Decision Analysis Models for Aircraft Engine Maintenance Planning Using Discrete Event Simulation

by

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Abstract

With stringent standards for materials, manufacturing, operation, and quality control, jet engines in use on commercial aircraft are very reliable. It is not uncommon for engines to operate for thousands of hours before being scheduled for inspection, service or repair. However, due to required maintenance and unexpected failures aircraft must be periodically grounded and their engines attended to. The tasks of maintenance and repair without optimal planning can be costly and result in prolonged maintenance times, reduced availability and possible flight delays. These factors have a negative impact on both the airline operators and the passengers alike. Aircraft manufacturers and maintainers, who provide after sale services, see significant benefits in constantly improving health management and maintenance practices by deploying the most effective maintenance strategies. Maintenance is seen as an imposed cost that ought to be minimized. Airlines must evaluate new technologies and their possible role in reducing the long term expenditure for operating a fleet of aircraft throughout its life cycle. A significant share of these expenses goes towards maintenance of these aircraft, especially their engines.

This study presents a model-based integrated decision making system for aircraft engine maintenance planning. The goal is to determine the optimum number of engines on an aircraft for maintenance based on logged engine operation data in order to maximize the use of estimated remaining time to the next service as well as to minimize

the duration of downtime. To achieve this, engine condition is used in a set of preliminary Discrete Event Simulation (DES) models to evaluate and provide the most effective maintenance policies for the aircraft engines. To assess options for making decisions, a comprehensive model is developed based on the integration of the smaller preliminary maintenance models for one, two, three and four engine maintenance cases. Results from these analyses determine the optimal number of engines tagged for maintenance on any aircraft in the fleet that arrives at the service facility. Since the materials, technicians and other costs are proprietary information, this study is time-based but allowance is made for the user to include associated costs and thus perform cost-based decision making.

Preface

This thesis entitled "Decision Analysis Models for Aircraft Engine Maintenance Planning Using Discrete Event Simulation" presents the research performed by Behnam Razavi. The research conducted in this thesis was supervised by Dr. Farrokh Sassani. The following are the publications that have resulted from this thesis [7, 46].

- **Behnam Razavi and Farrokh Sassani, 2013, "*Aircraft Fleet Maintenance Planning Using Combined Cost Benefit Model and Branch and Bound*", ASME International Mechanical Engineering Congress and Exposition, IMECE, San Diego, CA, USA.** This paper presents a maintenance planning method for determining the time of maintenance based on the historical engine operation data. Data from each engine with most chance of failure is then selected and fed into an extended Branch and Bound (B&B) routine to determine the best optimum sequence for entering the facility in order to minimize the waiting time. The author of this thesis was the principal researcher of this publication. Dr. Farrokh Sassani assisted with formulating the initial problem, and with writing and editing the manuscript.
- **Behnam Razavi and Farrokh Sassani, 2014, *"Optimal Aircraft Engine Maintenance Planning Using Discrete Event Simulation"*, Department of Chemical & Biological Engineering, Research Day, October 1, University of British Columbia, Vancouver, Canada.** This was a poster which illustrated the

overall maintenance planning and decision making procedure proposed for Integrated Scenario Selection (ISS). The model developed and simulated in Arena® discrete event simulation. Results reported in this poster are from the material presented in chapters 2 and 4. Dr. Farrokh Sassani assisted with modeling the problem and preparing the poster.

- **Behnam Razavi and Farrokh Sassani, 2015, "*Decision Analysis Model for Optimal Aircraft Engine Maintenance Policies Using Discrete Event Simulation*". Integrated Systems: Innovations and Applications. In Press: Springer - Verlag Berlin Heidelberg.** This manuscript presents the development of Discrete Event Simulation (DES) models that utilize aircraft flying, grounding and engines service times, Time-On-Wing (TOW) data for each engine since its last service, and Remaining-Time-to-Fly (RTTF) to aid optimal maintenance policy decision making. The proposed models and techniques are explained and discussed in chapters 3 and 4. The author of this thesis was the principal researcher of this work. Dr. Farrokh Sassani assisted with modeling the problem, and with writing and editing the manuscript.

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k	Number of channels
L	The average number of units in the system
L_q	The average number of units waiting for service
P_0	The probability that all k service channels are idle
P_n	The probability of n units in the system
P_w	The probability that an arriving unit must wait for service
W	The average time a unit spends in the system (waiting + service)
W_q	The average time a unit spends waiting for service
x	Number of arrivals per unit of time
λ	Average number of arrivals in a specific period of time
μ	Average number of units serviced in a specific period of time

Glossary

AHP	Analytical Hierarchy Process
AI	Artificial Intelligent
CBM	Condition Based Maintenance
CM	Corrective Maintenance
DEDS	Discrete-Event Dynamic Systems
DES	Discrete Event Simulation
FIFO	First-In-First-Out
HMM	Health Management and Maintenance
ISS	Integrated Scenario Selection
LAV	Lowest Attribute Value
MRO	Maintenance, Repair and Overhaul
PM	Preventive Maintenance
RTF	Run To Failure
RTTF	Remaining Time to Fly
TNOW	Time Now (current clock in Simulation)
TOW	Time-on-Wing
Trs1	Primary Threshold
Trs2	Secondary Threshold

Acknowledgements

This research project would not have been possible without the support of many people. First and foremost, I offer my sincerest gratitude to my supervisor, Professor Farrokh Sassani, who has supported me throughout my thesis with his patience and knowledge as well as his encouragement, guidance, unconditional help and effort. Additionally, I would like to express my sincere gratitude to Professor de Silva and Professor Dunbar, members of my supervisory committee, for their support and guidance.

I would like to thank my colleagues at Process Automation and Robotics Laboratory (PAR-LAB) for their friendship and invaluable assistance, notably Atefeh Einafshar, Morteza Taiebat, and Abbas Hosseini and Dr. M. Karafi. Very special thanks go to Soroush Sharifi and Hediyeh Tehrani for their assistance and input.

I would also like to acknowledge the sources of financial support for this research, namely: Natural Sciences and Engineering Research Council (NSERC) of Canada, CRIAQ (Consortium de Recherche et D'Innovation en Aerospatiale au Quebec), and GlobVision Inc.

I cannot end without thanking my family, on whose constant encouragement and love I have relied throughout my time finishing the work. Finally, I would like to thank my father and mother who are the source of all greatness; brother, sister and brother-in-law; Behrad, Behnaz and Hossein, for their everyday support, and my late sister, Bahareh, whose thought will always be in my mind.

Dedication

I dedicate this work to my father, Dr. Jalil Razavi, who is the greatest role model and a friend. He has taught me to work hard for the things I aspire to achieve in my life. He is the source of my motivation and inspiration.

“Success is about dedication. You need to have vision and think ahead which will lead you to an incredible end”.

Chapter 1

Introduction

1.1 Preliminary Remarks

Measures are taken by many industries to keep machines and operating systems in trouble-free condition and are collectively termed maintenance engineering. After an equipment is designed, fabricated, installed and gained an operational status, it is the duty of maintenance department to look after the health of the system to make sure it has the operational availability. A system which is properly maintained and serviced during its entire life cycle, in an ideal case, will reach its maximum availability. An engine on an aircraft and holistically a fleet of aircraft is no exception. Considering the scale and scope of the operation of a fleet, the associated times, costs and consequences of inefficient maintenance can be very significant [1].

In regards to the traditional viewpoint, maintenance is required to repair and fix the worn or damaged components of a system triggered by extended use or failure. A more recent view of maintenance is defined in [2] as “all activities aimed at keeping an equipment in or restoring it to the physical state considered necessary for the fulfilment of its intended function”. Viewing this in a bigger scope, some more practical operations could be included such as routine servicing and periodic inspections, preventive replacement and condition monitoring. For instance, to improve engine reliability, decisions could be made for component replacement (maintenance) or make some positive modification to a design (fabrication). Therefore, in order to properly manage maintenance, it should cover every stage in the life cycle including component specification, data acquisition, planning, operation, and performance evaluation.

1.2 Impact of Maintenance

Maintenance is one of the tools for ensuring satisfactory system reliability. At a time, however, when this approach is constrained, the mechanical components are forced to get the most out of the system through more effective operating policies, including improved maintenance programs. In fact, maintenance is becoming an important part of the operation of any system. The implementation of effective maintenance programs can represent a significant step in the direction of “getting the most out” of the equipment installed. Monitoring the operating condition of equipment and their components has recently been facilitated by means of developing computer-based maintenance planning for better precision and accuracy; and thus effective cost reducing techniques.

Maintenance costs are usually a major portion of the total operating costs in most operations [3, 4].

The concept of maintenance comes with the idea that it can be planned and managed in such a way that it provides an efficient continuous operating conditions at all times. In addition, the maintenance can be treated as an investment rather than a cost cumulative procedure. The need for maintenance can be predicated before an actual failure and ideally, maintenance is performed to keep equipment and systems running efficiently for at least the designed life of the component(s). As such, the practical operation of a component is a time-based function. If one were to graph the failure rate of a component population versus time, it is likely the graph would take the “bathtub” shape, as illustrated in Figure 1.1. In this figure the vertical and horizontal axes represent the failure rate and time, respectively. From its shape, the curve can be divided into three distinct: early failure, useful life, and wear-out periods [5].

The initial region that begins at time zero characterizes a high but rapidly decreasing failure rate. This region is known as the *early failure period*. This period typically lasts several weeks to a few months depending on the case. Next, the failure rate stabilizes and remains roughly constant for the majority of the useful life of the component. This long period of a constant failure rate is known as the the *useful life period*. Most systems spend much of their lifetime operating in this flat portion of the bathtub curve. Finally, if the product remains in use long enough, the failure rate begins to increase as materials wear out and degradation failures occur at an increasing rate. This is the *wear-out failure period*.

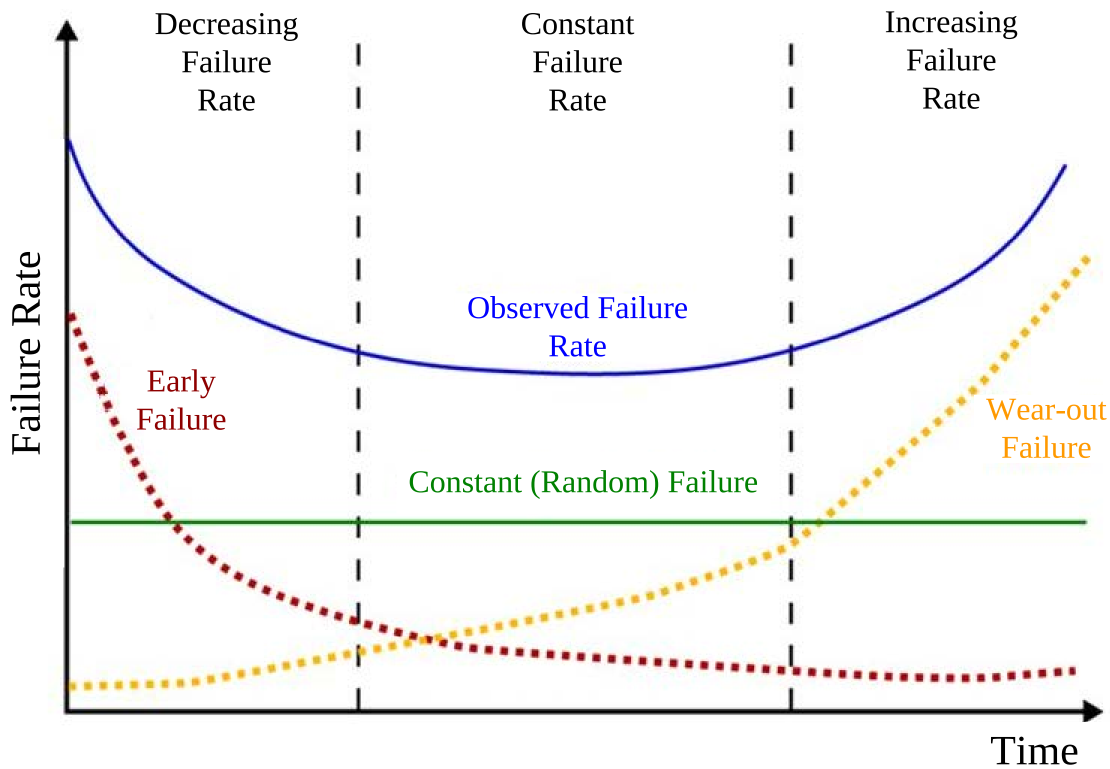

Figure 1.1: Component Failure Rate over Time

When a system breaks down, it needs to be properly attended to in order to bring it back to its normal operation. This conventional maintenance management philosophy is categorized into two types: Run-to-Failure (RTF) and Preventive Maintenance (PM) [3].

The logic of RTF management is simple. As the name implies when an equipment or a machine breaks down, repair it. This “if it is not broken, do not fix it” method has been a major part of maintenance operations for long time. The RTF concept waits for system failure before any maintenance action is taken. No capital or effort is spent until the system fails to operate normally and requires attendance and repair. This in fact is a most expensive method of maintenance management with many disadvantages. For instance, a system at any time must anticipate a sudden failure and have the capability to react in order to overcome consequences. It is indeed unimaginable, unlikely and legally forbidden that one could use this technique for aircraft maintenance operation which in case of a sudden failure will have catastrophic ramifications.

All preventive maintenance management programs are time driven or in other words the maintenance is based on the number of hours of operation. As shown in Figure 1.1, the probability of a failure is more likely at the beginning of the operation. The probability of failure decreases and then increases as the time passes and the normal life operation period ends. Preventive maintenance is scheduling on a pre-determined interval on the basis of statistics and knowledge of historical data. In general, it can be defined as actions performed on a time based schedule that prevent degradation of a component or equipment with the aim of extending system useful life time through controlling degradation to an acceptable level.

While preventive maintenance is not the optimum maintenance program, it does have several advantages. By performing the preventive maintenance, the life of the equipment is extended. This translates into dollar savings. However, PM could be costly if the failure occurs sooner than the system is scheduled for maintenance. As a result, RTF type maintenance may be implemented and this will be even more costly than the same repair made on a schedule basis. Preventive maintenance will generally run the equipment more efficiently, reduce the probability and the number of failures. Minimizing failures translate into maintenance and capital cost savings [5].

1.3 Maintenance and Aircraft Industries

Aviation maintenance activities are the backbone of all successful aviation industries. Good maintenance provides safer and more reliable aircraft. It increases aircraft usage, and provides confidence of air travel to the thousands or millions of travelers who want to enjoy the safety of modern aircraft and transportation. A good maintenance management is an asset that can provide the aviation industry the essentials necessary to establish flying confidence in the public. Without having such good maintenance in place, aviation industries can suffer severely if travelers face delays and cancellations, and lose confidence in certain airlines for instance [6].

Any engine is prone to failure; however, properly maintained aircraft engines could reduce the occurrence of failures. Therefore, aircraft manufacturers and users will generally benefit from implementing Health Management and Maintenance (HMM) techniques by developing effective maintenance planning and strategies. The goal of HMM techniques is to reduce the life cycle costs for operating the entire aircraft fleet. Considerable shares of these life cycle costs are expenditures for Maintenance, Repair and Overhaul (MRO) of the individual aircraft engines [7].

The mechanical complexity of aircraft engines results in considerable labour working hours for MRO related tasks such as disassembly, inspection and replacement of expensive worn parts, reassembly and re-commissioning [8]. Therefore, engine MRO is considered as a cost driver and it is in the interest of aircraft operators to estimate the life cycle and the costs when making decisions regarding their aircraft fleet.

Moving forward from conventional maintenance strategies, at the present time the newly formed maintenance operations are categorized into three types of maintenance strategies: 1) Corrective maintenance in which the system is partially or completely shut down and one or more of the components are replaced. However, the system condition may not become as good as new. 2) Preventive maintenance which is performed based on a predetermined interval. It aims to prevent problems associated with corrective maintenance and to reduce system downtime. 3) Condition Based Maintenance (CBM) is a form of preventive maintenance but is scheduled and performed based on the 'live' knowledge of the condition of the system components [9, 10].

Maity et al. [11] studied an automated scheduling model that took CBM into account along with traditional preventive maintenance guidelines and used the information such as part and facility availability, to arrive at an optimum maintenance schedule. The model used Generic Constraint Development Environment (Gecode software) alongside multiple constraints such as ordering of parts and crew availabilities. Two issues, namely improving efficiency and reducing cost were treated.

Halasz et al. [12] put into practice an integrated system of remote monitoring and decision support for a fleet of aircraft. An Artificial Intelligence (AI) program was used to remotely monitor a fleet of commercial aircraft and alert maintenance staff in advance to deal with an expected difficulty or fault which could disrupt the operation. One of the main requirements for the system was to have vast information base such as a communication network, document delivery and equipment dispatch regulations. The system is yet to be implemented and tested against a real system and further improvement is required such as maintenance cost evaluation.

Yanqing and Xueyan [13] developed an Analytical Hierarchy Process (AHP) to tackle uncertainty factors in the process of aircraft safety risk management. Using AHP, the priority weights of factors that affect aircraft flying safety was calculated. AHP both assessed the safety and identified the hazards during the aviation maintenance in order to improve the safety level. The degree of success in this study was dependent upon the amount of information the aviation industry share with the authors and level of uncertainty during the maintenance. Rad et al. [14] studied the effect of spare part availability, their effect on maintenance planning, negative cost impact on flight cancellation and airline performance. They used the available operational information in Analytical Hierarchy Process (AHP) to classify the importance of the spare parts, usage rate, unit price and reliability. The drawback for using AHP in this study was the unavailability of such information.

Altuger and Chassapis [15] developed an Arena® based discrete event simulation model for a decision making to select a PM scheduling plan for a manufacturing process that gave the best utility and performance. Based on desired preferences, different criteria with different confidence intervals were considered to evaluate and to assess the available preventive maintenance schedules. They showed the advantages of discrete event simulation in emulating real scenarios.

1.4 Research Objectives

Figure 1.2 shows the overview of the maintenance related operations envisaged for a fleet of aircraft, where research activities within each box are conducted by a different group of researchers. The arrows indicate the information flow. The research conducted within the dashed-line box is the scope of the present thesis. Essentially, the in-flight monitoring information is passed to the Diagnosis and Prognosis Group which then forwards its analysis results to the Operations and Maintenance Task Planning Group.

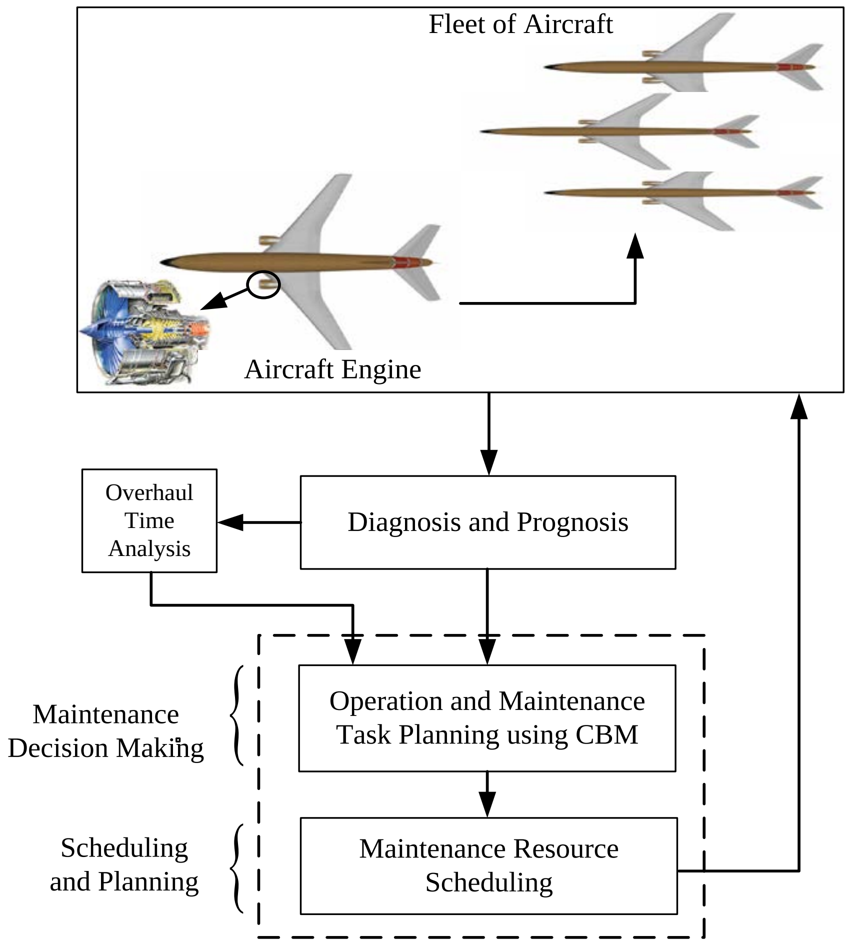

Figure 1.2: Graphical Representation of Maintenance Operation

The research objectives within this group (the present thesis) were to:

1- Model and evaluate various CBM engine maintenance policies for a fleet of aircraft aiming to maximize the estimated remaining useful time to the next service and minimize the duration of downtime.

2- Provide management and maintenance personnel with a simple decision making tool to readily examine other alternatives and variations to the existing policies.

1.4.1 Aircraft Overhaul Planning

As engines on an aircraft are generally at different state of health, it is often one engine that initiates the need for maintenance. However, an analysis is performed to see while the aircraft is at the service facility, whether it is cost- or time-effective to extend the preventive maintenance to other engines of the aircraft, and if so determine the number of engines so as to minimize the total time of the overhaul, which equally means maximize the available flying time.

The objective of Maintenance, Repair and Overhaul (MRO) planning is to estimate and to utilize the maximum remaining useful life of the system components, improve safety, and reduce maintenance down times. To meet these objectives, studies have discussed different approaches [16]. For MRO, industries usually consider a few parameters when monitoring a system. In aircraft, each engine should have sufficient performance margin time between repairs to carry it through to the next overhaul. Each engine in the system is represented by its own Time-On-Wing (TOW) graph which shows its condition over time, and from which the Remaining-Time-to-Fly (RTTF) value can be estimated.

As shown in Figure 1.3, if the engine is close to the maximum certified operating limit, it must be sent for overhaul. The goal is to safely identify any of the engines in operation and place them for maintenance when their remaining flying time is near the assigned typical threshold of 100 hours. However, there are no clear policies as to how many of the engines should be attended to once an aircraft is grounded due to one engine. Therefore, the aim of this study is to develop detailed simulation models where different policies can be examined.

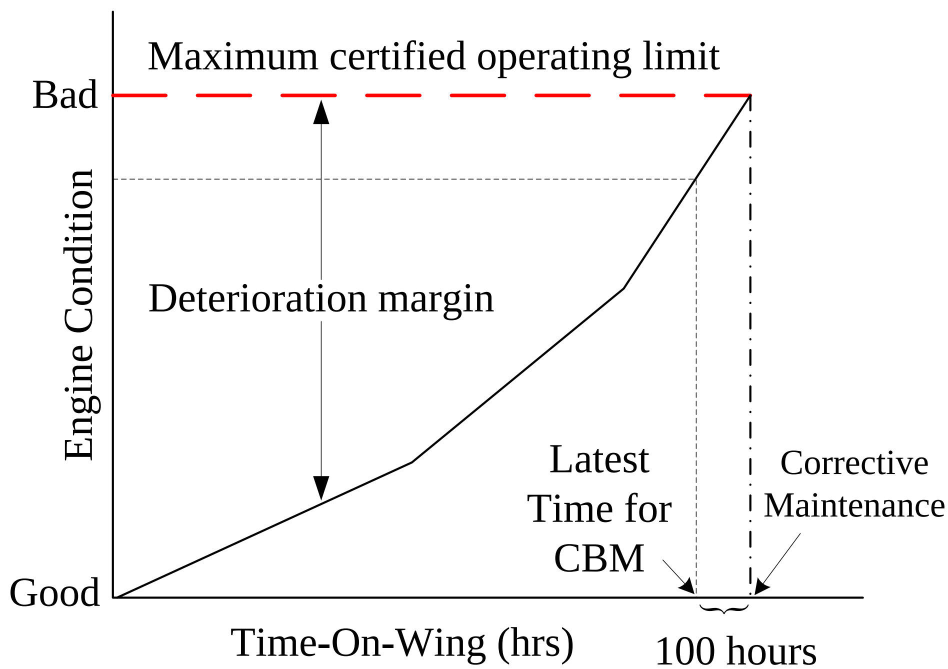

Figure 1.3: TOW Graph Representing Engine Deterioration

One of the main challenges associated with this study was its confidentiality issues related to the release of information by the company involved. Due to the proprietary information, the simulation model developed is based on synthetic data. The verification of simulation model was achieved through simplified and alternative modeling analysis. The industrial partner/user will undertake running the model with real proprietary data in confidence once the working model is concluded.

The plan of study presented here is to develop aircraft engine maintenance scenario analysis models using discrete event simulation for a fleet of aircraft. This is to help the maintenance managers evaluate alternate policies and take the best course of action that is most effective in reducing the grounding and service times. This maximizes the availability of aircraft in the fleet. Since discrete event simulation requires deep knowledge of discrete event modeling concept which have slow changing learning curves, an extended plan is to re-cast the simulation results from the discrete event modeling onto a "queuing concept modeling". Queuing models can be represented in mathematical equations that can be readily manipulated to assess many alternative policies.

1.5 Organization of the Thesis

In Chapter 1, an introduction to a typical aircraft industry and the related current and common maintenance schemes were introduced. Planning different methods of maintenance, which has always been an essential part of any industry and has been a major challenge for the aircraft industry, was brought into the forefront. Some of the common difficulties that arise in obtaining optimal maintenance planning were discussed.

Next, a review of literature related to aircraft and maintenance was presented, and the main objectives of the current research were outlined.

