Journal Pre-proof

Optimal Selection of Touristic Packages Based on User Preferences During Sports Mega-Events

Simona Mancini, Chefi Triki, Sujan Piya

PII: S0377-2217(22)00065-0
DOI: https://doi.org/10.1016/j.ejor.2022.01.031
Reference: EOR 17690

To appear in: *European Journal of Operational Research*

Received date: 15 February 2021
Accepted date: 17 January 2022

Please cite this article as: Simona Mancini, Chefi Triki, Sujan Piya, Optimal Selection of Touristic Packages Based on User Preferences During Sports Mega-Events, *European Journal of Operational Research* (2022), doi: https://doi.org/10.1016/j.ejor.2022.01.031

Highlights

- We introduce a new decision problem arising in the context of touristic packages offering.
- We model it as a Nested Multi-Dimensional Multi-Knapsack Problem with Conflicts, which has never been studied previously in the literature
- We provide a mathematical formulation for its solution.
- We propose a new matheuristic framework based on the concept of consensus (CKS)
- Our approach is easy to generalize to broad classes of stochastic and bi-level problems.
- We compare our matheuristic with the classical Kernel Search and we show that it systematically provides better solutions for our problem

Optimal Selection of Touristic Packages Based on User Preferences During Sports Mega-Events

Simona Mancini

University of Klagenfurt, Department of Operations, Energy, and Environmental Management, Klagenfurt, Austria
simona.mancini@aau.at

University of Eastern Piedmont, Department of Science, Innovation and Technology, Via Teresa Michel 11, 15121 Alessandria, Italy.
simona.mancini@uniupo.it

Chefi Triki

University of Kent, Kent Business School, Canterbury, UK
c.triki@kent.ac.uk

University of Salento, Department of Engineering for Innovation, Lecce, Italy
chefi.triki@unisalento.it

Sujan Piya

Sultan Qaboos University, Department of Mechanical and Industrial Engineering, Muscat, Oman
sujan@squ.edu.om

Abstract

Sport mega-events, such as the Soccer World Cup or Olympic Games, attract many visitors from all over the world. Most of these visitors are also interested in, besides attending the sports events, visiting the host nation and the neighboring countries. In this paper, we focus on the upcoming FIFA World Cup Qatar 2022. As per the schedule of the tournament, a national team can play 7 matches at most. Therefore, a supporter will have six short breaks (of three to five days) between consecutive matches in addition to two longer ones, immediately before and after the tournament, during which they can plan some touristic trips. We study the problem faced by a touristic trip provider who wants to offer a set of touristic packages, chosen among a very large set of options, devoted to World-Cup related tourists. The number of packages offered must be limited due to organizational reasons and the necessity to guarantee a high participation in each trip. In this study, a set of user profiles is considered. It represents different categories of tourists, characterized by different preferences and budgets. Each user is supposed to pick the packages that maximize their satisfaction, considering their budget and time restraints. The goal of the company is to choose the set of packages to be offered that would maximize the average users satisfaction. To address this NP-Hard combinatorial optimization problem we provide a mathematical formulation and a matheuristic, named Consensus-Based Kernel Search (CKS), wherein an alternative rule is used to create the initial Kernel and partition variables in buckets. Computational results evidence the excellent performance of CKS and prove that the newly introduced algorithm systematically outperforms the classical Kernel Search.

Keywords: Combinatorial Optimization; Knapsack; Kernel Search; Sports Mega-Events, FIFA World Cup 2022.

---

1. Introduction

Travelling to attend sports events is a very old phenomenon that started centuries ago with the Olympic Games and has continued till today with an increasing number of world wide sport mega-events. FIFA World Cup (FWC) tournament is an example of mega-events whose purpose goes beyond the level of simple sports competitions. These mega-events often present opportunities for cultural exchange, political visibility, and economic development for the organizing countries. For this reason, huge investments are often allocated to ensure adequate transport infrastructure, public services, and utilities. According to Pop et al. (2020), the cost of organizing the FWC has remarkably increased with time reaching (in USD billion) 7.5 in 2010 (South Africa), 14 in 2014 (Brazil), and 21.5 in 2018 (Russia). In the case of FIFA 2022, that will be held in Qatar, the cost will be much more substantial, since the total budget is estimated to be USD 200 billion to be spent on improving the port, airport, railway, stadiums, and roads (Abeza et al. (2020)). On the other hand, FWC games have a positive impact on the host countries' economy and tourism. For example, in the case of FIFA 2018 , the cumulative impact on the Russian economy has been estimated to be USD 31 billion, 21% of which was accounted for by the related tourism revenue. Moreover, the number of foreign sport tourists was estimated to be 1.6 million, with an average stay of 12 nights each, which is much longer than stays for any other tourism purpose (Pop et al. (2020)).

Some studies have claimed that in these kinds of mega-events, not all visitors are really interested in the games, and almost 20% attend only to give company to their relatives or friends (Weed (2006)). Such visitors would be interested in activities other than the sporting event. To attract such travelers to FIFA 2022, it is important to provide touristic packages that can amplify their interest in attending in the sports event and enrich their tourism experience. Moreover, even committed fans often seek to "get engaged in other activities as well, such as leisure, adventure, cultural or make visits to religious or historical places" (Kapur (2018)). Thus, all visitors will have greater motivation to attend the 2022 FWC in Qatar in knowing that they can engage in touristic activities during the breaks between games. Significant efforts should be directed at selecting and planning, in advance, a set of local and regional touristic packages that suits all potential visitors' interests. According to a recent survey, over 92% of touristic providers think that touristic planning is an urgent necessity in the context of sports tourism and over 87% believe that appropriate planning can promote the development of the tourism industry in the future (Dhahir et al. (2019)).

The purpose of this paper is to help select and plan a set of touristic packages that will let the FIFA 2022 visitors plan their trips based on their preferences. It takes into account the schedule of the FWC tournament and the geographical characteristics of the host country in proposing a decision support tool that will help the FIFA 2022 participants and visitors in planning their trips. The idea is to develop an optimization model that selects an optimal set of touristic packages to be scheduling between games based on traveler preferences (budget, interest, geographical range, etc.). To the best of our knowledge, this is the first study that intertakes the planning of touristic itineraries around sports mega-events. We also develop an innovative matheuristic method, called Consensus-based Kernel Search, that efficiently solves the resulting touristic package selection problem.

The main contributions of this paper can be summarized as follows:

- We introduce a new decision problem arising in the context of touristic package offering.
- We model it as a Nested Multi-Dimensional Multi-Knapsack Problem with Conflicts, which has never been studied previously in the literature, and we provide a mathematical formulation for its solution.

- The proposed model not only describes the application under study but can also be applied to other contexts such as portfolio optimization and retail management.
- We propose a new matheuristic framework that introduces, for the first time, the concept of consensus in the context of touristic package selection. Our approach is easy to generalize for other applications and is specifically suitable for addressing broad classes of stochastic and bi-level problems.
- We compare our matheuristic with the classical Kernel Search and show that it systematically provides better solutions for our problem.
- We perform a sensitivity analysis in order to study how the instances' parameters influence the difficulty of solving the problem.

The paper is organized as follows. We summarize the relevant literature in the next section. In Section 3, a formal definition of the problem is given, alongside our suggested knapsack-based model. Section 4 will be devoted to the description of our solution method. Our computational analysis is summarized in Section 5, and finally, some concluding remarks and future avenues of research are presented in Section 6.

2. Literature Review

The topic of this paper finds its root in two different streams of research. The first one is related to the interdisciplinary field of sport tourism, which succeeded in attracting an increasing attention as an independent topic of research during the last few decades (Daniell (2013)). However, according to Dhahir et al. (2019), the integration of tourism planning will be extremely significant in the development of sports tourism. Therefore, it is necessary to consider tourism planning in terms of the tour packages offered by tour operators and create itineraries to satisfy the need of tourists in order to improve sport tourism. The topic of touristic packages for itinerary planning has flourished as a separate research stream in the last few years, and the issue has been modeled by many researchers as a knapsack problem, a modeling approach that has been intensively and efficiently used in the context of touristic itinerary planning.

2.1. Sport Tourism

According to Csoka et al. (2019), sport tourism can be defined as “any travelling that is done to participate in a sporting event – including just watching”. The authors also claimed that sport tourism constitutes an increasingly growing segment of the tourism industry and, more generally, the global economy. For example, in 2008, more than 55 million people from the USA travelled to participate in a sporting event, which resulted in revenue growth of 6.6% with respect to 2007 and 31% with respect to 2003 (Daniell (2013)). Csoka et al. (2019) reported that sports tourism was a business worth USD 15.8 billion in 2016 and is expected to quadruple in the upcoming years.

Weed (2006) has identified three main stakeholders with a major role in sports tourism: participants, policy-makers, and package providers. This work is focused on package providers, who need to offer attractive touristic packages. Within this context, Weed and Bull (2012) proposed a sport tourism diagram that correlates the level of participation in sports events with the level of importance assigned to the trips by travelers. The graphical depiction of the model (Figure 1) shows how the level of participation increases with the importance assigned to the corresponding trip. The same graph allocates different names characterizing the increasing level of commitment towards sports events and even identifies participants with negative importance, i.e., those who attend the events only as companions.

