Network topology and robustness of Physical Internet

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Abstract

The Physical Internet (PI) is a new paradigmatic concept for logistic systems, characterized by flexibility and efficiency through decentralization and standardization. In the PI, the delivery route of freight can be chosen flexibly from available paths at the moment, better utilizing transportation resources than traditional systems. However, the knowledge on the congestion dynamics of traffic in the PI is still limited. Here, to contribute to the understanding of the dynamical features of the PI, we examine the robustness of a network delivery system by using a simple model that extracts the essence of the problem. We performed extensive Monte Carlo simulations on various conditions on the type of algorithm, network structure, and transportation capacity, and three scenarios that mimic changes in demand: (i) locally and temporally increased traffic demand; (ii) globally and temporally increased traffic demand; and (iii) permanent change in demand pattern. We show that adaptive algorithms are more effective in networks that contain many bypass routes (e.g., the square lattice and random networks) rather than the hub-and-spoke networks. Furthermore, the square lattice and random networks were robust against the change in the demand pattern and temporal blockage (e.g., due to high demand) of delivery paths. We suggest that such preferable properties are in a trade-off relationship between the redundancy of networks and that the bypass structure is one of the important criteria for designing network logistics.

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1 Introduction

Logistics systems are becoming more complex and interrelated, from the operational level to the strategic level, due to economic globalization, offshoring of production, increasing product complexity, and fast-changing trends, etc. (Harland et al., 2003; Dolgui et al., 2020; Choi et al., 2001). Under these circumstances, companies have tried to pursue various types of efficiency improvements in their quest for greater competitiveness. One of the main pillars of such measures is consolidation of logistics systems (Buffa, 1987; Hall, 1987; Cetinkaya et al., 2006). Logistics integration is now being practiced not only within the same company but also between different companies, which is called the horizontal collaboration (Chan et al., 2004; Cruissen et al., 2007; Naesens et al., 2009). However, while it is clear that this concept would ideally reduce costs, the process of actually integrating the operations is not easy. To achieve the integration, companies have to connect to and use each other’s system, which has been studied as a critical issue (Chen et al., 2008; Barthe-Delanoë et al., 2014; da Silva Serapião Leal et al., 2018; Pan et al., 2021).

Meanwhile, the concept of the Physical Internet (PI) is gaining attention as a new paradigm for supply chains (Ballot et al., 2011; Montreuil, 2011; Sternberg and Normann, 2017; Treiblmaier et al., 2020). The PI is a decentralized logistics network, characterized by the use of modularized containers (called “PI containers”) and standardized distribution centers (called “PI hub”) that connect to each other. Analytical and simulation studies have shown that the PI outperforms the traditional logistics network in terms of economic and environmental efficiencies (Ballot et al., 2011; Sohrabi and Montreuil, 2011; Hakimi et al., 2012; Sarraj et al., 2014; Fazili et al., 2017). Past researches have also proposed and examined the various elements that make the distributed functions of the PI viable (Sternberg and Normann, 2017; Treiblmaier et al., 2020), e.g., the PI container (Montreuil, 2011; Montreuil et al., 2014; Sailez et al., 2016), PI hub (Ballot et al., 2012; Meller et al., 2013; Chargui et al., 2020), dynamic pricing (Qiao et al., 2019; Lafkihi et al., 2020), and data management (Tretola and Verdino, 2014; Tretola et al., 2015).

Since the PI has not yet been realized, although its feasibility has been extensively discussed, it is important to predict and understand the actual behavior of the entire system to guarantee its performance and sustainability. Because numerous internal and external factors affect the system, the dynamic behavior of the PI is considerably complex by nature. However, theoretical contributions to this problem are still scarce (Treiblmaier et al., 2020). In this article, we examine the robustness of the system against various types of perturbations and how it is affected by the network structure.

To this end, we take a model-based approach. Such an approach has provided useful insights into the PI. In this context, the typical use of mathematical models can be divided into three main categories: analytical computation, optimization, and simulation. For example, Ballot et al. (2011) considered the different types
of network topology and evaluated the performance of the PI using the analytical computation based on the continuous approximation method (Langevin et al., 1996). Optimization studies have shown the efficacy of the PI (Sohrabi and Montreuil, 2011; Venkatadri et al., 2016) and the PI with inventory management (Pan et al., 2015; Ji et al., 2019). Unlike these two uses of a model, simulation allows for more complex settings, such as route finding algorithms and dynamic changes in the environment. For example, past studies have simulated a relatively large-scale system considering realistic operations (Hakimi et al., 2012; Sarraj et al., 2014), a logistic system in a road network (Fazili et al., 2017), and disruptions in the network (Yang et al., 2017). Although these findings are very useful, our knowledge of the dynamic behavior of the system is still limited. In particular, understanding of congestion and concentration of delivery demand is critical from an application perspective. Moreover, knowing the relationship between the topology and dynamics of the network not only allows us to evaluate the performance of the system, but also provides guidelines on how to design the structure of the network.

