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Abstract: To improve working conditions at sorting centers and to reduce the burden, La Poste wants to automate a part of the container-handling process. This mainly concerns containers that belong to the destinations with highest traffic since they demand an important effort and time amount from the operators especially in critical times like truck-departure times, when the operators must quickly load the containers in carts to be transported in trucks so that no delay will occur to the delivery date of the mail items. In this paper, we give a mixed integer linear program to assign the tasks to the robots, in order to maximize the workload of the robots and minimize the effort made by the operators. In addition, a greedy heuristic is proposed. Experiments performed on realistic data confirm the performance of the greedy algorithm. In addition, a sensitivity analysis of the heuristic is given to test its robustness on noisy data.

Keywords: Operations research, Intelligent manufacturing systems, Heuristics, Production control, Sensitivity analysis.

1. INTRODUCTION

As part of the transition towards industry 4.0, La Poste (French postal service), as many companies (Briand and Parlouar, 2019), is aiming to optimize the sorting process in its sorting centers through robotizing the loading step of the mail flow orientation process. This loading step consists in loading on carts the containers full of mail waiting on the conveyors (after the sorting step). A specific destination is assigned to each cart, and once it is full, the cart is sent to its specific location inside or outside the sorting center.

To date, the different destinations of each pusher conveyor, which is the conveyor descending from the loop conveyor, assigned to the different carts placed around it, are predefined and the operators load manually the containers from the pusher conveyor to the carts. Operators repeat this task several times a day, which could be very painful, especially when the containers are full with professional mails (publicity, administration, taxes, etc.). To optimize work conditions for employees and accelerate the sorting process, La Poste is planning to install several robotics modules to automatically load containers from the pusher conveyors to the carts.

This project raises several questions: how many robots must be installed, how to make them efficient, how many containers should be handled every day to make the robots profitable, what are the destinations to be handled by the robots, etc (Daoud et al., 2014).

To be profitable, the robots must handle most of the loading process. Therefore, the destinations assigned to robots or humans must be carefully chosen. The contribution of this paper is twofold. First, the destinations assignment problem is formally stated. Second, a greedy heuristic is proposed to solve the problem. Some experiments (conducted on data provided by La Poste) show that the greedy algorithm performs well. In addition, the greedy algorithm is very simple, and can be implemented in an Excel Spread Sheet. In addition, we analyze the sensitivity of the solutions obtained by the proposed offline algorithms to the variability in the workload per destination. Two efficiency indicators, (1) the number of containers handled by the robots and (2) the average of the percentages of cart loaded by all the robots, are computed for different sets of inputs representing different postal days. As a result, it appears that the values of the indicators don't fluctuate much due to the noise introduced. The importance of the fluctuation depends on the percentage of variation of the data around the original data.

This paper is organized as follows. First, Section 2.2 presents the industrial context, as well as the need for automatizing the carts loading process at the exit of the

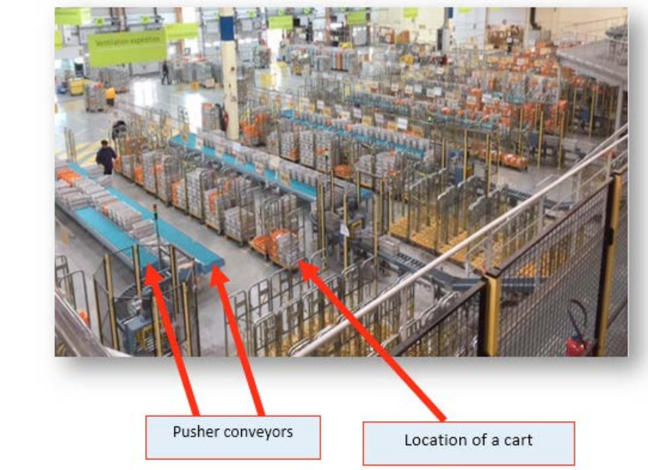

Fig. 1. Pusher conveyors in a postal sorting center.

pusher conveyor. In addition, Section 2.2 gives a formal description of the considered problem and a mathematical formulation. Section 3 presents the greedy heuristic. The experimental results are given in Section 4, whereas the sensitivity of the heuristic method to changes in the workload is analyzed in Section 5. Finally, Section 6 gives a conclusion on the use of different methods and perspectives on future works.

