Latest Advances in Computer Science 2018
Últimos Avances en Informática 2018 (UAI 2018)

On the planning of healthy and balanced school lunches through multi-objective evolutionary algorithms

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- San Cristóbal de La Laguna, Spain – December 10, 2018 -

Outline

1. Introduction
2. Literature review
3. Our formulation of the multi-objective menu planning problem
4. Experimental assessment
5. Conclusions and future research
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Motivation

- One of the main problems nowadays is the inappropriate eating habits exhibited by a significant part of the population:
  - Consumption of fast food and snacks.
  - Low frequency of physical activity.
  - Economic crisis: increment of the poverty rates of the population.
  - Malnutrition problems, which are especially serious regarding children.
- It is vital, therefore, to have a healthy and balanced diet.

Motivation

- Controlling the feeding of children at home is quite an impossible task for us.
- However, educational institutions can take steps to improve the nutrition of children in school.
- In general, a balanced diet should be manually designed and reviewed by a nutrition expert.
- By considering general criteria for children nutrition and a predefined set of meals, however, it is possible to properly formulate the problem to automatically plan school menus.

What do we propose?

Novel *Multi-objective Menu Planning Problem* (MMPP)

- It considers the cost of the menu and the degree of repetition of the meals in the plan, as the two objective functions to be minimised.
- The nutritional features of meals and menus are handled as the problem constraints.

Differences with respect to previous formulations

- Our formulation only focuses on recommending lunch menus.
- The target audience are children ages 4 to 13.
- A gender distinction is not made in practice in school cafeterias.
- It is intended for groups of people, rather than individuals.

Contributions

- An extensive experimental evaluation is conducted in which well-known *Multi-Objective Evolutionary Algorithms* (MOEAs) are applied to solve different instances of the MMPP.
- Quantitative and qualitative analyses of the resulting menu plans are provided that show their suitability from the standpoint of their nutritional value.
- The multi-objective nature of the novel MMPP is demonstrated.

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The menu planning problem

- The *Menu Planning Problem* (MPP) involves generating a daily, weekly or monthly diet plan.
- The different meals that comprise every menu in the plan should be fully specified.
- The plan should be adapted to the specific needs for the user:
  - Preferences on the type of food.
  - Cost of the menus.
  - Variety of the meals.
  - Aesthetic features of the food.
  - Preparation methods.
  - Incompatibilities: allergies, intolerances, diseases, specific lifestyles.
- In any case, it is necessary to define which objectives are going to be optimised, and which is the set of constraints.

Common objective functions and constraints

Objectives

- There is a clear tendency to consider the cost of the menu as an objective to be minimised.
- Other authors usually include the user preferences for certain foods or the level of adequacy as the objective to be optimised.

Constraints

- Nutritional requirements are usually grouped into multiple constraints.
- Other constraints include the variety of the menu meals and the time required to prepare them, among many others.
- User data or personal preferences (weight, height, physical activity level, health goals, allergies and intolerances) are common as well.

Summary of most significant previous works

	Meta-heuristics		Other methods	
	Reference	**Approach**	**Reference**	**Approach**
Single-objective	[Bulka et al., 2000]	GA	[Stigler, 1945]	LP
	[Gaál et al., 2005]	GA	[Leung et al., 1995]	MILP
	[Kahraman and Seven, 2005]	GA	[Petot et al., 1998]	CBR and RBR
	[Wang et al., 2008]	GA	[Khan and Hoffmann, 2003]	CBR
	[Kashima et al., 2009]	GA	[Alfaro, 2003]	MILP
	[Osthus, 2011]	GA	[Noah et al., 2004]	RBR
	[Funabiki et al., 2011]	Greedy	[Kashima et al., 2008]	FMP
	[Gumustekin et al., 2014]	EDA, GA	[Aberg, 2009]	Branch&Bound
	[Isokawa and Matsui, 2015]	GA	[Lee et al., 2010]	T2FO
	[Hernández-Ocaña et al., 2018]	BFOA	[Hsiao and Chang, 2010]	Branch&Bound
			[Jothi et al., 2011]	CBR
			[Kovásznai, 2011]	CBR
			[Chávez et al., 2014]	MP and BM
			[Kale and Auti, 2015]	DT
Multi-objective	[Kaldrim and Köse, 2006]	MOEA		
	[Seljak, 2006]	MOEA		
	[Moreira et al., 2017]	MOEA		

Genetic Algorithm (GA), *Estimation of Distribution Algorithm* (EDA), *Bacterial Foraging Optimisation Algorithm* (BFOA), *Linear Programming* (LP), *Mixed Integer Linear Programming* (MILP), *Case-based Reasoning* (CBR), *Rule-based Reasoning* (RBR), *Fuzzy Mathematical Programming* (FMP), *Type-2 Fuzzy Ontology* (T2FO), *Mathematical Programming* (MP), *Belief Merging* (BM), *Decision Trees* (DT)

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General considerations

- One of the main goals herein is to automatically design menu plans for school cafeterias.
- Therefore, only lunch menus are considered through the plan.
- Plans are designed for large groups of children.
- The recommended daily amount of nutrients for children between 4 and 13 years old does not differ by gender. Moreover, such a distinction is not made in school cafeterias.

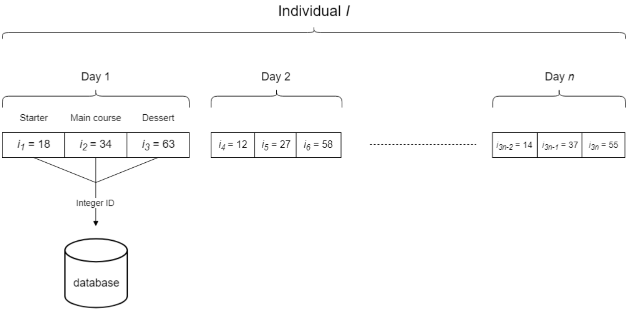
Considerations regarding the objective functions

- In school cafeterias, menu prices should be reasonable. Therefore, the first objective is to minimise the plan cost.
- The second objective is the minimisation of the degree of repetition of the meals included in the plan.
- Children need a varied diet, not only for health reasons, by including in the plan all the nutritional food groups required, but also to avoid detesting certain foods, by varying the specific courses.
- The second objective was designed by considering advice given by nutrition experts from the *Intervention Program for the Prevention of Childhood Obesity* of the the *Government of the Canary Islands*.

