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SIMHEURISTICS: AN INTRODUCTORY TUTORIAL

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ABSTRACT

Both manufacturing and service industries are subject to uncertainty. Probability techniques and simulation methods allow us to model and analyze complex systems in which stochastic uncertainty is present. When the goal is to optimize the performance of these stochastic systems, simulation by itself is not enough and it needs to be hybridized with optimization methods. Since many real-life optimization problems in the aforementioned industries are NP-hard and large scale, metaheuristic optimization algorithms are required. The simheuristics concept refers to the hybridization of simulation methods and metaheuristic algorithms. This paper provides an introductory tutorial to the concept of simheuristics, showing how it has been successfully employed in solving stochastic optimization problems in many application fields, from production logistics and transportation to telecommunication and insurance. Current research trends in the area of simheuristics, such as their combination with fuzzy logic techniques and machine learning methods, are also discussed.

1 INTRODUCTION

Since uncertainty is present in most real-life systems, simulation methods are frequently employed to analyze complex systems in industries such as manufacturing and production logistics, transportation, health care, finance, smart cities, and telecommunication. Usually, the uncertainty in these systems is modeled via probability distributions, either theoretical or empirical ones. Then, a logical model of the system is built, and computer simulation is utilized to get insight on the system performance under different scenarios, each of which represent a possible system configuration. As pointed out by some authors, the advances in computer power and simulation software have transformed simulation into a 'first-resource' method for analyzing complex systems under uncertainty (Lucas et al. 2015).

Still, simulation by itself is not an optimization tool, since it does not contain a mechanism to efficiently explore the vast solution spaces that arise in combinatorial optimization problems. Therefore, if our goal is to solve stochastic optimization problems, we need to complement simulation with an optimization engine. Examples of such problems are: finding the best distribution plan in a vehicle routing problem (VRP) with random demands, finding the best scheduling plan in a flow shop problem with random processing times, or finding the best configuration of assets in a portfolio optimization problem with random returns, among many others. Most of these optimization problems happen to be NP-hard in nature, which limits the capabilities of exact solvers to the case of small- and medium-sized instances. Unfortunately, real-life instances are frequently of large size, which calls for the use of metaheuristic algorithms. These algorithms cannot guarantee optimality, but they can offer high-quality solutions in reasonable computing times even for large-sized instances, which makes them a 'first-resource' approach when solving real-life optimization problems.

It seems obvious then that a well-designed hybridization of simulation methods (in any of its different variants) and metaheuristics algorithms might result in an effective and efficient strategy to solve many real-life optimization problems under uncertainty conditions. Therefore, many authors have proposed the combination of simulation and optimization methods to handle such problems (Figueira and Almada-Lobo 2014; Amaran et al. 2016). Simulation-optimization approaches include different optimization methods, such as mathematical programming, metaheuristics, or machine learning. In addition, statistical and machine learning methods can be used to build surrogate models based on the simulation output (Xu et al. 2015). These models represent analytical relations among the system variables, and can be employed to obtain estimates of the simulation output in shorter computing times. Figueira and Almada-Lobo (2014) classified simulation-optimization approaches based on the simulation usage. Thus, according to these authors, simulation could be utilized to: *(i)* evaluate an objective function, or a constraint, in a stochastic optimization problem; *(ii)* generate solutions for an optimization problem; or *(iii)* enhance an analytical model. Excellent reviews and tutorials on simulation-optimization approaches can be found in Fu et al. (2005), Chau et al. (2014), and Jian and Henderson (2015).

During the last decades, hybridizing metaheuristics with simulation is becoming popular as a standard procedure to deal with stochastic optimization problems (Bianchi et al. 2009; Juan et al. 2021). Glover et al. (1996), Glover et al. (1999), and April et al. (2003) are among the first authors discussing the marriage of both methodologies. These authors developed the OptQuest software (www.opttek.com/products/optquest), a proprietary simulation-optimization engine that is integrated into several commercial simulation packages. OptQuest can also be combined with other optimization solvers or heuristics, for example, Ugray et al. (2007) combined gradient-based local nonlinear programming solvers with OptQuest to find global optima for pure and mixed integer nonlinear problems. Still, being a proprietary software, it performs like a 'black-box' approach, with internal mechanisms that are not fully explained. Following similar principles, simheuristic algorithms also combine metaheuristics with simulation. Hence, they can be classified as a subset of simulation-optimization methods and, in particular, of simulation-based optimization procedures (April et al. 2003). As it will be discussed later in more detail, simheuristic and algorithms are 'white-box' approaches specifically designed to solve large-scale and NP-hard combinatorial optimization problems with stochastic elements, which can be present in the form of stochastic objective functions or probabilistic constraints (Fu 2002). For a more detailed review of simheuristics and simulation-optimization concepts and applications, readers can refer to Juan et al. (2018) and Chica et al. (2020). Since the seminal paper by Glover et al. (1996), simheuristics have been applied in a myriad of industrial applications (Gruler et al. 2017b). Actually, the first time the term 'simheuristics' appeared in a journal article was in Juan et al. (2014). Since then, the use of this terminology has been raising consistently, from 9 articles in 2014 up to 145 in 2021 (Figure 1).

