COMBINING THE INTERNET OF THINGS WITH SIMULATION-BASED OPTIMIZATION TO ENHANCE LOGISTICS IN AN AGRI-FOOD SUPPLY CHAIN

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ABSTRACT

This paper discusses how the Internet of Things and simulation-based optimization methods can be effectively combined to enhance refilling strategies in an animal feed supply chain. Motivated by a real-life case study, the paper analyses a multi-period inventory routing problem with stochastic demands. After describing the problem and reviewing the related literature, a simulation-based optimization approach is introduced and tested via a series of computational experiments. Our approach combines biased-randomization techniques with a simheuristic framework to make use of data provided by smart sensor devices located at the top of each farm silo. From the analysis of results, some managerial insights are also derived and a new business model is proposed.

1 INTRODUCTION

In feed manufacturing, distribution, and replenishment planning, efficient decision making can reduce feed stocks, minimize wrong or excessive orders, cut down urgent orders, and limit the impact of uncertainty in the supply chain. Furthermore, it allows feed manufacturers to secure their supply of raw materials and operate with lower capacities, service times, and production buffers. For these reasons, as increased feed prices have had the largest impact on animal growers' and feed manufacturers' margins, there is a clear ongoing need for the investment in how animal feed distribution to farms is managed. In such complex decision-making environments, it is common to employ simulation and optimization methods. On the one hand, optimization methods are employed to find optimal or near-optimal configurations for distribution plans. Often, the associated optimization models are based on some simplifying assumptions. These assumptions contribute to making the problem easier to solve, but at the cost of ignoring the real-life uncertainty that characterizes these systems. On the other hand, simulation approaches are also used to model and compare the performance of different system configurations in a variety of scenarios. With the increasing advances in computing hardware and software, simulation has become a 'first-resource' method for analyzing complex systems under uncertainty (Lucas et al. 2015). However, simulation approaches alone are not able to generate optimal or near-optimal distribution plans in scenarios with many possible configurations. Hence, it makes sense to consider hybrid simulation-optimization methods that combine the best of both worlds.

Real-life optimization problems are often *NP-hard* and large-scale in nature, which makes traditional exact methods an inefficient solution approach – at least in reasonable computing times (Juan et al. 2009). Thus, the use of heuristic algorithms to obtain high-quality solutions in low computing times is required
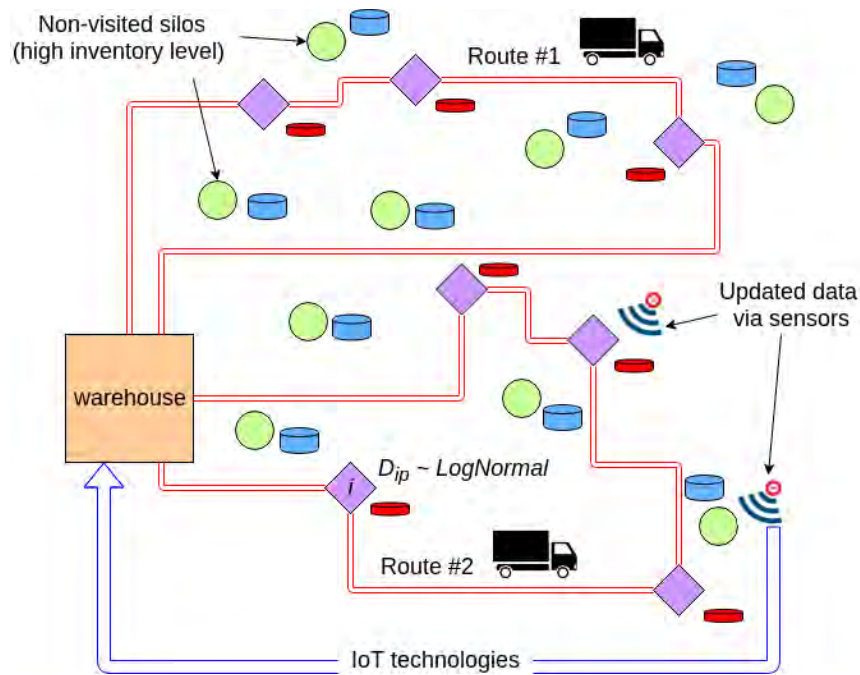
Figure 1: A schema of the stochastic and sensorized inventory routing problem.