Considerations regarding the constraints

- The nutritional quality of the meal plans are treated as the problem constraints.
- General recommendations on intakes of nutrients, fats, carbohydrates and proteins were considered in this formulation of the MMPP, for which we followed the suggestions given in the *White Book on Child Nutrition* and other consensus documents and guides on school diets.
- Food intolerances, allergies, illnesses, and other types of food incompatibilities were not considered.
- Finally, it was necessary to design a database of courses and ingredients with information on their respective nutritional specifications.

Encoding of solutions



Size of the search space S

$$|S| = (I_{st} \cdot I_{mc} \cdot I_{ds})^n$$

For instance, by only considering $I_{st} = I_{mc} = I_{ds} = 10$ and a weekly menu plan, i.e., $n = 5$ days, the number of potential solutions $|S|$ would be equal to 10^{15}.

Objective functions

First objective: minimisation of the menu plan cost

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

The costs for the starter, main course and dessert for day j are given by c_{st_j}, c_{mc_j} and c_{ds_j}, respectively.

- 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.

Objective functions

Second objective: minimisation of the degree of repetition of courses and food groups

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

- The compatibility, in terms of food groups, among courses st, mc and ds for day j is represented by v_{MC_j}.
- The penalty constants are given by p_{st}, p_{mc} and p_{ds}, while 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.
- The penalty value for repeating food groups in the last five days with respect to day j is given by v_{FG_j}.
- The food groups considered are $G = \{$*other, meat, cereal, fruit, dairy, legume, shellfish, pasta, fish, vegetable*$\}$.

Penalties

- Penalties are operations performed on the second objective function in order to determine the quality and variety of a meal plan.
- They directly affect the way a meal plan is obtained and can be used by the decision-maker in order to establish preferences.
- Penalty values were set by performing a preliminary study where the features of the solutions obtained were analysed in terms of

Types of penalties

- Repetition of food groups (p_1–p_{10}). These penalties are used in the computation of v_{MC} and v_{FG}.
- Repetition of the same food group from one to five days prior to the current day (p_{11}–p_{15}). These penalties are considered in the calculation of v_{FG}.
- Repetition of specific courses ($p_{16} = p_{st}$, $p_{17} = p_{mc}$, and $p_{18} = p_{ds}$).

Penalties

Penalty	Description	Value
p_1	penalty for repeating *other* food group	0.1
p_2	penalty for repeating *meat* food group	3
p_3	penalty for repeating *cereal* food group	0.3
p_4	penalty for repeating *fruit* food group	0.1
p_5	penalty for repeating *dairy* food group	0.3
p_6	penalty for repeating *legume* food group	0.3
p_7	penalty for repeating *shellfish* food group	2
p_8	penalty for repeating *pasta* food group	1.5
p_9	penalty for repeating *fish* food group	0.5
p_{10}	penalty for repeating *vegetable* food group	0.1
p_{11}	penalty for repeating the same food group one day before	3
p_{12}	penalty for repeating the same food group two days before	2.5
p_{13}	penalty for repeating the same food group three days before	1.8
p_{14}	penalty for repeating the same food group four days before	1
p_{15}	penalty for repeating the same food group five days before	0.2
$p_{16} = p_{st}$	penalty for repeating a starter	8
$p_{17} = p_{mc}$	penalty for repeating a main course	10
$p_{18} = p_{ds}$	penalty for repeating a dessert	2

Penalties

Computation of v_{FG_j}

$$v_{FG_j} = \sum_{i=1}^{min(j-1,T)} \left(\sum_{g=1}^{|G|} x_{g_i} \cdot p_g\right) + (y_i \cdot p_{|G|+i})$$

- The number of previous days considered is given by $T = 5$.
- $|G| = 10$ is the number of food groups.
- $x_{g_i} \in \{0, 1\}$ indicates whether the food group g is repeated at day $j - i$ ($x_{g_i} = 1$) or not ($x_{g_i} = 0$) with respect to day j.
- $y_i \in \{0, 1\}$ indicates whether any food group was repeated i day(s) before the current day j ($y_i = 1$) or not ($y_i = 0$).
- p_g and $p_{|G|+i}$ are the corresponding penalty values.

Penalties

Computation of v_{MC_j}

$$v_{MC_j} = \sum_{g=1}^{|G|} x_g \cdot p_g$$

- $|G| = 10$ is the number of food groups.
- $x_g \in \{0, 1, 2, 3\}$ is the number of times a particular food group is contained in the three courses (starter, main course and dessert) of the meal for day j.
- p_g is the corresponding penalty value for repeating the food group g.

Constraints

Types of nutrients

$H = \{$*folic acid, calcium, carbohydrates, energy, phosphorus, total fat, iron, magnesium, potassium, proteins, selenium, sodium, vitamin A, vitamin B1, vitamin B2, vitamin B6, vitamin B12, vitamin C, vitamin D, vitamin E, iodine, zinc*$\}$

Constraints

$$\forall h \in H : r_{min_h} \leq r_h \leq r_{max_h}$$

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Multi-objective evolutionary algorithms

- *Non-dominated Sorting Genetic Algorithm II* (NSGA-II).
- *Improved Strength Pareto Evolutionary Algorithm* (SPEA2).
- Adaptive version of the *Indicator-based Evolutionary Algorithm* (IBEA).

Variation operators

- Uniform crossover operator.
- Mutation operator. Every gene of a particular individual, i.e., a daily meal consisting of a starter, a main course and a dessert, will be randomly replaced by another daily meal with probability p_m.
- Repair operator. Each daily meal for an infeasible individual will be modified by following the same procedure implemented in the mutation until the individual becomes feasible.

Description

Experimental procedure

- All the algorithms, as well as the MMPP, were implemented through the *Meta-heuristic-based Extensible Tool for Cooperative Optimisation* (METCO).
- The experiments were executed on a Debian GNU/Linux computer with four AMD® Opteron™ processors (model number 6348 HE) at 2.8 GHz and 64 GB RAM.
- Each run was repeated 30 times, unless the opposite is established.
- With the aim of statistically supporting the conclusions extracted, a statistical testing procedure was applied to conduct comparisons between approaches with a significance level $\alpha = 0{,}05$.
- The *hypervolume* was selected as the metric to perform the comparisons among the different approaches.

