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Social-economic sustainable Vehicle Routing Problem for local e-commerce platforms

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Abstract: As all sectors, e-commerce should consider social sustainability which is gaining importance within society. To integrate these themes into the logistics of e-commerce platforms, a mathematical model is proposed for a socially and economically sustainable Vehicle Routing Problem (VRP) that optimizes the drivers energy consumption along with delivery costs. The model is solved through Simulated Annealing and is validated with a realistic case study for an e-commerce platform. The results show that by assigning a small weight to the social sustainability dimension, the platform can improve by 20% this aspect with a worsening in the economic performances of just 4%.

Keywords: Vehicle Routing Problem, social sustainability, multi-objective, Simulated Annealing, e-commerce platform, energy consumption.

1. INTRODUCTION

Since Internet users is growing every year, the online purchases are always more common in the population. 2020 is the year when a larger increase in online shopping can be observed due to COVID-19 pandemic. In particular, Italy, which was one of the country most affected by the pandemic, experienced a 14.28% growth in the number of e-shoppers (Lone et al., 2021). To help local retailers during the COVID-19 pandemic, where people could not visit the physical shop, a lot of regional initiatives have been established to support them in switching from the offline to the online world (Nair et al., 2021). During last years, e-commerce, as all sectors, is affected by sustainability themes that are gaining importance both within governments and within society. Regarding Europe, the program "Horizon Europe", among its funding schemes, aims at tackling green and digital transition and improving the scientific research (*Horizon Europe*). Besides the governments, the entire society is today interested in social sustainability. For example, Sajid et al. (2021) perform a survey to Chinese e-commerce consumers and found that they are more likely to positively participate in social factors than in economic factors. As stated before, several aspects, like sustainability, must be taken into account in design and manage an e-commerce platform and for this reason this is a complex activity (Bortolini et al., 2017). A fundamental component of a supply chain is the distribution process and its efficient management allows companies to save costs to deliver goods to the final customer. Accorsi et al. (2017), in their IoT architecture, among the different ecosystem features varied also the distribution process to evaluate the performance in terms of food delivery and food waste. These distribution problems, in literature, fall into the so-called Vehicle Routing Problem (VRP). VRP is defined as the problem of "distribution of goods between depot and customers". In particular, this problem consists in constructing routes to serve a certain number of customers with a specific number of vehicles, that start and end at one or more depot, in a predefined amount of time (Toth and Vigo, 2002). E-commerce platforms, especially local ones, support companies with logistics services for the transportation of goods (Ying and Dayong, 2005). In details, these platforms provide the transportation facilities with VRP algorithms that represent a useful tool for the couriers to assign requests to vehicles in an efficient and effective way. To integrate the social sustainability dimension into the logistics of e-commerce platforms, we developed and implemented a mathematical model for the VRP optimizing not only the economic aspects but also the ethical aspects. In details, we developed a metaheuristic Simulated Annealing (SA) algorithm with a set of Local Search (LS) logics specifically designed for our problem, with tailored parameters and constraints. This algorithm is designed to be a practical support for the transportation companies involved in the delivery of goods traded by e-commerce systems.

2. RELATED WORKS

VRP is a well-known problem in the literature which concerns the distribution of goods between depots and customers (Toth and Vigo, 2002). The basic kind of VRP is called Capacitated VRP because the only constraint is the capacity of the vehicles which deliver goods. Indeed, the routes must be designed so that the total demand of the client assigned to a particular vehicle does not exceed its total capacity in weight and/or volume. Máximo and Nascimento (2021) deal with a Capacitated VRP with a heuristic algorithm called Iterated Local Search (ILS), because for a predefined number of iterations the reference solution is modified through LS logics

