ABSTRACT

Title of dissertation:	STOCHASTIC MODELS FOR AIRPORT FACILITY DEVELOPMENT
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An essential task of airport authorities is to plan airport facilities that meet future traffic needs in a dynamic and uncertain environment. Major technical difficulties in airport facility development stem from: (1) distinct construction and operating characteristics of different airport components; (2) nonlinear congestion effects affecting most airport facilities; and (3) complex interactions between airport user flows and facilities, which means that decisions regarding various facilities are interrelated. Potential demand fluctuations in a deregulated aviation market, combined with various other uncertainties, add further dimensions to the airport capacity planning problem. The core of airport facility development is to determine the timing and sizing of facility expansion projects.

The traditional airport master planning has been criticized for its limited ability to cope with future uncertainties. Although there are several general procedures and frameworks for improving the planning flexibility or adaptability in uncertain environments, these macro analyses are considered only conceptually useful and

cannot generate detailed plans for implementation. Very few relevant studies are found and all of them focus on a single component (e.g., passenger terminal) or specific facility. However, an airport is a system of many components, which can operate in parallel or in series. In airport development, it is desirable to roughly equalize the capacities of facilities operating in-series. Therefore, the present work is distinguished by the design of global planning models which can coordinate the development of various components under several sources of uncertainties.

Due to the intricacy of the airport facility development problem, this dissertation presents a series of applied decision tools sequentially. Practical considerations, such as economies of scale, future cost discounting, nonlinear congestion, and project implementation time requirement, are captured in proposed optimization models which combine the difficulty of optimizing over binary variables and handling nonlinear relations. After examining the structural properties of optimization models, some simplification techniques are proposed, such as the out-approximation and discrete-approximation linearization methods, for enhancing solution efficiency and quality. Computational experiments demonstrate the benefits of such models. For instance, the total cost could be reduced significantly (e.g., by 18.8% in one test) with the proposed stochastic model, compared with decisions based on the average conditions. The decision tools developed can augment the airport master planning process in its ability to address future uncertainties. This work also offers methodological contributions in the field of infrastructure development, such as modeling of complex facility performances and a method for coordinating the development of various types of facilities.

STOCHASTIC MODELS FOR AIRPORT FACILITY DEVELOPMENT

by

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Dedication

In memory of my grandfather.

Acknowledgments

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Chapter 1: Introduction

1.1 Background and Problem Definition

The aviation sector fosters a nation's prosperity by facilitating economic activity and creating jobs. However, infrastructure aging and congestion at major airports greatly concern economists, policymakers and transportation engineers, due to their threats to the regional and national economic health. Airport development decisions are critical, because (1) substantial capital investments are needed and they are usually irreversible [2]; (2) the development of an airport can have significant social, economic and environmental impacts [3, 4]. For the airport itself, insufficient capacity can quickly lead to deteriorating airport performance, characterized by enormous delays. Consequently, the airport's attractiveness and competitiveness are jeopardized. While excess capacity can alleviate congestion, it might also be costly and unnecessary. Premature facility improvements usually impose heavy financial burdens on underused airports and such expansions are unlikely to be approved by aviation funding agencies, such as the Federal Aviation Administration (FAA) in the United States.

The facility development decision is not only critical but also difficult. Many practical considerations should be incorporated in this decision making process, such as economies of scale, time value of money, lumpiness in expansions, and nonlinear congestion effect. Although at one level some airport components, e.g., passenger gates, air cargo facilities, and general aviation facilities, operate in-parallel, the major airport components, such as runways, passenger terminals and ground access facilities, mostly operate in-series, as shown in Figure 1.1. In optimizing the overall performance of the airport system, it is desirable to roughly equalize the capacities provided by these components acting in-series, so that a certain user flow passing through these in-series facilities does not experience heavy delays at the bottleneck facility. The capacities should be only roughly equalized because the costs of additional capacity and costs of lacking capacity differ for different components. The problem is even more challenging in the presence of various uncertainties, which can affect the overall volume of air traffic levels as well as the mix of traffic. In such a case, decisions have to be made first, while uncertainties are only observed later.

For airport authorities, the core of airport facility development is making good strategic decisions on what facilities to develop at what time, i.e., the timing and sizing of facility expansion projects. While several conceptual methods are available on the airport facility development, e.g., dynamic strategic planning [5], design flexibility [6], and dynamic adaptive planning [7], systematic methodologies and practical decision tools are still lacking, which motivates this study. Therefore, this dissertation presents a series of applied computation tools for optimizing airport facility decisions. The objective is to coordinate the expansions of various airport facilities with explicit considerations of impacts of various uncertainties.

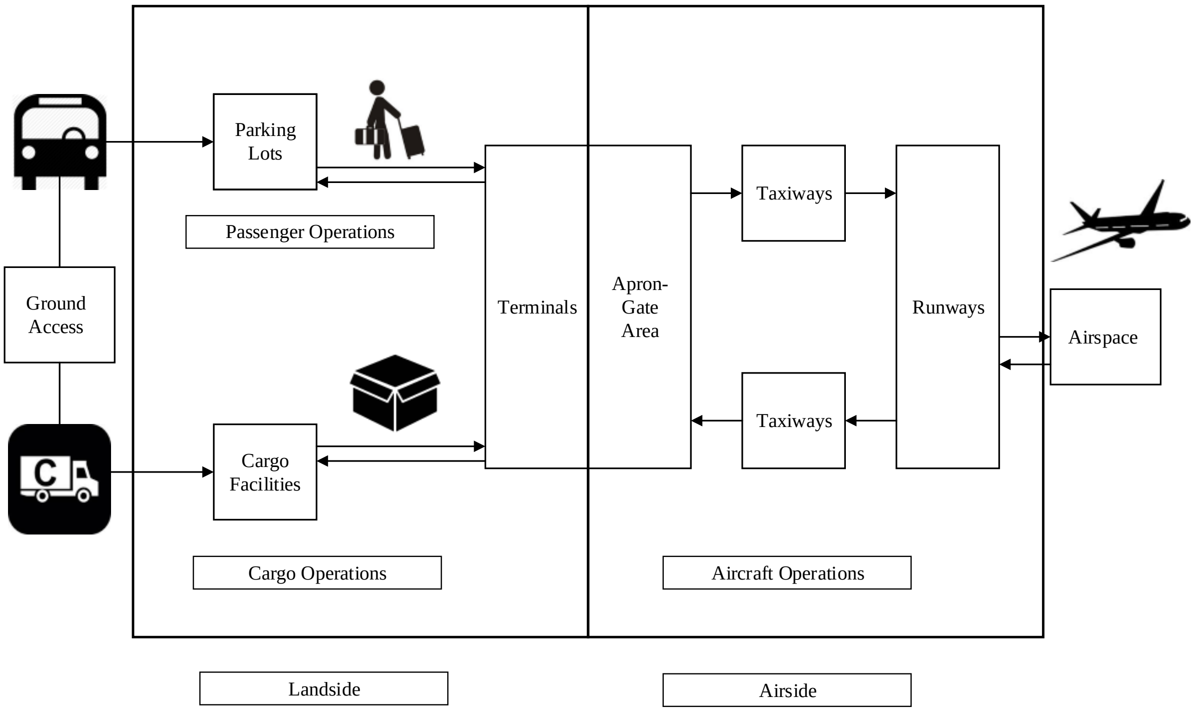

Figure 1.1: Interactions between airport components

1.2 Practical Factors in Airport Development

Practical considerations in airport development are briefly explained as follows:

1. Economies of scale

   It is often less expensive to combine multiple capacity enhancements during implementation, due to fixed costs and other factors. For example, it would be very inefficient to build new gates or car parking spaces one at a time due to the substantial fixed cost of terminal building expansion. Thus, in these cases, the one-time expansion in a relatively large step is favorable as shown in Figure 1.2.

2. Time value of money

It is standard practice to consider time value of money in evaluating overall capital investments over a long-term planning horizon. The costs of later enhancements are more heavily discounted when converted to present values. Therefore, it is beneficial to postpone unnecessary capacity expansions to the future periods, thus leading to an incremental expansion path as shown in Figure 1.2. Scale economies and future cost discounting are thus two conflicting factors in the airport facility development.

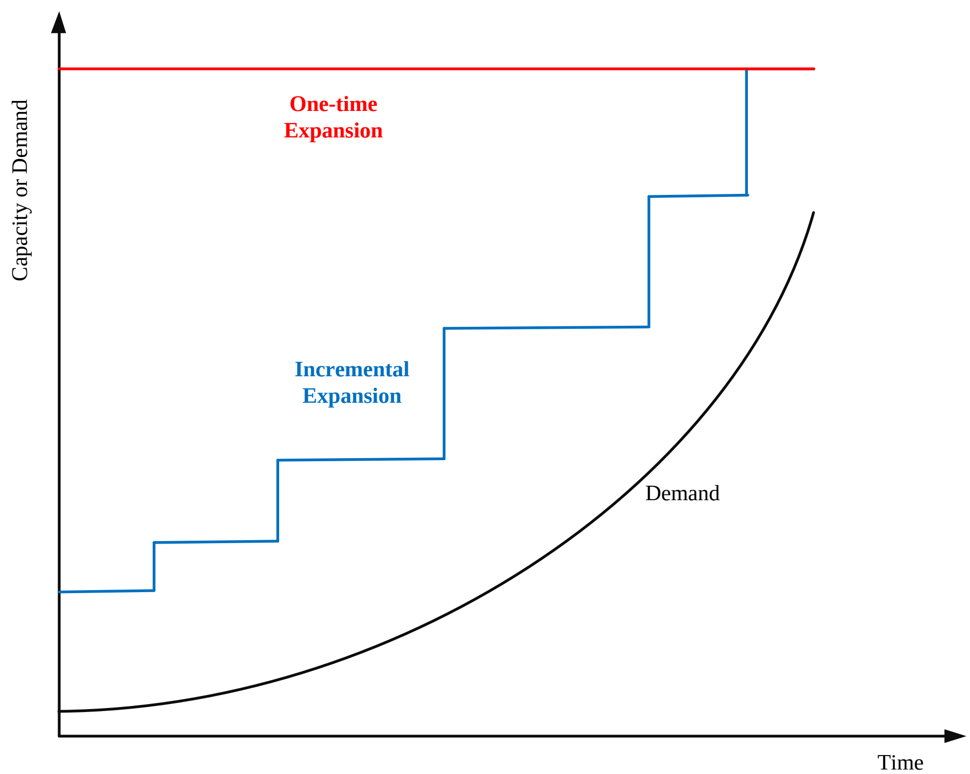

Figure 1.2: Economies of scale vs time value of money

3. Discrete expansion

Capacities cannot be increased continuously (as shown by the continuous expansion curve in Figure 1.3), but only in integer or at least discrete steps (step curve in Figure 1.3), such as by one complete runway or one whole ground access lane.

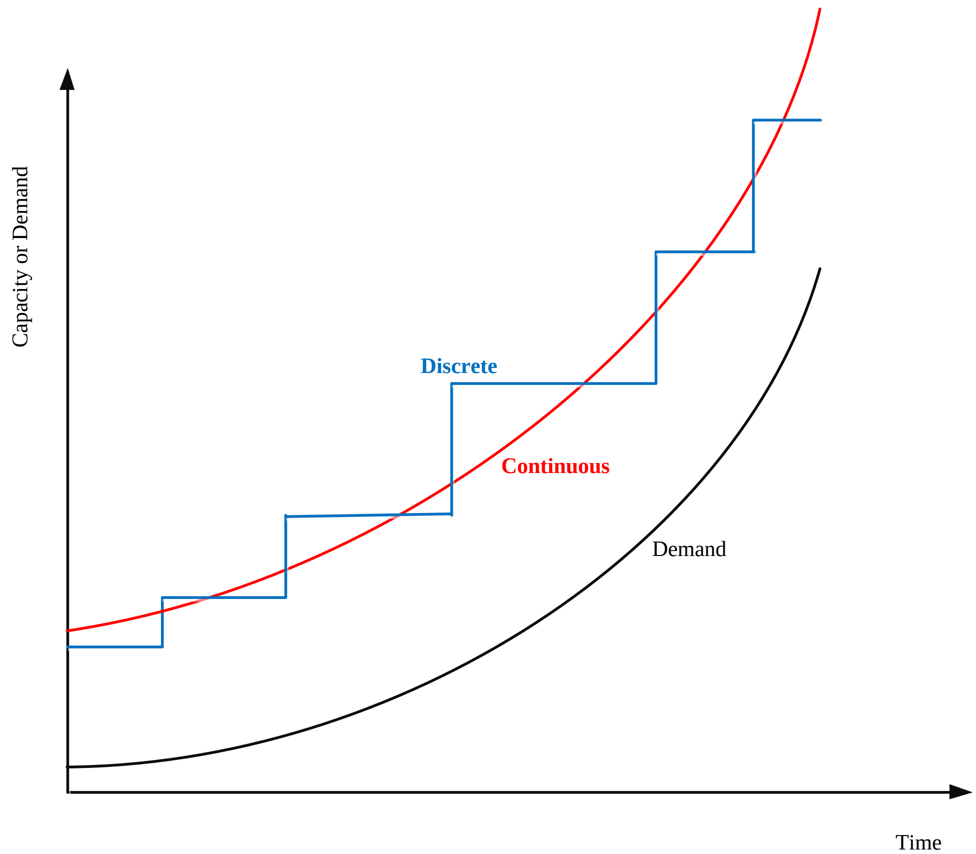

Figure 1.3: Discrete expansion

4. Nonlinear congestion effects

Due to fluctuations in user arrivals and the stochastic nature of service times, airport users experience various levels of congestion. Users could be passengers, ground vehicles, cargos or planes. Such nonlinear effects should be well addressed in making facility development decisions in order to maintain certain levels of service. As shown graphically in Figure 1.4, the demand curve should never reach the capacity expansion path, which will result in enormous delays.

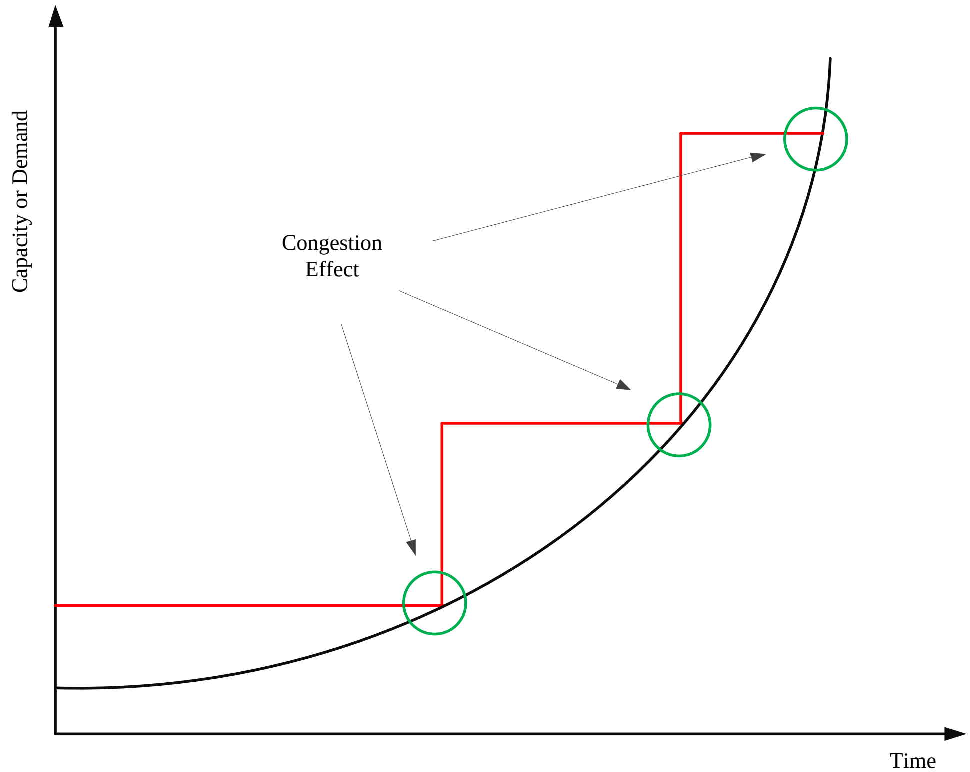

Figure 1.4: Demand touches capacity

5. Projection implementation time

   Capacities cannot be added instantaneously. It takes significant time to implement major facility development projects due to the mandatory proposal and approval process. The horizontal distance between the dashed and solid expansion paths in Figure 1.5 represents the minimum project implementation time.

6. Various uncertainties

   Various types of uncertainties from different sources are faced by airport au-

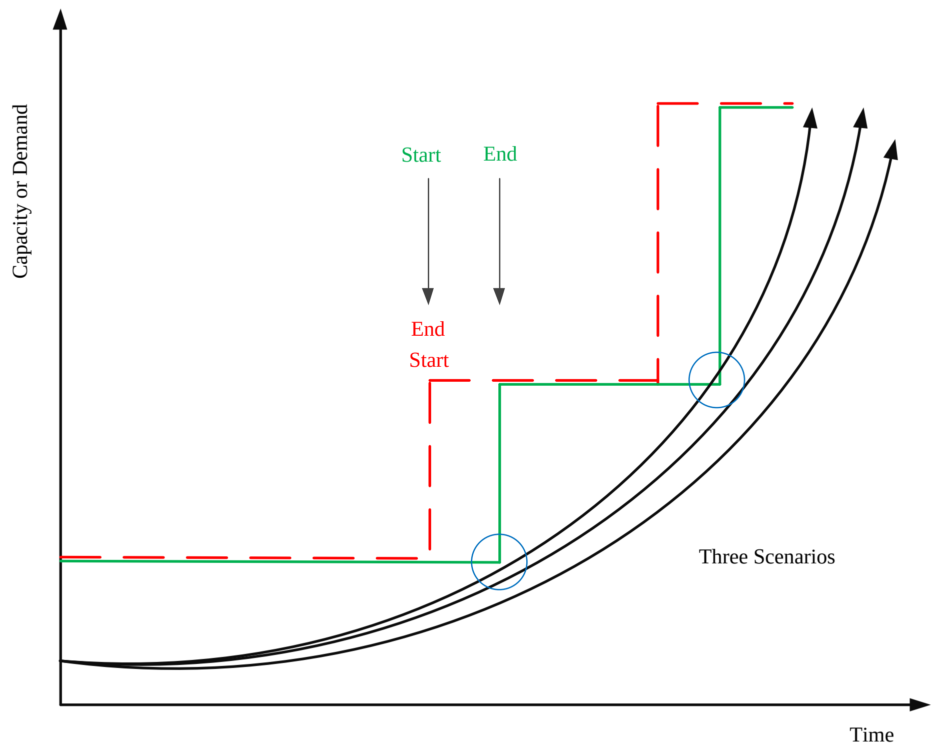

Figure 1.5: Project implementation time

thorities. Since the volume of air traffic depends on a region's or nation's economic development, forecasts of future airport activity can be derived from a model based on a statistical relation between air demand and gross domestic product. Any mis-specification of the parameters used in such a model could result into erroneous forecasts. It is widely known that long-term projections are hardly to be accurate and any standard forecast is inevitably subject to forecast errors [6].

Potential technological innovations can significantly impact the design and operation of airport facilities. For example, the introduction of new large aircraft could lead to the reconfiguration of terminals [8] and airsides [9]. The implementation of the Next Generation Air Transportation System transforms the air traffic control system of the United States, leading to the reduction of traffic delays and increase of airspace capacity. The construction of facilities could also cost less thanks to the emerging technologies.

Government decisions, such as those on the immigration policy, security check, emission restrictions, can affect the air traffic, too. Environmental concerns might lead business travelers to fly less and to have more online meetings. Stringent safety checking could shift some travelers to other transportation modes.

Competition among airports may get fiercer as air carriers are free to move their hub operations from one to another, in a deregulated market [10]. The loss of a major airline leaves airport facilities empty.

Other uncertainties in project implementation time, facility performance relations regarding capacities, and financial situations could also have profound implications in airport facility decisions.

Uncertainty about air traffic can manifest itself in two ways: (1) the volume, such as total passenger enplanements, total cargo tons and total aircraft movements; (2) the type, domestic vs international, heavy vs small aircraft, business vs non-business. Figure 1.6 presents several plausible demand growth patterns.

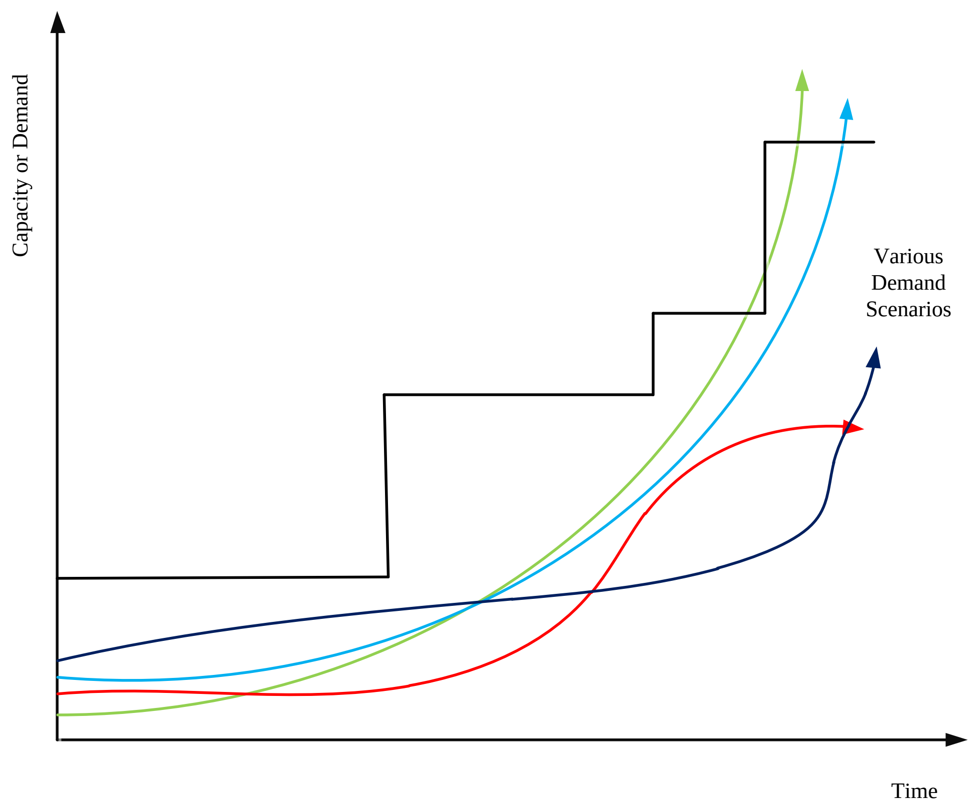

Figure 1.6: Multiple demand scenarios

7. Component interactions

Airports can be realistically modelled as a system consisting of components (e.g., runways, taxiways, terminals, air cargo terminals, maintenance facilities, etc.), which mostly operate in-series, although some components (passenger gates, air cargo facilities, general aviation facilities, maintenance facilities) also operate in-parallel, as shown in Figure 1.1. In optimizing overall system performance it is desirable to roughly balance (i.e. equalize) the capacities of the various components acting in-series. The differing magnitudes of minimum practical capacity increments for different components (e.g. one runway versus a few passenger gates or automobile parking spaces), imply that the capacity expansions in various components should be coordinated through phased developments, as suggested in Figure 1.7, in which the components with the largest capacity increments (which for airports usually are new runways) dominate the determination of phases.

1.3 Prior Studies

The existing airport development studies can be divided into macro and micro streams. At the macro level, de Neufville and Odoni [5] develop the concept of dynamic strategic planning in airports; Kwakkel et al. [7] propose another concept called dynamic adaptive planning. Although macro models can be useful for the preliminary evaluation of various airport development plans at the airport level, they cannot systematically generate detailed plans of interest given their design purpose. There are few relevant studies at the micro level. For example, Solak et

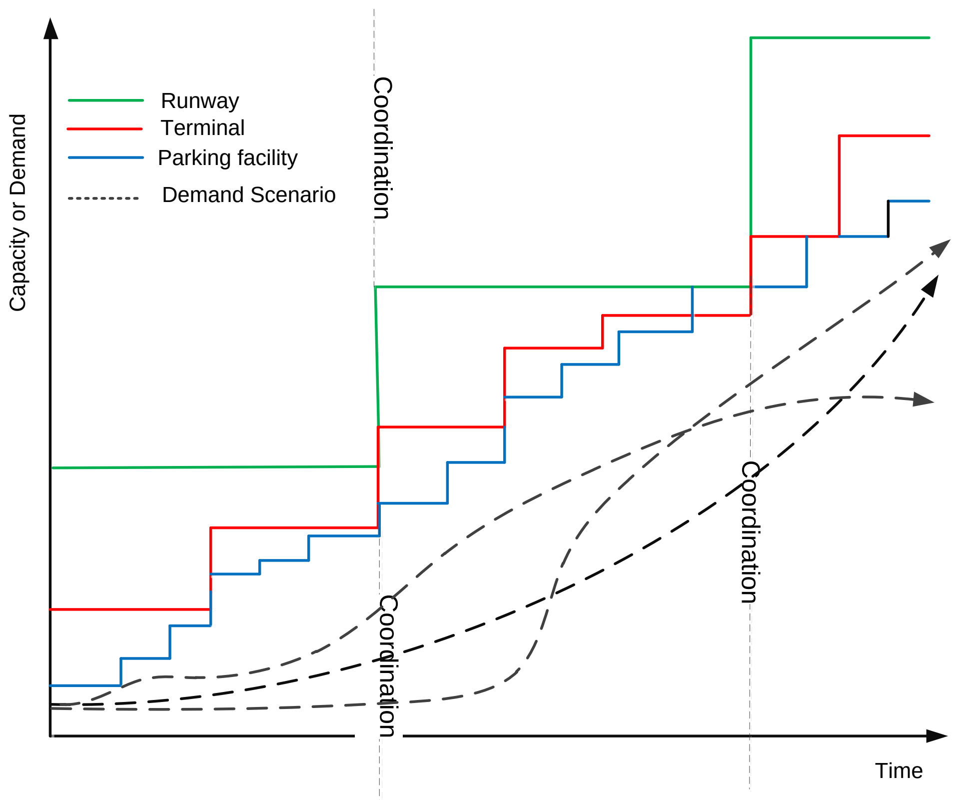

Figure 1.7: Coordinated development

al. [11] present a relevant study on airport terminal capacity planning; Yoon and Jeong [12] study how a baggage carousel should be expanded over a series of periods. Several ACRP (Airport Cooperative Research Program) reports [13–16] cover the planning methodologies for some specific airport components.

Although these studies are not reviewed in detail here (in-depth reviews are provided in Chapter 2), it is clear that previous studies focus on only one specific component of the airport system. Hence, a global airport planning model is still needed to coordinate the development of various components in a holistic manner. In fact, such a research need was mentioned by Solak et al. [11] in their suggested extensions.

1.4 Dissertation Structure

All factors mentioned above should be explicitly addressed in the decision making process, but not necessarily with one single model. This airport facility development problem is quite challenging and the methodological development is also unlikely to be completed in one step, for reasons provided below.

First, since uncertainty and nonlinear congestion effect are integrated into the capacity sizing and project scheduling problem, the resulting program combines the complexities of solving the Integer Program (IP), the Stochastic Program (SP) and the Nonlinear Program (NLP). To simplify the problem and finally solve it, a linearization approximation should be developed to remove nonlinearities so that the problem can be solved with more efficient LP algorithms. Only in certain circumstances can stochastic programs be converted into deterministic ones.