Description

Instances

- The number of days for which the meal plan will be designed has to be specified.
- A starter, a main course and a dessert have to be selected for each day.
- In the particular case of our implementation, a total number of 67 courses consisting of $l_{st} = 19$ starters, $l_{mc} = 34$ main courses and $l_{ds} = 14$ desserts are provided.
- Considering, for instance, a menu plan for 5 days, the size of the search space would be $|S| = (19 \cdot 34 \cdot 14)^5 = 6{,}051 \cdot 10^{19}$ potential solutions.
- For more information, visit `https://github.com/Tomas-Morph/On-the-Design-of-Healthy-Menus-through-Evolutionary-Computation`.

First experiment: parameter setting

Main goal

- Conducting a study involving the values that parameters belonging to the MOEAs selected for comparison should take, since we are dealing with a novel MMPP.

Parameterisation of NSGA-II, SPEA2 and IBEA

Parameter	Value	Parameter	Value
Stopping criterion	$4 \cdot 10^8$ evals.	Mutation prob. (p_m)	0.05, 0.1, 0.15
Population size (n)	25, 50, 100, 250 inds.	Crossover prob. (p_c)	0.8, 0.9, 1

- Particularly, a total number of 36 different configurations of each MOEA were applied in order to yield a 20-day meal plan.
- Executions were only repeated 10 times.

Performance of the NSGA-II at the end of the runs

Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
NSGA-II_ps_250_pm_0.1_pc_0.8	0.8634	0.8666	0.8696	0.8691	0.8713	0.8743	28	0	28
NSGA-II_ps_250_pm_0.05_pc_0.8	0.8598	0.8654	0.8675	0.8679	0.8703	0.8767	24	0	24
NSGA-II_ps_250_pm_0.15_pc_0.8	0.8541	0.8619	0.8675	0.8678	0.8728	0.8818	18	0	18
NSGA-II_ps_50_pm_0.1_pc_0.8	0.8553	0.8589	0.8619	0.8660	0.8694	0.8871	11	0	11
NSGA-II_ps_50_pm_0.15_pc_0.8	0.8474	0.8596	0.8668	0.8643	0.8686	0.8740	10	0	10
NSGA-II_ps_100_pm_0.1_pc_0.9	0.8463	0.8581	0.8632	0.8640	0.8720	0.8770	10	0	10
NSGA-II_ps_100_pm_0.05_pc_0.9	0.8525	0.8571	0.8647	0.8639	0.8709	0.8728	10	0	10
NSGA-II_ps_250_pm_0.1_pc_0.9	0.8492	0.8597	0.8640	0.8632	0.8678	0.8782	10	0	10
NSGA-II_ps_250_pm_0.05_pc_0.9	0.8567	0.8587	0.8629	0.8629	0.8653	0.8709	11	2	9
NSGA-II_ps_50_pm_0.05_pc_1.0	0.8501	0.8568	0.8620	0.8627	0.8701	0.8725	9	1	8
NSGA-II_ps_100_pm_0.05_pc_0.8	0.8528	0.8588	0.8613	0.8624	0.8687	0.8706	10	2	8
NSGA-II_ps_100_pm_0.1_pc_0.8	0.8480	0.8565	0.8616	0.8619	0.8659	0.8785	9	1	8
NSGA-II_ps_50_pm_0.05_pc_0.8	0.8514	0.8588	0.8611	0.8615	0.8657	0.8694	9	2	7
NSGA-II_ps_50_pm_0.1_pc_0.9	0.8470	0.8521	0.8638	0.8612	0.8686	0.8762	5	1	4
NSGA-II_ps_100_pm_0.15_pc_0.8	0.8415	0.8600	0.8609	0.8599	0.8650	0.8696	6	2	4
NSGA-II_ps_50_pm_0.05_pc_0.9	0.8472	0.8553	0.8594	0.8599	0.8637	0.8745	6	2	4
NSGA-II_ps_25_pm_0.05_pc_0.9	0.8483	0.8580	0.8597	0.8598	0.8632	0.8676	7	3	4
NSGA-II_ps_250_pm_0.05_pc_1.0	0.8541	0.8550	0.8572	0.8595	0.8625	0.8687	7	3	4
NSGA-II_ps_25_pm_0.15_pc_0.8	0.8493	0.8586	0.8598	0.8587	0.8601	0.8635	7	3	4
NSGA-II_ps_250_pm_0.15_pc_1.0	0.8480	0.8559	0.8569	0.8587	0.8616	0.8722	6	3	3
NSGA-II_ps_100_pm_0.15_pc_0.9	0.8333	0.8547	0.8598	0.8576	0.8647	0.8671	4	2	2
NSGA-II_ps_50_pm_0.15_pc_0.9	0.8457	0.8511	0.8634	0.8592	0.8653	0.8684	4	3	1
NSGA-II_ps_50_pm_0.1_pc_1.0	0.8442	0.8530	0.8614	0.8586	0.8643	0.8677	4	3	1
NSGA-II_ps_250_pm_0.15_pc_0.9	0.8409	0.8481	0.8627	0.8594	0.8687	0.8757	1	1	0
NSGA-II_ps_25_pm_0.05_pc_0.8	0.8449	0.8558	0.8578	0.8574	0.8624	0.8647	4	5	-1
NSGA-II_ps_25_pm_0.1_pc_0.8	0.8371	0.8509	0.8564	0.8571	0.8671	0.8749	0	3	-3
NSGA-II_ps_250_pm_0.1_pc_1.0	0.8303	0.8425	0.8501	0.8518	0.8576	0.8808	0	10	-10
NSGA-II_ps_100_pm_0.1_pc_1.0	0.8427	0.8487	0.8505	0.8534	0.8569	0.8686	0	13	-13
NSGA-II_ps_25_pm_0.05_pc_1.0	0.8385	0.8461	0.8558	0.8528	0.8577	0.8647	0	13	-13
NSGA-II_ps_25_pm_0.1_pc_0.9	0.8422	0.8477	0.8560	0.8535	0.8582	0.8614	0	16	-16

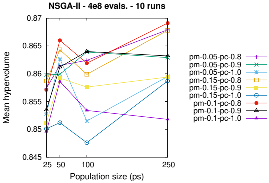
Performance of the IBEA at the end of the runs

