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Integration of planning and scheudling using approximate dynamic programming

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Abstract

This thesis presents the optimization of various cases for planning and the approximation approach of integration of multiple decision stages including planning and scheduling using approximate dynamic programming. The integration of planning and scheduling is arising issue in operation research and engineering. First, the optimization of each stages are studied. In planning optimization, two cases are presented:

The first example presents a mathematical framework for planning an energy supply system. The proposed model presents an optimization approach and formulation that divides the total energy resource optimization problem into two separate, manageable ones: the traditional and renewable energy resource planning problems, respectively. The renewable energy planning problem is based on the standard portfolio, often set by the government. This separation can provide more manageable and relevant sensitivity analysis for each variable. Compared to the multiregion approaches for energy planning, this study suggests an improved approach to defining subsystems by reflecting the characteristics of each region and the flow of energy resources

In second cases, the optimal replacement of water pipes is presented. Pipe breaks in municipal water distribution network cause significant damage economically and socially. Existing methods for optimal replacement scheduling of pipe under limited resources do not provide actual indicator to select an individual deteriorated pipe. This chapter reformulates the selection problem as the decision of preference ordering or ranking and proposes a bipartite ranking based approach. The suggested approach also considers loss from broken pipes in water supply network in terms of the costs

associated with broken water main and its repair. We use rank aggregation method to integrate multiple ranks into replacement order of water mains. The suggested framework prioritizes current pipe sections for replacement according to the rank aggregation. Multiple ranks given by the reliability of water pipe sections are aggregated and a cost effective policy is derived to guarantee reliability of each pipe.

In case of scheduling, we present new formulation based on previous researches. Scheduling is a key decision process in manufacturing system of chemical process. There are many uncertainties to affect scheduling including rush order or machine breakdown. These uncertainties affect decision in overall manufacturing system and bring not only infeasibility of scheduling but also, other step such as strategic planning and process control. Thus, scheduling problems that exclude various uncertainty are not appropriate to deal with real situation. For treating uncertainty in scheduling, 2 methods are often employed, proactive scheduling and reactive scheduling. Proactive scheduling makes decision prior to scheduling using the knowledge of the uncertainty that can be generated. In contrast, reactive scheduling is to modify production schedule when unexpected event occurs.

Previous reactive scheduling solves optimization problem or obtains solution considering only current situation in each decision epoch when unpredicted event occurs. However, it is optimal solution until another unpredicted event occurs, which means in a long term, these solutions cannot guarantee to be optimal. To improve this problem, probability should be reflected in each time. In other words, solution of scheduling in each decision epoch needs to be proactive. But, it is nearly impossible to obtain solution of this type of problem in real time in previous stochastic formulation. If we can give proper solution in time, it is very helpful to deal with unpredicted situation using state transition and each solution is proactive. For this, we propose dynamic programming framework that provides stochastic optimal solution when unpredicted event occurs. And to deal with computation complexity, we introduce approximate dynamic programming. We use previous example in Kondili et al. First, Markov decision process based on previous MILP for STN is built. And

instead of price optimization, we reformulate the problem that minimizes makespan with uncertainty including machine breakdown and demand. The decision epoch depends on operation availability in each equipment. This value function can deduce proactive optimal policy for stochastic scheduling and when uncertain situation occurs, we can regard it as state transition and it is possible to produce optimal policy online in real time. This value function also can help to discuss feasibility in current situation when unpredicted events occur.

Finally, the integration framework of planning and scheduling is suggested. Based on previous chapters researches, we can get the optimal planning and scheduling policy. Scheduling provide the information of feasibility to planning whereas planning provide the amount of product needed to scheduling. These interchange of information does not require the time-consuming jobs and it is possible to update the new information in real time. The ability that make decision proactively and handle uncertainty online can be identified.

Keyword: Scheduling, Planning, Approximate dynamic programming

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Chapter 1

Introduction

1.1 Process scheduling and planning

In recent years, the need for improvement of productivity to increase the global competiveness brings interest for supply chain management. Supply chain means multiple decision steps for meeting customers demand at low cost as presented in figure 1.1.

Among these steps, planning and scheduling are the most influential decision steps in real cases. Planning is the uppermost level in decision steps and can be divided to 2 types, strategic and tactical planning. Strategic planning is a series of decisions for establishing the total network, such as number, locations and capacity of entities. Based on strategic planning, tactical planning make decision related to allocation of resources and transportation. Scheduling, also called operation planning, determines allocation and sequence of tasks into units.

Scheduling is very important step because of playing a role as connection between operation level and planning level. This characteristic bring interest for many researchers in engineering and operation research. It has various form from each industry in objective function and modeling environment. Generally, time-related objective

functions, makespan (the time required to complete all tasks)or latness/tardiness minmiziation is employed. In other hand, in chemical process, the maximization of profit or minimization of cost becomes typical objective function. It is caused that chemical plant is heavily loaded facilities where all production can be solved [1].

For formulation of production process in chemical scheduling, 2 characteristics must be considered in advance. First, the most important issue is the time representation, discrete and continuous approach. In discrete time representation, start and end time of task can arise at only bound of time intervals. Generally, the key factor of discrete time formulation is the binary variable $W_{i,j,t}$. That determines whether or not allocating a task i to machine j at the beginning of time interval T. The advantage of this formulation is the effectiveness of representing and solving the problem. In discrete time representation, the mathematical programming can be well structured. In this framework, representing all constraint can be easier and simpler to solve, especially storage and resource limitation. These point brings interst of researchers and examples based on this approcah include those present by Kondili et al [2], Shah et al [3] and Rodrigues et al [4]. But, it accompanied disadvantage, disobeying continuous nature of time, which makes solution suboptimal, and even infeasible in worst case and making integer variable of problem very large.

It brings additional research to devise techniques for diminishing computational complexity of large MILP of discrete models. Reformulation means replacement of new constraint for reducing integrality gap. Orcun et al use Reformulation linearization technique to MILP scheduling to reduce the integrality gap [5] and Yee et al reformulate the allocation and batch-sizing constraints based on variable aggregation and disaggregation [6]. Adding the integrality gap is the one of most widely

used method for reducing solution time in branch and bound process. Dedopoulos et al introduce additional constraints that build clear relationship between binary variables for scheudling of multipurpose plants [7]. Burkard et al add a number of additional constraints such as lower bounds of the number of batches and total batch size according to demands for each final product and intermediate material [8]. Decomposition is the representative method to overcome the computational difficulty for the solution of large MILP problem. Pinto and Grossman suggest decomposition scheme that MILP model for determining assignment binary variable and optimization to minimize earliness with fixed binary variable in multistage batch plants [9]. Bassett et al introduce time-based decomposition scheme [10] and Harjunkoski et al applied decomposition scheme to steel plant. In these framework [11]. Customer orders is divided into groups based on similar properties and each group is scheduled independently.

To improve these drawbacks of discrete formulation, continuous time representation is introduced. The most important value of continuous formulation is to preserve problem exactly. It has various form from type of process. For example, global time points and unit-specific time events can be used for general network process. But, in sequential process, time slot and precedence-based approach is the proper method; In global time points, unit shares global time but timing of time interval is the variable of new model. It can incorporate a wide variety of considerations in process scheduling including intermediate storage, change-over, operational modes, due dates and various objective functions. These time point methods need to predefine the number of timing and event points. These factors affect the optimality of scheduling. If fewer point is used, schedule is suboptimal of infeasibility whereas excessive point can lead

to unnecessary computation load. Hence, for this, iterative framework method is suggested. Unit-specific method is proposed an original concept of event points but in different unit, location of event points is different. These heterogeneous locations help to reduce required the number of event points in comparison to global event based model. It also has determining of event point and it can

In the other hand, time slot can be used, which means set of predefined time interval with unknown duration. Slot based method determines the number of time slots to allocate them to batch. It brings a large number of binary variable and predefined number of time slot is used and hence optimality cannot be guaranteed. Alternative method for sequential process is introduced by Mendez et al. It is precedence based approach It does not rely on time slots for task unit allocation and hence can be more accurate and lead to better solution. However, in real cases, this technique leads to large-scale mathematical programming.

Second characteristic is the process network representation. STN (State Task Network) is first introduced by Kondini et al [2]. STN consists of 3 elements: state node to represent all type of material including raw materials, intermediate product and final product denoted by a circle, task node to represent an operation denoted by a rectangle box and arc for connecting the corresponding state and task nodes. RTN formulation is the extended ideas from STN by Pantedlias et al. and it describes network by all resources such as equipment, storage, material and utility as resource in a unified way [12]. In this formulation, circle represents states and also other resources such as processing units and vessels. Figure 1.2 presents process as stated in Kondini et al using each technique [2]. Besides, changeover, storage policies and so on can affect to represent environment of network process. Based on this formulation,

a considerable methods are applied to a wide variety of real-world problems.

Though dealing with one decision-step problem is also issue, many researchers focus on integration of decision steps, such as control and scheduling or (tactical) planning and scheduling. Seemingly, theses stages are entirely separated, but they are actually highly interconnected, which affect optimality or feasibility of other decision stages. The importance and difficulty of integration had been reported for a long time [13]. The first method that figure is following hiercherical nature of decision stages, namely sequential framework It is the simple and fundamental strategies and the information can flow only from higher level to lower level. It does not require higher computation. Instead of delivering information of higher level into lower level, we can devise model that includes scheduling for all planning period and solution can give all the information. These solution strategies have great advantages that all information can be shared in both level. However, for horizon of planning, scheduling problem evolve an enormous size of problem and hard to solve and need advance solution technologies. Hence, some researchers propose decomposition method based on structure such as Bender decomposition [14] and Lagrangian relaxation [15]. Instead of both method, arbitration plan can be used. Iterative methods can make information flows from the scheduling problem to planning problem. It helps to provide tighten cut. More specific details are included in Maravelias et al [16].

In reality, there are various uncertainties in planning and scheduling problem such as raw material availability, price, machine reliability and market requirement, and these make optimization of supply chain problem more difficult. By Janak et al, slight variaiton in system makes problem infeasible [17]. In the intergration framewrok, it becomes more severe becaus of possibility that affects other decision steps. As a

result, systematical method for handling unceratinties is also antoehr importnat issue in supply chamin management.

In scheduling, there are two method for treating uncertainties. First, considering uncertain parameter, scehdule is preventively made. It is called proactively method. For solving these problem, we can use algorithm for stochastic optimization. Two-stage stochastic programming approach is one of representative methodology for stochastic scheduling. In the first stage, variables that must be ascertained are fixed before the uncertain parameter can be known and in the second stage, expectation is evaluated to represent recourse decision that are enacted upon the realization of the given uncertain parameters. However, it has shortcomings which it requires expensive computational load if scenarios we need to consider increase. Although this disadvnatage, it had been studied by many researchers [18, 19]. Robust optimization techniques gurantee that the obtained solution is feasible for the nominal state set of system condition, as well as robust with regard to the multiple forms of uncertainty present within the system under investigation. Lin et al applied the robust optimization to MILP models when aggregate demends, processing times, or prices are uncertain [20] . Also, chance constraint programming [21, 22] and fuzzy programming [23, 24] are developed for uncertain scheduling. However, these techniques can handle event after exeucution of scheduling. For real world, another approach is necessary to revise existing scheduling. This approach is called for reactive scheduling. It is online optimization to adjust the current schedule upon realization of uncertain parameters. Most of these techniques rely on mostly heuristics and Li and Ierapetritou summarazied these rule for reactive scheduling [25].

The difficulty of uncertainty in planning and scheduling is intensified in integration problem of planning and scheduling and it is almost impossible to optimize online when unexpected event occurs. As a result, Integration of planning and scheduling with uncertainties need to elegant technology. Li et al make up rolling horizon framework for integration of planning and scheduling using parametric programming [26, 27]. This methodology s worth that the proposed solution framework can also be applied to address the long-and mid-term scheduling problem. Y chu et al developed a hybrid method combined with multiple methods including mixed-integer linear programming solver for the planning problem, an agent-based reactive scheduling method and a cutting plane constraint when constraint is not met. From the statistical test on the final solution, it can be validated if the service level constraints are satisfied with the given probability confidence. However, these methods cannot be formulated with proactive and reactive scheduling based on optimization, not heuristics. To improve these disadvantages, new methodology need to be introduced.

1.2 Approximate dynamic programming for planning and scheduling

All the type of scheduling with uncertainties result in stochastic sequential decision optimization problem. Generally, for describing the environment and variation of process, it needs some elements: state, policy transition probability. State express the overall information for optimization. In this, information for representing the constraint and objective function must be included. Action evolves current state to next states. This action means only all policy that we can control. Hence, in deterministic problem, next state can be visited using only current state and action.

But, in case of stochastic optimization, there is no way to identify the next state until this uncertain information becomes real situation and we can know only the possibility that may visit the other state from the current state, which is called for transition probability.

Given these factors, decision will be made according to immediate rewards and the expected future rewards. Some solutions provide the large immediate reward but poor future reward. However, it means that overall reward is not optimal. For optimal solution in long term, maximizing the expected rewards over a given horizon become main objective. With uncertainties, it cannot grasp the next state, and also any reward except immediate reward. Thus, based on current state, we can represent reward from the current decision and overall next reward. In other words, from repeatedly decision, we can gain the reward and it is represented as recursive optimality equation, called for Bellman optimality equation.

$$V(s) = \max_{a \in A} \{C(s,a) + \gamma \sum_{s' \in S} V(s' \mid s)\} \tag{1.2.1}$$

where $V(s)$ is the value of being in state s and contribution $C(s,a)$ generated by action a in current state s. For solving this euqation. two techniques are generally employed: value iteration and policty iteration. Two tehcniques is different from whether properties are converged but have similair process unitl converging optimal vlaue and optimal policy. In simple problem, state space and action space is small and it is possible to solve this problem. But, in real cases, technique mentioned before cannot be calculated in the limited time because of curse of dimensionality. Curse of dimensionality is inherent property that explode the number of states or outocme as variables growth. Even more, expectation make to devise solution algorithm more difficult. In other word, by nature, dynamic programming is conceptually elegant,

but computationally inefficient.

To improve this problem, approximate dynamic programming was introduced. The interesting thing is that the similar techniques are developed though different reason. Most famous and representative method is reinforcement learning designed in artificial intelligence community. It springs from imitating reinforcement mechanism that learn how to make good decision by observing their own behavior and improve their action. In some control and engineering community, neuro-dynamic programming is suggested by Bersekas [28]. It can be summarized as dynamic programming with function approximation using neural networks.

Most important and valuable technique in approximate dynamic programming and relatively difference with reinforcement learning is methodology that chooses to construct architecture for approximating value function. There are some methods for approximating value function: hierarchical aggregation, nonparametric function, parametric function and piecewise linear, separable function.

For applying approximate dynamic programming, more issues are discussed. First, post decision varialbe is another key concept developed in approximate dyanmic programming. It is way to overcome difficulty of calculating expecation. When using the post decision state, Bellman equations can be broken into two steps.

$$V_t(S_t) = \max_{a_t}\{C(S_t, a_t) + \gamma V_t^a(S_t^a)\} \tag{1.2.2}$$

$$V_t^a(S_t^a) = \mathbf{E}\{V_{t+1}(S_{t+1}) \mid S_t^a\} \tag{1.2.3}$$

If we substitiute equation 1.2.2 into 1.2.3, Bellman's equation can be obtained. In the other hand, if we substitute equation 1.2.3 into 1.2.2, we can obtain the optimality equations around the post-decision state variable.

$$V_{t-1}^{a}(S_{t-1}^{a}) = \mathbf{E}\Big\{ \max_{a_t}(C(S_t, a_t) + V_t^a(S_t^a) \mid S_{t-1}^a)\Big\} \tag{1.2.4}$$

This equation brings expectation outside of the max operator. It can give a tremendous computaional advantage. It represents a significant point of departue of our treatment of approximate dynamic programming. And, exploration versus explotation is also important problem. Only, usage of explotation drives local optimum but usage of only exploration cannot obtain optimal policy. Thus, right balance of exploration and explotation for improving policy is necessary.

For planning in supply chain, previous researchers apply approximate dynamic programming to optimize planning and in other hand, research is not sufficient to use approximate dynamic programming [29, 30]. Reinforcement learning has been applied for scheduling, especially, Q-learning. But, Q-learning is not appropriate for large-stochastic optimization online and to compress information. Roconi et al. tried to minimize tardiness in parallel machines to uncertain demand [31]. But it is not applied to chemical plant and nitration framework.

1.3 The scope of thesis

This dissertion present integration and optimization method for scheduling and planning using approximate dynamic programming. In chapter 2, we introduce planning in case of energy resource allocation. In this chapter, we show how to formulate energy resource problem for Korea energy situation from public data And we generate various scenarios for factor that affects the optimal policy choice. Chapter 3 presents chemical scheduling using approximate dynamic programming. For dynamic programming, we need to formulate Markov chain using previous formulation from

MILP. And we compare with MILP solution and our solution. Also, we need to consider what type of state function can be represented well of value function. Also, uncertainty affects our results of optimal scheduling. Chpater 4 represent integration framework of planning and scheduling. It needs to identify what type of information flow and when we need to interconnect. Finally, in chapter 5, the contribution and conclusion of this research are discussed along with future research directions.