Second, structural properties of the program are unclear and they need to be explored so that specialized solution methods may be designed accordingly. It is unclear whether the global optimum can be claimed and if so, how much computational effort is needed. When needed, model enhancements might be necessary to reduce the computation burden.

Lastly, but more importantly, development decisions for various facilities are interrelated. If all facilities are operated in parallel, the overall problem can be decomposed into independent and smaller ones, which are easier to solve. New formulations are needed for reflecting interactions between various flows and facilities in the airport system and efficient solution techniques are also required for solving such models.

Three optimization models are thus presented in Chapters 3, 4, and 5, after extensive literature reviews in Chapter 2. Table 1.1 outlines the main contents of Chapters 3-5. Chapter 3 presents the first model, whose distinct feature as compared with other two models is to enforce the project implementation time constraint. The outer-approximation technique is proposed to linearize the model. The model in Chapter 4 is different since capacity can change in both directions, i.e., expansion and contraction. A discrete approximation method is used, which does not require differentiability of the delay function. Chapter 5 presents a network flow formulation for coordinating the development decisions. An additional improvement over models in Chapters 3 and 4 is to further consider the effect of uncertain aircraft mix. Chapter 6 concludes with summaries and extensions.

Table 1.1: Content outline

Chapter	Factors Considered	Main Technique
Chapter 3	Economies of Scale Time Value of Money Capacity Expansion Only Uncertainty Demand Project Implementation Nonlinear Congestion Effect Time	Outer-Approximation
Chapter 4	Economies of Scale Time Value of Money Capacity Expansion & Contraction Uncertainty Demand Nonlinear Congestion Effect	Discrete Approximation
Chapter 5	Economies of Scale Time Value of Money Capacity Expansion Only Uncertainty Demand and Aircraft Mix Component Interdependence Nonlinear Congestion Effect	Network Flow Formulation

Chapter 2: Literature Review

2.1 Capacity Expansions in Non-aviation Areas

Capacity planning is the process of determining the path of capacity provision levels over a planning horizon. In the context of expected long-term demand growth, the core of this strategic planning process is intended to determine the optimal timing and level of capacity acquisition or "expansion." This decision process is crucial in a wide array of practical applications, such as telecommunications [17], manufacturing [18], oil industry [19], network design [20], electricity generation [21] and urban water resource systems [22].

Although studies in other contexts are valuable and helpful, this review focuses on transportation due to the considerable difference in the nature of these technological systems. For example, congestion effects which are essential characteristics of most transportation facilities, seem to be absent in some other applications, such as urban water supply systems. If no congestion effect is considered, all costs tend to be linear as in [22]. Sometimes nonlinear congestion might be simplified partially due to the modeling philosophy of "Do not introduce nonlinearities unless necessary." This is quite reasonable in terms of modeling level of sophistication and convenient in utilizing efficient linear program algorithms. For instance, in facility location modeling, as long as a service center has sufficient capacity to cover several demand nodes even when the system is operating at its design capacity, no penalties are incurred. In reality, customers might experience nonlinearly increasing waiting as the system capacity utilization grows. In other words, such congestion effects exist in the facility location problems; however, they are simplified or neglected. While the simplification is justified in certain areas, that is not the case in general transportation planning and operations.

Transportation network design, as an important topic in transportation studies, has been continuously studied during the last several decades. A survey paper by Farahani et al. [23] covers its definitions, formulations, classifications, and solution techniques. Nonetheless, this review focuses only on deterministic models. Recently, effects of uncertainties have been analyzed either with stochastic programming [24, 25] or robust optimizations [26–29]. Usually one type of uncertain variable, namely demand, is considered [25, 27]. Siu and Lo [30] consider uncertainties on both the supply and demand sides. By noticing that most problems involve only one time period, Ukkusuri and Patil [24] formulate a flexible network design problem for obtaining optimal capacity improvements in a multi-period horizon, which represents an innovative effort. Chen et al. [31] provide a relevant review of transportation network design problem under uncertainty. Interested readers are directed to this paper [31].

Bilevel programming is naturally used in modeling the hierarchical situation where network planners make decisions at the upper level and roadway users react to these decisions by deciding whether to travel or not; if so, where to go in what mode at what time and via what route. As a norm in the roadway network design, the congestion is modelled with the Bureau of Public Roads (BPR) link performance function in the lower level user choice model. Specialized methods are available in transforming these bilevel programs into mathematical programs with equilibrium constraints. More discussions can be found in the review article [23].

While congestion is generally considered in roadway network designs, it is often neglected in public transit [32] and railway network [33] expansion studies.

Marin and Jaramillo [32] present a bilevel program for optimizing the multi-period expansion of a rapid transit network. The upper level problem concerns station location decisions and the lower level considers user routing choices. The resulting large scale mixed integer program is solved with heuristics. Neither uncertainty nor nonlinear cost is involved in this study.

More recently, Lai and Shih [33] propose a stochastic model to select capacity expansion projects for North American freight railroad networks. They assume that all capacity enhancement alternatives can be generated and impacts of implementing those projects can be evaluated. Their model accounts for periodical budget constraints and demand uncertainties; the objective is to minimize total costs including investments, train flow costs and penalties for unfulfilled demands. While Lai and Shih [33] make significant progress, especially in terms of realistic network size, important difficulties remain in their study: (1) the number of expansion alternatives grows exponentially due to the combinatory nature of enumerating improvement choices about multiple system components; (2) some input parameters for their models are hard to obtain. For example, the capacity increment (in units of trains/day) resulting from implementing one project is difficult to estimate due to the complex interactions among various railroad system components. More importantly, the penalty costs due to congestion effects should be nonlinear with respect to demands, contrary to the assumed linear relation.

From the above review, we can find that among capacity expansion instances in the general transportation area, roadway network design has been most widely and deeply studied in terms of realistic congestion modeling and uncertainty consideration. Experiences from developing roadway network expansion models might apply to the airport case.

2.2 Airport Development in Practice

Without additional specification, the following terms are considered interchangeable: airport development, airport facility development and master planning of airports. The most rigorous terminology used in the airport context is Master Plan. According to the definition by the International Civil Aviation Organization (ICAO), "an airport master plan presents the planner's conception of an airport." [34] Three notions of this definition as summarized by de Neufville and Odoni [5] are revisited:

- Ultimate vision, which means the future view after a considerable long period, e.g., 20 years;
- Development, the construction and building of physical facilities, such as runways and terminals, rather than operational or management issues;

- Specific airport, not a system of several airports.

The master planning process is the same for almost all airports. The 2011 master plan of the Baltimore/Washington International Airport (BWI) is cited as an example, which includes:

1. Inventory of existing conditions;
2. Aviation demand forecast;
3. Facility needs assessment;
4. Alternatives;
5. Implementation plan;
6. Financial plan;
7. Environmental overview.

The master plan of airport is of paramount importance, partially because both international and national aviation funding agencies, such as the FAA in the United Stations, would provide funds only to airports with approved master plans.

Many sources of uncertainties are inherent in the airport development process. These uncertainties can affect the overall volume of air traffic levels (e.g., annual enplanements, total number of aircraft operations and cargo volumes) as well as the mix of traffic (e.g., domestic vs international passengers, wide-body vs narrow body aircrafts). A rather complete list of uncertainties involved in the airport long-term planning is provided in ACRP Report 76. To name a few, global, regional, or local economic conditions, airline merges or bankruptcies, regulatory changes, and other shock events, such as terrorist attacks and pandemics. Figure 2.1 [1] presents the changes of international passenger enplanements at the Baltimore/Washington International Airport (BWI) due to various events. The traffic level can build up quickly to create severe congestion and it can also drop even faster, resulting in underutilized facilities.

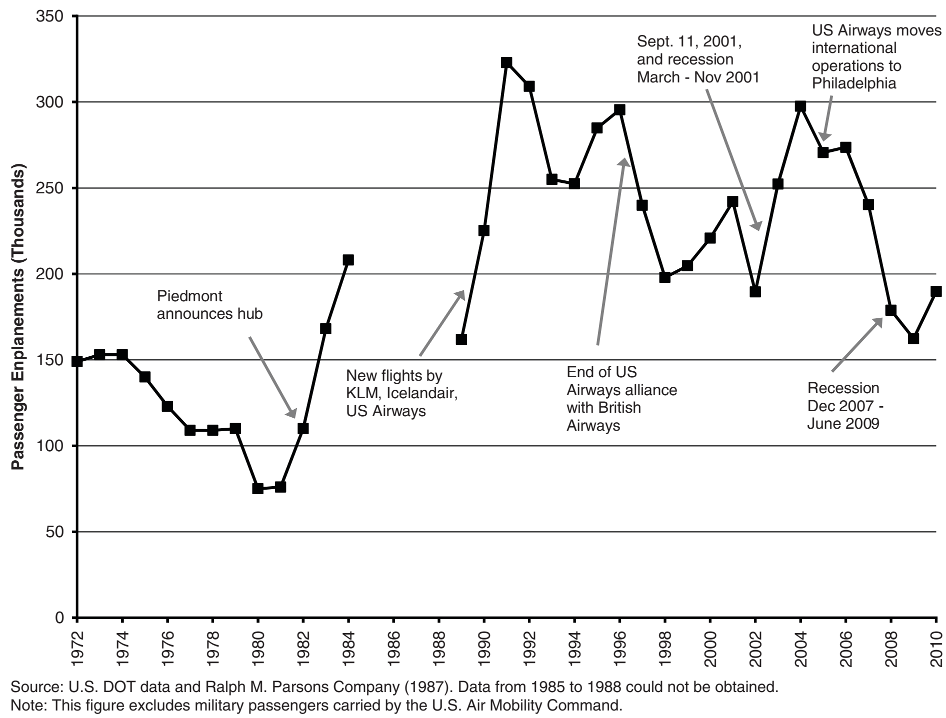

Figure 2.1: International passenger enplanements at BWI [1]

Although uncertainty is handled in the master plan by supplementing the base-case forecast with high- and low-case forecasts to account for a range of potential outcomes, this approach only provides a cursory understanding of future changes [1]. The ACRP Report 76 also illustrates other standard ways of addressing uncertainties, such as what-if analysis and sensitivity analysis. These procedures are “rarely incorporated into the planning process in any meaningful way" [1]. de Neufville and Odoni [5] comment that only one forecast is considered in the master planning process, which is "fundamentally flawed." de Neufville and Scholtes [6] argue that master plan and its equivalents lead toward a fixed and static view of the future. They criticize the standard process by saying "the usual design and evaluation procedures focus on an unrealistically narrow description of the possibilities." Caves and Gosling [35] also criticize the traditional master plan by noting the destructive impacts of a planners belief in the "myth of predictability": presuming the past trends would continue into the future. They further mention that early errors in describing the complex system tend to propagate downstream to other planning processes in a unidirectional way. Such practice would lock-in inefficient designs in early planning stages, which lack expandability or flexibility in the face of future uncertainties.

Despite the recognition of uncertainties, international aviation industry organizations reveal a high dependence upon the rather narrow point estimates. The Manual on Air Traffic Forecasting [36] requests the Council "must foresee future developments likely to require action by the Organization and must initiate such action in good tim". However, this task would be almost impossible in the current rapidly changing world. Although forecasting accuracy is discussed, no methods are provided regarding how these prediction inaccuracies should be incorporated in subsequent planning stages.

2.2.1 Trigger Point Approach

One widespread method for determining the timing of a new expansion project in practice is called the threshold or trigger point approach [1]. For instance, when traffic reaches 80% of the current capacity, predefined facility expansion projects are initiated. Such a timing approach is helpful when traffic keeps increasing steadily, while projects might be wrongly launched when traffic fluctuates greatly. No theoretical studies have been found to justify the optimality of such a capacity expansion policy; even assuming that such a threshold-based approach can produce optimal results, the trigger point seems arbitrary without sufficient quantitative support. For example, how can we determine these trigger points (e.g., 85%, 90% or 95% of the existing capacity) and the size of capacity increments for various facilities?

An analogy can be found in the inventory management problem. A simple inventory policy (s, S) specifies that a manager should restock up to the level S if the inventory drops below the level s. Such a simple policy was proved to be optimal by Arrow et al. [37] and by Scarf [38], among others, while methods, e.g., Veinott and Wagner [39], for finding such a policy (characterized by values of s and S) became available after some additional years. Therefore, compared to the well-developed inventory policy, the validity of the trigger point approach is largely unexamined.

One additional problem arises when demand drops, which means capacity might also be reduced. What methods can be used to derive the trigger for capacity contraction?

Even if such a threshold policy is proved to be optimal and rigorous methods have been developed for determining relevant triggers, such a policy can only provide guidance on the development of a single facility and it would not apply to a group of interrelated facilities.

2.3 Airport Development Studies

Airport development studies addressing uncertainties can be naturally grouped into two categories: macro analyses and micro ones. At the macro level, several conceptual methods and procedures are proposed, e.g., de Neufville and Odoni [5] and Kwakkel et al. [7]. Usually these methods are not readily available as detailed planning tools, although they are based on real-world experiences. In the second group, more practical computational models are designed to facilitate the airport capacity planning at a fine level. Specific facility development plans can be expected from these studies, such as Solak et al. [11] and Yoon and Jeong [12]. Due to the difference in method focus, studies at these two levels are reviewed separately.

2.3.1 Macro Approaches

As pioneers advocating explicit treatment of uncertainties in airport master planning, de Neufville and Odoni [5] develop the concept of dynamic strategic planning in airports. They argue that airport traffic forecasts are "always wrong" and the unreliability of forecasts has crucial implications for airport planning. However, the traditional process for developing an airport master plan is essentially reactive. To make the plan proactive and flexible, they propose a modified form of master planning by considering several possible levels and types of future traffic. Although they mention some measures for increasing the planning flexibility, such as shared use between domestic and international services and reconfiguring the layout of baggage facilities, this dynamic strategic planning approach is considered only conceptually useful [1].

In the book *Flexibility in Engineering Design* by de Neufville and Scholtes [6], the authors further criticize the standard planning approach due to its inability to react to future conditions and extend the analysis beyond the airport by stating flexible design can increase expected values. The basic four-step process is described as follows:

1. Identify major uncertainties or risks the project is going to encounter.
2. Determine specific components of the system to provide the flexibility best suited to address recognized uncertainties in above step.
3. Evaluate alternatives and incorporate these into the design.
4. Implement the chosen plan by satisfying various stakeholders and monitoring condition evolution.

They provide several examples from various fields, such as parking garages and high-rise buildings, to illustrate the process.

A similar five-step framework, as listed below, for addressing uncertainty about future airport activity levels is provided in the ACRP Report 76 [1].

1. Identify and quantify risk and uncertainty.
2. Assess cumulative impacts.
3. Identify risk response strategies.
4. Evaluate risk response strategies.
5. Risk tracking and evaluation.

Kwakkel et al. [7] propose another concept called dynamic adaptive planning. They also argue that uncertainties are largely ignored in the dominant approach in infrastructure planning. To increase the planning adaptability, they establish a new approach which is claimed to outperform in most cases a static rigid plan through the specific example of airport strategic planning. They generate the contingency plan by recognizing various future scenarios. For instance, if the noise in the study area increases by 20% compared to the base year, take defensive (DA) action; if by 50%, take capitalizing (CP) action; if by 75%, reassessment (RE) action. They specify each type of action (i.e., DA, CP and RE) for each future change, such as demand, noise level and wind condition.

In addition to the conceptual planning concepts reviewed above, other macro methods are available for addressing uncertainties in airport planning. In particular, three streams of studies are reviewed: (1) option valuations, (2) system dynamics, and (3) microeconomics.

The concept of “real options” is adapted from financial options. Investors have the right rather the obligation to buy or sell a security or other assets at an agreed price during a certain period of time. "Options" can be real in the sense that they have physical characteristics compared to financial ones. de Neufville and Odoni [5] think that options are particularly useful in highly risky situations because owners of options can respond to future changes by making adaptive decisions. In a master thesis [40] advised by de Neufville, four maneuvers, namely buy, sell, expand and contract, are considered. The planners can compare the value of option with the acquisition cost. This option is incorporated into the planning only when the expected value exceeds the cost. Candidate decisions could be: land banking, preserving right-of-ways for public transit access to the airport [5]. It seems that these buy or sell decision are heavily site-specific: good decisions (land banking) made for one airport could be useless for others. In addition, the real value of an option might be difficult to estimate.

Suryani et al. [41] develop a system dynamics framework to forecast air passenger demand and evaluate some policy scenarios related to runway and passenger terminal expansions. After recognizing that air passenger demand can be affected by both internal (e.g., airfare and level of service) and external factors (e.g., gross domestic product and demographic factors), they build a casual loop diagram to model the casual mechanism between demands and facility capacity expansions. With validated models, they develop two scenarios, namely optimistic and pessimistic ones. A fundamental principle underlying system dynamics studies is information feedback control: air travel demands will grow as general economic conditions go upwards and increased demand will force the airport authority to expand existing facilities. Because such a feedback principle is generalized from macro analyses, methods based on this principle are unlikely to be used in guiding practical facility development. As the authors state in the concluding section, “a pilot study to decide when the airport should expand.”

Xiao et al. [42] study the effects of demand uncertainty on airport capacity choice from a microeconomic prospective. They focus on the difference between various airport ownership alternatives (profit maximizing and welfare maximizing) and market structures (e.g., two airports controlled by one authority); however, the time dimension is not included in the decision making process. Thus, this method is incapable of determining capacity choice over time.

In summary, there are quite a few alternative planning procedures at the macro analysis level. These methods can be useful for the preliminary evaluation of various airport development plans at the airport level rather than at the component or facility level. Several considerations have been incorporated into remedying the conventional planning approach. Nonetheless, these macro-level methods cannot systematically generate detailed plans of interest given their design purpose.

2.3.2 Micro Approaches

There are very few micro analyses of the airport facility development problem in the literature. Only three relevant studies conducted in recent years have been found, by Solak et al. [11], Chen and Schonfeld [43] and Yoon and Jeong [12]. These studies are reviewed below.

By noting that earlier studies either do not account for facility expandability (e.g., a single period is analyzed) or focus on solely a specific area of an airport terminal, Solak et al. [11] present a holistic model for airport terminal capacity planning during the initial building phase as well as expansions in future periods. Since field observations or computer simulations are usually employed to model passenger flows in airport terminals with rather complex configurations, which create difficulties in feeding these inputs into analytical optimization framework, the authors derive closed form functions to approximate the maximum delay in airport terminals. Then they present a multi-stage stochastic programming model to minimize total delay costs subject to budget and pedestrian flow constraints. Although all constraints are linear, the objective is nonlinear since approximated delay functions are essentially nonlinear, which induce the design of heuristics to generate tight upper bounds in the proposed branch and bound algorithm. Due to the non-convex structure, no global optimum can be found. This study is especially innovative in modeling airport terminals holistically without significantly sacrificing the realism of terminal operations. The authors suggest that future extensions should include: (1) new approaches to account for the highly nonlinear and non-convex model structures; (2) a global capacity planning model incorporating other airport components, such as the airside.

Chen and Schonfeld [43] present a model for optimizing the timing and number of new airport gates subject to demand and construction time uncertainties. By assuming that the Pollaczek-Khintchine formula [44] is applicable, they analytically derive the critical demand boundary to trigger the capacity addition. However, this paper's application is limited to airport gates expansion and the derived critical boundary (i.e., the future arrival rate over the threshold of service rates) depends heavily on the assumed delay function. One contribution of this work is that the authors further consider the uncertainty in construction times in addition to the uncertain demand. Interval uncertainty measurement of a variable x is $[x_{lb}, x_{ub}]$, where x_{lb} is the left endpoint of the interval and x_{ub} is the right end. Uncertainties of x and y can be combined: $x + y = [x_{lb} + y_{lb}, x_{ub} + y_{ub}]$. Although other basic operations besides addition can be designed, due to the complex relations between random variables, uncertainties cannot be combined simply with these addition, subtraction, multiplication and division operations. For instance, uncertainties in annual aircraft operations, mix of domestic and international passengers and fixed capital costs cannot be jointly considered with the interval arithmetic method.

Another airport facility study is presented by Yoon and Jeong [12], where the baggage carousel is expanded over a series of periods. Unlike the analytical approximation method adopted by Solark et al. [11], they employ discrete-event simulations to fully capture the complexities of passenger movements in the baggage claim areas. For example, they consider that workloads will be redistributed and travelers' waiting times might increase at other carousels during the construction period of one carousel. Such operational details are unlikely to be considered analytically. After the simulation evaluation module, they design a heuristic to select the most cost-effective expansion plan with a real world case study of the Incheon International Airport. This study reports innovative research efforts of using micro-simulation techniques to evaluate capacity expansion decisions for a very specific type of terminal facility. Several aspects of this problem are still quite simplified. For instance,

(1) the sizing of capacity expansion is trivial because the existing conveyor can only be extended to 110 meters if it is selected for expansion; (2) no economies of scale are considered; (3) uncertainty is not addressed; (4) the solution space is relatively small.

The following conclusions can be drawn from reviews of micro expansion models:

- No global planning model is available. Global planning means here an integrated model which jointly considers multiple airport components, e.g., airside, landside and other support facilities. Since we know an airport is an integrated system with close component interactions, a global method to coordinate its development is developed.

- Various accuracy degrees for facility performance modeling are selected depending on the application context. While computer simulations best reflect the performance change after implementing a capacity change, their analytical intractability creates difficulties in designing optimization methods. Note that the solution space in Yoon and Jeong [12] is relatively small, as reviewed above. The analytical evaluation of facility performance is preferable in terms of optimizing capacity expansion decisions; however, operational details are thus sacrificed to some extent.

- Uncertainty is considered, but far from sufficiently. The model developed by Solak et al. [11] is already complex when only demand uncertainty is considered. Although Yoon and Jeong [12] consider demand fluctuations over periods of a day through simulations, uncertainty analysis is not incorporated. Chen and Schonfeld [43] consider both the demand and construction time uncertainties. The simple method of treating uncertainty with an interval measurement is insufficient when complex interactions are present among various types of uncertainties.

- It seems that there is no consensus in choosing appropriate optimization methods. Solak et al. [11] model the problem as a multi-stage stochastic program and solve it with branch and bound algorithms; Chen and Schonfeld [43] derive all solutions analytically; Yoon and Jeong [12] employ heuristics.

Table 2.1 provides a brief comparison of these airport facility development studies at the micro level.

Table 2.1: Summary of micro analyses of airport facility development

Authors & Year	Component	Facility Performance	Uncertainty	Optimization Method
Solak et al. [11]	Passenger terminal	Analytical approximation	Only demand	Multi-stage stochastic program
Chen and Schonfeld [43]	Boarding gates	Analytical function	Demand and construction time	Analytical
Yoon and Jeong [12]	Baggage carousels	Simulation evaluations	NA	Heuristics

It is worth mentioning a study [45] on the long-term expansion of a network of airports. Instead of making decisions for each component of a single airport, Santos and Antunes [45] optimize strategic decisions regarding the expansion of airport network of a country or several countries. Each airport in the airport network is treated as a node and no subcomponents of airports are studied. Therefore, a single demand measurement, i.e., the number of enplanements, is used. The proposed model is static, because the best timing for implementing the expansion is not involved. The model is also deterministic and does not accommodate uncertainty issues.

2.4 Summary

To augment existing airport master planning methods, which are heavily criticized due to their limited ability to address uncertainty, various macro and micro modeling tools are developed. The so-called trigger point approach might be promising; however, it has not yet been examined rigorously. Quite a few macro procedures can be useful for the preliminary evaluation of various airport development plans at the airport level. However, these macro-level methods cannot systematically generate detailed plans of interest given their design purpose. Therefore, a series of optimization models, which can determine capacity levels for each airport component over a long horizon under uncertainty, are proposed to extend the existing micro models.

Chapter 3: Airport Capacity Expansion Model

This chapter presents an optimization model for optimizing the airport facility development decisions under uncertainty, which is the first in the model series proposed in this dissertation. Basic considerations, such as economies of scale, time value of money, and nonlinear congestion effect, are included, while its distinct feature, compared to the two other models proposed later in this dissertation, is to incorporate a restriction on the project implementation time. Its primary methodological contribution is to introduce an effective linear approximation technique so that an interactive solution framework is possible.

A deterministic total cost minimization model is proposed and then extended into stochastic programs, by including uncertainties in traffic forecasts. After the exploration of properties of the delay cost function, an Outer-Approximation (OA) technique is designed. After model enhancements, an efficient solution framework based on the OA technique is used to solve the model to its global optimality by interactively generating upper and lower bounds to the objective. Computational tests demonstrate the validity of developed models and efficiency of proposed algorithms. The total cost is reduced by 18.8% with the stochastic program in the numerical example.

3.1 Formulation

3.1.1 Notation

Sets and Indices

i = component of airport system $I = \{1, 2, \ldots, l\}, i \in I$

j or t = time period within the planning horizon $J = \{0, 1, 2, \ldots, m\}, j, t \in J$

k = project of the project set $K = \{1, 2, \ldots, n\}, k \in K$

Parameters

f_{ij} = fixed capital cost of adding capacity to component i in period j

v_{ij} = variable capital cost of adding capacity to component i in period j

o_{ij} = unit operating cost of component i in period j

q_{ij} = demand on component i in period j

e_i = required project implementation time for component i

γ = discount coefficient

Decision Variables

x_{ijk} = the amount of capacity added to i in j through project k

y_{ijk} = whether project k for component i is started in period j

z_{ijk} = whether project k for component i is finished in period j

3.1.2 Assumptions

Some simplifying assumptions are made here:

1. The economic life of new infrastructure exceeds the planning horizon (typi-

cally 20 or 30 years), i.e., infrastructure replacements or demolitions are not considered;

2. While demands may decrease, capacity never decreases in any component of an airport;

3. Various demand measures (e.g., enplanements, number of aircraft operations, tons of cargo shipped) are estimated for each individual airport component and capacity is analyzed separately for each component.

4. Project implementation time is integral, i.e. covers the entirety of an integer number of planning periods;

5. For the same airport component (e.g., airfield or passenger terminal), a subsequent project can only start after the current one ends, i.e., only one project is active at the same time for a single component.

3.1.3 Cost Functions

Capital costs

Capital costs include fixed costs and variable costs. Once a project is initiated, the fixed cost f_{ij} is incurred, which does not depend on the capacity increment size x_{ijk}. The added capacity is available only after the required implementation time e_i. The variable capacity cost $v_{ij}x_{ijk}$ is then paid.

