

Aircraft total turnaround time estimation using fuzzy critical path method**Ehsan Asadi^{a*} and Hartmut Fricke^a**^a*Technische Universität Dresden, Institute of Logistics and Aviation, 01062, Dresden, Germany***CHRONICLE****ABSTRACT***Article history:*

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Airport Collaborative Decision Making (ACDM) flight scheduling plans rely on accurate predictions of both optimal and reliable aircraft turnaround times, which is one of the most difficult things to complete. In order to account for the effects of randomness and fuzziness on the turnaround process duration, this paper deals with transforming the probability distribution of well-fitted sub-processes into a cumulative density function, which is equivalent to the fuzzy membership function (FMF), and then using goodness-of-fit to determine the fuzzy membership grade of each turnaround sub-process. The turnaround time is calculated using the fuzzy critical path method (FCPM), which is a combination of the Critical Path Method (CPM) and fuzzy set theory. In order to verify this estimate, we created the FMF using historical data and compared it to turnaround times based on FCPM. A linear regression model is used to examine the relationship between arrival delays and the FCPM-based turnaround process. We also use historical data to generate fuzzy sets of different arrival delays using Frankfurt airport data from the summer of 2017 and conclude that delays are positively correlated with the FCPM-based turnaround process.

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1. Introduction

The ground operations of airlines are a difficult task in an environment where air traffic density is increasing and the global civil aviation industry is rapidly expanding. Despite the pandemic situation in 2020-2021, considering the need for extremely cost-efficient operations due to critical financial conditions for the entire ATM industry and, on the longer term, the return to scarce airport capacities is a piece of importance (Schultz et al., 2020). Air traffic control (ATC) is in charge of the majority of the on-block time calculations (the time between arriving at the gate and leaving it for departure). A-CDM, which is backed at large airports by Arrival Manager (AMAN) and Departure Manager (DMAN), and advanced approach procedures such as optimized trombones as P-RNAV processes or Point Merge Systems are examples of complex decision support mechanisms that have been standardized (PMS). As a result, the turnaround period continues to be the only time period during which an airline has significant, but not exclusive, control over the operations of its aircraft. It is necessary to transfer a large portion of ground operations into the digital era in order to unlock additional efficiency gains due to the extremely complex nature of the turnaround, which involves the interaction of various stakeholders for multiple simultaneous (Fricke & Schultz, 2009; Oreschko et al., 2012).

While the primary focus should be on reducing reactionary delays, it is equally critical to reduce inbound delays. A strategy that is both feasible and effective in dealing with this issue is to precisely estimate aircraft turnaround time under certain conditions. However, the outcome of the dozens of sub-processes that make up the aircraft turnaround are unknown due to the large number of participants, which include airlines, ground handling agents, airport operators, and air traffic control.

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As a result, in order to undertake robust net planning, the airspace user will need to view aircraft as stochastic. In addition, correct scheduling of turnaround time allows for the efficient integration of resources into the turnaround process, resulting in an effective reduction of financial losses due to flight delays, as previously stated. When looking at the big picture, the short and carefully scheduled turnaround times may actually improve the airline's economic efficiency by increasing aircraft utilization and lowering costs.

The way in which ground handling activities are controlled is largely dependent on the individual expert knowledge of the involved experts from airline operations centers (AOC) and ramp agents, who coordinate the turnaround processes using deterministic planning tools and via headset/telecommunication. With the newly proposed idea of information sharing in the framework of Airport-Collaborative Decision Making (A-CDM), it is possible to handle timestamps from touch-down till departure, thereby integrating on- and off-block timings per movement (AONT/AOBT) (Eurocontrol, 2017; Netto et al., 2020). The inbound side has been the only one to benefit from proactive considerations based on A-CDM time stamps so far. This includes preparing for potential arrival delays by implementing time buffers in the block times planning, which allow for the absorption of such deviations at the expense of reduced plan efficiency on average (Wu & Caves, 2004; Ahmadbeygi et al., 2010; Silverio et al., 2013). In order to deal with time differences between turnaround activities, it is common practice to include additional buffer times. As a result, the accuracy integration of process uncertainties and variable process executions into the aircraft turnaround problem is the basic goal of this research, which employs the Fuzzy critical path approach (FCPM) to accomplish this. FCPM differs from probabilistic approaches to critical path analysis in that it considers all possible outcomes. It is our goal to highlight the benefits of FCPM, to study the insertion of a fuzzy length of activities into the critical path analysis, and to offer a basic computational approach for FCPM in this paper.

The article begins with an introduction of FCPM in Section 2, followed by a description of the outcomes of its application to an example aircraft turnaround in Section 3. Refer to Section 4 for a description of the application of the novel approach to turnaround control while taking historical data and different delay sets into consideration. The results of the application are then reviewed and evaluated in this section. Section 5 develops conclusions and gives a view on several fields of research.

2. Methodology

The problem features are described in this section, along with an explanation of why FCPM is a promising strategy for incorporating uncertainties into the prediction of stochastic processes such as turnarounds with their target times. Finally, the basic mathematical approach for a different turnaround process network is introduced.

2.1. Fuzzy numbers and fuzzy sets

Logistic processes can be classified into two major groups based on their behavior: deterministic and uncertain. The latter is frequently subdivided further into randomness and ambiguity. As a result, we employ three distinct types of mathematics to analyze the corresponding data sets. The first type is deterministic mathematics, which examines an object with certainty. There must be some required relationships between the objects, which can be modeled differentially. The second category is stochastic mathematics, which is founded on probability theory. Monte Carlo Simulation, Bayesian Networks, and Markov Chains are all frequently used techniques for discovering incidental correlations between items. The final kind is found in fuzzy mathematics, which is concerned with the study of vague phenomena (Zadeh, 1999; Novák, 2005). This article will discuss the third type, the fuzzy number.

