Adapting public transport to COVID-19 contingencies: evaluating unlock policies in the metropolitan area of Milan through DMCI simulation

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Abstract

COVID-19 global outbreak profoundly affected the way of living for billions of people worldwide. Transportation systems, which provide essential services to every socio-economic activity, were particularly affected by the rules adopted to contain the pandemic. Limiting individuals' mobility reduces the transmission but it should be balanced with the society's need. The metropolitan area of Milan was severely impacted by COVID-19. The immediate response to face the emergency was the full lockdown, starting from 9 March 2020. The paper reports on the use of the DMCI simulation model to evaluate the effects of different unlock strategies related to the public transportation system in the so-called 'Phase 2' and 'Phase 3'whose goal are to progressively ease the lockdown measures. The study considers both the limitations in the service capacity (due to the social distancing requirements) and the reduction in demand (due to the lockdown measures). The possible unlock strategies envisage modifications of the work hours and workdays. Leveraging on the logical interdependencies modelled in DMCI, it is shown that the worsening effect of the public transport capacity reduction can be adequately managed by a combination of proposed unlock strategies and the level of flexibility in the system. The presented analysis supported the regional decision-makers in making the most informed decisions when adapting to the circumstances surrounding Coronavirus.

Keywords: Covid-19, Transport, Simulation, Critical Infrastructure

1. Introduction

COVID-19 global pandemic, as declared by the World Health Organization (WHO) in March 2020, profoundly affected the way of living for billions of people worldwide. The virus has reached ever corner of the world putting the population under lockdown to contain the spread of the virus. Many countries have closed their borders and imposed curfews, resulting in sharp reductions in transport demand also on regional and continental level. The Coronavirus outbreak will likely have longer-lasting impacts on our individual behavior and lifestyle, the way we work, consume and travel.

Critical Infrastructure (CI) systems are critical for the maintenance of vital societal functions, providing services that society and citizens rely on in their daily life (EC, 2008). Transportation systems, securing the mobility of passengers and goods, are among the priorities being directly linked to economic development.

COVID-19 presence is causing a mismatch between the capacity and the demand across public transport means, causing significantly grater delays (traffic jams, rail/metro station queues) than usual disruptions. While there are limitations in the existing studies on the precise economic implications of transportation disruptions, it is absolutely certain that travel delays are a primary contributor to economic impact (Kurth et al., 2020).

In the context of networked CI systems, the concept of resilience can be defined (CNSS, 2015) as the ability of a system to:
(1) provide continuous operation;
(2) recover effectively if a disruption does occur;
(3) scale to meet rapid or unpredictable changes in demand.

Enhancing resilience in transport systems is considered imperative since such systems provide critical support to every socio-economic activity and are currently themselves one of the most important economic sectors (Bellini et al., 2017). At the same time, the ways in which people and goods move are the same through which the virus is spread. While limiting individuals' mobility and reducing the risk of transmission, the containment measures may also deteriorate other critical societal functions, thus compromising the overall resilience (Massaro et al., 2018). The COVID-19 crisis has shown again that transportation system, serving essential workers in health care, emergency services, food services, and other sectors, is vital to keeping cities running. Reduction in travel bring a reduction of the number of infected individuals, but the risk of disease transmission should be balanced with the society's need for maintaining certain critical functions and resilience (Massaro et al., 2018).

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Current challenges faced by public transport and mobility due to COVID-19 are forcing transport planners to rethink modes of operation in order to adapt to the new situation. Reduced public transport services in combination with changes in people's behavior, such as avoiding travel and using public transport fearing risks of infection and switching to private cars, creates the need for a well thought and coordinated demand management. Cities worldwide are coping with the current problem with various solutions, such as expanding their cycling networks and encouraging people to use bikes for their daily commute. In the city of Beijing commuters can use 'Subway by appointment' to reduce coronavirus crowding by making appointments through mobile apps to enter two of the Chinese capital's busiest subway stations during rush hours (Salo, 2020)..