To consider the time value of money, the capital cost in period j is discounted with the coefficient γ^j. Then the capital cost of component i in period j can be written as:

$$C_{ij} = \gamma^j \sum_k (f_{i0} y_{ijk} + v_{i0} x_{ijk}), \forall i \in I, j \in J \tag{3.1}$$

or more compactly as:

$$C_{ij} = \sum_k (f_{ij} y_{ijk} + v_{ij} x_{ijk}), \forall i \in I, j \in J \tag{3.2}$$

Figure 3.1 presents these symbols regarding the project implementation graphically. The capacity of component i in period j is the capacity in the immediately

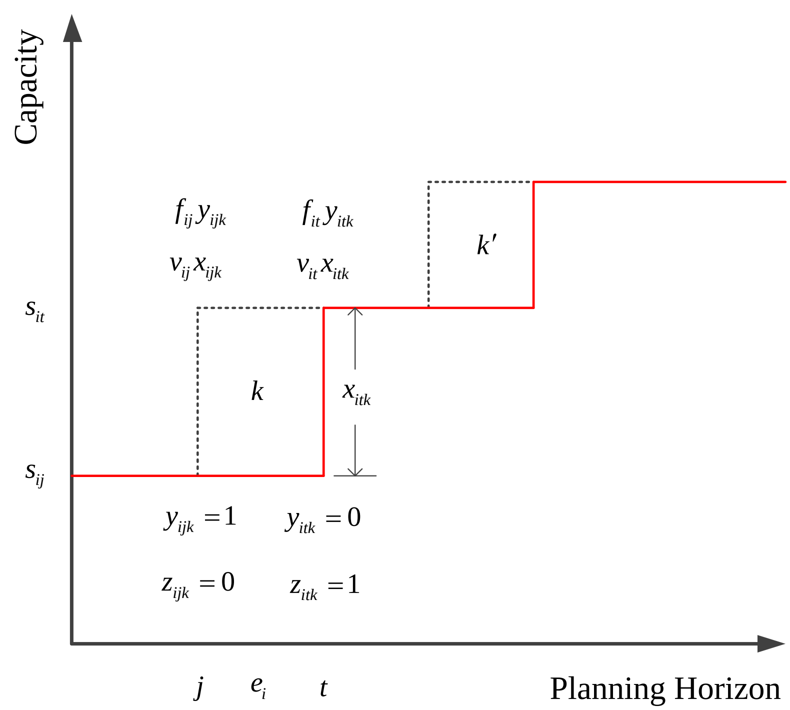

Figure 3.1: Notation regarding project implementation

prior period $s_{i,j-1}$ plus added capacity x_{ijk} through all projects. In fact, in a period (e.g., period t in Figure 3.1) when the capacity is increased, only one x_{ijk} is positive for all k because for a certain component only one project can be active at the same time.

$$s_{ij} = s_{i,j-1} + \sum_{k} x_{ijk}, \forall i \in I, j \in J \tag{3.3}$$

If the starting capacity of component i is s_{i0}, Equation (3.3) can be rewritten as:

$$s_{it} = s_{i0} + \sum_{j=1}^{t} \sum_{k} x_{ijk}, \forall i \in I, t \in J \tag{3.4}$$

In words, the capacity in period t is the initial capacity plus capacities from period 1 to period t.

Operating costs

To avoid early addition of capacities unwarranted by demand, operating costs are considered. The operating costs of component i in period j is the unit operating cost o_{ij} multiplied by the supplied capacity s_{ij}:

$$O_{ij} = o_{ij} s_{ij}, \forall i \in I, j \in J \tag{3.5}$$

Delay Costs

Operating costs are discounted in the same way as capital costs. We denote the delay function as:

$$d_{ij} = F_i(\rho_{ij}), \forall i \in I, j \in J \tag{3.6}$$

where d_{ij} = delay level of component i in period j

ρ_{ij} = capacity utilization of component i in period j, i.e.,$\frac{q_{ij}}{s_{ij}}$

Although various functional forms are usable, we find that delay curves have the following two important properties in common:

1. Delay level d is nondecreasing in the capacity utilization ρ.

2. Delay level d is convex in the capacity utilization ρ.

The first property does not require much justification and the second one can be illustrated with Figure 3.2.

The tangent function traversing a given point $(\bar{\rho}, d(\bar{\rho}))$ of delay function $d(\rho)$ is $\tilde{d}(\rho) = d(\bar{\rho}) + d\prime(\bar{\rho})(\rho - \bar{\rho})$, where $\tilde{d}(\rho)$ is the linear function of the tangent line and $d\prime(\bar{\rho})$ is the derivative of delay function $d(\rho)$ at point $\bar{\rho}$. Since the tangent line $\tilde{d}(\rho)$ lies below the nonlinear curve $d(\rho)$ at the given point $(\bar{\rho}, d(\bar{\rho}))$, we have $d(\rho) \geq \tilde{d}(\rho) = d(\bar{\rho}) + d\prime(\bar{\rho})(\rho - \bar{\rho})$. Because such a relation $d(\rho) \geq d(\bar{\rho}) + d\prime(\bar{\rho})$ holds for any feasible point, we can claim that $d(\rho)$ is convex in ρ.

Intuitively, the convexity arises because delay level grows increasingly faster (i.e., its derivative is increasing) as capacity utilization increases. Delay costs are demands multiplied by delay level, which can be written as:

$$D_{ij} = F_i(\frac{q_{ij}}{s_{ij}})q_{ij}, \forall i \in I, j \in J \tag{3.7}$$

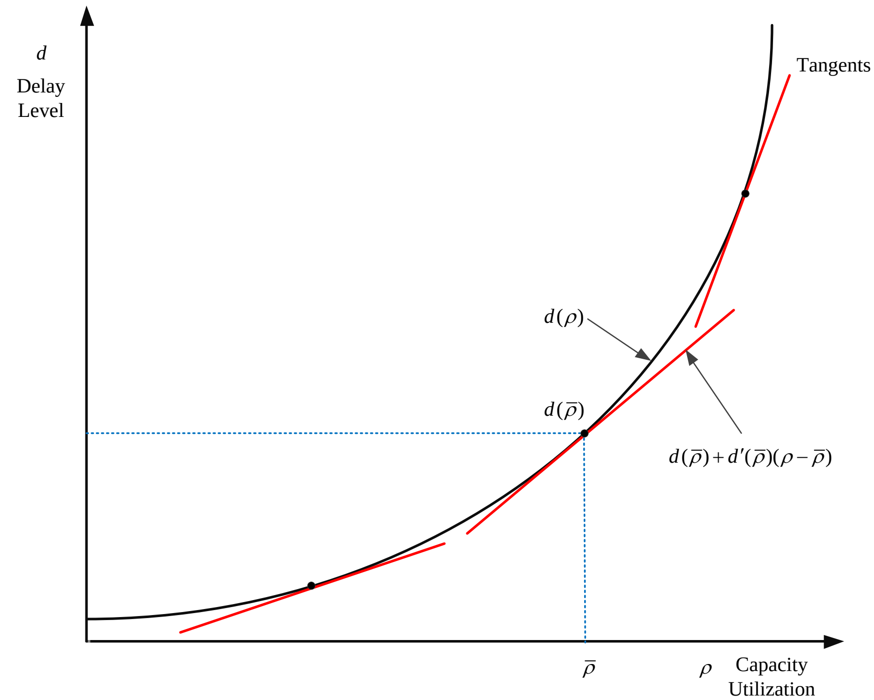

Figure 3.2: Convexity of a delay function in capacity utilization

3.1.4 Deterministic Model

The airport capacity expansion problem can be written as:

$$\min_{\{x_{ijk}\geq 0, y_{ijk}, z_{ijk}\in\{0,1\}\}} \sum_i \sum_j \sum_k (f_{ij}y_{ijk} + v_{ij}x_{ijk}) + \sum_i \sum_j o_{ij}s_{ij} + \sum_i \sum_j \gamma^j F_i(\frac{q_{ij}}{s_{ij}})q_{ij} \tag{3.8}$$

subject to

$$\sum_{j} y_{ijk} \leq 1, \forall i \in I, k \in K \tag{3.9a}$$

$$\sum_{j} z_{ijk} \leq 1, \forall i \in I, k \in K \tag{3.9b}$$

$$\sum_{j=0}^{t} z_{ijk} \leq \sum_{j=0}^{t} y_{ijk}, \forall i \in I, t \in J, k \in K \tag{3.9c}$$

$$y_{ijk} + z_{itk} \leq 1, \forall i \in I, j \in J, k \in K, t = j, j+1, \ldots, j + e_i - 1 \tag{3.9d}$$

$$x_{ijk} \leq M_i z_{ijk}, \forall i \in I, j \in J, k \in K \tag{3.9e}$$

$$s_{it} = s_{i0} + \sum_{j=1}^{t} \sum_{k} x_{ijk}, \forall i \in I, t \in J \tag{3.9f}$$

$$q_{ij} \leq s_{ij}, \forall i \in I, j \in J \tag{3.9g}$$

The objective of this program is to minimize the net present value of total cost which includes capital costs, operating costs and delay costs. Constraints (3.9a) and (3.9b) specify that any project only starts or ends at most once. We do not know how many capacity expansions should be planned for a component over the entire planning horizon, i.e., the project set K is unknown. For component i, due to the minimum project implementation time e_i, the maximum number of expansions n is bounded by $\frac{m}{e_i}$, where m is the length of the planning horizon. However, it is highly possible that fewer projects than the upper bound $\frac{m}{e_i}$ are needed. In this case, for a planned project k both y_{ijk} and z_{ijk} equal 1; while for an unplanned one, both indicators are 0. This explains why an inequality rather than a strict equality sign appears in Constraints ((3.9a)-(3.9b)). Constraint (3.9c) guarantees that a project ends no earlier than its start. Constraint (3.9d) enforces a required implementation time e_i between the start and end of a project. Constraint (3.9e) specifies that added capacities x_{ijk} are available only when a projects is finished (i.e.,$z_{ijk} = 1$). Constraint (3.9f) defines how capacities are accumulated. Constraint (3.9g) specifies that demands cannot exceed capacities, at least over extended periods. It should be noted that such a constraint may be superfluous since delay costs, which are included in the objective function, rise very sharply as demands approach the corresponding capacities.

3.1.5 Stochastic Model

In deregulated air transportation markets, airlines can and do make sudden changes to fares, flight schedules and service networks [10]. For instance, the introduction of low fare services can generate huge traffic increases at an airport very quickly; however, the traffic falls back when the airline collapses or abandons the hub operations at the airport. For smaller airports, that may cause traffic to double or halve in a few years. Such radical changes also affect major airports significantly. Therefore, airport authorities are justified in considering multiple plausible demand patterns due to uncertainties in anticipated social, economic and demographic changes. Similarly to the scenario-based approaches used for analyzing the airport ground holding problem [46], we consider a range of traffic scenarios here.

The stochastic version of airport facility development is then written as:

$$\min_{\{x_{ijk}\geq 0, y_{ijk}, z_{ijk}\in\{0,1\}\}} \sum_i \sum_j \sum_k (f_{ij}y_{ijk} + v_{ij}x_{ijk}) + \sum_i \sum_j \mathbb{E}_\xi Q_{ij}(S,\xi) \tag{3.10}$$

subject to Constraints (3.9a) - (3.9e). where $Q_{ij}(S,\xi(\omega))$ is the optimal value of the second-stage problem

$$\min_{s_{ij}\geq 0} o_{ij}s_{ij} + \gamma^j F_i(\frac{q_{ij}(\omega)}{s_{ij}})q_{ij}(\omega) \tag{3.11}$$

subject to

$$s_{it} = s_{i0} + \sum_{j=1}^{t} \sum_k x_{ijk}, \forall i \in I, t \in J \tag{3.12a}$$

$$q_{ij}(\omega) \leq s_{ij}, \forall i \in I, j \in J, \omega \in \Omega \tag{3.12b}$$

Here ξ denotes the random demand, whose realization is denoted as $\omega \in \Omega = \{\omega_1, \ldots, \omega_R\}$. In total, R scenarios are considered. All capacity decision variables, x_{ijk}, y_{ijk} and z_{ijk} are the first-stage variables, as they have to be determined before the outcome of the demand scenario ω is observed. Supplied capacity s_{ij} is considered a second-stage variable. In fact, in this stochastic program, second-stage variables are determined after the first-stage variables are fixed. The objective of the second-stage problem, which is to minimize operating costs and expected costs, depends on ω. In one sense, the two-stage stochastic program can be reduced into a single stage problem because optimal first-stage variables lead to the second-stage optimal solutions directly through Constraint (3.12a).

Since demand scenarios considered here are discrete (e.g., high, medium, low) and the number of scenarios is finite, we can write:

$$\mathbb{E}_{\xi} Q_{ij}(S, \xi) = \sum_{r=1}^{R} p_r Q_{ij}(S, \xi(\omega_r)), \forall i \in I, j \in J \tag{3.13}$$

where p_r is the probability associated with scenario ω_r.

With Equation (3.13) we can formulate the stochastic program as a deterministic equivalent with the following objective:

$$\begin{aligned} \min \sum_i \sum_j \sum_k (f_{ij} y_{ijk} + v_{ij} x_{ijk}) + \sum_i \sum_j o_{ij} s_{ij} + \\ \sum_i \sum_j \gamma^j \sum_r p_r F_i(\frac{q_{ij}(\omega_r)}{s_{ij}}) q_{ij}(\omega_r) \end{aligned} \tag{3.14}$$

subject to both first-stage and second-stage constraints in the original SP, i.e., Constraints (3.9a)-(3.9e) and (3.12a)-(3.12b).

The final program is a Mixed Integer Nonlinear Program (MINLP). The binary variables are introduced to describe the logical relations in project scheduling. The nonlinear function is required to accurately reflect the physical properties of traffic congestion. This problem combines the difficulty of minimization over binary variables and handling of nonlinear relations. Therefore, MINLP is considered a class of challenging optimization problems.

3.2 Solution Method

3.2.1 Outer Approximation

We first prove the problem to be convex so that the global optimality is guaranteed. Then we present an interactive framework for finding the optimal solution, in which an alternative delay approximation technique is used.

From Properties 1 and 2 of the delay function, we find that the delay function $F(\rho)$ is convex in the capacity s, where $\rho = \frac{q}{s}$ and q is a fixed constant. Appendix provides the proof.

Since delay level $F_i(\frac{q_{ij}}{s_{ij}})$ is the only nonlinear item and it only appears in the objective, due to the convexity in s_{ij}, we can linearize $F_i(\frac{q_{ij}}{s_{ij}})$ around a given point $\hat{s}_{ij}$ and we find that:

$$F_i(\frac{q_{ij}}{s_{ij}}) \geq F_i(\frac{q_{ij}}{\hat{s}_{ij}}) + \nabla F_i(\frac{q_{ij}}{\hat{s}_{ij}})(s_{ij} - \hat{s}_{ij}), \forall i \in I, j \in J \tag{3.15}$$

where $\nabla F_i(\frac{q_{ij}}{\hat{s}_{ij}})$ is the derivative at the given $\hat{s}_{ij}$.

If we replace $F_i(\frac{q_{ij}}{s_{ij}})$ with an auxiliary variable μ_{ij} in the objective and add the following constraint to the original program,

$$\mu_{ij} \geq F_i(\frac{q_{ij}}{\hat{s}_{ij}}) + \nabla F_i(\frac{q_{ij}}{\hat{s}_{ij}})(s_{ij} - \hat{s}_{ij}), \forall i \in I, j \in J \tag{3.16}$$

we have a so-called "Out-Approximation" program, which underestimates the objective through the relaxation of a convex function. The resultant program, called

Master Program, is

$$\min_{\{x_{ijk}\geq 0, y_{ijk}, z_{ijk}\in\{0,1\}\}} \sum_i \sum_j \sum_k (f_{ij} y_{ijk} + v_{ij} x_{ijk}) + \sum_i \sum_j o_{ij} s_{ij} + \\ \sum_i \sum_j \gamma^j \sum_r p_r \mu_{ij} q_{ij}(\omega_r) \tag{3.17}$$

subject to Constraints (3.16), (3.9a)-(3.9e) and (3.12a)-(3.12b).

If we fix all integer variables y_{ijk}, z_{ijk}, the relaxed MINLP is converted into a convex Nonlinear Program (NLP), which is called the Subprogram. Since the optimal solution to the Subprogram and fixed integer variables are feasible for the original MINLP, the Subprogram provides an upper bound.

By solving the Subproblem and Master Problem interactively, Duran and Grossmann [47] prove the convergence of the process, which is describe as below.

Step 0: $Iter := 0$, $\theta^U := +\infty$. Select the initial value of integer variables $\hat{y}_{ijk}^{Iter}$ and $\hat{z}_{ijk}^{Iter}$.

Step 1: Solve the Subproblem $Sub(\hat{y}_{ijk}^{Iter}, \hat{z}_{ijk}^{Iter})$ and optimal s solutions are s_{Sub}^{Iter}. If the current upper bound is lower, i.e., $\theta_{Sub}^{Iter} \leq \theta^U$, update best upper bounds and solutions, i.e., $\theta^U := \theta_{Sub}^{Iter}$, $s^* := \theta_{Sub}^{Iter}$.

Step 2: Solve the Master Problem $Master(s^*)$ provided s^* as the relaxation point and optimal y solutions are y_{Master}^{Iter}. If the current lower bound is higher, i.e., $\theta_{Master}^{Iter} \geq \theta^U$, go to Step 3; otherwise $y_{Master}^{Iter+1} := y_{Master}^{Iter}$, and go to Step 1.

Step 3: Algorithm terminates and outputs s^* and θ^U as optimal solution and objective.

In solving Master Problems, integer solutions in previous iterations should not be enumerated again to avoid loops. We forbid y_{ijk} to assume any previous value $y_{ijk}^{Iter}, \forall Iter \in ITER$ with,

$$\sum_i \sum_j \sum_k |y_{ijk} - y_{ijk}^{Iter}| \neq 1, \forall Iter \in ITER \tag{3.18}$$

where $ITER$ is the set of previous iterations which have been run.

Duran and Grossmann [47] introduce a way to remove the absolute value symbol, thus avoiding nonlinearities to the MIP. We adopt the method and derive the following set of constraints,

$$\sum_{(i,j,k) \in B^{Iter}} y_{ijk} - \sum_{(i,j,k) \in N^{Iter}} y_{ijk} \leq |B^{Iter}| - 1 \tag{3.19}$$

where $B^{Iter} = \{(i,j,k) : y_{ijk} = 1\}, N^{Iter} = \{(i,j,k) : y_{ijk} = 0\}$ and $|B^{Iter}| = \sum\limits_{(i,j,k)} y_{ijk}^{Iter}$

Similar constraints can be imposed on z_{ijk}.

3.2.2 Tighter Formulation

The following aspects are addressed to provide a tighter formulation that brings the feasible region as close as possible to the region containing only feasible integer solutions. The computation time is greatly reduced through breaking symmetry, selecting an appropriate value of M and providing a better estimate of the project set K.

The symmetry in capacity expansion projects is problematic during implementation. For instance, there is in fact no difference between $x_{1,1,2} = 10, x_{1,5,3} = 5$ and $x_{1,1,3} = 10, x_{1,5,2} = 5$. We can interpret both cases in this way: 10 units of capacity are added in period 1 and another 5 are added in period 5 for component 1. The trivial difference between those two is: the project finished in period 1 is named "2" and the other is named "3" in the first case while named "3" and "2" otherwise. However, MIP algorithms cannot distinguish this subtle difference. We can set priorities to projects to avoid the symmetry, which would greatly reduce the computational time. Similarly to Constraint (3.9c), the following additional constraints about y_{ijk} are used.

$$\sum_{j=0}^{t} y_{ijk} \geq \sum_{j=0}^{t} y_{ijk\prime}, \forall i \in I, t \in J, k \in K, k\prime \geq k \tag{3.20}$$

Constraints about z_{ikl} are omitted. Essentially, Constraint (3.20) ensures that a project with a smaller index is implemented with a higher priority.

A Big M formulation such as $x \leq My$ is used to model the fixed capital cost. The selection of the value of M during computer implementation is nontrivial. M should be sufficiently large so that the "Big M" constraint does not cut feasible regions. However, an extremely large M value may have several drawbacks. For instance, a relatively small $\frac{x}{M}$ due to a large M most likely forces the branching algorithm to start with $y = 0$ in solving the linear relaxation of the integer program, which is far from its integer value (y should be 1 since x is positive). In this problem, $M_i = 2 \times \max\{q_{ij}(\omega)\}$. In words, the capacity added in one planning period is bounded by twice the largest possible traffic level over all periods and scenarios.

The third issue is with project set K. As we have argued, K is unknown, i.e., we do not know how many capacity expansions should be planned. We propose an upper bound to the number of capacity expansions, which is $\frac{m}{e_i}$. For instance, if each project requires 5 periods to implement, we can plan 4 projects at most in a horizon of 20 periods. During implementation, we find that the number of expansion projects $|K|$ is largely determined by economic factors rather than project implementation time requirements. To reduce the size of decision space (noting that all binary variables have an index of $k \in K$), we propose another way of finding a tighter bound as follows:

1. Determine $|K|$ according to $\frac{m}{e_i}$;

2. Solve the modified problem with only Constraint (3.9e) replaced by

$$x_{ijk} \leq M_i y_{ijk}, \forall i \in I, j \in J, k \in K \tag{3.21}$$

   By doing so, we force all z_{ijk} to be 0, implying the project implementation time is 0.

3. Updating K by setting $|K| = \max_i \left\{\sum_j \sum_k y_{ijk}\right\}$, i.e., the maximum of $\sum_j \sum_k y_{ijk}$, which is the number of expansion on component i

The argument is that in cases with nonnegative (including 0, obviously) implementation time, the number of expansions is no greater than that in cases with 0 project implementation time.

3.3 Numerical Example

3.3.1 Data Inputs

In the numerical examples, we consider three major components of airports, namely the airfield system, passenger terminal and cargo facilities. Demand measures for these three facilities are aircraft operations, enplanements and cargo tons per period, respectively. Three plausible demand growth patterns are considered, as shown in Figures 3.3, 3.4, and 3.5.

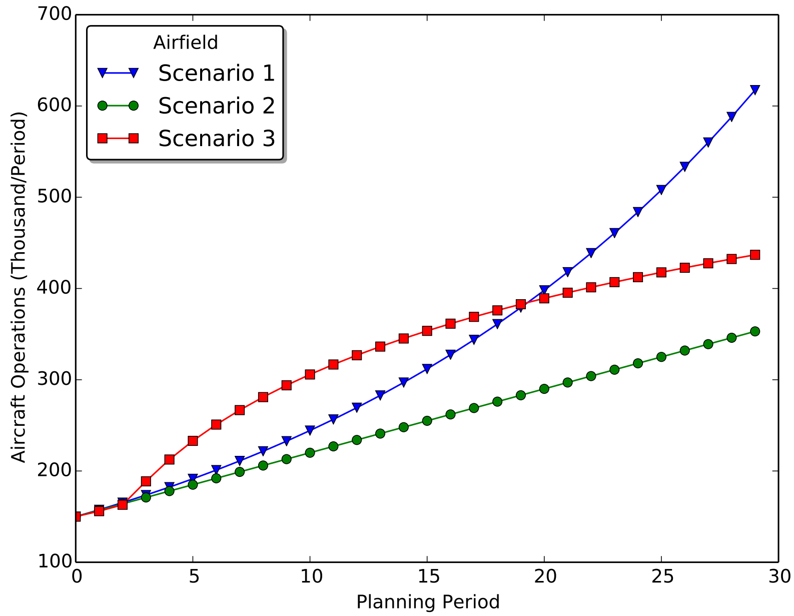

Figure 3.3: Demand forecasts for the airfield

The probabilities associated with those scenarios are 0.4, 0.3 and 0.3, respectively. The proposed model can take any scenario probability distribution and accommodate any demand growth pattern, as long as the demand can be estimated for each component in a certain period. Table 3.1 presents cost-related data for

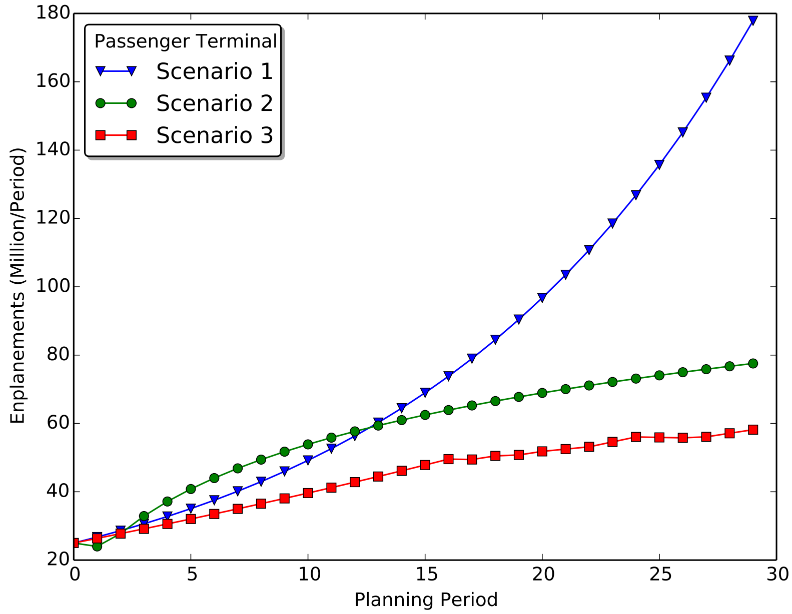

Figure 3.4: Demand forecasts for the terminal

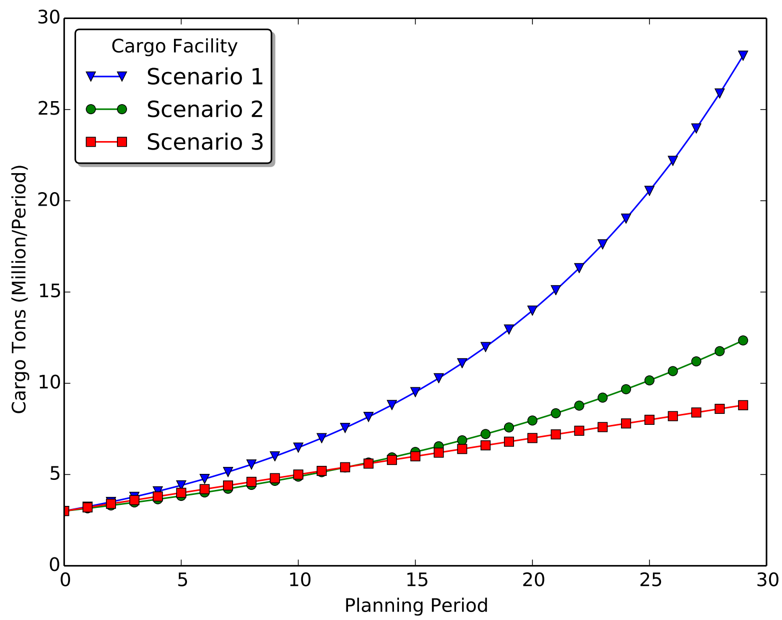

Figure 3.5: Demand forecasts for the cargo facility

each airport component. Those cost data can be derived with methods developed by [48]. Delay functions are also specified as standard mathematical formulas for convenience; however, the model can consider other delay curves, on the condition that they satisfy Properties 1 and 2, as discussed in subsection 3.1.3.

The discounting coefficient $\gamma = 0.97$. The planning horizon $m = 30$. Minimum period of project implementation time e_i is 5, 4, and 1, for airfield, passenger terminal, and cargo facility, respectively.

Initial values of integer variables are specified as follows: $y_{i,0,0} = 1, z_{i,6,0}$ and other binary values are zero. In words, for each component i, only one capacity expansion project indexed 0 is planned in period 0 and finished in period 6. Obviously, the starting values are feasible since they satisfy the minimum project implementation time constraint.

Table 3.1: Parameters of cost functions (Million $)

Component	Fixed capital	Variable capital	Operating	Delay Function
Airfield system	65	0.4	0.1	$0.05(\frac{1}{1-\rho} - 0.9)$
Terminal	30	0.5	0.15	$0.5(e^{\rho} - 1)$
Cargo facility	2	0.8	0.15	$2\rho^3$

The model is implemented in GAMS v24.1.3. The MIP solver is CPLEX v12.5.1.0. and the NLP solver is CONOPT v3.15L. The relative optimality gap is set 0. The program runs on a regular desktop (Intel Core Quad CPU 2.83 GHz, 3.25 GB RAM).

