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ANALYZING AIRLINE DELAY PROPAGATION AND DELAY CAUSE USING A GAUSSIAN NETWORK

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We developed a delay propagation model for an airline network using a Gaussian network approach. By analyzing US flight data in a case study, we evaluated the effects of delay propagation within an airline network. The model has several advantages, such as accounting for non-independent and identically distributed delay profiles, providing a more accurate representation of the observed delay propagation process, and identifying weak links in an airline network. Various scenario studies of delay propagation revealed that the Gaussian network model could capture the effect of delay propagation more precisely than previous studies. Moreover, the Gaussian network model could identify weak links through a statistical approach in an airline network. These perspectives may be valuable in developing approaches for managing the delay propagation and alleviating its subsequent effect.

Keywords: Airline Network; Delay Propagation; Gaussian Network; Flight Delays; Scenario Analysis.

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1. INTRODUCTION

In December 2019, the initial case of COVID-19 was reported in Wuhan, China, and soon after, the virus rapidly spread beyond China, causing a global pandemic and economic difficulties across various industries. The COVID-19 pandemic has had severe economic ramifications worldwide and harshly hit the entire US airline industry. Statistical predictions indicated that the number of passengers might not return to pre-pandemic levels in 2019 for the airline industry. On April 16, 2020, at the beginning of the outbreak, the US Transportation Security Administration (TSA) reported that only around 95,000 passengers were screened at US airports, a 96 percent drop compared to the same day in the year of 2019, as 2.6 million passengers were screened.

However, according to the *International Air Transport Association (IATA)*, the profitability of the airline industry in 2023 will be recovered to its former state to achieve $8.8 billion in profits across North America in 2022 (IATA, 2023). As time passes, strong pent-up demand for traveling and trade will soar again, bringing up the number of passengers to 72 percent of pre-pandemic levels in 2022. With expectations on a post-pandemic air traffic recovery, challenges of resolving airline delays and congestion at airports would be highlighted again as they have always been important issues for traditional airline passenger transportation.

Airline delays can have significant impacts. Economically, the costs manifest in several ways, such as the following: direct costs to airlines from wasted fuel, increased maintenance, and potential compensation to passengers. Indirect costs from missed opportunities or additional expenses, such as accommodations, also cost airlines money. Prolonged issues with delays could deter frequent flyers, leading to a reduction in overall demand and a subsequent loss of revenue for the industry. From a service-level perspective, airline delays disrupt operational efficiency. Delay propagation, the domino effect of one delayed flight, can lead to subsequent delays, causing scheduling and logistical challenges. This can also result in

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overcrowded airports and increased pressure on airport facilities and staff. In the long term, delays can negatively impact an airline's service level, leading to a loss of market share as customers switch to competitors perceived to be more reliable.

From a cost perspective, the delay propagation can have a substantial financial impact. When a flight is delayed, it incurs additional operational costs. These can include increased fuel consumption, additional crew time, and increased maintenance costs due to extended aircraft use. Depending on the jurisdiction and the extent of the delay, airlines may need to provide passengers with compensation, which could include monetary reimbursement, accommodation, meals, and alternative transportation. In a real-world case, the airline Southwest canceled and delayed more than 16,700 flights between December 23 and December 31, 2022. In a report released by the US *Federal Aviation Administration (FAA)*, losses for the fourth quarter of 2022 are expected to be between $725 million and $825 million.

The main objective of this paper is to develop a mathematical model of the way delays spread throughout an airline network. Delay propagation is a typical and frequent occurrence in airline networks that are interconnected, where flights rely on resources to be carried out. Delays by resources, such as a delayed incoming plane, can cause serial postponement for all of related activities and may result in further delays for other interrelated activities that exploit the same resources. Consequently, analyzing delay and its cause is closely related with airline scheduling and routing (Pelegrín et al., 2016).

Delay propagation can also have a significant impact on airline operations due to the high level of synchronization among resources in the network (Wu, 2016). Daily airline operations are often disrupted by schedule perturbations, and delays can extensively spread through airports or flights vulnerable to delay, resulting in economic losses by aircraft and passenger delays. In this regard, various methods have been proposed to address delay propagation in airline networks. The purpose of modeling delay propagation is to increase the robustness of flight schedules and to supplement buffer time in the network, thereby improving the resilience of the airline network against unexpected disruptions by making tactical adjustments to flight times.

The adjustment of flight time has played a key role as a major strategy in recent literature on robust scheduling to effectively manage disruptions (Mansi et al., 2012). In general, these studies assumed that the distribution of flight delay is *independent and identically distributed (IID)*. Although the IID assumption simplifies delay propagation modeling and flight re-timing, it can lead to an overestimation of the scheduled buffer time, as demonstrated in Wu (2006). This unfavorable observation is due to the feature of an IID assumption assumes that each individual flight time distribution is independent of others and disregards the impact of delay propagation. In reality, delays or *on-time performance (OTP)* of preceding flights can affect the flight time distribution via shared resources.

Based on the analysis of schedule operations and delay data, it is evident that flight time distributions exhibit varying features that depend on several key factors. These factors may include the operating environment, operating efficiency, probability of disruptions, flight characteristics, and the connectivity of flights in aircraft routing (Wu and Law, 2019). To ignore the *non-independent and identically distributed (non-IID)* nature of delay time profiles may result in misrepresenting delay models, and the opportunity to schedule optimal buffer times in an airline network would be forfeited.

1.1 Delay Propagation in an Airline Network

Filar *et al.* (2001) examined the domino effect on multiple flights and airports and discussed airport disturbance handling and recovery from airline schedule disruptions. AhmadBeygi *et al.* (2008) developed a propagation tree model to assess the impact of delay propagation resulting from aircraft and crew connections. This model was later used by AhmadBeygi *et al.* (2010) to optimize flight schedules by re-timing flights and adjusting schedule buffer times between flights. In Wu and Law (2019), the delay propagation tree model was integrated with a Bayesian network to quantify the degree of delay propagation in a mathematical way. However, this model based on a Bayesian network oversimplified the extent to which delays propagate because they discretized continuous variables (time) for the fast calculation.

Several statistical models have examined the causal relationships between various factors, such as arrival/departure delays, buffer times, and schedule-related, onboard-related, and operation-related factors. Hao and Hansen (2014) and Wu (2016) utilized regression models, while Zhang and Nayak (2010) provided a macroscopic model for estimating a single airport's delay impact. However, analytical methods may not be suitable for estimating the delay propagation of individual flights. Nosedal S´anchez and Piera Eroles (2018) used system dynamics to analyze causal factors in aircraft turnaround. Jia *et al.* (2022) proposed using complex network theory to examine the structure of delay propagation in an airline network.

Delay propagation models are frequently employed to enhance the resilience of airline schedules against unforeseen delays that may arise during daily operations, with the aim of achieving robust airline scheduling (Ng *et al.*, 2022).

