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Research Article

Fuzzy Inference Based A Posterior Decision-Making for Multi-Objective Diet Optimization Problem

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Abstract

We propose a Mamdani-Type Fuzzy Inference based posterior decision-making approach to multi-objective diet optimization problem. We optimize the multi-objective diet problem with evolutionary algorithms that result in tens/hundreds of non-dominated solutions which is too large to pick one of them by the decision-maker. Even though all the solutions are optimized for all the objectives simultaneously, not all objective functions may be equally important to a user and, also their importance may change for that user over time. Our main goal is to develop an applicable method for representing and incorporating a decision maker's (DM) instant preferences for objectives into decision-making stage. The FIS based decision making can guide users to decide on the most suitable menus. User's instant preferences for each objective form rule sets. Using Mamdani type FIS in the post-decision process of the multi-objective diet problem is a novel contribution. A desirability measure is calculated by using rule sets and membership functions considering the objective values, and based on the desirability measure the most preferred menu(s) are provided to the user. Our method can direct the DM to the region of interest in the search space of the multi-objective diet problem. Thus, the daily menu suggestions become more applicable, practical, and desirable for the users.

Keywords: Fuzzy Sets, Fuzzy Inference Systems, Multi-Objective optimization, Diet Optimization.

Çok Amaçlı Diyet Optimizasyon Problemi İçin Bulanık Çıkarıma Dayalı Sonradan Karar Verme

Öz

Çok amaçlı diyet optimizasyonu problemine Mamdani Tipi Bulanık Çıkarım tabanlı sonradan karar verme yaklaşımı öneriyoruz. Çok amaçlı diyet problemini, onlarca/yüzlerce baskılanamayan çözüm ile sonuçlanan Evrimsel Algoritmalarla optimize ediyoruz. EA'lar ile önerilen günlük menü sayısı, bunlardan birini seçmek için çok fazladır. Tüm çözümler aynı anda tüm amaçlar için optimize edilmiş olsa da, tüm amaç fonksiyonları bir kullanıcı için eşit derecede önemli olmayabilir ve ayrıca zaman içinde o kullanıcı için önemleri değişebilir. Ana hedefimiz, bir karar vericinin hedefler için anlık tercihlerini temsil edebileceği ve çok amaçlı diyet optimizasyon probleminin karar verme aşamasına dahil edebileceği için uygulanabilir bir yöntem geliştirmektir. Bulanık çıkarım tabanlı karar verme, kullanıcılara yüzlerce uygulanabilir çözüm arasından en uygun menüleri seçme konusunda rehberlik edebilir. Her amaç için kullanıcının anlık tercihlerini alarak yeni kural setleri oluştururuz. Mamdani tipi Bulanık Çıkarım Sistemi'nin çok amaçlı diyet probleminin karar sonrası sürecinde kullanılması yeni bir katkıdır. Amaç değerleri dikkate alınarak kural kümeleri ve üyelik fonksiyonları kullanılarak bir tercih edilirlik ölçüsü hesaplanır ve istenirlik ölçüsüne göre kullanıcıya en çok tercih edilen menü/menüler sunulur. KV'nin sözlü ifadeleriyle, yöntemimiz KV'yi çok amaçlı diyet probleminin optimizasyonu ile oluşturulan çözüm kümesinin arama uzayında ilgili bölgeye yönlendirebilir. Böylece günlük menü önerileri kullanıcılar için daha uygulanabilir, pratik ve arzu edilir hale gelmektedir.

Anahtar Kelimeler: Bulanık Kümeler, Bulanık Çıkarım Sistemleri, Çok Amaçlı Optimizasyon, Diyet Optimizasyonu

