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Measuring the resilience of airlines operation networks

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***Abstract*—Incorporating resilience into the airline's network planning and assessment prepares the airline for disruptive events. To measure and improve the resilience of an airline's network, quantitative or qualitative metrics are required. In this work, we first propose a novel modeling approach by the leverage of temporal network theory to analyze the resilience of an airline's operation network. A two-layer network is generated from an airline's scheduling data and operation data using the proposed approach. By taking interactions of the network's components and time-attributed information into consideration, the instantaneous network efficiency is defined to measure the performance of the network. We then develop a new resilience metric, average efficiency loss ratio (*AELR*), for airline's operation network based on the instantaneous network efficiency. The proposed approach and metric are applied to four major U.S. airlines' networks, including AA, UA, DL and WN using a publicly accessible dataset. Results show that Delta airlines has the highest resilience, but is more susceptible to severe flight delay and cancellation. The flight delay and cancellation effects on Southwest and American airlines operation network are similar. Our work may open an avenue for managing the resilience of airline's networks.**

Keywords- airline operation; air transport network; performance measurement; network resilience

I. INTRODUCTION

Air transport is vital for human and freight mobility. According to World Air Transport Statistics published by the International Air Transportation Association (IATA), more than 4.4 billion passengers were serviced by airlines globally in 2018[1]. Like other transport systems, the air transport system (ATS) is also under the threat of various types of disruptive events, for example, extreme weather, volcanic eruption, equipment breakdown, and terrorist attack[2]. These disruptions usually lead to unexpected and costly consequences because of the interactions of elements within the ATS and the interdependence among other systems[3]. Traditional risk assessment relies on the combination of probability and magnitude of consequences and attempts to predict and avoid failure[4]. However, it is widely recognized that many important events in the life cycle of a complex system cannot be foreseen in advance[5]. For rare events, insufficient historical data could be used. This recognition calls attention to the ability of systems to recover from disruptions along with predicting and preventing, that is, the system's resilience.

According to the National Academy of Sciences, resilience is the ability of the system to "plan and prepare for, absorb, respond to, and recover from disasters and adapt to new conditions"[6]. A commonly adopted definition characterizes resilience with four properties, i.e., Robustness, Redundancy, Resourcefulness, and the Rapidity of recovery, which is also referred to as 4Rs[7]. Robustness and redundancy account for the ability to resist the effects of disruptive events, while resourcefulness and rapidity are used to describe the ability to recover from disruptions. The system's resilience and disruptive events that happened on it determine the system's performance. Hence, a typical resilience analyzing framework observes how a system's performance changes in the dynamic process after a perturbation[5].

Given the complex nature of the ATS, many researchers applied network theory to system modeling and resilience analysis[8]. An ATS consists of several sub-systems, including airlines, air traffic control units, airports, contributing to the multilayer structure of the air transport network (ATN)[9]. Recently, with the rapid development of high-speed rail, the combined effects of multiple transport modes have attracted attention from both industry and academia[10]. A complex network offers a relatively simple but informative approach by modeling the system's components as nodes and interactions between components as links. Network models make it possible to study dynamic behaviors between different layers and to evaluate the resilience of the whole multilayered system.

There are extensive discussions on the topological structure and robustness of different layers of ATN[11], ranging from airport networks[12], air route networks[13][14], airline networks[15], to sector networks[9]. These studies commonly used the strategies of randomly removing node(s) or removing targeted node(s) to simulate disruptive events[16]. Network connectivity-based metrics, including giant component size, network efficiency and average path length, are proposed to assess robustness. In a typical airport network, nodes represent the airports, and an edge will be added between two nodes if there is at least one direct flight between the corresponding airports[12]. Flight time, departure time, arrival time, turn-around time, and other time-attributed information are aggregated or discarded in the network modeling process[8]. However, the ATS is a time-varying system, which means that the network connectivity and flows on edges change over time.

The static network modeling methods, which disregard time-stamped information in the operational data, are limited in capturing dynamic processes in the ATS[9]. In practice, disruptive events usually result in the service capacity decline of the components rather than a subsystem failure[17]. Obviously, the node removal simulation deviates from the actual operation. Wang et al. developed a simulation model to study the resilience of the Chinese airport network when given airports operate at degraded capacity rather than completely shutting down[17]. However, their findings are not verified by real-world operational data.

Some researchers employ conventional performance indicators, including punctuality and average arrival delay, to measure resilience[18]. However, the interacting components of an ATS produce nonlinearity, feedback loops, and other properties, which leads to the overall system-level performance more than a simple summation of the individual-level[19]. These statistical indicators that ignore differences and interactions between individuals are hard to capture the actual system's performance. There are also some works related to dynamics on ATS. Kafle and Zou proposed an analytical-econometric approach to study how propagated and newly formed delays are absorbed by the buffer[20]. Pyrgiotis et al. developed an Approximate Network Delays model to study the delay propagation within a major airport network[21]. These models and methods have different applicable scenarios and objects. It is important to develop a framework that can be used in system-wide resilience evaluation and optimization.

This paper aims at developing a novel resilience measuring metric by taking the network interaction effect and time-varying operation into consideration. We apply the temporal network theory to model airline networks considering flight schedules and actual operational data. Such network is named as airline operation network (AON) to distinguish from the current static airline network. Rather than aggregating flights connecting the same OD pair on the same edge, AON can preserve the flight connecting information and better model the operational dynamics on the top of the structure by adding a time dimension. Then a metric is proposed to measure the resilience of AON. Based on the proposed resilience metric, we also carry out an empirical study using historical data to analyze the resilience of four major airlines in the U.S. Flights are the media of connections between nodes; in other words, the dynamic behaviors on ATN depend on the flight flows. Generally, airlines are responsible for flight scheduling[22]. When disruptive events occur, the airlines' operation control group will respond by taking cancellation, flight swap, ferrying, and other tactics. These behaviors influence the dynamics of the whole ATN. Therefore, AON can be considered as the fundamental layer of ATN. Studying the resilience of AON will pave the way for understanding the resilience of the whole ATN and will support optimizing system performance.