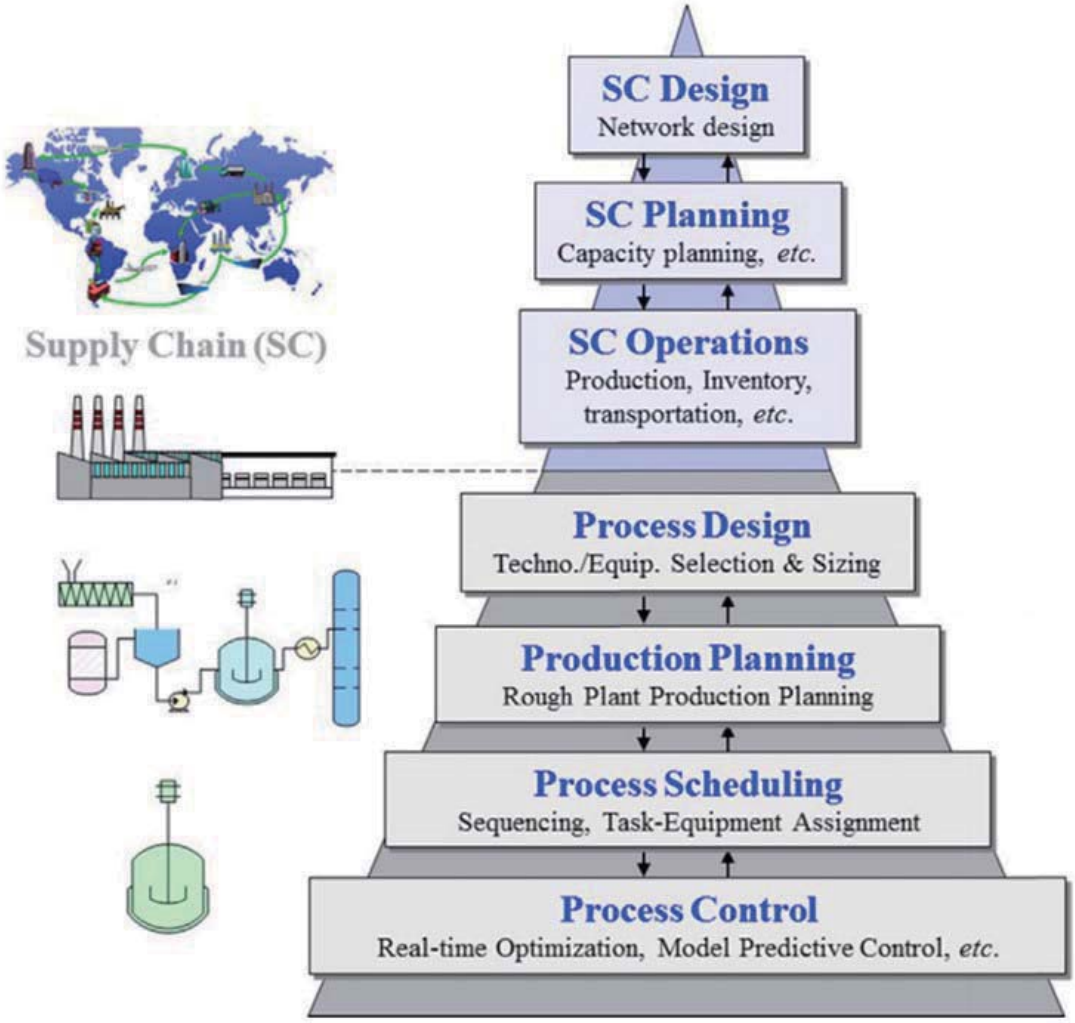
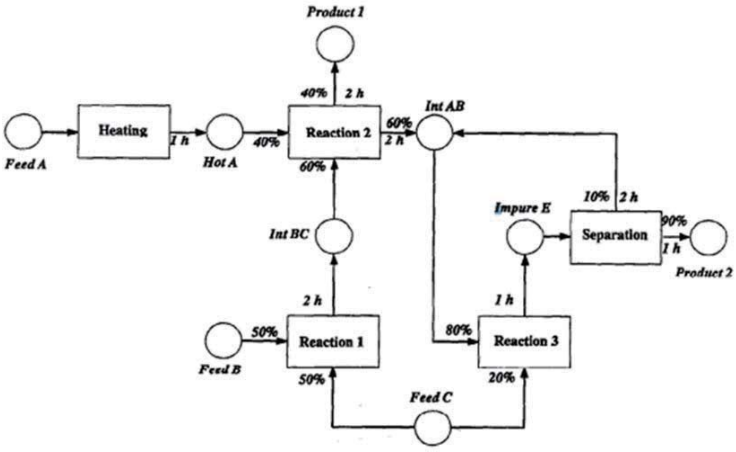
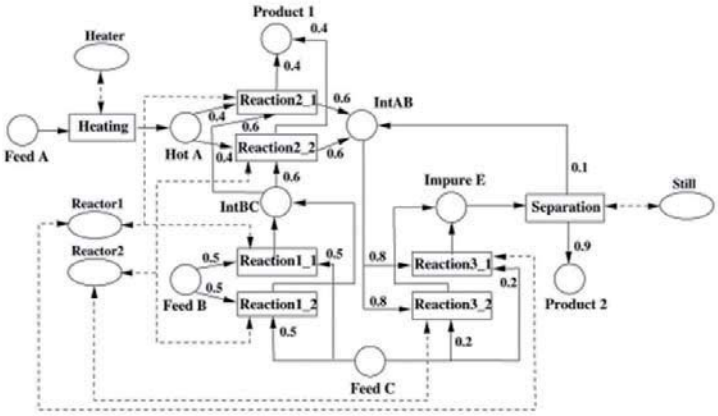


Figure 1.1: Configuration of supply chain



(a) State Task Network



(b) Resource Task Network

Figure 1.2: Network representation of process

Chapter 2

Planning in case of energy resource alloction in South Korea

2.1 Introduction

This chpater presents a mathematical framework for planning an energy supply system. Its model takes into account important factors affecting the total cost of supplying commercial energy such as market prices and waste disposal costs. As there is uncertainty in market prices and fuel demands, forecasting models are used to predict future prices and demand levels. Given a renewable energy portfolio standard that promotes energy generation from renewable sources, the large nonlinear planning problem can be decomposed into a mixed integer linear program and a nonlinear program for traditional and renewable energy sectors respectively), based on the portfolio standard. The nonlinearity arises in the learning curve that describes cost changes through future improvement in technologies for for exploiting renewable energy sources. The suggested approach can provide insights for crafting long-term policies, which can then be revised with updated information. The modeling framework is illustrated using public data from South Korea, interpreted in light

of country's policies. Results based on various scenarios indicate that uncertainty and the cost of waste disposal facilities signi

cantly affect the optimal policy choice.

2.2 Problem formulation for energy resource management in South Korea

2.2.1 Overall structure

The objective of the suggested modeling framework is to find an optimal energy planning policy that minimizes total cost at the level of nation, which is divided into several regions. The optimal policy must also satisfy each region's demands for energy sources such as oil, natural gas and electricity under uncertain market prices of these resources. Nuclear and renewable energy sources are used only to generate electricity in this problem. The decision variables are the construction of new power plants including the number, locations, and types and the allocation of energy resources including the source-specific amount of fuel imported into each region, electricity production, and electricity dispatch between regions.

The total cost consists of power capacity expansion, fuel purchase, and electricity production costs. Figure 2.1 shows the overall framework of the proposed model. Since the decision is made annually with the total cost summed based on multiple time periods in the future,(i.e., 20 years ahead), the raw material costs of traditional resources for electricity generation, which fluctuate over time, must be predicted every year in a receding horizon fashion. While planning for capacity expansion of

traditional energy-based power plants depends mainly on the capital cost and fuel prices, that for constructing renewable energy power plants is based on technological improvements, as renewable energy's current price is less competitive. Demand is another uncertain parameter that must be predicted every year because decisions are made based on the demand for each type of energy source.

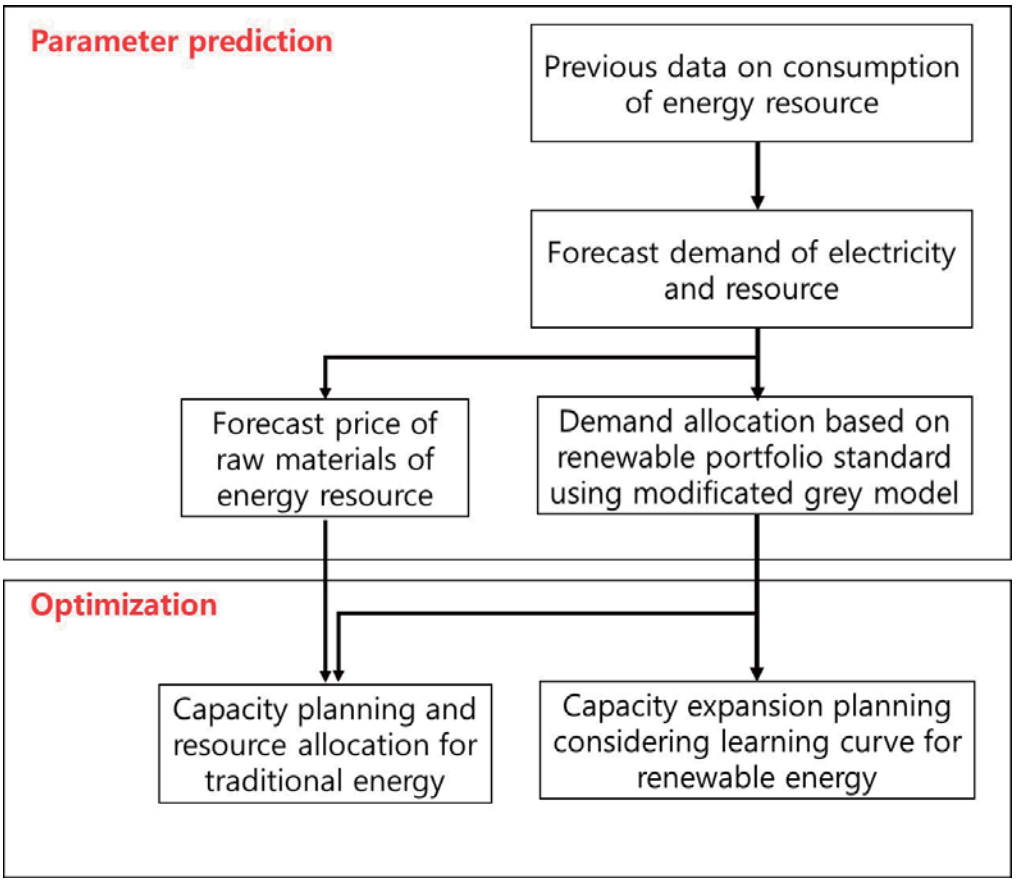


Figure 2.1: The overall process of optimizaiton

Since one large system cover the power generation ratios in the country as a whole, not production scheduling of power plants in a given region, the model decomposes the system into several subsystems. Within these subsystems, regional characteristics

such as port access can be reflected and the computational time can be reduced. The model assumes that each subsystem has four nodes representing the state variables for a given region. The demand, storage, conversion, and electricity demand nodes respectively represent the amount of energy demand, resource storage capacity, electricity production capacity of power plant, and electricity demand. Figure 2 shows a typical configuration of nodes and input/output for a subsystem. The subsystem acquires raw materials through import or transportation from other subsystems and uses them to satisfy the demand for a given resource or to produce electricity. Extra energy resources can be transported to other subsystems. The model makes annual decisions for the next 20 years for multi-geographic dimensions, i.e., at regional and national levels.

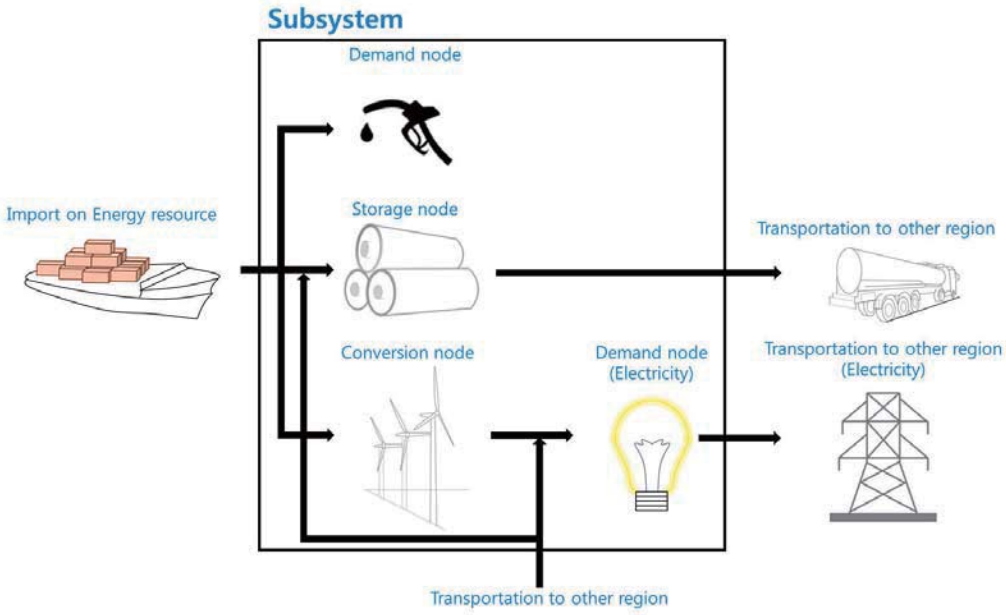


Figure 2.2: Configuration of subsystem

2.2.2 Model parameters and forecasting

Besides demands and prices, the remaining parameters such as the current state of energy resources and the conversion rates between different types of energy sources can be easily obtained. Information on the current state of reserved energy resources and power plants is available from the relevant institutions, such as the EIA in the US and the Korea Energy Statistics Information System (KESIS) in South Korea. The conversion factor is the ratio of electricity generated to the amount of raw materials used expressed in tonne of oil equivalent (TOE).

Methods for predicting uncertain parameters can be classified into two general groups : input-output and time series. Models in the first set identify causal variables that affect the parameters and finds a functional relationship. Models in the second category analyzes past trends in uncertain parameters using stochastic variables. Most parameters used in planning models are difficult to obtain using an input-output model because of the difficulty in identifying causality.

Demand

Many techniques have been suggested for demand forecasting including standard regression, time series model, econometric decomposition, cointegration, ARIMA, grey prediction methods, input-output models, fuzzy logic, integrated model and bottom up model. Among these, grey prediction methods can handle a system with only partially available information [32]; these model predicts the future values of a time series using recent data given a predictor size. In the present study, energy demand levels are related to gross domestic product or population but the exact relationships are not precisely known; we thus use a grey prediction scheme. We denote GM(n, m) as

a grey model with an order difference n^{th}equation and m variables. GM(1,1) is most widely used and can be used for a positive data sequence. Equation 2.2.1 shows a typical GM(1,1) model in discrete time where $x_p^{(0)}(k+H)$ represents the predicted value at time $k+H$. To obtain a and b, least squares method given a set of accumulated data $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$ is used.

$$x_p^{(0)}(k+H) = \left[x^0(1) - \frac{b}{a}\right] e^{-a(k+H-1)}(1-e^a) \tag{2.2.1}$$

The accuracy of the grey model can be improved using Fourier series of error residuals [33]. This residual is used to adjust the predicted value as in equation 2.2.2 and 2.2.3 [34].

$$\epsilon^{(0)}(k) = x^{(0)}(k) - x_p^{(0)}(k) \qquad k = 2, 3, ..., n \tag{2.2.2}$$

$$x_{p_f}^{(0)} = x_p^{(0)}(k) - \epsilon^0(k) \qquad k = 2, 3, ..., n+1 \tag{2.2.3}$$

where $x_{p_f}^{(0)}$ is the predicted value with the adjustment of using the residual $\epsilon^{(0)}(k)$. Details on the parameter choice are provided in Section 5.1

Price

Commodity price with uncertainty in continuous time can generally be expressed as a geometric Brownian motion (GBM):

$$dS = S_t(\mu dT + \sigma dz) \tag{2.2.4}$$

where S_t is the asset price at time t, dS is the increment in the asset price over dt, and dz is the increment in the Wiener driving uncertainty described by the logarithm of the randomly varying quantity following a Brownian motion. μ is the constant

drift and σ represents asset volatility. This model follows a lognormal distribution and has been applied to financial commodities [35]. However, it cannot describe long-term trend in natural resource prices, which tends towards an equilibrium value over a long-time horizon. On the other hand, the mean reverting model in equation 2.2.5 can converge to a long-run equilibrium, but cannot describe a price jump. Considering this, we suggest the mean reverting jump diffusion model(MRJD) given by equation 2.2.6.

$$dS = S_t(\mu - \ln(S))dt + \sigma S dz \tag{2.2.5}$$

Equation 2.2.6 represents a modified GBM process of continuous diffusion process with mean reversion and volatility terms. It is further extended to include the Poisson distribution to describe discontinuous jumps:

$$dS = S_t(\mu - \mu_k\phi - \ln(S))dt + \sigma S dz + \kappa S dQ \tag{2.2.6}$$

where μ_k is the mean jump size, ϕ is the average number of jumps per year, κ is the size of jump and dQ is the infinitesimal increment of a Poisson process.

2.2.3 Resources

Though most renewable energy sources are not economically competitive with fossil fuels, the use of renewable energy is expected to reduce dependence on conventional resources and mitigate their environmental impacts. In this respect, many countries require a certain percentage of electricity be produced from renewable sources.

Traditional resources

This study considers four types of traditional energy resources: coal, oil, natural gas, and uranium. The decisions to be made regarding these traditional resources include

the amounts to be imported and converted to electricity.

Fossil fuels Different types of power plants may use identical energy resources. For example, representative types of power plant using coal are the pulverized coal (PC) and integrated gasification combined cycle power plant(IGCC). In this paper, coal and liquid natural gas(LNG) are considered in two types of power plants: PC and IGCC for coal and natural gasification combined cycle (NGCC) and combined cycle for LNG. While fossil fuels are economically efficient at producing energy, their efficiency may give rise to environmental problems. Among these, CO_2 emitted from the combustion of fossil fuels is a major cause of global warming. There are ongoing efforts worldwide to develop technology associated with carbon capture and sequestration (CCS). CCS is concerned with the whole supply chain from separation of CO_2 in flue gas to transportation to storage facilities. Many countries regulate CO_2 emission by adding a carbon tax to existing environmental levies. Certified Emission Reductions (CERs) are the rights to emit CO_2 into the atmosphere and these are priced per the ton of CO_2. Our proposed model considers both CCS and CERs as ways of regulating CO_2 emissions [36].

Nuclear power generation The operational costs of nuclear power plant are typically much lower than those of a coal or natural gas plant, but radioactive wastes can become a critical issue in countries with insufficient storage capacity. Hence, the model must consider nuclear disposal, which can be classified into two methods: direct disposal and reprocessing. Direct disposal involves burying nuclear wastes without adding any fuel pellets to withdraw residues from waste. This process involves not only geological storage but also interim storage, packing and monitoring.

Reprocessing obtains plutonium or uranium from the waste and falls into two major categories: water or pyro-reprocessing. Each country chooses the method best suited to its circumstances.

Renewable energy This study considers three types of renewable energy resource: biomass, photovoltaic cells and wind. These are the dominant types although there is almost no power plant capacity currently using them. As mentioned above, renewable energy industry is too premature to compete directly with traditional resources in terms of overall cost. However, technological advances can make renewable energy cost-competitive. This technological progress can be described by a learning curve, where the total cost is given as C':

$$C' = \sum_{t=1}^{T} \left[\frac{Capa(t)}{Capa(0)} \right]^{\alpha} \cdot C(t) \tag{2.2.7}$$

where $C(t)$ is the total cost without learning effect, $Capa(t)$ is the cumulative capacity from time 0 through t and α is the discount factor associated with the learning rate of a particular renewable energy system. The following equation shows one possible relationship between α and the learning rate β.

$$\alpha = \frac{\ln(1 - \beta/100)}{\ln 2} \tag{2.2.8}$$

β is the percentage reduction in cost for every doubling of cumulative capacity. In other words, more cumulative experiences reduce the cost of capacity expansion and operation. The learning effect β is adopted from [37], and is assumed to be constant over the optimization time horizon. Intermittency is also another important factor to operate renewable power plant. In case of biomass, load of power plant is similar to traditional energy resource. However, because of unstable supply of renewable energy

such as wind and solar energy, the availability factor of plant is different for each season, and they need to be reflected in the constraints.

2.3 South Korea : a case study

We now construct an optimization model to reflect the current circumstances and issues in South Korea. Regarding CO_2 disposal, two offshore storage sites have been identified as candidates through government-sponsored research. The model evaluates the additional costs of CCS for coal power plant using amine-based capture plant and offshore storage [38]. For nuclear power plant, we only consider direct disposal because South Korea does not reprocess nuclear wastes owing to the Korea-US atomic energy agreement [39, 40].

Though the energy demand keeps increasing annually in South Korea, importation from other countries is almost the only way to supply energy resources. As such, each region is modeled as obtaining resources from its ports. We spatially divide the country into six regions for three reasons. First, the third basic plan for long term electricity supply and demand announced in 2006 divides the country into five districts to ensure an economical and stable electricity supply [41]. Second, administrative districts are considered for the expansion of power plant and supervision of energy resource facilities. When determining regions, the third consideration was whether large-scale industrial sites exist in the region. In this regard, Gyeongsang-do was divided into two regions: Gyeongsangnam-do (South Gyeongsang) and Gyeongsangbuk-do (North Gyeongsang)-with the demand of each of the two regions being almost the same as the demand of other regions. Hence, the proposed model is based on a total of six subsystems, as shown in Figure 2.3.