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1. Introduction

Majority of the real-world problems have multiple objectives that need to be optimized simultaneously, which makes them more complicated than single-objective optimization problems. In case of the single-objective optimization problem, the goal is to find the optimal solution for a single criterion. For example, minimizing the cost or environmental effect of the dietary planning problem. Multi-objective optimization (MOO) problems fall under the multi-criteria decision-making branch of mathematical optimization and deal with optimization problems involving two or more objective functions, some of which are to be minimized while others are to be maximized (Deb (2001)). In MOO, the main goal is to determine the optimal input values that will give the desired outputs for all the objective functions. In most cases, the objectives are conflicting with each other, meaning that the improvement in one objective may have a negative impact on another (Deb and Jain (2014), Purshouse and Fleming (2007)). Therefore, all the objectives that specify the optimization system should be considered together. When some objectives conflict, there is generally no single optimal solution, but a pareto set which includes non-dominated solutions, none of which need to be a global optimum for any given objective. Solution approaches for MOO problems generate hundreds of viable solutions while dealing with multiple objectives; this complicates the optimization problem in terms of computational resources. It also makes it hard for the Decision Maker (DM usually a human who is an expert in the domain) to pick the most desired solutions among the large number of multi-criteria non-dominated final solution sets. Therefore, in most cases, the main goal of solving a MOO problem must include an approach to help the DM in finding the most preferred solution among the feasible solution set based on his/her preferences (Miettinen (2012)). This can be done by considering the DM's preference for each objective in the problem. These preferences can be in the form of coefficients or importance specifying verbal expressions.

MOO Approaches can be grouped into three main categories based on DM's intervention, namely a priori, a posteriori and interactive methods. A priori methods usually focus on solving MOO problems by converting the original problems with multiple objectives into single-objective optimization problems. A priori methods require adequate preference information before the optimization process (Miettinen (2012), Miettinen et al. (2008)). In an interactive approach, the DM continuously interacts with the optimization process while it iteratively searches for the most preferred solution Miettinen (2012). The DM is part of the optimization process as the optimization algorithm iteratively searches for the most preferred solution. In each iteration of the optimization process, pareto optimal solutions are presented to the DM to give his/her preferences that indicate how the solutions can be improved. Interactive approaches require continuous intervention of domain expert DM, which is hard to supply. On the other hand, a posteriori approaches aim to produce numerous pareto optimal solutions and attempt to expand the search space as much as possible. Following the conclusion of the search procedure, desired solutions are chosen by the DM.

A Fuzzy Inference System (FIS) based interactive/aggregating decision-making approach for MOEAs was proposed by Balcı (Balci (2018)). He reduced four objectives into two using fuzzy rule sets predefined by the DM. This gave him the ability to solve MOO problems as reduced search spaces by interactively aggregating objectives during the optimization process. Another advantage of this approach is that the algorithm does not require a continuous DM interference. The DM only declares his/her preferences for objectives once then based on these preferences his FIS based decision-making approach aggregates all objectives but one into a new objective called desirability.

Aggregating and interactive approaches have various drawbacks in handling MOO problems, such as local optimization, information loss, additional constraints, single solution output, effectiveness on non-convex problems etc. (Deb (2001)). Therefore, solving problems with multi/many objectives as MOO problems and optimizing all objectives simultaneously is an important field of research. These kinds of algorithms try to overcome the problem of computational bottlenecks that arise due to the large objective space. Despite difficulties they can reach higher optimization levels. Therefore, post-decision making is the most effective approach for MOO problems (Deb (2001).).

Multi-objective evolutionary algorithms (MOEAs) are a special form of Evolutionary Algorithms (EAs) which have proven to be quite effective in locating well-converged, well-diversified, non-dominated solutions for optimization problems involving more than two objectives (Deb and Jain (2014)). The fundamental advantage of MOEAs is to generate solution sets and enable the estimation of the entire Pareto front when solving MOO problems. The main disadvantage of MOEAs is low speed due to high computations needed for multidimensional problems. Unfortunately, MOEA's results in hundreds/thousands of optimal solutions which is not feasible for DMs in real life, especially when the number of objectives is high. In such scenarios, the search space for the DM is too big, and it needs to be narrowed through the region of interest where the user's preferences are satisfied best.

To address this problem, in this work, we add a FIS based posterior decision-making step to a multi-objective dietary planning problem with three objectives which was proposed by Turkmenoglu in their work (Turkmenoglu et al. (2021)) in which they added "preference" and "preparation time" objectives to the classical diet problem to transform it into a multi-objective healthy eating problem. The first objective of the diet problem is to minimize the cost of a recommended daily menu. The second objective is to maximize the average preference which reflects personal taste for food items included in the recommended daily menu. The last objective is to minimize the preparation time spent for preparation and cooking. The cost and preparation time objectives represent the resources spent for diet optimization problem that need to be minimized while preference objective represents the profit which needs to be maximized. To address the many-objective dietary optimization problem, this method involved applying a well-known many-objective evolutionary algorithm: the Non-dominated Sorting Genetic Algorithm III (NSGA-III) (Deb and Jain (2014)). NSGAIII performs well in most of the popular multi/many-objective problems.

