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FLIGHT RISK MANAGEMENT AND CREW RESERVE OPTIMIZATION

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FLIGHT RISK MANAGEMENT AND CREW RESERVE OPTIMIZATION

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This dissertation is dedicated to my parents, Yanmei Shao and Shijun Zhang for their love, support and encouragement.

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ABSTRACT

There are two key concerns in the development process of aviation. One is safety, and the other is cost. An airline running with high safety and low cost must be the most competitive one in the market. This work investigates two research efforts respectively relevant to these two concerns.

When building support of a real time Flight Risk Assessment and Mitigation System (FRAMS), a sequential multi-stage approach is developed. The whole risk management process is considered in order to improve the safety of each flight by integrating AHP and FTA technique to describe the framework of all levels of risks through risk score. Unlike traditional fault tree analysis, severity level, time level and synergy effect are taken into account when calculating the risk score for each flight. A risk tree is designed for risk data with flat shape structure and a time sensitive optimization model is developed to support decision making of how to mitigate risk with as little cost as possible. A case study is solved in reasonable time to approve that the model is practical for the real time system.

On the other hand, an intense competitive environment makes cost controlling more and more important for airlines. An integrated approach is developed for improving the efficiency of reserve crew scheduling which can contribute to decrease cost. Unlike the other technique, this approach integrates the demand forecasting, reserve pattern generation and optimization. A reserve forecasting tool is developed based on a large data base. The expected value of each type of dropped trip is the output of this tool based on the predicted dropping rate and the total scheduled trips. The rounding step in current applied methods is avoided to keep as much information as possible. The forecasting stage is extended to the optimization stage through the input of these expected values. A novel optimization model with column generation algorithm is developed to generate patterns to cover these expected level reserve demands with minimization to the total cost. The many-to-many covering mode makes the model avoid the influence of forecasting errors caused by high uncertainty as much as possible.

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1.1 Introduction

As one of the most rapidly and continuously growing transport modes, in the next ten years, aviation is predicted to grow at an annual rate of about 6%. In 2012, the United States had an International Flight frequency of 9,560,451. According to the report in 2015 from Air Transport Association (IATA), the revenue of the U.S. airline industry has doubled in the past decade from $369 billion in 2004 to $746 billion in 2014. The growing rate of international market is significantly faster especially in developing countries such as China. The reliable data of the frequency of passengers carried by Air Transport in the year 2012, obtained from the International Civil Aviation Organization (ICAO), has been published by the World Bank. The United States of America has the largest number of Commercial Air Transport Passengers totaling 756,617,000, followed by China with 318,475,924.

Safety in aviation is a critical problem all over the world today. In addition to human injuries and fatalities, aviation accidents could hurt the reputation and financial performance of an airline, or even the whole air transportation industry of a country. The Civil Aviation Authority, JAR and EASA have published that there is a fatal accident ratio of one per million flights. According to the safety report in 2014 from ICAO, the total number of worldwide plane accidents in 2013 was 90. Various levels of risks could be associated with flights, mainly including crew proficiency, equipment, environment, performance, and external pressures. Airlines often take countermeasures to mitigate these risks such as flight changes, crew changes, maintenance changes, weather changes etc. However, the effectiveness of those measures on safety enhancement is not clear so it is important to validate their effectiveness and proactively manage them. Currently, flight managers at airlines do not have a comprehensive system to measure and rate the safety risk factors of each operating flight in real time. A Flight Risk Assessment and Mitigation System (FRAMS) is needed to allow flight managers and other related staff to make aircraft dispatching decisions that could improve flight safety.

FRAMS is expected to consider all flight risk factors, apply scientific techniques to score predicted risk, and alert the flight operations division if a flight exceeds the acceptable levels of alertness. Furthermore, FRAMS is also expected to help the flight operations division to mitigate risks on flights and keep them within the acceptable limits by using optimization techniques. When threats happen to a certain flight, the system can help to analyze the consequence of the threats and identify measures to mitigate those threats to avoid additional errors occurring.

A sequential stages approach is developed in this chapter to support this FRAMS system. All main risks factors are validated first and a fault tree is developed to describe them and their relationships with the weights estimated by using the Analytical Hierarchy Process (AHP). AHP is an effective method to analyze a system when there is not enough available data, especially in the rare possibility with severe consequence system like aviation. The process of validating risk factors is continuous. When a new risk factor is found, AHP is a good tool to analyze it and add it into the fault tree system. For each flight, a risk score is estimated based on all relevant risk factors for supporting a real time system. Unlike traditional fault tree analysis, severity level and time level are taken into account when calculating the risk score. Additionally, synergy effect is considered to calculate the risk score of upper event in fault tree by combining two simultaneous risk factors in lower levels.

To proactively manage the risk, an optimization model is built to mitigate risk for high risk flight with the objective to minimize the total cost of mitigation measures at specific time periods. Time is considered, in the model, as an effector of risk and the cost of risk mitigation. The solution of this model is a set of recommended measures which can decrease the risk with least cost in a specific time. A real world data base named LOSA is analyzed and a risk tree is built based on it. The risk tree is created to analyze the risk data set in flat shape (a lot of risk factors in few levels with complex intersections). It is a good network map which can help remind crew and staff to pay attention to the possible errors which may by triggered by occurring threats. A risk mitigation optimization model is built for the risk tree and a case study partially based on this data set and assumptions are made. The solving time is ideal for providing real time decision making support. Solving the model in real time will provide support for flight managers to make decisions when the risk of flight has exceeded the acceptable risk level. A real time risk monitoring and mitigating system is expected in future work to include all above functions.

1.2 Literature Review

1.2.1 Risk Management in General Area

In terms of safety, the risk can be thought of as a combination of the probability or frequency of occurrence with the magnitude of consequences or severity of the hazard event (Bahr, 1997). However, (Aven, 2010) argues that such perspectives and definitions of risk based on probabilities are too narrow. The important uncertainty aspects should not be overlooked or truncated. Risk management (RM) is defined as the effect of uncertainty on objectives in ISO3100. It is the identification, assessment, and prioritization of risk followed by coordinated and economically applied resources to minimize, monitor, and control the probability and/or the impact of unfortunate events (Hubbard, 2009) or to maximize the realization of opportunities. The objective of risk management is to ensure that uncertainty does not deviate the endeavor from the business goals (Antunes, 2015).

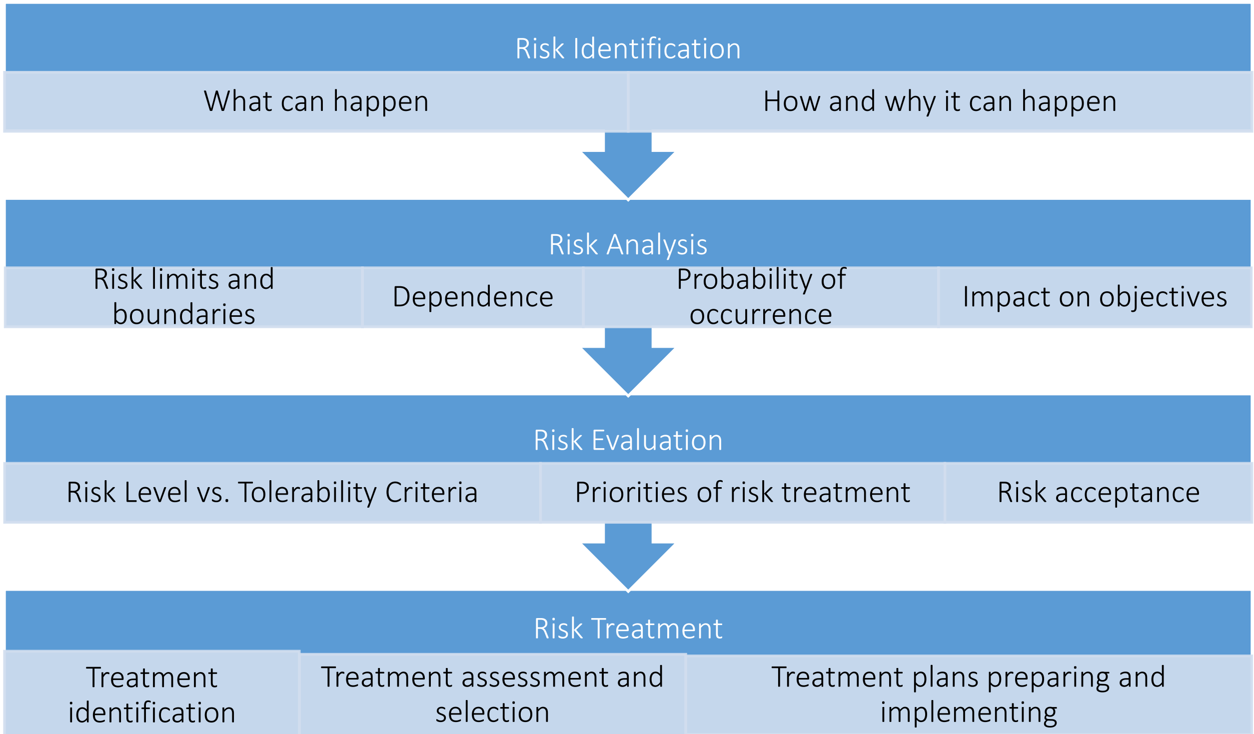


Figure 1. Process of Risk Management.

The development of how to deal with uncertainty has led to the application and development of tools, techniques, processes and methodologies which are typically classified under the label of RM. RM can be classified into two categories: the business risk management and the operational risk management. The former is mainly concerned with monetary gains and losses which is a sub-specialty area in the fields of finance and insurance. The latter is always concerned with how to control the inherent uncertainty in the execution of the activities in order to safely and efficiently fulfill their objectives and goals. (Raz & Hillson, 2005) point out that the operational risk management has led to the development of a number of standards that prescribe and advise organizations on the best way to manage their risks. They discuss nine major standards for RM with their commonalities and differences. It shows that the general process of RM consists of four main steps: risk identification, risk analysis, risk evaluation and risk treatment. The detail of this process is shown in Figure 1. This literature review will follow this structure.

1.2.1.1 Risk identification

As the first stage of the RM process, risk identification develops the basis for all the next steps. Correct risk identification ensures RM effectiveness. The risks not identified will later become non-manageable risks (Greene & Trieschmann, 1984). One important peculiarity of risk identification is that it is a continuous process, we should continuously monitor all risks sources and keep seeking new risks not included in the system. If any new risk is found, update the list of risks. (Tchankova, 2002) describes the risk identification stage with the following four basic elements: risk sources, the factors of hazard, perils to risk and exposures to risk. Risk sources are elements of the environment that can bring some positive or negative outcomes. The factors of hazard are circumstances or situations that increase the chance of gains or losses. Peril, which is close to the risk, has non-positive and non-profitable consequences. The last one is the object facing possible losses or gains.

Most of the techniques and tools listed in Table 1 are qualitative and descriptive in nature, and there are very few analytical methods based on mathematical or statistical techniques.

1.2.1.2 Risk assessment

The stage of risk assessment generally includes two main steps: risk analysis and risk evaluation. The details are shown in Figure 1. How to deal with the uncertainties for decision support is the core problem in this stage. There are two different types of uncertainty that can be essentially considered. One is the randomness on the system due to inherent variability and the other is the imprecision due to lack of information and knowledge of the system. The former kind of uncertainty that occurs in the population of consequences of its stochastic process of behaviors is often referred to as aleatory, stochastic, objective, while the latter kind is often related to as epistemic, state-of-knowledge, subjective (Helton, 2004).

(Aven & Zio, 2011) provide a good review of various approaches that exist for describing and representing this. The primary categories are listed as follows:

a) Probabilistic analysis proposed by (Apostolakis, 1990);
b) Probability bound analysis (combining probability analysis with interval analysis) proposed by (Ferson S, 1996);
c) Imprecise probability proposed by (Walley, 1991) & the robust Bayes statistics area proposed by (Berger, 1994);
d) Random sets in two forms proposed by (Dempster, 1967) and (Shafer, 1976);
e) Possibility theory proposed by (Dubois & Prade, 1988) and (Dubois, 2006) which is formally a special case of the random set theory and the imprecise probability theory.

Among these approaches, the probabilistic analysis has been used as the foundation of the analytic process in the stage of risk assessment for more than 30 years (RP., 1999). Probabilistic Risk Assessment (PRA) and Quantitative Risk Assessment (QRA) are used as the common terms. The first application of PRA/QRA to large technological systems dates back to the early 1970s.

Table 1. The Consolidated List of Techniques & Tools for Risk Identification. (Raz & Hillson, 2005)

The techniques & tools		
Assumption analysis	Examination of vulnerabilities and weaknesses	Project monitoring
		Prompt lists
Benchmarking	Expert opinions	Prototyping techniques
Brainstorming	Fault tree analysis	Questionnaires
Cause and effect diagrams (Ishikawa of fishbone diagrams)	Flow chart analysis	Risk assessment workshops
	Hazard and operability studies (HAZOP)	Root cause analysis
Checklists analysis	Historical data analysis	Scenario analysis
Constraints analysis	Incident investigation	Stakeholder analysis
Delphi techniques	Influence diagrams	Structured interviews
Documentation reviews	Interviewing	SWOT
Evaluation of other projects	Lessons learned	Systems analysis
Event tree analysis	Nominal group technique	Taxonomies
Examination of past risk experience in the organization and similar organizations	Peer review	Technology readiness levels
	Personal observation	
	Previous experience	Testing and modeling

(NRC., 1975), specifically in nuclear power plants. The elementary principles of this analysis have not been changed a lot. However, in some common conditions of poor or limited knowledge on the high-outcome risk problem, a purely probability analysis assessment based on subjective judgments made by a group of experts and analysts may not be satisfied enough. That is the reason why categories b) to e) were developed.

Probabilistic approach to risk analysis (PRA) has presented as an effective way to analyze system safety. It is not limited only to take worst case accident scenarios into account but extended to consider all feasible scenarios and their relevant consequences. The occurring probability of such scenarios becomes an extra key aspect to realize quantification for the sake of objectively and rationally dealing with uncertainty (Aven & Zio, 2011). Uncertainties can be classified in two categories: epistemic uncertainties and inherent variability uncertainties. These epistemic uncertainties are due to incomplete or lack of knowledge in this research area and inherent variability uncertainties exist because of the many changing factors' impact which are hard to manage and quantify.

(NUREG., January 1983) summarize the three essential problems are addressed by PRA to systemize the uncertainties and knowledge about the phenomena studying.

1) The sequences of undesirable events transform the hazard into an actual damage;
2) The probability of each of these sequences;
3) The outcomes of each of these sequences.

For PRA, the outcome of a risk analysis is a number of scenarios quantified on the basis of probabilities and consequences, which collectively represent the risk. Two fundamental probabilistic analysis approaches are the Bayesian approach and traditional frequentist approach (Bedford T, 2001).

The Bayesian approach is suitable for the case of a scarce amount of relevant data and subjective probabilities are used as the basis. These subjective probabilities are also called "judgmental probability" or "knowledge based probability". Although these predictive distributions are not objective, they still mirror the constitutive variability that is characterized by the fundamental probability formulations.

The traditional frequentist approach is based on notorious theory of statistical deduction, the application of probability models and the clarification of probabilities including hypothesis test, confidence intervals estimation, relative frequencies and basis point value (BPV) and is generally used in the case of large amount of related data.

The traditional process of PRA can be described in the following four steps:

1) Build adequate probability models to represent the aleatory uncertainties based on the study of the variabilities in phenomena;
2) Use subjective probability distributions obtained in advance to represent the uncertainties which are reflected on the parameter values of the model;
3) Update the representation of uncertainties in terms of the posterior distributions by using Bayes' formula when new data on the study of phenomena become available
4) Derive the predictive distributions of the quantities of interest by applying the law of total probability.

There are some new methods introduced to solve the problem in this research area. Some of the main ones are listed as follows:

a) BBNs: Bayesian Belief Networks
b) MCS: Monte Carlo Simulation
c) MRA: Multi-state Reliability Analysis
d) BDDs: Binary Digit Diagrams
e) Petri Nets

(Zio, 2009) provides an introduction for these new methods. He mentions that Monte Carlo *simulation* (Dubi, 1998) (Marseguerra M, 2002) turns out to be an effective method to catch the naturalism facets of the stochastic behavior in a *multi-state* dynamics *system (MSS)* quantitatively (Zio, M.Marella, & Podofillini, 2007).

Petri Nets are an effective approach that can properly represent and model the multi-state dynamics system and its components. This capability makes the application to realistic cases become feasible. The works of (Dutuit Y, Chaˆtelet E, Signoret JP, & P., 1997) (Larsen KG, 2000) (WG., 2004) and (Sachdeva A, 2007) describe more details about this approach.

Another effective approach, that can also make the application to realistic cases become feasible, *is biasing technique.* This technique stems on the chance to evaluate the model in reasonable computing times. The works of (Marseguerra M, 1993) (Marseguerra M, 2000a, 2000b) (Labeau P, 2001) present more details about this approach.

Fault tree analysis (FTA) is initially present at Bell lab by H.A. Watson in 1962 for U.S. Air Force. It is often applied by reliability experts as a failure analysis tool which is defined as an inferential failure analysis from top to bottom in which an analysis is made for undesired status of the system based on Boolean logic combining all groups of events at lower levels (Wikipedia.org). It is one of the most effective analytical tools for the safety and reliability of complex systems with both qualitative and quantitative analysis.

FTA is also a comprehensive method which not only includes this stage but also the first phase risk identification (shown in Figure 1). This helps decision makers understand the ratios of the safety event as an accident or a specific functional failure in the system level and the last phase risk treatment to find the best way to decrease the risk to an acceptable level. Additionally, since FTA presented a series of graphic symbols for cause and effect analysis, it is really a good tool to show the whole picture of the system to help decision makers understand all detailed risk contracture. The typical symbols are shown in the following Table 2 (pg.9) (Ostrom & Wilhelmsen, 2011).

(W. S. Lee, Grosh, F.A.Tillman, & Lie, 1985) and (Dr. Michael Stamatelatos, 2002) provide a detailed review of the methods and applications for FTA. There are four main steps in a FTA which are listed as follows:

1) System definition;
2) Fault-tree construction building;
3) Qualitative evaluation;
4) Quantitative evaluation.

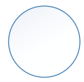
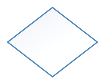
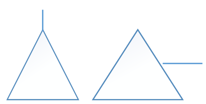
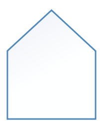
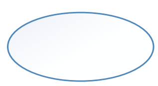
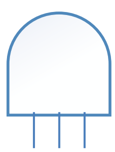
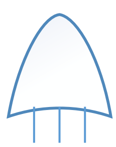
Qualitative evaluation consists of common-cause failure analysis and the minimal cut sets determining (minimal path sets determining) which can be done by two main approaches: deterministic methods and Monte Carlo simulation.

Deterministic method is a direct reduction or extension of the top event of a fault tree in accordance with the component bottom events by using Boolean algebra. The methods of deterministic methods in literature include PREPE, MOCUS, ALLCUTS, GO, DICOMIC, FATRAM, SETS, FAUTRAN, ELRAFT, MICSUP, Nakashima & Hattori and Kumanoto & Henley.

Using Monte Carlo simulation to determine minimal cut sets rely on repeated random sampling to obtain numerical results. The process is described by (Salem, Apostolakis, & Okrent, 1976) with the following three steps:

1) Assign failure time to each risk factor: For each risk factor, a failure time is assigned to it which is chosen by producing a random number (between 0 and 1) following uniform distribution for each risk factor first and then finding the corresponding time failure. It is conventional based upon a failure exponential distribution;
2) Produce a cut set: the time to failure is generated for one risk factor at a time when Monte Carlo run once. After, the status is changed to "failed", time is increased until the top event is created to produce a cut set;
3) Reduce the cut set to a minimal cut set.

Table 2. Common Fault Tree Symbols.

Symbol Name	Symbol	Description
Basic Event		Basic-fault-event
Undeveloped Event		A fault event that is considered basic and the possible causes are not developed further.
Output Event		An event that results from the combinations of fault events through the input logic gate
Transfer		Transfer In/Transfer Out to a sub tree or continuation to another location
External Event		An external event that is usually expected to occur. In general, these events can be set to occur or not occur
Conditioning Event		A specific condition or restriction that can apply to any gate.
And Gate		The output event occurs if and only if all of the input events occur.
Or Gate		The output event occurs if and only if one of the input events occurs at least.

In fault tree analysis, the approach of quantitative evaluation is based on the quality evaluation solution. The first step is to structurally represent the top event according to the levels of basic events. The approach of seeking minimal cut sets can be used to accomplish this. The statistical probability or expectation of the top event can be determined based on the possibility of occurrence and fault duration for each basic event and the statistical dependency between each pairs of basic events (assumed or known) (Lambert, 1975). When the system does not emphasize failure but success, the s-coherent structure theory is the foundation of reliability theory. The bond between fault tree and s-coherent structure theory can be provided by the Boolean representation (Barlow & Proschan, 1975). The methods of Qualitative evaluation options and quantitative evaluation options are shown in Table 3 (W. S. Lee et al., 1985).

The last stage, risk treatment, will be discussed in the next section, since different industries have different approaches for treating risks. There is not a lot of overlap between them. The scope of this dissertation is the aviation area, thus other risk treatment methods are not included.

1.2.2 Risk Management in Aviation with Risk Mitigation

The increasing growth of aviation makes safety more important. Safety in aviation is always considered the most important issue all over the world. In addition to human injuries and fatalities, aviation accidents could hurt the reputation and financial performance of an airline, or even the whole air transportation industry of a country. (Shyur, 2008) states that when forecasting accidents for 2015 by applying 2008's accident rate, the outcome would be almost an accident of an airliner once a week somewhere over the world.

As a complicated system, aviation consists of a complex, interconnected, distributed network involving technical/technological systems, programs and human operators. Traditionally, risk in aviation has been linked to air traffic accidents which are relatively rare but with a high possibility of resulting in severe consequences. (Fedja Netjasov, 2008) provides a detailed survey of the methods applied when dealing with risk assessment problems for aircraft, individual and air traffic management/control (ATM/ATC) operations. The following four categories of safety assessment models are highlighted by the author: causal for the operations of ATM/ATC, human error, third-party risk and crashing risk.

The causal for ATM/ATC operations builds a theoretical framework of reasons with all possible aircraft accidents it might lead to. A hierarchical or diagrammatic depiction for risk factors linked with accidents that might be initiated is first provided by the qualitative analysis, and then the occurring probability for each risk factor is estimated; thus the risk of accident is estimated as the quantitative analysis. This method could be bound to pure statistical analysis with available data set or it can combine such data with

Table 3. The List of Qualitative & Quantitative Evaluation Options.

Qualitative Evaluation	Minimal Cut Sets	Monte Carlo simulation	PREP (FATE option)
		Deterministic Method	PREPE (COMBO option)
			MOCUS
			ALLCUTS
			MICSUP
			ELRAFT
			FAUTRAN
			SETS
			FATRAM
			DICOMIC
			Kumanoto & Henley
			Nakashima & Hattori
			GO
	Common-Cause failure-analysis		COMCAN
			BACFIRE
			Wagner
Quantitative Evaluation	Measures of importance		
	Probabilistic evaluation of fault tree	Coherent structure theory	
		Monte Carlo simulation	RELY4
			SAFTE
			SAMPLE-WASH 1400
			REDIS
			Crosetti, code
		Analytic method	KITT
			Caldarola & Wickenhauser
		Other methods	ARMM
			GO
			NOTED
			WAM-BAM
			PATREC
			SALP
			Digraph Technique
			Bit Manipulation

Table 4. Applications of Causal Methods.

Causal Method	Origin	Application
FTA: Fault Tree Analysis	1962	- Safety assessment - Aircraft reliability - ATM/ATC components
Bow-Tie analysis	1970s~1980s	Control flight into terrain (CFIT) accidents
CCA: Common cause analysis	1975	The US National Aeronautics and Space Administration (Dr. Michael Stamatelatos) use it since 1987
ETA: Event tree analysis	1980	The combination with FTA for almost all technological systems such as aircraft and ATM/ATC computer components
BBN: Bayesian Belief Networks	Mid-1980s	The scoping of the aviation system risk model (ASRM) developed by NASA and the Federal Aviation Administration (FAA)
TOPAZ accident risk assessment methodology	1990s	All types of system safety issues including human factors, environment factors, organization factors, technological/technical factors, other threats and their combinations

subjective judgement on causes from experts. Some main causal methods are shown in Table 4.

Third-party risk is defined as when an aircraft crashes, the risk for an individual on the ground being injured or killed by a grounding accident. According to the report of Boeing Commercial Airplanes in 2006, about 70% of air accidents happen around airports, thus the assessment of third party risk needs to be taken into account. However, it will not be involved in this dissertation.

As one of the common causes of aviation accidents, human error is defined as a mistaken execution of a specific action resulting in a series of responses when operating other tasks subsequently, which then may result in a severe aircraft accident. Three levels of possible outcomes may follow the occurrence of an error and crew reactions. These three levels are generally used as a standard to analyze the severity of each error. They are listed as follows in the work of (Helmreich et al, 1999):

a) Inconsequential: The error has no negative influence for completing the flight safely, or is eliminated through the process of crew error management successfully. It demonstrates the robustness for the performance in the aviation system.

b) Undesirable aircraft state: A condition where the aircraft is unnecessarily put into a condition that increases risk to flight safety which include landing in the wrong airport or in wrong runway, deviations from desired navigational altitude or path, low fuel state, long landing, unstable approach, improper landing, etc.
c) Additional error: An additional error or subsequent error may result from the response to the error, in which the flight-crew can start the cycle of response over again.

(Klinect et al, 1999) states that the analysis conclusion indicates that 15% of the flight crew errors triggered an additional error or undesired aircraft state and 85% of them lead to inconsequential outcome. Figure 2 describes the flow chart of error management.

In the aviation area, risk treatment is commonly called risk mitigation, which is usually realized by monitoring, discovering and proactively preventing human factor errors. Several methods have been developed to mitigate human error which are listed in Table 5 (pg. 14) according the work (Fedja Netjasov, 2008).

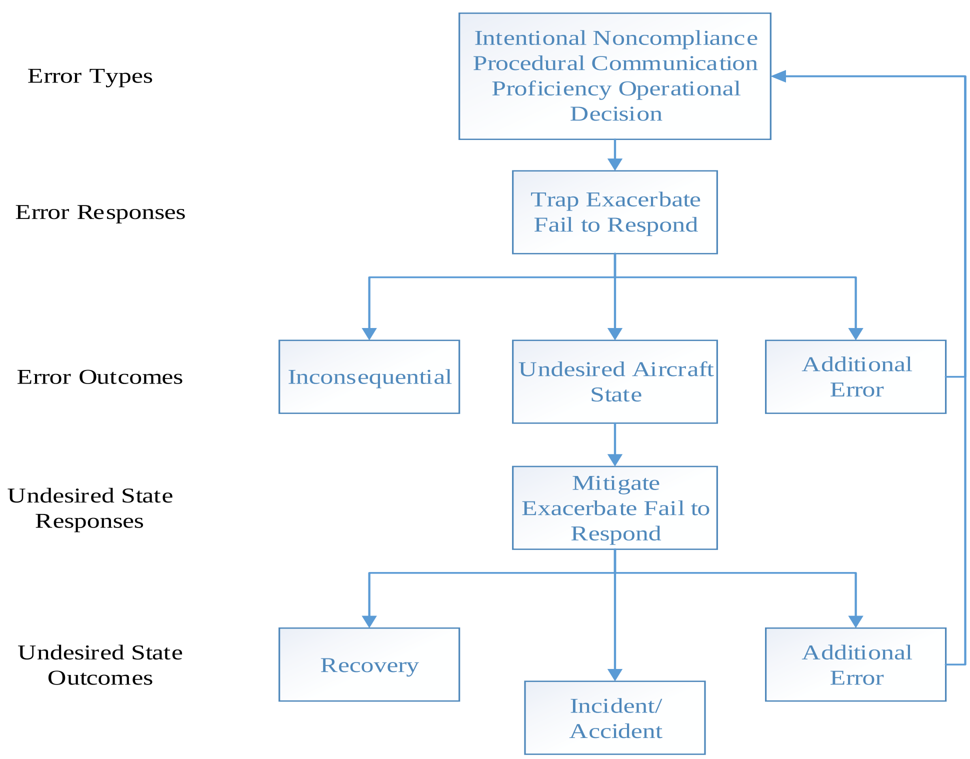


Figure 2. The Flow Chart of Crew Error Management. (Helmreich et al, 1999, p.3)

Table 5. Applications for Human Error Mitigation Methods.

Human Error Mitigation Method	Origin	Application	Description
HAZOP: The Hazard and Operability method	1970s	The UK National Air Traffic Service (NATS)	- Planning and assessing risks - Producing input to ETA and FTA
HEART: Human Error Assessment and Reduction Techniques	1985	UK NATS	Discover potential human factor errors in two ATM/ATC enroute sectors of the national airspace
TRACER-Lite: The Technique for the Retrospective Analysis of Cognitive Errors	1999	- UK national airspace - EUROCONTROL projects	Predicting human errors and deriving error prevention measures
HFACS: The Human Factor Analysis and Classification System	2000s	- FAA Civil Aerospace Medical Institute - NASA's ASRM	Facilitate consistency in the application of various causal factors
HERA: The Human Error in ATM approach	2000s	EUROCONTROL staff educational and training system	Applied to ATM/ATC safety management

As mentioned in the previous section 1.2.1.2.3, fault tree analysis (FTA) is a useful tool that is typically represented by graphic symbols for cause and effect analyzing. An undesired status of a complex system is analyzed by combining a group of events in lower level. For the aviation area, the FTA is analyzed with accident as top event and risk factor as lower level events. In this dissertation, FTA incorporates the draft decision tree to describe the levels of relationships between these risks. In current literatures, a number of methods are applied to model a FTA and the most popular and common way can be summarized in the following steps: 1) Define undesired event to study (top event); 2) gain comprehension for the system; 3) construct building; 4) quantitate evaluation; 5) identify controlling hazards. The details are shown in section 1.1.1.2.3 and the interrelationship of analysis phases are shown in Figure **3**.

When building fault tree construct for aviation from higher level failure to lower level failure, in other words from output to inputs, the most common used gate categories are the Or-gate and the And-gate. The way these two gates represent the relationship between events are compared to the Boolean algebra, so that the fault tree quantitative analysis can be done through Boolean algebra.

The Or-gate represents that at least one input event must occur to trigger the higher level event on the gate that follows. This characteristic is similar to the Boolean operation with symbol "+". For instance, there are two basic events A and B with higher event Q on the Or-gate. The expression can represent the relationship of them shown as follows:

$$Q = A + B.$$

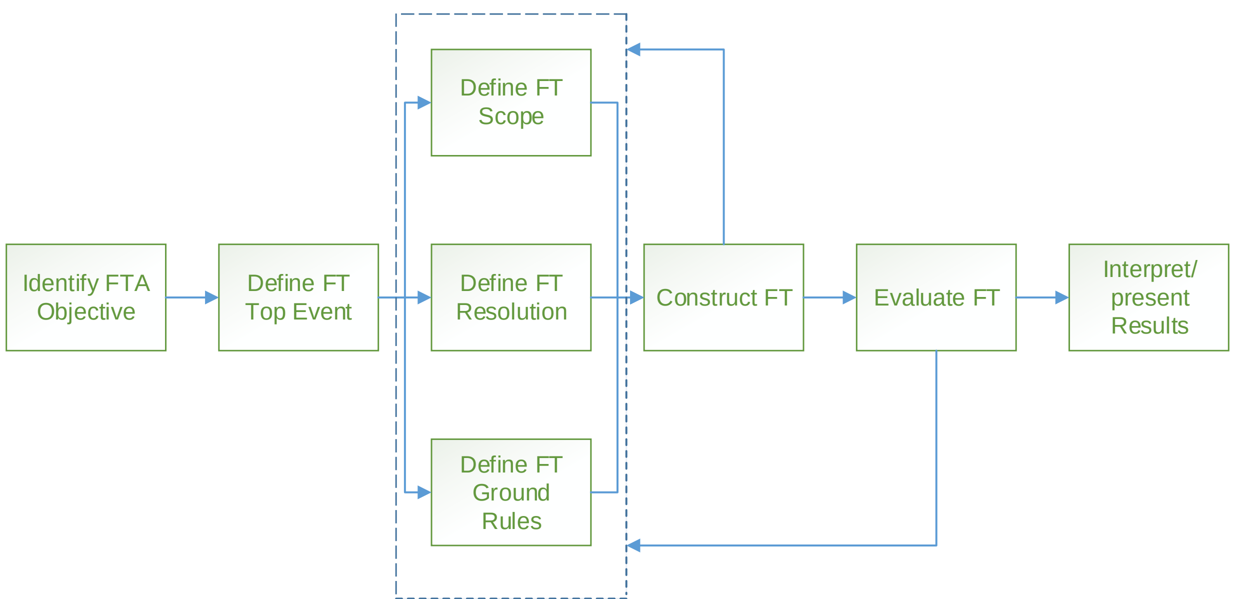


Figure 3. Interrelationship of FTA Phases. (Michael S. etc., 2002)

This Boolean equivalence with "+" indicates that the three conditions can make Q come up: A is True, B is True and both of them are True. The probability of the output event can be calculated by the following expression:

$$P(Q) = P(A) + P(B) - P(A \cap B)$$
$$= P(A) + P(B) - P(B)P(A \mid B)$$

The following observations can be made:

a) When A and B are mutually exclusive events, $P(A \cap B) = 0$ and then $P(Q) = P(A) + P(B)$;
b) When event A is completely dependent on event B, that is, whenever A occurs, B also occurs, $P(B \mid A) = 1$ and then $P(Q) = P(B)$;
c) When A and B are independent events, $P(B \mid A) = P(B)$ and then $P(Q) = P(A) + P(B) - P(A)P(B)$; In this case, when the A and B are events with low probability (e.g. $P(A), P(B) < 10^{-2}$), $P(A \cap B)$ is small compared with $P(A) + P(B)$ so that $P(A) + P(B)$ is an accurate approximation of $P(Q)$;

Also, the approximation $P(Q) \cong P(A) + P(B)$ is a conservative estimate for the probability of the output event Q, because of $P(A) + P(B) \geq P(A) + P(B) - P(A \cap B)$ for all A, B.

Since "+" is used to represent the relationship like this, it is usually drawn inside the Or-gate symbol. For more than two events as the inputs of the Or-gate, the expression will be:

$$Q = E_1 + E_2 + \dots + E_n$$

The And-gate describes that all of the input events attached to the And-gate must occur to trigger the higher level event on the gate to follow. This characteristic is similar to the Boolean operation with symbol "•". For example, there are two basic events A and B with higher event Q on the And-gate. The expression can represent the relationship of them and is shown as follows:

$$Q = A \bullet B.$$

This Boolean equivalence with "•" indicates the only condition can make Q come up: both of them occur. The probability of the output event can be calculated by expression as follows:

$$P(Q) = P(A)P(B \mid A) = P(B)P(A \mid B)$$

Since "•" is used to represent the relationship like this, it is usually drawn inside the And-gate symbol. For more than two events as the input of the And-gate, the expression will be:

$$Q = E_1 \cdot E_2 \cdot \dots \cdot E_n.$$

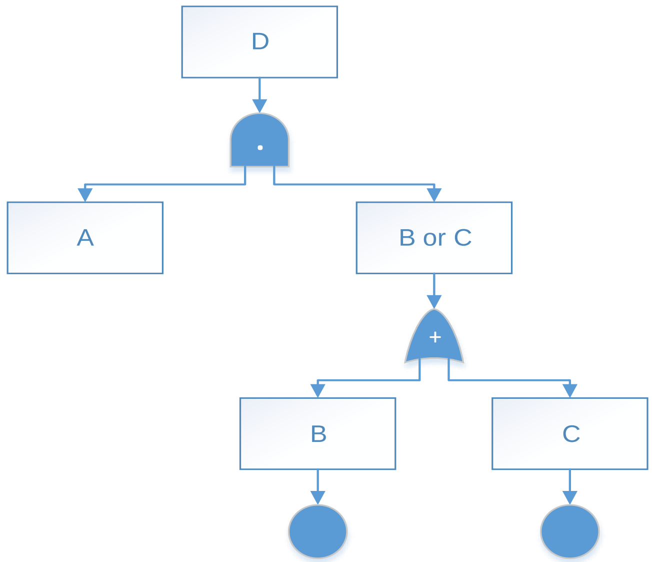


Figure 4. A Sample Fault Tree.

The following observations can be made:

a) When A and B are independent events, $P(B \mid A) = P(B)$, $P(A \mid B) = P(A)$ and then $P(Q) = P(A)P(B)$;
b) When A and B are not independent events, then $P(Q)$ may be significantly greater than $P(A)P(B)$. For instance, in the extreme case where A completely depends on B, that is, whenever B occurs, A also occurs, then $P(A \mid B) = 1$ and $P(Q) = P(B)$.

Figure 4 is a sample fault tree structure. Applying Boolean algebra to this tree, the event D can be expressed as:

$$D = A(B + C) = (A \cdot B) + (A \cdot C).$$

Figure 5 (pg. 18) illustrates a fault tree (FT) built by Kornecki and Liu (2013). The ultimate disaster, an accident in aviation (Top Event), is the final result of a series of joint events during system operation ("OP" in FT) as well as a lack of in time effective control of these operations ("Control" in FT). The error of the OP may be attributed to external, internal or equipment failure. In turn, external malfunction may result from the human error (made by air traffic controllers, crew members or other personnel) or environmental issues, while equipment factors include design errors ("ED" in FT), erosion, material defect, etc. They develop "Gateway System" software based on the analysis of this fault tree. Their work considered an aviation accident the ultimate hazard, but equipment and external factors (e.g., environmental factors and human factors) were treated as undeveloped events and out of the scope of their research.

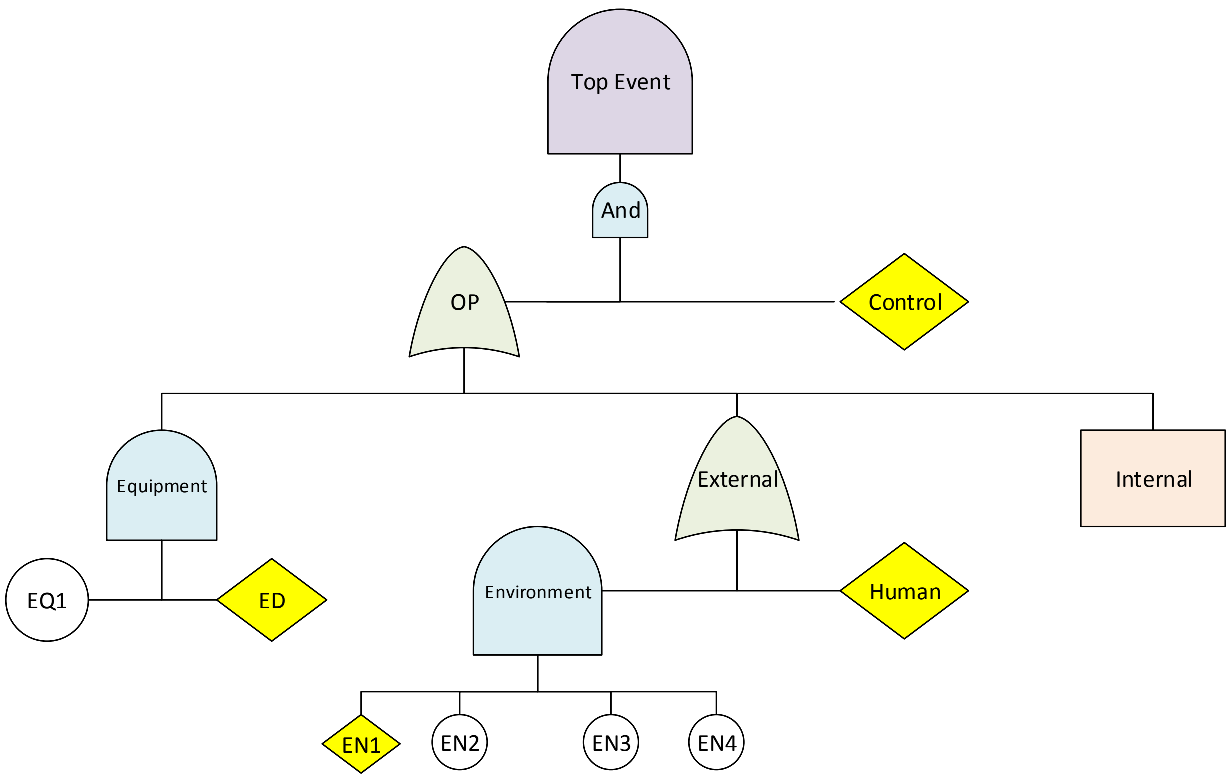


Figure 5. Top Level Fault Tree Diagram. (Kornecki & Liu, 2013)

In fact, equipment factors, environmental factors and human errors make significant contributions to aviation risks and it got approved in our AHP research too. Airlines have been paying more and more attention to external factors. There have been several studies analyzing these factors, but no one has provided a quantitative analysis that can be combined with other factors to achieve a comprehensive FT. An FT incorporating those external factors is built in section 2.3.3.