3.3.2 Results

The resulting capacity provision level vs each possible demand growth scenario for every airport component is plotted in Figures 3.6, 3.7, and 3.8. Two capacity expansion levels are planned for the airfield and passenger terminal while four expansions are planned for the cargo facility. Taking Figure 3.6 as an example in interpreting the results, we observe that the first project is initiated in period 1 and finished in period 6. The incremental size can be read by measuring the vertical difference.

We examine the time difference between starting expansion and delivering capacity and find that the project implementation constraint is binding for all projects, which means capacities should be added as soon as possible. This is not surprising in cases with zero uncertainty regarding capital costs. Once the fixed capital cost is incurred, it is better to deliver the capacity (thus reducing the delay) than postpone the delivery, although variable costs are more heavily discounted in later periods. Nonetheless, project implementation constraints are not necessarily binding when potential technological innovations or other factors change capital cost parameters. The same modeling framework would also be effective when uncertainties in capital costs are considered.

We can also study tradeoffs among various types of costs. We use the passenger terminal component as an example, with results plotted in Figure 3.9. As traffic grows, delays increase, which triggers capacity expansion decisions, with their fixed capital costs. After the required project implementation period, planned capacities

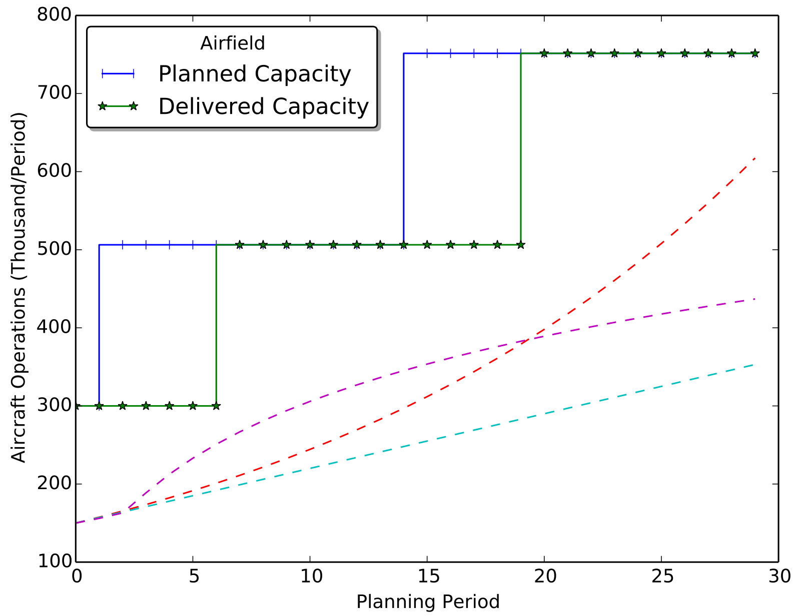

Figure 3.6: Capacity expansion path for the airfield

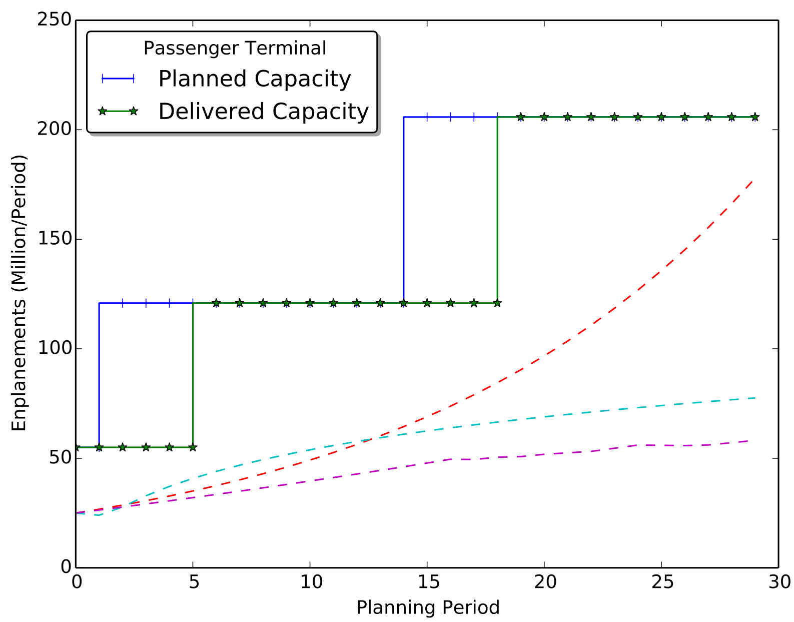

Figure 3.7: Capacity expansion path for the passenger terminal

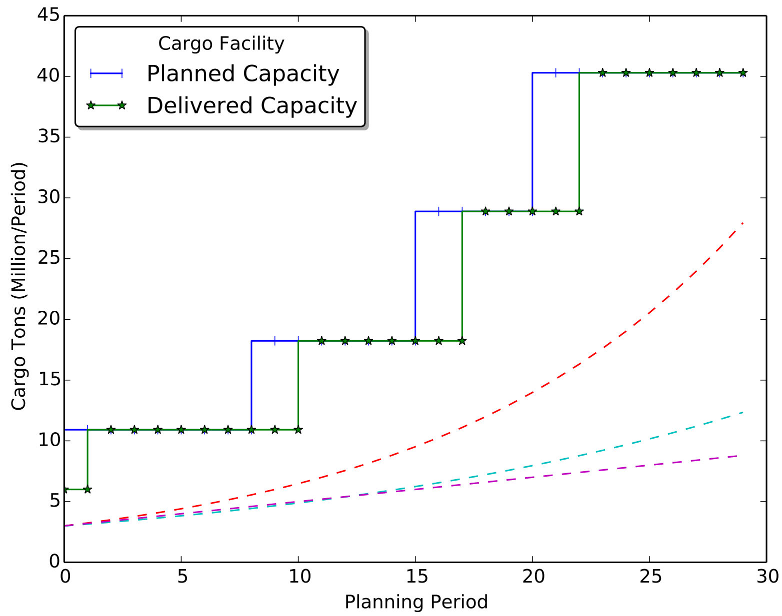

Figure 3.8: Capacity expansion path for the cargo facility

are available and variable cost is expended. Due to the capacity increase, the operating cost jumps to new levels because operating cost is proportional to the capacity provided. Then delays start to grow again, leading to the next cycle of expansion. Note that all costs shown are discounted costs, which explains different fixed costs in periods 2 and 15, as well as the downside slopes of operating costs after capacity expansions, for instance, from period 6 to period 18.

3.3.3 Value of Stochastic Solution

Without solving the Stochastic Program (SP), we can insert the average demand scenario into the deterministic program, which is smaller and thus solvable faster. From Figure 11 we observe that the average traffic level is roughly midway between the highest demand growth and lowest one. Therefore, it seems that the

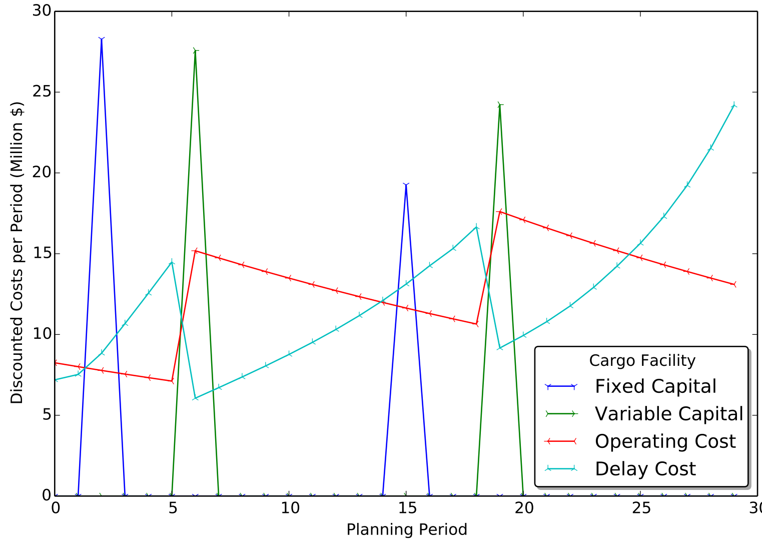

Figure 3.9: Tradeoffs among various costs

average is a good approximation. With this average traffic level, we solve a deterministic version of the capacity expansion problem whose objective is Equation (3.8). Instead of presenting all results, we only examine the relation of the delay cost for the airfield in each scenario vs the delay cost resulting from a single traffic scenario. In Figure 3.11, the delay resulting from the single traffic level is highly skewed to the lowest scenario while underrepresenting the possible high cost in a high demand scenario. If decisions are made only based on the average scenario, enormous delays are expected if the high traffic scenario occurs. In this example, the total cost is $3,140.76 million if the single traffic scenario is used (thus solving a deterministic program), which is 23.1% above that using the proposed stochastic program. Equivalently the cost reduction is 18.8% using the stochastic program. The value difference between making decisions on the average condition and considering a range of possible scenarios is called the Value of Stochastic Solution [49] or referred to as “Flaw of Averages” [6].

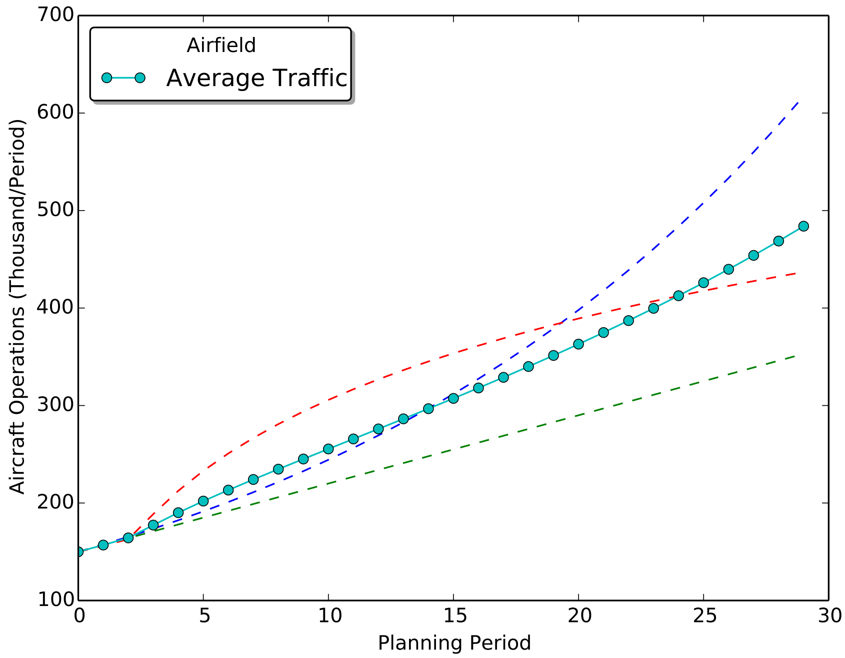

Figure 3.10: Average traffic level

3.3.4 Algorithm Performance

As argued previously, more efficient algorithms are required to handle additional considerations. The Outer-Approximation (OA) method is proved to be suitable for solving such a capacity expansion problems with nonlinear delays. We plot the upper and lower bounds generated in each iteration in Figure 3.12. Note that the upper bound is obtained from solving a Subproblem and the lower bound is the objective of a Master Problem. The algorithm converges in iteration 9. In fact, the relative gap drops below 1% after only 5 iterations. Figure 3.13 shows the relative gap and running time in each iteration. The relative gap changes from 0.2 in iteration 0 to 0.003 in iteration 4.

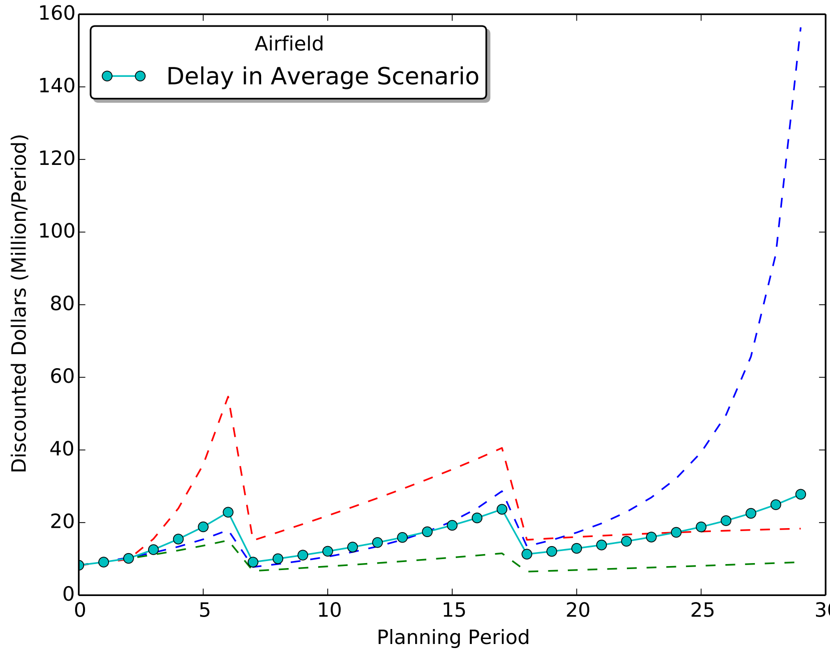

Figure 3.11: Delay costs in each scenario vs delay cost in the average scenario

Figure 3.13 also presents the solution time at each iteration. The time for solving a Subproblem is negligible (around 0.5 seconds) and remains stable while the MIP solution time increases quickly with iterations because additional linear inequalities and integer cuts are added after each iteration. In iteration 4, the MIP solution time is around 160 seconds. For this problem, even without further maintenance of additional constraints added to the MIP, the computation time (around 288 seconds to achieve a percentage gap of 0.3%) is acceptable since the strategic capacity expansion problem is solved on a low frequency basis.

We further increase the number of scenarios from 4 to 7 and plot their converging processes in Figure 3.14. It can be seen that the relative gaps drop to 0.01 (i.e., 1%) after Iteration 4 for all cases. After Iteration 5, the gaps are below 0.001 (i.e., 0.1%) except for 7 scenarios. The gap is 0.0068 in Iteration 5 and it becomes

0.00026 in Iteration 6 (which is not shown here) if 7 scenarios are considered. These 7 airfield demand scenarios are shown in Figure 3.15.

Since the computation time is around 300 seconds in Iteration 4, which leads to a 1% gap, the method can be expected to be efficient in solving larger problems. Note that computation time is less critical for such a long-term planning problem than it would be for a real-time decision making problem. In practice, usually fewer than 7 scenarios are available. For example, in the master plans of Hong Kong International Airport (HKG) [50] and Baltimore Washington International Airport (BWI) [51], only three scenarios (i.e., high, base, and low) are considered.

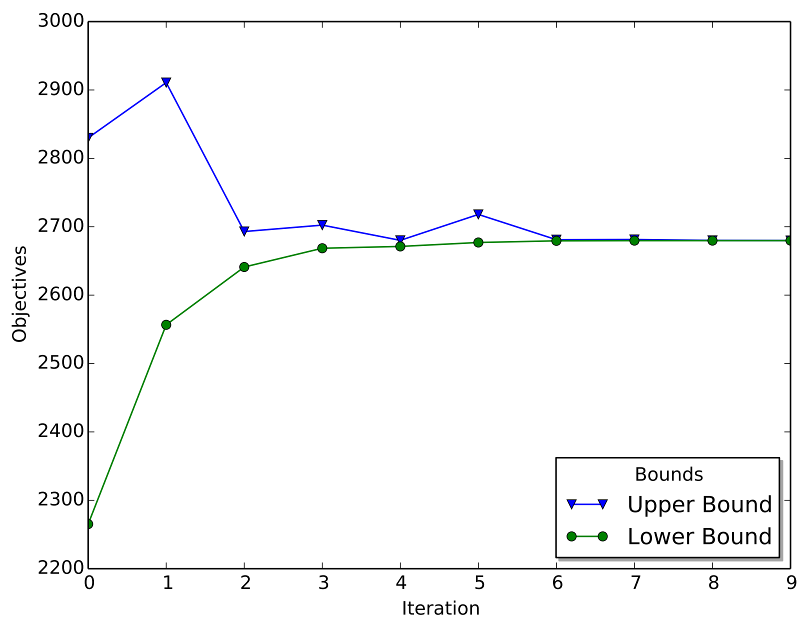

Figure 3.12: Convergence process

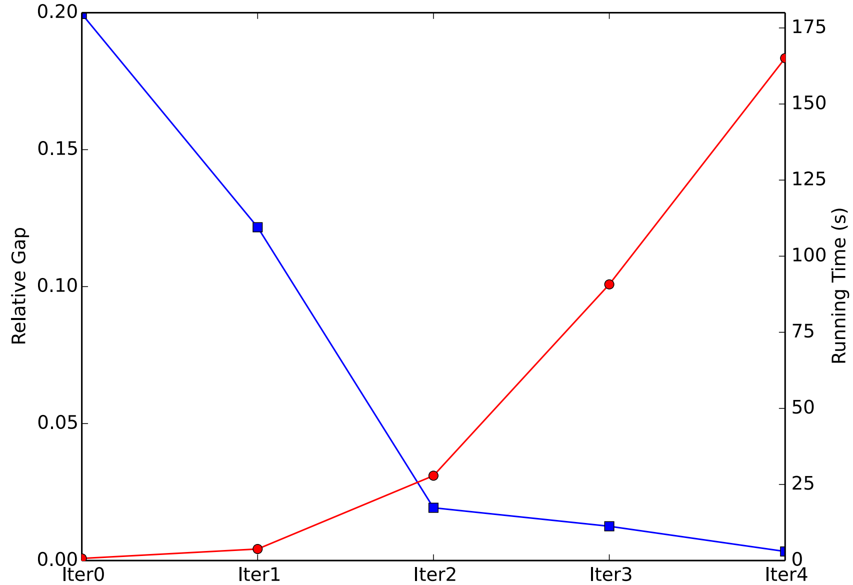

Figure 3.13: Relative gaps and running time in each iteration

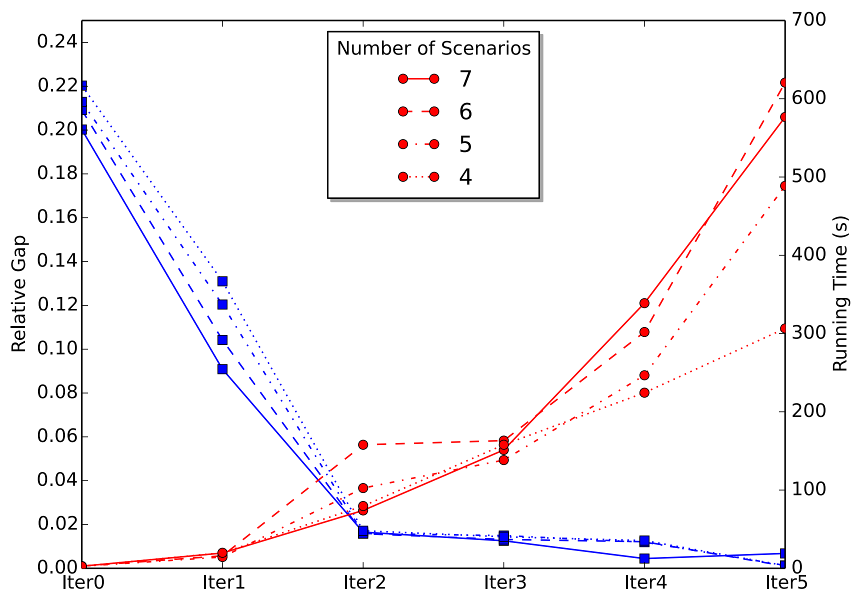

Figure 3.14: Computation tests for larger problems

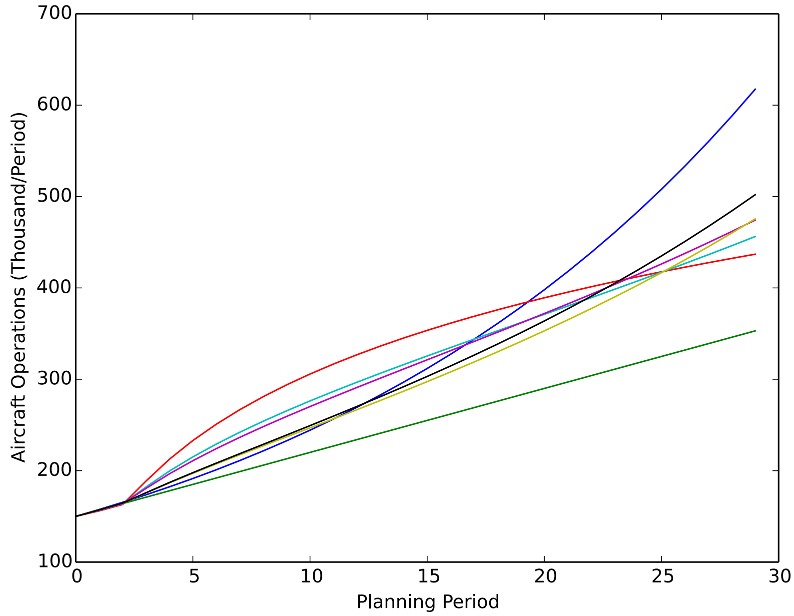

Figure 3.15: A set of 7 scenarios

3.4 Conclusions

The primary contribution made in this chapter, i.e., the introduction of the outer-approximation technique, is based on the convexity analysis of the delay cost function. It is first argued that the delay cost is convex in the capacity utilization rate and then proved that the delay is also convex with respect to the supplied capacity, which is the decision variable. Based on these analyses, the model is solved to its global optimality with an interactive solution framework. After additional efforts to provide a tighter formulation, the effectiveness of the model and efficiency of the algorithm are demonstrated with results from numerical studies. Significant gains (18.8% of total cost reductions in the example) are achieved by using the proposed stochastic model for optimizing airport capacity expansions.

Although the OA method enables the design of much more efficient algorithms than previous ones based on discrete approximation, this method requires the delay cost function to be continuously differentiable. Considering that most delay curves result from computer simulations and empirical studies [52], the delay function does not always have the desired differentiability property. Then, other linear approximation techniques may be used, as shown in Chapter 4.

Chapter 4: Airport Capacity Investment Model

Generally, Chapter 4 follows the modeling framework of Chapter 3; however, the following two major assumptions from Chapter 3 are relaxed:

1. While demands might drop, capacity never decreases in any facility of an airport;

2. The delay cost function is continuously differentiable.

The first assumption reduces the capacity planning model to a capacity expansion model, which disallows potential capacity contractions. If both capacity expansion and contraction are allowed, the model is called a capacity investment model. The term "investment" is used to indicate the change of capacity in both directions [53, 54]. The consideration of capacity contraction is quite important, especially when demand changes sharply. For example, when US Airways moved its hub operations from the Baltimore-Washington Airport (BWI) to nearby Philadelphia, it left a large underutilized passenger terminal.

The differentiable property of the delay curve enables the design of a specialized linear approximation technique, as described in Chapter 3. The available literature does not explore what methods can be used if this property is missing. This is a serious gap, since noting that most delay curves are obtained from computer simulations and empirical studies [55, 56], meaning that delay functions are mostly non-differentiable.

4.1 Formulation

4.1.1 Notation

Sets and Indices

$i =$ component of airport system $I = \{1, 2, \ldots, l\}, i \in I$

j or $t =$ time period within the planning horizon $J = \{0, 1, 2, \ldots, m\}, j, t \in J$

$k =$ step of a discrete delay function $K = \{1, 2, \ldots, n\}, k \in K$

$a =$ capacity management choice $a \in A = \{1, 0\}$

When $a = 1$, additional capacities are purchased, i.e., facilities are expanded; otherwise, existing capacities are salvaged.

Parameters

$f_{ij}^a =$ fixed capital cost of adjusting capacity of component i in period j when the capacity management choice is a

$v_{ij}^a =$ variable capital cost of adjusting capacity of component i in period j when the capacity management choice is a

$o_{ij} =$ unit operating cost of component i in period j

$q_{ij} =$ demand on component i in period j

$b_i^k =$ stepping points of the delay function of component i

$c_i^k =$ delay level in interval k of delay function i

$\delta =$ discount factor

M_i = the maximum capacity change (expansion or contraction) to component $i \in I$ in any single period

N_i = the maximum supplied capacity of component $i \in I$

Decision Variables

x_{ij}^a = the amount of capacity adjusted to component i in period j when the capacity management choice is a

y_{ij}^a = whether to adjust capacity to component i in period j when the capacity management choice is a

4.1.2 Assumptions

Although some assumptions made in Chapter 3 are relaxed in this chapter, other assumptions still apply, as described below:

1. The economic life of new infrastructure exceeds the planning horizon (typically 20 or 30 years), i.e., infrastructure replacements or demolitions are not considered;

2. Various demand measures (e.g., enplanements, number of aircraft operations, tons of cargo shipped) are estimated for each individual airport component and capacity is analyzed separately for each component.

4.1.3 Cost Functions

Capacity adjustment costs

Capacity adjustment costs are capital costs, which include fixed and variable parts. The capital cost of component i in period j can be written as:

$$C_{ij} = \delta^j \sum_{a \in A} \left(f_{i0}^a y_{ij}^a + v_{i0}^a x_{ij}^a \right), \forall i \in I, j \in J \tag{4.1}$$

where δ is used to discount future values,

or more compactly as:

$$C_{ij} = \sum_{a \in A} \left(f_{ij}^a y_{ij}^a + v_{ij}^a x_{ij}^a \right), \forall i \in I, j \in J \tag{4.2}$$

When capacities are salvaged ($a = 0$), the decision maker can receive a variable value $\left| v_{ij}^0 \right|$ per unit capacity salvaged, but at a one-time fixed cost f_{ij}^0. Since v_{ij}^a is defined from the perspective of cost, v_{ij}^a should be negative when $a = 0$, meaning that some positive values will be received due to the salvage. When $v_{ij}^0 + v_{ij}^1 = 0, \forall i \in I, j \in J$, the variable capital cost is reversible; when $v_{ij}^0 + v_{ij}^1 > 0, \forall i \in I, j \in J$, investments can only be partially recovered. Particularly, when $v_{ij}^0 = 0, \forall i \in I, j \in J$, no investments can be reversed. Note that, in most practical cases, it is impossible to have $v_{ij}^0 + v_{ij}^1 < 0, \forall i \in I, j \in J$, i.e., the salvage value should not exceed the purchase price.

The capacity of component i in period j is the initial capacity s_{i0} plus net adjusted capacity in each period, as shown in Equation (4.3)

$$s_{it} = s_{i,0} + \sum_{j=1}^{t} x_{ij}^1 - \sum_{j=1}^{t} x_{ij}^0, \forall i \in I, t \in J \tag{4.3}$$

Operating Costs

The operating cost of component i in period j is the discounted unit operating cost o_{ij} multiplied by the supplied capacity s_{ij}:

$$O_{ij} = o_{ij} s_{ij}, \forall i \in I, j \in J \tag{4.4}$$

Delay Costs

Airport congestion constitutes a major problem for airport authorities and their customers. Due to the dynamic characteristics of demands, i.e., daily pattern, day-of-the-week pattern, and seasonal pattern, airport delays are difficult to estimate. In practice, advanced computer-based tools (simulation or analytical) are needed to obtain good approximations of airport facility delays. Although complex short-term behaviors of delays exist, in the long run, major airport components experience increased delay costs when demands grow, especially when the demands approach the capacity limits.