(a) The third power plan (b) Administrative districts (c) Proposed model

Figure 2.3: Geological divisions

In addition, South Korea has a petroleum-stockpiling program that requires reserving a certain amount of oil and gas to hedge against a worst-case scenario such as an oil crisis. In this model, a minimum amount of oil and gas kept in storage facilities for the forthcoming year is specified [42]. Another constraint incorporated into the model is that the law does not allow nuclear power plants to be constructed in the Seoul metropolitan region for safety considerations.

South Korea's power plant companies were requested to begin complying with renewable portfolio standards in 2012. According to this regulation, the renewable energy ratio is expected to increase by 1% per annum for the next 10 years [43]. Considering the learning rate associated with renewable energy resources, the regional and global learning rates may differ. Since South Korea makes significant investments in research on renewable energy and adopts the advanced technologies of leading countries, our model follows typical learning rates from previous researches [44, 45] as shown in Table 1. The size limit for the availability and technological level of renewable energy in South Korea can be also obtained from previous studies [46, 47]. Regarding the intermittency of renewable energy in South Korea, past availability

factors for each month can be found in the previous studies for solar and wind energies [48, 49].

2.4 Mathematical programming of the proposed model

The combined model is expressed through mixed integer linear and nonlinear programs for traditional and renewable energy resources, respectively. Previous studies on energy planning in South Korea suggest a minimum portion of electricity generation must be required to come from renewable sources [46, 50, 51]. If this requirement is not included in problem formulation, the optimization may result in no additional extension of power plants. Hence, this study divides the optimization problem into traditional and renewable energy resource problems with renewable portfolio standards. Then, the optimization problems for the two types of resources are independent of each other except for the demand and separable as follows:

$$\min_{u1,u2}\{f_{trad}(u_1) + f_{renew}(u_2)\} = \min_{u_1}(f_{trad}(u_1)) + \min_{u_2}(f_{renew}(u_2)) \tag{2.4.1}$$

2.4.1 MILP formulation for energy planning using traditional resources

Objective function

$$
\begin{aligned}
\min_{u_1}(f_{trad}(u_1)) = \min & \sum_{i\in P}\sum_{y\in Y}\sum_{r\in R} C_{\text{import}}(y) \times I(i,r,y) \\
& + \sum_{i\in P}\sum_{y\in Y}\sum_{t\in T} C_{\text{convr}}(r) \times Cv_{\text{elec}}(i,t,y) \\
& + \sum_{i\in P}\sum_{j\in P}\sum_{y\in Y}\sum_{r\in R} C_{\text{dispatch}}(i,j,r) \times Di(i,j,r,y) \\
& + \sum_{i\in P}\sum_{y\in Y}\sum_{t\in T} \left(\frac{1}{1+d}\right)^t C_{\text{Ext}}(t) \times NV_{\text{ext}}(t) \times Ext(i,t,y) \\
& + \sum_{y\in Y} \left(\frac{1}{1+d}\right)^t C_{\text{Ext,Nu}} \times Ext_{\text{Nu}}(y) \times NV_{\text{ext,Nu}}(t) \\
& + \sum_{i\in P}\sum_{y\in Y}\sum_{t\in T} C_{\text{emits,CCS}}(t,y) \times CO2_{\text{emit}}(i,t,y) \\
& + \sum_{i\in P}\sum_{y\in Y}\sum_{t\in T} \left(\frac{1}{1+d}\right)^t C_{\text{Ext,CCS}}(t,y) \times Ext_{\text{CCS}}(i,t,y) \times NV_{\text{Ext,CCS}}(i,t,y) \\
& + \sum_{i\in P}\sum_{y\in Y}\sum_{t\in T} C_{\text{oper,CCS}}(t,y) \times CO2_{\text{CCS}}(i,t,y)
\end{aligned}
\tag{2.4.2}
$$

The objective of the problem is to minimize the total cost of satisfying demand at the national level. This implies that the planning of electricity generation depends only on electricity demand and the cost of generating electricity associated with each resource, not on the flat rate or dynamic price in the domestic electricity market. Then the objective function of MILP in yearly optimization can be written in dquation 2.4.4.

Capital means the set including all the proper elements, for example, R is all the resources resources {coal, oil, natural gas, uranium}. The first term is the importing

cost of energy resources. In sequence, each subsequent term represents the costs of electricity generation, dispatch between subsystems, capacity expansion of power plant, extension of nuclear waste sites, certification of CO_2 emission, CO_2 capture and storage, and operation of CCS processes. Depreciation is included in the extension cost through a discount rate of d.

Constraints

Demand In order to meet customer demand, resources must be imported or shipped, or stored resources must be used. The equations below are the supply and demand balances for each year with equation 2.4.5 describing the relationship between energy resources and electricity generation. The conversion factor ϕ also includes the generation efficiency, load factor and capacity factor. Even though it is not considered in many energy resource problems for long-term, peak load is still another important constraint, which is difficult to include in yearly constraints. Since the proposed formulation is for long term planning, the hourly loads cannot be considered. In order to address the issues, peak reserve constraints in equation 2.4.7 is included. Peak load demand in peak season is represented as several times higher than the average yearly demand.

$$\sum_{i \in P} Di(i,p,r,1) - \sum_{i \in P} Di(i,k,r,1) - D(p,r,1) + I(p,r,1) \\ - Cv(p,r,y) = S(p,r,1) - S_0(p,r) \qquad \forall p \in P \quad \forall r \in R \tag{2.4.3}$$

$$\sum_{i \in P} Di(i,p,r,y) - \sum_{i \in P} Di(i,k,r,y) - D(p,r,y) + I(p,r,y) - Cv(p,r,y) = S(p,r,y) - S(p,r,y-1) \qquad \forall p \in P \quad \forall r \in R \quad \forall y \in \{2..20\} \tag{2.4.4}$$

$$\sum_{t \in T} Cv_{elec}(p,t,y) = -\sum_{i \in P} Di_{Elec}(i,p,y) + \sum_{i \in P} Di_{Elec}(p,i,y) + D_{Elec}(p,y) \times R_{Elec} \qquad \forall p \in P \quad \forall r \in R \quad \forall y \in Y \tag{2.4.5}$$

$$\sum_{t \in T} Cv_{Elec}(p,t,y) = \phi(r) \times Cv(p,r,y) \qquad \forall p \in P \quad \forall r \in R \quad \forall y \in Y \tag{2.4.6}$$

$$Cv_{Elec}(p,t,y) \leq Capa_{max}(p,t,y) \quad \forall p \in P \quad \forall t \in T \quad \forall y \in Y \tag{2.4.7}$$

$$\sum_{t \in T} Capa_{max}(p,t,y) \geq D_{Elec,peak}(p,y) \times (1+\delta) \quad \forall p \in P \quad \in R \quad \forall y \in Y \tag{2.4.8}$$

Extension Additional capacity for storage and electricity generations must exceed a certain value. Without this constraint, the optimization may yield unrealistic results such as a 1 kW power plant. Hence, a nominal capacity value is specified based on the literature [52].

$$S_{max}(p,r,y) = S_{max}(p,r,y-1) + NV_{storage}(r) \times S_{ext}(p,r,y) \qquad \forall p \in P \quad \forall r \in R \quad \forall y \in Y \tag{2.4.9}$$

$$S_{max}(p,r,1) = S_{max,0}(p,r) + NV_{storage}(r) \times S_{ext}(p,r,1)$$
$$\forall p \in P \quad \forall r \in R \quad (2.4.10)$$

$$Capa_{max}(p,t,y) = Capa_{max,0}(p,t) + \sum_{y_{pr}} Nv_{Ext}(t) \times Ext(p,t,y)$$
$$\forall p \in P \quad \forall t \in T \quad \forall y \in Y \quad (2.4.11)$$

Regional constraints Some regions of South Korea cannot import certain types of resources because unloading or storage facilities are not available. These are expressed in Eqs 2.4.12-2.4.14. Additionally, the oil reserve program requires that at least one quarter of the expected volume of oil demand in the following year be stored.

$$I(\{3,4\},3,y) = 0 \quad \forall y \in Y \tag{2.4.12}$$

$$I(3,2,y) = 0 \quad \forall y \in Y \tag{2.4.13}$$

$$I(\{2,3,4,6\},5,y) = 0 \quad \forall y \in Y \tag{2.4.14}$$

$$\sum_{r=\{2,3\}} \sum_{p=\{Place\}} S(p,r,y) \geq \frac{1}{4} \times \sum_{r=\{2,3\}} \sum_{p \in P} D(p,r,y) \qquad \forall y \in Y \tag{2.4.15}$$

Nuclear wastes and CCS Amounts of nuclear waste and CO_2 from power plants must be assigned to processing facilities as follows:

$$\sum_{p \in P} \sum_{y \in Y} Cv(p,4,y) \times \phi_{Nuc} \geq \sum_{y \in Y} Ext_{Nuc}(y) \times NV_{Ext,Nuc} \tag{2.4.16}$$

$$\phi_{CO2} \times Cv_{elec}(p,t,y) = CO2_{CCS}(p,t,y) + CO2_{emit}(p,t,y) \quad \forall p \in P \quad \forall t \in T \quad \forall y \in Y$$
$$(2.4.17)$$

$$\sum_{y \in Y} NV_{Ext,CCS}(p,t,y) \times Ext_{CCS}(p,t,y) \geq CO2_{CCS}(p,t,Y) \quad \forall p \in P \quad \forall t \in T \quad \forall Y \in Y$$
$$(2.4.18)$$

2.4.2 NLP for optimizing electricity generation from renewable energy resources

The total cost of generating electricity from renewable sources includes capital cost, fixed cost and variable costs. The capital cost is strongly affected by the learning curve. With depreciation, the objective function can be written as

$$\begin{aligned} \min \sum_{r \in R'} \sum_{y \in Y} \left(\frac{1}{1+d} \right)^{y} \left(\frac{Capa_{max}(r,y)}{Capa_{max,0}(r)} \right)^{\alpha} \times C_{Ext}(r,y) + \\ Capa_{\max}(r,y) \times C_{fix}(t) + C_{convr}(r) \times Capa_{\max}(r) \times \phi(r) \end{aligned} \tag{2.4.19}$$

Constraints There are several types of constraints. First, electricity generation must meet the allocated demands.

$$\sum_{r \in R'} Capa_{\max}(r,y) \times \phi(r) \geq D(y) \times (1 - R_{elec}(y)) \tag{2.4.20}$$

Second, capacity limits exist for wind and solar power plants, whereas biomass power plants using wood or agricultural products do not have such constraints.

$$Capa_{\max}(r,y) \leq SL_y \qquad \forall y \in Y \tag{2.4.21}$$

In addition, intermittency of renewable energy resource causes unstable generation of electricity. Thus, to differentiate availability factors for each month, these factors for renewable power plant, especially solar and wind energy, are applied to the installed capacity.

$$\sum_{r \in R'} Capa_{\max}(r,y) \times \phi_{month}(r) \geq D_{month}(y,t) \tag{2.4.22}$$

$$\sum_{r \in R'} Capa_{\max}(r,y) \geq D_{peak}(y) \tag{2.4.23}$$

2.5 Results and Discussion

2.5.1 Demand and price forecasting

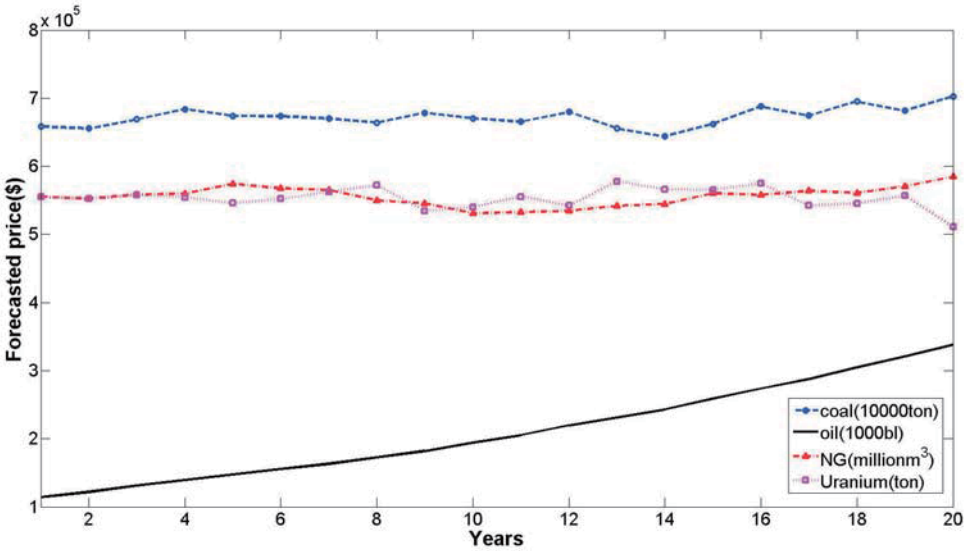


Figure 2.4: Forecasted price of energy resources

Our proposed prediction model given in Eqs.(1)–(3) forecasts future demand level and resource prices over the next 20 years using historical data on resource consumption in each administrative district of South Korea from 1990 to 2011 and imported material costs for the past 20 years [53]. Demand data for the administrative districts was converted to cover the subsystems. Figure 2.4 shows the forecasted price of energy resources, using a maximum likelihood approach (as in [54]) to estimate the parameters of the MRJD model. Model uncertainties are represented by a Wiener process for fluctuations and a Poisson process for jumps or spikes, and the size of the jumps follows a log normal distribution. The MRJD is solved using numerical integration.

Using Monte Carlo simulations, we generated 1000 samples to calculate the average parameter values.

The model prediction for the coal price is similar to that predicted by the EIA. On the other hand, the predicted price in LNG of the model is nearly double the price that in EIA 2013's report. This is because previous prices of LNG in KESIS increase continuously, while the price predicted by the EIA dropped sharply in early 2010 [52]. The EIA considered the impact of shale gas production on the natural gas prices, while the grey model depends on the historical data from KESIS.

In the case of demand prediction, the area around Seoul has more demand than any other region for all types of energy sources, except oil. For oil, Jeolla-do is following a trend of quickly increasing usage; the oil demand in Jeolla-do is thus expected to be the highest eventually, and the fluctuation due to the Wiener process is negligible because of this strong growth tendency. In the long term, the prices for most types of energy resources show either a slight increase or a constant value in the long term. The exception is the continuously increasing price of oil, which is attributable to past trend-namely the soaring after the 1980's oil crisis.

Traditional energy The proposed model provides power plant planning for each resource in a district using the predicted price, demand and other parameters, as shwon Tables 2–4. First, our model assumes that only oil and LNG can be stored because of the strategic stockpiling of oil and LNG in South Korea. Figures 2.8 and 2.9 show that the import trend for importing coal is different from that for oil. The amounts of coal to be imported gradually increase over time, whereas oil is imported mostly during the first ten years of the planning horizon with a decreasing trend because of increasing oil prices over the next 20 years. In addition, coal cannot be

stored and thus only the needed amount should be imported every year, while oils can be stored.

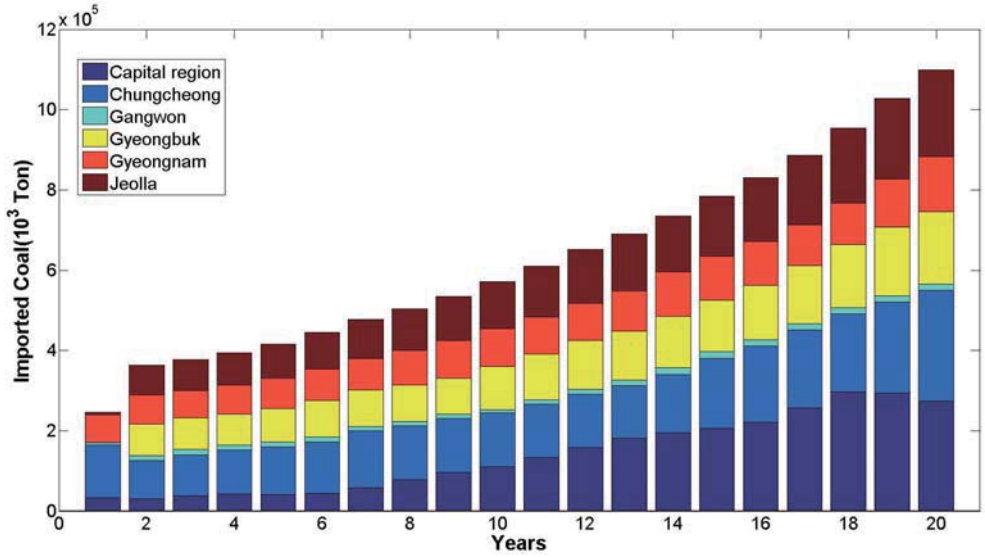


Figure 2.5: Amount of coal imported

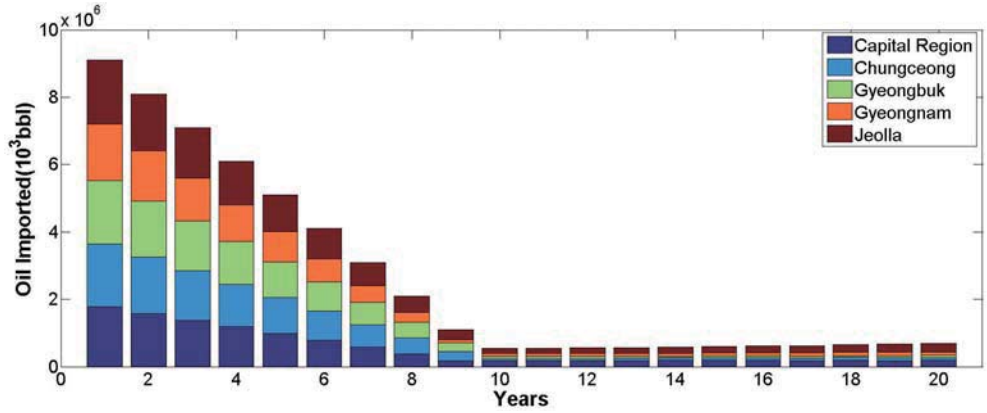


Figure 2.6: Amount of Oil imported

Figure 2.11 shows that coal-based power plant account for the highest portion of

electricity generation even though nuclear power plants have the highest caloric value-to-resource price ratio. This is because the cost of handling nuclear wastes becomes the dominant factor. Since PC technology is less expensive than that of IGCC, the share of the PC-type power plants is larger. Although coal power plants generate more CO_2 than do LNG power plants, they can be cost-competitive even with CERs. The price of the CO_2 emission tax including CERs is shown to be below \$25/ton CO_2 after 2009 and maintained at around \$10/ton CO_2 in 2011 [55]. LNG is the second most used resource in electricity generation. While its main purpose at present is to supplement coal power plant, LNG may still become the most widely used energy resource. Moreover, if the price for CERs increases or CCS becomes a mandatory process in coal-based power plants, LNG may become the most important resource from both an economic and an environmental perspectives. In the case of the United States, construction of LNG power plants takes a higher priority.