In contrast to the human inclination for ambiguous measurements, computers operate entirely on binary logic and hence can only characterize data with exact bounds. In practice, however, operators frequently encounter complex quantitative situations that are difficult to comprehend exactly with predetermined boundaries. To describe such inaccurate information, mathematical techniques called fuzzy sets were developed in the literature (Li and Lau, 1989). Fuzzy sets are a type of mathematical framework that alleviates the ambiguity associated with the absence of precise rules for identifying members (Zadeh, 1973). Due to the fact that the inputs do not have the same range, it is required to normalize the values using the fuzzy membership function $\mu_{\tilde{A}}$ to $[0,1]$.

$$\mu_{\tilde{A}} = \begin{cases} U \rightarrow [0,1] \\ u \mapsto \mu_{\tilde{A}}(u) \end{cases} \quad (1)$$

where $u \in U$ and the value of the function $\mu_{\tilde{A}}$ reflects the membership level of the fuzzy set \tilde{A} , respectively (Lee, 2004).

$$\mu_{\tilde{A}} = \{(u, \mu_{\tilde{A}}(u)) \mid u \in U\} \quad (2)$$

because this work solely needs and discusses fuzzy addition and subtraction, these two arithmetic rules are introduced. Assuming that $\forall a_1, a_2, b_1, b_2 \in U$ and $\tilde{A} = (a_1, a_2)$ and $\tilde{B} = (b_1, b_2)$, the fuzzy addition and subtraction may be expressed by Eq. (3) and Eq. (4), respectively.

$$(a_1, a_2)(+)(b_1, b_2) = (a_1 + b_1, a_2 + b_2) \quad (3)$$

$$(a_1, a_2)(-)(b_1, b_2) = (a_1 - b_1, a_2 - b_2) \quad (4)$$

2.2. Fuzzy Membership Functions (FMF)

Many sorts of data with ambiguity and uncertainty can be represented by fuzzy membership functions (FMFs), and there are different FMF types, including trapezoidal, triangular, Bell-shaped, Sigmoid, and Gaussian FMFs (Zhao and Bose, 2002). This section introduces two often used fuzzy membership functions, triangular and trapezoidal FMF, and evaluates which is more appropriate for turnaround modeling. These two memberships were chosen for their straightforward arithmetic operations.

Triangular fuzzy membership functions

Assume that the membership function of a triangular fuzzy number $\tilde{A}(a, b, c)$ has a lower limit of a , an upper limit of c and a value of b . To execute arithmetic operations on two triangular FMFs, the Eq. (5) and Eq. (6) are defined.

Trapezoidal fuzzy membership functions

$$\tilde{A} + \tilde{B} = (a_1, b_1, c_1)(+)(a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (5)$$

$$\tilde{A} - \tilde{B} = (a_1, b_1, c_1)(-)(a_2, b_2, c_2) = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \quad (6)$$

The membership function of a trapezoidal fuzzy number $\tilde{A}(a, b, c, d)$ has a lower bound a , an upper bound d , a lower support bound b , and an upper support bound c , where $a < b < c < d$. To conduct arithmetic operations on two trapezoidal FMFs, Eq. (7) and Eq. (8) should be defined.

$$\tilde{A} + \tilde{B} = (a_1, b_1, c_1, d_1)(+)(a_2, b_2, c_2, d_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2) \quad (7)$$

$$\tilde{A} - \tilde{B} = (a_1, b_1, c_1, d_1)(-)(a_2, b_2, c_2, d_2) = (a_1 - d_2, b_1 - c_2, c_1 - b_2, d_1 - a_2) \quad (8)$$

2.3. Probability-possibility transformations

Statistics extend mathematics from a specific to incidental phenomena, whereas fuzzy numbers extend mathematics from the deterministic to the vague world. Zadeh, 1999 proposed the possibility theory, stating that the link between fuzzy numbers and possibility distributions might be akin to the relationship between random numbers and probability distributions. Probability theory serves as the foundation for statistics, which is concerned with the study of quantitative laws of chance, specifically the probability that a given element occurs in a universal set (Lee, 2004), whereas possibility theory is concerned with the state of being believed and plausible (Pota et al., 2013), and reflects imprecise information using a fuzzy membership degree normalized to $[0, 1]$.

Numerous pieces of research have attempted to modify the probability-possibility distribution in a variety of ways. Klir, 1990 proposed numerous approaches for converting probability distributions to possibility distributions. The most promising technique is the "interval scale method," which utilizes both the Shannon entropy $H(p)$ and the Dempster-Shafer theory $V(p)$. The former sought to quantify decision-making uncertainties using a probabilistic technique, whereas the later used a fuzzy set \tilde{A} of "U-uncertainties". By analyzing the relationship between probability-possibility transitions, confidence intervals, and probability inequalities, Dubois et al., 2004 created a technique for measuring probability under non-deterministic settings. Akbarzadeh-T and Moshtagh-Khorasani, 2007 developed a workable approach for converting statistical data to a fuzzy rule base using "hierarchical fuzzy rules" and used it to the diagnosis of medical aphasia. From a likelihood standpoint, Pota et al., 2011 offered a method for transforming probability-to-possibility distributions through

FMF. The approach generates a conventional fuzzy set, which is equivalent to a triangular or trapezoidal FMF. The input probability distribution was used to match the optimal parameter combinations for that set. Pota et al., 2013 proposed another "Hypothesis Test" technique for directly obtaining fuzzy sets from probability distributions by simulation of multiple decision procedures.

2.4. Probabilistic data of aircraft A320 turnaround

Calculating the target off-block time (TOBT) for a specific flight accurately is a critical step in properly implementing A-CDM. The challenge originates from the complexity of the current aircraft turnaround and the large number of resources and staff members engaged, both of which have an effect on the TOBT and other A-CDM timestamps. International Air Transport Association (IATA) ground operations manual ((I)GOM) for an A320 aircraft contains twelve linked activities (see Fig 1), each of which is subdivided into around 150 unique sub-tasks and involving up to 30 different players, depending on the operator's specific interest (Asadi et al., 2021). Although not all processes are required for every turnaround (for example, low-cost carriers (LCCs) typically cater or clean their aircraft less frequently, depending on the flight characteristics), there are a number of mandatory processes that frequently define the turnaround's critical path (red boxes in Fig 1).