For a specific airport component, its operating characteristics can be described with the delay level as a function of the capacity utilization, i.e., the ratio of the demand q divided by the capacity s. For component i, we denote the delay function as:

$$d_{ij} = F_i(\frac{q_{ij}}{s_{ij}}), \forall i \in I, j \in J \tag{4.5}$$

where d_{ij} = delay level of component i in period j

$F_i(\cdot)$ = delay function of component i in period j

Delay costs are demands multiplied by the delay level, which can be written as:

$$D_{ij} = F_i(\frac{q_{ij}}{s_{ij}})q_{ij}, \forall i \in I, j \in J \tag{4.6}$$

Note that delay level is measured in dollars per unit of demand while delay cost is measured in dollars.

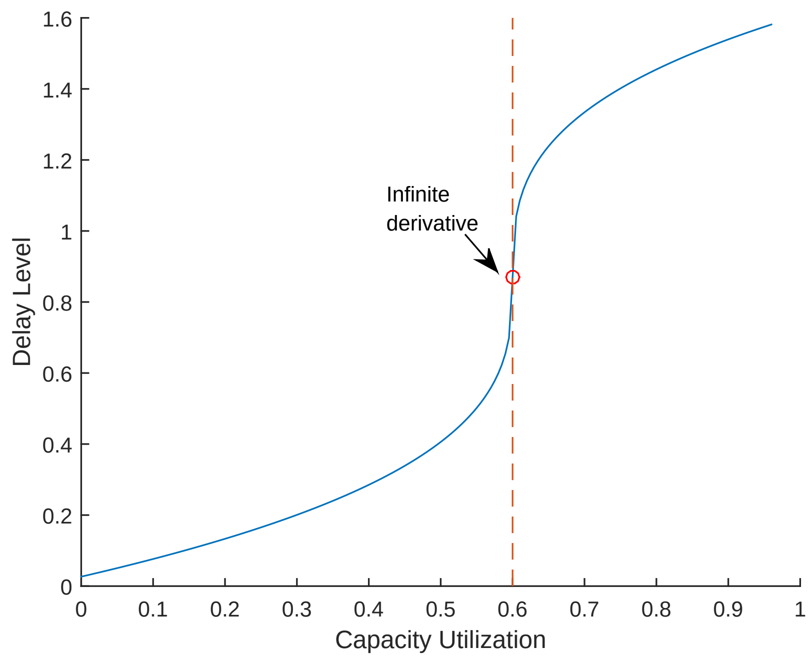

Figure 4.1: Non-differentiable delay curve - Example 1

In airports, various airside and landside facilities have different operating characteristics. Simulation is the dominant method for quantifying the capacity and performance of airside facilities, especially runway systems; queueing methods are sometimes used to assess the demand needs and estimate the delay level for terminal facilities, such as boarding gates. Whatever specific function form the delay function for a facility assumes, delay costs are essentially nonlinear, which creates difficulties in utilizing linear programming techniques to solve airport capacity planning prob-

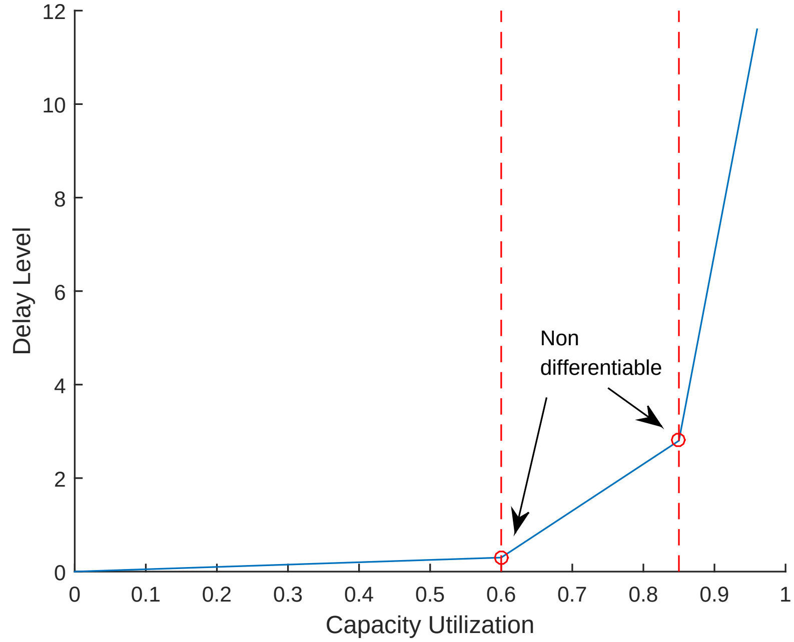

Figure 4.2: Non-differentiable delay curve - Example 2

lems. In Chapter 3, the convexity of the delay function is identified and the function is assumed to be continuously differentiable. However, the delay function estimated either from empirical studies or computer simulations does not necessarily have such desired properties as continuous differentiation. Even a closed-form expression of the delay curve is unavailable in some cases. Two examples of non-differentiable delay curves are shown in Figure 4.1 and 4.2. Therefore, another method which does not reply on such properties should be developed.

4.1.4 Mixed Integer Nonlinear Program

After definitions of various costs, the airport capacity investment model, which is a total cost minimization problem, can be written as:

$$\min_{\{x_{ij}^a \geq 0,\ y_{ij}^a \in \{0,1\}\}} \sum_i \sum_j \sum_a (f_{ij}^a y_{ij}^a + v_{ij}^a x_{ij}^a) + \sum_i \sum_j o_{ij} s_{ij} + \sum_i \sum_j \delta^j F_i(\frac{q_{ij}}{s_{ij}}) q_{ij} \quad (4.7)$$

subject to

$$x_{ij}^a \leq M_i y_{ij}^a, \forall i \in I, j \in J, a \in A \quad (4.8a)$$

$$s_{it} = s_{i,0} + \sum_{j=1}^{t} x_{ij}^1 - \sum_{j=1}^{t} x_{ij}^0, \forall i \in I, t \in J \quad (4.8b)$$

$$q_{ij} \leq s_{ij}, \forall i \in I, j \in J \quad (4.8c)$$

The objective function is the net present value of total cost, which includes capital costs, operating costs and delay costs. While the first two are incurred by the airport authority, delay costs are borne by airport users, e.g., aircraft operators, passengers and cargo shippers. Constraint (4.8a) guarantees that no capacities can be added (i.e., $x_{ij}^1 = 0$) unless the capacity expansion decision is made ($y_{ij}^1 = 1$) or no capacities can be reduced ($x_{ij}^0 = 0$) unless the salvage decision is made ($y_{ij}^0 = 1$), where M_i is the maximum capacity change (expansion or contraction) to component i in any single period. Constraint (4.8b) defines the supplied capacity of component i in period j. Constraint (4.8c) specifies that demands cannot exceed capacities, at least over extended periods.

Proposition 1. *Due to the two-sided fixed costs, i.e., since there are fixed costs when the capacity is either increased or decreased, we have the following valid inequality:*

$$\sum_{a \in A} y_{ij}^{a} \leq 1, \ \forall i \in I, j \in J \tag{4.9}$$

Proof. Intuitively, we need to show that at most one capacity management choice can be selected.

If both choices are selected for component i in period j, i.e. $y_{ij}^{0} = 1$ and $y_{ij}^{1} = 1$, the capital cost C_{ij} is:

$$C_{ij} = f_{ij}^{1} + f_{ij}^{0} + v_{ij}^{1} x_{ij}^{1} - \left| v_{ij}^{0} \right| x_{ij}^{0}, \forall i \in I, j \in J \tag{4.10}$$

Depending on the relation between x_{ij}^{1} and x_{ij}^{0}, we have the following three cases.

When $x_{ij}^{1} > x_{ij}^{0}$, we can drop f_{ij}^{0} from C_{ij} and then $C_{ij} > f_{ij}^{1} + v_{ij}^{1} x_{ij}^{1} - \left| v_{ij}^{0} \right| x_{ij}^{0}$. Noting $v_{ij}^{1} \geq \left| v_{ij}^{0} \right|$, we have $f_{ij}^{1} + v_{ij}^{1} x_{ij}^{1} - \left| v_{ij}^{0} \right| x_{ij}^{0} > f_{ij}^{1} + v_{ij}^{1} \left(x_{ij}^{1} - x_{ij}^{0} \right)$, which further leads to $C_{ij} > f_{ij}^{1} + v_{ij}^{1} \left(x_{ij}^{1} - x_{ij}^{0} \right)$. $f_{ij}^{1} + v_{ij}^{1} \left(x_{ij}^{1} - x_{ij}^{0} \right)$ is the capital cost of only increasing the capacity by $\left(x_{ij}^{1} - x_{ij}^{0} \right)$.

When $x_{ij}^{1} < x_{ij}^{0}$, we can obtain $C_{ij} > f_{ij}^{0} - \left| v_{ij}^{0} \right| \left(x_{ij}^{0} - x_{ij}^{1} \right)$, whose right-hand-side represents the capital cost of only decreasing the capacity by $\left(x_{ij}^{0} - x_{ij}^{1} \right)$.

When $x_{ij}^{1} = x_{ij}^{0}$, we have $C_{ij} > 0$.

Combing the above cases, we conclude that at most one management choice is needed, i.e., $\sum_{a \in A} y_{ij}^{a} \leq 1, \ \forall i \in I, j \in J$. □

Equation (4.9) can be added to the original problem, which significantly reduces the solution space.

4.2 Reformulation

4.2.1 Model Linearization

A discrete approximation technique is proposed to convert the MINLP into a linear program, so that the problem can be solved much more efficiently. A general delay function, which is not necessarily differentiable or continuous, is approximated by a step function, as shown in Figure 4.3.

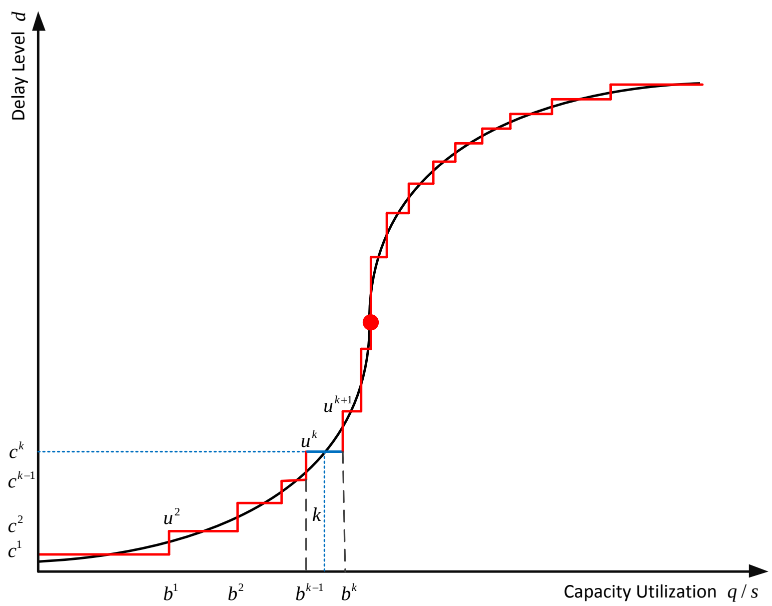

Figure 4.3: Discrete approximation of delay level

For sufficiently small step sizes, we assume that if the capacity utilization rate is within the interval k, i.e., $b^{k-1} \leq \frac{q}{s} \leq b^k$, the delay level is approximated by c^k. To find the corresponding approximated delay level at a given demand level, we formulate the following mathematical program:

$$\min_{\{r, z^k \geq 0, u^k \in \{0,1\}\}} r \tag{4.11}$$

subject to

$$r \geq u^k c^k, \forall k \in K \tag{4.12a}$$

$$(b^k - b^{k-1}) u^{k+1} \leq \frac{z^k}{s} \leq (b^k - b^{k-1}) u^k, \forall k \in K \tag{4.12b}$$

$$\sum_k z^k = q \tag{4.12c}$$

where z^k = increment of demand corresponding to the kth interval of the capacity utilization rate in Figure 4.3.

$u^k = 1$, if $\frac{q}{s} > b^{k-1}$; $u^k = 0$, otherwise

Note that Constraint (4.12b) is still nonlinear, and capacity s as an auxiliary decision variable appears as the denominator. If we multiply both sides by s, Constraint (4.12b) is transformed into:

$$(b^k - b^{k-1}) u^{k+1} s \leq z^k \leq (b^k - b^{k-1}) u^k s, \forall k \in K \tag{4.13}$$

To remove the product of two auxiliary decision variables, we substitute $u^k s$ with nonnegative w^k. We add four additional constraints to ensure the equivalence of this substitution.

$$w^k \leq Nu^k \tag{4.14a}$$

$$w^k \leq s \tag{4.14b}$$

$$w^k \geq 0 \tag{4.14c}$$

$$w^k \geq s - (1 - u^k)N \tag{4.14d}$$

where N is a sufficient bound on s.

If u^k is 1, Constraint (4.14a) is inactive, Constraint (4.14b) and Constraint (4.14d) together restrict w^k to be s. If u^k is 0, from Constraints (4.14b) and (4.14c) we have $w^k = 0$.

4.2.2 Mixed Integer Linear Program

The deterministic version of airport capacity expansion problem in linear form can be written as:

$$\begin{aligned} \min_{\{x_{ij}^a, r_{ij}, z_{ij}^k, w_{ij}^k \geq 0, y_{ij}^a, u_{ij}^k \in \{0,1\}\}} & \sum_i \sum_j \sum_a (f_{ij}^a y_{ij}^a + v_{ij}^a x_{ij}^a) + \sum_i \sum_j o_{ij} s_{ij} \\ & + \sum_i \sum_j \delta^j r_{ij} q_{ij} \end{aligned} \tag{4.15}$$

subject to constraints Constraints (4.8a), (4.8b), (4.8c), (4.9),and

$$r_{ij} \geq u_{ij}^k c_i^k, \forall i \in I, j \in J, k \in K \tag{4.16a}$$

$$(b_i^k - b_i^{k-1}) w_{ij}^{k+1} \leq z_{ij}^k \leq (b_i^k - b_i^{k-1}) w_{ij}^k, \forall i \in I, j \in J, k \in K \tag{4.16b}$$

$$\sum_k z_{ij}^k = q_{ij}, \forall i \in I, j \in J, k \in K \tag{4.16c}$$

$$w_{ij}^k \leq N_i u_{ij}^k, \forall i \in I, j \in J, k \in K \tag{4.16d}$$

$$w_{ij}^k \leq s_{ij}, \forall i \in I, j \in J, k \in K \tag{4.16e}$$

$$w_{ij}^k \geq s_{ij} - (1 - u_{ij}^k) N_i, \forall i \in I, j \in J, k \in K \tag{4.16f}$$

The first group of constraints (i.e., Constraints (4.8a), (4.8b), (4.8c), and (4.9)) duplicate those used in the MINLP to restrict capacity expansion variables. The second group of constraints (i.e., Constraints (4.16a) - 4.16c) are used to approximate the delay costs. Other constraints are auxiliary constraints to preserve the linear property of this program.

4.2.3 Two-Stage Stochastic Program

Future air traffic demands are quite difficult to predict accurately due to various economic fluctuations, technology innovations, competition among airports and competition among transportation modes. For long-term forecasts, aviation analysts develop a range of plausible scenarios after considering all the factors relevant to airport facility development.

To account for the uncertainties in demand forecasts, multiple discrete demand patterns are considered. The stochastic version of airport capacity expansion problem in linear form can be written as:

$$\min_{\{x_{ij}^a \geq 0, y_{ij}^a \in \{0,1\}\}} \sum_i \sum_j \sum_a (f_{ij}^a y_{ij}^a + v_{ij}^a x_{ij}^a) + \sum_i \sum_j \mathbb{E}_\xi Q_{ij}(S,\xi) \tag{4.17}$$

subject to (4.8a), and (4.9), where $Q_{ij}(S,\xi(\omega))$ is the optimal value of the second-stage problem

$$\min_{\{r_{ij}(\omega), z_{ij}^k(\omega), w_{ij}^k(\omega), s_{ij} \geq 0, u_{ij}^k(\omega) \in \{0,1\}\}} o_{ij} s_{ij} + \delta^j q_{ij}(\omega) r_{ij}(\omega) \tag{4.18}$$

subject to

$$q_{ij}(\omega) \leq s_{ij}, \forall i \in I, j \in J, \omega \in \Omega \tag{4.19a}$$

$$r_{ij}(\omega) \geq u_{ij}^k(\omega) c_i^k, \forall i \in I, j \in J, k \in K, \omega \in \Omega \tag{4.19b}$$

$$(b_i^k - b_i^{k-1}) w_{ij}^{k+1}(\omega) \leq z_{ij}^k(\omega) \leq (b_i^k - b_i^{k-1}) w_{ij}^k(\omega), \forall i \in I, j \in J, k \in K, \omega \in \Omega \tag{4.19c}$$

$$\sum_k z_{ij}^k(\omega) = q_{ij}(\omega), \forall i \in I, j \in J, \omega \in \Omega \tag{4.19d}$$

$$w_{ij}^k(\omega) \leq N_i u_{ij}^k(\omega), \forall i \in I, j \in J, k \in K, \omega \in \Omega \tag{4.19e}$$

$$w_{ij}^k(\omega) \leq s_{ij}, \forall i \in I, j \in J, k \in K, \omega \in \Omega \tag{4.19f}$$

$$w_{ij}^k(\omega) \geq s_{ij} - (1 - u_{ij}^k(\omega)) N_i, \forall i \in I, j \in J, k \in K, \omega \in \Omega \tag{4.19g}$$

In this program, $\omega \in \Omega = \{\omega_1, \ldots, \omega_R\}$ is the realization of the random demand

ξ. R is the number of scenarios considered. Capacity management decisions, i.e., x_{ij}^a and y_{ij}^a , have to be determined before the random demand is observed. Other decision variables, e.g., z_{ij}^k and w_{ij}^k are second-stage variables, which depend on ω.

Usually these demand scenarios are discrete, e.g., pessimistic or optimistic, we can replace $\mathbb{E}_\xi Q_{ij}(S, \xi)$ with $\sum_{r=1}^{R} p_r Q_{ij}(S, \xi(\omega_r)), \forall i \in I, j \in J$, where p_r is the probability associated with scenario ω_r. Uncertainty is usually characterized by a probability distribution, which is either assumed to be known or can be estimated. In cases where such a distribution is difficult to obtain, e.g., uncertainty parameters are known within certain bounds, robust optimization can be used to protect the system again the worst case scenario, which is considered overly conservative by some researchers. After such a replacement in objective (4.17), the stochastic program is converted to its deterministic equivalent.

4.2.4 Decomposition

Although multiple airport components are considered in the optimization problem, the resulting large-scale mixed integer program can be partitioned into manageable subproblems, which are also independent. Note that each constraint is defined separately for each component and the objective includes three separable cost components. The structure of the large-scale program can be illustrated with Figure 4.4.

Assuming that three airport components are considered, the overall problem is thus partitioned into three subproblems, each of which is for the development of one airport component. Such a transformation provides significant savings in computational time because the solution time for linear programs grows quickly with the number of constraints. In general, according to Bradley et al. [57], if the number of subproblems were k, the solution time would be $\frac{1}{k^2}$ times that required for an unstructured problem of comparable size.

Such a decomposition is possible only because the interactions between airport components are not considered, which renders these subproblems independent of each other.

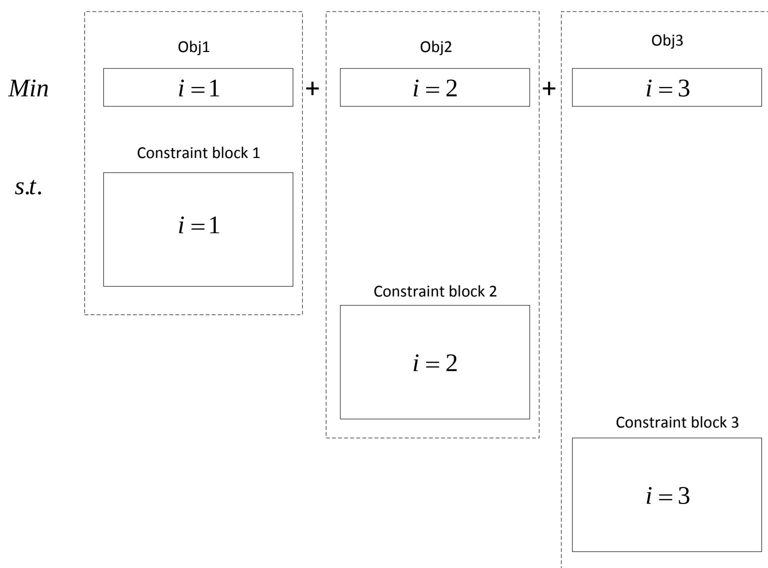

Figure 4.4: Discrete approximation of delay level

4.3 Numerical Example

4.3.1 Data Inputs

Three major components of airports, namely the airfield system, passenger terminal and cargo facility, are considered. Demand measures for these three facilities are aircraft operations, enplanements and cargo tons per period, respectively. Four plausible demand growth patterns are considered, as shown in Figures 4.5, 4.6, and 4.7.

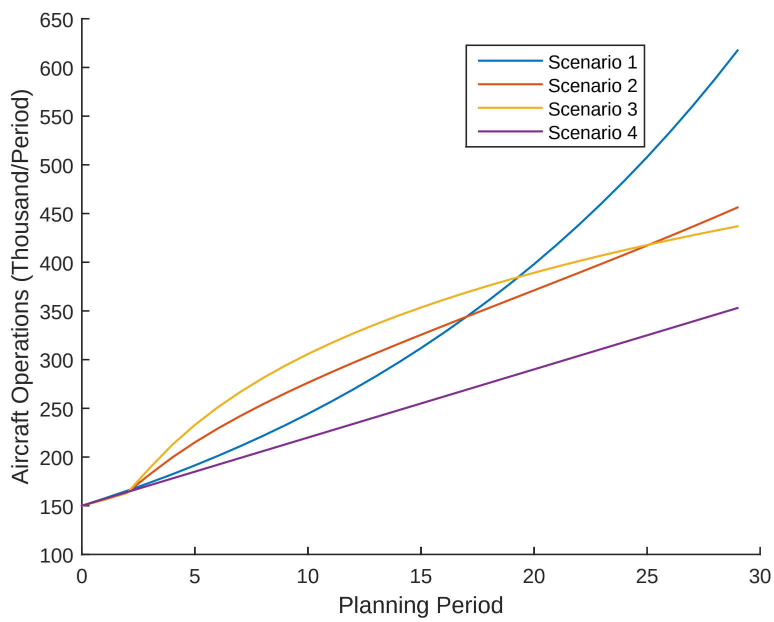

Figure 4.5: Demand forecasts for the airfield

The probabilities associated with those scenarios are 0.2, 0.2, 0.3 and 0.3, respectively. The proposed model can take any scenario probability distribution and accommodate any demand growth pattern, as long as the demand can be estimated for each component in a certain period. Table 4.1 presents cost related data for

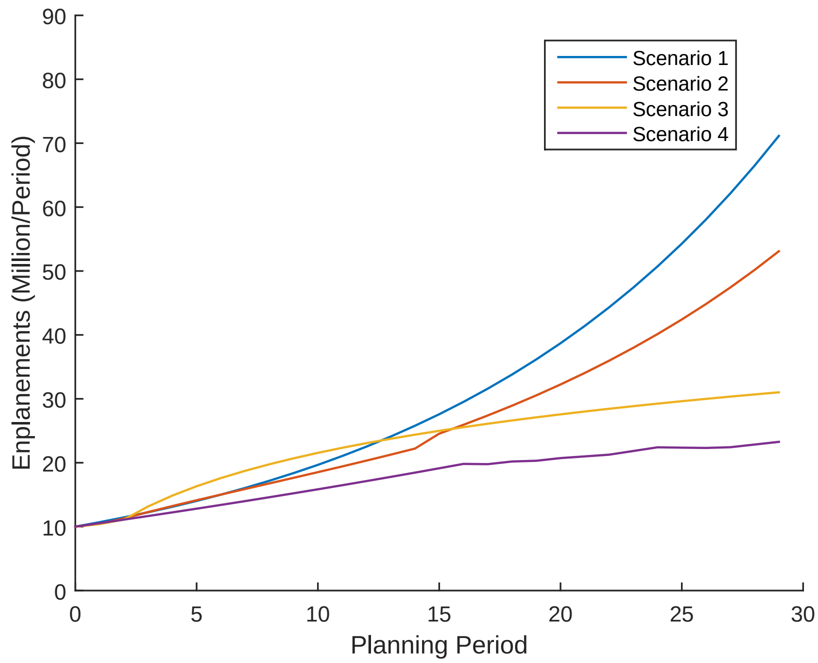

Figure 4.6: Demand forecasts for the terminal

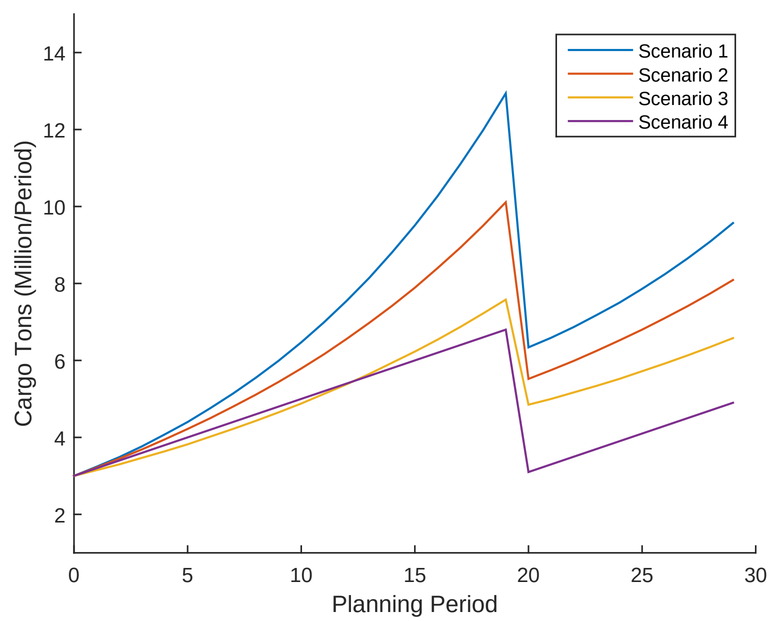

Figure 4.7: Demand forecasts for the cargo facility

each airport component.

Table 4.1: Cost parameters (Million $)

Component	Fixed capital		Variablecapital		Operating
	Purchase	Salvage	Purchase	Salvage	
Airfield system	720	216	3.2	-1.28	0.8
Passenger terminal	220	66	6.5	-2.6	1.0
Cargo facilities	16	4.8	6.4	-2.56	1.2

The discrete delay functions shown in Figure 4.8 are used in numerical analyses. The number of steps in the delay function is 30, i.e., $n = 30$. More steps can provide better approximations at the cost of additional computations.