1.2 Prediction of Flight Delay

Schaefer and Millner (2001) employed a simulation model to determine how delays propagate across an airline network. Wu (2006) utilized a simulation model based on routing to illustrate the idea of inherent delays in an airline schedule. These models considered operational disruptions, stochastic operation times, and the effects of delay propagation. They showed that both delays and on-time performance (OTP) of flights could spread through the network. Gui *et al.* (2019) developed random-forest-based and Long Short-Term Memory (LSTM)-based architectures to predict individual flight delays.

On the other hand, flight re-timing has emerged as an effective planning method for improving the robustness of airline schedules in recent studies (AhmadBeygi *et al.*, 2008; Wu, 2006; Lan *et al.*, 2006). Specifically, Yan and Chen (2022) proposed a network flow approach to manage flight rescheduling and passenger transportation issues resulting from typhoon disruptions. Most studies have relied on aggregate statistics from historical data to model flight re-timing, such as the mean values of flight delays, and they followed the IID assumption for the distribution of flight delay times. Although this assumption simplifies delay propagation modeling and flight re-timing, it may result in overestimating buffer times could be an issue. Delays or OTP of previous flights can influence flight time distribution through resource connections.

Gaussian network (GN) is a probabilistic graphical model which has nodes as continuous random variables. Several graphical models have been used to predict flight delays in an airline network (Xu *et al.*, 2005; Rodriguez-Sanz *et al.*, 2019; Wu and Law, 2019). These studies suggested a Bayesian network, which assumes discrete variables as graph nodes. Wu and Law (2019) applied a Bayesian network discretizing delay distribution by specific time intervals for computational efficiency. On the other hand, the GN model can handle continuous distributions and identify weak links by detecting the uncertainty of airline delay in a network. A weak link is a node in a probabilistic network based on a certain probability distribution with high uncertainty. A standard deviation, a measure of uncertainty in the probability distribution, can be a mathematical criterion for identifying weak links. Gaussian networks have been used to discover and predict weak links in other research areas (see, for example, meteorology, Cano *et al.* (2013), biophysics, Erman (2006), and communication problems (Kim *et al*., 2011)).

In the cited research, probabilistic models were primarily restricted to modeling delays on individual routes or at smaller airports. They rather focused on delay propagation resulting from aircraft connections and other potential delay-causing factors. Instead, our GN model effectively captured the continuous characteristic of flight delays across multiple flights. As a result, we can evaluate various scheduling scenarios and concurrently determine the probability of delay/OTP propagation. This probability-based model can be well used for integration into future schedule optimization models.

Table 1 comprehensively summarizes several distinctive features of our model to highlight the contribution of this study compared with the existing literature on flight delay and delay propagation in airline networks. This paper offers several advancements to the existing literature. To the best of our knowledge, we were the first to present a new probabilistic graphical model, a GN, to deal with airline delay propagation, considering flight delays as a continuous random variable. Second, by analyzing a sample dataset, we demonstrate that flight delay distributions are heterogeneous and non-IID, and different delay profiles result in different delay/OTP propagation patterns across flights. Third, we established a multi-airport probability model for delay propagation and highlighted its effectiveness in determining delay causes and probability distributions. Fourth, we specifically address delay propagation through aircraft connections of multiple flights using the GN model, taking into account non-IID delay profiles of incoming aircraft. Also, we develop a method for finding weak links suffering capacity fluctuation, which has the opportunity to improve efficiency in an airline network.

Table 1. Relevant Studies Related to Flight Delay Prediction and Delay Propagation in an Airline Network

Author (year)	Delay propagation	Heterogeneous and non-IID delay	Random variables on flight delays	Methodology
Schaefer and Millner (2001)	✓		continuous	Simulation model
Wu (2006)	✓		continuous	Simulation model
AhmadBeygi et al. (2008)	✓		continuous	Propagation tree
Zhang and Nayak (2010)	✓		continuous	Multivariate simulation model
Wu and Law (2019)	✓	✓	discrete	Bayesian network
Gui et al. (2019)		✓	continuous	Recurrent neural network
Jia et al. (2022)	✓		continuous	Network theory
This study	✓	✓	continuous	Gaussian network

The remainder of this paper is as follows. We provide a problem description of delay propagation in an airline network in Section 0 and develop a GN model of the airline network in Section 3. The case study will be fully described along with the data source in Section 4. Lastly, Section 5 presents the result of our analysis of detecting delay sources and the effectiveness of heterogenous and non-IID delay with managerial insights. We conclude in Section 6.

2. PROBLEM DESCRIPTION

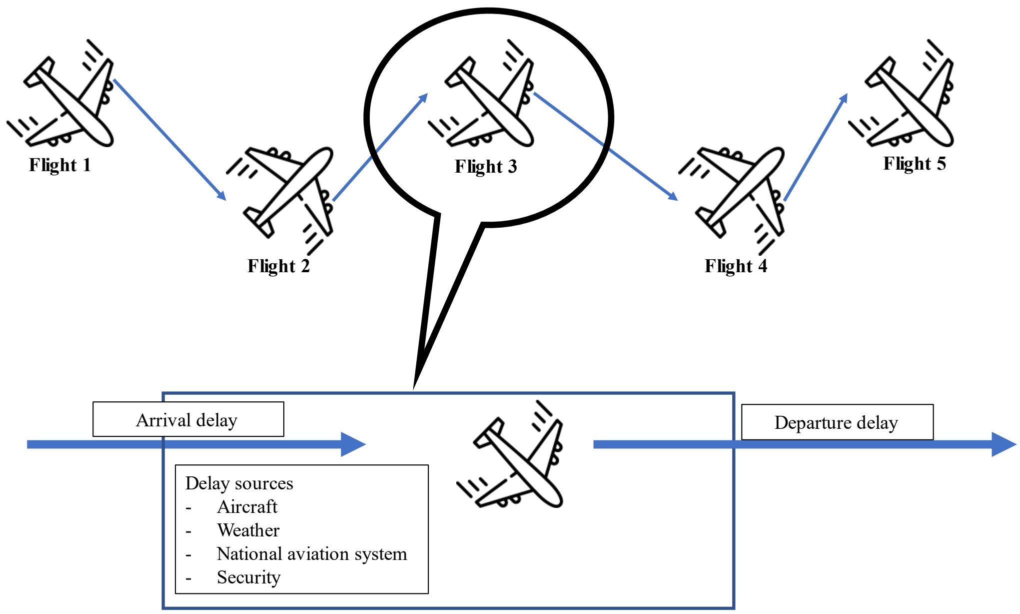

Figure 1. Gaussian Network Model Illustrating Causal Relationships

In an airline network, we suppose that delay propagation occurs through consecutive flights. Many factors may contribute to flight delays, including weather, airline operations, passenger and cabin crew connection, except consecutive flights, etc. However, due to the incompleteness of connected information, the connection of aircraft on consecutive flights is only observed in an airline network. The GN structure shown in Figure 1. models the causal relationships in delay propagation. To be more specific, the delay of flight j is a function of possible delay sources, including (1) aircraft delays caused by circumstances within the airline's control, such as crew problems, maintenance issues, aircraft cleaning, and baggage loading; (2) significant weather conditions like tornadoes, blizzards, or hurricanes; (3) *National aviation system (NAS)*; (4) delays from security. Description of considered delay sources in this study will be suggested in Section 4. For the GN model, each node in Figure 1 represents the departure delay of a flight in a GN (e.g., the delay t of Flight 3 in Figure 1) and is affected by other delay variables that are represented by inbound arcs, such as those connecting to Flight 3.