2. PROBLEM STATEMENT

2.1 Industrial context

La Poste's mail sorting center can be seen as a cross-docking station (Ladier and Alpan, 2016). The technique of cross-docking consists on unloading items from incoming trucks, sorting and dispatching them to be loaded to outgoing trucks to be distributed to different customers taking into account the minimization of the storing time. Cross-docking techniques found in the literature are used to solve problems like minimizing the number of products stocked (Bartholdi III and Gue, 2000), minimizing the lateness of shipment and the tardiness of outbound trucks (Boysen and Fliedner, 2010), minimizing the overall transportation costs within the cross dock system (Gelareh et al., 2018), maximizing the number of direct transfers (Maknoon and Baptiste, 2009), etc. Here, inbound trucks bring mails from a location, that must be dispatched into outbound trucks containing mails to deliver to a common destination. The sorting center has three main steps, namely, container unloading, mail sorting, and container loading.

The present work focuses on the container loading step.No similar problem was found in the cross-docking literature. After the sorting step, the mails are placed in two types of containers; *Large Mailboxes* or *Small Mailboxes* depending on the size of the mailed items. Large Mailboxes or Small Mailboxes have different sizes (the distribution is made according to the maximum authorized mass per container, that is, about 20kg maximum). These containers are placed on a loop conveyor, called a sorting ring, and directed to locations in one of the descending conveyors according to their destinations.

Fig. 2. Automatic loading module simulated using Flexsim.

The number of descending conveyors depends on the size of the sorting center and on the size of its daily mail flow (Selma et al., 2018). Each descending conveyor consists of 2 pusher conveyors (see Fig. 1), and each pusher conveyor has up to 15 physical plug locations for operators. The operators handle the containers to carts with wheels which standardize (and thus facilitate) their transport to other platforms in trucks, to storage areas on the road, back to sorting machines for more complex sorting operations requiring multiple passes, or to manual sorting sites in case of problems with the automation of sorting. The (Fig. 1) shows the descending conveyors (with two pusher conveyors each) that transports the containers from the sorting ring. (Fig. 1) also shows the location of the carts (at the side of each pusher conveyor) where the containers are loaded manually. The flow rate of the sorting ring and of the pusher conveyor are 12000 containers/hour and 1200 containers/hour, respectively.

In the current fully manual operating system, operators load containers to the right cart according to their destinations. The destinations are directly indicated on a sheet attached above the location of each cart, and the operators repeat this loading task throughout the day.

A daily transport plan organizes the evacuation of the container from the sorting machines several times a day before the departure of the corresponding truck. Consequently, many containers can be sent to the pusher conveyors in a very short period of time, and this further increases the difficulty of the loading task for operators.

The over-execution of heavy items lifting task is a cause of injuries. To reduce the burden of this task, and to reduce the total loading time of the carts, La Poste decided to install automatic loading modules in addition to the positions already provided for manual loading. Each module consists of a robotic arm with 8 cart positions (see Fig. 2) to ensure an automatic loading of the containers on the carts. Once a cart is fully loaded at the robotic locations, an operator evacuates the cart, before replacing it with an empty one.

The destinations assigned to robots and humans must be carefully chosen. On one hand, the robots are expensive, and they must handle at least 50% of the flow to be profitable (this is why the busiest destinations must be loaded by the robots). On the other hand, to pick and place the containers the robots are slower than humans and their limited capacity prevents them to process the urgent destinations. In addition, while the destinations assigned to a resource can be changed during the day, these changes of destination are undesirable, since they may lead to non-full cart evacuations, a waste of time (setup time required to change a full cart into another empty one), and an increase in the physical effort made by the operators to change the cart each time the destination is changed (since each cart must contain containers with the same destination).