The main objective of the paper is to present a simulation approach to evaluate the effectiveness and appropriateness of different Covid-19 unlock strategies related to the public transportation system. The paper shows how simulations can be used to support decision-makers in making the most informed decisions when adapting to the circumstances surrounding coronavirus,

The study exploits the DMCI (Dynamic functional Modelling of vulnerability and interdependencies of CI) modelling approach (Trucco et al., 2014) for transportation network characterization and evaluation of the strategies (and combinations of those strategies) identified as feasible for implementation.

2. DMCI simulation model and related works

2.1 *DMCI simulation model*

The first version of the DMCI model was released in 2012 (Trucco et al., 2012) with the aim of modelling different types of interdependencies between networked critical infrastructure systems, taking a functional perspective of the demand-supply flows (Ouyang, 2014).

The DMCI is a discrete event simulation which analyzes the dynamic behavior of the CI system-of-systems as a result of a threat impacting on one or more infrastructural nodes. The formalism of the DMCI model is characterized by:

- vulnerable nodes (susceptible to threats which can affect the operations of the node);
- threats that cause service loss (SL) in vulnerable nodes;
- interdependencies between different nodes;
- propagation of inoperability (disruption of node service due to cascading effects) and demand variations throughout the nodes of the same infrastructure and between interdependent CI.

2.2 *Geographical context*

Lombardy (Lombardia in Italian) is one of the 20 Italian regions, located in the north. A sixth of Italy's population lives in Lombardy (around 10 million citizens) and it accounts for around 20% of Italy's GDP, making it the most populous and richest region in the country and among the richest in Europe.

In 2012, the Lombardy Region Government has promoted a public-private collaboration (PPC) aimed at establishing a regional Critical Infrastructure Protection and Resilience Programme, developing a model of integrated and shared management that is capable of supporting a higher level of collaboration within the processes of prevention, risk monitoring and emergency management related to regional CIs. The preliminary study carried out by a team of academics and consultants provided a complete picture of the actual status of the vulnerability of regional infrastructural nodes and the corresponding emergency management processes adopted by the regional CI operators.

2.3 *Previous studies - VNA of road transport infrastructure in the Milan metropolitan area*

The DMCI was applied to analyze the wider *EXPO 2015* area in Milan (Italy), where 169 transport nodes under high service demand and electrical energy vulnerable nodes were mapped (Highways, Motorways, Railways, Train stations, Airports, Metro lines). The analysis supported the evaluation of possible protection and resilience strategies for the transport CI system.

The model was calibrated and configured to carry out a Vital Node Analysis (VNA; Luiijf et al., 2003; Petrenj and Trucco, 2014) on the reference CI system. The analysis focused on identifying:

- nodes with the highest impact on the inoperability or service loss of the entire CI system (critical nodes); and
- nodes that are the most frequently disrupted (sensitive nodes) by cascading effects triggered by the inoperability of other nodes in the CI system.

In this analysis the level of Missed Service Demand (MSD) is measured as the difference between the actual service demand and the service provided. The analysis is practically implemented through a simulation campaign in which each experiment postulates the total loss of functional integrity of one node for a constant time period (thus the number of experiments equals the total number of nodes in the study area).

Another study (Petrenj and Trucco, 2014) analyzed complex disruption scenarios and simulated the behavior of the system after impact by several threats or a single threat that is able to affect more than one vulnerable node concurrently. By modelling and simulating a real complex scenario disrupting the transportation system in the metropolitan area of Milan, heavy snowfall in December 2009, we were able to analyze the behavior of the system and estimate the global and local effects of different resilience features and response strategies, compared to what actually happened (the baseline scenario).

The original DMCI model was further enhanced in recent years and integrated into GRRASP (Geospatial Risk and Resilience Assessment Platform) developed by the JRC (Galbusera and Giannopoulos, 2016). The latest version of the model (DMCIe; Galbusera, Trucco and Giannopoulos, 2019) is currently being used within the Interreg project SICt (Security of cross-border Critical Infrastructures, 2018-2021).

3. COVID-19 pandemic in Lombardy and its impact on the transportation system

The ‘Phase 2’ is the first step of the gradual transition from lockdown to a sustainable “new normal”, where the reopening of some sectors would take place under preventive measures. In public transport, those measures would include increasing the distance between passengers to minimize the risk of infection transmission.