(Faulin et al. 2008). Simheuristic algorithms integrate simulation within a metaheuristic optimization framework to deal with large-scale and *NP-hard* stochastic optimization problems. Hybridization of simulation techniques with metaheuristics allows us to consider stochastic variables in the objective function of the optimization problem, as well as probabilistic constraints in its mathematical formulation (Fu 2002). As pointed out by Fu et al. (2005), the combination of simulation with metaheuristics is a promising approach for solving stochastic optimization problems that are frequently encountered by decision makers in many industrial sectors. In this sense simheuristics extend metaheuristics by integrating simulation within them. In Grasas et al. (2016), the authors discuss how to extend an iterated local search framework into a simheuristic. Likewise, in Ferone et al. (2019) the authors explain how to extend a GRASP framework into a simheuristic. A simheuristic algorithm is typically composed of two different components: an optimization component – which searches for promising solutions – and a simulation component – which assesses the promising solutions in a stochastic environment and provides feedback to the optimization component.

As illustrated in Figure 1, in this work we model the feed distribution and replenishment planning as a multi-period inventory routing problem (IRP) and then propose a simheuristic algorithm for solving it (Juan et al. 2018). Our approach allows for establishing good refill policies for each customer-period combination, i.e., those individual refill policies that minimize the total expected cost over the periods. This cost is the aggregation of both expected inventory and routing costs. Our method allows us to consider the inventory changes between periods generated by the random demands. Notice that the specific values of these random demands in one period might have a significant effect on the quantities to be delivered in the next period. Therefore, they might also impact the associated routing plans. In addition, we also modify the former strategy by using online data on the real demands as it is available. This allows us to update the refill strategy as new data become available, thus generating a reactive algorithm. A range of computational experiments are carried out in order to evaluate the potential benefits of our simulation-optimization approach for the discovery of insights that can then influence decisions and drive change on animal feed distribution.

The remainder of this paper is structured as follows: Recent publications on the stochastic IRP are reviewed in Section 2; more details on the case study and the problem considered in this paper are provided in Section 3; Section 4 outlines the proposed simheuristic approach; in Section 5 some computational

experiments are described and their results analyzed; finally, Section 6 highlights the main contributions of this work.

2   PREVIOUS WORK ON THE STOCHASTIC IRP

Despite its relevance for real-life applications, the stochastic IRP has not received as much attention as their deterministic counterpart. Some of the contributions address the problem of random demands by using incremental approaches to improve the cost (Jaillet et al. 2002). Markov decision processes are commonly used to deal with this stochastic behaviour as done by Kleywegt et al. (2004), or Hvattum and Løkketangen (2008). The latter work models random demands by using discrete distributions and assuming an initial scenario tree, which is solved with a greedy randomized adaptive search procedure (GRASP). Dynamic programming models are also commonly used for tackling problems with stochastic demands (Bertazzi et al. 2013), as well as mixed-integer linear programming formulations (Solyal et al. 2012). Most works consider order-up-to level inventory strategies, where the retail center is filled to its target capacity each time it is visited. Also, they assume that demands follow a uniform probability distribution. However, our approach explores a range of refilling strategies that minimize the total costs based on distinct probability distributions for modelling customers' demands. Huang and Lin (2010) adapted an ant colony optimization metaheuristic to deal with uncertainty in the multi-product IRP. Li et al. (2016), with special attention to produce robust solutions, generate IRP policies under stochastic customer demands and replenishment lead times. Roldn et al. (2016) contribute to the dynamic and stochastic IRP problem. Yu et al. (2012) introduce service level constraints to his stochastic IRP solution. Environmental concerns are considered in Soysal et al. (2015), jointly with demand uncertainty, estimating CO_2 emissions while planning the routes. A fuzzy probabilistic approach is proposed by Niakan and Rahimi (2015), dealing with CO_2 emission minimization for an IRP related to medical distribution. Rahim et al. (2014) reduce the multi-period IRP problem with stochastic stationary demand to a deterministic equivalent approximation model. Chen and Lin (2009) introduce risk aversion concepts into their stochastic IRP solution. Juan et al. (2014) propose a hybrid simulation-optimization approach, combining a multi-start metaheuristic with Monte Carlo simulation, to address the single-period IRP with stochastic demands. An enhanced algorithm for the single-period IRP with stochastic demands is discussed in Gruler et al. (2018a). Finally, Gruler et al. (2018b) provide a new heuristic-based algorithm for the multi-period IRP with stochastic demands. The present work extends the latter by incorporating a reactive concept which makes use of online data as it becomes available for the decision maker.