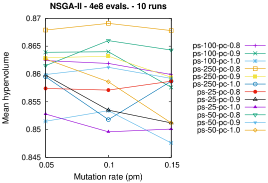
Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
IBEA_ps_250_pm_0.1_pc_0.8_sFactor_0.002	0.8594	0.8640	0.8657	0.8657	0.8689	0.8703	32	0	32
IBEA_ps_250_pm_0.05_pc_0.8_sFactor_0.002	0.8489	0.8580	0.8645	0.8623	0.8690	0.8707	28	0	28
IBEA_ps_250_pm_0.1_pc_0.9_sFactor_0.002	0.8519	0.8566	0.8593	0.8608	0.8636	0.8710	28	1	27
IBEA_ps_250_pm_0.15_pc_0.8_sFactor_0.002	0.8346	0.8589	0.8651	0.8620	0.8700	0.8739	25	0	25
IBEA_ps_100_pm_0.05_pc_0.8_sFactor_0.002	0.8488	0.8538	0.8614	0.8588	0.8630	0.8672	25	1	24
IBEA_ps_100_pm_0.1_pc_0.8_sFactor_0.002	0.8461	0.8547	0.8586	0.8582	0.8631	0.8702	24	1	23
IBEA_ps_250_pm_0.15_pc_0.9_sFactor_0.002	0.8444	0.8537	0.8576	0.8578	0.8629	0.8704	23	1	22
IBEA_ps_250_pm_0.05_pc_0.9_sFactor_0.002	0.8344	0.8486	0.8620	0.8583	0.8666	0.8787	20	0	20
IBEA_ps_250_pm_0.1_pc_1.0_sFactor_0.002	0.8428	0.8532	0.8549	0.8543	0.8554	0.8614	19	3	16
IBEA_ps_100_pm_0.15_pc_0.9_sFactor_0.002	0.8401	0.8514	0.8557	0.8538	0.8570	0.8610	19	3	16
IBEA_ps_100_pm_0.05_pc_1.0_sFactor_0.002	0.8257	0.8516	0.8528	0.8513	0.8565	0.8601	19	5	14
IBEA_ps_100_pm_0.05_pc_0.9_sFactor_0.002	0.8303	0.8514	0.8529	0.8517	0.8567	0.8671	12	3	9
IBEA_ps_100_pm_0.1_pc_0.9_sFactor_0.002	0.8391	0.8472	0.8511	0.8507	0.8563	0.8600	14	7	7
IBEA_ps_100_pm_0.15_pc_0.8_sFactor_0.002	0.8385	0.8456	0.8509	0.8507	0.8575	0.8593	13	7	6
IBEA_ps_250_pm_0.15_pc_1.0_sFactor_0.002	0.8355	0.8445	0.8492	0.8500	0.8561	0.8666	10	6	4
IBEA_ps_250_pm_0.05_pc_1.0_sFactor_0.002	0.8300	0.8453	0.8509	0.8492	0.8556	0.8609	10	7	3
IBEA_ps_50_pm_0.05_pc_0.8_sFactor_0.002	0.8336	0.8396	0.8478	0.8473	0.8549	0.8621	9	8	1
IBEA_ps_50_pm_0.1_pc_0.8_sFactor_0.002	0.8293	0.8436	0.8482	0.8468	0.8500	0.8618	9	11	-2
IBEA_ps_50_pm_0.05_pc_1.0_sFactor_0.002	0.8299	0.8404	0.8481	0.8456	0.8510	0.8596	9	11	-2
IBEA_ps_50_pm_0.15_pc_0.8_sFactor_0.002	0.8314	0.8421	0.8455	0.8455	0.8505	0.8555	9	11	-2
IBEA_ps_100_pm_0.1_pc_1.0_sFactor_0.002	0.8338	0.8403	0.8466	0.8444	0.8475	0.8531	9	12	-3
IBEA_ps_50_pm_0.05_pc_0.9_sFactor_0.002	0.8317	0.8374	0.8463	0.8444	0.8507	0.8540	8	11	-3
IBEA_ps_50_pm_0.1_pc_0.9_sFactor_0.002	0.8287	0.8417	0.8431	0.8441	0.8484	0.8599	8	11	-3
IBEA_ps_100_pm_0.15_pc_1.0_sFactor_0.002	0.8370	0.8396	0.8424	0.8436	0.8466	0.8543	9	14	-5
IBEA_ps_50_pm_0.1_pc_1.0_sFactor_0.002	0.8243	0.8335	0.8419	0.8421	0.8520	0.8541	7	13	-6
IBEA_ps_50_pm_0.15_pc_0.9_sFactor_0.002	0.8234	0.8302	0.8409	0.8407	0.8487	0.8583	7	14	-7
IBEA_ps_50_pm_0.15_pc_1.0_sFactor_0.002	0.8237	0.8330	0.8408	0.8390	0.8461	0.8505	7	16	-9
IBEA_ps_25_pm_0.05_pc_0.8_sFactor_0.002	0.8277	0.8324	0.8376	0.8376	0.8430	0.8479	7	22	-15

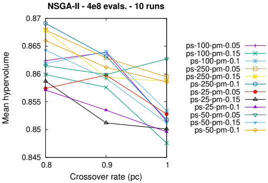
Performance of the SPEA2 at the end of the runs

Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
SPEA2_ps_100_as_100_pm_0.05_pc_0.8	0.8642	0.8699	0.8752	0.8748	0.8792	0.8880	34	0	34
SPEA2_ps_50_as_50_pm_0.05_pc_0.8	0.8513	0.8636	0.8710	0.8680	0.8742	0.8763	18	0	18
SPEA2_ps_100_as_100_pm_0.1_pc_0.8	0.8527	0.8638	0.8663	0.8673	0.8744	0.8777	18	1	17
SPEA2_ps_100_as_100_pm_0.05_pc_0.9	0.8583	0.8620	0.8661	0.8670	0.8701	0.8831	18	1	17
SPEA2_ps_250_as_250_pm_0.05_pc_0.8	0.8553	0.8591	0.8653	0.8662	0.8723	0.8790	17	1	16
SPEA2_ps_250_as_250_pm_0.1_pc_0.9	0.8537	0.8595	0.8641	0.8638	0.8692	0.8721	15	1	14
SPEA2_ps_100_as_100_pm_0.1_pc_0.9	0.8549	0.8596	0.8611	0.8633	0.8677	0.8761	14	1	13
SPEA2_ps_100_as_100_pm_0.15_pc_0.8	0.8496	0.8605	0.8646	0.8629	0.8652	0.8719	14	1	13
SPEA2_ps_50_as_50_pm_0.15_pc_0.8	0.8494	0.8618	0.8639	0.8627	0.8672	0.8687	14	1	13
SPEA2_ps_50_as_50_pm_0.1_pc_0.8	0.8548	0.8583	0.8620	0.8627	0.8644	0.8735	14	1	13
SPEA2_ps_250_as_250_pm_0.15_pc_0.8	0.8559	0.8585	0.8609	0.8625	0.8657	0.8719	14	1	13
SPEA2_ps_50_as_50_pm_0.15_pc_0.9	0.8547	0.8569	0.8620	0.8618	0.8660	0.8698	13	1	12
SPEA2_ps_250_as_250_pm_0.1_pc_0.8	0.8478	0.8575	0.8636	0.8633	0.8694	0.8779	12	1	11
SPEA2_ps_50_as_50_pm_0.05_pc_0.9	0.8463	0.8564	0.8632	0.8625	0.8699	0.8820	10	1	9
SPEA2_ps_50_as_50_pm_0.1_pc_0.9	0.8466	0.8558	0.8609	0.8614	0.8684	0.8766	10	1	9
SPEA2_ps_250_as_250_pm_0.05_pc_0.9	0.8505	0.8580	0.8620	0.8613	0.8636	0.8730	10	1	9
SPEA2_ps_250_as_250_pm_0.15_pc_0.9	0.8491	0.8553	0.8619	0.8607	0.8631	0.8750	10	1	9
SPEA2_ps_100_as_100_pm_0.05_pc_1.0	0.8464	0.8494	0.8608	0.8600	0.8664	0.8766	10	1	9
SPEA2_ps_100_as_100_pm_0.15_pc_0.9	0.8483	0.8576	0.8613	0.8600	0.8618	0.8712	10	4	6
SPEA2_ps_100_as_100_pm_0.1_pc_1.0	0.8556	0.8563	0.8580	0.8595	0.8623	0.8676	10	5	5
SPEA2_ps_250_as_250_pm_0.1_pc_1.0	0.8460	0.8526	0.8550	0.8573	0.8596	0.8753	9	5	4
SPEA2_ps_50_as_50_pm_0.05_pc_1.0	0.8432	0.8521	0.8576	0.8568	0.8598	0.8679	9	6	3
SPEA2_ps_50_as_50_pm_0.1_pc_1.0	0.8490	0.8521	0.8565	0.8564	0.8597	0.8653	9	12	-3
SPEA2_ps_250_as_250_pm_0.15_pc_1.0	0.8422	0.8513	0.8557	0.8555	0.8590	0.8691	9	12	-3
SPEA2_ps_50_as_50_pm_0.15_pc_1.0	0.8333	0.8471	0.8537	0.8526	0.8606	0.8737	8	12	-4
SPEA2_ps_100_as_100_pm_0.15_pc_1.0	0.8336	0.8433	0.8529	0.8520	0.8627	0.8703	8	13	-5
SPEA2_ps_250_as_250_pm_0.05_pc_1.0	0.8323	0.8391	0.8492	0.8488	0.8567	0.8659	5	20	-15
SPEA2_ps_25_as_25_pm_0.15_pc_1.0	0.8228	0.8373	0.8402	0.8426	0.8502	0.8597	2	24	-22
SPEA2_ps_25_as_25_pm_0.15_pc_0.9	0.8224	0.8310	0.8388	0.8399	0.8511	0.8559	0	26	-26
SPEA2_ps_25_as_25_pm_0.1_pc_1.0	0.8172	0.8287	0.8416	0.8395	0.8501	0.8599	0	26	-26

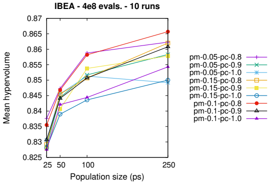
Mean hypervolume values achieved by the NSGA-II at the end of the executions

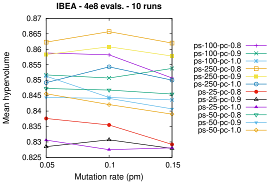


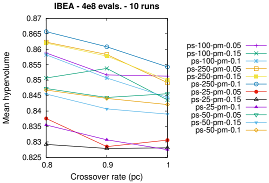




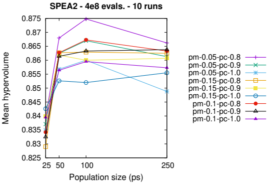
Mean hypervolume values achieved by the IBEA at the end of the executions

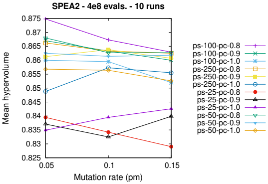


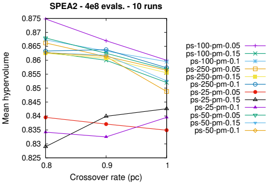


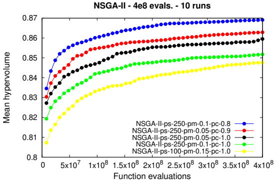


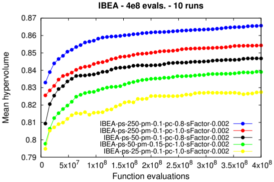
Mean hypervolume values achieved by the SPEA2 at the end of the executions

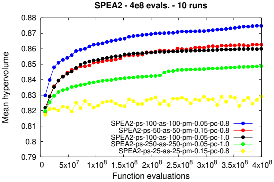







NSGA-II - 4e8 evals. - 10 runs
Mean hypervolume
Function evaluations
NSGA-II-ps-250-pm-0.1-pc-0.8
NSGA-II-ps-250-pm-0.05-pc-0.9
NSGA-II-ps-250-pm-0.05-pc-1.0
NSGA-II-ps-250-pm-0.1-pc-1.0
NSGA-II-ps-100-pm-0.15-pc-1.0


IBEA - 4e8 evals. - 10 runs
Mean hypervolume
Function evaluations
IBEA-ps-250-pm-0.1-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.1-pc-1.0-sFactor-0.002
IBEA-ps-50-pm-0.1-pc-0.8-sFactor-0.002
IBEA-ps-50-pm-0.15-pc-1.0-sFactor-0.002
IBEA-ps-25-pm-0.1-pc-1.0-sFactor-0.002


SPEA2 - 4e8 evals. - 10 runs
Mean hypervolume
Function evaluations
SPEA2-ps-100-as-100-pm-0.05-pc-0.8
SPEA2-ps-50-as-50-pm-0.15-pc-0.8
SPEA2-ps-100-as-100-pm-0.05-pc-1.0
SPEA2-ps-250-as-250-pm-0.05-pc-1.0
SPEA2-ps-25-as-25-pm-0.15-pc-0.8

Second experiment: designing menu plans for a variable number of days

Main goal

- Analysing the performance of the different MOEAs when they are applied to produce menu plans for a variable number of days.