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to find better solutions. Several LS are proposed by the literature. These are commonly divided between inter- and intra-route considering that the former performs movements between different routes while the latter performs movements of nodes within a single route (Kalayci and Kaya, 2016). Nagy and Salhi (2005) suggest that between the different inter-route LSs, two are of significant importance due to their efficiency and applicability, as the exchange procedure, which consists in switching 2 nodes from 2 different routes, and the shift procedure, which consists in moving a node to another route. Regarding the intra-route LS, Babaee Tirkolaee et al. (2019) propose as two of the most promising ones the 2-opt procedure, which consists in changing two arcs of the same route, and the insert procedure, which consists in moving a node within the same route. Classical VRPs just consider an economic objective function but recent contributions have integrated also social and environmental sustainability aspects (Pilati et al., 2020). Regarding social VRP, some researchers focused on the route balancing in terms of delivery to vehicle drivers assignment, and, consequently, time balancing (Jozefowiez et al., 2009; Sharafi and Bashiri, 2017). Even if these papers had both economic and social indicator, authors do not implement a sensitivity analysis to observe the change in the objective function according to the importance of each aspect. A second property considered in the social sustainability is the ergonomic performance of the routes. Indeed, to work safely a driver cannot exceed the 33% of its total daily energy capacity, as suggested by National Institute for the Occupational Safety and Health (NIOSH) (1981). Thus, contributions which focus on such aspect try to balance the energy consumption among all the drivers with the goal of minimizing the total energy spent by the crew. Rattanamanee et al. (2015) developed an optimization model for this problem and they differentiate the energy capacity according to the physical condition of each driver. In fact, NIOSH states that the two most important factors that affect one person energy is gender and age. The main weakness of this contribution is the limited case study used, distinguished by just 20 customers. Optimization models face huge difficulties to solve real case studies distinguished by a large number of nodes to be visited. Thus, it is extremely important to define and implement an effective heuristic or metaheuristic algorithm for an efficient solution of such problems. One of the most promising is Simulated Annealing (SA). SA is widely adopted because it accepts worse solutions to avoid falling into local minima. The final result of a SA algorithm depends on the starting point, that is the cooling schedule set before the algorithm implementation. Since experimental design is very resource consuming to be performed, different techniques are developed to set the parameters of the cooling schedule (Park and Kim, 1998). If the quality of the parameters is poor, the solution of the SA will be far from the global optimum or it will take more time to reach a close-to-optimum solution (Askarzadeh et al., 2016). From the gaps detected in the literature, we developed a SA algorithm to solve the VRP that transportation companies must address in e-commerce systems. This SA algorithm is designed with multiple LS logics to find the best one that minimize not only an economic objective function but also a social one related to the energy expenditure of the drivers. Indeed, this latter objective function adopts a min-max approach, as the equity function to measure the social impact, which minimizes the maximum workload among all the drivers (Matl et al., 2019). In particular, different scenarios are proposed obtained by the change of the importance of both aspects to find the best trade-off configuration. Moreover, we tested this algorithm in a realistic and large size case study that well reflect the reality of an e-commerce platform, located in the north of Italy, in particular Trentino region.

3. PROBLEM DESCRIPTION

The problem that this research wants to tackle consists in the development and implementation of a mathematical model and related metaheuristic algorithm to efficiently solve a VRP considering both economic and social aspects. The problem is characterized by several customers spread all over a specific area who request online purchased commodities, some capacitated vehicles to deliver the products and one depot where the vehicles start and end their journeys. Thus, every day a set of delivery orders is generated by the e-commerce platform. These orders must be assigned to the different vehicles and the route must be defined for each vehicle to optimize a specific objective function. This function, in the proposed research, is composed by two aspects. On one hand, the economic aspect depends on the distance travelled and the time spent by each driver to deliver the assigned orders. On the other hand, the social aspect represents the ergonomics of the activities performed by each driver. In details, as stated by Rattanamanee et al. (2015), the energy spent by each operator due to working activities cannot exceed the 33% of his or her daily energy capacity and this total capacity depends on the single person characteristics as gender and age (Fig. 1).

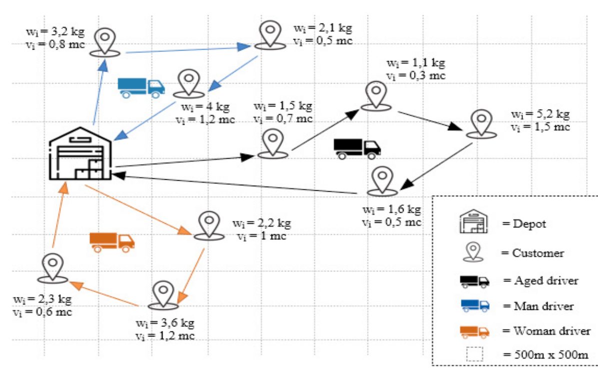

Figure 1. Problem representation

In this section the mathematical model is described, including the definition of the objective functions and the different variables and parameters. These are described in depth below.