Based on the Bayes theorem, the probability of flight j being delayed by t minutes (denoted by $P_j(t)$) under the influence of delay sources listed above and the preceding flight i can be expressed as a conditional probability as follows:

$$P_j(t|\text{delay sources}) = \frac{P(t,\text{delay sources})}{P(\text{delay sources})} = \frac{P(\text{delay sources}|t)P_i(t)}{P(\text{delay sources})} \quad \forall j.$$

We are able to infer the posterior delay probability of flight j, $P_j(t|\text{delay sources})$ based on our prior belief from historical delay data of flight i, $P_i(t)$ and new observations of the presence of delay sources, *P*(delay sources).

We created schedules that adjust aircraft turnaround times (buffer times) to investigate how the change in departure times of flights could affect delay and OTP propagation. Buffer time serves to reduce delays accumulated from prior flights and contributes to reducing propagated delays. Delay distributions with varying buffer times were not accessible from historical data. Hence, we estimated the impact of adding buffer times to the current scheduling of flights by shifting the departure time distribution.

3. ANALYTICAL FRAMEWORK

3.1 Characteristics of an Airline Network

Suppose we have an airline schedule that aims to maximize the use of resources, such as crew and aircraft, by minimizing the time between two consecutive flights. This time, also known as connection time, turn time, sit time, or ground time, must meet a minimum requirement. For instance, there must be sufficient time between flights for passengers to disembark, catering and cleaning the interior of aircraft, and for new passengers to board. It is assumed that this planned schedule adheres to the minimum time between assignments for all crew and aircraft. Such a schedule optimizes resource utilization and minimizes excessive pay for crews. However, if a flight is delayed by 30 minutes without any compensatory increase in travel speed, it will also arrive 30 minutes late, causing a delay to its next flight. If the crew and the aircraft do not stay together, then the next flight will also experience a 30-minute delay. If the cabin crew separates from the aircraft and cockpit crew, it could cause a third flight delay. Additionally, if flights are held for connecting passengers from this flight, these flights will also be delayed.

In contrast to aircraft connections, which can be traced from data using registration numbers, identifying historical crew pairings was challenging due to the limited data available. Because the network in this study was only a portion of the original airline network, pilot and cabin crew pairings were reconstructed from the available flight data using industry-standard criteria outlined in Wu and Law (2019). To construct possible original crew connections within the study network, historical flight data were used for crew pairing to select suitable pairings with satisfying criteria.

3.2 Gaussian Network

A Gaussian network is a directed graph, all of whose variables and corresponding nodes are continuous. These variables can be either a constant or an uncertain quantity. Assign indices to the nodes and variables in the model so that the nodes are given by $N = \{1,\cdots,n\}$ and correspond to variables $X_1,\cdots,X_n$. The conditioning variables for X_j have indices in the set of parent $\mathrm{PA}(X_j) \subset V(G)$. Let Y be a linear Gaussian of its parents $X_1,\cdots,X_k$:

$$p(Y|x) = \mathcal{N}(\beta_0 + \beta^T x; \sigma^2)$$

Assume that $X_1,\cdots,X_k$ are jointly Gaussian with distribution $\mathcal{N}(\mu; \Sigma)$. Then:

- The distribution of Y is a normal distribution $p(Y) = \mathcal{N}(\mu_Y; \sigma_Y^2)$ where:

  $$\mu_Y = \beta_0 + \beta^T$$
  $$\sigma_Y^2 = \sigma^2 + \beta^T \Sigma$$

- The joint distribution over $\{X, Y\}$ is a normal distribution where:

  $$Cov[X_i; Y] = \sum_{j=1}^{k} \beta_j \Sigma_{i,j}$$

3.3 Inference for Continuous Variables

We will show an inference with continuous variables in a Gaussian network in which the value of each variable is a linear function of the values of its parents. That is, if PA_X is the set of parents of X, then

$$x = w_X + \sum_{Z \in \mathrm{PA}_X} b_{XZ} z,$$

where w_X has density function $\mathcal{N}\left(\mathrm{w}, \sigma^2_{\mathrm{W_X}}\right)$, and W_X is independent of each Z. The variable w_X represents the uncertainty in X's value given values of X's parents. For each root X, we specify its density function $\mathcal{N}(x; \mu_X, \sigma_X^2)$. A density function equal to $\mathcal{N}(x; \mu_X, 0)$ means we know the root's value, while a density function equal to $\mathcal{N}(x; 0, \infty)$ means complete uncertainty as to the root's value. Note that $\sigma^2_{W_X}$ is the variance of X conditional on values of its parents. So, the conditional density function of X is

$$\rho(x|pa_X) = \mathcal{N}\left(x, \sum_{Z\in \mathrm{PA}_X} b_{XZ}\, z\sigma^2_{W\,X}\right).$$

When an infinite variance is used in an expression, we take the limit of the expression containing the infinite variance. For example, if $\sigma^2 - \infty$ and σ^2 appears in an expression, we take the limit as σ^2 approaches ∞ of the expression. All infinite variances represent the same limit. That is, if we specify $\mathcal{N}(x; 0, \infty)$ and $\mathcal{N}(y; 0, \infty)$, in both cases ∞ represents a variable t in an expression for which we take the limit as $t \rightarrow \infty$ of the expression. The assumption is that our uncertainty as to the value of X is exactly the same as our uncertainty as to the value of Y. The formula for X is as follows:

$$x = w_X + \sum_{Z\in \mathrm{PA}_X} b_{XZ} z$$

4. CASE STUDY OF US AIRLINE NETWORK

4.1 Data Sources

Our case study primarily relied on the Airline On-Time Performance Database obtained from the Bureau of Transportation Statistics. This database comprises flight-level data submitted by US-certified air carriers that generate at least one percent of domestic scheduled passenger revenues. It provides information on scheduled and actual departure and arrival times for most commercial flights operating in US airspace, including on-time data for non-stop domestic flights operated by major US airlines. The Office of Airline Information defines a major carrier as a US-based airline that generates over $1 billion in revenue during a fiscal year. They regularly issue directives for accounting and reporting purposes, which specify the airline groupings for the following calendar year that each airline must comply with.