Parameterisation

- The first-ranked configurations of the NSGA-II, IBEA and SPEA2 were applied.
- Three different values were tested in the second experiment for the mutation rate, such that the meals for one, two o three days were changed.
- The above configurations were applied to design menu plans for 5, 10, 20 and 40 days.
- Every run was repeated 30 times.

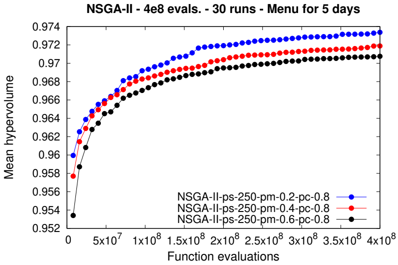
Performance of the MOEAs at the end of the runs - 5 and 10 days

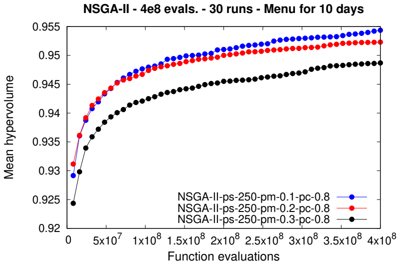
Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
Menu plannings for 5 days									
Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
NSGA-II_ps_250_pm_0.2_pc_0.8	0.9603	0.9706	0.9752	0.9734	0.9773	0.9801	7	0	7
NSGA-II_ps_250_pm_0.4_pc_0.8	0.9482	0.9696	0.9731	0.9719	0.9750	0.9792	6	0	6
NSGA-II_ps_250_pm_0.6_pc_0.8	0.9561	0.9688	0.9714	0.9708	0.9741	0.9783	6	1	5
IBEA_ps_250_pm_0.4_pc_0.8_sFactor_0.002	0.9401	0.9604	0.9639	0.9625	0.9670	0.9697	3	3	0
IBEA_ps_250_pm_0.2_pc_0.8_sFactor_0.002	0.9474	0.9560	0.9619	0.9610	0.9666	0.9701	0	3	-3
SPEA2_ps_100_as_100_pm_0.2_pc_0.8	0.9435	0.9562	0.9617	0.9602	0.9652	0.9719	0	3	-3
SPEA2_ps_100_as_100_pm_0.6_pc_0.8	0.9396	0.9583	0.9612	0.9595	0.9637	0.9664	0	4	-4
IBEA_ps_250_pm_0.6_pc_0.8_sFactor_0.002	0.9412	0.9568	0.9580	0.9592	0.9656	0.9700	0	4	-4
SPEA2_ps_100_as_100_pm_0.4_pc_0.8	0.9407	0.9554	0.9588	0.9580	0.9638	0.9665	0	4	-4
Menu plannings for 10 days									
Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
NSGA-II_ps_250_pm_0.1_pc_0.8	0.9378	0.9508	0.9549	0.9544	0.9597	0.9674	7	0	7
NSGA-II_ps_250_pm_0.2_pc_0.8	0.9278	0.9481	0.9523	0.9523	0.9594	0.9642	5	0	5
IBEA_ps_250_pm_0.3_pc_0.8_sFactor_0.002	0.9337	0.9453	0.9491	0.9487	0.9537	0.9611	4	1	3
NSGA-II_ps_250_pm_0.3_pc_0.8	0.9371	0.9420	0.9482	0.9487	0.9532	0.9630	4	1	3
IBEA_ps_250_pm_0.2_pc_0.8_sFactor_0.002	0.9367	0.9423	0.9497	0.9479	0.9524	0.9586	4	2	2
SPEA2_ps_100_as_100_pm_0.1_pc_0.8	0.9279	0.9397	0.9440	0.9442	0.9482	0.9593	1	5	-4
IBEA_ps_250_pm_0.1_pc_0.8_sFactor_0.002	0.9272	0.9379	0.9448	0.9441	0.9496	0.9623	1	5	-4
SPEA2_ps_100_as_100_pm_0.2_pc_0.8	0.9299	0.9390	0.9432	0.9440	0.9491	0.9574	1	5	-4
SPEA2_ps_100_as_100_pm_0.3_pc_0.8	0.9093	0.9308	0.9396	0.9385	0.9443	0.9591	0	8	-8

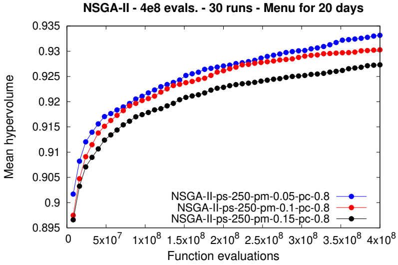
Performance of the MOEAs at the end of the runs - 20 and 40 days

