On the automatic planning of healthy and balanced menus

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ABSTRACT

With the raise of diseases related with unhealthy lifestyles such as heart-attacks, overweight, diabetes, etc., encouraging healthy and balanced patterns in the population is one of the most important action points for governments around the world. Furthermore, it is actually even a more critical situation when a high percentage of patients are children and teenagers whose habits consist merely in eating fast or ultra-processed food and a sedentary life.

The development of healthy and balanced menu plans becomes a typical task for physicians and nutritionists, and it is at this point that Computer Science has taken an important role. Discovering new approaches for generating healthy and balanced, as well as inexpensive menu plans will play an important role to reduce diseases from current and new generations.

In this paper, a recently proposed multi-objective evolutionary algorithm is compared to traditional multi-objective evolutionary algorithms for solving a novel multi-objective formulation of the Menu Planning Problem designed for school cafeterias. In order to evaluate the performance of the approaches selected for comparison, an exhaustive experimental assessment was made. Firstly, we focused on performing a suitable election of the parameter values of the algorithm, so afterwards the best configuration found could be compared to the remaining multi-objective optimisers.

CCS CONCEPTS

• **Mathematics of computing → Evolutionary algorithms**;

KEYWORDS

menu planning, evolutionary computation, multi-objective optimisation

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1 INTRODUCTION

The Menu Planning Problem *(MPP)* is a well-known NP-Hard problem, which was firstly proposed in 1960 [5]. In essence, the MPP consists of finding a set of dishes combination which satisfies some restrictions of budge, variety and nutritional requirements for a period of n days. In addition, it can include other constraints such as user preferences, cooking time or the number of meals considered for each day. Even though there is not consensus about the number of objectives that a formulation of the MPP may have, in almost every formulation the cost of the menu plan is considered as one of the main objectives to be optimised [6]. But, it also supports other objective functions, like maximising the variability and minimising the cooking time, among others. For instance, in [7], a multi-objective variant of the MPP was solved by applying the *Nondominated Sorting Genetic Algorithm II (NSGA-II)* [1]. The authors proposed a weekly plan consisting of seven daily menus with five meals each. The cost, seasonal quality and other aspects related to the food, were considered as objectives, while the users personal preferences and nutritional requirements were managed as constraints. Furthermore, in [2], the authors also tackle a multi-objective formulation of the MPP. This formulation considered the cost and personal preferences for food as objectives. It also took into account the gender and age of the user to generate a menu suited to said parameters.

There is a certain variety within the optimisation methods for solving multi-objective MPP approaches. Despite that, Evolutionary Computation *(EC)* techniques, are mostly cited in the related bibliography as a suitable choice [5, 6].

This paper is organised as follows. Section 2 introduces a novel *Menu Planning Problem* formulation. Section3 presents the experimental evaluation performed and finally, Section 4 concludes this paper.

2 MULTI-OBJECTIVE MENU PLANNING PROBLEM FORMULATION

In this particular case, a novel formulation of the Menu Planning Problem proposed for school cafeterias is considered. The authors defined two objectives: meal cost and variety of dishes. First of all, as usual in MPP, one goal is to minimise the total cost of the meal plan generated. Since the meal plan is designed for school cafeterias, the authors considered three meals in each menu: first course, second course and dessert. Formally, the meal plan cost can be defined as follows:

$$C = \sum_{j=1}^{n} c_{st_j} + c_{mc_j} + c_{ds_j}$$

where c_{st_j}, c_{mc_j} and c_{ds_j} are the costs for the starter, main course and dessert, respectively, for day j. The cost for a given course is calculated as the sum of the costs of its ingredients. For each ingredient, the database stores its price per kilogram, and for each course, the number of grams of a given ingredient required to prepare that course is also stored.

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Table 1: Hypervolume comparison of NSGA-II, SPEA-2 and MOEA/D with different MPP instance sizes after 1e8 evaluations. Each configuration was repeated independently 25 times.

