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LARGE SCALE LOGISTICS NETWORK SIMULATION AND ITS APPLICATION IN JD LOGISTICS

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ABSTRACT

This paper proposes a large-scale logistics network simulation method to reduce package delivery delay and package loss caused by the sudden increase of package transportation demand during large-scale promotion activities such as November 11th and June 18th. A large-scale logistics network simulation software for a large logistics enterprise has been developed. According to its actual logistics network, its equivalent virtual logistics network has been established in the simulation software. The virtual logistics network has been simulate and adjusted in advance. The actual logistics network is regulated according to the virtual network. As result, transportation time, transportation distance, and transportation costs for the logistics enterprise are reduced. The simulation software can complete the distribution of a month with 500 million packages in less than 30 minutes on a personal computer.

1 INTRODUCTION

With the progress of electronic commerce, in recent years the express logistics industry has experienced a rapid development. A large number of logistics enterprises have been developed and built all over the world (Sheffi 2012). In China, for example, JD, ShunFeng, and YuanTong deliver over 10 million packages per day, respectively. They manage a large-scale logistics network that contains ten thousands of nodes and transportation lines. They provide efficient logistics and express services for people (Jiao 2018).

However, there are still some serious problems in the express logistics industry. For example, because the number of orders from customers increases prominently during grand promotion periods, such as November 11th and June 18th, there appears a critical backlog of packages in the logistics network. Consequently, the labor intensity of employees increases while the delivery speed slows down (Chen 2016). There is a lack of an accurate approach for predicting the load of each sorting hub and transporting route in a large-scale logistics network. There is also a lack of efficient methods for creating, verifying, and optimizing resource allocation schemes for a large-scale logistics network. As a result, it is hard to exactly increase manpower and vehicles in a short period of time to meet the demand without waste. This not only increases transportation costs but also leads to more exhaust emissions (Zhao 2020).

In the logistics network of a large logistics enterprise, usually about 1,000 warehouses and sorting hubs and about 20,000 express stations are interconnected by more than 20,000 transporting routes. More than 100,000 people and more than 100,000 trucks, trains, and planes work together in the network. This kind of logistics network is undoubtedly a typical complex system. Traditional approaches have severe difficulty in analyzing its load status, describing its evolution, and obtaining efficient resource allocation approaches (Madala 2019). Accordingly, as a preferred method for studying complex systems, simulation is undoubtedly suitable for solving such problems (Timm and Lorig 2015).

The relevant research covers logistics simulation, modeling, analysis, management, and control of logistics systems. For example, in the area of logistics simulation, Tako and Robinson reviewed the application of discrete event simulation and system dynamics as decision support systems for logistics and supply chain management between 1996 and 2006 (Tako and Robinson 2012). Chong and Osorio (2017) bring out a simulation-based optimization algorithm for dynamic large-scale urban transportation problems. Van Heeswijk et al. (2020) evaluate urban logistics schemes using agent-based simulation models. Straka et al. (2018) design large-scale logistics systems using computer simulation with a hierarchic structure. Fanti et al. (2015) implement a simulation-based decision support system for logistics management. Van Der Vorst et al. (2009) provide a simulation modelling method for food supply chain redesign. Liebler et al. (2013) introduce an order-to-delivery network simulation and decision support systems in complex production and logistics networks. Rabe and Dross (2015) propose a reinforcement learning approach for a decision support system for a logistics network that contains over 100 warehouses in different countries and an inventory of around 150,000 items on permanent stock. Rabe et al. (2017) suggest a method to model actions for discrete event simulation of logistics networks that contains almost 500 warehouses and an inventory of around 150,000 items in permanent stock. Poeting et al. (2017) bring out a combined simulation optimization framework to improve operations in parcel logistics. Rossetti and Bright (2019) model and simulate a large-scale bulk petroleum supply chain that is impacted by a Category 4 hurricane scenario. Rabe et al. (2018) discuss how to use domain-specific information for the optimization of logistics networks. Rabe and Schmitt (2019) introduce a domain-specific language for modeling and simulating actions in logistics networks. Serrano-Hernandez et al. (2021) present a hybrid modeling approach for automated parcel lockers as a last-mile delivery scheme. Hunker et al. (2022) propose a new data farming procedure model for a farming for mining method in logistics networks.