Finally, an overview of maintenance operation, and the basic concept of Condition Based Maintenance (CBM) were graphically presented.

In Chapter 2, various forms of maintenance, specifically, CBM are introduced and discussed in greater detail. As well, the overall problem statement under consideration is explained.

The development of discrete event models and simulation that are relevant to the current study are undertaken in Chapter 3. Specifically, Arena® based discrete event simulation models with respect to aircraft engine maintenance planning is developed.

In Chapter 4, the simulations with the developed DES models for aircraft maintenance are carried out. Results for the proposed methods of maintenance are shown, followed by discussions on the outcome of the maintenance schemes. At the end, the simulation results obtained using Arena® are verified against a parallel work developed and implemented in SIMIO discrete event simulation software.

In Chapter 5, queuing theory is introduced and used based on both the existing information from data logs and the results obtained from the discrete event simulations.

Chapter 6 draws conclusions from the modeling and simulation results of the study. Recommendations are made on possible future work for improvement of the developed techniques.

Chapter 2

Maintenance Opportunities and Planning

2.1 Introduction

This chapter describes and discusses the overall project aim, the challenges associated with this study and the current problems the aircraft industry face, and the methodologies proposed in this study. As indicated in the previous chapter, the main focus of this research is to obtain efficient and cost effective policies of maintenance which would prolong the useful life of aircraft engines. An effective policy is one that allows aircraft to have longer flying periods which in turn minimizes the downtime and maximizes the overall profits. Achieving these objectives provides the aircraft industry/user a system with an optimal performance and aircraft engine conditions which meet the desired and regulatory criteria of being healthy and safe. The effort here is to develop Condition

Based Maintenance (CBM) plans and avoid un-timely costly repairs or Corrective Maintenance (CM).

Condition inspection frequency and condition based maintenance and their relations to component failure and deterioration are explained in section 2.2 and 2.3, respectively. This is followed by the problem description and the main challenges associated with this study in section 2.4.

In section 2.5, the proposed simulation based maintenance policy development and related literature review are presented. Implementing different sequencing methods of entity arrivals in the proposed maintenance system are discussed in section 2.6.

2.2 Condition Inspection

A major disadvantage of the time based/planned preventive maintenance is that some useful life of the equipment that still remains is lost when earlier-than-needed service is performed. However, taking into account the consequence of a failure, it is a better option to use preventive rather than corrective maintenance. When dealing with capital intensive systems, it is more logical to inspect them regularly before removing and subjecting them to maintenance. Through this 'condition monitoring', a better understanding of the system health can be achieved and maintenance performed in a time-optimal fashion that allows longer uninterrupted in-operation periods for the system.

2.3 Condition Based Maintenance (CBM)

Every manufacturer or service company has a set of defined assets on which its existence depends. Continuation and availability of these assets will ensure the business productivity while it is in operation. In a large enterprise, reducing costs related to maintenance, repair, and ultimate replacement is at the top of the management concerns. Downtime in any industrial system ultimately results not only in high repair and other costs, but also in customer dissatisfaction and lower potential income [17].

Figure 2.1 represents the common types of maintenance. In general, the concept of maintenance is divided into *unplanned* and *planned* [18, 19]. Unplanned maintenance, or sometimes referred to as *reactive maintenance*, is performed when a failure occurs in the working system and it is required to restore the system to its original or near-original condition. This restoration through maintenance is also referred to as *corrective maintenance*. There are cases when an immediate action is required in order to avoid hazardous situations. This urgent type of maintenance is sometimes referred to as *emergency maintenance*. Planned maintenance, or so called *proactive maintenance*, categorizes into: *preventive maintenance* or *predictive maintenance*. Kothamasu and colleagues [18] investigated three types of preventive maintenance: *constant interval*, *age based* and *imperfect*. Furthermore, they also investigated types of predictive maintenance and they categorized it into *Reliability Centered Maintenance* (RCM) and *Condition Based Maintenance (CBM)*.

Maintaining processes and systems have evolved dramatically over the years. Nowadays, effective maintenance systems are expected to detect early forms of degradation in predictive maintenance practices using Condition Based Maintenance (CBM). Basically, condition based maintenance is a methodology that combines predictive and preventive maintenance with real-time monitoring. CBM detects faults and identifies sources sufficiently ahead of likely failures. This characteristic makes this type of maintenance a proactive process which acts in advance to deal with unexpected and impending faults.

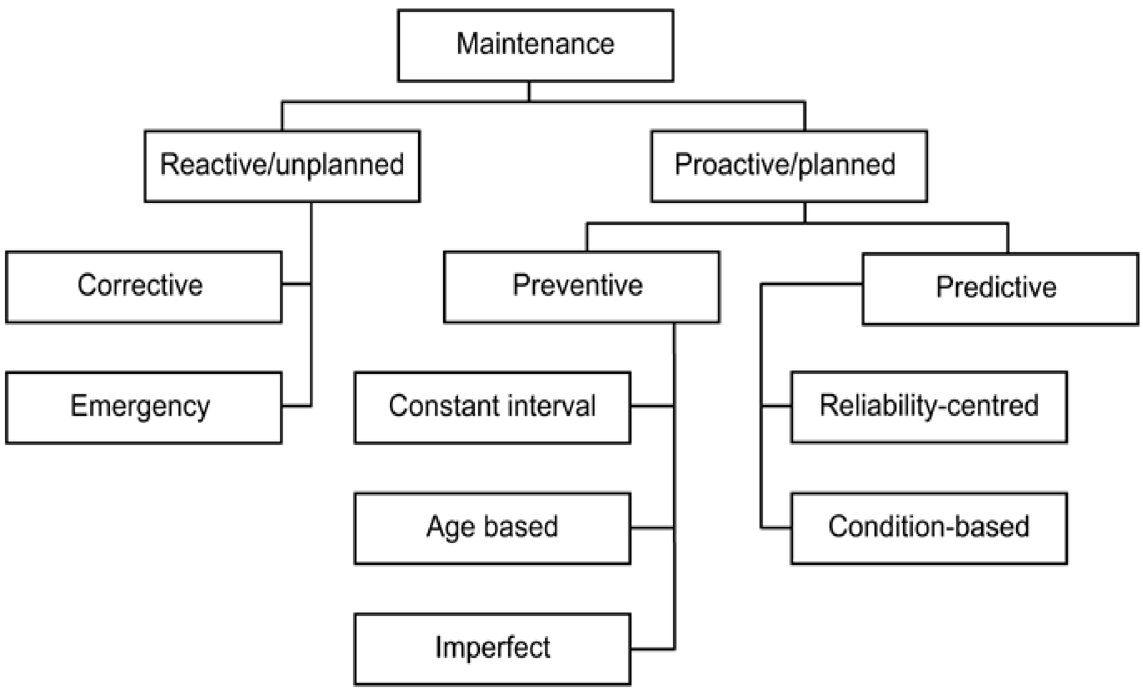

Figure 2.1: Maintenance Categories [18]

Actions that extend the life of equipment include: lubrication, cleaning, adjusting and the replacement of numerous minor components like drive belts, gaskets, filters, etc. Actions that prevent unnecessary failure include timely and consistent equipment inspection, and an aggressive use of non-destructive testing techniques such as vibration analysis, infrared testing, or in-system sensor-based techniques. Through the utilization of various non-destructive testing and measuring techniques, predictive maintenance significantly improves estimating equipment health status as well as the best time for maintenance before costly repairs are required [20]. Thus through CBM, the time of initiation of failures is predicted long before it occurs based on the knowledge from system components [3, 20].

Al-Najjar and Alsyouf [21], Rosqvist et al. [22, 23], Waeyenbergh and Pintelon [24, 25] and Wang et al. [26, 27] provided some insight into when a particular maintenance technique should be employed. CBM and its advantages have been discussed in many studies [19, 28-30]. However, with some exceptions, surprisingly little attention has been paid to different aspects and types of condition based maintenance. Jardine et al. [31, 32] provided an overview of different types of tasks within a CBM program such as data acquisition, data processing and maintenance decision making, algorithms and technologies for each task.

2.4 Problem Description

Nowadays, the actual life of an aircraft fleet is not the same as the expected life of the original design. To a great extent, it is determined by the degree of maintenance, the maintenance expenditure, and the economic considerations required for the fleet to continue its operational requirements. Due to the development of health monitoring technologies, Condition Based Maintenance (CBM) policies have become increasingly suitable for application in areas such as aircraft industry. Engine health management, engine life management and maintenance decision making are the primary content of an engine CBM policy [10].

The problem in CBM and preventive maintenance arises when one tries to examine the stored and collected engine performance data to gain knowledge of the current condition, predict degradation trend curves, and to optimally determine the proper maintenance times. This information is essential in order to best manage the estimation and improve the engine life, provide spare parts, prevent fatal injuries, and to substantially reduce the cost of operations and maintenance as a whole. However, due to its physical construct, maintenance of a single engine by itself is a very involved task. When this is compounded with the need to maintain a fleet of engines within many stringent constraints and standards, the problem can become prohibitively large, operationally inefficient and costly.

Development of a decision support scheme for an aircraft fleet is essential for tracking individual engines within a fleet, and producing safe and cost-effective maintenance plans. Implementing any technique that uses a large volume of monitoring data with many operational details requires very precise and careful data mining, interpretation, and modeling, before any useful application can be imagined. A small part of this study involves analyzing health trend curves, or so called Time-on-Wing (TOW) graphs, as a function of flying time for different engine models. Figure 2.2 elaborates on TOW graph a single engine.

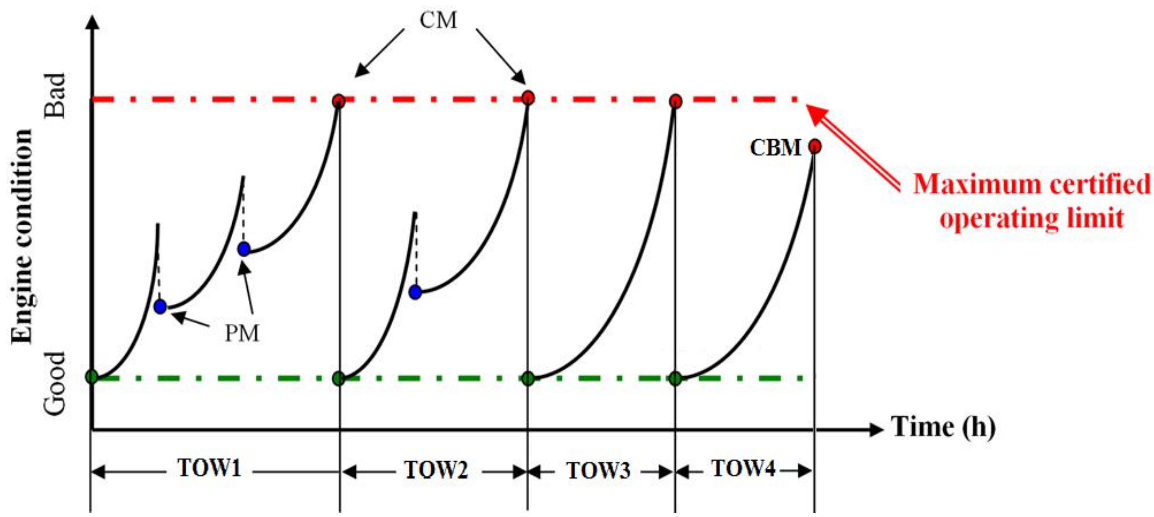

Figure 2.2: Engine Condition and Time-on-Wing Characteristics

The engine condition deteriorates as the number of flying hours increases. Preventive maintenance (PM) is performed to improve engine condition and to maximize its TOW operation before reaching the maximum certified operating limit or complete failure of a component in which a costly removal-from-the-wing and corrective maintenance (CM) must be performed. In CBM, the knowledge about the system component will help correctly decide on the cycle of PM only when it is needed to reduce unnecessary costs and maximize the profits.

The trend of these TOW graphs are expected to be non-linear, and will be updated as new data become available to better estimate the time margin (remaining time) of safe operation. As will be thoroughly explained in later sections, utilizing flight information and system analysis techniques, such as Discrete Event Simulation (DES) modeling, will help to investigate and to predict the engine overhaul needs and remaining TOW.

Each engine in the system is represented by its own TOW graph which shows its condition over time, and from which the Remaining-Time-to-Fly (RTTF) value can be estimated. The objective here is to develop a detailed DES model for a fleet of aircraft which can examine different scenarios using identified engines with their RTTF near assigned typical threshold of 100 hours of reaching maximum operating limit. DES can assist the user in selecting suitable policies for minimizing downtime and maximizing aircraft availability.

2.5 Simulation Based Maintenance Policy Development

Discrete event simulation has been suggested and used by many researchers for development of system analysis and decision making tools as it allows numerous options to be evaluated before the best scenario can be selected. Various researchers have reported significant benefits from the use of simulation-based models for process improvement, scheduling and scenario comparisons [6]. Some studies have used DES to design efficient production and business systems, to validate alternatives and propose solutions to improve performance, sales and profits [33, 33-35]. Other investigators have used it for decision making in preventive maintenance scheduling, network behaviour and personnel scheduling and maintenance operation for flight training department [15, 36-38]. Different scheduling approaches for dynamic manufacturing shops and facilities, and evaluating the performance and the profit of manufacturing systems are other examples of the use of DES [39, 40].

In DES, the system status progression depends on the initiation and occurrence of events at different times by different objects or entities. For example, in a fleet operation, the arrival of an aircraft for maintenance is an event of interest, and its arrival time or duration can be variable, depending on the current state of the system and the condition of the engine. These kinds of systems, characterized by discrete variables and continuous time, are called Discrete-Event Dynamic Systems (DEDS) [41]. The different methods for modeling and simulation of DEDS are called discrete event modeling and simulation [42]. Although time is continuous, discrete-event modeling and simulation assumes that only a finite number of events can occur in a determined period. To this extent, a discrete-event simulation can be very efficient since it only needs to represent the changes of state as an event takes place, rather than continuously.

Health management technologies monitor systems and detect abnormal behaviour and then relate it to useful information about the system's condition. When the condition of a system, such as its degradation level, is continuously monitored, a Condition-Based Maintenance (CBM) can be implemented [43-45].

As shown in Figure 2.3, condition data of each engine in the fleet is captured using in-flight sensory systems. This information is received and used as an input in the “engine RTTF analysis” block. In the time analysis block, some maintenance policies are defined and implemented within the DES and the maintenance plan is decided upon before any aircraft is dispatched to the service facility [46].

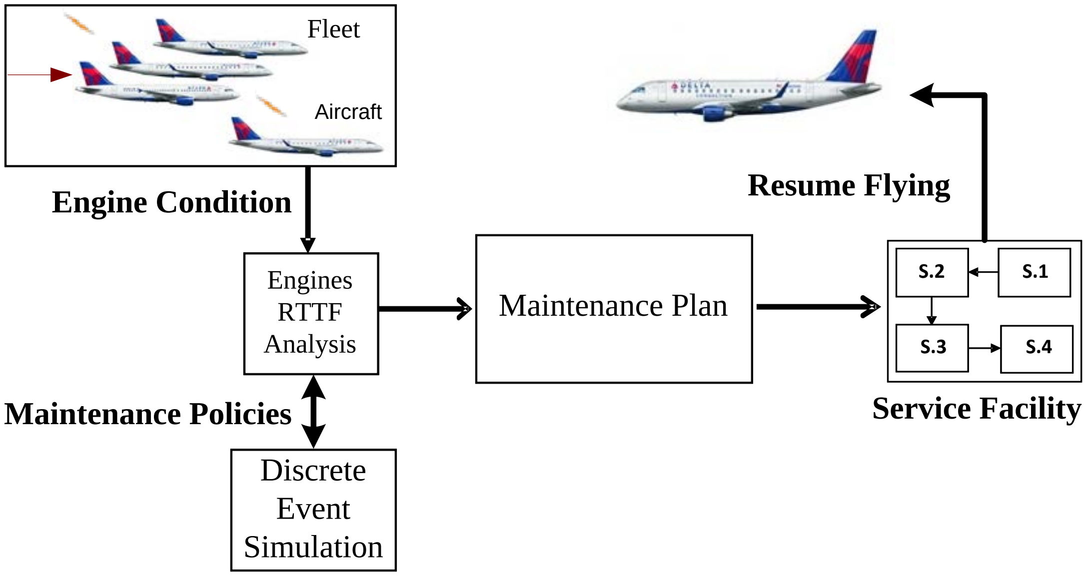

Figure 2.3: Schematic Flow Chart of Problem Description

When the status of ‘one’ of an aircraft’s engines is near its assigned threshold of reaching maximum certified operating limit, a maintenance activity is assigned and the aircraft is put into the maintenance planning system. Once the plan is set, an overall overhaul time analysis is conducted to see whether it is beneficial to perform maintenance on more engines, rather than on the ‘one’ that initiated the maintenance, while the aircraft is grounded.

Inside the service facility there are four stages of maintenance activity for each engine which are laid out in series as shown in Figure 2.4. The time it takes to perform each stage is determined by the user based on the type of the engines on a specific aircraft. Since this complete information is not available due to confidentiality, based on limited information made available, approximate hypothetical/synthetic data will be randomly generated and used in the simulations carried out in this study. Engine diagnosis and disassembly, repair and maintenance, indoor assembly and partial testing, and outdoor engine testing and release are the four tasks performed in series that are designated by S.1, S.2, S.3 and S.4, respectively.

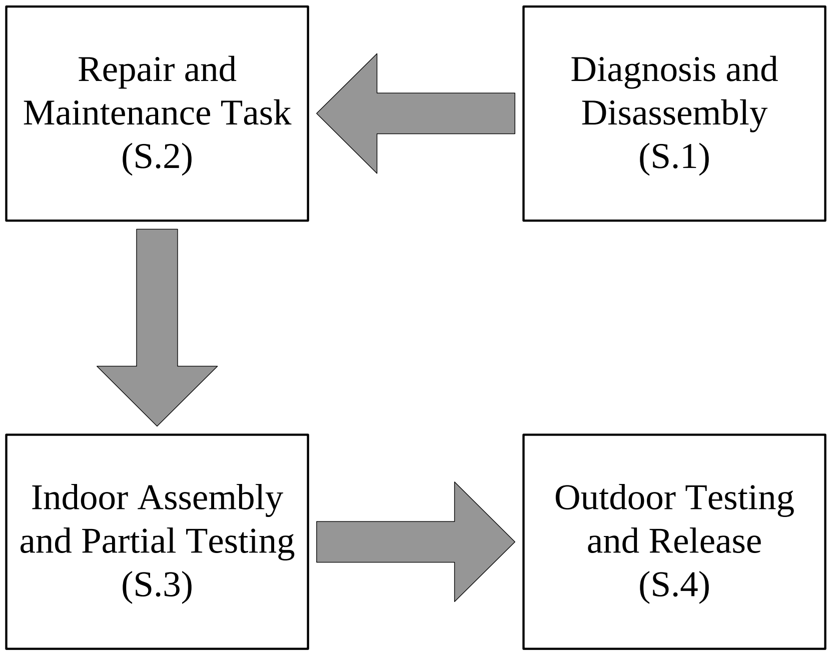

Figure 2.4: Engine Maintenance Overhaul Process

In engine diagnosis and disassembly module, the engine is disassembled into parts if necessary, and sent to part inspection module for cleaning, functionality assessment, non-destructive testing, detecting cracks, and dimensional checks on blades and vanes, for example. In Repair and maintenance module, parts are repaired or replaced and sent for re-assembly and indoor partial testing. The next step is to complete the final stage of the testing outdoor if needed, and discharge the engine. Once the engine is released, engine status is updated and recorded as engine service history for future use and reference.

2.6 Scheduling and Sequencing Methods of Arrivals

Scheduling deals with the planning of operations. The task is essentially the 'placement for service'. Whereas sequencing concerns the maintenance facility where a decision has to be made as to the priority of the services performed. In the DES models developed in this work, two sequencing rules are implemented as described below.

2.6.1 Lowest Attribute Value (LAV)

The Low attribute value is used for the grounding of aircraft for maintenance. (The term Attribute becomes clear when the Arena® concepts are described in Chapter 3.) LAV is the natural and desirable choice since the aircraft closest to the assigned threshold (lowest safe flying time remaining) aircraft must be grounded first. As such, it is enforced by default in the modeling concepts used in this work.

2.6.2 First-In-First-Out (FIFO)

In the maintenance facility for the queue of aircraft, if there is no specific reason to resort to a particular priority rule or a sequencing algorithm, the best heuristic rule that minimizes 'Mean Flow Time' and the 'Work-In-Progress' is the 'Shortest-Service-Time-First'. Since, a maintenance facility is a dynamic system where there is constant arrival of aircraft; such a policy can consistently disadvantage some aircraft waiting for service. From commitment-to-return-to-particular-flying-route, and uniformity of maintenance service provided, it was decided that it is both acceptable and 'fair' to use the convenient and most practical 'Fist-In-First-Out' queue discipline [47-49].

Chapter 3

Discrete Event Modeling and Simulation

3.1 Introduction

Experimentation is still one of the principal methods of problem solving. However, when problems are more complex and do not readily lend themselves to experimentation alone, they must be tackled in some other ways. One solution to study such a problem thoroughly is to divide it into smaller sub-problems and create feasible models that make the solution and analysis possible [42]. Discrete event simulation software is a versatile and powerful tool for modeling and investigating the performance of complex systems.

In this chapter, discrete event simulation, Arena® simulation software, modeling concepts, and the simulation models developed in this study are presented.

The organization of the material in this chapter is as follows: simulation, its benefits and disadvantages, and different phases involved in simulation modeling are discussed in section 3.2. This is followed by an introduction of Arena® based discrete event simulation for the maintenance system being studied in section 3.3. Application of Arena® simulation in the present study is discussed in section 3.4 and model formulation discussed in section 3.5.

3.2 Simulation

Discrete event modeling and simulation technique is intended to 'copy' a real-world process or system and mimic its operation over time. To simulate, it first requires a model to be developed. This model represents the key characteristics or functions of the selected physical system or process. The model represents the system itself, whereas the simulation represents the operation of the system over time [50] as events take place. Each event occurs at a particular instant in time and marks a change of one state, and may cause initiation of other (future) events in the model. As consecutive events take place in the model and simulation advances in time from one event to the next, changes occur in system states, and relevant statistics are collected. In the field of maintenance and planning, many studies have been conducted using DES modeling [15, 34, 38, 39, 47, 51-58].

Discrete event simulation has been identified as one of the most used techniques in the area of operations management [59]. Simulation models have been applied to maintenance [15, 60] to increase production output in the manufacturing systems. Roux and colleagues [61] studied a new approach that combined optimization algorithms and simulation methods in an effort to evaluate the performances of various maintenance strategies for manufacturing systems. Oyarbide-Zubillaga [51] has opted to focus on the preventive maintenance in the manufacturing field. His main objective was to find the optimal frequencies for the preventive maintenance of multi-equipment systems using cost and profit criteria.

3.2.1 Simulation Benefits and Disadvantages

There are many benefits as to why simulation is an appropriate tool as outlined in [62]. Some of these benefits are:

1. Simulation enables the study of internal interaction of a subsystem with the complex parent system.
2. Informational, organizational and environmental changes can be modelled and their effects studied.
3. A plan can be visualized with animated simulation.
4. Simulation can be used with new designs and policies before any implementation. At the same time this tool can help to understand why certain phenomena occur in a real system.

There are also reasons why simulation can sometimes be inappropriate:

1. Modeling is a costly process.
2. Simulation requires special training and most likely the models generated by different modellers to represent a system of interest will be different.

3. It is sometimes difficult to know if a simulation output is a result of system interrelationships or randomness as some simulation outputs are based entirely on random inputs (i.e. random number generation). Therefore, if it is used, correct interpretation of results is very important.

3.2.2 Simulation Modeling Phases

Modeling is the process of producing a replica that represents construction and working of a system of interest. A model can be similar to but sometimes is simpler than the system it represents. A model can be reconfigured and experimented as it is usually expensive and sometimes impossible or impractical to implement changes in the actual real system it represents. In a simulation study, human decision making is required, namely, in model development, experiment design, output analysis, conclusion formulation, and decision making [63, 64]. Experienced problem formulators, simulation modellers and analysts are essential for a successful simulation study. Figure 3.1 shows the steps used in modeling and simulation. These steps are described in detail below [42]:

1. *Problem Formulation*: this is the first step in the simulation process and begins with understanding the problem in hand. In the case of an aircraft maintenance planning, it is desired to develop new strategies to obtain cost effective maintenance plans to minimize downtime. This stage requires understanding of the system's operational behaviour and the activities that take place within its framework. Based on the stated criteria and constraints, acceptable concepts must be narrowed down.