Football spectators are placed in the highest zone of the participation-importance triangular model. With reference to the sports tourism literature, football fans are classified as committed and even regarded as driver participants, to the point that they are sometimes resembled to religious devotees (Weed (2006)). They are increasingly willing to support their teams even beyond their local and regional boundaries. An example of such commitment can be seen in the English Premier League, that attracts not only a huge television audience worldwide but also eight-hundred thousand international visitors annually. Moreover, statistics confirm that sports tourists who include a football game in their touristic plan stay longer in the UK compared to other tourists (Rudkin and Sharma (2020)). This has been obtained by applying a quantile regression model to investigate the effect of attending live football games on the total expenditure by sports tourists. While the employment of quantitative approaches is very rare in the context of sports tourism, scholars have dealt with many other topics of research such as developing conceptual consensus on sport tourism (Daniell (2013)), achieving sus-

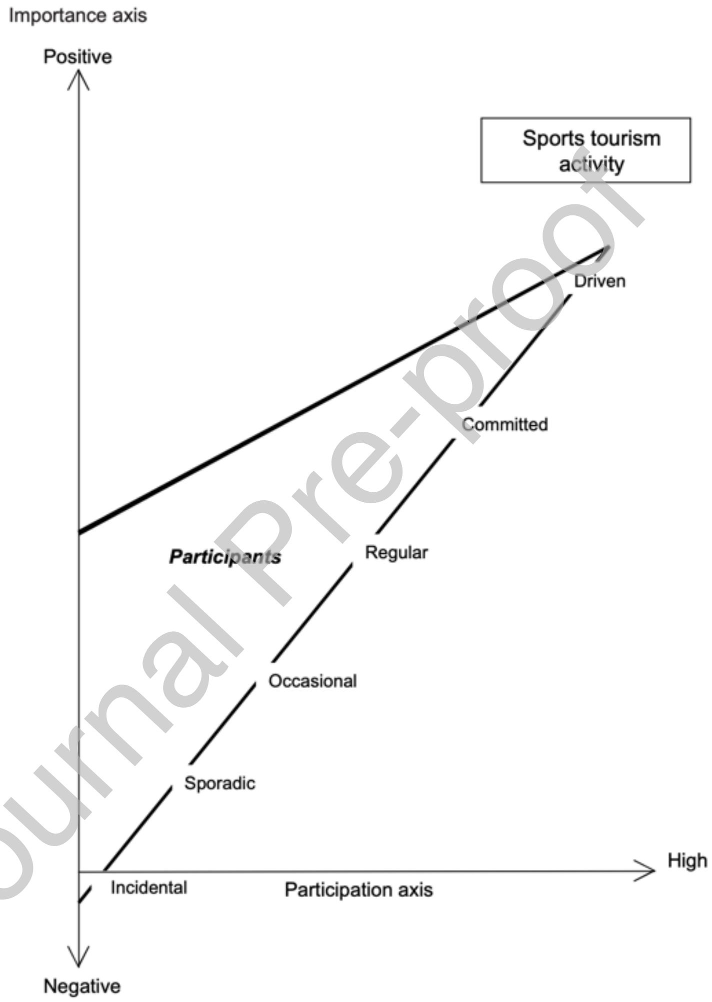

Figure 1: The Sports Tourism Participation Model (from Weed and Bull, 2012)

tainability while organizing sports events (Kersulic et al. (2020)), exploring country-oriented behavior in sports tourism (Swart (1998); Xia et al. (2013); Wickramaratne and Kumari (2016); Csoka et al. (2019)), studying the relationship between sports tourism and tourism management (Daniell (2013)), examining corporate social responsibility within sport tourism (Heuwinkel and Bressan (2016)), analyzing the social impact of organizing large scale sporting events (Kim et al. (2015)) and so on. The most relevant paper related to our study by Dhahir et al. (2019), who studied the importance of tourism planning in the development of sports tourism and boosting of the organizing country's economic growth. However, to the best of the authors' knowledge, neither this paper nor any other work has explored the use of optimization techniques/models to plan touristic packages surrounding sports mega-events.

2.2. Knapsack Problem

The Knapsack Problem (KP) is one of the most widely investigated problems in the field of optimization techniques due to its ability to represent and solve complex real-life issues (Wilbaut et al. (2008)). Given a set of composite items, with each item having its own weight and profit, the goal of the classical knapsack optimization model is to load a set of possible items into the knapsack such that the total profit of the selected items has the maximum value while respecting the weight knapsack capacity. For a review on the exact and heuristics methods used for the KP we refer the readers to Kellerer et al. (2004) and Martello and Toth (1990). Moreover, the 0–1 KP with single and multiobjective versions is a well-studied combinatorial optimization problem (Erlebach et al. (2002); Lust and Teghem (2012)). Research has shown that the multiobjective variant of the problem is much harder to solve than the single objective problem (Kumar and Banerjee (2006)). Various effective solution approaches have been proposed to solve the multiobjective version of the problem (Sato et al. (2007); Bazgan et al. (2009); Gao et al. (2014); Kantour et al. (2019)).

Among the many variants of the KP, the most well-known extensions are the Multiple Knapsack Problem (MKP), Multiple Choice Knapsack Problem (MCKP) and the Multi-Dimensional Knapsack problem (MdK), which have received considerable attention from the operational research community in the last decades. For surveys on these problems, we refer the readers to Dell'Amico et al. (2019), Zhong and Young (2010), and Fréville (2004). In an MKP, multiple knapsacks are available, each with a possibly different capacity. The goal is to determine a list of items to select from and assign them to knapsacks in order to maximize the total collected profit, while respecting the capacity constraint. In an MCKP, a set of items is partitioned into categories and exactly one item must be picked per category. This means that an MCKP adds additional constraints that prohibit the inclusion of an item in the solution set if another item of the same category is selected (Nauss (1978)). In the MdK, items are instead characterized by two or more dimensions (e.g., weight, volume, etc.), and the knapsack has a limited capacity for each dimension. These problems find application in several fields, such as logistics, finance and so on. Several variants of MKP, MCKP and MdK have also been studied in the past (Tönissen et al. (2017); Lahyani et al. (2019); and Meng et al. (2019)). However, for brevity, we focus our attention on that which are closer to our problem.

An extension of the MdK, considering assignment constraints between items and knapsacks was introduced by Kataoka and Yamada (2014), and efficient algorithms to solve it have been proposed in Martello and Monaci (2020). A robust version of the multiple choice multidimensional Knapsack problem (MMKP) was introduced in Caserta and Voβ (2019). Recently, Lamanna et al. (2021) proposed a two-phase heuristic framework to solve the MMKP. Another variant of the KP close to our interest is the Nested knapsack, which addresses situations where items must be loaded into a knapsack and successively packed into disjoint compartments within it (Johnston and Khan (1995)). Despite its practical relevance in logistics, this problem has received limited attention in the literature compared to other more popular KP variants. The issue of mutual exclusivity of items in KPs has been broadly addressed. Many exact and heuristic algorithms have been proposed to handle this feature, among which we cite Bettinelli et al. (2017) and Basnet (2018). Nested MCKP is the generalized form of MCKP where several resource constraints are nested across the multiple choice classes. Last, but not least, literature on KPs involving families of items is particularly rich. We cite the paper by Mancini et al. (2021), which reports an application in resource management of distributed computing, as well as all the references therein.

2.3. Touristic Packages and Itinerary Planning

The other stream of research that is of great relevance to our topic is the selection of touristic packages for itinerary planning. Several works have been published in this vein, including Souffriau et al. (2011), Malucelli et al. (2015), Maimani et al. (2016), Tricoire et al. (2016), Mancini and Stecca (2018), Pan and Wang (2018), Exposito et al. (2019), and Zhou et al. (2019). An insightful review of the models and methods adopted for designing touristic packages can be found in the recent paper by Yochum et al. (2020). However, we will focus here on the approaches based on the use of knapsack models that will be adopted in this study. Several researchers have modeled the touristic package generation problem as a special case of the KP and have sometimes combined it with the Traveling Salesman Problem (TSP) modelling features (Herzog and Worndl (2014); Nakamura and Shimbo (2016); Deolekar et al. (2019), etc.).

More specifically, Liu and Chen (2008) proposed a two-step procedure to develop a tour plan. In following this procedure, first, the touristic spots are selected using the 0-1 KP, and the tour route is then developed using a spanning tree-based Genetic Algorithm (GA). Picot-Clemente et al. (2012) presented the tour planning problem as an MMKP. Given the complexity of the MMKP, Khalili-Damghani et al. (2013) solved it by using a combination of Simulated Annealing (SA) technique and semantic web technologies. Campos et al. (2014) proposed a heuristic method that combines the GRASP procedure with path-relinking methodologies to find approximate solutions to the same optimization problem. Bolzoni et al. (2014) presented the cluster itinerary planning algorithm as a MdKP. The algorithm can recommend tour itineraries with constraints on the maximum number of times each Point Of Interest (POI) can be recommended. Wang and Chen (2015) developed a Decision Support System (DSS) based on a tourism information system, called MAP technology, to achieve a cross-check of space and attribute data and then explore the KP using GAs. Their DSS optimize the travel path inquiry and provide the latest shareable maps for tourists. Cvetkovic et al. (2016) presented a personalized trip planner that can be accessed via a web browser or a mobile application. The planner algorithm is based on implementing concepts related to the TSP and is a suitably modified version of the KP. More recently, Pan and Wang (2018) modeled the tour planning problem as a multi-attribute 0-1 KP. They solved the problem by using the Analytical Hierarchy Process (AHP) and a greedy SA technique. In the first step, the identified spots were evaluated comprehensively using AHP, and then the greedy SA was adopted to select the best spot with the highest evaluation score. Finally, Deolekar et al. (2019) developed an integrated approach that combines a clustering algorithm with the KP to achieve the selection of the best candidate POIs to visit alongside a TSP method to identify the corresponding visit sequence.

From the above literature review, it appears clear that even though optimization techniques have been heavily used to design touristic packages, they have never been implemented in consideration of sports events. This study will bridge this gap and develop an ad-hoc knapsack-based approach for designing touristic packages in combination with major sports events.