In this paper, we will study a logistics network that contains over 500 million packages. Obviously, existing methods are difficult to solve the large-scale logistics network simulation problem. We will bring out a simulation-based method to optimize the whole large-scale logistics network in a large logistics enterprise. A discrete event simulator is embedded in our logistics network simulation software.

2 ACTUAL PROCESSES IN A LARGE-SCALE LOGISTICS NETWORK

In order simulate the logistics network, a virtual logistics network model should be created in advance. The virtual logistics network runs under the same constraints of multiple package-relevant processes as the actual one. Figures 1 to 4 present four typical package-relevant processes in a large-scale logistics network. Figure 1 describes the global package process. Packages are created by packing goods from warehouses or from customers. Transporters carry them to sorting hubs, where they are unloaded and sorted. After being sorted, they are loaded to transporters and carried to other sorting hubs or express stations. In express stations, packages are unloaded from transporters and delivered to customers. Packages can be carried from one sorting hub to another by road, rail, or air.

Figure 2 describes the unloading, sorting, and loading processes in a sorting hub. When a full truck from other hubs arrives at the sorting hub, it can be unloaded only when the sorting hub has free unloading ports. Otherwise, it will wait in a queue. When a truck finishes packages unloading, it releases an unloading port and leaves from the sorting hub, and the earliest arrived truck in the waiting queue will occupy the released port and unload packages. Unloaded packages will be sorted immediately. After being sorted, packages will be allocated to a transporting route according to their destinations. After sufficient number of packages in a transporting route has been sorted, an empty truck will be called to load these packages if the sorting hub has free loading ports.

Figure 3 shows the sorting shift cycle in each sorting hub. A sorting hub usually works in two or three shifts. When a sorting shift in a sorting hub begins, packages are unloaded from trucks that occupy unloading gates, and sorters will begin sorting packages. If the sorting hub has free unloading gates and the waiting queue has full trucks, the full trucks will occupy the free unloading gates and be unloaded. When a sorting shift ends, packages are paused from being unloaded from trucks, and sorters pause sorting packages. Figure 4 displays the transporting cycle of each transport route. A transport route calls a transporter at a certain time before the departure deadline if the departure sorting hub of the transportation route has free unloading gates. After arrival, the transporter begins loading sorted packages of the transportation route. At the departure deadline of the transport route, it sends all transporters that belong to it.

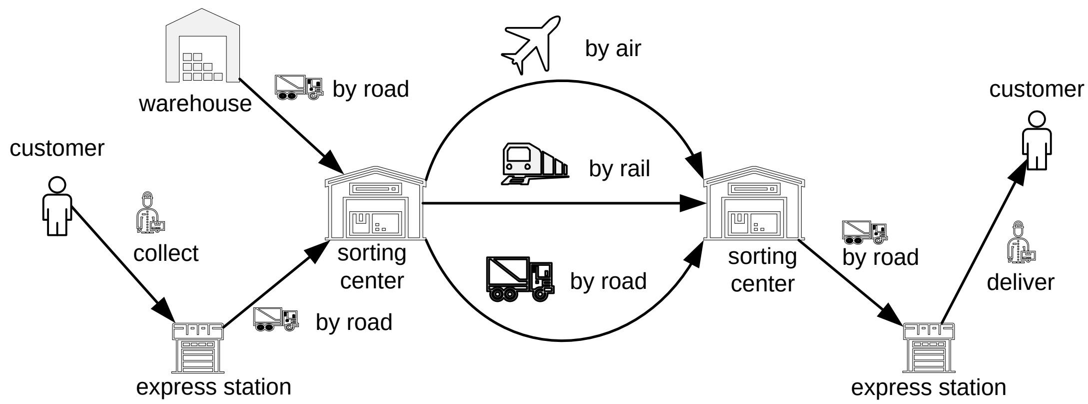

Figure 1: The global package process in a large-scale logistics network.

