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# Dynamic Resilience of Public Transport Network: A Case Study for Fleet-Failure in Bus Transport Operation of New Delhi

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## Abstract

The paper presents a methodology to measure the dynamic resiliency of a public transport network. Variability in service supply that arises from normal day-to-day service fluctuations leads to negative passenger experiences and therefore satisfaction. The paper explores the utilization of dynamic data to develop a systematic approach analysing disruption impacts with respect to service-wide capacity changes due to fleet failures. In order to measure the dynamic resilience, an index is formulated that covers the magnitude of changes in the network performances in terms of robustness, reliability, and residual capacity; measures that describe the network complexity in a physical and a service operational specification. In this regard, the relationship between system components is characterized by network topology, passenger flow, and service performance dynamics. Our proposed approach captures the dynamics of the resilient system and quantifies the extent to which operational strategies can deliver efficient systems. We illustrate our model by an application to the New Delhi bus transport system and demonstrate how system resiliency for different fleet-failure states can be quantified.

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*Keywords:* resilience index; reliability; robustness; residual capacity; disruption; performance

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## 1. Introduction and Literature Review

An efficient public transport (PT) system should be resilient, which means able to preserve a good quality of service even when faced to perturbations. Inevitable disruptive events could result from various reasons including small-scale or large-scale manmade, natural or common failures. Due to the network's complex structure and the level of strain that disruptions may put upon related infrastructure and service stream, the dynamic nature of operation then plays a

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vital role in determining the level of system's capacity to function under disruption's impact. By definition, in order to persuade travelers to use PT system, implemented strategies need to be able to have a capacity to remain functional, prevent damage to the system before and mitigate losses during and after the disruption (Angeloudis and Fisk, 2006; Hosseini et al., 2016; Jin et al., 2014; Mattsson and Jenelius, 2015).

According to recent studies, system resiliency can be described through structural frameworks using deterministic (Cox et al., 2011) or probabilistic (Barker et al., 2013; Chen, 1999) approaches; either through dynamic or static performance-based measures (Rose, 2007). Furthermore, the impacts of disruptions vary among network elements (Cats et al., 2016) and depending on the goal of the analysis, various categories of disruption scenarios are introduced; i.e. scenario specific, strategy specific and simulation-based mathematical programming approaches (Murray et al., 2008). Apart from these approaches, assessment of the resilient system also has been characterized by a definition of dimensions of the problem; i.e. robustness, reliability, redundancy, vulnerability, resourcefulness, recoverability, rapidity, adaptability, and absorbability (Bruneau et al., 2003; Cats et al., 2017; Cats and Jenelius, 2015; Zhang et al., 2015). Henceforward, the system can be assessed categorically by referring these dimensions to different time states; i.e. before-disruption (while the operation is running according to schedules called baseline), during-disruption (degraded operation time) and post-disruption (recovering operation time).

Practically, resiliency of PT networks has to consider the duration and strength of degradation of scheduled services resulting in damage to physical infrastructure, service delays or cancellation, increased travel time and change in passenger behaviour due to the impact of disruptive events. One significant barrier towards achieving resiliency is the variability in service supply that arises from normal day-to-day service capacity fluctuations because of fleet failures. It leads to negative passenger experience and service inefficiency. Thus, the overall objective when dealing with disruptions in a dynamic context is ensuring the system is reliable, robust and residual to capacity fluctuations. Considering the interaction between these dimensions supports describing the ability of the system to withstand the impact with minimal suffering loss of functionality.

By exploring the relation between capacity fluctuations (residual capacity), reliability, and robustness within an aggregated context, the aim of the study is to develop a performance measurement procedure through an index value that reflects the dynamic system resiliency. The analysis facilitated by a large database on fleet failure disruptions of New Delhi bus transit operation. The remainder of the paper is organized as follows. A method to assess the aggregated system resiliency in Section 2 followed by its application to New Delhi bus transit network in Section 3. Results include resilience index values for each transit route, impact analysis of the disruption scenario and discussion over dynamic nature of system resiliency at disruption states. Finally, the conclusions are summarized in Section 4.