1.3 Aviation Risk Identification and Assessment

1.3.1 Draft Decision Tree

A draft decision tree of the comprehensive flight risk management system has been built based on previous investigations as shown in Figure 6. All factors are identified by a group of senior pilots based on flying practice and interactions with many years of rich experience.

This decision tree includes dozens of factors and their possible levels. The tree also incorporates the logical relationship between those factors and overall risk. However, this is a regular decision tree but using the signal of fault tree. Also, this tree does not have weights for each factor though all stakeholders agree that factors have different contributions to the overall safety in practice. Our task is to make it professional and practical for future analysis.

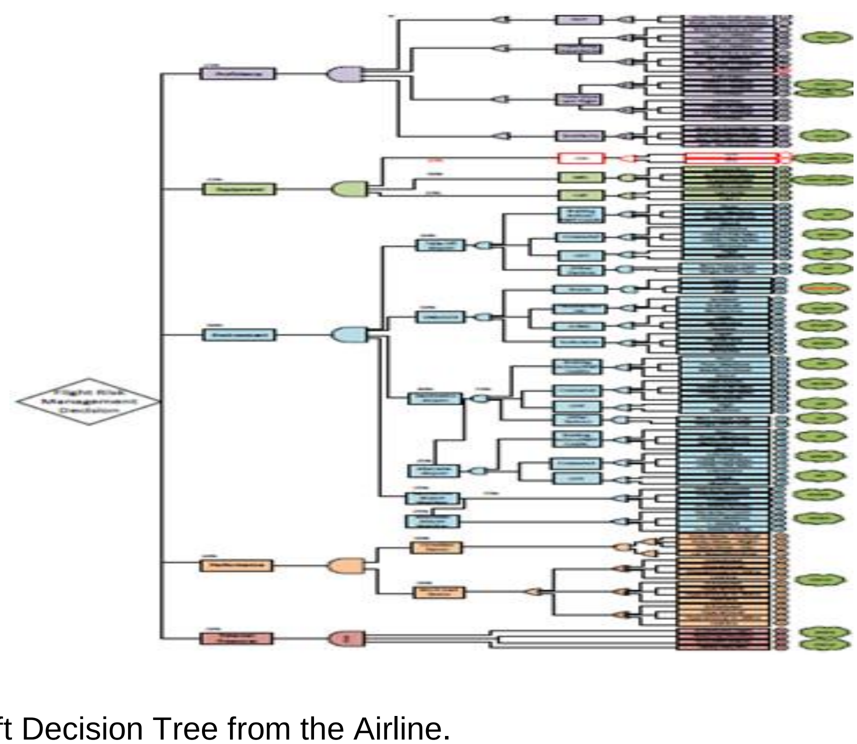


Figure 6. Draft Decision Tree from the Airline.

1.3.2 AHP for Determining Weights

After validating all levels of risks, a group of experts were asked to estimate the weights of all factors using the brain storming method. In order to make these weights more objective and reliable, we implemented the AHP to evaluate and adjust the weights of risks. The designed interviews for experts from relevant departments helped us set priorities among the risk factors of the hierarchy by making pairwise comparisons of these risk factors.

As a structured technique for dealing with complex decisions making, analytic hierarchy process (AHP), initially proposed by Thomas Saaty in 1980, is an effective tool which can help obtain both subjective and objective aspects of a complex decision. First, AHP breaks down the complex decision making problem into a series of more simply comprehended sub-problems following hierarchy order. Each of the sub-problems will be independently solved. The components in it are allowed to be relevant with any type of decision problem—tangible or intangible. Secondly, by comparing each pair of elements according to their impact on the factor above them in the building hierarchy, the risk factors can be systematically evaluated. In the process of making comparisons, the participation of experts usually use subjective judgement about each factor's importance even though they still can get help from concrete practical data.

The detailed steps of AHP with one specific example are shown below:

Step 1: Broad spectrum of interviews to cover all related departments as much as possible

We invited experts from departments which have a background in flight, including crew members, duty officers, flight safety groups, scheduling groups, and management groups. The background in flight allows them to compare two risks based on real situations. The comprehensive knowledge of their field work helps them have a context to think about which aspects of risk should be considered. From the answers of these experts from all relevant departments, we can get the results to be used for the system which can satisfy all customers.

Step 2: Individual interviews

In order to make them think seriously and provide us relatively accurate answers, we conducted face-to-face interviews with these experts from different departments. All these experts are at higher level positions, which makes it difficult to coordinate their schedules. To avoid any influence from others' opinions, we decided to interview them one by one. Most experts have limited interview time, so we designed all the details of the process to improve the efficiency of the interview. We need to get the most reliable information as we can in a limited time. These face-to-face interviews also helped us further understand the identified risks. For example, in 1999, the US National Transportation Safety Board (NTSB) states that based on statistics from the Federal Aviation Administration (FAA), the prevalence of fatigue-related accidents in aviation was 21%. Does that mean as one of the performance factors, fatigue is a high weight risk factor? In our interviews, one crew member explained why he thinks the “performance” is more risky than “equipment”: before an aircraft can be flown, they receive a lot of systematic training about how to deal with different situations when equipment trouble happens during a flight but they seldom know how to face the fatigue problem from their own body and have not received any training on the fatigue issue.

The AHP method is not only a powerful tool but also a flexible one because the scores, and thus the final ranking, are acquired on the basis of the pairwise relative evaluations of both the options and the criteria. In the preparatory phase before interviews, the relative risk between pair of factors is measured with regard to a numerical scale from 1 to 9 which are listed in Table 6. However, only the second part of this sheet was shown to interviewees, which only has integers but no fractional numbers. We converted their answers into relative scores in the process of analysis after the interviews. This ensures the interviewees do not need to calculate anything so that the math does not confuse them in short time thinking. We wanted them to focus 100% on the questions during the interviews.

When comparing each pair of two risk factors, the only two questions we need to ask are “Which risk do you think is more risky in your mind, A or B?” and “Which score number can describe the severity between these two risk factors 1 to 9?” The assumption of these questions is that the other situations of the flight are all normal. This makes the comparisons based on each pair of risks independently. Considering more than two risks will make the analysis complicated and confuse interviewees, so the combining effect of multiple risks will be considered in the later fault tree analysis based on historical flight data.

Table 6. Relative Scores in AHP

Degree of preference	Relative Factor Weighting Score
Extremely less risk	1/9
	1/8
Very strongly less risk	1/7
	1/6
Strongly less risk	1/5
	1/4
Moderately less risk	1/3
	1/2
Equal risk	1
	2
Moderately more risk	3
	4
Strongly more risk	5
	6
Very strongly more risk	7
	8
Extremely more risk	9

When comparing each pair of two risk factors, the only two questions we need to ask are “Which risk do you think is more risky in your mind, A or B?” and “Which score number can describe the severity between these two risk factors 1 to 9?” The assumption of these questions is that the other situations of the flight are all normal. This makes the comparisons based on each pair of risks independently. Considering more than two risks will make the analysis complicated and confuse interviewees, so the combining effect of multiple risks will be considered in the later fault tree analysis based on historical flight data.

Another group of sheets were designed to help us improve the accuracy and speed of recording the answers through the interviews. Each row of this sheet indicates one pairwise comparison. Different factors are highlighted with different colors, so that the comparison looks more obvious. One example sheet is shown as Table 8 (pg. 23). We marked the numbers in each rows on these sheets according to the oral answers provided by interviewee through interview. Volunteers didn’t need to wait between questions and it is helpful for their consistently thinking. Also, we always have two people recording the answers and verifying the answers after interview to make sure there is no typo or mistake in scoring sheets. The number highlighted in the table is the answer we got from one volunteer in an interview. I will use this as a case study to show how we apply AHP in this work.

Step 3: Computing the weight vector of factors
The pairwise comparison example is shown in analysis Table 7 with $m = 5$ factors. Each entry a_{ij} represents the risk level of the i^{th} factor relative to the j^{th} factor. If $a_{ij} > 1$, then the i^{th} factor is considered more risky than the j^{th} factor. If two factors have the same risk, then a_{ij} is 1. The entries a_{ij} and a_{ji} satisfy the following relationship.

$$a_{ij}.a_{ji} = 1$$

Table 7. Pairwise Comparison Matrix.

$\boldsymbol{a_{ij}}$	**Proficiency**	**Equipment**	**Environment**	**Performance**	**External Pressures**
Proficiency	1	1/5	1/2	1/3	2
Equipment	5	1	3	2	4
Environment	2	1/3	1	3	4
Performance	3	1/2	1/3	1	5
External Pressures	1/2	1/4	1/4	1/5	1
Sum	11.5	2.283	5.083	6.533	16

Table 8. Scoring Sheet for Interviews.

Factor	Weighting Score of Factor																	Factor
	More Risk than								Equal	Less Risk than								
Proficiency	9	8	7	6	5	4	3	2	1	2	3	4	**5**	6	7	8	9	Equipment
Proficiency	9	8	7	6	5	4	3	2	1	**2**	3	4	5	6	7	8	9	Environment
Proficiency	9	8	7	6	5	4	3	2	1	2	**3**	4	5	6	7	8	9	Performance
Proficiency	9	8	7	6	5	4	3	**2**	1	2	3	4	5	6	7	8	9	External Pressures
Equipment	9	8	7	6	5	4	**3**	2	1	2	3	4	5	6	7	8	9	Environment
Equipment	9	8	7	6	5	4	3	**2**	1	2	3	4	5	6	7	8	9	Performance
Equipment	9	8	7	6	5	**4**	3	2	1	2	3	4	5	6	7	8	9	External Pressures
Environment	9	8	7	6	5	4	**3**	2	1	2	3	4	5	6	7	8	9	Performance
Environment	9	8	7	6	5	**4**	3	2	1	2	3	4	5	6	7	8	9	External Pressures
Performance	9	8	7	6	**5**	4	3	2	1	2	3	4	5	6	7	8	9	External Pressures

A normalization is conducted to make the sum of the *m* entries in each column equal to 1. Each entry $\bar{a}_{ij}$ is

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}.$$

Then, the average of the entries on each row is calculated as:

$$w_i = \frac{\sum_{j=1}^{m} \bar{a}_{ij}}{m}.$$

The results of the example shown in Table 8 from one interviewee are shown in Table 10 (pg. 25). Here, the weight of each factor is listed in the column of Average.

Step 4: Checking the consistency
The AHP method contains an effective approach that is used to check the consistency of the evaluations provided by a subject expert. The approach relies on calculating the *consistency index (CI)*. First, constraint measures CM_i for each factor is calculated based on:

$$CM_i = \frac{\sum_{j=1}^{m} a_{ij} w_j}{w_i}.$$

Furthermore, CI is calculated based on:

$$CI = \frac{\frac{1}{m}\sum_{i=1}^{m} CM_i - m}{m-1}.$$

If $\frac{CI}{RI} < 0.1$, the inconsistencies are tolerable and a reliable result can be expected from the AHP. Here, RI is the Random Index listed in Table 9.

Table 9. Values of the Random Inconsistency Index (RI) for Small Problems (Satty 1980).

m	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

Table 10. Weight Calculation.

$\overline{a}_{ij}$	**Proficiency**	**Equipment**	**Environment**	**Performance**	**External Pressures**	**Average (w_i)**	**Consistency Measure (CM_i)**
Proficiency	0.0870	0.0876	0.098	0.0510	0.125	0.0898	5.33
Equipment	0.4345	0.438	0.590	0.306	0.250	0.404	5.52
Environment	0.1734	0.146	0.197	0.459	0.250	0.245	5.72
Performance	0.261	0.219	0.0656	0.153	0.313	0.202	5.20
External Pressures	0.0435	0.109	0.0492	0.0306	0.0625	0.0591	5.20
						Average	5.39

In the example data set in Table 10, the calculation results are shown as follows:

$$CI = \frac{\frac{1}{m}\sum_{i=1}^{m} CM_i - m}{m-1} = \frac{5.39-5}{5-1} = 0.0979,$$

$$RI(5) = 1.12, \qquad \text{and}$$

$$\frac{CI}{RI} = \frac{0.09785833}{1.12} = 0.08737351 < 0.1.$$

Therefore, the data from this specific interview is considered consistent. In order to keep the result reliable, all the inconsistent data which make $\frac{CI}{RI} \geq 0.1$ are removed.

Step 5: Data Analysis

After checking consistency, we got all the weights through the method of Aggregating Individual Priorities (Kaipatur & Flores-Mir). Two example results of the comparisons of the weights before and after this AHP process are shown in Figure 7 and Figure 8 (pg. 24). Some of solutions of AHP are close to the results of brain storming method such as what are shown in Figure 7. As shown in Figure 8 (pg. 27), before and after are very different. We totally underestimated the weight of performance before AHP analysis. The weights for two factors of performance are not equal but significantly different. Based on this result, our department is collecting data and developing the system to do further research now. We call it the fatigue risk management system. This system can record all the fatigue events and analyze the sleep data for pilots and also value the design of pairing and give advice to the scheduler who can improve their work.

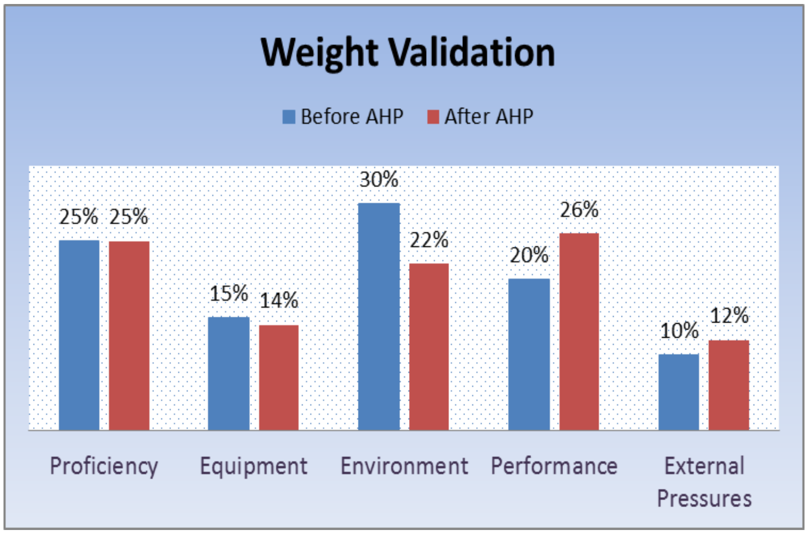


Figure 7. The Comparison of Risk Weights before AHP and after AHP.

Figure 8.The Comparison of Weights for Sublevel Risks of Equipment (Left) and Performance (Right) Before and After.

AHP is an effective tool for analyzing complex problems without enough available data, especially for the low probability and high consequence events such as the accidents of aviation. Not a lot of data about accidents can be obtained and the related reasons for one accident are complicated. However, we still need to find a reliable way to estimate the risk and protect from any severe accidents. When the data comes in, the system can be further improved based on them. In this dissertation, one data base is used as input for the risk mitigation model in a case study. A lot of effort is spent on collecting safety data all over the world. A fault tree analysis based on all trustable data can be expected, however, since the system is a continuously developing system, when new risk factors are discovered, the AHP is a good method to attach weight to it when adding it into the fault tree. More importantly, the weights can be used to estimate the risk when more than one risk occurs together. It will be discussed in Section 1.3.3.

A basic fault tree structure is built in the next section and also more detailed fault trees are built based on real data as well. The detailed fault tree includes lower levels of risk factors which can help target the reason of each occurring error. The risk tree is built based on real data and can help remind us what errors may be triggered after one threat occurs. More discussion is in Section 1.4.2.

1.3.3 Fault Tree Analysis

Based on the AHP process, we obtained the risk weights that can also be called as the significance level of each factor's risk. At this step, we developed an FT based on the historical data of the flight's events that have happened and incorporated the decision tree to calculate the importance and the sensitivity of each factor corresponding to the different levels of failure events and then estimated the final risk scores for every flight.

1.3.3.1 Fault Tree Structure Building

The basic structure has been built in Figure 9 (pg. 26).

The top event is named Aviation Accident Risk. The first level of risk includes "System Operation Risk" and "Control Risk". The sublevel of system operation risk includes "Equipment Risk", "External Risk" and "Internal Risk". The internal risk factors are the events inside the gateway system including "Flight Function Mishap" and "Transmission". However, this research will not focus on these internal factors but on the "Equipment Risk" and "External Risk" which includes "Environment Risk" and "Human Risk" instead. For human risk, we will focus on the crew members in this research which include "Pilots Proficiency" and "Pilots Conditions for Trip".

1.3.3.2 Risk Score

The purpose of building a fault tree is to estimate the risk level for each flight so that we can proactively control some risk. A risk score will be calculated through the fault tree. The traditional way to calculate is from bottom to top. In our method, the full risk score, which represents the highest risk, is set in advance. The risk score compared with the full score can illustrate the whole picture with acceptable boundary of each level risk factors.

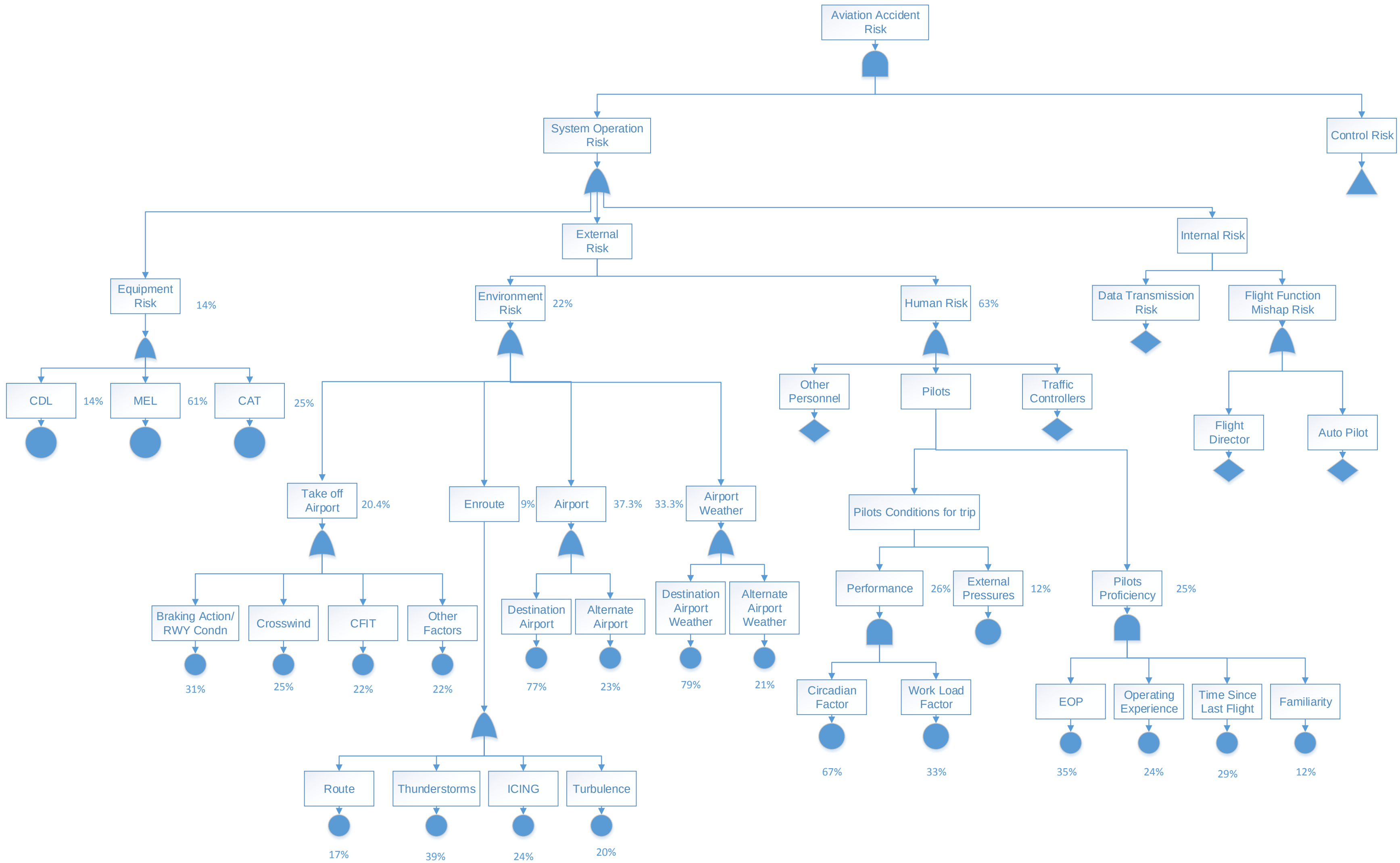


Figure 9. The Basic Structure of the Fault Tree.

Table 11. Risk Score Distribution

Risk Factors				Risk Score
Equipment				140
External	Environment			220
	Human	Proficiency		250
		Condition for Trip	Performance	260
			External Pressures	120
Total				1000

A full risk score R is set to the top event. W_j^i indicates the weight of ith risk factor in level j. For example, the top event has weight W_1^1. Based on the weight of lower level W_i, the full risk score R_j^i for each risk factor can be calculated as $R_j^i = W_j^i \times R_{j-1}^*$, where R_{j-1}^* denote the full risk score of the higher event which attached on the same gate.

Assume the full risk score for the top event is 1000, the full risk score for the lower level of events are calculated based on the weights in fault tree shown as Figure 9. In turn, the full risk score for basic risk factors can be calculated. One example for basic risk factors of risk “Equipment” is shown in Table 12. The full risk score is 140 which can be obtained from Table 11 and the weights can be obtained from the fault tree in Figure 9.

The next step is to calculate the risk score from basic events to top events. Unlike the traditional method, we add two indexes to better describe the risk. One is severity level and the other is time.

Table 12. Risk Score Distribution for Equipment.

Equipment	Weight	Risk Score
CDL	14%	20
MEL	61%	85
CAT	25%	35
Total	100%	140

1.3.3.3 Individual Risk Score Calculation with Severity Level and Time Level

As we can see in the Figure 9, the aviation accident as the top event is triggered by two lower level factors under And-gate. One is operation error and the other is control from human. It means that the only way to trigger this accident is if both of them failed. When one operation error occurs, if some appropriate responses can be done in time, the accident can be avoided. Hence, the occurring time for each basic event (threat or error) is one important index to estimate the risk too. The more respond time left the more chance we have to fix the error. Additionally, the occurring time period can also be analyzed in the same way. There are five categories of time period for one air operation process: Preflight/Tax, Takeoff/Climb, Cruise, Des/App/Land and Taxi/ Park. Same errors occurring in different time periods may produce different risk. The analysis of it will be discussed in Section 1.4.

Different risk factors may be sensitive with time in different levels. The time sensitive coefficient ∂_r for each risk factor r are needed to be set by a group of experts. ∂_r is 1 if the risk factor is not time sensitive, and a higher number indicates a higher sensitive level. When calculating the risk score of the bottom level, the occurring time periods as factor t is considered to get a reasonable risk score for the up level risk. The set of levels of t is I with the index i. The value of time level i is t_i.

On the other hand, another index that should be considered are the severe levels of conditions for each occurring risk. For example, the risk factor weather has different conditions, the high severity level of which may result in a bad outcome. However, the acceptable level of weather risk can be handled by most pilots.

The set of severe levels of risk r is J with the index j. The value of risk severity level j is v_j. Thus the adjustment coefficient of risk score is calculated as:

$$e_{ij} = r_j \times t_i{}^\wedge\partial_r.$$

The risk score $\tilde{f}_r$ can be calculated as:

$$\tilde{f}_r = f_r \times e_{ij}/(r_{|J|} \times t_{|I|}^{\partial_r}) ,$$

where f_r is the full risk score for risk factor r.

An example is given to explain this method. We assume that there are four levels for the condition of this risk (Acceptable, Low, Medium, High) and five levels of occurring time period (Preflight/Tax, Takeoff/Climb, Cruise, Des/App/Land and Taxi/ Park). A risk factor r in the fault tree with full risk score 160. This error occurs in one flight in “Des/App/Land” time period and the severe level is “Medium”. The time sensitive coefficient ∂_r is set as 1.5. The value of each coefficient are shown in Table 13 (pg. 33) and Table 14 (pg. 33).

The Time coefficient of risk score is calculated as:

$$e_{V,III} = r_{III} \times t_V^{1.5} = 33.54.$$

The results are shown in Table 15 (pg. 33). The cell highlighted by green denotes that the severity level III threat occurs at time level V which is "Des/App/Land".

The adjusted score can be calculated as:

$$\tilde{f}_r = f_r \times \frac{e_{V,III}}{r_{|J|} \times t_{|I|}^{\partial_r}} = 160 \times 33.54/44.72 = 120.$$

The variation trend is shown in Figure 10 (pg. 34). Compared with the trend line with time sensitive coefficient 2 which is shown in Figure 11 (pg. 34), we can see that the increase speed with smaller weight coefficient is lower.

1.3.3.4 Risk Score Calculation with Synergy Effect

After the calculation in the last step, all the individual risk factors that occur in one flight is obtained. The task of this step is to calculate the higher risk factors' score based on the hierarchy of the fault tree. The calculation methods are different for Or-gate and And-gate. For Or-gate, since each lower level risk can trigger the higher level risk independently, simply multiply the weight to each risk score and summing them together can give us the higher level risk when more than one lower level risk occurs. However, the lower level risks attached to And-gate need to be considered together to calculate the risk of the higher attached risk factor. Unlike the traditional way to calculate risk with Boolean algebra, in this fault tree analysis, the synergy effect between two risk factors is taken into account.

The consideration of synergy effect can be described as the effect "One plus One is greater than Two". In other words, each of two errors may not affect the flight safety a lot but two risks occurring together may cause a greater risk.

The Steps for calculating the risk score with consideration of synergy effect:

1) Calculate the Combination Coefficient β for basic risk factor A with weight w_A and basic risk factor B with weight w_B.

$$\beta = Max(w_A, w_B)/Min(w_A, w_B)$$

2) The set of severe levels of risk A is H with the index h. The value of risk severity level H is v_h. The set of severe levels of risk B is K with the index k.

Table 13. Severity Coefficient of Basic Event.

Risk Severity Category	Severity Level	Value
I	Acceptable	1
II	Low	2
III	Medium	3
IV	High	4

Table 14. Time Coefficient of Basic Event.

Time Level Category	Threat Start Time Period	Value
I	Taxi/Park	1
II	Preflight/Taxi	2
III	Cruise	3
IV	Takeoff/Climb	4
V	Des/App/Land	5

Table 15. Severity Coefficient of Basic Event.

Risk Score Adjustment Coefficient		Risk factor (weight 60%)			
		I	**II**	**III**	**IV**
Time factor (Weight *40%*)	**I**	1	2	3	4
	II	2.828427	5.656854	8.485281	11.31371
	III	5.196152	10.3923	15.58846	20.78461
	IV	8	16	24	32
	V	11.18034	22.36068	33.54102	44.72136

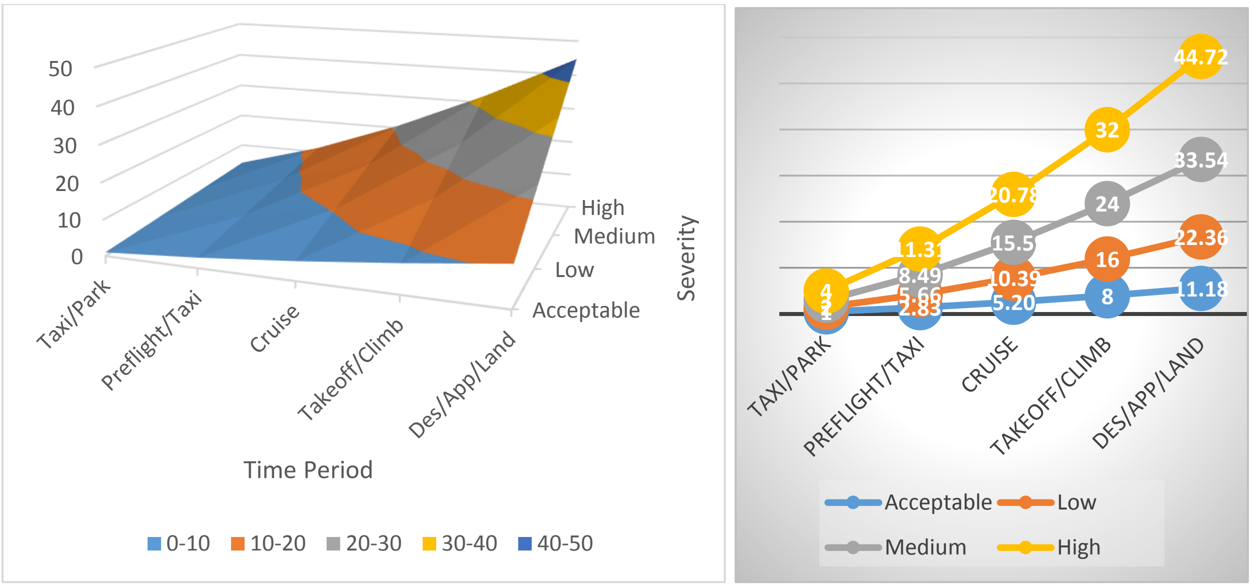


Figure 10. The Variation Trend with Weight Coefficient: 1.5.

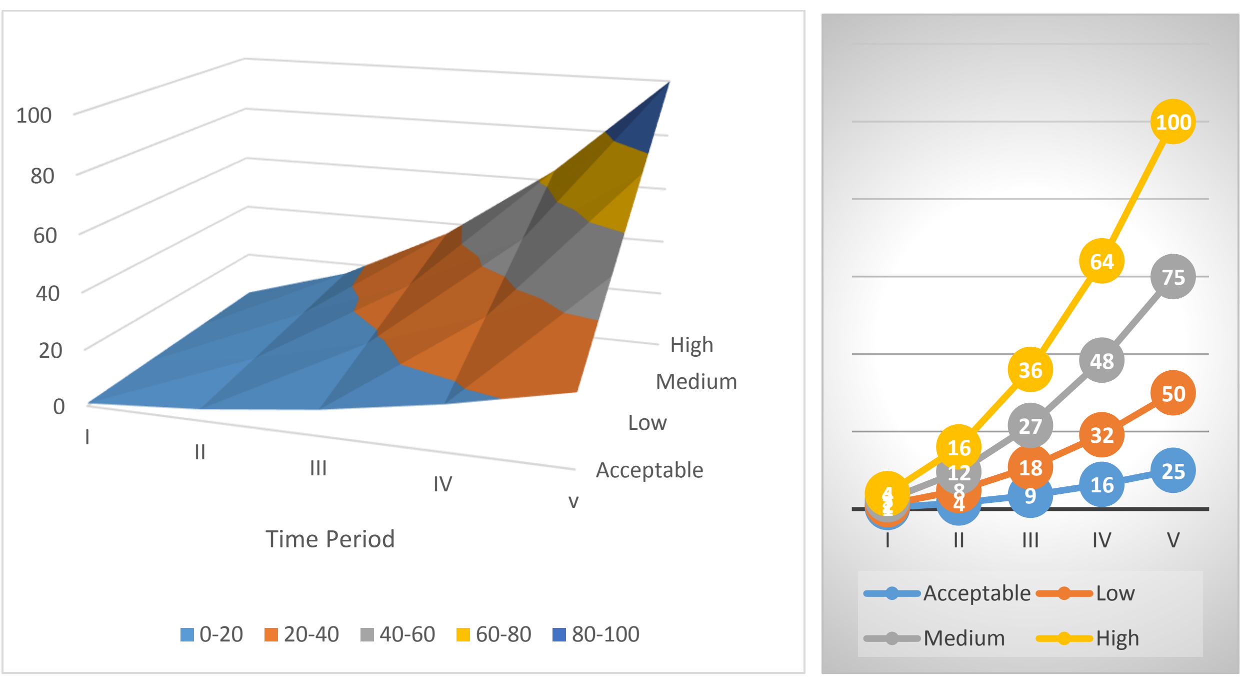


Figure 11. The Variation Trend with Weight Coefficient: 2.

The value of risk severity level k is v_k. Calculate Risk Score Adjustment Coefficient l as follows:

If $w_A < w_B$:

$$l_{hk} = v_h \times v_k{}^\wedge\beta$$

If $w_A > w_B$:

$$l_{hk} = v_k \times v_h{}^\wedge\beta$$

3) Get the higher lever risk factor Q the full risk score F

4) Calculate the risk score of attached higher level risk score:

$$f_Q = F \times l_{hk}/(v_{|H|} \times v_{|K|}^{\beta})$$

Two factors at the bottom level of Performance risk can be analyzed as a good example. Workload and circadian are two classic fatigue risk factors. Based on our human performance data set, the synergy effect of them is significant. High workload with hard circadian always generate a fatigue event. The flight pairing with this fatigue problem is always needed to be fixed with high cost because of the high risk. Pilots aren't as tired if the workload is full but the circadian is fine. When both circadian risk and work load risk exist in one flight, we need to consider them together to get a reasonable risk score for the upper level risk which in this case is "performance". The relative weights for them are shown in the fault tree in Figure 8. Also, we need to consider the different conditions for each risk when we combine them as discussed in a previous section. As a case study, we assume there are three severity levels for the condition of these two risk factors which are "Negligible", "Marginal", and "Critical". Their basic risk coefficients are shown in Table 16. A group of experts with rich experience may be needed to provide their suggestions for these numbers, since they will seriously affect the results of analysis. The exponential adjustment coefficient can be calculated as dividing the higher weight of risk factor by lower weight of risk factor as described in step 1 which is shown as follows:

$$\beta = Max(w_A,\ w_B)/Min\ (w_A, w_B)$$
$$= 67\%/33\% = 2$$

Table 16. Assumed Basic Risk Coefficient for Fatigue Risk.

Risk Severity Category	Classification Definition	Basic Risk Coefficient
I	Negligible	1
II	Marginal	2
III	Critical	3

Table 17. Combination Risks.

Risk Score Adjustment Coefficient		Work Load (weight 33%)		
		I	**II**	**III**
Circadian (weight 67%)	**I**	1	2	3
	II	4	8	12
	III	9	18	27

We assume that there is a flight. Based on the information of this pairing design, we know that the level of work load is level II and the severity level of circadian is III. When we calculate the risk score for the pilot's performance, we calculate an adjustment coefficient for it which is shown in Table 17. Since $w_A > w_B$, the following expression is used:

$$l_{hk} = v_k \times v_h^{\beta} = 2\times3^2 = 18$$

The full risk score of Performance is 260 and can be obtained from Table 1.11. Hence, the risk score for performance in this flight can be calculated as follows:

$$f_Q = F \times l_{hk}/(v_{|H|} \times v_{|K|}^{\beta})$$
$$= 260 \times 18/27 = 173.$$

The fault tree analysis based on these steps produce a risk score for each flight. An acceptable risk score level can be set to alert that some mitigation measures need to be made for this flight. Also, we can set some warning level for each sub-risk factors. For example, a warning from the system should show up when the risk score for performance or fatigue is higher than the acceptable level. It means this flight is not safe enough because of high fatigue risk and needs to be fixed to decrease the risk score.

A risk management system will be developed based on the fault tree with weight. For applying this FT system, quantitative data bases from all relevant departments are needed to connect with the system. To make real time function work, a lot of programming work is going on now. The system is expected to give a total risk score for each flight in real time and advice about a list of announcements. For the flight with high risk score that exceed the acceptable level, some mitigation measures will be recommended to apply and control the risk. A risk mitigation optimization model is developed in the next section.

1.3.4 Risk Mitigation Optimization Model

The definition of optimization is making a single choice from a range of feasible ones with the most cost effective or highest achievable performance under the given constraints to achieve the best results (maximizing desired factors and minimizing undesired). This best choice that meets the objective the most is also called optimal solutions. This optimization model for flight risk management is to mitigate the risk for a specific trip or flight with the lowest cost in required time.

In general, let L indicate the set of levels of risk factors in fault tree with l as index and T_l denotes the set of all possible risk factors in level l, $l = 1, 2, \ldots |L|$. Let S_l denote the size of T_l and t_l indicates the individual risk factor in set T_l, $t_l = 1, 2, \ldots, |S_l|$. T_1 is the set of basic risk factors which are the bottom factors in fault tree with t_1 as index and the $T_{|L|}$ only include one element $t_{|L|}$ which is the top event of the fault tree.

Define b_{t_1} such that b_{t_1} is 1 if the basic risk factor t_1 occurs in the targeted trip/flight, and is otherwise 0. The risk score for each existing basic risk factor is set as w_{t_1}based on severity level and occurring time. Let $P_{t_l t_{l+1}}$indicate the transferred possibility from lower level risk factor to higher level risk factor. Now the quantitative representation of the fault tree is done.

Let M denote the set of all possible measures available for the company with *m* as the element. The cost of each measure is based on the occurring time period i.
The cost of applying measure m at the time period i is set as C_{mi}. Define binary variable x_{mi} such that x_{mi} is 1 if measure m is selected to apply at time period i, and is 0 otherwise. After applying the measure m, the mitigation of basic risk factor t_1 is denoted as a_{mt}. We assume that for each t_1, $\sum_{m \in M} a_{mt_1} \leq 1$. The risk score of risk factor t_l after applying selected measures will be y_{t_l}, and then the score of higher level risk becomes $y_{t_{l+1}}$.

The objective function is to minimize the total cost of measures applied to control the risk at specific time period i. The acceptable risk level for the flight is set as R. Since the model should fit the real time function, when programming, the event that trigger the model to run should be set. It could be that some basic risk factors occur or the specific time point. As time goes on, the model can be solved at every time period until the appropriate measures applied to make the score lower than R. The assumption is that the risk factors in the same level are independent with each other. An optimization mode is built as follows:

$$min \sum_{m \in M} C_{mi} x_{mi} \tag{1.1}$$

Subjective To:

$$b_{t_1}w_{t_1} - \sum_{m\in M} a_{mt_1}b_{t_1}w_{t_1}x_{mi} \le y_{t_1} \qquad \forall t_1 \in T_1 \tag{1.2}$$

$$\sum_{t_l\in T_l,\ t_{l+1}\in T_{l+1}} P_{t_lt_{l+1}}y_{t_l} = y_{t_{l+1}} \qquad \forall l \in L \tag{1.3}$$

$$\sum_{t_{|L|}\in T_{|L|},\, t_{|L|-1}\in T_{|L|-1}} P_{t_{|L|-1}t_{|L|}}y_{t_{|L|-1}} = R \tag{1.4}$$

$$x_{mi} \in \{0,1\}\,, \forall m \in M\ ; \quad y_{t_l} \ge 0 \quad \forall l \in L. \tag{1.5}$$

In this model, constraint set (1.2) is used to calculate the risk score of each basic risk factor after applying all selected measures. Constraint set (1.3) is used to calculate the risk score of each upper level risk factor based on the lower level risk factors. Constraint (1.4) is used to ensure that the risk score of the top event is in the acceptable level and (1.5) is used to restrict all risk score is nonnegative.

1.4 Risk Mitigation Optimization Model

1.4.1 Data Material Description and Basic Analysis

To accomplish quantifications of a fault tree, the quantitative input data of basic events is needed as input of the FTA model. The simplest configuration of the input data is assigning probabilities for each basic event of the fault tree. In turn, the possibility of each higher event of the fault tree can be calculated based on the basic event probabilities and their weights through equations until the probability of the top event is acquired. Real world data set is extremely valuable since an accident in aviation is a rare event with serious consequences. It is challenging to have enough data to directly represent the risk of the top event, so that the FTA model should be built to help by using the basic data of bottom events to estimate.

The data set used in this section of dissertation is provided by a major airline in the U.S. named as Line Operation Safety Assessments (LOSA) data. The population of this data base is about 45,000 observations represent flights during a period of two months. The detailed records of 592 flights with threats and/or errors exist during the observing period. The observed flights were randomly selected by professional observers. Professional observers flew together with the crew and recorded everything they observed including threats, errors and crew responses which is required by the FAA.

