POSTER

Towards multi-objective optimization of sustainable insect production chains

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Published: 09 July 2022

Citation in BibTeX format

GECCO '22: Genetic and Evolutionary Computation Conference
July 9 - 13, 2022
Massachusetts, Boston

Conference Sponsors:
SIGEVO

GECCO '22: Proceedings of the Genetic and Evolutionary Computation Conference Companion (July 2022)
https://doi.org/10.1145/3520304.3528898
ISBN: 9781450392686

Towards Multi-Objective Optimization of Sustainable Insect Production Chains

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ABSTRACT

Due to the relatively recent history of industrial insect farming, there are still no extensive studies on the optimization of insect production chains. In this context, the present work aims to be a first step in filling this gap. A tentative set of mathematical models is proposed to take into account three different, conflicting objectives: maximizing economic viability, minimizing environmental impacts, and maximizing societal benefits. The state-of-the-art multi-objective algorithm NSGA-II is used to obtain an approximate Pareto fronts of solutions, that are later analyzed to identify suitable trade-offs. While preliminary, the results are encouraging enough for the computer-assisted design and development of sustainable insect production chains. Future works will take into account more extensive models, able to simulate scenarios in different European countries, and include parts of the chain such as transportation of goods to and from the production facilities.

CCS CONCEPTS

• **Information systems → Recommender systems**; • **Mathematics of computing → Mathematical optimization**; • **Applied computing → Industry and manufacturing**.

KEYWORDS

life cycle assessment, sustainability, insects, decision making, genetic algorithm, multi-objective programming, NSGA-II;

ACM Reference Format:

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1 INTRODUCTION

The human need for food increases with the population growth that is anticipated to reach 9.7 billion by 2050 [5]. In particular, the amount of animal protein required to meet human life needs is expected to double by 2050 [8]. In order to meet human nutritional needs, a negative environmental impact is certain as long as animal meat is considered the principal source of protein. Thus, the transition toward a sustainable source of proteins is a challenge of considerable magniture.

At present, insects are a potential non-conventional source of proteins. However, despite the environmental and socioeconomic benefits of insect production, the development of this new sector has some difficulties and challenges. Indeed, insect products are expensive (about 1 €/kg in Europe) due to the cost of labor and the competition with animal-based protein production. Thus, the two main priorities for the field are improving consumer acceptance and increasing the scale of production.

In this paper, we propose a first set of mathematical models to describe different conflicting aspects of the insect production chain, we perform an optimization with a state-of-the-art multi-objective evolutionary algorithm, NSGA-II [1], and we analyze some of the solutions on the resulting set of non-dominated solutions. To the best of our knowledge, the present work is the first that involves a set of trade-offs in the decision framework of insect production. Thus, the aim of this work is to develop a multi-objective optimization framework for describing different aspects of sustainability of insect production. The objectives considered take into account three aspects, namely environmental impact, societal concern and economic viability. The results, while preliminary, seem encouraging enough for the proposed approach to represent a first step towards a more realistic simulation and optimization of sustainable insect chains.

2 PROPOSED APPROACH

For this work, we propose a set of models to describe the conflicting objective functions for the optimization of sustainable insect chains that should all be optimized simultaneously. Then, we perform an optimization with a state-of-the-art multi-objective evolutionary algorithm NSGA-II,

2.1 Multi-objective Models for Insect Production

we introduce the proposed mathematical model including that includes three conflicting objective functions: the annual operating profit, the social aspect and the environmental impact.

2.1.1 Economic Aspect.

The economic objective considered in this work is the maximization of the operating profit. This latter is composed of the gross

GECCO '22 Companion, July 9–13, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9268-6/22/07.

https://doi.org/10.1145/3520304.3528898

margin minus the overhead costs. After subtracting the variable costs, that are the feed costs, the energy and water costs, from the gross revenue, that is the cash sales, the difference is the gross margin. Since we don't have complete data on real-world, large-scale insect production chains, the identification of all elements of the operating profit is complicated. Thus, for the moment we restrict the economical profit to the sale price of insect-based products. Thus, the objective function $\mathcal{F}_1$, that is to be maximized, can be optimized by increasing the insects biomass, that is a function of the amount of insect feed AIF_{fd} and the type of feed, decreasing the real wage RW and the number of labourers NL.

$$\begin{aligned}\mathcal{F}_1 = (P - EWC - R) * \sum_{fd \in FD} \left(FCE_{fd} * AIF_{fd}\right) - \\ -RW * NL * 12 - \sum_{fd \in FD} \left(feed_{fd} * AIF_{fd}\right) - LS\end{aligned} \tag{1}$$

where P is the price of 1 tonne of insect protein (€), EWC is the Energy and Water Cost necessary to produce 1 tonne of insect protein, R is the rent for 1 tonne of insect protein (€), FCE_{fd} is the Feed Conversion Efficiency of feed fd, $feed_{fd}$ is the Sales price fresh produce [€/tonne], LS is Labor Safety cost expressed in equation 3.