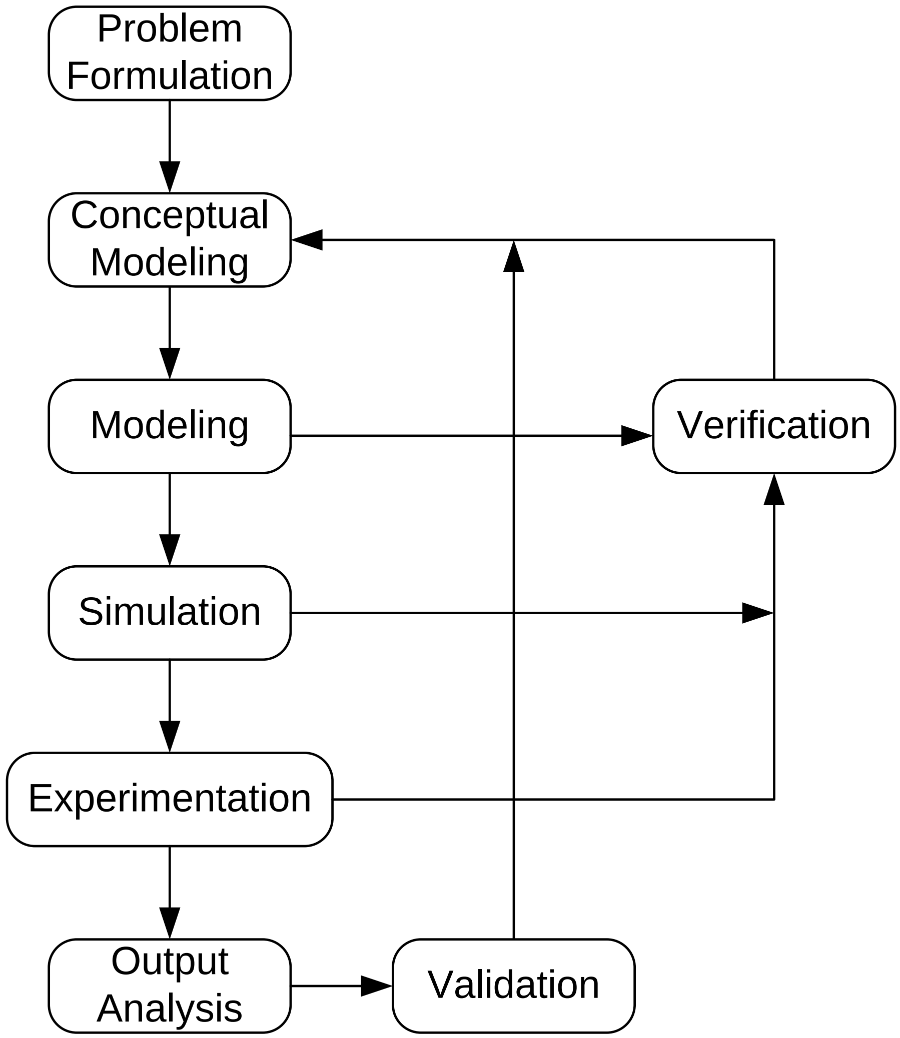

Figure 3.1: Schematic Block Diagram of Simulation Process

2. *Conceptual Model*: in this stage, it is required to identify all the objects (entities) and their characteristics (attributes) and to construct a high-level structural and behavioural description of the system. State variables are needed to be defined, their relationship and importance to the study needs to be justified. Essential elements, most important system requirements, possible future changes and operational environment are expressed and considered.

3. *Modeling*: in the modeling stage of simulation, on the basis of the defined objects, their characteristics and system behaviour, building a detailed representation of the system based on the conceptual model is undertaken. In the model any assumptions related to the system simplification must be stated.
4. *Simulation*: in this phase, a proper programming language and tools must be used to implement the model and run simulation for results.
5. *Experimentation*: once the conceptual model is set, simulation is then executed and the result is revealed which is often a set of numbers. Simulations are often run multiple times to obtain a range of results. The output must be evaluated to determine the precision level of the built model.
6. *Simulation Output Analysis*: in this phase the analysis of the simulation output is needed in order to understand the system behaviour. At this stage, visualization tools, graphical representation of simulation outputs, can be used to help with the process. The goal of visualization is to provide a deeper understanding of the real system being investigated and to help explore the large set of numerical data produced by the simulation. This phase can sometimes be combined with *Experimentation* stage in which the output is revealed, for instance, in the form of statistical graphs or charts.
7. *Verification and Validation*: Verification ensures that the model correctly represents the real system in terms of its elements, functions and events [65]. There are two common ways of verification. One method is to use ‘specific inputs’ with known and ‘expected output’, and observe whether the model satisfies the expectations. The other approach is to model the system using a secondary modeling means, such as a

simplified analytical method. Validation ensures that the model and simulation re-produce output data very close to that of the real system. This gives confidence that a model is a vey close representation of the real system, and any changes in the model parameters will produce meaningful results. This however, is only possible when a real system does indeed exist. Otherwise, a properly conducted verification is assumed sufficient.

3.3 Arena® Based Discrete Event Simulation

Arena® is a high-level simulation software that functions through a graphical user interface. This flexible and powerful tool can create simulation models which can accurately represent a system. The entire graphical model development of a system is an object-oriented design process. System components are built using graphical objects, or modules, which are placed in the layout window. Once a graphical simulation model is created, the Arena® simultaneously generates the underlying model in an executable code which performs the actual simulation runs [66, 67]. The modeling structure it follows is very similar to that of a flowchart style model building regardless of their modeling complexity. It consists of many modeling features, or templates, that are designed for many different types of applications.

Figure 3.2 represents the Arena® home screen with some explanation of its components and features. The Arena® main template consists of a panel or a set of panels that include modeling constructs for a particular application, system, class of systems, or general target environment.

A template panel contains modules collected into a file and intended to be presented as a self-contained group. The panels commonly used for standard Arena® modeling include: Basic Process, Advanced Process, and Advanced Transfer [68]. Arena® modellers attach template panels to the Project Bar in the application window of the Arena® modeling environment. The Project Bar hosts the primary objects used to build a model, so the modeller selects modules from the appropriate Project Bar panel and places them in the model window.

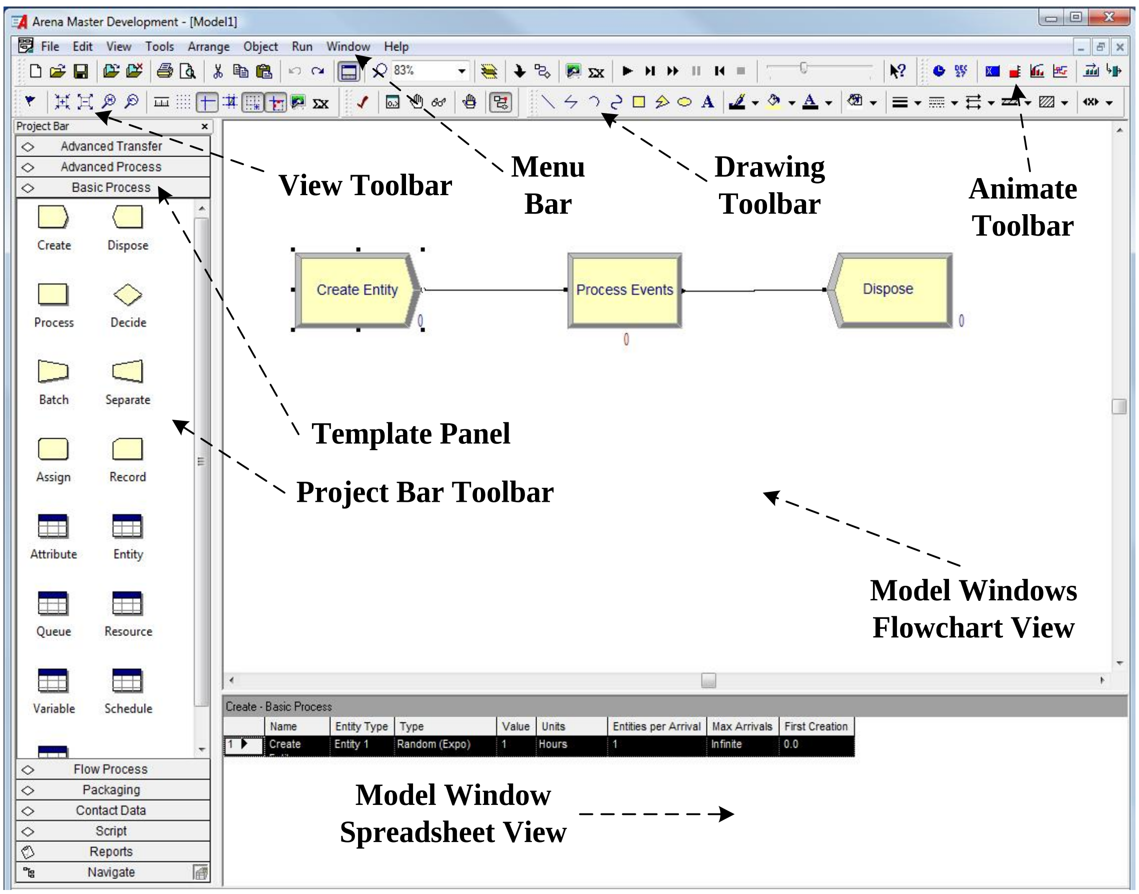

Figure 3.2: The Arena® Home Screen

Liu et al. [69] used Arena® based DES in their study of personnel planning for materials handling at a center for unloading cargo from an incoming trailer truck and loading them directly onto outbound trucks. The implementation of their proposed method in Arena® proved to be a powerful tool in assisting logistics managers in their personnel planning. Shih and Chin [70] presented a model for parts distribution center developed in Arena®, which aimed at providing information about the total time of the retrieving process as the system was working under readily unpredictable demands. The results obtained using simulations made the dynamic system more understandable for the management. It was also used as a supporting tool to make decisions in estimating the required number of employees for the retrieving process.

3.3.1 Simulation Components in Arena®

Different modeling components and constructs are used to build a working simulation model. Some of the main components of Arena® are described in this section [71].

Entities

An 'Entity' refers to an object in the simulation that can move, change properties, and carry information through model. What role it plays depends on what is being modelled and what is intended by the model builder. As well, entities can be created at any time, leave the simulation or keep circulating in the system. They can change status and affect the performance measures, and can be affected by other entities and the state of the system. Most entities represent real objects in a simulation and a model can consist of different entities representing different objects.

Attributes

Each entity in simulation has both a specific characteristic and a value with which it differentiate itself from another entity. It is up to the modeller to assign or to change certain attribute of an entity when modeling a system. It is important to note that values associated with attributes are only tied to specific entities. Another way of understanding attributes is to think of them as tags attached to entities which reveal their characteristics. Arena® automatically keeps track of attributes which are defined, value assigned to or changed for the entities in the system. Examples of assigning attributes are the "time of entrance" and "maintenance durations".

Variables

Variables reflect system characteristics regardless of the number of entities in the system. Variables are unique and a model may have many of them defined for the system of interest. There are two different ways variables can be defined in Arena®, one is defined by the modeller (user-defined variables) and the other is defined variables that already exist (built-in variables). Unlike attributes, variables do not belong to a specific entity but rather tied to the whole system. Any entity in the system can use the defined variables and/or change them based on system specifications or operation.

Variables are used for many different purposes. For instance, the pre-defined grounding time in this model is the same throughout and is called "threshold". This variable is set to an appropriate value and then used whenever this constant is needed. In a modified model and investigation where this "threshold" is set to a different value (in one place), it will be the same and available throughout the simulation for access and use by all system entities.

Resources

Entities receive services from *resources* that could represent personnel, equipment or space in a storage area of limited size. The resource is given or assigned to an entity when it is available and needed. Commonly, it is said that the entity *seizes* the resource for an activity and then *releases* it when the activity is completed. A resource can represent a group of several individual task performers or servers who perform multiple tasks as intended by the model developer. For instance, a repair facility can have few stations where the staff amongst other activities, take a break based on a pre-defined schedule or rules.

Queues

When an entity arrives for a service and the resource has already been seized by another entity, it will have to form a line, or stay in a queue, until the resource is released. In some models queues have a capacity assigned by the modeller and cannot accommodate when the number of entities exceed that capacity. Various disciplines can be used at queuing nodes such as *First-In-First-Out*, *Last-In-First-Out* and *Priority*.

Events

An *event* is a concept that occurs at an instant of time while the simulation is running and that might change attributes or model variables. An example of an *event* is the arrival of an entity or its departure. In this study, aircraft in queue leave the line and enter the service facility which changes the system status, but this occurs because an end of service event has occurred and another aircraft has left the facility and caused other changes. In Arena® this information is stored in an *event calendar* using a simulation block called *record* which stores all the information (schedule) for future events.

Simulation Clock

The simulation must keep track of the current simulation time, in a unit suitable for the system being modeled. In discrete event simulations, the clock skips to the next event start time as the simulation proceeds. In other words, unlike real time, the simulation clock does not take on all values and it launches from the time of one event to the time of the next event.

Starting and Stopping

Another task in a simulation is to plan its start and stop times. The modeller must determine the appropriate starting condition, how long a run should last, and whether it should stop at a particular time (say, for 1 year) or when a specific condition has been reached (say, 1000 services have been performed). Assigning and setting proper values for starting and stopping can have a great effect on the simulation outcome.

3.4 Arena® and Aircraft Maintenance Planning

Research on discrete-event simulation techniques resulted in the development of advanced simulation languages like SLAM@, Arena®, Simula@, and SimScript@ [72-74].

Simulation languages can be used to model complex problems in significant details. Although using simulation languages help with problem solving and experimentation, in most cases, simulation models are difficult to develop, test, maintain, and verify.

Referring to Figure 3.3, in aircraft engine health monitoring, the in-flight information is passed on to the MRO for diagnostic and prognostic analyses. The results are then used for scheduling and decision making on maintenance.

In a recent study on multi-criteria preventive maintenance scheduling, a decision making approach was implemented through Arena® based simulation modeling and the best maintenance option was selected which gave the best utility and performance values [15]. In another work, a two-case study was examined to show how simulation supports the continuous process improvement [75]. A real world semiconductor manufacturer example was discussed to highlight the benefits received from implementing simulation at the plant [76]. Simulation was used in an application to identify the bottleneck of a manufacturing line, where the engineers were then able to determine and verify a solution to the problem which resulted in annual savings [77]. Discrete event simulation was also used to design efficient production and business systems, to validate alternatives and propose solution to improve system performance, sales and profits [33, 34].

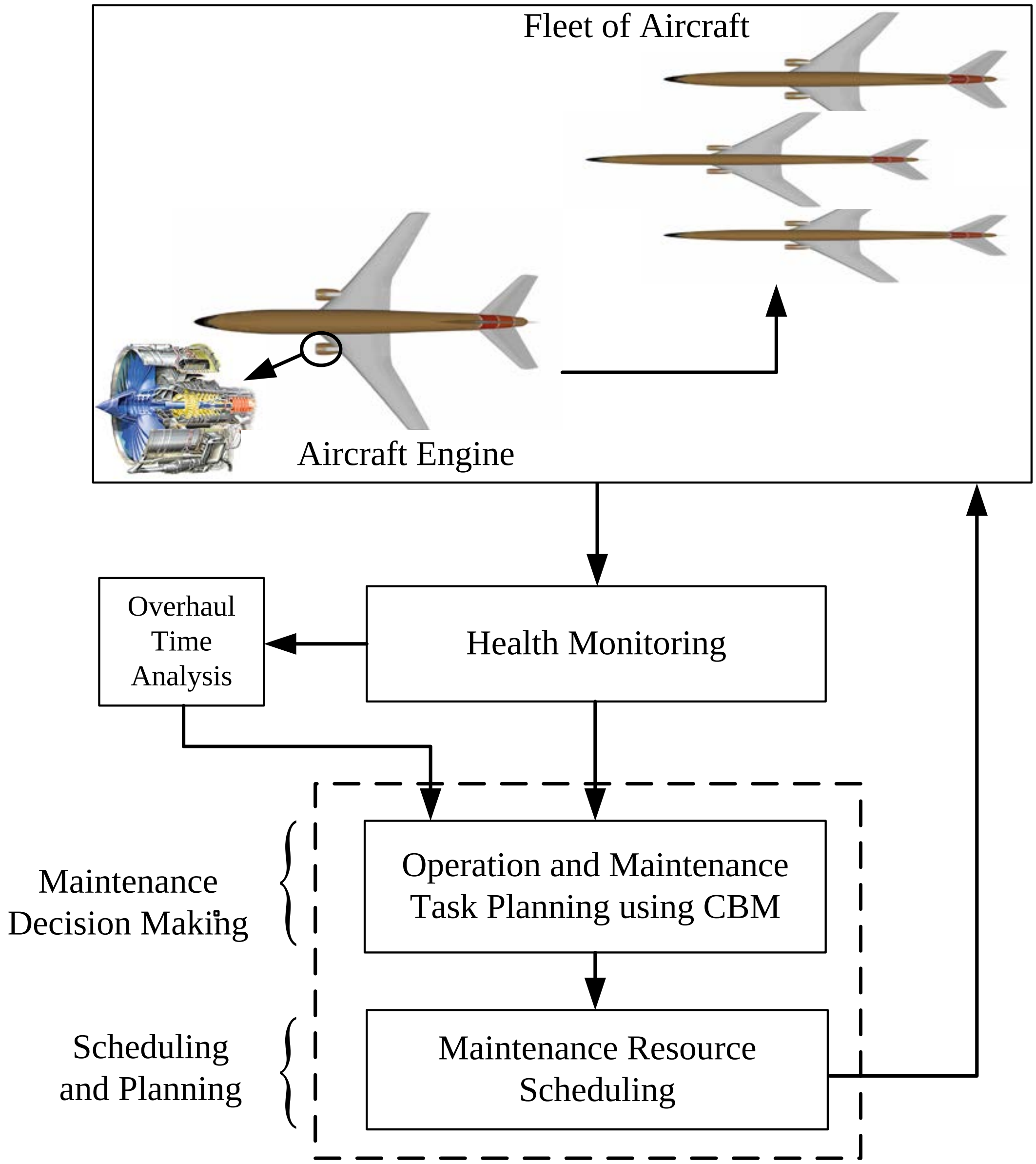

Figure 3.3: Graphical Representation of Maintenance Operation

In another study simulation was used to identify and understand the impact of different failures on the overall production in a chemical plant [52]. Different scheduling approach for a dynamic manufacturing environment was modelled in discrete event simulation based on past performance [39]. Johanson et al. examined to what extend discrete event simulation can be applied to evaluate the performance and the profit of a manufacturing system. The results showed that there is a large potential to increase the productivity when all scenarios are correctly modelled [40]. In line-production systems, engineers did benefit from simulation application as they mimicked the system behaviour to perform extended analysis to compare different scenarios and to support their decision-making processes [78]. Van Den Bergh implemented DES in testing his methodology for obtaining the optimal schedule for aircraft line maintenance personnel [37].

Bell studied two types of maintenance schedules in army aviation in term of operational readiness. This study models the tradeoffs of one method versus the other using discrete event simulation knowing the operational data set from a deployed aviation unit. The effectiveness of each method is measured in the time each airframe is in for mission [79].

A case study was conducted to compare traditional discrete event simulation against an agent-based modeling approach that involved the implementation of two functionally identical repair models based on a realistic aircraft gas turbine operation. It was shown that agents were time-driven rather than event-driven. The discrete-event model followed an event list which was faster and thus desirable [80].

An aviation industry investigated the use of three levels of aircraft maintenance. This work examined the effect of maintenance resource sharing between facilities and a centralized repair facility on a critical line replacement unit. Maintenance data was collected and summarized into probability distributions and then was used in a discrete event simulation model to examine the impact of changes to the maintenance structure. Combining resources and personnel, independent versus sharing bases and cost associated with shipping between them, effectiveness of processing time and machine utilization were also considered [81]. In other works, modeling the life cycle cost of aero-engine maintenance was studies [82].

From the forgoing, it is apparent that for the type of systems considered and the kind of issues examined, DES is a useful tool that allows many operating conditions and constraints to be included and modelled. To refresh, our goal is to develop aircraft engine maintenance models using discrete event simulation that allow examination and evaluation of various scenarios for a fleet of aircraft. As engines on an aircraft are generally at different state of health, it is often one engine that initiates the need for maintenance. To address the first objective of this thesis, many scenarios will be examined. At the outset we state that models will be developed and analyses will be performed to see while the aircraft is at the service facility, whether it is economical and time-efficient to attend to other engines of that aircraft, and if so, determine the number of engines that could be subjected to preventive maintenance.

3.4.1 Maintenance Model Development

A notable part of the work was to study health monitoring and engine inter-turbine temperature sensor logs to extract useful data for simulations. The remainder of this chapter shows how the structure of the models is developed; the simulations and their results are reported in Chapter 4.

Modeling Concepts

For the purpose of this work, a fleet of 50 aircraft is assumed. The objective is to minimize the total off-flying time, the number of off-flying occurrences and the total overhaul time cumulatively calculated for 50 aircraft. Overhaul time is also referred to as the grounding time. Essentially it is the duration of the time taken out of the available flying time.

Since the out of service grounding and the maintenance cost rates are generally case dependent and specifically unavailable in this study due to confidentiality, it was agreed to base our deliberations on the “total grounding time”, “total maintenance time”, and “total wait time” over a specific period of operation simulated.

Every repair/maintenance process has several steps that here are grouped into four and are as follows:

1. Diagnosis and disassembly
2. Repair and maintenance tasks
3. Indoor assembly and partial-testing
4. Outdoor testing and release

Since these activities are sequential and for the purpose of analysis “additive” all four steps above are treated as one collective ‘maintenance operation’. The triangular distribution is often used in business decision making, particularly in simulation [83, 84]. The duration of this total maintenance operation is assumed to be a triangular distribution between 2 and 6 days with an average of 4 days. Five policy scenarios are considered and respective simulation models are developed using the Arena® Discrete Event Simulation software.

The first four scenarios are preliminary defined such that when an aircraft is scheduled for maintenance, the maintenance facility has the options of performing maintenance on one, two, three or four engines. After these preliminary analyses are conducted, in the next step all four scenarios are integrated into one main model. This fifth model is so constructed to examine and to select one of the four maintenance scenarios (one, two, three or four engines) for every arriving aircraft based on a number of user-defined conditions. It is envisaged that with proper selection of these condition effective policies can be developed. All these scenarios are described in detail in the remainder of this chapter.

Scenarios Considered

Each of the 50 aircraft within the fleet is assumed to have four engines. Each of the 200 total engines is assigned a RTTF value randomly drawn between 7,000 and 10,000 hours, based on and obtained from the typical logged data. Once all the aircraft are "created" (in the paradigm of the simulation software), and entered into the model, a normal "operating" status is assumed. Since Discrete Event Simulation (DES) is used, the "time" is advanced in discrete steps to the time of the pending event (which then becomes the "current time" or "Time Now": TNOW in the language of the software) where the statistics and status of every entity of the model become available. The statistics and other data are continually and automatically updated during the simulation at every event times by the software, and subsequently are used for decision making by the user as needed.

A significant amount of time is consumed when an aircraft is taken away from its normal flying service and sent for repair or maintenance. As briefly mentioned earlier, this is usually triggered due to the status of ‘one’ engine. While an aircraft is at the service/maintenance facility more than one engine can be serviced (upgraded/updated in health status). This may appear to be more economical than attending to one engine only. However, this very much depends on the service history of the engines. The combined simulation model is developed such that more than one engine can be serviced depending on certain user set thresholds. The threshold values are based on TOW or RTTF, and can be altered to examine numerous alternatives to arrive at an optimal arrangement.

Since DES is not a self-optimizing method, with experimental planning, a manageable number of cases are simulated to determine effective solutions. The simulation model produces many statistics that must be carefully interpreted and used to improve the maintenance operations in many aspects. However, it appears that the single most important factor here is the ‘overall cumulative overhaul time’.

3.5 Building the Models

As shown in Figure 3.4, the overall maintenance procedure consists of five blocks. System is initialized when an aircraft enters the maintenance model. A random value of RTTF between 7000 to 10,000 hours (obtained from engine data-logs) is assigned to each engine and then aircraft proceeds to flying operation. Grounding for maintenance is triggered when any of the RTTF values are equal or less than 100 hours (this value is set as system "primary threshold", which is referred to as Trs1. Also see Figure 1.3).

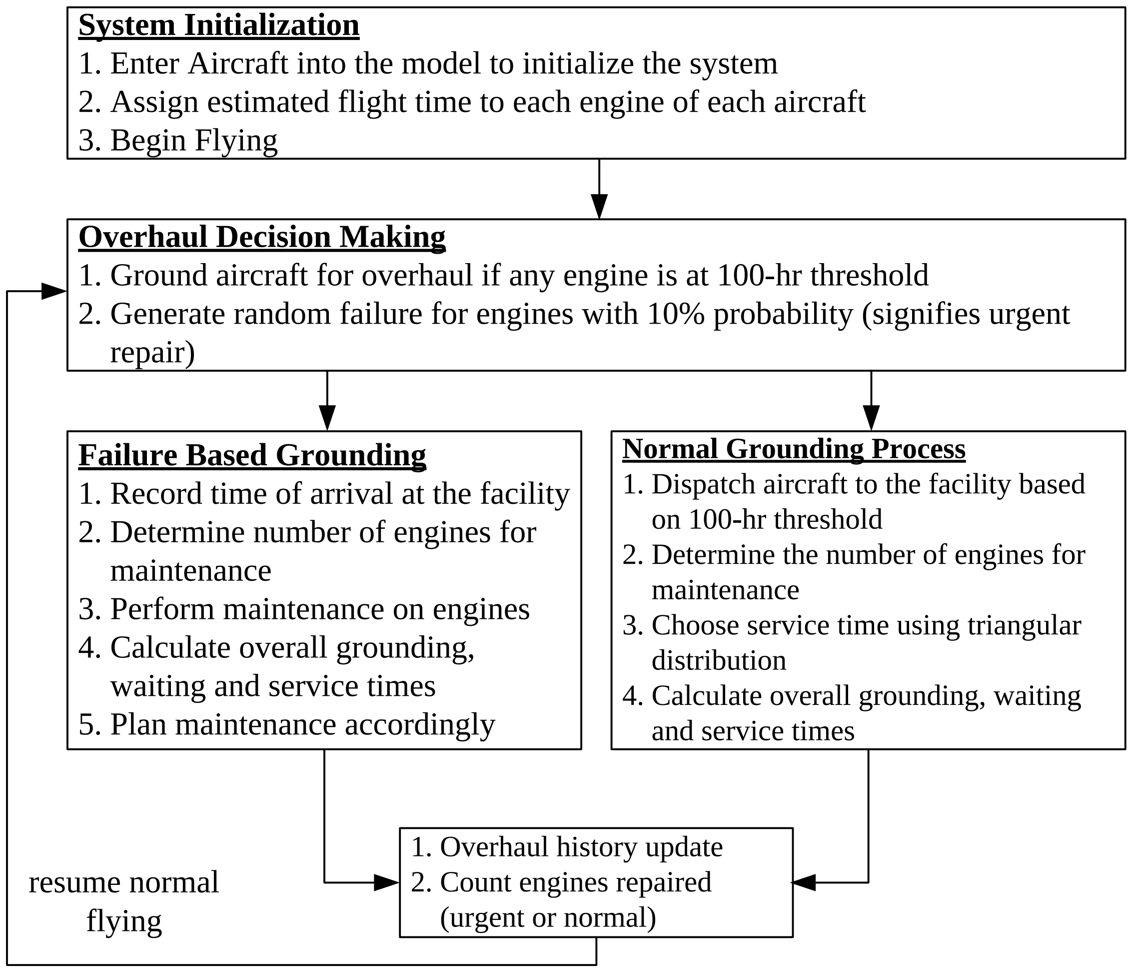

Figure 3.4: Simulation Model for Engine Maintenance

In the "Overhaul Decision Making" block, the model determines whether any engine's RTTF has approached the threshold and must be scheduled for maintenance. In addition to normal service, there are sudden failures that are assumed to occur 10% of the times.

