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The problem of marketing fattened pigs to the abattoir: A team orienteering problem approach

MASTER THESIS IN
COMPUTATIONAL ENGINEERING AND MATHEMATICS

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I would like to finish with a live memory of those relatives who passed away and certainly celebrate also this achievement.

Lleida, 4 September 2023

Abstract

In the context of pig farming, this paper deals with the optimization problem of collecting fattened pigs from farms to deliver them the abattoir. Assuming that the pig sector is organised as a competitive supply chain with narrow profit margins, our aim is to put analytics into practice coping at a time with the uncertainty in production costs and sale prices. Motivated by a real-life case, the paper analyses a rich team oriented problem with homogeneous fleet, stochastic demands, and maximum work load. After describing the problem and reviewing the related literature, we introduce the PJs heuristic. Our approach is validated and tested using a series of adapted instances to explore the gap between the solutions it provides and the ones generated by existing approaches.

Keywords: marketing problem; stochastic production and demand; VRP; PJs heuristic

Resumen

En el contexto de la ganadería porcina, este artículo aborda el problema de optimización de la recogida de cerdos de engorde al matadero. Asumiendo que el sector porcino está organizado como una cadena de suministro competitiva con estrechos márgenes de beneficio, nuestro objetivo es poner en práctica métodos analíticos para hacer frente a la incertidumbre en los costes de producción y los precios de venta. Motivado por un caso real, el trabajo analiza un problema orientado a equipos con flota homogénea, demandas estocásticas y capacidad máxima de carga. Tras describir el problema y revisar la literatura relacionada, introducimos la heurística PJs. Nuestro enfoque se valida y se pone a prueba utilizando una serie de instancias reales adaptadas para explorar la diferencia entre las soluciones que proporciona y las generadas por los enfoques existentes.

Palabras clave: problema comercialización; producción y demanda estocástica; VRP; heurística PJs

Contents

1 | Introduction

The pig sector is very important in Spain and it is very competitive (see Figure 1.1). For that reason decision making processes are becoming more and more complex and pig companies require specialized models to maintain competitiveness. Spain is the first producer in Europe with a particular organization of the sector where vertically integrated companies abounds while independent individual farmers are scarce. The integration of the pig sector started mostly around feed mills in the seventies of last century and less, but also, around meat packing plants. During last decades, economies of scale have continued to accelerate changes and promoting vertical integration (Nadal-Roig et al., 2019; Perez et al., 2009) and Spanish pig production evolved embracing other connected business activities like consultant services, medical products, veterinary services or engineering offices being part or participated by the integrator, legally established as private company or cooperative. Therefore, while in the past, the farmer was the main decision-maker, now main decisions relies on integrator headquarters since they have to coordinated the pig supply chain (PSC) conformed by different decision making units or agents. Consumer concerns about climate change, environmental impact, animal welfare, food safety and food quality are new challenges to consider (Rodríguez et al., 2014; Plà-Aragonès, 2021). As consequence, the specialization and technical improvement in the sector have complicated the way of making decisions as it requires a whole chain vision (Perez et al., 2009; Rodríguez et al., 2014) . New Decision Support Systems (DSS) emanated from the Internet of Things (IoT) are needed to improve the coordination of the PSC (Mateo-Fornés et al., 2021).

Most of the models proposed for pig production planning have adopted the perspective of individual farms responding to realities existing in countries where farmers have more autonomy. The schematic representation of the problem is shown in Figure 1.2 and illustrates the problem of optimal delivery of pigs to the abattoir studied by different authors like Jones et al. (2017). As result, almost none decision model in the literature adopts the PSC perspective that involve the management of many fattening farms at a time (Nadal-Roig et al., 2019; Perez et al., 2009). Thus, the interest of a PSC manager relies on the optimization of the abattoir operation and the coordination of fattening farms to deliver optimal fattened pigs on time to cover pig-meat demand. This way, the

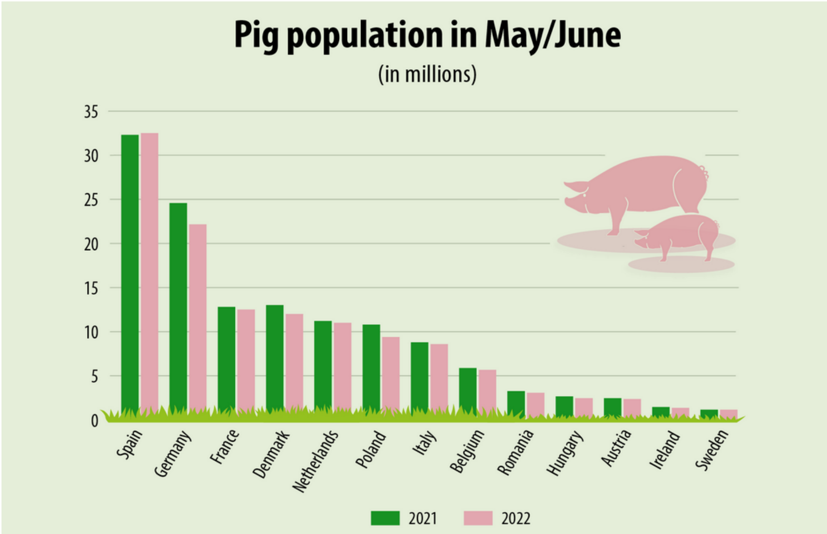


Figure 1.1: Pig census in the European Union (source EUROSTAT).

collection of fattened pigs within a marketable weight among integrated farms has to be planned weekly by the abattoir and coordinated by the pig supply chain manager to avoid disruptions at farming level and stops in the meat packing plant. The integrator has a fleet of vehicles to do the transportation and it can be assisted by subcontracted companies when needed.

Therefore, according to the previous example, the optimal solution of delivery pigs to the abattoir for an individual farmer is not useful nor optimal for the abattoir. The optimization model suitable for the abattoir must consider the coordination of all the fattening farms marketing pigs. So that, the fleet of vehicles in charge of the collection and delivery of pigs to the abattoir correspond to the Team Orienteering Problem (TOP). The TOP approach to this specific problem aims to optimize the routing of a set of trucks who can collect pigs of different reward value by visiting a subset of farms within a limited time frame. The objective is to maximize the total collected rewards while considering constraints such as time limitations and limited capacity. The goal of TOP is to maximize the collected rewards or rather than solely optimizing the routing. In addition, the postponement of a visit to a farm and the collection of pigs may have a cost or a reward depending on the growth state of the pigs and sales' price.

Considering that farms and abattoir's operations planning are scheduled weekly and the road map for truck drivers is planned monthly, the objective of this Master Thesis is to propose a TOP model formulation to plan the weekly collection of pigs to be delivered to the abattoir. Expected contributions of the Thesis are:

- A conceptual description of the problem of marketing fattened pigs to the abattoir

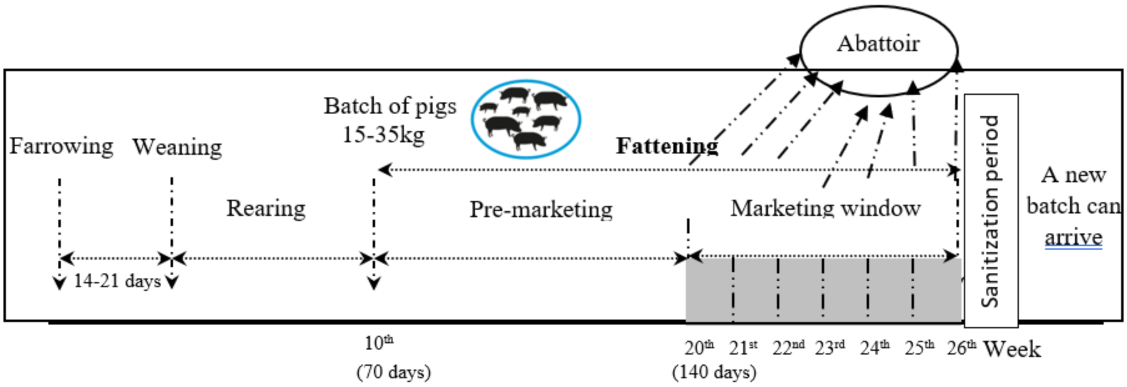


Figure 1.2: Overview of the fattening process within the pig production cycle.

from the abattoir perspective.

- Formulate a TOP and solve some instances showing the inefficient approach using LP solvers for large instances.
- Implement a metaheuristic based on PJS heuristic and solve a problem based on a realistic data set.
- Improve the previous heuristic introducing a Biased Randomized Heuristic.
- Creation of a data set of instances to perform tests with different heuristics to solve the same problem.

The rest of the thesis is structure as follows: in Chapter 2 it is presented the state of the art regarding the TOP based on a literature review of recent papers published in JCR journals. The real problem under abattoir perspective is described in Chapter 3 while the LP formulation and the approximate approach are presented in Chapter 4. In Chapter 5 the data available of a real case is presented and also the criterion used to generate the different instances. Results of computational experiments and the discussion of the more relevant results are introduced in Chapter 5 while main conclusions and future outline are presented in Chapter 6.

2 | Literature review

The proposed problem of delivery pigs for slaughtering under the perspective of the abattoir is modeled as a TOP. The TOP was introduced by Chao et al. (1996) as an extension of the Orienteering Problem (OP). The same OP is also called as the Selective Traveling Salesman Problem (STSP) according to Laporte and Martello (1990). In contrast to the TOP, the OP has been widely studied and a variety of heuristics have been developed and tested (Chao et al., 1996; Angélica Salazar-Aguilar et al., 2014). For that reason, there are not specific reviews on TOP but some in the OP. The last and sole extensive literature review found on this topic was published by VAN (2011). In the TOP, given a fixed amount of time for each member of the team, m, the goal is to determine m routes starting and ending at a specific point through a subset of locations in order to maximize the total reward while in the OP the team has only one route, i.e. member) to find. This connection between OP and TOP makes solving strategies for OP serve as inspiration point for solving TOP besides others already proposed specifically for TOP.