The remainder of this paper is organized as follows. Section II describes the airline operation network's modeling method based on temporal network theory. In section III, we propose a metric to measure the resilience of the airline operation network. Section IV presents an empirical analysis using historical operation data. Section V gives the concluding remarks and discusses future studies.

II. MODELING THE AIRLINE OPERATION NETWORK

A. *Data Source and Processing*

We obtain flight schedule and actual operation data from the Airline On-Time Performance Data published by the Bureau of Transportation Statistics (BTS). This dataset provides detailed information on the individual, domestic flights operated by major carriers. This information includes origin, destination, airline, scheduled departure time (STD), scheduled arrival time (STA), actual departure time (ATD), actual arrival time (ATA), and cancellation state of each flight. The data from March 26, 2017, to March 24, 2018, is selected to analyze in this paper. Both summer and winter seasons are considered. We focus on four major airlines: American Airlines (AA), United Airlines (UA), Delta Airlines (DL), and Southwest Airlines (WN). Southwest is included, allowing us to compare between point-to-point and hub-and-spoke structures. Since all the time-stamped data is recorded using local time, all these data are converted according to the Eastern Standard Time (EST). Also, we exclude flights with origin or destination in Alaska, Hawaii, and other overseas territories.

B. *Modeling the Airline Operation Network*

The airline's flight schedule development process comprises four phases[23], i.e., *market service planning, schedule generation, resource allocation, and schedule execution*. According to different phases, the airline operation network can be further divided into two layers: the scheduling layer and the execution layer, corresponding to the second and fourth phases.

We proposed a temporal network-based approach to construct the airline operation network. A temporal network consists of nodes and a set of interaction events between every pair of nodes[24]. Each event can be represented by a triple (u, v, t), which is referred to as a contact from u to v at time t. If a transmission is not instantaneous, the duration δt of this event should be involved.

We use a graph $G^T = (N, F^T)$ to represent the operation network of an airline, where N is the set of airport nodes, F^T is the set of direct flights between airports, and T is the observation period. Without loss of generality, assuming the observation begins at 0, the observation period is $[0, T]$. Set N is static, and the elements are all the airports under operation in that season. Flight set F^T records the trace of interactions between airports. Each flight $f = (i, j, t^D, \delta t)$ carries information including the origin airport i, destination airport j, departure time t^D and flight time δt. The arrival time, thus, can be calculated as $t^D + \delta t$. In the scheduling layer, F^T consists of all the scheduled flights. i is the scheduled departure airport, while j is the scheduled arrival airport. t^D equals to the STD, and δt equals to the scheduled block time (SBT). In the execution layer, F^T is the set of all realized flights including delayed and diverted flights but not cancelled flights. i is the scheduled departure airport, while j is the scheduled arrival airport. t^D equals to the STD. In the execution layer, δt is the effective flight time (EFT)[22] of flight f, which can be calculated as:

$$EFT^f = ATA^f - STD^f. \tag{1}$$

Fig. 1 illustrates the comparison of EFT, SBT and actual block time (ABT). EFT can better help to capture the effect of flight delays on the connectivity efficiency between airports. In addition, flight schedule is the basis for passengers to make travel plans and airlines to allocate resources[23]. While flight f departed at ATD, for passengers who took this flight, their journey actually started at STD and finished at ATA. For the aircraft executing this flight, its actual occupation time is EFT rather than ABT. For these reasons, we select EFT to be the flight time for flights in the execution layer. With respect to diverted flights, ATA is the actual time when flight f arrived at scheduled destination airport. If flight f did not arrive at its scheduled destination, then it will be considered as cancelled.

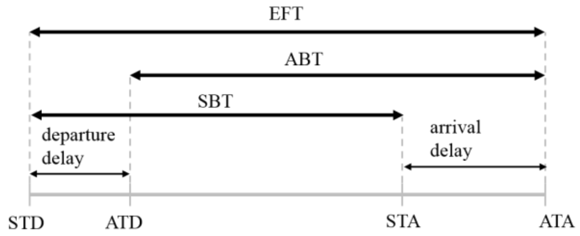

Figure 1. Comparison of EFT, SBT and ABT. Adapted from Ref. [22]

C. Reachability and Shortest Path

In an AON, an airport k could be reached from airport i by direct flights or a sequence of flights. For the latter case, this sequence of flights should satisfy the time-ordered connecting constraint. Consider two flights: $f_1 = (i, j, t^D{}_1, \delta t_1)$ and $f_2 = (j, k, t^D{}_2, \delta t_2)$. The prerequisite for establishing a path from airport i to airport k through these two flights is: $t^D{}_1 + \delta t_1 + \tau^{TA} \leq t^D{}_2$. τ^{TA} is the minimum turnaround time. That is, f_2 should depart after f_1 arriving at j plus the turnaround time. We set a lower and an upper limit of waiting interval between two flights at airport j. Considering the minimum turnaround time of aircrafts and minimum passenger transfer time, we use $\underline{t_w}$ to be the lower limit. If two flights have a long waiting interval, it will be inefficient to regard them to be connected. Thus, the upper limit $\overline{t_w}$ is introduced. Then the constraint that flight f_1 and f_2 can be connected is:

$$t^D{}_1 + \delta t_1 + \underline{t_w} \leq t^D{}_2 \leq t^D{}_1 + \delta t_1 + \overline{t_w}. \quad (2)$$

In previous works, researchers usually use average flight time as the edges' weights in static network. Fig.2 exhibits the connections in temporal and static networks. Since a static network cannot capture the connecting constraint, a path always exists from airport i to k passing through airport j.