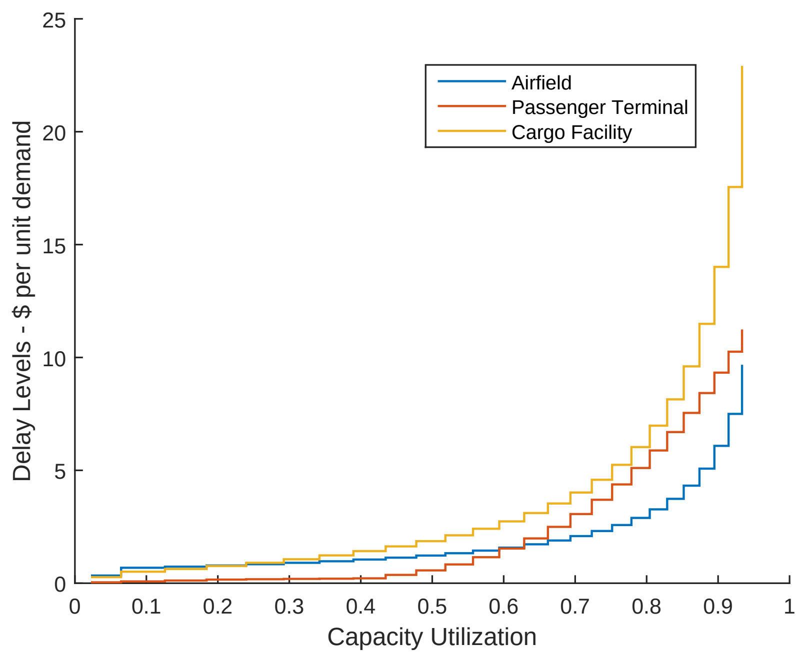

Figure 4.8: Discrete delay levels

The discounting coefficient $\delta = 0.97$. The planning horizon $m = 30$. In implementation, $M_i = 2 * \max\{q_{ij}(\omega)\}$ and $M_i = 4 * \max\{q_{ij}(\omega)\}$, where $q_{ij}(\omega)$ is the maximum possible demand on component i across all scenarios and periods.The model is implemented in GAMS v24.7.1 and the MIP solver is FICO-Xpress 28.01.

4.3.2 Optimization Results

The development plan for cargo facilities is shown in Figure 4.9. It can be observed that two capacity expansions are planned, first in period 6 and then period 13, with the magnitude of each capacity addition specified in Figure 4.9. Due to the expected demand drop, the capacity is reduced in period 20.

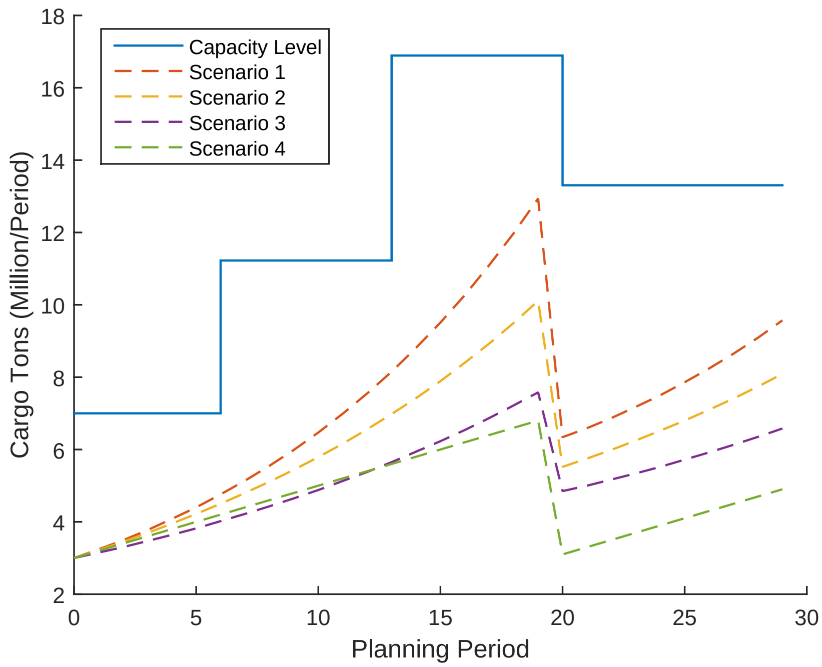

Figure 4.9: Capacity over time for cargo facilities

The resulting costs in each period for the cargo facility are plotted in Figure 4.10. The figure can clearly show the tradeoffs among capital costs, operating costs and delay costs. As traffic grows, delays increase, which requires capacity expansion decisions (and thus capital cost expenditures). As capacities increase, operating costs jump to new levels because operating cost is linear with respect to the capacity provided. Then delays start to grow again, leading to the next cycle of expansion.

When demand drops suddenly, capacity is reduced in order to (1) obtain the salvage value, and (2) reduce the operating cost.

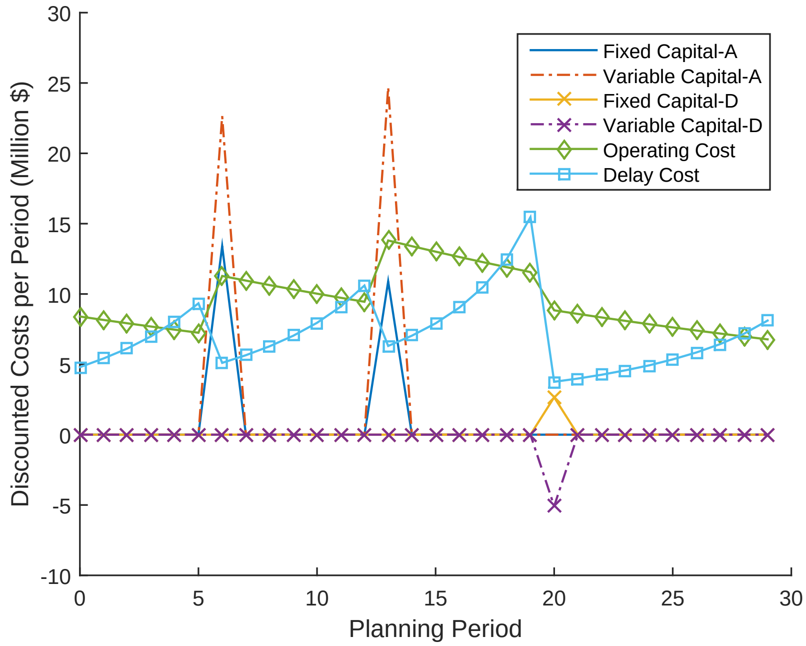

Figure 4.10: Resulting costs in each planning period for cargo facilities

Without using the stochastic program, we can formulate a deterministic version with the average value of demand forecasts. The resulting capacity level over time based on the expected scenario is shown in Figure 4.11. Clearly, when the first scenario occurs, demand will exceed capacity in some periods, which implies enormous delay costs. The term "Flaw of Averages" [6] refers to the value loss from the practice of making decisions based on average future conditions. The potential saving obtained from considering a range of future scenarios and solving a stochastic program is also called the Value of Stochastic Solution (VSS) in Birge and Louveaux [49].

The resulting capacity provision level vs each possible demand growth sce-

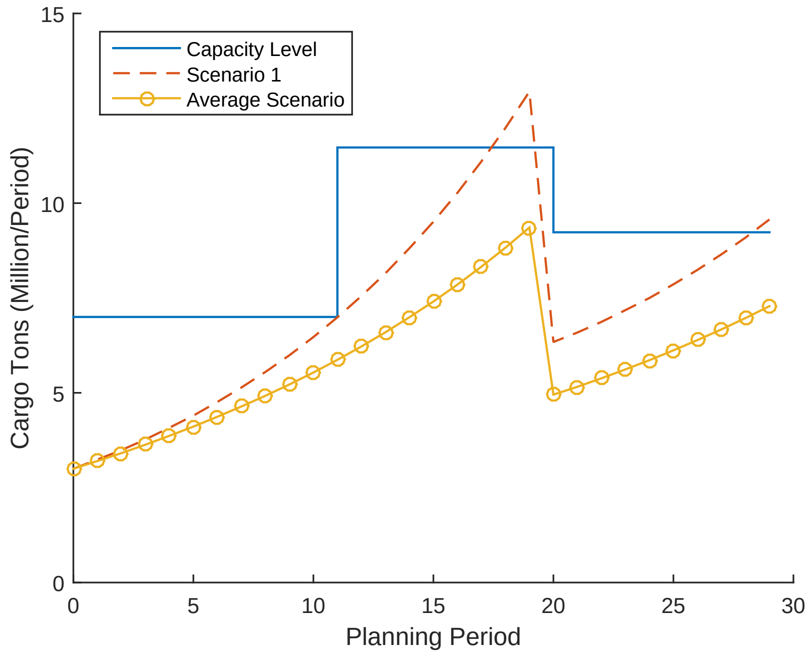

Figure 4.11: Capacity decisions for cargo facilities based on the average scenario

nario for each of two other airport components is plotted in Figures 4.12 and 4.13. Two capacity expansions are planned for both the airfield and passenger terminal. The computation time for solving the passenger terminal subproblem on a desktop computer (Intel Core Quad CPU 2.83 GHz, 3.25 GB RAM) is shown in Figure 4.14. When the optimality gap is 0.01 (meaning near-optimal), it takes less than one hour to solve the subproblem. Since the evaluation of long-term capacity decisions for airport facilities occurs once every few years, the computational time is acceptable, even without refinements of solution methods.

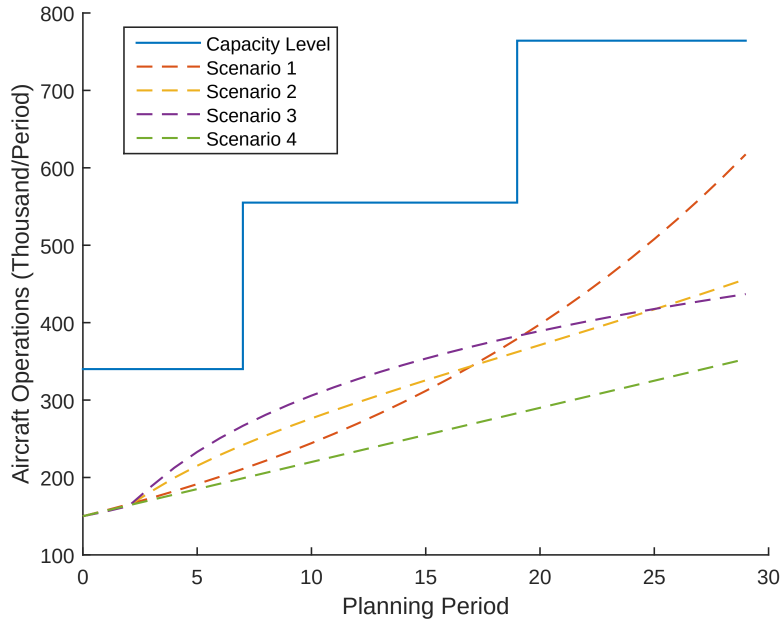

Figure 4.12: Capacity expansion path for the airfield

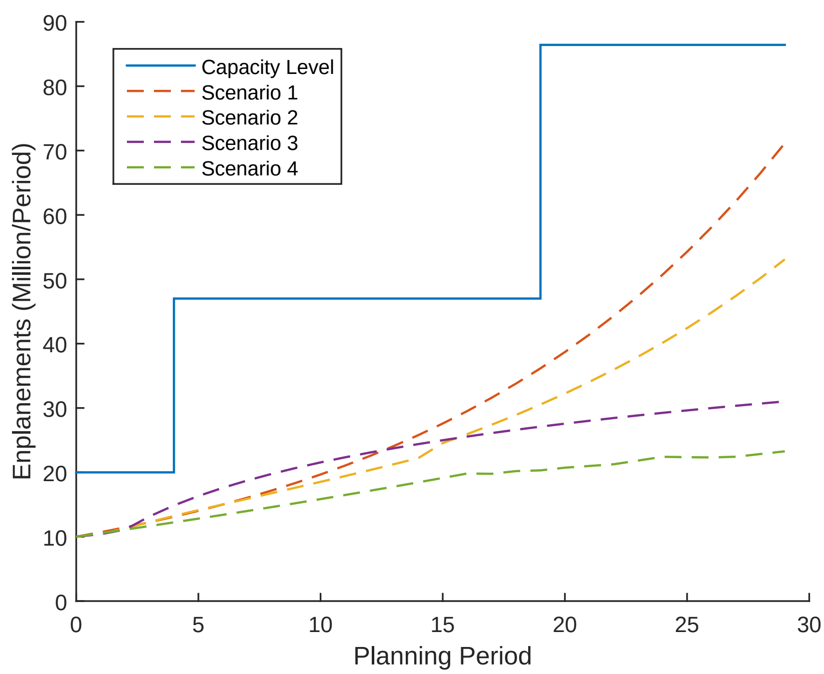

Figure 4.13: Capacity expansion path for the passenger terminal

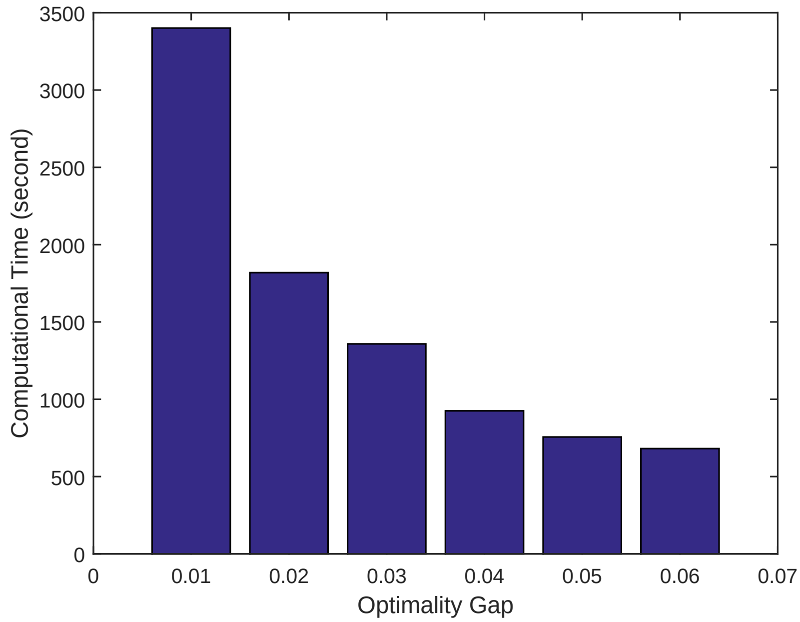

Figure 4.14: Computation time for solving the passenger terminal subproblem

4.4 Conclusions

This chapter presents a stochastic model for optimizing the strategic facility development decisions for airport systems in the presence of demand uncertainty. A mixed integer nonlinear program is proposed as a starting model and then reformulated into a mixed integer program after the delay costs are approximated and linearized. The linearization removes nonlinear properties of this program, enabling the design of efficient and reliable solution methods. After the inclusion of demand uncertainties, the deterministic model is extended into a stochastic program, which can yield better results than deterministic ones using average values of demand estimates. The stochastic program is solved in its deterministic equivalent form since discrete demand scenarios are assumed. Numerical case studies are conducted to demonstrate the capabilities of the proposed model and tradeoffs among various costs are also analyzed. In addition, the "Flaw of Averages" due to decisions based on averages is identified in the illustrative example.

Compared to the outer-approximation technique which requires differentiability, the discrete approximation is more widely applicable. As a result, the computation time is longer than that in Chapter 3. Without further improvements to the solution methods, the near-optimal solution (e.g., optimality gap of 1%) can be found on a standard desktop computer within one hour, which is acceptable considering that it is a long-term planning problem. The method proposed in this study is also more flexible than that in Chapter 3 because demand decreases as well as increases are allowed.

This study might also be improved in the following ways:

Coordinated development.

Although several airport components are considered and each has different operating and construction characteristics, the interactions among them are ignored in this chapter, which is why the model can be decomposed into independent subproblems. Methods which coordinate the development of various interrelated facilities are highly desirable.

Other uncertainties.

Only demand uncertainty is considered. Additional factors, such as aircraft characteristics and traffic mix might also be uncertain and should be included. In Chapter 5, the effect of uncertain aircraft mix is considered.

Chapter 5: Coordinated Airport Development Model

Although multiple airport components are considered in previous two chapters, it is assumed that various demand measures (e.g., enplanements, number of aircraft operations, tons of cargo shipped) are estimated for each individual airport component and capacity is analyzed separately for each component, as in Figure 5.1. Therefore, the problem presented in Chapter 4 is decomposed into smaller problems, with each one solved separately. However, airport facilities can be operated in parallel or in series, as in Figure 5.2. If a major flow passes through two facilities sequentially, it is likely that development decisions for these two facilities should be coordinated. If only one facility is expanded, the flow experiences less delay at this facility while it still faces severe congestion at the other facility.

While the concept of coordinated development might be not novel, a systematic methodology and a practical decision tool are still lacking.

The primary methodological innovation made in this chapter is to propose a network flow formulation for coordinating the development decisions so that a balanced capacity configuration is likely to be obtained. In this formulation, a flow can pass through several facilities and a facility can serve several types of flows, although flows through the same facility can consume various units of capacities.

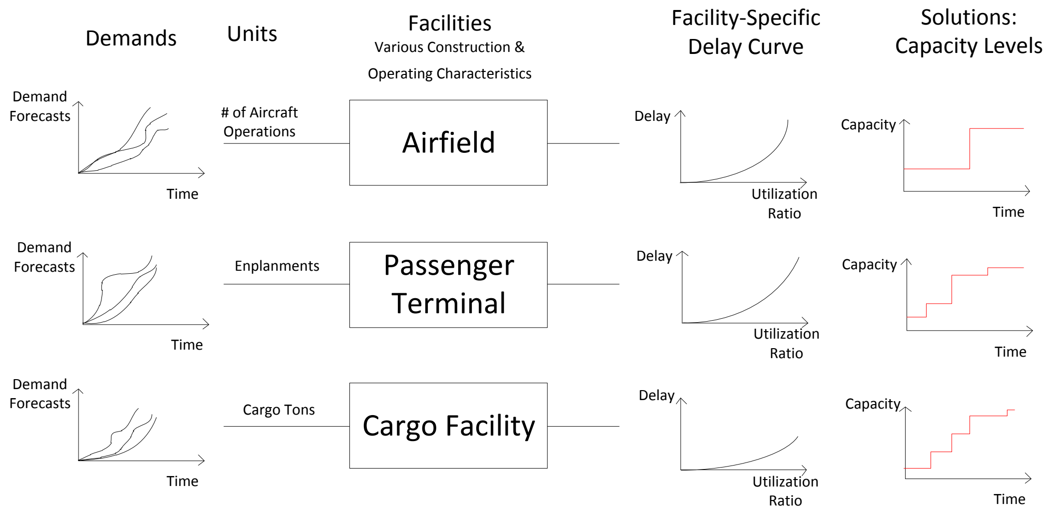

Figure 5.1: Independent development

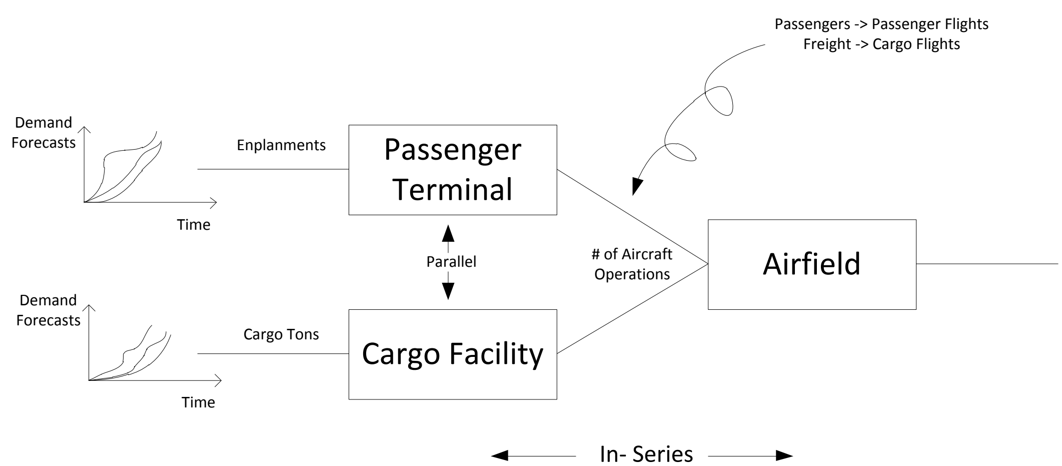

Figure 5.2: Coordinated development

Each facility is characterized by a facility performance function, which relates the delay level to the capacity utilization ratio. The task is to make capacity decisions for each facility over an extended planning horizon in an uncertain environment, with the objective of total cost (capital, operating and delay) minimization.

Another improvement over models in Chapter 3 and Chapter 4 is to jointly consider multiple sources of uncertainties. The effect of uncertain aircraft mix on the airfield capacity is captured in the present model.

Therefore, this chapter presents an applied computation tool for coordinating various airport facility expansions with explicit considerations of impacts of various uncertainties.

5.1 Model

5.1.1 Notation

Sets and Indices

i = flow type, $i \in I = \{1, 2, \ldots, |I|\}, I = I_{Air} \cup I_{Land}$

a = aircraft type, $a \in I_{Air} = \{1, 2, \ldots, |I_{Air}|\}, I_{Air} \subset I$

j = facility type, $j \in J = \{1, 2, \ldots, |J|\}, J = J_{Air} \cup J_{Land}$

k or t = time period within the planning horizon $K = \{1, 2, \ldots, |K|\}$

Parameters

f_{jk} = fixed capital cost of increasing capacity of facility j in period k

v_{jk} = variable capital cost of increasing capacity of facility j in period k

o_{jk} = unit operating cost of facility j in period k

q_{ik} = volume of flow i in period k

p_{ik} = the number of aircraft movements needed in period k for serving landside flow $i \in I_{Land}$

l_{ia} = average load per movement of aircraft type $a \in I_{Air}$ if flow $i \in I_{Land}$ is loaded

u_{ij} = consumption coefficient, i.e., how many standard units of facility j's capacity are consumed by one unit of flow i

δ = discount rate

Decision Variables

x_{jk} = the amount of capacity added to facility j in period k; continuous variable

y_{jk} = whether to add capacity to facility j in period k; binary variable

Auxiliary Decision Variables

s_{jk} = capacity of facility j in period k; continuous variable

$\tilde{s}_{jk}$ = adjusted capacity of facility j in period k; continuous variable

5.1.2 Cost Functions

The capital cost incurred in expanding facility j in period k is expressed as:

$$C_{jk} = \delta^k (f_{jk} y_{jk} + v_{jk} x_{jk}), \forall j \in J, k \in K \tag{5.1}$$

where δ is used to discount future costs. The characterization of capital cost is consistent with economies of scale in infrastructure expansion.

The operating cost of facility j in period k is linear with respect to the supplied capacity s_{jk}.

$$O_{jk} = \delta^k o_{jk} s_{jk}, \forall j \in J, k \in K \tag{5.2}$$

For facility $j \in J$, a facility performance function $F_j(\cdot)$ is defined to characterize the relation between delay level e_{jk} and capacity utilization ratio ρ_{jk} , as follows:

$$e_{jk} = F_j(\rho_{jk}), \forall j \in J, k \in K \tag{5.3}$$

where ρ_{jk} is the ratio of standardized demand d_{jk} and adjusted capacity $\tilde{s}_{jk}$:

$$\rho_{jk} = \frac{d_{jk}}{\tilde{s}_{jk}}, \forall j \in J, k \in K \tag{5.4}$$

Delay cost E_{jk} is defined as:

$$E_{jk} = e_{jk} d_{jk}, \forall j \in J, k \in K \tag{5.5}$$

The concept of standardized demand is introduced because multiple flows can route through the same facility and they consume different amounts of capacities. For example, both domestic passengers and international passengers use the waiting area in the passenger terminal and international passengers usually spend more time there because they are required to arrive earlier than domestic passengers prior to the flight departure time. For another example, faster or heavier aircraft may require longer runway occupancy times. Mathematically, the standardized demand on facility j in period k is calculated as follows:

$$d_{jk} = \sum_{i \in I} u_{ij} q_{ik}, \forall j \in J, k \in K \tag{5.6}$$

Table 5.1 is used to further illustrate such a concept. In this example, one international passenger is equivalent to 1.3 domestic passengers in terms of consuming passenger terminal capacity. If flow i does not pass through facility j, the consumption coefficient u_{ij} is zero.

Table 5.1: Example of consumption coefficient

Type of Flow	Airfield	Passenger Terminal	Customs	Cargo Building
Domestic Passengers	0	1	0	0
International Passengers	0	1.3	1	0
Freight	0	0	0	1
Heavy Aircraft	1.5	0	0	0
Large Aircraft	1.2	0	0	0
Small Aircraft	0.8	0	0	0

Airfield capacity is mainly determined by the number and layout of active runways [58]; it also depends on quite a few other factors, such as aircraft fleet mix, visibility, meteorological conditions, and ATC (Air Traffic Control) procedures. Given the required separation for each pair of aircraft of different types (as in Table 5.2 for instance) and the pairing probabilities (Table 5.3 for example), the expected time separation, i.e., headway, is then computed by multiplying corresponding inter-arrival time and its probability. Mathematically, the average headway is computed as $H = \sum_l \sum_t Prob_{lt} Time_{lt}$, where $Prob_{lt}$ is the probability of occurrence of the pair of leading aircraft l and trailing aircraft t and $Time_{lt}$ is the time interval between the movements of leading aircraft l and trailing aircraft t.

Table 5.2: Aircraft separation requirements

Inter-Arrival time (sec)		Trailing Aircraft		
		Heavy	Large	Small
Leading aircraft	Heavy	106	167	217
	Large	70	79	117
	Small	70	79	92

Table 5.3: Probabilities of a pair of aircraft types

Pair probabilities		Trailing Aircraft		
		Heavy=0.3	Large=0.4	Small=0.3
Leading aircraft	Heavy=0.3	0.09	0.12	0.09
	Large=0.4	0.12	0.16	0.12
	Small=0.3	0.09	0.12	0.09

Then a new aircraft mix changes the average headway. A larger headway means a smaller capacity. We can define the adjusted airfield capacity after considering the effect of aircraft mix as follows:

$$\tilde{s}_{jk} = s_{jk}\frac{H_0}{H(\beta_k)}, \forall j \in J_{Air}, k \in K \tag{5.7}$$

where s_{jk} is the airfield capacity by assuming a default aircraft mix, which leads to the expected headway H_0. $H(\boldsymbol{\beta}_k)$ is the expected headway resulting from a new aircraft mix $\boldsymbol{\beta}_k$ in period k. $\boldsymbol{\beta}$ is a vector whose each element represents the percentage for a specific type of aircraft, e.g., $\boldsymbol{\beta} = [0.3, 0.4, 0.3]$ as used in Table 5.3. The percent of aircraft type $a \in I_{Air}$ in period k, denoted as β_{ak}, is defined as follows:

$$\beta_{ak} = \frac{q_{ak}}{\sum_{i \in I_{Land}} p_{ik}}, \forall a \in I_{Air}, k \in K \tag{5.8}$$

where p_{ik} represents the number of aircraft movements in period k for serving landside flow $i \in I_{Land}$ and $\sum_{i \in I_{Land}} p_{ik}$ is the total number of aircraft movements in period k.

