Multi-Objective Evolutionary Beer Optimisation

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ABSTRACT
Food production is a complex process which can benefit from many optimisation approaches. However, there is growing interest in methods that support customisation of food properties to satisfy individual consumer preferences. This paper addresses the personalisation of beer properties. Having identified components of the production process for beers, we introduce a system which enables brewers to map the desired beer properties into ingredients dosage and combination. Previously explored approaches include direct use of structural equations as well as global machine learning methods. We introduce a framework which uses an evolutionary method supporting multi-objective optimisation. This work identifies problem-dependent objectives, their associations, and proposes a workflow to automate the discovery of multiple novel recipes based on user-defined criteria. The quality of the solutions generated by the multi-objective optimiser is compared against solutions from multiple runs of the method, and those of a single objective evolutionary technique. This comparison provides a road-map allowing the users to choose among more varied options or to fine-tune one of the preferred solutions. The experiments presented here demonstrate the usability of the framework as well as the transparency of its criteria.

CCS CONCEPTS
• Mathematics of computing → Bio-inspired optimization.
• Information systems → Personalization.

KEYWORDS
personalisation, NSGA-II, beer

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1 INTRODUCTION
Optimisation of food production processes, given its real-world significance, has been seen primarily through the lens of process optimisation with the sole objective of finding solutions that meet the precise characteristics of the product. Acknowledging the potential for several viable solutions when optimising the food processes, this real-world problem poses itself as a challenging task with an inherently underdetermined characteristic [5]. This work addresses the issue through a workflow based mainly on a multi-objective optimiser to (1) generate solutions with the required characteristics defined by the domain experts, and (2) investigate solutions quality.

The proposed method aims to map the brewing elements onto target properties. Basic knowledge is acquired through ‘reverse engineering’ of some well-recognised labels based on their known characteristics. These characteristics allow both the validation of the generated solutions, and lay the foundations to reformulate the task as a multi-objective problem. The motivation is to demonstrate the system’s ability in offering various solutions, in order to allow the domain experts the ease and flexibility of choosing from a suite of validated solutions. This is of practical relevance when either the diversity of the solutions is a priority, or the ability to fine-tune one or more of the identified solutions.

2 BACKGROUND
Several attempts have been made at optimising various elements of beer brewing; this is because of the its mix of standardisation and ingredient-based variability. Previous work have however, most often, considered specific or causal relationships between ingredients and individual properties known to play a significant role in consumers’ preferences (e.g. foamability, flavour profile, temperature, aroma) or process parameters (e.g. processing time). These work can be categorised as process-centric, when the objective is process improvement, often with the intention to partially automate, or outcome-centric when researching the determinants of beer quality and organoleptic properties. In the latter case, focus can be on specific determinants or adopt a more global perspective on the end-product. Related research into the topic are provided in [1].

Process equations related to original gravity (OG) which is the gravity of the wort pre-fermentation, final gravity (FG) referring to the gravity post fermentation, alcohol by volume (ABV), bitterness or international bitterness unit (IBU) and colour (using Standard Reference Method or SRM) are provided in [1].

The framework presented in this work relies mainly on the multi-objective optimiser (non-dominated sorting genetic algorithm II or NSGA-II [4]), yet provides both a comparison and a potential integrative workflow with a single objective evolutionary optimiser, differential evolution or DE (using DE/best/1 which is known for its competitiveness and robustness [3]).

3 EXPERIMENTS AND RESULTS
In this work, the optimiser takes (a) an inventory of the existing ingredients and their weights (as dimensionality of the problem and
bounds to each dimension respectively) as shown in Table 1 along with (b) a desired set of organoleptic properties for a particular product as presented in Table 2, and returns an optimal set of ingredient lists and their associated amounts (as solution vectors) which facilitate the production of the target product.

