Optimizing Route Planning for Minimising the Non-added-Value Tasks Times: A Simultaneous Pickup-and-Delivery Problem

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Abstract: The quick-change industrial environment pushes organisations to find new ways to improve efficiency, flexibility, and responsiveness. To do so, companies must not solely focus on improving the main value chain, but also the support services that provide for it. To this end, this paper focuses on a route optimization study, inspired by a real-case problem of the Manufacturing Tool Repair Service, from an automotive company. The problem consists of a vehicle routing problem with simultaneous delivery and pickup and time windows, subjected to specific service constraints. To solve it, we propose a Mathematical-Integer Linear Programming model, which is triggered by real-time data from the shopfloor. The approach was tested, and the results show an average of 30% improvement compared with the current situation. Additionally, the model was tested using modified benchmark instances and a time windows sensitivity analysis was performed. Considering the results obtained, future work regarding the application of a hybrid algorithm is proposed

1 INTRODUCTION

The ever-rising market competitiveness pushes organisations to find new ways to continuously improve. As a result, it is not effective for organisations to simply improve production process. Rather, they must also improve other services that support the value chain. In this perspective, the current work intents to improve the manufacturing tool pickup and delivery (P&D) service of an automotive company. This problem is a practical application of a vehicle routing problem (VRP) with simultaneous delivery and pickup, and time windows (VRPSDPTW). When applying time windows (TW) and simultaneous P&D constraints to the VRP, we obtained the problem addressed in this paper. Here, each customer can be, simultaneously, a pickup and a delivery customer, and the P&D must be done within pre-defined TW. As it will be presented ahead, the workers of the Manufacturing Tool Repair (MTR) service are responsible for picking the used tools from the production lines, repair them, and, after repair, deliver them. The absence of real-time information on the number of tools available, forces MTR workers to constantly leave their workplace, to check the tools' availability onsite. As a result, time lost travelling around the shopfloor is significant and the tool repair activity is constantly delayed. Thus, the present work intents to optimize this process, eliminating unnecessary dislocations and minimising the total travel times, using a Mathematical-Integer Linear Programming (MILP) model. To do so, it is considered that: (i) The MTR service uses 2 different vehicles with distinct capacities; (ii) A production line is more critical than another, if the time until the line stops, due to a lack of tools, is smaller. To the extent of our knowledge, despite the amount of literature about P&D, the VRPSDPTW is not commonly considered, although being usual in real-world situations. Thus, this paper presents the following contributions:

- Application of the VRPSDPTW in a real-world situation, which considers the demand and minimal stock requirements at the customer;

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- Real-time route trigger, definition, and optimization, by connecting the MILP and the company's e-Kanban (presented in Romeira et al. (2021)), which is continuously monitoring the number of tools to P&D.

This paper is organized as follows: In section 2, a brief review of other works, related to the VRPSDPTW is presented. The current problem, the optimization approach and the data pre-processing process are described in detail in section 3. In section 4, the MILP model used is shown and the computational results of our approach are presented in section 5. Also, additional test results obtained with benchmark instances and a sensitivity analysis are presented. A summary and future works are presented in section 6.

2 RELATED WORKS

In this section a collection of works related to the VRPSPDTW is offered. Table 1 introduces a summary of the constraints used in these works, and Table 2 summarizes the related objective function(s).