3.1 *Transportation system model*

The used model comprises 183 nodes, which cover the transportation infrastructure in the metropolitan area of Milan and towards the border with Switzerland (about 5 million inhabitants). The considered infrastructure comprises national roads, highways, stations, railways, metro lines and airports. A single node represents a piece of infrastructure with a specific direction, e.g. a segment of a national road is modeled with two nodes, one for each driving direction. Each node is characterized by two time-dependent parameters: the nominal capacity and the nominal demand, which are and how many of them are requiring to use the node, respectively.

The possibility of reproducing the real dynamics of the CI network through the DMCI model largely depends on the quality of the input data. The most important information needed to model each single node are: *Maximum Service Capacity* (the number of people that can be transferred in a fixed time slot), *Standard Demand* (the number of people requiring to use the node in the same time period) and *Interdependencies between the nodes* (physical, cyber, geographical and logical). The required data were collected directly from the CI operators or from publicly available sources and then validated by the operators, thanks to their participation in the PPC set by the regional government.

3.2 *Current state and considered unlock strategies for the Phase 2*

3.2.1 *Demand considerations*

In the lockdown state, where only the workers of essential services continued to commute, the situation was (Galasso, 2020):

- remote-working – 38%
- home (not working) – 45%
- workplace (commuting) – 17%

The first hypothesis was to estimate a partial unlock where at least 50% of the workers would get back to their workplace, while the other 50% would stay at home (the majority of them, i.e. > 45%, smart-working). The mobility of high school and university students accounts for around 20% of the public transport demand under normal conditions. If in Phase 2 schools would continue to operate with distance learning solutions, the overall public transport demand could be estimated as:

- 50% of extra-urban demand compared to normal conditions (pre-pandemic).
- 40% of the urban demand compared to the normal conditions.

Under the hypothesis of a return to school with in presence classes (and universities still in distance learning mode), the urban demand would increase up to 85%, compared to the normal conditions.

3.2.2 *Capacity considerations*

Due to the social distancing requirements, set to prevent spreading of the virus, the entire local public transport (LPT) is organized to operate with reduced capacity. This applies in particular to railways and the metro system.

To evaluate the system performance, 12 different levels of residual capacity were tested: from 15% to 70% of the full (nominal) system capacity, with 5% steps.

3.2.3 *Unlock strategy considerations*

With the aim of reducing the systemic inefficiencies introduced by the reduction of LPT capacity, a set of feasible strategies have been proposed. These envisage modifications of the work hours and workdays, implying changes in the daily profile of demand, mainly obtained by breaking down morning and evening peaks.

- Switching from 1 to 2 daily 8-hour shifts would split the rush-hour and flatten the daily demand profile in the entire network. The shifts are assumed to be 08:00h - 16:00h and 12:00h - 20:00h.

- Switching to 6 workdays – where each worker would still work 5 days per week but with different schedules (different 2 days off). This strategy aims to reduce the overall daily demand.
- Switching to 7 workdays – following the same approach as the previous one, where the workday demand would further drop having workers spread their activity (and commute) over the entire week.

The effects of each of the listed strategies on the shape of the typical demand profile is explained in more detail in the following section.

4. DMCI configuration and simulation campaigns

4.1 *Demand shift*

The DMCI model takes into account also the demand shift from rail to road (logical interdependencies). People may switch due to two main reasons:

- they see personal vehicles as safer than public transport due to the COVID-19 pandemic;
- the reduced capacity of the public transport is not enough to fulfil the demand, especially in the peak hours, i.e. not everyone would be able use the public transport to commute (at least not in reasonable time).

Compared to previous studies, where DMCI was used to analyze specific disrupting events hitting a stable system, in the current study DMCI was used to simulate the behavior of a new configuration of the entire transportation system operating under unconventional constraints. This mainly influences the demand shift modelling. In a previous study on the CI resilience against heavy snowfall events (Petrenj and Trucco, 2014), different levels of demand shift were tested and the conclusion was that the overall system achieved the best performance only with a small demand shift (4%). However, in the current scenario, people is already aware of the new constraints and of the available mobility options, i.e. they are better prepared to adapt their plans to the prevailing situation. Thus, we assumed that the vast majority (80%) of people not being able to use public transport would switch to road mode.