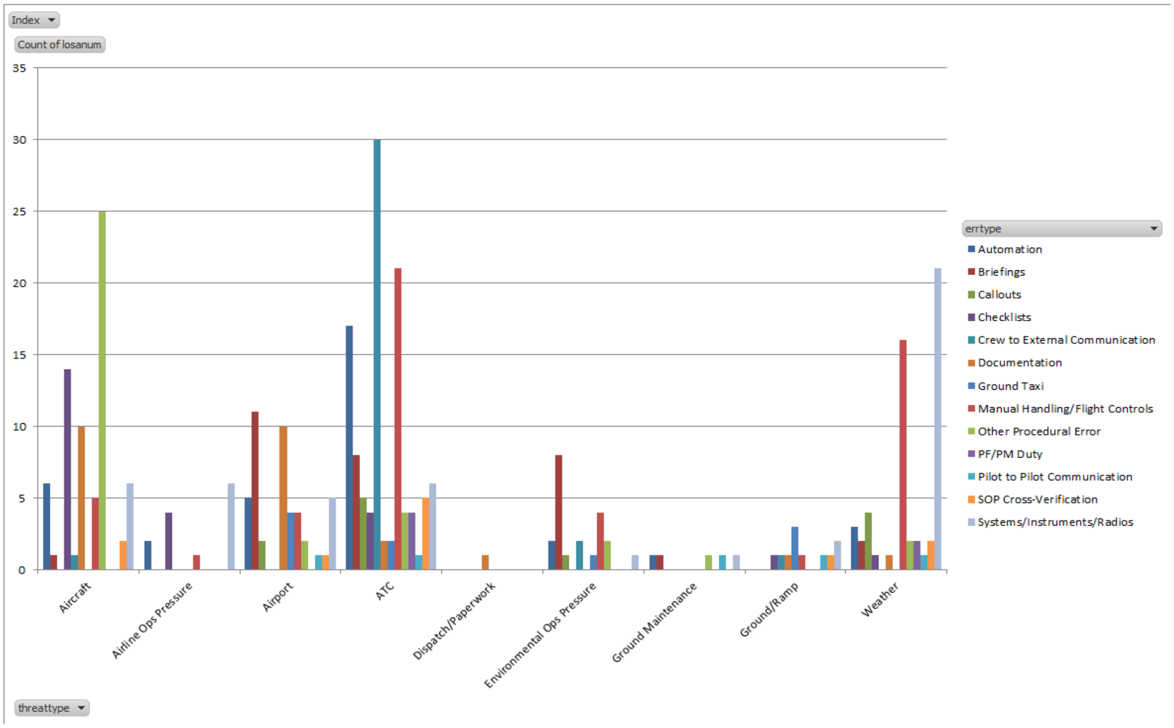


Figure 12. The Relationship between Threats and Errors.

The first data set in it focuses on the threats including information such as ID number of flight in which the threat happened, the code of the threat, the type of threat, when and where this threat occurred and whether this threat caused any error(s) which is related to the column “threatlink” in the second data set which represents whether or not the threat is directly related to the error.

The second data set in it focuses on the errors which are higher level events of threats. It is linked to the first data through the ID of the flight. This data set stores the information such as the code of the error, the type of the error, when and where the error occured, which position was responsible for this error, the outcome of this error and if any undesired aircraft state occurred. If there is “No undesired aircraft state”, the “erroroutcome” can only be “Inconsequential” or “Additional error”. The flow chart of these outcomes belonging in the crew error management is shown in Figure 12. The column “threatlink” shows if the errors have any relationship with the threat which can linked to the first data set.

The third data set is called “Markers”. This data set provides all other related information about these flights and includes the departure airport, the arrival airport, the type of aircraft, the pilot employee number, etc.

In the 592 flights of this data base, there are 330 events that have a direct relationship between threats and errors. In these 330 events, there are 9 kinds of threat types

(Aircraft, Airline Ops pressure, Airport, ATC, Dispatch/Paperwork/ Environmental Ops Pressure, Ground Maintenance, Ground/Ramp and Weather) and 13 kinds of errors (Automation, Briefings, Callouts, Checklists, Crew to External Communication, Documentation, Ground Taxi, Manual Handling/Flight Controls, Other Procedural Error, PF/PM Duty, Pilot to Pilot Communication, SOP Cross-Verification and System/Instruments/Radios) included in this dataset. Each threat type has several different kinds of threat codes with a total of 51 and error types with a total of 116 sublevel errors. There are four categories of positions shown in the data set: “Captain”, “First Officer”, “All Crew Members” and “SO/FE”. Since this is out of the range of this research, it will not be discussed here.

The preliminary statistical analysis of these threats and errors in the dataset are illustrated in Figure 12. We can see that the threat “ATC” and “aircraft” may cause more errors. “Automation” “Crew to External Communication” and Manual Handling/Flight Controls” are three main errors that are correlated with threat “ATC”. “Checklists” and “Other procedural Error” are main errors that are correlated with threat “Aircraft”.

As mentioned in a previous section, after the error occurs and the crew responds, there are three possible outcomes: “Undesired aircraft state”, “Inconsequential” and “Additional error”. Their frequencies of error outcome of the dataset are shown in Figure 13. Since the accident of aviation is a rare event, the outcome of the errors is used to represent the top event risk. Based on the definition of each error outcome code, the possibility of errors with code “Undesired aircraft state” or “Additional error” are seen as the input rate of trigger of the top risk in the optimization model.

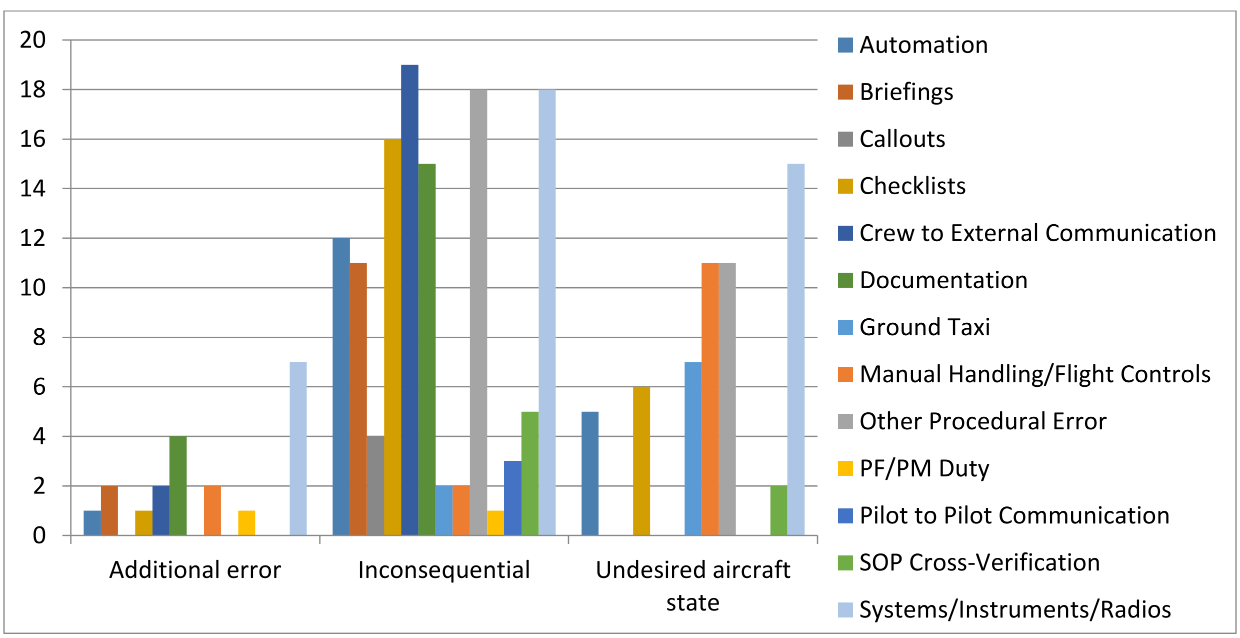


Figure 13. The Frequency Distribution of Error Outcome.

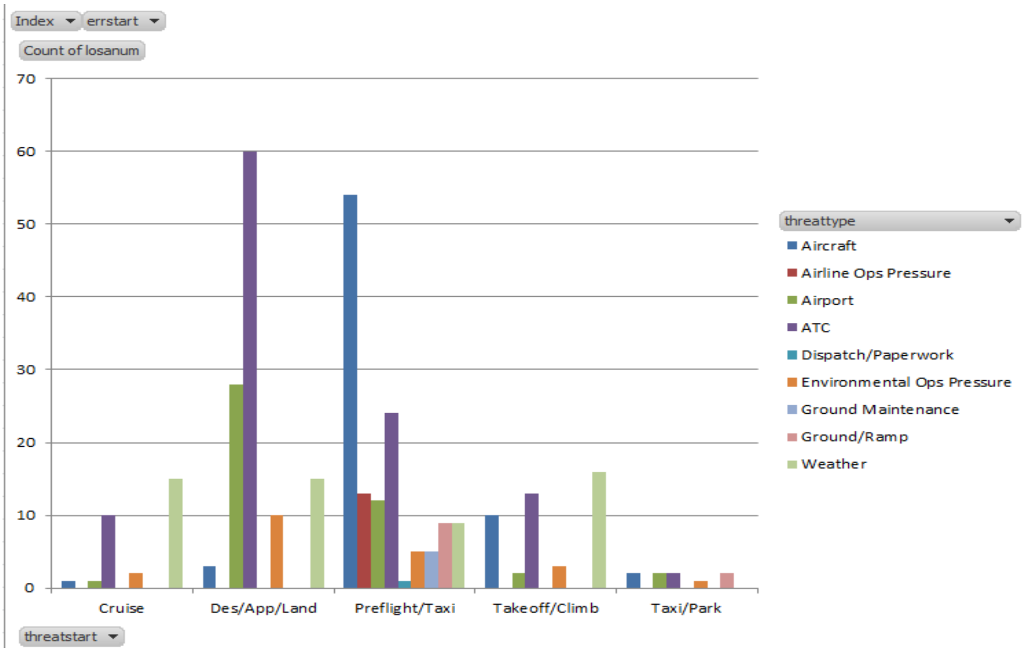


Figure 14. Threat Distribution in Different Occurring Time.

The same threat happens in different time periods may be totally different stories for a flight. In LOSA data set, the threat start time has five time periods “Preflight/Taxi”, “Takeoff/Climb”, “Cruise”, “Des/App/Land” and “Taxi/Park”. For each time period, the frequency of same threat are different as shown in Figure 14. More threats occurring in the “preflight/Taxi” time period and the most frequent threat type is “Aircraft”. The second to the fourth place are “ATC”, “Airline Ops Pressure” and “Airport”. In “Des/App/Land” time period, the most frequent threat type is “ATC”. The second to the fourth place are “Airport”, “Weather” and “Environmental Ops Pressure”. In “Take off/ Climb” time period, the most frequent threat type is “Weather”. The second to the fourth place are “ATC”, “Aircraft” and “Environmental Ops Pressure”. In “Cruise” time period, the most frequent threat type is “ATC”. A few threat occur in “Taxi/Park” time period.

Another set of information we can obtain from this chart is in which time period each threat most likely happens. For example, the threat in type “ATC” most likely happens in the “Des/App/Land” time period and the threat in type “Aircraft” most likely happens in the “Preflight/Taxi” time period. The information presented in this chart can be a useful guide for the user of flight risk management system to which areas need more attention in different time periods.

1.4.2 Risk Tree for LOSA Data

As we know, the fault tree is powerful for reason tracking. When errors happen, the fault tree can help find all the possible threats as triggers. Fault trees are built for the LOSA data base. This fault tree only has two level events; threats and errors. Threats are included in nine type groups and errors are included in 13 type groups. Errors are high level events and threats are basic events, but the total number of errors are greater than threats. Additionally, no accidents occur, only risk exists. The outcome of errors which are in category “Undesired aircraft state” or “Additional error” is viewed as top event. The complicated relationships between threats and errors make the structure of fault tree in a flat shape with a bigger middle level and a lot of intersections between lines. A better way to illustrate the internal relationship of LOSA data should be developed. Based on the structure of this kind of risk data, an invert fault tree which is called Risk Tree is built for the risk management system with LOSA data. The beginning event is threat and nine types of threats are included. Each threat type is linked to the sub threats’ code. Each sub threat is linked with all errors which are directly triggered by it. The threats belonging in different types are highlighted in different colors. The arc attached with it is the same color in order to track all errors linked to it. Errors belonging in different type group are in different colors. The error type group is listed below the tree. In risk tree, the gate signal would be described as a direct relationship between the threat and the attached error. It is a many to many network which is also a good map for tracking reasons when any error occurs in flight. One piece of risk tree is shown in Figure 15. There are four threats included in this piece of risk tree and 11 different groups of error types are involved. One threat may be linked with more than one error, and one error may be linked with more than one threat. These threats may be from different threat type groups which can be shown as arcs with different color links to one error. The highlight error is in this situation.

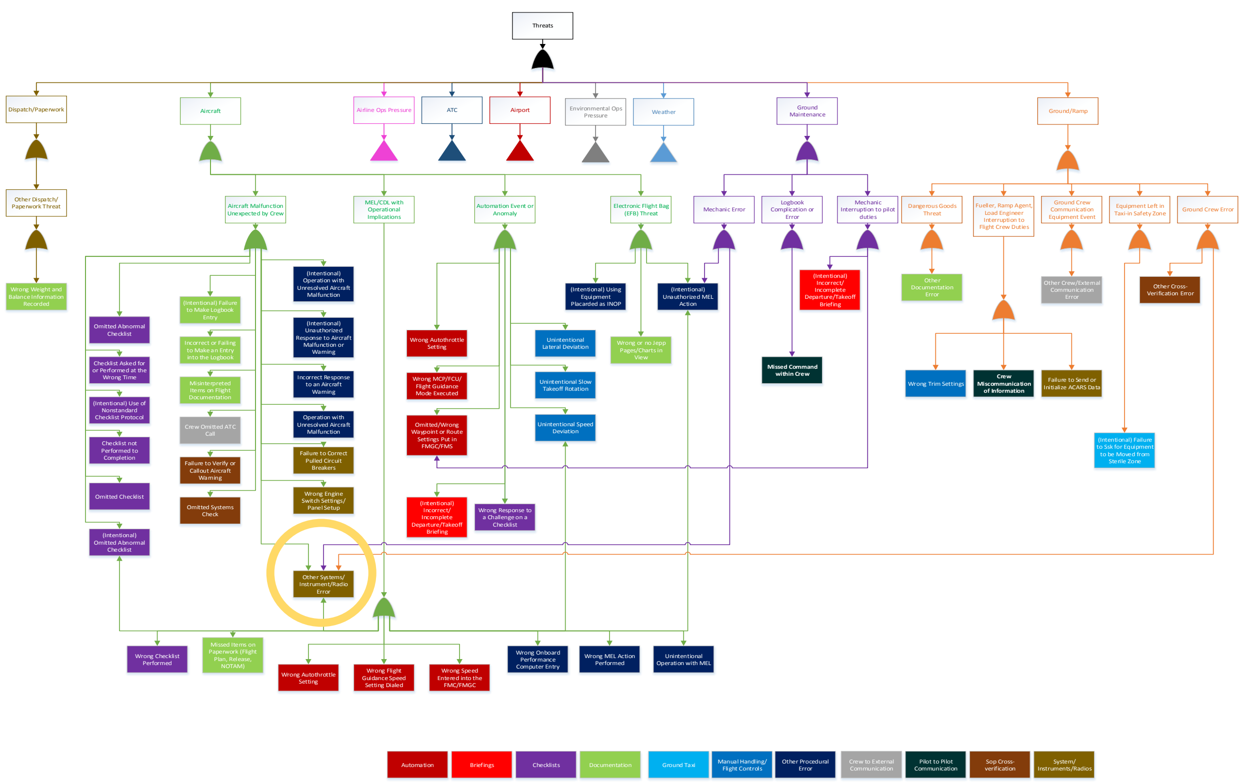


Figure 15. The Risk Tree Based on the LOSA Data Set.

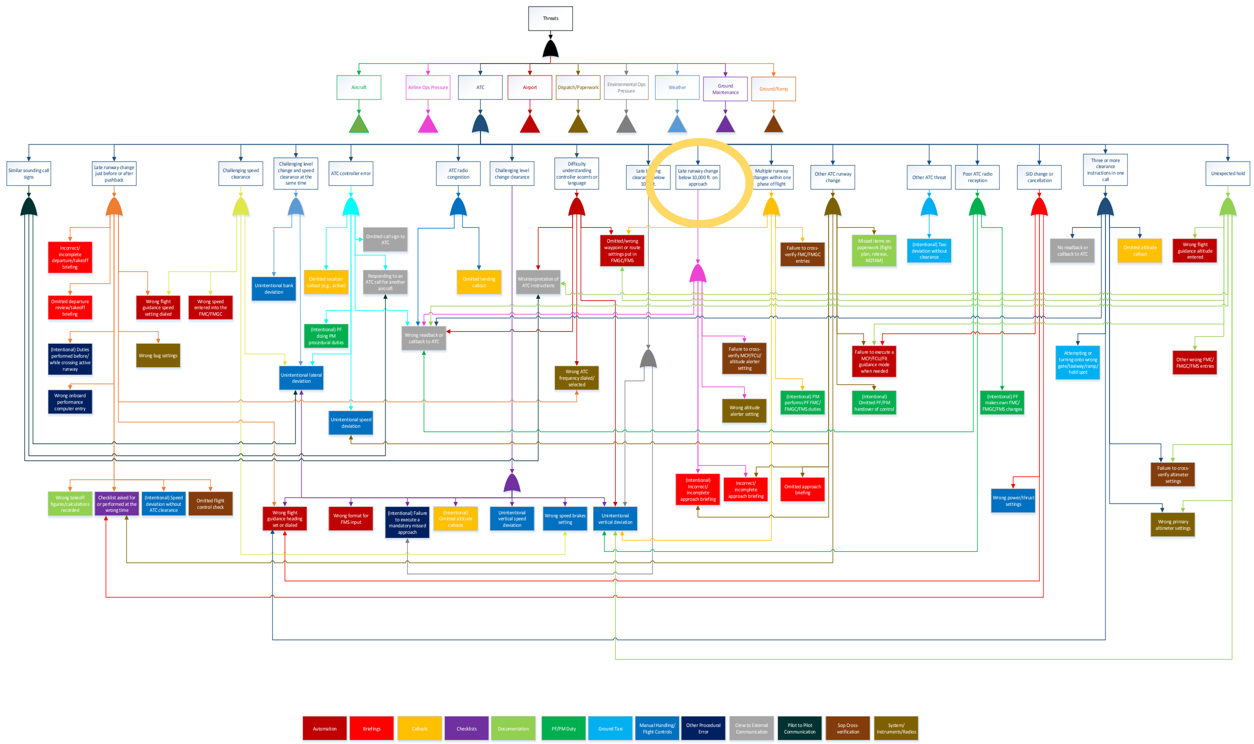


Figure 16. ATC Threat in the Risk Tree.

The quantitative analysis can be solved based on the conditional probability of causal factor error given the presence of threat. When one threat exists in the flight, a risk score is given to it according to its severe level and occurring time. This risk score is transmitted to all errors the threat may trigger based on the conditional probability of each pair of threat and error with link between them. Since threats in one type group may not be independent, we can use the link of threat type to error type to calculate the conditional probability to avoid statistical error. In turn, the risk of this flight can be represented based on the risk score of errors and the probability of error outcome with code “Undesired aircraft state” or “Additional error”.

This risk tree, with detailed network of threats and errors, can help the system build a reminding function. When some threats exist in one flight, the system can remind the crew and other relevant staff which kind of error may be triggered by them so that they can pay more attention to these areas and check the relevant index to make sure that no additional error will be triggered. The mitigation measures will be recommended by the optimization model in the system. For example, Figure 16 illustrates the map of threat ATC with all sub-threat and related errors. All 13 groups of error types are involved. On one flight, when an ATC threat “Late runway change below 10,000ft” occurred, the system can target all possible errors that may happen after that following the pink arc in the risk tree. According to the color of the event, the five errors found by the system belong to four different error types: “Briefings”, “System/

Instruments/Radios", "Sop Cross-verification" and "Crew to External Communication". The occurring possibility for each of them will be listed in order to alert the crew.

1.4.3 Risk Mitigation Optimization Model for LOSA data

In general, let T denotes the set of all possible threats may occur before or through flight with t as element. Define b_t such that b_t is 1 if the threat t occur in this flight, and is 0 otherwise. The risk score for each existing threat is set as w_t based on severe level and occurring time. Follow the risk tree from top to bottom, the set of all errors caused by these threats is set as E with e as its element. Based on the data base, the probability of error e triggered by threat t is calculated as P_{te}. At the end, the probability of fault triggered by error e is set as $\breve{P}_e$. Now the quantitative representation of the risk tree is done.

Let M denote the set of all possible measures available for the company with m as the element. The cost of each measure is based on many factors including time period i. The cost of applying measure m at the time period i is set as C_{mi}. Define binary variable x_{mi} such that x_{mi} is 1 if measure m is selected to apply at time period i, and 0 otherwise. After applying the measure m, the percentage of threat t is mitigated as a_{mt}. We assume that for each threat t, $\sum_{m\in M} a_{mt} \leq 1$. The risk score of threat t after applying selected measures will be y_t, and then the score of error e becomes z_e.

The objective function is to minimize the total cost of measures applied to control the risk at specific time period i. The acceptable risk level for the flight is set as R. The assumption is that the threats are independent of each other and so are errors. An optimization model is built as follows:

$$min \sum_{m\in M} C_{mi} x_{mi} \qquad (1.6)$$

$S.t.$

$$b_t w_t - \sum_{m\in M} a_{mt} b_t w_t x_{mi} \leq y_t \qquad \forall t \in T \qquad (1.7)$$

$$\sum_{t\in T} P_{te} y_t \leq z_e \qquad \forall e \in E \qquad (1.8)$$

$$\sum_{e\in E} \breve{P}_e z_e \leq R \qquad (1.9)$$

$$x_{mi} \in \{0,1\}, \qquad y_t \geq 0, \quad z_e \geq 0 \qquad (1.10)$$

In this model, constraint set (1.7) is used to calculate the risk score of each threat after applying all selected measures. Constraint set (1.8) is used to calculate the risk score of each upper level event error and constraint (1.9) is used to ensure that the risk score of the top fault is in the acceptable level. (1.10) is used to restrict all risk score is nonnegative.

1.4.4 Case Study

LOSA data is used in this case study, the threat level includes nine types of threat which are used as the threat set T. The error level includes 13 types of errors which are used as the error set E. The probability of error e triggered by threat t is calculated based on the real data in LOSA data base as:

$$P_{te} = P(e/t) = P(e \cdot t)/P(t).$$

The probability of the fault triggered by error e $\breve{P}_e$ is calculated as dividing the sum of the number of flights with error outcome “Undesired aircraft state” and “Additional error” by the total number of flights with the error occurring. The acceptable level of the risk score of fault for the flight R is set as 600, and in order to check the sensitivity, a loop is set in Python to run the model once the score decreased by 50. Additionally, another loop is set for time periods which are shown as follows:

$$i = \left\{ \begin{array}{ll} 1 & 96\ hours\ before\ departure \\ 2 & 48\ hours\ before\ departure \\ 3 & 24\ hours\ before\ departure \\ 4 & 12\ hours\ before\ departure \\ 5 & 6\ hours\ before\ departure \end{array} \right\}.$$

Assume there are 25 measures that can be used to mitigate the flight risk and the costs of them are different for each time period. For some measures, the closer to departure, the more cost of the measure will be. However, there are still some measures which are not sensitive to time at all, so the cost is the same no matter which time period it is in. Randomly simulate for each threat that which measure can mitigate the risk of it and how much percentage of it can be mitigated by this measure.

We simulate a flight with some threats occurring and the risk score of each threat is randomly simulated. The optimization model is run on an HP EliteBook 820 server running i5-4300U CPU. The Gurobi 6.0.4 is used to solve this test instance. Since this model is built for the risk management system, which is a real time risk monitor, the advice of how to mitigate the risk need to be obtained in a short period of time. The solving time of this model is like a second that is satisfied the requirement of real time function. The solutions not only include the measures that can be applied to mitigate the risk to the acceptable level and the total cost of these applied measures but also involve the risk score for each level of events (threats and errors) after applying the measures.

According to the solution shown in Table 18 (pg. 47), we can understand how these measures mitigate the total risk of the flight. Also, through the comparison of the solutions for different acceptable levels, we can see how much more it will cost when the acceptable level decreases. Comparison of the solutions for different time periods can tell us how important it is to apply the measure in time. Different measures should be applied for different acceptable levels in different time periods. Additionally, the different increasing speeds for different acceptable risk levels are shown in Figure 17.

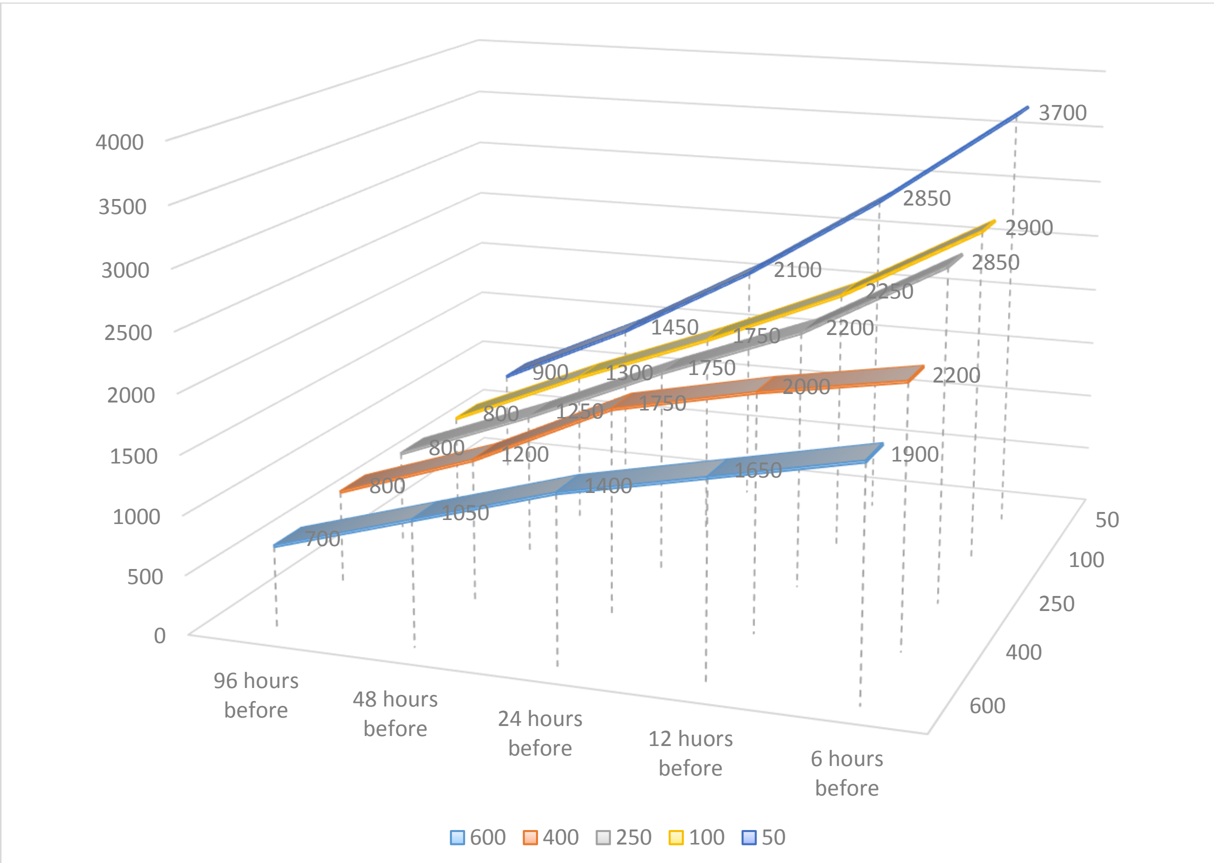


Figure 17. Results Comparison for Different Acceptable Score Level in Different Time.

Table 18. Results Comparison for Different Acceptable Risk Score Level in Different Time Period.

Acceptable Risk Level		Time Period				
		96 hours before	**48 hours before**	**24 hours before**	**12 hours before**	**6 hours before**
600	**Cost**	700	1050	1400	1650	1900
	Measures	(12, 18, 22)	(5, 13, 18, 19)	(6, 18, 22)	(6, 18, 22)	(6, 18, 22)
500	**Cost**	700	1100	1400	1650	1900
	Measures	(6, 18, 22)	(6, 18, 22)	(6, 18, 22)	(6, 18, 22)	(6, 18, 22)
400	**Cost**	800	1200	1750	2000	2200
	Measures	(5, 12, 18, 22)	(6, 18, 20)	(5, 6, 12, 22)	(6, 15, 22)	(6, 15, 22)
300	**Cost**	800	1250	1750	2200	2500
	Measures	(5, 12, 18, 22)	(1, 5, 12, 18, 19)	(5, 12, 18, 22)	(5, 6, 12, 22)	(6, 15, 18, 22)
250	**Cost**	800	1250	1750	2200	2850
	Measures	(5, 12, 18, 22)	(1, 5, 12, 18, 19)	(5, 12, 18, 22)	(5, 6, 12, 22)	(5, 6, 12, 22)
200	**Cost**	800	1250	1750	2200	2850
	Measures	(5, 12, 18, 22)	(1, 5, 12, 18, 19)	(5, 12, 18, 22)	(5, 6, 12, 22)	(5, 6, 12, 22)
150	**Cost**	800	1300	1750	2250	2900
	Measures	(5, 12, 18, 22)	(5, 12, 18, 22)	(5, 12, 18, 22)	(5, 12, 18, 22)	(6, 12, 18, 22)
100	**Cost**	800	1300	1750	2250	2900
	Measures	(5, 12, 18, 22)	(5, 12, 18, 22)	(5, 12, 18, 22)	(5, 12, 18, 22)	(6, 12, 18, 22)
50	**Cost**	900	1450	2100	2850	3700
	Measures	(5, 18, 19, 22)	(5, 18, 19, 22)	(5, 18, 19, 22)	(5, 18, 19, 22)	(5, 18, 19, 22)

CHAPTER II
CREW RESERVE ANALYSIS, FORECAST AND OPTIMIZATION

2.1 Introduction

Intense competitive environment makes cost controlling more and more important for airlines all over the world. As one of highest contributors, crew cost is a hot topic in research areas. The key concept to control cost is not to save money from the crew but to minimize the waste of crew efforts. High coefficient crew planning and scheduling can make it happen. A lot of work on crew planning and scheduling is applied successfully, however, most of them are not on reserve crew but on regular crew.

The high uncertainty of freight/passenger demand and the availability of each individual pilot presents a big challenge for pilot planning and scheduling. A lot of different conflicts and disruptions cause a large amount of trips drop out from regular lines which are called open time trips. A pilot may be called in hours before a scheduled trip/flight and notify the planner that she or he cannot fly because of illness or other reasons. On the other side, freight/passenger demand is difficult to estimate because of its volatility of nature. Occasionally, extra flights may be triggered by an unexpected surge in demand. Therefore, airlines always keep reserve pilots, in addition to regular pilot line holders, who have been assigned with scheduled flights. Unlike the regular crew, reserve crew is a group of pilots who are on call for a number of days in a month. Some airlines, such as US Airlines, carry permanent crew members while other airlines have different ways to let the crew decide their monthly status. For instance, in one large US cargo airline, the crew can choose to bid regular line or reserve line before the start of the bid month. The detail will be presented in Section 2.3.

The pilots in reserve stay ready for possible flight needs and are paid whether they actually fly or not. In addition, volunteering pilots may be called in when the open time flight demand cannot be satisfied by the reserve pilots. (M. Sohoni, Johnson, & Bailey, 2006) report that the utilization of reserve crew is less than forty percent for the schedule instances they considered. Hence, how to efficiently plan and use reserve pilots is a good indicator of efficient crew management. Currently the management of crew reserves uses the following major procedures:

1) The required reserve capacity (i.e., head accounts) is estimated based on the historical reserve usage, the predicted cargo volume, and the current trip design;
2) The demand of open time trips are predicted based on historical data and the Bidpack released. The forecasting trips will be provided to the crew planning department as input of the line building solver;
3) Based on the scheduled trips and estimated reserve capacity, a set of schedule patterns is created for best covering predicted needs under various constraints

and regulations. The needs are also influenced by pilots who would like to have make-up flights. Each pattern specifies the working schedule of a pilot. The patterns are created by a solver;

4) Pilots in reserve bid for patterns;
5) Assign trips to reserve crew, following a pre-specified order and policies, when there are flight needs. The needs could be known in advance or arise spontaneously;
6) When the reserve cannot meet all needs, other draft or volunteer pilots are called in to fulfill requirements, but they will be paid at higher rates. The calls are a volunteer system, in general, that also follows all regulations.

These procedures are implemented monthly. Improvement opportunities exist on how to improve the required reserve capacity estimation (determination), to improve the forecasting of reserve demand and to generate high quality patterns for optimizing both the coverage and the crew utilization.

After meeting with related personnel of a U.S. major airline to understand the current practice regarding all the six major steps of reserve management, a business flow chart is developed to summarize all the involved activities. An integrated approach is developed for improving the efficiency of the reserve crews planning and scheduling. Unlike the other technique in literature, this approach integrates the demand forecasting, reserve pattern generation, and selection (optimization). After statistical analysis of the real historical data, a forecasting tool is developed in the SAS Enterprise Guide. The key variables of the model inside are trip length, month and weekday which are decided by a series of analyses. Holiday includes most of the national holidays is taken into account as well.

Unlike the traditional method, forecasting the frequency of required coverage, this forecasting approach will estimate the possibility of each type of trip which dropped out from the regular line. The reason for this is, along with the development of the market, the frequency of total scheduled trips is increasing, which will make the frequency of dropped trips increase too. The rate of market development needs to be predicted and applied to the process of forecasting. It must more or less influence the currency of forecasting. Also, in some months with peak flying demand, such as December, the frequency of dropped trips is always higher than that of other months. It makes the forecasting results be influenced, while forecasting the dropping possibility can avoid this kind of influence.

Unlike many optimization models in this research, using the daily reserve demand as input, which does not capture the varying duration of reserve demands, the method in this tool considers all different durations of reserve demand and uses them as the input of the optimization model. The reason is even if there are enough crew members available in one day, they may not be available during the whole trip duty. Consecutive days demand is more reasonable to use in the reserve forecasting process.

The expected value of each type of dropped trip is predicted based on the dropping rate and the total scheduled trips without any round process at the end. Unlike current applied methods that usually round the result into integer, the rounding step in this approach is avoided in order to keep as much information of historical data as possible. When rounding up any fraction number to integer, the optimization steps after this always view this demand as an event with 100% occurring possibility. When rounding down any fraction number to an integer, the optimization steps after this always view this demand as an event with 0% occurring possibility. Both rounding processes make the forecasting solution lose partial information from historical data. The reserve forecasting tool is friendly to users, which can let users select the target period at specific base, seat and time segment. The historical data that used to forecast can be selected by users to avoid the outliners and unreliable data. In a sense, the forecasting stage is not entirely completed in this stage, it just creates the input for next stage. The optimization process can be viewed as a part of the forecasting stage. The characteristic of high uncertainty limits the accuracy of the prediction. When generating the patterns to cover the demand, this point should be considered to weaken the uncertainty as much as possible. The integrated concept is applied into our approach to make the process not too sensitive to the uncertainty. That is one of the key contributions of this research.

A novel optimization model with column generation aspects is developed along with algorithms to optimize the reserve scheduling by minimizing the total cost. Two costs are included: one is the cost of awarding one reserve pattern to crew, and another is the uncovered trip cost. For the cost of the uncovered trip, the cost is considered based on the length of the trip which makes the long trip have higher value when generating patterns to cover them in the optimization process.

Unlike the traditional method of generating patterns to cover the reserve demand one-to-one, this model designed patterns to cover reserve demand in many-to-many mode. Each selected pattern is not only generated for covering one set of trips without overlap but for covering some possible sets of trips with overlap between them. In this way, even the predicted reserve requirement of this type of trip will not occur, the pattern can still be used to cover other reserve demand.

One key difficult challenge of the crew scheduling optimization problem is too many scenarios of coverage exist in the solving process means the model can’t be solved in reasonable time. For reserve pattern generation, there are usually several billion legal pattern types involved. Most studies restricted the size of pattern set first and use column generation algorithm to solve the problem. The column generation is a great technique for this type of optimization problem, but downsizing the pattern types first may lose some feasible solutions which may include the optimal ones. In the approach of this dissertation, a new description way is developed for the reserve pattern type. The patterns are designed inside the model and almost all legal pattern types are included. Additionally, this built-in pattern generation method avoids the comparison of all listed pattern types, so that the solve time is reduced.

The solution does not only provide support to reserve crew scheduling but also provides support to assign trips at the daily operation process. A list of trips can be covered by each pattern and a list of patterns, which can be used to cover each trip, consist in the output. When daily operations begin, schedulers can stochastically exchange the forecasted demand into real occurring demand and update the available reserve patterns to rerun the model every day. The solution from the model can provide support to decide if specific dropping requirement can be accepted or not through comparing reserve demand left with the available reserve patterns when assigning trips to reserve patterns. Case studies, all based on real data, are present at the end. As two key indexes to evaluate the quality of reserve scheduling, utilization and coverage are both improved as shown in the results.

2.2 Literature Review

Several researches, especially in operation research and management science research areas (Ormsbee & Lansey), applied for solving airline planning and operation problems which consists of fleet planning, crew planning, airline recovery and so on. The topic of reserve crew scheduling in this dissertation can be classified into the subfield of airline crew scheduling, which is widely viewed as one of the most challenging problems in areas of airline scheduling. The cost of crew resource composes the second largest component of direct operating costs after fuel cost for all the major airlines. For large airlines, it has easily exceeded a billion dollars annually. In 1991, American Airlines (AA) reported spending $1.3 billion on crew resource. United Airlines (UA) spent $0.6 billion and Northwest Airlines spent $1.05 billion in 1989 just on their crew members (Gopalakrishnan & Johnson, 2005).

Generally, airline crew members can be classified into two categories: regular crew members and reserve crew members. Typically, regular crew members are used to cover the regular pairings and their monthly flying schedules are optimized to maximize such coverage with minimization of cost. However, in most airlines following a bid-line system to award crew schedules, a large portion of the flights are dropped out from these optimized work schedules because of various conflicts such as phase-in conflicts, training, vacation, sickness and fatigue. During disruptions to normal operations, some of the flights remain unassigned by any crew member. Almost all of these uncovered or unassigned flights are primarily need to be covered by reserve crew members or volunteered crew members with high cost. Some large U.S. airlines carry up to 30% crew members as reserve pilots (M. Sohoni et al., 2006). While other large U.S. airlines do not carry fixed crew member groups but flexibly let crew members bid from regular lines and reserve lines. How to use crew resources efficiently is an important topic for all airlines and many researchers analyzed this from different viewpoints with different methods.

Based on various stages of planning in airline operations time line, which are shown in

Figure 18 (pg. 53), the studies of crew planning can be classified into four categories: long range planning, tactical planning, pre-month planning and daily operations. Some researchers consider the schedule in three layers: crew, aircraft and cargo/ passenger. The layer above the time line is about the stuffing or crew planning area. The layers below the time line are included in other research areas which are out of the range of this dissertation. Figure 18 illustrates which stage to reserve scheduling research field in and how all the overarching research areas about airline planning relate to it via different levels of subfields in those academic areas. In the pre-month planning stage of airline scheduling, reserve crew scheduling is the subfield research area of crew scheduling which includes pairing optimization, bidding awards and conflict resolution, initial or recurrent training scheduling, flight instructor scheduling and others. Also, as we can see in the field of airline recovery in the stage of daily operation, reserve assignment policies, which is the subfield of crew recovery, has a close relationship with the research area of reserve crew scheduling. How to use the real time reserve crew is the task of the air operations recovery department and it is highly affected by the quality of the work of the reserve crew scheduling. The sections of literature review in this chapter summary use existing ORMS research in this area and follow the order of four stages in the time line and the inclusion relationship in them Figure 18.

2.2.1 Long Range Planning

The analysis of airline network, route plan designing and profitability, fleet and crew resource planning help airlines with future development planning. When conducting long range manpower planning, airline should accurately predict crew needs based on future business developing plan requirements including new market, fleet plans, business and contractual constraints, staff to fill the needs at a minimal cost and optimize the training schedule. (Yu, Dugan, & Argüello, 1998) describe the complexity of manpower planning, and discuss an integrated decision support system for solving it using a heuristic approach. They also describe a mathematical framework for the training assignment module. The pilots who will fly new types of aircraft should assign initial-training while the recurrent-training should be assigned by all crew members to remain qualified to fly in their current fleets. During the time of training, the pilots are removed from the regular roster and a significant cost is imposed. An integer programming formulation is built by (X. Qi, Bard, & Yu, 2004) for the initial-training schedule while minimizing the total weighted length of all classes as the objective.

Furthermore, long-range crew staffing can also be affected by inefficient operational reserve utilization with a result of higher training and new-hire cost. An optimization strategy is proposed by (Milind G. Sohoni, Johnson, & Bailey, 2004) to estimate long-range crew staffing combining operational reserve utilization and premium operational costs due to voluntary and involuntary flying for long-term business needs. The model they use describes this planning problem as a multi-period network flow problem with side constraints. Unlike other researches using average utilization numbers for regular crews, their model proposes an approach that estimates the average line-cap values of constructed regular lines. This index has smaller monthly variation and can be efficiently controlled.