In Shahabi-Shahmiri et al. (2021) an hybrid approach was used to solve the heterogeneous VRPSPDTW (HVRPSPDTW) with cross-docking networks, split delivery and perishable products The authors achieved a 10% reduction in the travel time and a 29% reduction in the travel costs, when compared to a previous approach. Zhang et al. (2020) applied two different approaches to solve the same problem: an exact and a metaheuristic approach. These were tested in 15 instances obtained from company data. Their conclusions show that for larger instances the exact approach cannot reach the solution in a reasonable computational time (CPU). Then, the metaheuristic approach is used to solve those instances and compared to several state-of-the-art algorithms, showing that it converges quicker and has a better performance. L. Li et al. (2019) also solved this problem using a metaheuristic approach, which, for real-world instances, obtained solutions within a low CPU time (81 seconds). In the work of Madankumar and Rajendran (2019), an exact approach was used and tested with 24 modified instances given by Solomon (1987). The results show that it obtained optimal solutions with better CPU times than the model of Wang and Chen (2012). Using 8 to 10 of the same benchmark instances, Gupta et al. (2017) compared their metaheuristic approach to the best-known results. For instances C1 and C2, their approach matched the best-known results, and for R and RC, it obtained lower travel distances with a small trade-off in the number of vehicles. Moreover, in real-world instances it increased flexibility within the company when compared to the current situation. Besides the previously referred works, several others may be of interest. Liu et al. (2021), Zhou et al. (2020), H. Li et al. (2018) implemented metaheuristic approaches to solve the VRPSDPTW. Liu et al. (2021) solved the problem using metaheuristics aiming to minimise the transportation costs. The approach was tested with benchmarks instances generated by Wang and Chen (2012) and the results proved its effectiveness. Having a multi-objective VRPSDPTW, both Zhou et al. (2020) and H. Li et al. (2018) applied a metaheuristic approach. Both approaches outperformed algorithms proposed by J. Wang et al. (2016) in terms of convergence and diversity properties. In contrast, Ji (2019) applied an exact model to minimise the travel distance. By testing 2 instances of the Solomon (1987) benchmarks, the author proved that the method is not suitable for large-size instances. Tang et al. (2021) proposed a hybrid approach, which found a good solution in 66% of the benchmark instances (H. F. Wang & Chen, 2012) and 10 new best-known solutions. Lastly, Hof and Schneider (2019), using a hybrid approach, focused on minimising the number of vehicles, travel distance and TW's penalties. This approach, for medium-size instances, reduced the number of vehicles and the travel distance in 31 instances. For large instances, the best solution had a 16.93% GAP, and used less CPU time than the approach proposed by Wang et al. (2015).

Table 1: A summary of the VRPSPDTW constraints found in the literature.

	Shahabi-Shahmiri et al. (2021)	Zhang et al. (2020)	L. Li et al. (2019)	Madankumar & Rajendran (2019)	Gupta et al. (2017)	Our Work
Vehicles' capacity	x	x	x	x	x	x
Vehicles' type	x					
Fleet's size		x	x			x
Each customer is visited by only one vehicle		x	x	x		x
Time windows (Customers, Workers, etc)	x	x	x	x	x	x
Each customer must be visited exactly once		x		x	x	x
Each customer must be assigned to a route	x	x	x	x	x	
Other constraints	x	x	x	x	x	x

Table 2: A summary of the VRPSPDTW objectives found in the literature.

	Shahabi-Shahmiri et al. (2021)	Zhang et al. (2020)	L. Li et al. (2019)	Madankumar & Rajendran (2019)	Gupta et al. (2017)	Our Work
Minimise travel time	x					x
Minimise travel distance			x		x	
Minimise number of vehicles					x	
Minimise transportation costs	x	x		x		
Minimise waiting times					x	
Minimise time windows' penalties	x	x				
Minimise emissions					x	

To finish, Table 3 summarizes the approaches referred throughout this section.

Table 3: A summary of the VRPSPDTW approaches found in the literature.

Paper	Exact	Meta-heuristic	Hybrid
Liu et al.(2021)		x	
Shahabi-Shahmiri et al. (2021)			x
Tang et al. (2021)			x
Zhang et al. (2020)	x	x	
Zhou et al. (2020)		x	
Hof & Schneider (2019)			x
Ji (2019)	x		
L. Li et al. (2019)		x	
Madankumar & Rajendran (2019)	x		
H. Li et al. (2018)		x	
Gupta et al. (2017)		x	
Our Work	x		

3 CASE STUDY

3.1 Current MTR Service Description

The MTR support service is responsible for the repair and calibration of the tools used in the company's machines. As these tools have limited lifespans, which are related to the number of parts produced, the MTR workers pick the used tools from the production lines, and deliver, new or repaired ones. Currently, the MTR service team performs the following tasks: (i) Repair and calibration of tools (Value-added activity); (ii) Pick used tools from the production lines; (iii) Deliver repaired, or new, tools to the production lines. Since no production line must ever stop for lack of tools, and there is no real-time information on their availability to be collected, the MTR workers are forced to go onsite and check the stocks. This is a waste of time and productivity. Thus, the P&D activities must be minimised. Currently, to go to production, the workers follow 3 different standardized routes (A, B and C – Figure 1). This process takes an average of 18, 15 and 8 minutes, respectively. Presently, each route is done at least 2 times per shift. However, sometimes there is an average of 6 additional trips per shift. The P&D is performed using one of 2 different vehicles: an automatic and a manual vehicle. The first has a higher average speed and a capacity of 150 tools, while the other a capacity of 90 tools.