The service time is chosen using triangular distribution with a minimum of 2, average of 4 and a maximum of 6 days. The wait, service and total grounding times are determined and statistics are collected. Upon the completion of maintenance, the aircraft returns to normal flying operation.

In the “Failure Based Grounding” block, once the system generates a sudden random failure, the aircraft is placed in the queue to enter the service facility. From engine RTTF values, the model determines whether any of the other engines should also be serviced while the aircraft is at the facility for maintenance.

At the final stage of the service, before the aircraft resume its flying operation, the overhaul history is updated and total number of engines serviced is recorded.

If the maintenance facility is to perform maintenance on more than one engine, the estimated time from the triangular distribution is multiplied by 1.5, 2, and 2.5 for two, three and four engine maintenance, respectively. The service times are not multiplied by the respective number of engines, since much of the set-up and preparation times are not repeated.

The simulation run time is set to 200,000 hours. In fact, it is common to run simulations for prolonged periods but apply the results to a shorter time span. This large duration assures that the events and measures within the model reach steady state conditions. Further, the output data were averaged over multiple simulation runs. The suitable number of replications was found to be 5 and any larger number did not notably affect the convergence of the output data. This is demonstrated in chapter 4 when the simulations are run. In the following sections each of the scenarios are explained and the results are discussed.

3.5.1 1-Engine Maintenance

In this scenario, the maintenance model is set to perform service on one engine only. As shown in Figure 3.5, after any of the four engines reaches the primary threshold (Trs1), the aircraft is grounded, maintenance is performed, RTTF and the engine condition are updated and the grounding, wait and service times are calculated.

When an aircraft is released back into the normal operation, the model continues to monitor and evaluate the TOW information until the threshold is reached again by one of the engines. The threshold is a user-defined variable and can be changed to arrive at any other optimal or desirable maintenance policy depending on what is desired.

There are four conditions defined in the decision block. Every time the model attempts to schedule a service, the current conditions of the four engines (RTTF1, RTTF2, RTTF3, and RTTF4) are examined. For instance, let us use a condition where first engine requires maintenance. If we set the threshold to 100 hours, and assume the following arbitrary values: RTTF1 = 80, RTTF2 = 200, RTTF3 = 250 and RTTF4 = 350, the condition is such that only RTTF1 is below 100. Although in this example for clarity the lowest RTTF is given a value less than 100, and symbolically in scenarios 2, 3 and 4, and the Figures 3.5 to 3.8 the 'check condition' is shown as 'RTTF<100', however, the construct of the simulation models are such that the lowest RTTF is selected at exactly

100 hours. At the end of the service of the engine with the lowest RTTF, the maintenance history, and the total number of engines serviced, either urgent or normal, are updated.

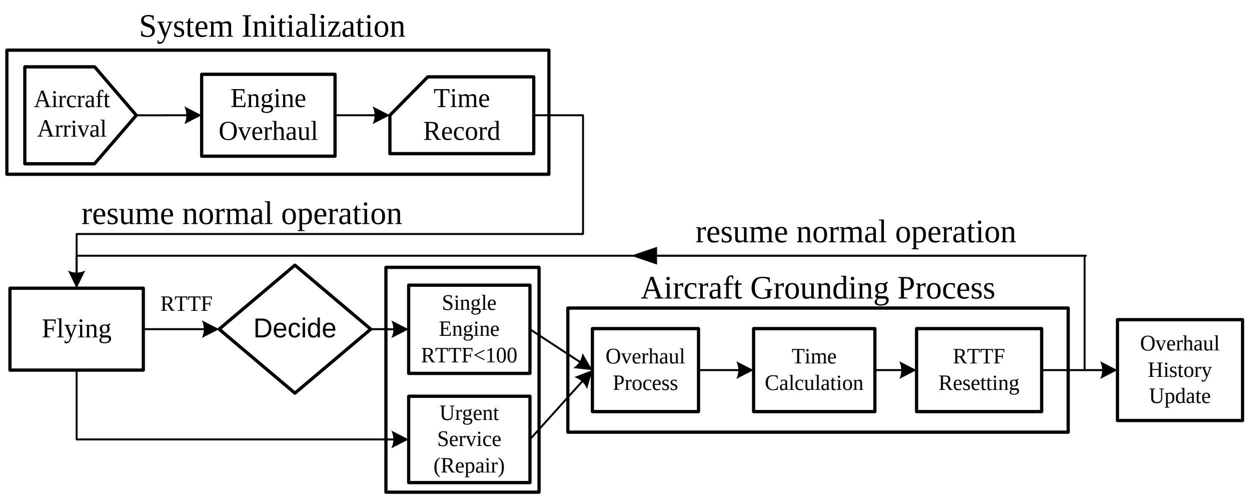

Figure 3.5: Block Diagram for 1-Engine Maintenance

3.5.2 2-Engine Maintenance

In the second scenario, the model carries out the maintenance on two of the engines of the aircraft that arrives at the facility. For this case, Figure 3.6 represents the model overview which is very similar to that of the 1-Engine maintenance.

In this scenario, after initializing the simulation, the model determines the engines with the two lowest RTTF values. Once the first engine of the aircraft is selected for maintenance using the primary threshold, the model checks the other three engines in order to find the second lowest RTTF. The second engine is selected by comparing the three remaining engines against the first one. For instance, assuming arbitrary values of RTTF1 = 80, RTTF2 = 200, RTTF3 = 250 and RTTF4 = 350, the model selects engines 1 and 2 from checking the following conditions:

$(\mathrm{RTTF1} < 100)$

$(\mathrm{RTTF1} < \mathrm{RTTF3})$ and $(\mathrm{RTTF1} < \mathrm{RTTF4})$

$(\mathrm{RTTF2} < \mathrm{RTTF3})$ and $(\mathrm{RTTF2} < \mathrm{RTTF4})$

In case of an urgent service, the same procedure is followed. Once an aircraft is destined to the facility for service, the status of the other engines is checked to identify the second engine with the lowest RTTF.

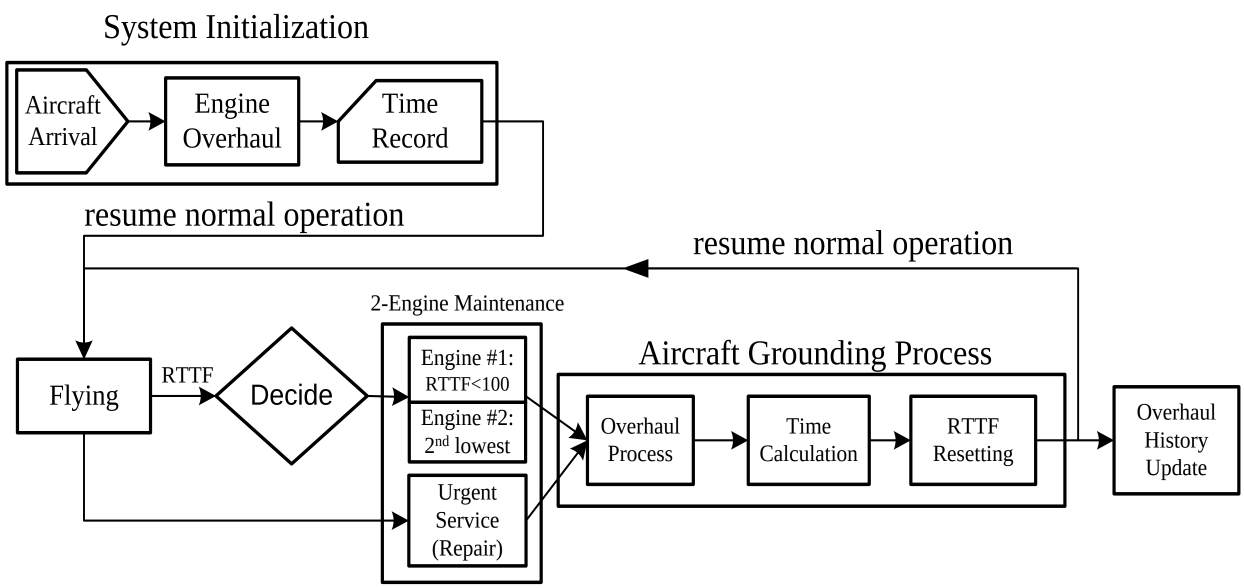

Figure 3.6: Block Diagram for 2-Engine Maintenance

3.5.3 3-Engine Maintenance

For this scenario, as illustrated in Figure 3.7, the simulation model is designed to perform maintenance on three engines once an aircraft arrives at the facility. Similar to the last two scenarios, the need for maintenance is initiated based on the status of one engine that has a flying time, RTTF1, less than the defined primary threshold (Trs1). To identify the three engines for maintenance the model again compares all the RTTF values. For example, the following conditions are true when engines 1, 2 and 3 are selected:

$(\mathrm{RTTF1} < 100)$

$(\mathrm{RTTF2} < \mathrm{RTTF4})$ and $(\mathrm{RTTF3} < \mathrm{RTTF4})$

In case of an urgent repair, the model performs the same as the previous two scenarios but this time services three engines.

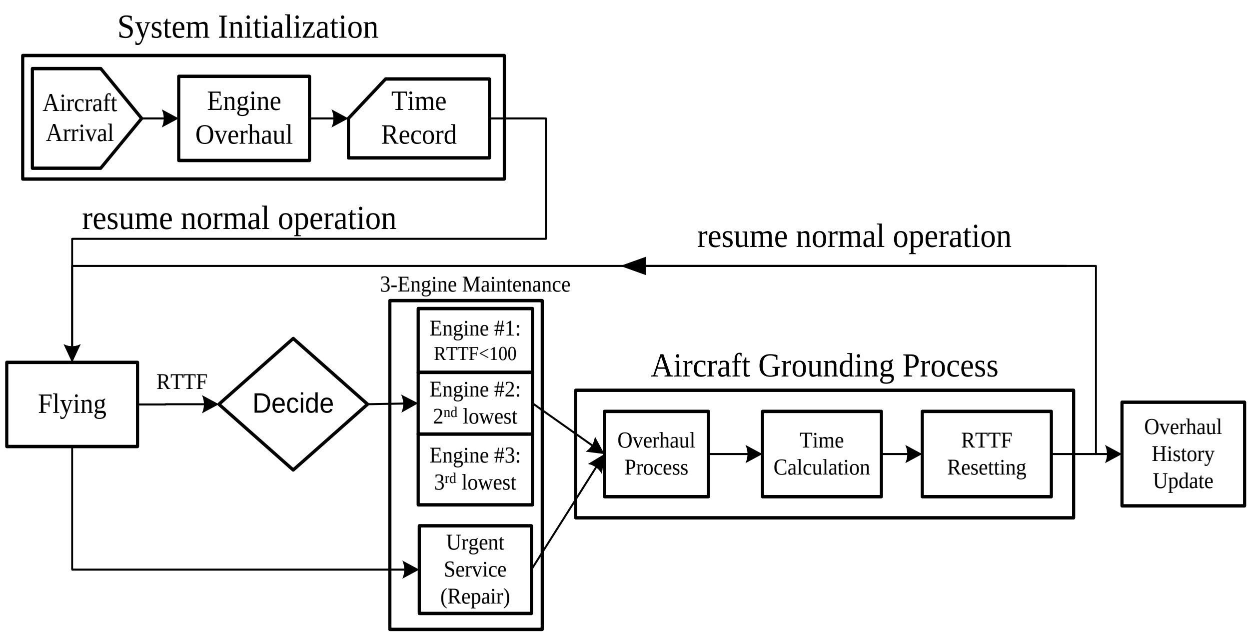

Figure 3.7: Block Diagram for 3-Engine Maintenance

3.5.4 4-Engine Maintenance

As shown in Figure 3.8, the simulation model for 4-Engine maintenance determines whether any of the aircraft engines has a flying time less than the defined threshold. If this is the case, all four aircraft engines are marked for maintenance. The condition defined in the "*Decide*" block is true only when any of RTTF1, RTTF2, RTTF3 or RTTF4 is less than the threshold value as shown below:

$(\mathrm{RTTF1} < 100)$ or $(\mathrm{RTTF2} < 100)$ or

$(\mathrm{RTTF3} < 100)$ or $(\mathrm{RTTF4} < 100)$

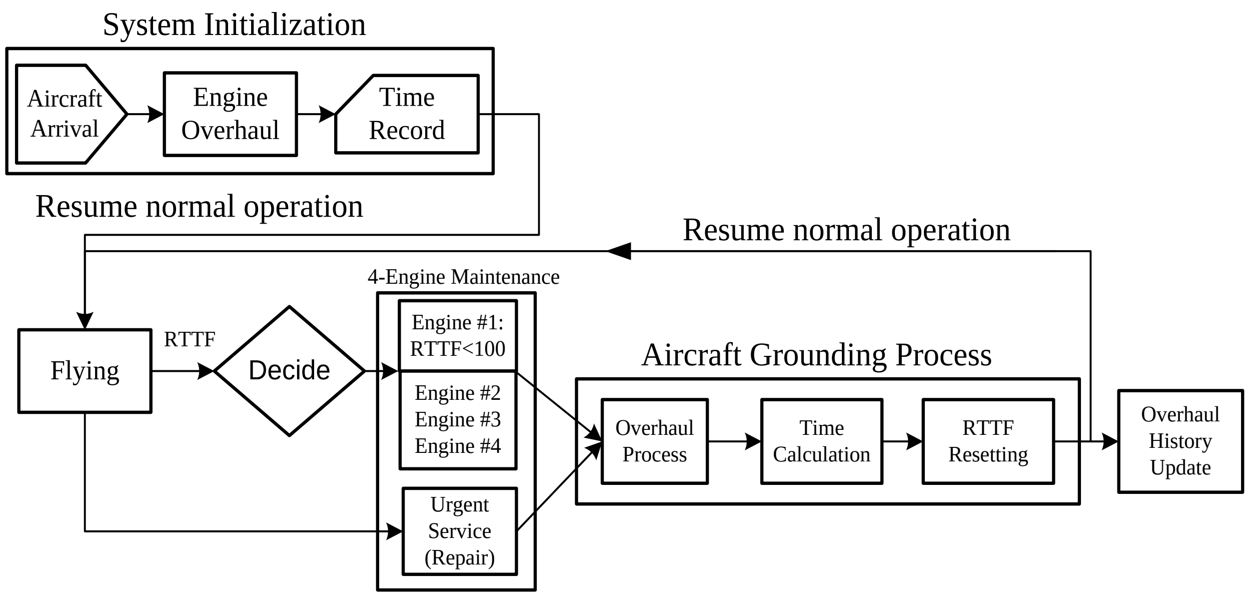

Figure 3.8: Block Diagram for 4-Engine Maintenance

3.5.5 Integrated Scenario Selection (ISS) Engine Maintenance

The consideration of the previous four scenarios was to examine whether any "fixed" policy, say 2-Engine maintenance, can be justified; where the user can set a threshold and arrive at a good policy. However, using a "fixed" policy seems rather indiscriminate and somewhat unsystematic. The purpose of the foregoing scenarios was to have the models available for the management should they decide on experimenting with such fixed policies. Whereas any of the policies appear an unlikely choice, the greatest and perhaps the only advantage can be realized if the maintenance facility is “permanently” set up to perform the service systematically and fast.

In this section, a detailed model is proposed, which is referred to as the Integrated Scenario Selection (ISS). As opposed to the previous four scenarios, where the policy was to consistently use only one fixed policy, this model combines all four previous scenarios. In other words, this model examines all scenarios, before selecting optimal number of engines for maintenance every time an aircraft is to pass through the service facility.

The maintenance is initiated by the needs of one engine, which requires service and enters the overhaul system, as illustrated in Figure 3.9. The “*Decide*” block identifies the particular engine that has RTTF less than the primary assigned threshold (Trs1). In this model a secondary threshold (Trs2) is introduced as a variable which can be altered in repeated simulations in order to determine the condition for optimum maintenance. Within the simulations Trs2 is used to determine the “relative difference” of RTTFs between the engines. Once a difference is within the range, the respective engine is also selected for overhaul. The value assign to this threshold can play a major role in selecting the engines. In fact, Trs2 is a decision variable, and will be used and discussed in the next chapter.

Let us illustrate the engine selection of this model by using an example. Assuming hypothetical values of RTTF1 = 80, RTTF2 = 200, RTTF3 = 250, RTTF4 = 350, Trs1 = 100 and Trs2 = 110 hours, the following conditions lead to maintenance being carried out on two Engines:

$(\mathrm{RTTF1} < 100)$ and $(\mathrm{RTTF2} - \mathrm{RTTF1} < 110)$ and

$(\mathrm{RTTF3} - \mathrm{RTTF1} > 110)$ and $(\mathrm{RTTF4} - \mathrm{RTTF1} > 110)$

Each of the devised individual scenarios (1-Engine, 2-Engine, 3-Engine and 4-Engine), and the Integrated Scenario Selection (ISS) engine maintenance have been explained and their related modeling structures discussed. In the next chapter these scenarios are built as models in Arena® discrete event simulation software. In addition, statistics for each scenario is collected and discussed to decide on optimal aircraft maintenance policy and planning.

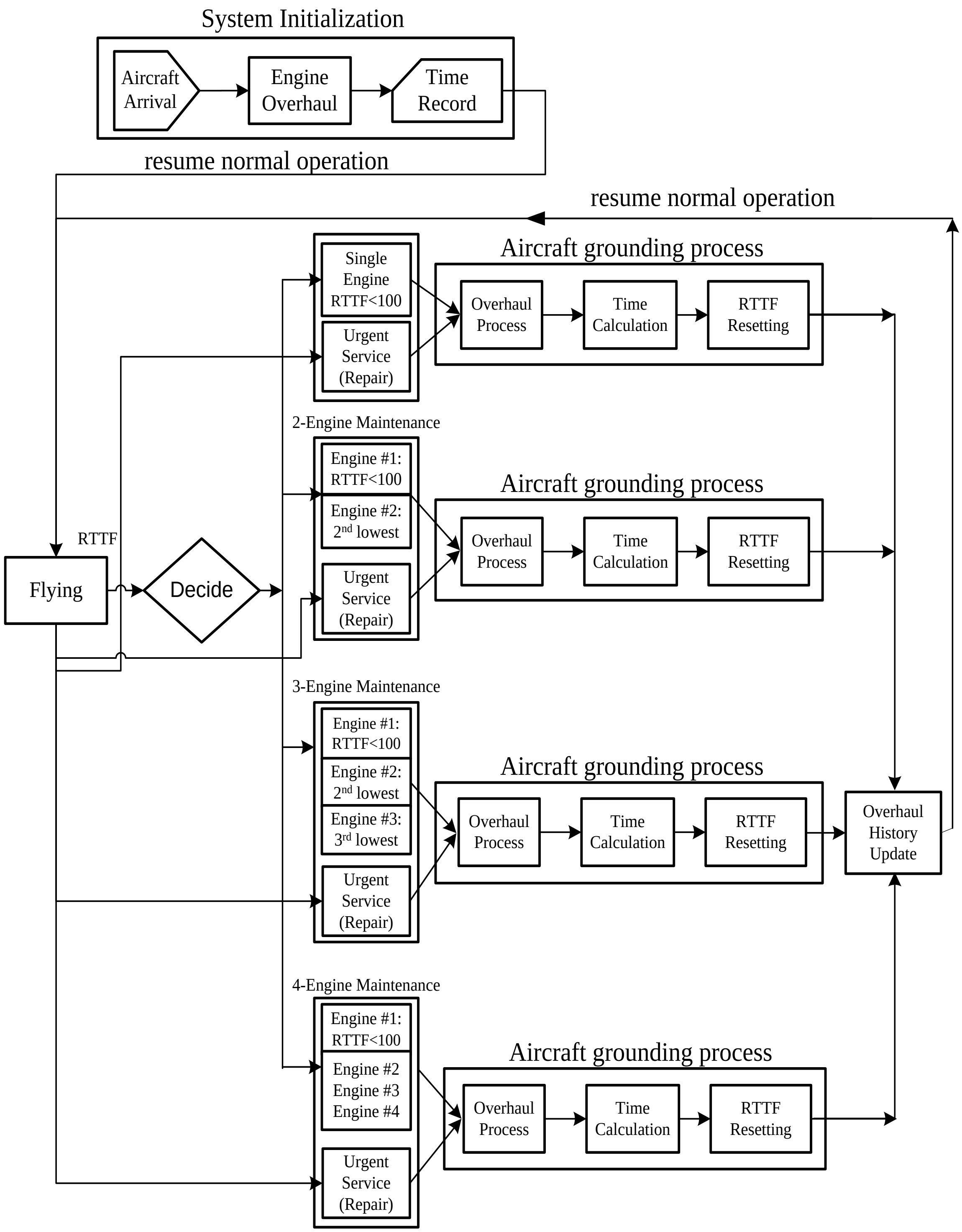

Figure 3.9: Block Diagram for ISS Engine Maintenance

Chapter 4

Engines Maintenance Planning and Discrete Event Simulation Analysis

4.1 Introduction

Suggestions have been made to ensure that not only all the engines are maintained in an efficient manner, but that their scheduled maintenance cycles are carried out simultaneously so that the aircraft has fewer trips to the maintenance facility [85]. However, such pre-planned maintenance can be impractical and uneconomical. (In fact in chapter 3, the 4-Engine maintenance is a related scenario.) After a short period of time in operations, even for a new aircraft, the engines on the aircraft can and will begin to behave and prove their ‘individuality’. Despite identical looks, due to statistical variations in material properties, manufacturing and assembly, no two products are made the same. With typically over 20,000 components, aircraft engines are no exception. Each engine will deteriorate at its own pace and will require maintenance and service at its own specific time. Subjecting all engines to the same maintenance schedule can thus be uneconomical. Therefore, cost reduction may be achieved through other means such as reducing downtime, repair costs and improving the quality of products and faster services. Use of dynamic maintenance planning in a fleet, in other words condition-based maintenance (CBM) rather than time-based maintenance will significantly contribute to achieving this objective.

The purpose of this thesis is to conduct the analysis required to determine if CBM is advantageous in comparison to the current periodic maintenance. This chapter presents results obtained through implementation of CBM using discrete event simulation software Arena® in order to arrive at an aircraft maintenance policy which minimizes the total downtime and overall cost of the maintenance operations. Section 4.2 gives an overview of the proposed engine maintenance scenarios and section 4.3 discusses the simulation results. In section 4.4, the proposed method is validated through a secondary discrete event simulation "Simio".

4.2 Overview of Engine Maintenance Scenarios

To perform maintenance on aircraft, either due to a problem in one engine, or due to a set time for service, a number of options are available. One option is to consider a policy in which a 'fixed' number of engines are serviced. That is, the enterprise uses a policy in which for any aircraft at the time of maintenance, consistently 'n' engines are serviced. For a four-engine aircraft, for instance, this will be 1-Engine, 2-Engine, 3-Engine or 4-Engine choices. This may have the convenience that the maintenance facility is always set-up to run a fixed routine. One can anticipate that this approach will most likely be uneconomical. These options were examined in chapter 3. Another approach, which seems plausible, is to service a 'variable' number of engines, based on engine status and some reasonable set of conditions. In this section, we examine these options and policy scenarios. For each of the scenarios outlined in chapter 3, in this chapter a model in Arena® is developed and simulations carried out.

4.2.1 Maintenance Scenarios with a Fixed Number of Engines

As shown in Figure 4.1, the model starts by generating aircraft entities. The number of aircraft is selected based on the user need. The next step is to assign specific attributes which are characteristics or factors specific to an aircraft. 'Entity' and 'Attribute' are technical terms used in most simulation software, as described for Arena® in chapter 3, which refer to objects and their tagged-on data, respectively. One example of an attribute is the aircraft ID that enables the modeller to track any aircraft in the model at any instant of time. Another important attribute is RTTF values for each engine and this is determined and assigned using a uniform distribution with a minimum of 7,000 and a maximum of 10,000 hours. The variation takes into consideration the age of the aircraft and the confidence in the degree of restoring the functionality of the engines after each maintenance operation.

The current condition of each aircraft, i.e. RTTF, in the model must be known for estimating the time of maintenance. Once the aircraft are put into operational flying mode, the model checks the RTTF of all engines of each aircraft at the simulation "event times". For maintenance scenarios with more than 1-Engine, the engines with second and third lowest RTTF, respectively, are selected. Referring to Figure 4.1, depending on the policy being examined only *one* scenario from the block marked "Individual Scenario Selection" is used for the entire simulation.