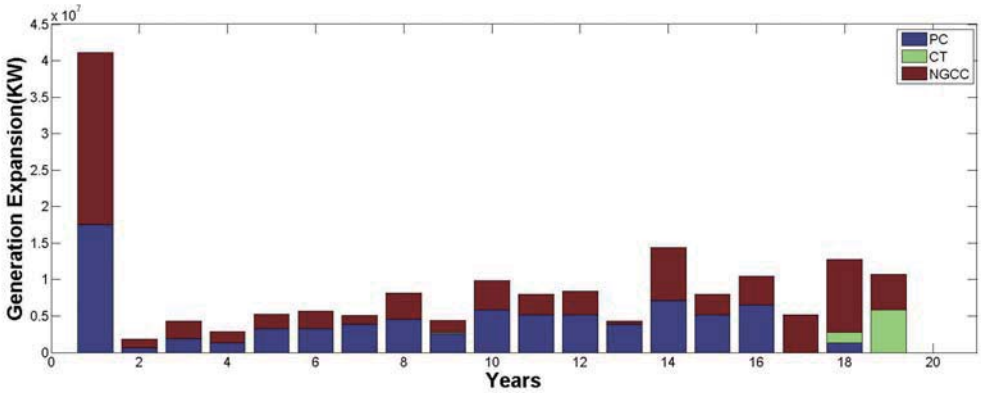


Figure 2.7: Overall extension of power plant

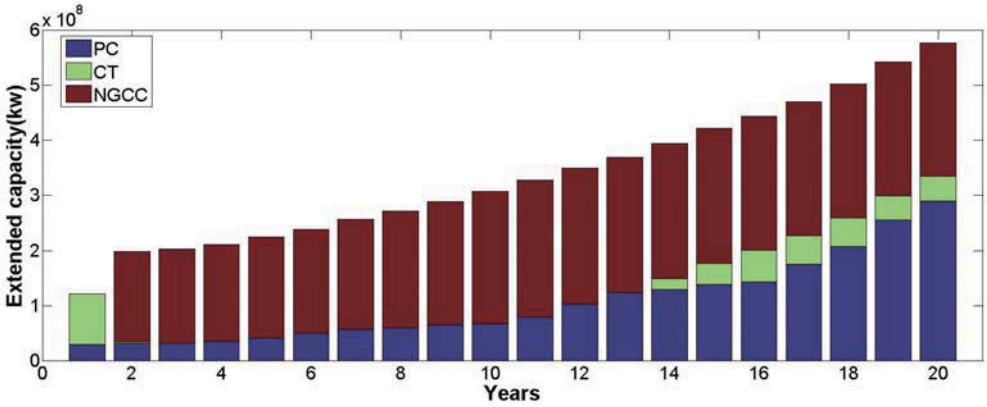


Figure 2.8: Overall extension of power plant in capital region

The optimal solution recommends extending coal-based power plant based on price forecasting. It should be noted that the recent decrease in LNG cost owing to shale gas development is not reflected here because the predicted cost is based on historical data [52]. In the next section, we provide an alternative scenario involving low LNG cost with reference to EIA reports.

For hydroelectric power, the volume generated remains relatively small and fixed, accounting for only of South Korea's energy supply. Hence, 8% of the total demand was allocated to hydropower generation. Total electricity generation is thus analyzed in terms of coal, NG, nuclear and renewable energy. Figure 2.10 show the extension plans. Figure 2.11 and 2.12 shows the amounts of electricity to be generated using each type of resource for the entire country and the capital region, respectively.

Renewable energy While wind power has the lowest cost for electricity generation, its growth is limited by the size of available wind farms. Photovoltaic power plant may also have a limit but this upper bound is too large to practically exceed.

The quantities of agricultural products and wood available as biomass for energy generation can be limited and the size limits are suggested in Table 5. Because maize or candy corn used as an energy crop, is rarely cultivated in South Korea, other sources, such as woodchip and waste become major raw materials for biomass. These resources neither limit the size of the power plant, nor affect the biomass price. Figure 2.13 shows the optimal cumulative capacity of renewable energy power plant for the next 20 years. This result is similar to a previous study that strongly recommended construction of photovoltaic power plants [46]. Size limit is most critical constraint that restricts more addition of wind capacity which is considered as the cheapest renewable energy. Except this constraint, monthly availability factor affects crucially composition of renewable energy power plant. For grasping effect of monthly constraint, sensitivity is analyzed with cage of monthly demand from -10%,-5%,5%,10%, which shows year when capacity of photovoltaic power plant reaches size limit changes slightly.

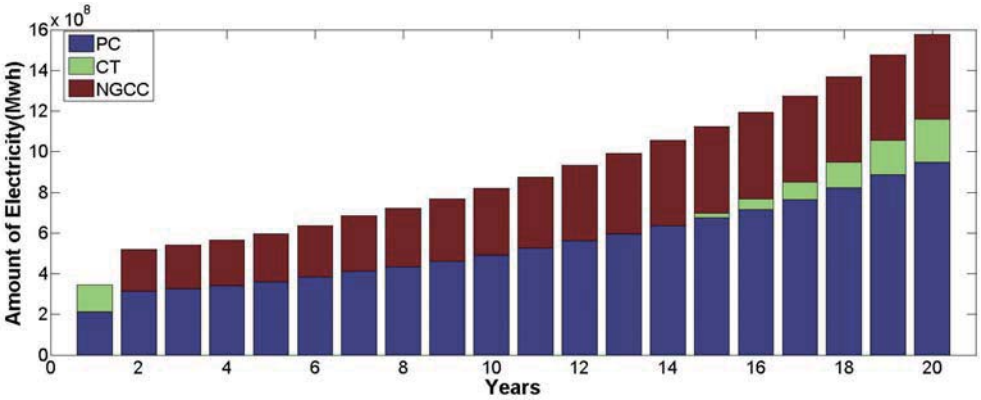


Figure 2.9: Amount of electricity generation using each type

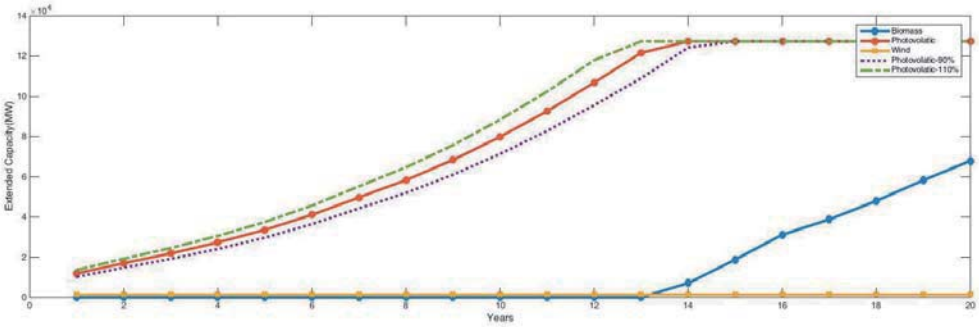


Figure 2.10: Extension of renewable power plant

Byproduct treatment process Because nuclear power plants entail an risks of leakage or explosions that can bring about critical damages, construction of nuclear power plant is declining globally. In addition, considering the disposal cost of nuclear wastes, the total cost of electricity generation is no cheaper than that using other traditional energy resources. Table 4 shows that the cost of managing nuclear wastes can be low if temporary storage in power plant is used as is currently done. This temporary storage scenario is analyzed in 5.2.

For CO_2 disposal, the model chooses CERs over CCS owing to a much lower overall cost. Some studies have reported that the emission tax level increases until CCS has economic benefits [56, 57]. Previous work also shows that the price of CERs or other emission trading rights may exceed \$70/ton CO_2 if the considers the whole chain of CCS [36, 38]. In this study, we examine the total cost over CCS for the next 10 years including constructing facilities and capturing, transporting, and storing of CO_2. Figure 2.14 shows that the break-even price is around \$160/ton CO_2. The difference between our result and previous works is that our model considers the total cost for all amounts of CO_2 generated while others consider the COE (cost of

electricity) only. Consequently, the result shows that the current price of emission trading including CERs is lower than that of CCS. This implies that either increasing the price of emission trading or improving the efficiency of CCS is necessary to reduce CO_2 emissions.

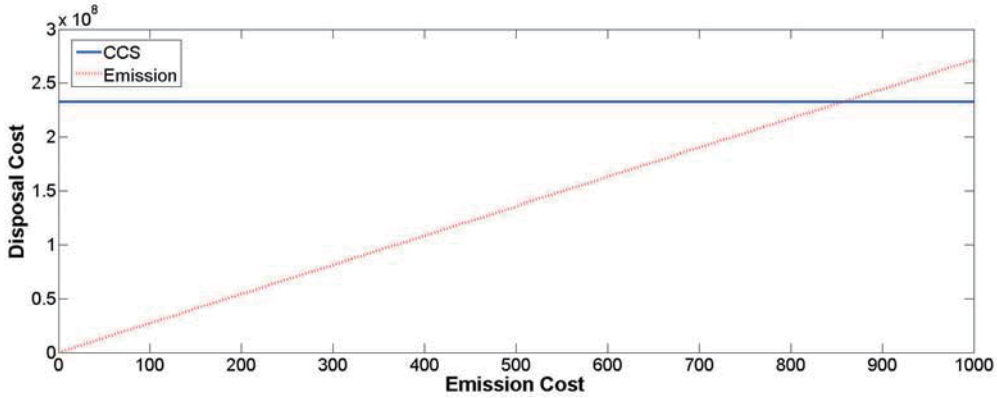


Figure 2.11: Breakeven price of CCS process compared to CO_2 emission

2.5.2 Sensitivity analysis and Additional scenarios

Demand In order to identify the effect of uncertainty, sensitivity analysis has been conducted with the variations of 5% and 10% in the electricity demands as shown in Table 6. When the demand varies with 5% and 10%, the ratio of energy resources for the power plant expansion does not change, meaning that small variations in the demand do not affect the overall decision related to the capacity expansion of power plant as well as the total cost of electricity generation.

Low LNG prices As shale gas is under active development, the price of natural gas is expected to decrease. Many researchers have studied the effect of shale gas development on the LNG supply [58, 59]. Since the EIA forecasts the price of LNG

to be about half of the forecasted in this model, we also analyze a new scenario using half the forecasted price, as shown in Figure 2.15. Compared with the results in Figure 2.12, LNG becomes a major source for generating electricity. This is caused by both a decrease in the price of LNG of raw materials and lower CO_2 generation compared to coal. These two scenarios show that coal and LNG can be major electricity. Moreover, CO_2 emission and resource prices are revealed as important factors in choosing the type of energy resources used.

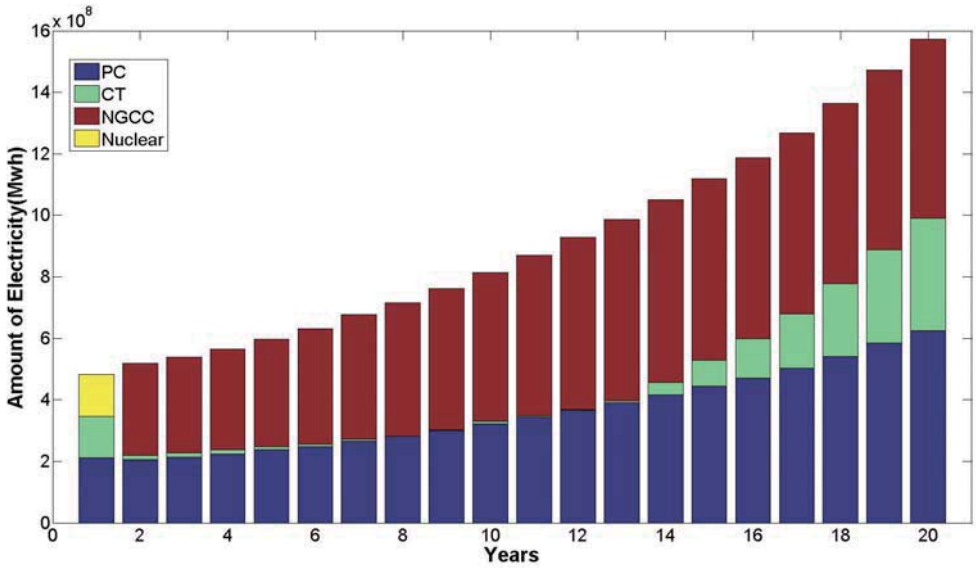


Figure 2.12: Amount of electricity generation using each type in case of low price of LNG

CCS At present, the CCS process is not cost-competitive in the CO_2 emissions trading market compared to CERs. Hence, a new scenario including CCS regulation is analyzed. In the early phase, coal is the most consumed resource for electricity generation. However, the share of electricity generated using LNG gradually increases

over time, more than in the original scenario. This is due to lower levels of CO_2 emissions and lower costs for CCS for LNG power plant than for coal-type plants. If CCS becomes a requirement or economically viable, there is expected to be a synergistic effect of LNG power plant with low LNG prices.

No nuclear waste disposal Low-level wastes is disposed of in Gyeongju-city, but high-level wastes, which incur much higher costs are temporarily stored in power plants. The storage capacity of the power plants has almost reached its limit [60]. Hence, the optimal model solution shows that nuclear power plant is no cheaper than fossil fuel plants if the disposal of nuclear wastes is considered. However, a different scenario could be analyzed if assuming that power plant storage was available, as it is now. Figure 2.17 shows that nuclear power plant can be more effective and become major sources. This indicates that nuclear wastes is a major factor in the total cost; the results are also similar to the ratio of electricity generated in South Korea, where nuclear energy remains the lowest-price resource [61]. However, the additional cost of nuclear wastes and other safety factors may prevent nuclear energy from becoming a major electricity-generating resource.

2.6 Conclusion

This paper has developed an overall model framework for energy resource supply that optimally considers the price of raw materials, technical improvement in renewable energy and waste disposal. Overall energy planning was separated into two problems based on South Korea's renewable energy portfolio. In the case of traditional energy resources, the model was formulated as a mixed integer linear programming

model of competing energy resource and demands. Two important factors, demand and price were predicted using a stochastic model and Monte-Carlo simulation. The determination of the level of renewable energy is formulated as a nonlinear programming model, taking into consideration the learning effect to account for technological improvements.

The results of the model can help decision-makers derive policies based on the scenarios that they want to examine. The analysis of basic scenario shows a different result from previous studies [46, 51] which recommend that construct nuclear power plant as major type of power plant. The sensitivity analysis and additional scenarios show that the uncertainty of price and strategic planning for waste disposal can considerably affect the optimal policy more than the demand variations. Considering these scenarios, other traditional energy resources such as coal, gas, and oil might be promising depending on the situation. The results of the renewable energy analysis show the potential of each type. Although wind is the cheapest renewable resource able to meet the allocated demand, the optimal solution shows that photovoltaic energy should be responsible for the largest share.

The proposed model might be improved by introducing more rigorous treatment of uncertainty including stochastic dynamic optimization techniques such as dynamic programming. However, simultaneously considering the uncertainty and subdividing the model makes it difficult to formulate the problem for stochastic dynamic optimization. The major strength of the model presented here is its ability to provide meaningful results based on various scenarios with simple formulations.

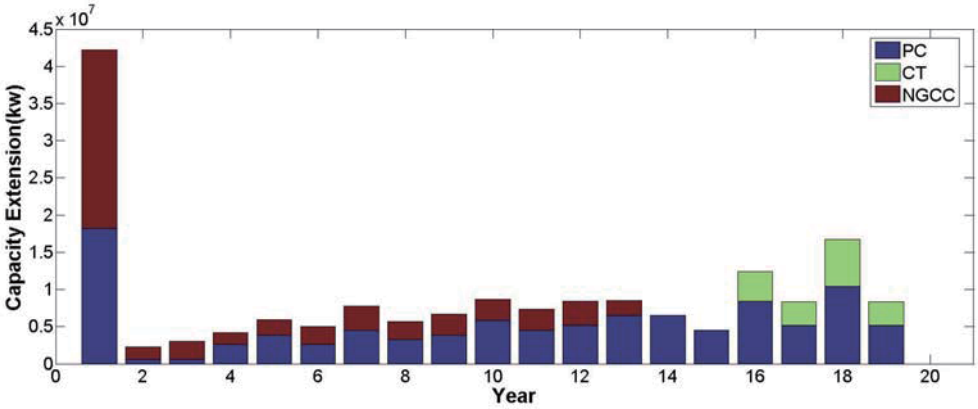


Figure 2.13: Overall extension of power plant using each type in case of CCS disposal

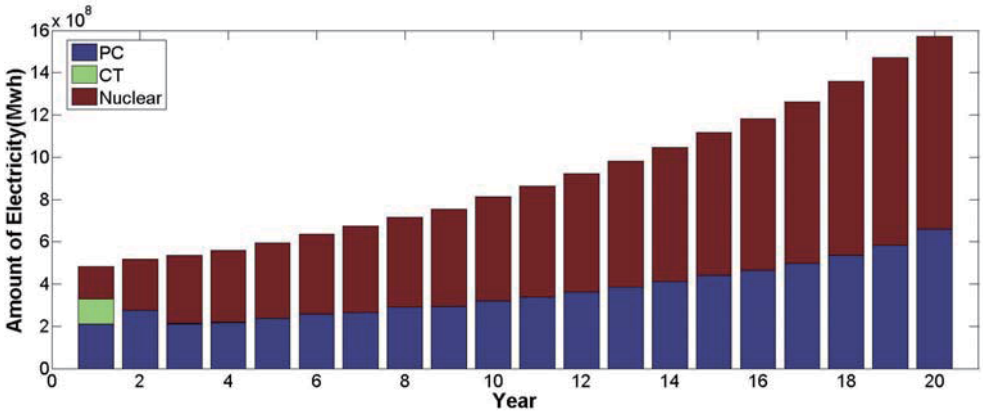


Figure 2.14: Amount of electricity generation using each type in case of no nuclear waste disposal

Appendix A

Outline

The basic indices we use in this model are

$y =$ time point of decision making, year $(1 \cdots 20)$

$p =$ region (1: Capital area, 2: Chungcheong, 3: Gangwon,4: Gyeongbuk, 5: Gyeongnam, 6: Jeolla)

$r =$ resource (1: Coal [10^3ton], 2: Oil [10^3bl], 3: Natural Gas (NG) [$10^3 m^3$], 4: Uranium [t

$t =$ power plant type (1: IGCC, 2: PC, 3: Oil, 4: CC 5: CT, 6: Uranium)

Cost parameters are :

$C_{\text{import}}(y)$ = unit cost of resource r at place i in year y

$C_{\text{dispatch}}(i, j, r)$ = shipping cost of resource r from place i to place j in year y

$C_{\text{Fixed}}(t)$ = fixed cost of power plant type of t

$C_{\text{convr}}(t)$ = variable operation and maintenance (O&M) cost of power plant type of t

$C_{\text{Ext}}(t)$ = cost for constructing additional power plant type of t

$C_{\text{Ext,save}}(r)$ = cost for constructing additional storage for resource r

$C_{\text{Ext,Nu}}$ = cost for additional disposal facility of nuclear waste

$C_{\text{Ext,CCS}}(t)$ = cost for constructing additional CCS process type of t

$C_{\text{fix,CCS}}(t)$ = fixed cost of CCS process type of t

$C_{\text{convr,CCS}}(t)$ = variable O&M cost of CCS process type of t

$C_{\text{emit,CCS}}(t)$ = CO_2 emission cost per ton

$C_{\text{oper,CCS}}(t)$ = operation and transportation cost for captured CO_2 in CCS plant

Conversion factors for generating electricity or waste from resources r are:

$\phi(r)$ = generated electricity from unit of resource r considering generation efficienc

$NV_{\text{ext}}(t)$ = nominal generation capacity for the construction of power plant type t

$NV_{\text{ext,Nu}}(t)$ = nominal capacity for the construction of nuclear waste disposal facility

$NV_{\text{ext,CCS}}(t)$ = nominal capacity for the construction of CCS plant

ϕ_{Nu} = amount of nuclear wastes from uranium power plant

ϕ_{CCS} = amount of CO_2 from power plant type t

The decision variables are:

$$I(i,r,y) = \text{amount of imported resource } r \text{ at place } i \text{ in time } y$$

$$S(i,r,y) = \text{amount of storage for resource } r \text{ at place } i \text{ in time } y$$

$$S_0(i,r) = \text{initial amount of storage for resource } r \text{ at place } i$$

$$Di(i,r,j,y) = \text{amount of resource } r \text{ shipped from place } i \text{ to } j \text{ in time } y$$

$$S_{\max}(i,r,y) = \text{maximum capacity of storage for resource } r \text{ at place } i \text{ in time } y$$

$$S_{\text{ext}}(i,r,y) = \text{additional capacity of storage for resource } r \text{ at place } i \text{ in time } y$$

$$Cv(i,r,y) = \text{amount of resource for power generation using resource } r \text{ at place } i \text{ in ti}$$

$$Ext(i,t,y) = \text{extension of power generation type } t \text{ at place } i \text{ in time } y$$

$$Di_{\text{elec}}(i,j,y) = \text{amount of electricity dispatched from place } i \text{ to place } j \text{ in time y}$$

$$Capa_{max}(i,t,y) = \text{maximum capacity of power plant type } t \text{ at place } i \text{ in time } y$$

$$Cv_{Elec}(i,t,y) = \text{amount of electricity generation in plant type } t \text{ at place } i \text{ in time } y$$

$$Ext_{Nu}(y) = \text{additional extension of disposal facility for nuclear waste in time } y$$

$$Ext_{CCS}(y) = \text{additional extension of CCS process for power plant type } t \text{ in time } y$$

$$CO2_{CCS}(i,t,y) = \text{amount of } CO_2 \text{ captured from power plant type } t \text{ at place } i \text{ in time } y$$

$$CO2_{emit}(i,t,y) = \text{amount of } CO_2 \text{ emitted from power plant type } t \text{ at place } i \text{ in time } y$$

Chapter 3

Plannig in case of water pipe management using ranking algorithm

3.1 Introduction

Systematic management of the water distribution network is becoming more important. Recently, the Korea environmental ministry reported that a ratio of pipe buried under the ground that are more than 20 years exceeded 30% nationally, and the average age of the pipeline in the capital region is over 30 years [62]. These deteriorations may bring about pipe breakage, property damage and problems in human life such as contaminated drinking water. Indeed, the major cause of pipe break accidents is deterioration of water mains, about 30% of the total accidents from 2008 to 2013, and the total damage from this breakage of water mains was estimated to be about 8.5 million dollars in South Korea [63].