## 2. Method

In this research work, we implement a practical framework to assess the dynamic system resiliency due to failures of operating fleet. Within an aggregated context, accumulated effect of disrupting events are evaluated based on robustness, reliability and residual capacity dimensions. It is thus necessary to establish performance measure indicators that quantifies the relation between supply and demand components. In this regard, we explore the utilization of dynamic data to develop our evaluation method. Different number of factors influence PT operations. When dealing with fleet failure as a disruption event, depending on location and time of the disruption, the operational performance is negatively influenced. It usually affects categories of components (i.e. fleet, passengers, and infrastructure) and its operational procedures (i.e. time and capacity). Thus, characterizing system resiliency can be assessed as follow:

- One way of characterizing system resiliency is to assess the change in topological properties of the network due to the failure impact. Studying topological properties of the network provides insights into the structure of the network, importance of the transit stops, connected links and correlations in-between (Angeloudis and Fisk, 2006; Derrible and Kennedy, 2010; Mishra et al., 2012; Reggiani, 2013); representing the robustness of the system. For instance, node degree distribution indicator represents a total number of direct connections a transit stop/node has to other stops; the size of which indicates its importance. The indicator evaluates each stop separately in terms of the degree distribution; revealing how many connections the stop has before and after the disruptive state. Global efficiency indicator represents the minimum number of links that need to be removed to disconnect the remaining nodes from each other (Latora and Marchiori, 2007). It refers to the overall network efficiency for characterizing the performance of the networks with respect to their resilience to disruptive events. The measure tries to find

how information is efficiently exchanged between nodes in the network. Assortativity indicator describes the correlations between the properties of neighbour nodes in terms of the mean Pearson correlation coefficient. In other words, it characterizes the connectivity tendency of a network, whether nodes (transit stops) of similar or dissimilar degrees are more likely to be connected (Newman, 2002). A network is said to be assortative when high degree transit stops are, on average, connected to other transit stops with high-degree and low degree transit stops are, on average, connected to other transit stops with low-degree. On the other hand, a network is said to be dis-assortative when, on average, high-degree transit stops are connected to transit stops with low degree and, on average, low-degree transit stops are connected to transit stops with high-degree.

- Furthermore, characterizing system resiliency also needs to account the magnitude of capacity fluctuation. Indeed, while a disruption occurs at a specific service-time, the impact of the event is more likely to spread to next available service dispatching; many passengers would experience additional waiting time and operation would experience some quality degradation. Studying functional reliability in terms of the ability of the service to carry the additional passengers due to disruptions provides insights into the service-related performance of the operation.

Therefore, in order to assess the impact, the dynamic nature of PT operation is considered by means of experienced additional waiting time, capacity change, passenger overload, and on-time performance while considering topological properties of the network as well. Using the system resiliency performance indicators, identified according to robustness, reliability and residual capacity dimensions, two outcomes are projected for this specific failure type:

- (1) Monitoring daily failure of each service and identifying the level of service and route criticality
- (2) Assessing the system resiliency by estimating value of cumulative failure of each route; defined in terms of system resilient index

In this section, the assessment procedure is elaborated as follow:

- Network description; the network is described as a combination of a network of transit stop connections, physical infrastructure and passenger flows.
- Disruption scenarios; creating disruption scenario platform subject to fleet-failures
- Resilient index; aggregated performance measurement is developed through an index value.
- Performance indicator; It is a combination of topological properties of the network describing system robustness and passenger flow and system capacity components describing system reliability and residual capacity.

### 2.1. Network description

The network ( $G$ ) is represented by directed graph  $G(N,V)$ , where node set ( $N$ ) represents transit stops and the link set ( $V$ ) represents segments between transit stops. The ( $G$ ) network consists of a set of routes  $R = (R^1, R^2, \dots, R^k)$ . A

transit route ( $R$ ) is defined by a sequence of stops  $R_{i:j:m}^k = (n_i^{R^k}, n_j^{R^k}, \dots, n_m^{R^k})$  where  $n_i^{R^k}$  is origin stop,  $n_j^{R^k}$  is

destination stop of the link and  $n_m^{R^k}$  is destination stop of the route ( $R^k$ ). In this formulation, we freely interchange terms transit stops/nodes and failure/event/disruption without any meaningful difference. The connection and physical infrastructure in graph ( $G$ ) are quantified by a set of matrices, each representing the relationship between elements of the network and related services including (1) dynamic transit adjacency, (2) dynamic passenger travel time and (3) dynamic passenger volume matrices.