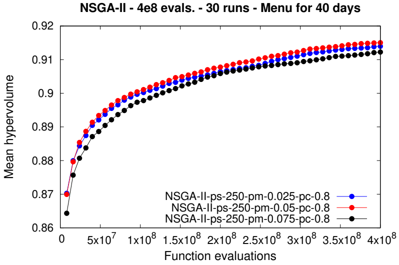
Menu plannings for 20 days									
Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
SPEA2_ps_100_as_100_pm_0.1_pc_0.8	0.9166	0.9316	0.9358	0.9359	0.9428	0.9498	5	0	5
SPEA2_ps_100_as_100_pm_0.05_pc_0.8	0.9130	0.9278	0.9328	0.9335	0.9390	0.9530	4	0	4
NSGA-II_ps_250_pm_0.05_pc_0.8	0.9043	0.9263	0.9346	0.9332	0.9418	0.9475	4	0	4
IBEA_ps_250_pm_0.05_pc_0.8_sFactor_0.002	0.9144	0.9275	0.9320	0.9318	0.9382	0.9430	3	0	3
NSGA-II_ps_250_pm_0.1_pc_0.8	0.9169	0.9255	0.9310	0.9303	0.9357	0.9393	1	1	0
IBEA_ps_250_pm_0.1_pc_0.8_sFactor_0.002	0.8966	0.9239	0.9306	0.9282	0.9340	0.9412	0	3	-3
NSGA-II_ps_250_pm_0.15_pc_0.8	0.9084	0.9225	0.9265	0.9273	0.9330	0.9417	0	4	-4
SPEA2_ps_100_as_100_pm_0.15_pc_0.8	0.9137	0.9223	0.9285	0.9272	0.9324	0.9419	0	4	-4
IBEA_ps_250_pm_0.15_pc_0.8_sFactor_0.002	0.9080	0.9208	0.9259	0.9256	0.9297	0.9398	0	5	-5
Menu plannings for 40 days									
Configuration	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	W	L	Ranking
SPEA2_ps_100_as_100_pm_0.025_pc_0.8	0.9111	0.9180	0.9254	0.9261	0.9340	0.9414	7	0	7
SPEA2_ps_100_as_100_pm_0.05_pc_0.8	0.9117	0.9180	0.9225	0.9234	0.9276	0.9418	6	0	6
SPEA2_ps_100_as_100_pm_0.075_pc_0.8	0.9023	0.9143	0.9197	0.9194	0.9243	0.9335	6	1	5
NSGA-II_ps_250_pm_0.05_pc_0.8	0.9012	0.9106	0.9147	0.9150	0.9209	0.9263	2	3	-1
NSGA-II_ps_250_pm_0.025_pc_0.8	0.8937	0.9071	0.9134	0.9140	0.9208	0.9287	0	3	-3
NSGA-II_ps_250_pm_0.075_pc_0.8	0.8874	0.9074	0.9135	0.9123	0.9180	0.9250	0	3	-3
IBEA_ps_250_pm_0.05_pc_0.8_sFactor_0.002	0.8942	0.9050	0.9091	0.9109	0.9170	0.9327	0	3	-3
IBEA_ps_250_pm_0.025_pc_0.8_sFactor_0.002	0.8947	0.9058	0.9108	0.9106	0.9168	0.9243	0	4	-4
IBEA_ps_250_pm_0.075_pc_0.8_sFactor_0.002	0.8975	0.9035	0.9096	0.9098	0.9147	0.9314	0	4	-4

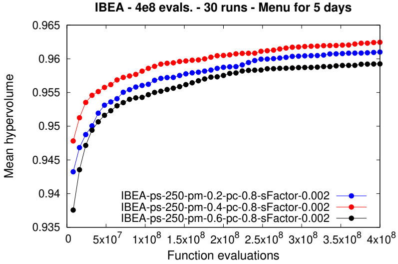
Run-time behaviour of the NSGA-II

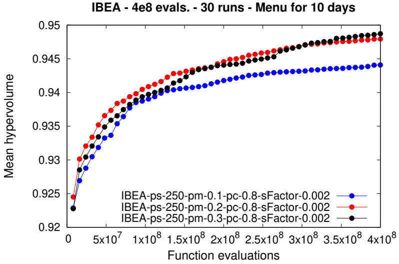


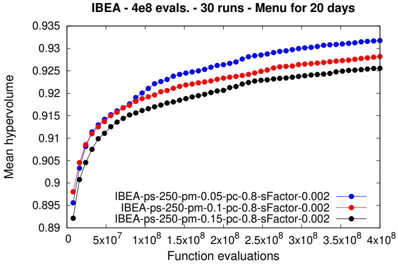


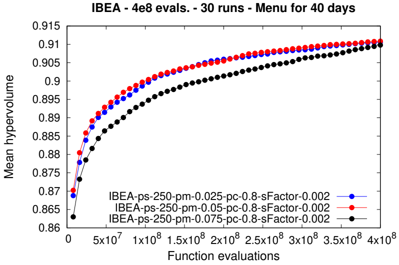




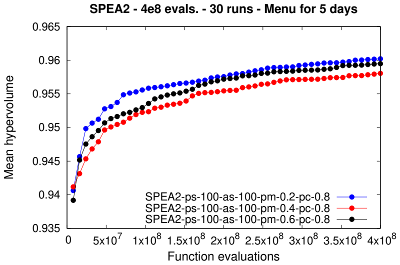

IBEA - 4e8 evals. - 30 runs - Menu for 5 days
Mean hypervolume
0.935
0.94
0.945
0.95
0.955
0.96
0.965
Function evaluations
0
5x10^7
1x10^8
1.5x10^8
2x10^8
2.5x10^8
3x10^8
3.5x10^8
4x10^8
IBEA-ps-250-pm-0.2-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.4-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.6-pc-0.8-sFactor-0.002

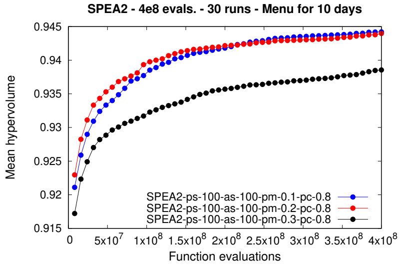

IBEA - 4e8 evals. - 30 runs - Menu for 10 days
Mean hypervolume
0.92
0.925
0.93
0.935
0.94
0.945
0.95
Function evaluations
0
5x10^7
1x10^8
1.5x10^8
2x10^8
2.5x10^8
3x10^8
3.5x10^8
4x10^8
IBEA-ps-250-pm-0.1-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.2-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.3-pc-0.8-sFactor-0.002

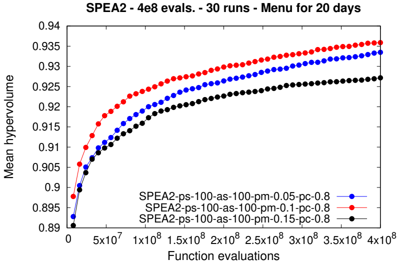

IBEA - 4e8 evals. - 30 runs - Menu for 20 days
Mean hypervolume
0.89
0.895
0.9
0.905
0.91
0.915
0.92
0.925
0.93
0.935
Function evaluations
0
5x10^7
1x10^8
1.5x10^8
2x10^8
2.5x10^8
3x10^8
3.5x10^8
4x10^8
IBEA-ps-250-pm-0.05-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.1-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.15-pc-0.8-sFactor-0.002

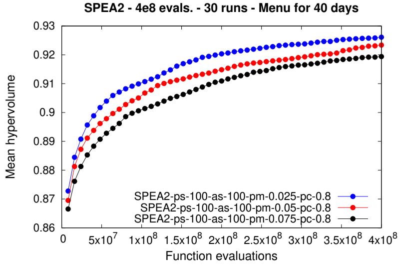

IBEA - 4e8 evals. - 30 runs - Menu for 40 days
Mean hypervolume
0.86
0.865
0.87
0.875
0.88
0.885
0.89
0.895
0.9
0.905
0.91
0.915
Function evaluations
0
5x10^7
1x10^8
1.5x10^8
2x10^8
2.5x10^8
3x10^8
3.5x10^8
4x10^8
IBEA-ps-250-pm-0.025-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.05-pc-0.8-sFactor-0.002
IBEA-ps-250-pm-0.075-pc-0.8-sFactor-0.002