4.2 *Framing the problem*

In classical transport optimization problems, many variables come into play. In this study, we aim to evaluate different unlock strategies without changes in the system configuration, i.e. we do not consider changes in the timetable (scheduling) of the public transport or changes in routing. We also do not consider DMCI use for real-time decision-making and measure implementation. The problem at hand can be framed as evaluating the options across three main dimensions:

- Urban/non-urban residual demand: the public decision maker is interested in evaluating the impact of a set of unlock strategies under different conditions, each corresponding to a specific stage of the post-Covid-19 unlocking process. These conditions are summarizes into three cases: strong demand limitation (40% urban, 50% extra-urban), mild demand limitation (85% urban, 50% extra-urban) and full demand (100% for both).
- Local Public Transport (LPT) residual capacity: social distancing strongly affects the effectiveness of the public transport system, reducing the available capacity. Several options (12) were considered, starting from a residual capacity of 70%, down to 15%, at intervals of 5%.
- Unlock strategies: as a consequence of the capacity reduction, rethinking the settings of work organisation was necessary to ensure the overall system stability. Starting from the three suggested strategies, the analysis also included the no-action case (baseline).

4.3 *Modelling different mobility demand profiles*

In order to automatize the process of adapting the demand to each unlock strategy, it was deemed necessary to classify the demand profiles in a set of normalized sample profiles. For the sake of a quick and easy application, these samples are expressed in percentage terms over the maximum demand of the corresponding node: before running the simulations, input data on the demand is built by multiplying the profiles (which depend on the considered strategy) and the maximum demand of each node (given by urban/non-urban residual demand case).

Depending on the traffic dynamics that was observed on each piece of infrastructure, all the 183 nodes were classified into four categories:

(i) Constant daytime demand: nodes such as airports and stations (Fig. 1);

(ii) Two equal peaks demand (morning and afternoon): applicable to areas where traffic has no preferential direction in different time slots, such as the city centre (Fig. 2);

(iii) Morning-skewed demand, such as the one of nodes that bring workers into the city area in the morning (Fig. 3);

(iv) Afternoon-skewed demand, such as the one of nodes that bring workers out of the city are in the afternoon (Fig. 4).

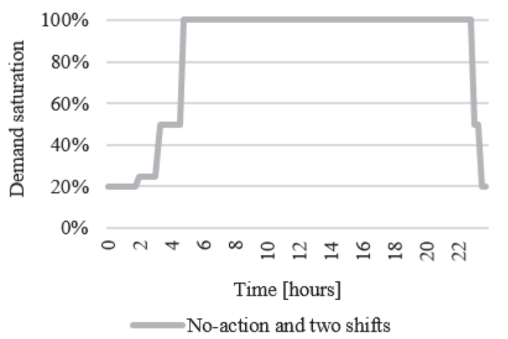

Fig. 1. Profile of the constant daytime demand category in case of no action and two shifts

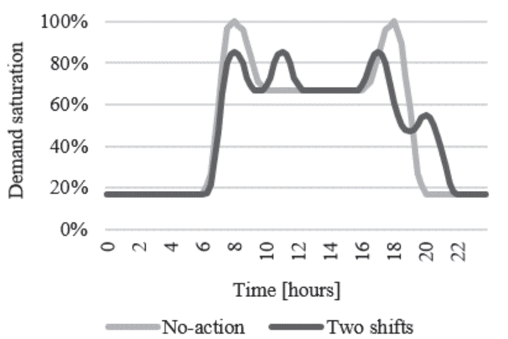

Fig. 2. Profile comparison of the equal peaks demand category for the single and double shift setting

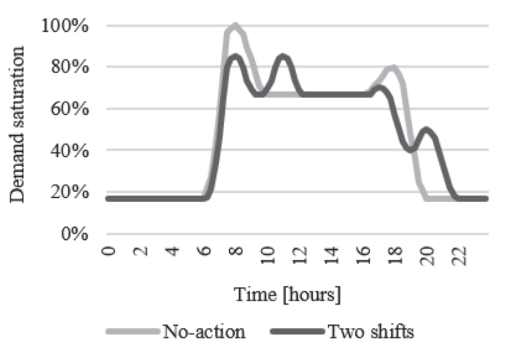

Fig. 3. Profile comparison of the morning-skewed demand category for the single and double shift setting

For example, the morning-skewed category reaches full demand (100%) around 8 a.m., while it is limited to 80% during the afternoon peak at 6 p.m. Different nodes could share the same category, but result in profiles of different magnitude, due different values of maximum demand.