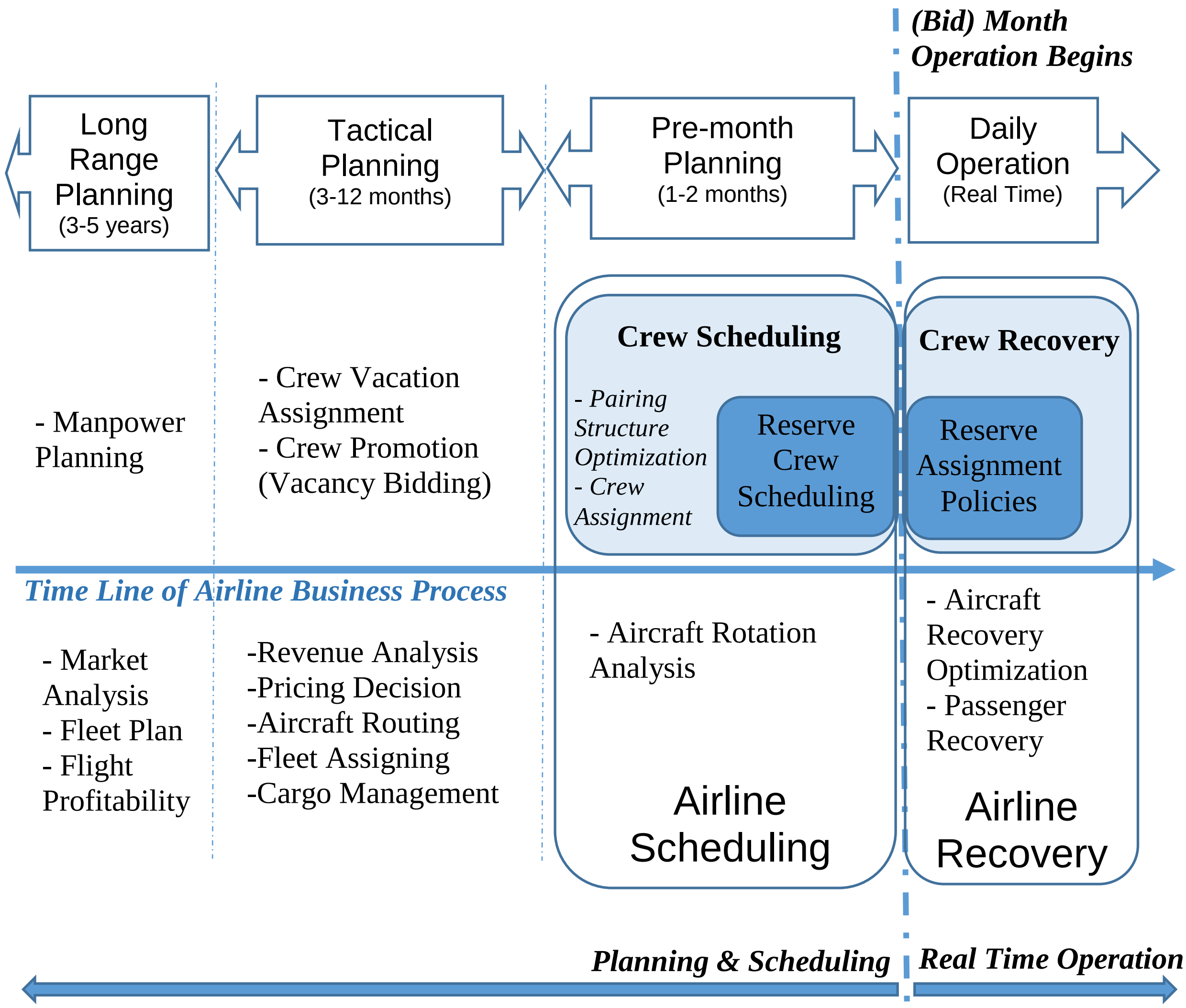


Figure 18. Research Field in Time Line of Airline Operations.

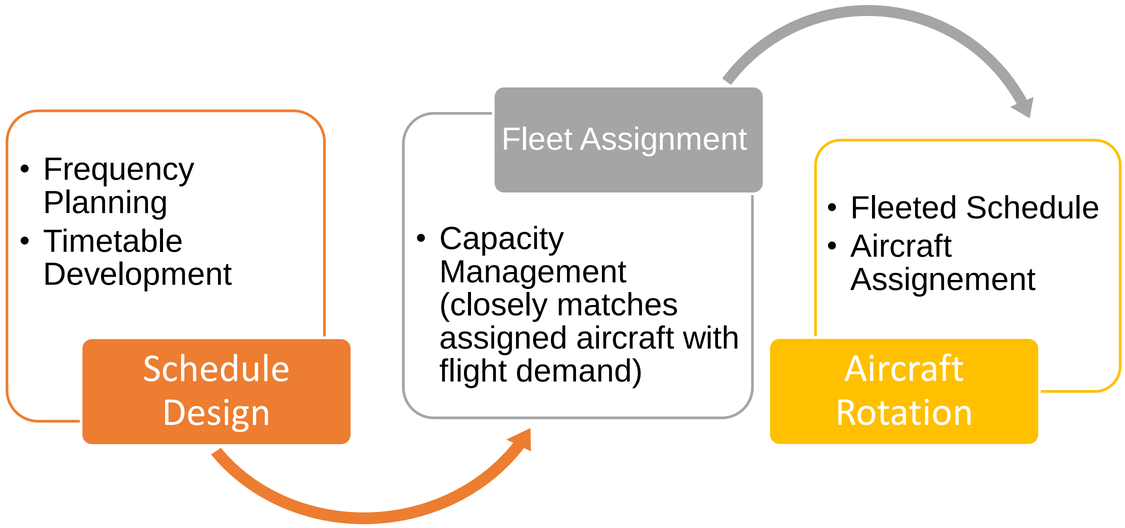


Figure 19. Process of Schedule Development.

2.2.2 Tactical Planning

Schedule planning is a complicated decision-making process engaged by airlines to produce operational schedules. Most of the time, it starts from an existing schedule. The changing demand and environment are reflected by the changes introduced to the existing schedule. These changes are referred to as *schedule development*. The steps of schedule development are shown in
Figure 19.

Airline schedule design is the first stage of schedule development and involves determine makings when and where to offer flights can maximize the profits. The second phase fleet assignment involves assigning aircraft types and amount to flight legs minimizing operating cost and maximizing revenue. Then in the last stage aircraft rotation, routes of flights must be decided to be flown by individual aircraft. The routing design need to ensure that all assigned flights are exactly included in one route and all aircrafts can be maintained when necessary. (Christopher A. Hane et al., 1995) deal with a basic domestic fleet assignment problem as a huge daily multi-commodity flow problem. The side constraints in the model define on a time extended network. Model aggregation and perturbation, dual steepest edge simplex, interior-point algorithm, prioritizing the order of branching and set-partitioning constraints branching are used for attacking this problem. (C. Barnhart et al., 1998) build a single robust model with solution approach which can acquire costs related to aircraft network and complicated constraints like maintenance requirements to solve simultaneously the aircraft routing and fleet assignment problems. They also include additional constraints to require equal aircraft utilization to extend their model to solve aircraft routing problems with solution approach. (C. Barnhart, Kniker, & Lohatepanont, 2002) describe an itinerary-based fleet assignment model and a solution algorithm by considering how to assign aircraft types to flight legs can maximize the profit. (Lohatepanont & Barnhart, 2004) build integrated models with solution approaches simultaneously optimizing the flight legs selection with the assignment of aircraft types to them. Vacation Assignment and Crew Promotion (Vacancy Bidding) are also included in this stage, but very few researches touch the vacation assignment optimization field because it is too sensitive to make any change of it. The only approach in my mind is developing a win-win situation through game theory, but it is not the topic included in this dissertation.

2.2.3 Pre-month Planning

Premonth planning is the third stage developing an schedule for the next bidmonth/month one to two months prior to the beginning day of operation of the whole plan. As stated previously, the research area of reserve crew scheduling is subfield of crew scheduling in this stage. Since it is a critical task that need knowledge in all phase of crew scheduling, a whole picture of relevanct concepts and processes in this stage will be described in this section. Also, reserve crew scheduling is in this stage does not mean it is independent with other stages. The consequence form previous stage tactical planning affect the phase of reserve crew demand estimation and the policies of assign reserve pattern in next stage daily operation also influence the effect of reserve crew scheduling.

(Cynthia Barnhart et al., 2003) provide a detailed overview of the airline crew scheduling problem and (Gopalakrishnan & Johnson, 2005) expand it and describe the reasons why this problem is challenging to address: extremely large number of pairing, complicated work rules and safety regulations from FAA have to be satisfied, the cost structure depending on complex and highly nonlinear crew pay guarantees. Figure 20 describe one simple processes of crew scheduling.

Crew scheduling process is a large complex problem that is always tackled sequentially in many steps such as pairing optimizers, bidline generators and training assigners which are shown in two parallel dotted blocks in Figure 20 (pg. 56) also serve as models in tactical planning stage, but are running during pre-month planning stage once the schedules planning is confirmed to fix. Open time trips is the collection of trips that drop out from regular lines due to any reason such as conflict or iregular operation. Schedules built based on demand estimation during pre-month planning are executed during the (bid)month of operation as assigning open trips to reserve crew members. The detailed concepts and relevance optimization in this process will be discussed in following sections.

2.2.3.1 Pairings Optimization

Pairing is generating sequences of flight legs or crew duties that begin and end at a crew domicile or base such that, in a sequence, the arrival airport of the previous

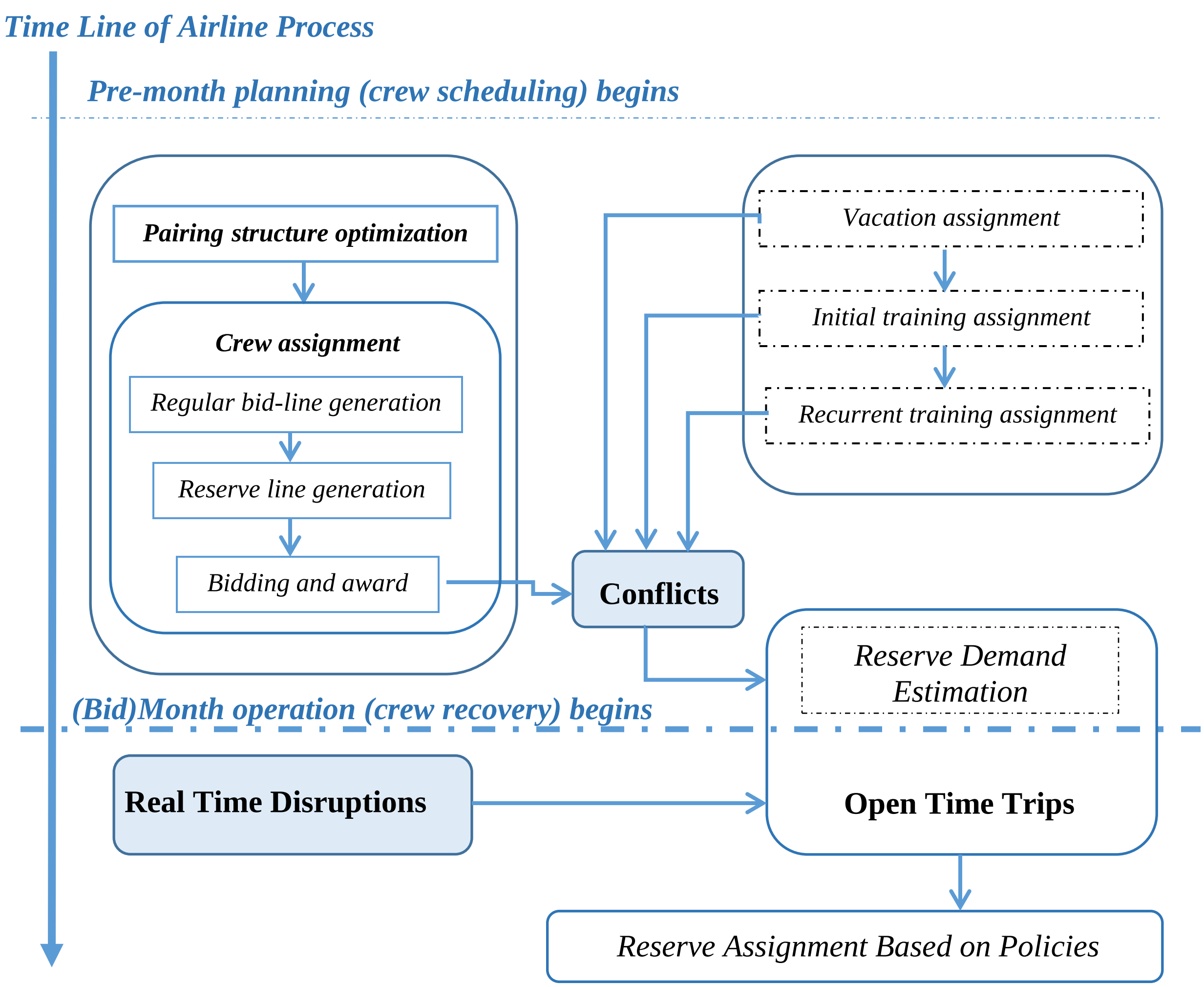


Figure 20. Pre-month Planning Process for Bid Line System Related Airlines

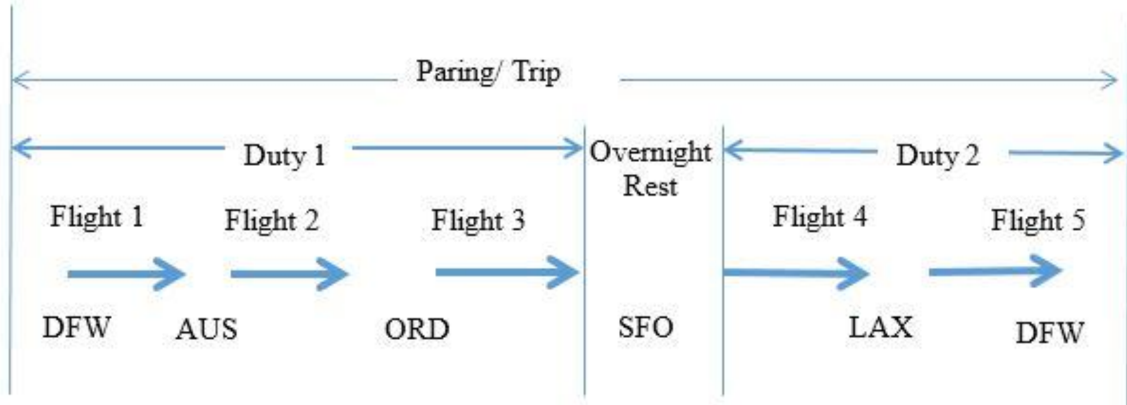


Figure 21. A Sample Pairing Schedule.

flight leg coincides with the departure airport of the following flight leg. A simple sample pairing schedule, including two duties and five flight legs, is shown as Figure 21. Each pairing/trip, including deadhead and layover rest facility, has a respective cost associated with it. The objective of pairing is to find a network with a subset of these pairings to cover all the flight legs in the schedule, minimizing the total cost. Additionally, the optimization model includes a large number of regulations and other side constraints need to be satisfied too.

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Crew seats/category include captain(CAP), first officer (F/O), second officer (S/O) etc. Crew ranks and qualification, such as pilots, are qualified to fly only certain aircraft types and apply different rules for each category. Hence, the pairing problem needs to be decomposed by crew category.

The objective function for pairing the optimization model always need to consider minimizing the total cost and the cost structure of legal duty periods while pairings are defined by FAA and union contract rules. The salaries of crew members almost dominate the overall personnel costs. However, many pairing optimization models only consider the “pay-and-credit” cost that is associated with the time away from base(TAFB) and the cost of deadhead (Glenn W. Graves, 1993).

In most large airlines in the US, the Trip Guarantee (TG: the crew cost of a pairing) is computed as maximizing three quantities that include:

1) Minimum duty guarantee (PMDG): the minimum number of hours that the pilot is guaranteed to be paid for each duty in a pairing irrespective of the length of the duty period;
2) Trip rig: TAFB times the Factor of it which is used as 1 credit hour (CH) for each spesific amount of hours in advance;
3) Total Duty Cost: the sum of the credit hour values of the duty period which is computed using the following formula:

$$Max\{MPDP,\ \ Block\ hours,\ \ Duty\ Rig\}$$

MPDP: minimum pay per duty period
Block hours: the time from block-out to block-in (equal to filght time plus the taxi time) computed on a minute by minute basis.
Duty Rig: the pay credit based on the amount of duty time

Consequently, the following formula can describe how to compute TG:

$$Max\left\{\#duties * PMDG,\ \ Trip\ Rig, Max\{MPDP,\ \ Block\ hours,\ \ Duty\ Rig\}\right\}$$

Regular crew members who are awarded a line shall have a Bid Line Guarantee (BLG) equal to the total TG of all trips in the line. The BLG shall not be less than the minimum bid period guarantee (MBPG) specificed in advance.If the sum of TG for all trips on a crew member's regular line is less than MBPG, such pilot's BLG shall be increased to the MBPG. For each duty, there is a limitation for duty hours based on the period of the duty rig which include day duty, night duty, critical duty and blended duty. These limitations should be taken into consideration when optimizing the pairings. Additionally, for different duty periods, the pay rate is different.

A lot of time and effort was spent on this research area. (Gopalakrishnan & Johnson, 2005) state that a lower bound on the cost of a given schedule can be retrieved from the total time of flights and the pairings with high TAFB associates, with the total flying time are *expensive pairings*. The primary goal of crew pairing optimization is to cover all the flight legs in the schedule exactly once by a subset of pairings with as low cost as the total time of flights in the schedule. This can be solved in two steps: generate all legal pairings with their cost calculated, and choose an optimal subset in these pairings to cover schedule flight legs.

A set partitioning problem(SPP) is a commonly used model for crew scheduling problems to find a subset of pairings covering scheduled fight legs with the least cost has been in the operations research literature for more than 50 years. (Marsten & Shepardson, 1981) improve problem conceptualizations and decompositions. Additionally, they introduce new solution approaches employing Lagrangian relaxation and subgradient optimization. Their application has been successful in airline industry, but still needs to be limited to either small fleets or short round trip durations. (Chu, Gelman, & Johnson, 1997) use a set partitioning zero-one integer program to optimize crew pairing and obtain dual values by solving successive large linear program relaxations which are used to prune the search tree. Other developed formulations based on this basic integer linear program, which is given as follows, have also been used successfully.

$$Minimise: \sum_{j=1}^{n} c_j\, x_j \tag{1}$$

$$s.\text{t.} \quad Px = e \tag{2}$$

$$x_j \in \{0,1\} \quad for\ j = 1,2,\dots,n. \tag{3}$$

In this model c_j is the cost of the column or pairing j and x_j is the binary decision variable to define if pairing j is selected or not. In constraint (2), vector e on right side has m entries equal to one. The matrix P such that each column of the $m \times n$ matrix P represents a legal pairing j and each row represents a flight leg i is constructed as follows:

$$p_{ij} = \begin{cases} 1 & \text{if flight } i \text{ is covered by pairing } j \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Additional constraints, called the “crew base constraints” in the crew scheduling problem, may occasionally be required which basically restrict the TAFB within specified limits. These constraints significantly constrain the allocation of available crews among flights and contribute to the difficulty of solving the crew scheduling problem. These constraints can be fomulated as follows:

$$L_r \leq \sum_{j \in S_k} t_j x_j \leq U_r \tag{5}$$

S_k is representing the set of all pairings that start at the crew base k. t_j is the TAFB associated with pairing j . U_r and L_r are the upper and lower time limits (in hours) for the total TAFB for all the crews relative to pairing j stationed at the crew base k. The set covering problem (SCP) is a closely related problem to SPP which is solved in many ways more easily and is used in many practical applications. The fomulation can be described as follows:

$$Minimise: \sum_{j=1}^{n} c_j\, x_j \tag{6}$$

$$s.\text{t.} \quad Px \geq e \tag{7}$$

$$x_j \in \{0,1\} \quad for\ j = 1,2,\dots,n. \tag{8}$$

In constraint (7), if having “≤” instead of “≥”, the formulation become another problem named set packing problem.

Another contribution factor of pairing cost that needs to be taken into consideration during modeling is deadhead. A *Deadhead flight* (DH) is a transportation of crew members as passengers to resume duty at another location or to return to the base. (Bornemann, 1982) applies the set covering formulation instead by considering deadheadings when the deadheading cost is almost the same as flying a flight leg. (C. Barnhart, Hatay, & Johnson, 1995) propose an approach that all deadhead possibilities can be taken into account by using a network where each arc represents one flight leg.

Based on current literature, approaches to generate pairings can be categorized into three classes: row approach, column approach and network approach. The work from (Ball & Roberts, 1985), (Baker et al., 1985), (Gershkoff, 1989) and (Glenn W. Graves, 1993) are using row approach (Gopalakrishnan et al., 2005). Some pairing systems, such as the TPACS system (Jerrold Rubin, 1973), the ALLPS system (Gerbracht, 1978)the TRIP system (R. Anbil et al., 1991) are using row approach to solve the crew pairing problem. The TPACS system was previously used by several major airlines such us United Airlines and the TRIP optimiser, which is the result of imporving interior point methods and computer rachitecture, is used by American Airlines and Continental Airlines. A methodology is developed during a joint study by American Airlines Decision Technologies and IBM by (R. Anbil et al., 1991) using the IBM Optimization Subroutine Library in conjunction with TRIP to improve solutions on crew-pairing by taking a global approach.

Column generation scheme is usually employed for implicitly generating legal pairings. Many papers spend time emphasizing the value of putting time and effort into this algorism for solving pairing problem. For instance, a noval column generation strategy, a pricing network design and a pairing elimination heuristic are developed by the work of (Zeren, 2016). The master problem of the column generation is a set covering problem and the pricing sub problem is modeled as a short path problem. His work is applied by Turkish Airlines and obtains a very competitive solution compared to the current approach. Also, legal pairings can also be generated using a Dantzig-Wolfe column generation technique (Dantzig, 1960). Since the approach in this dissertation is using column generation too,more details of it will be described in Section 2.2.7.

The network approach is developed from the column approach as basic logic while generating the columns by using the flight leg or duty network. (Lavoie et al., 1988) first introduced this approach and used a flights’ time-space network. (Desaulniers et al., 1997) fomulated a crew pairing problem as an nonlinear, integer multi-commodity network flow problem with additional resource variables. Nonlinearities not only occur in the objective function but also in a large subset of constraints. A branch-and-bound algorithm is used to solve this model based on an extension of the Dantzig-Wolfe decomposition principle. (C. Barnhart et al., 1994) efficiently applied the network approach to solve long haul crew pairing problems. For short haul crew pairing problems, a duty network can be used in place of the network of flight legs, see (R. Anbil et al., 1998), (Desrosiers, 1991), and (Pamela H. Vance et al., 1995).

Multifarious solution strategies have been investigated for the optimization problem of crew pairing over its nearly four decade history. Several approaches are suggested by researchers. (R. Anbil et al., 1991) use special LP and branch-and-bound procedures to solve the resultant SPP to near-optimality, while (K. L. Hoffman & Padberg, 1993) use branch-and-cut solver which introduces an exact algorithm consisting of a joint of a branch-and-bound algorithm with a cutting plane method that relies heavily on facet-generation shcemes. (J.E. Beasley * 1996) presents a tree search procedure incorporating the lower bound which is provided by relaxing the zero-one integer linear programming in a lagrangean way and is improved by subgradient optimization. (Ball & Roberts, 1985) deal with the airline crew scheduling problem through a graph partitioning approach. In their model, flights are corresponded as nodes and crew pairings are corresponded as paths that visit a sequence of flights (nodes). Multiple domiciles as well as deadhead are considered in their model. At each iteration of their algorithm, a set of pairings are extended with an extra flight to proceed. The next iteration is a phase of pairing improvement with a feasibility check for considering acceptance of the pairing set. The main solution strategies used in researches are shown in Table 19 (pg. 62).

2.2.3.2 Crew Assignment (Bid-line Generation)

Crew assignment follows crew pairing optimizing how to assign pairings to individual crew. Different ways of crew assignment are performed by different airlines including bid line, rostering and preferential bidding. In this dissertation, the bid-line generation is highlighted in this chapter. Based on seniority order as well as other considerations, the crew can bid the pairing lines generated from the previous stage. The exact number of cockpit crew members that the airline will require for the next bid period is determined in the crew assignment stage. This problem can be classified into a personnel scheduling problem which includes day-off scheduling (decide work-on-days and work-off days for crew), shift scheduling (choose these crew's actural working hours) and tour scheduling (organization with flexible off-days within a week and flexible shifts within a day).

The bidline generation problem is similar to the crew pairing generation problem. It can be modeled using the set patitioning problem as well. An optimization based bid-line generation system is developed by (Ahmad I. Z. Jarrah, 1997) for a major US airline efficiently reducing the time and sources needed. An automated bid line generator was built by (Campbell, Durfee, & Hines, 1997) for Federal Express airlines to perform what-if analyses of work rules during negotiating contracts with the bargaining unit for the crew. The objective is to minimize the amount of bid lines produced and the amount of flying not assigned to bid-lines.

Table 19. Solution Strategies List.

<table>
<tr><th colspan="3">Solution Strategies</th><th>Literatures</th></tr>
<tr><td colspan="3">TPACS[1]/TRIP[2]</td><td>(J. Rubin, 1971),(Jerrold Rubin, 1973), (R. Anbil et al., 1991) and (Gerbracht, 1978)</td></tr>
<tr><td rowspan="2">Linear programming algorithms</td><td colspan="2">SPRINT</td><td>(Forrest, 1989)</td></tr>
<tr><td colspan="2">Volume algorithm[3]</td><td>(Barahona & Anbil., 1997), (R. Anbil, J. Forrest, and W. Pulleyblank, 1998)</td></tr>
<tr><td rowspan="5">Integer programming methodologies</td><td rowspan="3">Branching techniques</td><td>Follow-on branching[4]</td><td>(Ryan & Foster, 1981), (Vance et al. 1997), (A. J. Hoffman, A. Kolen, and M. Sakarovitch, 1985)</td></tr>
<tr><td>Timeline branching</td><td>(D. Klabjan, E. Johnson, G.L. Nemhauser, E. Gelman, and S. Ramaswamy., 2001)</td></tr>
<tr><td>Stronge branching</td><td>(Linderoth & Savelsbergh, 1999),(Bixby, W. Cook, & Lee., 1995), (D. Klabjan, Johnson, Nemhauser, Gelman, & Ramaswamy., 2001)</td></tr>
<tr><td colspan="2">Branch and cut</td><td>(K. L. Hoffman & Padberg, 1993)</td></tr>
<tr><td colspan="2">Branch and price[5]</td><td>Desrochers et al. (1995), (Anbil et al. 1998), (P.H. Vance et al., 1997)</td></tr>
<tr><td colspan="3">Parallelization</td><td>(Ralphs, Ladanyi, and Trotter 2001), (Panayiotis et al. 2000), (Carmen Systems, 1998), (Klabjan and Schwan 2002)</td></tr>
</table>

1. TPACS: Trip Pairing for Airline Crew Scheduling
2. TRIP: Ttrip Re-evaluationand Improvement Program
3. Volume algorithm: An extention to the subgradient algorithm to produce primal as well as dual solutions present by Barahona and Anbil (1997)
4. Follow-on: The second of a pair of consecutive flights flown in a pairing.
5. Brance and price: The focus is on pricing or dynamically generating columns rather than row or constraint generation as in branch-and-cut. (Gopalakrishnan & Johnson, 2005)

(Christou, Zakarian, Liu, & Carter, 1999) developed a two-stage algorithm to deal with bid line generation problems for Delta Airline. The two phases are the purity phase and the GA phase. The algorithm constructs high-quality lines, as many as possible, in the purity phase and high-total-value valid lines from the remaining open trips to complete the assignments in the GA phase. (Weir, 2002) proposed a three phase methodology to solve bid-line problem. The first phase is to model pattern generation as a bin packing problem. The second phase builds feasible dated bid-lines using the mixed integer programming (MIP) model. The third phase combines the techniques used through the two phases before to solve the problem based on the reduced size of the fixed bid-lines from the second phase.

2.2.3.3 Reserve Scheduling

Most work on crew scheduling are directly aimed at regular crew scheduling and only a few are concerned with reserve crew scheduling. (M. Sohoni et al., 2006) states that while most airlines employ substantial resources to increase their regular crew utilization, not much effort is spent on investigating to increase reserve crew availability and utilization.

Since reserve crew scheduling is a subfield of crew scheduling, some algorisms can be commonly applied for both areas. However, there are a lot of different characteristics that exist between these two research problems. The main considerations are highlighted as follows:

a) Crew cost structure is different for regular crew
b) Reserve line structure is different with regular line
c) Demand forecasting with higher uncertainty with personal factors
d) Complex real time trip assignment decision

The ORMS researches about reserve crew in airlines from two main viewpoints: long-range reserve manpower planning and short-range reserve scheduling. (M.G. Sohoni, 2002) introduce a robust optimization approach for reserve crew manpower planning of airlines. (Gaballa, 1979), (Milind G. Sohoni et al., 2004) and (Boissy, 2006) address reserve scheduling from the manpower perspective as well and the details are discussed in a later paragraph. Other literatures mentioned in this section later have a short-range viewpoint. The latter need the support of good forecasting under uncertainty. Considerations of more complex regulations is the research area focused on in this section. The approach in this dissertation is also from the short-range perspective.

Unlike the cost structure of regular crew cost, reserve crew members in most of airlines are guaranteed pay. They can always be paid with a fixed number of credit hours every bid period no matter if they are assigned to any duty or not. This guaranteed credit hours pay for the crew who awarded a reserve line during the month of operation is called *Reserve Line Guarantee (RLG)*. The exact number of RLG, usually a few credit hours below the TG, is pre-negotiated. In one bid period, RLG is equal to the number of R-days scheduled on a reserve line multiplied by the value of one R-day. The value of one R-day shall be calculated based on fractional rate between the average of BLG for regular lines published in the bid period package and the scheduled R-days number in one reserve line. In spite of maintaining reserve crews, other crew cost contributors are called *premium pay* and the overtime flying cost should be considered. The premium pay which is much higher than R-day value multiplied by duty days, is from uncovered or unassigned flights left for volunteer and draft crew members, by regular line carriers to cover before or during flight operations. The process of reserve scheduling associated with cost generation is shown in Figure 23 (pg. 64).

Unlike the structure of regular line, the reserve line, also called reserve pattern, does not consist of any pairing strung or flights but is composed of on-duty day blocks and off-duty day blocks. Each block consists of different numbers of consecutive days. When an open time trip operates on a day, no matter how many duty hours, that trip is said to intersect this day and it should be counted as a *reserve demand*. There are many ways to define a reserve pattern type. Since pattern types are contract dependent, the potential number of legal patterns can vary from a few thousand to several million. (Milind G. Sohoni et al., 2004) introduces one way to define the pattern type which is determined by the grouping of on-duty days and the grouping of the off-duty days. One sample reserve pattern type 4-2-2-3: 6-4 is given as Figure 22. Reserve pattern type 4-2-2-3: 6-4 implies a reserve line with one block of four consecutive off-duty days in a row, two blocks that include two consecutive off-duty days and one block that consist of three consecutive off-duty days, separated by, at most, six and at least four on-duty days in a row.

Currently, most of the traditional reserve crew model includes three steps which are shown in page 66.

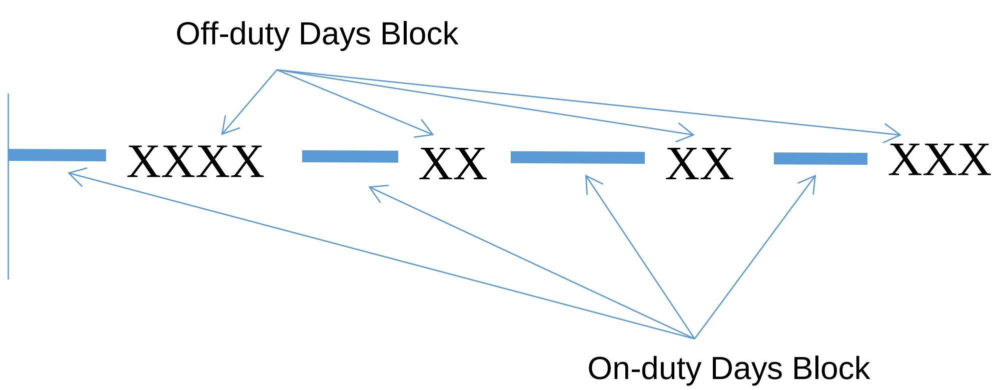


Figure 22. A Sample Reserve Schedule Line Based on a 4-2-2-3: 6-4 Reserve Pattern.

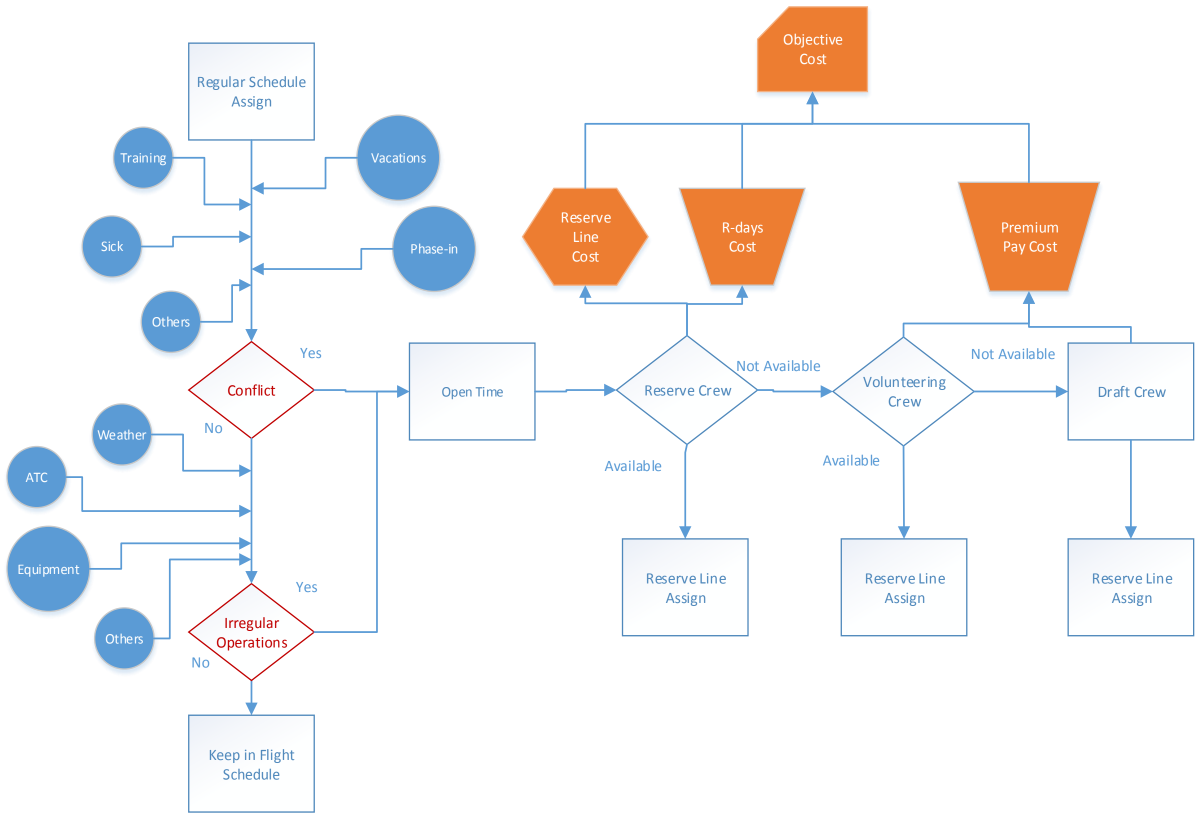


Figure 23. Flow Chart of Assignment for Open Time.

Step1: Estimation of reserve demand (Identify operational reserve requirements): Daily demand or Consecutive days demand;
Step 2: Generation of legal reserve work schedules;
Step 3: Selection of reserve work schedules subset.

Higher reserve availability makes better reserve demand coverage. In other words, reserve scheduling depends on good forecast of open time trips or other kinds of reserve demand. In step one, there are two main ways to define the reserve demand. One is defined by how many required days in each day of the period and another is defined by the consecutive days demand starts on each day.

The work of (Milind G. Sohoni et al., 2004) is a typical example which estimates the reserve demand in required days. Based on this estimation, they develop a two-stage stochastic integer programming formulation to select reserve patterns over a finite number of possible scenarios which specify the number of open time trips occurring on each day of a bid month. The objective function to minimize the total cost including reserve pattern costs and uncovered trip cost.

Reserve crew scheduling is performed in a sequential manner in the work of (M. Sohoni et al., 2006). They designed a multi-staged strategy for reserve scheduling optimization to increase the availability of reserve coverage during real time operations. This strategy is based on planning reserve demand within consecutive days. Multiple optimization models, included in their work, solve the problem step by step as shown in Figure 24.

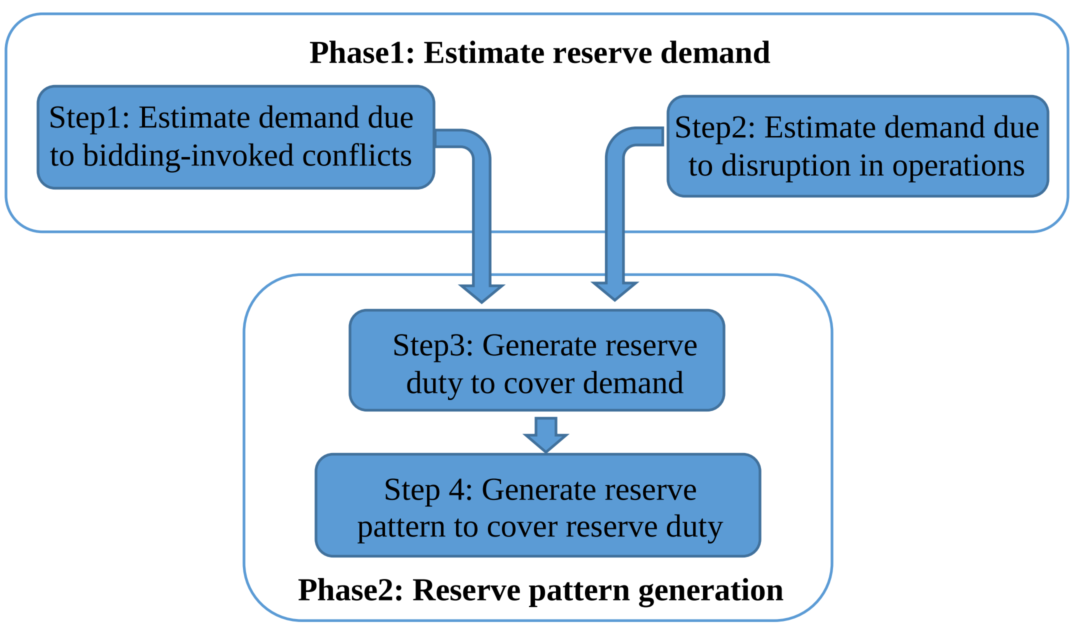


Figure 24. Reserve Crew Scheduling Process.

In the first step, they estimate the reserve demand by building a model maximizing the possible conflicts. They limit the number of conflicts in constraint to make the prediction realistic. In the second step, the simulation tool SimAir is modified to simulate monthly irregular daily operations due to weather and unplanned maintenance. Phase two is split into two steps. First, they generate the reserve duty period to cover all open trips by minimizing the over covering and the total duty periods. This step can be viewed as convert the reserve demand into duty period demand. The last step is to generate reserve schedule to cover these duty periods produced by previous step. The model minimize the total cost associated to the uncover cost and pattern's cost which include a multiplier to score the pattern.

In this dissertation, the reserve demand is forecasted as the second type: consecutive days demand. Since in short-range scheduling, this type of demand is more precise which can direct the optimization model to design better reserve lines to cover them. Comparing with the first type, this type of reserve demand is more difficult to forecast since it include two dimension index. The start date of the open time trip and the length of it need to be ascertained when forecasting. However the output of model is more reliable and it approve that the effort spent on it is valuable.

On the other hand, the reserve demand forecasting is under high uncertainty. Several factors including human factors affect the outcome such as maintenance, vacation assignment, training assignment, sick, fatigue, etc. Different work predicted reserve demand in different way considering different factors. (Milind G. Sohoni et al., 2004) predict reserve demand focusing on conflicts with reoccurring training since they think it one of leading cause of open time trips. (Gaballa, 1979) estimates reserve demand using expected overnight delays and call-out rates for reserve cabin crews and deals with the problem how to determine the capacity of reserve crews with the objective to minimize the total cost of both the reserve crew cost and overnight delays cost. The recommendations were accepted by Qantas Airways Limited in 1977 and resulted in a total annual savings of about AUST. $600,000. (Boissy, 2006) introduces a forecasting model for absenteeism and defines tension as the number of disruptions divided by the number of reserve crews. Using more reserve crew decreases tension but increases the planned crew cost. The model is used to find the optimal tension by minimizing the reserve crew cost and crew missing cost. (Christopher Bayliss et al., 2014) propose a MIP Simulation Scenario model to schedule the reserve crew with the objective to minimize the overall level of disruption over a set of scenarios. The airline's daily operations are simulated with stochastic journey time and the disruption scenarios are generated using crew absence inputs and missing reserve crew. (Bayliss, 2016) develops separate probabilistic models for reserve demand and usage with both crew absence and delay disruptions. The forecasting method in this dissertation is based on historical data of a large US cargo airline. The main reason of producing open time trips may different from passenger airlines. The analysis in different perspective are provided in section 2.3.