Meanwhile, it is noteworthy that the fields of applied mathematics, statistical physics, and network science have advanced our understanding of the fundamental characteristics of traffic congestion on networks in various contexts (Boccaletti et al., 2006; Tadić et al., 2007; Chen et al., 2011). Note that past literature has also pointed out the usefulness of such findings in supply chain management (Hearnshaw and Wilson, 2013). Such theoretical studies have elucidated the emergence mechanisms of congestion in computer networks (Ohira and Sawatari, 1998), road networks (Biham et al., 1992), airport networks (Ezaki and Nishinari, 2014), production networks (Ezaki, Yanagisawa and Nishinari, 2015), etc. Past studies have found critical determinants of transport performance, such as network topology (Guimerà et al., 2002; Zhao et al., 2005), capacity distribution (Zhao et al., 2005; Wu et al., 2008), routing algorithm (Echenique et al., 2004; Zhang et al., 2007; Ling et al., 2010; Ezaki, Nishi and Nishinari, 2015). These factors were taken into consideration in this study.

Although such theoretical studies have provided useful implications to various applications, the conclusions are not directly applicable to the design of the PI for the following reasons. First, these studies use very simple models to allow mathematical analysis, which might be too simple for the PI. Also, because the PI is a relatively new concept, problem settings in the context of the PI have not been examined yet. Second, because the focus of these studies is often on the (very) large scale behavior of the system, such as scale-free networks and phase transitions, the conclusions may not be true in a realistic system of small size. In addition, for this reason, heuristic algorithms with very low computational costs were preferably used as the routing algorithms (Chen et al., 2011). However, given the distributed nature of the PI, the routing should be assumed to be more high-performance.

In this paper, we use a simple model that does not lose the essence of network logistics to investigate
how the response of the system to various disturbances is affected by the structure of the network, capacity
distribution, and the routing algorithm. We examine three types of disturbances, i.e., two temporal and one
permanent disturbances, and measure the performance of the traffic. We find that the network topology
significantly affects the performance in all the cases and show that hub-and-spoke networks are not robust
against the changes in the demand in general.

The remainder of the article is organized as follows. First, Sec. 2 defines the model and scenarios we
examine in this paper. Then, Sec. 3 shows the comprehensive simulation results. Finally, in Sec. 4 we
summarize the results and discuss their implications and future prospects.

2 Model

2.1 Overview of the models

Consider a network of transit centers. The transit centers connected by a link can send freight to each
other. Here we call the minimum unit of delivery a packet. A link has a capacity that is the maximum
number of packets it can carry at the same time. A cost for delivery is also defined on each of the links. If
demand exceeds capacity, packets must wait until demand on that link falls below capacity or use a bypass
route. We put \( N \) packets in the system. When each packet is generated, we randomly chose the origin
and destination nodes and computed the route plan by using one of the algorithms, which will be explained in
Sec. 2.4. We updated the system in discrete time. At each time step, each packet was allowed to jump to
the next node if the capacity of the link is not exceeded. When a packet arrived at the destination node,
the packet was removed from the system, and a new packet was generated with a randomly chosen origin
and destination. Note that we did not refer to the transit center (node) and packet as the PI hub and PI
container, respectively, to explicitly show that we consider a more simplified system than that the original
PI envisions.

2.2 Networks

We consider three types of networks each having 25 nodes. In the square lattice network (Fig. 1(a)), nodes
adjacent to each other on the top, bottom, left, and right are connected together. On the link, the cost and
capacity values are defined in both directions separately (i.e., cost and capacity values of the link from node
1 to node 2 may be different from those of the opposite link). The cost value of the link from node \( i \) to node
\( j \) (\( 1 \leq i \neq j \leq 25 \)), denoted by \( c_{ij} \), is uniformly randomly chosen from an interval \([0.5, 1.5]\). We used three
different ways of determining capacity values, which are explained in the next subsection. The lattice has
40 bidirectional links (= 80 directional links). This type of network is often used to model a road network (Zeng and Zhang, 2014).