The experiments conducted in this section are to cater for a proof of principle study, which simulate a realistic scenario in a small-scale brewery, where the brewer’s efficiency is set to 58%\(^1\), boil size of 24L, batch size of 20L, and boil time of 60 minutes. Despite following a simulative approach, the grounding for our experiments is found in the pre-existing descriptions associated to commercial products being “reverse engineered”. This covers all the relevant parameters as well as user preferences and organoleptic properties through respectively published ingredients, label contents, advertising material and product reviews.

### 3.1 Experiment Setup

The population size for NSGA-II is set to 100, generating the same number of offsprings. In each generation, duplicate individuals are removed, and given the continuous nature of the solution space, simulated binary crossover and polynomial mutation are used. The crossover probability is set to \(p_c = 0.9\) and using distribution indexes, the crossover and mutation operators are set to \(\eta_c = 15\) and \(\eta_m = 20\) respectively. The termination criterion is set to 1000 generations. The population size in DE is 100, and \(F\) and \(C_R\) are set to 0.5. The termination criteria are set to either reaching 100,000 function evaluations or the error threshold defined below.

In the experiments, at the end of each run, the number of successful solution vectors in the population with the overall error of \(e \leq 0.05\) (which is defined next) is used as one of the performance measures, along with the count of non-dominated solutions for NSGA-II. There are 30 independent runs for each experiment and the results are summarised over these independent simulations.

In this work, given OG, FG and ABV are interdependent [1], the task is formulated into a 3-objective problem with \(f_1\), which takes into account the Euclidean distance between the desired OG, FG, ABV and the corresponding generated values; \(f_2\), the proximity to user-specified IBU, and \(f_3\) which returns the distance from the desired colour.

\[
\begin{align*}
  f_1(\bar{x}) & = \sqrt{(f_{OG}(\bar{x}) - OG)^2 + (f_{FG}(\bar{x}) - FG)^2 + (f_{ABV}(\bar{x}) - ABV)^2} \\
  f_2(\bar{x}) & = \sqrt{(f_{IBU}(\bar{x}) - IBU)^2} \\
  f_3(\bar{x}) & = \sqrt{(f_{SRM}(\bar{x}) - SRM)^2}
\end{align*}
\]

where \(\bar{x}\) is the list of ingredients, and OG, FG, ABV, IBU and SRM represent the desired values for a product as provided by the brewers (in this case from Table 2).

The overall error, \(e = f_1 + f_2 + f_3\), is defined by the quality of the solution in terms of the proximity of the solution’s fitness to the objective values. Note that \(e\) is not used by the multi-objective optimiser to guide the optimisation.

### 3.2 Results and Discussion

Table 3-a reports the number of non-dominated individuals found at the end of the process; also, from these individuals, the ones with pre-determined proximity to the optimal values are indicated as successful solutions. During the optimisation process, the majority of individuals within the population approach constitute part of the Pareto front (\(\geq 95\%\)); however, not all return the desired overall error, \(e\). As shown in the table, for the majority of the products, approximately 20–50% of the individuals on the Pareto front are successful. In three of the products (i.e. 4, 7 and 14), no suitable solution is found. The reason behind these failures will be investigated by exploring each objective individually.

To evaluate the proximity of the objectives, \(f_1-3\), of successful solutions in each run, initially the standard deviation of each objective is calculated in each run; these values are then averaged to measure the nearness of the objectives, or their deviations. Table 3-b reports the results, which illustrate the closeness of each independent objective values.