3. Problem Statement and the Knapsack-Based Optimization Model

The visitors to Qatar on the occasion of FIFA 2022 World Cup are interested in attending some, but not all, of the football games and will be willing to take some trips between the games. The goal is, then, to provide the best touristic package combination based on user preferences. A set of available slots K is defined (Figure 2). Each slot between two consecutive games, k, is identified by its length, which is expressed in days, D_{uk} (depending on the specific games schedule of user u). A set of users, U, composed of N_u users is considered. Each user, u, gives his/her total budget B_u, which can be arbitrarily split across all the slots, and his/her preferences, expressed as level of interest, p_{uc}, for each activity category, c, from a set of categories, C (i.e., historical sites, cultural sites, religious sites,, beaches, nature, sports excursions, children's entertainment, relaxation and so on.) Each user can also provide a list of neighboring countries (or geographical areas) that they are not interested in visiting (because they have already visited them or because it is difficult to obtain entry visas). Thus, we introduce here a constant $w_{ua} \in [0, 1]$ for all countries a in the set of countries A to express the willingness of user u to visit a country or not (w_{ua} gets closer to 1 when the willingness increases). A set of touristic packages, I, is available. For each package, i, included in I, we know the destination country (or geographical area), α_i, the duration expressed in days, d_i, the purchasing cost, b_i and a score related to each category c, σ_c^i. The touristic operator can choose, from among the set of available packages I, a subset P composed of at most N_p packages, to offer to the user. Each user can select the combination of package, from among those offered by the operator that maximizes their collected score while respecting their own time and budget constraints. Packages must be assigned to one and only one slot, but a slot can contain more than one package, if they fit. Furthermore, only one package for a country/area can be picked by each user. (For example, if a user goes to Egypt in the first slot to visit the Pyramids, it does not make sense for them to, after coming back to Doha to watch a football match, visit Egypt again to see the Reef Barrier. It is better for them to stay longer in Egypt and choose a package that includes both the Pyramids and the Reef Barrier. Moreover, a mutual exclusivity holds for certain pairs of packages, i_1 and i_2, represented by a constant $h_{i_1 i_2}$, assuming a value of 1 when $i1$ and $i2$ are mutually exclusive and 0 otherwise. This exclusivity constraints model cases in which two very similar experiences are offered in different packages (i.e. scuba diving excursion in the Reef Barrier) and even a user who is very interested in such an experience would not perform it twice, preferring to spend their time in different activities.

The overall goal is to choose the combination of packages, P, that maximizes the average score collected by the users (3). The score perceived by user u while selecting package i is given by the sum of the scores obtained by i in each category c, σ_c^i, weighted by the preference level expressed by the user for this category, p_{uc}. The final score of user u is then obtained by multiplying this value with the times his/her willingness to visit the regional area, α_i, associated with package i, $w_{u\alpha_i}$. The score perceived by user u for each package i is computed as $s_{ui} = \sum_{c \in C} p_{uc} * \sigma_c^i * w_{u\alpha_i}$. This allows for a realistic representation of the fact that the perceived score of a package is clearly based on package features and attractiveness but can sensibly vary among users depending on their interests. Furthermore, the total score of user u collected for a given category c must be greater than or equal to a minimum value l_{uc}, which is equal to the level of interest shown by the user in this category, p_{uc}, multiplied by a given constant f. With the term *user*, we do not refer to a specific person but rather to a user profile with a predefined set of characteristics such as category preferences and budget.

3.1. Nested Structure of the problem

As discussed in Subsection 2.2, there are many variants of KP. Based on the discussion in Section 3, our problem can be modeled as a Nested Multi Dimensional Multiple Knapsack Problem with Items Compatibility (N-MDMKP-IC), which is an extension of the Multiple Knapsack, Multi-Dimensional Knapsack, Knapsack with Items Incompatibility and also of Nested Knapsack. In N-MDMKP-IC, items are grouped into families and there are further constraints limiting the maximum number of items, belonging to the same family that can be simultaneously selected. Although these problems have been separately studied in the literature, all these features

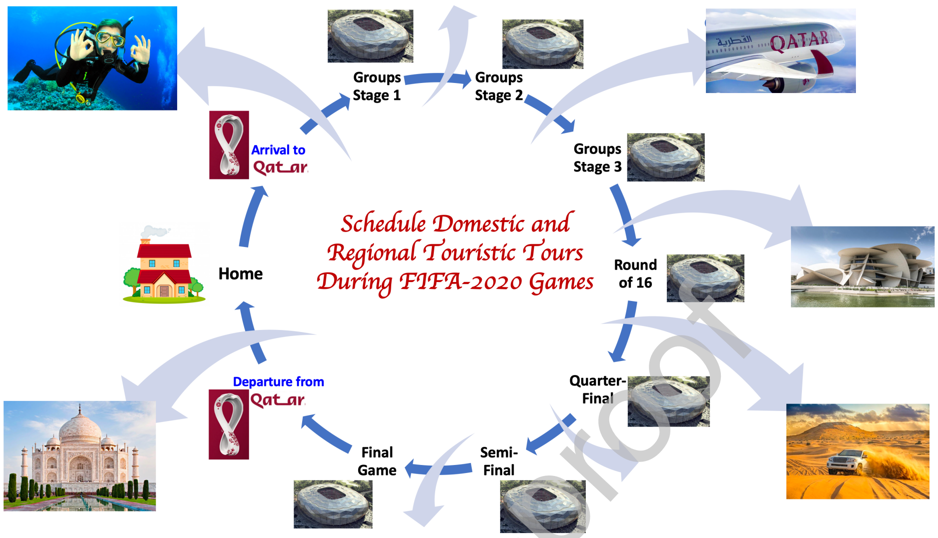

Figure 2: Touristic Packages Scheduling during FIFA-2022 Games

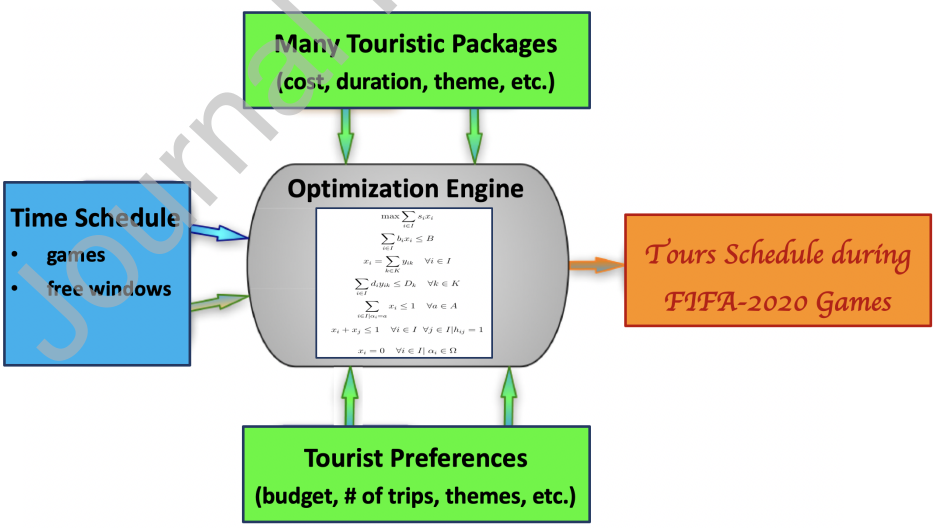

Figure 3: Input and Output of the Optimization Framework

have never been addressed together within the same optimization framework. Therefore, the problem we introduces is innovative and fills a gap in the literature in the context of KP extensions. Regarding its computational complexity, since the N-MDMKP-IC is a combination of problems that have already been proved to be *NP-Hard*, consequently it is *NP-Hard* too. In our N-MDMKP-IC, items represent touristic packages, while knapsacks are the available slots between two consecutive matches. The problem is multi-dimensional, since each item is characterized by two dimensions: cost and duration. It is a three-level nested problem in which the items must be inserted in a first knapsack representing the subset of items chosen to be offered by the touristic operator, characterized by only one dimension, i.e., the number of items. Then, this problem is connected to N_u nested knapsack sub-problems, one for each user. Each of these sub-problems is composed of a first knapsack representing the total excursion plan for the user, which is characterized by a maximum budget and a maximum duration. Within these constraints items must be partitioned into several mono-dimensional knapsacks, characterized by potentially different durations (expressed in number of days). Each user's sub-problem also considers mutual exclusivity between pairs of items. Furthermore, the problem is similar to the Multiple Choice Knapsack Problem, except for the fact that one item per category can be selected at most in the former while, in the latter, exactly one item per category must be picked. The nested structure of the problem is illustrated in Figure 4.

3.2. Integer Programming Model

In order to facilitate the reader to become familiarized with the notation, we reported in Table 1, the set of variables and parameters indexes.

$K = 1, ..., N_k$	set of time slots
$I = 1, ..., N_i$	set of available packages
$C = 1, ..., N_c$	set of categories
$U = 1, ..., N_u$	set of user profile

Table 1: List of sets of variables and parameters indexes

Moreover, we define the following decision variables:

- x_{ui}: binary variable stating whether package i is selected by user u or not

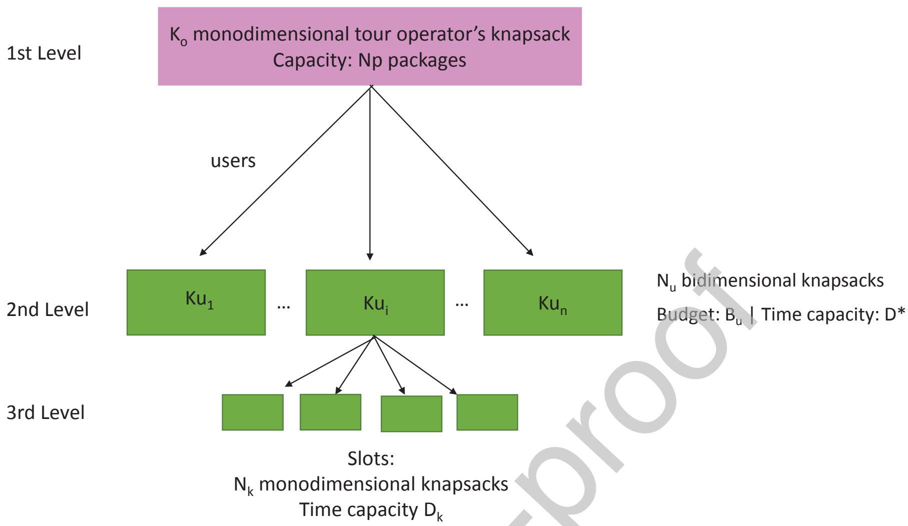

Figure 4: Illustration of the nested structure of N-MDMKP-IC

- y_{uik}: binary variable stating whether package i is assigned to slot k by user u or not
- z_i: binary variable stating whether package i is offered by the touristic operator

$$\max \sum_{u \in U i \in I} s_{ui} x_{ui} / N_u \tag{1}$$

$$\sum_{i \in I} b_i x_{ui} \leq B_u \quad \forall u \in U \tag{2}$$

$$x_{ui} = \sum_{k \in K} y_{uik} \quad \forall u \in U \quad \forall i \in I \tag{3}$$

$$\sum_{i \in I} d_i y_{uik} \leq D_{uk} \quad \forall k \in K \quad \forall u \in U \tag{4}$$

$$\sum_{i \in I | \alpha_i = a} x_{ui} \leq 1 \quad \forall a \in A \quad \forall u \in U \tag{5}$$

$$\sum_{i \in I} \sigma_{ic} x_{ui} \geq f p_{uc} \quad \forall c \in C \quad \forall u \in U \tag{6}$$

$$x_{ui} \leq z_i \quad \forall i \in I \quad \forall u \in U \tag{7}$$

$$\sum_{i \in I} z_i \leq |P| \quad \forall i \in I \tag{8}$$

$$x_{ui} + x_{uj} \leq 1 \quad \forall i \in I \ \ \forall j \in I | h_{ij} = 1 \quad \forall u \in U \tag{9}$$

The objective function aims to maximize the average score collected by the users. Constraint 2 imposes a maximum cumulative budget on all the slots, which is potentially different for every user. Constraints 3 state that, if a package is selected, it must be assigned to exactly one slot. Constraints 4 ensure that time capacity, expressed in days, is respected for each slot of each user. Constraints 5 imply that each user can select one package at most for each geographical area, while constraints 6 ensure that a minimum score is achieved in each category by each user, depending on user preferences and interests. Constraints 7 ensure that a user can select a package only if it has been offered by the operator. The number of packages that can be offered is bounded by constraints 8. Finally, mutual exclusivity between packages is modeled through constraints 9.

4. Solution Approach: A new Kernel Search-based matheuristic

Kernel Search, (KS) is a very effective general purpose matheuristic introduced by Angelelli et al. (2010). The algorithm can be applied to a broad class of 0/1 decision problems, where the decision-maker has to choose among a very large set of options, for instance, the KP and all its variants. It is based on the idea of identifying a small subset of potentially good variables, called kernel, and partitioning all the others into disjoint buckets. At each iteration of the algorithm a different bucket is picked and a restricted version of the original problem, involving only those variables belonging to the kernel and the selected bucket is solved. The restricted problem can be solved optimally, or run with a timelimit. If some of the variables belonging to the bucket are active in the optimal (or best found) solution of the restricted problem, they are permanently added to the kernel. The algorithm is terminated when all the buckets have been explored. The general KS framework is characterized by three main features: (i) the rule according to which the variables are inserted in the kernel, (ii) the number of buckets, their size and the rules according to which variables are partitioned into buckets, and (iii) the updating mechanism for the kernel. In the basic version of KS introduced in Angelelli et al. (2010), the linear relaxation (LP) of the model is exploited to identify the initial kernel, which is composed as a set of variables, N, given by the $|N|$ variables with the highest values in the optimal solution of the LP. The remaining variables are sorted in a non-decreasing order by the value they assumed in the optimal solution of the LP. The kernel size is always non-decreasing, i.e., new promising variables can be added to the kernel but no variables are removed from it.

The basic KS was applied, obtaining very good performances, on different combinatorial optimization problems such as multi-dimensional knapsack problem, (Angelelli et al. (2010)), portfolio selection problem, (Angelelli et al. (2012)), the capacitated facility location problem, (Guastaroba and Speranza (2012b)), and the multi-plant lot sizing problem with setup carry-over (Carvalho and Nascimento (2018)). Guastaroba and Speranza (2012a) proposed a variant of the KS, named *Improved Kernel Search* (IKS) that starts performing the Basic Kernel Search (BKS) and exploits information about the desirability of each variable to identify the most promising ones. All the improving solutions found by the BKS are analyzed, and the variables that are selected in a great percentage of the solutions are marked as promising, since the probability that they will also be selected in the optimal solution is very high. Subsequently, a MILP problem considering all the variables is solved, forcing the selection of the most promising variables setting the corresponding binary variables equal to 1. The authors successfully applied the IKS to the index tracking problem. A bi-objective version of the same problem was successfully addressed with KS in Filippi et al. (2016). Another variant of the BKS, named *Adaptive Kernel Search*, AKS, was presented in Guastaroba et al. (2017). According to this method, once the subproblems become hard to be solved within short computational times, due to the large size of the kernel, a kernel update procedure is applied, whereby variables that have not been recently selected in the optimal solution of the subproblems are excluded from the kernel. The aim of this operation is to reduce the size of the kernel by dropping less promising variables. The authors showed the effectiveness and efficiency of the AKS on a set of benchmark instances taken from different well-known combinatorial optimization problems. More recently, KS has been successfully applied also to bi-level programming problems, such as in

Santos-Penate et al. (2020), where the leader-follower location problem was addressed.

4.1. A New Consensus KS Method

All the KS versions published in the literature start from an initial solution based on the Linear Relaxation of the problem. Although this may be advantageous for some families of problems, there are other families for which the LP optimal solution greatly differs from the optimal solution of the original problem. In these cases, the convergence toward good quality solutions can be slow, as the search process starts from a very bad kernel. To overcome this shortcoming, we propose, in this paper, a new KS version, named Consensus-based Kernel Search (CKS), in which a different rule, based on consensus, is adopted to choose the variables to insert in the initial kernel, as well as to partition the remaining variables in buckets. This approach is not only suitable for addressing this specific problem but can also be adopted to address all problems sharing a similar structure. Among these, we can cite two-stage stochastic problems, where the value assumed by the first stage variables impact the solution of the second-stage for each scenario, as well as bi-level programming problems and problems in which the values assumed by a subset of variables act as input for a set of correlated sub-problems. More specifically, the Nested Multiple Knapsack Problem with Item Conflicts is suitable to describe portfolio problems in which a financial promoter has to provide, by choosing from a huge number of alternatives, a set of investments to the customers. Subsequently, each customer can select the most appropriate combinations of investment for their portfolio, based on their own budget, risk aptitude, and other characteristics. Item conflicts can represent cases in which the number of investments of a certain category is limited by certain financial rules. Another potential application could arise in the retailing industry. In fact, this model can be used to describe the problem faced by an owner of a store (retailer) who has to select a subset of items to order, among a huge number of options from various brands. Their objective is to attract different types of users to the store and to maximize the total profit.

The idea of *consensus* originated from the idea that a super-optimal solution is obtained when every user can freely choose their preferred packages out of the available packages. Since user preferences and characteristics are potentially very dis-homogeneous, it is very likely that they would select different packages and that the total number of packages selected would exceed the maximum allowed number, P. In this case, the super-optimal solution would turn out to be infeasible, but its value could act as an upper bound for the optimal solution. To move from this infeasible solution to a potentially good feasible solution, we encourage consensus among users in order to select the P packages to be offered. For this reason, the packages with the highest consensus, i.e., the ones that would be selected by most of the user, or the ones that would contribute mostly to the objective function, should most likely be offered. Following this main idea, we developed our novel CKS as described below.

We first solve separately a simplified problem for each user profile, u, which can be formulated as follows:

$$\max \sum_{i \in I} s_{ui} x_{ui} \tag{10}$$

$$\sum_{i \in I} b_i x_{ui} \leq B_u \tag{11}$$

$$x_{ui} = \sum_{k \in K} y_{uik} \quad \forall i \in I \tag{12}$$

$$\sum_{i \in I} d_i y_{uik} \leq D_{uk} \quad \forall k \in K \tag{13}$$

$$\sum_{i \in I | \alpha_i = a} x_{ui} \leq 1 \quad \forall a \in A \tag{14}$$

$$\sum_{i \in I} \sigma_{ic} x_{ui} \geq f p_{uc} \quad \forall c \in C \tag{15}$$

$$x_{ui} \leq z_i \quad \forall i \in I \tag{16}$$

$$\sum_{i \in I} z_i \leq |P| \quad \forall i \in I \tag{17}$$

$$x_{ui} + x_{uj} \leq 1 \quad \forall i \in I \;\; \forall j \in I | h_{ij} = 1 \tag{18}$$

where constraints (11)-(18) play the same role as constraints (2)-(9), respectively. The objective function of this problem is the maximization of the score collected by user u.

After solving the restricted problem for each user, we calculate the contribution of each package, i, to the global objective function, γ_i, as follows:

$$\gamma_i = \sum_{u \in U} s_{ui} x_{ui} \tag{19}$$

Please note that for packages that have not been selected by any user, $\gamma_i = 0$.

We order all the packages by γ_i in a non-increasing order and pick, out of those, the first $|P|$ ones, which contribute mostly to the global objective function, to be inserted in the initial kernel. All the other packages are partitioned into N buckets of homogeneous size. First, they are ordered in a non-increasing order with respect to the potential maximum contribution they can give to the objective function if selected by all the compatible users. This contribution, Γ_i, is computed as follows:

$$\Gamma_i = \sum_{u \in U} s_{ui} \tag{20}$$

Second, they are grouped into N buckets, where each bucket is generated sequentially by selecting $(|I| - |P|)/N$ items from the ordered list.