In the random network (Fig. 1(b)), 25 nodes are randomly connected by 40 bidirectional links. To wire the links, we randomly selected a pair of nodes that were not wired already, until the total number of links reached 40. If the generated network was disconnected (i.e., with isolated parts), we discarded it and regenerated a new random network. Same as the lattice, the cost value was randomly drawn from an interval [0.5, 1.5] for each direction of each link. This network was examined to test if the results were affected by the regular structures of the other two networks.

The hub-and-spoke network is shown in Fig. 1(c). This network has 25 nodes and 24 bidirectional (48 unidirectional) links. The cost value was randomly chosen in the same way as the other two networks. This type of network is widely used in traditional supply chains for their efficiency (Abdinnour-Helm, 1999).

2.3 Capacity

The capacity of a link from node $i$ to node $j$ ($1 \leq i \neq j \leq 25$), $C_{ij}$, defines the maximum number of packets that can pass through it at the same time. We used three types of capacity distributions (Fig. 2). The first one which we call “Single packet per link” defines the capacity to be $C^{\text{Single}}_{ij} = 1$ (packet) for all the links. The second one “Two packets per link” doubles this capacity to $C^{\text{Two}}_{ij} = 2$ (packets) for all the links.

The last one, “Weighted by betweenness centrality”, weights link capacities according to pre-estimated demand of use. The demand was estimated by the betweenness centrality (Yoon et al., 2006), which was computed as follows. First, find the shortest paths between all the possible pairs of nodes ($25 \times 24 = 300$ pairs). Second, for each link from node $i$ to node $j$ ($1 \leq i \neq j \leq 25$), count how many the shortest paths used the link. We denote this number by $n_{ij}$. Note that this definition gives the link (or edge) betweenness centrality, which is a derivative of the commonly used (node) betweenness centrality (Barthélemy, 2004). Finally, the capacity is computed by

$$C^{\text{Weighted}}_{ij} = 1 + \frac{n_{ij}L}{25 \times 25 \times 24},$$

where $L$ is the total number of (unidirectional) links (i.e., $L = 80$ for the lattice and random network and $L = 48$ for the hub-and-spoke network). Note that the sum of the capacity values, $C^{\text{Weighted}}_{ij}$, over the links coincides with that of $C^{\text{Two}}_{ij}$, allowing comparisons between the capacity distributions given the total capacity resources.
We did not limit the number of packets that nodes can hold.

2.4 Routing algorithms

Here we use three types of routing algorithms, i.e., static shortest path (SSP) algorithm, temporal fastest path (TFP) algorithm, and adaptive fastest path (AFP) algorithm. When a packet enters a system with randomly selected origin and destination nodes, a routing algorithm generates a path plan. Because the availability of a link changes over time due to congestion, a packet may not always be able to travel in the minimum time steps. A packet using the SSP algorithm always follows the pre-calculated shortest path. If a move is blocked, the packet waits until the link becomes available. The TFP algorithm considers the path plans of other existing packets and avoids the blocked link in the future if necessary. The AFP applies the TFP algorithm every time the situation is changed (e.g., when a new packet is added to the system or the pattern of link availability is updated). In the first two algorithms (i.e., the SSP and TFP algorithms), the planned path is reserved for the packet and thus not changed on the way to the destination node, while in the AFP algorithm, the planned path is updated adaptively to the environment.

The SSP algorithm follows the shortest path regardless of congestion. If a link in the shortest path is temporally unavailable (e.g., due to excess demand), the packet waits until it becomes available. The shortest path between nodes was computed by Dijkstra’s algorithm (Dijkstra, 1959) on the network with cost values. Note that capacity values were not used to compute the shortest path.