### 2.2. Disruption scenario

One of the inevitable disruptive events that cause damages to system's functioning is due to fleet failure that leads to fluctuations on system capacity. As mentioned earlier, the analysis is facilitated by a large database on fleet failure disruptions of New Delhi bus transit operation. For transit route ( $R^k$ ), we defined a dynamic matrix of performance measures ( $SP$ ) that will define our system resiliency index. The state of ( $SP$ ) is defined based on two time concepts.

First concept is scheduled service ( $SP^a$ ) and real service ( $SP^b$ ). The second concept is operation time before failure

( $t_0$ ) and operation time after failure ( $t_d$ ). **Fig.1** represents the dynamic concept of operating services running on a route.

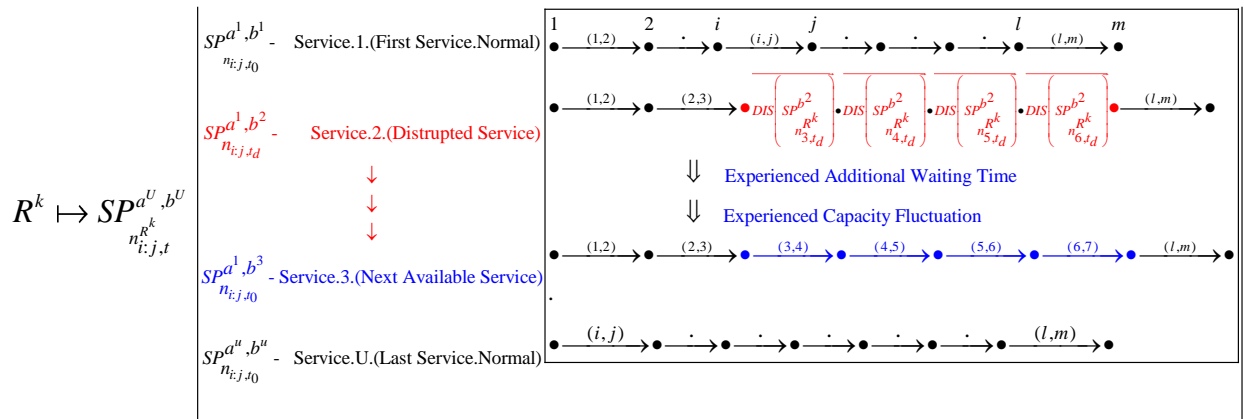


Fig.1 - Dynamic concept of operating services of a route

Where ( $U = [U_1, U_2, \dots, U_u]$ ) represents set of services running for a day for route ( $R^k$ ); operating from origin stop  $n_i^{R^k}$  to destination stop  $n_j^{R^k}$ . The disruption state ( $DIS(SP)$ ) then is defined based on fleet failure at real service time for link ( $i, j$ ). As mentioned earlier, while a disruption occurs  $DIS \left( SP^{b^2}_{n_{3,t,d}^{R^k}} \right) \cdot \dots \cdot DIS \left( SP^{b^2}_{n_{6,t,d}^{R^k}} \right)$ , the impact of the event is likely to spread to next available service dispatching ( $SP^{a^1, b^3}_{n_{i,j,t_0}}$ ); many passengers would experience additional waiting time and due to capacity fluctuations, operation would experience some quality degradation (See Fig.1).

2.3. Formulation of the system resilience index

The goal is to investigate the impact of the disruption. Consider disruption event ( $DIS(SP)$ ) for link  $DIS \left( SP^{b^2}_{n_{3,t,d}^{R^k}} \right) \cdot \dots \cdot DIS \left( SP^{b^2}_{n_{6,t,d}^{R^k}} \right)$  that causes degradation in the performance of the system. Therefore, due to the impact of the experienced disruption, reduced functionality of the link and the route is described as a function of aggregated reliability, robustness and residual capacity performance indicators.

- Let the effect of ( $DIS(ST)$ ) described through a reduction of performance ( $P$ ) with respect to reliability ( $RL$ ), robustness ( $RB$ ) and residual capacity ( $RC$ ) indicators (eq.1).

$$P(DIS(SP)) = f(RL, RB, RC) \tag{eq.1}$$

- The impact of disruption ( $\Delta P$ ) for a given route ( $R^k$ ) is then defined within two categories. Category one measures the difference between accumulated performance of real-service operation and scheduled-service operation (eq.2; P1); whereas category two measures the difference between accumulated performance of disrupted operation and normal operation of all services based on real-service operation data (eq.2; P2).