For each landside flow $i \in I_{Land}$, the needed number of aircraft movements can be obtained by calculating the expected load per movement, i.e., $\sum_{a \in I_{Air}} \beta_{ak} l_{ia}$. The following equation converts landside flows q_{ik} to airside flows p_{ik}.

$$q_{ik} = p_{ik} \sum_{a \in I_{Air}} \beta_{ak} l_{ia}, \forall i \in I_{Land}, k \in K \tag{5.9}$$

For a landside facility $j \in J_{Land}$ unaffected by the aircraft mix, the capacity is not adjusted:

$$\tilde{s}_{jk} = s_{jk}, \forall j \in J_{Land}, k \in K \tag{5.10}$$

5.1.3 Deterministic Model

The deterministic formulation of the coordinated development problem is written as:

$$\begin{aligned} \min_{\{x_{jk} \geq 0, y_{jk} \in \{0,1\}\}} & \sum_j \sum_k \delta^k (f_{jk} y_{jk} + v_{jk} x_{jk}) + \sum_j \sum_k \delta^k o_{jk} s_{jk} + \\ & \sum_j \sum_k \delta^j F_j (\frac{d_{jk}}{\tilde{s}_{jk}}) d_{jk} \end{aligned} \tag{5.11}$$

subject to

$$x_{jk} \leq M_j y_{jk}, \forall j \in J, k \in K \tag{5.12a}$$

$$s_{jt} = s_{j,0} + \sum_{k=1}^{t} x_{jk}, \forall j \in J, t \in K \tag{5.12b}$$

$$d_{jk} \leq \tilde{s}_{jk}, \forall j \in J, k \in K \tag{5.12c}$$

Constraint (5.12a) ensures that once some capacity is added to facility j in period k, i.e., $x_{jk} > 0$, the fixed capital cost f_{jk} is incurred. Constraint (5.12b) defines how the capacity is accumulated over time, where $s_{j,0}$ is the initial capacity of facility. Constraint (5.12c) restricts that over an extended time period, demand cannot exceed capacity.

5.1.4 Stochastic Model

In the deterministic model, all parameters are assumed to be known with certainty. In practice, some data could be very difficult to predict accurately and several plausible scenarios are generated by planners to reflect the underlying uncertainty. In some other cases, data could be obtained through expert opinion, which also leads to multiple discrete scenarios. In this chapter, two distinct sources of uncertainties, namely uncertain landside flow volumes and uncertain aircraft fleet mixes, are considered. Let $\boldsymbol{\xi}$ denote a vector of discrete air traffic predictions and $\boldsymbol{\mu}$ denote a vector of discrete random aircraft mixes. A particular realization of these random parameters is denoted by $\omega \in \Omega = \{\omega_1, \omega_2, \ldots, \omega_R\}$, where R is the number of possibilities.

In the stochastic optimization problem, capacity decisions have to be made based on the probabilistic data available at the current decision making time. After decisions are made, particular realizations can be observed. Such a problem is usually modelled with a two-stage stochastic program.

The first stage problem is:

$$\min_{\{x_{jk}\geq 0, y_{jk}\in\{0,1\}\}} \sum_j \sum_k \delta^k (f_{jk} y_{jk} + v_{jk} x_{jk}) + \sum_j \sum_k \mathbb{E} Q_{jk}(X, Y, \boldsymbol{\xi}(\omega), \boldsymbol{\mu}(\omega)) \quad (5.13)$$

subject to constraint (5.12a), where $Q_{jk}(X, Y, \boldsymbol{\xi}(\omega), \boldsymbol{\mu}(\omega))$ is the oracle that computes the operating and delay costs associated with a particular realization $\omega \in \Omega$, given capacity decisions $X = \{x_{jk} | j \in J, k \in K\}$ and $Y = \{y_{jk} | j \in J, k \in K\}$. The operator $\mathbb{E}$ is to find the expectation of $Q_{jk}(X, Y, \boldsymbol{\xi}(\omega), \boldsymbol{\mu}(\omega))$ over all realizations of the random event $\omega \in \Omega$.

$Q_{jk}(X, Y, \boldsymbol{\xi}(\omega), \boldsymbol{\mu}(\omega))$ is also the optimal value of the second stage problem.

$$\min_{s_{jk}\geq 0} \delta^k \left(o_{jk} s_{jk} + F_j\left(\frac{d_{jk}(\omega)}{\tilde{s}_{jk}(\omega)}\right) d_{jk}(\omega) \right) \quad (5.14)$$

subject to constraint (5.12b) and

$$p_{ik}(\omega) = \frac{q_{ik}(\omega)}{\sum_{a \in I_{Air}} \beta_{ak}(\omega) l_{ia}}, \forall i \in I_{Land}, k \in K, \omega \in \Omega \tag{5.15a}$$

$$q_{ak}(\omega) = \beta_{ak}(\omega) \sum_{i \in I_{Land}} p_{ik}(\omega), \forall a \in I_{Air}, k \in K, \omega \in \Omega \tag{5.15b}$$

$$d_{jk}(\omega) = \sum_{i \in I} u_{ij} q_{ik}(\omega), \forall j \in J, k \in K, \omega \in \Omega \tag{5.15c}$$

$$\tilde{s}_{jk}(\omega) = s_{jk} \frac{H_0}{H(\boldsymbol{\beta}_k(\omega))}, \forall j \in J_{Air}, k \in K, \omega \in \Omega \tag{5.15d}$$

$$\tilde{s}_{jk}(\omega) = s_{jk}, \forall j \in J_{Land}, k \in K, \omega \in \Omega \tag{5.15e}$$

$$d_{jk}(\omega) \leq \tilde{s}_{jk}(\omega), \forall j \in J, k \in K, \omega \in \Omega \tag{5.15f}$$

Constraint (5.15a) converts landside flows into aircraft flows through the expected aircraft load. Constraint (5.15b) actually replicates the definition of aircraft mix $\beta_{ak}(\omega)$. Constraint (5.15c) standardizes various flow types using the same facility through the capacity consumption coefficient u_{ij}. Constraint (5.15d) models how changes in the aircraft mix influence the airfield capacity. Landside facilities are not impacted and their capacities are unadjusted as in constraint (5.15e). Constraint (5.15f) is a stochastic version of constraint (5.12c).

Since random variables are discrete and the number of scenarios is finite in this study,

$$\mathbb{E}Q_{jk}(X, Y, \boldsymbol{\xi}(\omega), \boldsymbol{\mu}(\omega)) = \sum_{r=1}^{R} \lambda_r Q(X, Y, \boldsymbol{\xi}(\omega_r), \boldsymbol{\mu}(\omega_r)), \forall j \in J, k \in K \tag{5.16}$$

where $\lambda_r = P(\omega = \omega_r), r \in [1, R]$, representing the probability associated with a particular realization $\omega_r, r \in [1, R]$. With equation (5.16), the two-stage stochastic program is converted into its deterministic equivalent. Equation (5.16) states that the expected cost is the weighted sum of the scenario-specific cost, in which the weight is the probability associated with each scenario.

5.2 Solution

There are both continuous and binary variables in this optimization problem. All constraints are linear and all costs in the objective function are linear except delay costs. Therefore, the mathematical program is a mixed integer nonlinear program (MINLP), which combines the difficulty of optimizing over mixed integer variables with the handling of nonlinear relations. Traditionally, MINLP is considered a class of challenging optimization problems.

Although the problem is difficult to solve directly, an interactive process can be used to generate and refine bounds on the optimal value by noting the following: (1) lower bounds are generated by solving the relaxation of MINLP and (2) upper bounds are given by a feasible value to MINLP. Such a solution approach is effective and efficient if the objective is convex, which enables the design of specialized algorithms.

It has been proved that the delay cost is convex in the supplied capacity s, which is the decision variable in Chapter 3. Similarly, if the delay level $F_j(\rho_{jk})$ is convex in the capacity utilization ratio ρ_{jk}, the delay level is also convex in the adjusted capacity $\tilde{s}_{jk}$. The proof is almost the same as that used in Chapter 3. The reasoning is that $\tilde{s}_{jk}$ is simply linear with respect to s_{jk}, which does not affect the convexity. Based on the convexity, an outer-approximation technique can be adopted to linearize the delay cost. More technical details about the outer-approximation are available in Chapter 3. The proposed solution framework is shown in Figure 3.

Once integer variables are fixed, the resulting convex nonlinear program can be solved optimally. The optimal values of continuous variables are used to construct the mixed integer program by relaxing the nonlinear item around the given continuous variables. The solution of the mixed integer program further provides values of integer variables. In an iteration, one upper bound and one lower bound are thus generated. The algorithm terminates when the lower and upper bounds are within a specified tolerance.

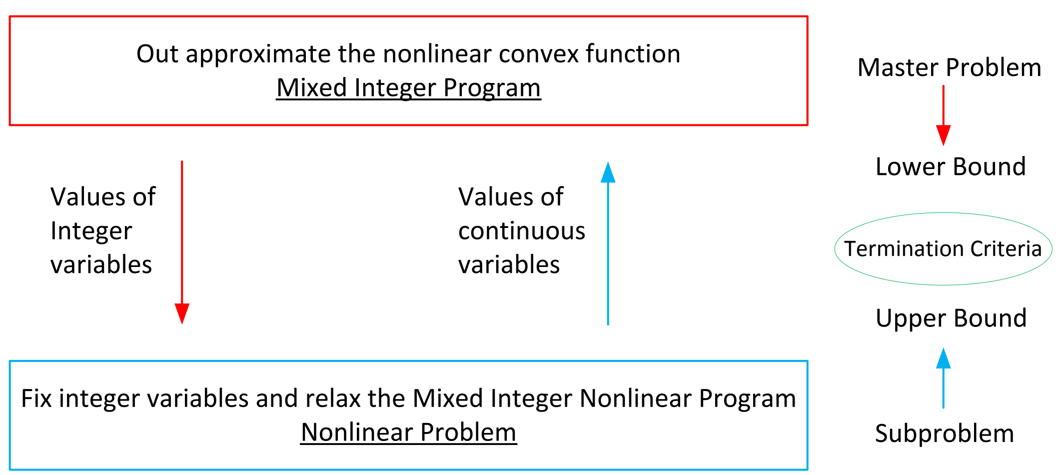

Figure 5.3: Iterative solution framework

5.3 Numerical Tests

5.3.1 Inputs

A hypothetical airport consisting of four components, as shown in Figure 5.4, is used to demonstrate the proposed methodology. There are three types of landside flows, namely domestic passengers, international passengers, and cargos. Three types of aircraft are considered, namely heavy, large, and small. Three scenarios (1-3) are shown for uncertain landside flows in Figures 5.5, 5.6 and 5.7. Two scenarios (A-B) for uncertain aircraft mixes are shown in Figure 5.8. In total, there are $3 * 2$ possible scenarios assuming that two sources of uncertainties are independent. For convenience, all scenarios are associated with the same probability, which is 1/6.

Cost-related data for each facility are presented in Table 5.4. Table 5.5 presents the average load per aircraft movement. Data in Table 5.2 are used to compute the expected headway given an aircraft mix.

It should be made clear that data presented here are only illustrative and the proposed model is able to accommodate other data specified by end users of such a model, e.g., airport facility planners. For example, additional facilities and landside flows can be added and other scenario probabilities can be used.

5.3.2 Results

The resulting capacity provision level vs each demand scenario for the customs is shown in Figure 5.9. Due to the relatively lower fixed expansion cost, capacity

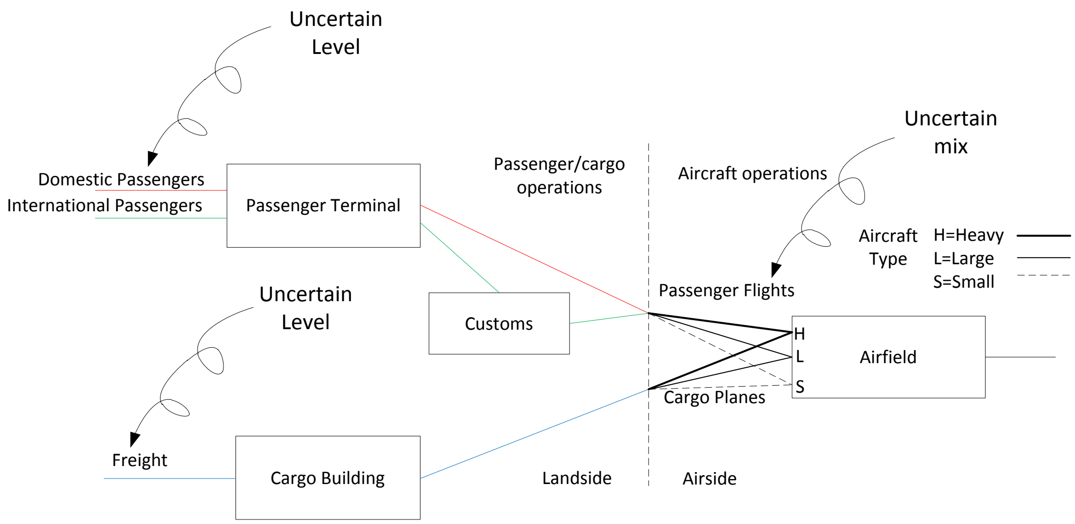

Figure 5.4: A network of airport facilities

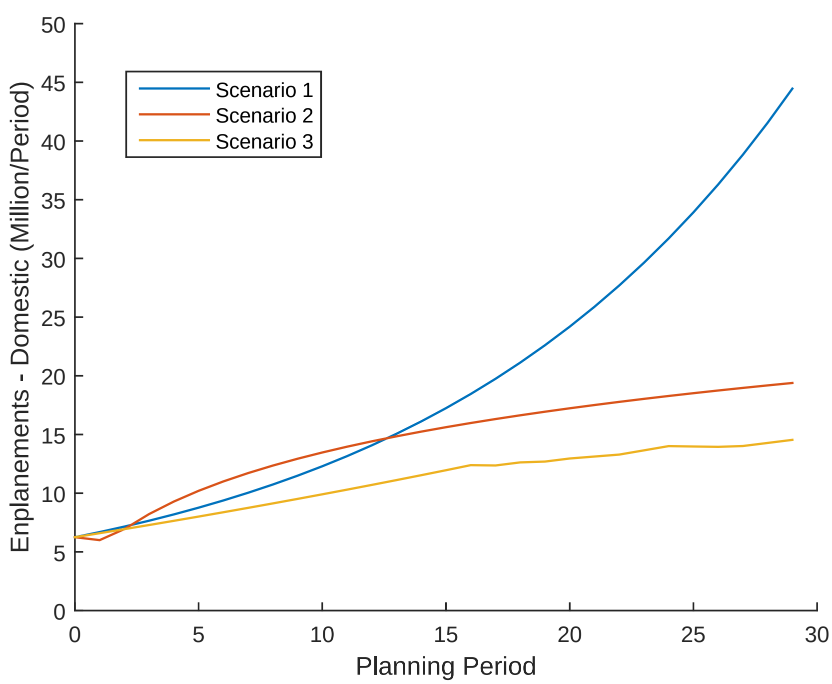

Figure 5.5: Forecasts of domestic passenger enplanements

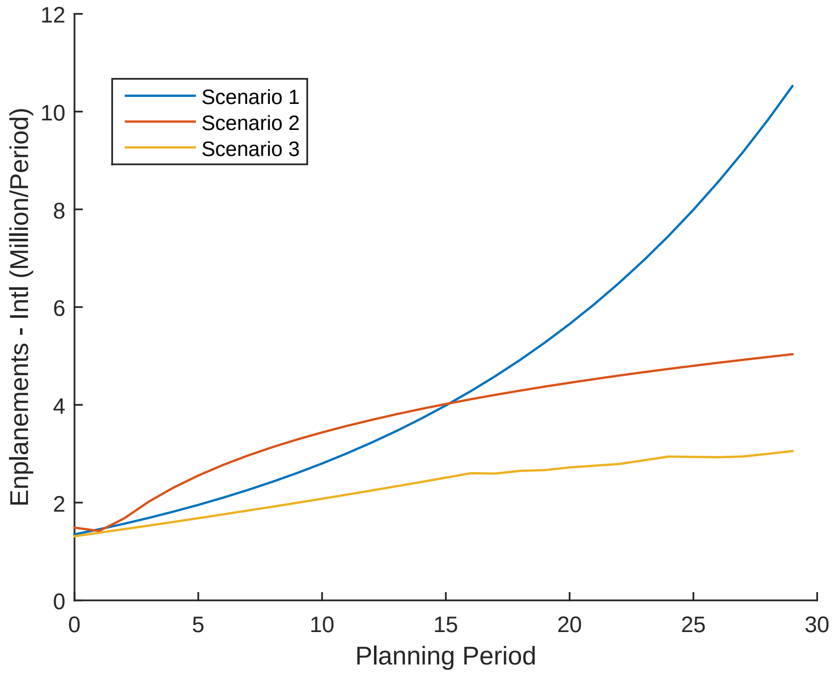

Figure 5.6: Forecasts of international passenger enplanements

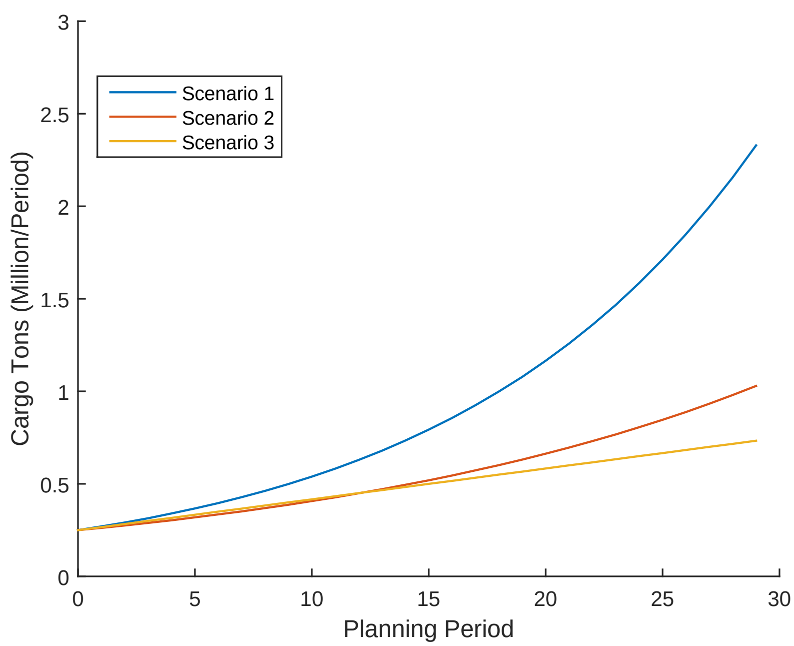

Figure 5.7: Forecasts of cargo tons

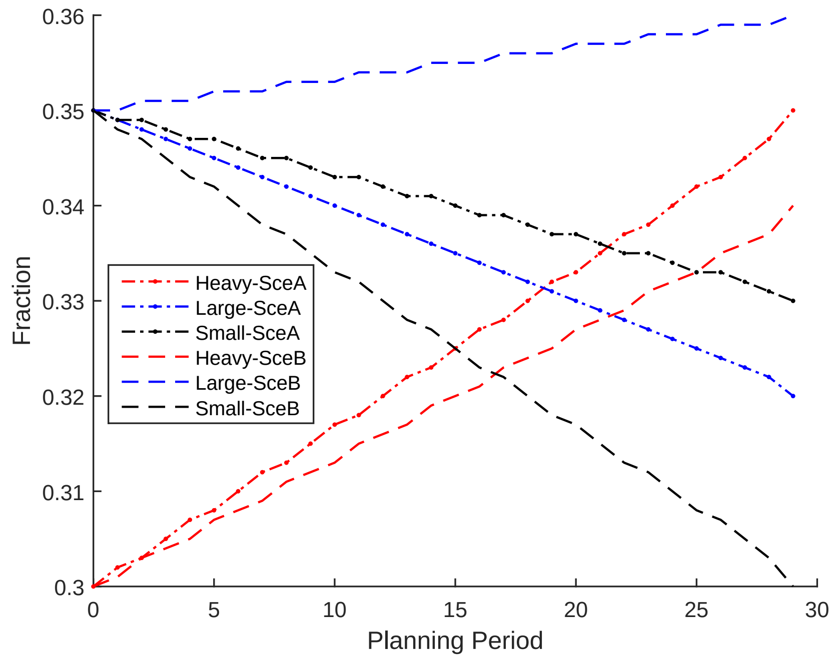

Figure 5.8: Forecasts of aircraft mixes

Table 5.4: Cost parameters (Million \$)

Facility type	Fixed capital	Variable capital	Operating	Delay
Airfield system	500	1.6	0.4	$0.1(\frac{1}{1-\rho} - 0.85)$
Passenger terminal	100	5	1.6	$0.2(\frac{1}{1-\rho} - 0.75)$
Customs	3	1.6	1	$0.3(\frac{1}{1-\rho} - 0.75)$
Cargo Building	2	2.2	1.2	$0.3(\frac{1}{1-\rho} - 0.7)$

Table 5.5: Load per aircraft movement

Aircraft type	Domestic Passengers	International Passengers	Cargos (tons)
Heavy aircraft	120	130	15
Large aircraft	80	80	10
Small aircraft	60	60	7

expansions occur multiple times throughout the planning horizon. Figure 5.10 shows the tradeoffs among capital costs, operating costs and delay costs. As traffic grows, delays increase, which triggers capacity expansion decisions (and thus capital cost expenditures). As capacities increase, operating costs jump to new levels because operating cost is linear with respect to the capacity provided (see Equation (5.2)). Then delays start to grow again, leading to the next cycle of expansion.

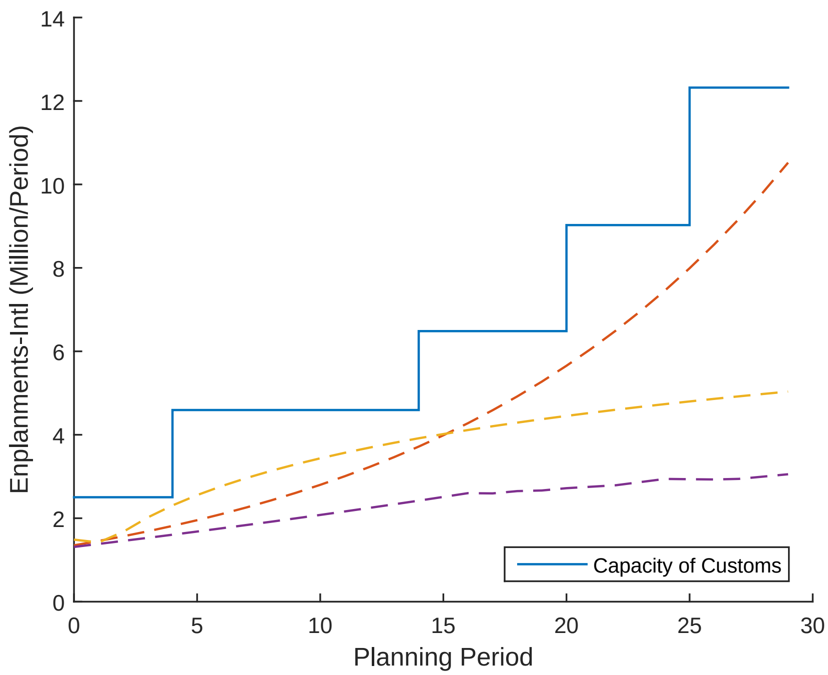

Figure 5.9: Capacity expansion path for customs facilities

For facilities with much higher fixed costs, such as airfield and passenger terminal, fewer expansions are planned, as shown in Figure 5.11. Because expansion is less frequent and these two facilities are operated in series, expansions for these two facilities occur at the same time. In this case study, since domestic passengers dominate on the landside and domestic passenger flights also dominate on the airside, it is economically justified to expand the in-series facilities serving this dominating

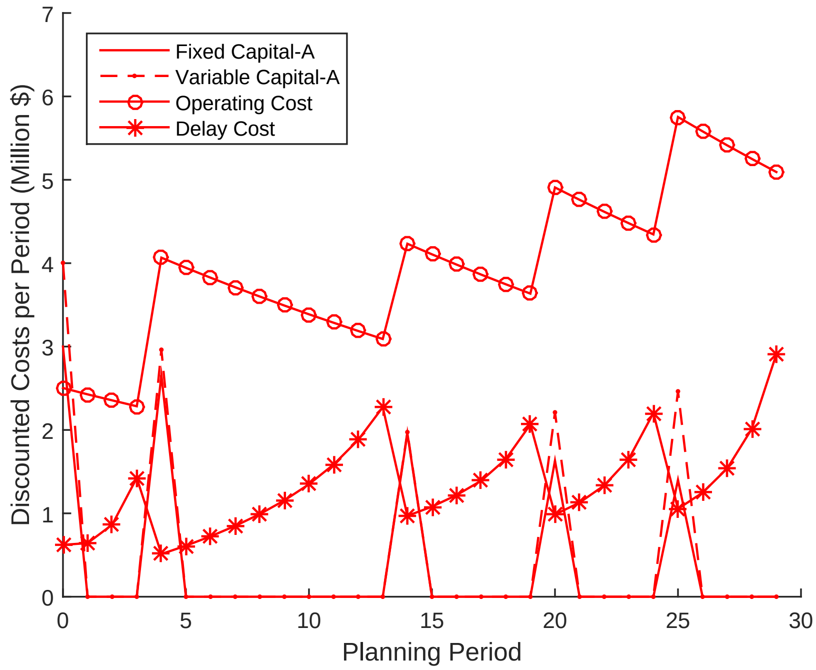

Figure 5.10: Resulting costs in each period for customs facilities

flow at the same time. Such a coordinated development is unlikely to be observed if these facilities are treated as independent or in-parallel.