To preprocess the data and make the set of data more manageable, we concentrate on the period between June and November 2022 and limit our analysis to nine major airlines. These airlines operate the majority of scheduled domestic flights and transport most passengers in a daily fashion. Furthermore, airlines vary in the number of hubs they utilize, their geographic location, the density of their routes, and the diversity of aircraft they employ. The goal of preprocessing is to establish a connection between these network characteristics and how delays behave across the flight network on a particular day.

An example of a routing schedule is illustrated in Table 2. In total, about one million samples were collected from routes, and the collected data was analyzed to produce arrival and departure time distributions for each flight. Additionally, the likelihood of various delay causes at each airport was determined.

Table 2. The Case Study Routing and Its Schedule

Flight number	Origin	Destination	Scheduled time of departure	Actual time of departure	Scheduled time of arrival	Actual time of arrival	Note
FLT012	C1	C	07:35	07:39	09:10	09:25	
FLT013	A	B	08:35	08:30	09:15	09:20	
FLT015	A	S	10:25	10:24	11:30	11:50	
FLT017	S2	A	12:20	12:25	14:00	14:14	
FLT019	C2	B	17:10	-	20:10	-	Canceled
FLT022	B	T	19:10	19:10	21:00	21:15	

The study assumes that flight delays on a particular route were the result of multiple factors. In this research, four primary categories of delay sources were considered: carrier, extreme Weather, NAS, and security. Carrier delays often stem from issues within an airline's control, such as maintenance issues, crew problems, cabin cleaning, fueling and baggage loading. Extreme weather delays occur when aircraft operations are suspended due to severe weather conditions like hurricanes, blizzards, lightning storms, or tornadoes. These conditions can induce dangerous turbulence, posing risks to the flight crew and passengers. The term "National Aviation System" encompasses various situations that can disrupt flight schedules, including airport operations, moderate weather conditions, high air traffic volume, and air traffic control setbacks. Among all types of flight delays, security delays are the most critical, often resulting from terminal or concourse evacuations, security breaches onboard an aircraft, lengthy queues at screening checkpoints, or faulty screening equipment. The percentage of the four categories of delay sources is illustrated in

Figure **2**.

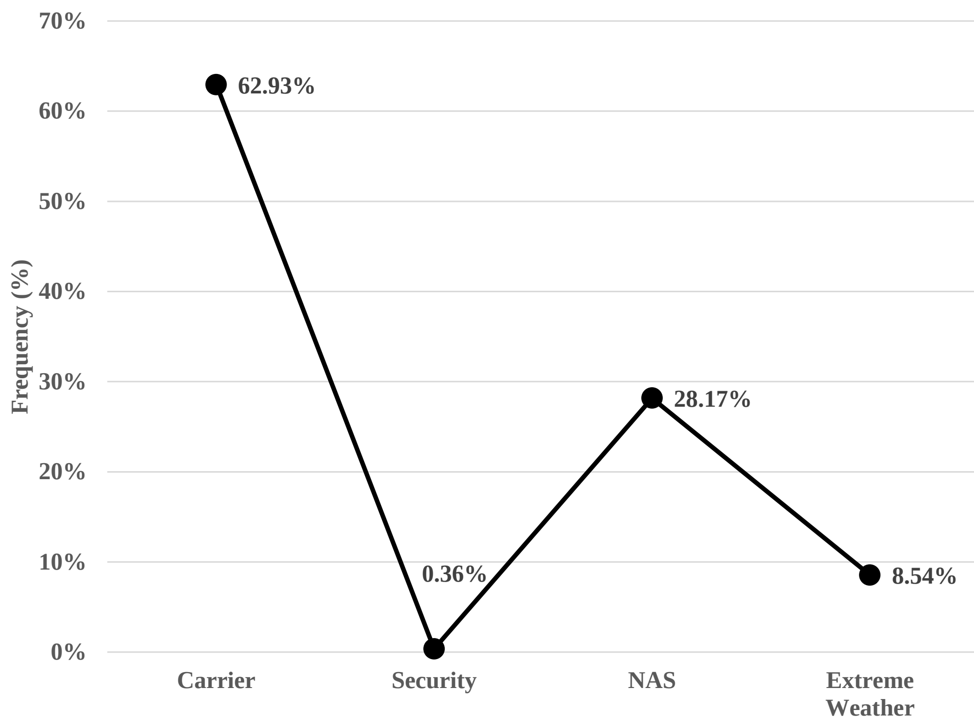

Figure 2. Categories of Delay Causes

4.2 Descriptive Statistics of Delay Causes

For turnarounds that took place at the same airport but at different times, disruption probabilities were calculated based on the scheduled time of each flight. Consequently, there were unique turnaround disruption profiles for MCO. These profiles reflect the on-time performance and efficiency of individual flights on operation at different airports. The contribution of delay causes at four different airports (ATL, ORD, MCO, and MSP) during one day is compared in Figure 3. Flights at ATL tended to have a higher likelihood of NAS delays than flights at other airports because the airport represents the hub airport in the airline network. Air carrier delays at ORD showed a lower chance of occurrence; a higher chance of on-time arrivals from other airports. This pattern is common in airports where many inbound aircraft are reported. In this case, ORD has many inbound aircraft that have departed from ATL. As a flight plan goes on, delays may propagate in the network and cause a pattern for a higher chance of propagated delays compared to other airports. This pattern is also universal in the flight operations of airline networks.

In Figure 4, when comparing air carrier performance during peak hours at the four airports, we observed that operations at MCO and MSP were more stable (with a higher chance of having on-time flights). Because ATL and ORD serve as hub airports on the airline network, more airline personnel are scheduled during peak hours. There are many outbound aircraft at the hub network, so that the hub airport during peak hours is overflowing with departing flights. Because of air traffic control coordinating aircraft at an apron, we can observe the occurrence of more NAS delays at hub airports (ATL and ORD).