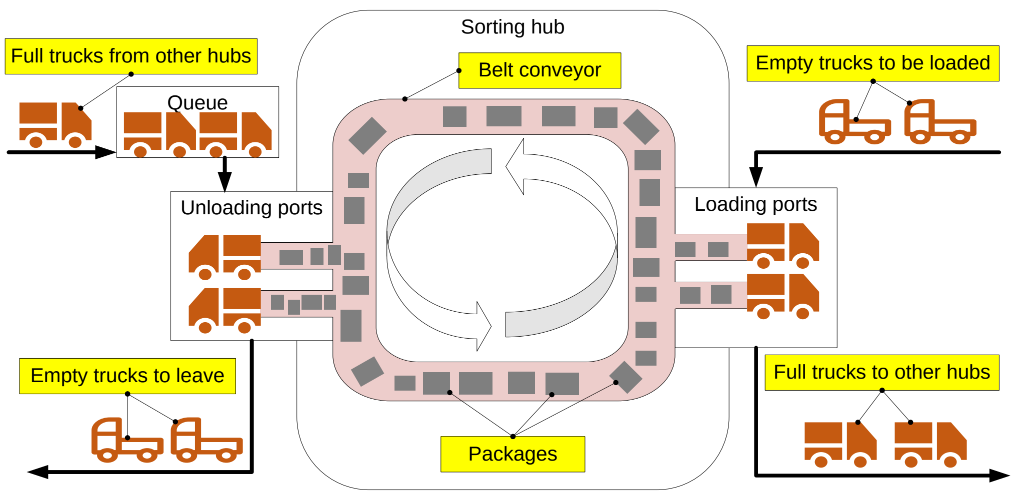

Figure 2: The unloading, sorting, and loading processes in a sorting hub.

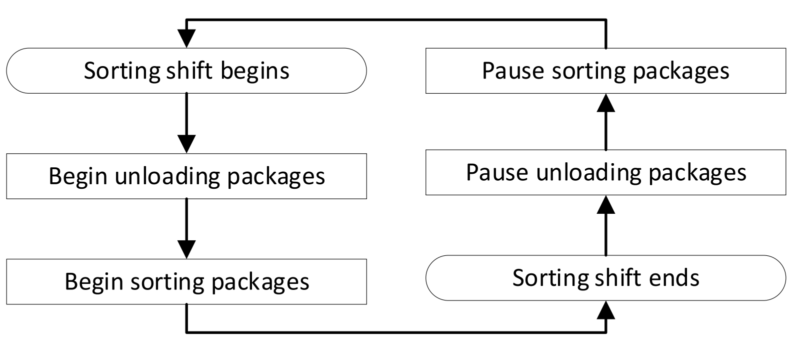

Figure 3: The sorting shift cycle.

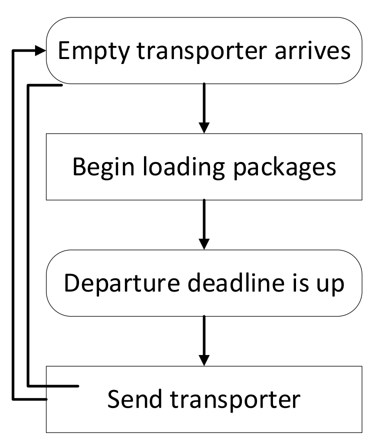

Figure 4: The transporting cycle.

3 LOGISTICS NETWORK SIMULATION AND OPTIMIZATION

3.1 Logistics Network Simulation

The virtual logistics network covers the whole network skeleton of a large logistics enterprise, which consists of nearly 1,000 sorting hubs and more than 6,000 transporting routes. The simulator is based on the discrete event simulation technique. It uses a small granularity, where the loading (unloading, sorting, and transporting) action of each package is described. Considering that no publication reports discrete event simulation of a logistics network that contains over 100 million running packages, a new simulation engine was designed and developed. In this section, the logistics network model is described and all the discrete events are determined that have to be handled by the simulation engine.