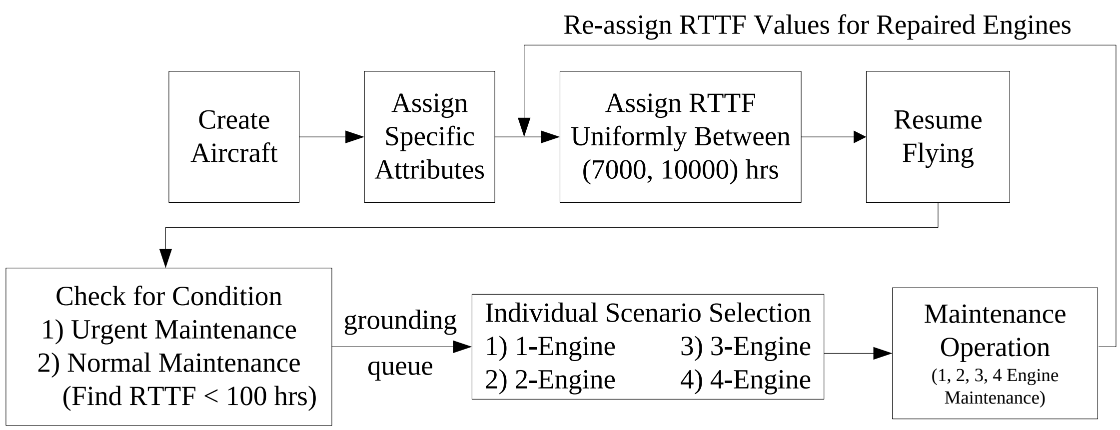

Figure 4.1: Maintenance Operation for "Fixed" Number of Engines

In addition, the model randomly generates sudden failure at the rate of 10% of all maintenance events. The grounded aircraft joins a queue before it enters the maintenance facility. At the completion of the service, the RTTF values are re-set before resuming normal flying operation. At the conclusion of the simulation, the statistics generated output are analyzed to make decisions that would improve the maintenance operations.

4.2.2 Integrated Scenario Selection (ISS) Maintenance

In ISS, as shown in Figure 4.2, the maintenance operation is very similar to the scenarios for maintenance on a fixed number of engines. The difference in ISS is that the model determines the number of engines for every maintenance instance based on the assigned value for the secondary threshold (Trs2). The significance of this will be explained later.

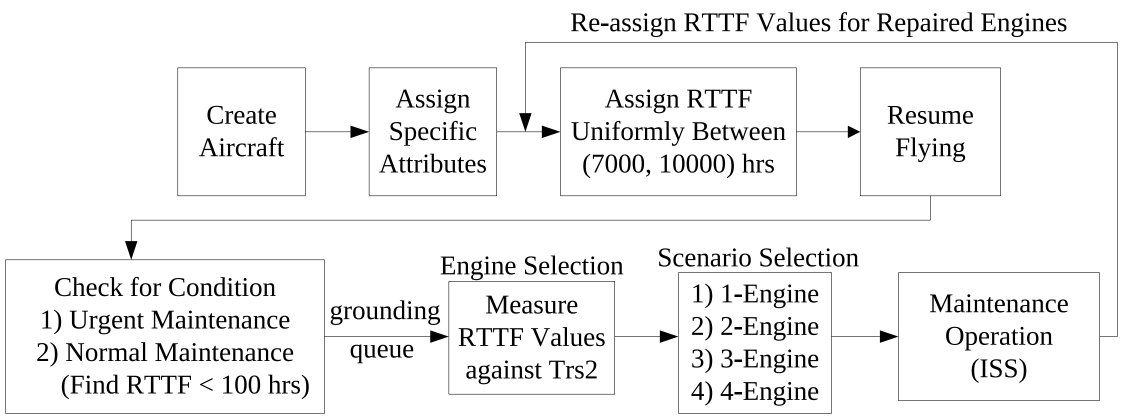

Figure 4.2: Graphical Representation of Maintenance Operation for ISS

To initiate the simulation, and before aircraft resume flying, attributes are assigned to each aircraft and values for RTTF are chosen uniformly between 7,000 and 10,000 hours based on the sample Inter-Turbine condition data. While flying, the model checks the conditions of the aircraft engines. Once the minimum RTTF value is reached or a failure occurs (set at 10% of all maintenance events) the aircraft is destined for grounding. Before entering the maintenance facility, the differences between the RTTF values for the other engines are compared against the Trs2 to select an appropriate maintenance scenario (number of engines for maintenance). At the end of the maintenance operations, statistics are collected for analysis and decision making.

4.3 Arena® Simulations

Simulation for individual "fixed" number of engines and ISS maintenance models for a fleet of 50 aircraft are run for 200,000 hours of fleet operation. In order to populate the simulation model with the 50 aircraft, they enter the model at an accelerated arrival with an inter-arrival time of 0 to 200 hours distributed uniformly over the range. At this rate (an average of 100 hours), within approximately the first 5000 hours of simulation run all 50 aircraft will have entered and dispersed throughout the model. With a random assignment of RTTF, it is safe to assume that the fleet will soon be in near normal operation status. In other words, the model transient will no longer be present.

4.3.1 Individual Maintenance Scenarios

In this section, first we study the results of the simulation for individual maintenance scenarios where a "fixed" number of engines per aircraft are serviced at the maintenance facilities. This starts by discussing the overall simulation stability and its appropriate replication number selection, and then a conclusion is made for optimal maintenance planning on the basis of overall cumulative time values. Using 1-Engine maintenance as an example, Figure 4.3 and 4.4 are the representation of Figure 4.1 modelled in Arena®.

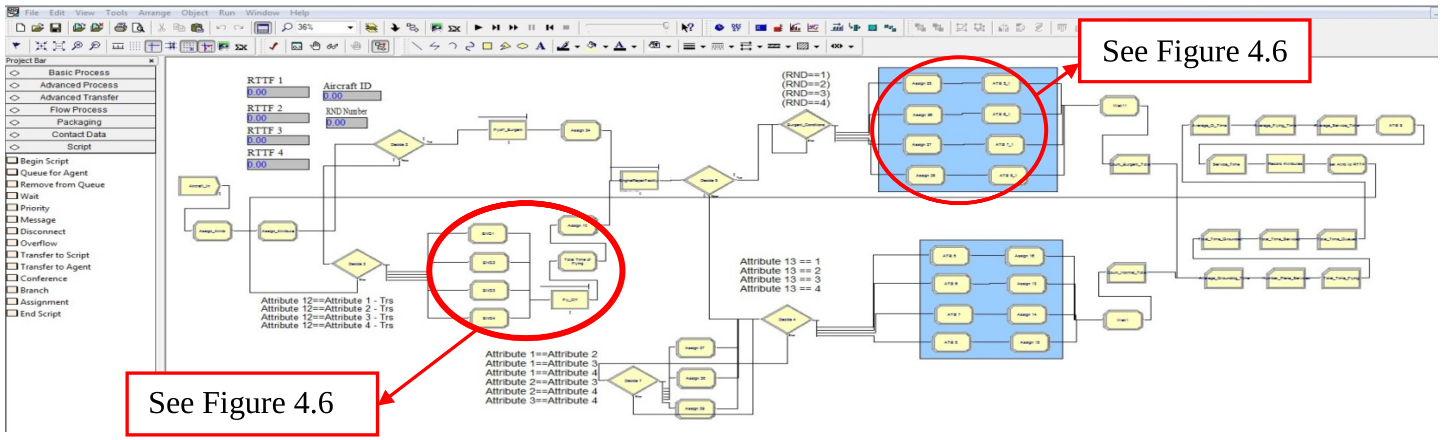

Figure 4.3: Screenshot of the Entire Arena® 1-Engine System

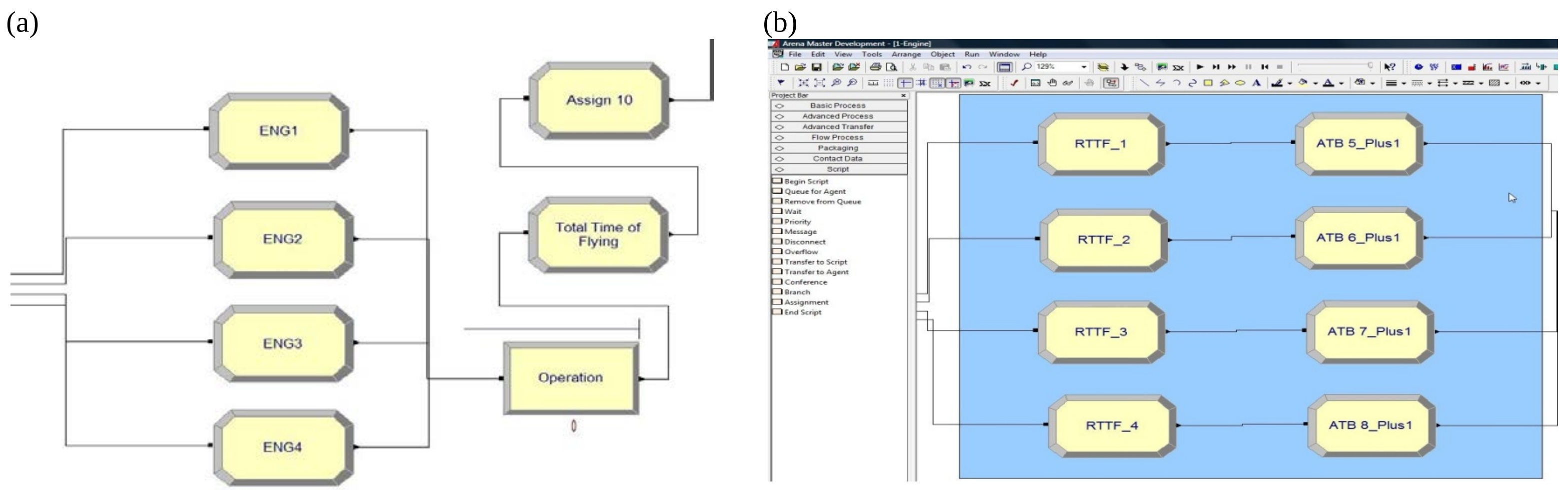

Figure 4.4: Screenshot of blocks: (a) Engine Selection for Maintenance, and (b) Service of Engines

Simulation Stability

One of the useful estimations required before running the simulation is the suitable number of replications which ensures the convergence of the output data to steady state averages and levels. For implementing this, average value of one of the outputs, specifically "Average Waiting Time", which represents the average time each aircraft spends in maintenance facility queue, was chosen. As illustrated in Figure 4.5, The Average Waiting Time for all scenarios appear steady with respect to the number of replications, but any number of replications greater than four seems reasonable as the average waiting time of each individual scenario converge to a more steady level, and that it will ensure the stability of other outputs. The number of replications is set at 5 for the simulations conducted.

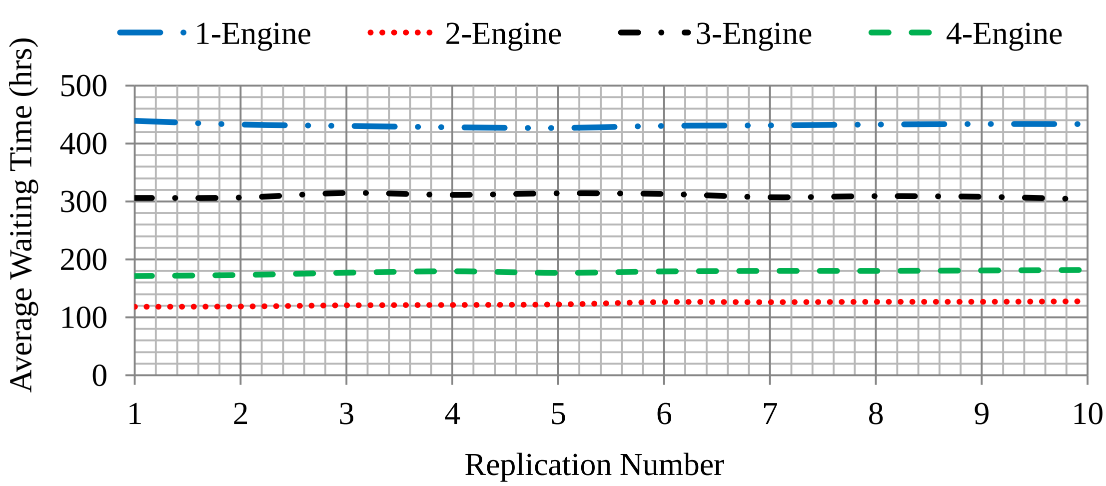

Figure 4.5: Estimating Replication Number for Individual Scenarios

Another criterion to consider after deciding the number of replication is the stability and uniformity of the simulation output for all the aircraft in the fleet. As shown in Tables 4.1 and 4.2, the number of times each of the 50 aircraft in the model has visited the service facility for the scenarios 1-Engine, 2-Engine, 3-Engine and 4-Engine were around 80, 45, 40, and 30, respectively. From these, it is evident that after 5 replications, steady state conditions can be assumed.

Table 4.1: Number of Times Each Aircraft Visits the Service Facility – Part 1

	Individual Scenario (Maintenance Type)			
ID #	1-Engine	2-Engine	3-Engine	4-Engine
1	82	44	40	29
2	82	46	39	30
3	81	45	40	29
4	82	46	39	29
5	81	45	40	29
6	83	45	39	30
7	81	45	39	29
8	79	45	39	29
9	83	44	39	29
10	82	45	39	30
11	82	45	40	30
12	80	45	38	30
13	81	46	39	29
14	80	45	39	29
15	79	45	39	30
16	79	45	38	29
17	79	44	38	31
18	79	46	39	29
19	81	45	39	30
20	80	44	38	29
21	80	45	40	30
22	78	45	40	29
23	76	44	39	29
24	78	45	38	29
25	82	45	39	29
26	79	44	39	29
27	77	44	38	29
28	78	44	38	29
29	77	46	39	29
30	80	44	38	30

Table 4.2: Number of Times Each Aircraft Visits the Service Facility – Part 2

	Number of Visits to Service Facility			
ID #	1-Engine	2-Engine	3-Engine	4-Engine
31	81	43	39	28
32	77	43	38	29
33	82	45	38	29
34	78	44	38	28
35	83	46	38	30
36	79	43	37	28
37	77	44	37	29
38	77	44	38	29
39	79	44	38	29
40	77	44	38	29
41	77	45	37	28
42	79	43	38	29
43	79	44	38	30
44	81	46	38	29
45	77	45	38	29
46	77	43	38	29
47	78	44	39	29
48	79	43	38	28
49	81	43	38	28
50	77	42	37	29

Statistical Results

After reaching steady state by establishing appropriate replication runs, the next step is collecting conclusive simulation results for maintenance planning. Table 4.3 presents the preliminary comparison between cumulative service times, and the total number of aircraft and corresponding number of engines serviced for the given scenarios for 200,000 hours of fleet operation.

Table 4.3: Preliminary Simulation Results for Individual Maintenance Scenarios

Maintenance Type	Total Service Time (Hours)	Number of Aircraft Serviced (Normal)	Number of Aircraft Serviced (Urgent)	Total Aircraft Serviced	Service Time Per Aircraft (Hours)	Single Engine Serviced (Hours)
1-Engine	389,626	3,661	400	4,061	95.94	95.94
2-Engine	327,820	2,052	231	2,283	143.59	95.72
3-Engine	371,921	1,740	198	1,938	191.91	95.95
4-Engine	356,550	1,332	154	1,486	239.94	95.98

Facilities can be permanently set up to efficiently perform maintenance on a fixed pre-determined number of engines, i.e. 1-Engine, 2-Engine, 3-Engine or 4-Engine, depending on the resource availability and the facility capacity. See also the discussion in section 3.5.5. For instance, to perform and complete 4-Engine maintenance in an optimal time, a facility needs to schedule more staff overtime, and to assess the inventory and spare part availability. These resource decision factors have weights and costs in $/hour associated with their importance that can play a major part in making the final decisions. However, these cost data are not available in this study and all the discussions are solely on time-based parameters such as engine RTTF.

In each of the four scenarios, maintenance was triggered when one engine's RTTF was at the threshold (Trs1) level and it required service.

A facility with a capacity to perform maintenance on a maximum of two engines at a time, can handle 1-Engine and 2-Engine maintenance. This analysis (1-Engine vs. 2-Engine) determines which type is the most optimal planning considering the lowest grounding time and highest flying hours. For the same reason, a facility with a capacity and resources available for three-engine maintenance, can consider 1-Engine through 3-Engine maintenance.

The data presented in Table 4.3 is informative. However, one of the drawbacks of these individual scenarios, specifically the analysis of the results, is that they are not intuitive and conclusive since a multitude of factors must be concurrently assessed. These factors will require a weight associated with their importance. Once these influential factors such as cost of personnel, assembly, part replacement, and facility usage (these are unknown due to confidentiality) are taken into consideration, these differences become more pronounced for decision making.

From preliminary individual scenario results it became evident that there is no practical way of distinguishing and selecting the best scenario when considering all four scenarios for a facility with a capacity of 4-Engine maintenance. Although amongst the four scenarios one scenario may prevail, the implementation of a single fixed scenario will unlikely be optimal or near optimal. As such, more detailed analysis of the individual scenarios is required in order to draw better conclusion in terms of which scenario truly prevails or offer some relative merits.

As to evaluation of individual scenarios in detail, various results extracted from the simulation output are used to compare them as shown in Table 4.4. Some examples of the data obtained for 200,000 hours of simulations are as follows: “Total Grounding Time”, “Total Flying Time”, “Total Service Time”, and “Total Waiting Time”. In addition, the average time values are also obtained from the simulations as shown in Table 4.5. The plots of these average values versus times are provided in Appendix A.

Table 4.4 shows that both 1-Engine and 3-Engine policies have the highest total waiting and service times and consequently, they have the highest total grounding times. The results show that the most favourable scenarios, based on the number of hours, are 2-Engine and 4-Engine maintenance due to their lower total grounding times and higher total flying times.

Table 4.4: Simulation Results for Individual Maintenance Scenarios – Part 1

Maintenance Type	Average Queue Length (Number Waiting)	Total Waiting Time (Hours)	Total Service Time (Hours)	Total Grounding Time (Hours)	Total Flying Time (Hours)
1-Engine	8.68	1,768,092	389,626	2,159,734	7,828,381
2-Engine	1.33	270,037	327,820	598,684	9,339,882
3-Engine	2.91	591,295	371,921	964,091	8,970,816
4-Engine	1.24	252,223	356,550	609,331	9,282,785

When the maintenance follows 1-Engine policy, the chances of any other engine approaching the 100 hours primary threshold is much higher than with the other scenarios. As a result, soon after resuming normal flying, the aircraft is grounded again for service of another single engine, thus the system accumulates the highest total grounding time. In addition, there are more aircraft waiting for service which reflects in the longer queue length. This is a recurring event throughout the 1-Engine maintenance policy.

Table 4.5: Average Time Values for Individual Maintenance Scenarios – Part 2

Maintenance Type	Average Waiting Time (Hours)	Average Service Time (Hours)	Average Grounding Time (Hours)	Average Flying Time (Hours)
1-Engine	439.34	96.51	535.34	1,927.42
2-Engine	118.41	144.13	262.53	4,095.29
3-Engine	306.33	192.16	498.49	4,635.21
4-Engine	171.08	240.30	411.30	6,245.16

The 3-Engine maintenance policy results in a similar behaviour as the 1-Engine maintenance. Upon reaching the primary threshold of 100 hours by any of the aircraft engines, 3-Engine maintenance is performed and the aircraft resumes its normal flying. However, it is very likely that the remaining fourth engine's RTTF reaches the 100 hours soon after and, therefore; the aircraft needs to be grounded again for maintenance. This in fact ranks the 3-Engine scenario second in terms of having the highest total waiting and grounding times and a long average queue length of 3 aircrafts considering a fleet of 50 aircraft.

In 2-Engine scenario, maintenance favourably alternates between pairs of engines. The simulation shows that with 2-Engine maintenance scenario, the lowest total grounding and waiting times is achieved. It is evident that when engines are serviced in pairs, they can fly for longer hours and achieve higher flying times. Consequently, average queue length is low and the waiting and grounding times are relatively lower compared to that of the 1-Engine and 3-Engine scenarios.

In regards to 4-Engine maintenance, it is shown that it has the second highest total flying time. This is due to the fact that, regardless of the values of engine RTTF, maintenance is performed on four engines. This to some extent prolongs the flying hours with an average flying time of 6,200 hours after every maintenance operation, unless the aircraft requires an urgent repair. Since the aircrafts are mostly in flying operation, the system barely sees a line-up and thus, it achieves the lowest total waiting time in the system. It was discussed earlier that cost-wise, this may not be a good policy.

In order to determine whether 2-Engine prevails over the 4-Engine policy or vice versa, a multitude of factors (such as the costs of downtime, technicians, spare-part, etc.) must be concurrently assessed for each scenario. However, what this study can suggest is optimal planning on the basis of cumulative operation and maintenance hours. It is, however, up to the industrial user to fully assess the outcome of the maintenance operation based on resource availability and their existing operational costs and the weights associated with their importance.

4.3.2 Integrated Scenario Selection (ISS)

In this section, simulation results of the ISS maintenance policy for a fleet of 50 aircraft over 200,000 hours of operation are presented and discussed. Aircraft are modelled to enter the system at an accelerated rate using a uniform distribution with inter-arrival time of between 0 to 200 hours distributed uniformly over the range. At this rate (an average of 100 hours), within approximately the first 5000 hours of simulation run all 50 aircraft will have entered and dispersed throughout the model. With a random assignment of RTTF, it is safe to assume that the fleet will soon be in near normal operation status.

In general it is believed that ISS provides a more effective policy as it constantly attempts to remain optimal in time by selecting various scenarios on case-by-case basis. In this section, ISS maintenance policy will be discussed in detail. See Figures 4.7 to 4.9 for the entire ISS System modelled in Arena®.

Simulation Stability

It is required to estimate a suitable number of replications for the simulations, which ensures the convergence of the output data to steady state values and averages. For this purpose it is sufficient to track only a few parameters. For brevity, here we report the replication results for the final value of the "Average Waiting Time". For the particular set of initial values used in the simulation, Figure 4.6 shows that any number of replications greater than 3 is reasonable. For all ISS engine maintenance simulations, the number of replications was then set at 5.