Economic and sustainable maintenance of pipe network requires reliable estimation of the pipeline condition to be preceded. Nevertheless, it is difficult to identify or estimate the condition of pipeline in a proactive manner because the water main

is a very complex and intricate network under the ground without much real-time information available. Most accurate and conclusive techniques to determine the states of water mains are visual examination with naked eye after digging in the ground and nondestructive inspection. However, if applying these methods to pipe buried in a wide area, the total cost including direct costs for digging and indirect costs for traffic jam and water outage may be prohibitive.

Alternatively, two types models, physical and statistical, are often used to reduce the costs. Physical or mechanistic models can be used to analyze the operational and environmental stresses imposed on the pipe from various external sources and the pipe capacity to hold the loads. Though the physical model can accurately describe degradation mechanism of a pipe, its application to real system in predicting water pipe breakage is limited because the deterioration mechanism is very different for pipe material types and pipe structural properties. Furthermore, modelling the physical degradation process is time consuming and requires expensive, extensive data. On the other hand, statistical models can be formulated only using historical records of pipe break events with failure time and environmental data.

There exist previous studies using simple regression models to predict the time to next break of water pipe based on some factors [64]. However, these techniques have been evaluated to be not enough to establish a policy for water main mangement because they exclude the usage of data of non-broken water pipe. The most representative method that can utilize all types of data is the survival analysis [65], which is applied to predict the probability of pipe breaks. In addition, advanced statistical tools such as artificial neural networks [66], fuzzy logic [67], and Bayesian belief networks [68] as well as a simple Poisson distribution [69] are used.

While many statistical models have been suggested, there is still much room for further improvement for predicting pipe breakage. Debon et al. conclude generalized linear model (GLM) is the best based on receiver operating characteristic curve [70], whereas Yamigala et al. report even GLM still needs to be further improved for better prediction accuracy [71]. Moreover, to the best of our knowledge, existing methods do not provide a straightforward indicator for selection of an individual pipe that needs to be replaced but more of indirect, abstract information such as prediction of the total number of failures or the annual frequency of breakages per unit length. Wang et al. propose a rank algorithm to provide candidate pipes for preventive maintenance based on their failure risks [72]. Rank algorithm can use historical data and draw a preference ordering for further investigation. The algorithm shows satisfactory results for proactive inspection given limited budgets. For instance, 50% of pipe breaks of waterworks in 2011 could be prevented by inspecting 6.98% of its pipe in advance using data set available at the end of 2010.

However, conditions leading to deterioration of water main are not the only the factors that affect the water pipe replacement policy and other various considerations are also necessary including the cost of damage occurred when water main is broken. The optimal decision that considers reliability will only indicate short-term cycle replacement of all the pipes. Hence, the optimal scheduling of water mains considering these several factors has been studied in the literature by primarily focusing on optimization methods. Qiang Xu et al. categorize the models for pipe replacement optimization into two types [73]. The first is for calculating the optimal replacement time, where the lifespan is calculated by minimizing the total cost in a multi-objective

optimization framework [74, 75, 76] and threshold break rate [77, 78, 79]. The second prioritizes pipes the pipe for replacement given budget constraints. It orders the sequence of pipes to replace based on the replacement cost and reliability of pipes [80, 81, 82].

The sequence of replacement from rank algorithm can be used as a criterion for selection in prioritizing pipes, but the total ranking considering reliability, failure and repair cost is necessary. For this, rank aggregation can be applied to integrate multiple ranks for optimal replacement of water mains. Rank aggregation has been mainly used for spam reduction and search engine comparison. It also shows proper performance to draw consensus of multiple ranks from various sources when aggregating ranking functions [83]. Hence, the final rank that contains essential factors can be used as a criterion for candidate pipes for replacement.

This work suggests a prioritization algorithm based on rank aggregation for replacing pipes. To estimate the degree of pipe deterioration, a rank algorithm is used. Based on this reliability rank, replacement cost and the number of household, final rank is determined by rank aggregation.

The rest of the paper is organized as follows: Section 2 presents algorithms for ranking and rank aggregation. Section 3 provides a case study where the proposed approach is applied to real field data obtained in one city of South Korea and shows the efficacy of the proposed scheme. Finally, Section 4 provides concluding remarks.

3.2 Problem statement

As mentioned in Introduction, water pipe management is concerned with replacing water mains given budget constraint. This type of problem can be formulated as an

optimization problem in (1) [80]. With appropriate assumptions, preference ordering problem can provide the same result with the optimization problem of (1).

$$obj = \min\{\sum_{i=1}^{n} C_{replacement}(i) \times x(i) + E[C_{breakge}(i)] \times y(i)\} \tag{3.2.1}$$

$$\text{s.t} \sum_{i=1}^{n} C_{replacement}(i) \times x(i) \leq \text{Budget}$$

$$x(i), y(i) \in 0, 1$$

$$x(i) + y(i) = 1$$

where $x(i)$ is 1 if pipe i is replaced, $y(i)$ is 1 if pipe i is maintained, n is the toal number of pipes and $E[C_{breakge}(i)]$ is the expected cost of damage if pipie i is broken.

First, it should be noted that replacing one pipe neither increases the failure rate of other pipes and nor gives meaningful benefits to other pipes. Second, instead of determining optimal replacement timing, we determine a series of pipes that should be replaced preferentially for a given period. Finally, breakage cost is greater than replacement cost. Given these assumptions, equation 3.2.1 can be reformulated as 3.2.4 and 3.2.5.

$$obj = \min\{\sum_{i=1}^{n} C_{replacement}(i) \times x(i) + E[C_{breakge}(i)] \times y(i)\} \tag{3.2.2}$$

$$= \sum_{i=1}^{n} E[C_{breakge}(i)] + \min\{\sum_{i=1}^{n} C_{replacement}(i) \times x(i) - E[C_{breakge}(i)] \times x(i)\} \tag{3.2.3}$$

$$= \sum_{i=1}^{n} E[C_{breakge}(i)] - \max\{\sum_{i=1}^{n} E[C_{breakge}(i)] \times x(i) - C_{replacement}(i) \times x(i)\} \tag{3.2.4}$$

$$= \sum_{i=1}^{n} E[C_{breakge}(i)] - \max\{\sum_{i=1}^{n} E[C_{addtionalbreakage}(i)] \times x(i)\} \tag{3.2.5}$$

It means minimizing the total cost can be replaced with minimization of the expected cost of damage by changing water mains under limit budget. Therefore, we only need to compare pairwise precedence among pipes. Hence, we can conclude that optimization formulation can be replaced with ranking problem for listing economic policies with reliability guarantee.

If this alternative is feasible, a ranking algorithm, which was shown to be effective for predicting reliability can be used for water management policy for industrial applications [72]. Because ranking for water replacement policy needs to account for not only reliability of water mains but also other criteria including economic damage, water quality, and the number of households where water can be cutoff, we need to formulate a ranking problem that yields consensus ranking of those factors. Whereas quantitative information such as costs and the number of households can be easily translated into precedence ordering, it is not straightforward to relate the historical events of pipe breakage and maintenance to the ranks. This work further utilizes such historical data and determines reliability ranks, which are subsequently aggregated to produce the final ranks that prescribe replacement planning of water pipe in numerical orders. Figure 3.1 shows the overall procedure of the suggested approach.

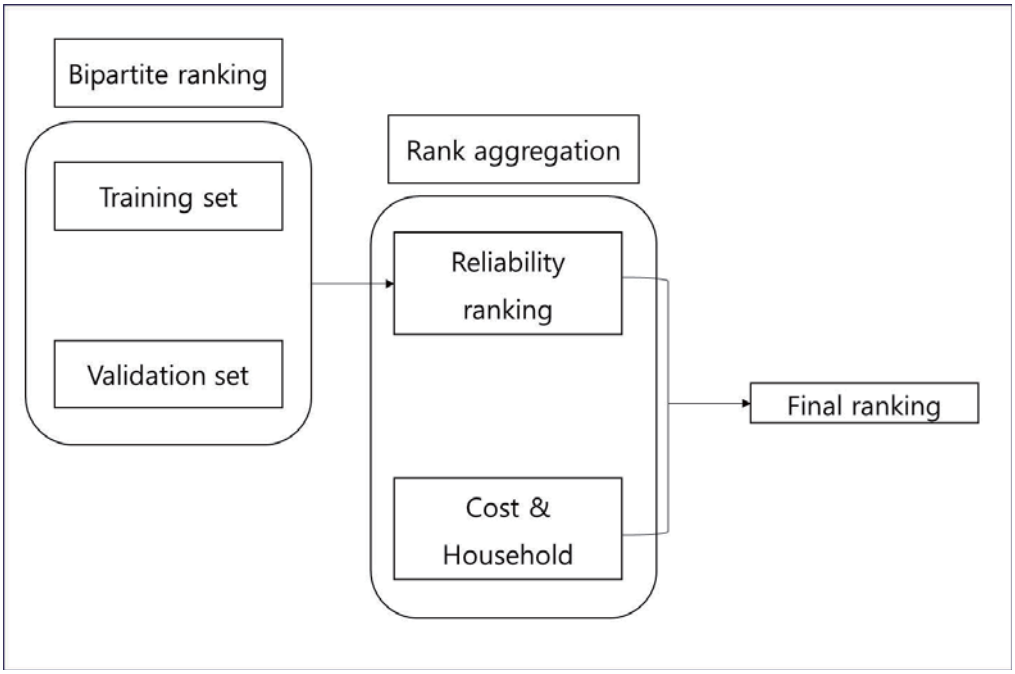


Figure 3.1: The overall algorithm of rank aggregation

3.3 Rank algorithm and rank aggregation

3.3.1 Bipartite rank algorithm

Processing of large data sets often requires preference judgments rather than classifications. Approach to preference judgement is quite different from classification. It needs only ordering to tell what is preferred, not the output with specific meaning or quantitative value allocated to each feature. Rank, a special kind of preference function, has been popularly used in the fields where user preference plays a key role, such as information retrieval, recommender system and autonomous agent. It is also

gradually applied in engineering fields such as machine translation [84] and bioinformatics [85]. There exist various ranking methods based on the ranked features and outputs from ranking algorithms including instance ranking, label ranking and objective ranking.

Bipartite ranking is one type of ordering problems that encounter in real world. It indicates that there are two disjoint sets of instances and all instances in one set outrank those in the other set. In terms of identifying a pipe that has high possibility to be broken, more preference is given to the broken pipe than the non-broken pipe, and these two sets of data are disjoint. Hence, the bipartite ranking can be applied to selecting candidate pipes for replacement. For this bipartite ranking problem, the Rankboost B algorithm developed by Freud et al [86] shows strong performance in practical applications [87]. This technique is one of boosting methods that can produce highly accurate preference order by iteratively combining various weak rules showing moderate accuracies. The procedure is shown in algorithm 1. At each round, weak ranks can be obtained using weak learner and update weights of each instance based on whether this ranking gives correct ranks. At last, final ranking is calculated as a weighted sum of the weak rankings. The weak learner is constructed by comparing the feature score of a given instance with a threshold value, theta. This process is shown in algorithm 2. More specific information on threshold and weak learning is available in Freud et al [86].

3.3.2 Rank aggregation algorithm

Rank aggregation has its origin in attempting to reach a consensus from multiple sources of information. It has been developed in social science for fair election from

Borda's election to Condorcet's criterion [88]. It started gaining attention in the fields where there is a need to integrate multiple sources of information, and has finally become a core technology of information retrieval for web search ranking and combatting spam. Moreover, in bioinformatics, this technique has enabled to merge expression data at DNA, RNA or protein level and even across diseases or species [89, 90]. As a consequence, rank aggregation approaches from many different areas have evolved to see their applications in various research areas.

For aggregation, a criterion is required to indicate which aggregated rank sequence is more meaningful. It can be represented as a distance and the most widely used distances are Kendall-tau distance and spear footrule distance. The aggregation that minimizes Kendall distance called Kemeneny optimal aggregation. However, in real case, Kemeneny optimal aggregation requires high computational complexity, hence, for some aggregation, they cannot optimize this criterion even though they show impressive performance. Condorcet's criterion is often introduced for defeating spamming with simple rank aggregation. It is based on transitivity, which means higher ranker in terms of Condorcet criterion preferred by more voters defeats any lower rankers.

Dwork et al. [83]classify rank aggregation into three types. The first method is the positional method. This algorithm finds the final sequence based on aggregated rank close to the average position of the elements before aggregation. This method has a major advantage of short computational time. It also has anonymity, neutrality, and consistency that are meaningful properties in the social choice literature. However, they cannot satisfy the Condorcet criterion. It is known that there are no methods to satisfy Condorcet criterion using a function of weighting position of each instance.

Most representative technique in positional methods is Borda method. It finds a sequence based on positional order that minimizes distance of each from the positional order of initial separate rank. Algorithm 3 shows a framework of Borda algorithm. The second method, footrule and scale footrule aggregation is often employed as an approximation scheme for Kemeny optimal aggregation. P. Diaconis et al. prove that the footrule distance between any two permutations approximates their Kendall-tau distance to within factor two [91]. This algorithm uses Sperman's footrule distance, defined as a function of permutation σ and ϕ by $F(\sigma, \phi) = \sum_j |\sigma(j) - \phi(j)|$. Finally, hybrid algorithm is suggested to combine positional and comparison based algorithms and it shows better performance than using a single method [83]. MC4 algorithm is one of four MC algorithms proposed by Dwork et al. [83] which is the most widely used algorithm among these. This algorithm is mainly used to combat search engine spamming. If there are search engines affected by spam, they may ranked high. Hene, MC4 algorithm tries to lower aggregate rank of instances that highly ranked in only a minority of lists. This algorithm is presented in Algorithm 4. The overall process using ranking algorithm and rank aggregation method is summarized in Figure 3.1. This study employs two techniques, Borda rule and hybrid algorithm because Borda rule is known to provide good approximation of the optimal Kemeney score.

3.4 Case study

3.4.1 Data

The proposed approach is applied to the real field data of the water supply system of "E" city in South Korea. This database includes the past history of pipe sections

in the network that had been buried, repaired and broken from 1975 to 2005. For enhancing reliability and efficiency of the algorithm, the data sets were preprocessed. First, historical incident data of water pipe is measured in days. The time unit was converted into months considering the decision frequency. We also excluded attributes with missing values, reliability issues and no relevance with pipe deterioration such as damage of gauge.

In the database, there are five types of pipe material, PVC (polyvinyl chloride), PE (polyethylene), CIP (cast iron pipe), HIVP (high impact PVC), and ductile iron. The number of data points for the ductile iron pipe is much larger than the sum of the rest. Hence, this work only considers the ductile iron pipe. This removes the categorial attribute, pipe material, and makes the data set containing only numerical and binary attributes. Moreover, the database contains only the information on breakage events and pipes themselves, which is not enough to predict pipe deterioration. To improve the accuracy of the proposed approach, we added the GIS data of E city and pH as shown Figure 3.2. We also included atmospheric temperature as a characteristic factor for deterioration. However, because E city is not big enough to have meaningful distributions in the thermal properties of each pipe, the result using temperature was shown to be less reliable than not. Hence, we did not include climate data for attaining the final list.

Figure 3.2: GIS map of water pipes buried in E city

The number of total instances was 1690 and that of the attributes was five: diameter, land development, pH, burial time and breakage time. It is noted that the breakage time may not be available for all the pipes, which can be considered as insufficiency of data. Nevertheless, we construct the list using these factors because we only require the list of pipes to be replaced and repaired preferentially. The ranking algorithm can then be applied to this result.

3.4.2 Ranking algorithm for the reliability

Many previous researches for data-based modeling of water pipe deterioration simply divides the data set of a certain time period into training and validation sets. However, this can result in uneven distributions because the data set tends to have more number of breakage events in the latter half of the time window. Considering this situation, we partition the dataset into training and testing set using random sampling. The

proposed approach is composed of two-step algorithms, weak learner and rankboost B, and implemented in Matlab R2015b.

In order to evaluate the performance of algorithm, a numerical performance index is necessary. In bipartite ranking algorithm, Area Under the receiver operating characteristic Curve (AUC) is most widely used [92]. The AUC of a classifier means the probability that their predicted pairwise ranking is correct. If all the instances in one class are ranked higher than the instances from the other, the AUC would be 1. If the rank classifier cannot discriminate each instance, the AUC would be 0.5. For AUC less than 0.5, reversal of rank can show better performance. Our result shows that the AUC for the validation set was 0.84, which is within the range of reliable results. For performance comparisons, we employ Cox model, one of survival analyses. The survival model predicts probability $h(t)$ for failure of target in infinitestimal time if it suvives until time t. There are many previous studies to predict failure rate of water pipes using survival analysis [65, 93, 94] and this technique is appropriate to compare with our result. AUC in validation set using cox model is 0.72. It is lower than the AUC value from our rank algorithm, which indicates the proposed ranking algorithm shows better performance than Cox model.

We use reliability rank as just one of orderings for rank aggregation. Two pipes having the same attributes except for only one are compared. For instance, pipes 19 and 114 have the same conditions except pH. Pipe 19 with pH 5.71 is preferred to pipe 114 with pH 8.5 for replacement. For pipes 85 and 86, the rank of pipe 85 with the diameter of 150 mm was higher that that of pipe 86 with diameter of 80 mm. Such results are in accordance with the general tendency of factors that affect water mains.