After defining the initial kernel and the buckets, our solution process adopts the classical KS framework proposed in Angelelli et al. (2010). We solve at each iteration a restricted version of the problem involving only the packages belonging to the Kernel and to a single bucket. If the optimal solution of this problem contains packages from the bucket, they are added to the Kernel for the following iterations. The procedure terminates when all buckets have been taken into consideration, i.e., after N iterations.

It is worth stressing that, even though the consensus method is inspired by the kernel search, it is an innovative and completely different approach since it adopts a different rule for partitioning the buckets. Indeed, the classical Kernel Search groups the variables in buckets, exploiting only information about the solution of the linear relaxation of the problem, while our method is based on the innovative idea of achieving consensus among scenarios (in this case, a scenario is represented by a single user profile). This allows for the exploitation of the information about how to select an item to be included in the first-level knapsack (i. e., the set of packages proposed by the tourist operator) impacts on the objective of each second level knapsack (i. e. the set of packages picked by a single user among those provided by the operator).

A pseudocode of the algorithm is reported in Algorithm 1.

Algorithm 1 CKS pseudocode

1. Solve the problem (10-18) for each user
2. Order the packages in decreasing order of the score obtained solving the problems for a single user
3. Select the first $|P|$ packages from the ordered list, and add them to the Kernel
4. Order the remaining packages by decreasing the potential score achievable if selected by all the compatible users
5. Split this ordered list into N homogeneous buckets

for all $n \in N$ **do**
  6. Solve the restricted problem involving only packages belonging to the Kernel and to the n-th bucket, with a short time limit
  if an improving solution is found **then**
    7. Keep it as current best solution
    8. Add to the Kernel all the packages selected in the current best solution that were not already in the Kernel
  end if
end for

4.2. Fast Upper Bounds

The relaxations used in CKS and KS to identify the initial kernel can also be exploited to provide fast upper bounds. For what concerns KS, the value of the optimal solution of the relaxation of the LP problem provides an upper bound for the original problem. This upper bound coincides with the optimal solution of the original problem, only in the case where the optimal solution of the LP relaxation results to be integer. A fast upper bound can also be obtained exploiting the relaxation used to identify the initial kernel in CKS. If we separately solve a single problem for each user, allowing the user to choose among all the packages, we can obtain an upper bound for the global problem since constraints 8 could be violated. In fact, if we allow each user to freely choose the most profitable items for them, we could come up with more than $|P|$ items selected. In this case, the solution value provided by the relaxation is an upper bound of the optimal solution, while, in case the number of packages selected is lower than or equal to $|P|$, this solution is optimal for the original problem as well. It is worth noting that while the optimal solution of the LP relaxation may potentially violate all the constraints of the original problem, the solution provided by solving the problem separately for each user can only provide an infeasibility for constraint 8, while all the other sets of constraints would be respected.

5. Computational Experiments

In this Section, we report the computational results obtained on instances with different number of packages (N_i) and geographical areas (N_a). Since this particular version of the KP is addressed for the first time in this paper, no benchmark instances are available in the literature. Hence, we generated 8 sets (S1-S8) composed of 5 instances each. Each set is characterized by a different combination of N_i and N_a, as shown in Table 2. The number of packages to be selected, $|P|$ and the number of users profiles Nu, are homogeneous across all instances and assume values equal to 20 and 10, respectively. We made this choice since those two parameters are generally fixed in a real application. The number of packages to be offered depends on organizational constraints, and a touristic company faces fixed costs when offering a package, even if no users select it. Therefore, on the one hand, the company would like to offer a rich portfolio of alternatives to its customers, but, on the other hand it must limit the organizational costs and useless efforts. With respect to the number of user profiles adopted, we believe that 10 is a sufficient number to cover a representative sample of user typologies. The number of score categories $|C|$ is fixed and equals to 5, while the number of knapsacks, i.e., the available slots for traveling, $|K|$, is given by the regulations of the World Cup, and it is equal to 8, as shown in Figure 2. In fact, the maximum number of matches a team can play during the competition is 7: three mandatory matches at the group stage, round-16, quarter-final, semi-final, and final. Therefore, a user would have 6 small-sized periods (3-5 days) between consecutive matches in addition to two longer ones, before the first match and after the last match.

All the instances have been generated according to the following procedure. For each user profile, the attractiveness of each category is a randomly generated integer number between 0 and 5. The attractiveness of a country (or geographical area) is equal to 1 with a probability of 80%, and a random value between 0 and 0.9 with a 20% probability. Values are rounded at the first decimal digit. The budget value is randomly selected between 5000 and 30000, considering only multiples of 1000. Concerning the packages, (i) we

SET	N_i	N_a
S1	100	10
S2	100	20
S3	200	20
S4	200	40
S5	500	20
S6	500	50
S7	1000	50
S8	1000	100

Table 2: Instances sets

consider the same number of packages for each geographical area, (ii) duration is randomly drawn between 2 and 7, (iii) costs are correlated with the duration, and are computed as "r1*100*duration+200", where r1 is an integer number that is randomly drawn between 0 and 4, (iv) scores for each category are correlated to the duration and are computed as "r2*(duration-1)" with r2 being an integer number that is randomly chosen between 0 and 10.

We compare the results obtained by the Integer Programming Model presented in Section 3.2, simply referred to as *MODEL* here onward, a traditional Kernel Search approach (KS) and the newly proposed Consensus based Kernel Search, (CKS).

All the procedures have been implemented in the Xpress-Model language, and both the MODEL and the IP models addressed in CKS and KS have been solved by means of the commercial solver Xpress 7.9, running on a system equipped with an Intel-i7-5500U processor with a 2.4 GHz clock speed and 16 GB RAM. For both KS and CKS, a number of buckets, N=10, have been used in all the computational tests. This parameter has been tuned based on the preliminary tests.

Our results are summarized in Table 3, which is organized as follows. Each row reports the average results for a different set. For the MODEL, we report the optimal objective function value, the optimality gap, and the computational time (expressed in seconds) required to solve the instance to optimality. For both CKS and KS, we report the best objective function value obtained, the gap with respect to the optimal solution value, the time elapsed, and the size of the final kernel, i.e., the number of packages belonging to the kernel after the last iteration. This number gives a measure of the quality of

			MODEL			CKS				KS			
SET	N_i	N_a	OF	OPT GAP	TIME	OF	GAP	TIME	—KERNEL—	OF	GAP	TIME	—KERNEL—
S1	100	10	3322.64	0.00%	60.64	3310.54	0.37%	25.83	26.80	3298.34	0.73%	20.67	46.40
S2	100	20	3926.30	0.00%	301.79	3893.06	0.86%	39.86	27.20	3883.38	1.10%	36.13	43.80
S3	200	20	4151.56	0.00%	240.71	4113.60	0.90%	50.99	27.60	4105.30	1.12%	44.36	45.00
S4	200	40	4284.42	0.00%	168.56	4270.62	0.33%	52.50	25.80	4253.72	0.72%	41.34	42.00
S5	500	20	4436.20	0.00%	383.97	4396.00	0.89%	96.60	34.20	4372.98	1.42%	91.55	52.00
S6	500	50	4873.22	0.00%	1801.30	4838.46	0.70%	106.63	26.00	4828.50	0.91%	104.61	43.60
S7	1000	50	4831.90	0.00%	2122.94	4820.68	0.23%	131.43	37.00	4711.62	2.49%	105.28	49.80
S8	1000	100	4895.74	0.00%	1905.61	4873.94	0.45%	133.45	27.80	4813.24	1.68%	103.16	45.40
AVG			4340.25	0.00%	873.19	4314.61	0.59%	79.66	29.05	4283.39	1.27%	68.39	46.00

Table 3: Comparison among MODEL, CKS, and KS

the initial solution and of the performance of the algorithm throughout the iterations. The larger this number is, the larger is the number of items that, if added to the initial kernel, improved the solution. A lower value means that the initial kernel already contained most of the items belonging to the optimal solution. Conversely, when the final size of the Kernel is large, it means that several items belonging to the optimal solution were not included in the initial kernel.

Both CKS and KS show excellent performances obtaining solutions that are, on average, only 0.59% and 1.27% far from the optimum. As reported in Figure 5, CKS systematically outperforms KS on all instances sets. The effectiveness of CKS is not significantly affected by the size of the instances, which is a very strong feature of the method. On the other hand, a slight worsening in the performance of KS can be noted with an increase in the number of packages involved in the instances. All these aspects make CKS remarkably preferable from an effectiveness point of view. The average computational times are slightly lower for KS (68 secs) with respect to CKS (79 secs), but both methods are more than 10 times faster than the MODEL. As can be evinced from Figure 6, the growth of computational times, with the increase of instance sizes, is very limited for both CKS and KS, while it is huge for the MODEL. This shows that both the proposed heuristics are very efficient.