In under-determined systems [5] where there are fewer equations than unknowns (and by extension, more solutions to a problem), the proximity of the objectives in solution vectors does not strictly imply the proximity of solution vectors themselves. To establish the distance of solution vectors within each run, a similar analysis is conducted, this time for each of the sixteen components in the solution vectors. The results indicate that in each of the independent instances not only the distances between the objectives

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**Table 1: Input ingredients and their properties**

| # | Hop      | Weight | \(\alpha\) | \(\beta\) | Time |
|---|----------|--------|-------------|-------------|------|
| 1 | Cascade  | 100 g  | 6           | 6           | 60   |
| 2 | Chinook  | 100 g  | 13          | 3.5         | 60   |
| 3 | Northern Brewer | 100 g | 9        | 4           | 60   |
| 4 | Magnum   | 40 g   | 13.5        | 6           | 60   |
| 5 | Fuggles  | 50 g   | 4.5         | 2.5         | 60   |

**Table 2: Product list and their characteristics**

| # | Product Name | ABV | IBU | SRM | OG | FG | Time |
|---|--------------|-----|-----|-----|----|----|------|
| 1 | Imperial Black IPA | 12.2 | 150 | 35  | 1.070 | 1.014 |
| 2 | Guinness Extra Stout | 5.1 | 40  | 40  | 1.070 | 1.034 |
| 3 | Atlantic IPA Ale | 8.4 | 80  | 13  | 1.074 | 1.011 |
| 4 | Tokyo Rising Sun | 15.4 | 85  | 71  | 1.125 | 1.023 |
| 5 | Punk Monk | 6.2 | 60  | 8.5 | 1.056 | 1.010 |
| 6 | Santa Powa | 4.7 | 31  | 22  | 1.048 | 1.013 |
| 7 | Summum Stout | 11.1 | 50  | 100 | 1.102 | 1.026 |
| 8 | Vice Bier | 4.4 | 25  | 15  | 1.043 | 1.010 |
| 9 | Blitzen Berliner Weisse | 4.3 | 4.5 | 1.040 | 1.097 |
| 10 | Jasmine IPA | 6.3 | 40  | 17.5 | 1.060 | 1.014 |
| 11 | No Label | 4.5 | 25  | 5   | 1.043 | 1.009 |
| 12 | Monk Hammer | 7.5 | 250 | 7   | 1.065 | 1.010 |
| 13 | Science IPA | 5.2 | 45  | 15  | 1.050 | 1.011 |
| 14 | Tropic Thunder | 7.5 | 25  | 86.36 | 1.074 | 1.020 |
| 15 | Blonde Export Stout | 7.7 | 55  | 5   | 1.075 | 1.020 |
| 16 | Indie Pale Ale | 4.8 | 30  | 8   | 1.044 | 1.008 |
| 17 | Punk X Punk | 7.2 | 42  | 12  | 1.058 | 1.004 |
| 18 | Atlantic IPA Ale | 8.4 | 80  | 28  | 1.074 | 1.013 |
| 19 | Korek Dark | 4.6 | 35.09 | 21.87 | 1.042 | 1.007 |
| 20 | Punk IPA | 5.6 | 40  | 7.6 | 1.053 | 1.011 |

* IBU gal per lb is 0 for all the fermentables.
Table 3: (a) Summary of non-dominant and successful solutions (b) Average objective deviation in independent runs