3   THE STOCHASTIC MULTI-PERIOD IRP

This section provides some additional details on the real-life case study that motivates this work, as well as a formal description of the associated optimization problem.

3.1 The Real-Life Case Study

Being motivated by a real-life case study, our IRP assumes that delivered feed quantities for a given set of farms must be determined each day within a planning horizon. Farms store feed within silos of known capacity. The planning horizon is usually defined as 2 or 3 days. Feed is transported by a fleet of homogeneous single-compartment vehicles of limited size. Every farm has a stochastic demand for feed, while the intensity of consumption varies between different farms. Each silo is equipped with a sensor that communicates the stock level to a central database every hour. As such every silo has a known consumption of feed, whilst at the same time the intensity of consumption varies between the silos belonging to a farm. The total inventory costs are assumed to be dependent on the sum of the average stock levels in each day of the planning horizon, whereas transport costs depend on a vehicle's travel distance. The replenishment policy refers to the different approaches that each farm can select for controlling how and when their silos are refilled.

3.1.1 Remote monitoring of inventories

Livestock farmers in the EU mainly use three methods to calculate the feed stock in their silos: *(i)* climbing and looking inside; the vast majority of existing farm silos ($> 95\%$) do not have any coupled technology to measure their filling level, so every week farmers must physically climb to the silo's tops to estimate their stock level; this method, besides being tough, risky, and time-consuming, provides inaccurate measures; *(ii)* weighing the silos with load cells or strain gauges; these systems have a good accuracy and little maintenance requirements; however, they are very expensive (2,500 – 3,000EUR per silo) and difficult to install (cutting the silo's legs and connecting to the farm's electricity supply) thus limiting their massive deployment on farms; and *(iii)* measuring the fill level with level sensors (ultrasound, radar, laser, cable, etc.); although they are easier to install and more affordable, the surface of the silo's content is extremely uneven since feed comes in the form of pellets or powder; this causes errors of up to 15-20% of the total silo's volume (Carson 2000), which is unacceptable for this use case. The proposed level sensor solution aims to: *(i)* optimize/reduce acquisition hardware needs/costs; *(ii)* simplify its installation; *(iii)* provide a smart computing layer for an IoT-based architecture which integrates image sensor data, and *(iv)* provide a model which is able to accurately estimate stock volumes in adverse data acquisition conditions.
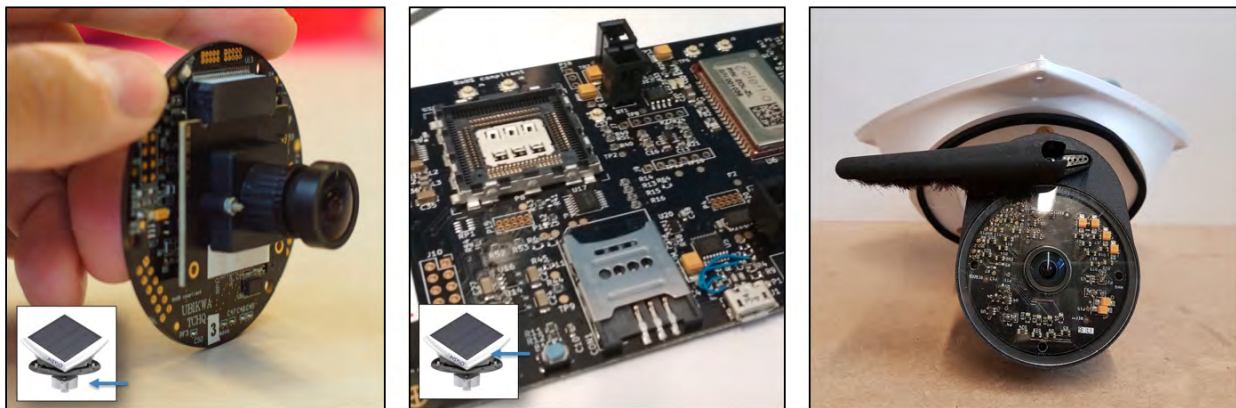

Figure 2: From left to right, the 3d sensor, communication electronics, and self-cleaning system.

