



# A three-step methodology for GI classification, GL estimation of foods by fuzzy c-means classification and fuzzy pattern recognition, and an LP-based diet model for glycaemic control



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## ABSTRACT

In this paper, a three-step methodology is proposed for assigning foods with measured glycaemic index (GI) values to GI classes by using the fuzzy c-means classification technique, assigning foods with no measured GI values to GI classes by using the fuzzy pattern recognition technique, and estimating the glycaemic load (GL) values of foods with no measured GI values. In this methodology, the decision rules for menu planning are also defined, and a Linear Programming-based (LP-based) diet model is developed with the objective function of minimizing the total dietary glycaemic load and the constraints of the daily nutritional requirements. An application based on the real data of GI, GL, and nutritional values of the foods is also provided.

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## 1. Introduction

A glycaemic index is defined as “the area under the blood glucose response curve for a food expressed as a percentage of the area after taking the same amount of carbohydrate as the reference food” (Jenkins et al., 1981). The reference food can be glucose or white bread, the blood glucose levels are generally measured over 2 h, and the results are generally means of 5–10 individuals (Jenkins, Wolever, Jenkins, Josse, & Wong, 1984; Jenkins et al., 1981). The GI value of a food can be between 0 and 100. GI has been widely used to evaluate the effects of different sources of carbohydrates on blood glucose levels. However, it also has some limitations. One of the limitations is that there may be different GI measurements for a specific food with a wide variation of values. In addition, the GI values of most foods have not been determined because of several reasons, such as the costly controlled process of GI measurement in a laboratory environment by the authorized organizations. Another limitation of GI values is that several factors, such as cooking method and ripeness, contribute to the glycaemic effect of a food. As a result, an alternative approach is needed to evaluate the glycaemic effect of foods rather than just evaluating their GI values.

Glycaemic load is a concept, defined in relation to GI, determined by multiplying a food's GI value by its total available carbohydrate content,

and it represents both quality and quantity of carbohydrates (Barclay, Brand-Miller, & Wolever, 2005; Salmeron et al., 1997). If the GL of a food is higher than 20, it is a high-GL food. Numerous articles have appeared in the literature regarding the association between high-GL diets and physical and psychological human wellbeing (Arikawa et al., 2015; Cheatham et al., 2009; Oskarsson, Sadr-Azodi, Orsini, Andrén-Sandberg, & Wolk, 2014; Runchey et al., 2013; Turati et al., 2015). Because the GI values of most foods have not been determined, an approach is also needed to estimate the GI classes and GL values of those foods with no measured GI values.

Although the GI and GL values of the foods provide means for evaluating the potential glycaemic effect of the foods, integrating them with various decision-making approaches, such as diet planning, would be more valuable than evaluating them independently. Thus, a systematic approach is required to link the GI and GL information of foods with decision-making approaches.

In this paper, a three-step methodology is proposed to address the issues regarding the GI and GL values of foods and their integration with diet planning. In Step 1, foods with measured GI values are assigned to GI classes with their membership values for each class by using the fuzzy c-means classification technique. The main motivation for Step 1 is that many foods have different GI values, so a specific food consumed by a person could belong to any of the GI classes based on the several measurements of the same food. Different fuzzy techniques have been used in the literature for the characterization, classification, grading, differentiation and evaluation of foods and liquids with respect to different criteria, including taste, quality,

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production level, and crispness. The most frequently used techniques have been fuzzy Artmap neural networks and artificial neural networks (Chao, Chen, Early, et al., 1999; Du & Sun, 2004; Garcia-Breijo, Garrigues, Gil Sanchez, et al., 2013; Gestal, Gomez-Carracedo, Andrade, et al., 2005; Haddi, Mabrouk, Bougrini, et al., 2014; Perrot et al., 2006). Some papers regarding fuzzy classification techniques, such as fuzzy c-means classification, K-nearest neighbour rules, and the adaptive neuro-fuzzy inference system (ANFIS) classifier, have also appeared in the literature, mostly for the quality classification of foods (Adelkhani, Beheshti, Minaei, et al., 2013; Casanovas, Hernandez, Marti-Bonmati, et al., 2011; Hu, Gosine, Cao, et al., 1998; Iliassafiov & Shimoni, 2007). However, none of the papers considered the glycaemic index or glycaemic load as a criterion in the classification of foods.

In Step 2, foods with no measured GI values are assigned to GI classes with membership values for each class via the fuzzy pattern recognition technique, and an approach is proposed for estimating the GL values of those foods. The literature on GI or GL estimation is limited. Gofii, Garcia-Alonso, and Saura-Calixto (1997) proposed a starch hydrolysis procedure to estimate the GI, and the food frequency questionnaire has been used for the GL estimation in some papers (Brenner et al., 2015; Oba et al., 2010). The main motivation for Step 2 is that many foods have no measured GI values, and thus an approach is needed to estimate at least the GI classes of those foods for an evaluation of their glycaemic effect. The estimation of the GL values of those foods is of great importance in its own sense but also for the possible use of the GL value as an input in decision-making processes, such as diet-planning models.