As shown in (Fig. 3) the containers can either be assigned to the manual work site (red boxes) or to a robotic module (blue boxes). In the latter, a check test must be done to test if the destination of the container corresponds or not to destination of one of the carts. If it's the case, the container is placed in the available cart that corresponds to its destination. If it's not, the container must wait (setup time) until the operator changes the full cart with an empty one, then it can be placed in the new cart.

2.2 Formal statement and mathematical formulation

This subsection first describes the considered destinations affectation problem (P), before giving its mathematical formulation.

As the flow of containers is relatively stable, the destination assignment is made on the basis of standard days. More precisely, the day is decomposed in T time periods, and the standard day gives the workload w_{dt} in period t for each destination d.

The problem is to assign the M busiest destinations per period to each robot. In addition, the total workload of a robot during each period cannot exceed its capacity C.

The objective has two components with respective weights γ_1 and γ_2. The first is to maximize the number of containers handled by the robots, the second is to minimize the number of destination changes between two consecutive periods. As robots are introduced in the sorting center for ergonomic reasons (i.e., to minimize the effort of the employees), we set γ_1 to the time required to load a box (container) in the cart, and γ_2 to the time required to load a cart in the truck. With this setting, the objective function computes the employees' workload reduction thanks to the robots.

The considered problem can be formulated as mixed-integer linear program (1)-(8), where:

- D and R denote the sets of destinations and robots, respectively.
- x^r_{dt} is equal to 1 if destination d is assigned to robot r in period t, and 0 otherwise.
- y^r_{dt} is equal to 1 if there is a change of destination toward destination d in period t for robot r, and 0 otherwise.
- z^r_t is the number of changes of destinations in period t for robot r.

The objective is given in equation (1). Constraints (2) state that each destination is assigned to at most one robot in each period, and Constraints (3) prevent to assign more than M destinations to a robot in each period. Constraints (4) state that the load of each robot cannot exceed its capacity. Constraints (5) set y^r_{dt} to 1 if there is a change towards destination d in period t for robot r. Constraints (6) compute the number of destination changes in period t. Finally, the domains of the variables are given in Equations (7) and (8).

$$\max \gamma_1 \left(\sum_{d\in D} \sum_{t\in T} \sum_{r\in R} x^r_{dt} w_{dt} \right) - \gamma_2 \left(\sum_{t\in T} \sum_{r\in R} z^r_t \right) \quad (1)$$

$s.t.$

$$\sum_{r\in R} x^r_{dt} \le 1 \qquad \forall\, d \in D, t \in T \quad (2)$$

$$\sum_{d\in D} x^r_{dt} \le M \qquad \forall\, t \in T, r \in R \quad (3)$$

$$\sum_{d\in D} w_{dt} x^r_{dt} \le C \qquad \forall\, t \in T, r \in R \quad (4)$$

$$y^r_{dt} \ge x^r_{dt} - x^r_{dt-1} \qquad \forall\, d \in D, t \in T, r \in R \quad (5)$$

$$z^r_t = \sum_{d\in D} y^r_{dt} \qquad \forall\, t \in T, r \in R \quad (6)$$

$$z^r_t \ge 0 \qquad \forall\, t \in T, r \in R \quad (7)$$

$$x^r_{dt}, y^r_{dt} \in \{0, 1\} \qquad \forall\, d \in D, t \in T, r \in R \quad (8)$$

3. OPTIMIZATION METHODS

First, we show that problem (P) is NP-hard, as the *subset-sum* problem reduces to (P). Given a set N of items, where item i has a weight ω_i, the subset-sum problem asks if there exists a subset O of N, such that the total weight of the items in O is exactly Ω. Given an instance I of the subset-sum problem, one can build an instance I' of (P) with a single period, a single robot, $\gamma_2 = 0$, $M = n$, and $C = \Omega$. Clearly, if the objective value of the optimal solution for I' is Ω, the answer to instance I of subset-sum problem is yes, otherwise, the answer is no. As the subset-sum problem is NP-Complete (Garey and Johnson, 2002), (P) is NP-hard.