3.1 Parameters

The problem can be represented by a graph G = (N, A), where N=0,…,n is the set of all nodes including the depot, and A=1,…,a is the set of all possible arcs which connect couples of nodes such that A={(i,j) : i,j ∈ N, i≠j}. Each arc is associated with a distance d_{ij} and a travel time t_{ij} as ratio between distance and average vehicle speed. There is a set of vehicles k=1,…,K which corresponds to the set of drivers since for each vehicle one driver is involved. The driver spends a constant time t^s to serve a customer node. Each node i is associated with a customer demand, characterized by a weight value w_i and a volume value v_i of each single load, and the number n_i of loads ordered. Each vehicle has a maximum weight capacity (W_k) and volume capacity (V_k) to be fulfilled. Regarding the economic aspect, there are different cost components to be considered. Each vehicle and driver have a hourly cost (respectively c^v and c^d) constant independently of both the vehicles, since they are all equal, and the driver category, while the travel cost depends both on the fuel consumption γ and on the fuel cost c^f. Regarding the social sustainability aspects, each driver k has a daily energy capacity EC_k according to his/her characteristics. In particular, NIOSH states that at the same age, a woman has the 70% of the man available energy while every 10 years the energy capacity decreases by 10% independently of the gender. The amount of energy spent in driving activities is e^d_k which depends on the unit of energy spent β, the body weight BW_k of the driver k and the time spent in travelling by the driver. Whereas, the energy expenditure for driver k of lifting the products of client i is e^l_{ik} and has the following equation (Iqbal et al., 2014):

$$e^l_{ik} = 0.01 \cdot [a_k + 0.4 \cdot BW_k \cdot (0.76 - h_1) + b_k \cdot w_i(h_2 - h_1)] \quad (1).$$

h_1 and h_2 are respectively the start and end height in meters of the lifting, a_k and b_k are parameters related to the gender of the driver k.

3.2 Variables

The first variable of the problem is x_{ijk}, a binary variable equal to 1 if the arc (i,j) ∈ A is travelled by vehicle k and 0 otherwise. A second variable is y_{ik}, which takes value 1 if node i is visited by vehicle k and 0 otherwise. Finally, the last variable of the model is E_k, an integer variable defined as the total energy expenditure of driver k.

3.3 Objective functions and constraints

Once defined the parameters and variables, the objective functions to be minimized are:

$$F^{eco} = \left(t^s \cdot (n-1) + \sum_{i,j \in \mathrm{N}} t_{ij} \cdot \left(\sum_{k=1}^{K} x_{ijk} \right) \right) \cdot (c^d + c^v) + c^f \cdot \gamma \cdot \sum_{i,j \in \mathrm{N}} d_{ij} \cdot \left(\sum_{k=1}^{K} x_{ijk} \right) \quad (2)$$

$$F^{soc} = max_k\{E_k\} \quad (3).$$

Subject to:

$$\sum_{i \in N} \sum_{k=1}^{K} x_{ijk} = 1 \qquad \forall j \in N \quad (4)$$

$$\sum_{i \in N} \sum_{k=1}^{K} x_{ijk} = 1 \qquad \forall i \in N \quad (5)$$

$$\sum_{i \in N} n_i \cdot w_i \cdot y_{ik} \leq W_k \qquad k = 1, \dots, K \quad (6)$$

$$\sum_{i \in N} n_i \cdot v_i \cdot y_{ik} \leq V_k \qquad k = 1, \dots, K \quad (7)$$

$$e^d_k = \beta \cdot BW_k \cdot \sum_{i,j \in N} (t_{ij} \cdot x_{ijk}) \quad (8)$$

$$E_k = \frac{e^d_k + 4 \cdot \sum_{i \epsilon N}(n_i \cdot e^l_{ik} \cdot y_{ik})}{EC_k} \qquad k = 1, \dots, K \quad (9)$$

$$x_{ijk} \in \{0,1\}, y_{ik} \in \{0,1\} \qquad \forall i,j \in N, k = 1, \dots, K \quad (10)$$