Moreover, it is interesting to see how the average size of the final kernel is greatly lower for CKS (29 items) with respect to KS (46 items). This means that most of the elements selected in the initial kernel of KS are not part of the optimal solution, i.e., the rule according to which the initial kernel is constructed, is not performing well in the case of KS. Conversely, the final kernel of CKS contains only 29 items (with respect to the 20 of the initial kernel), proving that the newly presented consensus-based approach

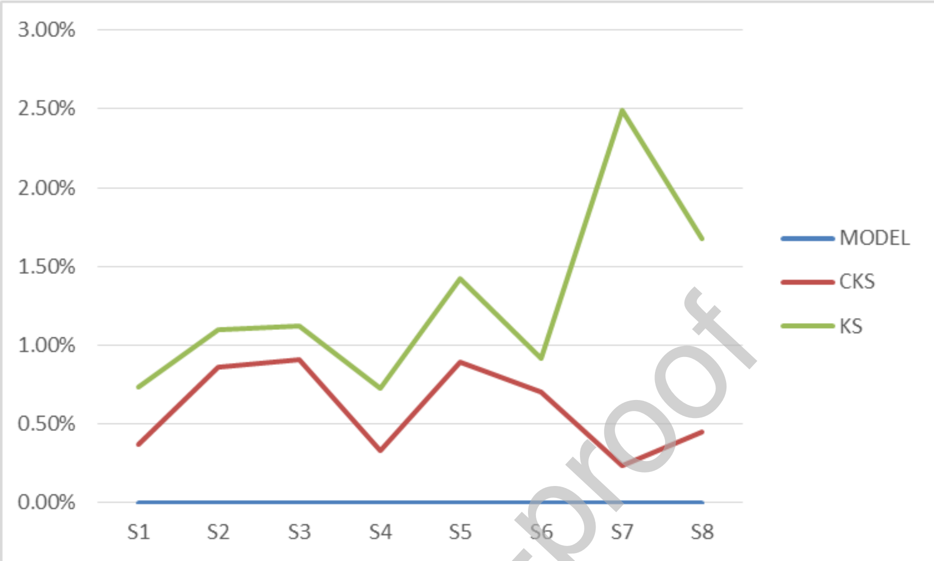

Figure 5: Optimality gap for MODEL, CKS and KS

is capable of generating a much better initial kernel. This fact is particularly evident in the small instances (S1 and S2) with 100 packages, for which KS needs to consider almost half of the items in the kernel in order to find the best solution (46 items), while only 5 items are added to the initial kernel by CKS to find the best solution, which is by far better than the one obtained by KS. In Figure 7, we compare the solution value obtained considering only the items belonging to the initial kernel of CKS and of KS. CKS systematically obtains much better initial solution values, confirming that the consensus-based strategy is more effective in identifying the most promising items that should be included in the initial kernel compared to the traditional strategy based on the LP relaxation of the problem that is normally adopted in the KS. Our last experiment consists in comparing the upper bounds that can be computed starting from the relaxation used, in CKS and KS, to determine the initial kernel, as explained in Section 4.2. Even in this case, CKS performs much better than KS, providing much tighter upper bounds, as shown in Figure 8. Finally, we show, in Figure 9, the percentage gaps between the initial solution value and the upper bound, both for CKS and KS. This gap is around 10% on average for CKS, whereas it is around 40% for KS, showing

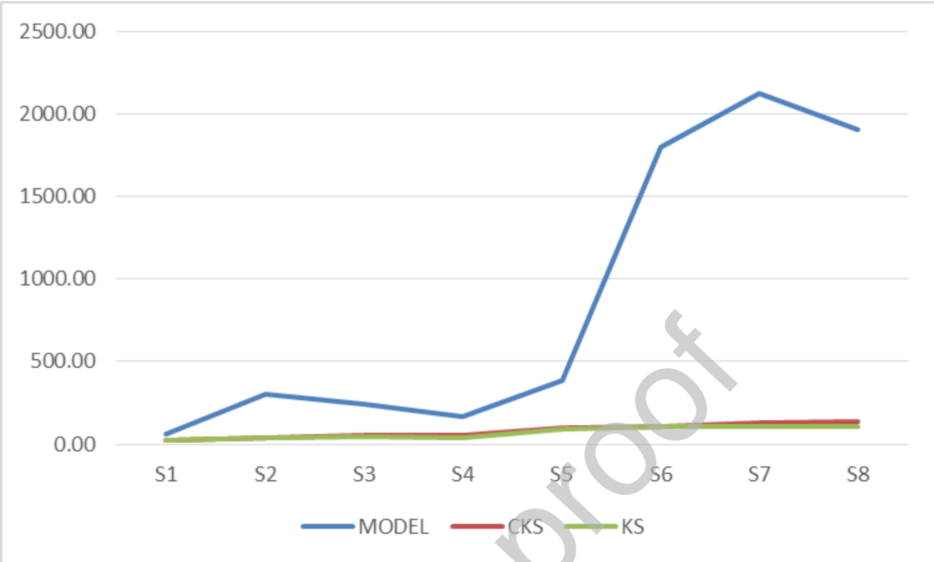

Figure 6: Computational times for MODEL, CKS and KS

once more that CKS is highly preferable over KS.

5.1. Analysis of the Impact of the Number of User Profiles

All the previous sets of instances (S1-S8) considered a fixed number of users profiles N_u, equal to 10. In order to analyze the impact of this parameter on the level of challenge of the instances, we generated 4 additional sets having 5 instances each, namely S9-S11. All the new instances have the same characteristics of S2 in terms of N_i and N_a but an increasing number of users profiles N_u, namely 20, 30, and 50.

In Figure 10, we report, the gap with respect to the best upper bound obtained by the MODEL within 3600 seconds of computation, for the best solution value obtained by the MODEL, CKS, and KS, at the variation of the number of users N_u. As clearly shown in the graphics, although KS performs only slightly worse respect to CKS on the instances with 10, 20, and 30 users, when N_u grows to 50, the performance of KS deteriorates and the gap rises to 6% compared to the only 0.91% obtained by CKS. This means that when N_u increases, KS is no longer competitive in providing good quality solutions, while CKS performances are only very slightly influenced by this

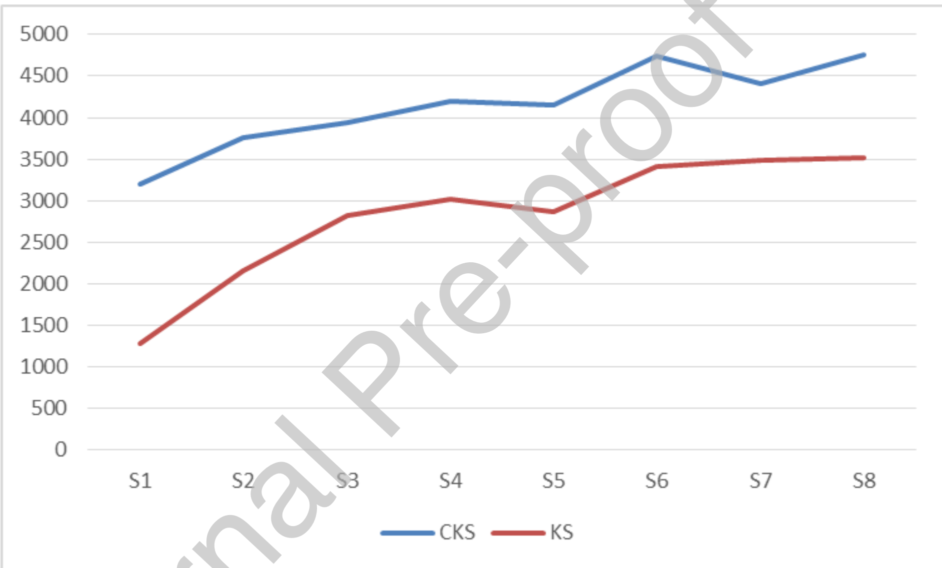

Figure 7: Comparison of the objective function of the solutions obtained considering only the items belonging to the initial kernel of CKS and KS

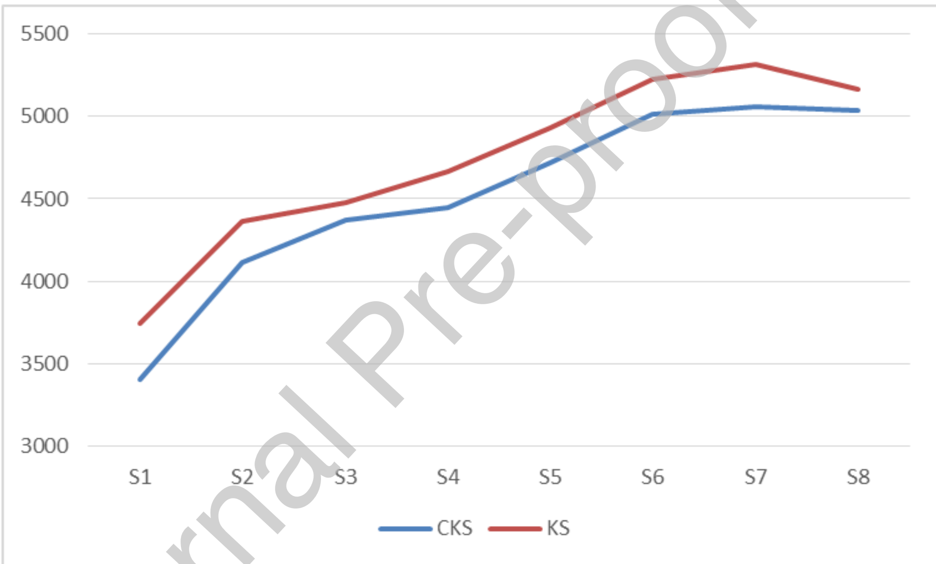

Figure 8: Comparison of the upper bounds obtained exploiting the relaxation used to identify the initial kernel in CKS and KS