Other models have been proposed within the rich variety of Vehicle Routing Problems (VRP) in which TOP falls as well since they share many resemblances. However, references to these models are sometimes limited to few publications or particular problems making difficult to establish a clear taxonomy. For example, the constrained VRP with Profits (Stavropoulou et al., 2019) aimed at maximizing the total collected profit, whereas minimizing the total traveling distance, while providing consistent customer service share many characteristics with our approach. For clarity and to avoid misunderstandings, we will keep tight to TOP formulation models published in literature as such.

2.1. Deterministic Orienteering Problem

The Deterministic Orienteering Problem (DOP) is a variant of the OP aiming at the maximization of the total profit collected by visiting a subset of locations within predefined distance or time constraints. Researchers have explored exact algorithms based on combinatorial optimization techniques, particularly in the context of route planning and tour optimization, and resource allocation (Gedik et al., 2017; Tae and Kim, 2015). However, they have also paid attention to heuristic/metaheuristic methods to tackle DOP instances efficiently due to its NP-hard nature. Many solution approaches have been proposed for solving OP based on metaheuristics including GRASP (Campos et al., 2014), iterated local search (Gunawan et al., 2015), particle swarm optimization (Yu et al., 2017), path-relinking (Souffriau et al., 2010), simulated annealing (Lin and Yu, 2017), tabu search (Tang and Miller-Hooks, 2005), variable neighborhood search (Palomo-Martínez et al., 2017), and other sophisticated metaheuristics (Ke et al., 2016).

2.2. Dynamic Probabilistic Orienteering Problem

The Dynamic Probabilistic Orienteering Problem (DPOP) is a dynamic and stochastic vehicle routing problem (DSVRP) which generalizes the Orienteering Problem (OP) as stated by Angelelli et al. (2021). Specifically, the stochastic feature refers to the presence of random requests from a set of potential customers, while the dynamic feature refers to the fact that random requests reveal over time and need immediate response. Moreover, a specific feature of the DPOP is that every acceptance/rejection decision is taken before the vehicle actually starts the tour. As a consequence, the order of visit of the accepted customers can be modified thoroughly after any acceptance decision. On one hand, this feature makes the problem very different from most dynamic routing problems, where requests arise while the vehicle is on the road. On the other hand, the same feature is shared by routing problems related to attended home delivery (AHD) services, where, however, the main issue is the management of delivery time windows.

2.3. The Team Orienteering Problem

According to Panadero et al. (2023), most of the existing articles assume deterministic versions of the problem. Many solution approaches have been proposed based on those already tested for the OP like constraint programming (Gedik et al., 2017) and branch-and-price approaches (Tae and Kim, 2015). Tang and Miller-Hooks (2005) have proposed a tabu search algorithm for the TOP, whereas Archetti et al. (2007) have proposed two variants of a generalized tabu search algorithm and a variable neighborhood search algorithm for the TOP and have shown that each of these algorithms outperforms previous heuristics.

A variant of the TOP, called the TOPTW because each vertex has an associated time window, was later introduced by Vansteenwegen et al. (2009a). The authors have proposed an integer linear programming formulation and an iterated local search heuristic for this problem. The same authors (Vansteenwegen et al., 2009b) have also proposed a path relinking algorithm for the TOP which outperforms the previous heuristics of Tang and Miller-Hooks (2005) and of Archetti et al. (2007), among others.

Lin and Yu (2017) investigated an extension of the TOPTW considering mandatory visits (TOPTW-MV). They designed a multi-start simulated annealing heuristic to solve the problem. Later on, Kirac et al. (2023) proposed a constraint programming (CP) approach for solving the same TOPTW-MV. The objective was to create a set of vehicle routes that begin and end at a depot, visit mandatory locations exactly once and optional locations at most once, while observing other restrictions such as time windows and sequence-based travel times. Aringhieri et al. (2022) presented two problems arising in the health care logistics that are modelled as team orienteering problem being the first applications to health care logistics problems. Panadero et al. (2023) dealt with a more realistic TOP version, where travel times were modeled as random variables, which introduces reliability issues in the solutions due to the route-length constraint. In order to deal with these complexities, the authors proposed a simheuristic algorithm that hybridizes biased-randomized heuristics with a variable neighborhood search and Monte-Carlo simulation.

2.4. The Team Orienteering Problem in Agriculture

Even TOP is not a novel problem in the operational research field, there are not many applications in agriculture. Doing a search in ScienDirect with the terms "Team", "Orienteering", "Problem" and "Agriculture" only 45 references appeared and not all of them applied TOP to solve agricultural problems, and only mention agriculture as a possible field of application. In fact, only four papers were truly related to the field. Two of them related with optimal spraying task in crop protection with multi-Unmanned Aerial Vehicle (UAV) systems (Li et al., 2022, 2023) and the other two devoted to farm monitoring, also by using UAV (Hafeez et al., 2023; Bottarelli et al., 2019). As these pubications are also quite recent, from 2019 to 2023, we could coclude about the novelty of the approach we are proposing in this Master Thesis.

Therefore, inspired by the paper of Panadero et al. (2023) to solve realistic instances, this study proposed a random biased PJS heuristic for solving a real-based TOP because it performs very well as demonstrated the same authors.

3 | Understanding the real problem for the abattoir

The problem studied in this Thesis arises from a real situation faced by PSC managers in coordinating the delivery of fattened pigs to the abattoir (Figure 3.1). Periodically, every week, the abattoir must plan its trips to collect the marketable pigs among different fattening farms belonging to the integrator. The number of marketable pig in each farm is estimated by a farm visitor, a person serving to the PSC manager making pig weight estimations by eye (Rodríguez-Sánchez et al., 2019). These estimations are used to determine the tentative date to start delivering pigs to the abattoir and emptying the farm. Fattening farms operate under all-in-all-out (AIAO) management, meaning that all pigs enters at a time on the farm as a batch and a new batch can only enter once all the pigs of the previous batch have been delivered to the abattoir. As not all the pigs grow at the same rate, not all of them reach the marketable time at the same time. For this reason, the delivery of pigs to the abattoir normally last four weeks between the first and the last load of animals (Rodríguez-Sánchez et al., 2019; Plà-Aragonés, 2015). In addition, since all the fattening farms serve to the same abattoir and belong the same integrator, the delivery of pigs over time must be balanced all around the year and farms house batches of pigs at different growing stages. At any case, all of the farms are available to deliver fattened pigs. The amount of weekly trips to the abattoir depends on slaughtering capacity. The number of trips per truck depends on the size of the available fleet owned by the integrator or abattoir.

Once the total number of pigs available to be collected on each farm is determined, the scheduling of load trucks is carried out by considering incompatibility constraints between workload tasks and ensuring that a minimum number of pigs are collected. Incompatibilities between farms can be the result of different breeds housed or sanitary status of herds. The abattoir is served by a team of truck-drivers based at the depot, i.e. the abattoir, which remains open until the last truck is downloaded. Every week, the team leaves the depot to perform the schedule for that week and then returns to the depot. The daily schedule of a week is flexible and serves only to fulfil abattoir demand and balanced

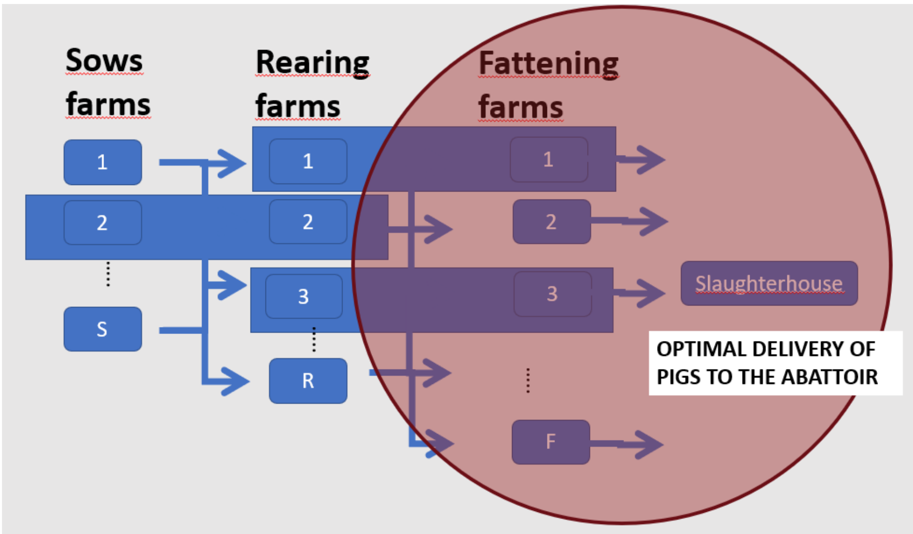


Figure 3.1: Pig supply chain structure and coordination.

workload of drivers. The time horizon usually considered is of one month equivalent to four weeks. A team operates for the same integrator and outsourcing is not considered though it is possible in real life during peak periods justified by the coordination of pig production on farms. Flexibility due to slaughter third party pigs is interesting, but limited since there is a minimum number of own slaughtered animals required just to keep the pig production flow over time balanced. There are sow farms producing piglets all the time with few stocking capacity related to housing capacity and regular operation of fattening facilities (see Figure 3.1).

Then, the problem consists of constructing a schedule of collection of pigs among farms over the planning horizon so that minimal abattoir demand is fulfilled, and the total reward associated with fattened pigs that are collected is maximized. Each weekly schedule is viewed as a route in the context of vehicle routing since a farm can only visited once a week. The reward of each farm is calculated according to Rodríguez-Sánchez et al. (2019) and applied to each pig. There are not taken considerations related to the rest of the system leaving aside considerations regarding other production stages like sow or rearing farms. The objective is to maximize the rewards derived from collecting pigs from farms minus the transportation cost. To the best of our knowledge, this problem has never been addressed in the scientific literature and it can be viewed as a TOP with additional constraints. Main constraints are:

- each vehicle route starts and ends at the abattoir;
- the accumulated quantity of pigs carried by each vehicle does not exceed the total carrying capacity due to animal welfare regulation of the EU;

- there is a maximum time limit for vehicle routes;
- each farm delivers at most only once by the same vehicle at the same period;
- a truck visiting a farm must collect all available pigs if truck capacity make it possible;

The expected results of the proposed approach benefits of the context understanding in which farmers and pig companies make decisions and it is expected they pave the way for the future deployment of new DSS tools (Rose et al., 2018). Moreover, taking into account the competitiveness of the sector and the lack of specialised tools to make data-driven decisions.