By analyzing package-relevant business processes of the logistics network described in Figures 1 to 4, four groups and 13 types of discrete events have to be processed by the simulation engine from the logistics network (Table 2).

Table 2: List of event types that are handled by the simulation engine.

Event group name	Event type name	When event occurs
shift	*shift_begin*	A shift begins in a sorting hub or a warehouse
	shift_end	A shift ends in a sorting hub or a warehouse
route	*route_call_empty_transporter*	A route begins calling an empty transporter
	route_send_full_transporter	A route begins sending a full transporter
package	*package_created*	A package has been created in a sorting hub or a warehouse
	package_unloaded	A package has been unloaded from a transporter
	package_sorted	A package has been sorted in a sorting hub
	package_loaded	A package has been loaded into a transporter
transporter	*full_transporter_departed*	A transporter has departed from a sorting hub or a warehouse
	full_transporter_arrived	A transporter has arrived at a sorting hub or a warehouse
	full_transporter_ready_unload	Packages can be unloaded from a full transporter
	empty_transporter_ready_load	Packages can be loaded to an empty transporter
	empty_transporter_departed	An empty transporter has departed from a sorting hub or a warehouse

Usually, billions of events are created and handled during the running of a large-scale logistics network simulation instance during a grand promotion. The main procedure of the logistics network simulation engine is shown in Figure 5. When the logistics network simulation engine starts, a set of initial events is created and inserted into an event queue. The types of initial events include *shift_begin*, *line_call_empty_transporter*, and *package_created*. The simulation engine iteratively picks out the earliest event from the event queue, processes it, and creates new events as necessary until an end condition meets.

3.2 Simulation-based Logistics Network Improvement

Simulation-based logistics network improvement consists of increasing persons in the sorting hub, adding vehicles, adding transportation routes, adjusting stowage of transportation routes, and enabling spare sorting hubs. The logistics network improvement starts with sufficient vehicles and persons. According to the output of each iteration of logistics network simulation, the packages are determined that cannot be delivered in due time as well as the number of available vehicles and persons. The routes are adjusted to move the delayed packages from sorting hubs whose workloads are saturated to the ones whose workloads are not saturated. The logistics network simulation is run again and move delayed packages until the delayed packages cannot be reduced by moving them. Finally, the reasonable number of persons is employed in all sorting hubs and the reasonable number of vehicles obtained.