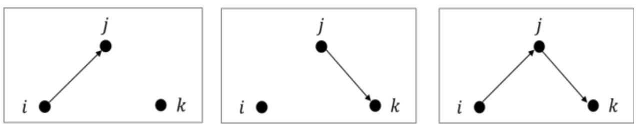

Figure 2. Paths in temporal (left and middle) and static networks (right).

Note that there is a turnaround time or transfer time at airport j, the actual travel time (ATT) from airport i to k should be $t^D{}_2 + \delta t_2 - t^D{}_1$, not $\delta t_1 + \delta t_2$. If the path from airport i to k are connected by a sequence of flights $SF_{ik} = \{f_1, f_2, \dots\dots, f_n\}, n \in Z^+$, then ATT can be obtained by:

$$ATT_{ik} = t^D{}_n + \delta t_n - t^D{}_1 \quad (3)$$

Static networks, which ignore time-ordered connecting constraint and ground time, will overestimate the network's connectivity and mask the dynamics behaviors.

In AON, shortest paths change with time. We define τ_{ij}^t as the shortest path length from airport i to j at time t. τ_{ij}^t can be obtained by:

$$\tau_{ij}^t = ATT_{ij}^t + t^D{}_1 - t \quad (t^D{}_1 \geq t). \quad (4)$$

This shortest path is established by SF_{ij}^t, which has the earliest arrival time at airport j. It should be noted that the start time $t^D{}_1$ of SF_{ij}^t cannot be earlier than t. ATT_{ij}^t is the actual travel time of this flight sequence, and $t^D{}_1 - t$ is the waiting time before the start of this trip.

III. RESILIENCE METICS

A. Generic Resilience Evaluation Method

The elastic modulus of a material is defined as the slope of its stress–strain curve in the elastic deformation region. Similarly, resilience of a system can be measured by its performance change under the applied perturbations[5]. Bruneau et al. proposed the "resilience triangle" [7], illustrated in Fig.3, to quantitatively evaluate resilience.

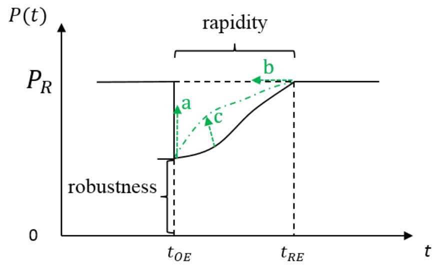

Figure 3. Illustration of the resilience tiangle. Adapted from Ref. [7]

The size of this resilience triangle simultaneously indicates robustness and rapidity of recovery, and therefore can be used to quantify the resilience:

$$RL = \int_{t_{OE}}^{t_{RE}} [P_R - P(t)]\, dt. \quad (5)$$

$P(t)$ shows how system's performance evolves. P_R denotes the performance of the reference state or desired state of the system. t_{OE} denotes the occurrence time of disruptive events, and t_{RE} is when the system returns to a stable state. The larger the area of the resilience triangle is, the worse the resilience of the system is. It can be found that (a) reducing performance degradation under perturbation, (b) increasing recovery speed, and (c) improving the profile of the performance curve during the recovery period can help to enhance system resilience[25].

This method uses system performance data to calculate resilience. It mainly has three steps:

(1) Define the system and its functions of interest: In this paper, we use AON to model airlines' operation. Airlines

provide air transport services for traveling passengers. So we regard the efficient connectivity as the function of AON.

(2) Define system performance indicators: System performance is defined as a time-varying measure to capture how well a system provides its desired function at a given time. The performance data comes from either historical records of actual operations or simulations.

(3) Calculate resilience using performance indicators: Resilience can be evaluated using the performance loss compared with thedesired state.

B. Performance Indicator

In previous researches, commonly used performance indicators to analyze resilience can be divided into two categories, i.e., conventional statistical performance indicators and static network connectivity-based metrics.

Conventional statistical performance indicators, including punctuality and average arrival delay, have been widely employed in evaluating and optimizing operations of the air transport system. The arrival delay of a flight is calculated as:

$$arr\_delay^f = ATA^f - STA^f. \quad (6)$$

In this paper, we keep the negative values for early arrivals. Punctuality indicator $A14$ is defined as the proportion of on-time arrivals to the total number of scheduled flights:

$$A14 = \frac{\sum_{f=1}^{n} O_f}{n}. \quad (7)$$

A flight is on-time if its arr_delay^f is less than 15 minutes. Let $O_f = 1$ if the flight f is on-time, and 0 otherwise. In addition to the delayed flight, we also considered cancellation. Cancel ratio is defined as the proportion of cancelled flights to total scheduled flights:

$$r_c = \frac{\sum_{f=1}^{n} C_f}{n}. \quad (8)$$

Let $C_f = 1$ if the flight f is cancelled, and 0 otherwise. We calculate the average arrival delay (minutes per flight), cancel ratio, and $A14$ of each airline for each day. Results are shown in Fig.4. The color of each node represents its $A14$ value. It can be found that a low average arrival delay and high punctuality can be achieved by sacrificing more canceled flights. Thus, a single such indicator cannot depict the actual system's performance precisely.