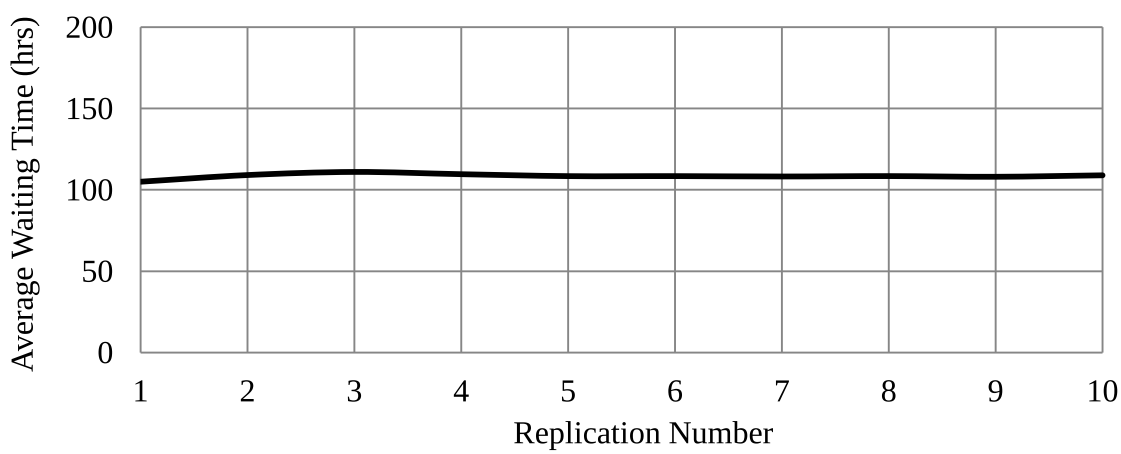

Figure 4.6: Estimating Replication Number Based on Waiting Time

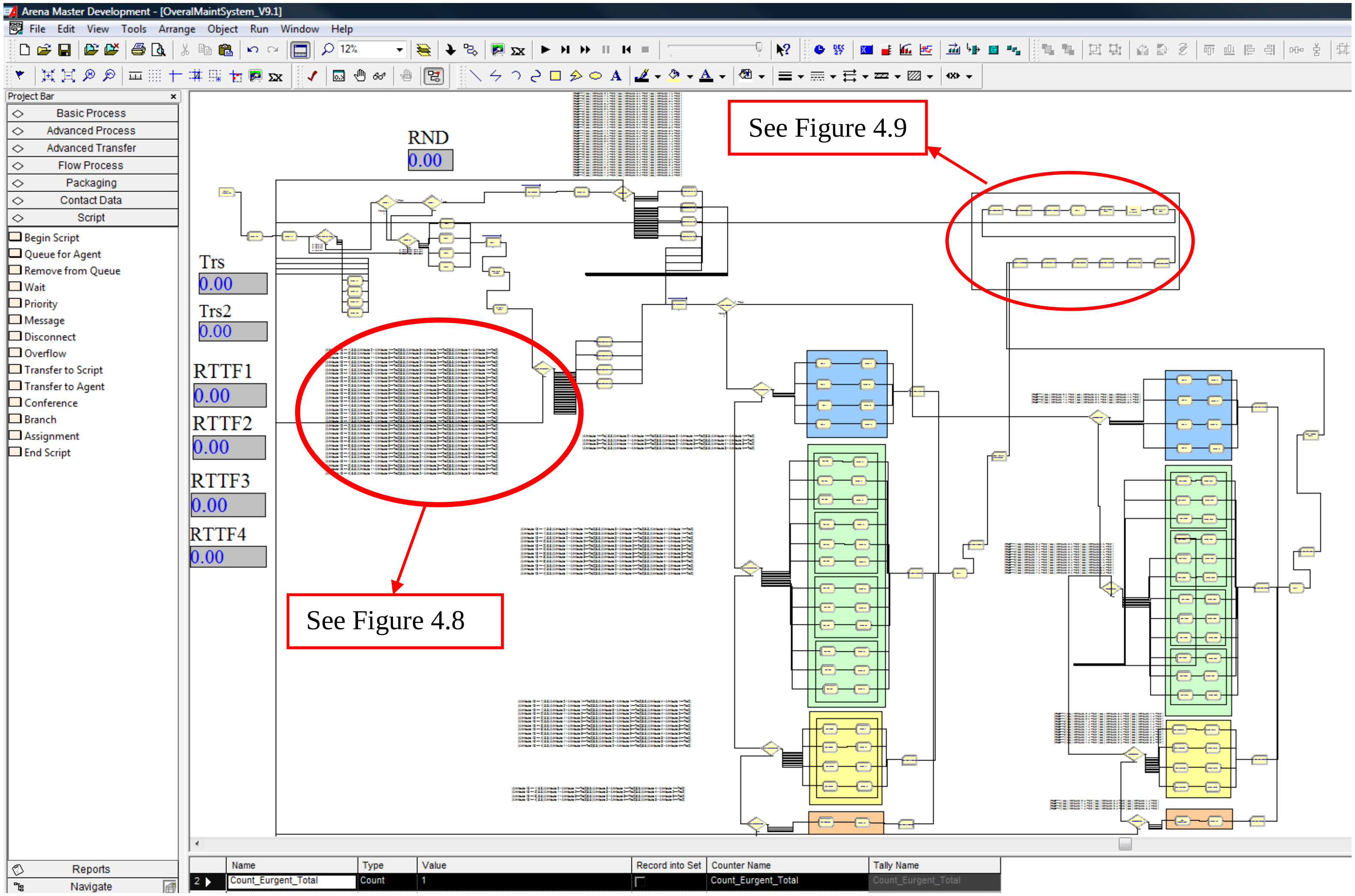

Figure 4.7: Screenshot of the Entire Arena® ISS Model

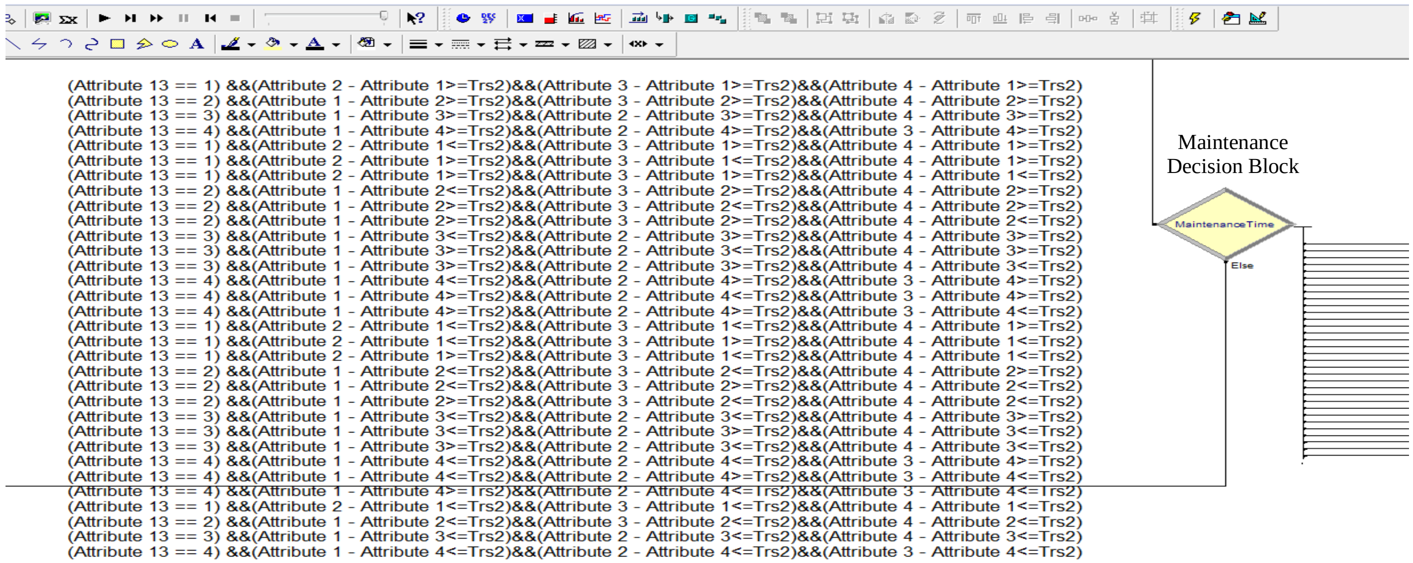

Figure 4.8: Screenshot of the Maintenance Decision Block

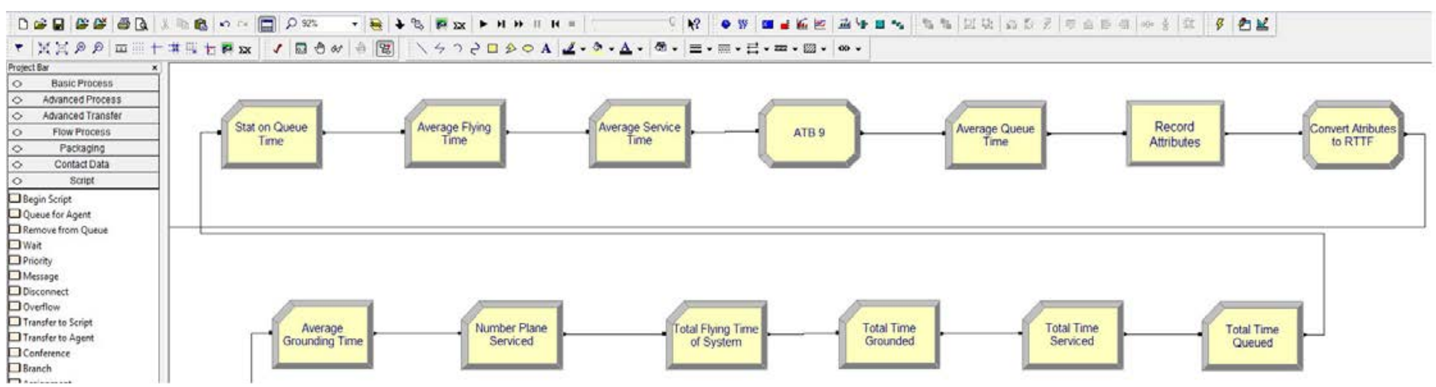

Figure 4.9: Screenshot of the Statistical Data Collection Block

The stability and uniformity of the simulation output is shown in Table 4.6 where the number of times each of the 50 aircraft has visited the service facility is about 48.

Table 4.6: Number of Times Each Aircraft Visits the Service Facility (ISS Scenario)

ID #	Number of Visits to Service Facility	ID #	Number of Visits to Service Facility	ID #	Number of Visits to Service Facility
1	46	18	51	35	47
2	48	19	48	36	49
3	43	20	52	37	42
4	51	21	48	38	49
5	50	22	47	39	45
6	48	23	50	40	50
7	46	24	49	41	47
8	48	25	44	42	46
9	49	26	48	43	45
10	44	27	48	44	45
11	48	28	47	45	45
12	46	29	45	46	43
13	52	30	44	47	44
14	45	31	48	48	47
15	48	32	47	49	47
16	49	33	50	50	45
17	45	34	44		

Statistical Results

Table 4.7 shows the breakdown of the different types of services performed for selected aircraft ID. One of the advantages of the proposed method is that it tracks every entity (aircraft) individually within the model and collects relevant information regarding its service and maintenance, as well as the fleet as a whole.

Table 4.7: Number of Different Service Type for Sample Selected Aircraft

Aircraft ID #	Total 1-Engine Type Service	Total 2-Engine Type Service	Total 3-Engine Type Service	Total 4-Engine Type Service	Total Aircraft Serviced	Total Sudden Failure Service
1	15	15	15	13	50	4
2	14	14	14	15	44	2
3	16	16	15	13	55	7
4	15	15	13	15	53	6
5	15	14	14	15	50	3
15	14	14	17	14	54	8
20	13	14	14	13	44	0
30	14	13	15	13	47	4
40	13	15	14	13	48	4
50	14	14	15	14	48	4

Many different results can be obtained from simulating the model. Table 4.8 shows the counts of different services performed during the simulations for the entire fleet. The mandatory primary threshold was set as $Trs1 = 100$ hours, and the secondary threshold, *Trs2*, was used as the policy optimization variable for the 21 cases assessed.

Table 4.8: ISS Engine Maintenance Policy Simulation Results – Part 1

Case #	Trs2 (hrs)	1-Engine Service Count	2-Engine Service Count	3-Engine Service Count	4-Engine Service Count
1	100	3,776	165	2	0
2	200	3,513	296	11	0
3	300	3,338	397	19	0
4	400	3,104	536	13	0
6	600	2,710	716	43	1
7	800	2,290	878	90	2
8	1,000	1,886	1,030	132	1
9	1,200	1,532	1,167	174	4
10	1,300	1,409	1,245	175	10
11	1,400	1,279	1,254	219	8
12	1,500	1,071	1,355	231	11
13	1,600	926	1,434	229	16
14	1,700	719	1,570	203	18
15	1,800	643	1,602	224	16
16	**1,900**	**536**	**1,638**	**237**	**19**
17	2,000	562	1,491	321	25
18	2,100	467	1,531	327	35
19	2,200	465	1,422	406	41
20	2,300	489	1,355	449	41
21	2,400	439	1,296	490	60

With simulation run time of 200,000 hours and a fleet of 50 aircrafts, there will be a cumulative available 'time' of 10×10^6 hours. This is roughly equal to the sum of ‘total flying time’ and ‘total grounding time’. Therefore, these measures are complementary and either can be used as one of the most important decision factors.

To further evaluate ISS in detail, various data are extracted from the simulation outputs as shown in Tables 4.8 and 4.9. The average values of some other parameters have also been extracted and plotted versus time, and these are given in Appendix B.

Referring to the data presented in Tables 4.8 and 4.9 (and in fact elsewhere too), as alluded earlier, we focus our discussions on pure time-based facts and figures. However, the industrial user must apply weights and proprietary cost data associated with the time-based factors in their decision making processes.

As concluded from individual scenarios, the optimal maintenance occurs with the 2-Engine type. In the ISS maintenance, too, this important finding emerges around case #16 (Table 4.8), where the greatest number of services is of 2-Engne type at the secondary threshold (Trs2) of 1,900 hours.

The column showing the total grounding time in Table 4.9 is in fact the total of waiting and service times. For ‘any cost rate’, it is envisaged that the minimum cost will emerged around case #15, corresponding to the secondary threshold (Trs2) of 1,900 hours. The total cumulative operation hours of simulation (total flying and grounding hours) for each case are seen to be near the expected 10×10^6 hours. It is also seen from Table 4.8 that 2-Engine service has been dominant as expected, recalling the inferences made during the discussion of the individual scenarios.

The total waiting time and the average queue length, from Table 4.9, are the indication of the ‘capacity’ of service facility. The user may interpret this “queue time” based on their priorities and finances, and run new simulation cases by proposing increased capacity, for example (Chapter 5, provides convenient means for this types of assessment).

Table 4.9: ISS Engine Maintenance Policy Simulation Results – Part 2

Case #	Trs2 (hrs)	Average Queue Length	Total Waiting Time (hrs)	Total Service Time (hrs)	Total Grounding Time (hrs)	Total Flying Time (hrs)
1	100	5.41	1,103,628	387,109	1,492,605	8,506,604
2	200	5.11	1,039,436	381,042	1,422,308	8,542,303
3	300	4.38	889,829	378,962	1,270,559	8,683,512
4	400	4.11	836,802	374,773	1,213,272	8,771,029
5	500	3.68	749,198	374,065	1,124,872	8,851,988
6	600	3.30	670,826	371,859	1,044,193	8,930,979
7	700	3.59	728,767	365,207	1,095,506	8,861,213
8	800	3.07	625,504	361,797	988,764	8,999,748
9	900	2.59	526,602	361,966	889,947	9,092,763
10	1,000	2.73	553,492	353,942	908,719	9,053,389
11	1,500	1.81	368,337	343,892	713,312	9,255,306
12	1,600	1.61	328,105	340,807	669,931	9,297,291
13	1,700	1.71	348,352	337,805	687,124	9,271,759
14	1,800	1.49	302,638	336,587	640,153	9,322,439
15	**1,900**	**1.30**	**263,487**	**335,906**	**600,282**	**9,350,188**
16	2,000	1.53	309,866	334,084	644,838	9,302,049
17	2,100	1.45	293,287	335,838	630,020	9,330,727
18	2,200	1.37	278,412	334,008	613,334	9,349,198

Clearly, increased capacity reduces the grounding time (equally the queue length and service time) and thus, there will be fewer number of aircraft in the queue. This will lead to a new state-of-affairs and total cost status; whereby the user can make an economic analysis of the capital invested in increasing the capacity of the service facility, and the return on investment in reducing grounding time.

The average values for notable cases of 10 through 18 representing Trs2 values of 1,000 to 2,200 hours (Table 4.9) are also given in Table 4.10.

Table 4.10: Simulation Average Time Values for ISS

Case #	Trs2 (hrs)	Average Wait Time (hrs)	Average Service Time (hrs)	Average Grounding Time (hrs)	Average Flying Time (hrs)
10	1,000	182	116.59	298.53	2,969.32
11	1,100	155.99	118.15	274.18	3,045.76
12	1,200	179.38	121.41	300.92	3,160.9
13	1,300	140.8	123.15	263.98	3,252.77
14	1,400	150.53	126.38	277.01	3,339.88
15	1,500	138.5	129.4	267.86	3,469.03
16	1,600	126.34	131.33	257.67	3,569.04
17	1,700	139.07	135.08	274.26	3,693.95
18	1,800	122.12	135.95	258.1	3,751.51
19	**1,900**	**108.84**	**138.74**	**247.53**	**3,847.83**
20	2,000	129.52	139.76	269.31	3,877.49
21	2,100	124.82	142.79	267.45	3,953.72
22	2,200	119.67	143.6	263.27	4,005.68

4.4 Model Verification for Individual Engine Maintenance Scenarios Using Simio Discrete Event Simulation

As stated earlier, one of the challenges associated with this study was the confidentiality issue and therefore, unavailability of real data related to the fleet operation, failures, repairs and maintenance. However, as a standard practice, simulation models must be verified, and the results validated if possible. Due to inaccessible data, the verification, and to some extent validation through extended verification, are performed through a secondary separate simulation modeling. As a result, "Simio" as an alternative simulation tool was chosen to model and replicate the existing individual scenarios (1-Engine, 2-Engine, 3-Engine and 4-Engine maintenance).

Due to general similarity of simulation languages, only introductory comments are provided and detailed modeling constructs and concepts of Simio are not reproduced.

4.4.1 Simio Discrete Event Simulation

Simio, similar to Arena®, is a simulation modeling framework that is designed to support the object modeling paradigm. Although its framework is focused on object-oriented modeling, it also supports a seamless use of multiple modeling paradigms including event, process, object-based modeling. An object might be a machine, robot, airplane, customer, ship, or any other entity that one might encounter in modeling a system. A Simio model looks similar to the real system. It is built by combining objects that represent the physical components of the system. The process of building an object is very simple and completely graphical. There is no need to write programming code to create new objects [86, 87].

Simio is a newly introduced discrete event simulation software that has been applied to various cases in industry and healthcare systems [88-91]. Each step in Simio model is a simple process such as holding the token for a time delay, seizing/releasing of a resource, waiting for an event to occur, assigning a new value to a state, or deciding between alternate flow paths.

4.4.2 Building the Models in Simio

Four separate models are built for simulation of 1-Engine, 2-Engine, 3-Engine and 4-Engine maintenance scenarios. A graphical representation of one of these models is given in Figure 4.10.

To initialize the system, 50 aircraft are created, and a Remaining Time to Fly (RTTF) randomly drawn between 7,000 and 10,000 hours is assigned to each engine of each aircraft. Same as before, grounding has two forms: 1) *Normal Grounding Process* where the aircraft is sent for service when any engine's RTTF value reaches the primary threshold (Trs1) of 100 hours. 2) *Emergency Grounding Process* occurs when an urgent maintenance is required. This failure is assumed to take place 10% of the times.

Referring to the overall maintenance block diagram (Figure 4.11), the maintenance is initiated when aircraft enter the system. In addition to the RTTF values a distinct ID number is also assigned to each aircraft. The ID numbers enable the user/modeller to track any aircraft in the model at any time. The aircraft grounding occurs when the primary threshold (Tr1=100 hours) is reached by any aircraft's engines. When an aircraft is grounded (either normal or urgent), the maintenance is performed on a pre-set number of engines as defined in scenarios 1-Engine, 2-Engine, 3-Engine and 4-Engine, respectively.

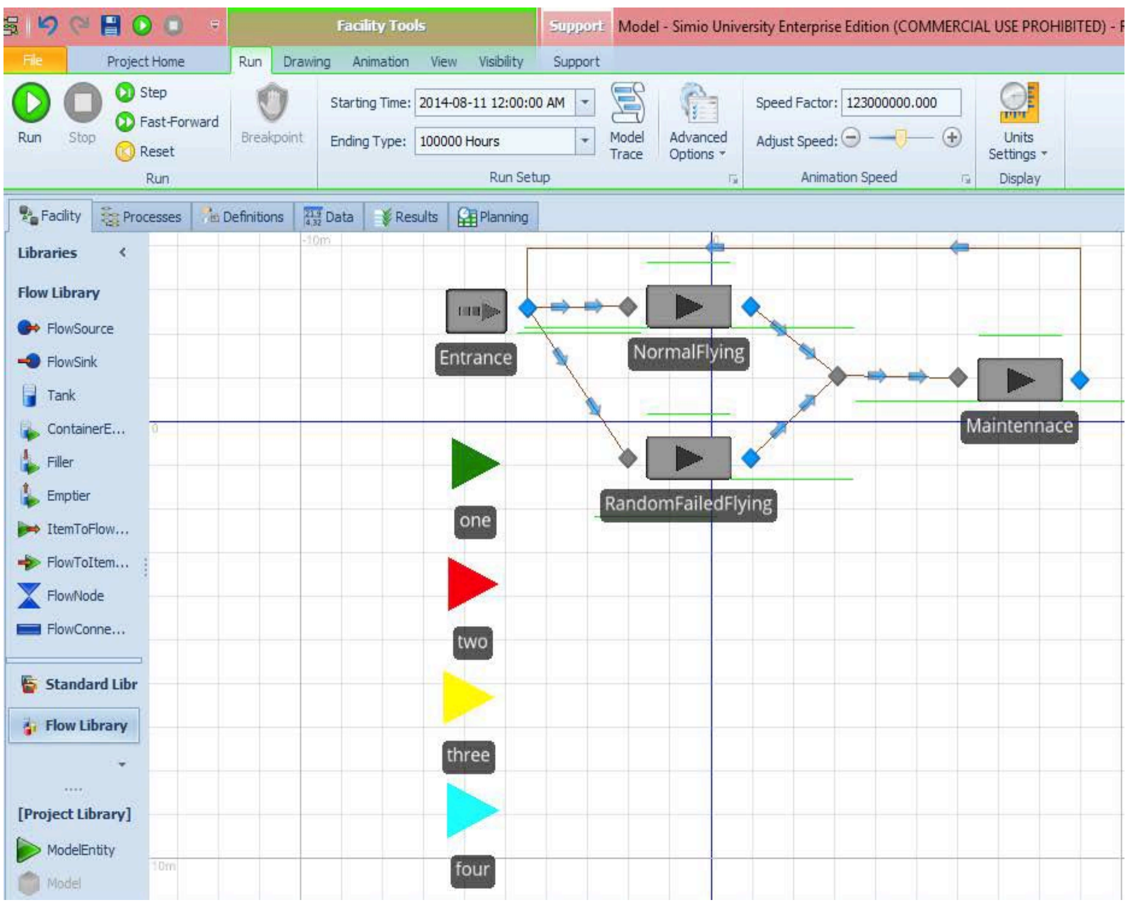

Figure 4.10: Graphical Representation of a Simio Model

As used in Arena® models, the maintenance processing times are drawn from a triangular distribution with a minimum of 2, a maximum of 6 and an average of 4 days.

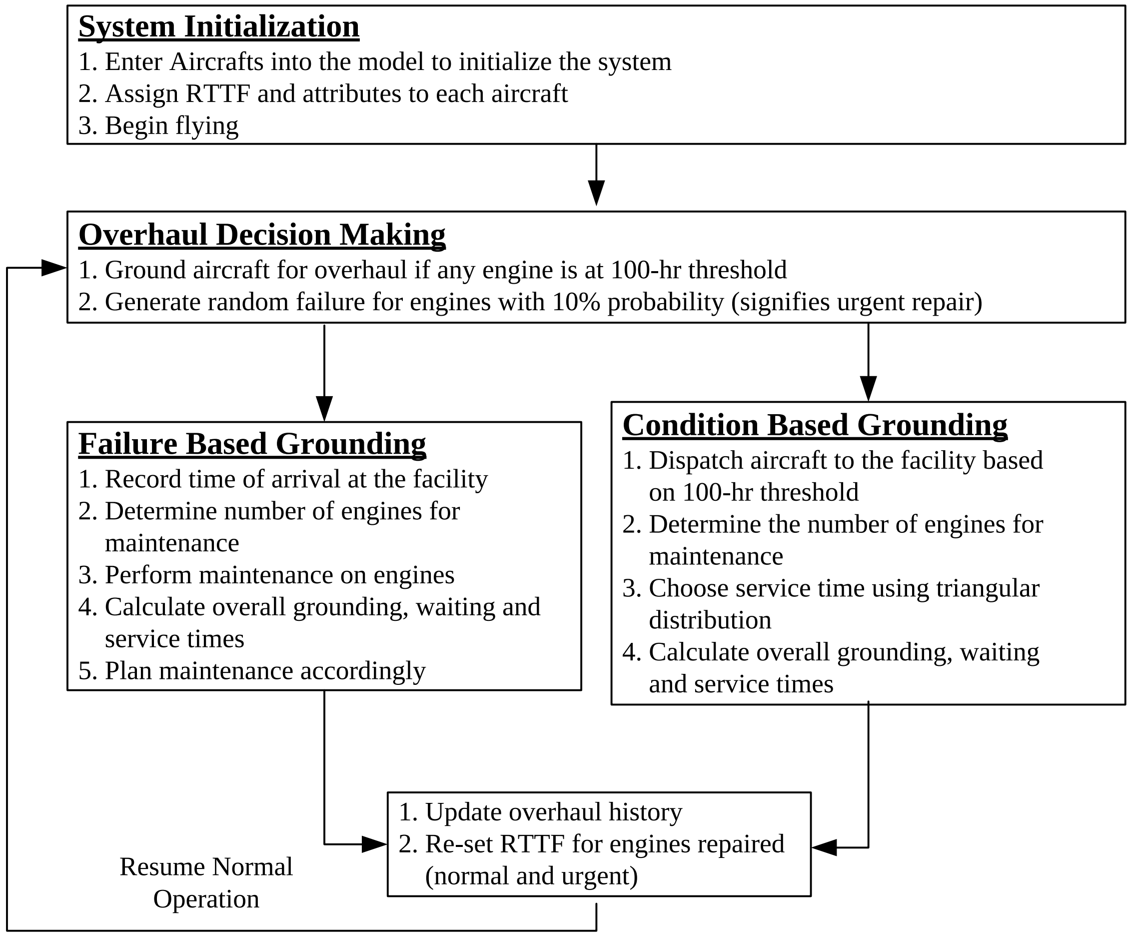

Figure 4.11: Overall Maintenance Procedure Flow Diagram

The processing time is multiplied by 1.5, 2, and 2.5 for two, three, and four engine maintenance, respectively. The First-in-First-Out discipline is used for the maintenance facility queue. At the end of the overhaul and before resuming normal flying, the maintenance history such as: grounding, waiting and service times are updated and the required statistics collected.

4.4.3 Simulation Stability

It is required to estimate a suitable number of replications for the simulations. Following the same process as in the Arena® simulations, and referring to Figure 4.12, choosing any replication number greater than four seems reasonable as the average waiting time of each individual scenario converges to a steady level. In simulations that follow, a replication number of 5 is used.

