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A Heuristic-Based Simulation for an Education Process to Learn about Optimization Applications in Logistics and Transportation

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Abstract: In the context of the DigiLab4U international project, this paper describes a simulation-based serious game that can be used as a virtual teaching lab in higher education courses, especially in Industrial and Systems Engineering, Data Science, Management Science and Operations Research, as well as Computer Science. The learning activity focuses on understanding distribution logistics problems related to transportation optimization using different techniques. These optimization challenges include the vehicle routing problem, the arc routing problem, and the team orienteering problem. As a result of the learning process in the virtual lab, it is expected that students acquire competencies and skills related to logistics and transportation challenges as well as problem-solving. These competencies and skills can be precious for students’ future careers, since they increase students’ analytical skills, capacity to understand heuristic-based algorithms, teamwork and interdisciplinary communication skills, programming skills, and statistical abilities. A preliminary version of this training activity has already been used in MSc and PhD courses held at universities in Spain, Italy, Ireland, and Portugal.

Keywords: serious game; distribution logistics; higher education; vehicle routing problem; arc routing problem; team orienteering problem

MSC: 90-05; 90B06; 90B15; 97P50; 97U99



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1. Introduction

Digitalization is changing business and industrial environments worldwide. It is expected that the economic impact of the Internet of Things (IoT) will be between 3.9 and 11.1 trillion USD by 2025 [1]. The core element of the IoT is the combination of physical and digital components to form new business models [2]. The integration of the IoT in higher education—that is, one of these new business models—has its benefits [3]. On the one hand, it enhances the perception of students and allows for location-independent learning. On the other hand, it possesses security and connectivity challenges. In order to fully benefit from the IoT in different business models, universities should offer digitalization opportunities for their students and researchers to utilize the IoT.

A research network composed by the University of Applied Sciences Stuttgart (HFT), the Bremer Institute for Production and Logistics (BIBA), the Institute for Knowledge Media (IWM) of the University of Koblenz-Landau, RWTH Aachen, and the University of Parma took a challenge to digitalize laboratories in a project funded by the German Federal Ministry of Education and Research (BMBF) [4]. They established a research project for

integrating IoT in higher education called Open Digital Lab for You (DigiLab4U for short). In this project, physical laboratories are digitalized and connected virtually with other laboratories, offering virtual laboratories to students and researchers. These laboratories might combine methods of engineering education and serious games [4]. Serious games aim to engage students while training students' skills [5–7]. These games facilitate educational purposes in a game nature. Thus, students become motivated and encouraged to proceed in the game, level up, and accordingly learn new strategies and skills (Section 2.1).

Offering and encouraging learning of optimization problems benefits students in the study programs of Industrial and Systems Engineering, Data Science, Management Science and Operations Research, as well as Computer Science. These students might solve problems in different fields, such as transportation and logistics. Heuristics might be used to solve optimization problems, and students must acquire the knowledge to apply these heuristics to solve optimization problems. The students might learn several of these heuristics in different courses offered in their study curriculum. However, different skills are required to be gained as well, such as teamwork, problem solving, and data analytics skills. In addition, the integration of IoT triggers the development of a virtual environment that satisfies learning objectives in an educational process.

In this paper, a virtual serious game is described that focuses on heuristics used to solve optimization problems in logistics and transportation and targets different students in different fields such as those mentioned above. The game handles popular transportation and logistics challenges (mainly related to distribution logistics processes). These problems are NP-hard in nature and could be used to model different real-world problems as described in Section 2.2. These problems include: the vehicle routing problem, the arc routing problem, and the team orienteering problem. This simulation-based serious game is designed as a virtual lab. Tutors may select instances of each of the aforementioned problems and ask students to organize themselves in small interdisciplinary teams. The teams carry out the following activities: (i) study the selected instances and propose an intuitive and feasible solution for each of them; (ii) use a biased-randomized heuristic, already implemented in a code that is provided to them, to generate high-quality solutions quickly; (iii) compare, using statistical tools, their original solutions with the one proposed by the algorithm; (iv) discuss the logic of the algorithm in order to make original proposals on how it could be improved further; (v) try to improve the algorithm logic so that it can provide even better solutions; and (vi) share their knowledge with other teams in the laboratory.

The game aims to develop different skills among students, including analytical and communication skills (Section 3.1). Different algorithms could become candidates to solve these problems (Section 3.2). The wide range of these algorithms, their parameters, and their application areas challenge students to identify appropriate algorithms to solve newly defined problems. The game is structured to train the basic skills and offer the required knowledge to handle the described problems (Section 3.3). Authors translate their knowledge in solving these problems to students in this structure. Skilled students are challenged with advanced exercises to improve the algorithm run or incorporate agile optimization techniques into them. In addition, preliminary experiments utilizing this serious game and students' feedback are provided (Section 4). Finally, some conclusions and open lines for future work are highlighted in Section 5.

2. Materials and Methods

This section initially presents a brief review of some of the works related to serious games in education indexed in databases such as Google Scholar and Scopus under the terms "serious games" AND "logistics and supply chain". Then, it presents the basic foundation on which the simulation-based serious game proposed in this paper is developed, describing the routing problems and their mathematical models. These routing problems are part of the learning objectives and should be learned by students.

2.1. Related Work on Serious Games

A serious game is a game whose main purpose is not to entertain players but rather to educate them, i.e., to train the players so they can understand the subject or topic on which the game is based [5]. The term serious games overlaps other terms, such as e-learning, edutainment, (digital) game-based learning [6], and simulation-based education [8]. However, the approach behind all these terms is the same: a game is developed considering that it is fundamental to allow players to reinforce their knowledge, skills, abilities, and competencies while playing the game in a simulated environment to apply them in the real world. Therefore, the role of a user is an active player, enterprising, able to interact with the surrounding environment and with those who are part of it [6].

Serious games have been developed in different application areas and target audiences. Examples of application areas are healthcare, city planning, and crisis or emergency management due to catastrophic events, e.g., fires, hurricanes, earthquakes, etc. [6]. Many authors highlight the importance of serious games adoption in the Science, Technology, Engineering, and Mathematics (STEM) areas of higher education Juan et al. [9]. As suggested by Breuer and Bente [10], serious games can be classified according to: (i) the area of application; (ii) the platform used; (iii) the topic; (iv) the learning objectives (e.g., learning a new language); (v) the learning principle adopted (e.g., exploration, trial and error, or memorization); (vi) the target audience; (vii) the modes of interaction between players and the game (e.g., single-player vs. multi-player); (viii) the interface adopted (e.g., mouse and keyboard, smartphone, or virtual viewer); and (ix) the common game labels (e.g., puzzle or simulation).