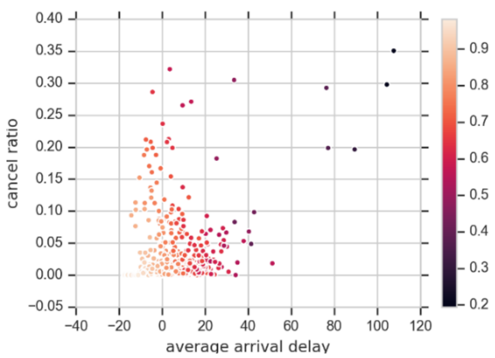

Figure 4. Average arrival delay, cancel ratio and A14

Common connectivity-based network metrics include giant component size, average path length, centrality, and algebraic connectivity[26]. Giant component size is defined as the number of nodes in the biggest connected subgraph[11]. These metrics are calculated based on static network, and have limitations in reflecting the dynamics of operation. For instance, the flight connecting information is hard to be captured by these static network metrics. Hence, we need a performance evaluation method to capture the operational dynamics and interactions of the network's components.

We develop instantaneous network efficiency E_t as the performance indicator to quantify the efficient connectivity[27][28] of AON, defined as:

$$E_t = \frac{1}{|N|(|N|-1)} \sum_{i,j \in N, i \neq j} \frac{1}{\tau_{ij}^t} \quad (9)$$

$|N|$ is the number of airports of set N. E_t measures the connectivity efficiency of the whole network at time t, and changes over time. The larger the value of E_t is, the more efficient the AON is, and the travel time between airports is shorter.

The connectivity efficiency of AON is influenced by the flight frequency and ATT of each path. Both flight delay and cancellation account for changes of E_t. Compared with conventional performance indicators, such as average arrival delay and punctuality, E_t can reflect the interactions among different components and depict performance on a system level. Since our AON modeling process takes ground time and flight connecting constraints into consideration, E_t can better reveal the actual connecting conditions of the network comparing to static network connectivity-based metrics.

C. Resilience Metric

The desired and actual state of performance should be defined in order to calculate resilience. In this paper, we employ the instantaneous network efficiency E_t^s of the scheduling layer to depict desired performance at time t. The instantaneous network efficiency E_t^e of the execution layer is applied to represent actual performance at time t. Fig.5 illustrates how E_t^s and E_t^e evolve.

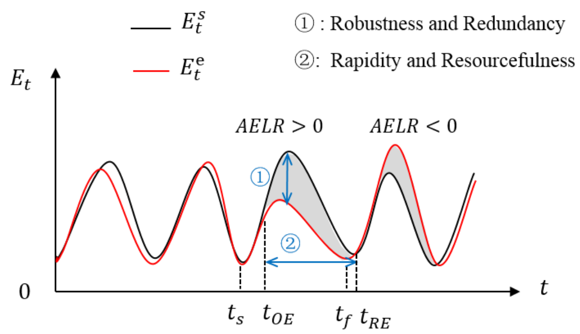

Figure 5. Evolution of network efficiency over time

t_s and t_f are the start time and end time of observation period, respectively. t_{OE} records the occurrence time of disruptions, and t_{RE} is when system returns to its desired state.

After t_{OE} , E_t^e presents a disruptive process followed by a recovery process. At first, E_t^e continuously deviates from E_t^s because of delayed and cancelled flights. Then, E_t^e gradually approaches E_t^s with the help of various recover measures. We consider the purpose of recovery as operating in consonance with schedules as much as possible. Robustness and redundancy determine the extent to which E_t^e deviates from E_t^s in a worse direction. Resourcefulness and rapidity influence the speed that E_t^e rebounds back to approach E_t^s.

By taking the idea of resilience triangle, resilience can be evaluated by performance loss. Hence, we propose the metric $AELR$ (average efficiency loss ratio) to quantify resilience:

$$AELR = \frac{1}{t_f - t_s}\frac{\int_{t_s}^{t_f} E_t^s dt - \int_{t_s}^{t_f} E_t^e dt}{\int_{t_s}^{t_f} E_t^s dt} \qquad (10)$$

$\int_{t_s}^{t_f} E_t^s dt$ represents the total desired performance according to schedules, while $\int_{t_s}^{t_f} E_t^e dt$ is the cumulative actual performance. In practice, airlines usually add buffer time in their flight schedules to account for contingencies and maintain on-time performance. Such strategy is also called schedule padding[29]. While SBT is lengthened, the likelihood of early arrival also increases[22]. It's possible that actual performance is higher than the desired one under good operation conditions. Therefore, $AELR$ can be negative. Positive $AELR$ illustrates that the desired performance is not satisfied in the actual operation. The maximum value of $AELR$ is 1, which means performance is totally lost. Under the same disruptive event, the larger the $AELR$ is, the lower the resilience of AON.

Note that the flight schedules are usually different day-to-day. Applying the average efficiency loss ratio of observing period $[t_s, t_f]$, rather than efficiency loss, allows us to compare the resilience of AON of different airlines under different observing periods.

IV. EMPIRICAL RESULTS AND DISCUSSION

This section performs an empirical analysis using the proposed method. We assume that each observation period or operation day lasts 24 hours (i.e., 1440 minutes), beginning at 06:00 am and ending at 05:59 am the next day. For each operation day, we construct the AON for four airlines, respectively. In total, there are 4*363=1452 networks, each of which has two layers (scheduling layer and execution layer). Then network efficiency E_t^s and E_t^e, as well as resilience metric $AELR$ are calculated.

A. Desired Performance

Table I summarizes the numbers of airports, routes and average daily flights in the study.

TABLE I. SUMMARIZATION OF HISTORICAL DATA

Airline	Summer Season			Winter Season		
	|N|	***Routes***	***Flights***	**|N|**	***Routes***	***Flights***
AA	96	693	2411	95	698	2337
UA	96	708	1584	94	663	1478
DL	143	849	2560	143	865	2372
WN	87	1372	3673	85	1360	3575

We first examine the desired performance of scheduling layer. Fig.6 presents the boxplot of the cumulative desired performance $\int_{t_s}^{t_f} E_t^s dt$ for all four airlines.