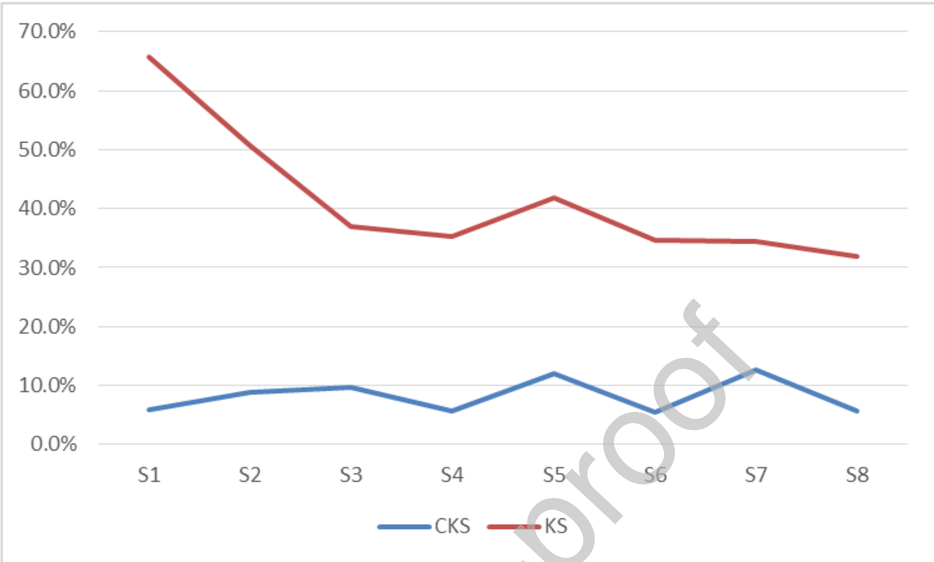

Figure 9: Comparison of gaps between the upper bounds and the initial solutions obtained by CKS and KS

parameter, which makes CKS strongly preferable. In Figure 11, we reported variation computational times (in seconds) with the increment of N_u. We can observe that both KS and CKS are much faster than the MODEL, and for both algorithms, the computational times are very slightly affected by this parameter. On the contrary, MODEL computational times quickly rise with the increasing of N_u. Indeed, MODEL is capable of solving all the instances to optimality within the 3600-second time limit, but this is only with the smaller number of users tested, $N_u = 10$. The very neglectable difference in computational times between CKS and KS, in favour of KS, which results to be slightly faster, does not justify the huge difference in terms of solution's quality observed on the larger instances ($N_u = 50$). Therefore, globally, CKS is strongly preferable over KS, since it provides much better solutions in greatly longer computational times.

6. Conclusion and Future Work

Some studies claim that in sports mega-events, such as Olympic Games or FIFA World Cup, not all visitors are interested in attending the compe-

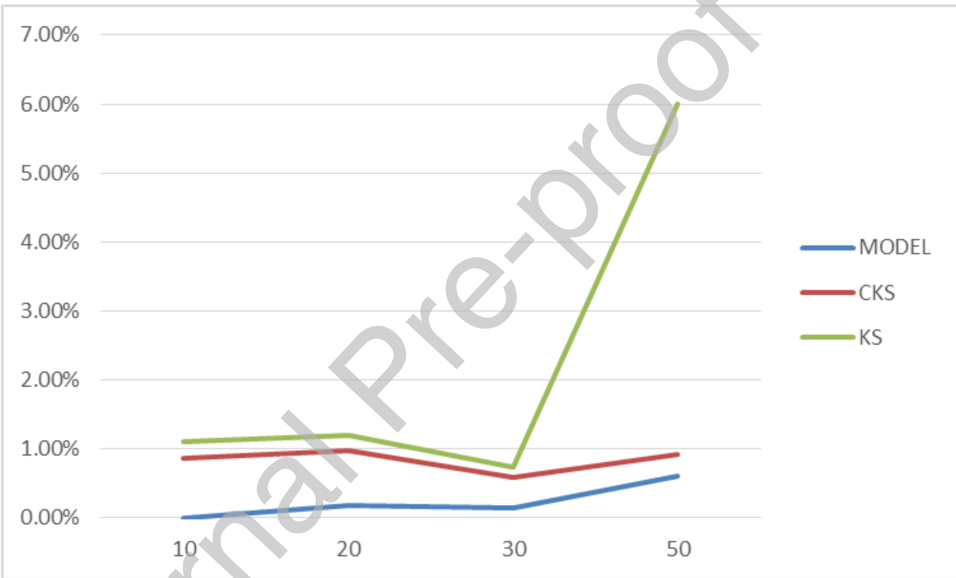

Figure 10: Variation of the optimality gap for MODEL, CKS and KS respect to different number of users N_u

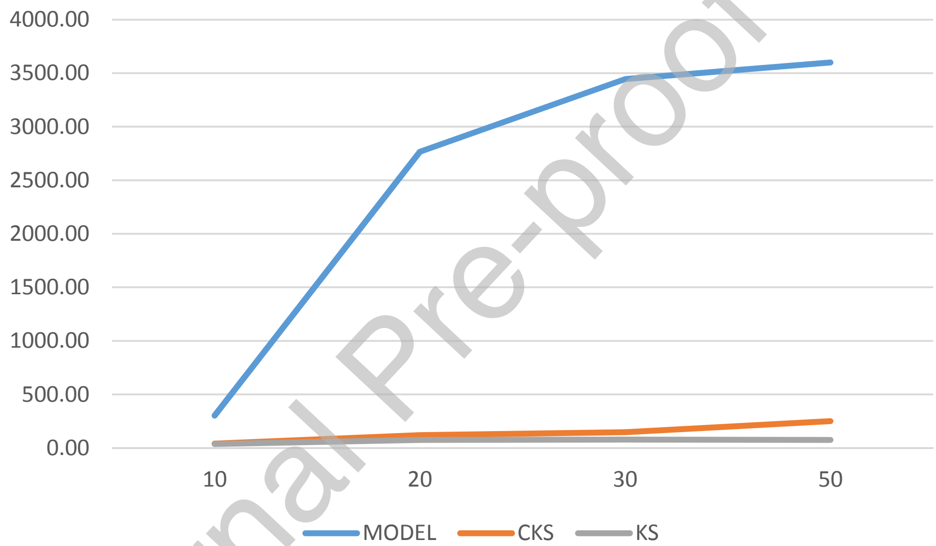

Figure 11: Variation of average computational times required by MODEL, CKS and KS respect to different number of users N_u

tition, but are simply accompanying relatives or friends and exploiting such visits to explore the host country and the surrounding areas. To attract this category of visitors, it is important to provide a set of touristic packages that can amplify their interest in participating in the sports event and can enrich their touristic experience. Moreover, even committed fans are often interested in participating in touristic activities when they are not attending the games. We focus our attention on the upcoming World Cup Qatar 2022. The schedule of the tournament allows small breaks between consecutive matches of the same team. In this case, supporters may have several small breaks (3-5 days) that they can spend travelling around and visiting the host country as well as the neighbouring areas. They may also be interested in planning longer trips before the starting of the tournament and after its conclusion, before getting back to their home countries. In this paper, we study the problem of selecting a set of attractive touristic packages to be offered in the World Cup period. Out of these users can pick the ones that best fit their preferences and their budget. We, therefore, introduce a new combinatiorial optimization problem in which the goal is to select, from a large set of options, a small number of packages that are to be offered to visitors, in order to maximize the average satisfaction among a set of user profiles that are characterized by different preferences and budgets. This problem is modeled as a Nested Multi Dimensional Multiple Knapsack Problem with Items Compatibility, (N-MDMKP-IC). To solve this problem, we provide an integer programming formulation and a matheuristic approach named Consensus based Kernel Search (CKS). In CKS, instead of using the LP relaxation to identify the initial kernel and to group the remaining items in buckets (as in traditional KS), we use a consensus-based rule, aiming at identifying the most attractive items for the users globally. We provide an experimental campaign carried out on instances of different sizes in order to test the performance of the developed matheuristic and to compare it with the traditional KS. Both CKS and KS show excellent performances, providing very good solutions (around 1% from the optimum) in reasonable computational times. We show how the newly proposed version, CKS, systematically outperforms KS in terms of both final solution quality and the provision of a better initial solution. Furthermore, the rule used to search for consensus in order to determine the initial kernel can be exploited to derive a fast upper bound. We show in the computational experiments that this upper bound is much tighter than the one provided by the LP relaxation commonly used in KS. We also discuss that the newly proposed CKS is not only perfectly suited to address this specific problem but can be used as a general framework for solving problems showing a similar structure, such as bi-level and stochastic problems. This work can be extended along several directions. Further methodological development in this field can address the generalization of the CKS approach and its application to other problems, while, from an application point of view, future research could address a bi-level version of the touristic package selection problem. In the bi-level formulation, the goal of the touristic provider would be not to maximize the tourists' satisfaction but rather to maximize their own revenue, based on the fact that users usually select packages that allow maximizing their personal satisfaction.

References

Abeza, G., Boesen, M.Q., O'Reilly, N., Braunstein-Minkove, J.R., 2020. Qatar 2022 world cup: Designing a context-based decision-making approach. Case Studies in Sport Management 9, 7–11.

Angelelli, E., Mansini, R., Speranza, M., 2010. Kernel search: A general heuristic for the multi-dimensional knapsack problem. Computers & Operations Research 37, 2017–2026.

Angelelli, E., Mansini, R., Speranza, M., 2012. Kernel search: a new heuristic framework for portfolio selection. Computational Optimization and Application 51, 345–361.

Basnet, C., 2018. Heuristics for the multiple knapsack problem with conflicts. International Journal of Operational Research 32.

Bazgan, C., Hugot, H., Vanderpooten, D., 2009. Solving efficiently the 0–1 multi-objective knapsack problem. Computers & Operations Research 36, 260–279.

Bettinelli, A., Cacchiani, V., Malaguti, E., 2017. A branch-and-bound algorithm for the knapsack problem with conflict graph. INFORMS Journal of Computing 29.

Bolzoni, P., Helmer, S., Wellenzohn, K., Gamper, J., Andritsos, P., 2014. Efficient itinerary planning with category constraints. In: Proc of SIGSPATIAL-2014, 203-212.

Campos, V., Marti, R., Sanchez-Oro, J., Duarte, A., 2014. Grasp with path relinking for the orienteering problem. Journal of the Operational Research Society 65, 1800–1813.

Carvalho, D., Nascimento, M., 2018. A kernel search to the multi-plant capacitated lot sizing problem with setup carry-over. Computers & Operations Research .

Caserta, M., Voβ, S., 2019. The robust multiple-choice multidimensional knapsack problem. Omega 86, 16–27.

Csoka, L., Gerdesics, V., Torocsik, M., 2019. Sports tourism and sports tourists-the hungarian characteristics of sports related travels. Journal of Tourism Challenges and Trends 12, 47–65.

