made as follows:

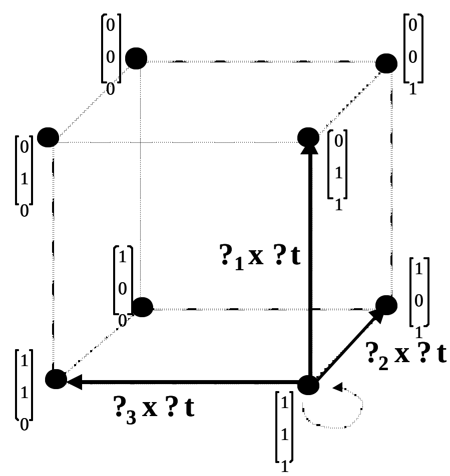


Figure 4.5: State Space For A 3-Line System Physical Reliability.

Assuming a season is short enough compared to the useful life time of transmission lines, the number of states to be considered can be limited to the immediate neighbors of the current state, neighbors that are only one event away, see figure 4.5 for a 3-line system. The only gain we have under this was of thinking, is we have limited the number of states to be considered to the number of lines. If we start with all lines operating, then the DP formulation will consider all cases where a single line is out. If we start with a state with one line down, we will do the same and also include the case where the repair rate is known and that way we can model probabilistic state changes as well as a deterministic change at the end of the repair period. (This approximates to random arrival of packets to a server of equal service length.)

As seen from the above definitions, the TSP bears the risk of system reliability which itself is hard to quantify for finite time horizons without being conservative. Next section describes priority-pricing scheme, which makes the users reveal their preference of service reliability for risk sharing.

4.3 Priority Pricing in Centralized Setup

As seen from the centralized TSP objective function under stochastic system conditions, but paying the users some compensation, TSP effectively absorbs all the risk that is in the system. While this ensures reliable operation, it burdens the TSP heavily causing it to become more conservative in its decisions, namely accepting fewer agreements. Thus, it is interesting to look for methods where TSP reduces or shares its risk.

Priority pricing scheme for bilateral agreements is a service that can be offered by the TSP that gives any party the level of priority servicing they asked for should the system face any congestion. This is a very effective way for TSP to learn better the preferences of the system users rather than assuming that they all share the same utility function. (Under the conditions where there are many small system users, with randomly different utility functions, law of large numbers can be used to model the user behavior.)

TSP prepares a menu of different priority services and the injection price for each of these options. Not only does this allow the TSP to make clever decision at times of congestion, but once requests come in TSP gains extra information about the utility, elasticity, of the users and can use this information for congestion relief. This is yet one other area where dynamic programming can be applied to optimally allocating resources season ahead as well as for real time supply-demand balancing and congestion management. (Note that this contract is done between the user and the transmission system owner only for the transmission service, not the energy.)

The most elaborated version of this approach can be found in [16]. Oren and Deng propose a zonal approach as follows. The system is exhaustively broken into zones. Inter-zonal operations: There is one single ex ante transmission access fee, per MWh, and one fixed priority table of fees that all the zone members receive. The transmission access fee charged to the users can also be thought of as insurance premium, different for every different level of priority, that entitles the user to service. Intra-zonal operations: This is more like spot market operation where the intra-zonal transactions are charged an ex post fee depending on the observed congestion. For purposes of looking at the priority schemes, only the intra-zonal part of the model is studied.

Under congestion, and when the TSP needs to curtail a system user's agreement, TSP is entitled to pay the customer a compensation which is equal to the spot price minus deductible, that is predetermined in the priority menu. Under this scenario, the TSP objective is to minimize the compensation paid. Please note that, this leads to agreements with low compensation charges, high deductibles to have a higher probability of curtailment. Therefore system users on congestion prone segments may choose to buy more insurance at low deductibles. (If all the users reveal their preferences truly by choosing the deductible, as their marginal cost, and if each bus in the system is considered a different zone, the result approximates the economic dispatch.)

This proposed scheme is a 3-stage process. First, assuming the physical topology stays the same, TSP prepares the menu of priority levels and their charges based on historical data about the probability of spot prices for the coming period. For every level of priority *c* (*c* also is the minimum price the users are willing to inject power), the users need to pay a premium $X_i(c)$ in zone *i*. Second, the users evaluate these prices and run their individual optimization function: Let *v* be the true MW cost of production, $p_i(c,s)$ be the probability of getting access to the transmission system when spot price, S_i, is higher than *c*, $O_i(c)$ be the set of all times $S_i>c$, and $G(s)$ is the CDF of spot spice distributions. Given the definitions, user optimization function is:

$$c_i^*(v) = \arg\max_c \begin{pmatrix} \int_{\Omega_i(c)} \left[p_i(c,s) \cdot \max(s-v,0) + (1-p_i(c,s)) \cdot \max(s-c,0) \right] dG(s) \\ + \int_{\overline{\Omega_i(c)}} [\max(s-c,0)] dG(s) \\ - X_i(c) \end{pmatrix} \quad (4.2)$$

As seen from the above, the TSP pays penalty when the user is at dispatchable region with its priority level higher than spot price, but does not get access right with $(1-p_i(c,s))$. And the penalty then is the difference between the spot price, *s*, and strike price and priority level, c. Again note that if users chose priority strike price same as their MW cost v, we get the following optimization, which becomes the economic dispatch problem.

$$c_i^*(v) = \arg\max_{c=v}\left(\int\left[\max(s-v,0)\right]dG(s) - X_i(c)\right) \tag{4.3}$$

(The conjecture here is that, if the users have close to perfect information about the expected system condition and use v equal to marginal cost, then the decision they make will be equivalent to a centrally made decision.)

The last stage is when TSP collects all the preferences from the users and runs its own optimization both to minimize the compensation it pays and to ensure meeting operational limits as spot prices are revealed with high accuracy. While this is very similar to the stochastic centralized optimization discussed in this chapter, addition of priority levels is the extra information that creates the difference. But the priority pricing schemes developed so far assume static system conditions and do the analysis in equilibrium, which is not sufficient to show that such methods are fully applicable to a dynamic transmission system.

4.4 Extension of Priority Pricing to Distributed Decision Making

Priority pricing setup where the users are treated as demand elastic, through their different priority requests, lends itself very well to a partially distributed method where each user can setup an individual profit maximization given a menu of priority service prices and associated insurance payments without re-communicating the information to a central body. In other words, priority pricing for transmission method approaches decentralization from a different perspective where the smart end users define the maximum price they would pay for the service, which automatically ranks their preference for reliable service with respect to the other users. This is analogous to work done in communication networks field where the idea is: Optimum is when users' choice of charges equals what the network allocates for them. Frank Kelly's work [23,24] aims to solve the problems about pricing and rate control in broadband networks based on three main assumptions:

1) The traffic is elastic and the end nodes respond to congestion immediately.
2) The users have different preferences for service, namely different utility functions.
3) System topology is static.

In his work Kelly explores the idea of fair min-max pricing, and smart market players in a dynamic network. He decomposes the system optimization into the user and the network optimization function. Relating to the case of TSP that would be the optimization by the transmission service provider and the end nodes respectively. Overall system optimization function maximizes social welfare, subject to physical constraints. (The concept of max-min fairness means that the flow of a user cannot be increased without decreasing another one. And any resource allocation is fair.) The solution can be uniquely found when the utility functions are concave and differentiable. Given the system welfare function:

$$\text{Flow pattern } \mathbf{y} \text{ supports rates } \mathbf{x} \text{ if } H\mathbf{y} = \mathbf{x} \text{ with respect to system capacity } \mathbf{C}.$$
$$\text{SYSTEM : max} \sum_s U_s(x_s) \text{ subject to } H\mathbf{y} = \mathbf{x}, A\mathbf{y} \le \mathbf{C} \text{ over } x, y \ge 0.$$

Lagrangian solution vector x solves the system optimization and the implied charges per user can be determined. The individual user optimization function maximizes the difference between utility and the charge of the service.

$$\text{User } s \text{ is charged } l_s \text{ per unit flow.}$$
$$\text{USER : max } U_s(x_s) - l_s x_s \text{ over } x_s \ge 0.$$

Conversely, the network optimization function maximizes the total system revenue, sum of all charges collected from the users.

$$\text{NETWORK : max} \sum_s l_s x_s \text{ subject to } H\mathbf{y} = \mathbf{x}, A\mathbf{y} \le \mathbf{C}.$$

Kelly’s work suggests: For a certain *?*, the solution x to USER optimization will also solve the NETWORK optimization yielding the answer to the SYSTEM optimization without solving it explicitly.

While the above approach focuses on customers getting service equivalent to how much they paid, it does not focus primarily on dealing with congestion or using dynamic pricing to regulate the usage of the system. This is based on the assumption that if there are many small users of the network with random demand elasticity’s and usage levels, optimal operation can be achieved faced with congestion similar to priority pricing, and the topology is considered to be static. Bringing together distributed network operation with congestion-dependent pricing, successful distributed model can be developed for networks where many users share a common resource. [29] Interest in this area mainly focuses on data networks, like today's Internet. And these concepts can be extended to the electricity networks. The goal is to maximize service provider's revenue, and the concept becomes similar to yield management of airlines. (Operation of large networks with high fixed costs with low marginal costs per user.) However, there are technical aspects that make it hard to apply yield management to electricity networks. Where a decision to increase the usage of a particular line or generation unit can have significant impacts on other users in networks, allocation decisions need to be. For the operation of the Internet network, some methods of congestion-based pricing have already been put forth [28]:

1) By Clark: Very distributed method. Users are charged ahead of time based on their expectation for amount of service regardless of how much of the resource they actually end up using. This model works well for large networks with many small users where law of large numbers model overall system operation to be not changing.

2) By Mackie Mason and Varian: A centralized approach. Smart market users bid their marginal prices and ones above the cutoff get served.

3) By Gibbens and Kelly: Distributed approach. Packet based pricing charge increases with usage, which treats all the packets and routes in the network the same, which does not apply well to the transmission system where congestion patterns are different for different lines.

4) By Kelly: Partially distributed method where network service charge increases with the amount of traffic, which we believe to be the most robust method for distributed operation of the transmission grid where a signal for the network charge is provided. Chapter 5 explores this approach.

4.5 Near Real Time Feedback

Even though this is a coordinated setup, both the TSP and the system users react to the evolution of the market over time. What happens if the system users learn in this auction environment for transmission resource allocation and how could TSP use this information? In the framework of auction behavior, gradual changes are induced on the system parameters by the decision control. Scenario#1: If the TSP does not accept a bilateral agreement request, he needs to update his expectation for the spot market that very period and next ones to include the rejected demand being served in the spot market. This is a case where depending on the control, more information can be learned for the coming periods. Also due to the nature of the problem where a central body is making decisions for allocation, the study of auction theory based on Markov decision processes can be used to update real time expectations. Scenario#2: Should the TSP not accept incoming bilateral requests at time $t = k$, depending on the user preferences, TSP can expect with probability $p_{ij}(u)$ that the system user will resubmit a bid at $t = k+1$ with a higher price to increase his chances of being served. Under both scenarios, it is seen that if TSP can attach probabilities to the outcomes of certain control, he can win another dimension of decision making to maximize his revenue. He can also adjust these probabilities as he learns at each process.

As TSP changes his expectations for the future time period parameters, he may find himself in situations where real time curtailment becomes more profitable despite the penalty of disrupted service. The below formulation takes into consideration curtailment through a control function F. This is not to say that two different mechanisms u and F control the system, but designating them separately makes the formulation clear. The detailed DP algorithm now looks like (4.4):

Current State:

$X_{ij}[k] = [Q_{ij}^{X}[k]\, P_{ij}^{X}[k]\, tr_{ij}^{X}[k]]$

Expected Incoming BA:

$Y_{ij}[k] = [Q_{ij}^{Y}[k]\, P_{ij}^{Y}[k]\, tr_{ij}^{Y}[k]]$

$\mathbf{u}[k]$: Accept or Reject Decision: $\{0,1\}$ $\mathbf{F}[\mathrm{k}]$ = Curtailment decision: $\{0,1\}$

State evolution function f:

$$f(\mathbf{X}[k], \mathbf{u}[k], \mathbf{F}[\mathrm{k}], \mathbf{Y}[k]) = T(\mathbf{X}[k] * \mathbf{F}[\mathrm{k}]) + T(\mathbf{u}[k] * \mathbf{Y}[k]) = \mathbf{X}[k+1]$$

where T terminates an agreement or update the commitment:

$$T(\mathbf{X}[k]) = \begin{Bmatrix} tr_{ij}[k] \le 1 \rightarrow Q_{ij}[k] = P_{ij}[k] = tr_{ij}[k] = 0 \\ tr_{ij}[k] > 1 \rightarrow tr_{ij}[k+1] = tr_{ij}[k] - 1 \end{Bmatrix}$$

Let the penalty of curtailment be the revenue lost from the service multiplied by some constant $y > 1$. The cost function becomes:

$$\underset{Y, W_S}{e} \{ g(\mathbf{X}[k], \mathbf{u}[k], \mathbf{F}[\mathrm{k}], \mathbf{Y}[k], \mathbf{W_S}[k]) \} =$$

$$= \underset{Y, W_S}{e} \left\{ \begin{bmatrix} \begin{bmatrix} \sum_{ij} u_{ij}[k] P_{ij}^{Y}[k] Q_{ij}^{Y}[k] + \\ \sum_{ij} F_{ij}[\mathrm{k}] P_{ij}^{X}[k] Q_{ij}^{X}[k] - \\ \sum_{ij} F_{ij}[\mathrm{k}] P_{ij}^{X}[k] Q_{ij}^{X}[k] tr_{ij}^{X}[k] y_{ij} \\ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k] \right) Q_{ij}^{W_S}[k] \end{bmatrix} \end{bmatrix} \right\}$$

Putting the cost functions together to determine cost-to-go expression and combining it with Bellman's equality:

$$J_N(\mathbf{X}_N) = g_N(\mathbf{X}_N)$$

$$J_k(\mathbf{X}[k]) =$$

$$\arg\max_{u[k]} \underset{W_S, Y}{e} \{ g_k(\mathbf{X}[k], \mathbf{u}[k], \mathbf{F}[\mathrm{k}], \mathbf{Y}[k], \mathbf{W_S}[k]) + J_{k+1}(f(\mathbf{X}[k], \mathbf{u}[k], \mathbf{F}[\mathrm{k}], \mathbf{Y}[k], \mathbf{W_S}[k])) \}$$

Chapter 5

Partially Distributed Decision Making

In this chapter, we present the framework behind a distributed solution to optimal transmission capacity allocation. First approach is the determination of price signals by a system supervisor that drives the individual decision making processes of all the users. The second approach eliminates the central supervisor but allows information exchange between small groups of system users in a localized manner to make decisions.