Results show that our FIS based posterior decision-making method can help DM to choose the best menu(s) among tens/hundreds of non-dominated solutions in the pareto set based on their instant preferences for objectives.

2. Materials and Method

2.1. Fuzzy Inference Systems

Fuzzy logic emerged in the context of the theory of fuzzy sets proposed by Lotfi Zadeh in 1965 (Zadeh (1965)). However, fuzzy logic has been investigated as infinite-valued logic since the early 20th century.

Fuzzy logic is based on the idea that people make decisions based on imperfect and non-numerical information. The term "fuzzy" refers to mathematical representations of ambiguity and imprecise data that are used to depict logical inference from ambiguous or imprecise assertions. This tries to emulate how people think about issues and make judgments, relying on ambiguous or inaccurate values rather than absolute truth or untruth. Fuzzy logic is a kind of many-valued logic in which the truth value of any real number between 0 and 1 may be used. When compared to the truth values of variables in Boolean logic, which can only be the integer values 0 (False) or 1 (True), it is used to deal with the concept of partial truth, where the truth value may be halfway between true and false (Pelletier (2000)).

From control theory to artificial intelligence, fuzzy logic has been used in various fields. Fuzzy inference systems can be used for decision-making processes of multi-objective optimization problems where a set of non-dominated solutions are presented to DMs, who are usually human.

2.2. Decision-Making in Multi-objective Optimization Problems

MOEAs produce a set of non-dominated solutions in the pareto set. When a pareto estimate is determined for a 2 or 3 objectives problem, the DM is usually expected to choose a single solution that best fits the expectations. Sometimes it is possible to visually inspect the Pareto front and choose the most interesting one. Unfortunately, this is not the case with problems that have more objectives where visualizing and examining the Pareto front is often difficult, if not impossible.

Selecting a single or several elements from a Pareto set has been discussed in various articles in the literature (Deb (2001)). A simple method is, considering that all objective functions are positive, taking the solution closest to the origin of the Cartesian coordinate system based on all objective values. Another way of choosing one or more solutions from the Pareto front is ordering the Pareto set based on some metrics. A metric can be obtained by a FIS which considers the user preferences in the search space. This approach can have an instant effect rather than general objective directions.

The fuzzy inference method was initially developed as a way to build a control system by combining a set of language control rules that were derived from experienced human operators. After defining fuzzy sets and the membership functions that go with them, these sets can be given linguistic labels. This method enables the conversion of linguistic reasoning in humans into mathematics. FIS uses previously created rule sets to produce outputs based on input values from the system. Fuzzy inference systems are composed of three main subsystems:

- Fuzzification: Translate input into truth values
- Rule Evaluation (inference): Compute output truth values
- Defuzzification: Transfer truth values into output

2.3. Fuzzification and Membership Functions

The fuzzification phase is to map crisp inputs (real-world data) from sensors to values between 0 and 1 using a set of membership functions.

Input membership functions can represent vague verbal categorizations concepts (linguistic variables) such as "long"-"short" or "like"-"don't like" or "expensive"-"cheap" where the definition of "long" and "short" may differ for each input. These concepts, their ranges and their numbers need to be defined by an expert or by using a systematic approach such as clustering. In this study, we used type-1 membership functions and defined their boundaries according to the general perception widely used in the literature. Input membership functions need to be designed for each input and output variable. There are different membership functions offered in the literature. Triangular, trapezoidal, and Gaussian membership functions are a few common and well-known types of membership functions. A set of membership values derived from the input values using input membership functions is created from the input values (Zadeh (1965)). Figure 1 shows an example as to how different membership functions divide the same universe of discourse.