Typically, the ground operations manual describes each process in terms of deterministic quantile values that indicate a standard period of recorded process uncertainties and time deviations. According to the ground operations manual, the key route of a typical turnaround consists of Fuelling from a collection of simultaneous candidate operations (Fricke and Schultz, 2009). As a result, additional procedures such as cleaning or catering may form the critical route. Stochastic process models are then used to express the probability set (Asadi et al., 2020). Minimizing turnaround time in the event of a schedule deterioration may entail interfering with many processes in order to ensure an efficient schedule recovery. Once these recovery procedures are implemented, calculating their influence on the TOBT is difficult.

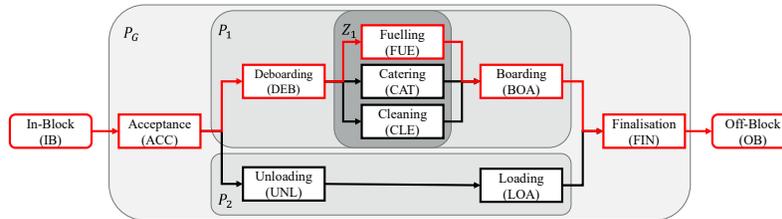


Fig. 1. Metra Potential Method (MPM) of a typical Turnaround

As previously stated, it is critical for an airline to continually check each time stamp, particularly the off-block time, in light of the inherent uncertainties. Due to the difficulty of managing stochastic interdependencies manually, this paper proposes automated decision support based on the transfer of knowledge about the time distributions and resource dependencies of each individual core process to a mathematical model that aggregates all distributions into a single one. To our understanding, this methodology produces more accurate findings than current purely stochastic approaches, which often rely on Monte Carlo simulations or state-transition models (Wu & Caves, 2004; Clarke, 2007; Oreschko et al., 2012). Numerous studies on the modeling of turnaround in the presence of uncertainty rely heavily on probabilistic theories, such as Bayesian networks or Monte Carlo simulations (Schultz et al., 2012; Jianli et al., 2015). Additionally, only a few attempts have been made to address turnaround as an issue of project scheduling in an unpredictable context. Additionally, without restarting the full simulation, the proposed model type may immediately compute the overall effect time of recovery measures (translated into parameter modifications) at a specified confidence interval.

Table 1

Stochastic turnaround process distribution

| Abbrev. | Name | Distribution | Mean (min) | Standard Deviation. (min) |
|---------|--------------|----------------------|------------|---------------------------|
| IB* | In-Block | - | - | - |
| ACC | Acceptance | Gamma (2.0,1.0) | 2.00 | 1.41 |
| DEB | Deboarding | Gamma (6.81,1.47) | 10.01 | 3.83 |
| CLE | Cleaning | Weibull (2.16,11.29) | 9.99 | 4.88 |
| CAT | Catering | Weibull (2.18,17.37) | 15.38 | 7.44 |
| FUE | Fuelling | Gamma (9.12,1.64) | 14.96 | 4.95 |
| UNL | Unloading | Gamma (11.29,1.24) | 11.10 | 3.71 |
| LOA | Loading | Gamma (15.34,1.24) | 15.48 | 4.38 |
| BOA | Boarding | Gamma (14.36,1.47) | 21.10 | 5.57 |
| FIN | Finalization | Gamma (4.0,1.0) | 4.00 | 2.00 |
| OB* | Off-Block | - | - | - |

*IB and OB have no duration because they are start and end events.

To account for the stochastic nature of each activity's processing durations, deterministic values of ground operations manuals are replaced by fitted Gamma- or Weibull-distributions, as seen in Table 1 and Fig 2. Since the Turnaround time cannot

be negative as it is time, both distributions are well-suited since they include no negative time values and have shown a high degree of fit when compared to operational analysis data (Asadi et al., 2020). Thus, the parameters for deboarding, fueling, catering, cleaning, and boarding were derived from prior research conducted (Fricke and Schultz, 2009). Additionally, all remaining processes were matched to Gamma-distributions that contained the relevant ground operations manual values as 80 percent quantiles. It should be emphasized that all parameters are general assumptions of the model variables and may be altered at any moment to account for airline/airport-specific operational factors.

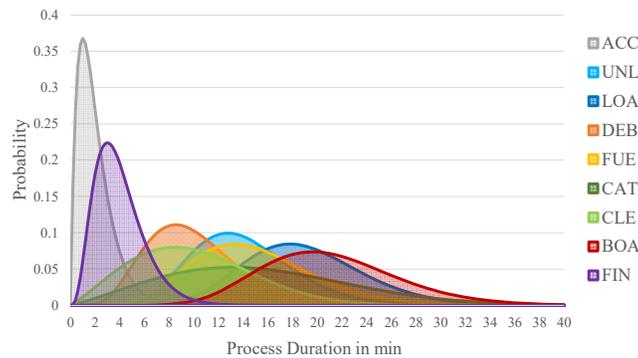


Fig. 2. Stochastic turnaround standard process distributions

All processes are presumed to be independent of one another in this method (i.i.d), as they are normally conducted by distinct resource entities. According to the execution times in Table 1, three handling agents are assigned to the cargo procedures UNL and LOA, whereas CLE, CAT, and FUE are assigned to a single servicing vehicle or crew, respectively. Parallel cabin and ramp procedures are not considered since they are meant to be centrally handled by the ramp agent. Strategic buffer periods are also removed, as they would be utilized first in the event of a delay and would have no direct influence on the execution of the individual processes (Evler et al., 2021). This leaves the Metra Potential Method network graph as shown in Fig 1, for which the stochastic processing time will be determined using fuzzy critical path method. Similar to the critical path method, sequential processes are multiplied by their time, however parallel activities must wait for their longest (critical) counterpart to complete before proceeding to the next activity. Due to the fact that the resultant function is not trivial and does not adhere to a well-defined distribution, it is important to characterize it in terms of its constituents.