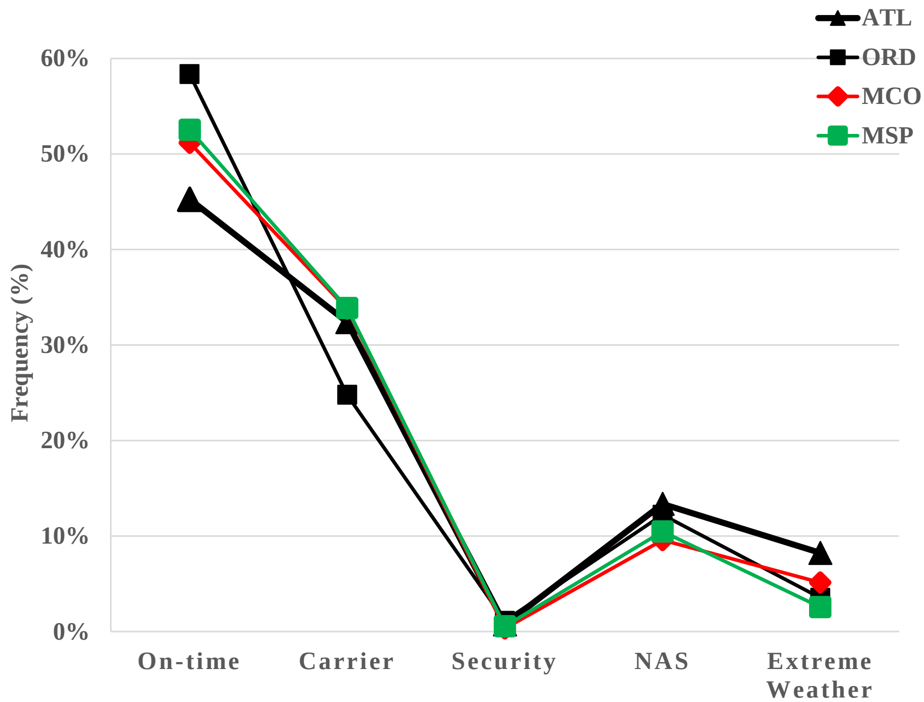

Figure 3. Categories of Delay Causes at Different Airports

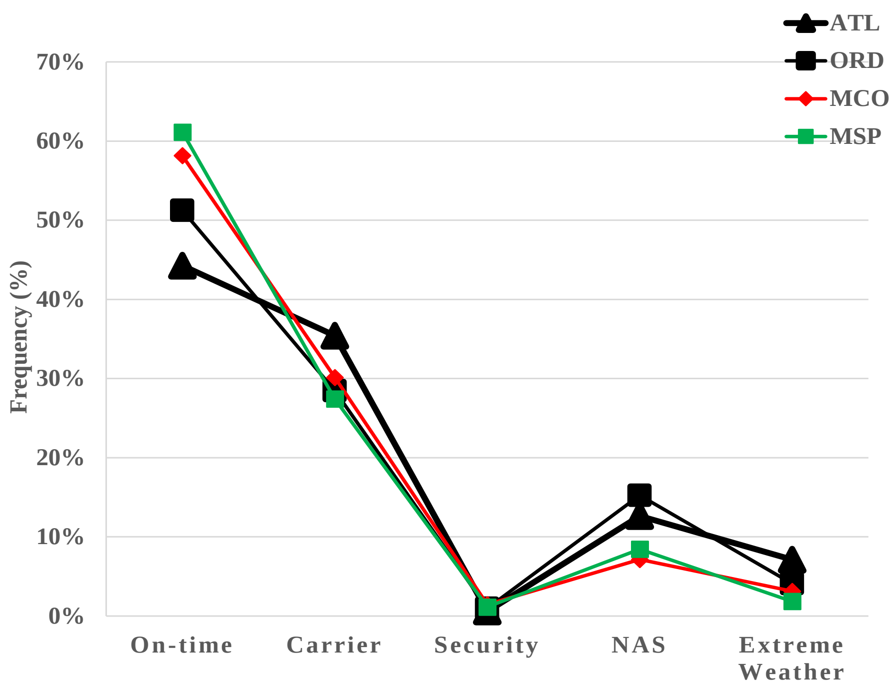

Figure 4. Categories of Delay Causes at Different Airports During Peak Hours

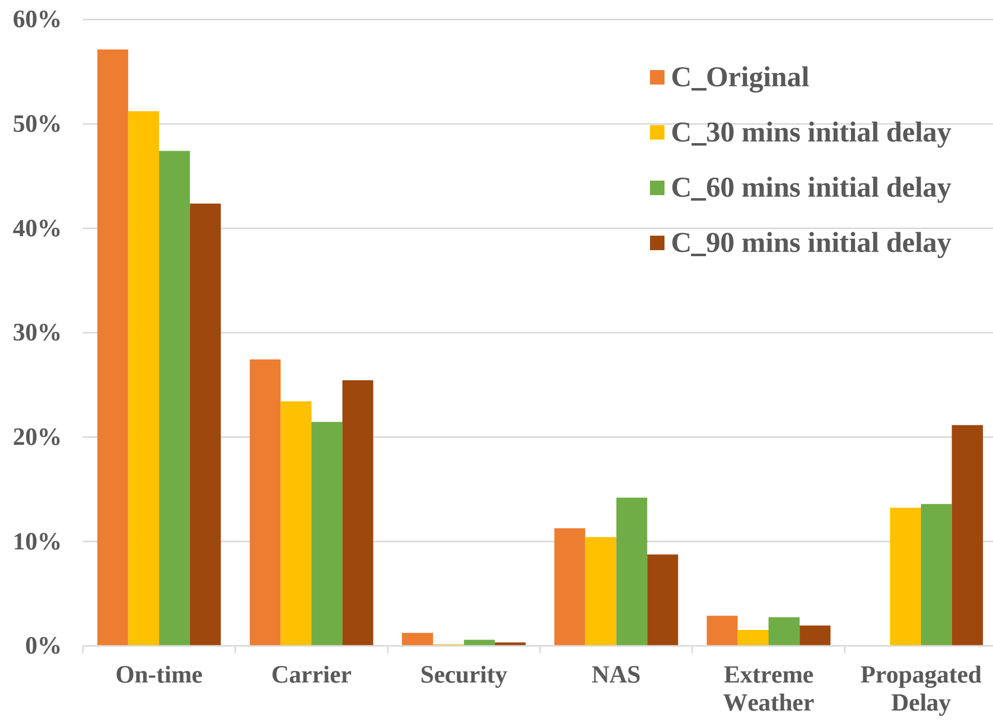

Figure 5. Probability Profiles of Delay (FLT002 at MCO)

5. RESULTS AND DISCUSSIONS

The Gaussian network was developed using a GeNIe Modeler (BayesFusion, 2017). GeNIe software has the capability of generating the conditional probability for a probabilistic graphical model, given that there is suitable data for learning. However, the software's capacity to infer continuous variables is limited, and hence, it cannot calculate every distribution of delay profiles. Thus, using Python packages, we could effectively estimate the likelihood of posterior delay.

5.1 Delay Causes and Inference using GN

The most significant advantage of the GN model is the ability to estimate delay distribution using historical data. Hence, we conducted a series of scenario studies to examine how initial delays contribute to delay propagation. For this case study, we selected FLT002, scheduled to turn around at MCO. MCO serves as a spoke airport in an airline network, which takes many inbound aircraft from ORD. We compared the original aircraft turnaround performance with the inferred delay distribution profiles (expectations) of delay scenarios with an initial delay of 30, 60, and 90 minutes, respectively, in Figure 5.