4 | Mathematical formulation of the Team Orienteering Problem

4.1. The mixed integer linear programming model

4.1.1. The general TOP formulation

The proposed TOP can be defined on a complete directed network. Let $G = (V', A)$ be a complete directed graph with vertex $0 \in V'$ representing the abattoir, where the route starts and ends, while set $V = 1 \ldots n \subset V'$ represents the farms' locations; set A is the arc set. Each vertex $i \in V$ has an associated profit $p_i \in \mathbb{R}^+$ and each arc $(i, j) \in A$ has a travel time $t_{ij} \in \mathbb{R}^+$ calculated from real distances among farms. We assume that travel times satisfy the triangle inequality. The length of a path (measured in time) cannot exceed the predefined time limit T_{max}. Every farm (vertex) can be visited at most once per week.

Variables:

- Binary decision variables x_{ij}^d, where:

$$x_{ij}^d = \begin{cases} 1, & \text{if farm } j \text{ is visited immediately after farm } i \text{, with truck } d, \\ 0, & \text{otherwise.} \end{cases}$$

- Integer decision variables $y_i^d \in \mathbb{N}$, where:

$$y_i^d = \begin{cases} z, & \text{if farm } i \text{ is the } z^{th} \text{ visit of truck } d, \\ 0, & \text{otherwise.} \end{cases}$$

The TOP model formulation:

$$\text{Maximize:} \sum_{d\in D}\sum_{(i,j)\in A} u_j \cdot x_{ij}^d \tag{4.1}$$

$$\text{s.t.: } x_{ij}^d \leq 1 \qquad \forall (i,j)\in A, \forall d \in D \tag{4.2}$$

$$y_i^d - y_j^d + 1 \leq (1 - x_{ij}^d)\cdot |V| \qquad \forall i,j \in V, \forall d\in D \tag{4.3}$$

$$\sum_{i\in V} x_{ij}^d = \sum_{h\in V} x_{jh}^d \qquad \forall j \in V, \forall d \in D \tag{4.4}$$

$$\sum_{j\in V} x_{0j}^d = \sum_{i\in V} x_{i0}^d = 1 \qquad \forall d\in D \tag{4.5}$$

$$\sum_{(i,j)\in A} t_{ij}\cdot x_{ij}^d \leq T_{max} \qquad \forall d \in D \tag{4.6}$$

$$x_{ij}^d \in \{0,1\} \qquad \forall (i,j)\in A, \forall d\in D \tag{4.7}$$

$$y_i^d \geq 0 \qquad \forall i \in V, \forall d \in D \tag{4.8}$$

Equation (4.1) denotes the objective function to be maximized. Constraints (4.2) ensure that each farm should be visited by a truck at most once during the whole time horizon. Constraints (4.3) prevent the construction of subtours. Constraints (4.4) is a flow balance constraint, and ensure that any arrival to a farm has to be compensated with a departure. Constraints (4.5) states that all the vehicles should leave and arrive to the abattoir (vertex 0). Constraints (4.6) state that the total travel time of each vehicle should not be more than its threshold. Finally, constraints (4.7) and (4.8) refer to the nature of x_{ij}^d and y_i^d variables.

4.1.2. The optimal delivery model

The presented model of optimal deliveries to the abattoir is based on the formulation proposed by Rodríguez et al. Rodríguez-Sánchez et al. (2019). We are considering a fattening farm, $j \in V$, fattening a batch of N_j-pigs. Pigs are distributed in $|P|$ growth categories. The aim is to plan the deliveries to the abattoir and maximize the profit.

$$\text{Maximize:} \quad \sum_{e \in E} \sum_{p \in P} b_{ep} \cdot s_{ep} \tag{4.9}$$

$$\text{s.t.:} \quad n_{1p} = N_j/|P| \qquad \forall p \in P, j \in V \tag{4.10}$$

$$n_{e+1,p} = n_{ep} - s_{ep} \qquad \forall e \in E \setminus \{e_{max}\}, \forall p \in P \tag{4.11}$$

$$n_{e,p-1} \geq n_{ep} \qquad \forall e \in E, \forall p \in P^{-} \tag{4.12}$$

$$n_{e+1,p} \leq n_{1p}(1 - d_{e,p-1}) \qquad \forall e \in E \setminus \{e_{max}\}, \forall p \in P^{-} \tag{4.13}$$

$$s_{ep} \leq n_{ep} \qquad \forall ep \in EP \tag{4.14}$$

$$s_{ep} \leq n_{1p} \cdot d_{ep} \qquad \forall ep \in EP \tag{4.15}$$

$$s_{e_{max}p} \geq n_{e_{max}p} \qquad \forall p \in P \tag{4.16}$$

$$\sum_{p \in P} s_{ep} \leq Kd \cdot t_e \qquad \forall e \in E \tag{4.17}$$

$$s_{ep} \geq 0, \quad n_{ep} \geq 0 \qquad \forall ep \in EP \tag{4.18}$$

$$t_e \in \mathbb{N} \qquad e \in E \tag{4.19}$$

$$d_{ep} \in \{1, 0\} \qquad ep \in EP \tag{4.20}$$

Equation (4.9) denotes the objective function to be maximized by delivering a batch of pigs from farm i to the abattoir. Constraints (4.10) represents the categories considered in a batch of fattening pigs. Constraints (4.11) keep the inventory of animals on farm. Constraints (4.12) force to keep on farm lighter pigs. Constraints (4.13), (4.14) and (4.15) control only adjacent categories of pigs can be delivered to the abattoir. Constraints (4.16) ensure that all pigs have been delivered at the end of the fattening period. Constraints (4.17) serve to define the number of trucks needed for deliveries. Finally, constraints (4.18), (4.19) and (4.20) refer to the nature of s_{ep}, n_{ep}, t_e and d_{ep} variables.

4.1.3. The TOP for deliveries to the abattoir

In this section, the TOP model of section 4.1 is updated considering the deliveries to the abattoir. In particular, the rewards u_j of equation (4.1) are calculated by the benefit of sales, i.e. $\sum_{p \in P} b_{ep} \cdot s_{ep}$. Pigs of a fattening farm are in a growth stage $e \in E$ with a distribution of $p \in P$ groups of weights. Then, considering the growth state in each farm determines the reward and the number of pigs delivered to the abattoir, we can re-formulate the new TOP model:

$$\text{Maximize: } \sum_{d\in D}\sum_{(i,j)\in A}(\sum_{p\in P} b_{e_jp}\cdot s^d_{e_jp})\cdot x^d_{ij} \tag{4.21}$$

$$\text{s.t.: } x^d_{ij} \leq 1 \qquad \forall (i,j)\in A, \forall d\in D \tag{4.22}$$

$$y^d_i - y^d_j + 1 \leq (1 - x^d_{ij})\cdot |V| \qquad \forall i,j\in V, \forall d\in D \tag{4.23}$$

$$\sum_{i\in V} x^d_{ij} = \sum_{h\in V} x^d_{jh} \qquad \forall j\in V, \forall d\in D \tag{4.24}$$

$$\sum_{j\in V} x^d_{0j} = \sum_{i\in V} x^d_{i0} = 1 \qquad \forall d\in D \tag{4.25}$$

$$\sum_{(i,j)\in A} t_{ij}\cdot x^d_{ij} \leq T_{max} \qquad \forall d\in D \tag{4.26}$$

$$\sum_{d\in D} s^d_{e_jp} \leq N_{p_j} \qquad \forall j\in V, \forall p\in P \tag{4.27}$$

$$\sum_{j\in V}\sum_{p\in P} s^d_{e_jp} \leq N^d_{max} \qquad \forall d\in D \tag{4.28}$$

$$s^d_{e_jp} \geq 0 \qquad \forall j\in V, \forall p\in P \tag{4.29}$$

$$x^d_{ij} \in \{0,1\} \qquad \forall (i,j)\in A, \forall d\in D \tag{4.30}$$

$$y^d_i \geq 0 \qquad \forall i\in V, \forall d\in D \tag{4.31}$$

Equation (4.21) denotes the objective function to be maximized by delivering $s^d_{e_jp}$ pigs from farm $j \in V$ at growth stage $e_j \in E$, group $p \in P$ by trip $d \in D$ to the abattoir generating a profit of b_{e_jp} euros per each of those pigs. We have added constraints (4.27-4.29) to represent the allowable number of pigs delivered in each trip to the abattoir.

If we consider just one period, therefore the model represented by Equations (4.21-4.31) is equivalent to the TOP model formulated by Equations (4.1-4.8) because the terms $b_{e_jp}\cdot s^d_{e_jp}$ become constant since for a specific week we know beforehand the number of animals we have susceptible of being collected (i.e. $s^d_{e_jp}$).