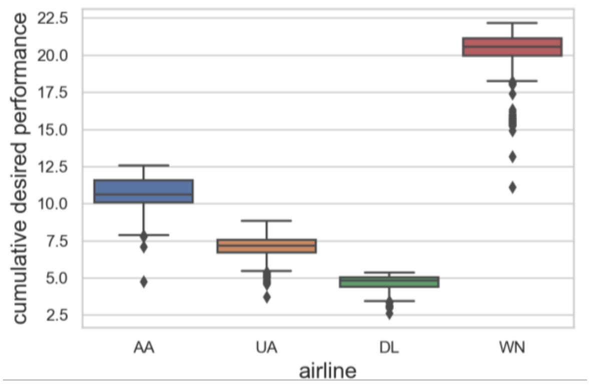

Figure 6. Boxplot of cumulative desired performance

It shows that Southwest has a significant higher desired performance than the other three airlines, which suggests that the average travel time between airports in the Southwest operation network is much shorter. It is consistent with the point-to-point (PP) structure, connecting each origin and destination via non-stop flights. With lower turnaround time and fewer intermediate stops, PP structure can reduce total travel time[30]. Combining with a higher traffic volume, the Southwest operation network finally presents high density and connectivity. Conversely, American, United, and Delta with hub-and spoke (HS) structure have relatively lower desired efficiency in their scheduling layers.

B. Resilience Analysis

The boxplot and empirical cumulative distribution function (ECDF) plot of $AELR$ are shown in Fig.7 and Fig.8 respectively.

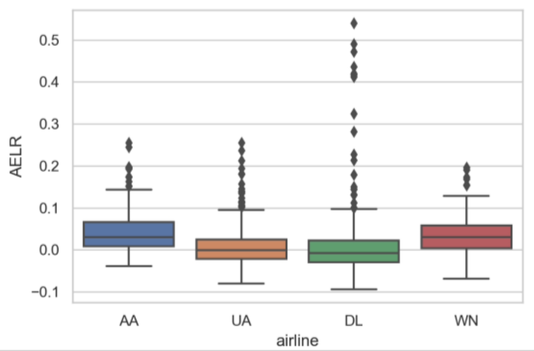

Figure 7. Boxplot of AELR.

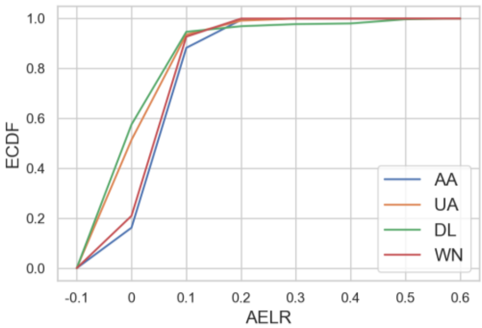

Figure 8. ECDF of AELR.

It can be found that about 90% of the operation days' $AELR$ values are less than 0.1, which means that the performance loss experienced by airlines is relatively small most of the time. In such modest damaged situations, it seems that Delta and United have a similar pattern, while Southwest and American are comparable. The Kolmogorov–Smirnov test (KS test) is applied to analyze the differences between ECDFs of airlines. The null hypothesis H_0 is: the CDF of airline1 is no greater than the CDF of airline2, i.e., $F_{airline1}(x) \leq F_{airline2}(x)$. The alternative hypothesis H_1 is: $F_{airline1}(x) > F_{airline2}(x)$. Table II shows the results of KS test.

TABLE II. RESULTS OF KOLMOGOROV–SMIRNOV TEST

airline1	***airline2***	***KS statistic***	***p-value***
DL	UA	0.0950	0.0395
DL	AA	0.4190	<0.0001
DL	WN	0.3827	<0.0001
UA	AA	0.3660	<0.0001
UA	WN	0.3463	<0.0001
WN	AA	0.0922	0.0477

Results show that $F_{DL}(x) > F_{WN}(x)$, $F_{DL}(x) > F_{AA}(x)$, $F_{UA}(x) > F_{AA}(x)$, and $F_{UA}(x) > F_{WN}(x)$ are significant at the 0.001 level, and $F_{DL}(x) > F_{UA}(x)$, $F_{WN}(x) > F_{AA}(x)$ are significant at the 0.05 level. Hence, it is reasonable to conclude that the ranking of the resilience of the four airlines from high to low is: Delta>United>Southwest>American. Wang et al. developed an econometric model to investigate the SBT-setting behaviors of these four airlines using the same dataset[31]. They found that when historical flight time, market share, OD pairs, aircraft type, departure time window, airport category, and other factors in the model are controlled, Delta and United prefer to set longer SBT for their flights. Interestingly, the sorting of the airline dummy variables' coefficients in their model is the same as the ranking of our resilience result. It suggests that buffer time in the schedule may absorb delays to some extent and enhance the ability to resist perturbations.

While Delta has relatively lower medium $AELR$ compared to the other three airlines, it has more outliers which represent the extreme disruptive scenarios. Table III lists the details of abnormal operation days detected by the $AELR$ outliers.

TABLE III. DETAILS OF ABNORMAL OPERATION DAYS

Date	***AELR***	***Average Arrival Delay (min)***	***Cancel Ratio***	***A14***	***Events***
2017-04-06	0.540	110.06	0.353	0.19	—
2017-04-07	0.490	105.14	0.294	0.20	—
2017-04-05	0.472	80.12	0.301	0.36	ATL[a] Thunderstorm
2017-04-08	0.436	89.68	0.189	0.30	—
2017-12-17	0.420	3.85	0.325	0.58	ATL Blackout
2017-12-08	0.417	35.31	0.309	0.47	ATL Snowstorm
2018-01-17	0.411	75.70	0.200	0.36	ATL Snowstorm
2017-09-11	0.324	14.62	0.271	0.57	ATL Hurricane Irma

a. Hartsfield–Jackson Atlanta International Airport

We found that these abnormal days were affected by various disruptive events. In the afternoon of 2017-04-05, severe thunderstorm weather covered Hartsfield–Jackson Atlanta International Airport (ATL), resulting in a nearly all-day ground stop at ATL[32]. More than 1004 flights were canceled. Since about 60% of Delta's aircraft fleet cycles through Atlanta, the weather had a huge impact on the company's entire operation in the following days. Events led to other abnormal operation days also happened at ATL. Wong et al. applied the node removal method to analyze the resilience of the above four airlines' networks using the same dataset[33]. Their results show that Delta, which has a highly hub-and-spoke like topology, is the most resilient to random removals but least resilient to targeted ones. The network topology structure makes it more susceptible to severe disruptions at critical airports, such as ATL.