The other two algorithms (i.e., TFP and AFP algorithms) take the number of time steps including wait time into consideration. They find the fastest path, i.e., the path that requires the least time steps to travel from the given origin to destination. (Note that the shortest path is the path that minimizes the total cost, but not including the waiting cost explained later.) If more than one fastest path is found, we select the path with the smallest total cost. In our model, because the cost values on the links were not significantly different from each other, the fastest path coincides with the shortest path in many cases when all the links in the network are available. To find the fastest path, we used Dijkstra’s algorithm on a time-expanded graph, in which a node in a network at different time points is represented by two different nodes (Fig. 3). The move from node $i$ to $j$ ($1 \leq i \neq j \leq 25$) available at time $t$ is represented by a transition link from node $i$ in time $t$ to node $j$ in time $t + 1$. The cost of using this transition link is $c_{ij}$. If a packet at node $i$ does not move at time $t$ (to wait until a link becomes available), the transition is represented by a transition link from node $i$ in time $t$ to node $i$ in time $t + 1$. The cost for using this transition link is defined as $c_W$. In this paper, we examine two conditions on the waiting cost, i.e., $c_W = 0$ and $c_W = 0.5$. On this time-expanded network, we computed the minimum cost to reach each of the nodes in each time step from a given node at a given time (nodes that cannot be reached at each time step are also identified in this process). The first
path that reached the destination was defined as the fastest path.

Technical details of this procedure are as follows. First, we found a time when the use of the reserved transition links would be completed, $t'$. We constructed the time-expanded graph from current time $t_0$ to $t'$. If the number of packets that will use a link from $i$ to $j$ at time $t$ is smaller than its capacity value, we put a transition link; otherwise, we did not. At time $t'$, we also put links between nodes that are connected. Because after $t'$, no link is planned to be blocked, the standard Dijkstra’s algorithm is available. If more than one fastest path was found, the path that approached the destination more quickly was adopted. For example, if one finds routes from node 1 to node 3, 1−1−2−3 and 1−2−2−3, the latter was adopted as the fastest path. This happens when the link from 2 to 3 is not available until the last time step because whether to wait at node 1 or node 2 has no effect on cost or time. Note that although Dijkstra’s algorithm [Dijkstra, 1959] is computationally affordable in the systems used in this paper, it is not applicable when the size of the network becomes large, in which case we need to use a more efficient algorithm.

To generate a time-expanded graph, we first identified which links would be available in the future, considering the already planned paths of existing packets. The TFP algorithm sets the path plan in this way and does not change it. The AFP algorithm performs these procedures every time a new packet enters the system or a blocked pattern of links is changed. When such an event occurs, we first cleared all the planned paths. Then, we recomputed the fastest paths for each packet in order of proximity to the destination node (i.e., the number of links in the shortest path from the current position to the destination node). This ordering was based on the premise that a packet far from the destination has a higher possibility of finding a good alternative path than a packet close to the destination even when a link on the shortest path is blocked by other packets, and that such an algorithm generates globally better path plans than the algorithm without ordering.

Note that for the simplicity of arguments, we did not consider the total-cost-minimization algorithms given the information of unoccupied links (i.e., temporal shortest path (TSP) algorithm and adaptive shortest path (ASP) algorithm) whereas we used TFP and AFP algorithms. Such algorithms yield paths that wait at a node when the cost of waiting is smaller than the additional cost of using a detour path. Therefore, the results are qualitatively expected to be interpolations of those obtained from the SSP and TFP/AFP algorithms (with the total cost larger than the SSP but smaller than the TFP/AFP, and the total time of travel smaller than the SSP but larger than the TFP/AFP). In fact, if one sets $c_W$ to a sufficiently large value, the TSP and ASP algorithms are reduced to the TFP and AFP algorithms, respectively. Also, if one sets $c_W = 0$, they are reduced to the SSP algorithm.
2.5 Scenarios

We performed simulations on four different settings. The first one is the baseline scenario, in which the system is not perturbed. The origin and destination nodes of each packet were selected uniformly at random. We examined how the three algorithms function in the three types of networks for various numbers of packets, three capacity distributions, and two waiting cost values.

The second one is the one-shot-demand-concentration scenario, in which a set of \( M (= 2 \text{ or } 5 > \text{capacity}) \) packets that cannot be sent at the same time are randomly placed in addition to the \( N \) regular packets already exist in the system (Fig. 4(a)). This examines the system behavior in response to a temporary and localized excess demand. These \( M \) packets had the same origin and destination. The origin and destination of the packets (including the regular packets) were selected uniformly at random. We traced these \( M \) packets and measured the time it took for the first and last packets to arrive at the destination. When a traced packet completed its travel, we removed it from the system. When all the \( M \) packets have arrived, we generated a new set of traced packets and repeated the measurement. The simulations were performed for the three algorithms, three types of networks, various numbers of packets, three capacity distributions, two wait cost values, and two packet numbers, \( M \).

