Coordinated production maintenance planning in airline flight schedule development
Dijkhuizen, van, Gerhard C.

Published: 01/01/1998

Document Version
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:
• A submitted manuscript is the author’s version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher’s website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

Citation for published version (APA):

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Download date: 20. Dec. 2018
Coordinated production maintenance planning in airline flight schedule development

G. van Dijkhuizen
WP-43
684
October 1998

Maintenance planning, queuing models, airline industry
Transportation research
Coordinated Production and Maintenance
Planning in Airline Flight Schedule Development

Gerhard van Dijkhuizen

October 6, 1998

Abstract

The Line Maintenance department of KLM Royal Dutch Airlines is responsible for the inspection, maintenance and repair of aircrafts during their stay at Schiphol Airport, as well as the assignment of aircrafts to flights within KLM's timetable. A decision support system has been developed with which maintenance managers are better equipped to determine how many maintenance slots of which type should be available in the timetable, and how many maintenance engineers of which type should be assigned to these slots, in order to satisfy the overall service levels set by higher management. The main objective of this study was to develop some fundamental and elementary queueing models, which could eventually assist maintenance managers in the formulation of several design criteria for KLM's timetables.

1 Introduction

KLM Royal Dutch Airlines has been the major Dutch airline since 1919. KLM's home base is Schiphol Airport nearby Amsterdam. Currently (1997), KLM owns about 90 aircrafts of 8 different types, which operate flights to and from about 150 cities in
Table 1: Major inspection intervals for the intercontinental fleet.

<table>
<thead>
<tr>
<th>inspection</th>
<th># weeks</th>
<th># flights</th>
<th># flight hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>A check</td>
<td>6</td>
<td>150</td>
<td>650</td>
</tr>
<tr>
<td>C check</td>
<td>18</td>
<td>1.300</td>
<td>7.500</td>
</tr>
<tr>
<td>D check</td>
<td>72</td>
<td>5.200</td>
<td>25.000</td>
</tr>
</tbody>
</table>

80 countries. Traditionally, the safety of passengers and crew has had top priority in KLM's mission statement. Therefore, KLM carries out high-quality maintenance, relying on approximately 3000 employees in its overall maintenance department. To be specific, each aircraft is maintained preventively through major and minor inspections, and correctively during its stay at Schiphol Airport. Major inspections are performed in KLM's hangars after a certain amount of time, flights and/or flight hours (see Table 1).

Minor inspections are conducted in between each arrival and departure at Schiphol Airport, and include a variety of so-called arrival, platform and departure services (Dijkstra et al. 1994). Amongst several other activities, arrival services consist of fixing ground power supply, compiling a list of technical complaints based on the crew's flight records, and collecting resources (e.g. mobile cranes and scaffoldings) for the platform services. Furthermore, platform services consist of checking the technical state of the aircraft, and performing repairs whenever necessary. Finally, departure services consist of a final technical check of the aircraft. In this study, we are mainly concerned with platform services, and performing repairs in particular.

These repair activities are carried out by employees of the Line Maintenance department. Currently, its workforce consists of approximately 250 highly-skilled and well-trained maintenance engineers. Their responsibility is to inspect, maintain, and repair KLM's aircrafts during their stay at Schiphol Airport. Due to internal and external safety rules, each maintenance engineer is licensed to carry out inspections
on a limited number of aircraft types, and also has a specific skill for avionic resp. me­
chanical systems. The engineers obtain their licenses and skills by attending training
programs consisting of theoretical and practical courses. Depending on their experi­
ence, it takes several months to several years to complete such a training program.

In general, the time required for arrival and departure services can be treated
as a given constant, depending on the aircraft type. For similar reasons, the time
required for preventive maintenance activities (platform check) is more or less fixed.
The remaining period of ground time can be used for planned and/or unplanned
corrective maintenance activities (i.e. performing repairs). It is determined by the
difference between arrival and departure time of the aircraft under consideration,
minus the required time for arrival services, departure services and platform checks.
As such, this length can be derived from the underlying timetable operated by KLM
Royal Dutch Airlines, in combination with the assignment of aircrafts to flights within
this timetable. The latter decisions are also the responsibility of the Line Maintenance
department.

Simply stated, KLM's timetable consists of a comprehensive collection of so­
called city-city pairs with scheduled departure and arrival times, and corresponding
aircraft type. Typically, this timetable follows a cyclical pattern, with a cycle length
of exactly one week. On an average day, some clearly distinguishable peaks can be
observed, caused by KLM's marketing strategy to minimize waiting times for tran­
sit passengers (connecting flights). Several times a day, a batch of intercontinental
flights arrives at Schiphol Airport followed by a batch of continental flights to sev­
eral destinations allover Europe, and vice versa (see Figure 1). In this study, we
focus on the intercontinental fleet, which is mainly operated by the following aircraft
types: Boeing 747-300 Combi (B743C), Boeing 747-300 Full Pax (B743P), Boeing
747-400 Combi (B744C), and Boeing 747-400 Full Pax (B744P). For a variety of
technical, economical and operational reasons, these aircraft types are not mutually
interchangeable, i.e. each aircraft type operates its own timetable.