a

b

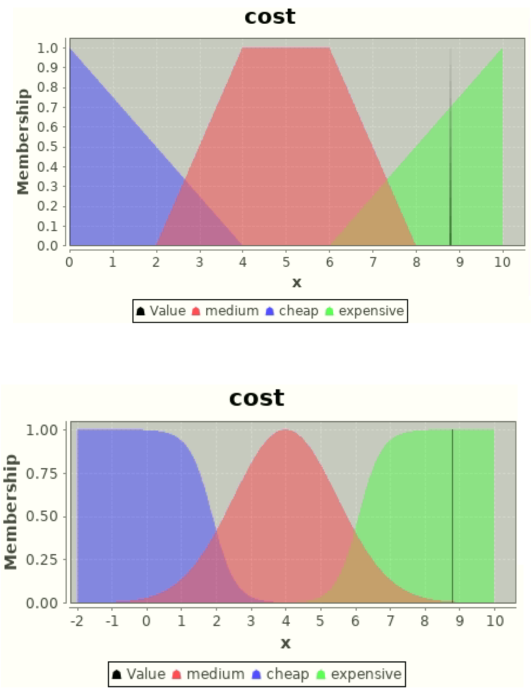


Fig. 1 Example trapezoidal (a), and Gaussian (b) membership functions for a Cost objective = 8.9.

2.4. Rule Evaluation and Rule sets

Fuzzy rules are a collection of linguistic expressions that define how FIS should classify an input or control an output according to input firing strengths and membership functions.
Fuzzy inference rules are in the following form:

$$IF\ \ x\ is\ A\ AND\ y\ is\ B\ THEN\ z\ is\ C \qquad eq.\ 1$$

Fuzzy rule inference has two main steps; determining the firing strength (activation level) of a rule and determining the geometric interpretation of the activation level in the output membership functions. Fuzzified inputs need to be combined according to the fuzzy rule set to establish a rule strength (firing strength). Input membership values create the section before "THEN" part of the form. Then the consequence of the rule needs to be determined as the last part of the rule form by combining the rule strength and the output membership function. These components are then combined and implemented as an AND or OR rule-based fuzzy set intersection. The term "T-norms" can also refer to fuzzy combinations. "AND", "OR" and "NOT" are interpreted as min function, max function and negation respectively in Mamdani-type FIS rules.

Once the firing power of a rule has been calculated, the resulting fuzzy set should be shaped using application functions properly. The way we implement functions has a huge impact on how FIS works. One of the most popular membership function types is the Mamdani-type. In this type, the area below the cropped output membership function is taken.

2.5. Problem Definition and Representation

The goal of the basic diet problem is to determine a set of food items, to be consumed by a person per day, which satisfies all nutrient requirements while minimizing the total cost. In this work, the classic cost-minimizing diet problem was modeled as a multi-objective optimization problem and formulated as a Multi-Objective Multidimensional Knapsack problem (MOMKP) (Kellerer et al. (2004), Lust and Teghem (2012)). Given a set of food items, the goal is to select a subset of food items which lead to all the objectives being optimized simultaneously while knapsack capacities are not exceeded. Here the knapsack capacities are daily nutrient limits based on a user's specifications such as gender, age, weight etc. (USDA (2022)). The three-objective diet problem has "preference", "cost" and "preparation time" objectives and it can be formulated as given in Eq. 2.

$$\begin{aligned} &\max Q_k(x) = \sum_{i=1}^{n} c_k^i x_i \quad k = 1,2,3,\dots,p \\ &\text{Subject to} \quad \sum_{i=1}^{n} w_j^i x_i \quad j = 1,2,3,\dots,m \\ &\qquad x_j \in \{0,1\} \qquad j = 1,2,3,\dots,n \end{aligned} \qquad \text{Eq.2}$$

where n is the number of items, m is the number of attributes, p is the number of objectives. The variable $x_i = 1$ means that the item i is selected to be in the knapsack and all coefficients c^k_i , w^j_i and, W_j are assumed to be non-negative. All objectives are assumed to be maximized.