The most well-known project scheduling tools are the Critical Path Method (CPM) and the Plan Evaluation Method and Review Technology (PERT), both of which are network analysis-based techniques for visualizing the tasks sequence (Aquilano and Smith, 1980). The Critical Path Method (CPM) is a time-tested approach to project scheduling that uses network analysis to visualize the task sequence as task length is calculated. As a result, we integrate CPM with fuzzy set theory in this paper. Fuzziness and randomness are sufficiently considered in network planning, e.g., by utilizing FCPM to attain a more realistic membership degree over the fuzzy network's complete duration. Prade, 1979 advocated combining the notion of fuzzy sets and the CPM approach, where fuzzy sets could be used to describe task durations in the presence of uncertainty and CPM could be used to explain the task sequence. Gazdik, 1983 attempted to define the task length in terms of fuzzy numbers and to determine the task's earliest start time. The time parameters for the job in the fuzzy network were determined in these investigations by doing forward and backward calculations using the CPM approach. However, when fuzzy numbers are added together, fuzzy number \tilde{A} plus fuzzy number \tilde{B} equals fuzzy number \tilde{C} . However, it is not possible to deduce that fuzzy number $\tilde{A} = \text{fuzzy number } \tilde{C} \text{ minus fuzzy number } \tilde{B}$. Thus, applying the CPM approach directly to a fuzzy set in the backward calculation would not produce the right values for the latest start and slack time. As a result, Nasution, 1994 used a technique called "interactive fuzzy subtraction" to create the fuzzy critical path and concluded that only the positive half of the fuzzy set (including zero) was practically relevant. Dubois et al., 2005 presented a universal method for computing a task's most recent start and slack time in order to extend backward calculations to all fuzzy networks. Atli and Kahraman, 2012 utilized the FCPM approach to derive a fuzzy critical path for aircraft maintenance projects in an unpredictable environment by taking decision-makers' risk tolerance into account.

3. Turnaround control application

A dependable target time for any turnaround operation is the first step in ensuring that an airline's operations are managed efficiently. In light of the tight schedules and complicated itineraries of aircraft, crew, passengers, and servicing resources, potential deviations from the turnaround target time from the original schedule can have significant propagation effects throughout the entire airline network, as cited by Beatty et al. (1999).

3.1. Fuzzify of the A320 turnaround data

The term “fuzzification of data” refers to the process of converting a probability distribution into a possible distribution. In order to implement the probability-possibility transformation several approaches have been tested, with the Hypothesis Test Method being the most successful in terms of preserving the original information in the conversion (see Klir, 1990; Dubois et al., 2004; Akbarzadeh & Moshtagh-Khorasani, 2007). The main idea is to use the continuous distribution function of the decision rule α to obtain the corresponding membership level of a fuzzy set cites Pota 2013 Transforming the Probability-Possibility Transformation.

The flowchart for performing the probability-to-possibility transformation is shown in Fig 3, where symbol x represents the time covered by each probability with an α significance level.

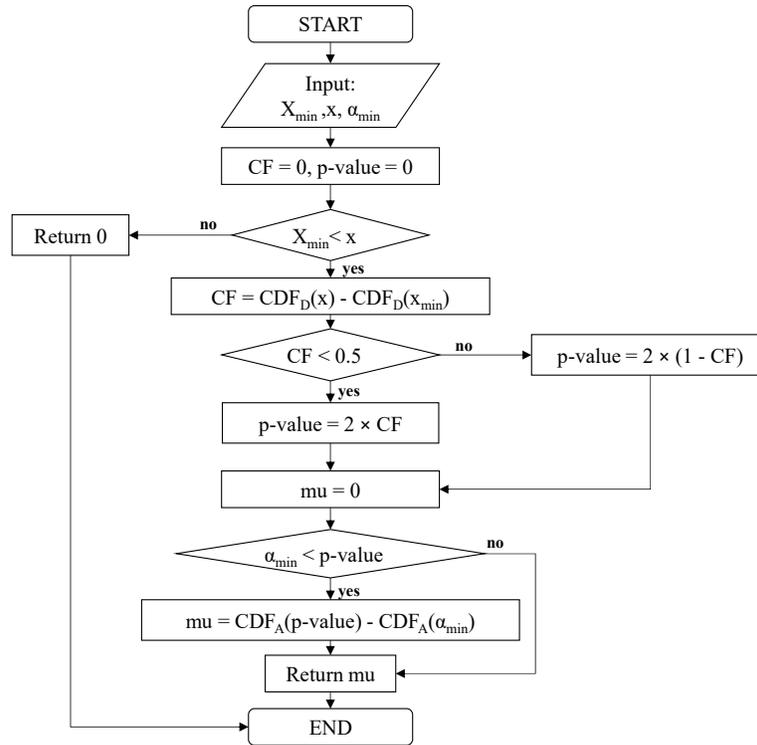


Fig. 3. Algorithm for probability-possibility transformation

The p -value data distribution of the test statistic may be determined using Eq. (9).

$$p\text{-value} = 2 * (0.5 - |0.5 - CDF_D(x)|) \quad (9)$$

The p -value denotes the likelihood that the observed sample would seem more extreme in the absence of H_0 rejection. However, it is reasonable to reject H_0 if $p\text{-value} > \alpha$, and vice versa. The parameter $\delta(H_0)$ in Eq. (10) is used to ensure that the decision-rule α is such that H_0 cannot be rejected.

$$\delta(H_0)(x, a) = \begin{cases} 1 & \text{if } [p\text{-value} > \alpha] \\ 0 & \text{if } [p\text{-value} < \alpha] \end{cases} \quad (10)$$

From α_{\min} to α_{\max} , the decision rule α is repeated and the probability density distribution function PDF_A is added to generate a cumulative distribution function CDF_A . According to Eq. (10), the probability distribution might be expressed as (11). The possibility distribution is calculated as the integral of the probability distribution obtained from a decision rule

α developed by simulations of various probability density functions. In Equation (11), $\Pi_A(x)$ represents the possibility distribution and $\mu_A(x)$ represents the fuzzy membership function.

$$\begin{aligned}\Pi_A(x) &= \int_{a_{\min}}^{\alpha_{\max}} \delta(H_0)(x, a) * PDF_A(a) da \\ &= \int_{a_{\min}}^{p\text{-value}} PDF_A(a) da \\ &= CDF_A(p\text{-value}) - CDF_A(\alpha_{\min})\end{aligned}\quad (11)$$

After obtaining each process distribution and its parameters from Table 1, the distribution calculator can be used to obtain the probability density function (PDF) and cumulative distribution function (CDF). After implementing the transformation algorithms, the transformation results for each sub-process duration are shown in Fig 4, where the x-axis represents the task duration (min) and the y-axis represents both the probability of the Probability Density Function and the possibility of the Possibility Function.