The key enabling technology consists of a camera with a commodity RGB-D sensor that capture color images along with dense pixel-wise depth information in real-time. With an embedded computer vision algorithm, it provides much more accuracy (error $< 3\%$) than traditional 1-point level sensors (error $= 15 - 20\%$). Instead of using a single point measure like lasers or ultrasound, a matrix of 320x240 readings over the feeds surface is taken. This device provides 24/7 reliability and is 100% independent of the farms power grid thanks to a set of rechargeable batteries and an integrated solar panel. Each device is equipped with M2M modules (GPRS/3G) that allows for using the cellular network when available, along with radio-frequency modules (6LowPan) that enable direct communication between devices (Figure 2).

This sensor has been designed to provide an easy installation and avoid maintenance tasks, so it is easy to operate and does not require any cleaning or maintenance after installation, since batteries must not be substituted and it has a self-cleaning system against dust and condensation (Figure 3).

The Information Management System (IMS) has been solved by using the FIWARE IoT stack, as an Open Initiative for this project (Krčo et al. 2014). The FIWARE architecture has been demonstrated as a powerful and reliable solution for the implementation of IoT-based applications. One of the key aspects of this architecture is the adoption of the OMA NGSI Context Management standard to manage and exchange context information about context entities (Ramparany et al. 2014).

As it is shown in Figure 4, the sensor measures the distance from camera (placed in the top of the silo) to the feed surface. Using this disparity map (320x240 distances), the sensor: *(i)* performs a 3D

Figure 3: Three steps of the sensor installation procedure with (a,b) drilling, (c,d) adapter ring placement, and (e) sensor fixation.
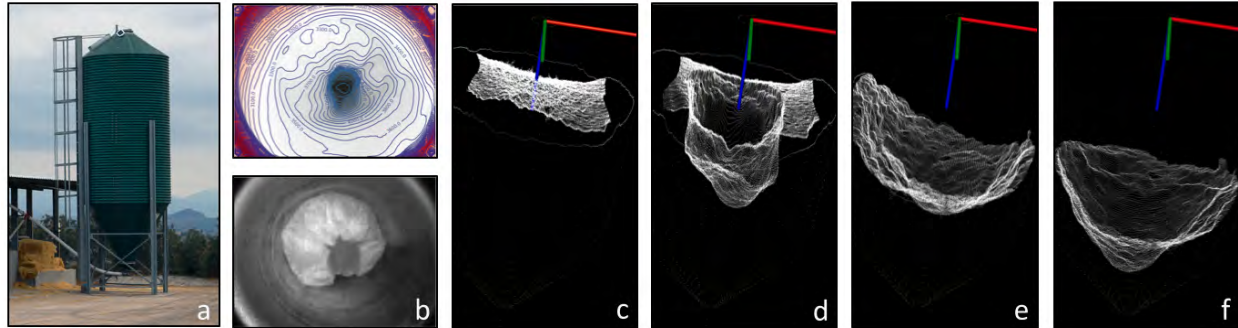

Figure 4: Illustrative example of feed bin (a), single shoot measured disparity maps (b top) and IR channel (b bottom) and feed surface reconstruction in distinct time steps (c-f) while feed is consumed.

reconstruction of the feed surface; *(ii)* intersects this surface with the user-defined bin geometry; and *(iii)* estimates the remaining volume. In order to validate the sensor's accuracy, some reference silos have been upgraded with weighting cells. Hence, for those silos the real weight is collected along with the new sensor based estimation.

3.2 A Formal Description

Let $V = \{0, 1, \ldots, n\}$ denote a finite set of locations consisting of the depot (node 0) and n demand nodes (DN). The set of demand nodes will be denoted by $V^* = V \setminus \{0\}$. With the goal of minimizing the total expected cost, the stochastic and periodic IRP combines inventory and routing decisions over a finite planning horizon P with $|P| \geq 1$ periods. The customers' aggregated demand at each demand node $i \in V^*$ during a period $p \in P$ is a random variable, D_{ip}, which follows a known probability distribution. It is assumed that these random demands are independent across demand nodes and throughout periods – and they do not need to be identically distributed. Likewise, it will be assumed that the customers' aggregated demand at each demand node and period will always be satisfied. Thus, should a stock-out occur during a period p at demand node i, an additional shipment from the depot to i will be placed by the end of period p to cover the non-satisfied demand. The cost of this extra shipment will be accounted as stock-out cost.