3.2 Optimization of the MTR Service

The company's e-Kanban system, developed in Romeira et al. (2021), gathers real-time data along the company's internal value chain. To this system, it was added a Manufacturing Tool Stock menu that allows us to know, in real-time, which tools are available in each P&D point (the production lines, and from now on called customers), and how many are available in the MTR service to be delivered. During, a production shift, these data is continuously processed, and a route is triggered when: (i) There are enough tools available to create a P&D route; (ii) The tools' stock is below the defined minimum stock values.

This pre-processing gives us the customers to be visited and the tools to be picked and delivered. Then, this information, together with all the considerations related to the vehicles (average speeds and capacities) and the priority levels of each customer, are used to compute the routes. The VRPSDPTW is solved using a MILP model, where the main objective is to minimise the total travel time for each vehicle, considering the following general constraints:

- Each customer is visited exactly once per route;
- MTR service and customers' TW (these indicate the priority level);
- Vehicles' capacities.

Figure 2, sums up the process to obtain the inputs for the MILP model and shows the given outputs. As can be seen, the e-Kanban is continuously analysing the tools onsite, and the tools available for delivery in the MTR service. Also, it is considered that:

- All tools have similar dimensions;
- The automatic vehicle only serves Route B, while the manual serves Route A and C;
- The vehicles have different average speeds and service times (the automatic vehicle has a higher service time);
- There are no circulation restrictions;
- When a customer has a higher priority (defined by the stock level), it must be served first;
- Every time a route alert is triggered, the MILP is called to compute a new route.

Data Pre-processing Process. The data pre-processing process is performed according to the flowchart in Figure 2, using the data retrieved by the e-Kanban regarding the tools' availability in the customers and in the MTR service. A new route is created when the stock in a customer is below the minimal stock level or, when the number of tools available for P&D is sufficient to make a distribution. For the first, whenever the minimal stock level is reached a trip alert is created, because the related customer is now considered a priority customer. Then, the decision process is performed according to the Figure 2 flowchart. Note that, before the MILP is called, the Availability of tools for P&D procedure must be performed. This verifies the existence of non-priority tools to be delivered and picked from these priority customers, with the aim of using the vehicle's full capacity. So, if the vehicle's capacity is not achieved with the priority tools, then for the same priority customers, the algorithm tries to load the vehicle with tools with the lowest stock level, re-stocking the customer and/or tools to pick. For the second option, when there are no tools below the minimal stock, another procedure is called: Tools for P&D. Here, it is verified if there are customers with pickup stock above a pre-determined level, and for those, the availability of tools to deliver is checked.

4 MILP MODEL

The VRPSDPTW is defined on a direct graph $G(C, A)$, where the depot and customers are represented by a set of nodes and with different geographical location. The set of nodes and the set of edges in G are represented as $C = \{1, \dots, c\}$ and $A = \{(i,j): i, j \in C, i \neq j\}$, respectively. The length of each arc is given by t_{ij}, which is the time needed to travel from customer i to j. Also, each customer has a P&D demand, represented by p_i and d_i, respectively. To deliver the required demand, a set of vehicles $V = \{0, \dots, v\}$ is available. Two vehicles are available, each with capacity Q_k, $k \in V$. Each customer $i \in C$ must be visited within a predefined time window $[a_i, b_i]$, and has a predefined service time st_i^k. Furthermore, the depot node (MTR service) also has a time window, $[a_0, b_0]$, which defines the total time available to execute the P&D requirements in each shift. To meet the TW, the decision variable s_{ik} defines the arrival time of vehicle $k \in V$ to customer i and to the depot. Another decision variable used is x_{ij}^k that takes value 1 if arc (i,j) is traversed by vehicle $k \in V$, and zero otherwise. Considering the nature of the problem, the following integer variables are also considered:

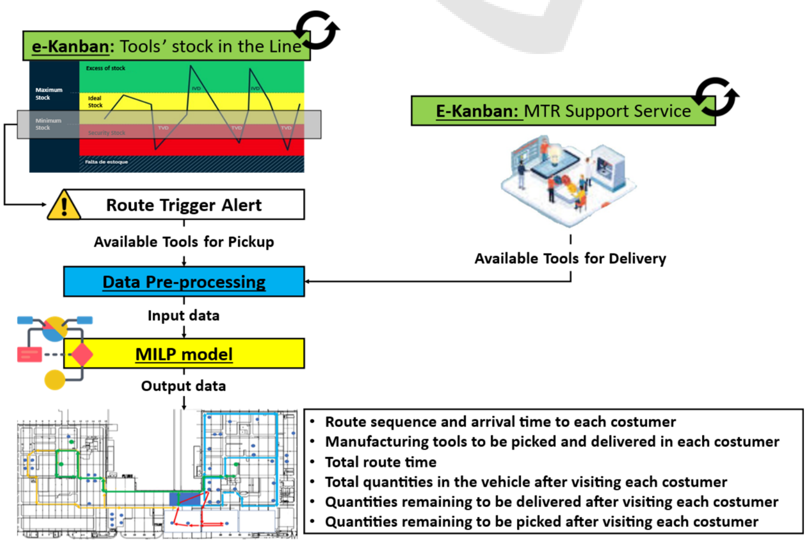


Figure 1: Route creation process and its outputs.

- l_i^k, gives the total amount of load after vehicle k visits customer i;
- ld_i^k, gives the amount of load that remains to be delivered, by vehicle k, to customer i and to all the following customers.
- lp_i^k, gives the amount of load that must be picked-up after vehicle k visits customer i.

Taking into consideration the above data and decision variables, a MILP vehicle-flow model was developed:

$$\text{Min} \sum_{k=1}^{v}\sum_{i=1}^{c}\sum_{j=1}^{c}(t_{ij} \times x_{ij}^k) \quad (1)$$

The objective (equation 1) is to minimise the total travel time and is subjected to the following constraints:

$$\sum_{k=1}^{v}\sum_{i=1,\, i\neq j}^{c} x_{ij}^k = 1,\ \forall\ j\neq 1 \in C \quad (2)$$

$$\sum_{k=1}^{v}\sum_{j=1,\, i\neq j}^{c} x_{ij}^k = 1,\ \forall\ i\neq 1 \in C \quad (3)$$

$$\sum_{i=1,\, i\neq h}^{c} x_{ih}^k - \sum_{j=1, j\neq h}^{c} x_{hj}^k = 0,\ \forall\ k\in V,\ \forall\ h\in C \quad (4)$$

$$\sum_{j=1}^{c} x_{1j}^k \leq 1,\ \forall\ k\in V \quad (5)$$

$$\sum_{i=1}^{c} x_{i1}^k \leq 1,\ \forall\ k\in V \quad (6)$$

$$s_i^k + st_i + t_{ij} - M_T(1-x_{ij}^k) \leq s_j^k,\ \forall\ k\in V,\ \forall\ i\neq j\in C \quad (7)$$

$$a_i \leq s_i^k \leq b_i,\ \forall k\in V,\ \forall\ i\in C \quad (8)$$

$$ld_i^k \geq ld_j^k + d_i - M_1(1-x_{ij}^k),\ \forall\ k\in V,\ \forall i,j\neq 1\in C \quad (9)$$

$$l_j^k \geq ld_j^k + d_j + p_j,\ \forall\ k\in V,\ \forall j\neq 1\in C \quad (10)$$

$$l_j^k \geq l_i^k + d_j + p_j - M_2(1-x_{ij}^k),\ \forall\ k\in V,\ \forall i\neq 1, j\neq 1\in C \quad (11)$$