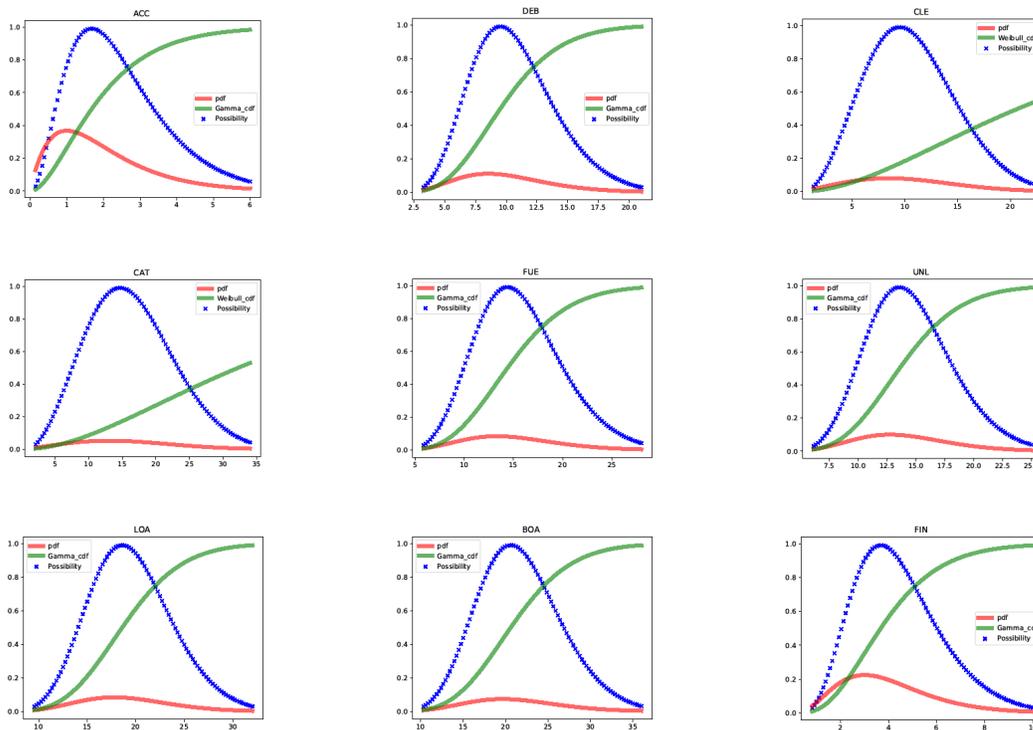


Fig. 4. Transformation Result for Process Duration

3.2. FCPM algorithm

As indicated in Section 1, fuzzy critical path method is an approach that combines critical path method and fuzzy set theory to solve project scheduling problems specially with uncertain task durations. FCPM is developed on two fundamental principles:

- 1st Principle: Only the positive section of fuzzy numbers has a physical explanation in this work, because the uncertain parameter is time, which is always positive (Nasution, 1994; Mares, 1991).
- 2nd Principle: The fuzzy critical path is represented by the fuzzy members' minimum ranking indices. In other words, after computing the potential fuzzy set of all pathways, the critical path is the one with the least flexibility (lowest ranking indices) (Chanas & Zieliński, 2001).

To determine the best fuzzy membership function between the trapezoidal and triangular FMFs described in Sub-section 2.2, in this paper we use the Kolmogorov-Smirnov test to compute the goodness-of-fit for the possibility distribution and determine whether the Triangular or Trapezoidal function is the best fitted function for each process. Fig 5 illustrates the results of goodness-of-fit calculation.

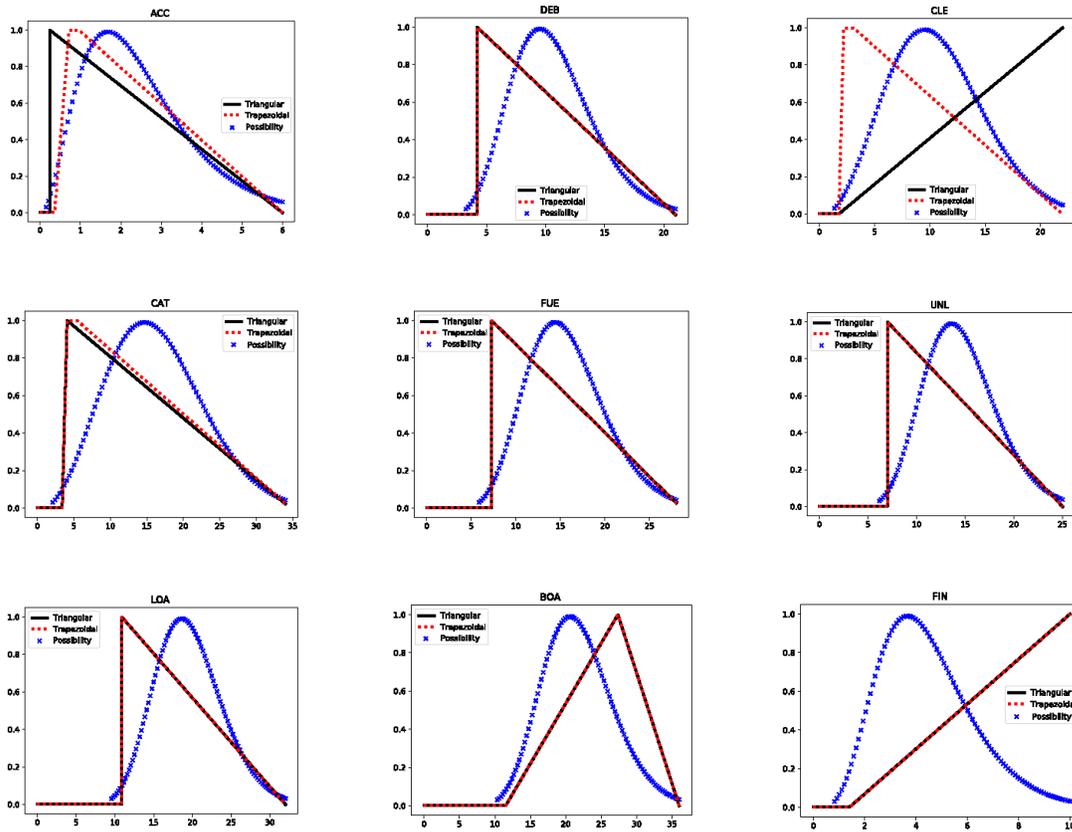


Fig. 5. Result of Goodness-of-Fit of K-S test for each Process Duration

The optimal combinations for the parameters of each fuzzy membership function are shown in Table 2. The K-S test indicated that each fuzzy membership function was stable between 0.08 and 0.09.