2.6. Data set

The daily menus are generated as breakfast+{lunch+dinner} where breakfast and the lunch+dinner parts include only certain food groups. The main data set used in this study is a food data set including 405 unique food items from varying food groups, 24 different nutrients and the quantity
of these nutritions in each food based on 100 grams. Dietary Reference Intakes (DRI) Dataset contains nutritional requirements for a person per day. DRI includes upper and lower bounds of each nutrient based on personal properties such as age, body index, gender, activity level, pregnancy, lactation etc. For each nutrient, upper and lower limits are needed to be the boundaries of the constraints for the diet problem. These limits are obtained from USDA
DRI documents which are based on (USDA (2022)). Food dataset includes preferences given by users based on their taste, food prices for 100gr and preparation time (preparing + cooking time). These values are used in objective function calculation. Further details of the modeling aspects of the multi-objective diet problem can be found in the article by Turkemenoglu et.al. (Turkmenoglu et. Al (2021)).

2.7. Experiments

In the case of multi-objective diet optimization, none of the solutions on the Pareto front is the best, but at an equally desirable level according to the user's expectations of an ideal diet menu. FIS can play a key role in deciding the perfect menus among the Pareto set based on the user's current preferences. Users may be loyal to default objective orientations and choose the solutions at the elbow of the Pareto graph (solutions closest to the origin of the Cartesian coordinates system for the problem when all objectives are being minimized) or may change their objective orientation (maximization, minimization or neutrality) depending on their current mood, time management and money. For example, a user can set the cost as the only main objective depending on the current amount of money they have, or redefine the cost objective to be maximized (or neutral/disregard) for suggested menus in the pareto set if they are holding a dinner party. Based on these new preferences, FIS rules are created and then, based on these rule sets, the proper menu(s) are provided to the user. A user determines her/his current preferences towards the problem's objectives using one of 4 expressions: High, Medium, Low, Don't care. Depending on the optimization orientation (maximization /minimization) those expressions can have different meanings. Although we are minimizing cost and preparation time but maximizing preference, all objectives have the same interpretation of the Cartesian coordinate system: values between 0 (most desired) and 10 (least desired). Therefore, the menu which has a preference value of 0 is one of the most proffered ones. High, Medium, Low expressions have the following meanings for different objectives (Table 1). In other words, for interpretation simplicity, preference objective is regarded as minimization.

Table 1: Interpretations of verbal expressions/preferences for different objectives

Expression	Cost	Prep. Time	Preference
Low	Expensive	Long	don't like
Medium	Medium	Medium	neutral
High	Cheap	Short	Like

We selected two among many possible rule sets and applied Trapezoid and Gaussian Membership Functions to show how different rule sets result in different Pareto front orderings and show the effect of the FIS in decision-making on the proposed

Pareto front. Since the preparation time has a large scale it has 4 membership functions in the rule sets: very long, long, medium and short. Using the rule sets, a desirability measure is calculated taking into account the objectives and then, based on the desirability measure, the most preferred menu(s) are provided to the user. The desirability variable is named as “ideal” and it has 3 membership functions: optimal, non-optimal and sub-optimal. To be compatible with MOEAs and easy interpretation all objectives are minimized. Preference is transformed into minimization by using it as (10-preference).

Rule sets

We defined two distinct rule sets to imitate two distinct user preferences towards 3 objectives (Table 2).

Table 2. Rule sets used in the experiments

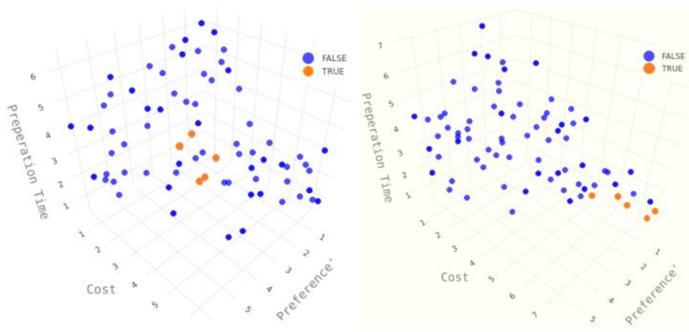
A:	**The user is loyal to general objective orientations: Cost ↓, Prep. Time ↓, Preference ↑**
1	IF preparationtime IS short AND cost IS cheap AND preference IS like THEN ideal IS optimal
2	IF preparationtime IS medium OR preparationtime IS long AND cost IS medium AND preference IS medium THEN ideal IS suboptimal
3	IF preparationtime IS verylong AND cost IS expensive AND preference IS dontlike THEN ideal IS nonoptimal
B:	**The user wants to choose expensive menus among those already optimized menus: Cost ↑, Prep. Time ↓, Preference ↑**
1	IF preparationtime IS short AND cost IS expensive AND preference IS like THEN ideal IS optimal
2	IF preparationtime IS medium OR preparationTime IS long AND IS suboptimal
3	IF preparationtime IS verylong AND cost IS cheap AND preference IS dontlike THEN ideal IS nonoptimal