This tutorial aims at introducing the main ideas behind the concept of simheuristics, as well as some of its most recent applications and some popular research lines that we are currently exploring. The tutorial also provides examples of actual Python code that shows implementation details of a simple simheuristics. The remaining of the paper is structured as follows: Section 2 describes the types of stochastic optimization problems that simheuristics are designed to solve. Section 3 explains how a simheuristics actually works,

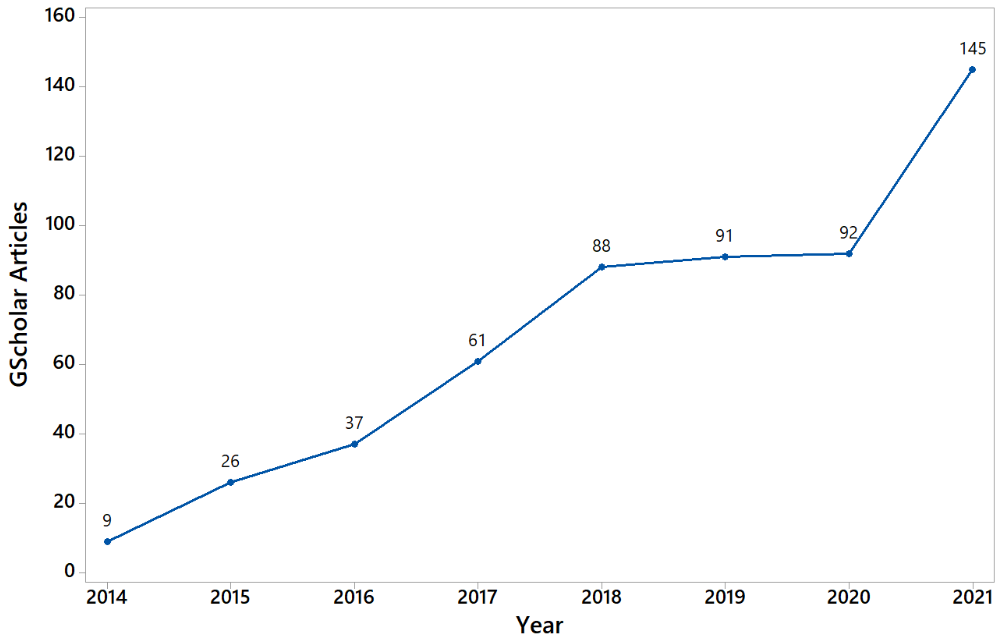

Figure 1: Google Scholar articles using the term 'simheuristics' for the period 2014 to 2021.

including the logical interactions among its different components and stages. Section 4 provides a hands-on case study in which the base code of a basic simheuristics is analyzed. Section 5 analyzes the most recent articles employing simheuristics to solve stochastic optimization in different application fields. Section 6 provides a numerical and visual summary of the results achieved using simheuristics in a variety of problems. Finally, Section 7 highlights the main contributions of this tutorial, and also points out some future research lines in the area of simheuristics.

2 WHAT OPTIMIZATION PROBLEMS DO SIMHEURISTICS SOLVE?

By analyzing the scientific literature on optimization, one can notice that many combinatorial optimization problems related to industries such as transportation, logistics, manufacturing, health care, telecommunication, or finance are still being formulated using static and deterministic models. These models do not consider the uncertainty and dynamism that characterize most real-life systems, e.g.: random travel and processing times, random customers' demands, random investment returns, etc. One of the main reasons for this oversimplification is the additional challenges that the introduction of stochastic components arise when using exact solvers: a large number of these problems are NP-hard and, thus, even their deterministic versions are time-consuming and arduous to solve, specially for realistic instances, which tend to be large-sized ones. All in all, a considerable number of works prioritize obtaining an optimal solution to a deterministic version of the problem than a near-optimal solution to a stochastic version of the same. Of course, this means generating an optimal solution to the wrong model, i.e., one that does not truly represent the real-life system. As a result, when the optimal solution to the deterministic model is employed in the real-life system under uncertainty conditions, it frequently becomes a sub-optimal solution –this can be easily observed by executing such an optimal solution into a simulation model of the system.

Simheuristic algorithms aim at addressing the aforementioned mismatch by considering stochastic optimization models that better represent the working conditions of the real-life system, and then obtaining near-optimal solutions to these models. Typically, the stochastic optimization models considered have the following shape:

$$\text{optimize } f(s) = \Phi(s, X) \tag{1}$$

subject to:

$$Pr\Big(g_i(s,X) \leq l_i(X)\Big) \leq t_i \qquad \forall i \in I \tag{2}$$

$$Pr\Big(g_j(s,X) > l_j(X)\Big) \leq t_j \qquad \forall j \in J \tag{3}$$

$$g_k(s) \leq t_k \qquad \forall k \in K \tag{4}$$

$$s \in S \tag{5}$$

where:

- The term s in Equation (1) represents a possible solution (configuration of decision variables) to the optimization problem, being S the space of solutions (Equation (5)).
- The term $\Phi(s,X)$ in Equation (1) represents a stochastic function that has to be optimized (either minimized or maximized), with X being a vector of random variables, each of them following a given probability distribution with known mean. Notice that $\Phi(s,X)$ does not necessarily has to be an expected value. Instead, it can be any stochastic measure, including a combination of statistics.
- Equations (2) and (3) represent probabilistic constraints related to the problem, e.g.: the probability that the number of serviced customers in solution s, $g_i(s,X)$, falls below a certain lower bound $l_i(X)$ is inferior to a user-defined threshold t_i, or the probability that the time delay in solution s, $g_j(s,X)$, exceeds a certain upper bound $l_j(X)$ is limited by a user-defined threshold t_j.
- Finally, Equation 4 represents typical deterministic constraints in combinatorial optimization problems.