Regarding inventory management, the decision variables refer to the quantity of product, $q_{ip} \geq 0$, which must be served at demand node i at the beginning of period p ($\forall i \in V^*$, $\forall p \in P$). If $l_i^+ > 0$ denotes the maximum storage capacity of center i, and L_{ip}^0 denotes the initial stock available at demand node i during period p ($0 \leq L_{ip}^0 \leq l_i^+$), then $q_{ip} \leq l_i^+ - L_{ip}^0$, the initial stock level for the first period ($p = 1$) is given as an input, i.e., $L_{i1}^0 = l_{i1}^0$, $\forall i \in V^*$. By the end of each period, once the customers' aggregated demands are known, the initial stock level for the next period can be computed as $L_{i(p+1)}^0 = max\{L_{ip}^0 + q_{ip} - D_{ip}, 0\}$. Likewise, at this point the holding- or stock-out inventory cost at demand node i and period p can be obtained by using Equation (1), where λ represents the unitary cost of holding surplus inventory by the end of a period, and c_{0i} represents the cost of a direct shipment from the depot to demand node i (this

value is doubled in order to account for the return trip to the depot):

$$f(q_{ip}, D_{ip}) = \begin{cases} \lambda(L_{ip}^0 + q_{ip} - D_{ip}) & \text{if surplus} \quad L_{ip}^0 + q_{ip} \geq D_{ip} \\ 2 \cdot c_{0i} & \text{if stock-out} \quad L_{ip}^0 + q_{ip} < D_{ip} \end{cases} \tag{1}$$

Accordingly, the total inventory cost can be expressed as shown in Equation (2):

$$I(q_{ip}, D_{ip} \mid i \in V, p \in P) = \sum_{p \in P} \sum_{i \in V^*} f(q_{ip}, D_{ip}). \tag{2}$$

For each period $p \in P$, a vehicle routing problem needs to be solved for those demand nodes i with $q_{ip} > 0$. As discussed in Faulin and Juan (2008), the vehicle routing problem can be defined on a complete and undirected graph $G = (V, E)$, where V includes the depot from which n demand points are served with a set K of homogeneous vehicles, and E is the set of edges connecting each pair of facilities in V. Each of the vehicles in the fleet has a maximum loading capacity given by $h > 0$. There is a traveling cost, $c_{ij} = c_{ji} > 0$ associated with moving from a facility i to a different facility j ($\forall i, j \in V, i \neq j$). The routing cost at period p depends on the binary decision variables x_{ij}^{pk}, which define whether or not the edge connecting facilities i and j is traversed at period p by a vehicle $k \in K$. Notice that this might depend upon the specific values of the customers' demands D_{ip}, i.e., $x_{ij}^{pk} = x_{ij}^{pk}(D_{ip})$. Accordingly, the total routing cost across all periods can be expressed as shown in Equation 3:

$$R(x_{ij}^{pk}, D_{ip} \mid i, j \in V, p \in P, k \in K) = \sum_{p \in P} \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} c_{ij} x_{ij}^{pk}. \tag{3}$$

The objective of simultaneously setting the q_{ip} and x_{ij}^{pk} decision variables in order to minimize the expected overall inventory and routing cost is formulated in Equation 4:

$$E[I(q_{ip}, D_{ip}) + R(x_{ij}^{pk}, D_{ip})] = \sum_{p \in P} \left(\sum_{i \in V^*} E[f(q_{ip}, D_{ip})] + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} c_{ij} E[x_{ij}^{pk}] \right). \tag{4}$$

The solution to the problem described will have the form of a matrix with $|V^*|$ rows and $|P|$ columns, where element (i, p) in this matrix will represent the refill policy associated with DN i at period p ($\forall i \in V^*$, $\forall p \in P$).

4 OUR SIMULATION-BASED OPTIMIZATION APPROACH

The main stages of our simulation-based optimization algorithm are described next and summarized in Figure 5:

- Firstly, a constructive heuristic is employed to generate an initial solution. This initial solution will be a 'homogeneous' matrix containing the same value in all its cells, i.e., it will propose a unique refill policy that will be systematically applied to all the demand nodes across the different periods. This strategy will generate a particular expected inventory cost (sum of all expected inventory costs for each center-period combination) as well as a specific expected routing cost (sum of all expected routing costs for each period). Notice that both the inventory cost associated with each demand node at the end of period p as well as the routing cost at period $p+1$ will depend on the precise values of the random demands of each center at period p (since these values will determine the inventory levels associated with each demand node at the end of period p).
- Secondly, biased randomization techniques are applied within the constructive heuristic, which is then integrated inside a multi-start stage. Biased randomization techniques allow for introducing a 'slight' random effect in the otherwise greedy behavior of the base heuristic inventory-management plans (Grasas et al. 2017). These techniques have been successfully applied to several optimization problems (Martin et al. 2016; Dominguez et al. 2016).
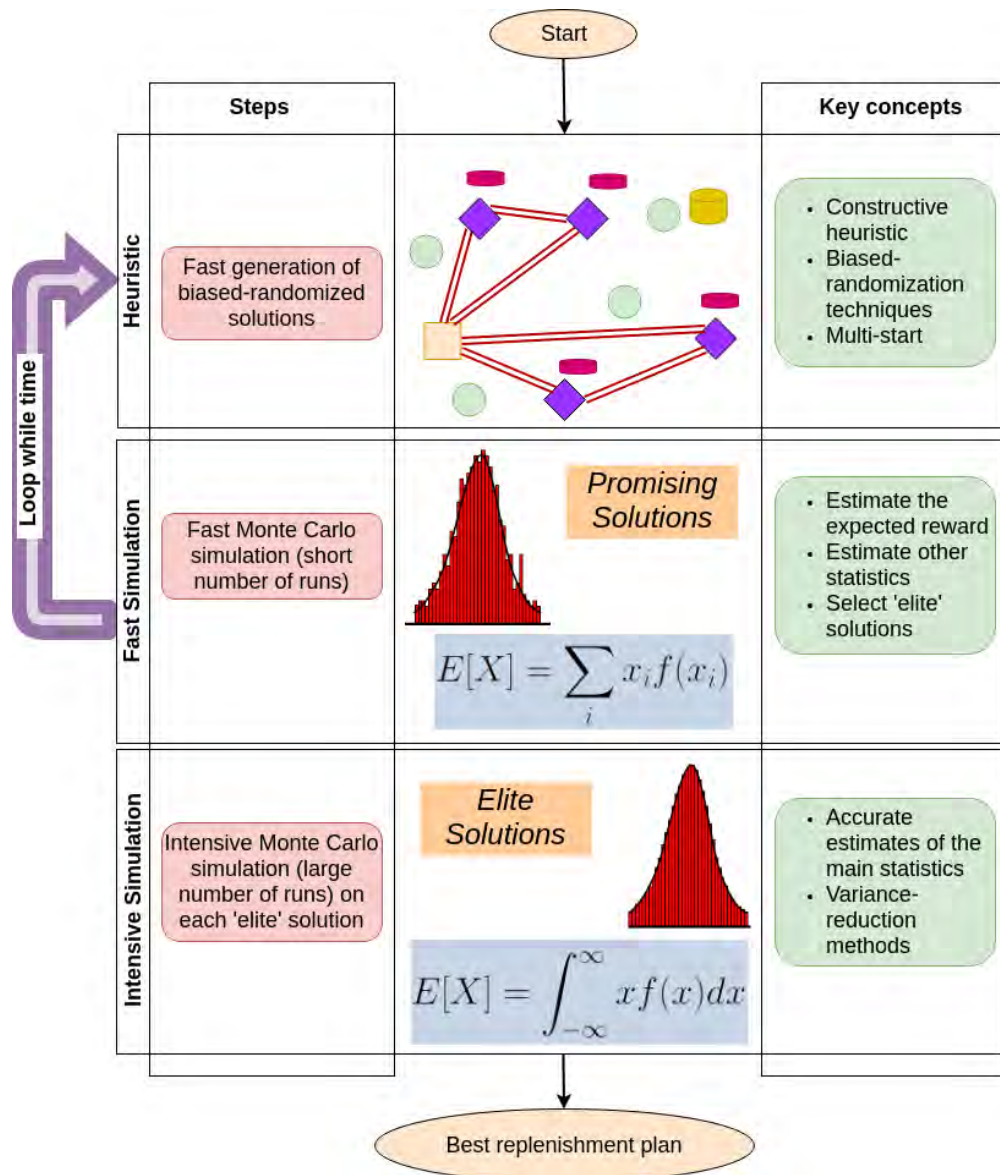
Figure 5: Visual overview of our simheuristic approach.

- At this point, the multi-start optimization framework is combined with Monte Carlo simulation in order to iteratively enhance the initial solution. Monte Carlo simulation is employed here to generate realizations of the random demands and then obtain an estimate of both expected inventory and routing costs.
- Finally, a refinement stage using a higher number of simulation runs is applied to the most 'promising' or 'elite' solutions obtained in the previous stage in order to obtain a more accurate estimation of the expected cost and select the final solution matrix.