Figure 5 shows the difference between the original delay and expectations when initial delays (30, 60, 90 minutes) occur. Moreover, by inference in the Gaussian network, expectations of delay propagation are calculated in each scenario. Although the initial delay lengthens from 30 to 90 minutes, we can see that security and extreme weather cannot contribute to a portion of the delay. For 30-minute and 60-minute initial delays for FLT002, the probabilities of delays due to carrier decrease. However, NAS delays increase with respect to the initial delays. This observation reflects the fact that the more delay occurrence of inbound delays, the more air traffic control is in the NAS system in the airline network. In particular, for a 90-minute initial delay, the probability of NAS delays decreased. For excessive initial delay of inbound aircraft, the influence of air traffic control diminishes, which means that the effect of delay propagation impacts on the departure flight magnificently.

To compare the effect of the delay propagation during peak time, we set another numerical experiment. The original delay profiles of MCO in normal (denoted by N) and in peak time (denoted by Peak) were provided in Figure 6. We can observe that the delay profiles at different operating times at MCO are similar with respect to the portion of delay causes. However, when there are 60-minute initial delays, the inferred delay cause distribution showed significantly different patterns during peak hours at MCO, as shown in Figure 7. It reveals that a 60-minute delay was considerably more likely to generate delay propagation. Moreover, air carrier delay was affected in normal operating times due to maintenance of late inbound aircraft. For peak hours, the airport was not available for accepting every inbound aircraft, and delay propagation almost doubled that of probability in normal operating time.

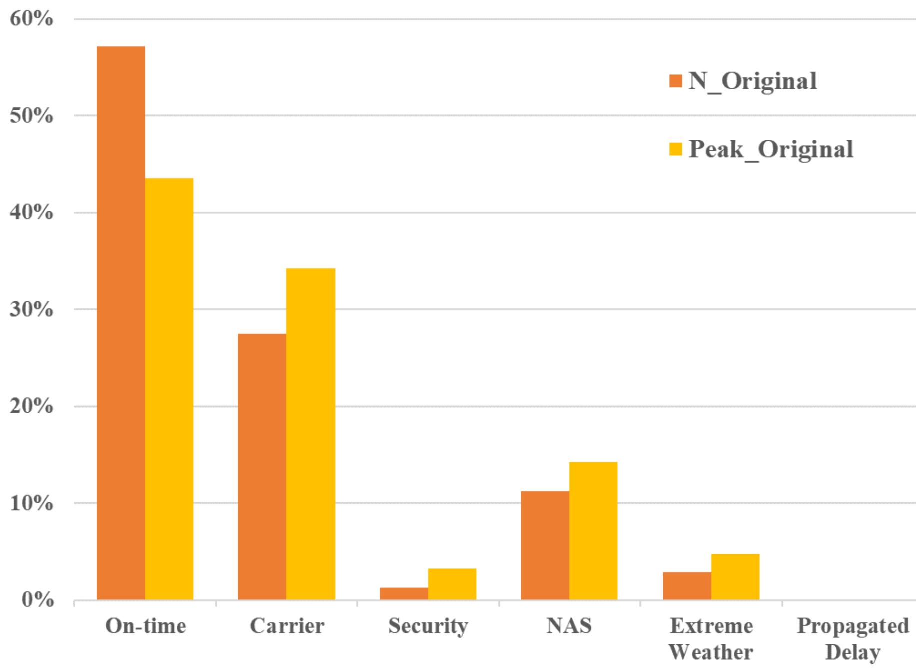

Figure 6. Categories of Delay Causes in Normal (N) and Peak (Peak) times at MCO

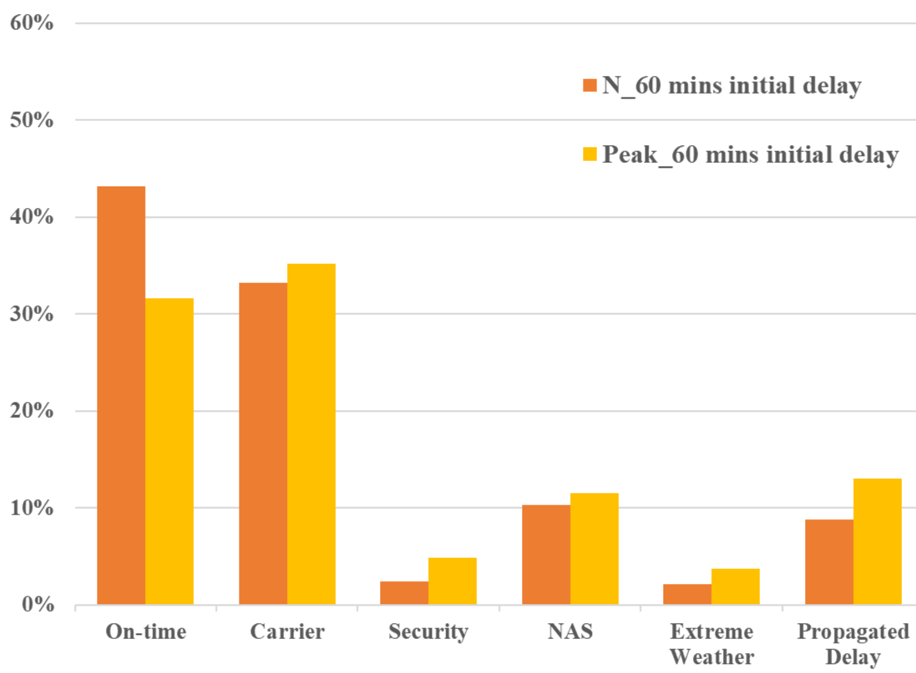

Figure 7. Comparison of Delay Profiles with a 60-minute Initial Delay at MCO in N and Peak

Because the likelihood of contributing factors with initial delay may differ, it is worth mentioning that a probability-based model, for example, the proposed GN model in this paper, can be highly effective in capturing the delay propagation effect in airline data analytics. Based on our case study, an airline should focus on reducing potential delay propagation for normal operations at MCO. In particular, the focus should shift to alleviating NAS delays to minimize delays during peak hours. The conventional approach, such as descriptive statistics in data analytics, cannot reveal hidden effects on the propagation of delay factors and initial delays.