We take the 2017-12-17 ATL blackout event as an example to illustrate how performance is affected by disruptive events. According to Cable News Network (CNN), the underground tunnels where the airport's electric system lives were on fire at 12:38 p.m. (t_{OE}) on Dec. 17 [34]. The fire soon damaged two substations serving the airport and the redundant system that should have provided backup power. The blackout led the Federal Aviation Administration to declare a ground stop at the airport, preventing Atlanta-bound flights in other airports from taking off and causing inbound flights to be diverted. Delta, which has its largest hub in Atlanta, canceled more than 900 flights. The airport restored the power supply at midnight (t_{TE}) on the 17th. However, airline's operation did not rebound immediately. About 300 inbound flights to ATL were canceled on the morning of 18th because of the disrupted aircraft's itinerary. Delta finally returned its schedule to normal in the afternoon (t_{RE}) of the18th.

Fig.9 displays the evolution of network efficiency during this event. The value of the time axis ranges from 0 to 2879. 0 represents 06:00 a.m. on the Dec.17, and 2879 represents 05:59 a.m. on the Dec.19. The time interval is set to be one minute, and there are 2880 minutes of two operation days.

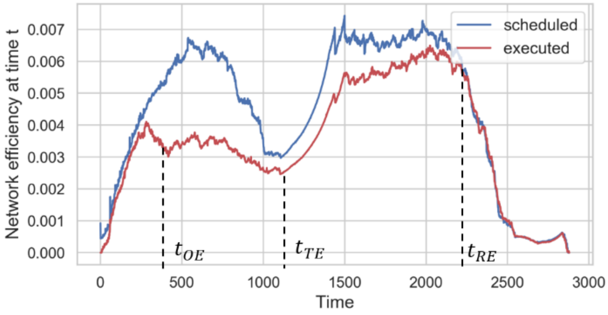

Figure 9. Evolution of network efficiency under ATL blackout.

The power outage occurred at t_{OE}. However, the actual executed performance degraded earlier according to the plot. This can be explained by the diverted flights. Recalling the execution layer modeling method (section II), if a diverted flight does not arrive at its scheduled destination within the observing period, it will be considered as cancelled. These diverted flights contribute to this phenomenon. After t_{TE}, the airline's operation began to recover. Trends of the two curves are similar, and the executed curve gradually approaches the scheduled curve. At t_{RE} (18:00 a.m. of 18th), the operation returns to its desired state. One can also employ signal processing methods to precisely identify a system's state changes under disruptions and characterize disruption-recovery patterns of a system[35].

The network efficiency of AON is determined by flight frequency, travel time between OD pairs, and the network structure. We develop a multiple regression model to analyze how these factors affect $AELR$:

$$\begin{aligned}
AELR &= const + \beta_1 * DL + \beta_2 * UA + \beta_3 * AA \\
&+ \beta_4 * DELAY2 + \beta_5 * DELAY3 + \beta_6 * DELAY4 \\
&+ \beta_7 * CANCEL2 + \beta_8 * CANCEL3 \\
&+ \beta_9 * DELAY2 * DL + \beta_{10} * DELAY3 * DL + \beta_{11} * DELAY4 * DL \\
&+ \beta_{12} * DELAY2 * UA + \beta_{13} * DELAY3 * UA + \beta_{14} * DELAY4 * UA \\
&+ \beta_{15} * DELAY2 * AA + \beta_{16} * DELAY3 * AA + \beta_{17} * DELAY4 * AA \\
&+ \beta_{18} * CANCEL2 * DL + \beta_{19} * CANCEL3 * DL \\
&+ \beta_{20} * CANCEL2 * UA + \beta_{21} * CANCEL3 * UA \\
&+ \beta_{22} * CANCEL2 * AA + \beta_{23} * CANCEL3 * AA
\end{aligned} \tag{11}$$

Average arrival delay $\overline{arr\_delay}$ is used to capture changes in travel time compared with schedules, and cancel ratio r_c is used to record the extent that flight frequency declines. They are converted into categorical variables respectively to investigate how different levels of flight delays and cancellation affect $AELR$. Airlines dummy variables are also included to examine the effect of different airlines networks on $AELR$. Table IV shows the description of these dummy variables. The reference categories are WN, DELAY1 and CANCEL1.

TABLE IV. DESCRIPTION OF DUMMY VARIABLES

Variables	***Description***
WN	1 if the network belongs to Southwest (reference)
DL	1 if the network belongs to Delta
UA	1 if the network belongs to United
AA	1 if the network belongs to American
DELAY1	1 if $\overline{arr_{delay}} \leq 0$ (reference)
DELAY2	1 if $0 < \overline{arr_{delay}} < 15min$
DELAY3	1 if $15min \leq \overline{arr_{delay}} < 30min$
DELAY4	1 if $\overline{arr_{delay}} \geq 30min$
CANCEL1	1 if $r_c < 0.005$ (reference)
CANCEL2	1 if $0.005 \leq r_c < 0.015$
CANCEL3	1 if $r_c \geq 0.015$

To explore whether the effects of delay and cancellation differ among airlines, interaction terms are also involved. $const$ is the constant of the model. 1452 pieces of record obtained using historical data are used to estimate the model. Table V summaries the estimation results using OLS regression.