In a multiperiod model this is not so. In this case, the resulting model (4.21-4.31) clearly would not be lineal, but since the objective function (4.21) in the case of multiperiod time horizon would be the result of multiply a linear function by a binary variable, and hence the reformulation of the model into a MILP by standard methods is easy:

$$\text{Maximize: } \sum_{d\in D}\sum_{(i,j)\in A} w_{ij}^d \tag{4.32}$$

$$\text{s.t.: } x_{ij}^d \leq 1 \qquad \forall (i,j)\in A, \forall d\in D \tag{4.33}$$

$$y_i^d - y_j^d + 1 \leq (1 - x_{ij}^d)\cdot |V| \qquad \forall i,j\in V, \forall d\in D \tag{4.34}$$

$$\sum_{i\in V} x_{ij}^d = \sum_{h\in V} x_{jh}^d \qquad \forall j\in V, \forall d\in D \tag{4.35}$$

$$\sum_{j\in V} x_{0j}^d = \sum_{i\in V} x_{i0}^d = 1 \qquad \forall d\in D \tag{4.36}$$

$$\sum_{(i,j)\in A} t_{ij}\cdot x_{ij}^d \leq T_{max} \qquad \forall d\in D \tag{4.37}$$

$$\sum_{d\in D} s_{e_jp}^d \leq N_{p_j} \qquad \forall j\in V, \forall p\in P \tag{4.38}$$

$$\sum_{j\in V}\sum_{p\in P} s_{e_jp}^d \leq N_{max}^d \qquad \forall d\in D \tag{4.39}$$

$$\sum_{p\in P} b_{e_jp}\cdot s_{e_jp}^d \leq M\cdot x_{ij}^d \qquad \forall (i,j)\in A, \forall d\in D \tag{4.40}$$

$$\sum_{p\in P} b_{e_jp}\cdot s_{e_jp}^d \geq -M\cdot x_{ij}^d \qquad \forall (i,j)\in A, \forall d\in D \tag{4.41}$$

$$w_{ij}^d \leq \sum_{p\in P} b_{e_jp}\cdot s_{e_jp}^d \qquad \forall (i,j)\in A, \forall d\in D \tag{4.42}$$

$$w_{ij}^d \leq M\cdot x_{ij}^d \qquad \forall (i,j)\in A, \forall d\in D \tag{4.43}$$

$$s_{e_jp}^d \geq 0 \qquad \forall j\in V, \forall p\in P \tag{4.44}$$

$$x_{ij}^d \in \{0,1\} \qquad \forall (i,j)\in A, \forall d\in D \tag{4.45}$$

$$y_i^d \geq 0 \qquad \forall i\in V, \forall d\in D \tag{4.46}$$

4.2. The PJS algorithm

Given the complexity of solving the previous model getting an exact solution with a reasonable computational time, a heuristic based on the PJS algorithm was proposed. The general algorithm is implemented in Phyton 3.11 and detailed in Algorithm 4.1. The basic idea is to explore the space solutions in an iterative way and keeping the best solution found. The main process of the algorithm is the $merge()$ function. It is this function that embed the PJH savings algorithm to build new solutions.

Algorithm 4.1 Algorithm adapted to the delivery of pigs to the abattoir

Data :$BR, maxSave, nodes, dMat, elapsed$
$sol \leftarrow genInitSol(maxSave, nodes, dMat)$
$eff\_list \leftarrow create\_eff\_list(sol)$
$eff\_list \leftarrow sort(eff\_list)$
while $elapsed < T_{max}$ **do**
    $new\_sol \leftarrow merge(BR, maxSave, nodes, dMat, eff\_list)$
    if $new\_sol > sol$ **then**
        $sol \leftarrow new\_sol$
    end if
end while
Print the best solution sol

The algorithm implement the PJH saving heuristic that is an improvement over the classic Clark and Writght savings algorithm. Algorithm 4.2 describe how the $merge()$ function operates iterating over an $efficient\_list$. All the elements of this list are checked one by one as possible candidates of improving current solution with a new solution.

Algorithm 4.2 Exploring new feasible Routes by merging existing ones

Data :$BR, maxCost, nodes, dMat, eff\_list$
$sol \leftarrow genDummySol(maxCost, nodes, dMat)$
$copy - eff\_list \leftarrow eff\_list$
while there are elegible edges in $copy - eff\_list$ **do**
    $e \leftarrow selectEdge(copy - eff\_list)$
    if nodes on e are merge-able **then**
        $iNode \leftarrow getOrigin(e)$
        $jNode \leftarrow getEnd(e)$
        $iRoute \leftarrow getRoute(iNode)$
        $jRoute \leftarrow getRoute(jNode)$
        $new\_sol \leftarrow joinRoutes(e, iRoute, jRoute, sol)$
    end if
end while

Important in our approach is the role played in the elaboration of the $efficient\_list$ as it is shown in 4.3. When an edge is created, the cost and efficiency is calculated.

In particular, efficiency is calculated as a linear combination between cost and reward depending on $\alpha \in [0, 1]$. Once all the edges are created with cost and efficiency calculated, they are ordered according their efficiency in the $efficiency\_list$. This list will be used to build new solutions, trying to combine the more promising edges. In addition, the selection of the elements of the list are selected at each iteration randomly (i.e. Bias Randomized) in order to better explore all the solution space and avoid the deterministic result we would obtain selecting always in the same order the elements of the list.

Algorithm 4.3 Building the efficient list

Data :$nodes, dMat, alpha$
for each $node$ in the list of $nodes$ **do**
  $af \leftarrow createEdge(abattoir, farm)$
  $fa \leftarrow createEdge(farm, abattoir)$
end for
for each i_node in the list of $nodes$ **do**
  for each $j\_node > i\_node$ in the list of $nodes$ **do**
    $ij \leftarrow createEdge(i\_node, j\_node)$
    $ji \leftarrow createEdge(j\_node, i\_node)$
    $Efficent\_list \leftarrow append(ij, ji)$
  end for
end for
$Efficent\_list \leftarrow sort(Efficent\_list)$

4.3. Computational experiments design

First experiment was intended to check the difficulties associated to get the exact solution of the problem using the formulation presented in section 4.1. The use of the model 4.1.1 would be enough without need to implement and solve the other models presented in the same section much more complexes.

The second experiment solved the same problem approximately by using the algorithm 4.1 presented in section 4.2. This solution is considered the base case for the comparisons performed with additional computational experiments detailed in what follows.

Further computational experiments were planned according the nature of available data to explore the goodness of the proposed method and the system performance as well.

In particular, we accounted for a network of 187 nodes, one of them acting as depot (abattoir). Descriptive statistics were used to explore the characteristics of the real sample using *JMP Pro* version 17. Results are shown in Figure 4.1. We can observe that the mean of the sample is 94 pigs, with a large standard deviation of 63.4. On the same figure we show the distribution fit by a three mixture normal distribution (best fit).

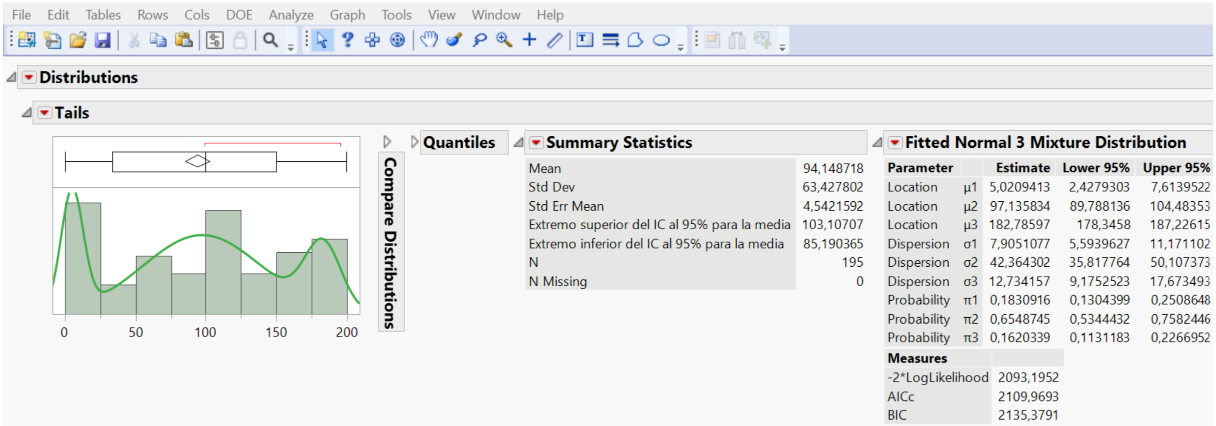


Figure 4.1: Descriptive statistics of the number of pigs per farm.

Since it is not the same a network with many farms offering pigs near to truck capacity than the case of many farms offering small number of pigs allowing transportation drivers to visit more than a farm to complete the load, we focused on the average number of pigs per farm to be delivered to the abattoir. However, another parameter that may impact to the TOP is the variability of the average number of pigs. It is not the same an average with all the farms having a similar number of pigs to slaughter than the same average with a broad dispersion. For this reason, the standard deviation of the average number of pigs was also considered. Another parameter to analyse was the truck capacity. A capacity of 200 pigs is predominant, but we can think in trailers with higher capacity of 300 or 400 pigs. Finally, since we are using approximate methods, the time devoted in searching improvements is relevant. Therefore, the same time amount was fixed to improve initial solutions.

The total number of experiments planned were: 10 (average values) $\times$ 5 (standard deviations) $\times$ 3 (maximum workload) $\times$ 2 (fixed elapsed times) $=$ 300 experiments. For this purpose the results issued in each experiment was recorded in a coded file named: $mXsdYZZZ - e$ where X refers to the average number of pigs per farm, Y the standard deviation, ZZZ the maximum workload of trucks and e the fixed time to improve solutions. The average values and standard deviation values were used to random generate normal observations for the number of pigs in each fattening farm. The same values were kept for the rest of parameters: ZZZ and e. Values out of the interval [0,200] were substituted by corresponding extreme value i.e. 0 or 200.

The outputs recorded in each experiment were: the solution number with best outcome, the cost, the reward and the number of routes. For further inspection, a more detailed file was recorded detailing the specific routes in the solution. Auxiliary calculations were performed to calculate auxiliary variables to get more insight in the analysis of results. These calculations are shown in Table 4.1.

	Calculation	**Explanation**	**Units**
Unitary	$cost/reward$	Transport time per pig	hours/pig
Intensity	$rewards/routes$	Pigs per route	#pigs/route
Duration	$cost/routes$	Transport time per route	hours/route

Table 4.1: Auxiliary outcomes calculated from instance results.

5 | Experimental results

Our algorithms were coded and run in Python 3.0 on a 2.10 GHz Intel(R) Core(TM) i7-1260P and 16 Gb of RAM under the Windows 11 Pro operating system. The experimental work was carried out over a large set of artificial instances based on a real case of a medium-big Spanish pig integrator company. We have analyzed the performance of our algorithms by considering different numbers of pigs available on fattening farms. A base case was established and additional analysis performed taking into account the four different cases: (i) changes in the number of marketable pigs; (ii) changes in the number of available trucks; (iii) changes in the dispersion of available pigs and (iv) considerations of maximum computational time for improving current solutions. We integrate a tuning of the alpha value involved in the PJS heuristic in view of balancing costs, i.e. travelling trip times, and rewards, i.e. collected pigs.