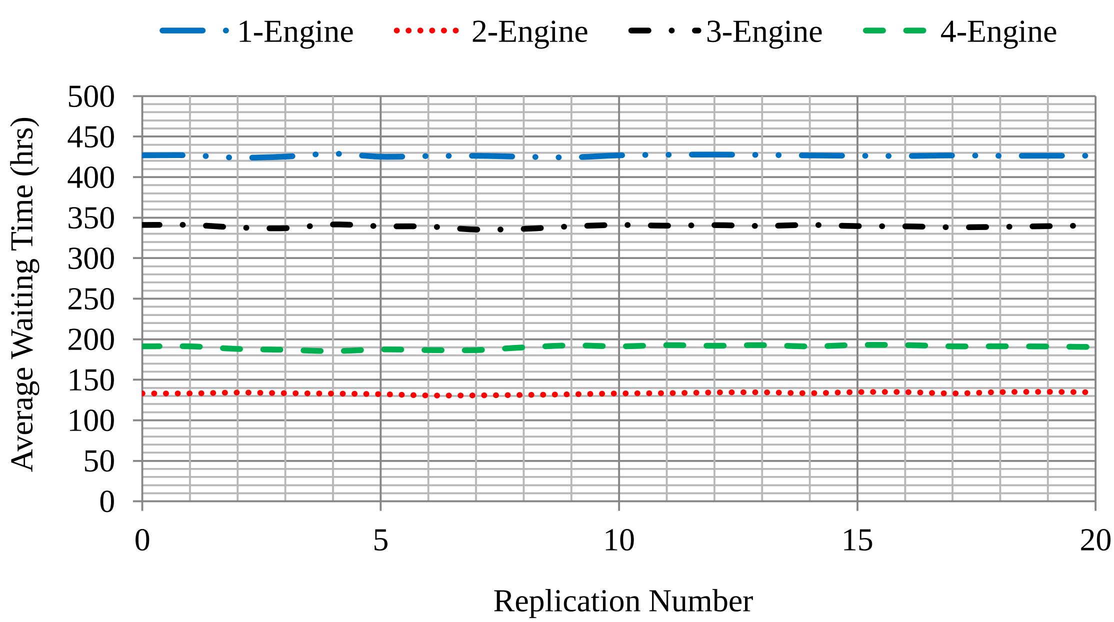

Figure 4.12: Estimating Replication Number for Individual Scenarios for Simio

4.4.4 Verification

To verify the Arena® models and simulations, the maintenance scenarios with "fixed" number of engines are modeled and simulated in "Simio" software. The outputs from these simulations are compared with those generated by Arena® as shown in Tables 4.11 to 4.16. For each aircraft in each scenario, the following statistical data are collected:

1. Total and average flying time
2. Total and average grounding time
3. Total and average waiting time
4. Total and average service time
5. Average queue length

Table 4.11: Average Values from Simio Simulations

Maintenance Type	Average Queue Length (Number Waiting)	Average Wait Time (Hours)	Average Service Time (Hours)	Average Grounding Time (Hours)	Average Flying Time (Hours)
1-Engine	8.56	426.86	96.1	522.83	1,921
2-Engine	1.44	133.05	143.9	276.64	3,945
3-Engine	3.23	340.95	192.11	532.98	4,436
4-Engine	1.39	191.11	239.85	430.35	6,243

Table 4.12: Average Values from Arena® Simulations

Maintenance Type	Average Queue Length (Number Waiting)	Average Wait Time (Hours)	Average Service Time (Hours)	Average Grounding Time (Hours)	Average Flying Time (Hours)
1-Engine	8.68	439.34	96.51	535.34	1,927
2-Engine	1.33	118.41	144.13	262.53	4,095
3-Engine	2.91	306.33	192.16	498.49	4,635
4-Engine	1.25	171.08	240.30	411.30	6,245

Table 4.13: Percentage Difference between Simio and Arena® Average Values

Maintenance Type	Average Queue Length (Number Waiting)	Average Wait Time (Hours)	Average Service Time (Hours)	Average Grounding Time (Hours)	Average Flying Time (Hours)
1-Engine	1.37%	2.84%	0.56%	2.34%	0.32%
2-Engine	7.38%	11.01%	0.37%	5.10%	3.68%
3-Engine	10.01%	10.15%	0.07%	6.47%	4.30%
4-Engine	10.30%	10.48%	0.44%	4.43%	0.04%

Table 4.14: Total Time Values from Simio Simulations

Maintenance Type	Total Wait Time (Hours)	Total Service Time (Hours)	Total Grounding Time (Hours)	Total Flying Time (Hours)
1-Engine	1,718,405	385,639	2,104,045	7,804,882
2-Engine	296,352	327,622	623,975	9,315,582
3-Engine	624,507	372,349	996,856	8,922,082
4-Engine	273,229	353,863	627,092	9,250,758

Table 4.15: Total Time Values from Arena® Simulations

Maintenance Type	Total Wait Time (Hours)	Total Service Time (Hours)	Total Grounding Time (Hours)	Total Flying Time (Hours)
1-Engine	1,768,092	389,626	2,159,734	7,828,381
2-Engine	270,037	327,820	598,684	9,339,882
3-Engine	591,295	371,921	964,091	8,970,816
4-Engine	252,223	356,550	609,331	9,282,785

Table 4.16: Percentage Difference between Simio and Arena® Total Time Values

Maintenance Type	Total Wait Time (Hours)	Total Service Time (Hours)	Total Grounding Time (Hours)	Total Flying Time (Hours)
1-Engine	2.81%	1.02%	2.58%	0.30%
2-Engine	8.88%	0.06%	4.05%	0.26%
3-Engine	5.32%	0.11%	3.29%	0.54%
4-Engine	7.69%	0.75%	2.83%	0.35%

Similar to Arena®, the statistical outcomes from Simio show that the scenario with 2-Engine maintenance prevails and the scenario with 4-Engine maintenance is the second best in terms of the total grounding and flying times. In addition, from Tables 4.13 and 4.16, for average and total time values, it was seen that the percentage difference between outcome of the Arena® and Simio is within the acceptable range of 10%.

4.4.5 Discussions and Conclusions

Tables 4.11 and 4.14, show that using 2-Engine scenario, where the maintenance events seem to alternates between pairs of engines, and the lowest total and average grounding and waiting times are achieved. It appears that when engines are serviced in pairs, they fall into a synchronized cycle that leads to a longer uninterrupted flying time. Consequently, the average queue length is short and the waiting and grounding times are also relatively low, compared to that of the 1-Engine and 3-Engine scenarios.

The same conclusion is made for maintenance using 4-Engine scenario in the simulations with Arena®. It has a low average queue length, as well as the second lowest total grounding, waiting and service times.

To summarize, looking at the results obtained from Simio simulation, the same conclusions as with Arena® simulations can be drawn based on the total grounding and flying times for the models. Overall, 2-Engine and 4-Engine maintenance result in the lowest total grounding times and consequently give the highest total flying times. Maintenance with 1-Engine and 3-Engine policies are the least desirable.

From the foregoing, and the fact that Arena® and Simio simulation results differ by 10% or less, the verification of the Arena® models has been achieved.

Chapter 5

Alternative Decision Support System Using Queuing Theory

5.1 Introduction

Any Discrete Event Simulation software has great utility as it allows almost any detail, condition or exception to be modelled. However, one of the biggest challenges associated with using simulation software is its gradual and at times plateau learning curve at the initial stages when a user without sufficient knowledge and experience attempts to develop models. Modeling and simulation requires special training. For non-experts, developing and verifying a model is rather challenging. Management often require good, but simple models of their systems so that they can readily evaluate modest changes and alternative policies. In the work carried out in the previous chapters, representative DES models of the aircraft maintenance operations were developed and verified. These models are available, reusable and can be modified to investigate many other alternatives. For management and technical staff of even reasonable ability, however, it is also advantageous and desirable to have models that can be run without specialized knowledge of a simulation software, or resorting to involved model modifications.

As the detailed information and databases were unavailable for this study, and data collection was not an option, the objectives of this study were to develop a) comprehensive model based on the available information (as per previous chapters), and b) from the results obtained develop a simple to use tool for convenient assessment of minor tweaks to the system.

This chapter addresses the latter goal, where an 'equivalent' queuing-theory-based model is developed. This requires extracting relevant system and operation data from the Arena® Simulations. The implementation of the queuing model is examined and the results are compared with the results of the Integrated Scenario Selection (ISS) simulation model for verification.

5.2 Waiting-Line Analysis of Maintenance Facility

Waiting in lines is part of the maintenance process that aircraft encounter during their service. Minimizing the wait times and queue lengths are synonym with maximizing the availability and longer flying times. How long an aircraft waits in line depends on many factors. Waiting time is related to the number of technicians performing maintenance, the number of service channels and equipment needed. In other words, the time it takes to service each engine.

Queuing theory and networks have been used vastly with success for analytical modeling of different systems. Assessment of traffic systems, manufacturing operations, and metro services are typical examples [92, 93].

Randomness in arrivals and service patterns makes waiting-line situations difficult to analyse. However, powerful models have been developed to provide quantitative measures of important characteristics of waiting-line systems.

A waiting line system (or queuing system) is defined by four elements: a) the population source of its entities (aircraft in this case), b) the process or service system itself, c) the number of service channels, and d) the queue discipline. In some instances additional conditions such as constraints may be included [94, 95]. It is important to note that the results of analytical waiting-line models describe the long-term behaviour of the system since they provide long-run statistics of the metrics used. Many forms of waiting-line models exist and some examples are shown in Figure 5.1. In this study the focus is on the existing multiple-channel (two-server), single waiting-line with Poisson arrivals and exponential service times.

To develop a waiting-line model for the maintenance facility some important characteristics of the system must be identified. The first is pattern or distribution of the aircraft arrival at the maintenance facility, and the second is the pattern or distribution for the service-time for the engines, and the third factor is the waiting-line or queue discipline for the aircraft. The number of service channels and phases are already known.

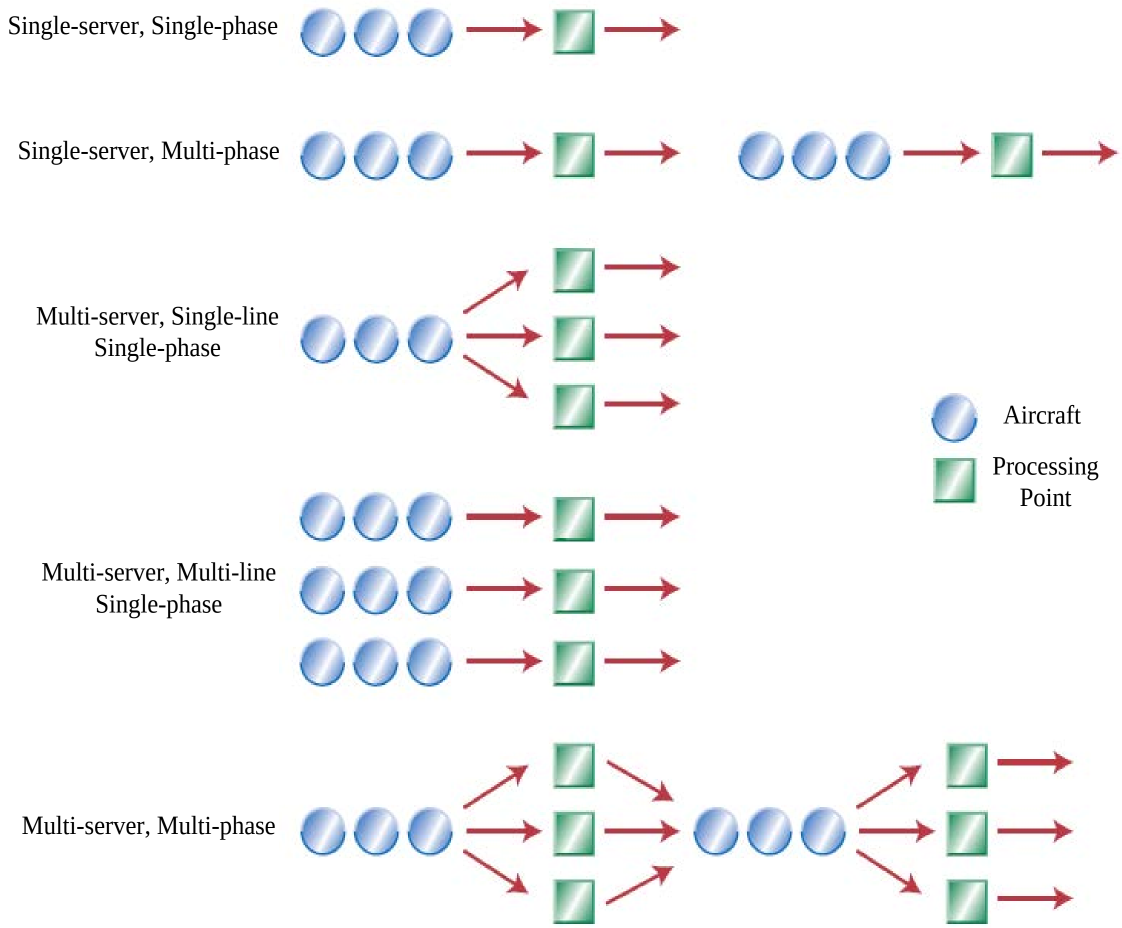

Figure 5.1: Examples of Waiting-Line Systems

We develop the waiting line system to be equivalent to the Integrated Scenario Selection (ISS) maintenance model so as to reproduce as closely as possible its appropriate performance measures.

5.2.1 Arrival Distribution

Arrival distribution for the waiting-line consists of the following factors:

1. Size of arrival population

2. Pattern of arrivals or its statistical distribution

Population sizes are considered either unlimited (infinite) or limited (finite). When the number of arrivals on hand at any given time is a small portion of all potential arrivals, the arrival population is considered unlimited or infinite. Most queuing models assume such an infinite arrival population. Example of unlimited populations includes arrival aircraft at the maintenance facility as it is a recurrent event.

Arrivals pattern is characterized by some known schedule (for example, one aircraft every 2 days) or else they arrive randomly. Arrivals are considered random when they are independent of one another and their occurrence cannot be predicted exactly. Frequently, in queuing problems and for many waiting-lines, operations researchers have found that the number of arrivals per unit of time can be best represented by a Poisson distribution [96-100]. For arrival time, a Poisson distribution is defined as:

$$P(x) = \frac{\lambda^x e^{-\lambda}}{x!} \quad \text{for } x = 0, 1, 2, \ldots \tag{5.1}$$

where: $P(x)$ = probability of x arrivals

x = number of arrivals per unit of time

λ = average arrival rate

The collected data obtained from ISS simulations maintenance for arrivals at the maintenance facility indicate that in most instances 9-10 aircraft arrive at the facility during a one month period, though at times it drops to 4-5 aircraft. Since the arrivals cannot be controlled and essentially in the reality the design of ISS model occur in an unpredicted manner, a random arrival pattern is assumed. With trial and error it is found that a Poisson probability distribution with an average rate of $\lambda = 7$ aircraft per month provides a good equivalent pattern of the arrivals. This will be determined and validated later through the redundant equations available.

5.2.2 Service Time Distribution

The second element of the queuing system is the service time characteristics. Two important properties are: 1) how long it takes to process an aircraft through the maintenance operation (service time) and 2) if random, what is the distribution of the service times. Service patterns are akin to arrival patterns in that they may be either constant or random. If service time is constant, it takes the same amount of time to process each maintenance task. More often, service times are randomly distributed. In many cases, operations researchers have assumed random service times whereby they are described by the exponential probability distribution [101-106]. The exponential distribution is defined as:

$$f(x) = \mu e^{-\mu t} \quad for\ x \geq 0 \tag{5.2}$$

where: x = service time

μ = average or expected number of aircraft that the service facility can process in a specific period of time

The probability of a service being completed within a specific period of time, *t*, is given by:

$$p(service\ time\ \leq t) = 1 - e^{-\mu t} \tag{5.3}$$

Data for the service facility obtained from the simulations of the ISS scenario suggest that the facility can service an average of $\mu = 5$ aircraft per months with an average service time of 108 hours per engine.

5.2.3 Queue Discipline

The maintenance facility in the Arena® ISS model operates by the First-In-First-Out (FIFO) discipline. The same discipline is used in the queuing model developed.

5.3 The Multi-Channel Waiting-Line Model

Multiple channel waiting-line refers to the presence of two or more parallel service locations or units $(k = 1, 2, \ldots)$ within the service facility. In this system, aircraft arrive at the facility, join a single queue, and proceed to the first available location for the maintenance operation.

In this section, relevant queuing formulas are reproduced as in [107] and used to compute and illustrate various operational characteristics of the queue. The following assumptions portray the system in this study:

1. Arrivals follow the Poisson probability distribution with a mean arrival rate of λ=7 aircraft per month.
2. The service time has an exponential distribution with a mean service rate of $\mu = 5$ aircraft per month for each service channel.
3. There are two parallel service channels, $k = 2$.

4. The arriving aircraft wait in a single queue and move to the first open channel for service.
5. The queue discipline is First-In-First-Out (FIFO).
6. For convergence to steady state operation and statistical values, the overall mean service rate, $k\mu$, must be greater than the mean arrival rate, $\lambda = 7$. Otherwise, the queue gradually grows infinitely large.
7. The term ‘system’ is interpreted as ‘queue plus the two service channels’.

Using the above data and conditions the operating characteristics of the waiting-line model can be calculated using the following formulas:

1. The probability that no aircraft is in the system:

$$P_0 = \frac{1}{\left[\sum_{n=0}^{k-1} \frac{\left(\lambda/\mu\right)^n}{n!}\right] + \left[\frac{\left(\lambda/\mu\right)^k}{(k-1)!} \frac{\mu}{k\mu-\lambda}\right]} \tag{5.4}$$

2. The average number of aircraft waiting for service:

$$L_q = \frac{\left(\lambda/\mu\right)^k \lambda.\mu}{(k-1)!(k\mu-\lambda)^2} P_0 \tag{5.5}$$

3. The average number of aircraft in the system:

$$L = L_q + \frac{\lambda}{\mu} \tag{5.6}$$

4. The average time an aircraft waits for service:

$$W_q = \frac{L_q}{\lambda} \tag{5.7}$$

5. The average time an aircraft spends in the system (wait time + service time):

$$W = W_q + \frac{1}{\mu} \tag{5.8}$$

6. The probability that an arriving aircraft must wait for service:

$$P_w = \frac{1}{k!}\left(\frac{\lambda}{\mu}\right)^k \frac{k\mu}{k\mu-\lambda} P_0 \tag{5.9}$$

7. The probability that n aircraft are in the system:

$$P_n = \frac{\left(\lambda/\mu\right)^n}{n!} P_0 \quad \text{for} \quad 0 \le n \le k \tag{5.10a}$$

$$P_n = \frac{\left(\lambda/\mu\right)^n}{k!k^{n-k}} P_0 \quad \text{for} \quad n > k \tag{5.11b}$$

5.3.1 Queuing Parameters

In sections 5.2.1 and 5.2.2, the queuing parameters λ and μ were ‘crudely estimated’ as 7 and 5 aircraft per month, respectively. These are used as initial guess values with the queuing theory equations. There are seven queuing theory equations, five of them with equivalent counterparts in the ISS model. Three of the equations are used. Two to more accurately determine the values for the parameters λ and μ, and the third to verify these values. From the Arena® ISS simulations we have the following statistics:

1. The average number of aircraft waiting for service, 1.30
2. The average time an aircraft waits for service, 108.84 hours
3. The average time an aircraft spends in the system, 247.48 hours

These values are respectively substituted in the left-hand-side of the equations (5.5), (5.7) and (5.8). Solving these equations, as explained above, with the initial estimates of λ and μ, we obtain the more accurate value of $\lambda = 6.8$ and $\mu = 5.3$.

5.4 Analysis of the Single-Line, Two-channel Waiting-Line

Many useful metrics can be obtained from the application of the queuing theory. One is the probability of a service being completed within a specific period of time. Using estimated λ and μ and the equation (5.3), Figure 5.2 shows the percentage of aircraft that will be serviced in *t* weeks or less. For example, 65% of the aircraft will be serviced in 1 week or less; and 96% in 3 weeks or less.

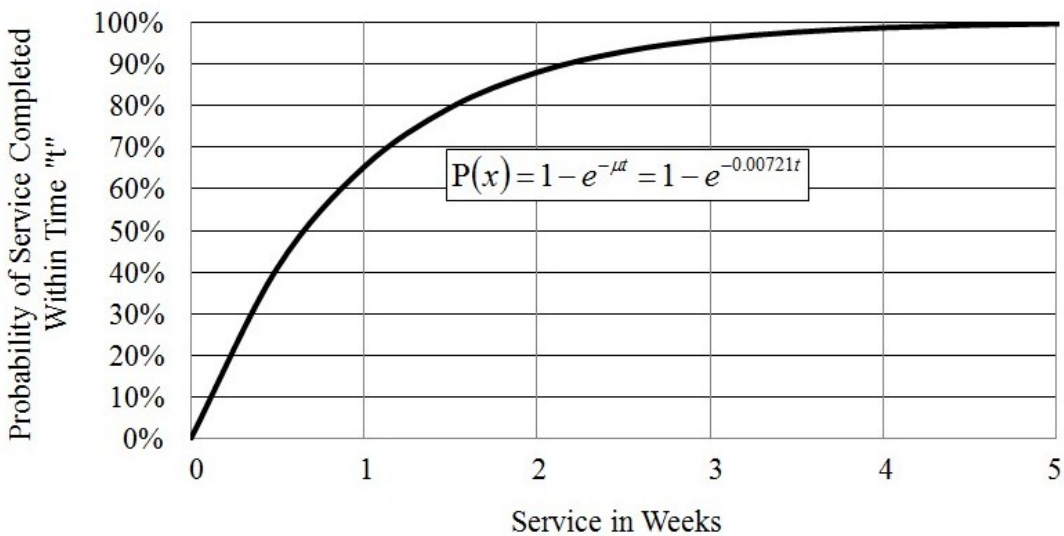

Figure 5.2: Percentage of Aircraft Serviced in *t* Weeks or Less

Using equations (5.4) through (5.10), the operating characteristics of the maintenance facility are determined as given in Table 5.1.

Table 5.1 reveals several important facts about the maintenance facility operation. The management has this equivalent queuing model whereby the effect of modest variations in the system parameters, namely λ, μ and k, can be readily determined.

It was pointed out in section 6.3 that the overall mean service rate, $k\mu$, must be greater than the mean arrival rate, λ. If this condition is not met, the waiting-line eventually grows infinitely large. Table 5.1 indicates that this condition is well satisfied.

Table 5.1: ISS Engine Maintenance Queuing Model Characteristics

Number of arrivals per month (λ)	6.8
Number of units serviced per month per channel (μ)	5.3
Number of service facilities/channels (k)	2
λ/μ	1.28
P_0	0.28
L_q	1.13
L	2.47
W_q	122.68 (*hrs*)
W	261.01 (*hrs*)
P_w	0.64
$k\mu > \lambda$	10.6 > 6.8

Figure 5.3 is a graph of the probabilities of certain numbers of aircraft in the system. For example, there is a 36% chance there are 2 aircraft in the system, and the probability that greater than 10 aircraft are in the system is insignificant.

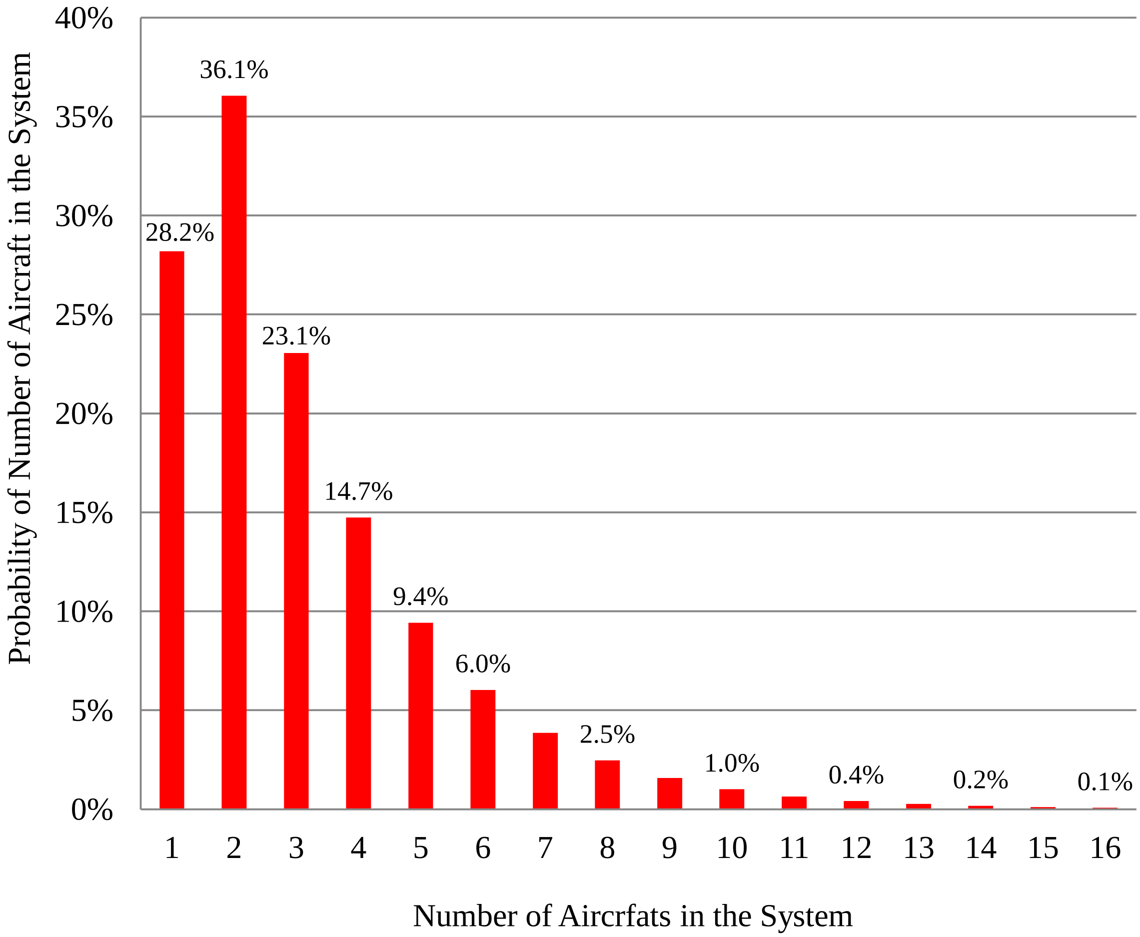

Figure 5.3: Probability of *n* Units in the System

Recalling from chapter 4, the ISS engine maintenance scenario was simulated with uniform distribution for its arrival rate and triangular distribution for its service rate. Here, for the queuing model Poisson and exponential probability distributions for the arrival and service-time patterns have been used, respectively. The new values of $\lambda = 6.8$ and $\mu = 5.3$ were implemented in the existing Arena® ISS model and simulated.