Finally, in Step 3, the idea of developing decision rules for menu planning is proposed with a basic concern of glycaemic control and nutritional variability, and an LP-based diet model is developed with an objective function that minimizes the total dietary glycaemic load of the meal and constraints to satisfy the daily nutritional requirements. Several diet models have appeared in the literature for human diet modelling with the aim of designing optimal food intake patterns and exploring different dietary preferences, individual diet modelling, and nutrient profiling (Clerfeuille, Vieux, & Lluch, 2013; Maillot & Drewnowski, 2011; Maillot, Ferguson, Drewnowski, et al., 2008; Maillot, Vieux, & Amiot, 2010; Okubo, Sasaki, Murakami, et al., 2015; Ward, Ward, Mantzioris, et al., 2014). In these papers, mostly the LP models have been developed and solved. LP diet models and other models including multi-criteria models, multiple objective programming and stochastic programming have also been used for feed formulation of dairy cattle, growing pigs, and black tiger shrimp (Dubeau, Julien, & Pomar, 2011; Moraes, Wilen, Robinson, et al., 2012; Pena, Lara, & Castrodeza, 2009; Zhang & Roush, 2002). However, none of the papers considered the glycaemic control as a criterion in diet modelling except Bas (2014), who proposed a robust optimization approach to the diet problem with the overall glycaemic load as the objective function.

An application with the real data of GI, GL, and nutritional values of the foods is also provided to illustrate the practical applicability of the three-step methodology, and discussions are provided regarding the main outcomes of the methodology.

## 2. Basics of interval arithmetic and minimization problems with interval objective functions

Let  $a = [a^l, a^r]$  and  $b = [b^l, b^r]$  be two closed intervals with given left limits (LL) and right limits (RL). The basic operations on intervals relevant to the use in this paper are given as follows (Ishibuchi & Tanaka, 1990; Sengupta & Pal, 2000):

$$a + b = [a^l + b^l, a^r + b^r] \quad (1)$$

$$ia = \begin{cases} [ia^l, ia^r] & \text{if } i \geq 0 \\ [ia^r, ia^l] & \text{if } i < 0. \end{cases} \quad (2)$$

If the centre and the width of a closed interval  $a = [a^l, a^r]$  are denoted as  $a_c$  and  $a_w$ , respectively, then the following equations hold (Ishibuchi & Tanaka, 1990):

$$a_c = \frac{1}{2}(a^r + a^l) \quad (3)$$

$$a_w = \frac{1}{2}(a^r - a^l). \quad (4)$$

Ishibuchi and Tanaka (1990) defined the  $\leq_{LR}$  and  $\leq_{CW}$  order relations of two closed intervals  $a = [a^l, a^r]$  and  $b = [b^l, b^r]$  as follows:

$$a \leq_{LR} b \text{ iff } a^l \leq b^l \text{ and } a^r \leq b^r \quad (5)$$

$$a \leq_{CW} b \text{ iff } a_c \leq b_c \text{ and } a_w \geq b_w. \quad (6)$$

Let  $z(x)$  be the linear objective function of a minimization problem such that

$$z(x) = \sum_{i=1}^n a_i x_i \quad (7)$$

where the parameters  $a_1, a_2, \dots, a_n$  are defined in intervals. Then, the minimization problem can be reformulated as the following biobjective minimization problem (Ishibuchi & Tanaka, 1990):

$$\min(z_R(x), z_C(x)) \quad (8)$$

with the following two objective functions

$$z_R(x) = \sum_{k=1}^n (a_{Ck} + a_{Wk})x_k \quad (9)$$

and

$$z_C(x) = \sum_{k=1}^n a_{Ck}x_k. \quad (10)$$

By using the weighting method of Chankong and Haimes (1983), the objective function in Eq. (8) reduces to the following single objective function:

$$\min(wz_R(x) + (1-w)z_C(x)) \quad (11)$$

where  $0 < w < 1$  is a real number as the weighting parameter.

## 3. Methodology

Fig. 1 summarizes the basic steps of the methodology, and the details of the steps are provided as follows:

Step 1: Assigning foods with measured GI values to GI classes by using the fuzzy c-means classification technique

The main objective of Step 1 is to assign the foods with measured GI values to GI classes and to determine the membership values of the foods in each GI class they are assigned to. Although the general approach is to classify the foods as Low GI, Medium GI, and High GI foods (with the one exception of the Montignac (2015) method in which Low GI foods are defined to be below 50, Very Low GI foods below 35, and High GI foods above 50), in this paper five GI classes are proposed as shown in Table 1. The main motivation for proposing

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