5.1. A realistic instance example: base case

In order to test our proposed model and proceed with computational experiments about the performance of our algorithmic approach, we had the permission of a real pig company (kept confidential) to use the location of their different farms and own abattoir. The abattoir have a capacity of slaughtering 5000 pigs a day and 186 fattening farms producing almost a million of pigs per year. The abattoir accepts third party pigs to slaughter but giving priority to those produced by the same company. This fact give flexibility in slaughtering their own production. The abattoir is in charge of organising the collection and transportation of fattened pigs from farms and this is done weekly. The truck capacity is normally between 200 and 220 heads depending on animal weight. Since the slaughtering weight has being increased in the last years, 200 pigs is the most usual capacity.

The company provided the latitude and longitude for all the farms and the abattoir. Figure 5.1 shows the geographical location of the facilities considered in this study on a map.

Figure 5.1: Distribution of farms around a geographical area.

A travel time matrix was build using the coordinates of all the farms and abattoir. For such purpose the URL `http://router.project-osrm.org/table/v1/driving/` was requested. This URL is an endpoint for the Open Source Routing Machine (OSRM) service, specifically for generating travel time and distance matrices for driving routes. Correct requests to this endpoint get a JSON response containing a matrix of travel times and distances between multiple pairs of locations based on driving routes. Only travel times were used in this Thesis.

Regarding fattening farm capacity, to simplify the operation of fattening farms several practical considerations are assumed:

- All the farms are supposed to be operating;
- The full capacity of farms is considered, however, we are only concerned with head or tails in batch production. This is sow because farms filling themselves a truck are not problematic;
- There are not considered constraints in fleet size, since all farms with commercial weight pigs must be collected and if needed third party transportation hired.

The results of the base case produce a reward of 17,119 pigs slaughtered with a transportation cost (time) of 1,541.4 hours, using for this 92 routes. Solving the problem with different load capacity of trucks produce the result shown in the Table 5.1. We observe how the cost does not change representing the travel time and the total number of routes involved are similar in all the cases. However, the reward changes as expected. Since the load capacity increases, the number of pigs a truck can collect is greater. The number of pigs delivered to the abattoir almost doubled when doubling the truck load capacity.

Truck load	Cost	Reward	Routes
200	1,541.4	17,119	92
300	1,515.4	25,519	89
400	1,549.0	33,919	87

Table 5.1: Main results of the base case.

5.2. Computational experiments

5.2.1. Exploratory analysis

According to the instance generation presented in section **??** and Appendix A were obtained the results of this experimentation are shown more in detail in Figure A.3 of Appendix A. A summary of the *Reward* and *Cost* is presented on Tables 5.2 and 5.3. This results correspond to the average calculated for the three different solutions obtained with different trucks (i.e. different load capacity).

	σ=**5**	σ=**25**	σ=**45**	σ=**65**	σ=**85**
μ=**9**	1823	2641	3856	6074	7588
μ=**29**	5407	6160	7030	7357	9321
μ=**49**	9324	9524	10001	9544	11572
μ=**69**	12892	13240	13244	13869	12439
μ=**89**	16577	16551	17708	17457	15390
μ=**109**	20403	20538	19780	19703	17949
μ=**129**	24126	23939	23693	21576	19555
μ=**149**	27755	27586	25961	23744	21034
μ=**169**	31486	30352	27056	25692	23136
μ=**189**	34790	30110	27624	26136	24843

Table 5.2: Reward expressed in number of pigs transported

Table 5.2 indicates that the more pigs are available on farms the more pigs are delivered to the abattoir. However, the variability observed in the number of pigs available (σ) does not always correspond to more pigs delivered to the abattoir. The reason is that random numbers are generated within the interval [0,200]. This observation corresponds to the associated cost (Table 5.3) since more pigs delivered implies a higher cost and vice versa.

	σ=**5**	σ=**25**	σ=**45**	σ=**65**	σ=**85**
μ=**9**	1233	1249	1292	1334	1340
μ=**29**	1287	1296	1341	1343	1380
μ=**49**	1366	1354	1371	1385	1367
μ=**69**	1379	1440	1448	1438	1398
μ=**89**	1482	1485	1453	1453	1430
μ=**109**	1633	1527	1510	1522	1477
μ=**129**	1639	1599	1587	1521	1490
μ=**149**	1657	1652	1602	1561	1514
μ=**169**	1790	1702	1627	1589	1568
μ=**189**	1774	1709	1647	1606	1559

Table 5.3: Cost expressed in hours

A summary of the correlation observed among is shown on Figure 5.2. On Figure 5.2 it is easy to decipher positive and negative correlations. We observe positive correlations between Trucks and Intensity (i.e. pigs per route) what is normal as more truck capacity, more pigs are transported.

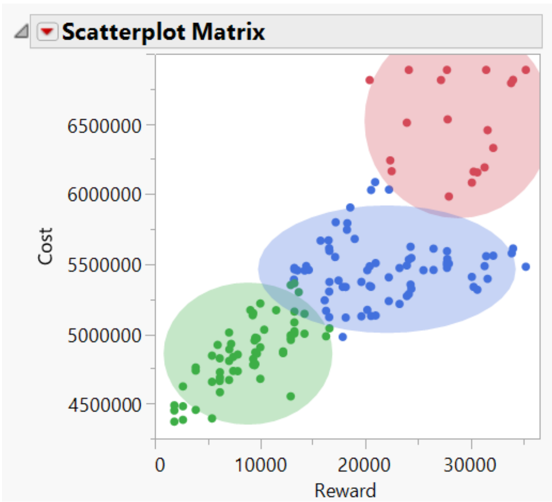
Correlations

	sd	Trucks	Sol #	Routes	Cost	Reward	Unitary	Intensity	Duration
sd	1,0000	-0,0000	0,0732	-0,1624	-0,1425	-0,0718	-0,1749	0,0727	-0,1564
Trucks	-0,0000	1,0000	0,0184	-0,3544	-0,3567	0,1597	-0,0813	0,9644	0,2203
Sol #	0,0732	0,0184	1,0000	0,7372	0,7171	0,8418	-0,6402	-0,0430	-0,6328
Routes	-0,1624	-0,3544	0,7372	1,0000	0,9878	0,7919	-0,5610	-0,4559	-0,6455
Cost	-0,1425	-0,3567	0,7171	0,9878	1,0000	0,7687	-0,5583	-0,4600	-0,6455
Reward	-0,0718	0,1597	0,8418	0,7919	0,7687	1,0000	-0,7061	0,1009	-0,6665
Unitary	-0,1749	-0,0813	-0,6402	-0,5610	-0,5583	-0,7061	1,0000	-0,0923	0,9292
Intensity	0,0727	0,9644	-0,0430	-0,4559	-0,4600	0,1009	-0,0923	1,0000	0,2014
Duration	-0,1564	0,2203	-0,6328	-0,6455	-0,6455	-0,6665	0,9292	0,2014	1,0000

Figure 5.2: Correlation among output variables of computational experiments.

The variable *Sol#* approximates the iteration of the best solution, and it is positively correlated with *Routes*, *Cost* and *Reward*. This can be interpreted as more computational time improve *Reward*, *Cost* and *Routes*. Another higt correlation is observed between *Routes* and *Cost* what is reasonable, since more routes implies more time to cover them. Among auxiliary variables, *Duration* (hours/route) is highly correlated with *Unitary* (hours/pig). Negative correlations are of less intensity than positive ones. The lowest value corresponds to *Unitary* (hours/pig) vs *Reward* (pigs) representing that more transportation time per pig delivered to the abattoir less pigs are delivered.

Before considering a deeper analysis on results, a clustering of all variables was performed to identify the relevant variables performing data classification. As there where three different load truck capacity it was considered this number of three good for clustering. Results are presented in Figure 5.3. We observe a very neat classification depending on *Cost* and *Reward* (Figure 5.3a). A further analysis of the rest of variables defining each cluster we observe that most of the experiments with lowest truck capacity are in cluster 1 while variability seems lower in cluster 1 than in the others. Mean values of variables for clusters 2 and 3 are similar in general showing more differences in the mean number of *Routes* and mean *Duration* (Figure 5.3b).



(a) Cluster scatter plot.

Cluster	Mean(Routes)	Mean(Trucks)	Mean(sd)	Mean(Duration)	Mean(Unitary)	Mean(Intensity)
1	158,85	250	32	11,6226	231,536	185,954
2	34,8852	304,918	46,3115	52,3603	725,726	267,566
3	82,5972	309,722	48,25	19,1593	264,66	275,883

(b) Cluster data classification k=3.

Figure 5.3: Results of the cluster analysis performed with k-means method and k=3.

5.2.2. Exploring the results on *Routes*

After the first results we observe the main outputs revolve around the number of routes, the cost and the reward. If we observe the distribution of Routes in Figure 5.4. It is clear how the number of *Routes* increase as the number of pigs per farm increase. At the same time, this increment makes the variability observed in the boxplot higher when the mean number of pigs on farms increases. The boxplot with mean 94 corresponds to the base case, i.e. real instance, while the rest corresponds to randomly generated instances.