Equation (2) represent the economic objective function while (3) is the objective function related to the social sustainability. Constraints (4) and (5) ensure that exactly one vehicle enters and exits each node. Constraints (6) and (7) are the capacity constraints of vehicles. Constraint (8) defines the energy spent in driving activities while constraint (9) defines the total energy spent by each driver k as a sum of the energy spent to drive and the energy spent to load and unload the goods from the vehicle. This latter component is multiplied by 4 because it is supposed that the driver performs 4 lifting activities for each order, 2 at the depot (from the warehouse to the ground and from the ground to the vehicle) and 2 at the customer location (from the vehicle to the ground and from the ground to the customer). Finally, constraint (10) defines the binary decision variables.

4. METHODS

Since the goal of the research is to find a solution for a real and large case study which makes the problem a NP-hard problem, linear optimization models cannot be used to solve it. For this reason, in this section a SA algorithm, with some specific LS procedures, is proposed that can deal with a VRP in a reasonable time and finding a very good solution. The flow diagram of the proposed algorithm is represented in Fig. 2 and consists, firstly, in the generation of an initial solution of the targeted problem through an Ergonomic Nearest Neighborhood (ENN) search. It consists in the selection, for the emptiest vehicle, of the node with the major weight demand until all the nodes are assigned to a vehicle, and then, for each vehicle, the algorithm selects the closest node to the last inserted within its nodes. The initial solution is the starting point of the SA. At each of the N^{iter} iterations, the reference solution S is modified through one of the 4 LS procedures described above in the literature section and the new solution $S1$ is compared with S. Since this specific case study falls into a multi-objective problem, the two objective functions are integrated in a joined objective function f. In details, f for a solution S is:

$$f(S) = w_1 \cdot \frac{F^{soc}}{F^{soc_{best}}} + w_2 \cdot \frac{F^{eco}}{F^{eco_{best}}} \quad (12).$$

w_1 and w_2 represents the weights given to the two components in each scenario ($w_1 + w_2 = 1$) and F^{soc_best} and F^{eco_best} are respectively the social and economic single optimal solutions. If the objective function of $S1$ $f(S1)$ is better than the one of S $f(S)$, $S1$ becomes the reference for the new iteration. If $f(S1)$ is better than the objective function of the best solution identified so far (f^{Best}) too, $S1$ replaces the best current solution (Best). Otherwise, if $S1$ is worse than S it can still be taken with a probability ρ equal to exp[$(\Delta f)/T$], where $\Delta f = f(S) - f(S1)$ and T equal to the current temperature of the SA. In details, ρ is compared to a number r randomly picked between 0 and 1 and the new solution $S1$ is accepted if $\rho > r$. The SA starts with an initial temperature T_0 defined through the formula:

$$T_0 = \frac{\Delta f^u}{\ln P} \quad (13).$$

Δf^u is the mean variation of objective function of uphill solutions from the objective function of the initial solution for the first N^{iter} iterations, while P is the probability to take a solution far by Δf^u from the initial solution. This temperature is reduced after the N^{iter} iteration through a decrease rate α and the algorithm ends when the current temperature T reaches the final value T^{end}, taking the best solution found during the multiple iterations.