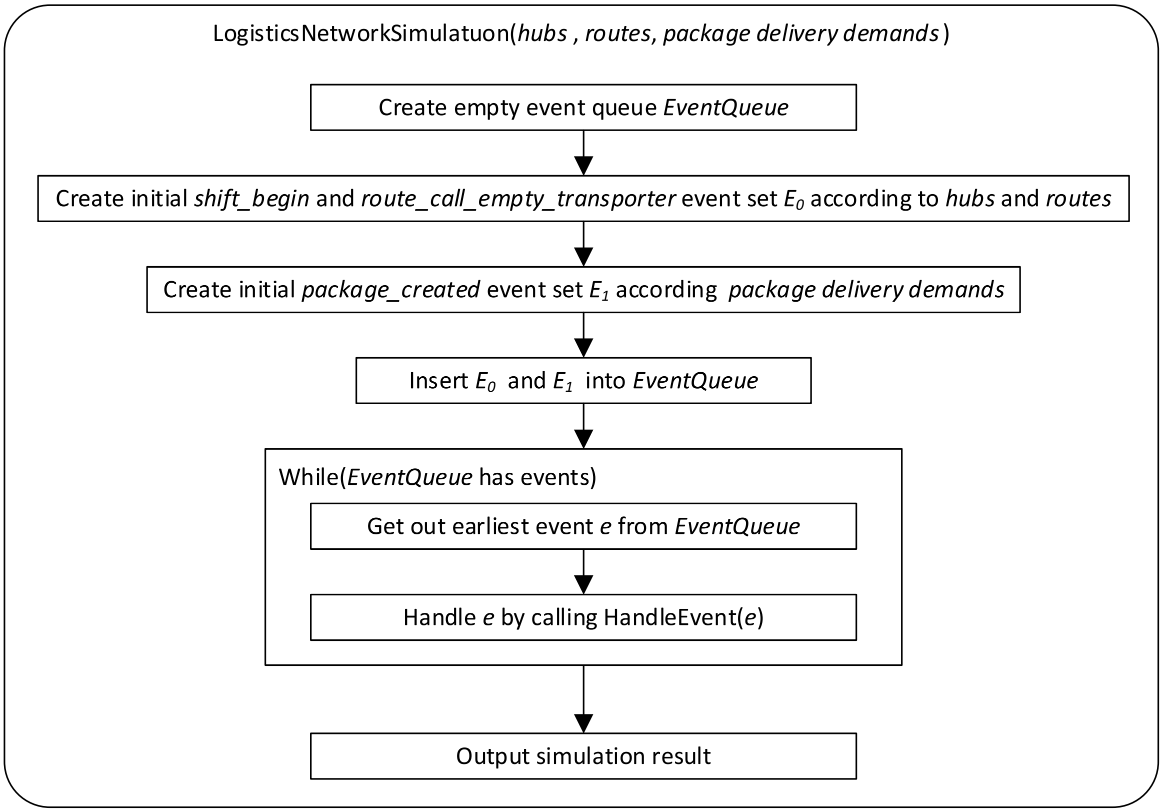

Figure 5: The main flow of the logistics network simulation.

4 DATA

The data of the logistics network simulation system consist of input data and output data. The input data are provided in the form of a database extract. They come from the database of a logistics enterprise. The output data are provided by the logistics network simulation system in the same form as the input data. There are many random variables in an actual logistics network. For example, the loading time, unloading time, and sorting time for a package are random. It proves to be feasible to use the average values instead of real random values for these variables in the logistics network simulation system. The input data and the output data are introduced in detail in Sections 4.1 and 4.2.

4.1 Input Data

The input data of the logistics network simulation contain the detailed information of all sorting hubs, all transportation routes, and all packages that need to be transported within a period of a logistics enterprise. The input data consist of five data tables, which are named as *sorting_hub_table*, *sorting_hub_shift_table*, *sorting_hub_gate_table*, *package_transport_demand_table*, and *transportation_route_table*. The detailed descriptions of every field in these tables are listed in Tables 3 to 7.

Table 3: Field names and descriptions of *sorting_hub_table*.

Field name	Field description
sorting_hub_name	Unique name of a sorting hub (referred as this hub in this table)
hour_capacity	Maximum number of packages that can be sorted in one hour in this hub
average_package_volume	Average volume of packages that start from this hub
average_package_weight	Average weight of packages that start from this hub
longitude	Longitude of the center position of this hub
latitude	Latitude of the center position of this hub

Table 4: Field names and descriptions of *sorting_hub_shift_table*.

Field name	Field description
sorting_hub_name	Name of a sorting hub (referred as this hub in this table)
shift_name	Unique name of a shift in this hub (referred as this shift in this table)
shift_start_time	Start time of this shift
shift_end_time	End time of this shift
shift_latest_arrive_time	Latest truck arrival time of this shift. If a truck arrives, this hub after this time, there may not be enough time to unload it during this shift.

Table 5: Field names and descriptions of *sorting_hub_gate_table*.

Field name	Field description
sorting_hub_name	Name of a sorting hub (referred as this hub in this table)
gate_type_name	Name of a gate type (referred as this gate type in this table)
gate_type_number	Number of gates of this gate type in this hub
loading_type	Identifies if the gate type in this hub for loading or unloading
maximum_vehicle_length	Maximum length of the vehicles that can connect to this gate type

Table 6: Field names and descriptions of *package_transport_demand_table*.