Although not discussed in this paper, there are other promising approaches for solving stochastic optimization problems such as chance constrained programming (Li et al. 2008), robust optimization (Gabrel et al. 2014), and stochastic programming (Birge and Louveaux 2011). As discussed in Onggo et al. (2019), when solving stochastic optimization problems one should always remember that any given solution $s \in S$ has a probabilistic behavior. Accordingly, statistics other than the expected value associated with s should be taken into account. For instance, in a stochastic VRP, even when our main goal might be minimizing the expected cost of a routing plan, other statistics such as the variance of the value associated with s, or its reliability value (i.e., the probability that the route can be completed without failures) should also be analyzed. Similarly, when minimizing the risk associated with a solution to the stochastic portfolio optimization problem, one might be interested in gathering information about the probabilistic behavior of the random returns associated with a given solution s (portfolio configuration). In other words, optimization under uncertainty conditions is a richer environment than optimization under deterministic (perfect information) conditions. Hence, the expert should not limit herself to provide one solution s that minimizes or maximizes an expected value, but she should provide information about the statistical and probabilistic behavior of several alternative solutions. This is precisely where simheuristic algorithms can make a difference, since they are not just effective in searching huge solution spaces thanks to their metaheuristic component, but they can also enrich the analysis of the solutions with the statistical and probabilistic patterns provided by their simulation component.

3 HOW DO SIMHEURISTICS ACTUALLY WORK?

Given a deterministic optimization problem, it seems reasonable to assume that its optimal and near-optimal solutions are likely to show a ‘good performance’ when moderated levels of uncertainty are introduced into the problem formulation. Thus, for example, we can assume that low-makespan permutations of jobs in a deterministic flow shop scheduling problem will also offer low values of expected makespan if a relatively small variance is introduced into some of the job processing times. Similarly, in a deterministic portfolio optimization problem, consider low-risk configurations of assets that guarantee a desired level of investment return, r_0. Then, in a scenario with random returns of moderated variance, the aforementioned asset configurations are likely to represent low-risk portfolios with expected returns that, with a certain probability, will exceed the value $r_0 - \varepsilon$ for some $\varepsilon > 0$. A series of key observations need to be made at this point: *(i)* given a solution s to a deterministic optimization problem, it has two associated values, the deterministic one, $det(s)$ (i.e., the value of $f(s)$ in the deterministic version of the problem), and the stochastic one, $stoch(s)$ (i.e., the value of $f(s)$ in the stochastic version, which can be estimated via simulation); *(ii)* under moderated levels of uncertainty, we are assuming the existence of a strong and positive correlation between $det(s)$ and $stoch(s)$ (i.e., good deterministic solutions are also likely to be good stochastic solutions, and vice versa); *(iii)* the aforementioned correlation will not be perfect, i.e., one solution s_1 could perform better than another solution s_2 with respect to the deterministic version of a problem (e.g., $det(s_1) < det(s_2)$ in a minimization problem) and, at the same time, s_2 could show a better stochastic performance than s_1 (e.g., $stoch(s_2) < stoch(s_1)$ in a minimization problem); *(iv)* as the level of uncertainty in the system grows (i.e., as we increase the variance of the random variables), we should expect the correlation between deterministic and stochastic values to diminish; and *(v)* for large levels of uncertainty (i.e., random variables with extremely large variances), it might make more sense to search for robust or reliable solutions instead of optimizing an expected value, since the latter might lead to solutions with a high variability.

Another key observation that deserves special attention is the potential use of the best deterministic solution found by the metaheuristic, $det(s^*)$. In optimization problems, it is usually the case that the optimal value of the objective function gets worse as we increase the uncertainty level. This is especially true when asymmetric effects apply on the objective function, e.g.: an improvement of the objective function due to a favorable realization of the random variables is significantly surpassed by a diminishment of the objective function due to a disadvantageous realization of the random variables. Hence, if s^* represents an optimal / near-optimal solution to the deterministic version of the problem, and s^{**} represents an optimal / near-optimal solution to the stochastic version of the problem, then one should expect the following inequalities to hold: *(i)* in a minimization problem, $det(s^*) \leq stoch(s^{**}) \leq stoch(s^*)$; and *(ii)* in a maximization problem, $stoch(s^*) \leq stoch(s^{**}) \leq det(s^*)$. In other words, the two values associated with an optimal / near-optimal solution to the deterministic version of the problem, where perfect information is available, define lower and upper bounds to the optimal value of the stochastic version of the problem, where uncertainty is present.

Figure 2 shows the internal logic behind our simheuristic concept: given a stochastic optimization problem, its deterministic counterpart is considered. This can be done, for instance, by replacing all random variables by their expected values, which leads to a simplified version of the stochastic problem in which uncertainty is not considered. Then, a metaheuristic component is employed to efficiently search inside the solution space, thus generating increasingly better solutions to the deterministic version of the problem.