The times between arrival and departure of KLM's aircrafts at Schiphol Airport are called ground times or slots. During these slots, several activities have to take place inside and outside the aircraft (e.g. cleaning, fueling, catering, boarding, etcetera), which usually take up to two hours on average. In the meanwhile, a post- and pre-flight inspection is conducted by specialized maintenance engineers. The remaining ground time is available for the elimination of (deferred) defects i.e. performing repairs. As a consequence, the minimal turn around time (i.e. if no corrective maintenance activities are carried out) equals approximately two hours, at least for the intercontinental fleet.

On the other hand, the maximum allowed time for an aircraft to stay at its gate is restricted by Schiphol Airport, and equals approximately four hours. In that case, the aircraft must be transported to and from a buffer, each of which takes another half an hour on average. In view of efficiency, it is therefore important to incorporate as few as possible ground times between say 4 and 6 hours in the design of a timetable (see Figure 2). It was one of the main objectives of this study to provide maintenance managers with decision support in this respect.

Of course, the possibilities to keep the technical state of the aircrafts within the constraints set by higher management, are strongly related to the time that is reserved for the elimination of (deferred) defects. In this respect, it is not only the total

\[\text{Figure 1: General structure of KLM's timetables.}\]
Figure 2: Maximum utilization for different ground times (slots) at Schiphol Airport, in terms of the fraction of available time that can be used for repair activities.

amount of ground time (quantity), but also the relative frequencies of different slot types (quality) that counts. This effect is even stronger if one realizes that different defects may require different repair times (e.g. 3, 6 or 12 hours) and capacity (e.g. 1, 2 or 3 maintenance engineers), and may carry different due dates (e.g. 3, 10 or 30 days) as well. Another complicating factor in this respect is that each defect refers to a so-called maintenance log (aircraft vs. cabine) and maintenance skill (avionics vs. mechanics), which must be treated separately. In addition, technical no-go’s i.e. defects that must be repaired before departure (zero due date) deserve special attention.

From a maintenance point of view, the timetable should provide enough opportunities to eliminate each defect before its due date, and within the amount of time and capacity that is available. On the other hand, such a timetable could never be optimal from an overall KLM perspective, since this would strongly reduce the number of scheduled flights, which is of particular commercial interest. Hence, the possibil-
ity of deferred defects, technical delays and cancellations is essential and inevitable in the design of KLM's timetables. In line with this, the performance of the Line Maintenance department is expressed in, and continuously monitored by two main elements. These are the technical dispatch dispunctuality (TDD), and the deferred defect list (DDL). In the remainder of this paper, we will present some fundamental and elementary queueing models, which could provide maintenance managers with reasonable predictions and/or indicators of these performance measures at a strategic and tactical planning level.

The technical dispatch dispunctuality corresponds to the percentage of aircrafts that does not leave on time due to technical problems. In general, technical delays are due to deferred defects which cannot be repaired in time, and technical no-go's in particular. Depending on the aircraft type, a small amount of delay is usually allowed (15 minutes for the intercontinental fleet, 5 minutes for the continental fleet). Currently, the service level for KLM's technical dispatch dispunctuality is determined at a maximum of 4% for Schiphol Airport, and 2% world-wide. The deferred defect list corresponds to the collection of all reported defects that have not been eliminated yet, e.g. due to lack of time, capacity, spare parts and/or information. In this respect, a clear distinction is made between defects that are reported in the aircraft maintenance log (AML), and defects that are reported in the cabin maintenance log (CML). At the time this study was conducted, the service level for KLM's deferred defect list was determined at a maximum of 4 AML and 3 CML deferred defects per aircraft on average.

In the past few years, the maintenance department has used a tool called critical flight analysis, in order to determine the feasibility of a timetable with respect to the technical dispatch dispunctuality. So far, this tool has performed reasonably, and there is no specific reason for dramatic changes. Therefore, we will mainly focus on the accumulated workload associated with deferred defects. This does not necessarily
mean, however, that there is no mutual relationship between these performance measures. After all, an increase in the number of deferred defects usually goes together with an increase in due date violations. In a similar way, an increase in due date violations implies an increase in technical delays and/or cancellations, and as such affects the technical dispatch dispunctuality.

The outline of this paper is as follows. In section 2, we present a more detailed description of the problem under consideration, and discuss some related issues as well. Subsequently, a short introduction into our newly developed decision support system will be given in section 3, and we discuss the role of the underlying queueing models in some more detail. In section 4, we present a so-called time-based modelling framework, which is mainly concerned with finding a proper match between large defects and large maintenance slots. In a similar way, section 5 comprises a so-called capacity-based modelling framework, which can assist maintenance managers in finding a proper match between overall workload and workforce, both expressed in man hours. In section 6, the results of our study are summarized, and some interesting opportunities for related research problems are discussed.