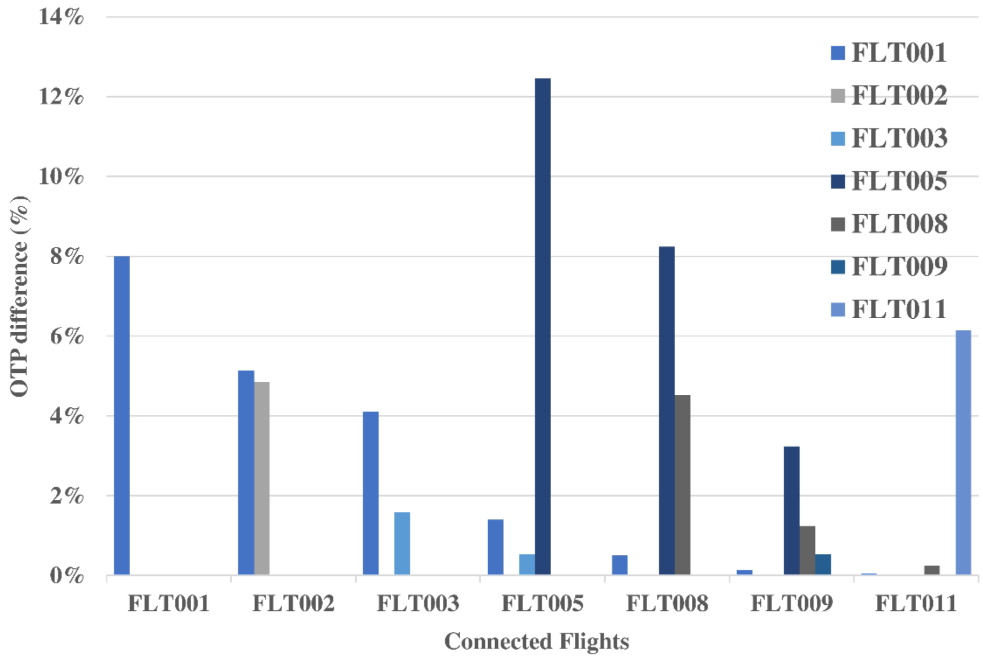

Figure 8. Propagation of OTP Improvement by Sequentially Adding a 15-minute Buffer to Each Flight

5.2 Heterogeneous and Non-IID Delay on OTP Propagation

To show the influence of heterogeneous and non-IID delay distributions on delay propagations, we added a 15-minute buffer to the first flights in the same routing. We then estimated the posterior OTP of all subsequent flights in the routing. This buffer allowed us to observe the delay and OTP propagation effects while accounting for the heterogeneous and non-IID nature of rescheduling in airline routings. Next, we sequentially added a 15-minute buffer to the subsequent flights in the routing while maintaining the schedule for other flights. This buffer allowed us to observe the delay and OTP propagation effects while accounting for the heterogeneous and non-IID nature of delay in airline routings. After these actions, we calculated the difference between the expected OTP and the original OTP in Figure 8.

The results in Figure 8 indicate that adding the buffer to the starting flight in the routing has OTP propagation on subsequent flights. The amount of OTP improvements of subsequent flights is labeled in Figure 8 when adding a buffer to the first flight in the routing. Specifically, OTP improvements of each flight affected by the same starting flight are color-coded with the same hue. In general, adding a 15-minute buffer significantly improved OTP at FLT001, FLT005, and FLT011 with more than a 6 percent increase. These flights can boost the OTP improvement of subsequent flights with an additional buffer time. FLT001 is a crucial flight for OTP improvements on the routing. However, Figure 8 also reveals the diminishing effects of OTP propagation. We can see the effect of OTP improvement is gradually decreasing when adding a 15-minute buffer to FLT001, FLT005, and FLT008.

Moreover, adding a 15-minute buffer to FLT002 did not achieve OTP improvement for all subsequent flights in the same routing because there was enough time to compensate for previous delays. This can explain the diminished OTP improvement at FLT002 when adding a 15-minute buffer to FLT001. We observed similar effects for other flights (e.g., FLT009) in Figure 8.

5.3 Comparison between IID and non-IID Profiles on Delay Propagation by Adding Buffers

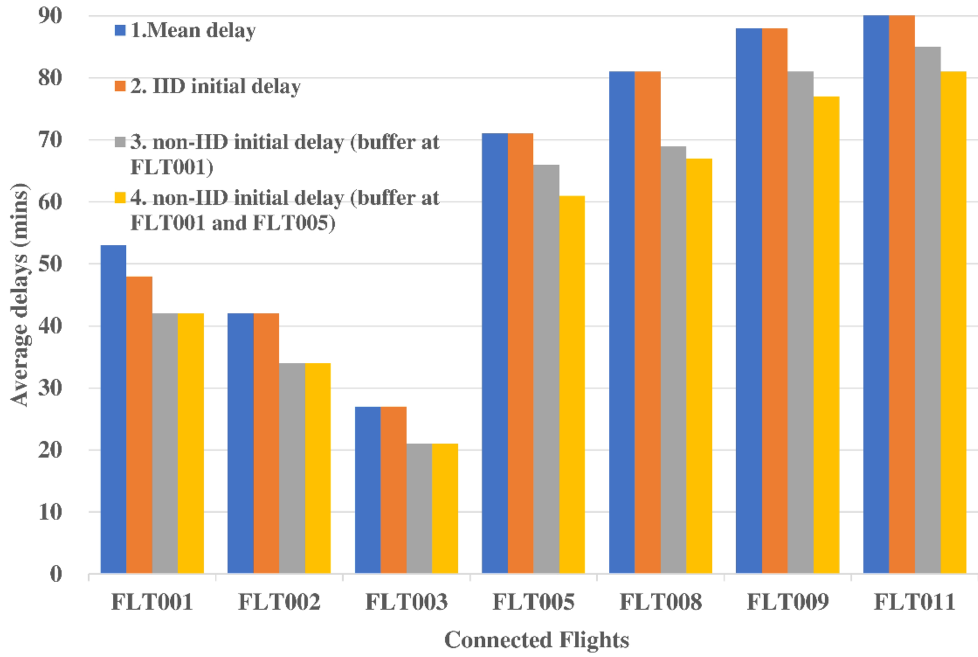

Figure 9. Potential OTP Propagation Effects with Different Scenarios

To compare the effects of IID and non-IID flight time profiles on adding buffers and delay/OTP propagation, we conducted a series of scenario analyses. Figure 9 illustrates the comparison of the following four scenarios:

1. The original delay profiles (Mean delay)
2. Adding a 15-minute buffer to FLT001 and assuming IID initial delays
3. Adding a 15-minute buffer to FLT001 and assuming non-IID initial delays using the GN model
4. Adding a 15-minute buffer to both FLT001 and FLT005, assuming non-IID initial delays using the GN model

Figure 9 shows that the assumption of IID (Case 2) had less effect of delay propagation compared to the current mean delay. For non-IID initial delay with adding buffers, the effect of delay propagation was more substantial than the effect in assuming IID initial delay. In other words, assumptions of non-IID initial delay have detailed explanations in the Gaussian network model. Adding buffers to a schedule did not reduce delays proportionally. Nevertheless, the OTP propagation persisted in subsequent flights on routing, and we could observe this effect in Cases 3 and 4. Moreover, delays were further reduced when an extra buffer was added to FLT005.