Such games are also a step towards the digitalization of education. The use of digital technologies to organize operational processes in different environments is considered effective and efficient [11]. Training students in virtual environments prepares them for the digital challenges they will face in the future. According to Khalid and Naumova [11], several programs and applications might be used in digitalization processes, especially since the COVID-19 pandemic. These programs and applications include 3D printing, computer-aided design and manufacturing, product life cycle management, customer relationship management programs, virtual assistance, artificial intelligence, and so on. Addressing these new technologies during the learning process of future professionals allows enhancing the digital development of supply chains.

Serious games result from blending fun and learning [10]. The games achieve their planned educational goal if they integrate learning within entertainment, i.e., the player does not feel the learning as an extra part of the game. Serious games challenge their players to solve problems [6], and the players stay motivated to continue playing as long as the challenge is compatible with their skills and knowledge [7,12]. The game becomes more complex as new game levels are explored and as the skill of a player improves. As a result, serious games have an impact on training players' motor skills, spatial abilities, strategic thinking [6], motivation, and increased interest [10]. A recent literature review underlines that 25% of the papers published utilizing serious games target professional training in areas such as healthcare [13]. Typically, users' satisfaction with the virtual environment is higher than with other learning methods. These games help reduce the gap between theory and practice, especially for students in STEM disciplines [7]. This, in turn, promotes skills improvement, greater student motivation, and teamwork skills.

Serious games reproduce plausible scenarios. They are often based on simulation of events or processes that happen every day and, therefore, they allow users to understand in advance how to behave to solve those particular types of problems [14]. Not only the real events but also the virtual events allow players to receive knowledge and information that remain firmly in their heads, thus allowing players to change their behavior through a "learning by doing" approach [14]. According to De Gloria et al. [15], scientific methods and engineering tools are increasingly required to develop serious games efficiently as effective learning resources. It requires the exploitation of advanced technologies (e.g., artificial intelligence, human-computer interaction, modeling and simulation, virtual reality, etc.) and research on the design of game formats, mechanics, and dynamics, which can

effectively merge educational and entertainment objectives in a meaningful and compelling way. The game proposed in this work uses a virtual environment to prepare the student for planning based on simulation and optimization techniques using digital tools in real environments. Many of the productive processes are being represented digitally as a digital twin. This technology is based on the integration of the IoT and artificial intelligence based on simulation, intelligent optimization algorithms, and automatic learning [16].

These games are designed to simplify the achievement of the educational objective by using an entertainment aspect. In essence, they use fun to introduce players to the subject and teach them something. This ensures that the player does not feel judged and can thus act spontaneously. Frequently, students (players) can play the game multiple times, which allows them to achieve the autonomy and experience that will be needed when they face the same situation in a real-life environment. In this way, they will be able to acquire experience and to develop problem solving skills [17]. In addition, serious games are often applied in education because players must necessarily put into practice what they have learned in previous phases to progress in the game. Hence, they can consolidate their knowledge. In this respect, serious games have a great impact at a corporate level: they represent means of refining and developing workers' skills. In particular, they allow workers to improve decision making processes [17] and optimize communication within and outside the corporation itself. Another serious game advantage is the active role that the player has to assume. Hence, increasing direct experience through a nearly real scenario makes players gain confidence in their skills. Moreover, this form of active learning is much more effective than the traditional method of studying and memorizing the contents of a manual [18].

In the last decade, several simulation-based serious games have been proposed that have allowed the development of specific skills in students [19,20]. Riedel and Hauge [21] identify and categorize, according to skills, some of the serious games for business and industry proposed up until 2011. According to them, today's changing environment requires education to prepare future professionals to face challenges in ways that require not only strong skills, such as understanding how complex systems, e.g., business or production systems, operate, but also soft skills, such as collaboration, creativity, and effective communication.

Being able to operate in a virtual and safe environment is also an advantage not to be underestimated. Players can experiment at the highest level without worrying about the consequences of their actions—which could cause a lot of damage in a real-life scenario. They are also able to participate in situations which, due to time or cost, would otherwise be impossible to experience in real life. Despite all the benefits of using serious games in education or training, serious games also have associated challenges [7]. The required digital skills, connectivity infrastructure, and heterogeneous student backgrounds constitute some of the main challenges to be overcome while planning the use of these games. Several authors have presented case studies on the use of simulation-based education in universities [7].

2.2. Fundamental Base

During the last 60 years, researchers and practitioners have been greatly interested in routing problems due to their large economic impact and the mathematical challenges involved in their study and solution. Routing problems can be classified into: (i) node routing problems, such as the vehicle routing problem (VRP) and the team orienteering problem (TOP), where nodes in a network can represent customers, and (ii) edge routing problems, such as the arc routing problem (ARP), where the service is performed on the arcs or edges of a network. These problems are combinatorial optimization problems, and solution methods are based on exact, heuristic, metaheuristic and hybrid algorithms. The characteristics of these problems are described in the following sections, including some of their most well-known variants.

2.2.1. The Vehicle Routing Problem

The VRP is an extension of the travel salesman problem (TSP). The VRP was originally proposed by Dantzig and Ramser [22]. It is a combinatorial optimization problem, and the objective function minimizes costs while delivering the right amount of goods to the right customers and satisfying a series of given constraints. The objective functions typically include reducing the number of utilized vehicles and the total travel distance or time.

According to Laporte [23], the VRP can be defined as follows: Let $G = (V, A)$ be a graph, where $V = 1 \dots n$ is a set of vertices representing cities with the depot located at vertex 1 and A is the set of arcs. Each arc $(i, j), i \neq j$, is associated with a non-negative distance matrix, $C = (c_{ij})$. In some contexts, c_{ij} can be interpreted as a travel cost or travel time. When C is symmetric, it is usually convenient to replace A with a set E of undirected edges. Further, there are m available depot-based vehicles where $m_L < m < m_U$. m is set to a fixed number when $m_L = m_U$, and m is said to be free when $m_L = 1$ and $m_U = n - 1$. A fixed cost, c_f , is associated with the use of a vehicle when m is not set to a fixed number. Thus, the VRP consists of designing a set of minimum-cost vehicle routes such that (i) each city in $V \setminus 1$ is visited exactly once by a single vehicle, (ii) all vehicle routes start and end at the depot, and (iii) some additional constraints (e.g., capacity, time, etc.) are satisfied. Figure 1a is a schematic representation of the VRP, where a fleet of vehicles, initially located at a central depot, completes closed routes (round trips). Each vehicle has a number of assigned customers to visit and a given loading capacity. The arrow indicates the direction of the route. The last connection between the customer and the depot is a trip where the vehicle may or may not be loaded, depending on whether it is a pickup or delivery route.