Each time the metaheuristic generates a ‘promising’ solution (i.e., one that is likely to perform well in a scenario under uncertainty), this solution is sent to the simulation component in order to assess its performance in the stochastic environment. The simulation component returns not only estimates of statistics –such as the mean, variance, and percentiles associated with the proposed solution–, but also probabilistic information that can be useful in risk or reliability analyses, as well as information about the status of different system variables. Since simulation is a time consuming procedure, it is usually a good idea to employ a short number of simulation runs every time a new promising solution is evaluated at this stage –otherwise, the simulation computing time might jeopardize the time required by the metaheuristic to converge to near-optimal solutions. Some useful recommendations to speed up these computations can be found in Rabe et al. (2020). The feedback provided by the simulation can then be processed by a machine learning component and then used to: *(i)* update and adjust the metaheuristic parameters to better

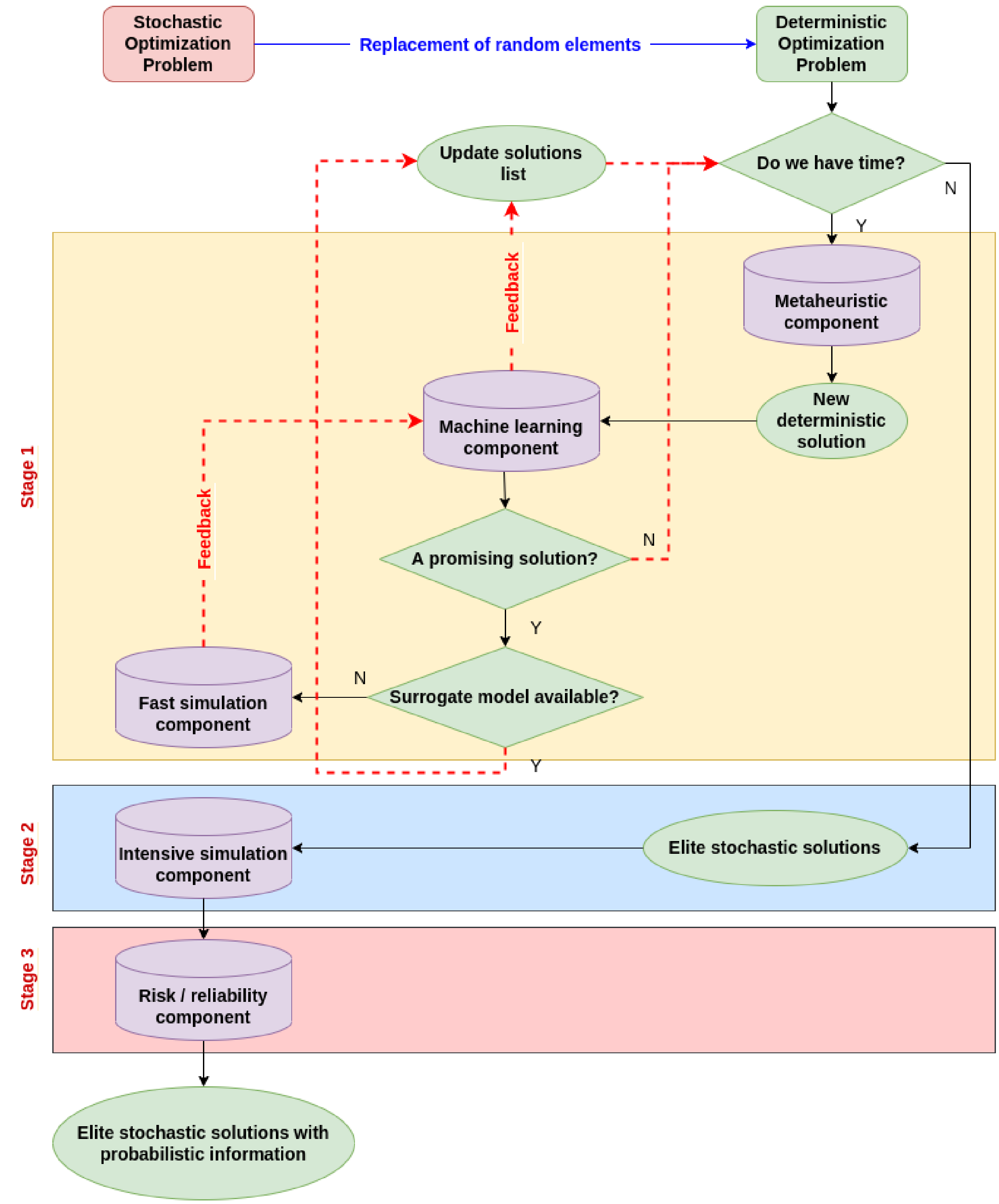

Figure 2: The logic behind simheuristics.

explore the solution space and increase the chances of obtaining new solutions with a high stochastic performance; *(ii)* build a classification or prediction model able to identify new promising solutions with a high accuracy –thus avoiding wasting time in simulating solutions that will offer sub-optimal values under uncertainty conditions–; and *(iii)* develop a surrogate model that, at least partially, substitutes time-consuming simulations when estimating the value of the stochastic objective function or probabilistic constraints associated with a new promising solution proposed by the metaheuristic component.