Run-time behaviour of the SPEA2









Third experiment: qualitative and quantitative analysis of solutions

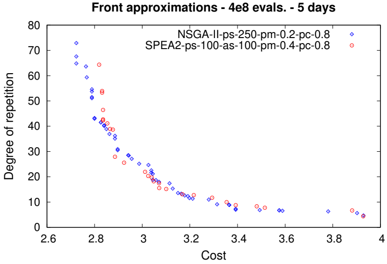
Main goal

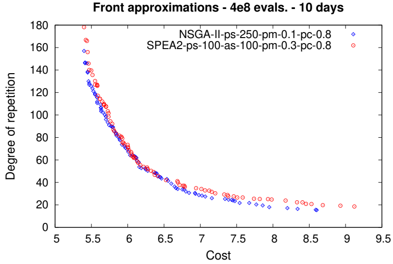
- Analysing the solutions attained by the MOEAs considered, not only from a quantitative point of view, but also from a qualitative one.
- We would like to validate the novel multi-objective formulation of the MMPP we are proposing in terms of the features of the solutions achieved.

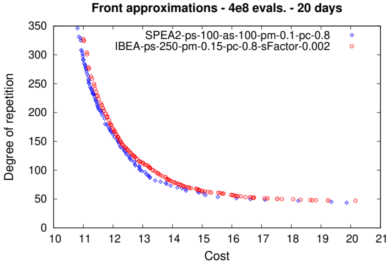
Parameterisation

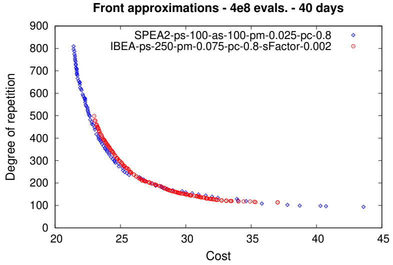
- For each menu plan length, we considered the solutions obtained in the second experiment by the best- and worst-performing configurations of each MOEA.

Examples of front approximations









Example of menu plan for 10 days - Composition

Day	Starter	Main course	Dessert
1	White bean salad	Hawaiian Pizza	Fruits of the forest yogurt
2	Mashed potatoes	Tuna patties	Banana
3	Country salad	Cuba style rice	Tangerine
4	Rice soup	Rice three delights	Fried milk
5	Cooked soup	Stuffed eggs	Flan
6	White beans with clams	Ravioli with tomato	Apple
7	Chickpea salad	Breaded chicken thighs	Fruits of the forest yogurt
8	White bean salad	Tuna pizza	Strawberry and banana liquid yogurt
9	Chicken salad with mayonnaise	Potato omelette	Tangerine
10	Mashed vegetables	Marinera potatoes	Watermelon

Example of menu plan for 10 days - Nutritional information

Nutrient (h)	**Amount** (r_h)	**Min. amount** (r_{min_h})	**Max. amount** (r_{max_h})
Folic acid	2097.52 μg	450 μg	2295 μg
Calcium	2177.83 mg	1950 mg	9945 mg
Carbohydrates	769.24 g	291.66 g	1487.5 g
Energy	7269.34 kcal	2333.33 kcal	11900 kcal
Phosphorus	4679.52 mg	1875 mg	9562.5 mg
Total fat	282.05 g	91 g	464.1 g
Iron	105.02 mg	28.5 mg	145.35 mg
Magnesium	1283.6 mg	375 mg	1912.5 mg
Potassium	13053.8 mg	6750 mg	34425 mg
Proteins	291.08 g	116.66 g	595 g
Selenium	196.08 μg	85.83 μg	437.75 μg
Sodium	3020.12 mg	2900 mg	14790 mg
Vitamin A	2937.55 μg	1500 μg	7650 μg
Vitamin B1	4.6 mg	1.36 mg	6.97 mg
Vitamin B2	4.73 mg	2.1 mg	10.71 mg
Vitamin B6	7.97 mg	1.8 mg	9.18 mg
Vitamin B12	11.84 μg	7.6 μg	38.76 μg
Vitamin C	248.9 mg	90 mg	459 mg
Vitamin D	24.08 μg	15.5 μg	79.05 μg
Vitamin E	101.27 mg	21 mg	107.1 mg
Iodine	633.70 μg	225 μg	1147.5 μg
Zinc	41.21 mg	22.5 mg	114.75 mg

Outline

1. Introduction
2. Literature review
3. Our formulation of the multi-objective menu planning problem
4. Experimental assessment
5. Conclusions and future research
6. Acknowledgements
7. References

Conclusions

- We have proposed a novel formulation for the MMPP.
- Since our plans are designed for school cafeterias, the cost of the menu, and the degree of repetition of courses and food groups are optimised.
- Suitable menu plans, in terms of their nutritional values, are provided.
- For shorter plans, the NSGA-II provided the best performance, while the SPEA2 was the best-performing approach when dealing with longer plans.
- The multi-objective nature of the novel MMPP was also demonstrated.

Further research

- A larger number of courses could be added to the database in order to provide a greater variety in the production of menu plans.
- Seasonal products could also be considered as a determining factor in the price and quality of the food.
- It would be interesting to carry out more tests with additional variation operators and even other MOEAs, including aggregation-based multi-objective optimisers.
- The repair method could be improved in such a way that it can obtain a feasible individual in a much smarter manner.
- For the plan generation, more objective functions and/or extra constraints based on other recommendations may be considered.
- Other paradigms: parallel approaches and machine learning, among others.

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Acknowledgements

- This work was supported by the Spanish Ministry of Economy, Industry and Competitiveness as part of the programme “I+D+i Orientada a los Retos de la Sociedad”, with contract number TIN2016-78410-R.
- The problem formulation and restrictions follow the recommendations of the school cafeteria programme of the Government of the Canary Islands: “Programa de Eco-comedores Escolares de Canarias”, which is a joint priority action of the “Instituto Canario de Calidad Agroalimentaria”, the “Dirección General de Salud Pública del Gobierno de Canarias” and the “Dirección General de Ordenación, Innovación y Promoción Educativa”.

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- San Cristóbal de La Laguna, Spain – December 10, 2018 -