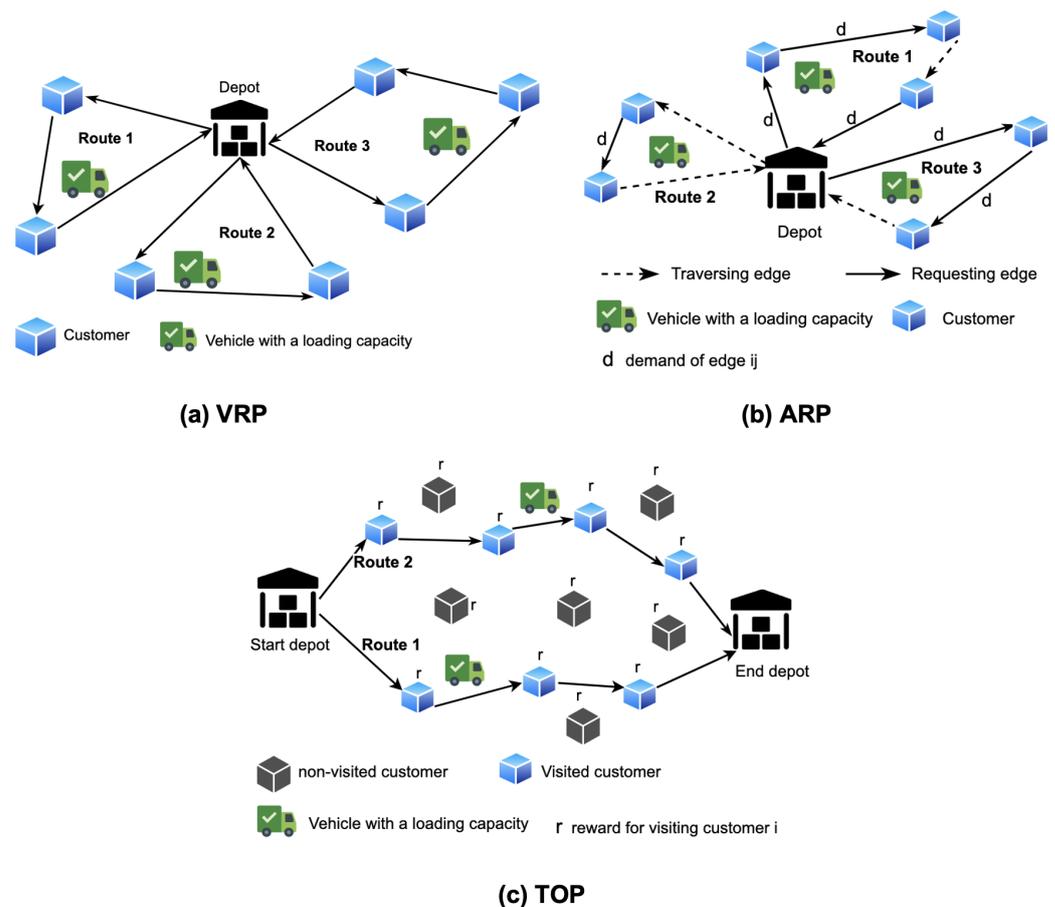


Figure 1. A schematic representation of a simple VRP, ARP, and TOP.

The mathematical formulation can be defined based on Laporte [23] as follows: Let x_{ij} be an integer binary variable which could take the values $\{0, 1\}, \forall \{i, j\} \in E \setminus \{\{0, j\} : j \in V\}$.

$$\min \sum_{i \neq j} c_{ij} x_{ij} \tag{1}$$

s.t.

$$\sum_j x_{ij} = 1 \quad \forall i \in V, \tag{2}$$

$$\sum_i x_{ij} = 1 \quad \forall j \in V, \tag{3}$$

$$\sum_{i,j \in S} x_{ij} \geq |S| - v(S), \quad \{S : S \subseteq V \setminus \{1\}, |S| \geq 2\}, \tag{4}$$

$$x_{ij} \in 0, 1 \quad \forall i, j \in E, i \neq j. \tag{5}$$

Equations (2) and (3) prohibit assignments in the main diagonal defining a modified assignment problem. Equation (4) eliminates the subtours using a $v(S)$ that is an appropriate lower bound on the number of vehicles required to visit all vertices of S in the optimal solution.

VRP variants are associated with constraints, which are defined based on real-life conditions, such as limited vehicle capacity, which gives rise to the capacitated VRP (CVRP) [24]. In the VRP with time windows (VRPTW), customers request time windows in which goods could be delivered. These time windows depend on the opening hours of a retail store, temporary time at holding ranges, or customers' organizational processes [25]. Two problems might be defined. In one problem, the delivery of goods outside the time window is not permitted, and in the other problem, this delivery is penalized. Other types of VRPs are the VRP with backhauls, in which goods are delivered from a depot to linehaul customers, and the VRP with pickup and delivery, in which goods are also delivered from backhaul customers to the depot [26].

There are many other variants, such as the multi-depot VRP, dynamic VRP, time-dependent VRP, green VRP, electric VRP, and stochastic VRP. They generally differ in the characteristics associated with one or more of the main elements in the VRP, such as the type of fleet, customer demand, or route characteristics.

2.2.2. The Arc Routing Problem

The ARP is a routing problem that has been known since 1960. It is based on the Chinese postman problem [27] and the rural postman problem [28]. Figure 1b shows a schematic representation of a basic ARP. There is a depot from which routes start and end, a homogeneous fleet of vehicles, as well as a set of nodes and edges. In these problems, some arcs or edges may require service (required arcs), and other arcs or edges are only traversed to reach the required arcs. Each required arcs has an associated positive demand, and it is traversed by at least one vehicle; each vehicle has a specific route associated with it. Traversing arcs assume a null demand with no impact on the result. The typical objective function minimizes total costs of designed routes that satisfy the demands of the arcs. These costs can be defined in monetary, time, or distance units.

The mathematical formulation of the ARP is defined as follows [29]:

Let $G = (V, E)$ be an undirected graph, where $V = \{0, 1, 2, \dots, n\}$ represents a set of $n + 1$ nodes (the node 0 represents the depot) and $E \subseteq \{e_{ij} | i, j \in V, i \neq j\}$ represents the set of marks connecting some of the nodes. Each edge $e_{ij} \in E$ has an associated symmetric cost, $c_{ij} = c_{ji} > 0$, and a non-negative demand, $q_{ij} \geq 0$. Edges with a strictly positive demand, $R = \{e_{ij} \in E | q_{ij} > 0\}$, are called required arcs and must be traversed at least once to be served.

A homogeneous fleet of K vehicles is available at the depot, each one with capacity W . It is assumed that $W \gg q_{ij}, \forall i, j \in V$.