Using the GN, we have shown how IID initial delay models overestimated the effects of adding flight buffers without considering the non-IID initial delay distribution, leading to an underestimation of the posterior delay distribution. This led to insufficient comprehension of the required buffer times for robust airline scheduling. Utilizing the GN, a probabilistic model considering delay profiles as continuous variables reflected the effects of non-IID initial delay distribution for routing in an airline network.

In conclusion, we discovered that the OTP improvement achieved by adding a buffer had different impacts on flights, depending on flight time profiles. For the initial non-IID delay profiles, the effect of OTP propagation decreases in subsequent flights on the same routing, and the decrement is different at each flight. Therefore, the case study airline should assess the efficiency of adding buffers and strategically place buffer in operations. This strategy can improve the robustness of the airline schedule and increase the ability to respond to disruptions.

5.4 Identifying Weak Links in an Airline Network

Using a GN, we can identify weak links in the airline network. In Section 3.2, using inference, we can estimate the conditional probability distribution of each node in a network. For identifying weak links, we calculated the posterior probability distribution of each airport in the case study of Section 5.3.

In Table 3, we compare the original mean delay and posterior distributions assuming IID initial delay and non-IID initial delay at each airport. The standard deviation is a measure of the level of uncertainty in a probability distribution. When considering the IID initial delay, the standard deviation of ORD is greater than that of ATL, even though the mean delay is less. For the case study network, both are hub airports that connect other airports within the network. During turnaround operations, ORD experiences a more fluctuating probability of disruptions in the airport as its high standard deviation. However, assuming a non-IID initial delay (more realistic), Airports C and E have a high standard deviation. This suggests that Airports C and E are not hubs but rather vulnerable nodes in the airline network. Furthermore, airports with greater standard deviation have insufficient buffer times for turnaround operations and have the opportunity for improving efficiency.

Table 3. Posterior Distribution of Each Airport in the Case Study

Airport	Original mean delay	IID initial delay	non-IID initial delay
ATL	75.12	$N(100.24,25.38^2)$	$N(83.49,30.59^2)$
ORD	103.51	$N(86.32,68.12^2)$	$N(120.61,73.52^2)$
MCO	69.14	$N(83.20,20.75^2)$	$N(92.54,62.75^2)$
MSP	87.12	$N(73.08,35.21^2)$	$N(83.14,51.65^2)$

5.5 Managerial Implication

First, our case study showed that past efforts to improve airline scheduling by adjusting flight times only assumed that flight delay times were IID. However, we explicitly found that both the historical data and inference of propagated delay can impact the robustness of flight operation. Overlooking the non-IID nature of flight delay patterns may cause an overestimation of on-time performance (OTP) propagation, leading to insufficient schedule buffers.

More specifically, a probability-based approach to model delay propagation can significantly improve schedule robustness and enhance future operations in an airline network. Utilizing the GN model, we demonstrated how a probability-based model could identify ‘weak links’ in a network, referring to a high standard deviation of posterior probability distribution. These links suffer significant operational fluctuation and can accommodate extra buffer times. With the capability of GN, we were able to infer the following: (1) certain behaviors of delay propagations; (2) OTP after adding extra buffers; (3) operation improvements; and (4) delay distribution profiles after propagation. Previous studies have mostly used descriptive statistics and a less explainable model, which cannot ease the comprehension of propagated delay in an airline network. In this paper, using a Gaussian network, we can calculate the posterior probability distribution of delay and gain the capability to capture the vulnerability of each node in the network.

Furthermore, the probability-based model can be fundamental to improving schedule optimization in the future. Existing literature commonly assumed IID profiles for the initial delay in an embedded calculation in a linear program (Lan *et al.*, 2006; AhmadBeygi *et al.*, 2008). The overestimation of OTP propagation confers the belief that incorporating buffer time to turnaround operations is a waste of resources. However, the proposed GN model can improve the effectiveness of estimation in schedule optimization models, allowing for strategic allocation of valuable airline personnel, thereby reducing scheduling costs while increasing OTP expectations in actual operations.

Consequently, a probability-based delay model can assist in pinpointing the causes of delay and weak links in an airline network. The advantage of a GN evidently indicated its ability to infer the posterior probability distribution of delay in post-operation analysis. As previously demonstrated, the GN model can be used to determine which factors have a higher probability of disruptions. These factors may include the probability distribution of inbound aircraft delay or sources of delay at an airport, such as carrier, NAS control, security, and weather. Scenario analyses can be conducted for a certain routing to identify the effect of delay propagation. This exploration can estimate propagated delays as well as delays due to specific ground operations at certain airports, leading to improvement of robustness of flight scheduling.

6. CONCLUSIONS

In this paper, we highlighted the importance of considering the continuous nature of flight delays and operational uncertainties with real flight operation data. Historical data analyses showed that the delay distribution of a flight could be influenced by various factors such as air carrier, security, national airspace system, or weather. However, delays are propagated with connected resources in an airline network. By the probability-based model or Gaussian network, we clearly showed how delays propagate in the network and demonstrated the mechanism of delay propagation.

Using the GN model, we revealed how an airline could use a probability-based model in capturing the delay propagation and its impact on an airline network by numerical analyses. Airline operations often experience operational disruptions daily. This frequency helped us infer probabilities of particular delay causes and delay propagation by allowing us to apply the proposed model through real-world historical data. The information and insight derived from the experiment can help airlines in future scheduling and also enhance the efficiency of improving their ability to adequately respond to disruptions.

Through various scenario studies, the results showed that the GN model can capture the effect of delay propagation more precisely than previous studies. Moreover, propagation of delays also applies to OTP propagation. In other words, adding buffer of a particular flight affects the OTP of its subsequent flights in the same service route. With the help in estimating the probability distribution of each node by the GN model, we can distinctly identify weak links in an airline network. Airports with a high standard deviation of posterior probability distribution have insufficient buffer times for turnaround operations. Considering the non-IID initial delay, we can pinpoint hidden weak links in an airline network and determine where to use additional resources to prevent propagated delays.

For future research, considering parameter learning of probabilistic graphical models might extend the scope of an airline network. Parameter learning is the process of using data to learn the distribution of a probabilistic graphical model when some data are insufficient in a network. We only focused on the sub-network in this study. However, expanding the study to the entire airline network or international network, which has incomplete data, might be an interesting research problem. Optimization problems in conjunction with the posterior probability distribution of delay are research issues derived from this paper. In mitigating airport congestion, optimization has been used to find the optimal solution for additional aircraft, network connectivity, etc. With the estimation of delay distribution at certain airports, researchers can build more efficient optimization models. We believe that the inference of delay distribution in an airline network proposed in this paper can be used as uncertainty parameters in optimization models such as airline crew pairing problems (Radman and Eshghi, 2023) and aircraft maintenance operation problems (Abdulmalek and Savsar, 2022).

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