Field name	Field description
origin_hub_name	Name of the sorting hub where the packages will depart from
destination_hub_name	Name of the sorting hub where the packages will arrive at
demand_create_date_time	Datetime when the package transport demand is created
package_number	Number of packages that need to be transported

Table 7: Field names and descriptions of *transportation_route_table*.

Field name	Field description
transportation_route_name	Unique name of a transportation route (referred as this route in this table)
depart_sorting_hub_name	Name of the sorting hub where the vehicles of this route depart from
arrive_sorting_hub_name	Name of the sorting hub where the vehicles of this route arrive at
depart_time	Departure time of the vehicles of this route
arrive_time	Arrival time of the vehicles of this route
span_days	Number of days spanning from vehicle departure to vehicle arrival of this route
transportation_type	Identifies packages on this route as transported by road, by rail, or by air
route_type	Identifies this route as trunk, branch, or ferry
vehicle_length	Length of the vehicles that are used for this route
arrive_handle_time	Span from the arrival time of a vehicle to the time when all packages in the vehicle are sorted. This field is used to compute routes for packages
stowage_hub_names	Names of sorting hubs that may be destinations of packages of this route

4.2 Output Data

The output data of the logistics network simulation are stored in three tables that are named *sorting_hub_output_table*, *vehicle_output_table*, and *package_output_table* . The fields of the three tables are defined in in Tables 8 to 10.

Table 8: Field names and descriptions of *sorting_hub_output_table*.

Field name	Field description
sorting_hub_name	Unique name of a sorting hub (referred as this hub in this table)
date_and_hour	Date and hour, for example, 2020/11/1 14:00-15:00
unloded_package_num	Number of packages that are unloaded at *date_and_hour* in this hub
sorted_package_num	Number of packages that are sorted at *date_and_hour* in this hub
loded_package_num	Number of packages that are loaded at *date_and_hour* in this hub
collect_package_num	Number of packages that are collected at *date_and_hour* in this hub
distribute_package_num	Number of packages that are distributed at *date_and_hour* in this hub
transfer_package_num	Number of packages that are transferred at *date_and_hour* in this hub

Table 9: Field names and descriptions of *vehicle_output_table*.

Field name	Field description
vehicle_name	Unique name of a vehicle (referred as this vehicle in this table)
transportation_route_name	Name of the transportation route that the vehicle belongs to
vehicle_length	Length of this vehicle
package_number	Number of packages that are carried by this vehicle
package_volume	Volume of packages that are carried by this vehicle
depart_time	Time when this vehicle departs from its origin
arrive_time	Time when this vehicle arrives at its destination
loading_time	Time that this vehicle spends loading packages
unloading_time	Time that this vehicle spends unloading packages
wait_unloading_time	Time that this vehicle spends waiting for unloading

Table 10: Field names and descriptions of *package_output_table*.

Field name	Field description
origin_hub_name	Name of the sorting hub where the packages will depart from
destination_hub_name	Name of the sorting hub where the packages will arrive at
demand_create_date_time	Datetime when the package transport demand creates
package_num_1_day	Number of packages that are delivered in 1 day
package_num_2_day	Number of packages that are delivered in 2 days
package_num_3_day	Number of packages that are delivered in 3 days
package_num_4_day	Number of packages that are delivered in 4 days
package_num_5_day	Number of packages that are delivered in 5 days
package_num_over_5_day	Number of packages that are delivered in more than 5 days

5 CASE STUDY

Based on the above-mentioned approach, a logistics network simulation system has been implemented using the Java programming language. The main interface of the system is illustrated in Figure 6. The lines denote the transportation routes while the circles denote the vehicles. The colors of the circles indicate whether the vehicles belong to trunk routes, branch routes, or ferry routes.