To formulate the mathematical model, the variable x_{ij}^k takes the values of 1 if vehicle k traverses edges e_{ij} from i to j , and 0 otherwise. In addition, the variable l_{ij}^k is 1 if the vehicle k serves edge e_{ij} while traversing it from i to j and 0 otherwise. Then, the model is formulated as follows:

$$\min \sum_{k=1}^K \sum_{e_{ij} \in E} c_{ij} x_{ij}^k \tag{6}$$

s.t.

$$\sum_{j \in N(i)} (x_{ij}^k - x_{ji}^k) = 0 \quad \forall i \in V \setminus \{0\}, \quad \forall k \in \{1, 2, \dots, K\} \tag{7}$$

$$x_{ij}^k \geq l_{ij}^k \quad \forall e_{ij} \in R, \quad \forall k \in \{1, 2, \dots, K\} \tag{8}$$

$$\sum_{k=1}^K (l_{ij}^k + l_{ji}^k) = 1 \quad \forall e_{ij} \in R, \tag{9}$$

$$\sum_{i=0}^n \sum_{j=0}^n l_{ij}^k \cdot q_{ij} \leq W \quad \forall k \in \{1, 2, \dots, K\} \tag{10}$$

$$\sum_{\forall i \neq j, (i,j) \in S \times S} x_{ij}^k - |V|^2 \cdot y_s^k < |S| \quad \forall S \subset V \setminus \{0\} \exists |S| \geq 1, \quad \forall k \in \{1, 2, \dots, K\} \tag{11}$$

$$\sum_{\forall i \neq j, (i,j) \in S \times S} x_{ij}^k + u_s^k \geq 1 \quad \forall S \subset V \setminus \{0\} \exists |S| \geq 1, \quad \forall k \in \{1, 2, \dots, K\} \tag{12}$$

$$u_s^k + y_s^k \leq 1, u_s^k, y_s^k \in \{0, 1\}, \quad \forall k \in \{1, 2, \dots, K\} \tag{13}$$

$$x_{ij}^k, l_{ij}^k \in \{0, 1\} \quad \forall i \neq j, \quad \forall k \in \{1, 2, \dots, K\} \tag{14}$$

Equation (7) ensures that the vehicle k with an assigned route leaves node i the same number of times it visits it. $N(i) = \{j \in V | e_{ij} \in E\}$ represents the subset of nodes adjacent to node i . Equation (8) guarantees that each served edge is traversed, since it is not possible to serve an edge without traversing it. Equation (9) establishes that all required edges are only served once, ensuring this with the restriction that the sum of the service variable l_{ij}^k is always equal to 1. Equation (10) represents the capacity constraint when each vehicle k has a limited capacity. This equation is only required when the vehicle capacity is limited. Equations (11)–(13) eliminate the possibility of disconnected subtours and allow routes that include two or more closed cycles. u_s^k and y_s^k are binary auxiliary variables used for any route k and subset of nodes S . Equation (11) avoids the formation of illegal subtours, and Equation (12) guarantees that there is always, at least, a traversed arc to go outside S .

The most popular ARP variants are those derived from capacity constraints, such as volume restrictions on the vehicle’s load capacity, which results in the capacitated ARP [30]. Similarly, time constraints associated with limited driving times lead to the time-capacitated ARP [31]. In general, ARP variants can be classified into periodic ARP, ARP with benefits, sufficiently close ARP, location ARP, and ARP with drones [28].

2.2.3. The Team Orienteering Problem

The TOP is associated with routing problems characterized by restrictions on the size of the fleet and the maximum length that can be covered on any given route. Unlike the VRP, not all customers have to be visited in the TOP. Each customer offers a reward to be collected by a vehicle during the first visit. The TOP is an NP-hard problem, and its typical goal is to maximize the total reward collected by a fixed fleet of vehicles. The single-vehicle version of the TOP, known as the orienteering problem (OP), is a combination of two classic combinatorial optimization problems: the knapsack problem and the TSP [32]. The TOP is an extension of the OP, since it uses a fleet of vehicles, generating multiple routes. Figure 1c

shows a schematic representation of the TOP. Vehicles depart from a source node (start depot), visit a set of customers, and proceed to the destination node (end depot). Only those customers that maximize the reward are visited.

TOP is modeled by Chao et al. [33] as a multi-level optimization problem. In the first level, the nodes to be visited are selected. In the second level, the selected nodes are assigned to the vehicles in the fleet. Finally, the construction of the routes for each vehicle is conducted in the third level. According to Gunawan et al. [34], the TOP can be mathematically defined as a set of nodes $N = [1, \dots, |N|]$, where each node $i \in N$ is associated with a non-negative reward, r_i . The start and end nodes are described by nodes 1 and $|N|$, respectively. The objective function of the TOP maximizes the total collected reward from selected nodes by determining routes that are limited by a given time budget, T_{max} . The time between nodes i and j is t_{ij} . It is assumed that collected rewards can be added and that each node can be visited at most once.

The problem is formulated as an integer programming model with the following decision variables: $x_{ij} = 1$ if a visit of node i is followed by the visit of node j and 0 otherwise; and u_i is used in subtour elimination constraints and allows us to determine the position of the visited nodes in a route. The objective function maximizes the total collected reward (15). The constraints ensure that: (i) the route starts from node 1 and ends at node $|N|$ (16); (ii) the connectivity of a route guarantees that each node is visited at most once (17); (iii) the total travel time is limited by T_{max} (18); and (iv) subtours are prevented (19,20).

$$\max \sum_{i=2}^{|N|-1} \sum_{j=2}^{|N|} r_i x_{ij} \tag{15}$$

s.t.

$$\sum_{j=2}^{|N|} x_{1j} = \sum_{i=2}^{|N|-1} x_{i|N|} = 1, \tag{16}$$

$$\sum_{i=2}^{|N|-1} x_{i|N|} = \sum_{j=2}^{|N|} x_{kj} \leq 1; \quad \forall k = 2, \dots, (|N| - 1) \tag{17}$$

$$\sum_{i=2}^{|N|-1} x_{i|N|} \sum_{j=2}^{|N|} t_{ij} x_{ij} \leq T_{max}, \tag{18}$$

$$2 \leq u_i \leq |N|; \quad \forall i = 2, \dots, |N| \tag{19}$$

$$u_i - u_j + 1 \leq (|N| - 1)(1 - x_{ij}); \quad \forall i = 2, \dots, |N| \tag{20}$$

Variants of the TOP arise according to time and the vehicle’s capacity constraints. The best known variants are the time-windows TOP, and the time-dependent TOP [34].