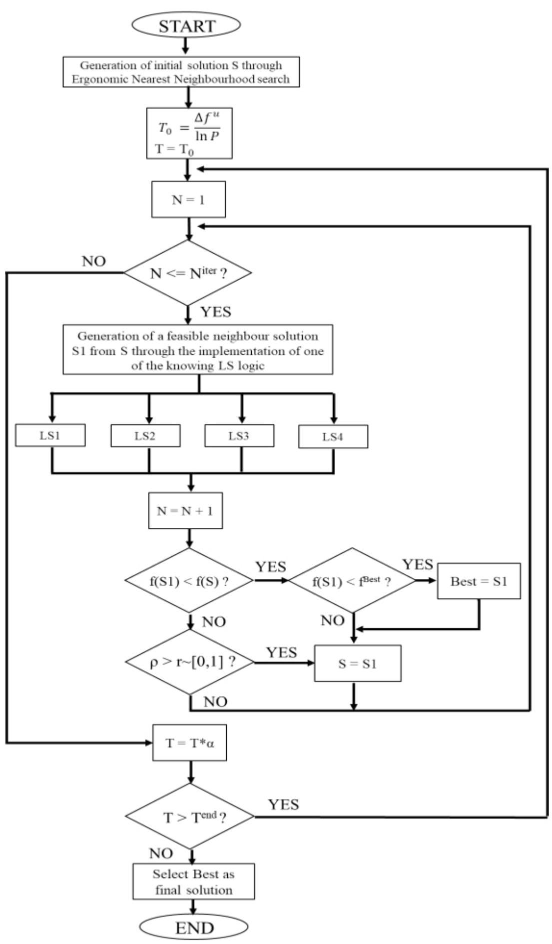

Figure 2. Flow diagram of the proposed SA metaheuristic algorithm

5. EXPERIMENTAL RESULTS

5.1 Case study

The code for the proposed SA is written in Python 3.8.10 and it is run in an Intel(R) Pentium(R) CPU 4415U 2.30GHz and 4.0 GB RAM. A realistic set of clients and requests is generated to test and validate the proposed metaheuristic. This dataset represents a typical VRP for an e-commerce platform of food produces delivery. It contains 60 customers, each of these creating an order, widely spread around the city of Trento (Italy) and a single depot from which all the vehicles start and end their routes. Each order is distinguished by the number, weight and volume of the commodities requested as well as by the customer address. After an experimental study, the best values of each parameter of the SA (e.g., P, N^{iter}, T^{end}, α) are obtained for the specific case study and, in addition, all the parameters of the proposed VRP model are set to well simulate a realistic case study of a food e-commerce platform (Table 1). In particular, β is taken from Dong et al. (2004), EC_k and BW_k are based on NIOSH, a_k and b_k derive from the experiments of Iqbal et al. (2014) while W_k and V_k are the typical capacities for an urban food truck, from which the parameters c^d, c^v, c^f and γ are taken too. Parameters w_i and v_i are typical weights and volumes of fresh food boxes while n_i is a typical range of number of boxes ordered. t^s is the average time to deliver these boxes to the customer. Finally, values of h_1 and h_2 are calculated based on a classic squat lift from the ground. Through several runs of the SA algorithm, it is determined that the LS procedure which optimizes the economic objective function is the shift procedure, which is used for the entire algorithm implementation.

Table 1. Parameters values for the specific case study

Parameter	Value	Units of measure
P	0.8	-
N^{iter}	3000	iteration
T^{end}	0.01	°C
α	0.95	-
w_i	Between 3.75 and 7	kg/box
v_i	0.048	m^3/box
n_i	Between 1 and 4	box
W_k	909	kg
V_k	3.12	m^3
t^s	3.0	min
c^v	17.40	€/h
c^d	21.30	€/h
γ	0.077	L/km
c^f	1.517	€/L
β	2.3	Kcal/h*kg
EC_k	15(Man); 10.5(Woman)	Kcal/min
BW_k	75 (M.); 60 (W.)	kg
a_k	-1.7 (M.); -1.3 (W.)	-
b_k	2.1 (M.); 2.3 (W.)	-
h_1	0	m
h_2	1	m

5.2 Results

The SA algorithm is run for 11 different values of w_1 (and consequently w_2) from 0 to 1 with a step of 0.1. For each weight, the two objective functions (social and economic) are computed and shown in Fig. 3. As Fig. 3 shows, when social aspects have no importance ($w_1 = 0$), F^{soc} has the maximum value while F^{eco} has the minimum one. However, significant improvements can be reached by just giving a minimum importance to the social sustainability, i.e., $w_1 = 0.1$. In details, with an increase in F^{eco} by 4.1% F^{soc} decreases by 20.1%. This is a relevant finding since it indicates that the logistics of e-commerce platforms could dramatically improve their social sustainability performance just by assigning little relevance to this aspect, with a very small worsening in their economic performance. Moreover, Fig. 3 shows that for each value of w_1, as long as it is greater than zero, the social and economic performances fluctuate within the same range and this suggests that increasing the importance in social aspects does not necessarily worsens the economic aspect and vice versa. This is due to the fact that the two objective functions are not completely independent of each other since both have a component that is related with the distance travelled by the drivers. Thus, improving one aspect can determine the enhancement of the other dimension too.