5 COMPUTATIONAL EXPERIMENTS

A set of computational experiments has been performed to illustrate our approach for solving the multi-period IRP with stochastic demands. The set of 27 vehicle routing instances instances proposed by Augerat

et al. (1995) and adapted for the IRP by Juan et al. (2014) are used as a testbed. These instances contain between 27 and 80 nodes, a single central depot, and a fleet of 5 to 10 homogeneous vehicles. The algorithm is implemented as a Java application and executed with the following parameter specifications:

- Inventory holding cost: $\lambda = 0.25$.
- Algorithm stopping criteria: 100 seconds $\times$ number of considered periods.
- # Simulation runs: 30.

The aggregated customer demands are assumed to follow a *Log-Normal* probability distribution with the same average values as the ones proposed in the original instances. However, five demand factors ($\gamma \in \{0.05, 0.1, 0.3, 0.5, 1\}$) have been considered to decrease this demand. As a result of applying γ factors to DN's average expected demand, we consider five distinct demand scenarios with averages of $2.5\%, 5\%, 15\%, 25\%$, and 50% of the DN's maximum capacity, where 50% corresponds to the scenario used by Juan et al. (2014). Considering each of these demand scenarios, three different variance levels are defined: low (factor $= 0.25$), medium (factor $= 0.50$), and large (factor $= 0.75$). Also, four different planning horizons are analyzed: 3, 5, 7, and 10 time periods.
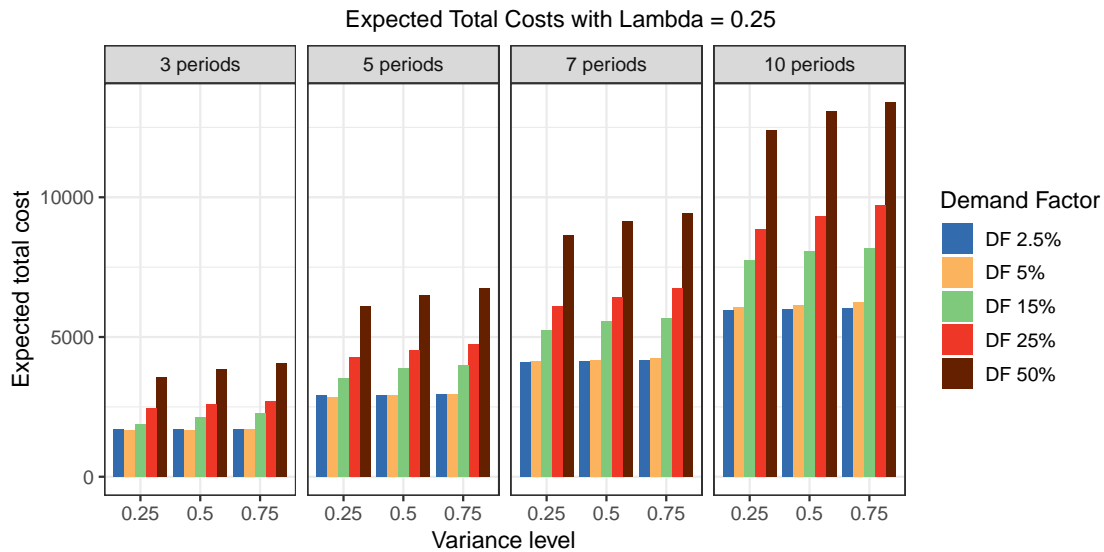

Figure 6: Expected total costs for different variance levels and planning horizons, $\lambda = 0.25$.

The average total costs over all instances for each variance level, demand factor, and planning horizon of the holistic multi-period planning framework can be seen in Figure 6. Accumulated routing and inventory costs are depicted for the baseline solution – in which the same replenishment policy is applied at all demand nodes in each individual period – and solutions found by the proposed simheuristic method for the multi-period IRP. Notice that increasing costs can be observed with higher levels of demand uncertainty, which can be due to higher inventory (holding or stock-out) costs.

We have included results obtained with $\lambda = 0.25$ in Table 1 using a demand factor $\gamma = 0.05$ (average expected demand with $5\%, 15\%$, and 25% of the DN's maximum capacity, respectively). The results obtained for these scenarios with our method show that the implementation of optimization techniques focused on feed distribution positively affect logistics costs – both the ones related to replenishment policies as well as the delivery routes – reducing the associated supply chain costs while ensuring distribution in scenarios with reduced demand. As shown in Table 1, evaluated instances show similar behaviour, with reducing total costs as expected demand is reduced.