5.1 Motivation

The distributed approach is the complement of the coordinated approach, which had put the intelligence in a central controller, the TSP. In the distributed version of the transmission allocation problem, the intelligence of the network is shared among the end users all of whom are expected to make optimal decisions for their utility function in a decentralized manner. The intuition behind distributed decision-making comes from the observation that any global objective function that is separable can be decomposed into *n* single-variable sub-problems solved by *n* users. This applies well to a deregulated environment in which system users are natural decision makers. In a distributed manner, each party can abide by its commitment to inject its generation output or withdraw its needed power though agreements and contracts. However, who will make sure that the global optimization function or the aggregate user optimizations will adhere to the transmission limits at the system level? [13] uses a Monte Carlo simulation to create random agreement vectors and studies the security of the system in a situation where all agreements are implemented as it would be under a distributed scheme. In other words, the analysis calculates the probability of such a random set of agreements to fall within the acceptable operational bounds of the transmission system in terms of its line capacities. The results show that not all agreements are simultaneously feasible and, if forced, will lead to system congestion. From these tests, it is seen that a completely distributed operation is very hard to accomplish in such a critical network where room for mistake is small. Therefore, the thesis suggests the assistance of network information provided by a supervisor, hence this is a partially distributed model. In [2], an assessment of possible distributed approached are proposed, a price signal based model, a model that suggests the use of technical information as a feedback from the system and a model where multiple iterations are proposed to converge at a sub-optimal decision. Among which, for this thesis the price signal model is studied.

We believe that with the right kind of market signaling from a central supervisor the problem of simultaneous feasibility can be solved achieving at least a sub-optimal operation of the transmission network. This is the sub-optimal of the optimal that is defined as the decision that would be made by a controller in a centralized manner. Many kinds of distributed methods are being developed to handle complex data and communication networks where some protocols are build into the system to inform the users about the technical status of the network. Consider the Transport Control Protocol congestion management where users all exercise additive increase until congestion is signaled by the network or the other end users at which point users start exercising multiplicative decrease. Such mechanisms also effectively make large networks more extensible and efficient in decision-making. This technical signal is the enabler of distributed operations. Another way to reach optimal operation is through iterative methods rather then requiring ‘perfect’ decision right away, the users can start operations at a hardly optimal, almost at an infeasible point. From where, the users then would correct their decision towards the optimal control path through iterative exchanges of information and internal learning algorithms. Even though there are differences between data and power networks, discussed in the conclusion, this does not hinder forming synergies between the tools that can be built for both systems.

This chapter visits the signaling by a supervisor option to enable distributed control in power transmission networks where individual objective functions all need to satisfy the global transmission constraint as well as reaching some sort of optimal allocation of transmission resource. Determination of the price signal under static and dynamic topologies is formulated as well as the end user decision-making problems. Lastly, possibilities for a totally distributed operation scheme and learning mechanisms are discussed.

To repeat, the main motivation behind considering distributed control is the current deregulation of the power markets enabling a system optimum to be defined by intelligent system users. A second motivation behind discussions for a distributed design is the computational issues faced under the coordinated methods as explained in Chapters 3 and 4. It is seen that even for a small system both for the deterministic and stochastic cases under the centralized approach lead to highly complex and computational problems. This section presents unrefined formulations at the high complexity level; however, approximate solutions can be exploited to reduce the computational burden.

5.2 Procedure

Seasonal operation in the distributed setup has three main procedural steps shown in the time line Figure 5.1:

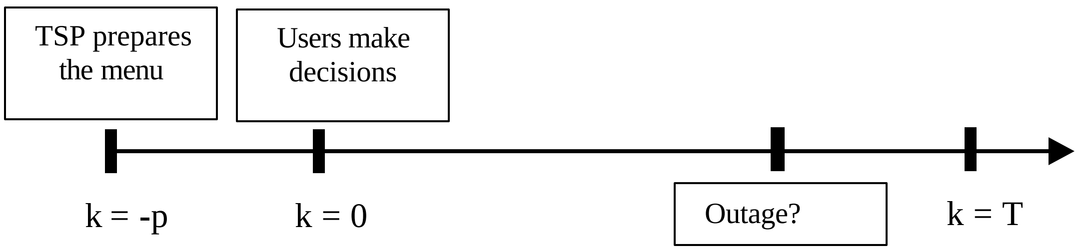


Figure 0.1: Time Line of Distributed Operations

- Step 1: Central supervisor determines the season-ahead price and communicates them to the users.
- Step 2: Users use the price signal information to determine their parameters of the contracts they would like to participate in by maximizing their individual season objective functions.
- Step 3: In case of a system failure where the operations move to alert operating condition, the TSP or the central supervisor takes control and practices central dispatch until the system resumes stable operations.

Unlike the coordinated system, in the partially distributed model, TSP's optimization does not just to maximize revenue but it also aims to ensure system stability and security both with and without a system outage. In the case of a system outage, this design puts the burden on the TSP to absorb the risk. In the absence of any physical uncertainties in the system, TSP is still responsible to ensure simultaneous feasibility of operations. For both cases, the challenge is one of finding the right price signals. TSP can use a couple of approaches to generate the price signal for a partially distributed system in the absence of the DP tool proposed in Section 5.3:

Option 1: TSP can use historical prices that it charged the end nodes under the centralized scheme, before deregulation, with an injection pattern matching the forecasted one for the coming season. Historic values will provide different price signals for all nodes. TSP can start using these values as a starting vector and can alter these values with time depending on the feedback received from the congestion levels. However, due to that increasing use of bilateral agreements under the distributed market system or any other change induced on the market behavior, the flow patterns might differ significantly from the past values.

Option 2: TSP can use trial and error to determine the right prices that will keep the system stable. These prices can either be the same for all nodes or customized for each node. There are two possible outcomes: 1) If the transmission price is underestimated, congestion will occur which can lead to loss of load. 2) If the transmission charge is overestimated that can lead to underutilization of the transmission system, an inefficiency deregulation definitely wants to avoid.

While these two approaches seem easy to implement, they have significant drawbacks as they lack incorporating system dynamics or long-term decision-making. Therefore, TSP needs a more systematic way to develop the price signals. Please note that under the following formulations, the end users have been assumed to be risk neutral where the utility of the users have been simplified to expected monetary value of their actions. This is just a simplification, and using convex utility functions may result in well-defined answers. Please also note that users are demand elastic, which is the force that prevents TSP from being too conservative by charging high prices.

5.3 Distributed Operation Under Static Topology

This section poses the price signal determination problem followed by how the system users, generators and loads, interpret the signal. It is assumed that the topology is static without any system outages.

5.3.1 Determination of Price Signals

Determining price signals for partially distributed setup ahead of time can be solved by concepts of congestion-dependent pricing in network theory. In congestion dependent pricing, price for required service is designed such that it regulates the elastic demand by decreasing it to a level that the system can technically handle. The charge depends on system congestion, characteristics of the requests and the user preferences. This subject has been visited many times in communication networks under call-admission schemes where the users dynamically share a scarce resource [28]. One of the main differences between modeling a communication system and the transmission system is the set of assumptions one can make. For instance, in data networks the arrival of admission requests are usually modeled as Poisson processes with exponential service times. However, in transmission, one cannot use generalized definitions for requests for service, but rather must use historical data that can be a reasonable forecast to future requests. This leads to enumeration of cases rather than functional closed form solutions to represent the system. In our problem, the goal is to design TSP's pre-season decision making for price signals that applies to injections from bilateral agreements. In other words the signal is the charge for contracts.

Let $l_{ij}(\cdot)$ be the user's static demand response function to a cost given for injection at node i and withdrawal at node j. In short, $l_{ij}(\cdot)$ determines their maximum demand given a charge for the service: $Q_{ij}^{BA,r}[k] = l_{ij}\left(P_{ij}^{BA,r}[k]\right)$ where r is the length of the BA contract that starts at k. (It will soon become clear why different price signals need to be defined for the same injection-withdrawal node, and starting at the same time period with different request lengths.) The response function $l_{ij}(\cdot)$ is assumed to be static for a whole season, which can be, relaxed in future refinements. $l_{ij}(\cdot)$ also captures the utility of the system user such that a threshold value for price drives the demand to 0. Given this definition, the cost optimization, or revenue maximization, function of the TSP per stage over all possible price signals $\left\{P_{ij}^{BA,r}\right\}$is as follows (5.1):

$$\text{Revenue}[k] = \max_{\{P_{ij}^{BA,r}\}} \left\{ \begin{array}{l} \sum_{ij} \sum_{r} \left[P_{ij}^{BA,r}[k] \times l_{ij}\left(P_{ij}^{BA,r}[k]\right)\right] \\ \sum_{ij} \sum_{r} \left[P_{ij}^{BA,r}[k - \left(r - tr_{ij}^{BA,r}[k]\right)]\right] \times l_{ij}\left(P_{ij}^{BA,r}[k - \left(r - tr_{ij}^{BA,r}[k]\right)]\right) \\ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k] \right) Q_{ij}^{W_S} \end{array} \right\}$$

The revenue streams of the distributed model are the same as the ones of the coordinated scheme described in Chapter 4. The first line refers to the agreements that are starting at time k and the revenue collected from their first period. The second line is the revenue collected from the agreements that were implemented before k with continuing service commitments each with their own time remaining component $tr_{ij}^{BA,r}$. Therefore the revenue of these agreements needs to be computed using the price determined at the strike of the agreement at *(k – (r – tr))*. And lastly, the third stream of revenue comes from the spot market. The dynamic programming formulation for price signals using the above cost function becomes (5.2):

Let **F** be the state defining the flows on the system lines that the TSP wants to keep within limits.
F = Vector of system flows determined by the injectios
to and withdrawa ls from the system through BAs, $\mathbf{X}^{\mathbf{inj}}$, and spot input.
The distibutio n matrix **D** determines the flows given injections .

$$\mathbf{F[k]} = \mathbf{D} * \left\langle \mathbf{X}^{\mathbf{inj}}\mathbf{[k]} + \mathbf{W}_{\mathrm{S}}\mathbf{[k]} \right\rangle$$

Control is the vector of price signals $\mathbf{P}^{\mathbf{BA}}\mathbf{[k]}$ determined by the flows on congested lines :

$$P_{ij}^{BA,r}[k] = f\left(\mathbf{D}, \mathbf{F[k]}\right) \quad \forall \text{r and } \forall i.j \in \{N_G, N_L\}, i \neq j$$

State evolution function f will evolve the system through t he distributi on matrix. :

$$\mathbf{F}[k+1] = f\left(\mathbf{F}[k], \mathbf{P}^{\mathbf{BA}}[k], \mathbf{X}^{\mathbf{inj}}[k], \mathbf{W}_{\mathrm{S}}[k]\right)$$

Per stage cost function :

$$g[k] = \max_{\{P_{ij}^{BA,r}\}} \left\{ \begin{array}{l} \sum_{ij}\sum_{r}\left[P_{ij}^{BA,r}[k] \times l_{ij}\left(P_{ij}^{BA,r}[k]\right)\right] \\ \sum_{ij}\sum_{r}\left[P_{ij}^{BA,r}\left[k-\left(r-tr_{ij}^{BA,r}[k]\right)\right]\right] \times l_{ij}\left(P_{ij}^{BA,r}\left[k-\left(r-tr_{ij}^{BA,r}[k]\right)\right]\right) \\ \sum_{ij}\left(P_i^{W_S}[k] - P_j^{W_S}[k] \right) Q_{ij}^{W_S} \end{array} \right\}$$

Putting the cost functions together to determine cost-to-go expression and combining it with Bellman' s equality :

$$J_N(\mathbf{X}_N) = g_N(\mathbf{X}_N)$$

$$J_k(\mathbf{X}[k]) = \arg \max_{P^{BA}[k]} e_{\mathrm{W_S}, X^{inj}} \left\{ g_k\left(\mathbf{F}[k], \mathbf{P^{BA}}[k], \mathbf{X^{inj}}[k], \mathbf{W_S}[k]\right) + J_{k+1}(\mathbf{F}[k+1]) \right\}$$

While this formulation states a very strong solution, in real operations, it is unlikely that the coordinator, or the price signal setter, will explicitly know the ? function of all the users. However, learning algorithms can be exploited by the TSP to learn the preferences of the users overtime and fine-tune the ?'s by temporal learning. Once the price signals for different nodes, different time periods and different commitment lengths are determined, the TSP relays this information to the system users. The next sections describe the procedures.

5.3.2 System User Optimizations

Given the price signals by the central body, the system users proceed to make their own decisions for the coming season. The generators maximize their revenue for its production, where as, the system loads try and minimize their cost of using the electricity transmitted over the transmission grid. The generators are assumed to pay for the transmission access fee in this design. This is not a strict condition, and can be relaxed.