The constraints might also vary between precedence conditions, dynamic rewards, and stochastic travel times, which make the problem even more challenging. Since it is a reward-based problem, there are many real-life activities that can be modeled as a TOP or one of its variants. Hence, its application extends to real-life situations associated with transportation networks [35] and customized electronic tour guides [36], among others.

3. The Design of the Game

Our serious game introduces challenges related to last-mile logistics and heuristics commonly used to solve these problems. These challenges target different skills that are detailed in Section 3.1, and the main heuristics used to solve the problems are presented in Section 3.2. The game is based on the description of the problems and the heuristics in a virtual environment (Section 3.3). Thus, students can learn the topics targeted by the game from the comfort of their homes.

3.1. Learning Goals

Section 2.2 differentiates last-mile logistics problems and illustrates the main differences between them. Students can remember these problems and distinguish them and their variants. Each of these problems and its variants found an application in real-life problems. The game challenges students to solve different instances of these problems. The difficulty of the problems varies according to the size of the specific instance being analyzed (i.e., the number of nodes, the required constraints, etc.). Of course, employing additional constraints gives rise to other variants of the problems.

The main learning objective of the game is to develop and strengthen students' soft skills, such as: communication, creativity, critical thinking, logical reasoning, and research skills. The challenges posed by the game lead students to develop their analytical skills. Students reach a stage in which they should identify the problem they are facing, identify its characteristics, decide the best method to solve it, and propose improvements in the basic solutions offered by the game. Reaching this stage demands possessing a basic knowledge of optimization and simulation methods.

In addition, the challenges must be developed in teams, which allows students to develop leadership and task management skills. In teamwork, team members are aware of their strengths and their contributions to solving challenges. Once experiments have been run, students must analyze the obtained results and present them to demonstrate the acquired skills. Plotting and tabulating the results are targeted by the game. Therefore, students must differentiate between the different heuristics used to solve the problems, differentiate between their different instances, and understand the results and their use according to the studied context.

Among the skills required for students to participate in this game is a basic programming knowledge of the Python language. Students are provided with a basic version of the different solution methods programmed in Python scripts. Therefore, students must reproduce the codes of the different heuristics to solve the problems and make minor modifications, as required by the different challenges presented in the development of the game. Students are challenged to modify and improve heuristics to solve the problems at advanced game levels. These improvements target local search and the construction of initial solutions in a heuristic procedure.

Additionally, the challenges in the game are based on real problems faced by the transport and logistics sector. Thus, students gain the knowledge to solve complex problems involving the main concerns of these sectors in relation to the sustainable development goals proposed by the United Nations for the year 2030 [37]. Students learn how to address constraints and targets associated with climate change in terms of transportation adaptation and mitigation of greenhouse gas emissions. Social sustainability is also associated with the pursuit of good health and wellbeing of society, considering road safety and air pollution. Energy efficiency is also a key factor for the future of the sector, so students will be able to ensure energy-efficient solutions that contribute to the goal of affordable and clean energy—as well as the responsible use and consumption of fuel.

Since the main focus is on last-mile problems, the problems are strongly aligned with sustainable urban transportation in smart and sustainable cities. Thus, students will learn the real problems of the transportation sector and the solutions through heuristic methods. In addition, they will develop the ability to interpret, analyze, and solve the posed problem logically and innovatively, considering all challenges that the transportation sector has in terms of environmental, economic, and social sustainability. The teamwork structure will allow students to improve their communication skills in a team and the ability to present results coherently.

3.2. Algorithms

This section presents the algorithms implemented in the proposed serious game. They are three well-known algorithms belonging to the wide plethora of heuristics developed by the scientific community. The choice of these frameworks and their inclusion in the

proposed serious game lie in the fact that they are among the most used simple approaches to solve the problems described in Section 2.2. At the end of this section, we also describe the biased-randomization technique, which may be used to incorporate all the previously described heuristics into a multi-start framework.

3.2.1. Clarke and Wright Savings Heuristic

The Clarke and Wright savings (CWS) heuristic [38] finds many applications in vehicle routing problems and its constrained versions, such as the capacitated VRP [39], the VRP with time windows [40], the 2D-loading VRP [41,42], the 3D-loading VRP [43,44], etc. Moreover, there are some applications to the internal logistics and picking contexts.

The whole algorithm is based on the concept of savings: given the set of nodes $N = \{1, \dots, n\}$ representing the customers to visit and the edges $E = \{1, \dots, m\}$ connecting these nodes, the CWS heuristic assigns to each edge a specific value called savings. Thus, if i and j represent two nodes connected by edge $e_{ij} = (i, j)$, the saving represents the advantage that is possible to obtain by visiting j immediately after i instead of visiting i , going back to the depot, and then moving to j . The classic formula to calculate the savings s_{ij} is therefore:

$$s_{ij} = c_{id} + c_{dj} - c_{ij} \tag{21}$$

where c_{ij} is the cost associated with traveling the edge (i, j) and d represents the depot. Once the savings for each edge have been computed, these edges are sorted from highest to lowest savings in the so-called savings list. Then, the CWS heuristic constructs a starting dummy solution, where each customer is served by a different vehicle; after visiting a customer, each vehicle returns to the depot. This solution may be feasible in terms of loading capacity but, of course, is not cost-efficient since it implies using a large number of vehicles traveling a long distance in total.

Next, an iterative merging process is carried out starting from the initial solution. The savings list is iterated, and, in each iteration, the next edge is considered. If nodes linked by an edge are currently visited by two different vehicles and the merging would respect all the constraints (such as the capacity of vehicles), then the vehicles' routes are merged into one. This process terminates when the savings list is concluded, the number of vehicles is under a certain threshold, or other user-defined stopping conditions are met. For the sake of clarity, the evolution of the solutions from the starting to final solutions in two benchmark instances is represented in Figure 2.

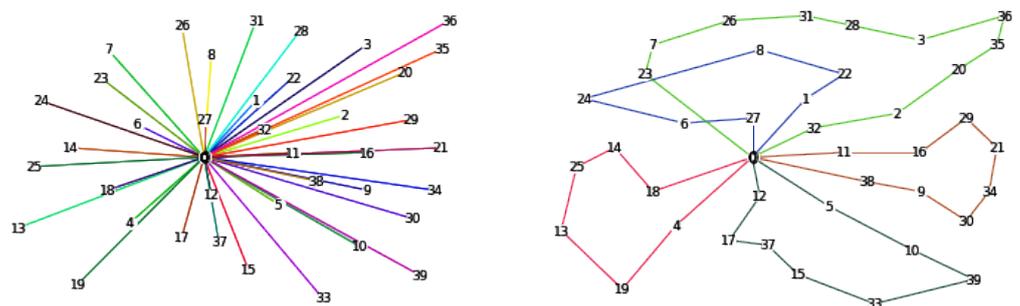


Figure 2. Comparison between starting and final solutions of the CWS heuristic.