3. Results

Using rule set A and rule set B, we applied posterior decision making to the pareto set produced by a 3-objective diet problem solved by NSGAIII. The Pareto set includes ~100 optimized, non-dominated solutions. Applying rule sets with Trapezoid and Gaussian membership functions, we want to show the easy applicability of FIS based posterior decision making to multi/many-objective problems (results shown in Figure 3) and observe the difference between Trapezoid and Gaussian membership functions on the decision-making process (results shown in Figure 4).

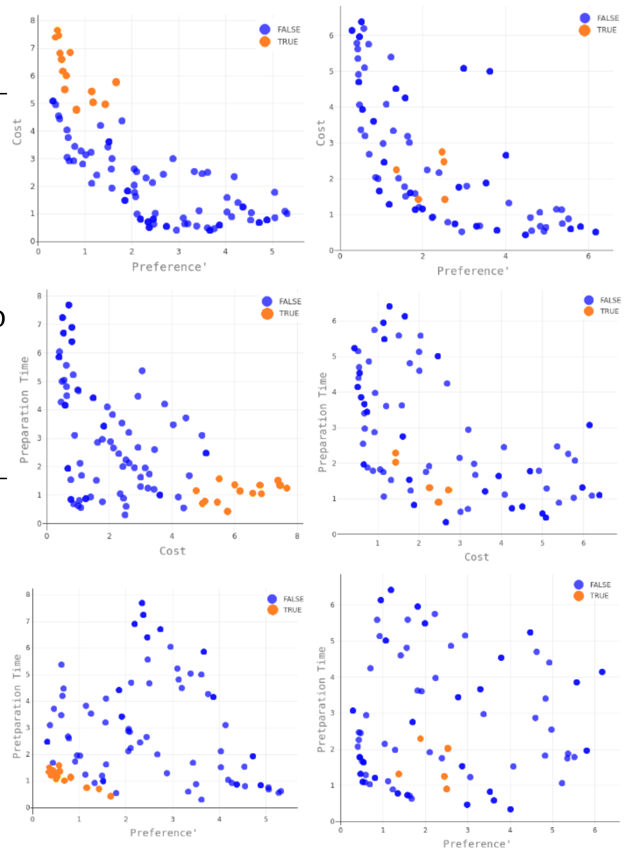
In all the graphs in Figure 3 and Figure 4, most ideal solutions (menus) have been chosen using a threshold on the “ideal” objective dimension. The user can just pick the menu with the highest “ideal” value or pick several of them and easily choose the best fitting one. Here, we select and color several of them with red on the graphs to show the general results of FIS.

In rule set A, the DM desires to find solutions which represent daily menus with short preparation time, high palatability, and low price. On the other hand, in rule set B, the DM desires to find solutions which represent daily menus that are quickly prepared, palatable and expensive.