Our experiments also confirm that problem (P) cannot be solved in a reasonable amount of time for realistic size instances (see Section 4). Therefore, a greedy heuristic is proposed below, and the resulting software is described.

3.1 Greedy Heuristic

We propose below a greedy algorithm (Greedy) for (P). Greedy focuses on the first component of the objective function, and it assigns the busiest destinations to the robots as long as the capacity of the robots are not exceeded.

More precisely, starting from scratch, Greedy builds a solution step by step. At each step, Greedy assigns the destinations of a robot in one period (starting from 0 until T). To select the destinations, Greedy sorts the

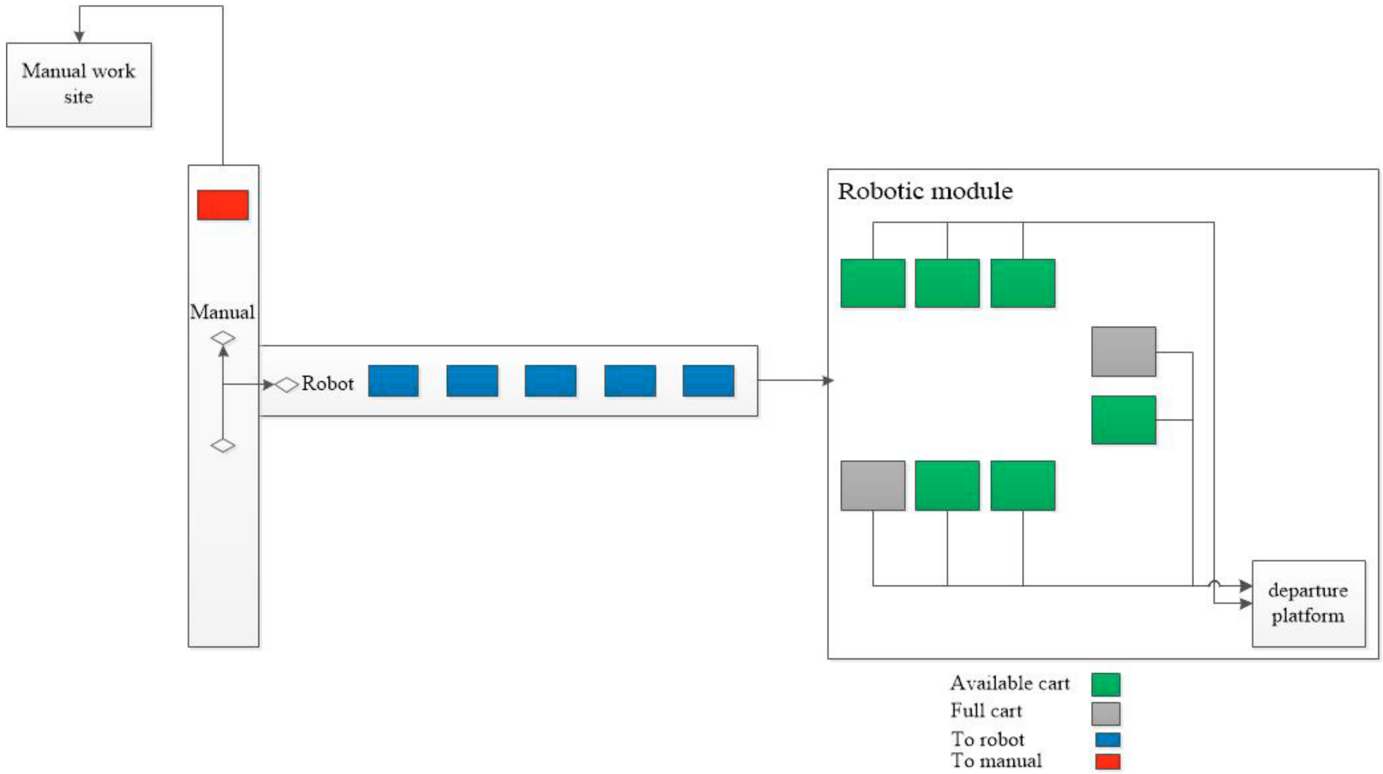

Fig. 3. Container handling by the robotic module.