Menu plannings for 5 days				
Configuration	Min.	Std	Mean	Max.
NSGA2_PopSize_250_pm_0.2_pc_0.8	0.956507	0.006186	**0.969247**	0.977835
SPEA2_ps_100_ArchSize_100_pm_0.2_pc_0.8	0.937224	0.007334	0.951471	0.964441
MOEA_D_PopSize_140_Neihb_42	0.747678	0.030129	0.827381	0.873078
Menu plannings for 10 days				
Configuration	Min	Std	Mean	Max.
NSGA2_PopSize_250_pm_0.2_pc_0.8	0.934024	0.008141	**0.948577**	0.961192
SPEA2_PopSize_100_ArchSize_100_pm_0.2_pc_0.8	0.9237	0.008851	0.941078	0.955088
MOEA_D_PopSize_140_Neihb_42	0.743725	0.030455	0.783656	0.83404
Menu plannings for 20 days				
Configuration	Min.	Std	Mean	Max.
SPEA2_PopSize_100_ArchSize_100_pm_0.1_pc_0.8	0.906556	0.011438	**0.925087**	0.945195
NSGA2_ps_250_pm_0.05_pc_0.8	0.940483	0.014064	0.921332	0.940483
MOEA_D_PopSize_140_Neihb_42	0.7161	0.03205	0.7834	0.8435
Menu plannings for 40 days				
Configuration	Min.	Std	Mean	Max.
SPEA2_ps_100_ArchSize_100_pm_0.025_pc_0.8	0.891074	0.012357	**0.910226**	0.929
NSGA2_ps_250_pm_0.05_pc_0.8	0.886774	0.008034	0.9019	0.918159
MOEA_D_PopSize_140_Neihb_42	0.65815	0.033453	0.716339	0.783212

The novel objective function modelling the degree of repetition of courses and food groups is calculated as:

$$R = \sum_{j=1}^{n} v_{MC_j} + \frac{p_{st}}{d_{st_j}} + \frac{p_{mc}}{d_{mc_j}} + \frac{p_{ds}}{d_{ds_j}} + v_{FG_j}$$

where v_{MC_j} represents the compatibility, in terms of food groups, among courses st, mc and ds for day j; p_{st}, p_{mc} and p_{ds} are the penalty constants, one per course type; d_{st_j}, d_{mc_j} and d_{ds_j} are the number of days since the corresponding course last appeared in previous days with respect to day j; and v_{FG_j} is the penalty value for repeating food groups in the last five days with respect to day j. The food groups considered for the available meals in this work are G = {*other, meat, cereal, fruit, dairy, legume, shellfish, pasta, fish, vegetable*}.

3 EXPERIMENTAL EVALUATION

In this section, the experimental evaluation will be introduced. For this purpose, the *Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D)* [8] performance was compared to other well-known multi-objective evolutionary algorithms, such as *Nondominated Sorting Genetic Algorithm II (NSGA-II)* [1] and *Strength Pareto Evolutionary Algorithm 2 (SPEA 2)* [3]. The algorithms and the experimental evaluation were developed through the same framework called *Metaheuristic-based Extensible Tool for Cooperative Optimisation (METCO)* [4].

Furthermore, with the aim of statistically supporting the conclusions extracted, the following the evaluation procedure was applied. The *hypervolume (HV)* normalised in the range [0, 1] was the metric selected to compare the different algorithms. So, the higher its value, the better the performance of the algorithm in question. Additionally, regarding the statistical tests, *Shapiro-Wilk, Levene, ANOVA or Welch* test were considered for results which follow a normal distribution or *Kruskal-Wallis* test otherwise. Several configurations of *MOEA/D*, *NSGA-II* and *SPEA-2* were considered and; in addition, each configuration was run for 5, 10, 20 and 40 days instances of the MPP. Each run was repeated 25 times setting 1e8 evaluations as the stopping criterion. Table 1 shows the minimum, mean, maximum and the standard deviation of the HV value for the best configurations of each algorithm for every single MPP instance considered.

4 CONCLUSION

As it can be observed in Section 3, *NSGA-II* was able to outperform both SPEA-2 and MOEA/D with statistically significant differences for this recently proposed MPP formulation. Regarding MOEA/D algorithm, the quite simple version developed for this research did not obtain as high quality solutions as NSGA-II or SPEA-2.

For further work, considering a new approach for initial weight generation may be a interesting choice as well as a more depth parameter setting evaluation for MOEA/D since only population size and neighbourhood size impact was studied. Moreover, increasing the number of function evaluations could be another alternative.

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