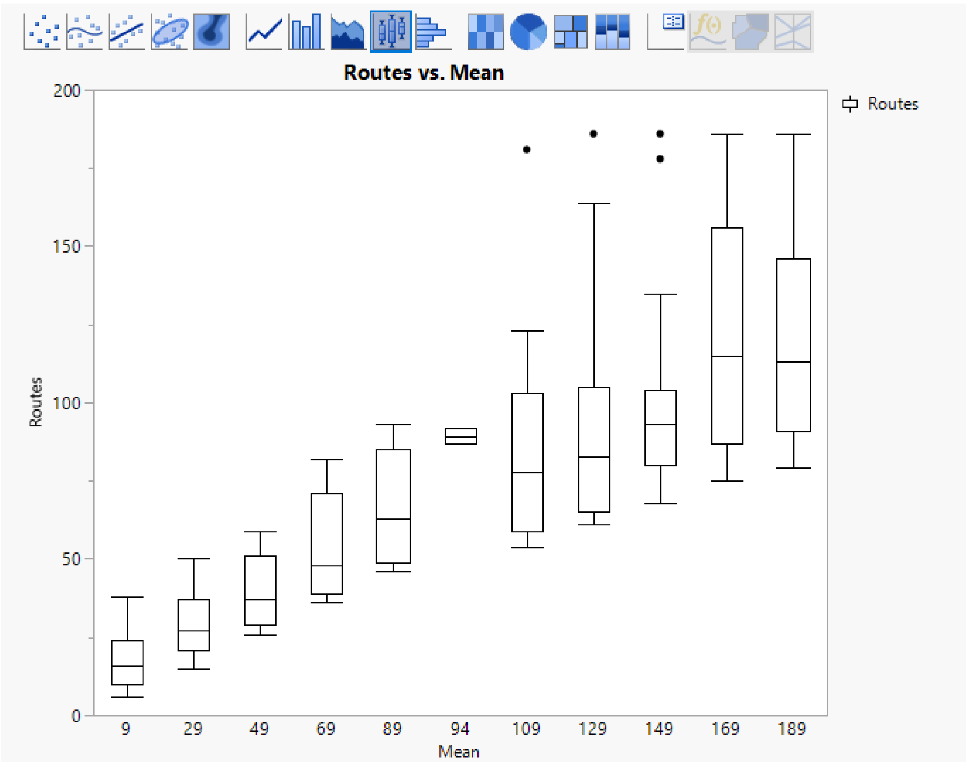
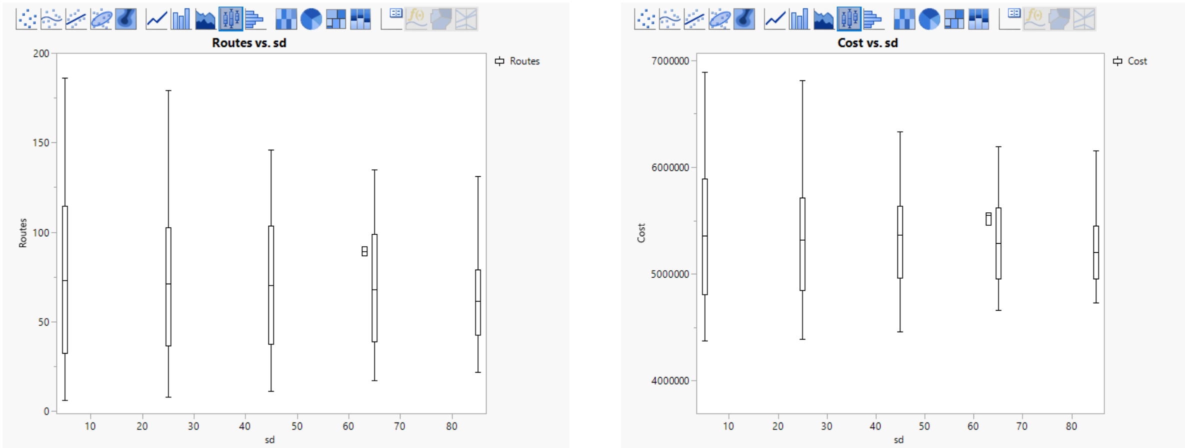


Figure 5.4: Boxplot of routes by mean number of pigs per farm.

We could think that variability observed in Figure 5.4 may be due to the variance in the random generation of pigs on fattening farms. However for each mean, five different standard deviations are considered. So that, Figure 5.5a represented the boxplot of the mean number of *Routes* by different standard deviation (sd). The variability represented by the boxplots indicates higher variability leads to less dispersion in the number of *Routes*. Investigating the reason, we concluded that bigger standard deviation around the mean number of pigs on farms provokes a variety of random values that makes truck load easier to complete. The different number of pigs available among different farms complement better each other to fill a truck. Figure 5.5b confirms the positive correlation between *Routes* and *Cost* since lesser variability in the number of *Routes* redounds in a lesser variability in associated *Cost*.



(a) Number of *Routes* by *sd*. (b) *Cost* by *sd*.

Figure 5.5: Results of *Routes* and *Cost* by standard deviation (*sd*).

5.2.3. Exploring the results on *Truck* capacity

As we are considering different load capacities for trucks, we can see the number of *Routes* we have to implement depending on truck capacity. This information is presented in Figure 5.6.

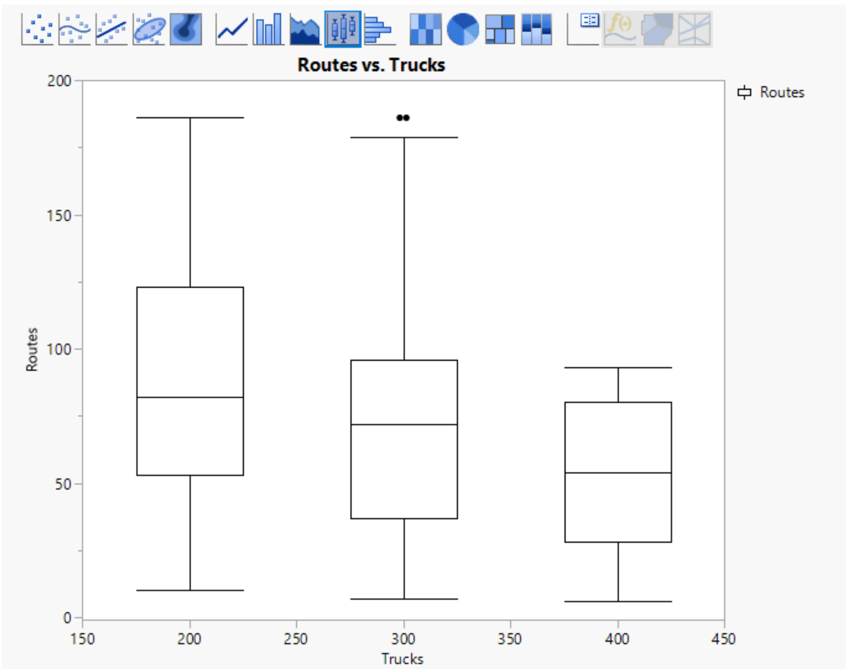
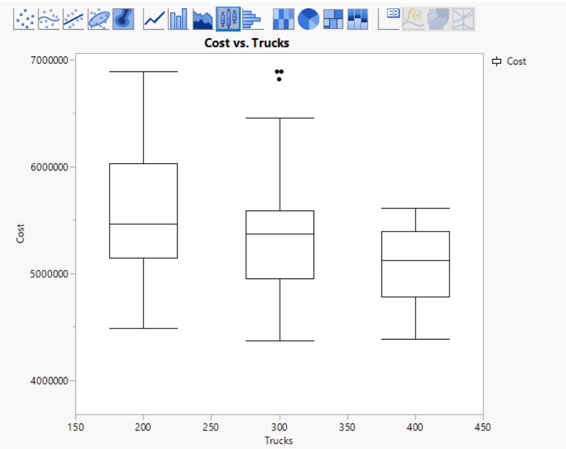
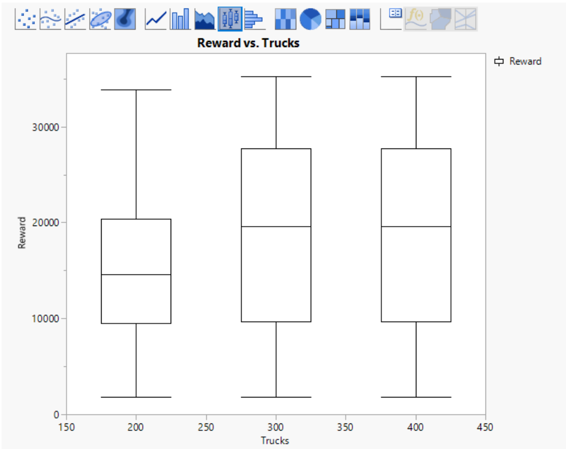


Figure 5.6: Boxplot of routes by truck load capacity.

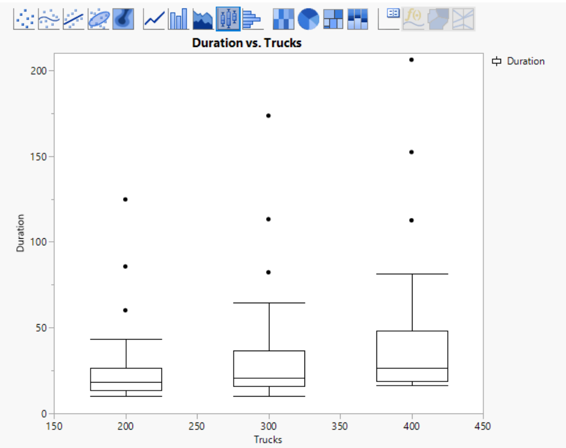
As expected, load capacity implies less *Routes* to cover. Figure 5.6 shows clearly a decrement in the number of *Routes* when increasing truck capacity. Other variables are also affected by the load capacity of trucks (see Figure 5.7). For instance, *Cost*, representing travel time, is reduced when capacity is higher (Figure 5.7a). However, the impact on *Reward* is more limited (Figure 5.7b) likely because the total capacity of the fleet overpass the available number of pigs on farms. In accordance to that, the *Intensity* of completing truck capacity increases with *Truck* capacity (Figure 5.7d) while trip times represented by *Duration* increase slightly because more truck capacity allow the company to plan longer *Routes* (Figure 5.7c) implying less cost per truck and more reward capacity.



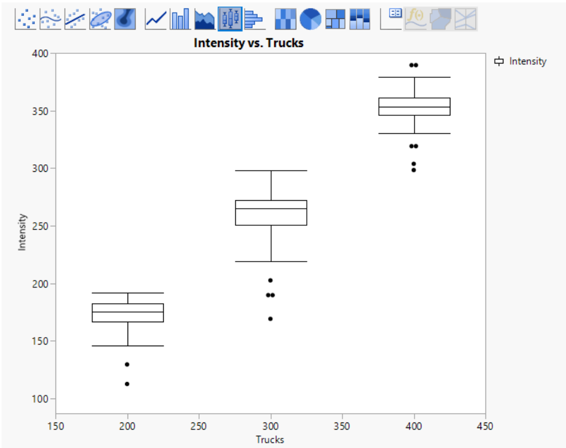
(a) *Cost* per *Truck* capacity.