The third one is the dynamical-demand-change scenario, in which a portion of links become temporally unavailable (Fig. 4(b)). Every 5 time steps, we selected 12.5%, 25%, or 50% of the links uniformly at random and blocked them for 5 time steps. We assumed that the routing algorithms could use the information about how long the link blockage would last. When the pattern of blockage changed, the AFP algorithm recomputed the path plans of all the packets. Note that because the SSP algorithm does not change the path, a packet using the SSP algorithm waits until the next link becomes available if the link is blocked. The TFP algorithm takes into account the blockage information available at the time (i.e., when a packet is generated), but is not flexible to new blockage patterns that will occur in the future. The simulations were performed for the three algorithms, three types of networks, various numbers of packets, three capacity distributions, two wait cost values, and three fractions of link blockages.

The fourth one is the permanent-demand-concentration scenario, in which the origin and destination of packets each concentrate on a different single node (Fig. 4(c)). When an origin (destination) node is to be selected, a single node is chosen with a probability of 0.5, while the other 24 nodes are selected with a probability of 0.5/24 each. This demand pattern was fixed throughout the simulation. The simulations were performed for the three algorithms, three types of networks, various numbers of packets, three capacity distributions, and two wait cost values.
2.6 Simulation conditions

We ran these procedures for $T = 1000$ time steps for each condition. Because the cost values and one type of the network (i.e., the random network) were generated at random, we independently generated 10 networks with cost values on the same condition and averaged the results over these 10 runs.
3 Results

3.1 Network statistics

Before going into details, we first report the statistics of the networks (Fig. 1). Figure 1(d–f) shows an example distribution of the length of the shortest paths computed for all the pairs of the nodes is shown for each network. The distributions for the square lattice (Fig. 1(d)) and random networks (Fig. 1(e)) both had a peak at length 4. Because the square lattice had no shortcut links, it had a larger percentage of node pairs with longer shortest paths than the random network. The distribution for the hub-and-spoke network had a peak at length 5, which is the maximum value of the shortest path length (Fig. 1(f)).

Figure 1(g–i) shows the distribution of the betweenness centrality of links, which is a measure of how likely a link is to be used in the shortest path. The distributions are similar between the square lattice and random networks, but the variance was smaller in the random network (Fig. 1(g, h)). Meanwhile, the betweenness centrality of the hub-and-spoke network took only two values, i.e., 24 or 114, corresponding to 40 (directional) links connecting to the peripheral nodes and 8 links connecting to the central node, respectively. These distributions were reflected to the capacity distribution (Fig. 2(d–f)).

3.2 Fundamental analyses on the system

3.2.1 Routing algorithm and network structure

We compare the total cost and time of travels of packets across network structures and waiting cost conditions for the baseline scenario.

First, we report the cases with $c_W = 0$ (i.e., the waiting cost being negligible) and the Single-packet-per-link capacity condition. On the lattice and random networks, the cost of travel was slightly larger in the TFP and AFP algorithms (Fig. 5(a, c)). However, when the number of packets in the system increased, these algorithms significantly reduced the travel time compared to the SSP algorithm, which suggests that they were successful in finding alternative routes efficiently (Fig. 5(b, d)). The performance measures of TFP and AFP algorithms were similar. Meanwhile, on the hub-and-spoke network, all the three algorithms resulted in similar travel cost and time (Fig. 5(e, f)), because this network has no bypass routes for any pair of nodes. Also, for this reason, the travel cost and time rapidly increased for an excess demand.

When the waiting cost was not negligible (e.g., $c_W = 0.5$), the cost of travel increased with the traveling time, significantly deteriorating the performance of the SSP algorithm (Fig. 6(a, c)). The presence of the waiting cost did not substantially change the travel time (Figs. 6(b, d, f) and 5(b, d, f)). As in the cases with $c_W = 0$, the performance measures of the three algorithms were similar on the hub-and-spoke network.
Because the waiting cost did not change the route choosing behavior significantly, we focus on the cases with $c_w = 0$ in the rest of the article and show the results for $c_w = 0.5$ in Appendices.

### 3.2.2 Capacity distributions

Next, we examine the effect of capacity distributions on the performance of the algorithms. The total capacities (i.e., the sum of the capacity values over all the links in the network) of the two capacity conditions, i.e., Two-packet-per-link and Weighted-by-betweenness-centrality conditions, are both twice that of the Single-packet-per-link condition.