The last, but not the least, consideration about the reserve crew scheduling problem that should be discussed here, is the quality of the reserve patterns generated by the optimization model. In a sense, the optimization problem of reserve scheduling can be formulated as minimizing the total number of reserve patterns (a sample shown in Figure 22) to cover the expected number of daily reserve demand as open time trips (a sample shown in Figure 21), which in turn minimizes the total cost of uncovered trip with premium pay and the reserve crew cost who awards the reserve line. The output of this problem is the reserve schedule which is composed of numerous patterns. Reserve demand can be covered by different type of patterns, even with the same total numbers. One duty block with five days can cover 16 different sets of trips, including at least one day at most five day trips. The questions are how to decide which pattern should be chosen and how to decide which set of trips should be covered by a selected pattern?

(Dillon & Kontogiorgis, 1999) proposed a slightly different model for planning reserve schedules at U.S Airways and the objective function of it included their awarded quality points to each bid line and subtracted points for each day with uncovered demand. Legal bid lines are used as the input and each of them has a base score. When they build these bid lines they consider the quality of the reserve crew's work life by adjusting the score based on if the weekend is occupied and if the rest period is long enough. They also mentioned Long reserve duty is better than short because it makes a reserve available to cover more types of open time, so that they give additional points to the pattern with a length of more than three days.

(M. Sohoni et al., 2006) give a similar statement. An example is given as Table 20. There are two duties that need to be covered: Duty 1 and Duty 2 operating on days which are indicated by "1" in the table. Three pattern can be chosen to cover them with "1" as on duty day in the table. The conclusion is given such that if exactly one pattern has to be chosen then choosing pattern 3 can provide a better solution and flexibility to cover any duty and if two patterns can be selected, they would prefer choosing pattern 3 twice rather than choosing pattern 1 and pattern 2 once. Hence, they introduce a function to set the pattern score as follows where S_p is the set of reserve duties can be covered by pattern:

$$I_p = \beta \cdot \ln\left(\left|S_p\right|\right) \tag{9}$$

Table 20. A Sample of Reserve Pattern Selection.

Day	Pattern 1	Pattern 2	Pattern 3	Duty 1	Duty 2
1	0	1	1	1	0
2	1	1	1	1	1
3	1	0	1	0	1

Behind this conclusion, there is an implicit assumption that the reserve demand, like the Duty 1 and Duty 2 in the sample, will equal 100% occur in the coming bid period. Since the demand is estimated by the previous stage, it also means that these demand as input of model is perfectly predicted. In this thesis, the coverage quality of the reserve pattern is considered and this assumption is released in the model and a new integrated approach will be presented in section 2.4.

2.2.4 Daily Operations with Reserve Crew Assignment

The ORMS for this stage includes models for crew recovery optimization, aircraft recovery optimization and passenger recovery optimization. Since the last two are out of the scope of this study we will focus on the crew recovery optimization in this section. Reserve crew assignment is the subfield of it which is highly relevant with the reserve crew scheduling in the previous stage. The biggest challenge of this research area is that the operational environment is complex and it is exacerbated by the need for obtaining a solution in as close to real-time as possible.

Flights are often disrupted by some irregular operations such as maintenance problems, ATC problems and weather conditions which are shown in “Month of Operation Begin” time period of Figure 20. Because of them, several flight delays and cancellation happen in daily operations. These flights are another main contributor of reserve demand. (Petersen, 2012 #46) mentions that because 22% of all flights have been delayed and 3% have been cancelled in the U.S. since 2001, schedule perturbations are inevitable and (Pita, 2013 #43) states that only the delays cost were estimated at around $32.9 billion in 2007 for the U.S. economy. These demands need to be covered in short time to reduce the loss. The reserve crew is a reliable group source that is on call, and the process of reserve crew assignment is applied. Different airlines follow different policies to assign them. The general optimal goal is to minimize the total cost including the operational difficulties and the impact on passengers with side constraints to restrict the safety rules.

Crew recovery for irregular operations is usually the bottleneck of the whole airline-recovering process due to complex crew schedules and restrictive crew legalities as well as the scope and size of the various networks adopted by major carriers. A system wide multi-commodity integer network flow model with a heuristic search algorithm is proposed by (Wei, Yu, & Song, 1997). They support crew management for their real time decisions during daily operations. A recovery plan is provided by (Lettovský, Johnson, & Nemhauser, 2000) to reassign crews to restore a disrupted crew schedule in almost real time applying preprocessing techniques to extract a subset of the schedule for rescheduling. They build a fast crew pairing generator to enumerate feasible continuations of partially flown crew trips and use several branching strategies to allow integer solutions generating fast. (Yu, Argüello, Song, McCowan, & White, 2003) provide an optimization model for crew recovery including a set-covering problem. Since it is a NP-hard problem, a heuristic-based search algorithm is adopted to solve it with a generate-and-test approach. (Bratu & Barnhart, 2006) present scheduling recovery models with algorithms. With an objective of minimizing estimated passenger delay and disruption costs and operating costs. Aircraft, passenger and crew recovery plans are developed simultaneously by determining which flight leg departures should be cancelled and which should be postponed. (Zhu, Cao, Wang, & Gao, 2014) build a constraint programming model to minimize crew recovery cost with temporal-special requirements, deadheading and time legalities considered as constraints. An algorithm based on sequential, least slack and greedy thoughts was designed to search the solution space. (C. Bayliss, Automated Scheduling, & De Maere, 2013) propose a method scheduling reserve crew to minimize the total expected crew related delay. A simulation parameter generation phase was used to derive probabilities of crew related delay and associated expected delay durations.

The current trend of airline recovery is taking all the risk factors into account. Since the process of recovery always needs to be finished in short time, a lot of risk factors exist with a higher possibility. For example, temporary changing of schedule is a big contributor of fatigue risk for the crew. In the sleep study, the crew are irregular sleepers and always need to manage their sleep for the whole trip duty so that they can be alert enough to handle their flying tasks safely. The recovering schedule process may be cost efficient but interrupt the plan of the pilot. Hence, more research is needed to integrate other considerations for optimizing the crew recovery.

2.2.5 Forecasting Techniques

Forecasting is a process of making estimations or predictions of the future by using the past and present data and most commonly by analysis of trends. (Y. D. Yang, 2015), (Dikos et al., 2006) indicated that two methods - Quantitative Method and Qualitative Method – were used to formulate the forecasting model in Figure 25.

Quantitative method includes time series, casual method, and artificial intelligence. Qualitative method contains informed judgement, market research and historical life-cycle analogy, but emphasizes subjectivity and experience of the decision maker: we will only discuss the Delphi method, scenario building and Cooke’s method in this research review. Quantitative method will be detailed in this study especially for time series, regression and artificial. In addition, forecasting contains other methods such as simulation, probability forecasting, etc.

Any kind of forecasting and prediction will bring risks and uncertainties, lower degree of uncertainty to realities is considered as good forecasting or prediction. The source data prepared for forecasting and prediction has to be up to date to improve the accuracy as much as possible.

Accuracy can be measured by error calculation shown in Table 21. Different representations of errors are used in different methods to identify probability distribution. Forecasting Accuracy:

$$E_t = Y_t - F_t \, .$$

Table 21. Error Calculation.

E: Average of Errors	$\bar{E} = \frac{\sum_{t=1}^{N} E_i}{N}$
MAD: Mean Absolute Deviation (with μ as mean)	$MAD = \frac{\sum_{t=1}^{N} \lvert E_t - \mu \rvert}{N}$
MAE: Mean Absolute Error	$MAE = \frac{\sum_{t=1}^{N} \lvert E_t \rvert}{N}$
MAPE: Mean Absolute Percentage Error	$MAPE = 100 * \frac{\sum_{t=1}^{N} \lvert E_t \rvert}{N}$
MSE/ MSPE: Mean squared error/ Mean squared prediction error	$MSPE = \frac{\sum_{t=1}^{N} E_t^2}{N}$
PMAD: Percent Mean Absolute Deviation	$PMAD = \frac{\sum_{t=1}^{N} \lvert E_t \rvert}{\sum_{t=1}^{N} \lvert Y_t \rvert}$
RMSE: Root Mean squared error	$MSE = \sqrt{\frac{\sum_{t=1}^{N} E_t^2}{N}}$
SS: Forecast skill	$SS = 1 - \frac{MSE_{forecast}}{MSE_{ref}}$

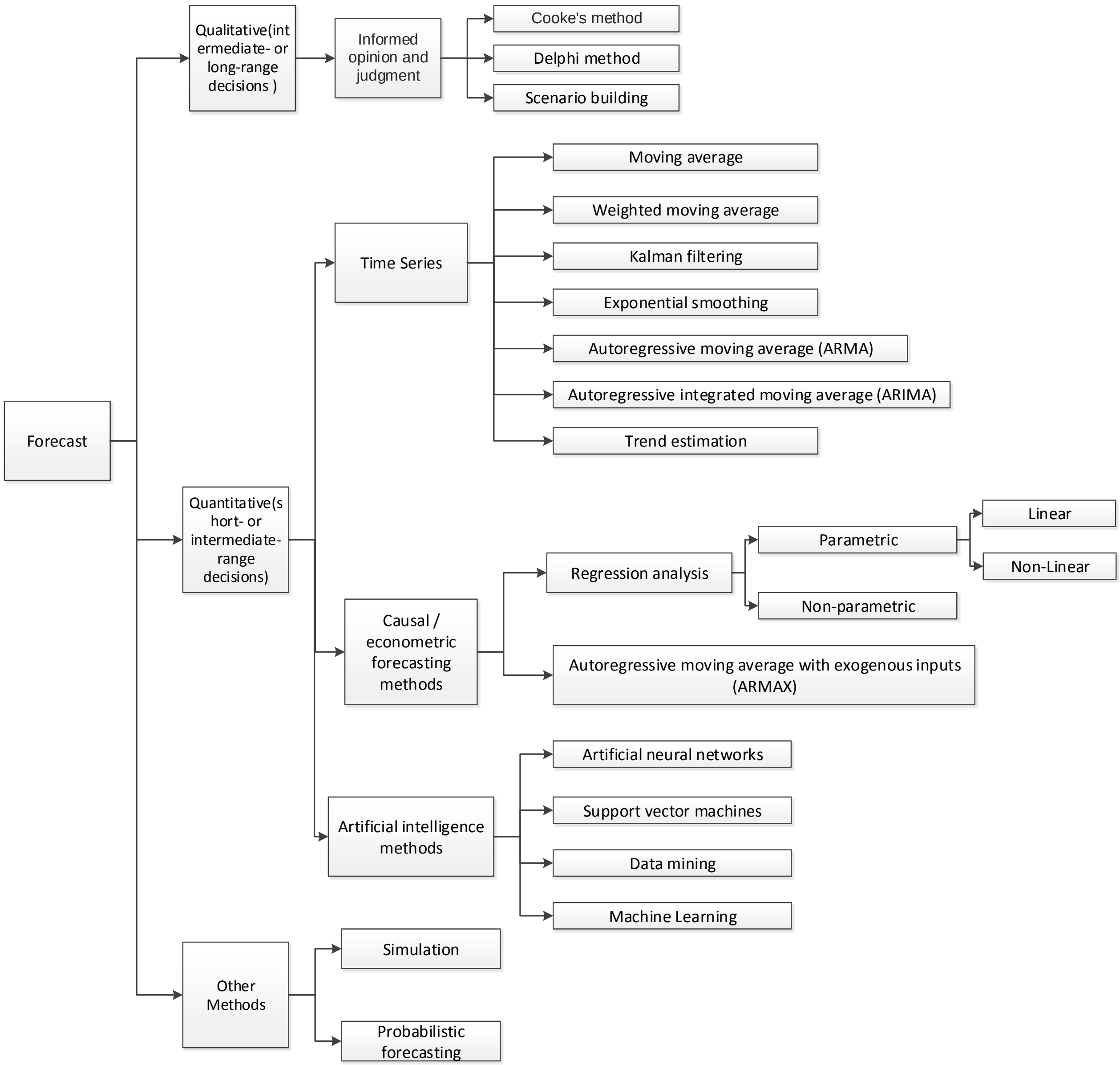


Figure 25. Classification of Forecasting.

Where *E* is the forecast error at period *t*, *Y* is the actual value at period *t*, and *F* is the forecast for period *t*.

2.2.5.1 Quantitative Method

Time series method uses historical pattern data to predict the future. Time unit is an independent variable and indicator; it could be hour, day, week, month, season, year or any regular interval. Time series data could reveal some time depended regular variation like seasonality, trend and cycle. For applied mathematical formulation to represent these changes, many time series techniques were developed. Trend estimation is another concern in time series, it is also an auxiliary tool to make a long term prediction in the qualitative method.

(Yule 1927) firstly proposed concepts of Autoregressive and Moving Average. (Kolmogorov 1941) raises to formulate linear forecasting and solved it. During the 1950s and 1960s, many literature summarized a lot of time series methods on forecasting (Winters, 1960), (Gardner, 1985). Moving average method was an important method on linear or non-linear patterns. (Muth, 1960) was the first to propose the simple exponential smoothing (ES) technique. (Roberts, 1982) and (Abraham & Ledolter, 1986) gradually improve ES in the linear forecast and relative variation: Autoregressive Integrated Moving Average (Tarassenko, Tarima, Zhuravlev, & Singh). All of these works led to deal with parameter estimation, model identifying and checking. Of all these studies, (Box and Jenkins 1970) propose a set of time series theory and main contribution to the ARIMA model which is used widely so far, but the non-linear ES method had not been expanded. In this period, some ARIMA models have equivalent performance on forecasts with the linear exponential smoothing methods. By plotting line according to wide time horizontal, trend, seasonality and cycle could easily be observed.

(Gardner & Mckenzie, 1988) indicated some rules to select proper ES by difference of variations of ES. In following years, ES was applied in various contexts such as computer components (Gardner, 1993), production planning (Miller & Liberatore, 1993) and air passengers (Grubb & Masa, 2001). Non-linear ES methods were developed by (Hyndman, Koehler, Snyder, & Grose, 2002). (Taylor, 2003), (Koehler, Snyder, & Ord, 2001) and (Chatfield, Koehler, Ord, & Snyder, 2001), and 15 different methods were also applied to deal with additive/no trend and additive/no seasonality.

When comparing ES and ARIMA, (Godfrey and Powell 2000) predicted origin-destination (OD) freight flows on a daily basis, authors developed the exponential smoothing method in multiple calendars. When comparing it to the ARIMA model, it has the same accuracy but has a simpler implementation. ARIMA needs historical data to evaluate stationary, besides, if new information is added, it will affect performance of ARIMA. Because, when facing thousands of OD freight flows, noise is not avoided, the parameter of ARIMA needs to be estimated very carefully.

Parameter Estimation is important to identify accuracy in ARIMA. (Box & Jenkins 1994) proposed many methods to evaluate ARIMA parameter, but when facing some finite data they do not work well, because different parameters seemed to have the same normal distribution. (Zellner, 1971) uses a Bayesian method to treat parameter as random variables. (Landsman & Damodaran, 1989) propose that James-Stein parameter estimator has a higher accuracy rate compared other methods. (Newbold, Agiakloglou, & Miller, 1994), recommend using maximum likelihood to estimate parameter by comparing results of different software packages. (J. H. Kim, 2003) found that the bootstrap parameter estimator is more accurate than the least squares estimator.

ARIMA modeling faced some challenges of stationary and non-stationary data. (Brockwell & Davis 1991) divide wide time series as weak stationary, covariance stationary or second order stationary. (Hotta & Cardoso Neto 1993) present that even if the model is not known, when the model is stationary, prediction of aggregate and disaggregate model is still efficient. (Huang et al., 1998) introduced an efficient method to deal with non-stationary time series data with the non-linear process. (Chevillon & Hendry, 2005) use multi-step estimation on stationary and non-stationary to analyze both relationship of forecast accuracy.

(Smith & Demetsky, 1997) indicate that missing data would result in an accuracy problem in time series rather than that in the regression method. (Shumway and Stoffer 1982) combine the expectation–maximization (EM) algorithm with the Kalman filter to allow missing values involved in forecasting. The Kalman filter is recursive algorithm developed by (Kalman 1960) for computing forecast.

Two main Casual/Economic Forecasting Methods are regression analysis and autoregressive moving the average model with exogenous inputs (ARMAX).

Regression method is a statistical process to estimate relationship among different variables. In forecasting, variables of regression are in terms of time horizontal such as day, week, month, season and year and is divided by parametric regression (linear and non-linear) and non-parametric regression. The plot graph needs to be presented the tendency over a certain time frame. One linear regression is actually to find a straight line best fitting all data points, which makes coefficient of the function minimum by equally or exponential weighted least-squares.

(Y. D. Yang, 2015) introduc the normal procedure to formulate the regression model. Before applying the regression method, it is significant to deal with data carefully. McGrill (1995) emphasized, the importance of data censorship in regression modeling when multiple classes exist in demand data. (Karlaftis, Zografos, Papastavrou, & Charnes, 1996) propos a sophisticated framework by using multiple regression methods integrated time series, which formulated the regression model for every time interval in time horizontal. This method was easy to model but parameter estimation relies on many factors, such as residual error, collinear, etc. (Webby & OConnor, 1996) suggest that two methods should be combined to predict a relative accurate result. Collinear exists in the process by using linear regression, and it will affect accuracy of the linear regression model. (de Grange, Farina, & Ortuzar, 2015) indicated the collinear would affect the parameter estimation and ridge regression and the estimator is effective to solve it.

When comparing it to ARIMA, (Chow et al.2010) indicate that methods, such as ARIMA model and linear model, were widely used in direct factoring which is based on economic data and link-to-link volume. However, the range of application is limited and its performances vary from case to case.

Comparing traditional linear regression, (Chou, Liang, & Han, 2011) predicted air cargo volume by using fuzzy linear regression to solve the problem, that is when applying linear regression, accuracy would be various from one case to another. Fussy theory is used to solve this uncertainty, and it also indicates accuracy of linear regression is not decided by measurement but uncertainty error.

The nonlinear model for time series could also be created from the nonparametric regression, that only a small portion of data or information is required (Hardle, Lutkepohl, & Chen, 1997), (Masry & Fan, 1997). However, the large sample sizes of data are probably necessary to formulate the nonparametric method.

ARMAX, derived from autoregressive moving average, has characteristics of time series. But when exogenous inputs are introduced to the mode, it is provided with linearity or non-linearity. Because of the complexity of ARMAX, many optimization or heuristic algorithms were used to solve such problems. (H. T. Yang & Huang, 1998) used fussy theory to solve electricity load demand forecast by applying ARMAX.

One combined optimization problem was proposed and solved with combinatorial methods of heuristics and evolutionary algorithm. One genetic algorithm was used by (D. G. Lee, Lee, & Chang, 1997) to the long-term load forecasting, by using the assumption of different functional forms and comparing the results in regression.

Efforts of researches are also spent on Artificial Intelligence methods such as an artificial neural network (ANN), support vector machine, data mining and machine Learning.

An artificial neural network (ANN) is an effective way for nonlinear process when having an unclear functional relationship and the result is hard to fit (Darbellay & Slama, 2000). The main idea of ANNs is to use one or more hidden layers (or neurons) to filter input or dependent variables, the output would be reached out by self-adaptive methods. (Hornik, 1993) states that one network method can approximately get any continuous function to any despised accuracy. (Hsu, Gupta, & Sorooshian, 1995) develop an artificial neural network in order to have a better representation than ARMAX on non-linear weather forecasting. (Balkin & Ord, 2000) state that ANNs ensure an optimal result for a long time series. Qi (M. Qi, 2001) points out that ANNs do better than other methods when the input data is retained in a recent period, meanwhile (Olson & Mossman, 2003) use recursive modeling to prove it.

Support vector machine is a new machine learning algorithms raised by (Vapnik, 2000) based on the statistics and the principle of structural risk minimization. SVM training algorithm has no problem with local minimum and dimension disaster, with automatic designing model complexity and generalization ability, and has been successfully used for optimal control, pattern recognition and financial forecasts, as well as other fields. (K. J. Kim, 2003) SVM forecasts the stock index and compares forecasting results with the back-propagation neural network method, and the results showed that SVM methods forecasted better than the back propagation neural network in the stock market, and SVM method would have good prospects in the stock market forecasts.

Data mining is used to extract patterns and important information from large data set in various areas. From the marketing side, data mining is largely applied to predict market activity and customer behaviors. The forecast result is usually represented by probability of patterns. The data mining technique is good for static data without a time series frame work. (Cabena et al. 1998) introduced development of data mining and its implementation in different areas. (Pyle 2003) indicated solutions and reliable algorithm when facing some realistic problem of data mining. But small size of data is not suitable for data mining, because some important information could be ignored.

Machine learning like data mining, it is a process to recognize the patterns. But after, some artificial algorithm would teach system to memorizes and learn, behave like human beings. (Werbos, 1988) applied classical models such as linear regression and Box–Jenkins approaches in machine learning. (Mitchel 1997) mentioned that many classical models were developed by machine learning to implement automatically. Some examples of nonparametric nonlinear models were also introduced, which use only historical data to learn the stochastic dependency between the past and the future. Others models appeared such as decision trees, support vector machines and nearest neighbor regression were applied by machine learning (Ahmed, Atiya, El Gayar, & El-Shishiny, 2010).

2.2.5.2 Qualitative Method

(Makridakis, 1988) proposes that judgement the forecasting method or qualitative method is not reliable when predicting economy. (Sanders 1992) and (Sanders and Manrodt's 1994) investigate why manufacturing managers preferred judgmental forecasting methods; the main reasons were accuracy, the difficulty in obtaining data and ease of use. Ease of use was also emphasized in the (McHugh and Sparkes 1983) study, where it was additionally found that the incorporation of experience was regarded as a major advantage for the use of judgmental assessments. Lack of technical knowledge was a main factor for the non-use of more formal techniques, especially for subjective methods such as Delphi and cross impact analysis.

Delphi method is an expertise system, by questioning a group of experts for 2 or more rounds to narrow down the problem and find the “correct” answer. This method has been used widely in many countries for decades (Chakravarti, Vasanta, Krishnan, & Dubash, 1998), (Shin, 1998). (Dransfeld, Pemberton, & Jacobs, 2000) use Bayesian weighting to combine responses to a Delphi questionnaire. They weighted the responses of the panel members on four different factors: experience in the industry, position in the company, position of the company in the industry, and self-rating on each question. For different questions, the ratings of the company in the industry would vary and self-ratings might vary.

Scenario building and forecasting tools help design the future of a project. It is a process of designing a hypothetical situation in a way that helps you predict the consequences of decisions and actions. The advantage of scenario building is simplifying reality for testing, exploring possible actions, and developing a common understanding. But it has some limitations: requires advanced technical skills, quality depends on data, long term presentation and communication.

Jerkins (1997) use morphological analysis to eliminate incompatible combinations of factors, and goal programming to obtain compatible probability estimates for combinations of factors. (Gausemeier, Fink, & Schlake, 1998) present a five-step scheme for developing and utilizing scenarios. (1) focusing on the decisions to be made; (2) taking into account the industry in which the forecaster is located; (3) the industrial environment (including suppliers, customers, competitors and replacement products); (4) the global environment. Proprietary software is used to generate a large number of scenarios; (5) identify the impacts of each possible cluster on the business. The intention of this scheme is to permit the business to prepare for an uncertain future by identifying the major uncertainties.

The classical method was introduced by Cooke (1991). It is used to combine expert’s judgement probability distribution to obtain a risk assessment. This method uses real data to evaluate and calculate weights to combine their probability. Scoring expert’s judgement is the important phase in this method. By surveying different experts, various proper scoring rules are formulated for different variables. This method uses probability theory to interpret variables and provide suggestions (Schervish, 1989). Furthermore, once the scoring rules are mature, the meaningful weights can be created in terms of the categories of variables (Genest & Mcconway, 1990). By scoring judgement, weight is calculated in terms of weight and probability distribution.

2.2.5.3 Other Methods

Probabilistic forecasting uses known results to predict future events. A probability to each of a number of different outcomes is used to merge a set of probabilities which represents probability forecast. The aim of probabilistic forecasting is to maximize the sharpness of the predictive distributions based on the available information. It outputs one scope of results and probability distributions to cross the range for calibrations. (Nuzzolo, Coppola, & Comi, 2013) introduce a research review on probabilistic methods of ground freight demand forecasting. Aggregated model focuses on current demand to predict the future. Minimization of transportation and logistics cost could be classified as an aggregate method. On the other hand, disaggregate model tends to use simulated forecasting of behavior of market players (Cascetta, 2009).

Few researches focus on air cargo, (Mitra & Leon, 2014) use disaggregate probabilistic choice model to identify critical factors impacting the selection of air carriers, but one important factor, logic cost, was not considered in the model. (Jiang,Johnson & Calzada 2011) conduct a national survey on shipper's mode choice data, and predict demand by using disaggregate probabilistic method, although many researchers use such a method to forecast freight demand, it has more limitations in the long term and lack of objective.

Simulation is used to imitate real-world process. However, simulation forecasting is a process by applying time series, causal/econometric forecast method or artificial forecasting to simulate models by inputting different data to evaluate predicted results. Scenarios building is favorable in simulation forecasting, (Ahuja & Nandakumar, 1985) used this method to simulate project cost and finishing time according to numerous uncertain variables including labor absenteeism, space congestion, weather, etc. In energy industry, this method was also used widely to predict different output (Kamal & Jafri, 1997).

In a word, regression model and time series are popular methods to forecast freight demand, but they have exclusive advantages and disadvantages. (Stergiou et al. 1997) compared time series and regression methods by using seven different techniques which belong to these two categories. Both methods have higher accuracy and much better performance, ARIMA and dynamic regression explain more variance than others. Table 22 (pg. 79) indicates difference among these techniques.

2.2.6 Integration Trend

Airline planning is a complex problem and therefore broken down into several stages. The five main stages of it can be summarized as schedule development, fleet assignment, aircraft routing, crew scheduling and airline recovery. Some planning processes may also comprise of aircraft maintenance routing and other stages as well.

Table 22. Pros VS. Cons for Different Forecasting Technique.

Method	Advantage	Disadvantage	Term
Time Series	Recognize trend; seasonality and cycle easily Fit for irregular variations and random variations	Result is sensitive to new variable; Cannot reflect causality between object and influence factors; external factor had big impact	Short - medium
Regression	Simple and convenient; Constant output; Recognize relation and fitness easily	Hard to select factor when multiple variables; Correlation; Collinear	Short - medium
ARMAX	Combine time series and regression concepts	Not easy to implement, need additional algorithm to improve	Short-medium
Artificial intelligent method	Good performance on non-linear; flexibility in changing the encoding of the data	Cannot extract what is the process going to the decisions the method is making; The error sometime is not predictable and accuracy is not stable	Short, medium, long term
Probabilistic	Allow uncertainty and missing value in data set	Cannot guaranteed to yield an ensemble distribution	Short - medium
Simulation Forecasting	Analyze different scenarios according to different method, compare different outputs; Low cost, low data requirement	Good theory needed; No standardize approach; Challenging to validate.	Short-medium
Scenarios Building; Cooke's Method	Simplifying reality for testing; Exploring possible actions; Developing a common understanding	Require advanced technical skills; Quality depends on data; Presentation, communication	Long term
Delphi Method	Saving time and cost of travelling is saved; More participant can involve; Provide a structure way	The process is time consuming; The decision-making process is less transparent; The participant may not go through the who process	Long term

Crew scheduling can be further divided into two phases such as pairing optimization and crew assignment. Reserve crew scheduling has similar solving phases. Ideally these should be solved as a single problem, but it is hard to solve in a reasonable time. Traditionally, these schedule stages are considered sequential. Breaking a complex problem into stages because of its combinatorial nature and can help easier manage each stage because one model focuses on one small part of the problem. However, for each stage, there is always an assumption that the result from the previous stage is optimal. Additionally, the available solution in the following stage may be removed meanwhile the region of solution spaces are removed when solving the problem in the current stage and the optimal solution may be included in it. Since there is always a gap in each solving process, more stages may produce more gap and it is not easy realize. The truly optimal solution is often precluded in the process of sequential approaches. Consequently, the recent trend in this area is integrated stages to solve the optimization problem. Combining some of closely related stages is possible and meaningful. (Gopalakrishnan & Johnson, 2005) state that it is estimated that by integrating crew and aircraft planning, the airline industry could save an additional half a billion dollars per year on crew costs alone. Some effort has been made to take this challenge of the integrated optimization problem.

Fleet assignment and maintenance routing are integrated in the work of (Barnhart, 1998 #49). Sequences of fights are designed as flight strings. A flight string model that can feasibly solve these two problems together is introduced. They assign these two to an aircraft, where origin and destination are at maintenance stations. As a result, any aircraft assigned to such a flight string is therefore maintenance feasible. The trend of integrating airline scheduling sub-problems is reflected in the airline recovery problem.

Integration of the crew scheduling and fleet assignment in the airline schedule problem have been attempted by many researchers. For example, an approach for tackling an integrated network design and fleet assignment problem is presented by (Büdenbender, 2000) in which a hybridized solution approach involving integer programming and a tabu search algorithm are used to solve the problem. An iterative algorithm to integrate crew pairing and fleet assignment is proposed by (Weide, 2009), and their work can iteratively increase the robustness of a given airline schedule. Flight scheduling and fleet assignment are integrated in the work of (Pita, 2013) under a major cause of delays due to airport congestion. Their mixed-integer linear programming model considers airline cooperation and competition. They estimate the market share based on the frequency of competitor's fights, and are acquired by calculating particular airport gate slots to serve demands for numerous origin destination pairs which are in terms of different time periods such as early morning, late morning and early afternoon. Real data from a national air transportation network is used to validate their approach.

About the integration of crew scheduling and aircraft routing, a partial integration of them has been considered by (Klabjan et al. 2002) and (Weide, 2010) propose an interactive approach to robust and integrated them too. (Jamili, 2017) improvably integrate scheduling and aircraft routing with consideration to fleet assignment.

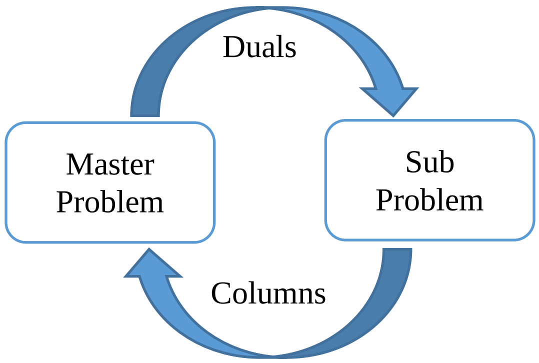


Figure 26. The Logic Circle in Column Generation.

Additionally, an optimization approach is used by (Petersen, 2012 #46) when addressing the full integrated airline recovery problem from schedule recovery through to passenger rerouting. In 2017, (Arıkan, 2017) develops a flight network with flow of each aircraft, pilot and passenger for the integrated airline recovery problem. The conic quadratic mixed integer programming formulation is solved in reasonable time with practical size instance. A novel model integrated Demand-Oriented scheduling and maintenance routing for point to point airlines is presented by (Faust, 2017 #23) with three solution algorisms to solve it.

All the recent works on the integrated airline scheduling problem contribute to a step move closer to achieving the dream of integrated scheduling. More works are needed to be done for developing efficient integrated approaches and solution methodologies to solve airline scheduling optimization problem. In this dissertation, one of the key contribution is integrating reserve forecast, reserve line generation and optimization.

2.2.7 Column Generation

Column generation is an efficient algorithm used for solving large mix integer linear problems. Since many linear programs are too large to solve with all variables explicitly in a reasonable time, column generation algorithm can be used to reduce the size by controlling the variable pool. Only the variables with the potential to improve the objective function are generated. In 1958, Ford and Fulkerson initially proposed the formulation of column generation. In order to solve the problem, it is split into two problems. The original problem carries as few variables as possible is called as master problem. After solving the relaxed master problem (RMP), the dual price for each constraint is obtained. The sub problem is created for identifying and bringing new variables into the basis as needed with objective function as the reduced cost of the new variable with respect to the current dual variables. The dual prices from the master problem are used to run the sub problem. The new column is continuously added to the master problem with the process repeating until no more good column can be found. These processes are like a circle which is shown in Figure 26. The process of adding the column triggers a new run of relaxed master problem. Finally, the master problem is solved with all variables including the ones added in process. Since not all possibilities are enumerated, it saves a lot of solving time. The classical example of a problem where this is successfully applied is the cutting stock problem. Crew scheduling is one key traditional problem which often apply column generation. It is also the case to a lot of the sub level problems of it.

In 1960, Dantzig–Wolfe decomposition algorithm is proposed by (Dantzig, 1960). This is also a efficient algorithm that can be applied to the problems in the crew scheduling research area such as pairing design. Some other algorithms are developed based on column generation algorithms in recent years. For example, column and row generation is developed to extend standard column generation to further save solving time by reducing the master problem's size through eliminating constraints. (Maher, 2016) use it to solve an integrated airline recovering problem and identify a number of general techniques to further enhance it. He also compared this column and row generation with the column generation algorithm.

2.3 Problem Description and Formulation

The problem addressed in this dissertation is based on the practices of one U.S. major carrier. They did a good job on scheduling management and some effective approach has been developed to deal with open time trips. Since the process has a high uncertainty, the time line is really important since the more information is known the better forecasting can be. To solve the reserve scheduling problem, the whole process of current reserve management process has to be understood. In order to understand the whole process in time line and the details need to be taken into account when modeling, a flow chart is developed which is shown in Figure 27 (pg. 83). Crew Reserve management starts a month before the Bid Month and runs through the stage of pre-month planning and daily operations. When Flight Schedule arrives, the process of Trip Development and Optimization begins. The trip pairings are designed in this process and as an input to be sent to the next steps of the process to build lines. The optimization model in the line building stage needs to take most of the regulations related to flying lines into account as makes sure all regular lines are legal ones.

When regular line building is finished through an optimizer, the BLG is fixed. All regular lines for each crew position will be ready for bid package releasing. At the same time, the number of available crew for reserve will be determined based on pilot staffing information, and this will be the capacity of the resource of reserve crew. The traditional way to calculate this number is to estimate the requirement of regular line holders and subtract it from the total active crew number. Unlike other airlines, this major airline developed an effective method to cover one type of open time trips which will be dropped out from regular lines because of in-phase conflicts. In-phase conflict is the biggest contributor for open time trips and the number of this demand is relatively easier than other effecting factors.

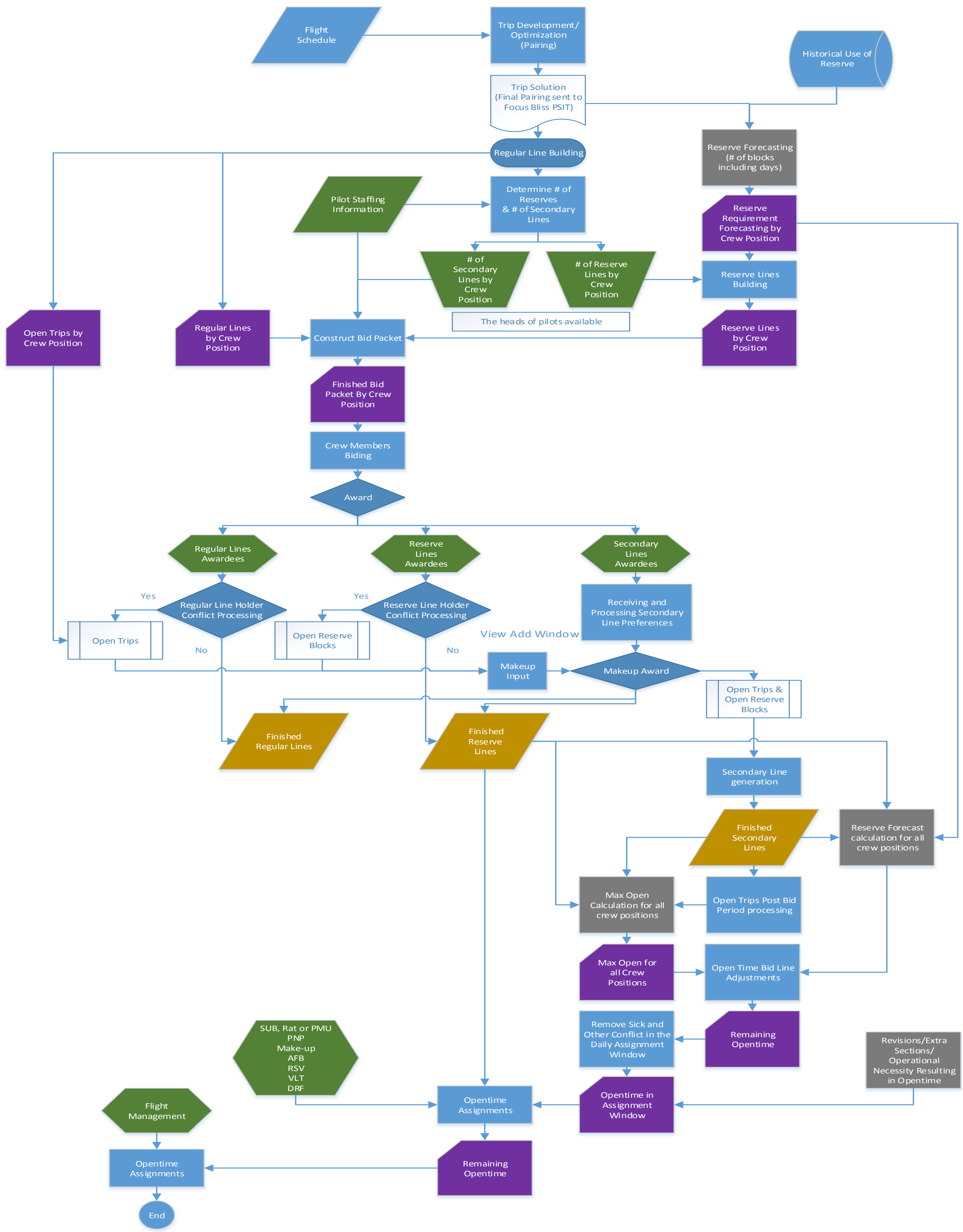


Figure 27. Flow Chart of Reserve Management.

Holding a group of crew to cover these trips before operations will highly relieve the pressure of reserve crew scheduling. This consideration became a reality several years ago and has been applied successfully so far. This special group of crew has be separated through stuffing process, so that the reserve crew capacity will be the total number of available crew minus the sum of the number of regular lines holder and the special lines holder. W is used to indicate this capacity.

The reserve forecasting process starts and in this step the reserve demand, such as the total reserve days, is estimated based on the schedule and the historical usage of reserve. The reserve demand can be predicted in two ways, as mentioned in section 2.2.3, the required days and the consecutive days demand starts on each day. The required days are called R-days. If open time trip insert the day no matter how many minutes, that day can be called R-day in demand forecasting process. The R-day is also the unit of payment for reserve line or bloke. The consecutive days demand is the demand of each trip type. Trip type is defined by two destinations: trip length and the start date of the trip.

The current reserve forecasting method includes two phases. The first phase is to forecast the total required R-days in the next bid month by multiplying the sum of the average of the last five bid month's percentage of open time trips left waiting to be covered by the reserve crew (RVDA rate) and the standard deviation of them by the total days in scheduled trips for the targeted bid month. This predicted R-days amount is used as the targeted total demand in the next phase. The reason to pick five months is because it is not too many to lose the develop trend or too little to be affected by the outlier. The second phase is forecasting the demand of each type of trip in the targeted bid month respectively. This method is reasonable because the specific length trip on a specific day has specific characters. For example, some of the trips are regularly flown following a same or similar time-table with a long history and they are bid by a similar group of crew. Separately forecasting them can highlight the hidden law of trips dropping in it. Since the crew only bid lines in his or her own position, the reserve demand needs to be separately forecast for different seats. Similar consideration is needed for Crew Base. For each trip type, there are four steps to complete the forecasting. The first step is using historical data to predict the number of actual trips. The historic ratio of schedule to actual trip is calculated based on the data in the last five months. The total number of scheduled trips in the last five months is divided by the total number of actual trips in the last five months to get this ratio. The second step is forecasting the dropping rate of this specific type of trip. The historical rate in the last five months is used to predict. The third step is to forecast the open time trips demand by multiplying the predicted number of actual trips to the RVDA rate. The last step is adjusting the numbers to make sure the total R-days demand obtained in the first stage are fully satisfied by all the reserve lines and also the fractional part is rounded into the integer.

December is the peak period, and the number of regular lines is always bigger than other months'. As a result, the number of trips dropped out from them is always much higher than other months too. They are treated as the outliners, so that the reserve forecast of this month is not involved in this method but predicted in another way.

One important aim, in this part of dissertation, is to improve this forecasting method, making this method the foundation of the whole process of analysis and forecasting in next section. More details will be discussed in Section 2.4.

The output of this forecasting stage is a metric with the predicted number of open time trips as elements. The column indicates the length of the trip and the row indicates the date in the bid period. This output will be the input of an optimizer with an optimization model which builds reserve lines to cover most of the forecasting reserve demand. The minimum percentage of coverage of these reserve demands is decided as a rule in advance. The number of lines is also restricted by the capacity of available reserve which is acquired in the previous stage.