Table 2
Parameter combinations of FMF for each process

| Process | Triangular FMF | Trapezoidal FMF |
|---------|---------------------|---------------------------|
| ACC | (0.24,0.24,6.00) | (0.36,0.72,0.96,6.00) |
| DEB | (4.20,6.20,21.00) | (4.20,4.20,6.20,21.00) |
| CLE | (1.76,22.00,22.00) | (1.76,2.20,3.08,22.00) |
| CAT | (3.40,4.08,34.68) | (3.40,4.08,5.34,34.68) |
| FUE | (7.28,8.28,28.56) | (7.28,7.28,8.28,28.56) |
| UNL | (7.00,9.00,25.00) | (7.00,7.00,9.00,25.00) |
| LOA | (10.88,11.88,32.00) | (10.88,10.88,11.88,32.00) |
| BOA | (11.52,28.96,36.00) | (11.52,26.16,28.96,36.00) |
| FIN | (1.40,9.00,10.20) | (1.40,8.00,9.00,10.20) |

We choose trapezoidal FMF to describe the entire turnaround duration in this paper because a triangular FMF can be considered as a special case of a trapezoidal FMF (when $b = c$), and also because trapezoidal FMF fits better than triangular FMF in some sub-processes, such as catering, with a better K-S test result (Vimala & Prabha, 2015).

3.3. Defuzzify of fuzzy membership functions

There are several defuzzification techniques for converting a fuzzy membership function to a crisp integer. These methods can be used to convert the trapezoidal FMF's parameter combinations to a crisp number in order to test if the conversion result is credible. By substituting $\tilde{A} = (a, b, c, d)$ for the trapezoidal fuzzy number, the defuzzification formula may be stated as Eq. (12).

$$Def(\tilde{A}) = \frac{(c^2 + d^2 + cd) - (a^2 + b^2 + ab)}{3[(c + d) - (b + a)]} \quad (12)$$

The outcome of defuzzification for each process may be determined by constructing the trapezoidal fuzzy membership function using the optimal parameter combinations described in Table 2. As seen in Table 3, the crisp values for each process duration have been returned by the fuzzy sets and they are realistic when compared to the mean value for each process from Table 2, which suggests that the transformation and goodness-of-fit process can be accomplished. As a result, a fuzzy set representing the length of the sub-process might be utilized directly to execute the computation.

Table 3
Defuzzification results for each turnaround process

| Process | Triangular FMF | Trapezoidal FMF |
|---------|------------------------------|-----------------|
| IB | (0.00, 0.00, 0.00, 0.00) | 0 |
| ACC | (0.36, 0.72, 0.96, 6.00) | 2.37 |
| DEB | (4.20, 4.20, 6.20, 21.00) | 9.87 |
| CLE | (1.76, 2.20, 3.08, 22.00) | 9.69 |
| CAT | (3.40, 4.08, 5.34, 34.68) | 13.39 |
| FUE | (7.28, 7.28, 8.28, 28.55) | 14.38 |
| UNL | (7.00, 7.00, 9.00, 25.00) | 13.07 |
| LOA | (10.88, 10.88, 11.88, 32.00) | 17.94 |
| BOA | (11.52, 26.16, 28.96, 36.00) | 25.16 |
| FIN | (1.40, 8.00, 9.00, 10.20) | 6.79 |
| OB | (0.00, 0.00, 0.00, 0.00) | 0 |

3.4. A320 turnaround calculation using FCPM

In this sub-section the calculation of aircraft A320 turnaround is introduced. To do the calculation, following symbols in the FCPM should be defined.

| | |
|-------------|---|
| A_{ij} | The task, which is connected between nodes i and j |
| FET_{ij} | Fuzzy duration of A_{ij} |
| FTS_{ij} | Fuzzy slack time of A_{ij} |
| FES_j | Fuzzy earliest time of node j |
| FLF_j | Fuzzy latest time of node j |
| $Pred_j$ | Predecessor tasks |
| $Succ_j$ | Successor tasks |
| P_i | Path i from the start node to the end node |
| $FCPM(P_i)$ | Fuzzy duration of the path i |
| $FCPM(P_C)$ | Fuzzy duration of the fuzzy critical path of turnaround |

To begin, we set the fuzzy earliest time of the first task to zero $FES_1 = (0, 0, 0, 0)$, and then add the fuzzy earliest time of the predecessor and the fuzzy duration of this task FET_{ij} using fuzzy trapezoidal addition (Eq. (7)) to obtain the fuzzy earliest time FES_j of task j . Additionally, there must be the largest FES_j in the forward calculation. The forward calculation is carried out with the help of Eq. (13).

$$\begin{cases} FES_j = (0, 0, 0, 0) & j = 1 \\ FES_j = \max\{FES_i(+)FET_{ij} \mid i \in Pred_j\} & j \neq 1 \end{cases} \quad (13)$$

Afterwards, we put $FLF_n = FES_n$, based on the concept that the fuzzy earliest time of the previous job is comparable to the fuzzy latest time of the previous task. FLF_j should be computed in reverse order from the end node to the start node ($j = n - 1, n - 2, \dots, 2, 1$). Then, using trapezoidal fuzzy subtraction by Equation (8), the fuzzy latest time of the successor subtracts the task's fuzzy duration FET_{ij} to yield the fuzzy latest time for each process, FLF_j . Using Eq. (14), FLF_j is calculated based on the minimum FLF_j between all possible paths.

$$\begin{cases} FLF_n = FES_n & j = n \\ FLF_j = \min\{FLF_k(-)FET_{jk} \mid k \in Succ_j\} & j \neq n \end{cases} \quad (14)$$