2.1.2 Social Aspect.

In the present work, the social impact of insect production is represented by Fair Wage Potential (FWP) and Labor Safety. The FWP is a social assessment method that describes the social sustainability of workers and the social impacts of a product during its life cycle [6]; in particular, we adopt the characterization model of FWP proposed by Neugebauer et al. [4]. Thus, in order to maximize the FWP, the variable RW becomes favored:

$$FWP = \frac{RW}{RWT} * \frac{CWT}{MLW} * \left(1 - IEF^2\right) \tag{2}$$

where RWT is the Real Working Time (hours/week) of workers, RWT is the Real Working Time (hours/week) of workers, MLW is the Minimum Living Wages [€/month], which has to be paid to the worker to enable an adequate living standard for an individual and/or family in the respective country or region and CWT is the Contracted Working Time per country or sector [hours/week] for workers (including vacation days).

Labor Safety (LS): to maximize the labor safety, the objective function LS aims to increase the number of Safety Equipment SE_e allowed to labors.

$$LS = \sum_{\substack{e \in E \\ s \in Sc}} (CPPE_e * SE_e) * NL * SF_{LS_s} * Sc_s \tag{3}$$

where $CPPE_e$ is the Cost of Personal Protective Equipment e, SF_{LS_s} is the Scaling Factor (depends on the scale of production) and Sc_s is the scale of the farm.

the potential fair wage and the labor safety are integrated in one objective $\mathcal{F}_2$ since they both represent the social aspect. Thus, introducing a weight w, the weighted sum of the objective functions is to be maximized:

$$\mathcal{F}_2 = w * FWP + (1 - w) * LS \tag{4}$$

2.1.3 Environmental Aspect.

Frass represents the excrement resulting from the digestive system of insects. The cost of using frass as fertilizer is high, thus here we assume that frass is disposed of using transport engines and that increase greenhouse gas emissions. Thus, through $\mathcal{F}_1$ the minimization of insect frass is introduced:

$$\mathcal{F}_3 = \sum_{\substack{fd \in FD \\ s \in Sc}} \frac{AIF_{fd}}{FCE_{fd}} * \left(1 - FCE_{fd}\right) * FrSF_s * Sc_s \tag{5}$$

with $FrSF_s$ is the Frass Scaling Factor (depends scale of production).

The three objectives function presented above are in conflict. On one hand, the optimization of function $\mathcal{F}_1$ disfavors variables RW and NL, which creates a conflict between objective function $\mathcal{F}_1$ and objective function $\mathcal{F}_2$, since this last one aims at the maximization of RW and NL. On the other hand, the social and the environmental aspect are also antagonists: the economic aspect is further in conflict with the environmental aspect, as the greater the operating profit, the greater the produced biomass, that is a function of AIF_{fd}. A maximization of $\mathcal{F}_1$ would increase the insect frass, as it is also a function of AIF_{fd}.

The resulting structure of an individual is summarized in Figure 1. In this particular structure for the candidate solutions, one of the main issues is to preserve locality of the changes in case of mutations of SC, a variable that can influence several other quantities, such as the total amount of feed that can be administered to the insects, or the maximum number of laborers in the facility. Inside the genome of an individual, SC is represented by an integer. We opted for an encoding where dependent quantities such as NL and AIF are expressed by values in $[0, 1]$, representing the point between the minimum and the maximum value for a given scale SC_i. For example, considering a candidate solution with $SC = 2, NL = 0.75, AIF = 0.5$, a mutation changing the scale of the facility from $SC = 2$ to $SC = 4$ would correspond to a larger facility, still employing 75% of the total possible amount of laborers, and using 50% of the maximum amount of feed as input.