TABLE V. MODEL ESTIMATION RESULTS

Variables	***Coefficients***	***Variables***	***Coefficients***
Constant	-0.0150***	*DELAY2*UA*	-0.0049
DL	-0.0089*	*DELAY3*UA*	-0.0286**
UA	-0.0088*	*DELAY4*UA*	-0.0903***
AA	0.0152***	*DELAY2*AA*	-0.0090
DELAY2	0.0415***	*DELAY3*AA*	-0.0097
DELAY3	0.0819***	*DELAY4*AA*	0.0253
DELAY4	0.1625***	*CANCEL2*DL*	-0.0068
CANCEL2	0.0139***	*CANCEL3*DL*	0.0473***
CANCEL3	0.0461***	*CANCEL2*UA*	0.0062
*DELAY2*DL*	0.0108*	*CANCEL3*UA*	0.0498***
*DELAY3*DL*	0.0235*	*CANCEL2*AA*	0.0074
*DELAY4*DL*	0.1546***	*CANCEL3*AA*	0.0104
R-square	0.755		

Variables are significant at the 0.001 level***, 0.01 level**, 0.05 level*

Results suggest that differences exist between airlines. According to airlines dummy variables *DL*, *UA*, and *AA*, the mean $AELR$ of Delta and United are significantly smaller than the mean $AELR$ of Southwest, while the mean $AELR$ of American is significantly larger than Southwest. According to *DELAY*airline* interaction terms, the effect of flight delays is stronger for Delta than for Southwest, while it is weaker for United than for Southwest. Interaction terms belonging to American are not statistically significant, so flight delay and cancellation effects on American and Southwest networks are not significantly different. Flight delay and cancellation also have significant impacts. In Southwest network, as delays and cancellations increase, the value of $AELR$ increases, which means more severe performance losses. This pattern also can be found in the other three airlines. The large and significant coefficients of *DELAY4*DL* and *CANCEL3*DL* illustrate that Delta is more susceptible to severe delay and cancellation. To exhibit more clearly, Fig.10 and Fig.11 present fitted $AELR$ of four airlines conditioned on *CANCEL1* and *DELAY1*, respectively.

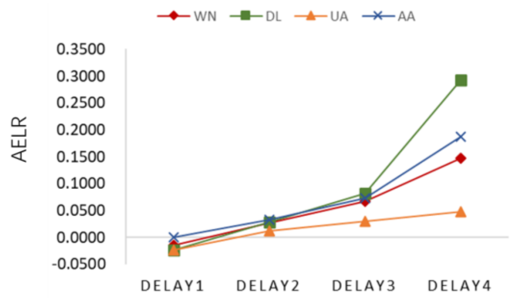

Figure 10. Fitted AELR conditioned on *CANCEL1*.

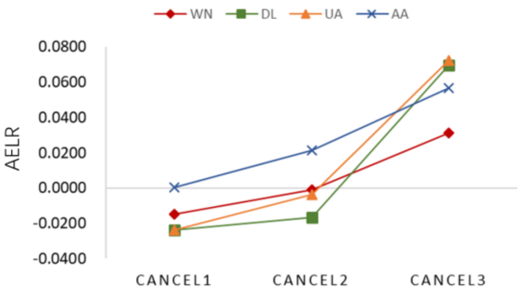

Figure 11. Fitted AELR conditioned on *DELAY1*.

V. CONCLUDING REMARKS

It is of great importance to construct a resilient air transport system. A framework and relative techniques are needed to support resilience analysis in the system's life-cycle covering planning, scheduling, operating, and ex-post evaluating phases, to achieve this goal. This paper focuses on investigating the resilience of the AON, which is the fundamental layer of the ATN. We apply the temporal network theory to AON modeling, leveraging its ability to maintain time-stamped information. Considering the airlines' scheduling process, we divided AON into the scheduling layer and the execution layer. Our study makes two main contributions. First, a performance indicator, instantaneous network efficiency is defined. Based on this performance indicator, a novel metric called average efficiency loss ratio ($AELR$) is developed to measure resilience of the AON. Compared with previous works, this metric can reflect time-varying and components' interacting characteristics simultaneously. Second, we perform an empirical analysis using the proposed metric. The resilience of four major U.S. airlines' networks is analyzed. We find that the AON of Delta has highest resilience, but is more susceptible to severe flight delay and cancellation. The flight delay and cancellation effects on Southwest and American airlines operation network are similar.

The proposed performance and resilience analyzing method can be further extended in several directions. First, this paper presents the first step to resilience analysis, and finds that differences exist between airlines. We can further explore the factors that cause these differences, such as flight schedules and network structure, to help improve the resilience. Second, here we only focus on the airlines' operation network. Further studies can consider airports and air routes capacity restrictions, and investigate dynamic behaviors as well as resilience of the multilayered air transport network. The calculation method of resilience metric proposed in this paper involves shortest path length of airport pairs. It is possible to investigate how tactical ATC and flow interventions affect the shortest paths of airport pairs and further affect the resilience of the air transport network.

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REFERENCES

[1] International Air Transportation Association "World Air Transport Statistics (WATS) ", 2019

[2] Roy, Sandip, Mengran Xue, and Banavar Sridhar. "Vulnerability metrics for the airspace system." Proceedings of the 2017 FAA/Eurocontrol Air Traffic Management Research and Development Seminar. 2017.

[3] Clark, Kevin L., et al. "Resilience of the US national airspace system airport network." IEEE Transactions on Intelligent Transportation Systems 19.12 (2018): 3785-3794.