(b) *Reward* per *Truck* capacity.



(c) *Duration* per *Truck* capacity.

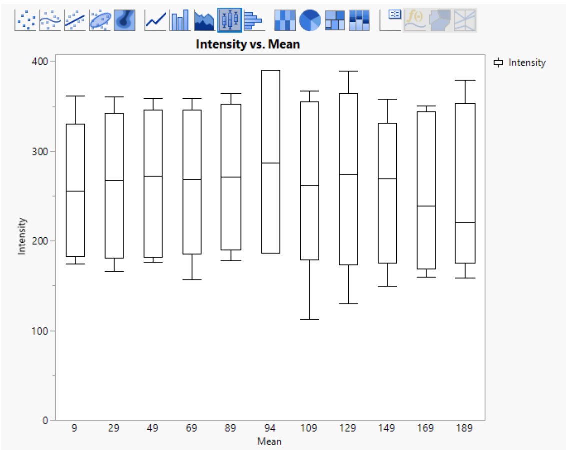


(d) *Intensity* per *Truck* capacity.

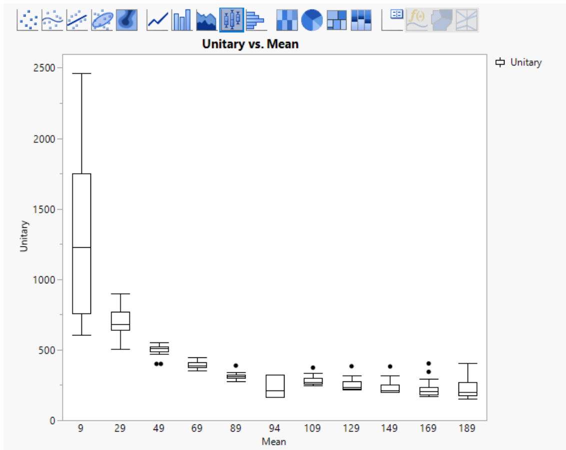
Figure 5.7: Results of *Cost* (5.7a), *Reward* (5.7b), *Duration* (5.7c) and *Intensity* (5.7d) per *Truck* capacity.

5.2.4. The impact of the number of pigs to collect

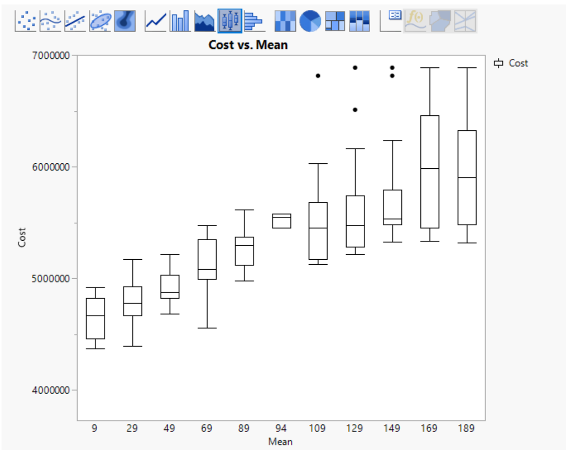
The number of pigs to be delivered to the abattoir is a crucial element to solve the TOP. Less pigs available may imply longer routes to fulfil truck capacity while more pigs may limit the flexibility to complete truck load. Figure 5.8 tries to summarize the impact of different averaged number of pigs available to be sent to the abattoir. The first observation is that the *Intensisty* is not affected by the number of pigs to be collected (Figure 5.8a) because we only have three different load capacities. However, the trip time per pig (*Intensity*) it is reduced as the mean number of pigs per farm increases (Figure 5.8b). This result suggest a better efficiency in transportation when more animals are available.



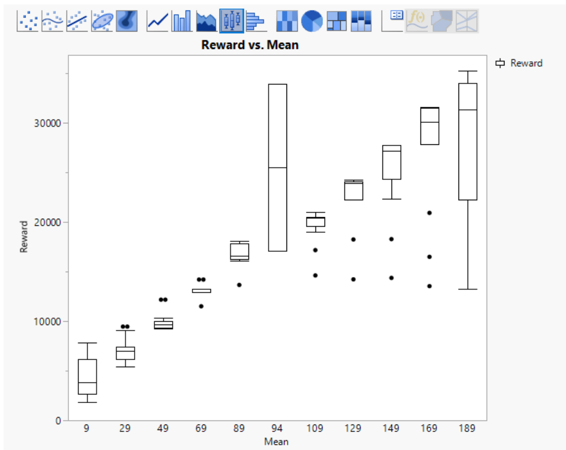
(a) Number of pigs per truck.



(b) Trip time per pig.



(c) *Cost* or averaged trip time.



(d) *Reward* or number of pigs collected.

Figure 5.8: Results of *Cost* (5.8a), *Reward* (5.8b), *Duration* (5.8c) and *Intensity* (5.8d) per *Truck* capacity.

Figure 5.8c represents the increasing cost when the average number of animals increase.

It is reasonable if there are more pigs in the system that more trips are required to the abattoir. This is confirmed with Figure 5.8d showing that the number of pigs generating rewards, increments according the mean value considered.

6 | Conclusions and future developments

6.1. Conclusions

According to the objective of this Master Thesis, we can conclude that we succed to describe the problem of marketing fattened pigs to the abattoir as a TOP model. We have formulated the TOP model as a MILP model what is inefficient for large instances. Therefore, we have solver the problem by a metaheuristic based on the combination of PJH savings and Biased randomized heuristics. We have created a data set based on a real case and demonstrated the utility to solve large problems.

Given the nature of the problem the most prominent alpha value used by the algorithm was 0 since the reward from pigs were more attractive than a mere reduction in transportation cost. Another important aspect was the truck capacity that limited the number of farms to visit and made easier the resolution of the problem.

6.2. Future work

However, even the computational experiments performed were successful, there are technical aspects to consider when analyszing other cases related to the algorithm like:

- The alpha parameter of the PJS algorithm;
- The biased random selection of elements from the candidate list;
- The uncertainty in rewards.

While other aspects relying on the problem also to consider are:

- The number of farms delivering pigs at a time;
- The capacity of trucks collecting pigs;
- The outsourcing of the transportation.

For that reason, in the near future, the extension of this work is foreseen. The first task will be to solve a multiperiod problem. This task is difficult since involve the implementation of model represented by equations 4.32-4.46 in case of require exact solutions. Easier would be the exension of the present algorithm to deal with this complexity.

The last extension of the model we would like to do is to include uncertainty in the process since either pig growth and sales' prices varies over time and are uncertain. The use of more advanced metaheuristics like simheuristics or learnheuristics seem interesting.

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A | Appendix A

The specific random numbers generated to represent the number of pigs available or the abattoir for each instance are available in the Excel file *InstancesEng.xlsx*. Figure A.1 show the file with some of the values generated randomly. In particular we observe the values generated for each node with the mean represented in the head of the column (m9,...,m189) and each sheet with a different standard deviation (sd5,...,sd85). The first column correspond to the base case. Then, we can deduce that there are 50 $\times$ 186 random values generated according to 50 different normal distributions.

	A	B	C	D	E	F	G	H	I	J	K
1	B	m9	m29	m49	m69	m89	m109	m129	m149	m169	m189
2	0	0	0	0	0	0	0	0	0	0	0
3	5	11	27	57	67	83	113	128	152	171	188
4	50	4	37	47	69	93	108	135	151	173	188
5	125	16	24	54	60	95	101	137	146	168	186
6	16	0	26	46	66	86	104	136	151	169	192
7	150	7	25	52	69	87	111	136	154	165	191
8	160	18	25	43	74	90	111	120	143	175	187
9	34	0	19	44	66	85	106	136	142	171	192
10	117	7	27	54	69	89	111	136	144	166	180
11	120	12	31	53	74	80	112	131	156	171	189
12	5	17	28	40	71	98	107	128	142	174	188
13	34	7	31	46	64	83	113	127	143	174	186
14	80	4	37	51	73	89	115	128	152	165	184
15	155	13	33	48	65	89	104	137	154	166	192
16	5	16	29	49	66	96	112	130	142	168	186
17	76	10	32	49	74	83	108	136	150	174	189
18	160	11	24	47	72	82	109	127	144	173	189
19	120	29	24	60	70	91	110	133	152	169	196
20	32	4	36	44	67	96	113	129	153	174	185
21	120	10	24	53	68	89	105	135	154	161	190
22	170	17	37	45	62	96	105	128	148	170	185
23	20	5	28	44	67	89	112	118	141	171	193
24	100	11	38	50	69	96	110	131	153	180	189

sd5 | sd25 | sd45 | sd65 | sd85

Figure A.1: Farm capacity generated randomly for each farm.

This way we have the observation of different distributions of pigs among the farms present in the system. Then, we can calculate the number of pigs available to collect one week as it is shown in Figure A.2.

	Base	m9	m29	m49	m69	m89	m109	m129	m149	m169	m189
sd5	17239	1823	5407	9324	12892	16577	20403	24126	27755	31486	35257
sd25	17239	2641	6160	9524	13240	16551	20538	23939	27786	31619	34043
sd45	17239	3856	7030	10001	13244	17841	20180	24293	27761	30123	32157
sd65	17239	6141	7424	9677	14202	18124	20970	23243	26477	30292	31336
sd85	17239	7855	9454	12172	12906	16257	19616	22222	24367	27936	30643

Figure A.2: Total number of pigs available in the system by instance.

The output of each instance was recorded in an Excel file. Figure A.3a displays an example with the main outputs recorded. An additional file had the extended information of each solution. In particular, the information regarding each route in the solution as shown in Figure A.3b.