| # | Non-dominant Median | Successful Median | Stdv | f1 | f2 | f3 |
|---|---------------------|-------------------|------|----|----|----|
| 1 | 100                 | 16.03             | 41.5 | 31.15 | 1.46E-04 | 3.88E-03 | 1.39E-03 |
| 2 | 96                  | 15.42             | 38   | 33.56 | 1.34E-04 | 4.75E-04 | 1.90E-04 |
| 3 | 95                  | 13.40             | 52.5 | 32.49 | 4.51E-04 | 6.90E-03 | 2.46E-03 |
| 4 | 100                 | 0                 | 0    | 0    | NA | NA | NA |
| 5 | 99                  | 11.36             | 53.0 | 32.67 | 5.63E-04 | 7.99E-03 | 4.02E-03 |
| 6 | 100                 | 0                 | 0    | 0    | NA | NA | NA |
| 7 | 100                 | 10.52             | 47   | 32.74 | 6.74E-04 | 9.25E-03 | 4.10E-03 |
| 8 | 100                 | 17.20             | 31   | 27.53 | 7.84E-04 | 9.46E-03 | 2.80E-03 |
| 9 | 97                  | 15.39             | 29   | 20.85 | 1.40E-04 | 7.85E-03 | 9.26E-03 |
| 10 | 98                 | 17.97             | 40   | 31.26 | 7.62E-04 | 7.55E-03 | 3.77E-03 |
| 11 | 100                | 10.61             | 33.5 | 34.58 | 6.74E-04 | 5.90E-03 | 5.26E-03 |
| 12 | 100                | 13.91             | 54.5 | 31.03 | 2.50E-04 | 5.07E-03 | 1.07E-03 |
| 13 | 97.5               | 15.99             | 25.5 | 29.61 | 7.55E-04 | 9.25E-03 | 2.90E-03 |
| 14 | 100                | 0                 | 0    | 0    | NA | NA | NA |
| 15 | 98.5               | 15.55             | 49.5 | 27.86 | 5.73E-04 | 8.49E-03 | 3.66E-03 |
| 16 | 100                | 13.38             | 27.3 | 30.92 | 1.20E-03 | 7.85E-03 | 5.59E-03 |
| 17 | 99.5               | 14.24             | 20.5 | 29.40 | 3.98E-04 | 4.52E-03 | 3.57E-03 |
| 18 | 100                | 18.93             | 41.5 | 31.05 | 3.94E-04 | 6.61E-03 | 2.51E-03 |
| 19 | 100                | 13.45             | 53   | 38.15 | 7.35E-04 | 5.67E-03 | 3.39E-03 |
| 20 | 99.5               | 15.63             | 43.5 | 28.70 | 8.06E-04 | 7.71E-03 | 4.71E-03 |

Table 4: Average distance from the optimal objective values in failed products

| # | f1  | f2  | f3  |
|---|-----|-----|-----|
| 1 | 1.954 | 11.932 | 13.181 |
| 2 | 1.189 | 80.645 | 92.672 |
| 3 | 685 | 53 | 92 |

are modest, but also the solutions are not radically distant (see Table 6 in [1]). This enables the optimiser to return several similar candidate solutions with delicate differences for the users to choose from depending on their production processes and criteria.

Fig. 1-a illustrates the closeness of solutions generated in a single NSGA-II run for one of the products, Guinness Extra Stout (the same observation is seen in the others products). This sample run, resulted in 53 successful solutions; each line on the y-axis represents a solution vector which illustrates the amount of uptake in each ingredients on the x-axis; a darker shade indicates a higher uptake from the existing ingredient (e.g. ingredient 15 representing flaked barley) and a brighter shade highlights a lower uptake (e.g. ingredient 10 referring to wheat malt).

To investigate whether more distinct solutions are available to this problem and if the optimiser (in each independent run) tends to 'navigate' the individuals towards a particular ‘zone’ within the Pareto front, the proximity of sampled solutions from each independent run is taken into account and visualised. Taking a sample solution from each independent run (i.e. naturally, with varying starting points) demonstrates a greater distinctiveness in the diversity of the solution vectors (see Fig. 1-b). This confirms that NSGA-II, in the context of this problem, leads the population towards a particular segment of the Pareto front in each run. This experiment evidences the availability of more varied solutions in the solution space (crowd distancing measures and diversity preserving/promoting strategies in this context can be beneficial [2, 6]).

To confirm this finding, DE, as a single objective evolutionary optimiser, is run and the generated solutions are visualised in Fig. 1-c.

The observations on the performance of NSGA-II are extendable to the objective space, which as shown in Fig. 3, demonstrate a stronger proximity in a single run NSGA-II, than sampling solutions from multiple runs of the algorithm.