Generators

Each generator itself produces a resource that needs to be allocated smartly. The generator first makes a decision to produce or not to produce. This the unit commitment problem in power generation and is beyond the scope of this thesis, please refer to [1]. Once the generator decides to commit to produce, he then has four choices as to where he would like to sell his product to maximize his revenue given some information about the season and his own expectations developed from historical performance. The main goal is to hedge against price uncertainties but also make use of the surging spot prices under possible congestion. This is the goal for a risk-averse generation unit; however, it should be noted that the unit optimization function is flexible to capture any level of risk-aversity. Vector a describes generator's dynamic allocation between choices of where to sell for the finite horizon optimization. To make the best decision in a distributed setup, the generator will have to know the topology of the system, the distribution matrix, other players, and their demand and supply functions. However, we believe that if each user just optimized their own functions with certain approximations without considering the reaction of the rest of the system, decentralized control can lead to some sub-optimal operation. We also believe that this method of internal optimization can be adjusted to include local information, for instance just information about the immediate neighbor nodes, to yield even better results getting closer to economic dispatch which is explored in Chapter 3 and 4. Below is the season-ahead optimization, planning, of the generation unit G_i (5.3):

$$\text{Let } Q_{Gi}[k] = \text{Quantity produced by Generator i at k.}$$

$$\mathbf{a}_{\mathbf{ij}}^{\mathbf{BA,r}} = \text{Fraction of production to be allocated to r-period BA from i to j, row vector } \forall \text{r}$$

$$\mathbf{a}_{\mathbf{ii}}^{\mathbf{BA,r}} = \text{Fraction of production to be allocated to r-period BA at the same node, row vector } \forall \text{r}$$

$$a_{\mathrm{ij}}^{\mathrm{S}} = \text{Fraction of production to be allocated to Spot from i to j.}$$

$$a_{\mathrm{ii}}^{\mathrm{S}} = \text{Fraction of production to be allocated to Spot at the same node.}$$

$$\mathbf{a[k]} = [\mathbf{a}_{\mathbf{ij}}^{\mathbf{BA,r}}\mathbf{[k]}, \mathbf{a}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]}, a_{\mathrm{ij}}^{\mathrm{S}}[k], a_{\mathrm{ii}}^{\mathrm{S}}[k]]$$

$$\text{Constraint}: \mathbf{a}_{\mathbf{ij}}^{\mathbf{BA,r}}\mathbf{[k]} + \mathbf{a}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]} + a_{\mathrm{ij}}^{\mathrm{S}}[k] + a_{\mathrm{ii}}^{\mathrm{S}}[k] = 1$$

$$\text{Constraint}: \mathrm{Q}_{\mathrm{Gi}}[k] \leq Q_{Gi}^{\max}$$

$$\mathbf{C}_{\mathbf{ij}}^{\mathbf{BA,r}}\mathbf{[k]} = \text{Charge to the loads, row vector } \forall \text{r}$$

$$Cost_{Gi}(Q_{Gi}[k]) = \text{Generation Cost Function} = a_{Gi}Q_{Gi}^{2} + b_{Gi}Q_{Gi} + c$$

Per Stage cost function:

$$\arg\max_{\mathbf{a[k]}} \sum_{k} \begin{bmatrix} \sum_{r}\sum_{ij}\left(\mathbf{C}_{\mathbf{ij}}^{\mathbf{BA,r}}\mathbf{[k]} - \mathbf{P}_{\mathbf{ij}}^{\mathbf{BA,r}}\mathbf{[k]}\right)\mathbf{a}_{\mathbf{ij}}^{\mathbf{BA,r}}\mathbf{[k]}Q_{Gi}[k] + \\ \sum_{r}\mathbf{C}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]}\mathbf{a}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]}Q_{Gi}[k] + \\ \sum_{ij} P_{j}^{S}[k]a_{\mathrm{ij}}^{\mathrm{S}}[k]Q_{Gi}[k] + \\ P_{i}^{S}[k]a_{\mathrm{ii}}^{\mathrm{S}}[k]Q_{Gi}[k] + \\ -Cost(Q_{Gi}[k]) \end{bmatrix}$$

As seen in the formulation, the optimization treats the charge to the customer as a given and only works with the allocation vector. This is not the only way to treat this problem; however, it is used to simplify the formulation. If the optimization function had given control to the price charged to the customer, then we would have a problem of price negotiation, which heavily relies on the preferences, and risk functions of the system users. Then the negotiation method would also call for a certain number of decision-making iterations between the users, which is not modeled here. But how does the charge for the customer determined after all? This is a function of the preferences of the generator in terms of risk.

Loads

The scenario is similar to the generator case for each individual load; they have their optimization functions as well. They would like to maximize their utility, which will be defined as minimizing cost for a desired level of service. In the case of the load, the elasticity of demand is captured in the ß vector (5.4):

$$
\begin{aligned}
&\text{Let } Q_{Li}[k] = \text{Quantity requested by Load i at k.}\\
&\mathbf{ß}_{\mathbf{ji}}^{\mathbf{BA,r}} = \text{Fraction of demand to be supplied from}\\
&\qquad \text{r - period BA from i to j, row vector } \forall \text{r}\\
&\mathbf{ß}_{\mathbf{ii}}^{\mathbf{BA,r}} = \text{Fraction of demand to be supplied from}\\
&\qquad \text{r - period BA at the same node, row vector } \forall \text{r}\\
&b_{\text{ji}}^{\text{S}} = \text{Fraction of demand to be supplied from Spot from i to j.}\\
&b_{\text{ii}}^{\text{S}} = \text{Fraction of demand to be supplied from Spot at the same node.}\\
&\mathbf{ß[k]} = [\mathbf{ß}_{\mathbf{ji}}^{\mathbf{BA,r}}\mathbf{[k]}, \mathbf{ß}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]}, b_{\text{ji}}^{\text{S}}[k], b_{\text{ii}}^{\text{S}}[k]]\\
&\text{Constraint}: \mathbf{ß}_{\mathbf{ji}}^{\mathbf{BA,r}}\mathbf{[k]} + \mathbf{ß}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]} + b_{\text{ji}}^{\text{S}}[k] + b_{\text{ii}}^{\text{S}}[k] = 1
\end{aligned}
$$

$$
\mathbf{C}_{\mathbf{ji}}^{\mathbf{BA,r}}\mathbf{[k]} = \text{Charge to the loads, row vector } \forall \text{r}
$$

Per Stage cost function:

$$
\arg\min_{\mathbf{ß[k]}} \sum_k \begin{bmatrix} \sum_r \sum_{ij} \mathbf{C}_{\mathbf{ji}}^{\mathbf{BA,r}}\mathbf{[k]}\mathbf{ß}_{\mathbf{ji}}^{\mathbf{BA,r}}\mathbf{[k]} Q_{Li}[k] + \\ \sum_r \mathbf{C}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]}\mathbf{ß}_{\mathbf{ii}}^{\mathbf{BA,r}}\mathbf{[k]} Q_{Li}[k] + \\ \sum_{ij} P_j^S[k] b_{\text{ji}}^{\text{S}}[k] Q_{Li}[k] + \\ P_i^S[k] b_{\text{ii}}^{\text{S}}[k] Q_{Li}[k] + \end{bmatrix}
$$

From the requirements of demand equaling supply, more constraints can be written for the overall system operation: Match the desires to participate in bilateral agreements assuming that there is only one load and generator at each bus (5.5):

$$\begin{aligned}
&\text{Balancing Constraints:}\\
&\forall k, \sum_i Q_{Li}[k] = \sum_j Q_{Gj}[k]\\
&\forall r, \boldsymbol{b}_{ii}^{BA,r}[k]Q_{Li}[k] = \boldsymbol{a}_{ii}^{BA,r}[k]Q_{Gi}[k]\\
&\boldsymbol{b}_{ii}^{S}[k]Q_{Li}[k] = \boldsymbol{a}_{ii}^{S}[k]Q_{Gi}[k]
\end{aligned}$$

Once the end users determine their optimal operation factors, they can then go and look for units to engage in bilateral contracts. Each unit will run iterations of its optimization function with different bids and requests from the other parties. Extra trades can be added to balance flows and engage third parties. This creates multilateral agreements as well as pure trading agencies, since adding more nodes to the system is very complicated, this thesis does not explore financial market layers that can be implemented on the proposed methods. Please see [34]. Even though these formulations capture the essence of the problem, the challenge of the distributed approach is the formation of price signals that will keep the system stable in the presence of uncertainties involving the physical system.

5.4 Distributed Operation Under Dynamic Topology

This formulation is iteration to the static topology model presented above with added complexity of the physical system uncertainties. It is hard to determine the financial burden TSP will take on in case of a physical system failure handled by a short-term switch to central operation However, it is not very unrealistic to assume that TSP might want to factor the uncertainties into his price signal as a fixed premium. Let s be the charge for ‘insurance’. Then the cost function becomes (5.6):

$$g[k] = \max_{\{P_{ij}^{BA,r}\}} \left\{ \begin{array}{l} \underset{X^{inj},\,l}{e} \left\{ \sum_{ij} \sum_{r} \left[\left(P_{ij}^{BA,r}[k] + s \right) \times l_{ij} \left(P_{ij}^{BA,r}[k] + s \right) \right] \right\} \\ \underset{X^{inj},\,l}{e} \left\{ \sum_{ij} \sum_{r} \left[P_{ij}^{BA,r} \left[k - \left(r - tr_{ij}^{BA,r}[k] \right) \right] + s \right] \times l_{ij} \left(P_{ij}^{BA,r} \left[k - \left(r - tr_{ij}^{BA,r}[k] \right) \right] + s \right) \right\} \\ \underset{X^{inj},\,W_S}{e} \left\{ \sum_{ij} \left(P_i^{W_S}[k] - P_j^{W_S}[k] \right) Q_{ij}^{W_S} \right\} \end{array} \right\}$$

where s can be determined as follows:

s = Average burden that will be included as premium will be the difference between the revenue that TSP collects under the distributed operation without the premium and the expected revenue he would collect under different system failure rates in a coordinated model after paying his penalties.

$$s = \frac{1}{\mathrm{k}} \frac{1}{\forall\{\mathrm{ij}\}} \left[R^{\mathrm{Distributed}} - \sum_{\Pi} p_{ij} \left(R^{Coordinated} | \Pi \right) \right]$$

Please note that a more realistic version would be to make s usage based. As shown below (5.7):

$$g[k]=\max_{\{P_{ij}^{BA,r}\}}\left\{\begin{array}{l}\sum_{ij}\sum_{r}\left[P_{ij}^{BA,r}[k]\times l_{ij}\left(P_{ij}^{BA,r}[k]\right)\right]+\\-\sum_{ij}\sum_{r}\left(1-p_{ij}[k]\right)\bullet\left[P_{j}^{S}[k]\times l_{ij}\left(P_{ij}^{BA,r}[k]\right)\right]+\\\sum_{ij}\sum_{r}\left[P_{ij}^{BA,r}\left[k-\left(r-tr_{ij}^{BA,r}[k]\right)\right]\right]\times l_{ij}\left(P_{ij}^{BA,r}\left[k-\left(r-tr_{ij}^{BA,r}[k]\right)\right]\right)+\\-\sum_{ij}\sum_{r}\left(1-p_{ij}[k]\right)\bullet\left[P_{j}^{S}[k]\times l_{ij}\left(P_{ij}^{BA,r}\left[k-\left(r-tr_{ij}^{BA,r}[k]\right)\right]\right)\right]\\\sum_{ij}\left(P_{i}^{W_S}[k]-P_{j}^{W_S}[k]\right)Q_{ij}^{W_S}\end{array}\right\}$$

$$p_{ij}[k]=p_{ji}[k]=\left\{\begin{array}{l}1\rightarrow \text{Operational Line}\\0\rightarrow \text{Failed Line}\end{array}\right\}$$

However, the complexity of the problem increases beyond the scope of this thesis. As suggested under this model, once a system outage occurs, the distributed operation is abandoned until the end of the season and the TSP becomes the coordinator. The first thing the TSP needs to handle in such a situation is ensuring a new dispatch within the constraints. [22] suggest an effective way of going from a pre-outage to a post-outage dispatch using linear programming that can simplify the calculations of the above problem.

5.5 Distributed Operation With Local Information

In the above formulations for distributed operation, we have treated each user as a stand-alone users receiving information only from the supervisor; however, any user's decisions influence all the users in the system. Thus, we would like to extend the definitions to include some local information collected by the system users from their neighbors. The conjecture is that, with more information distributed operations will be more effective and will get closer to coordinated system operation. Another drive to look at local information is the transmission system designs proposed by [21], the method of cluster-based congestion management. The idea in congestion cluster pricing is identifying the lines with highest likelihood to get congested given a likely pattern of loads and supplies. Then the system is separated into clusters arranged so that the tie lines between the clusters are the very lines identified above. The power of this grouping is to simplify the system such that the operator only monitors the tie lines and allows the clusters to arrange their operations internally. While clusters in this method are static over a certain period of time and exhausts the whole transmission system, the concept relates very well to distributed modeling. Any node can declare a cluster around itself as his range of interest and direct influence. This will effectively be the range of line flows he mainly influences. (This is an approximation since in an interconnected network, any injection to the system influences all line flows to a certain amount.) Note that each node defines its own cluster, and clusters of different nodes overlap. The center of this virtual cluster will be called the 'base', and the other nodes in base's interest region will be referred as the 'neighbors'. Each node ns a system is the base of its cluster. Please see Figure 5.2 for a simple representation of a few nodes and their clusters.