destinations by decreasing workload, and it iteratively assigns the available (i.e., not already assigned to a robot) destinations that do not exceed the robot's capacity.

Although Greedy focuses on the first objective only, if the workload is smooth (that is, the busiest destinations do not change drastically between periods), Greedy yields solution with a low number of destination changes.

3.2 Software

The proposed software allows the user to enter the following parameters in the interface page:

- The maximum number of destinations M per robot;
- The number of robots;
- The capacity per robot, expressed in number of containers per hour;
- The length (in minute) of a time period.

After setting these parameters, the optimization method is launched, and it shows the robot assigned to each destinations, along with the number of containers and the average filling rate of the carts. We obtain a layout shown in Fig. 4, the first column being the destination, the second the robot assigned, the third the number of containers supported during the slot, and the last column is the filling rate.

The program also allows you to create another spreadsheet, which presents the same results but in a way that can be used for a Java program, which allows it to simulate the solution in order to verify its feasibility and calculate indicators such as the actual utilization rate, the number of processed and unprocessed containers, waiting times... The latter vary between 280 and 160 seconds.

	A	B	C	D	E
1	Destinations during the crenal number 1				
2	X22	114	R0	0,95	
3	L29	103	R0	0,98	
4	X21	59	R0	0,98	
5	X20	75	R0	1,00	
6	O33	103	R0	0,98	
7	H35	55	R0	0,92	
8	H33	46	R0	0,77	
9	N33	165	R0	1,00	
10	F03	27	R1	0,90	
11	F13	30	R1	1,00	
12	J33	37	R1	0,82	
13	F06	19	R1	0,63	
14	I12	39	R1	0,87	
15	L28	34	R1	0,76	
16	I32	28	R1	0,93	
17	L31	17	R1	0,57	
18	O32	45	R2	1,00	
19	K33	36	R2	0,80	
20	K35	74	R2	0,99	
21	N10	29	R2	0,97	
22	H12	27	R2	0,90	
23	K15	62	R2	0,83	
24	I33	24	R2	0,80	
25	L32	34	R2	0,76	

Fig. 4. Excel sheet representing the results of the Heuristic.

4. EXPERIMENTS

The experiments are performed with data provided by La Poste. The data file contains the destination of each container and its arrival date and time.

The mixed integer linear program (MILP) was solved with CPLEX 12.9 (mathematical solver manufactured by ILOG Inc.) (Vamanan et al., 2004), whereas Greedy was implemented in Excel.

Tables 1 reports the results of the experiments. More precisely, Table 1 the objective value obtained with each method on the considered instance.

Table 1. Objective values obtained with MILP, and Greedy.

	MILP	Greedy
Number of containers handled by the robots	15976	16824
Number of destination changes	113	435

The number of containers handled by the robots doesn't vary much between both methods. For the number of the destination changes, in the exact method, the objective function takes into account the minimization of the number of changes, that's why it's considerably inferior to the number of destination of the second method since it doesn't take into account minimizing it.

To analyze the proposed methods, Table 2 presents some performance indicators of the solutions obtained on the instance: the average cart filling rate ; and the percentage of the load handled by the robots.

Table 2. Objective values obtained with MILP, and Greedy.