To further evaluate the solutions’ uniqueness, the distance between each pair is calculated. These values are presented as distance matrices and visualised in Fig. 2, showing that depending of the user-specific needs, from less diverse to more diverse set of solutions, the following is recommended: single run of NSGA-II and choosing successful solutions; multiple runs of NSGA-II with a sample solution picked from each run; and multiple runs of single objective differential evolutionary optimiser. The maximum distances between solution vectors, which are shown in the labelled colour bar in Fig. 2, are 0.0265 (Fig. 2-a), 3.5156 (Fig. 2-b) and 5.3905 (Fig. 2-c) respectively.

In the results reported, there have been instances where the optimiser fails to suggest suitable ingredient combinations, more specifically, in three products. The average objective values in the three failed products in 30 runs is calculated, where each run results in 100 non-dominant individuals. Average objective distance of the individuals from the desired objective values is shown in Table 4. Looking at the desired objective values in these products, there is a shared characteristic which prevents them from being optimised given the existing inventory. The reason lies in the high SRM values (≥ 71), which can only be achieved with greater availability of ingredients such as chocolate malt or roasted barley (i.e. ingredients 11 and 14 in Table 1 respectively). The optimiser aims to increase the SRM value by using the other fermentables, resulting in adverse effects on the objectives, including f1 and f2. To investigate the influence of the input ingredients, the amount of roasted barley, which offers a higher SRM value, is increased to 5 kg (from the original 0.5 kg) and the optimisation is re-run 30 times for one of the failed products, product 7 (i.e. Summaid Stout). The result demonstrates an uptake in using the ‘topped-up’ ingredient (on average 3.12 kg) to meet the objectives. In summary, the process returns 45±31 successful solutions, out of the 85±20 non-dominated ones, which is in line with the figures viewed for the other products.

To summarise, in instances where domain experts require more diverse set of solutions, the single objective optimisation method presents a greater promise. On the other hand, the multi-objective optimiser provides a delicate choice of solutions from a particular region within the solution space with inherent proximity in the objective space which allows the exploitation of a promising region of the solution space. Therefore, an overall suitable solutions can be identified through the first method, and then the second can be deployed to fine-tune the favourite solution.

4 CONCLUSION

When aiming for innovation, the high experimental costs associated with the beer brewing process is shown to be efficiently reducible by taking into account the key product characteristics (and reformatting them as objectives) along with the input ingredients. The proposed method automates the quantitative ingredients selection, which is one of the key experimental aspects of brewing. Although we established this primarily with volumes corresponding to low cost production environments, the presented system can be geared towards scalability. Therefore, the core challenge of generating novel and dynamically changing recipes, based on the product characteristics, is alleviated. This allows the design of high quality beer...
Figure 1: Ingredients combinations, or solution vectors generated by (a) NSGA-II in a single run returning 53 solutions (b) NSGA-II in 30 independent runs, 25 of which return at least one successful solution to pick from, and (c) DE in 30 independent runs, returning 30 successful solutions.

Figure 2: Distance matrices for solutions generated by (a) NSGA-II in a single run returning 53 solutions (b) NSGA-II in 30 independent runs, 25 of which return at least one successful solution, and (c) DE in 30 independent runs, returning 30 successful solutions.

Figure 3: Distribution of objective values, $f_{1-3}$, in successful solutions generated by (a) single run of NSGA-II, and (b) multiple independent runs of NSGA-II.

by commercial venues where quantities and varieties of ingredients are not hard constraints, as well as less equipped and more flexible microbreweries where constraints play a bigger role. A number of strategies are suggested depending on user preferences in terms of the solution choice, either from a narrow set of solution with delicate differences, or a diverse pool of potential solutions with further discriminability.

More investigation is required to determine the impact of multi-criteria decision-making (MCDM) methods on the existing workflow. An important next step, with a potentially greater impact, is to explore crowd distancing mechanism which may result in building a more comprehensive Pareto front, allowing control on either exploiting a narrow solution space, or covering a diverse set of more radically different solutions. Considering additional and more complex objectives, such as aroma profile, flavour and foam is part of an ongoing research.

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