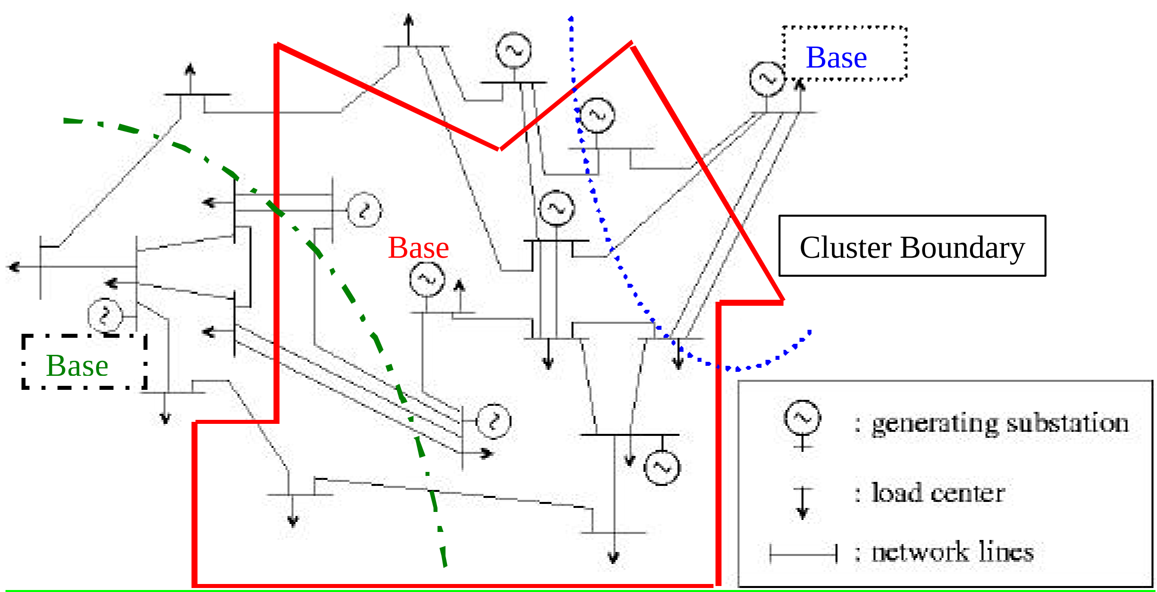


Figure 5.2: Base and Neighbors in a Cluster

Below is a first iteration at modeling the distributed decision making within a cluster (5.8):

X_b = Injection at the base. $\mathbf{X}$ = Injection vector of all nodes of the cluster.

F_{mn} = Flow on line m - n where m, n are neighbors of b, $\{m, n\} \in N$

$C_{mn}(F_{mn})$ = Cost of congestion caused by the flow on line m - n.

$\mathbf{F} = \mathbf{D} * \mathbf{X}$ s.t. $|\mathbf{F}| \leq \mathbf{F}^{max}$ with system cost $\mathbf{C}(\mathbf{F})$

The base will do the following test :

$\mathbf{F} + ?\mathbf{F} = \mathbf{D} * (\mathbf{X} + \Delta X_b)$;

Let $k_b(X_b)$ = Charge paid by the base $U_b(X_b)$ = Utility received by the base.

Inject decision n will be :

$$n_b = \begin{Bmatrix} 0 \text{ if } & U_b(X_b + \Delta X_b) - k_b(X_b + \Delta X_b) < 0 \\ 1 \text{ if } & U_b(X_b + \Delta X_b) - k_b(X_b + \Delta X_b) < 0 \end{Bmatrix}$$

This is the decision making going on at the base only, the complexity comes from the fact that all neighbors that make up the cluster are simultaneously doing the same calculations and altering their decisions. In this case if the nodes exchange information ex ante about their utilities, demands and related parameters, this solution may converge to a sub optimal level from where learning algorithms can be used to perfect the decision making. Moreover, this method welcomes the stochastic components of the system parameters. [31] studies decentralized decision making in a large team with local information, where the authors prove that stochastic strategies decentralize more gracefully, where in our problem strategy is a combination of changing demand, supply and physical system parameters.

In addition to learning, near real time feedback from the system can also be used for open loop control of the distributed system.

5.6 Bounds on Optimality

The long-term objective is to analyze how the distributed and the coordinated approach and establish conditions where the two may give a similar solution. These conditions are important for the following reasons. The coordinated approach is a computationally complex method where the system is analyzed with its dynamic behavior and uncertainties. It leads to an optimal solution depending on the objective function, maximum social welfare or revenue maximization. However, the dynamic programming poses many computational obstacles that get even more burdensome with the addition of system uncertainties such as equipment and line outages. However, the distributed approach is much simpler where each user does an internal optimization. The complexity of the system is done away with except for the partial complexity faced by the TSP to provide the price signals. Even though this method is much simpler and extendable, there is a chance that it may lead the system to instability unless some kind of an information exchange system is established. That is why, the goal is to define conditions that will allow simpler methods, such as the distributed approach with or without the local information exchange, but reach the same level of optimization and operational reliability as robust solutions like the centralized approach. It is often implied that the two approaches result in the same decision, which is true only at equilibrium.

Reliability-related risk management is also qualitatively different under these two methods, as well as the impact of this risk management on individual players. The two formulations have different implications on who will be the risk manager and will need to absorb the damages from a hazardous situation. In the coordinated approach, it is relatively straightforward to assign the transmission provider as the reliability gatekeeper, and TSP charges for reliability bundled in his service. But this becomes a challenge in the distributed setup where the end users are not necessarily aware of reliability issues facing the grid. While the price signals should include such information for planning ahead, is that enough to recover operation once system fails in a decentralized system? This deviation from equilibrium conditions is very crucial to handle. (It should also be noted that the concept of reliability in the deregulated industry is different that the conservative tools used before since now the TSP has incentive to optimally use its lines' capacity and extract the highest level of utility.)

In short, the thesis supports the distributed network control given the right mechanism of information flow is established such that the decision makers reach at clever decision that maximize overall welfare through maximizing individual welfare functions without pushing the system into instability.

Chapter 6

Simulations and Results

This chapter shows the implementation of some of the dynamic decision making tools on a simple 2-Bus system. The setup and the assumptions are presented followed by cases and simulated trajectories.

6.1 Basic 2-Bus Example and The Assumptions

The concepts introduced in the formulation of the coordinated decision-making are formalized in a 2-Bus example to enable the initial problem formulation to be simple and tractable. Figure 6.1 shows the simple setup. The generating units are *G1* and *G2* with generation cost functions $C_1(Q_{G1})$ and $C_2(Q_{G2})$; the loads are *L1* and *L2*. The two buses are connected with a single line of capacity *K* operated by the TSP. This section poses the season ahead decision-making problem where the season is analyzed at discrete time periods. The arrival of bilateral requests and the ending times for implemented requests can only happen at these discrete time periods. Similarly, the continuously changing spot market is sampled at discrete times.

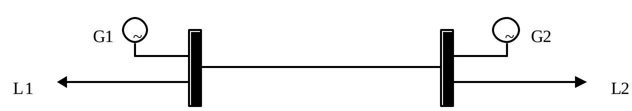


Figure 6.1: Sample Two Bus System

The proposed dynamic programming (DP) models call for some design considerations that will allow the simulations to be computationally more feasible. The design considerations and assumptions are below:

Unit Abstraction Using the information from the generation and supply sides, the TSP can determine its own estimates of what part of a unit is participating in the bilateral market and what part in the spot market. It can then use these estimates as a way to create the following setup for ease of computation. TSP then can treat a single generation unit as two, one that only operated in the bilateral market and one that operates in the spot market. These two can be kept separate until the TSP decides to curtail a bilateral agreement at which point it would have to account for that demand to transfer to the spot market. This is just an abstraction and does not have any indications. The new system users also shown in Figure 6.2 will be:

a. The generators that will only inject power for a bilateral agreement (P_{B1} and P_{B2}) and loads (L_{B1} and L_{B2}) those play a role only in a bilateral agreement. These generators and loads and their associated parameters are not included in the spot market considerations. In other words, the value of load for each bus under the spot market value does not include the power supplie d by the bilateral agreement. We assume the generator always has enough power for the agreement.

b. Users in the spot market where Bus1 and Bus2 are associated with some aggregate load and generation bid curves that are dispatched only in the real time market. (Generators P_{S1} and P_{S2} and loads L_{S1} and L_{S2}.)

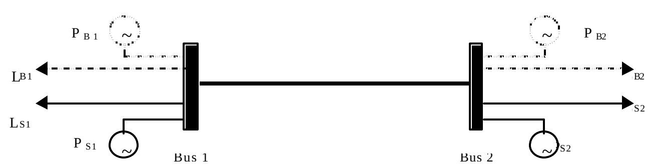


Figure 6.2: Modified Two-Bus Setup for calculations.

Number of Agreements In a system, node pairs that are connected by a single line are eligible to being pairs that can implement a bilateral agreement. So the numbers of lines indicate how many agreements can be made. The actual possible number of agreements is twice the number of lines since the lines are bi-directional. So in our system of 2 buses, we can have 2 bilateral agreements: inject from P_{B1} to L_{B2} or from P_{B2} to load L_{B1} . (In a large system, a worst-case scenario is when all buses are connected.)

Single Agreement Limit Although the number of pairs of buses is fixed in a system, if multiple agreements can be established between the same pair and the same direction for a single time period, then the number of cases that would have to be analyzed in order to find the optimal solution would be very big and would grow exponentially due to the combinatorial characteristics. In addition, building a tool which can handle variable number of cases is even harder, therefore, a simplifying assumption is made: At any time, between a pair, in one direction, only one agreement can be implemented or can be operating. In other words, if there is a bilateral agreement in place from bus1 to bus2, no new ones can be made. If there are no agreements, then one can be accepted given it leads to optimal resource allocation. A second issues arises here. What if multiple requests for the same pair and same direction come at once? This also would lead to variability and indefinite computation size in the system. Therefore, this is avoided by limiting the number of incoming requests per time, per node-pair per direction to one request. As the tool is made more efficient and rigorous, this can be relaxed.

Input Data Assumptions Even though the formulations above stressed very carefully the stochasticity of the market inputs to the optimization function, the simulation program does not resort to random number generators or the Monte Carlo analysis to develop possible trajectories but rather works with a data input whose content should be derived from historical data. (The examples below provide the information about BAs, spot market, and system topology.)

Implementation Code The source code is included in Appendix A. Files `hybrid.m`, `new2.m` and `new3.m` determine the admissible control space given the current system state and the incoming bilateral requests at any time k. For each control `new4.m` runs the optimal power flow analysis to determine the spot revenue that is associated with that time and control. `hybrid.m` file builds the DP tree and `new5.m` prunes it by determining the best decision path and the cumulative revenue that is obtained from that decision. Lastly `data.m` shows a sample input file.

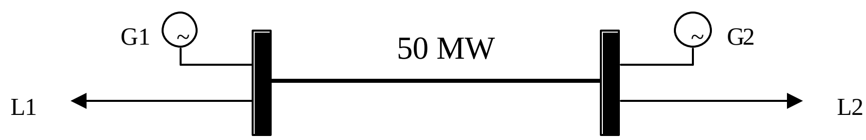
6.2 Simulated Cases

Since the simulation example is a 2-Bus system rather than a real transmission network, rather than exact solutions, the simulations aim to show, case by case, the strength of the dynamic programming tool, the importance of coupling the forward contracts with the spot market, and how crucial it is to include the uncertainties of the system. The simulation is build for a coordinated decision making setup with static topology. In the next section, for the comparative cases, simulations on the right and the left column of the pages are compared. For each case, the inputs are listed: the line capacity, the generation cost functions and the first graph shows the spot market demand at the two nodes. The results will be shown in the following graphs, which depict all the incoming agreements for the bilateral contracts from bus 1 to bus 2 and from bus 2 to bus 1. The dark lined ones (red in the original thesis) in the set are the agreements that are accepted and the plain ones (blue in the original thesis) are rejected.

6.2.1 Dynamic vs. Static Decision Making

This case compares the DP solution to a static decision heuristic, which accepts all incoming requests as long as it does not violate the single agreement limit.

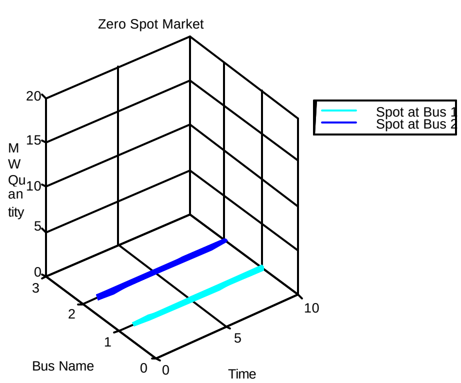
INPUTS:

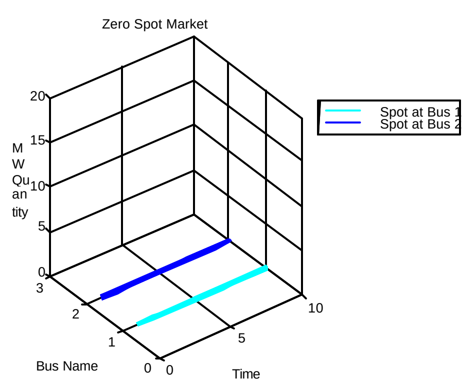


$C_1(Q_{G1})$ = 1.4 per MW

$C_2(Q_{G2})$ = 1.8 per MW

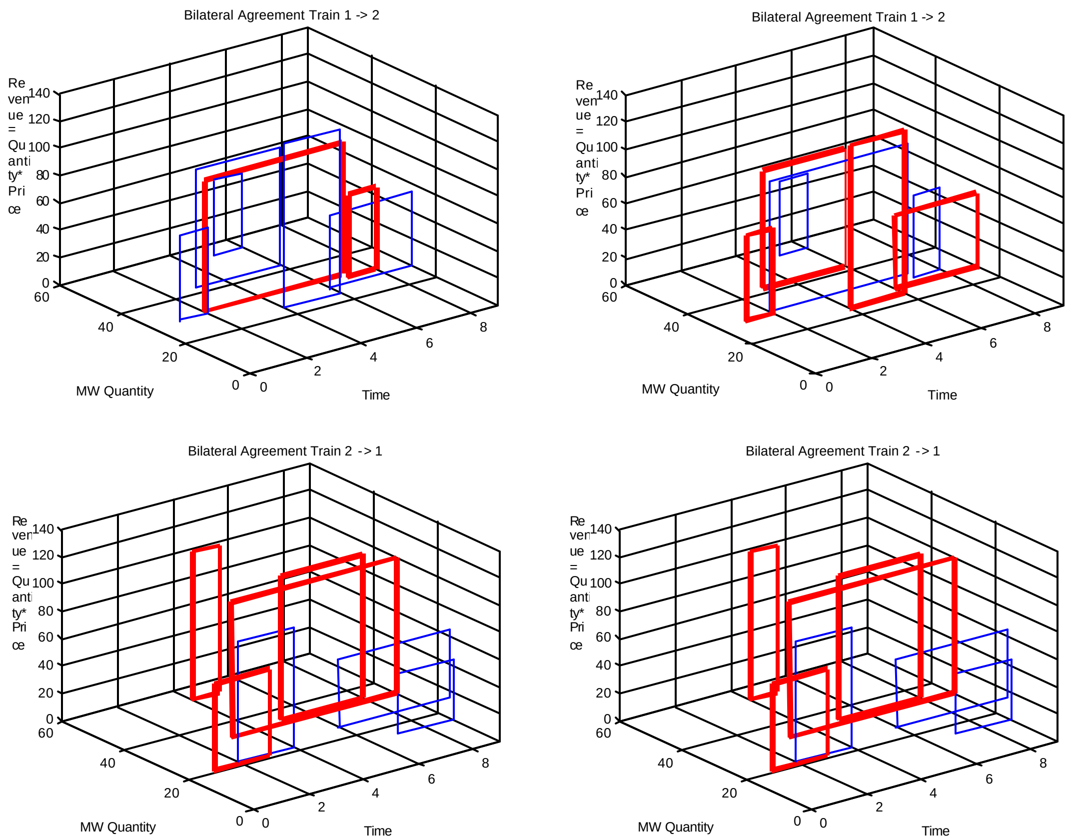
DYNAMIC DECISION **STATIC DECISION**





OUTPUT:

DYNAMIC DECISION **STATIC DECISION**

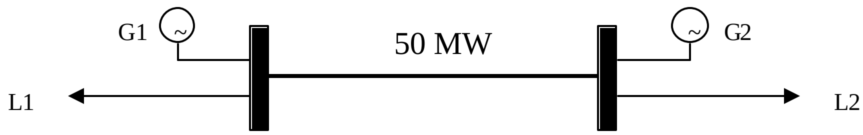


Revenue collected under the dynamic method is 1188 vs. 1059 collected under the static method. It is seen that for multi stage decision making with various length commitments, the decision is more optimal when DP is used.

6.2.2 Different Spot Market Conditions

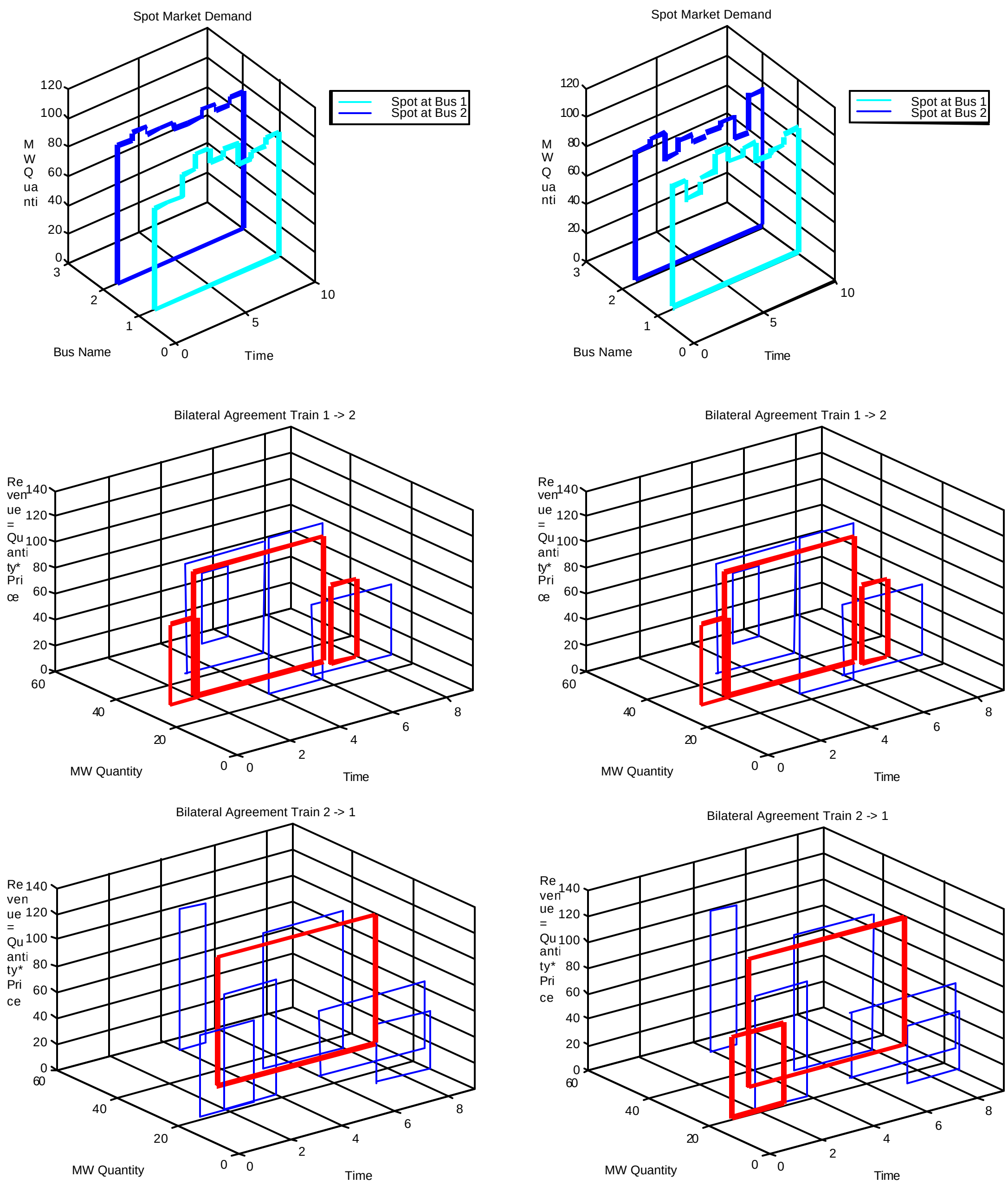
The following cases show how with different expected spot market parameters, the decision maker will choose different decision paths, allocations.

For all cases:

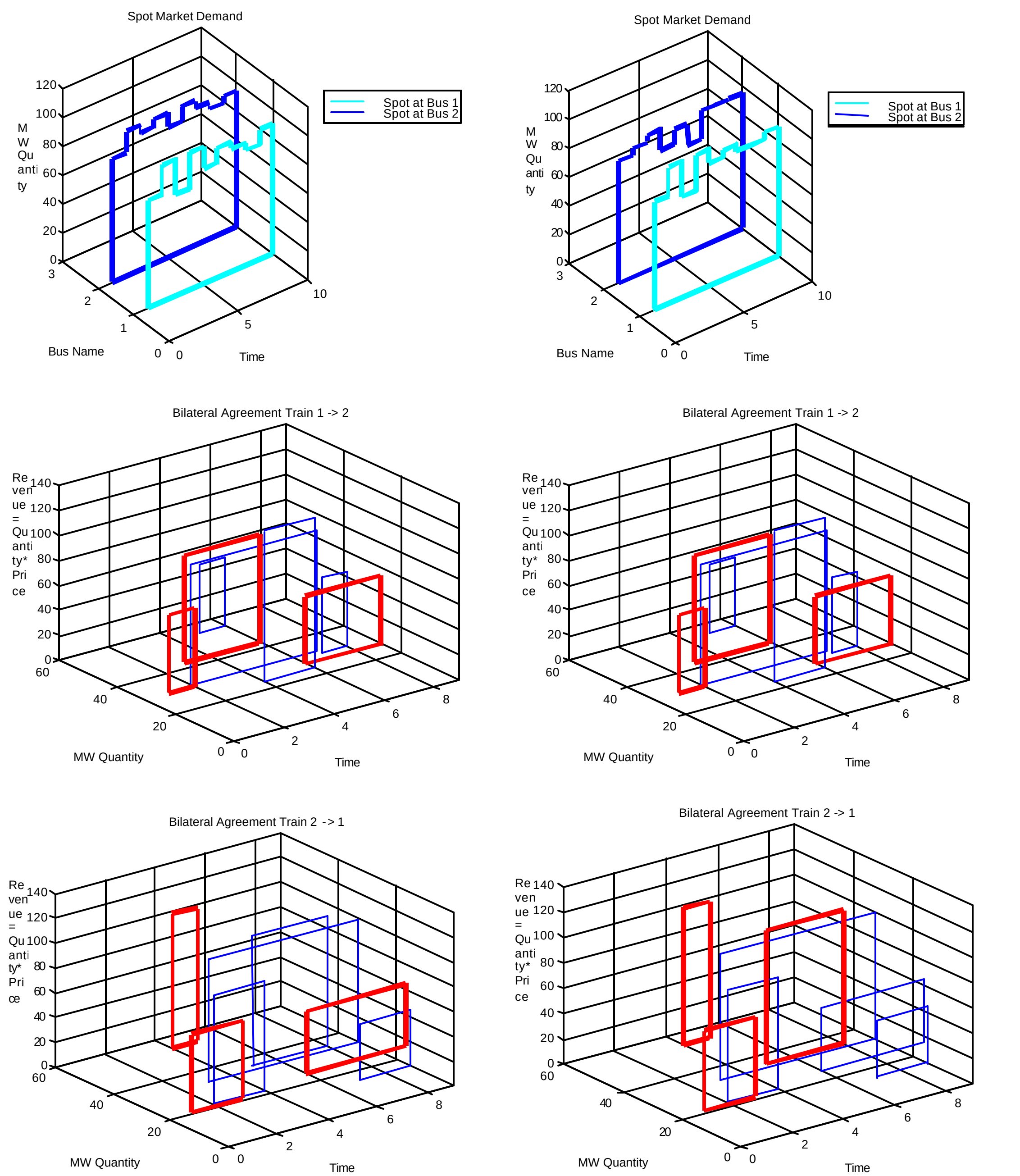


$C_1(Q_{G1}) = 1.4$ per MW $C_2(Q_{G2}) = 1.8$ per MW

CASE 1 **CASE 2**



CASE 3 **CASE 4**

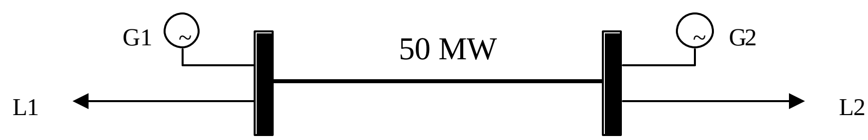


Even though the goal here is to show the different spot market conditions lead to different decision paths, it is curious to see if there are any patterns at least within the cases that have been simulated. Since the spot market demand values map to line flows through a transformation, and counter flows on a line decrease congestion by canceling each other, it Is not accurate to form a relationship between the spot demand and how much resources are allocated to the bilateral agreements, which can roughly be related to revenue collected from the agreements. Nonetheless, the above conditions suggest that higher spot demand leads t lower allocation to bilateral and thus less revenue comes from the agreements. Below is a table that shows the related values for the above cases.

	Case 1	Case 2	Case 3	Case 4
Spot Demand at Bus 1 (MW)	660	650	670	680
Spot Demand at Bus 2 (MW)	660	750	745	705
Total Spot Demand (MW)	1320	1400	1415	1385
Revenue from agreements ($)	1322	1196	916	1031

6.2.3 System Uncertainties

These cases aim to show how the decision path changes with changing system parameters. This is important to capture in the simulations to show how probabilistic analysis would lead to different decisions.