2 Problem Description

Since the introduction of the 3-wave system a few years ago, and the more recent introduction of the SCORE (Schiphol COnnection REdesign) system (Bootsma 1997), the ground times at Schiphol Airport have been under constant pressure. In the past few years, this has resulted in a different workload for the Line Maintenance department, which on its turn has resulted in an increase of technical dispatch dispunctuality and deferred defects. At the same time, the goals of KLM's maintenance department are to increase punctuality, to decrease ground times, to reduce the number of deferred defects, and to raise productivity.
Under this pressure, the managers main problem is to find a good match between workload and workforce, all against reasonable costs in terms of the associated time and/or capacity. The elements that play a significant, if not crucial role in this match are timetables, failure rates and capacity profiles (see Figure 3). In the following section, these factors will be addressed in more detail. Here, we only mention that the quality of such a match is mainly determined by the number of deferred defects, and the number of due date violations. Too many due date violations may lead to unacceptable problems in an operational planning phase, in terms of delays and/or cancellations, and must therefore be controlled at a strategical and/or tactical level. In a similar way, too much deferred defects may result in poor aircraft quality, which is in conflict with the overall company objective to provide high quality service to its customers.

Planning for a good match of workload and workforce is therefore important, and it involves both strategical, tactical and operational planning issues. At the strategical level, management has to formulate a variety of design criteria, in order to arrive at a concept timetable (draft) which can be realized against reasonable costs, and
within the constraints set. At the tactical level, management has to identify and solve (potential) problem areas within the draft, followed by a rough cut capacity planning for the maintenance department, in terms of the required number and type of maintenance engineers. At the operational level, management has to decide which aircraft should operate which flight, and which maintenance activities should be carried out by which maintenance engineers during the resulting ground times. In this study, we focus at strategical and tactical planning issues, which means that the actual timing of maintenance slots in the timetable are not contained in our analysis. To be specific, the following decision problems are addressed:

(i) how many maintenance slots of which type must be available in the timetable?

(ii) how many maintenance engineers of which type must be assigned to these slots?

Although the relative frequencies of different slot types are strongly related to the underlying structure of KLM's timetable, these figures can only be derived in an operational planning phase. After all, it depends on the day-to-day assignment of aircrafts to flight numbers, which slot types will actually be observed in practice, and with which relative frequencies (see Figure 4). At a strategical and tactical level, one often uses a last-in-first-out type of service discipline (LIFO) in order to derive the (expected) relative frequencies of different slot types within the timetable. By doing so, they usually overestimate the number of large slots, and underestimate the number of small slots.

The other way around, a first-in-first-out type of service discipline (FIFO) would normally underestimate the number of large slots, and overestimate the number of small slots. Throughout this study, we will assume that the relative frequencies of different slot types, as requested in the design of a timetable, can be realized in an operational planning phase. In the newly developed SCORE system, the differences between both methods are in fact quite small, since most intercontinental flights
Figure 4: The relative frequencies of different slot types depend on the day-to-day assignment of aircrafts to flights within the timetable.

arrive and depart in batches (see Figure 1). The reader is referred to Bootsma (1997) for a more detailed discussion on the structure of KLM’s timetables.

Traditionally, major and minor inspections are planned in advance, and have never caused severe planning problems. On the contrary, defects are unplannable, and their stochastic nature goes together with fluctuations in the amount of workload offered to the maintenance department. Obviously, this phenomenon undermines the objective of eliminating each deferred defect before its due date, and within the required amount of ground time. Before we started this study, the managers based their design criteria with respect to the timetable merely on experience and intuition. Mathematical models were only based on long run averages, thereby neglecting the randomness of such events completely, e.g. see Owusu and Jessurun (1993) and Van der Eijck (1995). As a consequence, management could not evaluate or foresee potential problems associated with a (conceptual) timetable to a sufficient level of detail.

In the past few years, and in accordance with the second performance criterion, management has mainly been focussed on reducing the number of deferred defects.
Table 2: Average repair times of deferred defects: 99% confidence intervals expressed in minutes (Van der Eijck, 1995).

<table>
<thead>
<tr>
<th>Aircraft Maintenance Log</th>
<th>B743C</th>
<th>B743P</th>
<th>B744C</th>
<th>B744P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cabine Maintenance Log</td>
<td>84 ± 10</td>
<td>78 ± 8</td>
<td>87 ± 9</td>
<td>83 ± 11</td>
</tr>
<tr>
<td></td>
<td>35 ± 3</td>
<td>37 ± 4</td>
<td>36 ± 3</td>
<td>38 ± 4</td>
</tr>
</tbody>
</table>

Therefore, small defects have usually received top priority in the operational planning and scheduling of maintenance activities. Simply stated, this priority setting strategy is based on the well-known shortest-processing-time (SPT) first service discipline (Silver et al. 1998), which aims at minimizing the average waiting time per defect. In line with this idea, large slots have often been used for the elimination of multiple small defects, rather than a few larger ones. Obviously, this cannot be the right planning strategy, since opportunities for large defects are scarce, whereas opportunities for small defects are (relatively) numerous. Throughout this study, we decided to reformulate the second performance criterion in terms of the workload associated with deferred defects, rather than the number of deferred defects itself.

In our view, this alternative performance criterion would lead to an important change in KLM's attitude towards corrective maintenance planning, and would eventually increase the overall performance of KLM Royal Dutch Airlines. At least, it served as a starting point for our analysis. Based on the average processing times of deferred defects within the intercontinental fleet (see Table 2), we proposed the following target levels: approximately 5 AML and 2 CML deferred man hours per aircraft on average.
In view of the addressed problem areas, the management of KLM's maintenance department had the impression that the quality of decision making could be improved by the introduction of a decision support system. Simply stated, the decision support system that we developed consists of four main elements, viz. a timetable module, a workload module, a workforce module, and an analysis module. With this decision support system, maintenance managers are better equipped to determine how many maintenance slots of which type should be available in the timetable, and how much capacity of which type should be assigned to these slots, in order to fulfil the overall company objectives within the constraints set by higher management. In the remainder of this section, a brief description of each module will be given.