JD Logistics (JDL) is a leading logistics company and the logistics arm of JD.com, the world's third-largest internet company by revenue. In order to illustrate the accuracy of the logistics network simulation engine, the virtual logistics network that is equivalent to the actual one is run on the simulation system. The simulation results are compared with the results of the actual logistics network, Q_{all} denote the number of packages in the actual logistics network, and $Q_{concord}$ denote the number of packages whose route in the simulation is the same as the one in the actual network. Then, the concordance rate of the package routing is defined as:

$$\text{concordance rate} = \frac{Q_{concord}}{Q_{all}} \tag{1}$$

The concordance rate of the static package routing of the two results is 99.7 %, and the accordance rate of the dynamic package routing of the two results is 94.2 %. The latter is lower than the former because the countermeasure is slightly modified to deal with unexpected situations (such as traffic accidents and bad weather) during a grand promotion. As a result, the logistics network simulation system appears to be reliable.

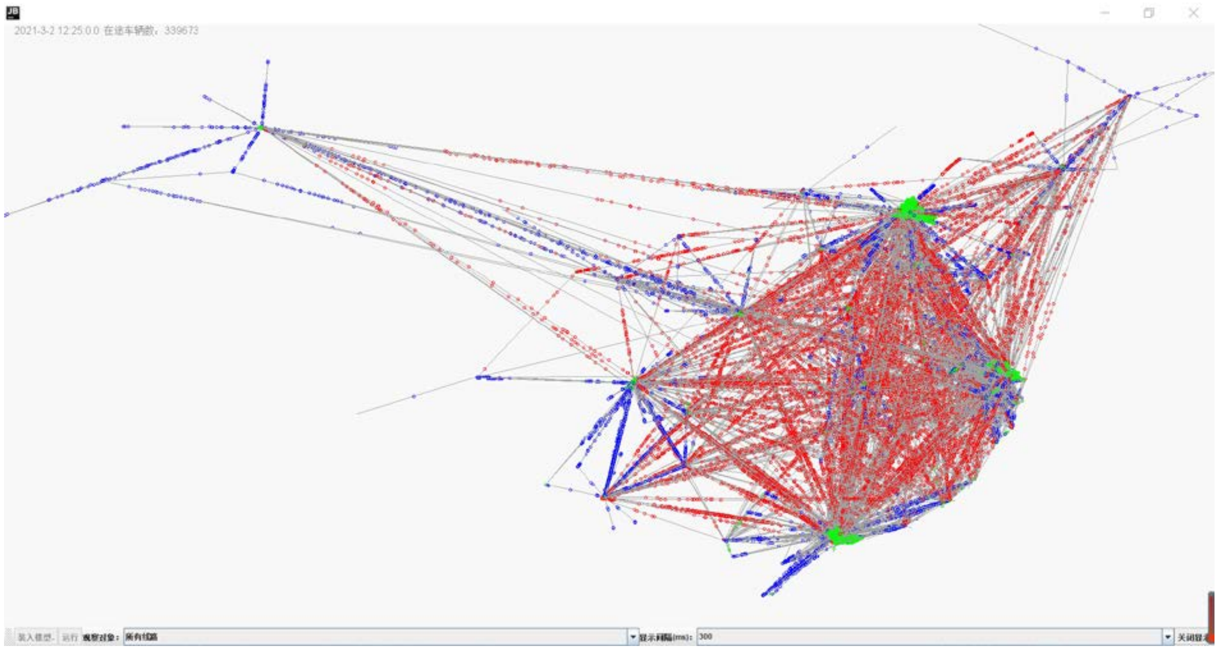

Figure 6: Interface of the logistics network simulation system.

JDL used the logistics network simulation system to optimize its logistics network during the grand promotion periods of June 18 and November 11 since 2020. Before the logistics network simulation system was adopted, JDL made package delivery countermeasures for the grand promotions by the exponential smoothing method (ESM) (Petropoulos and Apiletti 2022). It took dozens of people a few days to formulate the countermeasures before each grand promotion period. Now, with the logistics network simulation system, one person is able to formulate the countermeasure in a single day.