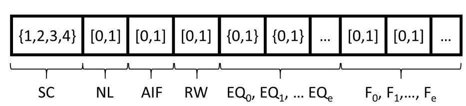

Figure 1: Structure of an individual. ***SC*** **is an integer that describes the size category of the production facility.** ***NL*** **and** ***AIF*** **are a floating point value in $[0, 1]$, representing the point between the minimum and maximum amount of laborers employed, and the minimum and maximum amount of feed in input to the facility, respectively, where the minimum and maximum depend on the value of** ***SC*****.** ***RW*** **is a value in $[0, 1]$, representing the real wages payed to the laborers as a point between the minimum allowed and the known maximum. $EQ_0, ...EQ_e$ are binary values $\{0, 1\}$, representing the use (or not) of safety equipment E_i. $F_0, ..., F_f$ are the ratios in $[0, 1]$ of the different types of feed provided to the insects; these values are constrained so that $\sum_i^f F_i = 1$.**

3 EXPERIMENTAL EVALUATION

All the models previously described for the objectives are implemented in Python 3, and we use the version of NSGA-II from the `inspyred` [2] library for the multi-objective optimization. All the code is freely available in the GitHub repository https://github.com/albertotonda/mo-insect-chain. The majority of existing works in

Table 1: Model parameters related to the scale of the facility.

Scale	AIF (tonne)	NL	FrsF	SF_{ls}
1	[25000, 75000]	[25, 75]	0.8	1
2	[75000, 125000]	[75, 125]	0.7	1
3	[125000, 175000]	[125, 175]	0.5	1
4	[175000, 250000]	[175, 250]	0.3	1

the current literature review on insect protein production are not complete, and based on interviews with insect farmers and experts. Thus, the choice of the insect Tenebrio molitor (T.molitor) in this study comes from the fact that it is the insect with the most data found in the report of Kooistra et al. [3]. For this reason, parameters such as IEF, RWT, MLW, CWT and RWT match with data from The Netherlands [4], since the study of Kooistra et al. [3] concerns that country. At the moment, the data in our possession makes it impossible to include decision variables related to positioning the insect production facility in different countries, so in the scope of the present work, we make the hypothesis of placing the facility in The Netherlands.

3.1 NSGA-II parameters and operators

After a few trial runs, NSGA-II is set with the following parameters: $\mu = 100$, $\lambda = 200$, $p_m = 0.2$, $p_c = 0.8$, stop condition based on maximum number of evaluations (2,000). p_c and p_m are the probabilities of applying a uniform cross-over or a mutation, respectively. For fitness function $\mathcal{F}_2$, we set weight $w = 0.5$.

If a mutation is selected, one of the parts of the genome summarized in Figure 1 is then randomly chosen with uniform probability, and a different type of mutation is applied, depending on the type of variables considered. For a categorical variable like SC, another value is randomly selected with uniform probability among the ones available. For continuous variables in $[0, 1]$ such as NL, AIF, or RW, a Gaussian mutation with $\mu = 0.0$ and $\sigma = 0.1$ is applied to the original value; should the resulting value go beyond the boundaries, the individual is repaired by resetting the value to the closest boundary. For strings of bits such as $EQ_0, ..., EQ_e$, a random number of bit flips is applied, following the alias method [7]. For sets of continuous values in $[0, 1]$ such as $F_0, ..., F_e$, a subset of indexes is selected again following the alias method, and to each corresponding value a small Gaussian mutation with $\mu = 0.0$ and $\sigma = 0.1$ is applied; if the new value is out of the boundaries, the individual is repaired by resetting the value to the closest boundary. $F_0, ..., F_e$ are then normalized, as we impose that $\sum_i F_i = 1.0$.

3.2 Results

At the end of the optimization process, the population is all disposed on an approximately optimal Pareto front, as shown in Figure 2 (two-dimensional projections of the populations are presented in Figures 3,4, 5). Interestingly, the visible discontinuity is tied to the absence of candidate solutions with $SC = 2$ or $SC = 3$, as only small and very large scale production facilities are present on the approximated Pareto front. This could imply that this type of industry is only viable in these two formats; but it must be noted that the simplifying assumptions described in Section 2 might impair the realism of the results. For example, scale effects related to the efficiency of waste disposal are ignored, and as a consequence the environmental impact of large-scale facilities are overestimated. Following the same considerations, larger companies could more easily afford to pay better salaries, but this information is currently not included in the models. The results obtained should thus be considered as a first proof of concept to validate the approach, rather than realistic recommendations for the design of an insect production facility. Table 2 represents a few selected non-dominated

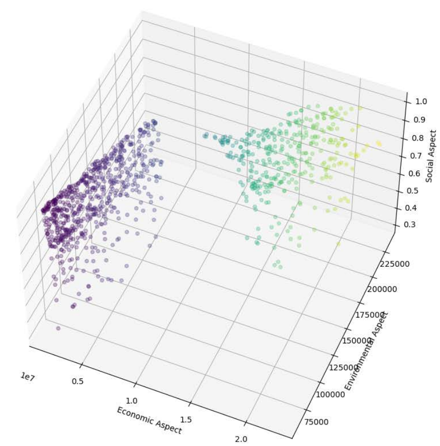

Figure 2: Pareto front resulting from the multi-objective optimization, showing all three objectives. The visible discontinuity is related to the absence of candidate solutions with $SC = 2$ or $SC = 3$, hinting that solutions including small and very large scale facilities dominate all others.