As a starting point, the timetable module contains several fundamental characteristics of KLM's timetable for a specific aircraft type. These are (i) the number of aircrafts, (ii) the average number of flights per aircraft per day, (iii) the average number of flight hours per flight, (iv) the average number of flights per cycle, and (v) the relative frequencies of different slot types. Here, a cycle is defined as a subsequent departure from and arrival at Schiphol Airport. This is an important quantity, since the majority of defects - the largest ones in particular - can only be tackled at Schiphol Airport, and not at so-called outbound stations. In general, most cycles consist of two flights, i.e. to and from a specific destination. Nevertheless, cycles of three or even more flights do also occur in practice, especially in the intercontinental fleet.

Secondly, the workload module contains the arrival rates of defects per flight and per flight hour, thereby making a clear distinction between different categories in terms of (i) the underlying maintenance log, (ii) the corresponding maintenance skill, (iii) the required repair time and capacity, and (iv) the associated due date. The underlying observation behind these so-called failure rates is that some deterioration
processes are flight dependent (e.g. motors, engines), some are flight-hour dependent (e.g. chairs, lights), and some are a combination of both. Nevertheless, a preliminary study by Van der Eijck (1995) pointed out that the majority of failures, at least in terms of the associated workload, is flight-dependent. Eventually, a database module should be incorporated, which keeps track of all flights, flight hours, and defects in the intercontinental fleet. By doing this, it might become possible to determine the above-mentioned failure rates automatically, e.g. by using a multiple regression technique (Dunn and Clark 1974).

Finally, the workforce module determines how much maintenance engineers of which type (avionics and/or mechanics) should be assigned to each type of slot in the timetable. By doing this, the user can investigate the consequences of different capacity profiles at a strategical planning level (e.g. high capacity on large slots and low capacity on small slots, or vice versa). From now on, a complete set of figures concerning data on the timetable, data on the workload, and data on the workforce, is called a scenario. The analysis module provides the user with extensive possibilities for analyzing different scenarios. It consists of routines which estimate the workload and workforce per week, and evaluate the quality of the match between workload and workforce. In the following sections, these routines will be addressed in more detail, as well as the underlying queueing models and assumptions. Here, we only mention that a clear distinction has been made with respect to time and capacity.

Simply stated, the timetable must provide enough time (large slots) in order to cope with large defects, and enough capacity (manhours) in order to cope with all defects. In line with this idea, we have developed a separate time-based and capacity-based modelling framework, in order to define the quality of the match between workload and workforce. The basic underlying motivation behind each modelling framework is that workload accumulates until the arrival of workforce, but workforce cannot accumulate until the arrival of workload. Since these arrivals take
place according to complex (stochastic) processes, the existence of deferred defects, and thus the possibility of due date violations, is inevitable. In line with this idea, management is primarily interested in the average amount of deferred workload, as well as the probability of due date violation for different types of defects. The analysis module provides reasonable estimates and/or indicators for these and other performance measures within a given scenario.

With this decision support system, it is of course also possible to compare different scenarios with each other in a strategical planning phase. In fact, and as long as our models have not been verified with actual data, this is exactly what our decision support system should be used, and was designed for. More specifically, our model outcomes for a specific scenario should be handled with care if interpreted explicitly, but may provide useful implicit information in relation to other model outcomes for other scenarios (see Figure 5).

From a practical point of view, this means that our models could be used to assist maintenance managers with comparative studies into alternative timetables. This is a potentially valuable insight, since there is still little on-the-job experience with our decision support system, and validation and/or modification of our models is yet to
come. Nevertheless, we believe that they contain some interesting features, which are worth mentioning here. In the following sections, we will briefly describe the underlying queueing models and assumptions for our time-based and capacity-based modelling framework.

4 TIME-BASED MODELLING FRAMEWORK

As a starting point, the time-based modelling framework is concerned with finding a proper match between large defects on the one hand, and large maintenance slots on the other hand. Since large slots should primarily be used for large defects, and as such should be treated with the highest priority, we assume that there is always enough manpower available to eliminate large defects. Therefore, the main ingredients of our time-based modelling framework are the complex stochastic processes associated with the arrivals of large defects and large slots.

4.1 Input and output specifications

As a starting point, the arrival rates of large defects are derived from the data provided by the timetable and workload modules, thereby making a clear distinction between different categories in terms of the required maintenance slot and the corresponding due date. In accordance with current KLM practices, we used 4 categories for large slots (>24 hours, 16-24 hours, 12-16 hours and 6-12 hours) and 4 categories for due dates (<1 day, 1-3 days, 3-10 days, and 10-120 days). Recall that maintenance slots of less than 6 hours can hardly be used efficiently, especially for large defects (see Figure 2). Nevertheless, our modelling framework could easily be generalized to cope with more (or less) categories.