Table 1: Total cost by demand scenario (*variance level = 0.50, inventory holding cost* $\lambda = 0.25$).

	Periods: 3				Periods: 5				Periods: 10			
	DF50 (1)	Gap DF25	Gap DF15	Gap DF5	DF50 (1)	Gap DF25	Gap DF15	Gap DF5	DF50 (1)	Gap DF25	Gap DF15	Gap DF5
A-n32-k5	3108	-30.6	-40.8	-53.2	5280	-29.5	-36.9	-53.4	7325	-27.9	-35.1	-51.0
A-n33-k5	2600	-26.6	-39.3	-48.4	4436	-24.1	-34.4	-46.8	6145	-23.5	-29.4	-44.7
A-n39-k6	3120	-26.6	-37.8	-48.5	5401	-24.5	-31.9	-48.5	7560	-22.6	-30.2	-46.5
A-n45-k6	3493	-28.4	-36.4	-49.3	5933	-26.6	-35.9	-47.8	8503	-27.2	-36.5	-47.9
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
A-n61-k9	3747	-29.7	-43.7	-52.7	6560	-29.1	-38.5	-52.7	9284	-27.9	-34.5	-52.4
B-n50-k7	2986	-26.8	-33.4	-46.9	5085	-27.4	-33.6	-45.4	7179	-26.4	-34.0	-44.7
B-n68-k9	4877	-43.7	-53.2	-70.2	8283	-39.5	-52.3	-69.7	11562	-37.9	-51.1	-69.0
B-n78-k10	4787	-39.4	-49.3	-63.9	8203	-35.6	-48.2	-63.6	11396	-35.0	-47.3	-62.4
Average	3839	-31.7	-42.7	-54.3	6509	-29.7	-39.1	-53.2	9149	-28.7	-37.7	-52.2

6 CONCLUSIONS

This paper presents a simheuristic algorithm to solve the multi-period inventory routing problem with stochastic demands. The integration of Monte Carlo simulation techniques into the metaheuristic framework allows for considering different probability distributions to model the randomly aggregated demands over various planning horizons. Our approach relies on the selection of the best-possible refill policies for each demand node and period configuration. Thus, a constructive procedure uses simulation to generate an initial solution, which is iteratively improved. That way the complexity of the problem – including the interdependencies between consecutive periods due to the random demands – is effectively addressed by the proposed simulation-based optimization method. We have observed from real scenarios – for instance, animal fattening farms – where an average silo stores 6–8t, that daily consumption is commonly within the range of 120kg–800kg of feed, which explains these low demand rates. Having this scenario in mind, it is commonly observed that the inter-period average demand varies between 2% and 10% of the maximum capacity. Likewise, being perishable, it is considered that animal feed has a relatively high holding cost as a product distributed to the farms. Hence, scenarios with higher holding cost ($\lambda \geq 0.3$) and reduced expected demand ($\gamma \leq 15\%$) show the closest behaviour to our real-world case study. Smarter feed supply chains for livestock can be achieved by focusing on the following three areas: *(i)* feed demand forecasting to predict the feed demand and the future stock levels in the farms, based on current stock levels and production data shared by farmers; *(ii)* automatic restocking processes that generate the restocking orders based on the selected restocking policies; farmers will receive alerts and will be able to confirm the restocking orders with a simple click; and *(iii)* feed suppliers can take full responsibility of the feed stocks (VMI) and process the restocking orders automatically, taking into account current stock levels, feed demand forecast, production data, and cost functions defined by the supplier.

From a more general perspective, this work proposes a closed-loop system where periodical measures gathered from the field are included in our heuristics to dynamically optimise inventories and routes. Thus, this updated information from real inventories will reduce the uncertainty with which heuristics deal with. Several future research lines are possible. On the one hand, our algorithm could be adapted to solve other multi-period routing problems. On the other hand, the IRP variant considered in this paper could be extended (e.g., by including a heterogeneous vehicle fleet, multiple depots, etc.) in order to address even more realistic IRP settings. Also, simulation techniques could be applied to consider further stochastic input variables, e.g., travel times or even distribution costs. A new scenario arises when we lower the served feed amounts, in which the number of visitable demand nodes is increased. Resiliency of the underlying supply

chain network could also be compared against the classical feed distribution schema based on maximum capacities.

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