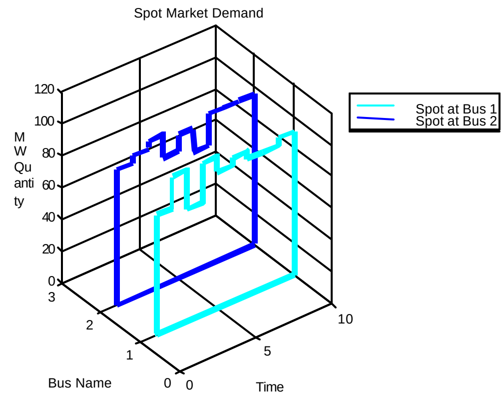
Different Generator Cost Functions

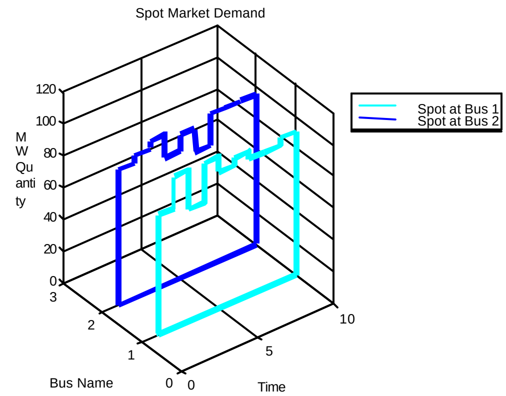
$C_1(Q_{G1}) = 1.8$ per MW

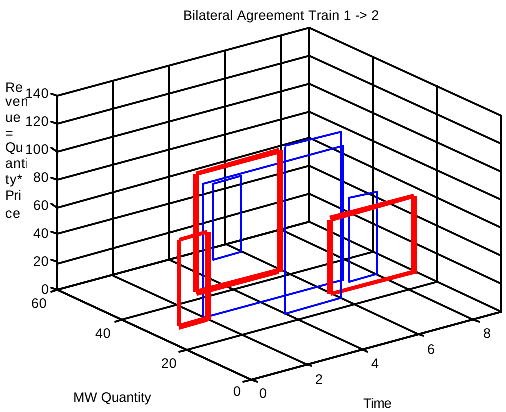
$C_2(Q_{G2}) = 1.3$ per MW

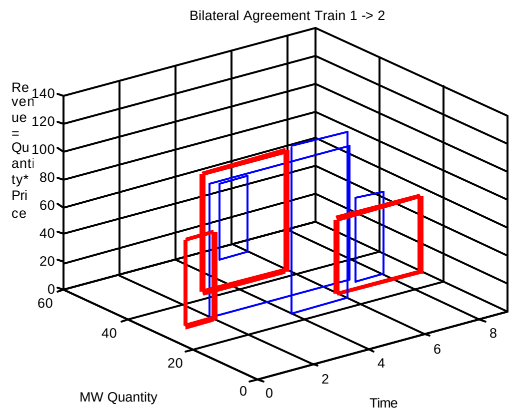
$C_1(Q_{G1}) = 1$ per MW

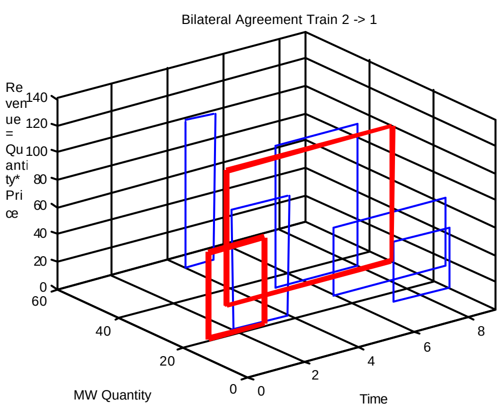
$C_2(Q_{G2}) = 2$ per MW

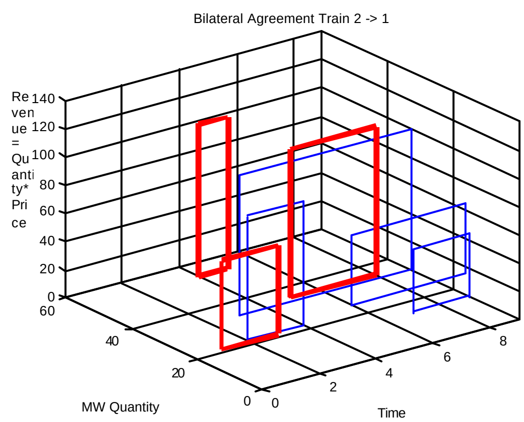




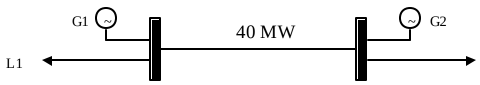


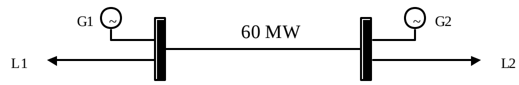


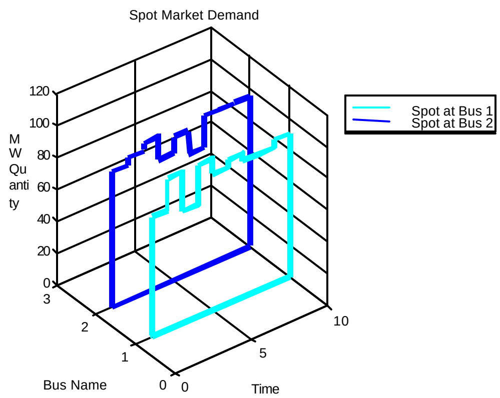


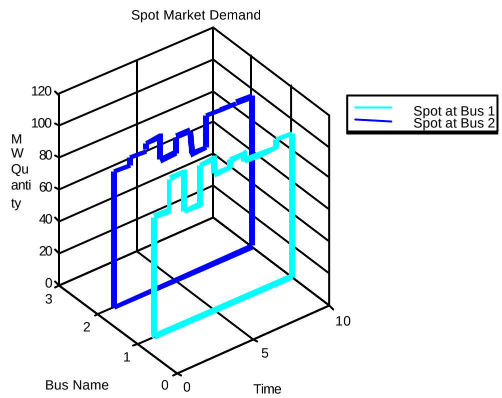


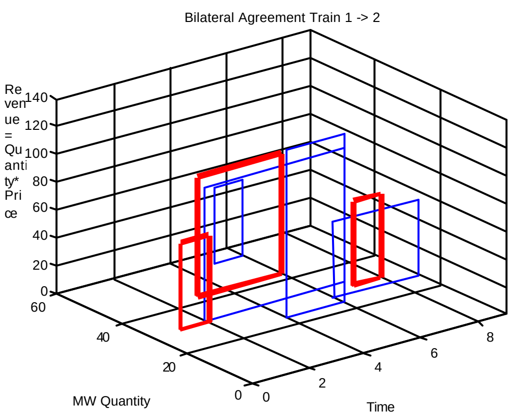
Different Line Capacities

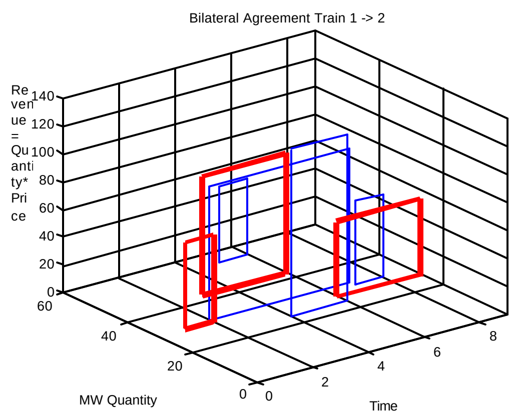


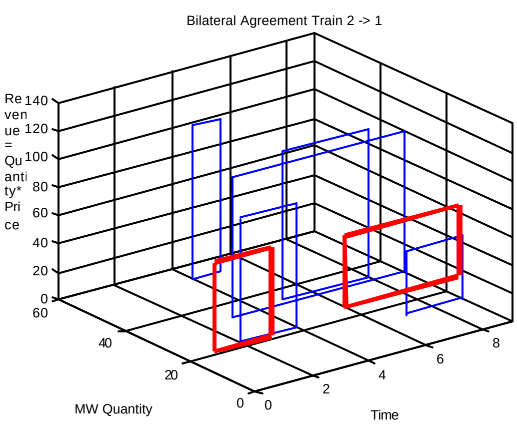


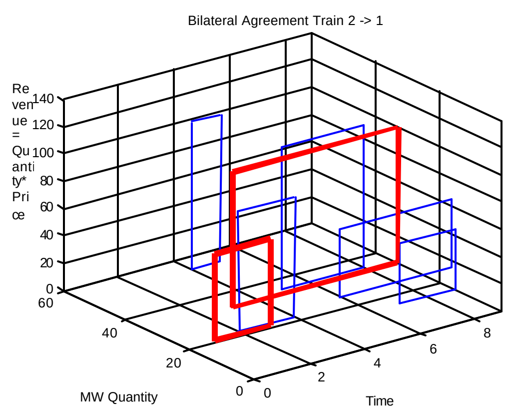












Chapter 7

Conclusion

We have identified two different approaches to Transmission Service Provision in the restructuring market. One is a centrally coordinated approach where the decision-making depends on a complex optimization under stochastic inputs. The other one bypasses the intelligence in the center provided by the TSP and puts the decision making on the end users. TSP faces a major challenge under both schemes to anticipate system reliability levels and in the distributed scheme translates it into price signals.

7.1 Preliminary Conclusions

This thesis structures a very important problem in the evolving deregulated power industry, namely the determination of the value of transmission and optimal allocation of the transmission capacity. 2000-2001 California Energy crises showed many of the missing pieces in the reengineered industry, one of which was the lack of decision-making tools in the transmission market. While complicated decisions we being made for the commodity, electricity, itself, same level of agreements for its transmission were not made becoming the bottleneck in the system operation.

Chapter 2 established the background information to develop the models for resource allocation. Dynamic Programming tool was introduced in this chapter that was extensively used for all the formulations. Chapter 3 formulated the problem from a centrally coordinated point of view, the TSP's point of view. This first formulation assumed that the physical uncertainties were not present and therefore assumed a static setup. This was the simplest formulation offered in the thesis; however, even at that level, the complexity and the computational intensity of the problem promoted the discussions around markov decision models, rollout algorithms, conservative dynamic programming and neuro-dynamic programming.

Given the static topology model, the thesis highly encouraged extending it to a dynamic model where system uncertainties in the transmission network are too crucial to ignore. Chapter 4 developed optimal transmission capacity allocation from a centrally coordinated point of view including the possibility of line outages. This introduced the compensation charge to the TSP for the load that was not served after an uncertainty, which once again encourages the coordinator to plan ahead carefully. This chapter also gives background to the concept of reliability in transmission systems and stumbles upon the issue for rare event approximation of outages with vast impacts on the system operation. At this point, the formulation in Chapter 4 captured all the uncertainties in the transmission system, which enabled discussions around materializing the risk in the system from the operator's side. Chapter 4 continues to introduce methods for risk sharing between the central coordinator and the system users, which leads the discussion to a distributed network control approach to transmission system operations.

Chapter 5 developed both mathematical formulations for the implementation of distributed control for the transmission networks. Chapter 5 concludes that a signal is required from a network supervisor to ensure stable and reliable operation of the network, which the thesis chooses to be a price signal. Chapter 5 shows the creation of the price signal as a dynamic programming problem, and also models the end user decisions once they receive the price signal. This chapter falls short in describing the conditions under which the coordinated and the distributed models meet. This is important to establish for a few reasons, a distributed model that is as successful as a coordinated model at finding the optimal dispatch is more favorable both from a control and a computational point of view.

Chapter 6 revisits the formulations of Chapter 3 through simulations to show the strength of the dynamic programming approach to blind decision making approaches as well showing how including the uncertainties of the system has an impact on the decisions made. Overall, we believe this thesis outlines a very crucial problem in power systems and brings viable approaches. These approached are complete in capturing the important aspects; however, they have disadvantages of being computationally expensive when it comes to implementation.

7.2 Future Research

Since tools for transmission service are just developing, there is lot of room left for new ideas and research. In light of the work done in this thesis, there are two very interesting areas that branch off. The first one is implementing the tools mentioned in Chapter 3, 4 and 5 for real time systems deploying some of the strategies explored in the thesis such as neuro-dynamic programming with temporal learning.

Another very interesting area to explore is comparing the transmission network to other large networks such as communication networks. These networks are inherently different in the way they deliver their services, real time delivery vs. best-effort delivery, routing vs. Kirchoff's laws. They are also different in system components such as lack of feasible storage in power networks compared to buffer mechanism in communication networks. The idea is not to make one look like the other but look for synergies in the tools developed for network management, congestion management and like tools. Work on distributed network operation was developed by the help of some ideas from congestion dependent pricing in data networks; however, much more can be learned from the extensive research that has evolved around data networks, and we believe that it would make challenging and intriguing new areas of research.