$$\Delta P \rightarrow \left[ \Delta P^{a,b} = \left( \sum_{lu} P^{SP^a}_{n_{i,j,t_0}^{R^k}} - \sum_{lu} P^{SP^b}_{n_{i,j,t_0}^{R^k} \& t_d} \right) \text{ and } \Delta P^b = \left( \sum_{lu} P^{SP^b}_{n_{i,j,t_0}^{R^k}} - \sum_{lu} P^{SP^b}_{n_{i,j,t_d}^{R^k}} \right) \right] \tag{eq.2}$$

The first category would indicate the magnitude of performance change between scheduled services and real operated services. The second category would indicate the real magnitude of disruption impact. The difference between two categories are relative to the way performance indicators are measured to assess the performance degradation. According to category one, the overall performance of real services (including normal and disrupted services ) is compared with ideal service operation (scheduled services). Note that the value of ( $\Delta P$ ) is dimensionless and is useful to compare the resilience of various services and routes. Category two indicates if the system is more capable of resisting a disruptive event, the less is ( $\Delta P$ ) the more resilient is the system. In order to quantify the aggregated system resiliency, the performance of operation at disrupted and normal services are evaluated through accumulated normalized values of related performance indicators.

### 2.4. Performance indicators

The impact of disruption of the fleet failure for a given route service of the network is defined in (eq. 2). Analysis of residual capacity, reliability and robustness of such failure event is significantly used to identify the nature of system resiliency and magnitude of the disruptive event. The different components observed at disruption that affects system performance are formulated as performance indicators (Table 1).

**Table 1. Formulation of Performance measure indicator**

No	Indicator	Dimension	Formulation	Expression
1	Volume Capacity (VC) Ratio	Residual Capacity	$VC \left( SP_{n_i; j, t_0, t_d}^{a^u, b^u} \right) = \left( \frac{\text{Volume}_{SP_{i,j,t_d}^{a^u, b^u}} + \text{Volume}_{SP_{i,j,t_d}^{a^u, b^u}}}{C} \right)$	C = Fleet Capacity
2	Experienced Waiting Time (WT)	Residual Capacity	$WT \left( SP_{n_i; j, t_0, t_d}^{b^u} \right) = \text{NEXT SERVICE } (T)_{SP_{n_i; j, t_0}^{b^u+1}} - \text{DIS } (T)_{SP_{n_i; j, t_d}^{b^u}}$	T=Time of Service
3	Affected Passengers (AF)	Residual Capacity	$PS \left( SP_{n_i; j, t_0}^{a^u, b^u} \right)$	-
4	Load Factor (LF) of Next Service	Residual Capacity	$LF \left( SP_{n_i; j, t_0, t_d}^{a^{lu}, b^{lu}} \right) = \left( \frac{MLS}{C} \right)$	MLS=Max Load Section
5	On-Time Performance (OTP)	Time Reliability	$OTP \left( SP_{n_i; j, t_0, t_d}^{a^u, b^u} \right) = \left( T_{n_i; j, t_0, t_d}^{a^u} - T_{n_i; j, t_0, t_d}^{b^u} \right)$	-
6	Node Degree Distribution (nd)	Robustness	$nd \left( SP_{n_i; j, t_0, t_d}^{a^u, b^u} \right) = \sum_i a_{ij}$	a=degree of stop (i)
7	Assortativity (asr)	Robustness	$asr \left( SP_{n_i; j, t_0, t_d}^{a^u, b^u} \right) = \left( \frac{l^{-1} \sum_{(i,j) \in V} nd_i \cdot nd_j - \left[ l^{-1} \sum_{(i,j) \in V} \frac{1}{2} (nd_i + nd_j) \right]^2}{\left[ l^{-1} \sum_{(i,j) \in V} \frac{1}{2} (nd_i + nd_j^2) \right] \left[ l^{-1} \sum_{(i,j) \in V} \frac{1}{2} (nd_i + nd_j) \right]^2} \right)$	l=
8	Global Efficiency (GE)	Robustness	$GE \left( SP_{n_i; j, t_0, t_d}^{a^u, b^u} \right) = \left( \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{L_{i,j}} \right)$	L =

#### 2.4.1. Time Reliability

Time reliability describes the degradation of performance of the operation with respect to delays in the service. Therefore, delays can be expressed in terms of difference between scheduled and real services that is called on-time performance  $OTP \left( SP_{n_i; j, t_0, t_d}^{a^u, b^u} \right)$  or can be expressed in terms of additional waiting time imposed to passengers who experienced a disruption. The later expression can be evaluated through a residual capacity function.