These two capacity distributions both reduced the time of travel in all the three networks and three algorithms both with $c_w = 0$ (Fig. 5) and $c_w = 0.5$ (Fig. 6). The total cost was not changed when $c_w = 0$, whereas it was reduced when $c_w = 0.5$ simply because the total cost is associated with the total time.

With the SSP algorithm, the total travel time more decreased in the square lattice and hub-and-spoke networks with the Weighted-by-betweenness-centrality condition (Figs. 5(b, h, n, f, l, r) and 6(b, h, n, f, l, r)), suggesting the capacity resource was effectively allocated to important links. In particular, the hub-and-spoke network benefited from this capacity distribution because the demands on the links are concentrated on the small number of links (Fig. 1(i)). In contrast, the difference between the two capacity conditions was not large in the random network, because it had smaller variance on the betweenness centrality than the other two networks, by which the shortest paths were more dispersed (Fig. 1(g–i)).

The TFP and AFP algorithms performed similarly in the two capacity conditions except in the hub-and-spoke network (Figs. 5(g–j, m–p) and 6(g–j, m–p)). These algorithms disperse the paths without significantly increasing the cost in the square lattice and random networks, and thus, the Weighted-by-betweenness-centrality condition was not superior to the Two-packet-per-link conditions. In the hub-and-spoke network, because these two algorithms generate similar paths to the SSP algorithm, Weighted-by-betweenness-centrality capacity distribution resulted in a larger decrease in the travel time (Figs. 5(f, l, r) and 6(f, l, r)).

### 3.3 One-shot demand concentration

Next, we examine the response of the system against a temporal and localized increase in the demand (i.e., the One-shot-demand-concentration scenario). We placed a set of $M$ (=2 or 5) packets having the same destination at a random position (Fig. 4(a)) and recorded the travel paths of the first and last packets to arrive. Figure 7 shows the total cost and time of the travels of the first and last packets, for $c_w = 0$ and $M = 5$. 

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Because the SSP algorithm generated the same paths for a set of traced packets, the total cost was the same between the first and last packets in all the networks (Note that $c_W = 0$). However, as the last packet had to wait until the previous packets had cleared out and the shortest path became available, the difference in the arrival times between the first and last packets was large (Fig. 4). The difference was smallest in the Two-packets-per-link capacity distributions, while the other two capacity distributions yielded similar time differences. This is in stark contrast with the baseline scenario, in which Weighted-by-betweenness-centrality capacity distribution performed the best in the majority of cases (Figs. 3 and A1). The time difference was not substantially influenced by the number of packets in the system in the range of $1 \leq N \leq 100$.

The TFP and AFP algorithms were successful in reducing the difference in the arrival time in the square lattice and random networks (Fig. 7(b, d, h, j, n, p)), because they disperse the paths increasing the effective capacity of delivery from the origin to the destination. The difference in arrival time was smallest in the Two-packets-per-link capacity distribution because detour routes are likely to exist everywhere, by not concentrating capacity resources to a limited number of links. The total cost for travel was only slightly greater for the last packet than for the first (Fig. 7(a, c, g, i, m, o)). On the hub-and-spoke network, the two algorithms yielded similar results to the SSP algorithm because no detour routes existed.

The pattern of the results remained the same when we set $c_W = 0.5$ (Fig. A1) except that the total cost increased as the travel time increased. When we set $M = 2$ (and $c_W = 0$), the results were qualitatively unchanged, but the difference in the travel time between the first and the last (i.e., the second) packets was small (Fig. A2).

### 3.4 Dynamical demand change

We consider a situation where some links are randomly closed for a certain length of time for external reasons (i.e., Dynamical-demand-change scenario, Fig. 4(b); see Sec. 2.5 for the details). Link closures that occur in the future are not taken into account by the routing algorithms (but information on current link closures, i.e., which links are being closed and until when, is available for TFP and AFP algorithms). We simulated the system dynamics with three different percentages of blocked links, i.e., 12.5, 25, and 50%.

Figure 8 shows the total cost and travel time with 25% of links being closed and $c_W = 0$. With the SSP algorithm, the travel time increased as compared to the baseline scenario (Fig. 5). The results were similar between the Two-packet-per-link and Weighted-by-betweenness-centrality capacity conditions because the negative impact of the closure of a critical link with a large capacity is large, which outweighs the advantage of the Weighted-by-betweenness-centrality capacity distribution.