Appendix A

Source Code

Below is the simulation code used to develop the data for Chapter 6. This code is build for a 2-Bus system with a third slack bus.

```
%HYBRID.M

function[tempbesttree]  = hybrid(time,BA, Spot, Gen ,cap)

     % Top Level function, takes in the data and builds
     % the Dynamic Programming tree.

t0 = clock; %to measure how long the simulation takes
clc
global T n Fcap

T = time; %number of time periods
n = 2 ;   %number of buses excluding the slack bus.

global mainW S_all bno Ncost
mainW = BA;

%the requests coming in for each bus
%total number of requests should be the product of
%number of bus pairs (bno as below)  and number of periods.


buslist = linspace(1, n, n);
buspairs = [];
temp = [];

for i = 1:n
   for j = i+1:n
   temp = [temp; buslist(i),buslist(j)];
   end
end

buspairs = [ temp ; fliplr(temp) ];
%number of bilateral agreements.
[bno, foo] =   size(buspairs);
clear foo;

xstart = zeros(bno, 3);
% we start with no agreements at none of the buses.

S_all = Spot; %accounts for changing spot demand.

Ncost = Gen;
Fcap = cap; %line MW between node 1 and 2.
Scap = 80; %line MW between node 2 and 3: slack bus
```

```
Fimp = 0.0999; %line impedence 1-2
Simp = 0.0001; %line impedence 2-3
n1cost = Ncost(1,1);
n2cost = Ncost(2,1); %generation costs

global otrans onodes ogen_nodes oload_nodes ogen_cost ospot

% prepares the raw data for optimal power flow analysis.

otrans = [ 1 2 1 1 Fimp 0 Fcap 0 0 0 0 0 0 0 0 0 0 ; ...
         2 3 3 1 Simp 0 Scap 0 0 0 0 0 0 0 0 0 0 ];

onodes = [  1 1 1 2 ; ...
            2 2 1 2; ...
          3 3 1 3];

ogen_nodes = [ ...
[1, 1, 0, 0, 9999.0, -9999.0, 1, 0, 100, 0, 0, 0, 0, 1, 1, 100, 9999,
0];...
[2, 1, 0, 0, 9999.0, -9999.0, 1, 0, 100, 0, 0, 0, 0, 1, 1, 100, 9999,
0];...
[3, 1, 0, 0, 9999.0, -9999.0, 1, 0, 100, 0, 0, 0, 0, 1, 1, 100, 9999,
0] ];

[hey, joe] = size(S_all);

oload_nodes  = [ 1 1 1 1 1 S_all(1,:) ;...
                 2 1 1 1 1 S_all(2,:) ;...
             3 1 1 1 1 zeros(1,joe)  ];
clear joe hey

ogen_cost = [ 1 0 0 n1cost ;...
              2 0 0 n2cost ; ...
              3 0 0 (20000*(n1cost+n2cost))];

[wa, foo] = size(mainW);

for i = 1:wa
 if mainW(i,3) > 0 &  mainW(i,1) == 0
    mainW(i,:) = zeros(1,3);
 elseif mainW(i,3) > 0 &  mainW(i,2) == 0
    mainW(i,:) = zeros(1,3);
 elseif mainW(i,1) > 0 & mainW(i,2) == 0;
    mainW(i,:) = zeros(1,3);
 end
end

%this makes sure that there is no misreported requests.
%such as those for 0 MW and 0 time period but for 2 dollars.

global baseU
baseU = [ 0 1 1 0 ; 0 0 0 0 ; 0 0 0 0 ; 0 0 1 1 ];
%this is the decision space corresponding to:

 %Reject 12, Reject 21
 %Accept 12, Reject 21
 %Accept 12, Accept 21
```

```
 %Reject 12, Accept 21

clear treenode
treenode(1) = struct('name','1','time',1,'parent','0','branches',[],...
                 'revenue',0,'state', xstart);

% this builds a tree structure to capture the information
% at the nodes of the DP tree.

total = length(treenode);
prevcreated = 1;

%iterate through each T
global t

for t = 2:T
  [treenode,prevcreated] = new2(treenode, mainW, S_all, t,
prevcreated);
  prevcreated;
end

treenode.name;
treenode.time;
treenode.parent;
treenode.branches;
treenode.revenue;
treenode.state;


new5;

% if the spot makret is taken to be zero
% revenue is soley from the BAs.

if (sum(sum(Spot,2))==0)
     hey = str2num(hey2);
     dec = [] ;
     remove = floor(hey/(10^(T-1)));
     hey = hey - (remove*10^(T-1)); % get rid of the '1'

     for p = 1:(T-1)
      k = T-1-p   ;
      remove = floor(hey/(10^k));
      dec = [ dec ;  remove];
      hey = hey - (remove*10^k);
     end

     dec ;

zerospotrev = 0;

     for a = 1:(T-1)
        get = dec(a,:);
        q = baseU(:,get)  ;
        y = reshape(q,bno,bno);
        agr = pickw(a+1,T,mainW,bno);
```

```
        revagr = [ agr(1,1)*agr(1,2)*agr(1,3) ;
agr(2,1)*agr(2,2)*agr(2,3) ];
        hrev = y*revagr;
        zerospotrev = sum(hrev) +  zerospotrev;
     end

else
end

zerospotrev

wow = etime(clock,t0)



% NEW2.M

function[treenode,prevcreated] = new2(treenode, mainW, S_all, t,
prevcreated)


global T bno n Fcap n1cost n2cost
global otrans onodes ogen_nodes ogen_cost ospot baseU

startingtotal = length(treenode);
clear S w
global S w

w = pickw(t,T,mainW,bno);
S = picks(t,T,S_all);

for q = 1:prevcreated,

    index = startingtotal - prevcreated + q;
    X = treenode(index).state;
    qparent = treenode(index).name;
    U = [];
    br = [];

% determines the admissable decison space
% given the current state

    if ( X(1,1)>0 ) & ( X(2,1)>0 )
        U= [baseU(:,1)];
        br = ['1'];
    elseif ( X(1,1)>0 ) & ( X(2,1)==0 )
        U = [baseU(:,1) baseU(:,4)];
        br = [ '1' ;'4' ];

    elseif ( X(1,1)==0 ) & ( X(2,1)==0 )
        U = baseU;
        br = ['1' ;'2'; '3'; '4'] ;

    elseif ( X(1,1)==0 ) & ( X(2,1)>0 )
        U = [baseU(:,1) baseU(:,2)];
        br = [ '1' ; '2' ];
    end
```

```
    [k,l] = size(X);
    wow = k*l;
    [foo, possible] = size(U);
    growingsize = length(treenode);

    if possible > 0
       for i = 1:possible
           thistime = U(:,i);
           bran = br(i,:);

           u = reshape(thistime,bno,bno) ;
           order = growingsize+i;
           newname = strcat(qparent,bran);
           treenode(order).name = newname;
           treenode(order).time = t;
           treenode(order).parent = qparent;
           treenode(order).branches = u;
         [totalrev, newX, u] = new3(S_all,S,Fcap,X,w,u,wow,t);

% builds a  tree node for each possible decision u

           treenode(order).revenue = totalrev;
           treenode(order).state = newX;
        end
    end

end

prevcreated = length(treenode) - startingtotal;
treenode;

% NEW3.M

function [totalrev, newX, u] = new3(S_all,S,Fcap,X,w,u,wow,t)

% determines the revenue for each decision

global T bno n mainW baseU
global otrans onodes ogen_nodes oload_nodes ogen_cost ospot

q12 = X(1,1);
p12 = X(1,2);
td12 = X(1,3);
q21 = X(2,1);
p21 = X(2,2);
td21 = X(2,3);

Xtemp = X;

for i = 1:2
    if X(i,1) > 0;
     Xtemp(i,3) = X(i,3) - 1;
    else
     Xtemp(i,3) = 0;
    end
```

```
end

%accept matrix.

A = [];
A = u*w;

wq12 = A(1,1);
wp12 = A(1,2);
wtd12 = A(1,3);
wq21 = A(2,1);
wp21 = A(2,2);
wtd21 = A(2,3);

Atemp = A;

for i = 1:2
    if A(i,1) > 0;
       Atemp(i,3) = A(i,3) -1;
    else
       Atemp(i,3) = 0;
    end
end

%new X from bilaterals only

newrevb = q12*p12 + q21*p21 + wq12*wp12 + wq21*wp21;

%these are new flow bounds and we have to make sure
%that spot market operates between these.

fupper = Fcap +(- q12 -wq12 + q21 + wq21);
flower = -Fcap + (- q12 -wq12 + q21 + wq21) ;

%new x[k+1]

newX = [];
newX = Xtemp + Atemp;

[newa , newb] = size(newX);

for i = 1:2
    if newX(i,3) <= 0
       newX(i,:) = zeros(1,newb);
    else
    end
end

for i = 1:2
    if newX(i,1) == 0
       newX(i,:) = zeros(1,newb);
    else
    end
end

%if there is no spot market
%and if the line limits are not met
```

```
%report zero revenue

if (S(1,1)==0) & (S(2,1)==0)
     if (fupper < Fcap) & (flower > -Fcap)
         totalrev = newrev;
     else
         totalrev = 0;
     end
else

  global day period lineout season_days

  day = 1;
  period = 1;
  lineout = 0;
  season_days = 2;

%optimal power flow program called

  [spotrev] = new4( T,t, day, period, lineout, season_days, fupper,
flower);
  totalrev = spotrev + newrevb;
end


% PICKW.M

function [f] = pickw(t,T,mainW,bno)

newt = t-1;

%pick from mainW the W for time period t.

if newt> T
   disp('no, no!')
   f = [];
else
   f = [ mainW(bno*newt-1,:); mainW(bno*newt,:)];
end

% PICKS.M

function [f] = picks(t,T,S_all)

newt = t-1;

%pick from Spot data for time period t.

if newt> T
   disp('no, no!')
   f = [];
else
   f = S_all(:,newt);
end
```

```
% NEW4.M

function [spotrev, lineflows, congest_freq, constrained_lines ,...
spotprice, x0 ] = new4(T,t, day, period, lineout,season_days, fupper,
flower)

% determines optimal dispatch

warning off

%global T
global bno n Fcap S_all baseU
global otrans onodes ogen_nodes oload_nodes ogen_cost ospot
global mc lds busno  congest_freq
global constrained_lines num_constrained total_cost num_fval

OPF = 1;  % OPF = 1 -> inelastic load,   OPF = 2 -> elastic load

% MVA base
Sbase = 100;


[busno, colno] = size(onodes);
[gens, colno] = size(ogen_nodes);
[loads, loadcolno] = size(oload_nodes);
[lineno, colno] = size(otrans);
[gcd_no, colno]=size(ogen_cost);

nodes = onodes;
gen_nodes = ogen_nodes;
load_nodes = oload_nodes;
trans = otrans;
gen_cost = ogen_cost;

congest_freq = zeros(lineno-1,4);
congest_freq(1:lineno-1,1:3) = otrans(1:lineno-1,1:3);
constrained_lines = zeros(1,5);

num_constrained = 0;
num_fval = 0;
total_cost = zeros(1,4);

nodes = sortrows(nodes,4);

a = zeros(busno,lineno);
i = 0;
j = 0;

for count = 1:lineno,
 for count2 = 1:busno,
       if trans(count,1) == nodes(count2,1),
        i = count2;       end

      if trans(count,2) == nodes(count2,1),
       j = count2;
```

```
        end
    end
    if trans(count,15) > 0.5,
     a(i,count) =  1/trans(count,15);
     a(j,count) = -1;
  else
     a(i,count) =  1;
     a(j,count) = -1;
     lmax(count,1) = i; lmax(count,2) = j;
    end
end

X = trans(1:lineno,5);
c = trans(1:lineno,6);
b = ones(lineno,1) ./(-1*X);
Y = (a * diag(b) * transpose(a)) - ...
     0.5 * diag(diag((a * diag(c) * transpose(a))));
invY = inv(Y(1:busno-1, 1:busno-1));
m=0;

for (l=1:busno)
     for (k=1:gens)
         if(gen_nodes(k,1)==nodes(l,1))
             m=m+1;
             gennodes(m,:)=gen_nodes(k,:);
         end;
     end;
end;

gen_nodes=gennodes;
clear gennodes;

lds = busno - gens;
[foo,boo] = size(gen_nodes);

up_limit(:,1) = gen_nodes(:,17)/Sbase;
low_limit(:,1) = gen_nodes(:,18)/Sbase;

mc = [nodes(:,1), zeros(busno,3)];
mc(1:busno,3)=0;

for (k=1:gcd_no)
     for (l=1:busno)
        if (gen_cost(k,1)==nodes(l,1))
           mc(l,2:4) = gen_cost(k,2:4);
              end;
     end;
end;

options=optimset('MaxIter', 999, 'TolX', 1e-10, 'Display', 'off',...
'DiffMaxChange', 1e-8, 'TolFun', 1e-10, 'TolCon', 1e-10);

Apos=diag(b)*transpose(a)*[invY(1:busno-1,lds+1:busno-1),zeros(busno-
1,1);...
                         zeros(1,gens-1),0];
Aneg=-diag(b)*transpose(a)*[invY(1:busno-1,lds+1:busno-1),zeros(busno-
1,1);...
```

```
                        zeros(1,gens-1),0];
A = [Apos;Aneg];

%distribution matrix

m=0;
for (l=1:busno)
     for (k=1:loads)
         if(load_nodes(k,1)==nodes(l,1))
             m=m+1;
             loadnodes(m,:)=load_nodes(k,:);
         end;
     end;
end;

load_nodes=loadnodes;
clear loadnodes;

S = picks(t,T,S_all);
Pload = [ S ; 0];

fupper = fupper;
flower = flower;

%these are in MW. and they arenot symmettic.

Bpos = fupper+diag(b)*transpose(a)*[invY,zeros(busno-1,1);...
zeros(1,busno-1),0]*Pload;
Bneg = -flower-diag(b)*transpose(a)*[invY,zeros(busno-1,1);...
zeros(1,busno-1),0]*Pload;
B = [Bpos;Bneg];

Aeq=ones(1,gens);
Beq=sum(Pload);
x0 = zeros(gens,1);

[x0, fval, exitflag, output, lambda] = fmincon('fun_constant', ...
x0, A, B, Aeq, Beq, low_limit, up_limit, 'fun3', options);

if exitflag ~= 1
   disp('HANDS UP')
break
else
end

[x0, fval, exitflag, output, lambda] = fmincon('fun', x0, A, B, ...
Aeq, Beq, low_limit, up_limit, 'fun3', options);

if exitflag ~= 1
  disp('HANDS UP')
 break
else
end

Bij = diag(b)*transpose(a)*[invY,zeros(busno-1,1);zeros(1,busno-
1),0]*Pload;
%power flow
```

```
Qij = Apos*x0 - Bij;

lineflows = trans(:,1:2);
lineflows = [lineflows,Qij];

num_const=0;

for (i = 1:lineno)

  if (lambda.ineqlin(i) > 0)
      num_constrained = num_constrained+1;
      constrained_lines(num_constrained,1) = trans(i,1);
      constrained_lines(num_constrained,2) = trans(i,2);
      constrained_lines(num_constrained,3) = day;
      constrained_lines(num_constrained,4) = period;
      constrained_lines(num_constrained,5) = lineout;
      k = 1;
      while ((congest_freq(k,3)~=trans(i,3)) & (k<lineno-1))
         k = (k+1);
      end;
      if (k < lineno)
         congest_freq(k,4) = congest_freq(k,4) + 1;
      end;
   end;
end;

for (i = 1:lineno)
   if (lambda.ineqlin(lineno+i) > 0)
      num_constrained = num_constrained+1;
      constrained_lines(num_constrained,1) = trans(i,1);
      constrained_lines(num_constrained,2) = trans(i,2);
      constrained_lines(num_constrained,3) = day;
      constrained_lines(num_constrained,4) = period;
      constrained_lines(num_constrained,5) = lineout;
      %m = m+1;
      k = 1;
      while ((congest_freq(k,3)~=trans(i,3)) & (k<lineno-1))
         k = (k+1);
      end;
      if (k < lineno)
         congest_freq(k,4) = congest_freq(k,4) + 1;
      end;
   end;
end;


num_fval = num_fval+1;
total_cost(num_fval,1) = day;
total_cost(num_fval,2) = period;
total_cost(num_fval,3) = lineout;
total_cost(num_fval,4) = fval;

hmatrix = diag(b) * transpose(a) * [invY,zeros(busno-
1,1);zeros(1,busno-1),0];
Hmatrix = [hmatrix;(-1. * hmatrix)];
```

```
spotprice = zeros(busno,1);
for k=1:busno
   spotprice(k,1) = lambda.eqlin - transpose(lambda.ineqlin) *
Hmatrix(:,k);
end;

spotrevall = x0 .*spotprice;
spotrev = sum(spotrevall);
fval;

% FUN.M
% the non linear optimization functions

function F = fun(x)

global mc lds busno

mc1 = mc(lds+1:busno-1,4);
mc1 = [mc1;0];
mc2 = mc(busno,4);
mc2 = [zeros(busno-1-lds,1);mc2];

%mc1 = mc(lds+1:busno,4);

F = sum(((0.5.*mc1).*x).*x) + sum(mc2.*x);

%F = sum((0.5.*mc1).*(x.*x));

return;

% FUN3.M

function [F,G]= fun3(x)

F =0;
G =0;

return;

% FUN_CONSTANT.M

function F = fun_constant(x)

global mc lds busno

F = sum(mc(lds+1:busno,4).*x);
return;

% NEW5.M

%this file will help move down the tree. inputs are just the treenode.
%save original treenode
otreenode = treenode;

clear treel;
treel = length(otreenode);
```

```
%get all the nodes at time T. the last nodes.

clear startnode
startnode = treenode(treel);

sl = 0;

for iter = 1:treel
    if eq(treenode(iter).time, T)
       startnode(sl+1) =  treenode(iter);
       sl = length(startnode);
    else
    end
end

%truncate for next periods

treenode = treenode(1:treel-sl);

clear tempbesttree
tempbesttree =
struct('name','','time',0,'revenue',0,'cumrev',0,'parent',...
                  '','best','');

sl = length(startnode);

for i = 1:sl
    tempbesttree(i).name = startnode(i).name;
    tempbesttree(i).time = T;
    tempbesttree(i).rev = startnode(i).revenue;
    tempbesttree(i).cumrev = startnode(i).revenue;
    tempbesttree(i).parent = startnode(i).parent;
    tempbesttree(i).best = tempbesttree(i).name;
end


%this is the end of temp data creation

clear tempbest

tempbest(1) = tempbesttree(1);
tl = length(tempbest);


for i = 2:sl
   if strcmp(tempbesttree(i).parent,tempbest(tl).parent) &...
      gt(tempbesttree(i).rev, tempbest(tl).rev)
           tempbest(tl) = tempbesttree(i);
   elseif strcmp(tempbesttree(i).parent,tempbest(tl).parent)&...
          gt(tempbest(tl).rev,tempbesttree(i).rev)
           tempbest = tempbest;
   else
           tempbest(tl+1) = tempbesttree(i);
           tl = length(tempbest);
   end
end
```

```
tl;

besttree = tempbest;
prevcreated = length(besttree);


%***********************
%do  the rest of the time
%***********************


for t = 1:T-1
      move = T-t;
      treel = length(treenode);

      %for eachtime we will start that fresh
      clear tempbest
      clear tempbesttree
      clear startnode
      startnode = treenode(treel);
      sl  = 0;

      %get the nodes that we are interested in.

      for iter = 1:treel

           if eq(treenode(iter).time, move)
              startnode(sl+1) =  treenode(iter);
              sl = length(startnode);
           else
           end
      end

      %for next periods
      treenode = treenode(1:treel-sl);
      treel = length(treenode);
      %get the info that we are intesrted in.
      tempbesttree =
struct('name','','time',0,'revenue',0,'cumrev',0,...
                    'parent','','best','');
      sl = length(startnode);
      for i = 1:sl
       tempbesttree(i).name = startnode(i).name;
       tempbesttree(i).time = move;
       tempbesttree(i).rev = startnode(i).revenue;
       tempbesttree(i).cumrev = startnode(i).revenue;
       tempbesttree(i).parent = startnode(i).parent;
      end

      %iterathe thru the nodes and get cumulative revenues:
       lbt = length(besttree);

      for i = 1:sl
         for k = 1:prevcreated
         look = lbt-k+1;
            if strcmp(tempbesttree(i).name, besttree(look).parent)
                  tempbesttree(i).cumrev = tempbesttree(i).rev + ...
```

```
                                          besttree(look).cumrev;
                  tempbesttree(i).best = besttree(look).best;break;
                tempbesttree(i).cumrev = tempbesttree(i).rev;
            end
         end
      end


     tempbest(1) = tempbesttree(1);
     tl = length(tempbest);




    for i = 2:sl

       if strcmp(tempbesttree(i).parent,tempbest(tl).parent) &...
          gt(tempbesttree(i).cumrev, tempbest(tl).cumrev)
                 tempbest(tl) = tempbesttree(i);
       elseif strcmp(tempbesttree(i).parent,tempbest(tl).parent)&...
              gt(tempbest(tl).cumrev,tempbesttree(i).cumrev)
                 tempbest = tempbest;
       else
                 tempbest(tl+1) = tempbesttree(i);
       tl = length(tempbest);
       end
    end

    bestl = length(besttree);

    for r = 1:tl
         besttree(bestl+r) = tempbest(r);
    end
    prevcreated = tl;


end

global hey1 hey2

hey1 = besttree(bestl).cumrev
hey2  = besttree(bestl).best


%sample input data file DATA.M

time = 8
cap =  60



BA =  [...

31 2 2  ; 21 3 1 ;  ...
32 3 5  ; 22 4 2 ;  ...
43 2 1  ; 33 3 1 ;  ...
24 3 2  ; 54 1 1 ;  ...
```

```
55 1 2  ; 35 3 3 ;  ...
27 2 3  ; 25 4 4 ;  ...
30 2 1  ; 15 3 2 ; ...
24 3 1  ; 0 0 0 ...

]

Spot =  [ ...

 75 95 70 95 85 90 85 85 90 ;...
 85 90 95 80 90 75 95 95 95 ...

]

Gen = [ ...

1 ;...
2 ...

]
```