Cvetkovic, B., Gjoreski, H., Janko, V., Kaluza, B., Gradisek, A., Jurincic, I., Gosar, A., Kerma, S., Balazic, G., Lustrek, M., 2016. e-Turist: an intelligent personalised trip guide. Informatica 40.

Daniell, R.B., 2013. SEC Football Away Game Consumption: The Roles of Motives, Subcultural Identification, Contextual Dimensions and Destination Image in Sport Tourism. PhD Dissertation, University of Tennessee Knoxville.

Dell'Amico, M., Delorme, M., Iori, M., Martello, S., 2019. Mathematical models and decomposition methods for the multiple knapsack problem. European Journal of Operational Research 274, 886–899.

Deolekar, R., Nerurkar, A., Deshpande, S., 2019. An Intelligent System for Tourism Management using k-medoids Algorithm. IEEE 2019 6th International Conference on Computing for Sustainable Global Development (INDIACom), 956-960.

Dhahir, A.M., Hasan, M.M., Abas, M.M., 2019. Role of tourism planning in the development of sports tourism. International Journal of Innovation, Creativity and Change 7, 371–392.

Erlebach, T., Kellerer, H., Pferschy, U., 2002. Approximating multiobjective knapsack problems. Management Science 48, 1603–1612.

Exposito, A., Mancini, S., Brito, J., Moreno, J.A., 2019. A fuzzy GRASP for the tourist trip design with clustered POIs. Expert Systems with Applications 127, 210–227.

Filippi, C., Guastaroba, G., Speranza, M., 2016. A heuristic framework for the bi-objective enhanced index tracking problem. Omega 65, 122–137.

Fréville, A., 2004. The multidimensional 0-1 knapsack problem: An overview. European Journal of Operational Research 155, 1–21.

Gao, J., He, G., Liang, R., Feng, Z., 2014. A quantum-inspired artificial immune system for the multiobjective 0–1 knapsack problem. Applied Mathematics and Computation 230, 120–137.

Guastaroba, G., Savelsbergh, M., Speranza, M., 2017. Adaptive kernel search: A heuristic for solving mixed integer linear programs. European Journal of Operational Research 263, 789–804.

Guastaroba, G., Speranza, M., 2012a. Kernel search: An application to the index tracking problem. European Journal of Operational Research 217, 54–68.

Guastaroba, G., Speranza, M., 2012b. Kernel search for the capacitated facility location problem. Journal of Heurstics 18, 877–917.

Herzog, D., Worndl, W., 2014. A travel recommender system for combining multiple travel regions to a composite trip. CBRecSys@ RecSys 1245, 42–48.

Heuwinkel, K., Bressan, L., 2016. Responsible high performance sports tourism-opportunities and limitations. BEST EN Think Tank XVI: Corporate Responsibility in Tourism: Standards Practices and Policies 269.

Johnston, R., Khan, L., 1995. Bounds for nested knapsack problems. European Journal of Operational Research 81, 154–165.

Kantour, N., Bouroubi, S., Chaabane, D., 2019. A parallel moea with criterion-based selection applied to the knapsack problem. Applied Soft Computing 80, 358–373.

Kapur, R., 2018. The Significance of Sports Tourism. Technical Report, University of Delhi.

Kataoka, S., Yamada, T., 2014. Upper and lower bounding procedures for the multiple knapsack assignment problem. European Journal of Operational Research 237, 440–447.

Kellerer, H., Pferschy, U., Pisinger, D., 2004. Knapsack Problems. Springer.

Kersulic, A., Peric, M., Wise, N., 2020. Assessing and considering the wider impacts of sport-tourism events: A research agenda review of sustainability and strategic planning elements. Sustainability 12.

Khalili-Damghani, K., Nojavan, M., Tavana, M., 2013. Solving fuzzy Multidimensional Multiple-Choice Knapsack Problems: The multi-start Partial Bound Enumeration method versus the efficient epsilon-constraint method. Applied Soft Computing 13, 1627–1638.

Kim, W., Jun, H.M., Walker, M., Drane, D., 2015. Evaluating the perceived social impacts of hosting large-scale sport tourism events: Scale development and validation. Tourism management 48, 21–32.

Kumar, R., Banerjee, N., 2006. Analysis of a multiobjective evolutionary algorithm on the 0–1 knapsack problem. Theoretical Computer Science 358, 104–120.

Lahyani, R., Chebil, K., Khemakhem, M., Coelho, L.C., 2019. Matheuristics for solving the multiple knapsack problem with setup. Computers and Industrial Engineering 129, 76–89.

Lamanna, L., Mansini, R., Zanotti, R., 2021. A two-phase kernel search variant for the multidimensional multiple-choice knapsack problem. European Journal of Operational Research .

Liu, C., Chen, J., 2008. The personal tour planning engine based on genetic algorithm. In Proceedings of the International Conference on Advanced Infocomm Technology, 1-5.

Lust, T., Teghem, J., 2012. The multiobjective multidimensional knapsack problem: a survey and a new approach. International Transactions in Operational Research 19, 495–520.

Maimani, A., Piya, S., Mamari, A., Hasania, R., 2016. Designing Optimum Personalized Tourism Packages by Means of Solving Multi-Objectives

Function. International Conference on Applied Mechanics and Industrial Systems.

Malucelli, F., Giovannini, A., Nonato, M., 2015. Designing single origin-destination itineraries for several classes of cycle-tourists. Transportation Research Procedia 10, 413–422.

Mancini, S., Ciavotta, M., Meloni, C., 2021. The multiple multidimensional knapsack with family-split penalties. European Journal of Operational Research 289, 987–998.

Mancini, S., Stecca, G., 2018. A large neighborhood search based matheuristic for the tourist cruises itinerary planning. Computers and Industrial Engineering 122, 140–148.

Martello, S., Monaci, M., 2020. Algorithmic approaches to the multiple knapsack assignment problem. Omega 90, 102004.

Martello, S., Toth, P., 1990. Knapsack Problems: Algorithms and Computer Implementations. Wiley.

Meng, F., Chu, D., Li, K., Zhou, X., 2019. Multiple-class multidimensional knapsack optimisation problem and its solution approaches. Knowledge-Based Systems 166, 1–17.

Nakamura, K., Shimbo, I., 2016. Formulation and solution method of tour conducting knapsack problem. In 2016 IEEE 5th Global Conference on Consumer Electronics.

Nauss, M., 1978. The 0-1 knapsack problem with multiple-choice constraints. European Journal of Operational Research 2, 125–131.

Pan, Q., Wang, X., 2018. Independent travel recommendation algorithm based on analytical hierarchy process and simulated annealing for professional tourist. Applied Intelligence 48, 1565–1581.

Picot-Clemente, R., Mendes, F., Cruz, C., Nicolle, C., 2012. TOURISM-KM, A variant of MMKP applied to the tourism domain. ICORES Report hal-00783660, Portugal, 421-426.

Pop, I., Bulin, D., Kanovici, A.L., Brad, L., 2020. Mega-Sport Events - Costs and Benefits for Russia. Hosting In: R. Pamfilie, V. Dinu, L. Tachiciu, D. Plesea, C. Vasiliu Eds. 6th International Conference on New Trends in Sustainable Business and Consumption. Messina-Italy, 540-547.

Rudkin, S., Sharma, A., 2020. Live football and tourism expenditure: match attendance effects in the UK. European Sport Management Quarterly 20, 276–299.

Santos-Penate, D., Campos-Rodriguez, C., Moreno-Perez, J., 2020. A kernel search matheuristic to solve the discrete leader-follower location problem. Networks and Spatial Economics 20, 73–98.

Sato, H., Aguirre, H.E., Tanaka, K., 2007. Local dominance and local recombination in moeas on 0/1 multiobjective knapsack problems. European Journal of Operational Research 181, 1708–1723.

Souffriau, W., Vansteenwegen, P., Vanden Berghe, G., Van Oudheusden, D., 2011. The planning of cycle trips in the province of east flanders. Omega 39, 209–213.

Swart, K., 1998. Visions for South African sport tourism. Visions in leisure and business 17, 4–12.

Tönissen, D.D., Van den Akker, J., Hoogeveen, J., 2017. Column generation strategies and decomposition approaches for the two-stage stochastic multiple knapsack problem. Computers & Operations Research 83, 125–139.

Tricoire, F., Parragh, S., Gansterer, M., 2016. The golf tourist problem, in Feichtinger, G., Dawid, H., Doerner, K. Dynamic Perspectives on Managerial Decision Making - Essays in Honor of Richard F. Hartl, Springer: 473-489.

Wang, S., Chen, L., 2015. Application of travel management system based on route inquiry. International Journal of Smart Home 9, 133–140.

Weed, M., 2006. Sports tourism and the development of sports events. Idrottsforum.org .

Weed, M., Bull, C., 2012. Sports tourism: Participants, policy and providers. Routledge.

Wickramaratne, V.C., Kumari, J.A.P., 2016. The impact of sports tourism on small scale business development in Sri Lanka: International cricket match. International Journal of Research in Humanities and Social Sciences 3, 33–38.

Wilbaut, C., Hanafi, S., Salhi, S., 2008. A survey of effective heuristics and their application to a variety of knapsack problems. IMA journal of management Mathematics 19, 227–244.

Xia, M., Wang, H., Wang, X., Su, Y., 2013. A research on the Sports Tourism Special Project In Hainan International Tourism Island. Open Journal of Applied Sciences, 143 .

Yochum, P., Chang, L., Gu, T., Zhu, M., 2020. An Adaptive Genetic Algorithm for Personalized Itinerary Planning. IEEE Access 8, 88147–88157.

Zhong, T., Young, R., 2010. Multiple choice knapsack problem: Example of planning choice in transportation. Evaluation and program planning 33, 128–137.

Zhou, X., Su, M., Liu, Z., Zhang, D., 2019. Smart tour route planning algorithm based on clustering center motive iteration search. IEEE Access 7, 185607–185633.