Following that, the task slack time FTS_{ij} is the permissible delay in task implementation as long as it does not affect the project's overall length. As a result, the critical path is the path which has no fuzzy slack time (Atli & Kahraman, 2012). The fuzzy slack time FTS_{ij} is presented by Eq. (15).

$$FTS_{ij} = FLF_j - (FES_i + FET_{ij}) \quad 1 \leq i \leq j \leq n \mid i, j \in N \quad (15)$$

The fuzzy duration of the path P_i in the project network is equal to the total of all conceivable fuzzy slack time, as defined by Eq. (16).

$$FCPM(P_i) = \sum_{1 \leq i \leq j \leq n \mid i, j \in P_i} FTS_{ij} \quad P_i \in P \quad (16)$$

The fuzzy critical path is a term that refers to the smallest fuzzy set of all feasible pathways in a project, as represented by Eq. (17).

$$FCPM(P_c) = \min FCPM(P_i) \quad \forall i \mid P_i \in P \quad (17)$$

The fuzzy critical path approach calculates both forward and backward processes that follow the CPM technique's procedure. The time of the fuzzy task FET_{ij} is derived from the goodness-of-fit result in Table 2. Table 4 summarizes each process's Fuzzy Slack Times (FTS). Calculations are performed using Eq. (13) and Eq. (14).

Table 4
Fuzzy Slack Times (FTS)

| Processes | Tasks | Fuzzy Slack Time |
|-----------|------------|-------------------------------|
| (1,2) | (IB, ACC) | (-76.99, -7.04, 7.04, 76.99) |
| (2,3) | (ACC, DEB) | (-76.99, -7.04, 7.04, 76.99) |
| (2,7) | (ACC, UNL) | (-48.44, 15.52, 26.80, 82.11) |
| (3,6) | (DEB, FUE) | (-76.99, -7.04, 7.04, 76.99) |
| (3,5) | (DEB, CAT) | (-83.12, -4.10, 10.24, 80.87) |
| (3,4) | (DEB,CLE) | (-70.44, -1.84, 12.12, 82.51) |
| (7,8) | (UNL, LOA) | (-48.44, 15.52, 26.80, 82.11) |
| (8,10) | (LOA, FIN) | (-48.44, 15.52, 26.80, 82.11) |
| (6,9) | (FUE, BOA) | (-76.99, -7.04, 7.04, 76.99) |
| (5,9) | (CAT, BOA) | (-83.12, -4.10, 10.24, 80.87) |
| (4,9) | (CLE, BOA) | (-70.44, -1.84, 12.12, 82.51) |
| (9,10) | (BOA, FIN) | (-76.99, -7.04, 7.04, 76.99) |
| (10,11) | (FIN, OB) | (-76.99, -7.04, 7.04, 76.99) |

Chang and Chen, 1994 provided a technique for identifying fuzzy critical pathways and fuzzy durations for networks by computing the risk index and ranking the fuzzy numbers of all potential paths in the project. The fuzzy number is ranked using the risk index β ($0 \leq \beta \leq 1$), which indicates the decision-attitude maker's toward risk. $\beta \geq 0.5$ denotes an optimistic attitude toward risk, whereas $\beta \leq 0.5$ denotes a pessimistic attitude toward risk. The ranking index β is calculated using Eq. (18).

$$\beta = \frac{\sum_i \sum_j \frac{b_{ij} - a_{ij}}{(b_{ij} - a_{ij}) + (d_{ij} - c_{ij})}}{n} \quad (18)$$

The fuzzy number of all feasible pathways in the project may be ranked and sorted using Eq. (19) and the risk index β .

$$R(\tilde{A}_i) = \beta \left[\frac{d_i - x_1}{x_2 - x_1 - b_i + d_i} \right] + (1 - \beta) \left[1 - \frac{x_2 - c_i}{x_2 - x_1 + a_i - c_i} \right] \quad (19)$$

According to this approach, the path with the lowest risk index is the critical path for the whole turnaround. According to Table 5, the path including the processes (IB, ACC, DEB, FUE, BOA, FIN, OB) is the crucial path, as predicted from the literature study discussed in Section 1, and any deviation in any of these processes can result in a delay in the whole turnaround.

Table 5
Ranking values of FCPM

| Rank | Tasks | FMF(P _i) | R(P _i) |
|------|-------------------|-------------------------------|--------------------|
| 1 | (1,2,3,6,9,10,11) | (-461.94,-42.24,42.24,461.94) | 0.425 |
| 2 | (1,2,3,5,9,10,11) | (-474.20,-36.36,48.64,469.70) | 0.426 |
| 3 | (1,2,3,4,9,10,11) | (-448.84,-31.84,51.40,472.98) | 0.433 |
| 4 | (1,2,7,8,10,11) | (-299.30,32.48,94.48,400.31) | 0.485 |

4. Application analysis

This section discusses the comparative verification and analysis of the results obtained in Section 3. Additionally, a comparison of the FCPM-based turnaround time to historical data is made, and the effect of delay on the turnaround process is explored through the use of linear regression analysis.

4.1. Historical data characteristics

The historical data for this article comes from over 50,000 Lufthansa A320 flights between March and October 2017, and includes both scheduled and actual turnaround time (TA) for each flight trip. According to historical statistics, A320 daily flights have a broad range of turnaround times. Along with delays caused by inclement weather or air traffic control, the flight schedule strategy has an effect on the aircraft turnaround time. To ensure the statistics' authenticity, past turnaround time data should be suitably filtered. Flights having turnaround periods more than 10 hours will be omitted from this article. Since all turnaround time are not actual times and they are affected from long aircraft maintenance and shortage of resources because of the weather or absence of crew, the schedule- and actual-TA values will then be sorted ascendingly to eliminate an additional 5% of historical data from the head and tail, respectively, to avoid trapping in unjustified and extreme values.