3.2.2. Savings-Based Heuristic for the Arc Routing Problem

The savings-based heuristic for the arc routing problem (SHARP) is a savings-based heuristic for the ARP [29]. It drew inspiration from the CWS heuristic, although it incorporates significant changes to allow its application to the case in which demands are on arcs instead of on nodes. The SHARP heuristic needs to treat the graph of nodes as complete. Hence, in a preliminary step, it implements the Floyd–Warshall algorithm [45] to compute the shortest paths for each pair of nodes. Having a complete graph, it is possible to calculate the savings associated with each arc (if it is either real or virtual) by using Equation (21).

However, in the case of the ARP, it is enough to compute the savings on arcs with demand higher than zero. These demanding arcs can then be included in the savings list.

A first dummy solution is then constructed by assigning a vehicle to each required arc in the list of demanding arcs. During this step, it is necessary to keep track of the required arcs and their orientations in routes, as the complete final route is reconstructed at the end. Additionally, it is suggested to keep track of nodes that constitute the extremes of routes, which are used in the next step to speed up the merging process.

Once the savings list and the dummy solution are provided, the iterative merging process can start: for each edge (i, j) in the savings list, if i and j are external nodes respectively for two different routes and the (prospective) merged route does not violate any constraint, the routes can be merged. When all the savings list has been iterated and the process is terminated, we should have a set of routes made of sorted and oriented edges with demands greater than zero. Therefore, the final solution can be constructed by using an all-pairs shortest path matrix, i.e., the matrix generated at the beginning of the procedure to compute the shortest path.

3.2.3. Panadero and Juan Savings Heuristic for the TOP

Similar to the SHARP, the Panadero and Juan savings heuristic (PJS) [46] adapts and extends the CWS heuristic considering the peculiarities of the TOP, such as the fact that origin and destination are different, the possibility to avoid visiting some nodes, and the customers' rewards.

First, the PJS heuristic generates a dummy solution in which one route per customer is considered—i.e., for each customer $i \in N = \{1, \dots, n\}$, a vehicle departs from the depot (node 0), visits i , and then concludes the trip at the destination depot (node $n + 1$). In this dummy solution, if a route does not satisfy the driving-range constraint, the associated customer is discarded (and not visited), since it cannot be reached with the current fleet of vehicles.

In the second step, the savings s_{ij} associated with each edge connecting two different customers are computed as:

$$s_{ij} = \alpha(c_{i(n+1)} + c_{0j} - c_{ij}) + (1 - \alpha) \cdot (u_i + u_j) \quad (22)$$

where c_{ij} is the cost associated with arc (i, j) (in this case, two arcs with different costs are associated with each edge), u_i is the reward obtained by visiting customer i , and $\alpha \in [0, 1]$ is a tuning parameter, which depends on the heterogeneity of customers in terms of rewards.

Arcs are therefore sorted for decreasing savings, thus building the savings list. Then, in a similar way as before, an iterative merging process is carried out. In each iteration, the next arc on the savings list is considered: if it links two routes that, once merged, constitute a new route that respects all constraints, then this merged route is constructed. Once the process is concluded, the obtained routes are sorted according to the total reward. This sorting allows us to select as many routes as possible, taking into account the restricted number of vehicles in the fleet.

A representation of the process that goes from the dummy solution to the final solution is shown in Figure 3.

3.2.4. Biased-Randomization Techniques

Biased-randomization techniques constitute a simple yet effective way to transform a deterministic heuristic into a probabilistic algorithm [47]. They achieve this goal by using a skewed probability distribution to introduce a non-uniform randomization pattern into a heuristic without destroying the logic behind it. Using a skewed probability distribution introduces an oriented or biased (non-uniform) random component in selecting candidates from a sorted list. Therefore, given a list of candidates $C = \{1, \dots, k\}$, which have been sorted according to an efficiency criterion, the next candidate to be employed during the solution-construction procedure will be selected based on the biased-random process. Notice that candidates that show a higher efficiency level receive a high probability of being selected, and vice versa. In this way, the selection of candidates is still based on

the efficiency criterion employed to sort the list, but a different selection path is chosen every time the randomized heuristic is run. The biased-randomization process is not only flexible and straightforward, but it has been shown to be quite effective in solving different combinatorial optimization problems, including those with non-smooth objective functions [47].

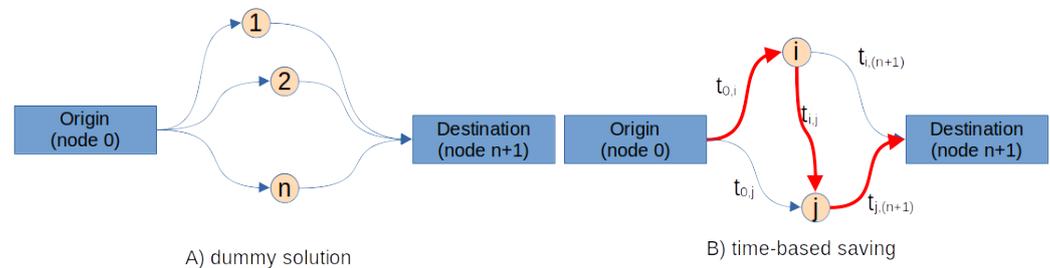


Figure 3. Resolution process implemented into the PJS heuristic.

Regarding the skewed probability distributions, the most employed in the literature is the geometric distribution, i.e., the distribution with a probability density function given by $f(x) = (1 - \beta)^x$, with β a user-defined parameter. This distribution is chosen because of the low number of parameters that it contains, which simplifies the parameter setting process.

Finally, one should notice that biased-randomization techniques can be incorporated into a meta-heuristic framework in (i) generating different initial solutions and (ii) a destruction–reconstruction process.