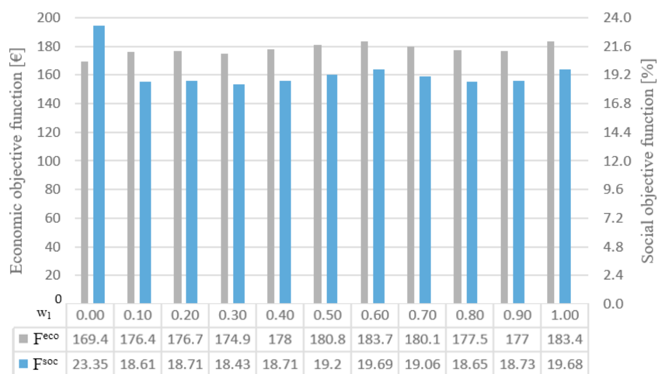

Figure 3. Objective functions trends in relation to w_1 variation

Besides the two objective functions, several KPIs are computed for each scenario to evaluate the social and economic performances of the VRP model. In detail, for each driver are assigned the distance travelled and the time spent to deliver all the assigned customer orders, the saturation rate of his or her vehicle, the number of clients served, the total weight lifted and, finally, the energy spent in driving as well as goods loading and unloading. Table 2 shows the values of these indicators for the chosen solution, e.g., the one distinguished by $w_1 = 0.1$.

Table 2. KPIs for the chosen VRP solution ($w_1 = 0.1$)

KPI	Driver 1	Driver 2	Driver 3
Distance travelled [km]	21.04	18.18	16.34
Total working time [h]	1.67	1.35	1.36
Vehicle saturation rate (weight)	28.93%	25.08%	28.27%
Vehicle saturation rate (volume)	78.46%	66.15%	78.46%
N° of client served	23	18	19
Total weight lifted [kg]	263	228	257
Energy spent in loading/unloading [Kcal]	75.08	50.57	59.91
Energy spent in driving [Kcal]	90.72	62.73	70.49
E_k	18.61%	18.17%	18.07%

In particular, the portion of energy spent compared to the personal energy capacity is equally distributed among the different drivers considering their personal characteristics. This suggests that the min-max approach adopted simultaneously minimizes the social objective function and it balances the energy consumption among all the drivers involved. Furthermore, it is important to highlight that even if driver 2 travels more km than driver 3, the latter spends more energy in driving activity compared to the former since it depends on BW_k. Indeed, the driver 2 is a woman with BW_k = 60 kg while the driver 3 is a man with BW_k = 75 kg.

7. CONCLUSIONS

This paper presents the development and implementation of a mathematical model and a related SA algorithm designed for a bi-objective VRP. The two objectives to be minimized are respectively the economic and social sustainability of the delivery activities. The former is represented by the distance travelled and the time spent by the drivers. The latter is the maximum percentage of energy spent by the drivers compared to their maximum capacity. The peculiarity of the proposed model is also represented by the fact that the total energy capacity available for each driver is not constant but it depends on the physical characteristics of the driver, i.e., gender and age. To integrate the social and economic objectives of the VRP, two weights are set that represent the importance of these two aspects in each tested scenario. The model is validated with a realistic dataset that well reflect the Trentino region e-commerce platform with a focus on food produces delivery for 60 customers. The results show that large improvements in the social sustainability aspect can be reached just by assigning small importance to this dimension, accepting a very limited worsening in the economic objective function. Moreover, the behavior of the two objective functions is not linear since they share a component that depends on the distance travelled and, so, increasing the social dimension importance the economic performance can enhance too, and vice versa. This trend suggests possible future research in implementing the Pareto frontier of such problem through multi-objective SA (MOSA) to find the best tradeoffs between social and economic dimensions by changing dynamically the assigned weights.

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