3.4.3 Rank aggregation

For deriving aggregated ranks, three factors are considered, the reliability rank, repair cost, and the number of households. The reliability rank is provided from the results in previous section. In case of breakage, there are direct and indirect costs. The direct cost is based on breakdown cost provided by the Waterworks Bureau as shown in Table 3.1. The indirect cost involves the additional costs associated with damage and repairment. However, this information cannot be determined specifically. Instead of using direct calculations in an ambiguous manner, weights can be given depending on the land type according to Dandy et al [74]. To exploit the three factors, we aggregate the total rank using Borda and MC4 method.

The result shows ranks reflecting each factor, but the analysis can be misleading by overestimating the number of households and breakage costs; it can provide a unreasonable result where a normal pipe is on the top of the list because of other high ranks. To address the issue, we consider two alternatives. The first method is to narrow down the choice to 100 candidates that is most possible to be broken in reliability rank and aggregate rank in this list only. The second method is to give more weights to the reliability rank. In viewpoint of reliability, AUC in the first method is 0.74 based on only 100 candidates. It is slightly lower than AUC of reliability because the number of failure data in the first method is much smaller than that of the overall test set. However, most of the pipes that have lower reiliability were removed so that reliability can be guaranteed. In the second method, reliability weights are given as 2 or 3. Results of cases with the weight more than 3 were the almost identical with the case of weight 3. AUC of Borda rank given weight 2 to reliability is 0.81 and in case of weight 3, AUC is 0.82. This value is lower

than AUC in reliability rank but is still higher than Cox model and difference with reliability rank is not significant. Hence, the aggregated ranks can be considered reliable. More specifically, we compared top 100 list of each aggregated rank. In case of rank aggregation using Borda method simply, the list includes 63 instances that is also contained in reliability rank. Because the first method is the same with reliability rank, comparison is meaningless. If the weight is 2, a total of 91 instances are the same with the two reliability ranks and aggregated rank and if 3, a total of 99 instances are the same. It means simple rank aggregation can mislead that pipes that are much less likely to be broken should be replaced. Ranks from Borda methods are similar, but result from MC4 is considerably different. For example, top 10 list from Borda method is almost the same. On the other hand, only one pipe in MC4 is included in the list of Borda method. Nevertheless, it is very interesting result because the results from each rank aggregation shows similar cost savings.

It is not easy to compare optimal cost for each case. Hence, we compare cost savings for selecting pipes based on reliability rank only and rank based rank aggregation. We assume we can have data up to one year before pipe is broken and can inspect 25% of the pipes in the test set. In South Korea, the portion of replaced pipes are only lower than 0.2% of the total waterworks annually. Given this, the number of pipes to be replaced is too small and rank of these pipes is not sufficient enough to serve as indicators. Hence, this study assumes 25% of the total pipes are inspected. Figures 3.3 shows the cost saving by the pipe inspections. Replacement policy based on reliability ranking will not replace pipes that will not be broken. On the other hand, rank aggregation-based replacement include one or two pipes that will not be broken. However, Figure 3.4 also shows that rank aggregation-based list is

more profitable than the reliability ranking and shows a similar number of households. In terms of the cost, the Borda method using top list and weight of 3 is the most advantageous. In terms of the number of households without water, MC4 is the best but the cost difference with the rank aggregation method is very small. Although the result is not from optimization and may require more number of data points for generalization, weighted Borda shows the best performance in terms of cost and the number of breakage for rank aggregation. The proposed approach performs better than simple reliability ranking for total cost while the reliability is also considered. If we keep track of the pipe states after breakage, the proposed rank aggregation method would be even more advantageous than using simple reliability ranks.

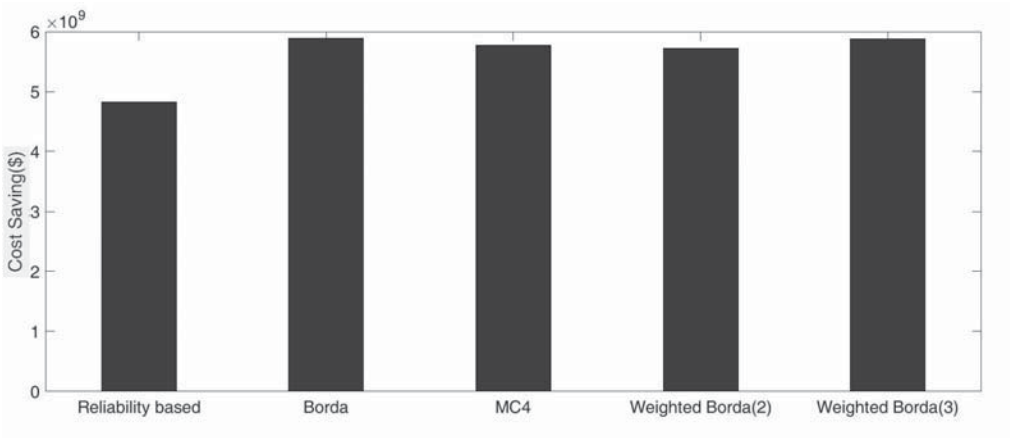


Figure 3.3: Cost savings by preventing breakage of water pipes depending on each ranks

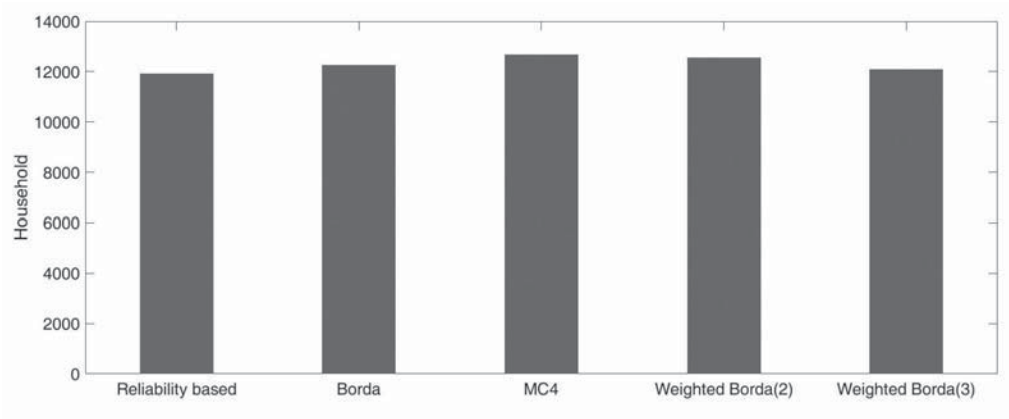


Figure 3.4: The number of households that can avoid cut-off by replacing water pipes

3.5 Conclusion

This paper provided an overall framework to schedule pipe replacements using rank aggregation and build prediction system for the water utility in E city of Korea. In reliability rank, we can identify tendency of feature is the same with previous studies, indicating the prediction capability is satisfactory. For rank aggregation, we can analyze a general aggregation method may not be appropriate because of the differences of importance of each attribute. Thus, we proposed a method guarantees reliability of pipe deterioration.

The proposed approach can provide a preferential sequence of pipes for repair and replacement under limited budget without complicated optimization. This list also helps to meet practical necessity of the waterworks and beneficial to preventive maintenance on other types of industrial assets. This study can be improved to consider some attributes that may be important and are not available in this study. It is probable that these additional attributes can further improve the prediction

Diameter(mm)	Construction	Materials	Destruction	Laying	Incident	Total
80	58.48	19.02	21.45	16.23	234.34	349.53
100	58.48	23.03	23.52	20.58	259.35	384.97
150	58.48	35.50	27.48	36.40	300.05	414.76
200	58.48	47.53	29.78	34.26	244.70	457.91
300	58.48	79.11	35.80	46.50	337.39	557.29

Table 3.1: Total cost($) for replacement of water pipes

performance and help better understand the deterioration mechanism of pipe.

Chapter 4

Chemical scheduling using MILP and approximate dynamic programming

4.1 Introduction

In this chapter, the comprehensive overview in chemical scheduling was presented. Basic formulation in previous studies are researched. In these studies, generally, cost is the objective function of scheduling in chemical engineering. However, in integration framework, cost need to be evaluated in planning stages. The role of scheduling in planning is to provide the information of feasibility that plants can produce during time horizon. Thus, instead of optimize the cost, we maximize the amount of product during certain horizon. Nevertheless, this simple MILP formulation cannot be used for stochastic optimization and especially, it cannot be handle the unexpected event, namely, play a role as reactive scheduling.

Based on this study, we reformulate new formulation of sequential process that can handle stochastic optimization. In this model, the decision epoch depends on operation availability in each equipment.

We generate from deterministic to stochastic case using Monte Carlo simulation and from this result, value function is learned repeatedly. This value function can deduce proactive optimal policy for stochastic scheduling and when uncertain situation occurs, it is regarded as state transition and it is possible to produce optimal policy online in real time. This value function also can help to discuss feasibility in current situation when unpredicted events occur From this configuration, we can find possibility of ADP as proactive scheduling and explicit instruction about uncertain situation.

4.2 General MILP

4.2.1 formulation

In chemical scheduling, STN is developed to express the process network. It consists of two types of node: state node for representing the all forms of resources including intermediate and final products and symbolized the circle, and task node for representing conversion state node to another type of state node such as heating, reaction, splitting and it can have one more input states or output states and symbolized the rectangular. It can be useful that to express the all types of process, batch, continuous. Generally, to model the process using STN, the following constraints are necessary [2].

$$\sum_{i \in I_j} W_{ijt} \leq 1 \tag{4.2.1}$$

It can be represented as

$$\sum_{i' \in I_j} \sum_{t'=t}^{t+p_i-1} W_{i'j't'} - 1 \leq M(1 - W_{ijt}) \tag{4.2.2}$$

$$W_{ijt} V_{ij}^{min} \leq B_{ijt} \leq W_{ijt} V_{ij}^{max} \tag{4.2.3}$$

$$0 \leq S_{st} \leq C_s \qquad \forall s, t \tag{4.2.4}$$

$$S_{s,t} = S_{s,t-1} + \sum_{i \in \bar{T}_s} \bar{\sigma}_{is} \sum_{j \in K_i} B_{i,j,t-p_{is}} - \sum_{i \in T_s} \sigma_{is} \sum_{j \in K_i} B_{i,j,t} \qquad \forall s, t \tag{4.2.5}$$

where S_i : set of states which feed task i, $\bar{S}_i$: set of states which feed task i, σ_{is} : the proportion of input of task i from state $s \in S_i, \sum_{s \in S_i} \sigma_{is} = 1$, $\bar{\sigma}_{is}$: the proportion of output of task i from state $s \in \bar{S}_i, \sum_{s \in \bar{S}_i} \sigma_{is} = 1$, P_{is} :: processing time for the output of task i to state $s \in \bar{S}_i$, p_i: the completion time for task i, K_i : set of units capable of performing task i.

The last parameter K_i relates the process equipment units to the STN. State s is defined by: T_s : set of tasks receiving material from state s; $\bar{T}_s$: set of tasks receiving material from state s; $\bar{C}_s$: maximum storage capacity dedicated to state s;

Equation 4.2.1 and 4.2.2 mean that at most one job can be allocated to machines and 4.2.3 represents the minimum and maximum amount of reactant in equipment and 4.2.4 is same meaning in case of intermediate storage. Finally, equation 4.2.5 stands for general mass balance.

Table 4.1: Parameters of the process

Types	Heator	Reactor 1	Reactor 2	Seperator	
Maximum capacity	10	8	5	15	
Task	Heating	Reaction 1	Reaction 2	Reaction 3	Sepearation
Processing time	2	3	2	3	3

4.2.2 Result

Based on the previous formulation, we can get the various result of deterministic scheduling varying with the objective function. The result as having objective function as maximum amount of product is represented as figure 4.1 $\sim$ 4.2. In deterministic case, we can easily find the maximum amount of each product that do not considering another product. However, to attain these value in stochastic case, we need the new technique that handle the uncertainty. Stochastic optimization based on previous MILP, is 2-stage optimization and parametric programming is one of method. J. Balasubramanian et al present a multistage stochastic mixed integer linear programming model, wherein certain decisions are made irrespective of the realization of the uncertain parameters and some decisions are made upon realization of the uncertainty [95]. Bonfill et al present the short-term scheduling problem in chemical batch processes with variable processing times with the aim to identify robust schedules able to face the major effects driving the operation of batch processes with uncertain times and model a two-stage stochastic approach accounting for the minimization of a weighted combination of the expected makespan and the expected wait times [96]. In parametric programming, Li and Ierapetritou utilized multiparametric programming to take into account multiple forms of parameter uncertainty within both the objective function and constraint set and demonstrated that parametric programming is

a rigorous way of generating a set of schedules which can accommodate all possible realizations of parameter uncertainty [97]. However, these technique is not enough to do both proactive and reactive scheduling for our research. Reactive scehduling need one of two, offlince calculation or online optimization. For this, approxiamte dynamic programming is employed and previous problem is reformulated as the Markov chain and optimize the stochastic sequential problem.

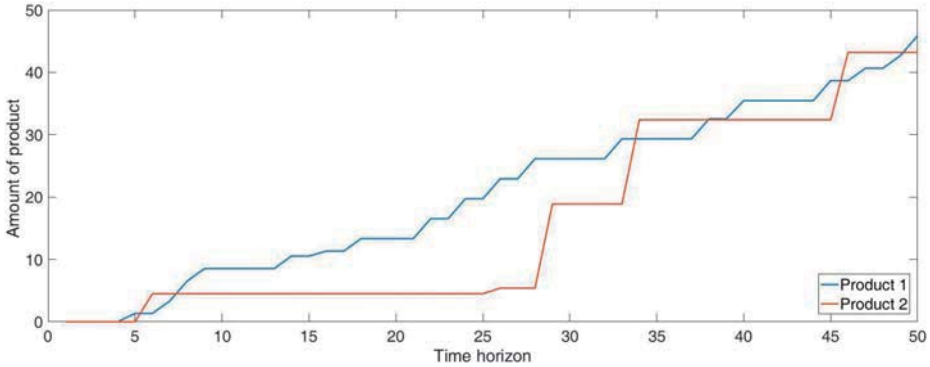


Figure 4.1: The amount of product to maximize product 1 in deterministic case

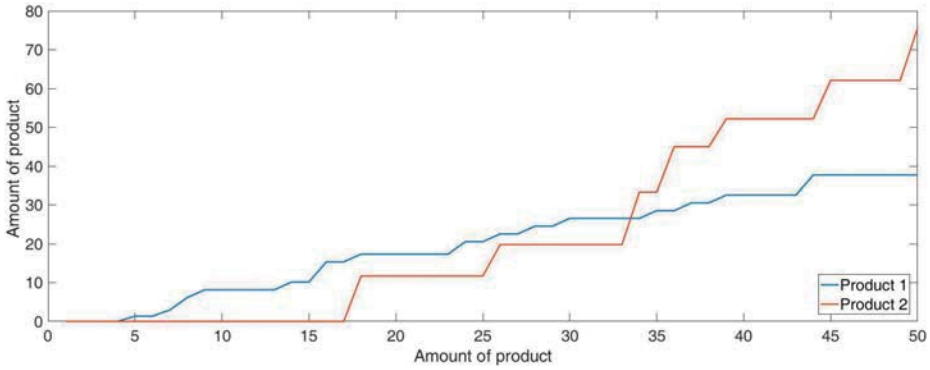


Figure 4.2: The amount of product to maximize product 2 in deterministic case

4.3 Approximate dynamic programming

4.3.1 formulation

For stochastic optimization, the new approach that is different from previous method is necessary. There are many formulations for stochastic modeling and in this research, Markov chain model is employed. Markov chain is a type of Markov process that has either discrete state space or discrete index set. In other words, it means the discrete process that have Markov properties. Markov properties can present like this.

$$P(X_n = x_n \mid X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, ..., X_0 = x_0) = P(X_n = x_n \mid X_{n-1} = x_{n-1}) \tag{4.3.1}$$

There are components representing Markov chain inclduing state and action sets, cost and transition probabilities. State corresponds to the current information of system. And action means instruction that current state progress the other state. However, when unceratinty exists, system alwyas heads the state intended to. To express these trend, transition probability $P(s \mid s, a)$ is introduced. It presents the probability that state s is visited if system is transfed to the next state following action a. Cost indicates reward or damage from the current state to the next state. These (s,s,a,$P(s \mid s, a)$,c) is all component for Markov chain.

To reflect the STN formulation to Markov chain, policy to store an intermediate product should be discussed. There are many storage policies in scheduling such as unlimited, limited capacity or no storage. Generally, the limited storage in only storage vessel is representative storage policy in chemical scheduling. However, in stochastic modeling, the amount of storage can be easily beyond maximum capacity

of storage vessel. It brings infeasibility of model and optimization. To overcome this obstacle, one additional assumption is considered. It is if the current intermediate storage exceeds the maximum capacity of storage vessel, the machine that finished latest cannot be operated until the amount of storage is lower than maximum capacity.

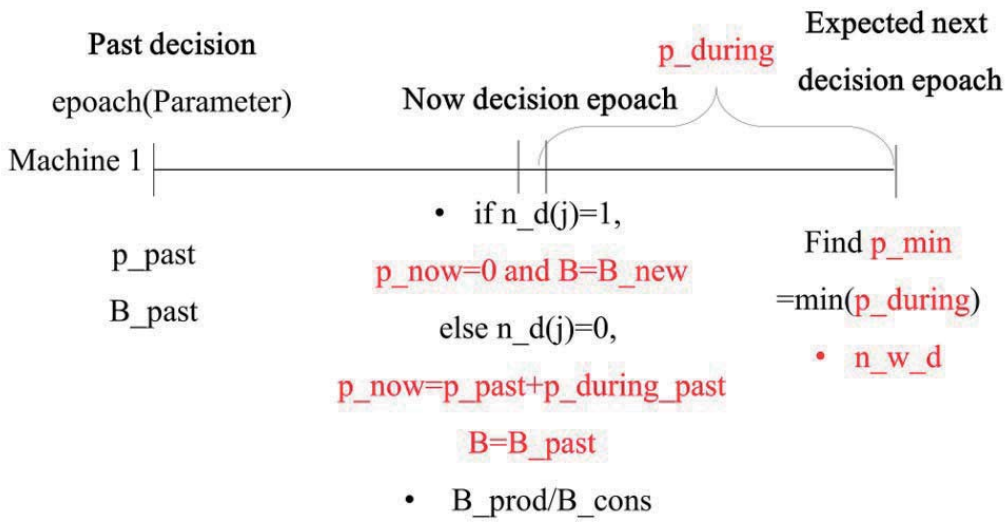


Figure 4.3: The maximum amount of each production

Another issue for formulatingthe Markov decision process is the decision epoch. Decision epoch means time at which decision are made. It can be classified into discrete/continuous or finite/infinite horizon. Decision epoch in this research cannot be divided equally because next decision epoch cannot be known until the current decision is made. In other words, next decision epoch is determined when at least one machine becomes idle states. For representing these relations, we need to introduce new variable p_{min} ,$p_{during}(j)$ and $npd(j)$. Each variables mean mimum time that at least one machine becomes idle, remained time that machine j beecomes idle and binary variable that indicate 1 if machine j will be idle at next decision epoch.

$$|p_{min} - p_{during}(j)| \leq M(1 - npd(j)) \tag{4.3.2}$$

$$\sum_j npd(j) \geq 1 \tag{4.3.3}$$

$$p_{min} \leq p_{during}(j) \tag{4.3.4}$$

Equation 4.3.2 $\sim$ 4.3.4 means process for finding the next decision epoch. From equation 4.3.2 and 4.3.3, the next decision epoch should be made among next time that machines become idle. From equation 4.3.4, p_{min} becomes the smallest value among $p_d uring$. And, equation 4.3.5 represents the total remained time in total horizon at current decision epoch and next.

$$D_{next} = D - p_{min} \tag{4.3.5}$$

Another additional variable is $n_d(j)$, which means mahcine j is idle now, i.e, mahcine j needs new decision. Equation 4.3.6 $\sim$ 4.3.10 indicate transtition of state in machine. If we can make decision on mahcine j, task of machine can be changed. However, if not, any task in machine j should be maintained. These relations are presented in equation 4.3.6 $\sim$ 4.37 when machines become idle, previous amount of equipment is transformed into another resrouces as represented in equation 4.3.8 $\sim$ 4.3.10.

$$\sum_i |W(i,j) - W_{past}(i,j)| \leq M n_d(j) \tag{4.3.6}$$

$$\sum_i |B(i,j) - B_{past}(i,j)| \leq Mn_d(j) \tag{4.3.7}$$

$$|B_{prod}(i,j) - B_{past}(i,j)| \leq M(1 - n_d(j)) \tag{4.3.8}$$

$$B_{prod}(i,j) \leq Mn_d(j) \tag{4.3.9}$$

$$|B - B_{past}(i,j)| \leq Mn_d(j) \tag{4.3.10}$$

Newly consumption for task can be represented likewise production.

$$St(s) = St_{past}(s) + \sum_{i \in I_{ps}} \sigma_p \sum_j B_{prod}(i,j) - \sum_{i \in i_{cs}} \sigma_c \sum_j B_{cons}(i,j) \tag{4.3.11}$$

And, previous equation 4.2.5 can be modified for expressing the mass balance into 4.3.11.