As a next step, the average number of large slots per week is calculated from the data specified in the timetable module, again for each of the above-mentioned
categories. Based upon these figures, the decision support system provides the user with reasonable estimates of the average waiting times for different types of defects, as well as the corresponding probabilities of due date violation. Subsequently, it determines a reasonable estimate of the average number of due date violations per week, which obviously is a useful performance indicator in view of comparing different scenarios with each other.

4.2 Model and assumptions

As we explained before, due dates are categorized into m different types, and maintenance slots into n different types. With \( d_i \) and \( t_j \), we denote the typical or average due date and slot size associated with type \( i \) resp. type \( j \). For notational convenience, and without loss of generality, we assume that \( d_1 < ... < d_m \) and \( t_1 > ... > t_n \). To continue our analysis, we denote with \( \lambda_{ij} \) the arrival rate of type \((i, j)\) defects, i.e. defects with a due date of type \( i \), that require a slot of type \( j \). In a similar way, we let \( \mu_j \) denote the arrival rate of type \( j \) slots. Finally, \( \pi_j \) reflects the probability that a slot of type \( j \) cannot be used for planned maintenance, e.g. due to a technical no-go or other causes. Currently, and in line with the above-mentioned modelling framework, KLM operates \( m = 4 \) different due date types, and \( n = 4 \) different slot types (see Figure 6).

Since there is no specific information available about the actual timing of large maintenance slots within the timetable, our modelling framework is based on the assumption that large defects and large slots arrive according to mutually independent Poisson processes. For similar reasons, we assume that each maintenance slot can be used for the elimination of at most one single defect. The question now remains which defect should be assigned to which maintenance slot. In general, this assignment should be based on the duration of the slot, and the due date of each defect. Since large defects should receive top priority, we adopted the following (approximate)
priority rule at this strategical/tactical level: amongst all defects with the largest but still appropriate slot type, select the one with the lowest due date type. For example, a type 3 slot (12-16 hours) examines the collection of deferred defects in the following sequence: (1, 3) → (2, 3) → (3, 3) → (4, 3) → (1, 4) → (2, 4) → (3, 4) → (4, 4).

Our analysis now proceeds as follows. As a starting point, we denote with $\bar{\lambda}_1 = \lambda_{11} + \ldots + \lambda_{m1}$ the arrival rate of defects that require a slot of type 1, and with $\tilde{\mu}_1 = \mu_1 \cdot \pi_1$ the arrival rate of such slots. By doing this, the waiting time of type $(i, 1)$ defects is equivalent to the sojourn time in a single-server preemptive priority queue, with exponentially distributed interarrival and service times for each priority class, in which the service of a lower priority job is interrupted as soon as a higher priority job enters the system. According to White and Christie (1958), this means that the following expression can be derived for the first two moments $E\{W_{i1}\}$ and $E\{W_{i1}^2\}$ of the waiting time $W_{i1}$ for type $(i, 1)$ defects. Here, we denote $\bar{\rho}_{i1} = \lambda_{i1}/\tilde{\mu}_1 < 1$ and $\bar{\sigma}_{i1} = \sum_{k \leq i} \bar{\rho}_{k1} < 1$ for notational convenience:

Figure 6: General structure of the time-based modelling framework
Let us now take a closer look at defects of type \((i,2)\), i.e. defects which require a slot of type 1 or 2. Since slots of type 1 are primarily used for type \((i,1)\) defects, it is easily verified that the arrival rate of these slots for type \((i,2)\) defects equals \(\lambda_2 = \bar{\lambda}_1 + \mu_2 \cdot \pi_2\), where \(\rho_1 = \bar{\rho}_{i1} + \ldots + \bar{\rho}_{m1} = \bar{\lambda}_1 / \bar{\mu}_1\). Clearly, the first term refers to slots of type 1 which are not used for type \((i,1)\) defects, whereas the second term refers to slots of type 2. Our analysis now proceeds by assuming that the waiting time of type \((i,2)\) defects can also be modelled as the sojourn time in a single-server preemptive priority queue. Of course, this reasoning can only hold approximately, since the arrival process of type 1 slots for type 2 defects is no Poisson process in general. In an analogous way, we can now approximate the first two moments \(E\{W_{i2}\}\) and \(E\{W_{i2}^2\}\) of the waiting time \(W_{i2}\) for type \((i,2)\) defects. Again, we denote \(\bar{\rho}_{i2} = \lambda_{i2} / \bar{\mu}_2 < 1\) and \(\bar{\sigma}_{i2} = \bar{\rho}_{i2} < 1\) for notational convenience:

\[
E\{W_{i2}\} = \frac{1}{\bar{\mu}_2} \cdot \frac{1}{(1 - \bar{\sigma}_{i-1,2}) \cdot (1 - \bar{\sigma}_{i2})}
\]

(3)

\[
E\{W_{i2}^2\} = \frac{2}{\bar{\mu}_2^2} \cdot \left\{ \frac{1}{(1 - \bar{\sigma}_{i-1,2})^2 \cdot (1 - \bar{\sigma}_{i2})^2} + \frac{\bar{\sigma}_{i-1,2}}{(1 - \bar{\sigma}_{i-1,2})^3 \cdot (1 - \bar{\sigma}_{i2})} \right\}
\]

(4)

For \(j > 2\), similar results can be obtained. Further details are skipped, since they are not so relevant for what follows. Our analysis is now based on the approximate reasoning that the waiting time \(W_{ij}\) of type \((i,j)\) defects is a Gamma distributed random variable, with known parameters \(\alpha_{ij} = E\{W_{ij}\}^2 / Var\{W_{ij}\}\) and
Table 3: A comparative study of 9 scenarios within the time-based modelling framework: average probability of due date violation per defect, in relation to the relative frequencies of different slot types (numerical example based on imaginary data).