To determine the data's tendency and hence the data's behavior, the mean, median, standard deviation, and quartile deviation of the data are calculated. Schedule and actual TA have a mean value of 69.92 min and 75.90 min, respectively. The schedule and actual TA median values are 60.00 min and 67.00 min, respectively. The schedule and actual TA standard deviations are 34.87 min and 33.98 min, respectively. Quartile deviation is a statistical technique that classifies all data in ascending order and then evenly divides it into quartiles to determine the data's dispersion. The value at the 25% position is referred to as the quartile and is represented by Q1, the median is denoted by Q2, and Q3 shows the value at the 75% position. The interquartile range *IQR* is determined using the reference Eq. (20).

$$IQR = \Delta Q = Q_3 - Q_1 \quad (20)$$

4.2. Comparison between real data and FCPM result

In Section 3, the ideal parameter combinations for trapezoidal FMFs are determined through optimization and iteration using the Kolmogorov-Smirnov test (see Table 2). Using these parameter combinations, the *p-value* in the K-S test achieved its maximum value. Fig 6 illustrates the outcome of the goodness-of-fit analysis of the real data. After calculating and updating the best parameter combinations for trapezoidal FMF, schedule turnaround has a parameter combination of (59.64,69.58,69.58,268.38) with a *p-value* of 0.036, while actual turnaround has a parameter combination of (9.92,9.92,9.92,248.00) with a *p-value* of 0.078.

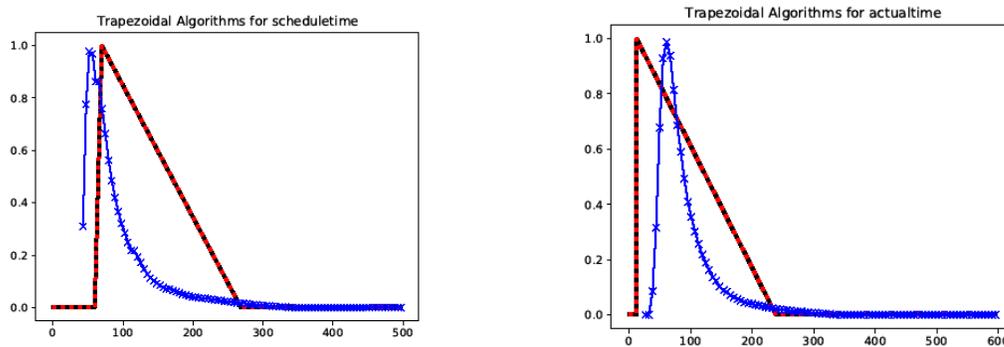


Fig. 6. Transformation result for real data (X-axis shows the duration in Min)

According to Principle 1, as mentioned in Section 3, only the non-negative component of a fuzzy number is meaningful practically. As a result, the FCPM-based turnaround time undergoes preprocessing, and only the positive values of the parameters are maintained. The comparison of FMFs is presented in the Fig 7.

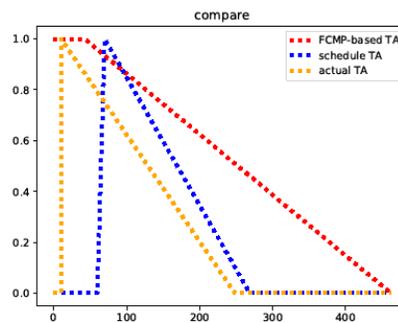


Fig. 7. Comparison of FMFs of the actual, schedule and calculated TA

In this study, we mimic real delays by creating a set of delay scenarios based on historical data and then using linear regression models to forecast the trend of different delay levels at the “On-Block” point to the FCPM-based turnaround time. The technique for probability-possibility transformation has been demonstrated to be helpful for irregular distributions as well. The process for constructing delay fuzzy sets is depicted in Fig 8.

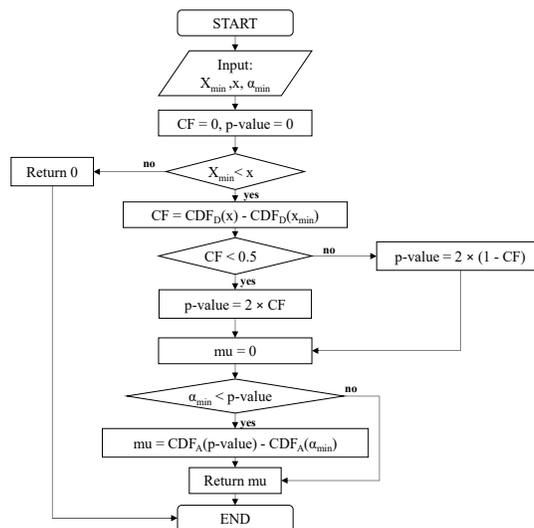


Fig. 8. Flowchart of constructing delay fuzzy set

Following the defuzzification of various delay fuzzy sets and associated FCPM-based turnaround times, a Simple Linear Regression (SLR) is utilized to highlight the link between delay situations and FCPM-based turnaround times, as illustrated in Fig. 9 and expressed by Eq. (21). The determination coefficient is (R^2) is 0.504 (the closer R^2 is to one, the better the model matches the data). According to Equation (21), delay situations have a positive relationship with the FCPM-based turnaround time.

$$Y = 231.368 + 2.462x + \varepsilon \quad (21)$$

5. Conclusion

This article demonstrated the effective implementation of the fuzzy critical path approach for estimating turnaround goal times, which opened up a plethora of new options for the creation of controller decision-support systems. To begin, the new method calculates the turnaround completion time following a selected data set and risk of decision-making level in real time and with high mathematical precision, thereby eliminating the need for conventional simulation methodologies. Additionally, in comparison to certain other often used methodologies, such as Monte Carlo simulation, FCPM eliminates massive repeated computations (Slyeptsov and Tyshchuk, 2000). Due to the algorithm's consideration of all network activities in aggregate based on their unique uncertainty parameters, the technique is extremely adaptable to any operational environment (any airline or aircraft type) and imposes no constraints on parameter distribution.

This research examined a limited number of network adaptations in the form of process and sequence changes and demonstrated the time-related considerations an AOC may make when assessing the effectiveness of prospective schedule recovery operations on a disrupted turnaround.

Additional in-depth evaluations of the separate processes will determine whether the present parameters should be fine-tuned to reflect actual weather, traffic, or personnel conditions.

Finally, more study will be conducted to determine how the present forecast can be transferred from a tactical to a real-time support tool, allowing for the estimation of the TOBT in the event of substantial disruptions to the ongoing turnaround, such as maintenance issues or resource shortages.

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