$$d_i \leq ld_i^k \leq Q_k,\ \forall k\in V,\ \forall\ i\in C \quad (12)$$

$$p_i \leq l_i^k \leq Q_k,\ \forall k\in V,\ \forall\ i\neq 1\in C \quad (13)$$

$$lp_j^k \geq lp_i^k + p_j - M_3(1-x_{ij}^k),\ \forall\ k\in V,\ \forall j,i\neq 1\in C \quad (14)$$

$$p_i \leq lp_i^k \leq Q_k,\ \forall k\in V,\ \forall\ i\in C \quad (15)$$

$$l_i^k = lp_i^k + ld_i^k - d_i,\ \forall k\in V,\ \forall\ i\neq 1\in C \quad (16)$$

$$x_{ij}^k \in \{0,1\};\ s_i^k \geq 0;\ l_i^k, ld_i^k lp_i^k \geq 0 \text{ and integer} \quad (17)$$

Constraints (2) and (3) ensure that each customer is visited exactly once and by only one vehicle. Constraint (4) guarantees the flow conservation, which means that if vehicle k arrives at customer i, it must also leave customer i. Both (5) and (6) ensure that each vehicle starts and ends its route in the depot. Inequalities (7) and (8) are related to the TW constraints. The first specifies the vehicle arrival time to a customer and the second guarantees that the vehicle arrives within the related TW. With constraint (9), the delivery quantity to be loaded at the depot is specified. Additionally (7) and (9) force an order for the vehicles visiting the routes, which ensures that no sub-tours without the depot are generated. Inequalities (10) and (11) indicate the amount of load in the vehicles after visiting the first customer and the other customers in the route, respectively. Constraints (12) and (13) guarantee that the vehicle capacity is not exceeded. For more information on the pickup loadings, 3 more constraints were added. With inequality (14) the pickup quantity that must be unloaded in the depot is determined. Constraint (15) guarantees that the vehicles capacity is not violated, and constraint (16) correlates the load variables to each other. Constraint (17) defines the variable's domains. Constraints (7), (9), (11) and (14) are disjunctive constraints that are linearized by using large multipliers (''big-M values''). To create valid inequalities, one set $MT = s_1^k$ and $M1 = M2 = M3 = maxQ_k$.

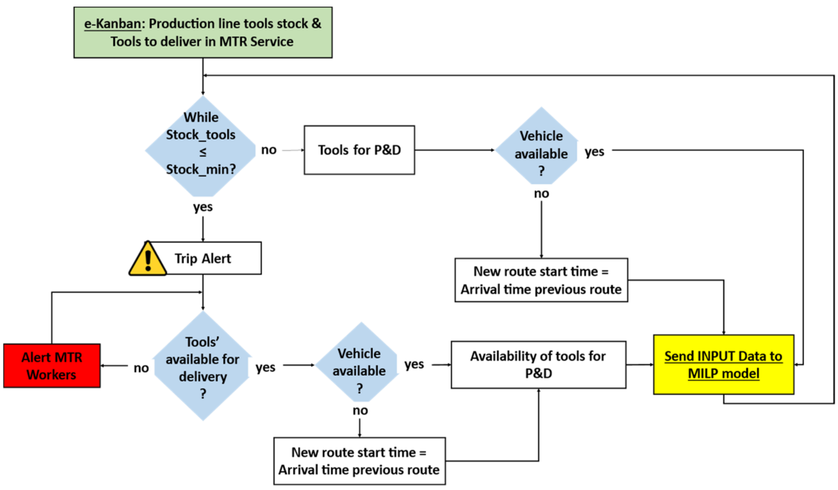


Figure 2: Data pre-processing process.

5 COMPUTATIONAL RESULTS

The model was tested with 10 types of instances from normal demand requirements and 3 types of instances with high demand quantities for each type of vehicle (the worst-case scenario). Thus, in total we analysed 26 instances, 13 for the manual vehicle and other 13 for the automatic vehicle. Each problem instance is defined by the quantity to P&D to each customer. The vehicles capacity is given in number of tools, and for the manual vehicle is equal to 90 and equal 150 for the automatic. Also, the customer's location was obtained from the company's layout (presented in Figure 1) and the travel arcs times were calculated according to each vehicles' average speed. For each customer the service times (st_i) and time windows ($[a_i, b_i]$) are defined according to real data. Note that, the TW are dynamic, based upon the customers' priority in the route creation moment. Based on this, the customer with highest priority has earlier and tighter TW than the others.