4.3.2 Algorithm

ADP is based on an algorithmic strategy that steps forward through time, using iterative algorithms that help to estimate the value function for future stages. In several ADP methods, the value table is constructed only for a small subset of states, and a function is used to interpolate among The sampled points are typically determined by running simulations with some known heuristics and/or random actions. The rationale is that, by simulating the conditions one can expect during real operations, one can sample the regions of the state space that are most relevant for constructing well-controlled trajectories [98]. In this section, an ADP-based procedure is proposed

as a solution method for the scheduling problem described in the previous sections. Powell appears to be the first book to recognize all three curses of dimensionality and propose practical solution methods [99]. A major problem occurs when the decision x_t is a vector, requiring the use of classical optimization algorithms. A practical issue is the presence of the expectation in Bellmans equation. This can be solved by using the concept of a post-decision state variable, which is the state immediately after a decision has been made, but before any new information has arrived [99, 100].

In this paper, we assume that the value function is a piecewise linear function with unknown parameter and we update our estimate of vector using recursive statistics. The overall strategy works as follows. For time representation, it is discrete and process is reversed based on time. At each instant t, we solve a scheduling problem is solved to allocate the task to the current idle machine with their known processing times. The timing that machine becomes idle can be known in deterministic problem whereas in stochastic cases, when machine become idle is uncertain. However, machine broken can become another machine process such as repair. At each time epoch, we solve MILP problem that optimizes bellman equation consisting of contribution that represent the amount of production during time interval and parametric approximation. And, after end of horizon is reached, we can update all contribution and approximated value function. These process can be listed in algorithm 3.1. In the process, we need to evaluate the value function at skipped epoch. If we do not calculate the expected value function in these points, we will loss the information of the expectation. Thus, we approximate the value function in these points from value function that we can expect.

Selection of basis function is the most important problem in approximate dynamic

programming. Main basis function for approximate dynamic programming in this research is amount of reactant and intermediate storage. Also, Ronconi et al studied idle time affects the value function and it is included as component of basis function [31]. Study and modification of basis function is analyzed in the next result chapter.

Algorithm 1: Approximate dynamic algorithm approach

```
Initialization ;
Choose a sample path w^n ;
for t = 0, 1, ..., T^horizon do
    solve: v_t^n = min_{x_t ∈ X_t^n} (Production(S_t^n, x_t) + V_t^{n-1}(S_t^x) | θ_t^{n-1}) ;
    and let x_t^n be the value of x_t that solves the above equation ;
    if t > − then
        update the vector of parameter θ_{t-1}^n and consequently the value
          function approximate and update the state of the system
Increment n by one. If n ≤ N, go to the first ;
Return the value function for t = 0, 1, 2, ..., T^horizon
```

4.3.3 Result

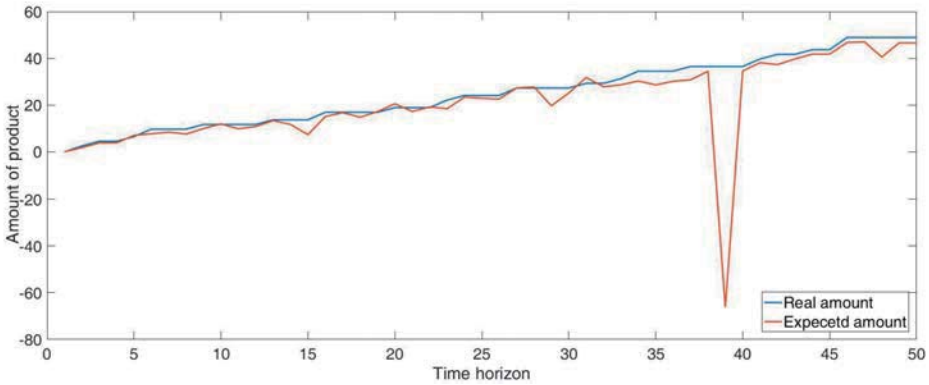


Figure 4.4: The real and expected amount of product 1 using approxmate dynamic programming

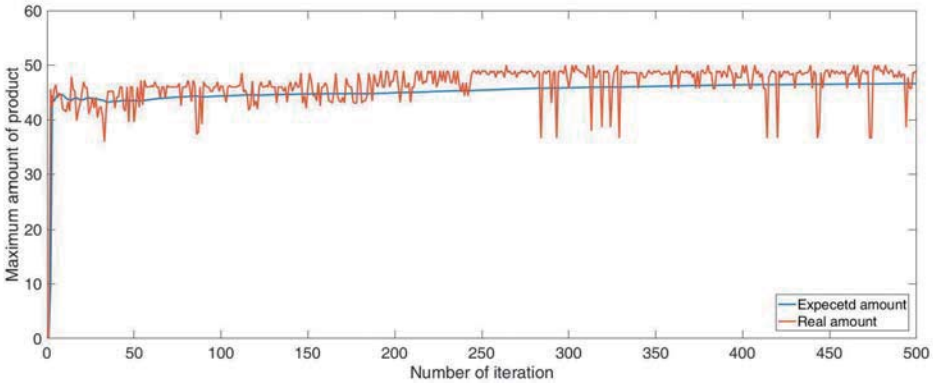


Figure 4.5: The real and expected maximum amount of product 1 using approxmate dynamic programming

Deterministic result We can get the results in figure 4.4 $\sim$ 4.5 to apply the algorithm in previous chapter to deterministic problem. In figure 4.3, we can identify the expected amount of product is the almost same with the real production except one points. It is caused that parameter update cannot reduce error and exploded in reverse direction. To improve the drawback, we introduce the new heuristic 1, which if parameters was updated to reverse direction that we can expect, these parameters will be restored to the basic direction that we expect. The results applied using heuristic 1 in is presented as figure 4.6 $\sim$ 4.7. These results show the expectation is more accurate than applying just simple value approximation.

However, in expecting the amount of product 2, the approximation becomes more difficult. Product 1 can be generated from only reaction and heating in a series of equpiments. However, for making the product 2, it cannot be generated from only reaction and the separator and recycle is necessary. These operations make the approximation of value function challenging. The approximation using same basis function and heuristics cannot expect even converged value that can be idendified

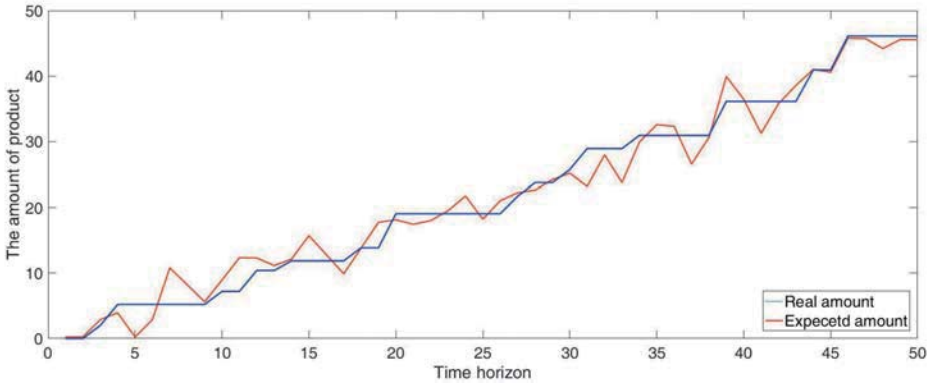


Figure 4.6: The real and expected amount of product 1 using approxmate dynamic programming and heuristics

in figure 4.8 $\sim$ 4.9. Thus, instead of using approximating vlaue function using ame basis function, more basis is introduced. It is defined using logical constraint and operational variable and named as K_v. It can be interpreted as the ampount of level that seperator is optiamlly operated. Using this variable, the convergence rate is very high and expectation is more accurate that can see figure 4.10 $\sim$ 4.11.

Stochastic result In stochastic scheduling, we assume the possibility of machine breakdown. We assume the machine can be broken with the frequency of 90% and in next decision epoch, we can reuse broken machine. From this uncertainty, we can get the result presented as figure 4.12 $\sim$ 4.13. Machine breakdown brings fluctuation of amount of real rpoduction but the expected value converges to the specific value. To identify this value, we average the amount of product after 50 iteration. The reason why selects iteration 50 is this value before a certain level of learning cannot be near-optimal. We can identify the expected value converge to this expected value. Figure 4.12 presents the total production amount of product and figure 4.13 shows the expected value and real production amount in intermediate time points. In product

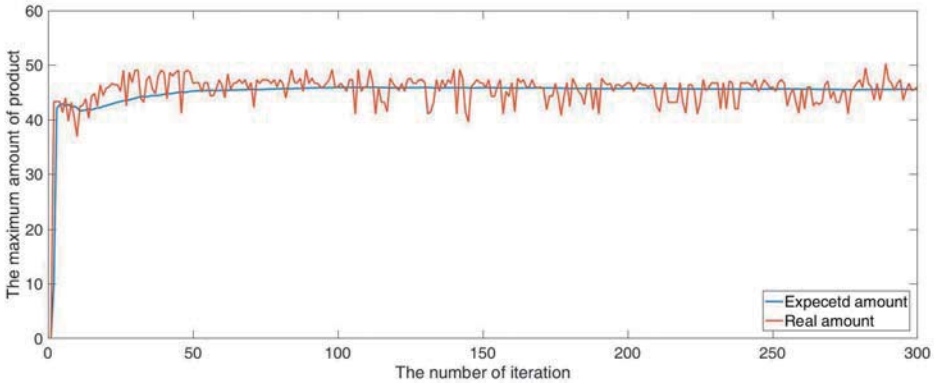


Figure 4.7: The maximum amount of product 1 using approxmate dynamic programming and heuristics

2, the result can be obtained and it is also converged to the expected level that can be idendified in figure 4.14 and 4.15.

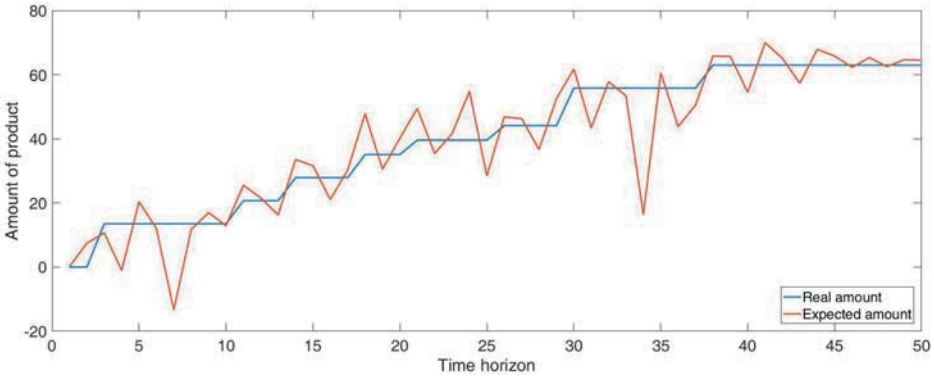


Figure 4.8: The real and expected amount of product 2 using approxmate dynamic programming

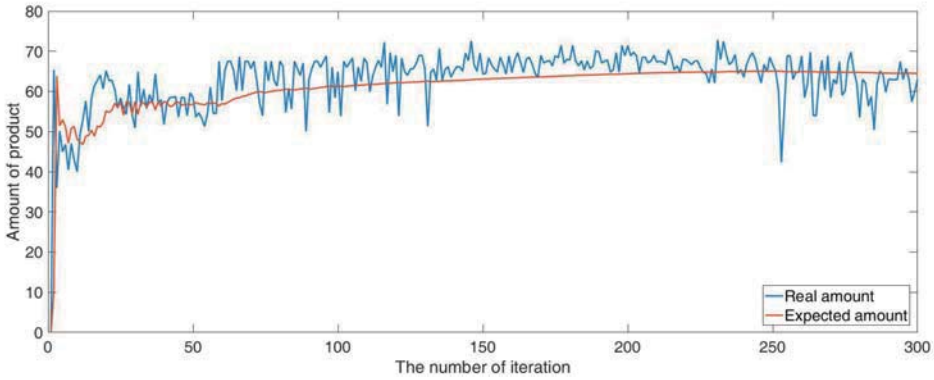


Figure 4.9: The real and expected amount of product 2 using approxmate dynamic programming

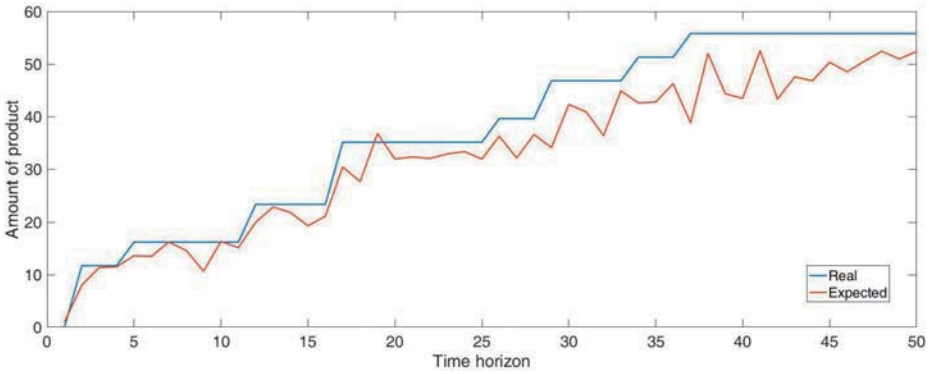


Figure 4.10: The maximum amount of product 2 using approxmate dynamic programming adding the new basis

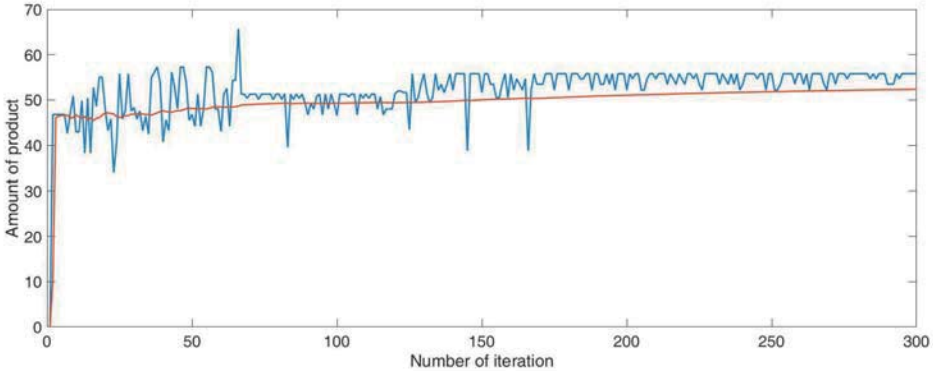


Figure 4.11: The real and expected amount of product 2 using approxmate dynamic programming adding the new basis

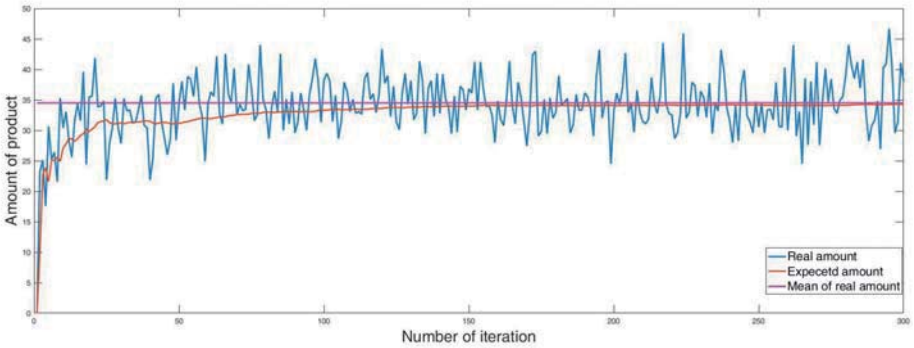


Figure 4.12: The maximum amount of product 1 using approxmate dynamic programming considering uncertainty

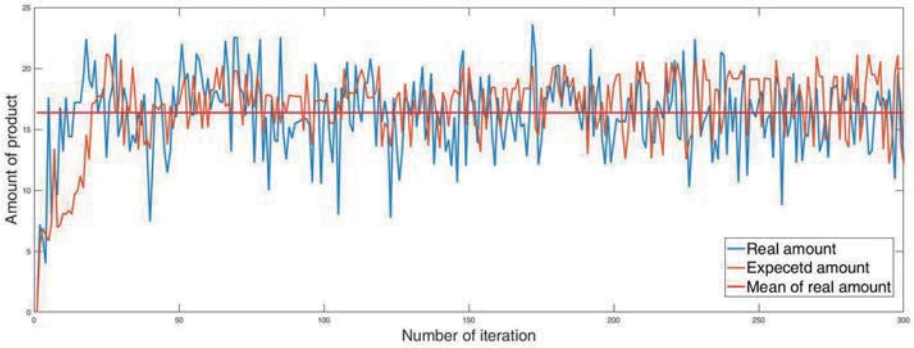


Figure 4.13: The real and expected amount of product 1 using approxmate dynamic programming considering uncertainty

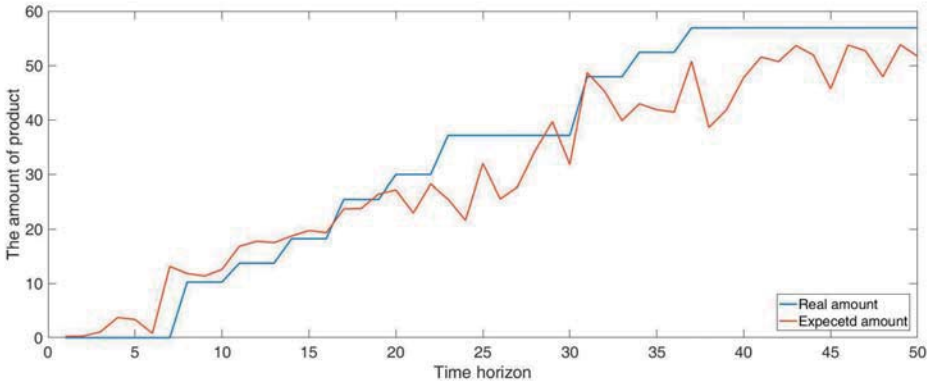


Figure 4.14: The maximum amount of product 2 using approxmate dynamic programming considering uncertainty

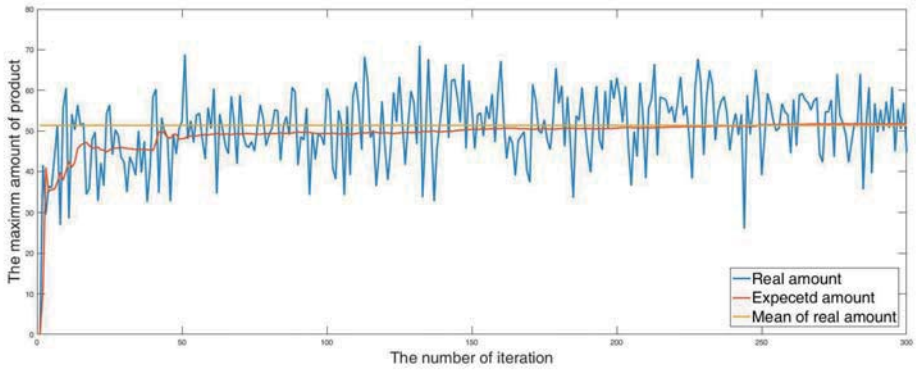


Figure 4.15: The real and expected amount of product 2 using approxmate dynamic programming considering uncertainty

Chapter 5

Integration of planning and scheduling using approximate dynamic programming

5.1 Introduction

Integration of planning and scheduling has been interested in researchers in various field including operation research, engineering and economic, but it is not easy to apply the real case of industry because of complexity of problem and gap between research and real industry. Especially, the existence of uncertainty makes more difficult problem of planning, scheduling and also integration problem.