Table 2: Fitness values for selected points on the non-dominated fronts.

Scale	Economic Aspect (€)	Environmental Aspect	Social Aspect
1	2,094,735.07	72,641.02	0.99
1	3,103,623.56	99,769.15	0.99
4	19,592,730.14	201,916.79	0.54

points, chosen as representative of different trade-offs. From these points, we can observe how small-scale facilities easily reach near-optimal values for social aspects; and how the social aspect value decreases when we pass to a larger scale of the farming production facility. Figure 3 shows that the approximate Pareto solutions are assembled in the bottom left corner and that is because in the small scales, frass is produced in lower quantities. Another limitation of the current models is that they only use frass as a proxy of environmental impacts, while more refined results of LCA could include

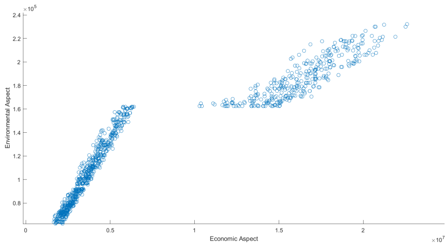

Figure 3: Two-dimensional projection of the population on the non-dominated front at the end of the optimization. This plot shows the trade-offs between economic (higher values are better) and environmental (lower values are better) aspects. It is interesting to notice how for part of the solutions there is a steep liner relationship between improving economic outputs and worsening environmental impacts; while after the discontinuity, solutions to the right of the graph show a softer trade-off.

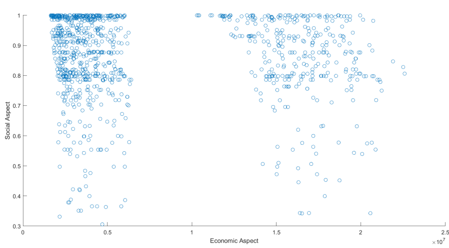

Figure 4: Two-dimensional projection of the population on the Pareto front at the end of the optimization. This plot shows the trade-offs between economic (higher values are better) and social (higher values are better) aspects. Candidate solutions in the cluster to the right, corresponding for the most part to small-scale facilities, can more easily find next-to-ideal values for the social aspect; while it seems more difficult for larger-scale companies, clustered towards the right, as the economic aspect improves.

scale economies that could favor larger factories. The same figure depicts a gap in the middle of the plot, explained by the fact that the approximate Pareto-optimal solutions found include either small scale and very large scale insect production facilities. In Figure 4, the non-dominated solutions are rather condensed in top left zone, as the more we go to a larger scale, the more it is difficult to satisfy safety conditions for all workers and to have a good fair wage potential. Figure 5 seems to show that there is no real antagonism between social and environmental aspects.

4 CONCLUSIONS

In this paper, we presented a first multi-objective optimization of a sustainable insect production chain. The mathematical model used to represent the chain includes economic, environmental, and social aspects that are clearly antagonistic. Preliminary experimental results show that the proposed approach is able to deliver sensible

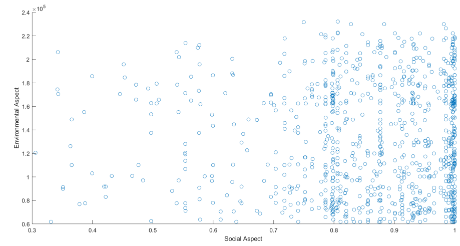

Figure 5: Two-dimensional projection of the population on the Pareto front at the end of the optimization. This plot shows the trade-offs between social (higher values are better) and environmental (lower values are better) aspects. Interestingly, a considerable number of solutions feature near-optimal values for the social aspect considered, with a wide range of possible values for the environmental impact.

approximate Pareto fronts that can be analyzed and studied by experts.

Future works on the multi-objective optimization of sustainable insect production chains will introduce different types of insects and different possible locations for the production facility, with variations over the country-dependent parameters, such a cost of labor and energy. We also plan to include more complex metrics into each objective, such as the complete LCA of the production facility into the environmental impact, and more accurate estimates of capital/operational expenditure into the economical viability.

ACKNOWLEDGMENTS

The authors would like to acknowledge funding from the European Union's Horizon 2020 Research and Innovation programme, via the H2020 project SUSINCHAIN

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