#### Residual Capacity

Residual Capacity can be measured in a dynamic context. It describes ability of service to carry the additional passengers that experienced delays due to the disruptions. In this regard, the components that play important role with respect to capacity and passenger flow are load factor of next available service  $LF\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$ , volume-capacity ratio of next available service  $VC\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$ , total number of affected passengers  $PS\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$  and experienced waiting time of affected passengers  $WT\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$ .

#### 2.4.2. Robustness

Topological properties of the network while system is running at its best, and while system is disrupted can be expressed in terms of change in node-degree distribution  $nd\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$ , assortativity  $asr\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$  and global efficiency  $GE\left(SP_{n_i,j,t_0,t_d}^{a^{1st},b^{1st}}\right)$ . In this regard, the dynamic nature of the operation can be integrated to robustness evaluation. For each service, the cumulative performance of the operation with respect to topological properties can be assessed for normal and disrupted services as well.

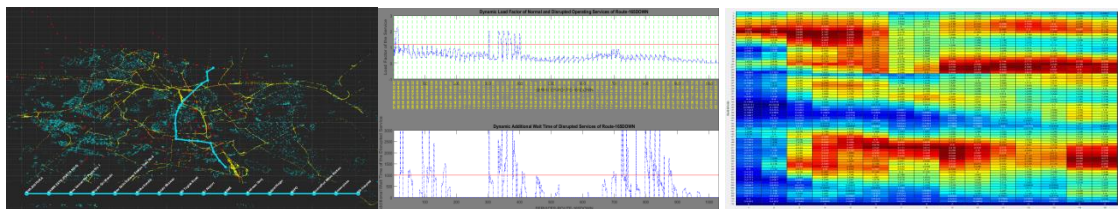
### 3. Application

In this section, we illustrate our evaluation method by an application to the New Delhi bus transit operation. It includes the details of the travel attributes included in the network performance measures, followed by a detailed account of the fleet failure scenario evaluation. The network, including 50 routes, 461 stops, 1064 links and total length of 1370 km (Table 2), is coded in Matlab using data for 30 days operation including scheduled services, real services, passenger load, passenger flow and full service timetable. Due to the limitations on the size of this presentation, the evaluation method for one of the routes (165 DOWN) are illustrated in detail.

**Table 2. Description of New Delhi Bus Transit Routes**

No	Route	Num. of Services	Num. of Stops	Length (M)	Avr. Delay (Min)	Start Time	End Time
1	165 Down	72	53   15	37405	36	'08:44:45'	'23:17:44'
2	165 UP	72	55   15	33752	19.5	'06:13:03'	'21:26:56'
3	185 Down	20	57   12	26895	47.8	'07:04:25'	'22:07:18'
4	185 UP	20	57   12	26266	29.1	'08:37:56'	'23:57:32'
.	.	.	.	.	.	.	.
49	311 Down	40	46   10	25194	11.9	'06:32:26'	'20:58:51'
50	311 UP	40	10	24391	17.4	'16:15:35'	'22:17:30'

Initially, the state of services experiencing impact from fleet failure were identified and percentage of abnormal and normal operations of the routes are mapped. We analyze the impact of the failure that spreads to next available service dispatching. Since the disruption is unplanned, the operator cannot apply some mitigation measures. Therefore, the second step is to identify number of affected passengers at each disrupted service, amount of experience additional waiting time imposed to affected passengers, the load factor of next available service (Fig.2).



*Fig2. Exemple of the resiliency platform results : (a) Route 165 Down (b) load factor and waitign dynamics of service day 1 (c) heatmap of load factor through a day*

System performance of route 165Down is evaluated for the period between '08:44:45' am and '23:17:44' pm. Two evaluation approaches are computed. First is the estimation of  $\Delta P^{a,b}$  that covers the system resiliency with respect to difference between performances of operation of scheduled services and real services. Second is the estimation of  $\Delta P^b$  that covers the system resiliency with respect to difference between performances of operation of normal services via disrupted services. Note that the failure of fleets on some services does not prevent other routes from running. The reason is that the routes in our case study have separate operation platforms having own fleet sizes. Therefore, passengers affected by the disruption would choose to take the next service on the same bus route with additional waiting time. Fig.3 shows the state of the 72 services of bus route 165Down, which run September 1<sup>st</sup>, 2016. It shows that a large share of the route service is disrupted (53% of services are disrupted; these services carried 39% of total route passenger volume).