As a result of this first stage, a reduced list of 'elite' solutions is obtained. According to our initial estimates, each of these solutions show a high performance in a scenario under uncertainty. Now, in order to increase the accuracy of our estimates, a more intensive simulation is executed on each of the elite solutions. Of course, variance reduction techniques (Fippel and Brainlab 2021), such as the use of common random numbers, can be employed here to speed up these simulations, which can also be run in parallel processors. As a final stage, the simulation outcomes might be employed to perform a risk or reliability analysis on each of these elite solutions. This analysis might enrich the decision-making process with detailed probabilistic information describing the stochastic behavior of each elite solution.

4 A CASE STUDY ILLUSTRATED WITH PYTHON CODE

In the following case study, we present a simple toy example using the simheuristics approach for solving an open vehicle routing problem (OVRP). The OVRP is an NP-hard combinatorial optimization problem consisting in designing a set of open routes to pick up the demands from the nodes. It differs from the classical vehicle routing problem (VRP) in that origin and destination depots have different locations, i.e., routes are not 'closed'. In OVRP, a fleet of k vehicles leave their origin depot and collect demand from several nodes before finishing the route at the destination depot. All the nodes in the problem should be visited by one of the vehicles. In this case study, the capacity of the vehicle is not considered. We assume that the set of vehicles is homogeneous and the fleet size is constant. The vehicles are considered electric; therefore, they have a maximum time to complete their route before the battery runs out. If the maximum allowed time is exceeded, a mandatory stop is needed to recharge the battery, and this extra time of recharge is added to the route. The travel time is considered stochastic as the real-life travel time in the city can be influenced by external factors such as traffic conditions, weather conditions, road disruptions caused by car accidents, etc. Finally, the objective of the problem is to define routes with minimum costs in terms of traveling time.

The simheuristic algorithm employed in this case study integrates Monte Carlo simulation (MCS) with a biased-randomized multi-start framework. The main part of the code is summarized in Figure 3 and described next in more detail. Firstly, an initial deterministic solution, *bestSol*, is generated by using a savings-based heuristic. Then, a fast simulation with a reduced number of runs (*shortSim*) is performed to get a first estimate of the average stochastic time required by the solution. This initial solution is stored as our best solution so far and included in a list of 'elite' stochastic solutions (*bestStochSolList*). Afterwards, a multi-start process is repeated until the stopping time, *MaxTime*, is met. In each iteration, a new deterministic solution, *newSol*, is computed by using a biased-randomized version of the savings heuristic (Belloso et al. 2019). If the new solution has lower deterministic travel time than the current best solution, a new fast simulation is applied to estimate the stochastic time associated with the new solution. If this stochastic time is also lower than the current best solution, then the *bestSol* is replaced by *newSol* and the *bestStochSolList* is updated. Once the iterations are completed, the stochastic time associated with each elite solution in *bestStochSolList* is estimated again using intensive simulation with *longSim* runs, which allows us to increase the accuracy of the estimation.

The MCS used in this case study employs a log-normal distribution, with mean 0 and variance 1, to sample the stochastic delay of the edges (Figure 4). This stochastic delay is added to the original deterministic travel time of the edges to form the stochastic travel time. If this new stochastic travel time exceeds the *maxRouteCosts*, the extra recharging time (*penalization*) is added to the route. This process is replicated *nsim* times to get the accumulated stochastic travel time of the route (*stochasticAcumRouteSim*). Once this process is completed, the average stochastic time of the route is computed. Finally, the stochastic travel time of the solution is obtained by summing up the average stochastic time of every route in the solution.

```python
from ElapsedTime import ElapsedTime
from RandS import RandS, Savings
from Simulation import Simulation
import numpy as np

def MultiStart(nodes, shortSim, longSim, Test):
    # nodes: list of nodes to be visited and depots
    # shortSim: number of replications for fast simulation
    # longSim: number of replications for intensive simulation
    # Test: Test class containing MaxTime, Seed, maxRouteCosts
    # Test.MaxTime: stop time for the multi start framework
    # Test.seed: seed for the random generador
    # Test.maxRouteCosts: maximum allowed route time
    # Test.penalization: extra recharge time for routes exceeding maxRouteCosts

    # Generates the initial solution
    bestSol = Savings(nodes)  # savings based heuristic
    rng = np.random.default_rng(int(Test.seed)) # seed for the random generador
    Simulation(bestSol, shortSim, rng, Test)  # fast simulation with shortSim runs
    start = ElapsedTime.systemTime()
    elapsed = 0.0
    bestStochSolList = [bestSol]  # create a list of elite solutions

    # Enter the multi start framework
    while elapsed < Test.MaxTime:
        newSol = RandS(nodes) # biased randomized savings
        if newSol.deterministicTime <= bestSol.deterministicTime:
            Simulation(newSol, shortSim, rng, Test)
            if newSol.stochasticTime < bestSol.stochasticTime:
                bestSol = newSol
                bestStochSolList.append(newSol)
                if len(bestStochSolList) > 10: # keep only 10 solutions in the list
                    bestStochSolList.pop(0)
        # Calculate elapsed time
        elapsed = ElapsedTime.calcElapsed(start, ElapsedTime.systemTime())

    # Select the best solution from the list
    for sol in bestStochSolList:
        Simulation(sol, longSim, rng, Test) # intensive simulation with longSim runs
        if sol.stochasticTime < bestSol.stochasticTime:
            bestSol = sol

    return bestSol #return best solution in terms of stochastic time
```

Figure 3: Python implementation of a multi-start algorithm.