[4] Linkov, Igor, et al. "Changing the resilience paradigm." Nature Climate Change 4.6 (2014): 407-409.

[5] Wied, Morten, Josef Oehmen, and Torgeir Welo. "Conceptualizing resilience in engineering systems: An analysis of the literature." Systems Engineering 23.1 (2020): 3-13.

[6] Cutter, Susan L., et al. "Disaster resilience: A national imperative." Environment: Science and Policy for Sustainable Development 55.2 (2013): 25-29.

[7] Bruneau, Michel, et al. "A framework to quantitatively assess and enhance the seismic resilience of communities." Earthquake spectra 19.4 (2003): 733-752.

[8] Zanin, Massimiliano, and Fabrizio Lillo. "Modelling the air transport with complex networks: A short review." The European Physical Journal Special Topics 215.1 (2013): 5-21.

[9] Wang, Yanjun, et al. "The structure and dynamics of the multilayer air transport system." Proc. 12th USA/Eur. Air Traffic Manage. R&D Seminar. 2017.

[10] Chen, Zhenhua, and Yuxuan Wang. "Impacts of severe weather events on high-speed rail and aviation delays." Transportation research part D: transport and environment 69 (2019): 168-183.

[11] Lordan, Oriol, et al. "Robustness of the air transport network." Transportation Research Part E: Logistics and Transportation Review 68 (2014): 155-163.

[12] Hossain, Murad, et al. "Australian airport network robustness analysis: a complex network approach." Australasian Transport Research Forum (ATRF), 36th. 2013.

[13] Kai-Quan, Cai, et al. "Analysis of the Chinese air route network as a complex network." Chinese Physics B 21.2 (2012): 028903.

[14] Kim, Seyun, and Yoonjin Yoon. "On node criticality of the Northeast Asian air route network." Journal of Air Transport Management 80 (2019): 101693.

[15] Sun, Xiaoqian, and Sebastian Wandelt. "Complementary strengths of airlines under network disruptions." Safety science 103 (2018): 76-87.

[16] Lordan, Oriol, et al. "Robustness of airline route networks." Physica A: Statistical Mechanics and its Applications 445 (2016): 18-26.

[17] Yanjun, W. A. N. G., et al. "Measuring the resilience of an airport network." Chinese Journal of Aeronautics 32.12 (2019): 2694-2705.

[18] Janić, Milan. "Reprint of "Modelling the resilience, friability and costs of an air transport network affected by a large-scale disruptive event"." Transportation Research Part A: Policy and Practice 81 (2015): 77-92.

[19] Sánchez, Marta, Izaro Etxebarría, and Andrés Arranz. "Dynamic Approaches from Complexity to Manage the Air Transport Network.", First SESAR Innovation Days.

[20] Kafle, Nabin, and Bo Zou. "Modeling flight delay propagation: A new analytical-econometric approach." Transportation Research Part B: Methodological 93 (2016): 520-542.

[21] Pyrgiotis, Nikolas, Kerry M. Malone, and Amedeo Odoni. "Modelling delay propagation within an airport network." Transportation Research Part C: Emerging Technologies 27 (2013): 60-75.

[22] Hao, Lu, and Mark Hansen. "Block time reliability and scheduled block time setting." Transportation Research Part B: Methodological 69 (2014): 98-111.

[23] Deshpande, Vinayak, and Mazhar Arıkan. "The impact of airline flight schedules on flight delays." Manufacturing & Service Operations Management 14.3 (2012): 423-440.

[24] Holme, Petter, and Jari Saramäki. "Temporal networks." Physics reports 519.3 (2012): 97-125.

[25] Gu, Yu, et al. "Performance of transportation network under perturbations: reliability, vulnerability, and resilience." Transportation Research Part E: Logistics and Transportation Review 133 (2020): 101809.

[26] Cai, Qing, Sameer Alam, and Vu Duong. "On robustness paradox in air traffic networks." IEEE Transactions on Network Science and Engineering 7.4 (2020): 3087-3099.

[27] Janić, Milan. "Modeling the resilience of an airline cargo transport network affected by a large scale disruptive event." Transportation Research Part D: Transport and Environment 77 (2019): 425-448.

[28] Reggiani, Aura, Peter Nijkamp, and Diego Lanzi. "Transport resilience and vulnerability: The role of connectivity." Transportation research part A: policy and practice 81 (2015): 4-15.

[29] Eufrásio, Ana Beatriz R., Rogéria AG Eller, and Alessandro VM Oliveira. "Are on-time performance statistics worthless? An empirical study of the flight scheduling strategies of Brazilian airlines." Transportation Research Part E: Logistics and Transportation Review 145 (2021): 102186.

[30] Cook, Gerald N., and Jeremy Goodwin. "Airline Networks: A comparison of hub-and-spoke and point-to-point systems." Journal of Aviation/Aerospace Education & Research 17.2 (2008): 1.

[31] Wang, Yanjun, et al. "Scheduled block time setting and on-time performance of US and Chinese airlines—A comparative analysis." Transportation Research Part A: Policy and Practice 130 (2019): 825-843.

[32] Passengers stranded at Atlanta Airport after severe weather ,https://www.11alive.com/article/news/local/passengers-stranded-at-atlanta-airport-after-severe-weather/85-429082872.

[33] Wong, Allen, et al. "Data-driven analysis of resilience in airline networks." Transportation Research Part E: Logistics and Transportation Review 143 (2020): 102068.

[34] Atlanta's Hartsfield-Jackson airport restores power after crippling outage ,https://edition.cnn.com/2017/12/17/us/atlanta-airport-power-outage/index.html

[35] Li, Max Z., et al. "Dynamics of Disruption and Recovery in Air Transportation Networks." International Conference on Research in Air Transportation (ICRAT). 2020.