	MILP	Greedy
Filling rate	72 %	81.8%
Load handled by the robots	50.34%	53.01 %

Regarding the rate of handling of containers by robots, greedy slightly outperforms MILP. The rate for the heuristic model is so close to the rate obtained using the exact resolution method. Concerning the carts filling rates, the dynamic model presents encouraging results since the average filling rate of the carts is 72% for 2-hour time slots. However, the shorter the slot, the lower the filling rate, although the number of containers supported increases. The results obtained using the heuristic are very close to the CPLEX method.

It should be noted here that waiting times vary according to the size of the slots: if the second is larger, so will the first.

5. SENSITIVITY ANALYSIS

In practice, there exists a daily variability in the workload per destination. In this section, we analyze the sensitivity of the proposed approach to these variations around the standard day.

To analyze the robustness of the destinations affectation program, the heuristic was used to calculate the results in terms of percentage of carts loading and the number of containers handled by the robots for different standard Postal days.

Collecting different data used to build the original standard day file is a complex task given the complexity of the Postal information system. As an alternative, a different procedure was used to generate different standard days based on introducing some noise in the original data. This procedure consists in modifying the 10 busiest destinations of the day (among the 381 destinations) in terms of number of containers and arrival date. The first analysis was conducted on the arrival date. In order to obtain the noisy data, the initial step consists in using a statistical analyzer to draw the actual distribution of a given destination (Fig. 5) and to determine the parameters of the statistical distribution that fits the best the sample. Then a new distribution is generated in coherence with the distributions estimated from the original data Fig. 6. Qualitative checking of the coherence of the data was performed thanks to these representations.

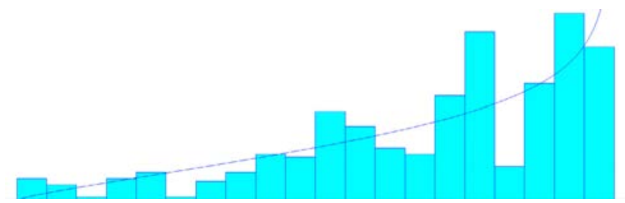

Fig. 5. The original distribution of a destination during a postal day.

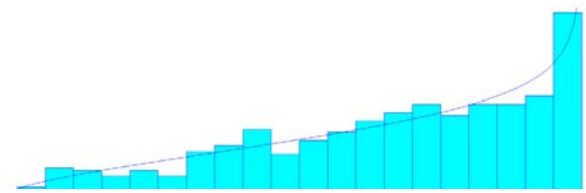

Fig. 6. The new distribution of a destination during a postal day.

About the noise concerning the number of containers, the idea is to modify the percentages of each single destination among the 10 busiest destinations. In a first test, the numbers of containers, in each one of the 10 busiest destination, varies between -10 % and +10%. In the second test, it varies between -30% and +30% following a uniform distribution. The rest of the data remains the same, since it represents less busy destinations with less important percentages. A macro indicator of the quality of the modification is the total number of containers to handle every day, which is checked to be strictly equal for each test to the initial data.

Running the program 10 times for each case, 10 files were obtained, each with different number of containers and different arrival times for the 10 busiest destination. The heuristic program was run for each one of the previously mentioned files. Two indicators are obtained as output of the heuristic;

- I1 : The average percentages of cart filling for those handled by the robots;
- I2 : The total number of containers handled by the robots.

For each test, the average value and the standard deviation of each indicator were calculated. Results obtained are presented in Table 4.

6. DISCUSSION AND CONCLUSIONS

To improve work conditions, reduce the hardship of manual work for operators at the sorting centers and to im-

Table 3. Results obtained for different tests

Tests	Test 1	Test 2
Average of I1	81.09%	81.06%
Standard deviation of I1	0.001	0.001
Average of I2	15566.5	15620.9
Standard deviation of I2	32.35	107.74

prove the effectiveness of its overall system, La Poste is willing to robotize a part of the containers-handling process. To make the project profitable, only destinations with high traffic rate must be handled by the robots. A dynamic model using CPLEX was used first to decide which containers to be handled by the robots. This method gives an exact resolution to the problem but is very costly in computing time.