<table>
<thead>
<tr>
<th>slot type</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
<th>IX</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;24 hours</td>
<td>2 %</td>
<td>2 %</td>
<td>2 %</td>
<td>2 %</td>
<td>4 %</td>
<td>4 %</td>
<td>4 %</td>
<td>4 %</td>
<td>6 %</td>
</tr>
<tr>
<td>16-24 hours</td>
<td>2 %</td>
<td>2 %</td>
<td>2 %</td>
<td>4 %</td>
<td>4 %</td>
<td>4 %</td>
<td>4 %</td>
<td>6 %</td>
<td>6 %</td>
</tr>
<tr>
<td>12-16 hours</td>
<td>4 %</td>
<td>4 %</td>
<td>6 %</td>
<td>6 %</td>
<td>6 %</td>
<td>8 %</td>
<td>8 %</td>
<td>8 %</td>
<td></td>
</tr>
<tr>
<td>6-12 hours</td>
<td>8 %</td>
<td>10 %</td>
<td>10 %</td>
<td>10 %</td>
<td>12 %</td>
<td>12 %</td>
<td>12 %</td>
<td>12 %</td>
<td></td>
</tr>
<tr>
<td>% too late</td>
<td>37.5 %</td>
<td>26.0 %</td>
<td>17.2 %</td>
<td>11.1 %</td>
<td>7.1 %</td>
<td>6.7 %</td>
<td>5.9 %</td>
<td>4.9 %</td>
<td>3.6 %</td>
</tr>
</tbody>
</table>

\[ \beta_{ij} = \frac{\text{Var}\{W_{ij}\}}{E\{W_{ij}\}}, \text{ where } \text{Var}\{W_{ij}\} = E\{W_{ij}^2\} - E\{W_{ij}\}^2. \]

Summarizing, this leaves us with the following approximation for the probability of due date violation for type \((i, j)\) defects. Here, \(\Gamma_\alpha,\beta(.)\) denotes the cumulative distribution function of a Gamma distributed random variable with mean \(\alpha \cdot \beta\) and variance \(\alpha \cdot \beta^2\):

\[
P\{W_{ij} > d_i\} = 1 - \Gamma_{\alpha_{ij},\beta_{ij}}(d_i)
\]

Together with the arrival rates \(\lambda_{ij}\) of type \((i, j)\) defects, this comes down to an arrival rate \(\sum_{i,j} \lambda_{ij} \cdot P\{W_{ij} > d_i\}\) of due date violations. In our view, this value could be of considerable interest in comparing different scenarios at a strategical planning level, in view of the match between large slots and large defects. Eventually, the management of KLM's maintenance department could set a threshold value, based on historical data and expert opinions. Moreover, they could use this time-based modelling framework in the identification of potential problem areas within a timetable, by taking a closer look at \(P\{W_{ij} > d_i\}\) and/or \(\lambda_{ij} \cdot P\{W_{ij} > d_i\}\) for all \(i, j\).
4.3 Numerical example

To illustrate our newly developed time-based modelling framework, we evaluated 9 different scenarios for the relative frequencies of different slot types in one of KLM's timetables. The results of this scenario analysis are depicted in Table 3. As we expected, the percentage of large defects which cannot be repaired before their due date, is strongly related to the relative frequencies of different slot types. For example, a closer look at scenarios I and VII indicates that the number of due date violations is reduced with a factor 6, if the number of large maintenance slots is increased with a factor 2. Obviously, such figures might provide maintenance managers with potentially valuable quantitative insights, which were previously not available.

5 Capacity-Based Modelling Framework

Our capacity-based modelling framework is concerned with finding a proper match between workload and workforce in terms of manhours. In this respect, a clear distinction must be made between released and unreleased workload. Simply stated, released workload refers to deferred defects that are waiting to be scheduled, whereas unreleased workload consists of deferred defects that cannot be scheduled yet (see Figure 7). In general, the existence of unreleased workload is due to e.g. lack of information, equipment and/or materials, whereas released workload is mainly caused by lack of time and/or capacity. Obviously, the unreleased workload cannot be reduced by providing more time and/or capacity in the timetable, since these defects are due to external factors. This is a potentially valuable insight, which is further exploited in our model.
5.1 Input and output specifications

First of all, information must be available with respect to the average workload per cycle expressed in man hours, thereby making a clear distinction between the required maintenance skill (avionics/mechanics) and the corresponding maintenance log (aircraft/cabine). Subsequently, the user must provide the relative frequencies of different slot types in the timetable, as well as the capacity in terms of the number of avionic and/or mechanic maintenance engineers that are assigned to these slots. Finally, the user must specify how much time it takes (on average) for a defect to become part of the released workload, the so-called external lead time. In addition, the user can specify the minimal turn around time and maximal gate time, which determine the relation between ground time and available repair time (see Figure 2). Based upon these figures, the decision support system provides the user with an estimate of the average number of deferred man hours, for the aircraft maintenance log as well as the cabine maintenance log.