3.3. The Pilot Game Design

The way in which we organized the activity in this course is described next and, to our best knowledge, might be generalized as a standard approach to be used. For each of the previously described optimization problems, the instructor selects instances of different sizes and characteristics and, hence, instances with different degrees of difficulty (the use of exact optimization methods is usually limited to the smallest degrees of difficulty). Then, students are organized in small teams of three or four members. Whenever possible, these teams are interdisciplinary (i.e., composed of students with heterogeneous backgrounds, including industrial engineers, mathematicians, computer scientists, or students from business and management studies). Each of these teams has to work on the following stages, with the support and guidance from the instructor (the instructor's role might depend upon students background and the expected learning outcomes of the game):

1. This stage involves studying the considered instances and trying to propose an intuitive and feasible solution for each of them. These solutions might be obtained by employing certain logic or intuition or by applying any method that students already know. For example, some students might develop or obtain a mathematical model of an optimization problem and solve it using a popular solver such as CPLEX or Gurobi. However, of course, being NP-hard optimization problems, even if students can model the problem in mathematical notation, they could only obtain the optimal solutions for the smallest instances.
2. In this second stage, students are provided with the heuristic codes/pseudo-codes (depending on their programming backgrounds) and asked to implement the code on their own to generate solutions for all instances. They must also implement the graphical visualization code of the solutions included with the algorithms. Students are expected to comment on the differences between solutions obtained in the first and second stages regarding the quality of the solutions and required computational times.
3. In the third stage, students are asked to extend the heuristic approach by incorporating biased-randomization techniques and, depending on their background, even advanced metaheuristic frameworks (tabu search, iterated local search, GRASP, simulated annealing, genetic algorithms, etc.). Again, at the end of this stage, students

should generate a scientific debate on the differences of the new solutions with respect to the ones obtained in previous stages. Although not mandatory, performing a statistical comparison is strongly recommended at this stage.

4. In the fourth stage, students are expected to discuss the logic behind the employed solving approaches or the managerial implications of using each of the different approaches in terms of cost savings and business performance.
5. In the fifth stage, students should think about creative ways to improve the respective solving approaches. This could be a theoretical contribution of ideas or, if there is enough time, students are encouraged to implement and test their proposals.
6. Each group shows and discusses their best results and conclusions at the final stage. Groups discuss their findings with the instructor, who will also assess the work conducted. Additionally, they share their knowledge with other teams to promote cross-fertilization of ideas, insights, and learning outcomes.

Each of the above-mentioned stages involves different skills and may be followed by different levels of feedback by the instructor. For example, critical stages and the end of the game are followed by detailed feedback and might be considered blocking points where the instructor can ask for a review. Conversely, the less critical stages are characterized by a small and not mandatory response. For the sake of clarity, a representation of the stages with the relative trained skill sets and suggested feedback by the instructor is provided in Figure 4.

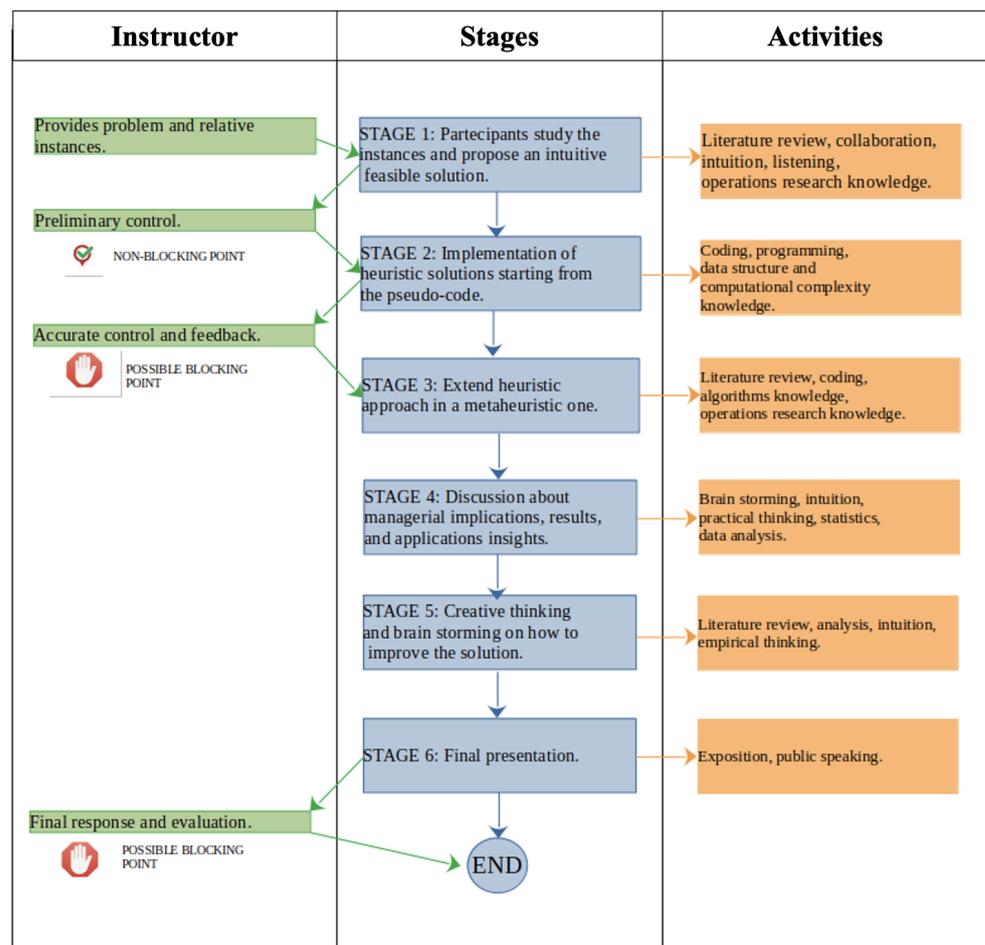


Figure 4. Representation of the game stages with relative required skills and responses by the instructor.

4. Preliminary Feedback from Students and Discussion

In 2021, a preliminary version of this training activity was already been used in MSc and PhD courses held at different European universities, which include: Universitat Oberta

de Catalunya in Spain (MSc in Computational Engineering and Mathematics), University College Dublin in Ireland (MSc in Business Analytics), Universidade Aberta in Portugal (PhD in Applied Mathematics and Modeling), and University of Modena and Reggio Emilia in Italy (invited course for MSc and PhD engineering students).

As a result of this learning process, it is expected that students acquire competencies and skills related to logistics and transportation challenges as well as problem solving. These competencies and skills can be valuable for students' future careers; they increase students' analytical skills, capacity to understand heuristic-based algorithms, teamwork and interdisciplinary communication skills, programming skills, and statistical abilities.

Additionally, skills such as reading and writing reports are targeted in several activities in the game. In general, the game targets analytical and problem-solving skills in logistics and transportation, e.g., routing of vehicles and vehicle scheduling. Teamwork as well as debugging and programming skills are trained. All these skills benefit the students in their future careers. Honorable mention should be given to the necessity to work in a team. Teamwork enhances personal growth, the finding of new ideas, and creativity, and, according to [48,49], it is one of the more requested skills by big technology companies.