5 RECENT PAPERS ON SIMHEURISTICS

This section provides a non-exhaustive review of some of the most recent applications of simheuristics in different areas. In particular, we have focused in articles published in 2018 or later, and in which simheuristics have been applied to transportation & logistics, production & manufacturing, finance & insurance, and telecommunication. For works before the aforementioned date, the reader is referred to Juan et al. (2018).

```python
def Simulation(sol, nsim, rng, test): # sol: deterministic sol, nsim: number of runs
    stochasticSolution = 0
    for route in sol.routes:
        stochasticAcumRouteSim = 0 # accumulative stochastic travel time of the route
        for i in range(nsim):
            stochasticRoute = 0 # stochastic travel time of the route
            for e in route.edges: # edge.costs: travel time of the edges
                # Adding the stochastic delay to the deterministic travel time
                stochasticRoute += e.costs  + rng.lognormal(mean=0, sigma=1)
            if stochasticRoute > test.maxRouteCosts:
                stochasticRoute += test.penalization # add the recharge time
            stochasticAcumRouteSim += stochasticRoute

        # Calculate average stochastic travel time of the route
        stochasticSolution += stochasticAcumRouteSim/nsim

    # Assign the stochastic traveling time to sol
    sol.stochasticTime = stochasticSolution
```

Figure 4: Python implementation of MCS.

5.1 Transportation & Logistics

Beyond any doubt, the transportation and logistics field is the initial arena where the simheuristic methodology was developed and where managed to reach its first successes (Juan et al. 2018). Some of the initial ideas of the simheuristic implementation were taken from the Vehicle Routing Problems (Juan et al. 2011), or Facility Location Schemes (de Armas et al. 2017). The clearest contribution to transport problems resolution, where simheuristics is presented as the natural procedure to solve mobility problems in sustainable transportation has been written by Rabe and Goldsman (2019). These two authors presented the conjoint use of optimization-simulation techniques using metaheuristics as the core of many procedures inside decision support systems which solve many logistic and transport problems. More recently, Latorre-Biel et al. (2021) presented an intertwined protocol of simheuristics with Petri nets to solve the Stochastic Vehicle Routing Problem with correlated demands. Furthermore, a good description of the current logistic and transport problems analyzed and solved by means of simheuristic techniques is presented by Juan et al. (2019) which can be helpful for the researcher searching for new application areas in transportation.

Focusing our attention on sustainable mobility, we can highlight the important contribution of simheuristic techniques to the quick resolution of routing problems of electric vehicles with limited driving ranges and stochastic travel times (Reyes-Rubiano et al. 2019). Likewise, Yazdani et al. (2020) expanded the use of simheuristics to solve evacuation problems in extreme weather disasters, where the authors presented an interesting application of optimization-simulation techniques to people evacuation policies. Hence, the range of optimization areas for simheuristics was expanded to waste collections services in smart cities, according to work led by Yazdani et al. (2021), who made a painstaking implementation of a simheuristic procedure to solve a set of waste collection problems in Sydney (Australia). Recently, Peng et al. (2022) analyzed the management of multimodal transportation networks in order to deliver long-haul merchandise considering uncertainty in transportation cost and time. All these applications can be completed with agile optimization of Unmanned Aerial Vehicles routes for different logistic purposes (Panadero et al. 2020), which reveals a fruitful future for simheuristics in urban and interurban mobility.

5.2 Production & Manufacturing

Simulation-optimization methods, including simheuristics, have their applications in production and manufacturing. They could support planning, such as material resource planning and job scheduling. For example, Seiringer et al. (2022) combined simulated annealing and simulation to support material planning in terms of specifying lot size, safety stock, as well as lead time. Researchers have studied different versions of the flow shop problem using simheuristics. Gonzalez-Neira et al. (2017) minimized the makespan and risk associated with found solutions in a stochastic version of a distributed assembly permutation flow shop problem using simheuristics. In other studies, Hatami et al. (2018) used simheuristics to solve the parallel flow shop scheduling problem, and Caldeira and Gnanavelbabu (2021) integrated Monte Carlo simulation in a gradient-free optimization algorithm to solve a stochastic and flexible job shop scheduling problem.

Inventory management is an important activity in production and manufacturing management. Thus, simheuristics and simulation-optimization approaches were utilized by researchers to solve problems related to inventory management. For example, Güller et al. (2015) studied a multi-echelon production-inventory system and utilized a simulation-optimization approach. They optimized inventory control parameters considering stochastic conditions and conflicting objectives. The objective functions minimized expected costs per year and maximized the service level. Likewise, Kamhuber et al. (2019) utilized a simheuristic approach to smoothen the production in food manufacturing and optimize inventory levels.