The output of the optimization model is a set of reserve lines which are also called reserve pattern carrying some blocks with on-duty days and some other blocks with off-duty days. The blocks with a few on-duty days in a row is called on-duty block and the blocks with a few off-duty days in a row is called off-duty block. The reserve pattern is not related to any real trips when a crew member bids them in this stage. Since the optimizer often builds too many short on-duty day blocks, before releasing these reserve patterns, schedulers need to manually adjust some of them according to their many years of practical experience in this area. For example, sometimes they combine the adjoining short on-duty blocks into a long one to increase the possibility of the availability of covering various types of trips.

Another aim of this part of the dissertation is to build high quality reserve patterns that can help schedulers' work. An approach with an optimization model and algorithm is provided for solving this problem in Section 2.5. This approach not only considers the coverage with the cost as least as possible but also takes the quality of the pattern into account. The quality of the pattern is described by the possibility of coverage of the various types of trips in the schedule. The process is to implicitly simulate the process in the schedulers' brain and more objectively and mathematical based. The final objective is that with this tool, the schedulers can have enough confidence of the reserve patterns output and will not need to adjust the reserve pattern manually any longer.

The reserve lines will be released at the same time with regular lines. The document which included these lines is called Bidpack. When Bidpack is released, the bidding process starts and not only the average BLG, the highest line credit, the low line credit and average days off but also the RLG and the credit value of R-day are shown to all crew. Crew members bid the lines in an order by seat which is called seniority order. The crew member who picks a regular line will be in the regular crew group and the crew member who bids a reserve line will be in the reserve crew group. In this way, the airline doesn't need to hold a permanent reserve crew group. This flexible way gives the pilots a chance to pick a good schedule which is suit to his or her own life in the targeted month. However, the coin has two sides. Since the reserve lines are bid in the same time window with regular lines, it is not possible to acquire the information of who holds which regular line. This information is really useful to predict the future dropping performance through data mining. This is a point to further improve reserve forecasting which will be discussed in Chapter III.

In the process of bidding lines, conflicts happen for various reasons. Some trips are dropped into open time trips pool waiting to be reassigned. These trips will not be assigned to reserve patterns until the daily operation stage. Another effort made by this major airline is to leave some open time trips in the awarding process and let crew members swap their trips with these open time trips. This is also a process to relieve the pressure of reserve crew scheduling. There are some other efforts made to cover open time trips better which will not be discussed in this dissertation because of limited space.

One of key contributions of this part of the dissertation is that the approach integrated the reserve demand forecasting stage and the reserve pattern design stage. The current traditional approach for solving this kind of problem always needs to consider them as two separate stages and sequentially solve them. The implicit assumption existing in the latter stage of this kind of approach is that the outcome of the previous stage is correct, which is not always the case. More details will be presented in Section 2.5.

Finally, the daily operation begins and the reserve pattern will be assigned some open time trips. At the same time, more trips are dropped out from lines because of irregular operations. These trips will be put into open time trip pool and need to be reassigned by reserve crew in short amount of time. A specific assignment policy is applied by schedulers in daily operations. The quality of the reserve patterns directly affect the work of the reserve assignment as mentioned in a previous section. The quality of assignment policy also directly affects the achievement of the use of reserve patterns. Also, a reserve assignment policy, which highly matches the priority of the reserve pattern, needs to be developed. This policy can have the greatest effect on all reserve patterns. Since it is another complex and tactical task in the airline research area, which is not what this dissertation focuses on, it will only be discussed in Future Work (Chapter III).

2.4 Crew Reserve Demand Forecasting

2.4.1 Data Material Description and Preparation

The historical data sets used in this dissertation are all provided by one major airline carrier. All data sets are the real data set including all data from 2001 until now. The size of the observation is more than 3 million.

FLEET2_DESC	[redacted]	RESERVE_SEGMENT_C...	SEAT1_CD	RSV_SEGMENT_LENG...	ADD_ASGMT_CD	BID_MTH_DT	RSV_START_DT	DAY_IN_MTH_NBR	WEEK_IN_MTH_NBR	WEEKDAY_NM
11	N	A	C	2	RSV	APR01	04/08/2001	7	1	Sun
11	N	A	F	3	AST	APR01	04/26/2001	25	4	Thu
11	N	A	F	4	AST	APR01	04/06/2001	5	1	Fri
11	N	A	F	4	SOF	APR01	04/23/2001	22	4	Mon
11	N	A	F	10	AST	APR01	04/11/2001	10	2	Wed
11	N	A	F	5	AVA	APR01	04/02/2001	1	1	Mon
11	N	A	R1	5	AVA	APR01	04/02/2001	1	1	Mon
11	N	A	R1	9	AST	APR01	04/21/2001	20	3	Sat
11	N	A	R1	4	RAT	APR01	04/23/2001	22	4	Mon

Figure 28. Data Set with Trips' Detail.

Data set one holds all detailed trip data including the reserve coverage information in which each row indicates one trip. The trips in this data set are actually operated by crew. Therefore, they are called actual trips. There are three indexes that need to be identified to each crew member: Base, Fleet and Seat. Base refers to crew base, that is the work location where one hub of airline is located and the beginning and ending of the trip are always at this location. Deadhead is also built into the pairing to transport crew to this base whose domicile is not at the same place. There are six crew bases in this major airline. Fleet is which aircraft type the crew member is active on, and there are five main fleets for this major airline. Crew Seat means the crew member's position on fleet including Captain, First Officer and Second officer. One crew can only bid the reserve line in one pool based on his or her three indexes. Another index which can be used to sub size the data base is called "Reserve Segment" respectively. "Reserve Segment" is the time period of the reserve duty. Each month, the proportion will be set to them as another query index. Based on these indexes, the data set can be separated into more than 360 subsets, which need to be analyzed separately since the trips have too many different characters. For example, the trip that starts in "Reserve Segment A" is during the day and the trip that starts in "Reserve Segment B" is at night. The possibility of dropping trips is affected by fatigue and other factors which make it different from each other. Additionally, for each fleet, the data in which years can be seen as reliable data are different. For example, Fleet X has a long service history so all the data since 2001 can be used for analysis. Fleet Y just started to service for several years so the data before 2010 may not be good for analysis. The range of data used for each Fleet needs to be decided in advance.

In this dissertation, the group of the captions flying Fleet X, whose base is in the biggest crew base, is sampled as the target for forecasting. For further query, the index "Segment" is set to "A". The size of this subset is around 0.2 Million. The sample of this data set is shown in Figure 28.

In each subset data base, the main details include the information of the trip such as the trip length, the start time of the trip and the code of assignment status. All confidential information will not be included in this dissertation, such as the flight number, the crew

Table 23. A Sample Day in Bid Calendar.

	Year	Month	Day	Weekday
Natural Calendar	2017	1	1	Sunday
Bid Calendar	2016	12	35	Sunday

ID number and the origin and destination of trip. Since this airline applies a different calendar for scheduling which is given the name “Bid Calendar”, there is another set of data that refers to this type of time information for the trip. Bid Calendar always includes twelve Bid Months and each of them starts from Monday and end Sunday. There are five Bid Months having five weeks and other Bid Months having four weeks. The day is numbered from one to 28 in four-week Bid Months and from one to 35 in five-week Bid Months. Another way to define the day in the Bid Month is by using “The Week in Month” index and the Weekday index. For example, day one can also be called the first Monday and day nine can also be called the second Tuesday. The day defined in Bid Month is often not the same as the date in the natural calendar because not all natural months start on Monday. However these two calendars have the same weekday. For instance, in Table 23, Sunday in Bid Month is also Sunday in Natural Month although the date is different in two kinds of calendars. The reason why the airline has a Bid Calendar is because it is good for scheduling reduplicative trips. However, crew live in a natural life with family and friends. Their behavior is inevitably affected by the natural calendar not only when they bid the line but also when they assign vacation, training and operating. Consequently, both of these two sets of indexes should be considered in the forecasting process.

Similar feature need to be considered for the trip start time as well. Two different ways to identify it are Base Time and Zulu Time. Since different Crew Base may locate in different time zones and international flights often fly through several time zones, Zulu time is needed to schedule trips. However, the regular habit of crew, as well as their life is based on local time. For example, the crew that operates night duty feels fatigue easier because of his circadian clock. This “night duty” is not relative to Zulu time or other time zones but the one at the base of this crew. The night in the US is the day in China. The analysis based on this data base need to consider this too. A sample is shown as follows:

DEC16	01/01/2017	35	5	Sun	01/02/2017	02JAN2017:01:10:00	02JAN2017:10:10:00
DEC16	12/31/2016	34	5	Sat	01/01/2017	31DEC2016:17:00:00	01JAN2017:02:00:00
DEC16	12/31/2016	34	5	Sat	01/01/2017	31DEC2016:23:00:00	01JAN2017:08:00:00
DEC16	12/30/2016	33	5	Fri	12/31/2016	30DEC2016:15:45:00	31DEC2016:00:45:00

Figure 29. Local Time vs. Zulu Time.

The columns from left to right indicates “Bid Month”, “The Start Date of Trip”, “The Bid Day in Month”, “The Bid Week in Month”, “Weekday”, “The Zulu Start Date of Trip”, “ The Local Start Time of Trip” and “ The Zulu Start Time of Trip”. As we can see in Figure 29, the same trip has two different start time indexes. The two time types can make the data grouped into different day of the month, different month in a year and even in different years. Hence, when preparing the data for forecasting, we need to take more care. All analysis in SAS for this data set below is based on local time because it can explain human performance better.

Another important index in this data set is the code of assignment which contains the information of which group the crew who operated this trip is in. Through this, the historical monthly usage of reserve crew, volunteer crew and other crew groups can be calculated.

Data set two holds the trip schedule information for each Bid Month including the number of each trip type. Trip type is identified by the trip start date and the trip length. The data set also needs to be split into subset based on the same query indexes as those in Data set one. Data set three holds the detail reason of open time trips and Data set four hold the usage information of reserve crew. All data sets are used in later analysis in this section. Some of them need to be merged into one and unify the format of the data.

Since each fleet, base, seat and reserve segment has its own characteristic, the analysis should be separated for each of them. One sub data set called “M1NAC” with specific fleet, base, seat and reserve segment is queried as a sample in this section.

2.4.2 Current Reserve Usage Analysis

(M. Sohoni et al., 2006) report that the utilization of reserve crew is less than forty percent for the schedule instances they considered. Eleven years later, is this number be improved? The Data set four is used to analyze the current utilization of the reserve crew. This data set includes the real time operations data of the reserve crew. Like regular line holders, the reserve line holder can also drop some reserve days in their active reserve pattern with reasons such as “Recurrence Training”, “Legality”, “Sick” and “Vacation”. One of the reasons is called “Released” is based on the regulation that the reserve crew cannot be on call for succeeding seven days. At least one day need to be released from the reserve pattern if this crew has been on reserve call for six days. Unlike the regular line building process, the stage of building reserve line does not include all regulations which will be taken into account in the stage of reserve crew assignment. The low utilization of reserve crew makes this reasonable, because if only 40% of reserve days will be used, the possibility of the chance to release these kind of reserve day is small. As we can see in Figure 30 and Table 24, the average of yearly utilization is around 36%. The best mean of monthly utilization is about 43% in 2014 and the lowest one is 28% in 2016. However, this utilization includes all dropped reserve days with any reason such as vacation and sick.

Table 24. Means and Descriptive Statistics for Utilization.

Bid Year	Mean	Std. Dev.	Minimum	Maximum
.	0.35605	0.090956	0.17043	0.56152
2010	0.37737	0.074069	0.22475	0.48211
2011	0.40941	0.065927	0.32212	0.53543
2012	0.31388	0.093255	0.17043	0.48030
2013	0.33002	0.072426	0.24702	0.49696
2014	0.42992	0.063016	0.32036	0.56152
2015	0.38203	0.090271	0.21047	0.53394
2016	0.27598	0.046691	0.19481	0.36430

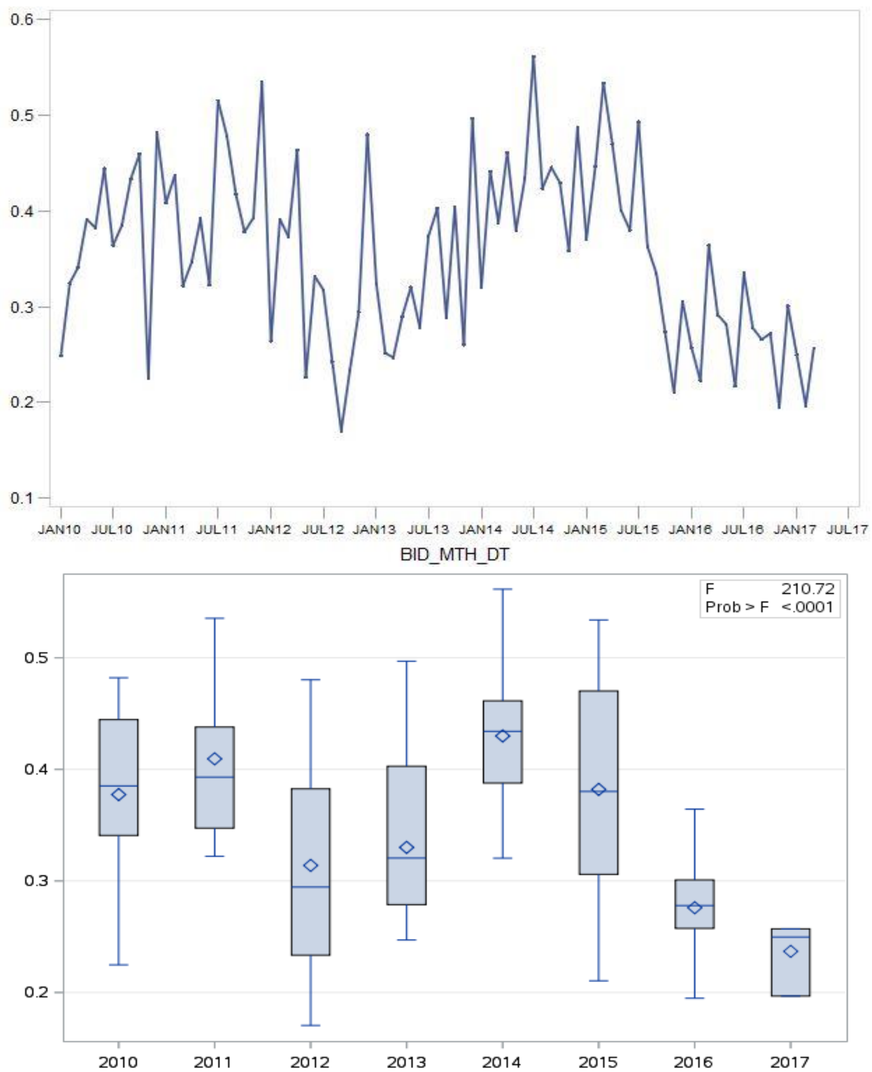


Figure 30. Utilization Distribution since 2010.

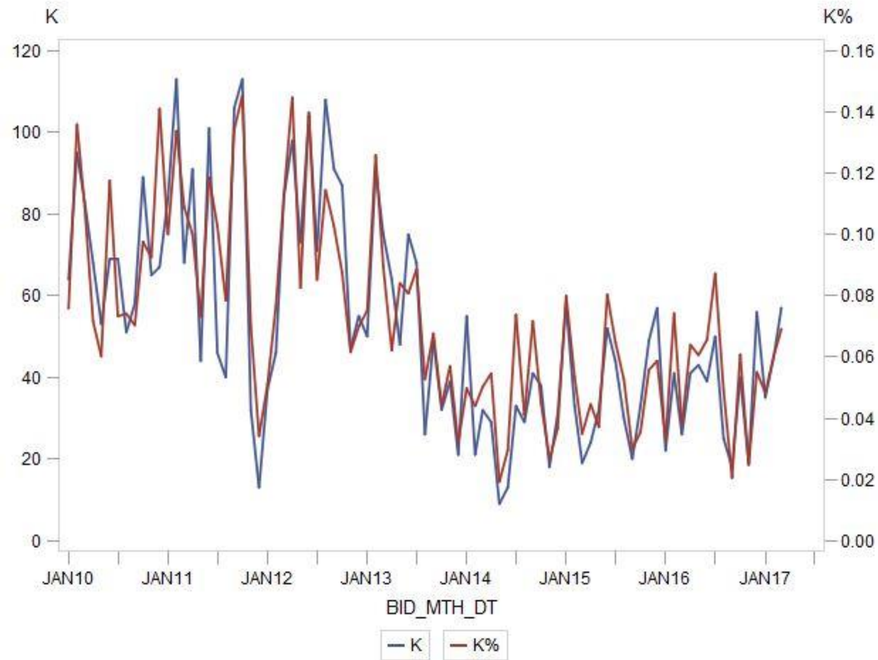


Figure 31. Dropping Reserve Days with Code Sick.

The number of reserve days dropped because of sick and the percentages are shown in Figure 31. It shows a good trend since both of them decreased since 2014. They still keep a low rate around 6%. Hence, sick is not the reason for the low utilization on 2016.

Further analysis is done to calculate the pure utilization in which only the assigned reserve days and the unused reserve days are included. The results are shown in Figure 32 (pg. 92) and Table 25. The mean of monthly pure utilization is 65% and the best mean of monthly pure utilization is 76% on 2014. The pure utilization on 2016 is still not high, but the deviation is lowest. The monthly utilizations in column "minimum" show that currently there are still some months waste more than 50% reserve days.

Table 25. Means and Descriptive Statistics for Pure Utilization.

Bid Year	Mean	Std. Dev.	Minimum	Maximum
.	0.65223	0.14625	0.35273	0.95500
2010	0.71229	0.13974	0.37890	0.89384
2011	0.72532	0.08873	0.58092	0.82993
2012	0.54601	0.14121	0.35273	0.78109
2013	0.59247	0.11511	0.46213	0.79177
2014	0.76430	0.12647	0.48895	0.95500
2015	0.70721	0.16395	0.42431	0.91060

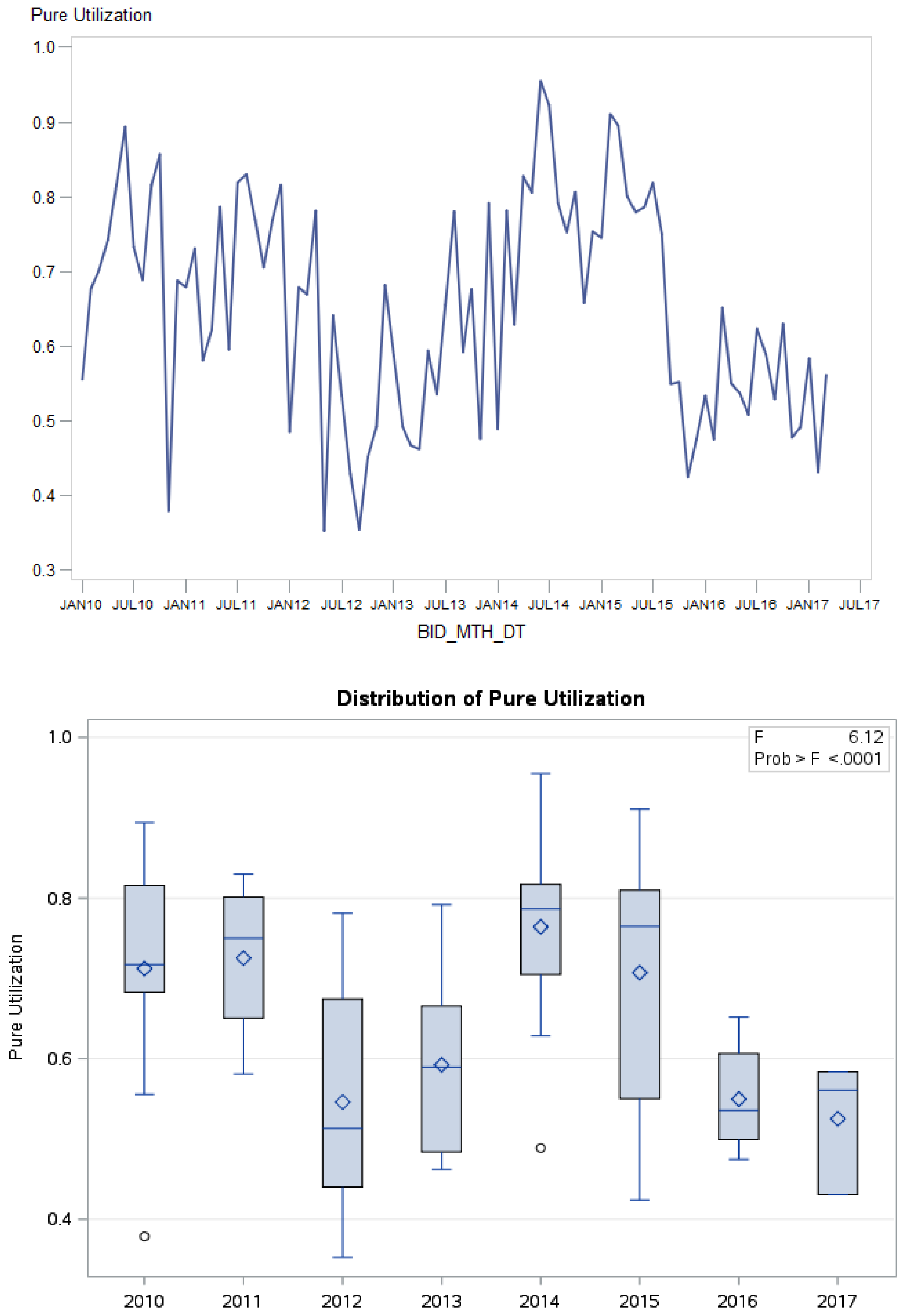


Figure 32. Pure Utilization Distribution since 2010.

2.4.3 Coverage Analysis

Utilization is one key indicator of reserve scheduling. Increasing utilization can save a lot of reserve crew cost for the airline. However, we can't get a conclusion only based on utilization because the purpose of reserve crew scheduling is to cover the open time trips dropped out of regular lines. Even if all the reserve crew are100% used to cover open time trips, the uncovered open time trips left would need to be covered by other volunteer crew with a higher cost. As a result, another key indicator of reserve scheduling needs to be analyzed when evaluating an optimization approach. The current coverage is analyzed based on the data in Data set three. As we can see in Figure 33 and Table 26 (pg. 94), the mean of monthly coverage is about 83%. The coverage is improved in this five years. However, there are still five months in 2016 with coverage lower than 70%. Developing a good approach to improve reserve scheduling is meaningful and valuable.

The analysis of the reason of dropping trips is also made based on Data set three. The main reason for regular line holder dropping trips is "Sick" which is 21.57%. Figure 34 shows four distributions for reason "Sick", "Training", "Vacation" and "Weather". The horizontal is the Bid Month time line and the vertical is percentage of the reason. The first two reasons do not show strong seasonality but the last two do. The peak for "Vacation" is March, July and November and the peak for "Weather" is winter.

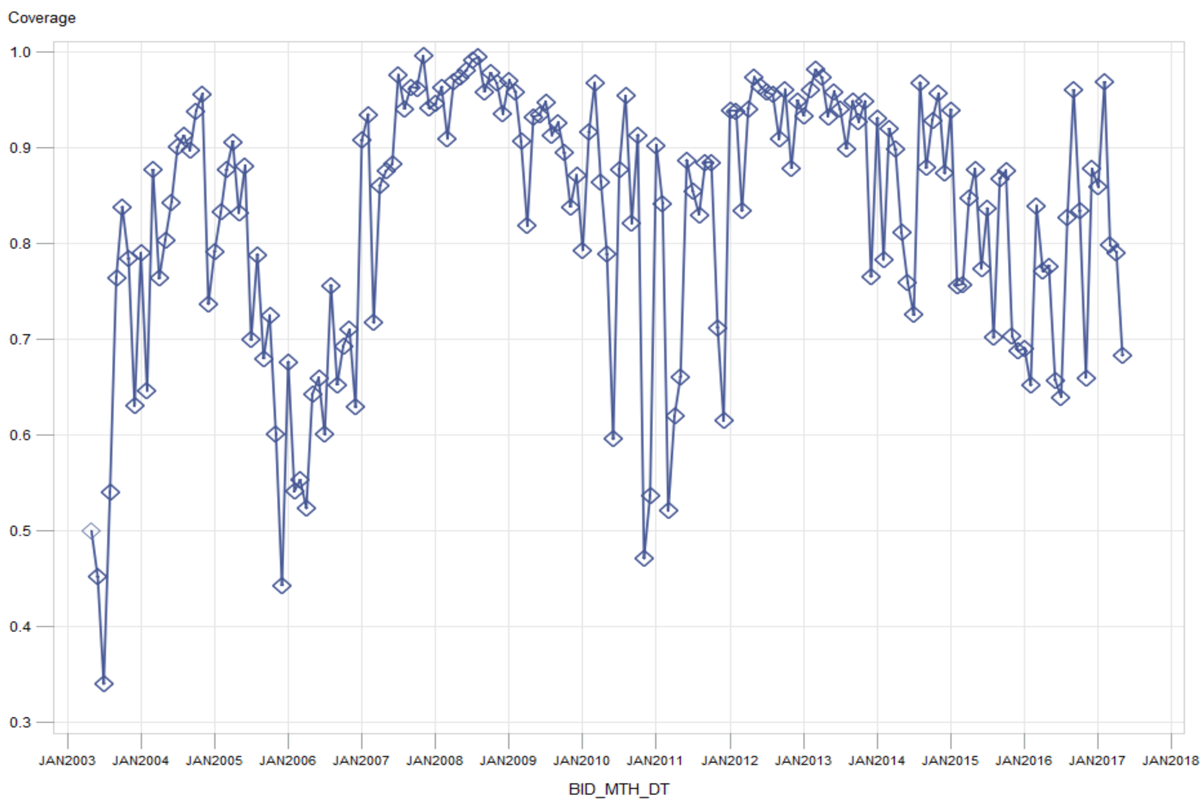


Figure 33. Coverage Distribution since 2003.

Table 26. Means and Descriptive Statistics for Coverage.

Bid Year	Mean	Std. Dev.	Minimum	Maximum
.	0.82742	0.13637	0.34066	0.99631
2003	0.61931	0.17339	0.34066	0.83838
2004	0.83932	0.08932	0.64677	0.95673
2005	0.75519	0.12953	0.44335	0.90686
2006	0.63681	0.06838	0.52402	0.75646
2007	0.91366	0.07179	0.71803	0.99631
2008	0.96444	0.02326	0.91017	0.99512
2009	0.90985	0.04504	0.81908	0.97110
2010	0.79211	0.16097	0.47165	0.96813
2011	0.76831	0.12902	0.52155	0.90323
2012	0.93390	0.03907	0.83483	0.97407
2013	0.93122	0.05440	0.76600	0.98198
2014	0.86997	0.07780	0.72589	0.96825
2015	0.80258	0.07978	0.68809	0.94005
2016	0.76589	0.10138	0.64010	0.96066

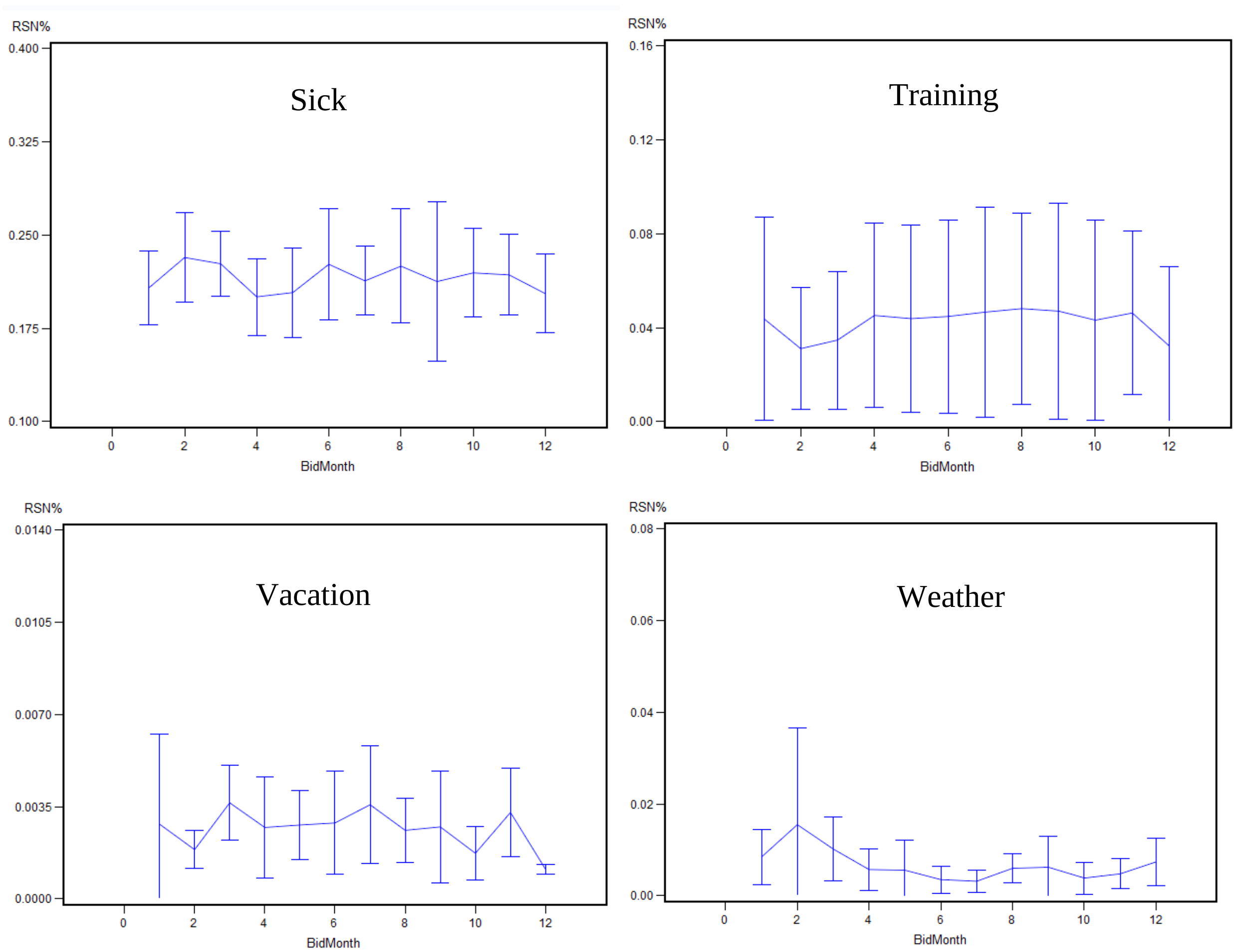


Figure 34. Distributions of Dropping Rate by Reason.

2.4.4 Preliminary Analysis

In order to predict monthly reserve demand, a number of analyses are done to target the key variables to build the forecast model.

In all data sets, the range of factor trip length is from 1 to 17. The mean distribution is shown in Figure 35. As shown in Table 27, the F statistic and corresponding p value are reported in the Analysis of Variance table. Because the reported p value (<0.0001) is less than the alpha level 0.05, we reject the null hypothesis. Hence, the means for different length trips are significantly different. Also, in Levene's Test, the p value (<0.0001) is less than the alpha level 0.05 too, so that the null hypothesis that the variances are equal is rejected too. Consequently, the factor trip length is one key variable for the forecast model.

Table 27. ANOVA Results for RVDA% by Trip Length.

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	98.879300	6.179956	105.35	<.0001
Error	40871	2397.509617	0.058660		
Corrected Total	40887	2496.388917			

Levene's Test for Homogeneity of Final RVDA% Variance ANOVA of Squared Deviations from Group Means					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
RSV_SEGMENT_LENGTH_QTY	16	6.0410	0.3776	12.85	<.0001
Error	40871	1200.8	0.0294		

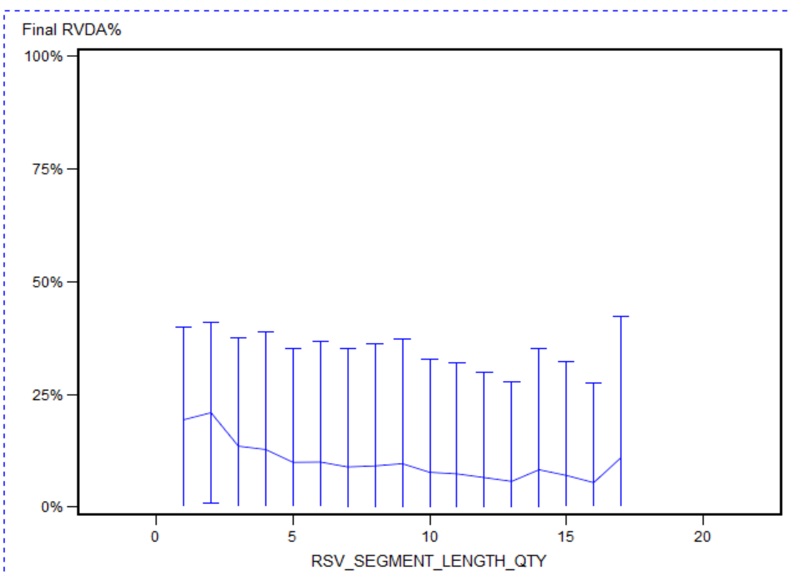


Figure 35. Mean Plot for RVDA% by Trip Length.

The range of factor Year is 2001 to 2016. As shown in Table 28, the result of one-way ANOVA indicates that the means of RVDA percentage for different years are significantly different. The rate around the year 2008 is relative low in Figure 36, but is reasonable because of the economic situation. However, there is no clear trend that can be followed to forecast the next year's rate mean. Year is not used as a main variable in forecasting model, but this analysis should be done every year to monitor the trend and if the economic has significant change an appropriate adjustment should be done for forecasting.

Table 28. ANOVA Results for RVDA% by Bid Year.

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	37.518055	2.501204	41.58	<.0001
Error	40873	2458.857661	0.060158		
Corrected Total	40888	2496.375716			

Levene's Test for Homogeneity of Final RVDA% Variance ANOVA of Squared Deviations from Group Means					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
BidYear	15	15.5683	1.0379	40.54	<.0001
Error	40873	1046.3	0.0256		

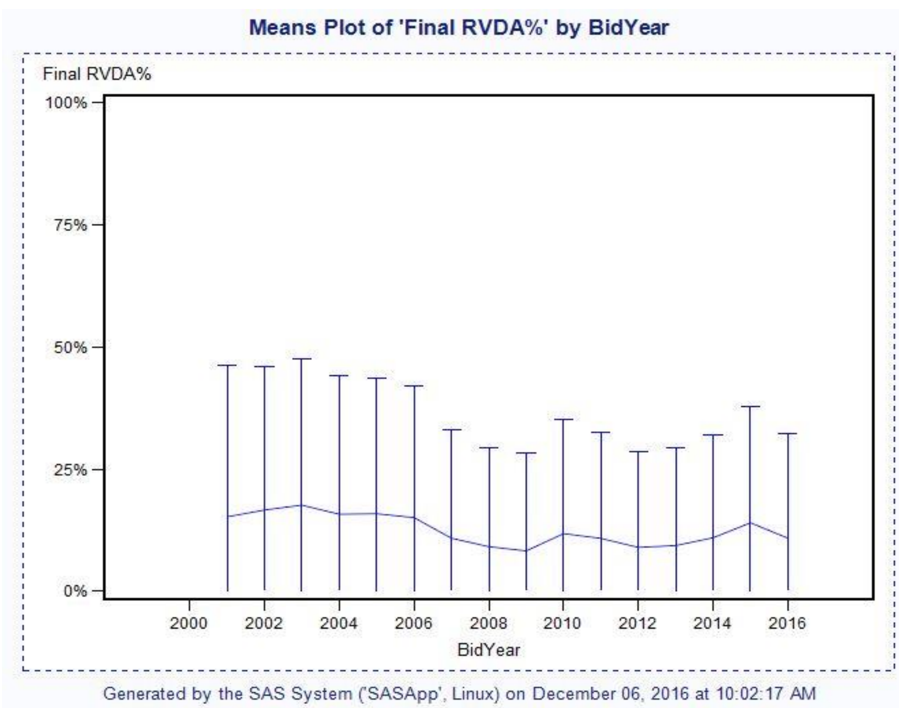


Figure 36. Mean Plot for RVDA% by Bid Year.

The range of factor Bid Month is from 1 to 12. As shown in Table 29, the result of one-way ANOVA indicates that the means of RVDA percentage for different months are significant different. Also, in Levene's Test, the p value (<0.0001) is less than the alpha level 0.05. Hence, the null hypothesis that the variances are equal is rejected too. As we can see in Figure 37, the peak takes place in March, July, November and December. The possible reason may be that spring break is in March. July is summer and Independence Day is in this month too. November with Thanksgiving and December with Christmas are both traditional holiday months in the US. Consequently, the factor of Bid Month is one key variable for the forecast model.

Table 29. ANOVA Results for RVDA% by Bid Month.

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	5.900030	0.536366	8.80	<.0001
Error	40876	2490.488886	0.060928		
Corrected Total	40887	2496.388917			

Levene's Test for Homogeneity of Final RVDA% Variance ANOVA of Squared Deviations from Group Means					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Month	11	1.0405	0.0946	3.49	<.0001
Error	40876	1109.3	0.0271		

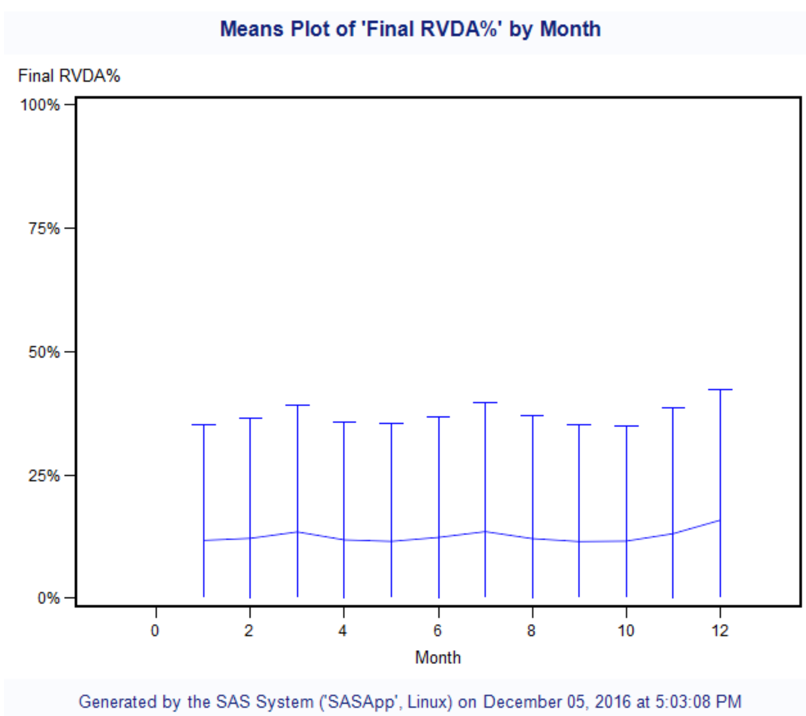


Figure 37. Mean Plot for RVDA% by Bid Month.

The factor Weekday is in the range from 1 to 7. Sunday is marked as 1 and Monday is marked as 2 and so on for each weekday. As shown in Table 30, the results of one-way ANOVA indicates that the means of RVDA percentage in different weekdays is significantly different. Also, in Levene's Test, the p value (<0.0001) is less than the alpha level 0.05 so that the null hypothesis that the variances are equal is rejected too. Consequently, the factor of Weekday is another key variable for the forecast model. As we can see in Figure 38, Sunday is a peak point. Secondary peak points are Wednesday and Friday. Since the trips on Sunday are much less than other days, the result should be further verified. Another consideration is that there are some holidays on Monday which make the schedule change in some rules. Also, several trips start on Monday, so the possibility of fatigue events is relevantly low compared with the later duty days in the trip.

Table 30. ANOVA Results for RVDA% by Weekday.

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	18.886396	3.147733	51.94	<.0001
Error	40881	2477.502520	0.060603		
Corrected Total	40887	2496.388917			

Levene's Test for Homogeneity of Final RVDA%% Variance ANOVA of Squared Deviations from Group Means					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Weekday	6	13.1537	2.1923	83.48	<.0001
Error	40881	1073.5	0.0263		

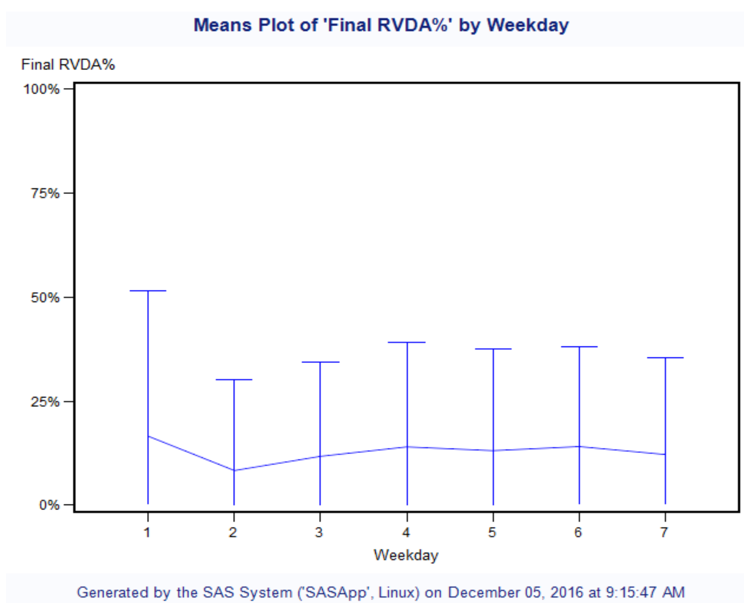


Figure 38. Mean Plot for RVDA% by Weekday.