a b

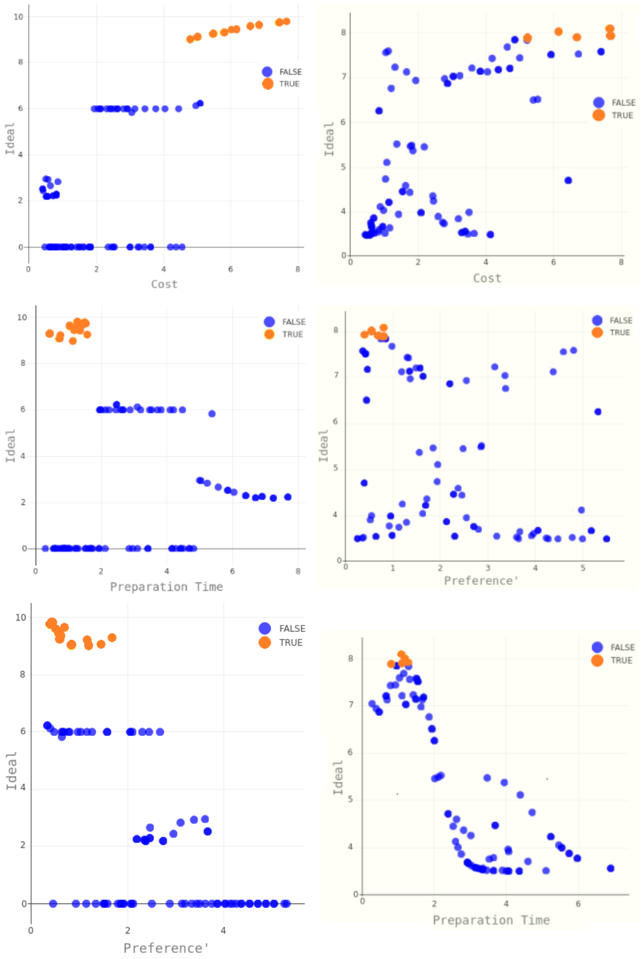
Fig. 2 Most desired menu(s) selected from the pareto set by rule set A (a) and rule set B (b) by Trapezoid membership functions in 3D.



(a) (b)

Fig. 3 Most desired menu(s) selected from pareto set by rule set A (a) and rule B (b) using Trapezoid membership function shown (objective pairs).

As can be seen Fig. 3 (a), rule set A aims to select one or more desired solutions among already optimized pareto set which are usually going to be solutions at the elbow of the Pareto graph (solutions closest to the origin of the Cartesian coordinates system for the problem when all objectives are being minimized).



(a) (b)

Fig. 4 Most desired menu(s) selected from the pareto set by Rule set B using Trapezoid and Gaussian membership functions.

4. Dicussion

As seen in the FIS experiment, the Gaussian membership function results in a more evenly distributed solution-set on the “ideal” dimension than the Trapezoid membership function. In the Trapezoid membership function case, most of the solutions could not be categorized or categorized and stacked on the very same value. Therefore, there is no smoothly distributed solution-set in this case (see Figure 4). The result graphs show that the DM is given the most desirable solutions representing daily menus based on his/her verbal expressions which are represented by fuzzy rule sets. Each rule set guided the DM to the region of interest based on DM’s instant preferences towards objectives.

5. Conclusion

Healthy eating continues to be a problem that affects a large part of the world’s population. Therefore, diets and nutritional habits have become increasingly important, especially with the devastating consequences of the Coronavirus Disease (Covid-19) (WHO (2022)). A user-oriented, realistic, and long-term diet plan can assist us to adopt a healthy eating habit by fulfilling the majority of the nutritional criteria without enforcing any restrictions.

In this study, we aim to optimize multiple objectives simultaneously while satisfying all constraints. Maximizing preferences, minimizing cost and preparation time were our objectives to be optimized. Nevertheless, considering a healthy and environment friendly diet (Abejón (2020)), more objectives can be included such as minimizing carbon footprint, maximizing availability of ingredients and rating, etc (Turkmenoglu et al. (2021)). The many-objective diet problem was solved using a well-known multi-objective evolutionary algorithm, NSGA-III. Since there are conflicting objectives in our problem, the Pareto set obtained by the NSGA-III consists of more than one optimized candidate menus. This leads us to a decision-making problem. To cope with this problem, we used a FIS based decision-making approach, which can lead the user to the region of interest in the search space of recommended menus. The FIS-based decision-making approach allows us to have control over the other objectives as well as the preference objective.

Our main goal is to create a practical way to represent and include DM's instant preferences for objectives into the decision-making step of the multi-objective diet optimization problem. The desirability functions that map the objective space to the desirability metric produce good results regarding the DM's instant preferences. Applying Mamdani type FIS for the posterior decision-making process of multi-objective diet problem is a novel contribution. Our method can lead the DM to the region of interest in the search space of the solution set produced by optimization of multi-objective diet problem by using the provided verbal expressions by the DM. As a result, the provided daily menu recommendations become more practical, convenient, and feasible for users.

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