Other researchers have utilized simheuristics to reduce costs or energy consumption in manufacturing processes. Heinzl and Kastner (2020) reduced energy costs and other production costs in an industrial bakery. They utilized a general variable neighborhood search metaheuristic and simulation to optimize the costs. In addition to energy consumption, Amelian et al. (2022) considered system reliability and tardiness in the optimization of a failure-prone job shop scheduling problem. They utilized simulation to handle stochastic variables in the problem and a genetic algorithm to solve it. Alves and Ravetti (2020) integrated simheuristics with a robustness approach to increase customer satisfaction and avoid machine failure. Hence, they used a simheuristic approach in the productive maintenance of a manufacturing system.

Simheuristics have also been utilized in the management of manufacturing systems. For example, Niño-Pérez et al. (2018) utilized a simheuristic approach to fine-tune a manufacturing line consisting of 50 workstations. In addition, simheuristics have been integrated into decision support systems. As a result, these systems optimize the considered manufacturing and production process. For example, Santos et al. (2020) evaluated a production rate in an ore crushing circuit at a Brazilian mining plant using simulation. They proposed a simheuristic-based decision support system to maximize the production rate.

5.3 Finance & Insurance

Financial investment plays a crucial role in a country's economic development. It is the main source of employment creation and the main factor of economic growth. One of the most studied problems in financial investment is the portfolio optimization problem (POP). The goal of the POP is to minimize risk for an expected portfolio return by allocating weights to considered assets. The traditional unconstrained POP can be solved efficiently by standard algorithms. However, with the increased portfolio size and additional real-world constraints –like cardinality constraints, buy-in thresholds, roundlots, etc.–, this problem becomes NP-Hard. In this case, the use of metaheuristic algorithms is needed to solve large-sized and highly constrained POPs.

Financial markets are characterized by their high volatility and uncertain environments, in which real-life financial transactions occur. Metaheuristics cannot fully account for random components of these problems, hence rendering them unrealistic. Some researchers integrated simulation with optimization approaches to lower this gap between theory and practice. For example, Panadero et al. (2020) integrated a variable neighborhood search metaheuristic with Monte Carlo simulation for solving large-sized stochastic instances of the project portfolio selection problem (PPSP). This problem aims to maximize the net present value of a project portfolio under uncertainty and rich conditions. Kizys et al. (2022) proposed a variable neighborhood search metaheuristic with Monte Carlo simulation to solve the POP with stochastic returns and noisy covariances, which were modeled as random variables. Computational results on benchmark instances show that the proposed approach outperforms classical metaheuristic approaches employed in the deterministic POP. Nieto et al. (2022) integrated Monte Carlo simulation at different stages of a genetic algorithm for solving a multi-period POP with assets and liabilities. A series of computational experiments, including advanced evolutionary strategies, illustrated the advantages of using the proposed algorithm in financial optimization problems under uncertainty.

6 CROSS-PROBLEM ANALYSIS OF COMPUTATIONAL RESULTS

This section summarizes results previously published in different papers about simheuristics, which have been selected to illustrate its effectiveness. Specifically, we focus on the use of simheuristics to solve different well-known NP-hard and large-sized optimization problems under uncertainty. Table 1 describes the selected problems and the references used to collect the computational results.

Table 1: Selected problems.

Problem	Acronym	Reference
Stochastic Porfolio Optimization Problem	SPOP-1	Panadero et al. (2020)
Stochastic Porfolio Optimization Problem	SPOP-2	Kizys et al. (2022)
Multi-Period Stochastic Portfolio Optimization Problem	MP-SPOP	Nieto et al. (2022)
Stochastic Permutation Flow Shop Scheduling Problem	SPFSP	Gonzalez-Neira et al. (2017)
Stochastic Distributed Permutation Flow Shop Problem	SDPFSP	Hatami et al. (2018)
Stochastic Team Orienteering Problem	STOP	Panadero et al. (2020)
Stochastic Arc Routing Problem	SARP	Gonzalez-Martin et al. (2018)
Two-dimensional VRP with Stochastic Travel Times	2L-VRPST	Guimarans et al. (2018)
Electric VRP with Stochastic Travel Times	EVRPST	Reyes-Rubiano et al. (2019)

Figure 5 depicts an overview of the results, with the vertical axis representing the gap obtained for the stochastic solutions with respect to the value of an optimal / near-optimal deterministic solution $det(s^*)$. As discussed before, this value can be frequently seen as a lower bound for the optimal value in a stochastic minimization problem (or as an upper bound in a stochastic maximization problem). When this deterministic solution, s^*, is evaluated in a stochastic scenario, we obtain its stochastic value, $stoch(s^*)$, which can be seen as an upper bound for the optimal value in a stochastic minimization problem (or as a lower bound in a stochastic maximization problem). Therefore, denoting by s^{**} the best stochastic solution produced by a simheuristic, its associated value, $stoch(s^{**})$, should be located between the corresponding lower and upper bounds.

In effect, this is what can be observed in all the analyzed problems: $stoch(s^{**})$ (blue and circular points) is always located between the $det(s^*)$ value (represented by the horizontal line with gap 0%) and the $stoch(s^*)$ (red and squared points). The results show that the solutions provided by the simheuristics outperform the best deterministic solutions when the latter are employed in a stochastic scenario. Of course, the gaps between $det(s^*)$ and $stoch(s^*)$ will be highly influenced by the specific problem being analyzed, as well as by the level of uncertainty considered. The numerical results confirm that that optimal or near-optimal solutions for the deterministic version of the problem are likely to be sub-optimal solutions when they are used in real-life scenarios under uncertainty. In other words, using the optimal / near-optimal solution to a deterministic version of a problem, s^*, in real-life scenarios could lead to inefficient decisions, causing unnecessary costs to enterprises. These costs will tend to grow as the level of uncertainty increases. Hence the importance of integrating simulation methods with metaheuristics when dealing with stochastic optimization problems.