The range of factor Day in Bid Month is from 1 to 35 for 5-week bid month and form 1 to 28 for 4-week bid month. The first Monday is marked as day 1 in bid month. As shown in Table 31, the result of one-way ANOVA indicates that the means of RVDA percentage for different days in month are significantly different. Also, in Levene's Test, the p value (<0.0001) is less than the alpha level 0.05 so that the null hypothesis that the variances are equal is rejected too. As we can see in Figure 39, all Sundays are peak points. Secondary peak points are 3rd, 17th, 26th and 31st which are on Wednesday or Friday. This chart has further proven that the weekday is a key effector. Since not all bid months have the fifth week, the results for the fifth week is not reliable enough and should be further verified.

Table 31. ANOVA Results for RVDA% by Day in Bid Month.

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	34	22.391517	0.658574	10.88	<.0001
Error	40853	2473.997399	0.060559		
Corrected Total	40887	2496.388917			

Levene's Test for Homogeneity of Final RVDA% Variance
ANOVA of Squared Deviations from Group Means

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
DAY_IN_MTH_NBR	34	14.4643	0.4254	16.29	<.0001
Error	40853	1067.1	0.0261		

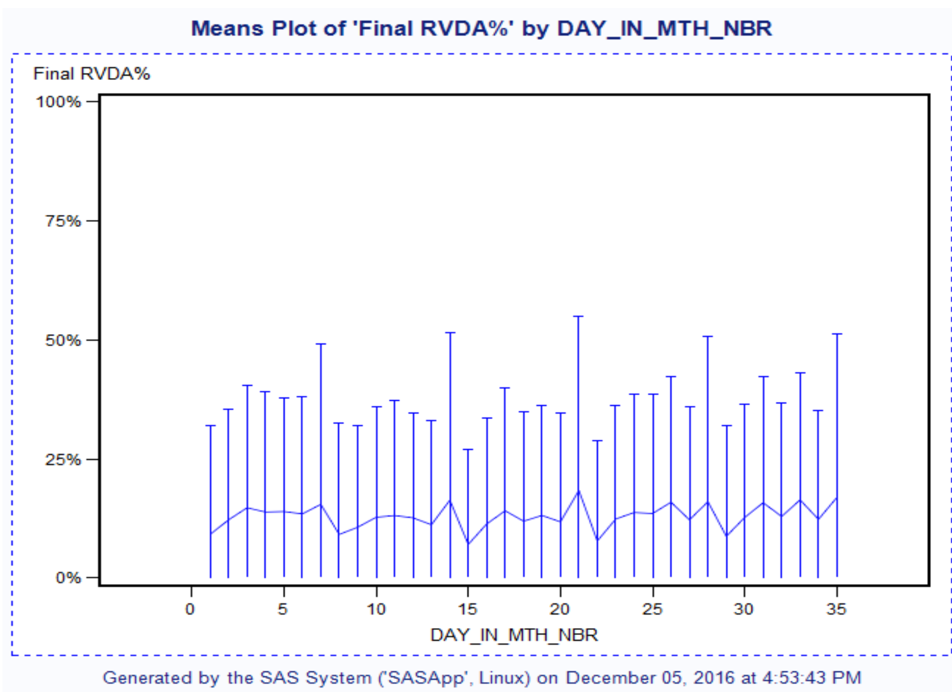


Figure 39. Mean Plot for RVDA% by Day in Bid Month.

Table 32. ANOVA Results for RVDA% of 3-Day Trip by Day in Month.

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	34	3.3565292	0.0987214	1.73	0.0053
Error	5112	291.4931170	0.0570213		
Corrected Total	5146	294.8496462			

For further analysis, the seasonality of the data and the causal factors behind it, a number of analyses for trips with different length were done. As we can see in the left top chart in Figure 40 (pg. 101), the seasonality is pretty strong, especially the peak on Sunday and the valley on Monday. Secondary peaks on Friday and Wednesday are also significant. However, the line on Sunday is much higher than others which indicates that the rate is 100% once in a while. The thing is very few trips start on Sunday and they are usually dropped. The chart at right top is for two-day trips. The seasonality is also strong, but Sunday is not always the peak. Friday, Saturday and Sunday become the peaks. These days are weekend days which make sense. The three-day trips dropping rate is shown in the chart at the bottom left. Monday is still on valley point, but the peak points are not on Sunday any more. The result from ANOVA, which is stored in Table 32, shows that the p value (0.0053) is less than 0.05 which means that the means for each weekday is still significantly different. The chart at bottom right is for four-day trips, and the seasonality is weaker, but somehow there still exist a trend such that the rate increases from the valley point on Monday to the peak around Wednesday and then decreases.

Comparing these four charts, we can see that the seasonality for short trips is stronger than long ones and the trend is not the same as each other.

To efficiently schedule all pairings, the definition of Bid Month is introduced as a bid period. The current forecasts are based on Bid month not calendar month. Some analyses are done for comparing the trend in these two types of month. As we can see in Table 33 and Table 34(pg. 101), both p value (0.0182 and <0.0001) are smaller than 0.05 which indicates the means in Bid Month and the means in calendar month are both significantly different.

Table 33. ANOVA Results for RVDA% by Day in November (Bid Month).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	34	4.8778441	0.1434660	2.23	<.0001
Error	3269	210.5709724	0.0644145		
Corrected Total	3303	215.4488165			

Table 34. ANOVA Results for RVDA% by Day in November (Calendar Month).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	29	3.0332855	0.1045961	1.63	0.0182
Error	3357	215.6078834	0.0642264		
Corrected Total	3386	218.6411689			

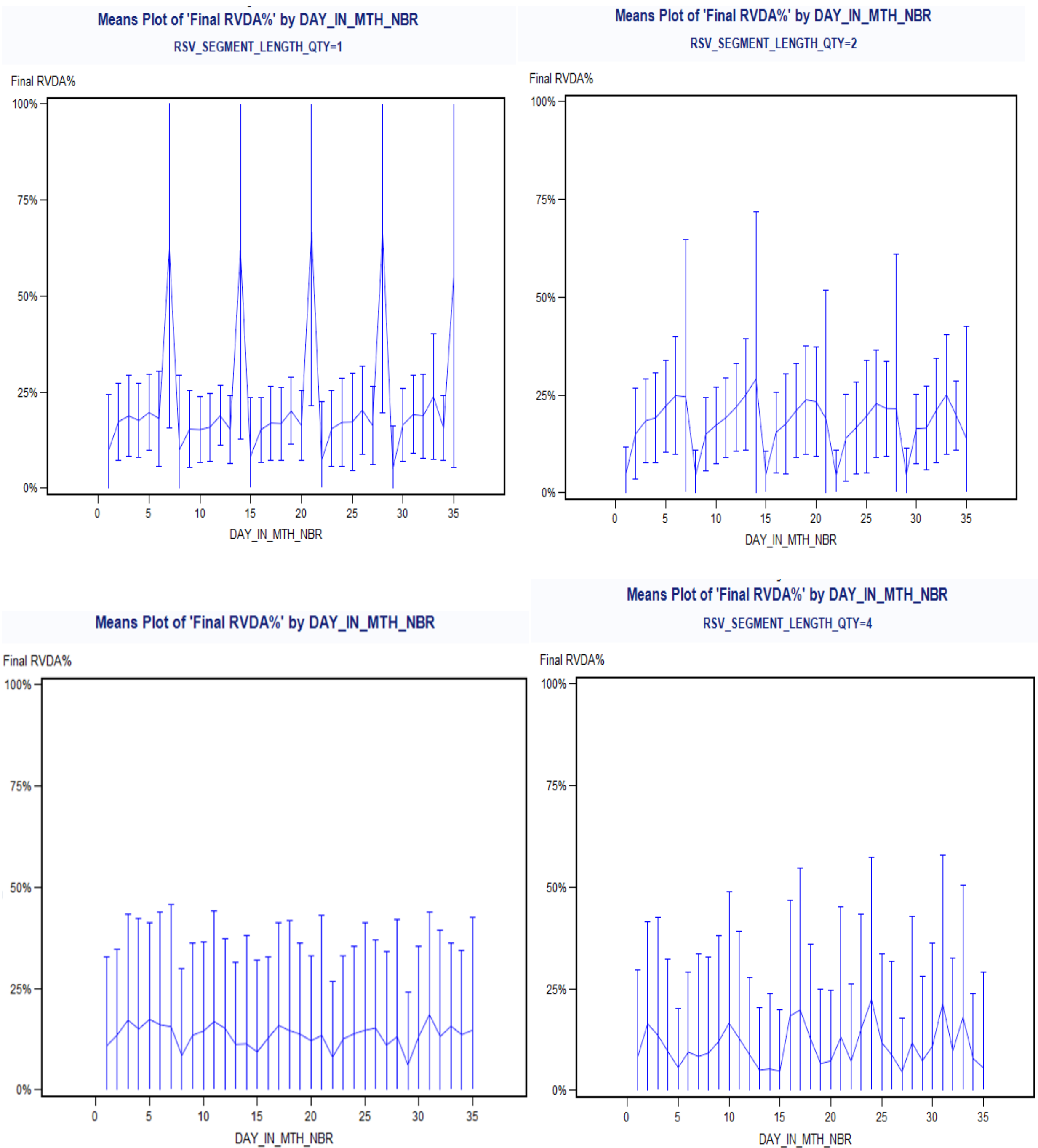


Figure 40. RVDA% Mean Plots for One-day Trip to Four-day Trip by Day in Bid Month.

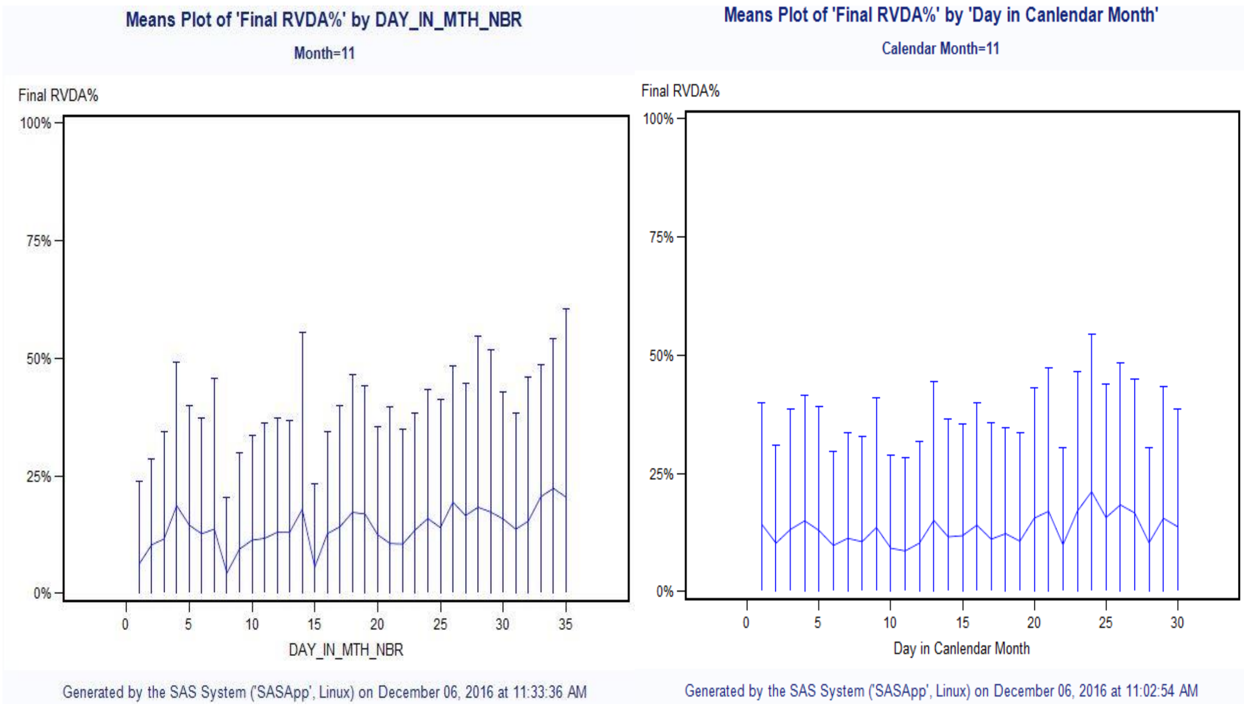
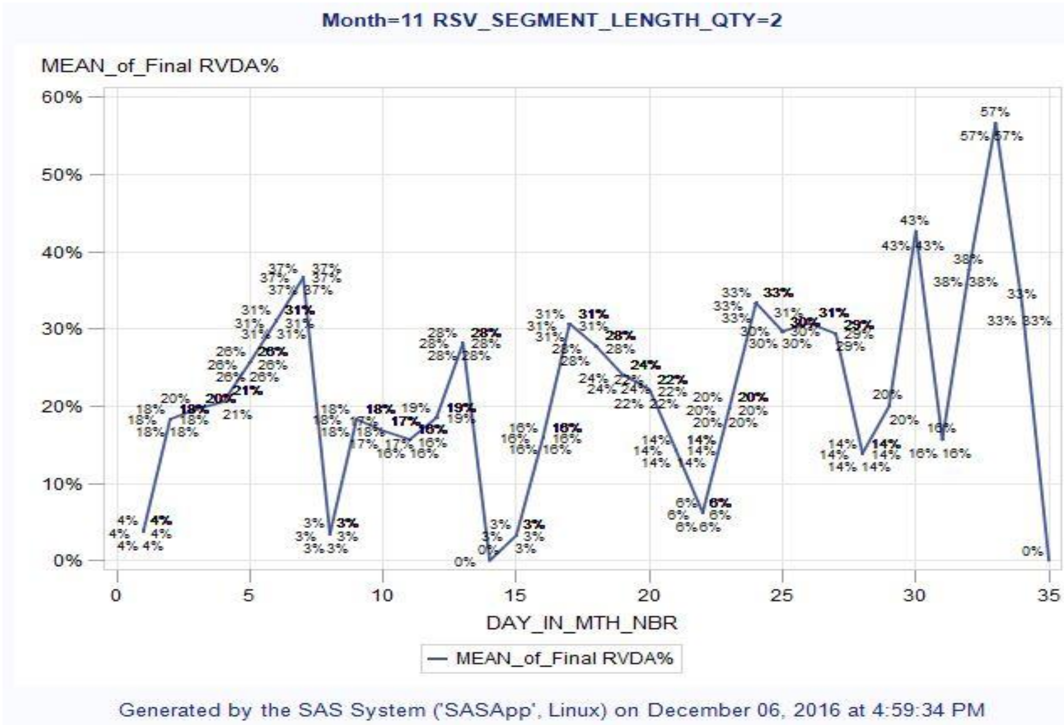


Figure 41. RVDA% Mean Plots for Bid Month and for Calendar Month.

However, the chart in Figure 41 shows the difference between these two types of month. The seasonality in Bid month is stronger than in calendar month and the last week seems to lose the trend. The rate in the last week of calendar month (23rd Nov to 27th Nov) shows a significant peak period. As we all know, this week is around Thanksgiving. Thanksgiving is always on the fourth Thursday on the calendar in November, but in 5-week Bid month it may become the fifth Thursday. The trend is weakened by the time method of Bid month. This solution also reminds me that the calendar month, which includes national holidays should be taken more considerations in the process of forecasting. The holiday effect should be further analyzed.

The analysis of holiday effect grouped by trip lengths are made. One sample for Thanksgiving Day is shown in Figure 42 (pg. 103). On the top of the chart, it shows the mean distribution for the rate of 2-day trips in Bid month number 11. The seasonality is strong but no holiday peak can be found. At the bottom of the chart, it shows the mean distribution for the rate of 2-day trips in calendar month November. No strong seasonality can be found but the Thanksgiving Day peak is significant. Another conclusion obtained from these analysis is that holiday effect is more significant for short trips such as one-day or two-day trips. Unlike Thanksgiving dates on the fourth Thursday of November, there still are some holidays date as the fixed calendar day in month such that Christmas Day is always on December 25 no matter which weekday it is. However, these holidays are not fixed in Bid month and are easily ignored in analysis. To figure out the holiday effecters, some more analyses are done.



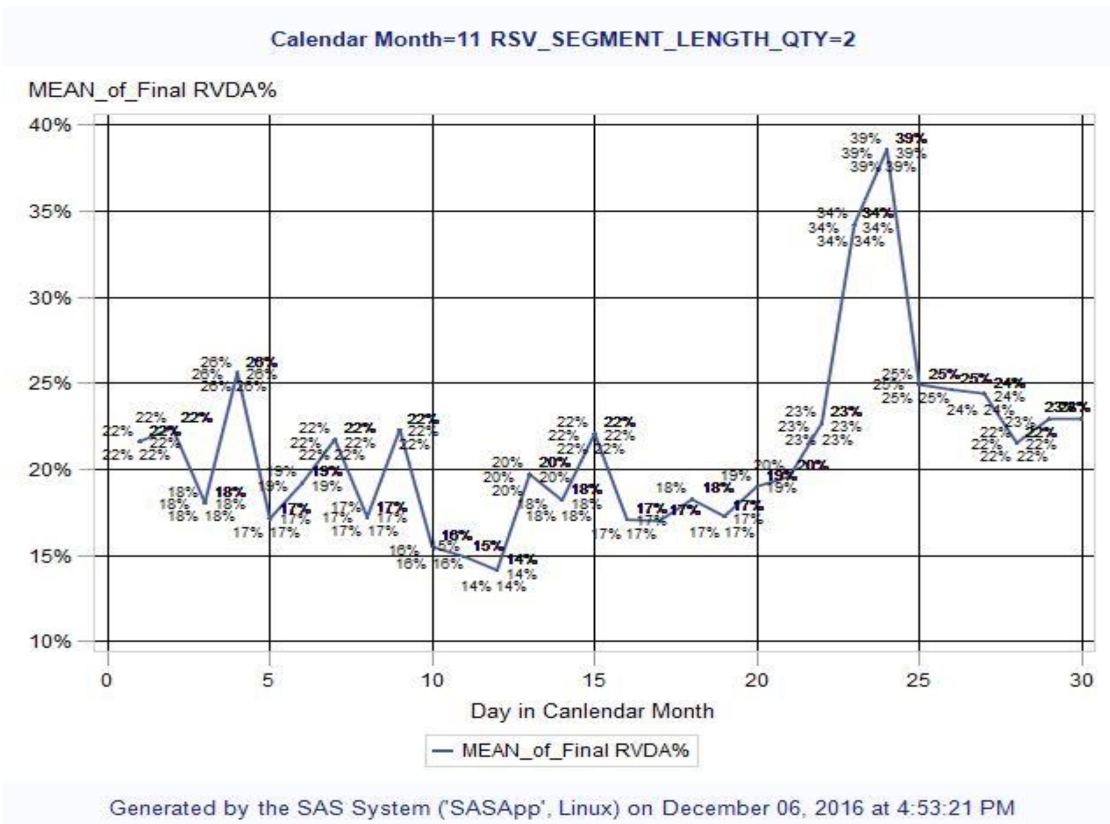


Figure 42. RVDA% Mean Plots of 2-day trips in Bid Month and in November.

Table 35. National Holiday Involved in Forecasting Model.

Holiday	Natural Calendar	Bid Calendar
New Year's Day	1th January	
Memorial Day		Last Monday on May
Independence Day	4th July	
Labor Day		First Monday on September
Thanksgiving Day	Fourth Thursday on November	Last Thursday on November
Christmas's Eve	24th December	
Christmas	25th December	
New Year's Eve	31st December	

Based on all analysis for comparing the holiday effect in Bid month and calendar month, the conclusions are using Bid month as a variable to forecast and is good for keeping the seasonality characters and using calendar month as a variable to forecast is good for keeping the holiday effect. For holiday effect, the short trips such as one-day trips and two-day trips are more significant than long trips. Consequently, the forecast model in the tool use Bid month as one variable and calendar date is added for each day as a second day index. Important national holidays are programed to mark on the calendar date for each year and are included in the model as a variable named holiday. The list of national holidays included in the forecast model is listed in Table 35. If the holiday in the natural calendar dropped on a weekend, the system will put the next Monday as a holiday. The other holiday can be added into the model if the tool is used by the airline in other country.

Since the development is fast in the aviation industry, the schedule may be changed and the new crew group may have different characteristics. Before applying the forecast model, a series of analyses are needed in a year. An analysis tool is built in SAS Enterprise guide with the Prompt function. Figure 43 (pg. 105) is the interface for users to choose which data set they want to analyze. Here we take 3-day trips which started on the third Wednesday of January, between 2001 and 2016, as an example. If the comparison is required in a range of trip length, just simply fill in the “From” box and “To” box under “Length”. Users can also set the “Base”, “Segment” and “Seat” in the prompt. The data set will be ready to run all the analysis in the project. The reports with relevance charts for all statistical analysis mentioned above will be ready to read. If the results of these analyses are not significantly changed, the reserve forecast tool can be used to estimate the reserve demand. All these tools combined with the optimization model can be used for built a system to support reserve scheduling in future work.

2.4.5 Reserve Forecasting

Based on the results output from the previous stage, a reserve forecast tool is developed in SAS Enterprise Guide. The Prompt function is also used for users to select the historical data set for forecasting which are shown in Figure 44 (pg. 105). The indexes include base, reserve segment, seat, trip length and Bid years.

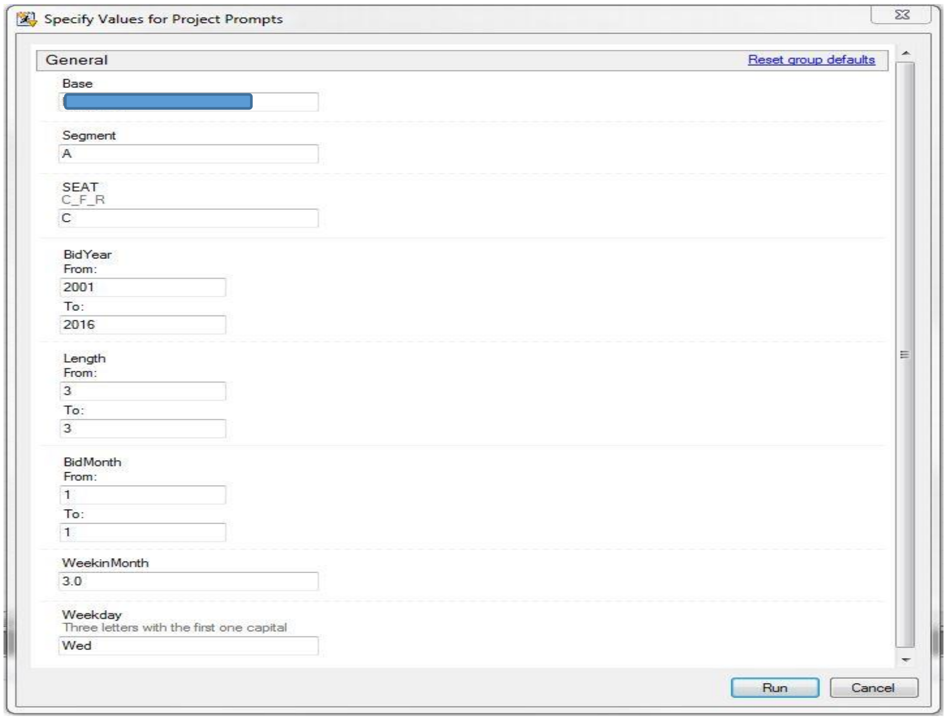


Figure 43. Prompts Function of the Analyzing Tool for Reserve Based on Big Data Set.

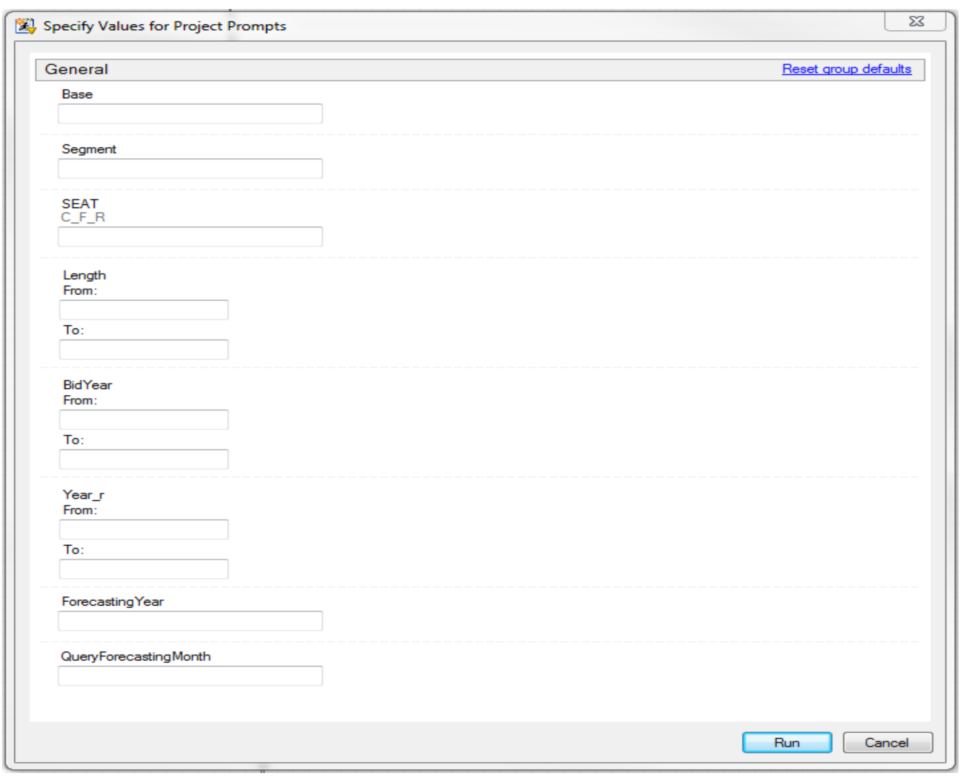


Figure 44. Reserve Forecasting Designed in SAS Enterprise Guide.

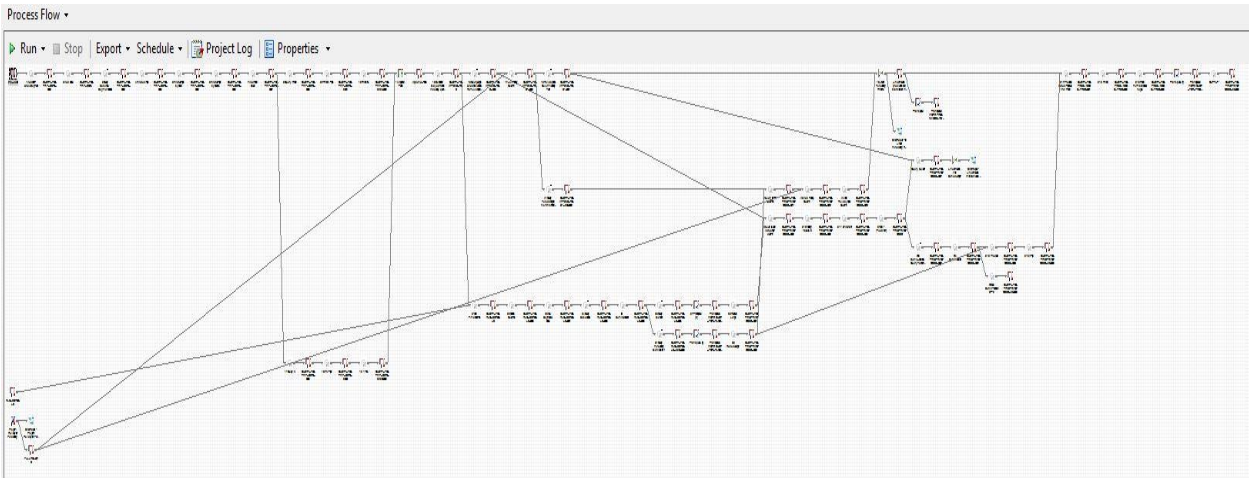


Figure 45. Reserve Forecasting Logic Map in SAS Enterprise Guide.

Since Trip length affected all other features such as Month, Weekday, Day in month, the forecasting is made for each trip length separately. Index “Year_r” is used to query the data in which year or years will be selected to predict the rate between schedule trips and actual trips. Usually, the last year’s data will be used to predict this year’s. The last two boxes are for selecting the target Bid month.

Figure 45 shows the map of functions inside the tool. Two real time data bases are included in the tool. One is for storing the trip schedules and the other one is for storing all details of actual trips, which are Data set one and Data set two mentioned in Section 2.4.1.

The forecast approach can be put into three steps:

1) Estimate the possibility of each type trip dropping out from the regular lines in data base of actual trips, which is called “RVDA%”.
   Multi-way ANOVA model is built including Trip Length, Bid month, Weekday and Holidays as key variables.
2) Predict the actual trips based on historical rate between schedule trips and actual trips by using formulation as follows:

$$\frac{Historical\ Total\ Actual\ Trips}{Historical\ Total\ Scheduled\ Trips} \times Scheduled\ Trips\ in\ Targeted\ Bid\ Month$$

3) Calculate the expected value of each type of trip by multiply RVDA% to the predicted actual trips number.

In Step two, there are three exceptions that need to be discussed, since the historical total scheduled trips for some types of trips may be 0 which will make the actual trips be viewed as a missing value in the forecasting process. However, sometimes actual trips occur when there is no scheduled trips. For example, no one-day trips are scheduled on Sunday, while some actual trip occurs in the historical data base in some week of the month. Additionally, if there are no $\text{Scheduled Trips in Targeted Bid Month}$, even the historical rate is not 0, still no actual trip can be predicted. How should these special situations be considered? They should be considered in the system, since missing value is not nothing and it involve the useful information as well. Three exceptions are listed as follows:

1) No scheduled trips on that day in history and No actual trips on that day.
   In this situation, the rate between scheduled trips and actual trips is viewed as 1 instead of NAN because no error in the forecasting process happened.
2) No scheduled trips on that day in history but some actual trips occur on that day.
   In this scenario, the number of total scheduled trips on that day is the forecasting error E, so the rate between scheduled trips and actual trips is calculated as the average possibility of error: $E/Total\ time\ period\ involved$. For example, the total number of one-day trip scheduled on the first Sunday of each month in the last year is 0, while three one-day trips did occur on the first Sunday. The rate between scheduled trips and actual trips will be calculated as 3/12= 0.25 which indicates that there is a 25% possibility that a trip will occur when there are no scheduled trips on that day.
3) No actual trips on that day in history but some scheduled trips exist.
   In this scenario, the rate between scheduled trips and actual trips should not always be 0 because different numbers of scheduled trips on that day indicates a different error rate. For example, one scenario is the total number of one-day trips that occurred on the first Sunday of each month in last year is 0, but the number of scheduled trip in one of the month is 1. Another scenario is no actual ones but there is scheduled trip on two of the months. Using 0 as the rate for both scenarios is not fair, because the error rate is different. Hence, the rate is calculated as 1-$E/Total\ time\ period\ involved$ where E is the difference between total scheduled trips and actual trips.

The output of this model is a matrix with the possibility of each type of open time trips as the element. The matrix of scheduled trips, which is released before the target Bid month, will be stored in. The expected value is calculated by multiplying the scheduled trips number by the drop possibility. One output sample is shown in Table 36 (pg. 108).

2.4.6 Availability Buffer

The output from the forecasting tool is the pure demand which needs to be covered by reserve days. However, when the crew award a reserve line, they have the similar right, as regular line holders, that they can also drop their reserve days because of released, sick, vacation and training, etc. As the analysis of section 2.4.2, the reserve days dropped from the reserve line affect the utilization of reserve lines. When building reserve lines to cover demand, the availability buffer may need to be considered

Table 36. Sample of Monthly RVDA Forecasting.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.156961	1.164178	0.313423	0.18659	0.330137	0	0	0.018608	0	0	0	0	0
2	4.191625	2.424754	0.369622	0.670399	0.289706	0.194076	0	0	0	0	0	0	0.034186
3	4.632764	3.203553	0	0.27864	0.289802	0	0	0.009958	0.006556	0.006476	0.018067	0	0
4	4.317753	2.880418	0.750831	0.256842	0	0	0.013243	0	0	0	0	0.055276	0
5	5.136665	2.688151	0.847206	0.075562	0.086078	0	0	0.006623	0.008296	0	0	0	0
6	2.945365	3.67511	0.295698	0.247705	0	0.068097	0	0	0	0	0	0.018874	0
7	0.252732	0	0	0	0.149184	0.301684	0	0.006	0.007062	0.005	0	0	0
8	0	1.006378	0.223873	0.336759	0.325049	0	0.23448	0	0	0	0	0	0
9	4.608803	2.897011	0.380309	0	0	0.169816	0	0	0	0	0.005198	0	0.039883
10	4.841218	3.331987	0	0.379964	0	0	0	0.004979	0.032778	0.012951	0.036135	0.039397	0.007022
11	4.762394	3.211827	0.762482	0.099132	0	0	0.006622	0.043731	0	0	0	0.046063	0
12	5.083473	3.186383	0.741904	0.084871	0.086078	0.030756	0	0	0	0.005347	0	0	0
13	2.918052	4.395145	0.209079	0.149156	0	0.136194	0	0	0	0	0	0	0.04719
14	0.101093	0	0.109247	0.01838	0	0.201123	0	0	0	0	0	0.002283	0
15	0	0.977817	0.272542	0.290062	0.35241	0	0.03908	0	0	0	0	0	0.030584
16	4.507862	2.921386	0.234246	0	0.129333	0.242595	0.005161	0	0.006881	0.010145	0	0	0.034898
17	4.787782	3.44618	0.167046	0.237477	0	0	0	0	0	0	0	0.047277	0
18	4.660197	2.981644	0.574238	0.100902	0	0	0	0.006247	0	0	0	0	0
19	5.166814	3.069864	0.692822	0.079091	0.086078	0	0	0.006623	0.008296	0.016041	0	0	0
20	2.823256	3.897957	0.21984	0.210573	0	0.097281	0	0.059783	0	0	0	0	0
21	0.454917	0	0	0	0.067811	0.201123	0	0.009	0	0	0	0	0
22	0	0.973747	0.232484	0.29145	0.329338	0	0	0	0	0	0	0	0
23	4.639906	2.764121	0.351606	0	0.12416	0.020216	0	0	0	0	0	0	0
24	4.761548	3.142331	0.15252	0.237477	0	0	0	0	0	0	0	0	0
25	4.567445	3.050842	0.548643	0.127809	0	0	0	0	0	0	0	0	0
26	5.245463	2.70749	0.85336	0	0	0	0	0	0	0	0	0	0
27	2.87144	4.018331	0	0	0	0	0	0	0	0	0	0	0
28	0.505464	0	0	0	0	0	0	0	0	0	0	0	0

because not all awarded reserve days are available for assignment. When the utilization is relatively low, the released reserve day may not be a significant affecter, but when utilization increases it may be reflected as a significant one. For example, the regulation of rule “1 in 7”: A pilot shall be relieved from all duty for at least 24 consecutive hours at least once during any seven consecutive days. When the schedule is tight, this rule will play a role in assignment process. Another method is protecting the high quality patterns and decide which day/days can be dropped based on the daily updated demand.

On the other hand, when recovering the trips in daily operations, deadhead time needs to be taken into consideration. In some situations, even if there is a pilot available to fly the trip on that day, it still needs time to transport this crew from the base or the last landing airport to the required trip’s origin airport. The cost always needs to be considered as well. Adding a deadhead buffer as a multiplier can solve this problem. Another way to add the deadhead buffer is by adding one day before the required trips to make the length of trip one day longer ensuring the trip includes enough deadheading time.

However, in this dissertation, all reserve demand trips start and end at the same crew base. No deadheading will happen. The only consideration is if the time between two trips violates the legality and if fatigue risk level is acceptable. A small hub turn buffer can be added as a multiplier into reserve demand to make sure the line is not too tight.

Schedulers can adjust these buffers to balance the utilization and the reserve line’s quality refer to the workload of crew. Increasing the buffer, system will create more pattern lines, in the meanwhile, the utilization will be decreased and the cost may be increased. The workload for pilots is sensitive, so a balance needs to be made in this process. This concern will be discussed in Chapter 3.

2.5 Crew Reserve Scheduling Optimization Model

2.5.1 Problem Definition and Solving Approach

In the previous section, the forecasting tool is used to estimate the reserve demand. The demand is the expected number of open time trips which is not necessary integer. Since reserve demand is under high uncertainty, in order to keep all useful information of historical data, the approach in this dissertation chose not to round the fractional numbers at all. The output matrix D , including all types of trips from the forecasting tool, is the input of the optimization model in this section with d as the index. The column of the matrix indicates the length of the trip type l and the row of the matrix indicates the starting date of trip t. The total number of days in the Bid Month is T and the element of the matrix n_d is the expected demand of trip type $(t, l) \in D$. For example, the trip (17, 9) indicates the trip is 9 days long and starts on day 17 of the Bid Month. The n_d could be fractional and could be greater than 1 or less than 1. In order to conveniently check if one reserve pattern i can cover a trip, a binary parameter is set as h_d^t to indicate the on-duty days of trip d. h_d^t is 1 if the trip d includes day t as an on-duty day, and is 0 otherwise. Based on h_d^t, the trip can be converted into another mode. Using the trip (17, 9) in a Bid Month which has 28 days as an example, the trips can be described as follows:

(0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 0 0)

Building a set of reserve patterns to cover these expected levels of demand with as little as possible cost is the objective. Unlike the regular line, the reserve patterns do not consist of any trips or pairings. Instead, they consist of blocks of consecutive on-duty days and blocks of consecutive off-duty days. The index P of pattern indicates the maximum total number of on-duty days in one bid period. Because of the special pay construct for reserve crew such that no matter how many days on operation, they will be paid at least RLG, as most as possible reserve days are expected to consist in the reserve pattern. Hence, the pattern always consists of the maximum on-duty days. In other words, P indicates the pattern's length unless the cost construct is changed.

The pattern type is traditionally defined to downsize the variable set. As mentioned in Section 2.2, in some works of researchers, pattern type is defined by the grouping of on-duty days and the groupings of the off-duty days. The sample is given as Figure 19. By determining the required number of each type of patterns can downsize the variable set and increase the solving speed. However, the type of pattern which is decided in advance becomes the parameter of the model. The limitation of the solution space exists in the meantime too since it is hard to list all types of patterns. In our approach, the pattern is defined by more elements which make all legal pattern types can be included. One pattern type is determined by the on-duty blocks type and the off-duty blocks type. On-duty blocks type is described by a vector variable, in which the number of elements is determined by how many on-duty blocks are in the pattern and the value of element is determined by the number of consecutive on-duty days in each block. Off-duty blocks is also a vector variable , in which the number of elements is determined by how many off-duty blocks are in the pattern and it is always equal to the number of elements in on-duty blocks type plus one because on-duty block is between two off-duty blocks. The value of element in off-duty blocks type is determined by the number of consecutive off-duty days in each block. The total value of elements in on-duty block type plus the total value of elements in off-duty blocks type is equal to the total days in the bid period. By adjusting the element value in off-duty block can design the on-duty days block type with various number of elements.

Different airlines have different rules to build the legal reserve pattern and the main difference is reflected on the length of pattern P and the minimum on-duty days in one block M. Let K denote the maximum number of on-duty blocks. Hence, the number of off-duty blocks is $K + 1$ with index k. Any block can be zero days long, but not all off-duty blocks are allowed to be zero at the same time. K can be calculated by dividing P by M and round it down to integer. For example, assuming that one airline allows the maximum length of pattern is 15 days and the minimum on-duty days in one block is 4 days, K can be simply calculated by rounding down 15/4, which is equal to 3 after rounding. The value of the element of off-duty blocks type y_k is an integer including 0. The off-duty blocks type can be indicated as $[y_1, y_2, \dots, y_{K+1}]$. If y_1 is 0, it means that the reserve pattern starts on the first Monday of the month. If y_{K+1} is 0, it denotes that the reserve pattern ends at the last Sunday of the month. If one y_k , where k is neither equal to 0 nor $K+1$,is equal to 0, it denotes the number of on-duty blocks is $K-1$. If two y_k , where k is neither equal to 0 nor $K+1$,are both equal to 0, it denotes the number of on-duty blocks is $K-2$ and the forth until only one on-duty block exist in pattern with P on-duty days . By this analogy, all on-duty block types with different number of elements from 1 to K can be identified. Let a_k denotes the element value of on-duty blocks type.

For each pattern i, let binary variable O_i^tdenote which day is an on-duty day and which day is an off-duty day in a pattern. Pattern i has a total P on-duty days in a bid period which has T days. O_i^t is 1 if day t is on-duty day in pattern i, is 0 if day t is off-duty day. One sample is shown as follows:

(0 0 1 1 1 1 0 0 0 1 1 1 1 0 0 0 0 0 1 1 1 1 1 1 1 0 0)

This sample pattern consists of three on-duty blocks and four off-duty blocks. The on-duty blocks type is [4, 4, 7] and the off-duty blocks type is [2, 3, 5, 2]. The pattern type is [4, 4, 7] _ [2, 3, 5, 2].