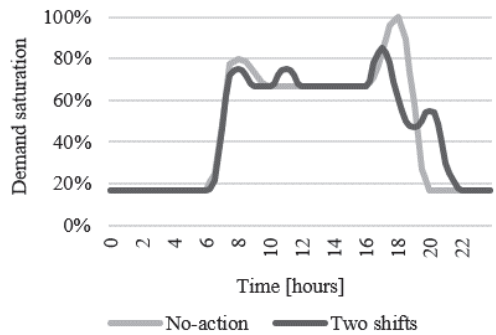

Fig. 4. Profile comparison of the afternoon-skewed demand category for the single and double shift setting

The profiles of the remaining strategies are obtained by normalising the previous profiles (no-action and two shifts) over different time periods. In fact, the only constraint of this process is to keep the same equivalent number of travellers on a weekly basis, meaning that the underlying area of the profiles must be the same for each category.

- Two daily shifts: the three categories that are characterized by differential demand during the day (i.e. those with peaks in the morning and in the afternoon) have been flattened by considering the area of each peak and distributing it into four peaks. The baseline traffic, which is the minimum level of demand recorded between the two peaks (e.g. the 67% threshold in Fig. 2), representative of that portion of traffic that is observed independently of the hour of the day, is kept the same, since it is assumed to be out of the decision maker's control. With respect to the first category (constant daytime demand), it remains unchanged.
- Six workdays a week: this strategy features the traditional two-shifts setting, but rescaled on 6 working days instead of 5. All demand profile categories are multiplied by a scaling factor equal to 0.92. The coefficient is calculated based on the number of full demand days in a week: in the reference case there are 6 full demand days (5 week days, 2 half days corresponding to the weekend), while now there are 6 full days and only half day for the weekend. In order to keep the same amount of transferred people the load of a single day of the reference case must be divided by 6.5 and multiplied by 6.

- Seven workdays a week: same as before, the profiles are rescaled with a factor of around 0.85. As in the six workdays case, the coefficient is calculated by dividing by 7 (all 7 week days are equal) and multiplied by 6 (5 week days, 2 half weekend days).
- Seven workdays a week on two shifts: as the superposition of two of the previous strategies, the applied profiles are those of the two shifts, scaled by 0.85.

5. Results

The key performance indicator that has been chosen as a measure of the system's inefficiencies is the *service loss* (SL). It summarizes the equivalent number of people that are not guaranteed with an access to mobility services, due to lack of transport capacity on the nodes that correspond to the path they are willing to take.

Since under normal conditions the Lombardy transportation system already experiences some SL, typically in the rush hours, the effect of each unlock strategy was computed in relative terms, as the percentage variation of the SL against standard conditions. First of all, the performance of the system is evaluated in the nominal scenario, where the demand profiles of the whole set of nodes match with those registered during a period of ordinary traffic. The results of this analysis identify the "reference case", which represents the baseline for the next step.

As it was previously introduced, the analysis evolves along three dimensions: the urban/non-urban residual demand (3 cases), the unlock strategy (5 cases: the no-action one, plus the 4 considered strategies) and the LPT residual capacity (12 levels). In total, considering also the reference case, 181 simulation runs were performed. The time horizon was set on 24 hours, and the time span of 30 minutes. The analysis was performed on a generic PC, equipped with average computing power. The total net computation time was about 20 minutes.

5.1 *Reference case*

The reference case showed a service loss value of 89.448 equivalent mobility units (person/node). Starting from this value, all the other cases where analyzed and compared to the reference one.

5.2 No action (*Residual demand: 100% urban and 100% extra-urban)*

The application of the set of strategies to the full demand setting resulted in substantial service loss variation even with the maximum residual LPT capacity (70%). The no-action strategy is overcome by all the alternative strategies: the two shifts, the six workdays, the seven workdays and the seven workdays on two shifts (in this order).