7 CONCLUSIONS

This paper has introduced the concept of simheuristics, which hybridizes simulation, in any of its forms, with metaheuristic algorithms with the purpose of solving stochastic optimization problems. The tutorial also explains why this optimization approach can be considered as a ‘first resource’ methodology when solving NP-hard and large-scale combinatorial optimization problems under uncertainty scenarios, as those that frequently appear in real-life applications in transportation, logistics, manufacturing, finance, insurance,

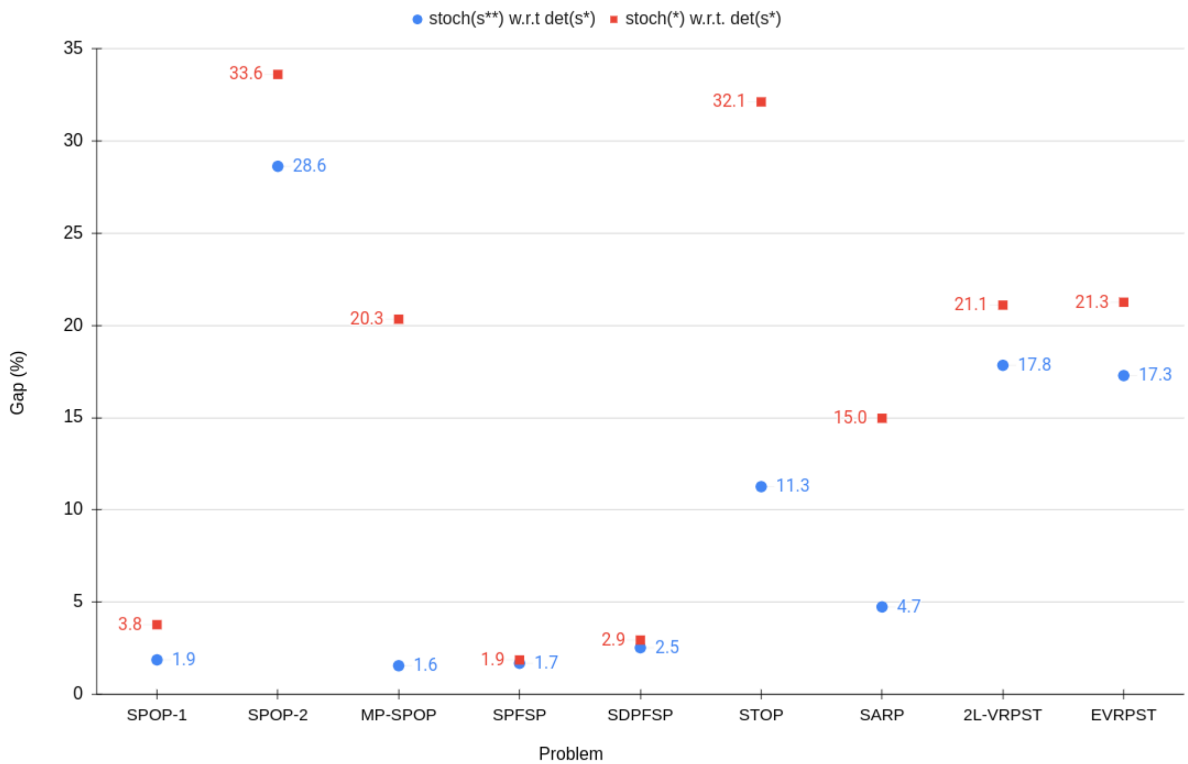

Figure 5: Gaps between $stoch(s^{**})$ and $stoch(s^{*})$ with respect to $det(s^{*})$ (baseline 0% gap).

or telecommunications. The way in which the different simheuristic components interact has been also discussed, putting a special emphasis in the different stages that can contribute to make the approach more efficient from a computational perspective.

In the second part of the tutorial, we have analyzed a hands-on case study in which a simple simheuristic is developed using Python code. Likewise, recent applications of simheuristics to different fields are commented, and a numerical summary of previous works illustrating the capabilities of simheuristics to provide high-quality solutions to different stochastic problems is also provided.

There are several lines of research that are still open in the field of simheuristics, among them we can highlight the following ones: *(i)* the introduction of more advanced machine learning methods –specially those based on supervised learning and reinforcement learning– that enrich the feedback provided by the simulation component to the metaheuristic one, allow for an accurate classification of promising solutions, and expedite the buildup of surrogate models that can speed up computations even further –notice that, by integrating a machine learning component into a simheuristic, we are already exploring the integration of the former with learnheuristics (Arnau et al. 2018), which is a broad research topic in itself–; *(ii)* the efficient and easy integration of metaheuristic code developed with modern programming languages with commercial simulators like FlexSim, which currently supports a friendly interaction with Python; and *(iii)* the extension of simheuristics into fuzzy simheuristics, which allow us to consider non-stochastic uncertainty as well as the stochastic one, as illustrated in Tordecilla et al. (2021).

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