The TFP and AFP algorithms both succeeded in reducing the travel time in the square lattice and random networks (Fig. 8). In particular, the AFP algorithm yielded faster travels than the TFP algorithm.
by adaptively rerouting the packets. The performance measures of these algorithms were similar between the Two-packet-per-link and Weighted-by-betweenness-centrality capacity conditions. The total cost was larger for the AFP, TFP, and SSP algorithms, in this order. In the hub-and-spoke network, no substantial difference was found among these algorithms.

The results remained qualitatively the same for different percentages of the link closure (i.e., 12.5 and 50%; Figs. A3 and A4, respectively) and a different value of waiting cost (i.e., $c_W = 0.5$; Fig. A5).

3.5 Permanent demand concentration

Finally, we examined the permanent change in the demand pattern (i.e., the Permanent-demand-concentration scenario, Fig. 4(c); Sec. 2.5). The permanent demand concentration caused significant increases in the cost and time of travel in all the cases (Figs. 9 and A6). The TFP and AFP algorithms effectively dispersed the travel paths to reduce the travel time as compared to the SSP algorithm in the square lattice and random networks. In the hub-and-spoke network, the three algorithms yielded similar results. The performance of the TFP and AFP algorithms was similar in all the networks.

The travel time was smallest in the Two-packets-per-link capacity distribution (Figs. 9(g–l) and A6(g–l)), because the uniform capacity distribution allowed detour routes to be found even when the pattern of demand is changed.

4 Conclusion

We examined the effect of network topology on the performance of the network logistics system under perturbations. The following results were obtained consistently for the three demand change scenarios. (i) Adaptive algorithms (i.e., TFP and AFP algorithms) performed better than the SSP algorithm except in the hub-and-spoke network where no difference was found between all the algorithms. (ii) The capacity distribution based on the betweenness centrality (i.e., Weighted-by-betweenness-centrality) was effective than the uniform capacity distribution with the same total capacity (i.e., Two-packets-per-link) in reducing the travel time when the demand was generated uniformly at random. In contrast, under the demand change scenarios, the Two-packets-per-link distribution reduced the travel time more than Weighted-by-betweenness-centrality condition. (iii) The performance of the square lattice and random networks were qualitatively similar. These results collectively suggest that the networks with redundancy can respond well to changes in demand, while hub-and-spoke networks without such redundancy cannot enjoy such benefits of the PI.

For redundant networks (i.e., square lattice and random networks), we also found the following results specific to the scenarios. (i) In the one-shot-demand-concentration scenario, the TFP and AFP algorithms
effectively reduced the difference between the arrival times of the first and last packet of a set of packets having the same origin, destination, and departure time. This quantity would be a useful measure for evaluating the performance of the PI. (ii) In the dynamical-demand-change scenario, the AFP algorithm effectively found a temporally better route than the TFP algorithm that does not change the route during the travel.

In this paper, we focused on the total cost and time of travel as measures of performance for the simplicity of the argument. However, other measures, including sustainability ones (Montreuil, 2011), should be considered when a more detailed evaluation of the system is necessary. For example, it has been shown that the PI can reduce the green gas emission from 14 to 50% (Pan et al., 2013). In our model, the length of travel is roughly measured by the total cost (when we set $c_w = 0$). We showed that travel time can be reduced on the redundant networks, without a substantial increase in the total cost, suggesting the efficiency of the algorithms in terms of sustainability.

It should be noted that we set the cost of using a link at random in the range of 0.5 to 1.5. In practice, the cost of travel may be significantly different between links if we include multimodal transportations. The same issue applies to the cost of waiting, $c_W$. In this paper, we did not pursue realistic settings for these values but focused on the general behavior of the system independent of the specific settings of the parameters. We believe that the main conclusion of the paper, i.e., redundant networks are robust, is not substantially influenced by the choice of the parameter values unless one sets extreme values. Also, in our model, the number of packets sent in a single transport on a link was limited to a small non-negative integer, while many packets can be sent at once in real logistics systems. We consider this does not substantially affect our conclusions. Even if we increase the capacity of the links and number of packets in the system, the fact still remains that a network with bypass routes allows for the efficient dispersal and delivery of packets when excess demand occurs.

In this paper, we examined three types of capacity distributions but did not try to find the best one. Because the packets interact with each other’s route, it is not straightforward to do so. For example, it has been shown in a previous study that traffic congestions cannot be predicted simply from the betweenness centrality (Holme, 2003). Finding an efficient capacity allocation given the network structure and operation of the PI is a subject of future research.