The development plan for the cargo facilities is shown in Figure 5.12. First, it has more expansions than the airfield or passenger terminal, because the costs of additional capacity and costs of lacking capacity differ for different components, as indicated in Table 5.4. Second, the development plan for the cargo facilities is not coordinated with the one for the airfield, which deserves further explanations. Both the passenger terminal and cargo facilities are in-series with the airfield, because the passenger flow passes through the passenger terminal and the airfield; the cargo flow passes through the cargo facilities and the airfield, as shown in Figure 5.4. Only development decisions for the passenger terminal and airfield are coordinated, because the passenger flow dominates the cargo flow. Figure 5.13 plots the number

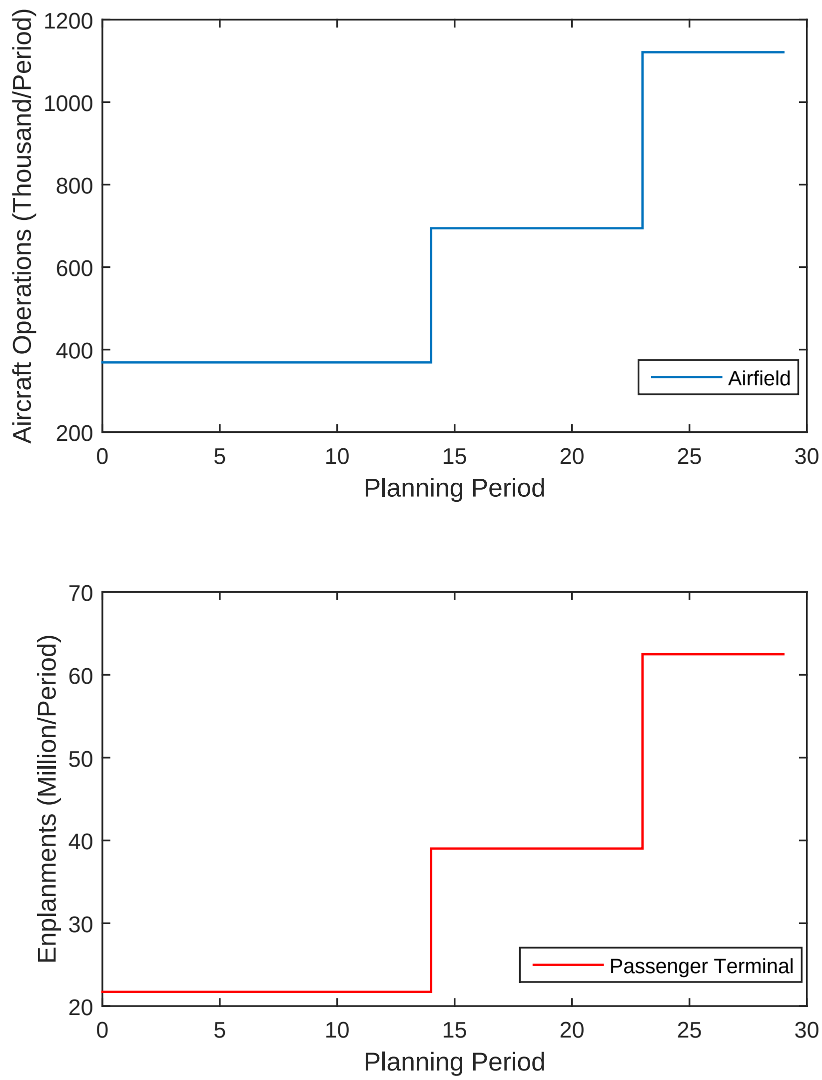

Figure 5.11: Development plans for airfield and passenger terminal

of aircraft operations for each type of landside flow in scenario 1-A (scenario 1 of the landside demand forecast and scenario A of the aircraft mix forecast). It shows that passenger flights greatly outnumber cargo flights. Assuming that there are two conflicting development plans (I and II) based on needs of the two flows, for instance, expansions in years 1, 3, and 5 according to Plan I and expansions in years 2, 4, and 6 according to Plan II, it is understandable that the need of the "more important" or "dominating" flow should be satisfied first.

Another point worth mentioning is that in this study it is implicitly assumed that there is no need to coordinate capacity decisions for facilities that operate in parallel. However, this might be invalid in some cases. For example, fixed capital costs might be reduced if one contractor is hired to improve two facilities, even if these facilities operate in parallel.

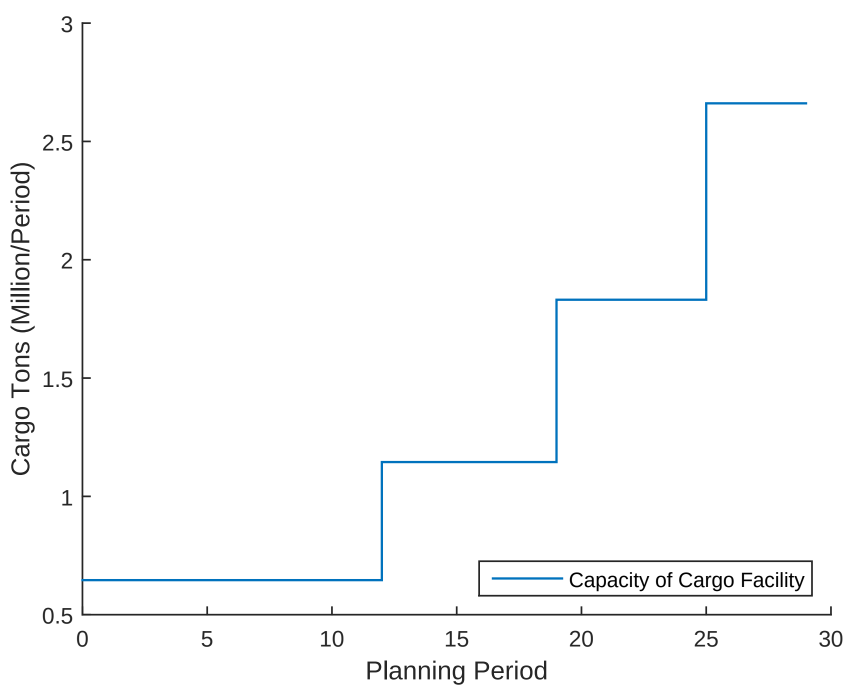

Figure 5.12: Development plan for cargo facilities

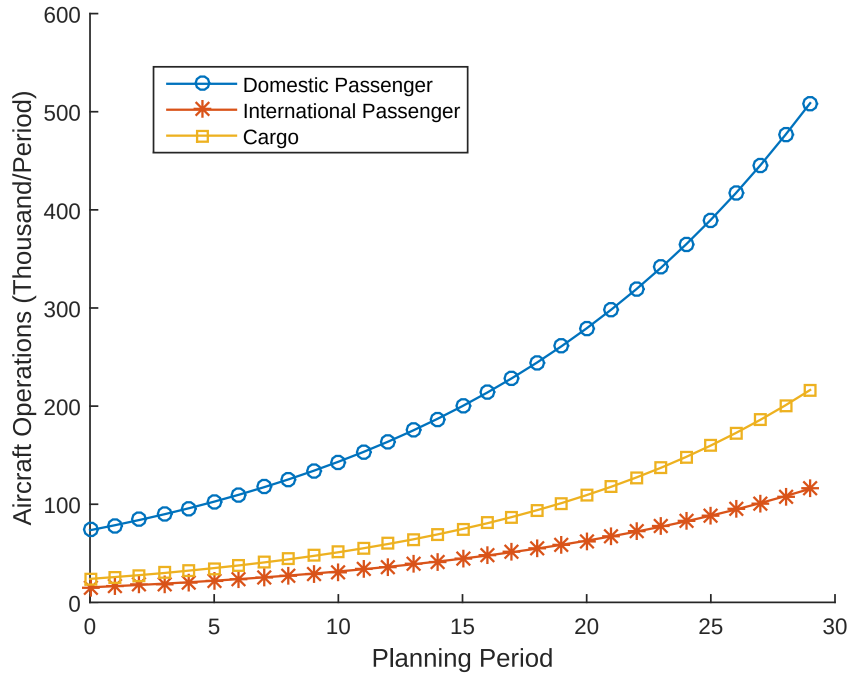

Figure 5.13: Aircraft operations needed for each type of landside flows (Scenario 1-A)

5.3.3 Algorithm Performance

The model is implemented in GAMS v24.7.1. The mixed integer program solver is CPLEX 12.6.3.0 and the nonlinear program solver is CONOPT 3.17A. The optimality gap is set to be 0.001. In the interactive process, when the percent gap between the upper and lower bounds is below 0.0001, the algorithm terminates. The algorithm is run on a desktop computer (Intel Core Quad CPU 2.83 GHz, 3.25 GB RAM).

The performance of the interactive solution process is shown in Figures 5.14 and 5.15. The algorithm terminates in iteration 12 and the total computation time is around 100 seconds. It can be claimed that the model is solved very fast to its optimality with a relative gap of 0.01%.

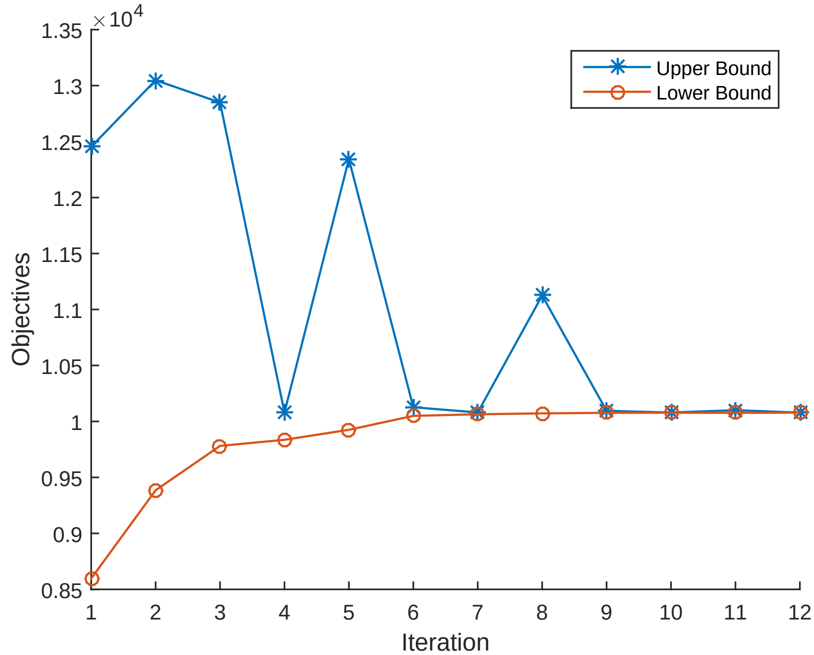

Figure 5.14: Convergence process

5.4 Conclusions

5.4.1 Summary

This chapter presents an optimization model for coordinated airport facility development with explicit consideration of uncertainties in air traffic levels and types. In the proposed network flow formulation, various airport user flows, such as passengers, cargos and aircraft, interact with related airport facilities, such as passenger terminal, cargo terminal and airfield, in the airport system. Each flow can pass through various facilities and multiple flows can share a facility while different units of capacities are consumed. Each facility has distinct construction

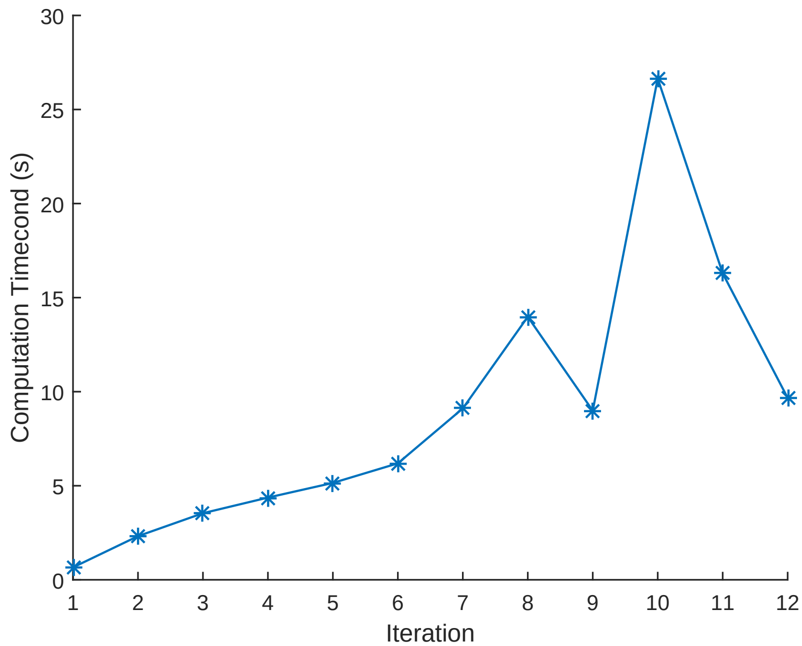

Figure 5.15: Computation time

and operating cost parameters and it is also characterized by a facility performance function, which relates the delay level to the capacity utilization ratio. The problem is to decide how much capacity should be added to which facility at what time, given these flow-facility interactions under uncertainty.

The final mathematical model is a stochastic mixed integer nonlinear program. The stochastic program is converted to its deterministic equivalent because scenarios considered in this study are discrete and the number of them is finite. After showing the convexity of the delay cost in the supplied capacity, an out-approximation technique is used to linearize the model. An interactive solution method is used to generate and refine upper and lower bounds on the objective value. The solution method is shown to be very effective and efficient by numerical tests.

5.4.2 Extensions

The following improvements might be considered in future developments of such models:

1. Infrastructure replacement is not considered, because the economic life of added capacity is assumed to exceed the planning horizon and the capacity is imperishable. Future work could consider the deterioration process of infrastructure.

2. The Next Generation Air Transportation System ("NextGen") is designed and implemented by FAA to transform the National Airspace System (NAS). It can have significant impacts on the airport facilities and operations. Future work should incorporate the effect of NextGen capabilities. A virtual facility "airspace", which is affected by NextGen capabilities, can be added to the current model.

Chapter 6: Concluding Remarks

6.1 Summary

The master plan is of paramount importance in the context of airport planning. However, the traditional planning process has been criticized heavily due to its limited ability to address future uncertainties. Several conceptual methods and procedures are proposed for promoting "flexibility" or "adaptability" in airport planning. Although these macro methods are useful for the preliminary evaluation of various airport development plans at the airport level, they are unable to generate quantitative decisions at the facility or component level, given their design purpose. There are few micro analyses of the airport facility development problem and they usually focus on a specific facility or component. Therefore, the primary contribution of this study is to present a global planning tool for coordinating the development of various airport facilities, which might operate in parallel or in series.

Due to the intricacy of the airport facility development problem, this dissertation presents sequentially a series of applied decision tools. Practical considerations, such as economies of scale, future cost discounting, nonlinear congestion, and project implementation time requirement, are captured in the optimization models, which combine the difficulty of optimizing over binary variables and handling nonlinear relations. After examining the structural properties of optimization models, some simplification techniques are proposed, such as the out-approximation and discrete-approximation linearization methods, for enhancing solution efficiency and quality. Computational experiments demonstrate the benefits of such models, for instance, the total cost could be reduced significantly (e.g., 18.8% in one test) with the proposed stochastic model, compared with decisions based on the average condition.

6.2 Data Collection

The increased availability of relevant data can facilitate the running of more detailed decision tools. The following paragraphs explain what methods are available for adequately preparing data for the proposed models.

6.2.1 Cost Parameters

Common methodologies for developing cost estimates include parametric estimates, estimating using historical bid prices, cost-based estimating, and risk/contingency analysis [59]. The ACRP Report 120 [60] develops a parametric cost-estimation methodology based on a mathematical relation between cost, the dependent variable, and a range of independent variables which are considered cost drivers, e.g., pavement area and length of runway. The selection of candidate independent variables is subject to engineering judgment and further tested for statistical validity. A spreadsheet-based tool is developed for computing the costs of eight project types based on the developed estimation method.

An econometric analysis of airports cost functions conducted with data from 161 airports worldwide is available [48]. The Airports Council International-North America (ACI-NA) also releases its estimate of the capital cost of airport improvements every five years [61].

Some state agencies also publish relevant cost estimates. For example, the Ohio Department of Transportation provides detailed estimates of airport development costs for airports in Ohio [62]. The unit construction cost for each facility type is quite useful. According to this document, one square foot of conventional hangar costs $87 and one square foot of general terminal building costs $150.

6.2.2 Generation of Future Scenarios and Their Probabilities

It is indeed a challenge to predict what may happen in the future. Readers are directed to two useful references de Neufville and Scholtes [6] and ACRP Report 76 [1]. Chapter 4 of de Neufville and Scholtes [6] provides a five-step process for estimating the distribution of future possibilities, as follows:

1. Identify the important factors;
2. Analyze historical trends;
3. Identify trend-breakers;
4. Establish forecast accuracy;
5. Build a dynamic model.

With such a procedure, a hospital example is analyzed to illustrate how uncertain demand can be estimated in order to plan the hospital capacity. In the last step, a line projection is altered by adding a random error to produce another projection, until a set of future scenarios is generated.

ACRP Report 76 [1] mentions brainstorming and elicitation techniques as main methods for identifying future possibilities, although analysis of historical data and other quantitative methods can also be used. As for the determination of probability distribution, the elicitation method and analyzing historical data are suggested as main techniques.

Various uncertainties are present in airport development. While some could be conveniently characterized with known statistical distributions, others can be quite difficult to model mathematically. For example, effects of election cycles and shock events can be difficult to quantify. More research efforts should be devoted to methods for dealing with such uncertainties.

6.3 Some Thoughts

6.3.1 Model Selection

Choosing the right technical model with appropriate level of detail and model performance [63] is difficult. To accurately reflect characteristics of the real world practice, the level of detail should be high. As a consequence, more data are needed to set up the model. The models complexity also grows, which leads to the models poor performance, e.g., extreme slowness. On the other hand, an oversimplified model might miss important aspects of the problem and is unable to predict correctly the behavior of a system. Therefore, model developers and end users should jointly determine what factors must be included and what characteristics could be simplified or ignored to strike a balance between complexity and realism, depending on the design purpose of the model.

For example, a choice between a two-stage stochastic program and a multi-stage stochastic program has to be made. Based on the observation that airport expansions may occur over a very long planning horizon, some might argue a multi-stage stochastic program is preferable. However, data regarding uncertainties in the context of airport planning are seldom available in the form of a scenario tree, which is essential for the implementation of a multi-stage stochastic program. Compared to the multi-stage stochastic program, a rolling horizon approach might be more appropriate, as explained below.

In practice, the planning horizon in an airport master plan is 20 or 30 years and the plan is updated every few years, e.g. 5 years. In addition, long-term forecasts tend to be less reliable than near-term ones. Therefore, capacity decisions in the near term are more crucial for airport planners. To this end, a rolling horizon approach seems desirable.

Another example regards the modeling of capacity as a continuous variable. In many capacity expansion studies, capacity is assumed to be divisible and modelled as a continuous variable. While this is a valid assumption in cases where the number of possible capacity sizes is quite large, capacity might be indivisibly "lumpy" and only incrementable in a limited number of feasible sizes. However, such integer restrictions could significantly complicate models and make them less amenable to analysis [53].

Other choices include: (1) discrete or continuous time dimension, (2) "power" function or "fixed charge" cost function to model economies of scale, and (3) finite or infinite planning horizon. When time is continuous, a power function $e^{-\gamma t}$ is more frequently used to discount the future value; when the planning horizon consists of a finite number of periods, a constant per-period discount factor γ is used. All these choices have to be evaluated carefully before the formulation.

6.3.2 Gap between Practice and Research

In airport planning, there is a major gap between the research community and the practitioners world. Theorists may pursue mathematical elegance and would like preserve the tractability of the model, even if problems are simplified to the extent that no practical values are obtainable. Practitioners complain about the complexity of the mathematical models and are unlikely to trust the results obtained from methods they are unable to understand.

For example, in two-stage or multi-stage stochastic programs, the probability distribution of the random data is assumed to be known [64]. In this study, the probability associated with each random scenario is thus assumed to be known. For the layman, such an assumption might be highly questionable. If such probability distributions are unknown, the problem falls into the realm of robust optimization.

The choice of a delay function provides another example. For practitioners, the delay curve of an airport facility is never a standard mathematical function, since their experiences, e.g., from running simulations, suggest that such a curve is more likely to be unsmooth. As shown in Chapter 4, the discrete approximation technique requiring no differentiability is much slower than the outer-approximation depending on such a property in Chapter 3. Practitioners might evaluate whether it is appropriate to use fitting functions rather than the original functions from computer simulations or empirical studies. It is also likely that for some practitioners, the computation time on the order of hours is acceptable since the problem solved is a long-term planning one.

6.3.3 Non-technical Factors

Although well-developed optimization models are very useful in making airport development decisions, it should be clear that airport development is a very complex, and not just a technical problem. The development plan of airport facilities is also affected by cultural, political and environmental factors, as illustrated in the case of Denver International Airport (DIA) [65]. Airport professionals should combine technical and social considerations in making applicable decisions.

6.4 Extensions

The proposed methods can be improved in the following aspects:

6.4.1 Expected Headway

The method used in Chapter 5 to incorporate the effect of aircraft mix on the airfield capacity is overly simplified. For instance, the pair probability of a large aircraft followed by a large aircraft is the fraction of large aircraft multiplied by the same fraction. Such a method assumes that all types of aircraft land and take off randomly. That assumption may be erroneous (and probably pessimistic regarding capacity) if aircraft are to some extent grouped by size and/or speed, and if different runways serve different types of operations (i.e. takeoffs or landings) or types of aircraft. The simplified method also assumes that the minimum required separation is the average one achieved in actual operations (although multiplying a coefficient greater than one can provide a rough adjustment). The latter assumption generally yields overestimates of airfield capacity due to different speeds at which successive aircraft approach runways and depart from them, as well as imperfect control of separations.

In future research, more realistic estimation of the impact of aircraft mix on the airfield capacity would be desirable. For example, a simulation module or more complex closed-form equations may be used to replace the current airfield capacity analysis module.

6.4.2 Uncertainty Modeling

The description of uncertainty and its resolution over time is arguably the most important element in a stochastic optimization problem. When only one type of uncertainty is involved and scenarios are discrete, we can convert the problem into a deterministic one [49]. Theoretically, the same method applies if we can sample according to the multivariate probability distribution when multiple uncertainties are considered. However, the number of scenario combinations grows quickly with the number of uncertain variables. For instance, there are 27 ($3*3*3$) scenarios when each of 3 random variables takes on 3 random values. Moreover, random variables do not necessarily follow discrete distributions, as shown in Figure 6.1. When the distribution is continuous, implying an infinite number of scenarios, a sample average approximation method can be introduced [64]. In addition, some random variables could be correlated and samples can be drawn from the joint distribution in such a case.

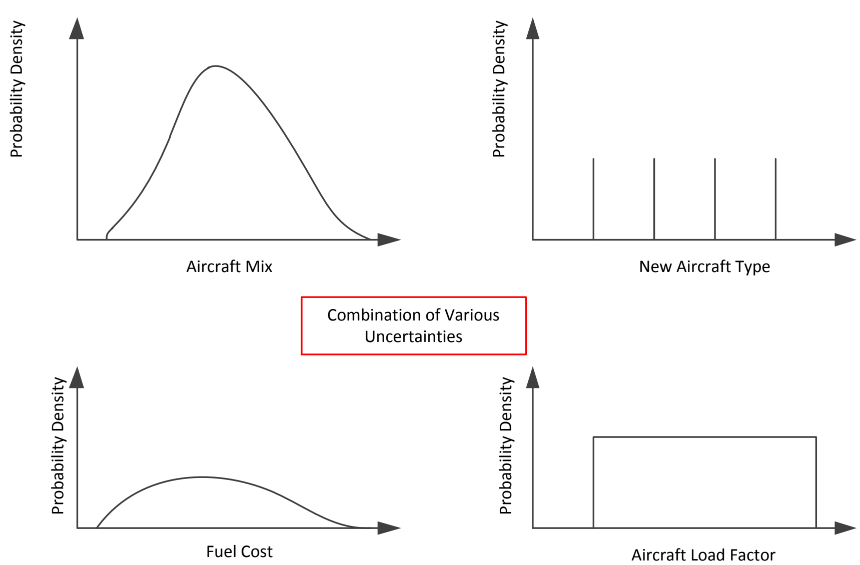

Figure 6.1: Combining various uncertainties

6.4.3 Threshold Policy

The trigger point approach used for initiating the next capacity expansion is analogous to the (q, Q) inventory policy. When the inventory level decreases below a specified level q, we restock up to another specified level Q. In the airport facility development, we can design a similar capacity expansion policy as follows: when the capacity utilization ratio reaches a limit S (e.g., 0.88), the capacity should be expanded so that the ratio is s (e.g., 0.66).

There are other similarities between these two problems. There are both fixed and variable costs and there is a lead time (implementation time or construction time) in delivering capacities.

Since the (q, Q) policy has been proven to be optimal in inventory management, the following questions arise: Is such an (s, S) also optimal in the capacity expansion problem? If such a myopic expansion policy is optimal, how can we find these two thresholds (i.e., values of s and S)? Will the optimality still hold when traffic might drop?

This is another good example of the gap between practice and research. Such a threshold policy is used in practice, although no quantitative support has been found to derive such "triggers" and no theoretical work has been found to prove the optimality of such a policy, if any.

6.4.4 Infrastructure Degradation

No facilities can last forever. The functionality of newly installed capacities diminishes over time. The infrastructure replacement problem should be studied in the future, in combination with infrastructure development.

6.4.5 Resource Constraints

Old facilities may have to be demolished first before new facilities are built due to resource constraints, such as on available land.

6.4.6 Sensitive Elasticity

Demand is assumed to be exogenous in this dissertation, which means demand is not lost even congestion is severe. In the real world, airlines might shift their flights to less congested hubs well before high delay costs are experienced.

6.4.7 Effects during Expansions

The operations of a facility can be disrupted while new capacities are added to the facility. For example, when major runway expansion projects are implemented, other runways could be completely shut down or at least their supplied capacities are reduced.

6.4.8 Marginal Cost of Expansion

A constant unit cost of capacity expansion is assumed, which might be reconsidered. Usually the effect of physical constraints, such as on the land space, manifests as reserved resources are nearly exhausted. In such a case, the marginal cost of expansion increases. It is getting increasingly difficult to add new capacities.

6.4.9 Translation of Capacity Units

The demand units assumed in this study, as in most other relevant studies in the capacity expansion or facility development literature, are enplanements per period, aircraft operations per period, and cargo tons per period. The optimized decisions are also measured in such units. For example, a facility should be expanded to satisfy additional 6 million passengers per year in Period 1. Additional methods are needed for translating such a capacity increase into detailed facility modifications, e.g., how many ticketing counters are added.

Appendix A: Convexity Proof

For convenience we write $F(\frac{q}{s})$ as $G(s)$. Suppose we have two feasible utilization rates, $\rho_1, \rho_2 \in [0, 1)$. By the definition of capacity utilization rate, we have two feasible capacities, $s_1 = \frac{q}{\rho_1}, s_2 = \frac{q}{\rho_2}$.

Since we wish to show $G(s)$ is convex in s, it suffices to show that

$$G(\alpha s_1 + (1-\alpha)s_2) \leq \alpha G(s_1) + (1-\alpha)G(s_2), 0 \leq \alpha \leq 1 \tag{A.1}$$

While Equation (A.1) cannot be shown directly, we first show that

$$F(\frac{q}{\alpha s_1 + (1-\alpha)s_2}) \leq F(\alpha\rho_1 + (1-\alpha)\rho_2) \tag{A.2}$$

Due to the non-decreasing property of $F(\rho)$ (i.e., Property 1), Equation (A.2) is equivalent to

$$\alpha\rho_1 + (1-\alpha)\rho_2 \geq \frac{q}{\alpha s_1 + (1-\alpha)s_2} \tag{A.3}$$

After rearrangements of Equation (A.3), we obtain another equivalent equation to (A.2)

$$\alpha^2 + (1-\alpha)^2 + \alpha(1-\alpha)(\frac{s_1}{s_2} + \frac{s_2}{s_2}) \geq 1 \tag{A.4}$$

Due to $\frac{s_1}{s_2} + \frac{s_2}{s_2} \geq 2\sqrt{\frac{s_1}{s_2}\frac{s_2}{s_2}} = 2$, Equation (A.4) holds. Because of its equivalence to (A.4), Equation (A.2) thus holds.

Due to the convexity of $F(\rho)$ (i.e., Property 2), the right hand side of Equation (A.2) satisfies

$$F(\alpha\rho_1 + (1-\alpha)\rho_2) \leq \alpha F(\rho_1) + (1-\alpha)F(\rho_2) \tag{A.5}$$

Combining Equations (A.2) and (A.5), we have

$$F(\frac{q}{\alpha s_1 + (1-\alpha)s_2}) \leq \alpha F(\rho_1) + (1-\alpha)F(\rho_2) \tag{A.6}$$

Noting that $G(s) = F(\rho)$, we obtain

$$G(\alpha s_1 + (1-\alpha)s_2) \leq \alpha G(s_1) + (1-\alpha)G(s_2) \tag{A.7}$$

for $0 \leq \alpha \leq 1$, which is exactly (A.1).

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