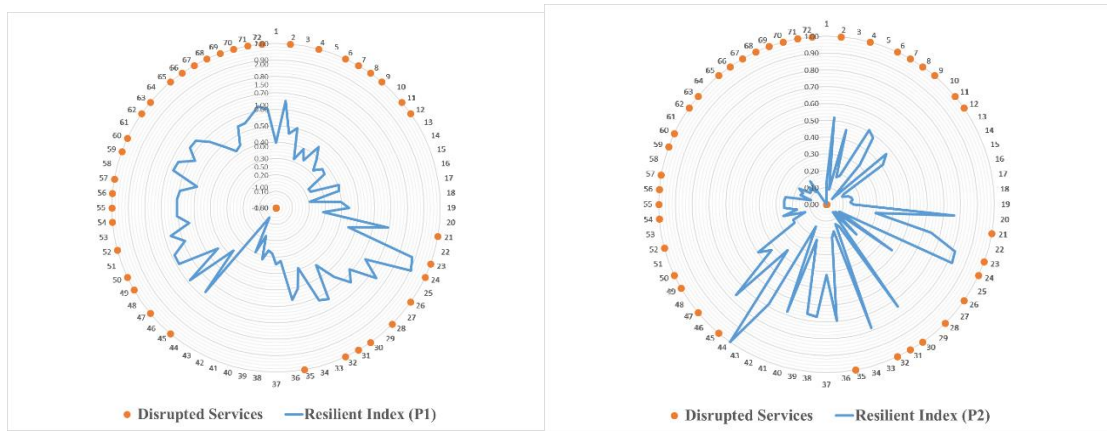


Fig3.- (a) Resilience Index ( $P1 = \Delta P^{a,b}$ ) (b) Resilience Index ( $P2 = \Delta P^b$ ) for Route 165DOWN – Day 1

Fig.3 gives also indicators P1 and P2, which are the sum of the normalized values of all indicators given on table 1. As explained on eq2; P2 is the difference between accumulated performance of disrupted operation and normal operation of all services. However, P1 is the difference between accumulated performance of real-service operation (including disruption) and scheduled-service operation. We identify available services that have served affected passengers within their accepted capacity level (i.e. based on standard thresholds = 1.3 LF) and services that have experienced overcrowding. Under normal operational conditions, the average load factor is 0.8 and under disrupted conditions the average load factor is 1.52. According to P1 estimation, results show that when the passenger are shifted to next available service, the flow of the service on average shifts from 0.5 VC to 0.8 VC ratio. According to P2 estimation, we observe maximum delay on services No. 44 and 24. The delay on service No.44 is because of poor on-time-performance of the operation and delay on service No. 24 is because of disruptions causing capacity fluctuations and additional waiting time. The maximum waiting time then occurs at service No. 24 with average 58 minutes. Table 3 shows the final average resilient index based on P1 and P2 evaluation methods.

Table 3. Description of Routes

Route 165DOWN – Day 1	$\Delta P^{a,b}$	$\Delta P^b$
<b>Route Resilience Index</b>	0.6	0.3

#### 4. Conclusion

To attract more passengers, public transport system must be able to withstand disruptions such as service, infrastructural and fleet failures. Because of the dynamic nature of the public transport system, disruptions spread across the network due to effects on the services and effects caused by the redistribution of passenger flows and capacity fluctuations. To study these effects, we utilize an aggregated resiliency evaluation method that takes into



consideration the interaction between supply and demand. The impacts of disruptions are analyzed studying change of the volume over capacity, experienced passenger waiting time, on-time performance fluctuations, estimated using accumulated resiliency index normalized value. The performance indicators are defined based on reliability, robustness and residual capacity dimensions.

The proposed method was applied to New Delhi bus transit network. The impact of disruption of the fleet failure for a given route service of the network is defined accordingly. Our findings show that the failures are not significantly related to topological properties of the network and the impact mostly is affected because of the duration of failure and passenger flow re-distributions. The analysis of disruption through aggregated context will facilitate the development of measures for improving system performance in planning and operations. It allows identifying critical service-times and critical infrastructure.

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