As stated in Section 2.2.3, the quality of the reserve pattern is one key to control the cost, since the uncovered cost rate of a trip is much more than the reserve cost rate. The conclusion obtained by researchers that the longer reserve block has high availability when covering various open time trips has its limitation. No matter how much or few the occurring possibility of open time trips, when it is put into model as an input or parameter, it is always considered as the demand with 100% possibility because the smallest nonzero integer is 1. The example shown in Table 37 is used to describe the limitation.

Table 37. Sample of Trip Coverage by Pattern.

Date	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8
Trip 1	(0	1	1	1	0	0	0	0)
Trip 2	(0	0	1	1	1	0	0	0)
Block 1	[0	1	1	1	0	0	0	0]
Block 2	[0	0	1	1	1	0	0	0]
Block 3	[0	1	1	1	1	0	0	0]

Trip 1 and Trip 2 are two open time trips that are needed to be covered in a bid period in which the first 8 days is shown in Table 36. Trip 1 is (2, 3) and Trip 2 is (3, 3). There are three different reserve blocks available to build. Which one should be chosen?

Apparently, Block 1 can only cover Trip 1 and Block 2 can only cover Trip 2. Block 3 can cover both of the trips. Can we get the conclusion that the decision of building Block 3 is always a good idea? Some assumptions need to be set first.

Assumption 1: The cost of these three blocks is the same even though they carry different on-duty days;
Assumption 2: Since the length of Trip 1 and Trip 2 are the same, their uncover cost is the same;
Assumption 3: Trip 1 and Trip 2 have equal likelihood to be dropped out and become open time trips.

With these three assumptions, we can say that if only one block can be selected, Block 3 is always the best choice. If Trip 1 and Trip 2 occur more than once and two blocks can be built, building two Block 3 may be a good decision.

However, in real world practice, these assumptions may not always be satisfied. For example, the pattern may hold 12 days or more and other on-duty blocks, which are not shown in Table 36, can be used to cover other trips that start after day 8. Assume one 9 days trip starts on day 9 needs to be covered, if you pick Block 1 or Block 2, although one 3-day trip may not be covered ,there are 9 on-duty days left, that can be built to cover that long trip. Instead, Block 3 has the chance to cover trip 1 and trip 2, but if it is selected, there are not enough on-duty days left to cover the 12-day long trip and it can't be used to cover both Trip 1 and Trip 2 at the same bid period in daily operations. In this scenario, the cost of an on-duty block is related to the block length, although the cost of pattern is the same.

Examples with more complex conditions are shown in Table 38. Trip 1 (2, 3) and Trip 3 (4, 5) are two possible open time trips. Block 1, Block 4 and Block 5 can be built to cover these two trips. Block 1 can only cover Trip 1, Block 4 can only cover Trip 3 and Block 5 can cover both of these two trips.

Table 38. Another Sample of Trip Coverage by Pattern.

Date	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8
Trip 1	(0	1	1	1	0	0	0	0)
Trip 3	(0	0	0	1	1	1	1	1)
Block 1	[0	1	1	1	0	0	0	0]
Block 4	[0	0	0	1	1	1	1	1]
Block 5	[0	1	1	1	1	1	1	1]

Table 39. Sample Cases of Occurring Possibility.

	Case 1	Case 2	Case 3	Case 4	Case 5
Trip 1	0.9	0.4	0.5	0.8	0.67
Trip 2	0.2	0.8	0.5	0.7	0.58

The length of trips is not the same and the length of blocks are different. In Case 1 at the first column of Table 39, the occurring likelihood of open time Trip 1 is 90% and 20% for Trip 2. Is Block 5 still the best choice? In other words, is it worth adding 4 days to the block for to cover Trip 3? I may say that Block 5 is better than Block 4 and I doubt it is better than Block 1. In Case 2, at the second column, the occurring likelihood of open time Trip 1 is 40% and 80% for Trip 2. Is it worth the 2 day increase of block to cover Trip 1? At least, I have more confidence to select block 5 in this case than Case 1, because 0.4×3 is greater than 0.2×5. In other word, the possible uncovered cost should be considered. In Case 3, at the third column, both occurring likelihood is 50%. It looks more reasonable to pick Block 5 rather than Block 1 or Block 4. In Case 4, at the fourth column, the occurring likelihood of open time Trip 1 is 80% and 70% for Trip 2. I would say that I may pick Block 1 and Block 4 to cover them if the capacity of reserve crew allows. In Case 5, at the last column, the occurring likelihood of open time Trip 1 is 67% and 58% for Trip 2. It is hard to decide how to select a block in this kind of case without any mathematical model's support. These 5 cases are typical at the daily work of schedulers. The situations they need to face are more complex than the cases in this example because they need to compare the full pattern but not only blocks. The size of open time trips and patterns are much more than what is in these examples in Table 37. They need to adjust the reserve pattern manually based on their experience accumulated in years. It is worth the time effort to develop a mathematical based decision making support tool.

An optimization model for solving reserve scheduling problems is developed to minimize the total reserve cost which includes two main costs: one is reserve crew cost and the other is the cost of uncovered trips. Let c denote the cost of one pattern and s_d is the unit cost of an uncovered demand of trip d, which is related to the trip length. The cost of uncovered trip $d\ (l,t)$ is $s_d \times l$. The other ideas mentioned above are all taken into account in this optimization model. Firstly, the approach integrated the reserve forecasting stage into the optimization stage by keeping expected levels of demand. If it is less than 1, it can be viewed as occurring likelihood or possibility. This information plays an important part in increasing the quality of reserve patterns such as increasing the availability when covering open time trips in the daily operation stage. Secondly, a definition is introduced into the optimization model which is named as "Coverage". Let J denotes the set of all possible coverages over all open time trips with j as index. One Coverage j is a vector consisting $|\mathrm{D}|$ elements that are in one-to-one correspondence with the pattern. Each element is the probability of pattern i may be used to cover open time trip d and is denoted by p_j^d . The value of p_j^d is in [0, 1]. This many-to-many coverage mode weakens the influence from high uncertainty. Last but not the least, column generation algorism is applied to build qualified reserve patterns and the sub-problem is built to ensure that all open time trips that can be covered by pattern i are considered in the optimization process. Additionally, all patterns can be used to cover open time trip d are compared in process too. q_d is used to indicate the possibility of the coverage of pattern i to trip d. Each possible pattern i is featured by a vector with T elements of binary values O_i^t .

The binary variable x_j equals to 1 and represents the coverage j is selected, or equals to 0 otherwise. The non-negative variable u_d represents the amount of uncovered open time trip demand d. The master problem of optimization model can be described as follows:

<u>Master Problem:</u>

$$Min\ c \sum_{j \in J} x_j + \sum_{d \in D} s_d u_d \tag{2.1}$$

Subjective To:

$$\sum_{j \in J} p_j^d x_j + u_d \geq n_d \qquad \forall d \tag{2.2}$$

$$x_j \in \{0,1\};\ u_d \geq 0 \tag{2.3}$$

The master problem (2.1-2.3) is the classical set cover problem and it is always feasible because of the existence of u_d. Constraint set (2.2) describes how the subset of coverage covers the reserve demand. When set J includes enough numbers of all possible coverage, the master problem can yield the best solution. In order to make the problem tractable, columns (associated with x_j) are iteratively created, following the column generation procedure. When its linear relaxation is solved to its optimality, the shadow price of constraint d is denoted by w_d. For each pattern , we can calculate its value by solving the following sub-problem. In order to reduce the solving time, the set of all possible patterns, I, is generated in the sub-problem. Variable r_t^f is used to locate all the on duty days in the bid period.r_t^f is 1, if day t is the fth on duty day in this pattern, and is 0 otherwise.

<u>Sub-problem:</u>

$$v_m = \max \sum_{d \in D} w_d q_d \tag{2.4}$$

Subjective To:

$$\sum_{d=1}^{D} h_d^t q_d \leq O_i^t \qquad \forall t \tag{2.5}$$

$$q_d \leq n_d \qquad \forall d \tag{2.6}$$

$$\sum_{t=1}^{T} O_i^t = P \tag{2.7}$$

$$\sum_{k=1}^{K+1} y_k = T - P \tag{2.8}$$

$$\sum_{t=1}^{T} r_t^f = 1 \qquad \forall f \tag{2.9}$$

$$O_i^t = \sum_{f=1}^{P} r_t^f \qquad \forall t \tag{2.10}$$

$$\sum_{t=1}^{T} r_t^f\, t = y_1 + 1 \qquad \forall f = (1,2,\ldots,a_1) \tag{2.11.1}$$

$$\sum_{t=1}^{T} r_t^f\, t = y_1 + a_1 + y_2 + 1 \qquad \forall f = (a_1+1, a_1+2, \ldots, a_1+a_2) \tag{2.11.2}$$

$$\sum_{t=1}^{T} r_t^f\, t = y_1 + a_1 + y_2 + a_2 + y_3 + 1 \qquad \forall f = (a_1+a_2+1, a_1+a_2+2, \ldots, a_1+a_2+a_3) \tag{2.11.3}$$

$$\vdots \qquad \vdots \qquad \vdots$$

$$\sum_{t=1}^{T} r_t^f\, t = \sum_{k=1}^{K} y_k + \sum_{k=1}^{K-1} a_k + 1 \qquad \forall f = (a_1+a_2+\cdots+a_{K-1}+1,\ a_1+a_2+\cdots+a_{K-1}+2, \ldots, a_1+a_2+\cdots+a_K) \tag{2.11.K}$$

$$0 \leq q_d \leq 1,\ r_t^f, O_i^t \in \{0,1\}, \quad y_k \geq 0 \text{ integer} \tag{2.12}$$

The largest v_m is selected to create a new column in the master problem with the coefficient vector of q_d. m denotes the element of set M which consists of all legal on-duty blocks types. Constraint set (2.5) describes that each duty day in trip d is also on-duty day in pattern i if pattern i is selected as a potential coverage to trip d. Constraint set (2.6) ensures that the coverage of trip d is not greater than its demand. The left constraints are all for building reserve patterns. Constraint (2.7) and (2.8) set the reserve pattern's length and the total off-duty days. Constraint set (2.9) ensures the fth on-duty days of the pattern only locate at one day. Constraint set (2.10) consists K constraints describing each on-duty blocks in pattern i. Constraint set (2.10) is used to locate all on-duty days at Bid calendar.

The overall algorithm can be described as follows:

<u>Overall Column Generation Algorithm</u>

Step 1: Solve LP Master Problem (2.1-2.3) with $x_j \in [0,1]$ to get w_d.
Step 2: Obtain all legal on-duty blocks types
Step 3: Solve all sub-problem (2.4-2.12) for all $m \in i$ and get v_m.
Step 4: Find the largest v_m.
Step 5: If the largest v_m is not greater that c, stop and go to Step 7.
Step 6: Insert the new coverage featured by q_d corresponding to the largest v_m into J with the new $p_j^d = q_d$. Go to Step 1.
Step 7: Solve Master Problem with $x_j \in [0,1]$ getting upper bound.

The solution of this optimization model not only include the set of selected reserve patterns and the uncovered trips but also the set of open time trips covered by each selected pattern and all patterns that can be used to cover each open time trips. Two situation of coverage of reserve demand may exist. One is that the demand is covered by fewer patterns but with high enough possibility compared with the value of demand. Another situation is the open time trips can be covered by more patterns with relatively low possibility. In this situation, although the possibility of one coverage is low, it can be covered by more patterns which makes it still have a good chance to be covered based on the expected level of demand.

There are some constraints that can be added to the model based on the different rules in different airlines. For example, the capacity of reserve crew can be added to master problem which is formulated as follows. However, it is not always necessary to be included because the optimization model can give a set of reserve patterns to be assigned to reserve crew. This set is the optimal solution the model found, the number of reserve patterns can be a suggestion to schedulers and they can adjust the other group of crew to find some crew to carry them. There are a lot of ways to improve the reserve crew management. For example, if a long range of reserve crew management is not good, the capacity of reserve crew in pre-month planning stage will be influenced. The optimal solution is restricted by the capacity. Another improvement example that can be given is assignment policy in daily operations. A good assignment policy that suits the design of patterns will benefit the coverage effect of patterns as much as possible. More detailed improvement methods will be discussed in Chapter 3.

$$\sum_{j \in J} x_j \leq W \tag{2.13}$$

A multi-stage stochastic optimization process is developed to decide if any trip can be dropped or not. When daily operations stage begins, reserve assignment process starts in the meantime. For each day of the bid period, the number of each open time trip types become as known information. After assigning them to some crew's reserve line, the value of the parameters of the optimization model such as the reserve demand matrix should be updated. The set of patterns obtained from the column generation algorithm becomes fixed input data after removing the reserve days which have assigned trips to and the ones which are released based on regulation.

Rerunning the optimization model with these updated parameters, the coverage will be updated to provide assignment suggestions for the next stochastic stage. A list of allowed dropping reserve days is given, in which the days dropped with high influence of coverage will be listed at the top. The pattern in higher order should be protected better. Some policies can be considered in assignment process when a set of feasible reserve blocks are found with long enough on-duty blocks for covering the open time trip:

1) Select the shortest ones in this set. Perfect match is the best.
2) If there is more than one block satisfied, select the one which has more unused reserve days or less duty hours before.
3) If there is still more than one block satisfied, consider if this long pattern should be saved for a long trip with relevant high possibility.

2.5.2 Case Study with Real World Data

The data is provided by a U.S. major carrier. One 4-week Bid Month is randomly selected as a target. The total number of days in the Bid Month T is 28. The range of trip length is from 1 to 13. The scheduled trips of this bid period are stored in a matrix shown as Table 40 (pg. 118) which is used as the input of reserve forecasting.

The forecasting tool in SAS Enterprise Guide is used to estimate the expected level of reserve demand. Since carry over trips are out of the scope of this research, they are temporarily removed from the output of reserve forecast tool before putting it into the optimization model.

Assume that the length of pattern is 15 days, so that the total off-duty days are 28-15=13. Each on-duty day block consists of at least 4 reserve days, so that the maximum number of on-duty blocks K is 3. The on-duty blocks types are listed as follows: [4, 4, 7]; [4, 7, 4]; [7, 4, 4]; [4, 5, 6]; [5, 4, 6]; [6, 5, 4]; and [5, 5, 5]. There are 4 off-duty blocks. When one block between two on-duty blocks is 0, the number of on-duty blocks is reduced to 2. If both off-duty blocks between on-duty blocks are 0, the pattern becomes a 15-day long pattern which only has one on-duty block. By setting the off-duty blocks, all qualified on-duty blocks types with less than 3 on-duty blocks are created in model such as: [4, 11]; [11, 4]; [7, 8]; [8, 7]; [6, 9]; [9, 6]; [5, 10]; [10, 5] and [15].

Table 40. Sample of Monthly Schedule.

D	1	2	3	4	5	6	7	8	9	10	11	12	13	TOTAL
1	2	25	3	2	8	0	0	0	0	0	0	0	0	40
2	27	14	3	4	2	1	0	0	0	0	0	0	1	52
3	28	16	0	1	1	0	0	0	0	0	0	0	0	46
4	28	14	4	2	0	0	0	0	0	0	0	1	0	49
5	27	10	6	1	1	0	0	0	0	0	0	0	0	45
6	18	14	3	3	0	1	0	0	0	0	0	1	0	40
7	0	0	0	0	1	1	0	0	0	0	0	0	0	2
8	0	20	3	3	8	0	1	0	0	0	0	0	0	35
9	29	16	3	0	0	1	0	0	0	0	0	0	1	50
10	28	16	0	2	0	0	0	0	0	0	1	1	0	48
11	28	14	4	1	0	0	0	0	0	0	0	1	0	48
12	26	12	5	1	1	0	0	0	0	0	0	0	0	45
13	18	15	2	2	0	2	0	0	0	0	0	0	1	40
14	0	0	1	0	0	1	0	0	0	0	0	0	0	2
15	0	20	3	3	8	0	0	0	0	0	0	0	1	35
16	30	16	2	0	1	1	0	0	0	0	0	0	1	51
17	28	16	1	1	0	0	0	0	0	0	0	1	0	47
18	28	13	3	1	0	0	0	0	0	0	0	1	0	46
19	27	11	5	1	1	0	0	0	0	0	0	0	0	45
20	18	14	2	3	0	1	0	1	0	0	0	0	1	40
21	0	0	0	0	1	1	0	0	0	0	0	0	0	2
22	0	20	3	3	8	0	0	0	0	0	1	0	0	35
23	29	16	3	0	1	1	0	0	0	0	0	1	1	52
24	28	15	1	1	0	0	0	0	0	0	0	0	1	46
25	28	13	3	1	0	0	0	0	0	0	0	0	0	45
26	27	10	6	1	1	0	0	0	0	0	0	0	0	45
27	18	14	2	2	2	0	1	0	0	0	0	0	0	39
28	0	0	0	0	1	1	0	0	0	0	0	0	0	2
Total	520	364	71	39	46	12	2	1	0	0	2	7	8	1072

The cost of awarding one reserve pattern to crew is assumed as 100 and the uncover cost for the trip per day is 15. The constraints used to generate the patterns in the sub-problem of model are shown as follows:

$$y_1 + y_2 + y_3 + y_4 = 13 \tag{2.14}$$

$$\sum_{t=1}^{T} r_t^f = 1 \qquad \forall f \tag{2.15}$$

$$\sum_{t=1}^{T} O_i^t = 15 \tag{2.16}$$

$$O_i^t = \sum_{f=1}^{P} r_t^f \qquad \forall t \tag{2.17}$$

$$\sum_{t=1}^{T} r_t^f \, t = y_1 + 1 \qquad \forall f = (1,2,\dots,a_1) \tag{2.18.1}$$

$$\sum_{t=1}^{T} r_t^f \, t = y_1 + a_1 + y_2 + 1 \qquad \forall f = (a_1+1, a_1+2, \dots, a_1 + a_2) \tag{2.18.2}$$

$$\sum_{t=1}^{T} r_t^f \, t = y_1 + a_1 + y_2 + a_2 + y_3 + 1 \qquad \forall f = (a_1+a_2+1, a_1+a_2+2, \dots, a_1+a_2+a_3) \tag{2.18.3}$$

Figure 46 (pg. 120) is one of the patterns in the solution. Columns denote the days in 4-week Bid Month. The first row is the pattern generated by the model the pattern type of which is [5, 4, 6] _ [2, 2, 2, 7]. The element with 1 in it indicates an on-duty day and nothing indicates an off-duty day. Each row, except the first one and the last one, denotes one open time trip that needs to be covered in forecast reserve demand. As we can see, 12 trips are forecasted to be covered by this pattern. For each on-duty day in the pattern, the total coverage stored in the row named "Utilization" is never greater than 1. The last column indicates the possibility of using the pattern to cover this trip. If the number of coverage is 1, no other trips existing in this matrix has overlap with it such as Trip (16, 1), Trip (17, 1) and Trip (20, 2). If the coverage is less than 1, overlap is allowed to exist and the total should be 1 or less. Trip (3, 5) and Trip (3, 2) have overlap which indicates that the possibility of using this pattern to cover Trip (3, 5) is 15.28% and the possibility of using this pattern to cover Trip (3, 2) is 84.72%. How about them both happen? Pattern 1 can only be used to cover one of them, but there are other patterns that can cover them as shown in Figure 47 (pg. 120) and Figure 48 (pg. 120). The total coverage of each trip is based on the forecast demand of it. When one open time trip occurs, all available patterns that can cover this trip should be compared and selected.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	Coverage
Pattern 1			1	1	1	1	1			1	1	1	1			1	1	1	1	1	1								
Trip (3,5)			1	1	1	1	1																						0.152793862
Trip (3,2)			1	1																									0.847206138
Trip (5,3)					1	1	1																						0.847206138
Trip (10,1)										1																			1
Trip (11,3)											1	1	1																0.762481962
Trip (11,2)											1	1																	0.237518038
Trip (13,1)													1																0.237518038
Trip (16,1)																1													1
Trip (17,1)																	1												1
Trip (18,1)																		1											1
Trip (19,1)																			1										1
Trip (20,2)																				1	1								1
Utilization			1	1	1	1	1			1	1	1	1			1	1	1	1	1	1								

Figure 46. The Coverage Solution_Pattern 1.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	Coverage
Trip (3,5)			1	1	1	1	1																						0.289802394
Pattern 1			1	1	1	1	1			1	1	1	1			1	1	1	1	1	1								0.152793862
Pattern 5		1	1	1	1	1	1										1	1	1	1			1	1	1	1	1		0.289802394

Figure 47. The Coverage Solution_Trip (3, 5).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	Coverage
Trip (3,2)			1	1																									3.278763523
Pattern 1			1	1	1	1	1			1	1	1	1			1	1	1	1	1	1								0.847206138
Pattern 5		1	1	1	1	1	1										1	1	1	1			1	1	1	1	1		0.710197606
Pattern 7			1	1	1	1			1	1	1	1	1			1	1	1	1	1	1								1
Pattern 18		1	1	1	1	1										1	1	1	1			1	1	1	1	1	1		0.721359779

Figure 48. The Coverage Solution_Trip (3, 2).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28		Pattern Type
1			1	1	1	1	1			1	1	1	1			1	1	1	1	1	1								3	[5,4,6]_[2,2,2,7]
2		1	1	1	1	1	1		1	1	1	1	1										1	1	1	1			4	[6,5,4]_[1,1,9,2]
3		1	1	1	1				1	1	1	1	1	1		1	1	1	1	1									3	[4,6,5]_[1,3,1,7]
4										1	1	1	1	1		1	1	1	1	1			1	1	1	1	1		3	[5,5,5]_[9,1,2,1]
5		1	1	1	1	1	1										1	1	1	1			1	1	1	1	1		2	[6,4,5]_[1,9,2,1]
6	1	1	1	1	1	1			1	1	1	1	1											1	1	1	1		2	[6,5,4]_[0,2,10,1]
7			1	1	1	1			1	1	1	1	1			1	1	1	1	1	1								5	[4,5,6]_[2,2,2,7]
8													1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		5	[15]_[12,0,0,1]
9			1	1	1	1			1	1	1	1	1										1	1	1	1	1	1	2	[4,5,6]_[2,2,9,0]
10		1	1	1	1	1										1	1	1	1	1				1	1	1	1	1	0	[5,5,5]_[1,9,3,0]
11		1	1	1	1					1	1	1	1	1									1	1	1	1	1	1	3	[4,5,6]_[1,4,8,0]
12									1	1	1	1						1	1	1	1	1	1	1	1	1	1	1	2	[4,11]_[8,5,0,0]
13			1	1	1	1	1	1	1	1	1	1	1	1	1	1	1												4	[15]_[2,0,0,11]
14	1	1	1	1	1	1	1									1	1	1	1					1	1	1	1		1	[7,4,4]_[0,8,4,1]
15		1	1	1	1	1	1	1	1	1	1	1					1	1	1	1									3	[11,4]_[1,4,0,8]
16		1	1	1	1	1											1	1	1	1	1		1	1	1	1	1		1	[5,5,5]_[1,10,1,1]
17									1	1	1	1	1	1	1	1	1	1	1	1	1	1	1						4	[15]_[8,0,0,5]
18		1	1	1	1	1										1	1	1	1			1	1	1	1	1	1		2	[5,4,6]_[1,9,2,1]
19		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1													4	[15]_[1,0,0,12]
20											1	1	1	1				1	1	1	1	1	1	1	1	1	1	1	4	[4,11]_[10,0,3,0]
81%	2	11	15	15	15	13	7	3	10	13	14	14	13	8	4	11	13	14	14	12	7	5	11	13	13	13	12	5	57	300

Figure 49. The Coverage Solution.

Figure 49 is the solution of this test instance which includes 20 patterns after the reserve assignment process. The open time trips are from the real historical data of this Bid month. Assignment process is manual and follows the time line assigning the trips once a day. No special policy is applied when assigning them. However, some ideas are considered when assigning trips:

1) Long trip is assigned first when comparing all open time trips which starts on the same day;
2) Assign the one which has been unused more days first;
3) Do not assign trip that is more than one day long to the pattern if it has a high possibility of being used to cover a long trip in future days.

Each row, except the last one, illustrates one pattern. Columns, except the last two, denote the days in a four-week Bid Month. The element with 1 in it indicates an on-duty day and nothing indicates an off-duty day. The one highlighted in red denotes the unused reserve day and yellow denotes assigned trip on it. The bold frame illustrates the length of an assigned trip. The number in the last row denotes the total available patterns on each day of the Bid month and the number in the grey column is the total unused days of the pattern. As we can see, the minimum number is 0 and the maximum number is 5. Hence, the utilization for each pattern is in the range of 67% to 100%. The total unused reserve days are 57 which make the average utilization of reserve patterns is 81% which is a pretty good rate. However, this assignment process does not consider the “released” rule such as “1 in 7”. The purple one is an example of an on-duty day which should be released because there are 6 continuous on-duty days prior. Which day should be released can be optimized. For example, some crew members hold a long on-duty block. If the availability patterns are much more than demand in some day of on-duty block, this day can be released for him/her. There are two more days in the same situation which are in the pattern 12 and pattern 20. They won’t affect the result a lot but still an issue should be fixed in future work.

Fifty days in 293 reserve demand are decided not to be covered by reserve patterns, so the coverage is end up with 82.935%. There are two reasons for uncovering patterns; one is high possibility but too short to use a 15 day pattern to cover. The other is with low occurring possibility.

Figure 50 illustrates the predicted coverages of pattern 6 in the solution of the model and the result after assigning trips. Pattern 6 in the green frame of Figure 49 is match with it. As we can see, the usage of pattern 6 is almost perfect. Only Trip (10, 2) is not assigned to it which is forecasted to occur. Actually, there is open time Trip (10, 2) that needs to be covered in daily operations. The reason why it is not assigned to Pattern 6 is in comparing all available patterns, there are other patterns which include more unused days prior. In order to balance the vacancy rate, this trip is decided to be assigned to pattern 3.

The optimization model is run on an HP EliteBook 820 server running i5-4300U CPU. The Gurobi 6.0.4 is used to solve this test instance in Pyhthon. Lp problem is solved in 227 minutes generating 512 reserve patterns. The optimal cost is 2039.15. The Ip problem provides a good solution in 1312 seconds and the cost is 2301.93. Some more case studies are done for different fleet and bid period. The results are shown in Table 40.

Table 40. Solution of Case Studies.

	Number of Scheduled Trips	Short trip (<3)	Medium trip	Long trip (>4)	Utilization	Coverage
Study 1	1072	82.46%	10.26%	7.28%	81%	83%
Study 2	123	91.06%	8.13%	0.81%	83%	93%
Study 3	110	77.27%	16.36%	6.37%	80%	83%
Study 4	17	41.18%	11.76%	47.06%	56%	90%

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	Coverage
Pattern 6	1	1	1	1	1	1			1	1	1	1	1											1	1	1	1		
Trip (1,5)	1	1	1	1	1																								0.330137109
Trip (1,4)	1	1	1	1																									0.186589604
Trip (1,3)	1	1	1																										0.313422774
Trip (1,2)	1	1																											0.01288913
Trip (1,1)	1																												0.156961383
Trip (2,5)		1	1	1	1	1																							0.156961383
Trip (3,1)			1																										0.01288913
Trip (4,3)				1	1	1																							0.326311904
Trip (5,2)					1	1																							0.186589604
Trip (6,1)						1																							0.330137109
Trip (9,1)									1																				1
Trip (2,5)										1	1																		1
Trip (12,2)												1	1																1
Trip (24,2)																								1	1				1
Trip (26,2)																										1	1		1
Utilization	1	1	1	1	1	1			1	1	1	1	1											1	1	1	1		

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	Coverage
Pattern 6	1	1	1	1	1	1			1	1	1	1	1											1	1	1	1		
Trip (1,5)	1	1	1	1	1																								0.330137109
Trip (1,4)	1	1	1	1																									0.186589604
Trip (1,3)	1	1	1																										0.313422774
Trip (1,2)	1	1																											0.01288913
Trip (1,1)	1																												0.156961383
Trip (2,5)		1	1	1	1	1																							0.156961383
Trip (3,1)			1																										0.01288913
Trip (4,3)				1	1	1																							0.326311904
Trip (5,2)					1	1																							0.186589604
Trip (6,1)						1																							0.330137109
Trip (9,1)									1																				1
Trip (2,5)										1	1																		1
Trip (12,2)												1	1																1
Trip (24,2)																								1	1				1
Trip (26,2)																										1	1		1
Utilization	1	1	1	1	1	1			1	1	1	1	1											1	1	1	1		

Figure 50. The Coverage Solution_Pattern 6 before and after Assignment.

2.5.3 Limitation

From the application point of view, the approach is practical and effective. The solving time is not unacceptable for running it once a month and it can be approved when running the model on a server with better CPU. Since there are some processes after solving the model, such as the shorter reserve block generation which can further cover the uncovered reserve demand, the gap between Lp problem and Ip problem can be filled in reality. However, in the methodology point of view, there are still a lot of work can be done to improve the approach. For example, some algorithms like Branch and Price, Row and Column Generation and etc. can be applied. More future work is discussed in next Chapter.

CHAPTER III
CONCLUSIONS AND FURTURE WORK

In this dissertation, two researches are involved. Chapter I related to risk management and Chapter II related to crew reserve management. These two important subjects should be viewed as a whole picture. All optimization in airlines should be based on safety. For planning and scheduling problems, the optimization always directly affects the cost. However, there may be more risk that exist because of the high efficiency schedule when the cost is reduced for airlines. Fatigue is one classic risk factor which is a hot topic in the risk management research area today. It will be discussed in this chapter.

The key Contributions of research about risk assessment and mitigation can be summarized as follows:

1) A method combining technique AHP and FTA is developed for risk identification and assessment. It is a good tool to support the FRAMS system to continuously discover the risk factors in airline and analyze them objectively. This method is also suitable for other system with rare events and severer consequence when there is not enough data available.
2) Time is taken into account with severity level to quantitate each basic risk factor of fault tree.
3) Synergy effect is considered to calculate the risk score in upper level by combining two simultaneous risk factors in lower level. Risk score for each flight is calculated based on the structure of fault tree.
4) An optimization model is developed to mitigate the risk with as least cost as possible. Time is considered to affect the cost of each measure application in the model.
5) Analysis of real world data is done and a reverse fault tree named Risk Tree is created for flat shape airline data. Risk tree is a good tool for reminding crew members the possible errors may triggered by existing threats in FRAMS system.
6) A case study is done for evaluate the whole approach. An optimization model for Risk Tree is used to run real world data. The model is solved in short time which is reasonable for applying this model in real time FRAMS system.

The main future work for this research is to complete the development of the real time FRAMS system which can improve the safety of every flight/ trip. Continuously improve the risk perception and the mansion learning technique can be used in the process.

The key contributions of research about reserve management can be summarized as follows:

1) A forecasting tool in SAS Enterprise Guide is developed to estimate the expected level reserve demand based on historical data. The demand is consecutive days demand for each trip type and the output is directly put into the next stage without rounding.
2) An integrated approach is developed to further forecast, to generate reserve patterns and to optimize them with the objective function of minimizing the total cost. The reserve pattern is described in a new way created in this dissertation. Column generation algorithm is improved in this novel optimization model. Many-to-many coverage mode makes the model have high error tolerance which can weaken the nature uncertainty in this kind of problem.
3) A multi-stage stochastic application of this optimization model is provided and some recommendations of assignment policies are provided as well.
4) Case studies are done to evaluate the approach. The solutions prove that the coverage and crew utilization are all improved by this approach.

When further applying the integrated approach about reserve in Chapter II to reality, some future works are introduced in this Chapter.

3.1 Carry-over Trips

The trips start in this month and end in the next month and are called carry-over trips. They are not included in this research, but they exist in practical work. Carry-over reserve patterns need to be generated to cover them. The on-duty days of Carry-over reserve pattern that in next month will not be restricted by the maximum days for one pattern. In other words, as long as the on-duty days in this month do not exceed the maximum number, the total on-duty days in pattern can be longer. For example, Figure 51 denotes a pattern with 3 on-duty blocks. The last one has 5 on-duty days in this month and 5 more on-duty days in the next month. It can be used to cover carry-over trips.

When a lot of reserve demands are predicted in the bid period but with limited reserve crew, generating this type of pattern may be a good way to make the staffing pressure loose.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	1	2	3	4	5
	1	1	1	1	1										1	1	1	1	1				1	1	1	1	1	1	1	1	1	1

Figure 51. A Sample of Carry-over Reserve Pattern.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
				1	1	1	1	1	1	1	1	1	1	1	1	1	1	1																
										1	1	1	1				1	1	1	1	1	1							1	1	1	1	1	
1	1	1	1												1	1	1	1	1			1	1	1	1	1	1							

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
						1	1	1	1													1	1	1	1	1	1
										1	1	1	1				1	1	1	1	1	1					
1	1	1	1	1	1										1	1	1	1									
										1	1	1	1	1	1	1	1	1	1								

Figure 52. Four-week vs. Five-week Bid Month.

3.2 Four-week Bid Month Vs Five-week Bid Month

There are two types of Bid months can be chosen when scheduling: four-week Bid month and five-week Bid month. The reserve patterns for five-week Bid Months can be longer than those in four-week Bid months. When the forecast reserve demand is high in some months, 5-week Bid month is better for covering them. For example, the maximum number of on-duty days per pattern in a four-week Bid month is 10 and in a five-week Bid month is 15. The total number of reserve days in demand is 300 in this month and 200 in the next month. If a four-week Bid month is chosen, 30 reserve crew are needed to cover them. While 20 reserve crew are needed for a five-week Bid month. Figure 52 is a good example showing the difference between these two covering periods. In the first 28 days, three reserve patterns can cover 40 days duty when it is a five-week Bid month, while in a four-week Bid month, four reserve patterns are needed to cover the same duty load. How do we make a good decision between them is an optimization problem which can effectively apportion a limited crew source.

3.3 Work Flow Improvement

In the flow chart, there are a lot of steps involved in the process of reserve crew management. The time line is really important since any information is important for forecasting. If the order or time window of them can be adjusted, more information can be retrieved to improve the forecasting. Data mining can be applied to discover the dropping habit for every individual pilot. When they are awarded to some trip on specific days with specific type, the high dropping possibility can trigger an increase of the forecasting number.

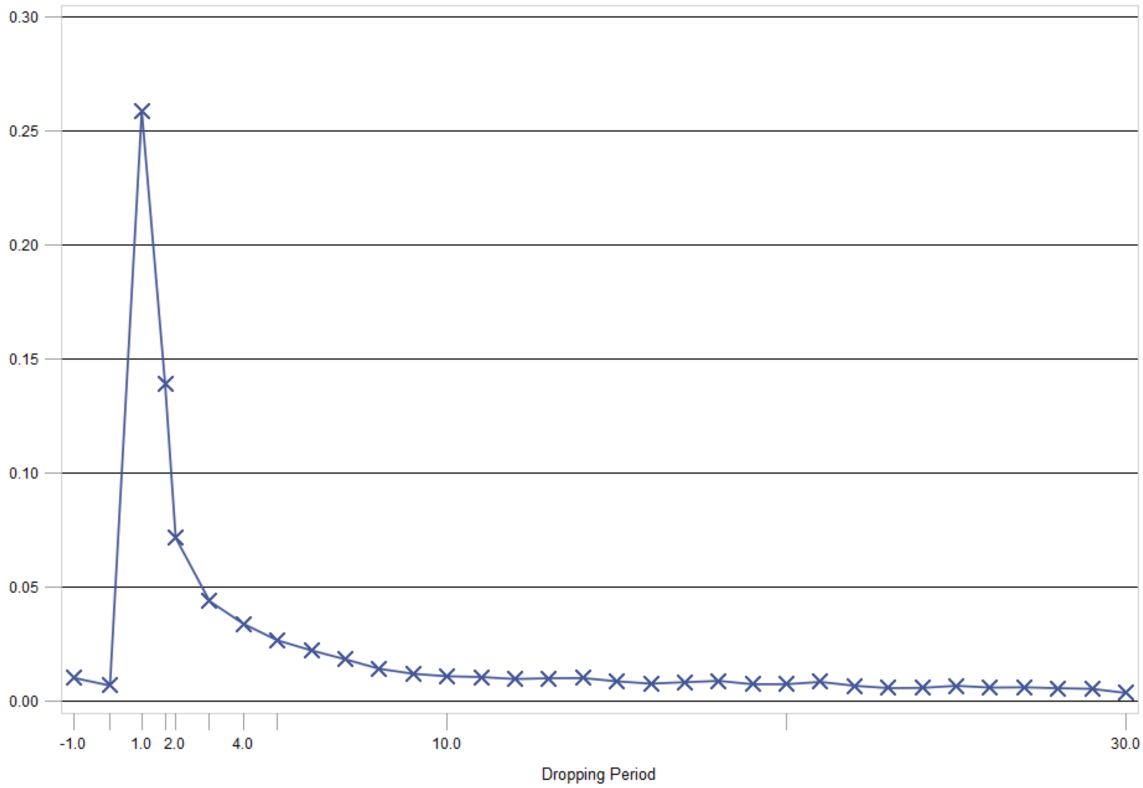


Figure 53. The Distribution of Dropping Time.

The time when the trip is dropped is another important information which can be used to improve forecasting. Some primary analyses about it have been done. Five dropping periods are used to analyze the distribution of dropping time. Figure 53 is the solution based on the sub data set used for analysis in previous chapter. In the results of one-way ANOVA, P value (<0.0001) is less than 0.05 and R value is 0.953, so that this model can explain the distribution of dropping time. As we can see, "-1" indicates all trips dropped after trip start time and the second point indicates 1.5 hours before trip start time. Around forty percent of trips are dropped in the time period from 1.5 hours before to two days before the trip start time and twenty five percent of trips are dropped in the time period from 1.5 hours before to one day before the trip. For each dropping period, the analyses of dropping reason are done. Sick is the main reason for dropping trips in first four dropping periods and in last dropping period (More than two days before trip start time), the main reason is the adjustment based on actual open time trips and forecasting by scheduler, which is good for cost control. More optimization can be done based on these analyses.

Additionally, some adjacent steps integrated can further improve the result. For example, in current approach, the reserve capacity is decided in prior step and as a parameter putting into optimization model. When the optimization model provides the optimal number of reserve crew, the two steps can be combined to adjust the distribution between regular crew group and reserve crew group to further manage the cost of each lines through different BLG and RLG.

3.4 Assignment Policy

Further researches are needed for assignment policy, because it highly affects the coverage. How to use the solution from the optimization model as a guide in daily operations is still a tackle task for future work. At least, the current assignment policy is needed to be understood to further evaluate the approach in this dissertation. If necessary, some adjustments should be considered to make the policy suit the approach. The integrated approach, which can include the process of reserve assignment, will highly approve the reserve scheduling efficiency. A comprehensive system which is user friendly is expected to be built in future. It will make schedulers' work much easier and more efficient than what it is now. More importantly, the system is effective in decreasing cost for companies.

3.5 Fatigue Risk Management

The high utilization makes the workload of crew increase. Fatigue risk is increased as well. How to take fatigue risk into account when modeling and optimizing the reserve patterns is a concern in future work. Any optimization action must be based on safety guarantee. The two systems in this dissertation may be integrated to further improve the design of reserve patterns. The solutions will be a good foundation as a guide to adjust regulations in future.

Unlike the regular line holders, reserve crew can't manage their sleep well when preparing for upcoming trips because they don't know which trip will be assigned to them and the detailed schedule. Even they are not used for some reserve day, they still spend effort being on call. When the reserve schedule is tight, they may be asked to fly another trip just after landing. The fatigue risk management should be considered to guarantee all flights are safe without fatigue risk.

3.6 Cooperation Management with Crew

The key concept to control cost is not to save money from crew salary but to minimize the waste of crew efforts. The increased utilization may result in more complaints from crew members. The cooperation of the crew is needed at this point. How to share the benefit after optimizing the scheduling process and balance the utilization and the quality of the crew's life will become more important. Game theory can be used to optimize these types of issues and create a win-win situation.

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APPENDIX

The uncovered reserve demand of the case study solution

u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.167045751269
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.119437953894
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.515644317299
u(0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.392509828968
u(0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.762139083152
u(0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.336759311163
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.280271194893
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0607339137056
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0) = 0.939113759696
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.942495759114
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0) = 0.0992034232057
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.257894676251
u(0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0814274571414
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.138403020121
u(1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.151288887483
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0) = 0.00534700345382
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0) = 0.0201890851697
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0) = 0.129332842638
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.516822387272
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.13460082208
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.33681494692
u(0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.247704953789
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1) = 0.0472768286427
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0) = 0.268036220373
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0457294755353
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0) = 0.362387050438
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.675877202662
u(0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0755621566089
u(0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.300082242604
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.27608279797
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.186382710103
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0) = 0.175109455251
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1) = 0.034898006062
u(1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0186080123376
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.0167725478019
u(0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.084611078882
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0) = 0.162547395999
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1) = 0.064685348108
u(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0.234246209417

VITA

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