5.2 Model and assumptions

As a starting point of our analysis, and in accordance with our time-based modelling framework, we assume that the arrival of defects can be modelled as a homogeneous
Poisson process. In order to determine the average amount of unreleased workload, it is now completely natural to assume that there is no correlation between the external lead times of different defects. By doing so, the unreleased workload can be modelled as a $M/G/\infty$ queue. Using Little's formula, it is easily verified that the average unreleased workload equals $\lambda/\mu$, where $\lambda$ denotes the mean arrival rate of workload (e.g. 20 manhours per day), and $1/\mu$ denotes the average external lead time (e.g. 1 day).

Our model for released workload is now based on the assumption that there is no correlation between the workload and workforce per cycle. In other words, workload and workforce are modelled as mutually independent stochastic processes, one that degrades resp. one that upgrades the technical state of the aircraft. More specifically, the workload and workforce per cycle are modelled as independent stochastic variables $Y$ and $Z$ respectively, with known distribution functions. Within this setting, it is immediately clear that the deferred workload $X$ just before departure must satisfy the following balance equation. Here, we define $[x]^+ = \max\{0, x\}$ for notational convenience:

$$X = [X + Y - Z]^+ \quad (6)$$

This equation is known as Lindley's equation (Lindley 1952), for which explicit solutions are not readily available. Nevertheless, explicit solutions can be found for $M|G|1$ and $G|M|1$ queueing models, see e.g. Heyman and Sobel (1982). More specifically, $P(X \leq x)$ and thus $E\{X\}$ can be determined analytically, if $Y$ is exponentially distributed with mean $1/\mu$:

$$P(X \leq x) = 1 - \alpha \cdot e^{-\mu x (1 - \alpha)} \Rightarrow E\{X\} = \frac{\alpha}{\mu \cdot (1 - \alpha)} \quad (7)$$

Here, $0 < \alpha < 1$ is the unique solution to $x = \mathcal{Z}(\mu \cdot (1 - x))$, where $\mathcal{Z}(.)$ denotes...
the Laplace-Stieltjes transformation of $G(.)$, and $G(z) = P(Z \leq z)$ denotes the cumulative distribution function of the workforce per cycle:

$$Z(s) = E\{e^{-sZ}\} = \int_{0}^{\infty} e^{-sz} dG(z) = \int_{0}^{\infty} g(z) \cdot e^{-sz} \, dz$$  \hspace{1cm} (8)

The question remains how to determine $g(z)$. To this end, recall that the user must define a collection of different slot types, as well as the relative frequencies of occurrence, and the capacities assigned to these slots. The decision support system converts these figures into a finite set of $m$ different workforce classes $[a_i, b_i]$, expressed in manhours, with relative frequencies of occurrence $p_i$. To achieve this, it uses the data with respect to minimal turn around time and maximal gate time (e.g. 2 resp. 4 hours in Figure 2). Subsequently, and in line with the above, we can define $g(z)$ rather straightforwardly as follows:

$$g(z) = \sum_{i: a_i \leq z \leq b_i} \frac{p_i}{b_i - a_i}$$  \hspace{1cm} (9)

With this in mind, we can easily derive an analytical expression for $Z(s)$. As a consequence, $\alpha$ can be determined numerically to a sufficient level of detail, using standard search techniques:

$$Z(s) = \sum_{i=1}^{m} \int_{a_i}^{b_i} \frac{p_i}{b_i - a_i} \cdot e^{-sz} \, dz = \frac{1}{s} \sum_{i=1}^{m} p_i \cdot \frac{e^{-sa_i} - e^{-sb_i}}{b_i - a_i}$$  \hspace{1cm} (10)

Of course, the outcomes of our models will strongly overestimate the actual values observed in practice. First of all, and in order to arrive at an analytical expression for $E\{X\}$, we modelled the workforce per cycle as an exponential distribution, whereas a Poisson or normal distribution would certainly be more realistic. Secondly, the workload per cycle $Y$ and the workforce per cycle $Z$ were modelled as mutually
independent random variables, and we can probably do much better in practice. In our decision support system, this has been accounted for by multiplying our model outcomes with a **correction factor**, such that the predicted values would correspond with reality. Unfortunately, and due to lack of information and available time, we have not been able to come up with a properly validated estimation of this correction factor. So far, we have used a rough impression of this correction factor instead. Nevertheless, our model was still considered as a useful tool for comparing different scenarios for slot type distributions and capacity profiles.

### 5.3 Numerical example

To illustrate our newly developed capacity-based modelling framework, we evaluated 7 different scenarios for the relative frequencies of different slot types in one of KLM's timetables. In each scenario, the numbers of avionic resp. mechanic maintenance engineers assigned to each slot type were fixed. The results of this scenario analysis are depicted in Table 4. As we expected, an increase in the average length of maintenance slots usually goes together with a decrease in (released) deferred workload. On the other hand, a closer look at scenarios I and IV shows that it is also possible to improve the performance in this respect, while at the same time reducing the average length of maintenance slots. The underlying reasoning behind this counter-intuitive behavior is that - once again - frequent and short interruptions of the production process are to be preferred above infrequent and long ones, all other things being equal. Since maintenance slots of 2-6 hours can hardly be used efficiently (see Figure 2), this means that the relative frequency of 6-12 hour maintenance slots should be increased. This explains the attractiveness of scenario IV in relation to all other scenarios.
Table 4: A comparative study of 7 different scenarios within the capacity-based modelling framework: average slot length, ground time, and deferred workload, in relation to the relative frequencies of different slot types (numerical example based on imaginary data).