To cope with these problem, a heuristic model based on a greedy algorithm was developed. For a standard postal day, the heuristic indicates that 16824 containers among 31732 are handled by the robots. The average filling rate of the carts is 81.8%. A sensitivity analysis was conducted to test the robustness and the performance of the heuristic when variations around the standard days happen. Regarding the complexity to collect original data, it was chosen to generate alternative days by introducing noise in the standard day, mainly about the arrival date and the number of containers of the busiest destinations.

For the first test, with $\pm 10\%$ of variation for the number of containers of the 10 busiest destinations, the average filling rate of the carts for 10 different input sets is 81.09% with a standard deviation of 0.001. As this indicator is an objective of the greedy algorithm, this result was expected. About the second indicator, the average number of containers handled by robots is 15566.5 containers with a standard deviation of only 32.35. The standard deviation is therefore of about 0.2% of the average, which is quite negligible. A variation of 10% around the standard postal day is therefore invisible.

Concerning the second test with $\pm 30\%$ of noise, the average filling rate is 81.06% with a standard deviation of 0.001. Again, the average of this indicator is stable despite the noise of the considered data, and is coherent with the initial expectations. The average of the number of containers handled by all robots is 15620.9 containers with a standard deviation of 107.74. Again, the standard deviation is under 1%, which is negligible.

The sensitivity analysis proved thus the robustness of the heuristic method. Values of both indicators are relatively stable for different variations of the standard days. This heuristic method has the advantage to be simple to use, very fast to compute, efficient and robust. Therefore, it seems compliant with a further integration in an online control system. Results obtained, will be used to decide which containers to send to robotic modules in a simulation model using FlexSim. This will help to analyze the behavior of the robots and the efficiency of the implemented rules. The Flexsim software, can be used in the first phase to model the current flows of containers in the sorting platform. In particular, the model makes it possible to visualize the loading operation of containers coming from the sorting ring until they arrive to the departure docks. In the second phase, the simulation will allow to test different rules of destination-assignment to the robotic modules and to calculate and monitor the evolution of the different performance indicators during the simulation. This makes it possible to compare the different decision-making algorithms.

REFERENCES

Bartholdi III, J.J. and Gue, K.R. (2000). Reducing labor costs in an ltl crossdocking terminal. *Operations Research*, 48(6), 823–832.

Boysen, N. and Fliedner, M. (2010). Cross dock scheduling: Classification, literature review and research agenda. *Omega*, 38(6), 413–422.

Briand, C. and Parlouar, R. (2019). Optimisation des opérations de pick-and-place de systèmes demballage robotisés. In *16éme Colloque National S-mart*, 1–6. Springer.

Daoud, S., Chehade, H., Yalaoui, F., and Amodeo, L. (2014). Efficient metaheuristics for pick and place robotic systems optimization. *Journal of Intelligent Manufacturing*, 25(1), 27–41.

Garey, M.R. and Johnson, D.S. (2002). *Computers and intractability*, volume 29. freeman New York.

Gelareh, S., Glover, F., Guemri, O., Hanafi, S., Nduwayo, P., and Todosijević, R. (2018). A comparative study of formulations for a cross-dock door assignment problem. *Omega*.

Ladier, A.L. and Alpan, G. (2016). Cross-docking operations: Current research versus industry practice. *Omega*, 62, 145–162.

Maknoon, M.Y. and Baptiste, P. (2009). Cross-docking: increasing platform efficiency by sequencing incoming and outgoing semi-trailers. *International Journal of Logistics: Research and Applications*, 12(4), 249–261.

Selma, C., Tamzalit, D., Mebarki, N., Cardin, O., Bruggeman, L., and Thiériot, D. (2018). Industry 4.0 and service companies: The case of the french postal service. In *International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing*, 436–447. Springer.

Vamanan, M., Wang, Q., Batta, R., and Szczerba, R.J. (2004). Integration of cots software products arena & cplex for an inventory/logistics problem. *Computers & Operations Research*, 31(4), 533–547.