The logistics network simulation system (LNSS) ran the logistics network from 2022/10/24 to 2022/11/24 during which the November 11 grand promotion of JD was open; in total, more than 500 million packages were delivered. The vehicles for transportation and the persons for package loading and unloading need to be arranged in advance. Before the logistics network simulation system was developed, JD adjusted the vehicles and persons according to the workloads as predicted by the ESM. We call this method PESM-A (predict by ESM and arrange). Now, JD predicts the workloads of the logistics network with the LNSS and optimizes the arrangement of vehicles and persons by human-in-loop optimization according to the output of the LNSS. We call this method PLNSS-A (predict by LNSS and arrange). In order to illustrate the efficiency of the LNSS for the grand promotions, the logistics network was first run with the arrangement of vehicles and persons obtained by PESM-A and the logistics network with the arrangement of vehicles and persons obtained by PLNSS-A. Here, the arrangement of vehicles and persons by PLNSS-A is obtained by eight iterations of human-in-loop simulation and optimization on LNSS. It takes a PC (CPU: i7 8700HQ at 4.6GHz, 32GB memory) less than half an hour to run one iteration of simulation. It takes one person and one PC about seven hours to generate the arrangement of vehicles and persons. According to the experimental experience, eight iterations of simulation and optimization are sufficient to get a good arrangement of vehicles and persons for JD's logistics network. All packages have been classified into three categories according to their delivery distances: short distance (≤600 kilometers), middle distance (600 kilometers–1,500 kilometers), and long distance (⩾1,500 kilometers). In order to evaluate the simulation result in a steady status, the analysis only covered the simulation data from 2022/11/1 to 2022/11/15, and not the data from 2022/10/24 to 2022/11/24. The results of PESM-A and PLNSS-A from 2022/11/1 to 2022/11/15 are listed in Table 3.

Table 11: The results of PESM-A and PLNSS-A for the logistics network.

	PESM-A	PLNSS-A
Transition time for short distance packages(days)	1.56	1.27
Transition time for middle distance packages(days)	2.53	2.36
Transition time for long distance packages (days)	3.41	3.19
Shipping distances (kilometers)	502	463
Sorting times	2.5	2.4

From Table 11, the average transition time of short-distance packages, middle-distance packages and long-distance packages from 2020/11/1 to 2020/11/15 by PLNSS-A is 19 %, 7 %, and 9 %, respectively, lower than that by PESM-A. It is obvious that packages can be delivered faster by PLNSS-A than by PESM-A. The average shipping distance and sorting times of packages from 2020/11/1 to 2020/11/15 by PLNSS-A are 8 % and 4 % lower than the ones by PESM-Ay. As a result, the shipping costs will be lower for PLNSS-A than for PESM-A as well the sorting costs. The number of undeliverable packages was significantly reduced. The average number of undeliverable packages by PLNSS-A is 70 % lower than that by PESM-A. Obviously, PLNSS-A provides a better customer experience than PESM-A. The logistics network simulation system offers great convenience to the network planning department of JDL.

6 CONCLUSION

This paper proposes a logistics network simulation method and system to enable large-scale logistics networks to run efficiently during grand promotions. In this method, a virtual logistics network is built on the computer to simulate, predict, and optimize the actual logistics network. By applying the logistics network simulation system to optimize its logistics network during the June 18 and November 11 grand promotions in 2022, JDL improved its customer experience and cut down its logistics costs. The logistics network simulation method and system can be expected to also serve other types of logistics networks.

The logistics network simulation engine in this paper ensures that the distribution of 500 million packages in 30 days can be simulated in half an hour on a personal computer. This is not fast enough to support real-time decision making. Future research should study how to accelerate the simulation and how to improve the logistics network structure in a limited number of simulation iterations. In addition to the grand promotion scene, logistics network simulation should also be applied in other scenes (e.g., how to reconstruct a logistics network when nodes are interrupted in an epidemic situation). Furthermore, the authors are now trying to build a logistics digital twin platform based on the network simulation system.

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