All unlock strategies start at a ratio between 0 and 5000% (with respect to reference case). When the residual capacity moves from 70% to 45%, the deterioration of the seven days-based strategy performance suggests their advantage on the rest. However, from 45% to the end, the effect of all strategies tends to linearity, while some of them superpose emphasizing the substantial collapse of the transportation system despite the selected strategy.

In general, it appears that the seven days settings (both with and without two shifts) ensure lower impact on the system by no less than 20 times the reference service loss straight from 65% capacity (Fig. 5). However, the difference is not significant, and it is limited to the medium/high LPT capacity spot. Towards higher LPT limitations, it becomes negligible.

5.3 Demand partially reduced *(Residual demand: 85% urban and 50% extra-urban)*

This case (Fig. 6) features a partial reduction of the LPT demand, in particular outside the urban area. In general, the benefit of all strategies, including the no-action one, increases but the SL still results unacceptable. It remains below 500% until 55% of LPT capacity and do not exceed 5500%. The trend is similar to the full demand case, with a partial superposition of no-action with two shifts, and seven workdays with seven workdays on two shifts.

5.4 Demand strongly reduced *(Residual demand: 40% urban and 50% extra-urban)*

The last case stretches the previous behavior even more, showing no substantial effect on the service loss until 40% LPT capacity (Fig. 7). Under these conditions, the differences between all strategies are definitely stronger. By combining the "two shift" and "seven working days" strategies the SL is negligible up to 25% of LPT residual capacity. The stratification across different modes of transport (Fig. 8).shows that the major part of the MSD comes from the 'transport on iron' (rail and metro).

6. Discussion & Conclusions

The present paper is a summary of a larger study that assisted the regional decision makers to evaluate the expected effects of different Covid-19 unlock strategies related to the public transport system.

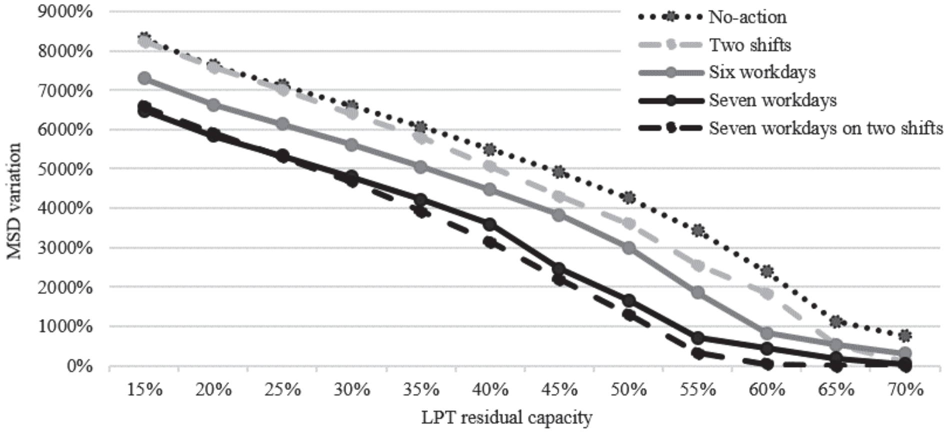

Figure 5: Missed Service Demand variation of the analyzed strategies from the reference case, in relation to the LPT residual capacity, under full demand