Our results suggest that hub-and-spoke networks are not robust against changes in the demand in general. However, such a structure is beneficial in terms of efficiency and is quite widely used in practice (Abdinnour-Helm, 1999). Thus, how to edit a part of the network to increase its robustness efficiently is a very interesting subject for future research. For example, it is known that adding nodes or links to a network can significantly change its transport performance (Huang and Chow, 2010), which may be extended to the
The robustness of a supply chain network is closely related to the concept of resilience (Ponomarov and Holcomb, 2009; Pettit et al., 2016; Tukamuhabwa et al., 2015; Ivanov, 2017; Hosseini et al., 2019; Dolgui et al., 2020). Resilience is a capacity of an enterprise that enables it to survive, adapt, and grow in the face of turbulent change (Fiksel, 2006). To achieve a resilient system, what is required for the PI networks to guarantee such stability of the system in the long term is an important issue that needs to be clarified in the future.
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Figure 1: Network structures and statistics. (a–c) Examples of three types of networks, i.e., (a) square lattice, (b) random network, and (c) hub-and-spoke network. The thickness of the line representing each link corresponds to the cost value, \( c_{ij} \) (1 \( \leq i \neq j \leq 25 \)). (d–f) Distributions of the length of the shortest path between a pair of nodes for each network. (g–i) Distributions of the link betweenness centrality for each network.
Figure 2: Capacity distributions. (a–c) Single-packet-per-link capacity distributions for each type of network. (d–f) Two-packets-per-link capacity distributions for each type of network. (g–i) Weighted-by-betweenness-centrality capacity distributions for each type of network. The thickness of the line representing each link corresponds to the capacity value, $C^X_{ij} \ (1 \leq i \neq j \leq 25, \ X = \text{Single, Two, or Weighted})$. 
Figure 3: Schematics of the routing algorithms. (a) Static shortest path algorithm (SSP). (b) Temporal fastest path algorithm (TFP). (c) Adaptive fastest path algorithm (AFP). (d) Time-expanded-network approach used in the TFP and AFP algorithms.
Figure 4: Scenarios with three different types of changes in demand. (a) One-shot demand concentration scenario. (b) Dynamical demand change scenario. (c) Permanent demand concentration scenario. A cyan and magenta circles represent nodes that are frequently (with probability 1/4) selected as an origin and destination with high demand, respectively.
Figure 5: Total cost and time of travel in the baseline scenario with no waiting cost (i.e., $c_W = 0$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure 6: Total cost and time of travel in the baseline scenario with positive waiting cost ($c_W = 0.5$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure 7: Total cost and time of travel in the one-shot demand concentration scenario with no waiting cost ($c_W = 0$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure 8: Total cost and time of travel in the dynamical demand change scenario with 25% of links being closed and no waiting cost ($c_W = 0$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure 9: Total cost and time of travel in the permanent demand change scenario with no waiting cost \((c_W = 0)\) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over \(T = 1000\) time steps and 10 independent runs.
Appendix
Figure A1: Total cost and time of travel in the one-shot demand concentration scenario with positive waiting cost ($c_W = 0.5$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure A2: Total cost and time of travel in the one-shot demand concentration scenario with $M = 2$ and no waiting cost ($c_W = 0$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure A3: Total cost and time of travel in the dynamical demand change scenario with 12.5% of links being closed and no waiting cost ($c_W = 0$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure A4: Total cost and time of travel in the dynamical demand change scenario with 50% of links being closed and no waiting cost ($c_W = 0$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure A5: Total cost and time of travel in the dynamical demand change scenario with 25% of links being closed and positive waiting cost ($c_W = 0.5$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, g, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.
Figure A6: Total cost and time of travel in the permanent demand change scenario with positive waiting cost ($c_W = 0.5$) under various conditions on the algorithms, types of networks, capacity distributions, and number of packets in the system. (a, b, h, m, n) Square lattice network. (c, d, i, j, o, p) Random network. (e, f, k, l, q, r) Hub-and-spoke network. (a–f) Single-packet-per-link capacity distribution. (g–l) Two-packets-per-link capacity distribution. (m–r) Weighted-by-betweenness-centrality capacity distribution. The results were averaged over $T = 1000$ time steps and 10 independent runs.