<table>
<thead>
<tr>
<th>slot type</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
</tr>
</thead>
<tbody>
<tr>
<td>24-32 hours</td>
<td>5%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>10%</td>
</tr>
<tr>
<td>16-24 hours</td>
<td>5%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>10%</td>
<td>4%</td>
</tr>
<tr>
<td>12-16 hours</td>
<td>5%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>10%</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>6-12 hours</td>
<td>10%</td>
<td>9%</td>
<td>9%</td>
<td>15%</td>
<td>9%</td>
<td>9%</td>
<td>9%</td>
</tr>
<tr>
<td>4-6 hours</td>
<td>25%</td>
<td>24%</td>
<td>30%</td>
<td>24%</td>
<td>24%</td>
<td>24%</td>
<td>24%</td>
</tr>
<tr>
<td>2-4 hours</td>
<td>50%</td>
<td>55%</td>
<td>49%</td>
<td>49%</td>
<td>49%</td>
<td>49%</td>
<td>49%</td>
</tr>
<tr>
<td>slot length</td>
<td>6.75</td>
<td>6.14</td>
<td>6.26</td>
<td>6.50</td>
<td>6.80</td>
<td>7.16</td>
<td>7.64</td>
</tr>
<tr>
<td>ground time</td>
<td>4.25</td>
<td>3.69</td>
<td>3.75</td>
<td>3.99</td>
<td>4.29</td>
<td>4.65</td>
<td>5.13</td>
</tr>
<tr>
<td>unreleased AML</td>
<td>1.46</td>
<td>1.46</td>
<td>1.46</td>
<td>1.46</td>
<td>1.46</td>
<td>1.46</td>
<td>1.46</td>
</tr>
<tr>
<td>released AML</td>
<td>3.50</td>
<td>5.08</td>
<td>4.85</td>
<td>3.49</td>
<td>3.05</td>
<td>2.88</td>
<td>2.82</td>
</tr>
<tr>
<td>total AML</td>
<td>4.96</td>
<td>6.54</td>
<td>6.31</td>
<td>4.95</td>
<td>4.51</td>
<td>4.34</td>
<td>4.27</td>
</tr>
<tr>
<td>unreleased CML</td>
<td>0.68</td>
<td>0.68</td>
<td>0.68</td>
<td>0.68</td>
<td>0.68</td>
<td>0.68</td>
<td>0.68</td>
</tr>
<tr>
<td>released CML</td>
<td>1.63</td>
<td>2.37</td>
<td>2.26</td>
<td>1.63</td>
<td>1.42</td>
<td>1.34</td>
<td>1.31</td>
</tr>
<tr>
<td>total CML</td>
<td>2.31</td>
<td>3.05</td>
<td>2.94</td>
<td>2.31</td>
<td>2.10</td>
<td>2.03</td>
<td>2.00</td>
</tr>
</tbody>
</table>
6 Concluding Remarks

Of course, the decision support system that we developed is still far from providing absolute answers to relevant questions. After all, we made a lot of assumptions in order to arrive at explicit formulas for a variety of useful performance indicators, and verification and/or modification of these models and assumptions is yet to come. Nevertheless, we believe that our decision support system contains some interesting elements, with which maintenance managers are better equipped to determine how many slots of which type must be available in the timetable, and how many maintenance engineers must be assigned to these slots. In addition, our models could also be used to provide valuable support in each of the following dimensions:

(i) the impact of new timetable structures,

(ii) the effect of aircraft fleet deterioration,

(iii) the influences of due date adjustments,

(iv) the benefits of external lead time reductions.

Summarizing, the decision support system provides the management of KLM's Line Maintenance department with information that was previously not available. It increases their insight into various strategical and tactical problems that must be solved within the maintenance department. On the other hand, we should keep in mind that the results obtained with our decision support system are based on approximate modelling techniques, and as such must be handled with care. Therefore, the user of our decision support system must judge the practical value of the model outcomes in light of considerations that were not explicitly accounted for.

To conclude this paper, let us now briefly discuss the need for a decision support system at the operational planning level. Simply stated, the maintenance department must decide (i) which aircrafts should operate which flights, (ii) which capacity should
be assigned to the resulting ground times, and (iii) which defects should be eliminated with this capacity. In general, these decisions relate to each other in a very complex manner. Moreover, they are restricted by several additional constraints, either economical, technological, combinatorial and/or political. In this respect, there is a huge potential of interesting research problems at the operational level, which could lead to an improved on-line decision support system for KLM's Line Maintenance department.

ACKNOWLEDGEMENTS

The author wants to thank Enryk Bakker, Peter Bos, Jos Goedhart, Ben Lammerse, and Klaas de Waal of KLM's Line Maintenance department for their cooperation, and useful remarks during the development of the decision support system.

REFERENCES