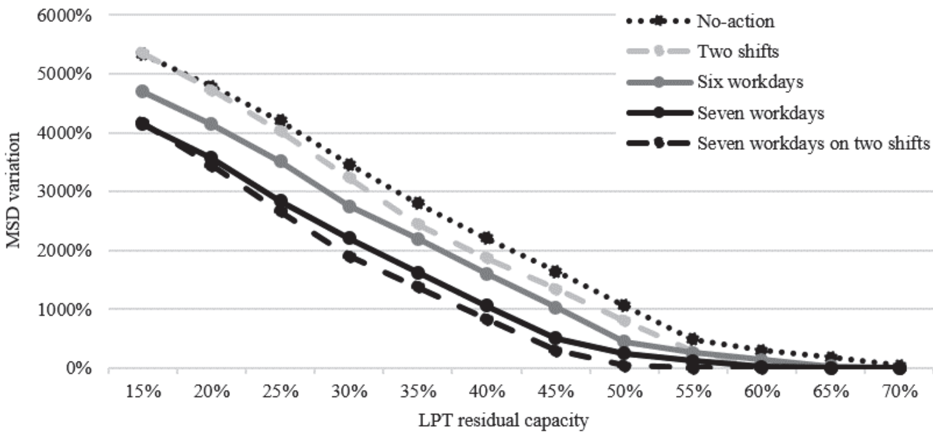

Figure 6: Missed Service Demand variation of the analyzed strategies from the reference case, in relation to the LPT residual capacity, under partially reduced demand

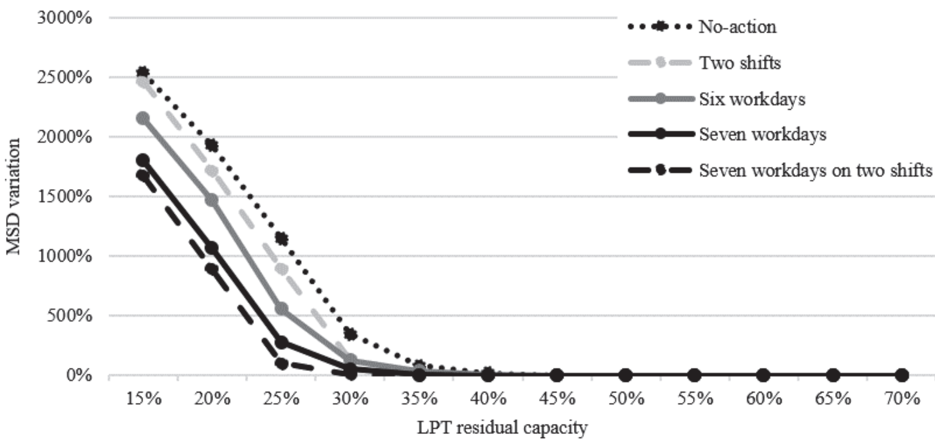

Figure 7: Missed Service Demand variation of the analyzed strategies from the reference case, in relation to the LPT residual capacity, under strongly reduced demand

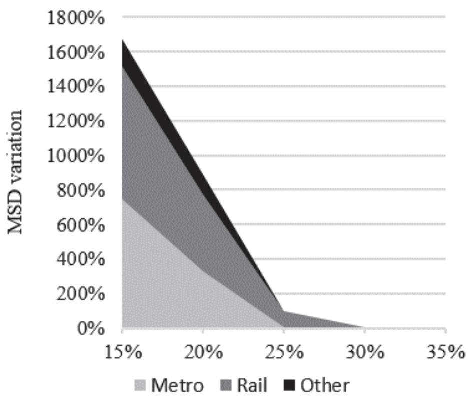

Fig. 8. MSD contribution by mode of transport, in the "Demand strongly reduced" case

The results show that the proposed strategies (and their combinations) can limit the worsening effect of LPT capacity reduction in different ways. The analysis of their impact under three demand conditions (corresponding to the evolution of the unlock process) allows to identify the differences among the strategies and to select the most appropriate in each step of the unlock. Moreover, it shows how their effectiveness changes with the local public transport capacity reduction introduced to apply social distancing.

A possible additional option, not evaluated here, would consist of stopping extra-urban cars at the city limits, to avoid inner-city traffic jams, and moving people to the public transport with the addition of supplementary metro and busses. A study in Singapore (Jin et al., 2014) showed that metro network resilience to disruptions can be enhanced significantly from localized integration with complementary public bus services.

As explained in the problem description, we do not consider adjustments to the timetables which would change the available capacity profiles. This possibility is left for assessment to the CI operators, based on the study outcomes and the orchestration of available resources. Other minor limitations of the study include no considerations about the staff availability nor taking into account the budget constraints in the new arrangements (operating costs vs. income).

One of the next steps of the study would be to collect the real data on the transportation system performance during the phase 2 of the Covid-19 unlock, collected by the CI operators. It would be used to validate (and/or better calibrate) the current model and use it for the planning of the "new normal" spanning at least over the entire 2021.

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