Results. The model presented was implemented using the CPLEX Studio IDE 20.1.0, and the experiments were run on an Intel (R) CORE(TM) i7-10750H CPU 2,60GHz with 16Gb of memory.

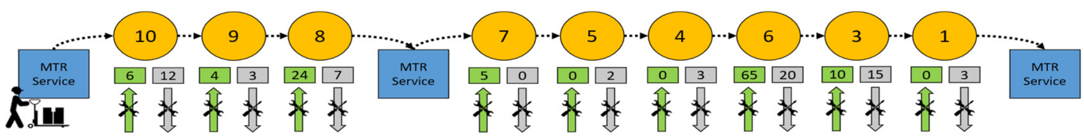
Table 4 shows the results obtained for the manual vehicle and Table 5 for the automatic vehicle. In the tables' second column, the number of routes that the vehicle must make (Trips) is presented. This means, the number of times that the vehicle must leave and return to the depot to fulfil the demand requirements. The other columns of the table present the objective function value (OF) – time needed to perform the route in minutes, and the CPU time in seconds.

The last column presents the GAP (in %), given by CPLEX, that is the tolerance on the GAP between the best integer solution and the best node remaining (best bound). For the manual vehicle, the results show that the optimal solution is achieved for 8 of the 13 instances. For the remaining instances the obtained GAP is in average 5%, except for test instance 8, where the GAP is 23%. The solutions were obtained within a low CPU time (average 0.21 seconds). Also, the number of trips needed to fulfil the customers' demand is 2, except for the last 3 instances (worst-case scenario instances). These are the ones which have a high number of P&D demands, which, in some customers equals the vehicles' capacity. For the instances with higher demand values, 2 optimal solutions were obtained within, approximately, 0.14 seconds. For the automatic vehicle, the model only reaches the optimum to 3 solutions out of 13. Although the results obtained have an average GAP of 9.6%, they were obtained within good CPU time (17.8 seconds). When it comes to the high demand instances, the CPU time required is much higher than the average for other instances, especially for the 11th instance. Figure 3 presents a diagram with the 1st instance solution representation for the manual vehicle. The yellow circles represent the customers, and the blue square the depot. In green, we can see the number of tools delivered to each customer and in grey, the pickup quantities. Below the diagram, a table with the following information is presented:

- Vehicle's arrival time at customer;
- Vehicle's departure time from customer;
- Picked load after leaving the customer (lp_i^k);
- Load to be delivered to the customer and the following customers (ld_i^k);
- Total load after the vehicle leaves the customer (l_i^k).

Table 4: MILP results for the manual vehicle.

Instance	Trips	OF (min)	CPU (s)	GAP (%)
1	2	9.22	0.17	0
2	2	9.22	0.17	0
3	2	9.22	0.22	5.83
4	2	9.22	0.17	5.04
5	2	9.22	0.09	0
6	2	9.22	0.82	5.1
7	2	9.22	0.13	0
8	2	9.22	0.17	23.03
9	2	9.22	0.16	0
10	2	9.22	0.09	0
11	4	17.77	0.13	0
12	4	15	0.23	4.82
13	4	17.77	0.14	0



Arrival(min)	0,65	1,59	2,3	2,75	1,37	4,07	4,85	6,74	9,38	11,2	13,19
Departure(min)	0,85	1,79	2,5	-	2,47	4,39	5,99	8,45	10,4	12,1	-
lp_i^k	12	15	22	-	0	2	5	25	40	43	-
ld_i^k	34	28	24	-	80	75	75	75	10	0	-
l_i^k	40	39	22	-	75	77	80	35	40	43	-

Figure 3: Solution of the 1st instance for the manual vehicle.

Table 5: MILP results for the automatic vehicle.