To solve the integration problem of planning and scheduling, 3 subproblems should be preferentially considered: planning, scheduling and integration framework of planning and scheduling. It is not appropriate to apply the original form of planning and scheduling problem, but reform each problems as subordinate stage that can provide the information to other states.

Generally, for formulation of the scheduling under integration framework, it can be grouped into three categories: 1) Detailed scheduling model 2) Relaxation/aggregation

of scheduling models 3) Surrogate model derived through off-line analysis of the manufacturing facilities. Detailed scheduling interchange each problem into constraints or variables of other stage problem. In other words, one problem belongs to another problem with other forms. These detailed scheduling makes the total problems large MIP problems that cannot be solved. To improve this problem, one of solution technologies is to develop an approximation of the original model which provides some short-term information while being easier to solve. The approximate model is obtained by removing some of the constraints, or by aggregating some of the decisions of the original scheduling formulation. An alternative method for generating an accurate but computationally tractable description of the resource constraints and production costs of a facility is to carry out off-line calculations. Also, hybrid modeling for rolling horizon approaches is one of solution between modeling accuracy and computational burden.

In integration framework, it can be also divided into 3 types: 1) hierarchical methods, 2) iterative methods. 3)full-space methods. In hierarchical methods, the master problem provides a set of high-level decisions, such as production targets and selection of tasks. This information is then fed as input to the lower-level scheduling subproblem with the goal of obtaining a complete scheduling solution. If a feasible schedule with predicted production amounts does not exist, then a feasible schedule in the neighborhood of this is sought out so as to have a globally feasible solution.

In the absence of detailed resource constraints and production costs, the production targets or task-unit assignments obtained by the first solution of the master problem are likely to be infeasible or suboptimal. Instead of trying to find feasible schedules that are in the vicinity of these decisions, iterative methods attempt to

lose the information loop from the scheduling subproblems to the master problem. The goal of such feedback is to find the true optimal high-level decisions. This can be achieved via the addition of integer cuts that exclude previously found solutions. Therefore, different solutions can be found by the master problem and evaluated by the lower-level subproblem. In addition, the master problem can provide an increasing lower bound while the subproblem can provide an upper bound. Thus, iterative methods can lead to optimal solutions if solved until the gap is closed.

In the full space, methods of this class consider the integrated problem, where a detailed scheduling model is used for the modeling of resource constraints and production costs. One of solution method is the solution of the full-space model using standard mathematical programming methods. Scheduling models by themselves, however, are hard to solve despite only covering a horizon of several days or weeks. If the same level of detail is maintained, therefore, the integration with production planning that extends the horizon to several months results in computationally intractable models. Hence, the second approach is to use heuristic methods such as simulated annealing. and genetic algorithms.

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We formulate the integration fraemwork of plnnaing and scheduling and apply the example cases. And, we anlayze this framework can handle the uncertainty in the problem.

5.2 Formulation and result

In this chapter, we only discuss the integration framework of planning and scheduling. The basic methodology of each subproblem including the planning and scheduling is the same with of previous chapter. We employ the iterative method between the planning and scheduling. The main objective is to minimize the total cost under meeting the demand. Preferentially, we need to grasp the expected amount of product in each plants. Based on this information, we can make an initial policy that provide the product to meet the demand in each region. And from this supply policy, we

can allocate plants to target amount of product in overall time horizon and make a schedule during the given horizon.

After plants are operated, we need to consider various uncertainties. There are 2 types of uncertainties in this problem, machine breakdown in scheduling and sudden demand occurrence in planning. Machine breakdown in scheduling affect the initial policy. To handle this problem, we revise previous policy after evaluating feasibility that can meet demands. If we cannot meet the demand until given horizon, we should pay the delay cost. For considering these factors, we make the new policy to minimize the total cost including the dispatch cost and backorder cost. In case of unexpected demand, before making the decision, we need to grasp the feasibility of each plant. This feasibility analysis helps to decision whether new demand is accepted or not. Based on feasibility analysis, we can make additional scheduling under meeting the new demand. This overall process is represented in figure 4.1.

To apply this framework, we assume the hypothetic area that has 3 same types of plant, which is different from size of production equipment and 2 demand region. We formulate the optimization to minimize the total cost. From dynamic programming, it can be given as equation 5.2.1

$$\min V(St) = \min_{x \in X}(C(St, x) + \mathbf{E}(V(St_{next}))) \tag{5.2.1}$$

$$C(St, x) = \sum_{p \in P, i \in I, j \in J} C(p) \cdot D_{satif}(p, i) - \sum_{i \in I, j \in J} C_{dispach}(i, j) \cdot Disp(i, j) - C_{backorder} \cdot St_{backorder}(i \tag{5.2.2}$$

where D_{satif} is the variable that indicates the real amount for demand in region.

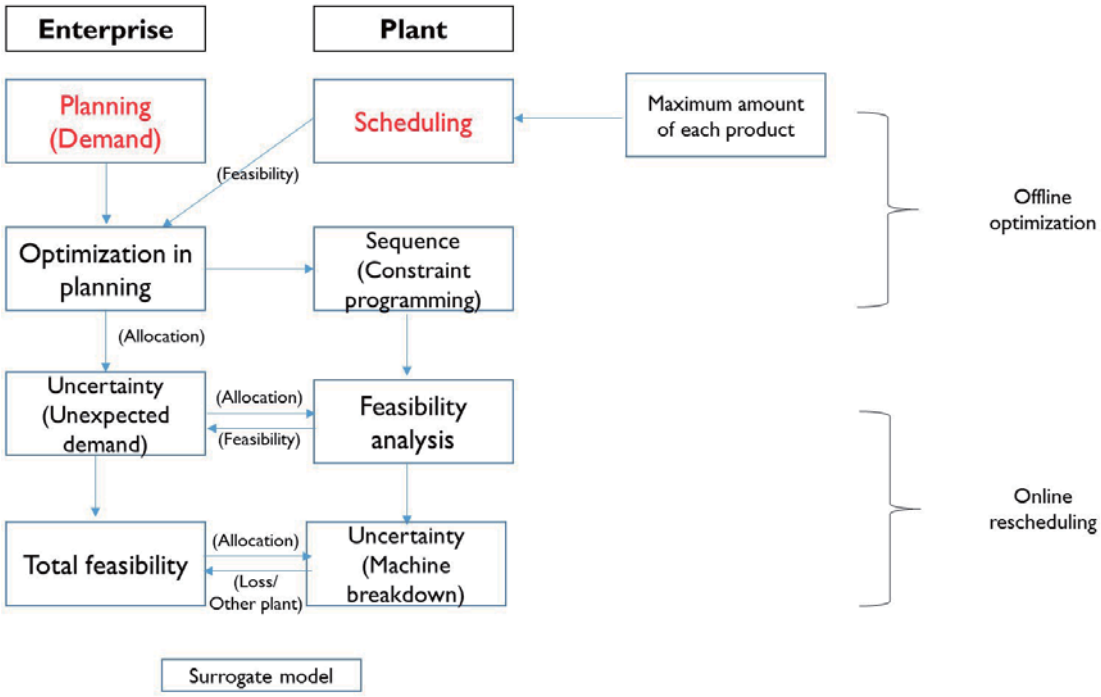

Figure 5.1: The overall integration framework of planning and scheduling

It can be represend following equations.

$$\begin{aligned} |D_{sat}(p,j,t) - D(p,j,t)| &\leq M \cdot n_{sat}(p,j,t) \\ |D_{sat}(p,j,t)| &\leq M \cdot (1 - n_{sat})(p,j,t) \end{aligned} \tag{5.2.3}$$

$$\begin{aligned} |St_{backorder}(p,j,t) - D(p,j,t)| &\leq M \cdot (1 - n_{sat}(p,j,t)) \\ |St_{backorder}(p,j,t)| &\leq M \cdot n_{sat}(p,j,t) \end{aligned} \tag{5.2.4}$$

$$\sum_{i \in I} Disp(i,j,t) = Demand(j,t) \tag{5.2.5}$$

$$St(p,i) = St_{past}(p,i) - \sum_{i \in I} Disp(i,j,t_{now}) + \sum_{i \in I} Prod(i,t_{now}) \tag{5.2.6}$$

$$St_{expect}(p, i, t+1) = St_{expect} - \sum_{i \in I} Disp(i, j, t) + \sum_{i \in I} Prod(i, t) \tag{5.2.7}$$

The concept of storage is divided into two, real amount of storage and expected amount of storage.

$$Feas_{product}(i) \geq Prod(i) + \sum_{t \in T_{previous}} Prod_{previous}(i) \tag{5.2.8}$$

$Feas_{product}(i)$ can be obtained from result of scheudling. And this only one step of formulation can learn the overall value function. For approximating the value function, basis function is needed. In case of integration of planning and scheudling, cumulative demand and feasibility that means generation ate of each product is selected as basis fucntion. And, cumulative demand is not just summation of demand, but weighted summation of demand considering remained time. Based on this formulation, the scenoario consdiering uncertainty is analyzed and result can be identified in figure 5.2. New decisions are only necessary when only unexpected events occur. From this, handling the unceratinty in real cases is possible using this framwork.

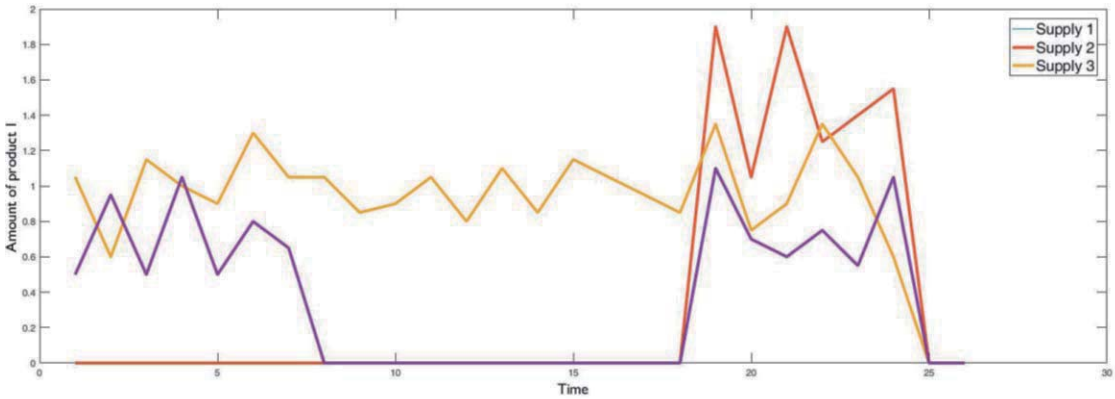

Figure 5.2: The amount of product generated in each supply plant

Chapter 6

Concluding remarks

This thesis present the general researches of planning, scehduling and integration of planning and scheduling using approximate dynamic programming for reactively and proactviely handling uncerainty. For this puprose. we study the various planning problem. In energy resource management, the mathematical optimization is employed.. And for water resource mangement, data mining method is empolyed. And, based on previous scheduling studies, we can formulate the Markov chain and optimze the shceudling problem using approximate dynamic programming. We approximate the value functino of vairous product s and one product given the minimum condition of another product. These scheduling can proivde the maximum amount of planning. It is based on surrogate model from previous researches, but in these researches, there are not proper methods that calculate the information offline. From evaluating approximate dynamic programming in this context, this technique is effective for surrogate model and making decision in online.

Based on this research, some of future works can be considered. First, integration framework prodcuing any types of product is one of remaining researches. In this

research, only 2 types of product is considred and one of product is given as constraints. However, in case of multiple product, these calucaltion need multiple stages. Adding one type of constraints, it need one more step to calculate value function and as a results, it becomes a huge size of problem and meaning of these research is faded. For this, more exquistie techniques are necessary. The next is to evaluating value function in more complex planning and scheduling. Scheduling can be very complex netowrk and it cannot be embodyed using value function. And in planning, it is not just mixed integer programming but mixed integer nonlinear programming. Especially, constraints rof eal problem make the optiziation problem having higher nonlienearity. It needs more researches for solving these problems and in the same vein these technique need to be tesed in various field. In this research, only chemcial scheduling is tested, but in other field, different form of scheduling emerged and it requires different evlaution form and approxiation of value fucntion.

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초 록

이 논문은 근사 동적 계획법을 이용하여 플래닝과 스케쥴링의 통합을 위한 근사적 방법을 제시하였다. 이러한 근사적 방법 이전에 일반적으로 많이 사용되는 최적화 기법들이 플래닝에 어떻게 적용될 수 있는지에 대해 논의해보고, 화학 플랜트에는 왜 적용하지 못하는 지, 근사적 방법이 필요한지에 대해 논의해본다.

먼저 첫번째로, 플래닝의 예시로서 에너지 시스템에서의 플래닝의 수학적 프레임워크를 제시하였다. 제시한 모델은 전체 에너지 자원 최적화 문제를 두 개개의 형태, 전통적 자원과 신재생 에너지 자원 플래닝 문제로 각각 나누었으며, 최적화를 적용하였다. 신재생 에너지 문제의 경우, 정부에 의해 정해진 할당량을 채울 만큼에 한해서 최적화가 이루어지게 되며, 이렇게 문제를 풀게 되는 경우, 각 변수에 대한 민감도 분석을 시행하기도 훨씬 유리하며, 최적화하기에도 유리하다. 에너지 플래닝의 다른 기법과 비교하여 보았을 때, 각 지역의 특성을 반영하고 에너지 자원의 흐름들을 살펴볼 수 있도록, 하위 시스템을 정의하는 등 조금 더 개선된 방법을 제시하였다고 볼 수 있다.

두 번째로는, 송수관 최적 관리를 위한 플래닝 기법에 대해 제시하였다. 도시 내 배수관망에서의 송수관이 파손되면, 경제적으로나 사회적으로나 매우 극심한 피해를 불러일으킬 수 있다. 제한된 예산 내에서 배수관의 최적 교체 계획에 대한 기존의 방법들을 각각의 노후화된 파이프를 선정하는데 실제적으로 활용하는 것은 굉장히 어렵다. 이 장에서는 이러한 최적 선정 문제를 랭킹 혹은 우선순위 결정 문제로 재구성하고, 두 개의 랭킹으로 구성된 순위 문제로 제시하였다. 이 제시된 방법은 또한 배수

관망에서의 파이프라 부서질 때 비용적이나 수리적인 측면에서 생길 수 있는 손실을 고려하게 된다. 이를 위해, 다양한 중요한 랭크들을 상수도관망의 교체 순위를 최종적으로 결정하기 위해 랭크 집합 방법을 이용한다. 이 제시된 기법에서는 랭킹 집합 방법을 통해 교체를 위한 현재 설치된 파이프들의 우선순위를 결정하게 되며, 이 때 상수도관망의 신뢰성, 비용 등을 고려하게 되는 것이다.

하지만 화학 플랜트에서는 이러한 플래닝 기법들을 적용하지 못하며, 스케쥴링 단계까지 고려할 필요가 있기 때문에, 근사적 방법들을 제시하게 되었다. 이를 위해, 스케쥴링 관점에서 이전의 기법들을 기반으로 하여 새로운 포뮬레이션 기법을 제사였다. 스케쥴링은 화학 공정의 제조 시스템에서 핵심 단계이나, 다양한 불확실성들이 영향을 준다. 이 불확실성은 단순히, 스케쥴링에서의 실행가능성 뿐만 아니라 제조 공정에서의 다른 단계, 플래닝과 컨트롤에도 영향을 주게 된다. 그러므로, 이러한 불확실성을 배제하게 된 스케쥴링은 실제 문제를 다루기에는 적절치 못하다. 그러므로, 이를 다룰 수 있기 위해 근사동적계획법을 제시하였다. Kondili에서 제시된 기존 예시를 사용하였으며, 가장 먼저 STN 형태의 기존의 MILP를 바탕으로 마르코프 체인을 형성하였다. 다음으로 가격을 최소화하는 목적 함수 대신 장치 고장과 추가적인 수요를 고려한 불확실성까지 고려하여 최종 생산물을 최대화하는 문제를 새로 만들었다. 이 때의 의사결정시점은 장비의 이용가능한 여부에 따라 결정되게 된다. 또한 이 때의 가치 함수는 추계학적 스케쥴링에 대한 최적 정책을 이끌어내며, 또한 불확실한 상황이 발생하게 되면, 이를 상태 전이로 간주하여, 실질적으로 온라인상으로 최적 정책을 만들어낼 수 있다. 이러한 가치 함수는 불확실한 상황이 발생하였을 때, 실행가능성에 대해 논의하는 데 도움을 준다.

마지막으로 위에 제시된 방법들을 기반으로 통합된 프레임워크를 제

시하게 된다 스케쥴링은 플래닝 단계에서의 실행가능성을 생산할 수 있는지에 대해 판단하며, 플래닝 단계에서는 스케쥴링에 어느 만큼 생산을 해야하는 지에 대해 결정을 하며 논의하게 된다. 이러한 정보의 상호교환은 추가적인 시간 소모를 거의 하지 않으며, 실질적으로 정보를 실시간으로 업데이트하게 하는 것도 용이하다. 즉 이러한 불확실성을 대비할 뿐만 아니라, 불확실한 상황이 발생할 때마다 대처할 수 있음을 확인할 수 있었다.

- 에너지 자원 최적화와 상수도 관망 관리 등의 다양한 예시들을 통해 최적화 기법을 분석
- 화학 공장에서의 최대 생산량 예측을 위한 근사동적계획법을 적용
- 공급망 관리에서 근사동적계획법을 이용하여 용 스케쥴링의 통합 프레임워크를 제시

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