Several feedback comments provided by 46 master students who participated in the serious game activity are included below. Approximately one-third of the participated students were from China, another third were from India, and the rest were from Europe, including Germany, Ireland, Italy, and the United Kingdom. In particular, these students belong to the MSc in Business Analytics offered at University College Dublin (Ireland). The feedback is consistent with our expectations as instructors. It represents opinions from students with different technical backgrounds (from students with solid engineering and computer backgrounds to students with training in business and management).

- "I found the activity quite challenging but enjoyed working through the different algorithms and the provided code. This was my favorite part of the course, to be able to actually see how these algorithms are implemented through programming. Many classes merely teach the theory of them but this activity went a step further. This practical aspect of the course was important to me... It was great to learn that such algorithms can actually impact real life".
- "I found the activity to be very interesting, with many new concepts introduced. I really enjoyed the way concepts such as Biased Randomized Algorithms were introduced and followed by a full activity devoted to recent applications... I felt that these algorithms could be revolutionary in solving these large scale NP-hard problems in near real-time. It was great to work collaboratively with my group. I think we all gained a lot from the shared learning involved in completing each stage".
- "As a student with business background, algorithms are supposed to be an unattractive, relatively difficult field for me. However, learning the algorithms that can be used to solve many NP-hard problems faster and more optimally, I am constantly impressed by the wisdom of those working in this field and grateful for their commitment to a smarter world in more efficient ways".

Apart from these samples of students' qualitative feedback, Figure 5 shows the result of a student survey on one of the courses implementing the serious game activity. This survey registers students' opinions, measured in an interval from low 1 to high 5, in several dimensions: understanding of the content, assessment activities, learning outcomes, teaching quality, and overall opinion. As one can notice, the average scores provided by the students for the course in which the serious game activity was included are clearly above the scores assigned to the entire master and the entire school.

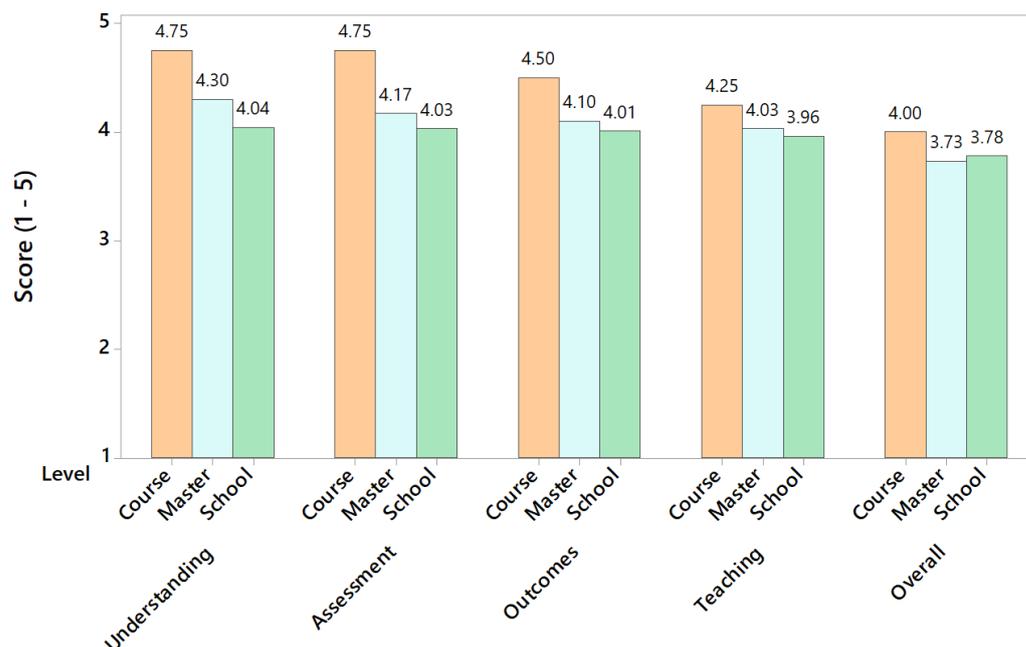


Figure 5. Scores assigned by students to a master course including the game activity.

Universities and research institutes could benefit from using the proposed serious game.

The utilization of the proposed game lightens the workload required by the instructors and provides them with the possibility to evaluate students under aspects that are difficult to understand through classic frontal lessons, such as teamwork, leadership, intuition, customer-oriented behavior, resilience, due dates management, ability to tackle problems never seen before, and many others. These skills, according to [48,49], are the most required by big technology companies, such as Google and Amazon, and are usually neglected by classic evaluation processes. Moreover, the stages of the proposed serious game (see Section 3.3) partially resume the steps made by researchers in the proposal of a new scientific contribution. This enhances the students' understanding of research activities and might be a good starting point to educate tomorrow's researchers in digital environments.

5. Conclusions and Future Work

The scientific novelty of this work mainly concerns the context of higher education and, more in detail, the use of serious games in the training of engineers and scientists. In particular, it shows how a heuristic-based serious game can be employed to teach optimization concepts related to the area of logistics and transportation. In parallel to learning optimization tools and their applications in solving challenging popular routing problems, serious games also promote the development of desirable skills and competencies among students. These skills and abilities include analytical, problem solving, programming, and teamwork and presentation abilities.

The described game focuses on three popular routing optimization problems that frequently arise in many transportation enterprises, namely, the vehicle routing problem, the arc routing problem, and the team orienteering problem. Students can use well-known and intuitive heuristics, which allow them to quickly generate efficient solutions to the problems while understanding the logic behind the solving methods. In a different stage of the game, the heuristics can be enriched by using biased-randomization techniques and advanced metaheuristic frameworks, which allow students to improve the previous solutions. A comparison of the obtained results among different groups and a proper discussion on why the proposed approaches work can be very beneficial for increasing the analytical capabilities of students.

In the context of the DigiLab4U international project, we have tested preliminary versions of the proposed serious game in different European universities and degrees. Students' feedback is quite positive, as well as our feedback as instructors in charge of the courses. The detailed design of the activities might depend upon students' backgrounds. For example, computer scientists are expected to focus more on the algorithms' code and how to extend or enhance it by adding additional optimization frameworks and advanced data structures and management students are supposed to invest more time in the business aspects of the challenges, e.g., how to re-design the business process so that a higher cost reduction can be achieved, how to involve concepts from sustainability and the circular economy trends, or how to benefit from horizontal cooperation strategies during the distribution actions.

Regarding future work, the following lines are open to further exploration: (i) the inclusion of similar challenges in other application areas of optimization, such as industrial manufacturing and production, quantitative finance and insurance, smart cities, or telecommunication systems; (ii) the inclusion of stochastic and fuzzy components in the aforementioned problems so that more complex scenarios under uncertainty can be considered and discussed during the serious game; and (iii) the development of an international experience, where students from different universities and countries can play the game online in hybrid teams.

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