Instance	Trips	OF (min)	CPU (s)	GAP (%)
1	2	6.96	2.97	10.69
2	2	6.4	2.08	20.19
3	1	5.62	0.72	6.05
4	1	5.62	0.28	0
5	1	5.62	0.61	3.91
6	2	6.96	8.36	12.5
7	1	5.62	0.34	0
8	1	5.62	0.39	0
9	1	5.62	0.42	6.41
10	1	5.62	0.53	4
11	5	12.09	169.58	0.91
12	4	9.93	12.42	18.17
13	4	9.93	20.3	13.59

The total travel time, which includes the arcs travel times, the service time and possible waiting times, for this route is 13.19 minutes, and the MTR worker needs to go 2 times to the depot, due to the lack of vehicle's capacity. With the current service organisation, the workers need 26 minutes to do the same service. This means that we reduced the time consumed by 49%. It is important to note that, even for the worst-case instances, the approach obtains a smaller travel time than the company's current one for normal demand values. For the automatic vehicle, we have in average a 14% reduction compared to the current time for the same demand.

Vehicle-flow model efficiency test and time windows sensitivity analysis. To test the model's efficiency in more challenging problem instances, the adapted benchmarks from Li and Lim (2001) were used. These problems' objective is to minimise the number of vehicles or routes. Due to the size of those instances, only the first 20 customers of each instance (IC2, IR2 and IRC2) were considered and adapted to a VRPSDPTW. The results are presented in Table 6. If the optimal solution is not reached within a pre-defined time limit (10 minutes), the costs' column shows the best integer solution, and the CPU displays a "-". Like in the real problems (section 5.1), the results in terms of solution GAP are not so good. According to the problems' characteristics, the CPU time is relatively low. For the IRC problems, the optimal solution was not achieved for the last 2 instances, within the time limit.

A time windows sensitivity analysis using the automatic vehicle data was also performed. The tests were made by reducing the time windows range. The size of the time windows decreases from Case 1 to Case 5. The results (Table 7) show that for tighter time windows, the GAP becomes smaller. However, this only happens until a certain point. This is, because of the reduced time windows, one single vehicle is no longer sufficient to make the route, not because of capacity, but because the depot TW (Case 5). Also, when the TW are small (Case 4 and 5), the OF values increase by 11% and 32%, respectively. This can be related to the need to meet the TW, which results in a visiting order that is not as efficient in terms of travel distance.

Table 6: Model results for the adapted benchmark problem instances.

Instances	Vehicle-Flow Model		
	Costs	CPU (sec)	GAP (%)
IC201	252	0.01	0
IC202	202	1.69	11.88
IC203	194	8.69	2.36
IC204	186	4.01	0.96
IC205	251	0.75	1.40
IC206	230	1.64	3.28
IC207	218	1.89	1.87
IC208	205	3.74	3.78
IR202	399	46.84	0.87
IR203	354	91.19	0.71
IR204	289	42.68	0.81
IR205	350	1.86	1.19
IR206	318	11.4	2.83
IR207	318	61.82	0.69
IR208	260	2.53	1.08
IR209	312	3.87	2.26
IR210	353	79.06	0.69
IR211	293	253.83	0.46
IRC202	341	156.23	3.16
IRC203	309	-	20.95
IRC204	268	-	17.91

Table 7: Time Windows Sensitivity analysis.

Case	Trips	OF (min)	CPU (s)	GAP (%)
Case 1	1	5.02	1.13	21.71
Case 2	1	5.02	1.22	18.63
Case 3	1	5.02	0.58	14.69
Case 4	1	5.62	1.42	10.50
Case 5	2	7.33	1.45	21.25

6 CONCLUSION AND FUTURE WORK

A real-world problem of a Manufacturing Tool Repair Support Service of an automotive company is presented. One of the most time-consuming activities performed by this service consists in the P&D of the company's manufacturing tools. Therefore, to minimize this time and to increase service efficiency, we modelled problem as a VRPSDPTW and solved it. The stock levels in the production lines, together with the number of repaired tools, are constantly monitored and processed. Hence, when needed, the MILP model generates routes with the sequence of customers to visit and the related tools to P&D. Also, compared to the current situation, the presented work shows that, by using this approach, we can reduce up to 49% the total travel time for one vehicle and 14% for the other. Even in a worst-case scenario, the model best results than the current ones for both vehicles. To further improvements a 3-dimentional packing problem integrated with the P&D problem is under study.

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