Mean	sd	Trucks	Sol #	Routes	Cost	Reward	Unitary	Intensity	Duration
94	63	200	3709	92	5549881	17119	324,1942	186,0761	16,75689
94	63	300	3744	89	5455457	25519	213,7802	286,7303	17,02702
94	63	400	3779	87	5576559	33919	164,4081	389,8736	17,80511
109	25	200	6607	123	6028804	20538	293,5439	166,9756	13,61519
109	25	300	6642	79	5337166	20538	259,8679	259,9747	18,76641
109	25	400	6677	56	5128448	20538	249,7053	366,75	25,43873
109	45	200	6712	106	5679287	18980	299,2248	179,0566	14,88283
109	45	300	6749	76	5455326	20180	270,3333	265,5263	19,93906
109	45	400	6784	56	5171831	20180	256,285	360,3571	25,65392
109	5	200	6496	181	6814680	20403	334,0038	112,7238	10,45838
109	5	300	6531	93	5483919	20403	268,78	219,3871	16,37969
109	5	400	6566	64	5342938	20403	261,8702	318,7969	23,18984
109	65	200	6819	103	5798424	17170	337,7067	166,699	15,63761
109	65	300	6854	80	5506473	20970	262,5881	262,125	19,1197
109	65	400	6889	59	5131794	20970	244,7207	355,4237	24,16099
109	85	200	6924	78	5457685	14616	373,4048	187,3846	19,4362
109	85	300	6959	72	5371796	19616	273,8477	272,4444	20,72452
109	85	400	7000	54	5125980	19616	261,3163	363,2593	26,36821
129	25	200	7166	164	6509997	23939	271,9411	145,9695	11,02642
129	25	300	7201	92	5489511	23939	229,3125	260,2065	16,57461
129	25	400	7236	65	5270646	23939	220,1698	368,2923	22,52413
129	45	200	7278	135	6163234	22493	274,0068	166,6148	12,68155
129	45	300	7313	88	5623214	24293	231,4747	276,0568	17,75004

(a) Results summary for each solution.

Base400.dat

```
Solucio #: 3779; Rutes: 87; Cost: 5576559.0; Reward: 33919.0
        Route reward: 400.0; Cost: 37414.0; Route: 0; 2; 92; 0
        Route reward: 400.0; Cost: 32072.0; Route: 0; 5; 113; 0
        Route reward: 400.0; Cost: 39993.0; Route: 0; 12; 154; 0
        Route reward: 400.0; Cost: 26881.0; Route: 0; 15; 68; 0
        Route reward: 400.0; Cost: 40515.0; Route: 0; 16; 63; 0
        Route reward: 400.0; Cost: 23619.0; Route: 0; 18; 112; 0
        Route reward: 400.0; Cost: 18528.0; Route: 0; 20; 146; 0
        Route reward: 400.0; Cost: 139257.0; Route: 0; 21; 182; 0
        Route reward: 400.0; Cost: 45123.0; Route: 0; 22; 64; 0
        Route reward: 400.0; Cost: 28040.0; Route: 0; 25; 55; 0
        Route reward: 400.0; Cost: 20525.0; Route: 0; 30; 56; 0
        Route reward: 400.0; Cost: 28311.0; Route: 0; 36; 174; 0
        Route reward: 400.0; Cost: 67434.0; Route: 0; 37; 35; 0
        Route reward: 400.0; Cost: 31997.0; Route: 0; 38; 142; 0
        Route reward: 400.0; Cost: 23158.0; Route: 0; 41; 109; 0
        Route reward: 400.0; Cost: 22316.0; Route: 0; 43; 23; 0
        Route reward: 400.0; Cost: 46337.0; Route: 0; 50; 29; 0
        Route reward: 400.0; Cost: 52098.0; Route: 0; 59; 60; 0
        Route reward: 400.0; Cost: 22868.0; Route: 0; 72; 54; 0
        Route reward: 400.0; Cost: 167493.0; Route: 0; 89; 158; 0
        Route reward: 400.0; Cost: 37690.0; Route: 0; 96; 62; 0
        Route reward: 400.0; Cost: 52299.0; Route: 0; 122; 105; 0
        Route reward: 400.0; Cost: 47526.0; Route: 0; 127; 169; 0
        Route reward: 400.0; Cost: 43711.0; Route: 0; 130; 119; 0
        Route reward: 400.0; Cost: 23671.0; Route: 0; 133; 145; 0
        Route reward: 400.0; Cost: 193378.0; Route: 0; 156; 44; 101; 0
        Route reward: 400.0; Cost: 171630.0; Route: 0; 164; 10; 39; 0
        Route reward: 399.0; Cost: 22777.0; Route: 0; 1; 31; 0
        Route reward: 399.0; Cost: 137032.0; Route: 0; 14; 149; 0
        Route reward: 399.0; Cost: 27348.0; Route: 0; 17; 48; 0
        Route reward: 399.0; Cost: 39995.0; Route: 0; 84; 181; 0
        Route reward: 399.0; Cost: 18991.0; Route: 0; 97; 144; 0
        Route reward: 399.0; Cost: 23528.0; Route: 0; 108; 90; 0
        Route reward: 399.0; Cost: 61009.0; Route: 0; 175; 136; 153; 0
        Route reward: 398.0; Cost: 33648.0; Route: 0; 26; 76; 0
        Route reward: 398.0; Cost: 23320.0; Route: 0; 27; 102; 0
        Route reward: 398.0; Cost: 55455.0; Route: 0; 33; 34; 0
```

(b) Routes recorded for each solution.

Figure A.3: Results of the computational experiments with (A.3a) more or (A.3b) less detail.

Correlations among variables in a multivariate plot is presented in Figure A.4. This figure allow us to get a general information about the different correlations among output variables and the positive or negative sense. For instance, it is clear the strong correlation between *Cost* and *Routes*.

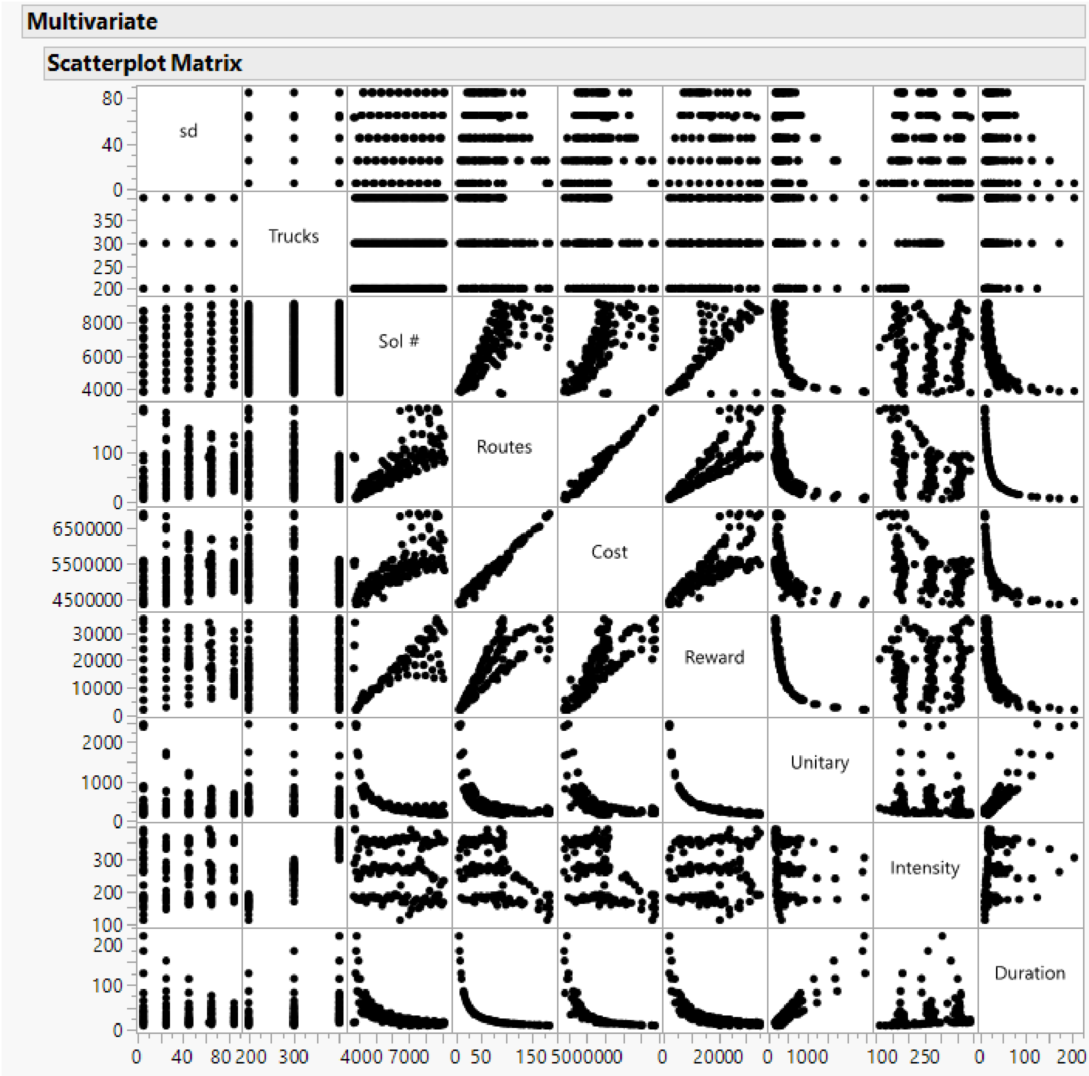

Figure A.4: Multivariate correlations between variables.

B | Appendix B: files and resources

All the files used in this Thesis are available on the cloud of Google Drive. The link to get temporary access is: *https://drive.google.com/drive/folders/1−Bf6GQRGYkjjC5LuLHyHjdr*
sharing

Files include the Python code, the Excel files with the parameters and instances, text and json files containing the results and other auxiliary material. In addition, some bibliography used to compose the Thesis is also available at the same link. The link will be active till mid-September. After that, the material will be available upon request to the author.

List of Figures

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Related work

Related to this TFM, a presentation was given at the International Federation of Operational Research Societies (IFORS) Conference held in Santiago de Chile in 11th July 2023. The work presented was a preliminary approximation of the Thesis presented here.

Plà, L.M., Juan, A., Panadero, J. 2023 The inventory routing problem of marketing fattened pigs to the abattoir.