Bibliography

[1] Eric Allen and Marija Ilic, *Price-Based Commitment Decisions In The Electricity Market*, New York : Springer, 1999.

[2] Eric Allen, Marija Ilic and Ziad Younes, "Providing for Transmission in Times of Scarcity: an ISO cannot do it all," *Electric Power and Energy Systems 21*, Elsevier 1999.

[3] Dimitri P. Bertsekas, *Dynamic Programming And Optimal Control, Volume I.* Belmont, MA: Athena Scientific, 1995.

[4] Dimitri P. Bertsekas, *Dynamic Programming And Optimal Control*, *Volume II*. Belmont, MA: Athena Scientific, 1995.

[5] Dimitri Bertsekas, "Neuro-Dynamic Programming: An Overview," MIT Laboratory for Information and Decision Systems, Cambridge, MA. Tech. Rep.

[6] Dimitri P. Bertsekas and D.A. Castanon, "Rollout Algorithms for Stochastic Scheduling Problems," MIT Laboratory for Information and Decision Systems, Cambridge, MA. Tech. Rep. LIDS-P 2413, April 1998.

[7] Dimitri P. Bertsekas and John N. Tsitsiklis, *Neuro-Dynamic Programming*. Belmont, MA: Athena Scientific, 1996.

[8] Dimitri Bertsekas, John Tsitsiklis and Cynara Wu, " Rollout Algorithms for Combinatorial Optimization," *Journal of Heuristics, 3*, p245-262, Kluwer Academic Publishers, 1997.

[9] R. Billinton, "Bulk System Reliability- Measurement and Indices" *IEEE Transactions on Power Systems*, Vol 4, No. 3, August 1989.

[10] R. Billinton, etal. "Current Industry Practices in Bulk Transmission Outage Data Collection and Analysis," *IEEE Transactions on Power Systems*, Vol. 7, No. 1, February 1992.

[11] Richard E. Brown and James J. Burke, "Managing the Risk of Performance Based Rates," *IEEE Transactions on Power Systems*, Vol 15, No. 2, May 2000.

[12] Christos G. Cassandras, David L. Pepyne, and Yorai Wardi, "Optimal Control of Systems With Time-Driven and Event-Driven Dynamics." In *Proceedings of the 37th IEEE Conference on Decision & Control* December 1998.

[13] John W.M. Cheng, Donald T. McGillis, and Francisco D. Galiana, "Probabilistic Security Analysis of Bilateral Transactions In a Deregulated Environment," *IEEE Transactions on Power Systems*, Vol 14, No. 3, August 1999.

[14] John W.M. Cheng, Francisco D. Galiana, and Donald T. McGillis, "Studies Of Bilateral Contracts With Respect To Steady-State Security In A Deregulated Environment," *IEEE Transactions on Power Systems*, 1997.

[15] Teofilo De La Torre, James W. Feltes, Tomas Gomez San Ramon, and Hyde M. Merrill, "Deregulation, Privatization, and Competition: Transmission Planning Under Uncertainty." *IEEE Transactions on Power Systems*, Vol 14, No. 2, May 1999.

[16] Shi-Jie Deng, and Shmuel Oren , "Priority Network Access Pricing for Electric Power," University of California Energy Institute Tech. Rep. [Online Document], February 2000. Available HTTP: `http://www.ucei.berkeley.edu/ucei/PDF/pwp072.pdf`

[17] G. Hamoud, "Assessment of Available Transfer Capacity of Transmission Systems," *IEEE Transactions on Power Systems*, Vol 15, No. 1, February 2000.

[18] Toshihide Ibaraki Naoki Katoh, *Resource Allocation Problems: Algorithmic Approaches*, Cambridge, MA: MIT Press, 1988.

[19] Marija Ilic, Francisco Galiana, and Lester Fink (Eds.), *Power Systems Restructuring: Engineering and Economics*, Boston, MA: Kluwer Academic Publishers, 1998.

[20] Marija D. Ilic, Jose R. Arce, Yong T. Yoon, and Elena M. Fumagalli, "Assessing Reliability as the Electric Power Industry Restructures." MIT Energy Laboratory, Cambridge, MA. Tech. Rep. 00-008, [Online document], 2000. Available HTTP: `http://web.mit.edu/energylab/www/pubs/publications.html#WP2000` . Also visit PhD Dissertation by Jose Arce.

[21] Marija Ilic and Shell Liu, *Hierarchical Power Systems Control*. London: Springer, 1996.

[22] Rabih A. Jabr, Alun H. Coonick, and Brian J. Croy "A Homogeneous Linear Programming Algorithm for the Security Constrained Economic Dispatch Problem," *IEEE Transactions on Power Systems*, Vol 15, No. 3, August 2000.

[23] Frank Kelly, "Charging and Rate Control for Elastic Traffic," *European Transactions on Telecommunications* Volume 8, 1997.

[24] Frank Kelly, A.K. Maulloo and D.K.H. Tan, "Rate Control For Communication Networks: Shadow Prices, Proportional Fairness And Stability," [Online document], 1998, Available HTTP: `http://www.statslab.cam.ac.uk/~frank/rate.html`

[25] A.M. Leita Da Silva, J. W. Marangon Lima, and G. J. Andres, "Available Transmission Capability – Sell Firm or Interruptible?" *IEEE Transactions on Power Systems*, Vol 14, No. 4, November 1999.

[26] Jean-Pierre Léotard, "Transmission Pricing And Incentives For Investments Under Uncertainty In The Deregulated Power Industry," MIT Master Thesis, 1999.

[27] T.L. Magnanti, A. Balakrishnan and P. Mirchandani, " Connectivity-Splitting Models for Survivable Network Design," MIT Operations Research Center, Cambridge, MA. OR 341-00, January 2000.

[28] P. Marbach and J.N. Tsitsiklis, "A Neuro-Dynamic Programming Approach to Call Admission Control in Integrated Service Networks: The Single Link Case," MIT Laboratory for Information and Decision Systems, Cambridge, MA. Tech. Rep. LIDS-P 2402, November 1997.

[29] I.Ch. Paschalidis and J.N. Tsitsiklis, "Congestion-Dependent Pricing of Network Services," MIT Laboratory for Information and Decision Systems, Cambridge, MA. Tech. Rep. LIDS-P 2431, October 1998.

[30] Eugene G. Preston, Martin L. Baughman and Mack Grady, "A New Model for Outaging Transmission Lines in Large Electric Networks," *IEEE Transactions on Power Systems*, Vol 14, No. 2, May 1999.

[31] Paat Rusmevichientong and Benjamin Van Roy, "Decentralized Decision-Making in a Large Team with Local Information," [Online Document], July 26, 2000, Available HTTP: `http://www.stanford.edu/~bvr/psfiles/chain.pdf`

[32] Arjen Siegmann, and Andre Lucas, "Analytic Decision Rules for Financial Stochastic Programs," [Online Document], May 1, 2000. Available HTTP: `http://www.unites.uqam.ca/ideas/data/Papers/dgruvatin20000041.html`

[33] Petter Skantze, Andrej Gubina, and Marija Ilic, "Bid-based Stochastic Model for Electricity Prices: The Impact of Fundamental Drivers on Market Dynamics" MIT Energy Laboratory, Cambridge, MA. Tech. Rep. 00-004, [Online document], 2000. Available HTTP: `http://web.mit.edu/energylab/www/pubs/publications.html#WP2000`

[34] Felix Wu and Pravin Varaiya, "Coordinated Multilateral Trades for Electric Power Networks: Theory and Implementation." University of California Energy Institute Tech. Rep. [Online document], January 1997. Available HTTP: `http://www.ucei.berkeley.edu/ucei/PDF/pwp031.pdf`

[35] Y.T. Yoon, M.D. Ilic, "Independent Transmission Company (ITC) and Markets for Transmission", 01SM140, IEEE PES Summer Meeting, Vancouver, BC, July 15 - 19, 2001

[36] Chien-Ning Yu "Hierarchical Congestion Management For A Deregulated Power Industry," MIT Ph.D. Dissertation in Mechanical Engineering, 1999.

[37] Chien-Ning Yu, Jean-Pierre Leotard and Marija Ilic, "Dynamic of Transmission Provision in a Competitive Power Industry," *Discrete Event Dynamic Systems: Theory and Applications,9,* Boston, MA: Kluwer Academic Publishers, 1999.

[38] David C. Yu, Thanh C. Nguyen, and Peter Haddawy, "Bayesian Network Model for Reliability Assessment of Power Systems," *IEEE Transactions on Power Systems*, Vol 14, No. 2, May 1999.