The results from the simulations show that replacing the arrival and service rates with the Poisson and Exponential distributions is a very reasonable attempt, as depicted in Table 5.2. In particular, it is shown that the percentage difference between the two sets of results is within an acceptable range.

Table 5.2: Comparison of Different ISS Models

	Uniform and Triangular Distribution (1)	Queuing Theory (2)	Poisson and Exponential Distribution	Percentage Difference between (1) and (2)
L_q	1.29	1.13	1.05	12.10%
L	N/A	2.41	2.33	N/A
$W_q\,(hrs)$	108.84	122.68	114.68	12.72%
$W\,(hrs)$	247.48	261.01	259.01	5.47%

From Table 5.2, it is concluded that with queuing theory, the effect of modest change in decision parameters on system performance can be assessed.

Chapter 6

Conclusions and Future Work

6.1 Summary

The objectives of the work presented were to develop decision making support tools and to assess different aircraft engine maintenance policies. Four preliminary models, one integrated comprehensive model, four confirmatory models for the verification of the preliminary models, and one queuing-theory-based equivalent model of the integrated model were developed. The preliminary models and their simulation provided initial insight and useful information about the behaviour of the maintenance operation, and later became parts of the integrated model. The integrated model can be reused and modified to investigate *major* changes to the aircraft fleet and maintenance facility operation. The equivalent queuing model is an easy to use tool for the management to conveniently assess *modest* changes in the fleet and maintenance facility. These include for example, increasing service the rate by adding technician and equipment, or increasing the arrival rate by operating a larger fleet.

6.2 Discussions

From the simulations the following major results were obtained.

1) Although 'fixed' inflexible policies are undesirable, but if a choice has to be made amongst the four preliminary fixed policies, the 2-Engine policy prevails. Lowest total and average grounding and waiting times, and shorter average queue length are the desirable performance indicators for this policy. It is postulated that despite randomness in flying times, since there are even number of engines (two pairs) on each aircraft, pair-wise engine service drives the system into a favourably synchronized and alternating service cycles between the two pairs of the engines resulting in prolonged uninterrupted flying periods in between.
2) The flexible ISS policy is indeed recommended as it is developed to work optimally, and has parameters that allow further optimization through multiple simulations. In the ISS model, the 2-Engine policy was also dominant and confirmed the earlier findings.
3) The equivalent queuing model reproduced satisfactory results, and proved that indeed, it can assist in management decision making when minor system modifications are intended.

6.3 Conclusions

From this study a number of important conclusions are drawn. It was shown that Discrete Event Simulation (DES) software provided significant capability for open-ended systems modeling where practically any degree of detail, constraints and conditions, both quantitative and qualitative can be implemented. Despite great utility however, using DES software or languages is not without challenges. One is their slow rising learning curve. Their essentially non-mathematical paradigm and modeling construct, such as entities, attributes, events, resources, and how simulations run, are unfamiliar concepts even to engineers, who most often are amongst the primary users of DES. The second is that DES models are dominantly data-driven, and availability of reliable input data is paramount in successful simulations. As in this study data was not abundantly and readily available, a good portion of time was spent to extract data from the limited engine monitoring logs.

The final challenge in using DES is that when real system performance data is unavailable for validation of the models, as was the case in this study, and this is not uncommon when a new real system is being developed for example, careful modeling and greater effort is put on verification to ensure the correctness of the models built.

In this way, overall, satisfactory results and verifications were obtained and tools were developed to support management in their maintenance policy decision making.

6.4 Suggestions for Future Work

The following suggestions may be considered as possible future work for the enhancement of optimal aircraft maintenance planning.

1. Modeling of the operation of the maintenance facility was carried out in isolation from aircraft flight schedules and commitments. In fact, at the time when a decision is made that an aircraft must be dispatched for service, it could be at a remote location. Therefore, it may be more practical that the aircraft are sent for service when they are geographically close to the maintenance facility. Alternatively, if an aircraft is to fly to a distant location, it should be considered in maintenance time decision making whether upon return of the aircraft the 'safe remaining flying time' still remains. In other words, the set service time threshold is not violated.

2. A user-friendly front-end graphical interface can be developed to facilitate the use of the ISS model so as to facilitate and expedite modification and inclusion of major changes to the operating system in the model.

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Appendix A: Individual Scenarios Steady State Graphs

As stated in Chapter 4, one other information collected and obtained from simulation was average times for each of the scenarios. Examples of these averages are “Average Grounding Time”, “Average Flying Time”, “Average Service Time” and “Average Waiting Time”. These average values are plotted versus time as illustrated below.

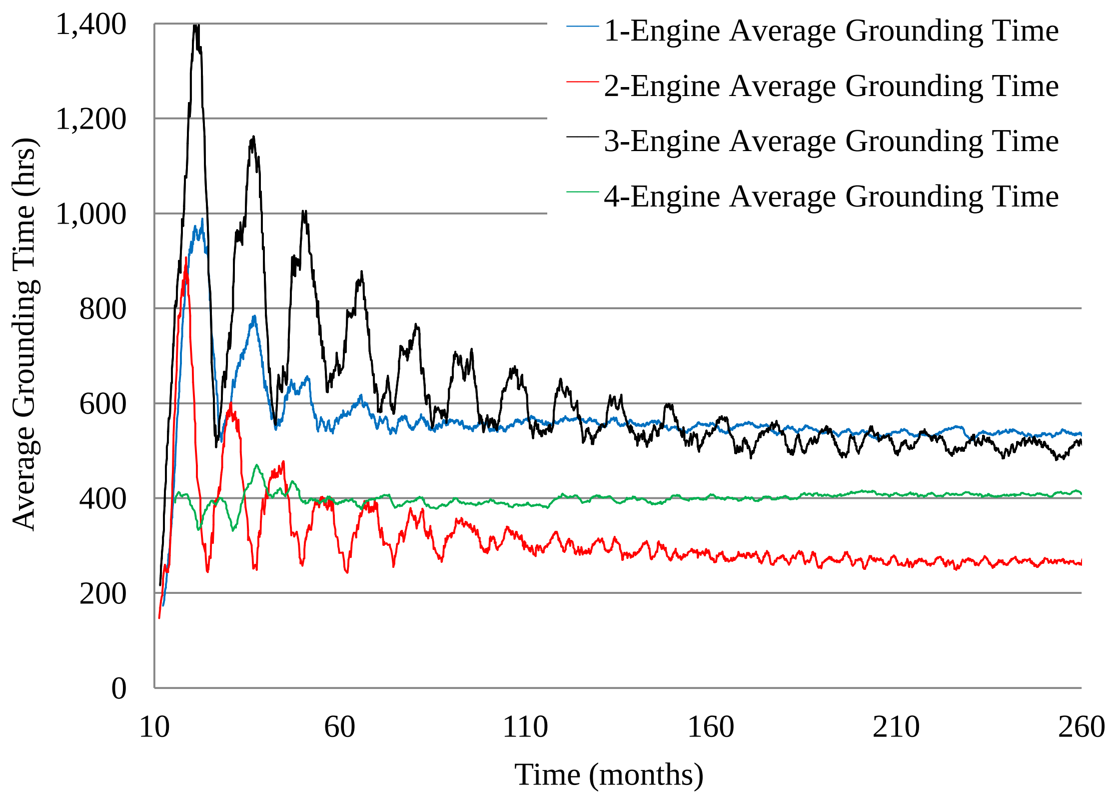

Figure A.1: Average Grounding Time for Individual Scenarios

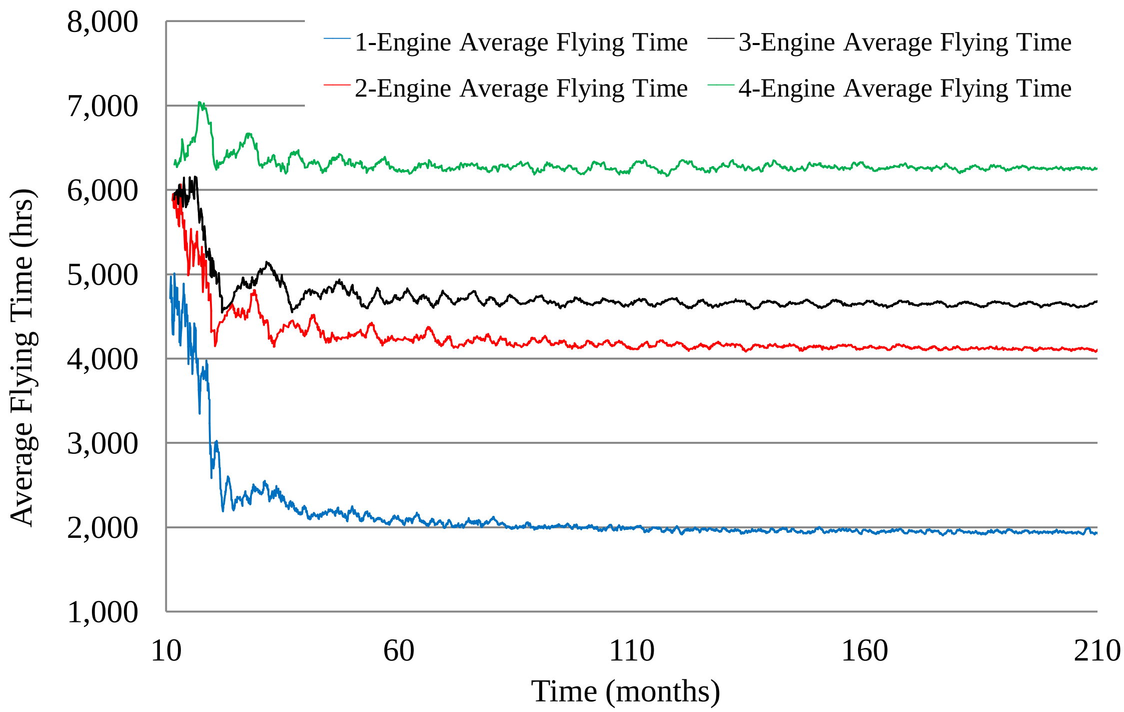

Figure A.2: Average Flying Time for Individual Scenarios

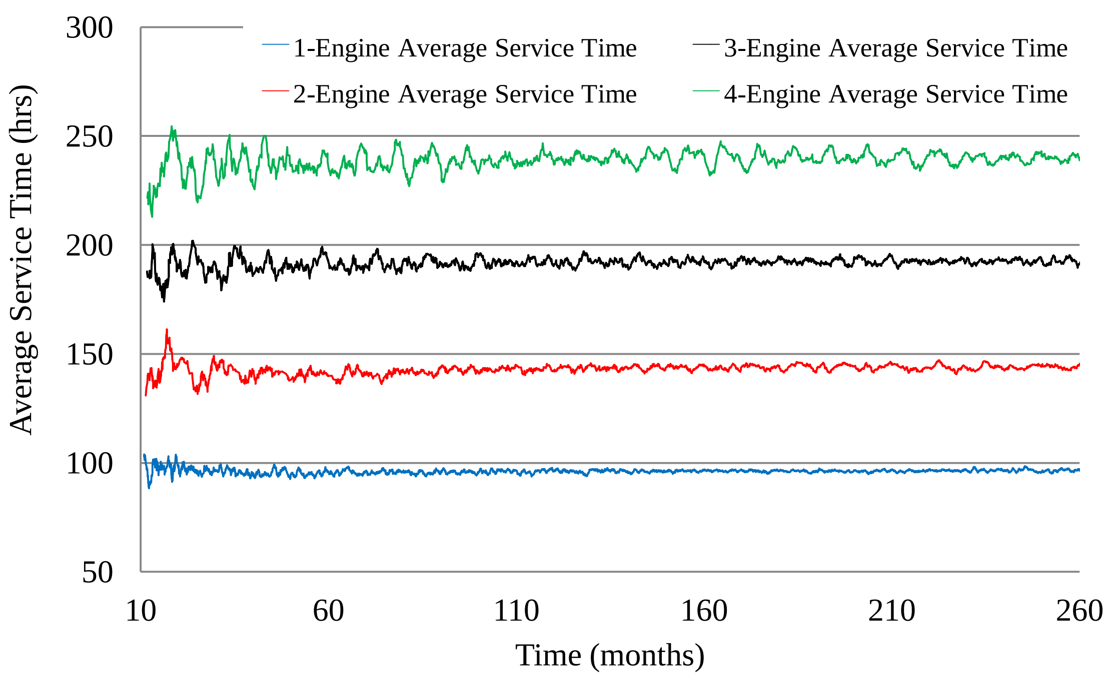

Figure A.3: Average Service Time for Individual Scenarios

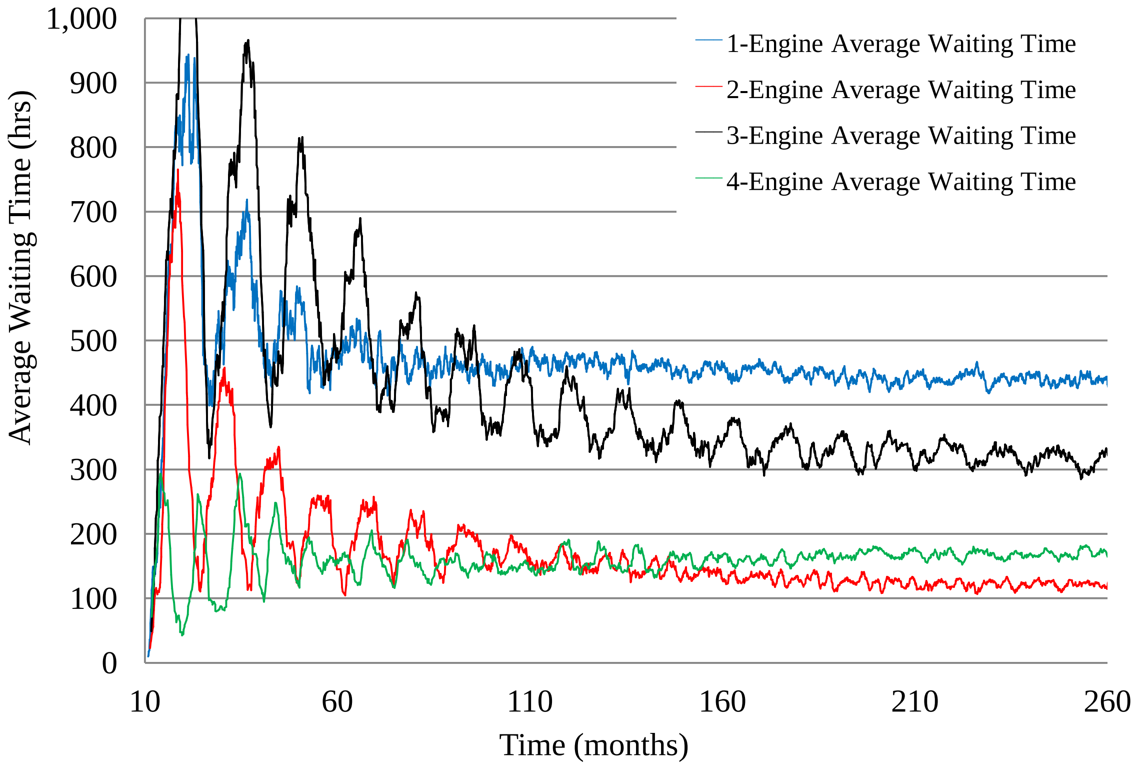

Figure A.4: Average Waiting Time for Individual Scenarios

Appendix B: ISS Maintenance Steady State Graphs

In this appendix, the average values for the information collected from simulation in Chapter 4 related to ISS maintenance scenario is illustrated. “Average Grounding Time”, “Average Flying Time”, “Average Service Time” and “Average Waiting Time” are the examples of these average values.

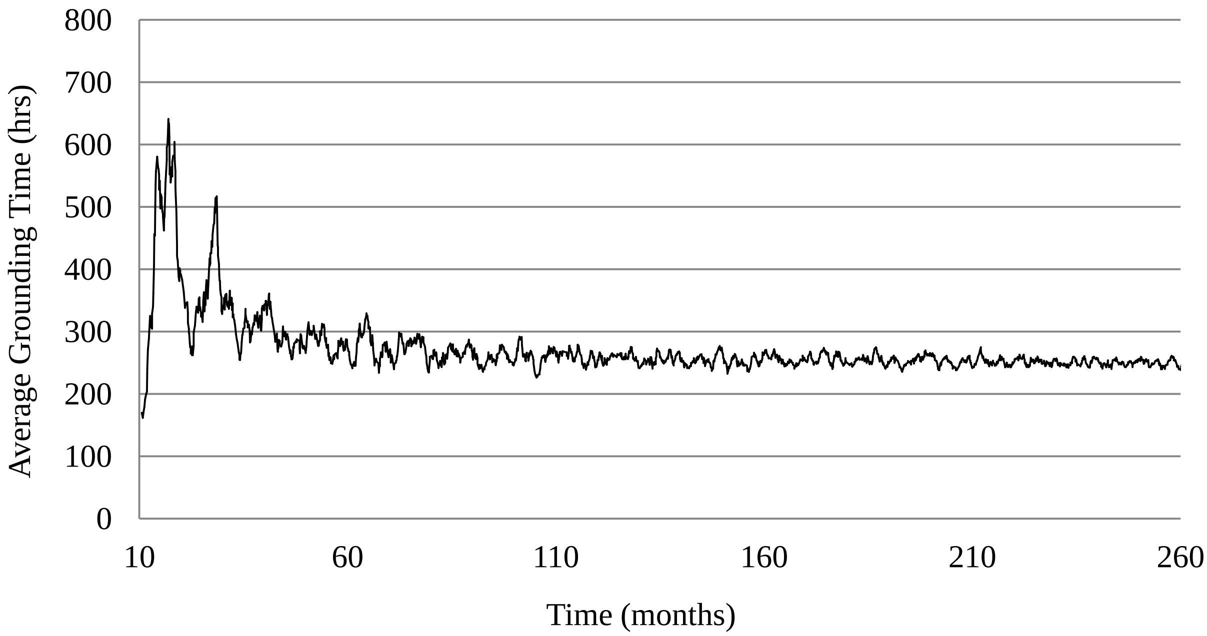

Figure B.1: Average Grounding Time for ISS Scenario

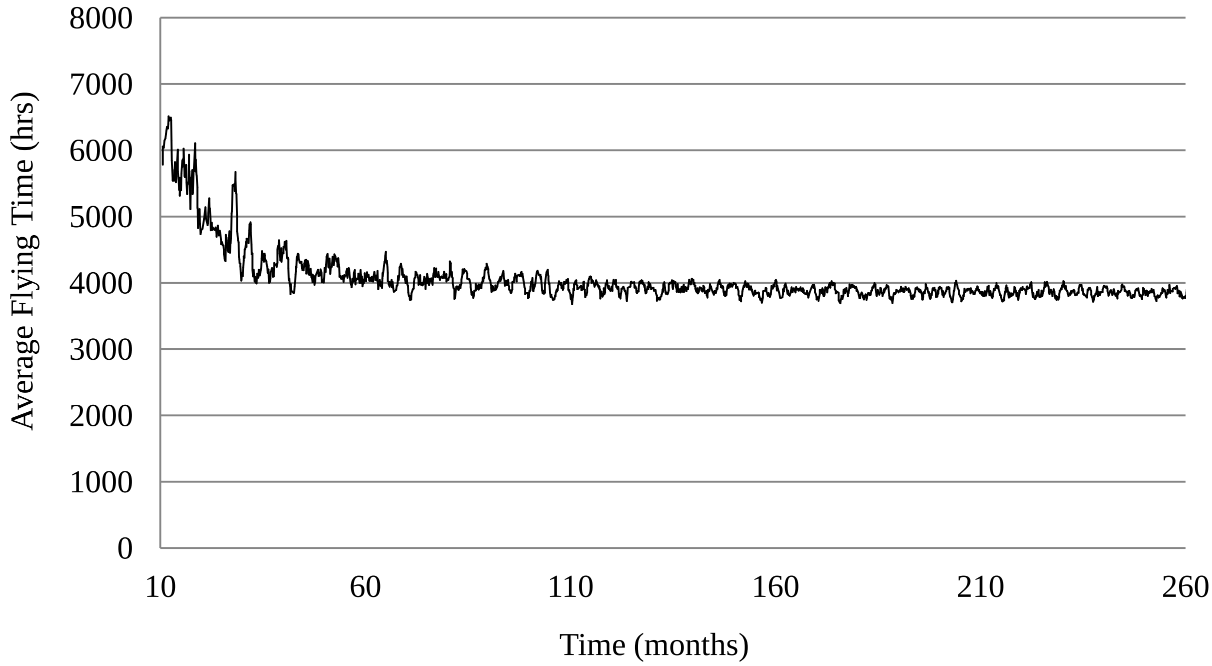

Figure B.2: Average Flying Time for ISS Scenario

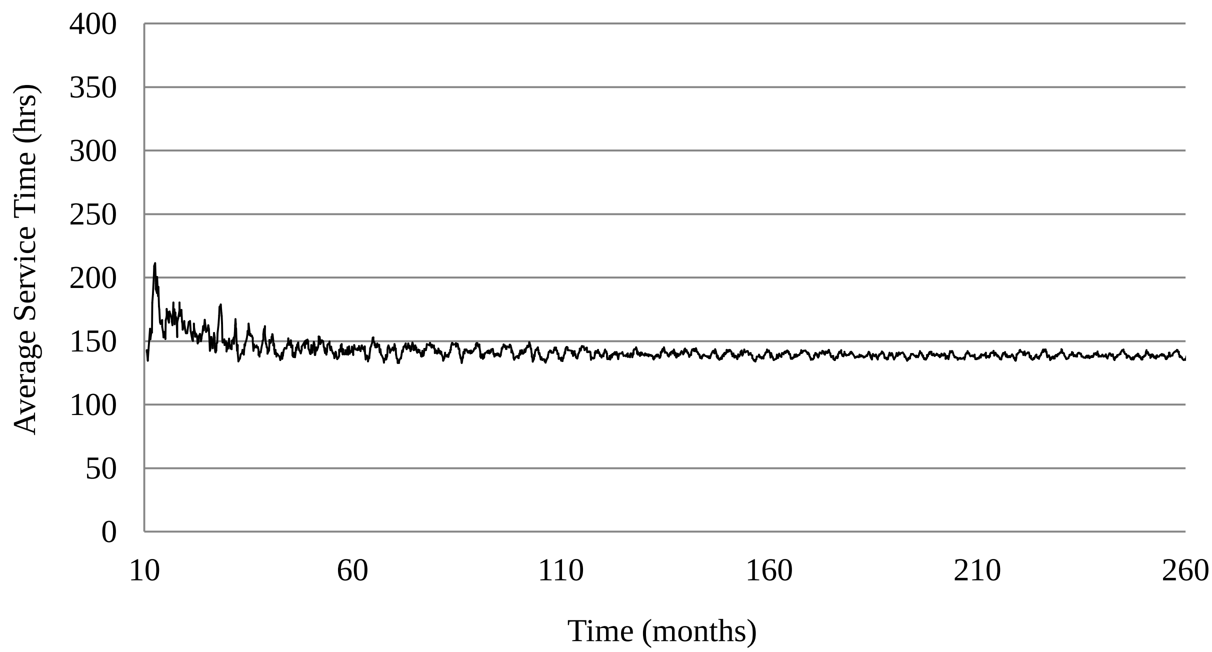

Figure B.3: Average Service Time for ISS Scenario

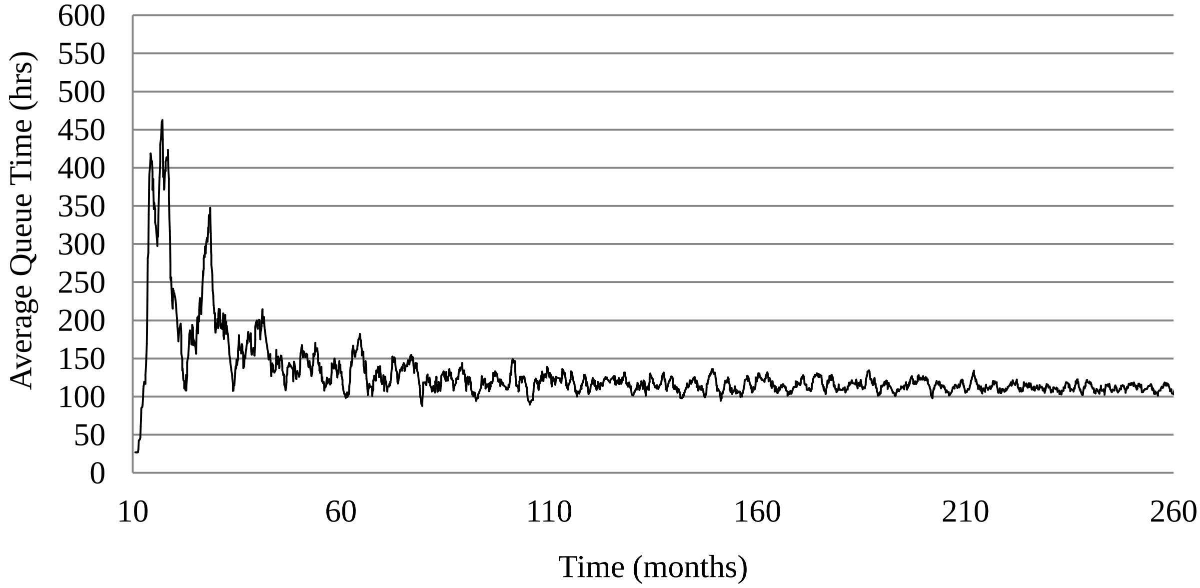

Figure B.4: Average Queue Time for ISS Scenario