MATHEMATICAL MODELING AND COMPUTING, Vol. 9, No. 3, pp. 607–615 (2022)

Optimal fuzzy deep daily nutrients requirements representation: Application to optimal Morocco diet problem

El Moutaouakil K.[1], Saliha C.[2], Hicham B.[3]

[1]*Engineering Science Laboratory (LSI), Faculty Polydisciplinary of Taza, USMBA, Morocco*
[2]*MorphoSciences Research Laboratory, Faculty of Medicine and Pharmacy, CAU, Morocco*
[3]*Biosciences and Health laboratory, Faculty of Medicine and Pharmacy, CAU, Morocco*

(Received 14 February 2022; Accepted 15 May 2022)

Solving the optimal diet problem necessarily involves estimating the daily requirements in positive and negative nutrients. Most approaches proposed in the literature are based on standard nominal estimates, which may cause shortages in some nutrients and overdoses in others. The approach proposed in this paper consists in personalizing these needs based on an intelligent system. In the beginning, we present the needs derived from the recommendations of experts in the field of nutrition in trapezoidal numbers. Based on this model, we generate a vast database. The latter is used to educate a deep learning neural network, the architecture of which we optimize by the fuzzy genetic algorithm method in the way of adopting a customized regulation term. Our system estimates nutrient requirements based only on gender and age. These estimations are integrated into a mathematical model obtained in our previous work. Then we again use the fuzzy genetic algorithm to draw up personalized diets. The proposed system has demonstrated a very high capacity to predict the needs of different individuals and has allowed the drawing up of very high-quality diets.

Keywords: *deep neural network, nutrients requirements, optimal diet, genetic algorithm, firefly algorithm, fuzzy quadratic programming, triangular fuzzy numbers.*

2010 MSC: 00A06 **DOI:** 10.23939/mmc2022.03.607

1. Introduction

Most of the solutions to the optimal regime problem are based on mathematical modeling implementing nonlinear optimization models with constraints [1–5]. The different components of these models are the translation of knowledge and recommendations of experts in the field of nutrition [6–9]. Most of the approaches proposed in the literature are based on standard nominal estimates which may cause shortages in some nutrients and overdoses in others nutrients.

We propose, in this work, an original intelligent system, implementing our mathematical model [2], allowing to draw up a personalized optimal diet based on optimal deep learning neural network that predict the individual dailly nutrients requirements. Three types of representations of daily needs are used: nominal representation [10] and [11], interval representation [12], and exhaustive representation [13]. The first two representations may cause shortages in some and overdoses in others [13] and [14]. The exhaustive representation results in giant tables that are difficult to manage in the model resolution phase [10, 11, 13, 14]. The approach proposed in this paper consists in personalizing these needs based on an intelligent system. In the beginning, we present the needs, derived from the recommendations of experts in the field of nutrition, by trapezoidal numbers. Based on this model, we generate a very large database. The latter is used to educate a deep learning neural network that we optimize the architecture by the fuzzy genetic algorithm method by adopting a customized regulation

This work was supported by Ministry of National Education, Professional Training, Higher Education and Scientific Research and the Digital Development Agency (DDA) and CNRST of Morocco (Nos. Alkhawarizmi/2020/23).

term. We used our system to estimate nutrient requirements based only on their gender and age. These estimation are integrated into a mathematical model that we have in our previous work. Then we used again fuzzy genetic algorithm to draw up personalized diets. The proposed system showed a very high capacity to predict the needs of different individuals and allowed to draw up diets of very high quality diets.

The rest of this paper is organized as follows: in the second section, we give, in summary, the optimization model that represents the optimal diet problem. In the third section, we give the nutrient knowledge representation and show how to generate the datasets associated with the nutrient requirements. In the fourth section, we present the optimal autoencoder based on our new control function. In the fifth section, we describe the system on which the fuzzy genetic algorithm is based. In the sixth section, we present some experimental results. At the end, we discuss some conclusions and future extensions of our systems.

2. Optimal Morocco diet modeling

To solve the optimal Morocco diet problem, we have proposed, recently, an approach based on a quadratic optimization programming (P) that permit to minimize the total glycemic load and unfavorable nutrients gaps [2]:

$$(P)\colon \begin{cases} \min g^T x + \beta \|Ex - f\|. \\ \quad \text{Subject to :} \\ \qquad Ax \leqslant b, \\ \qquad c_{car}^T x \geqslant 0.55(C^t x), \\ \qquad c_p^T x \geqslant 0.18(C^t x), \\ \qquad c_{tf}^T x \leqslant 0.29(C^t x), \\ \qquad c_{sf}^T x \leqslant 0.078(C^t x), \\ \qquad 0 \leqslant x_i \leqslant 6, \quad x \in R \quad i = 1, \dots, NF. \end{cases} \tag{1}$$

Where:
- $NF = 176$ represents the number of considered foods;
- $x = (x_j)_{j=1:NF}$ symbolizes the column formed by the serving sizes;
- $g = (gmin, gmax)$ represents the foods' glycemic load, $gmin$ minimum values and $gmin$ maximum values;
- A contains the 176 positive nutrients values of the foods for 100 g, b reports the daily needs in term of positive nutrients, E contains the 176 negative nutrients values of the foods for 100 g, and f reports the daily needs in term of negative nutrients;
- C is the column of calories extracted from A, c_{car} represents the carbohydrates calories, c_p symbolises the potassium calories, c_{tf} represents the total fat calories, and c_{sf} symbolises the satured fat calories;
- β is used to control the negative nutrients total gaps.

The constraints are none other than the advice of the experts of the dietary directives [6]. In fact, the maximum percentage of daily calories should be set for these nutrients with respect to the total daily calorie intake for a healthy and balanced daily diet.

The main propose of this work is to estimate daily nutrients needs of the positive and negative nutrients (i.e. we must estimate b and f) based on the age and on the sex of a given patient.

Example 1. The Committee of the Academies of Science, Engineering, and Medicine (NASEM) has identified Appropriate nutrient intakes (AIs) for different ages using the highest median potassium Intakes [7]. Table 1 lists the actual AIs for potassium for healthy people.

In this work, we generate a database based on Table 1 and the trapezoidal functions. One part will be used for training a neural network and another for testing. After learning, this network will be able to estimate the needs of an individual knowing its age and gender.

Table 1. Potassium Adequate Intakes (AIs).

Age	Male	Female	Pregnancy
Birth to 6 months	400 mg	400 mg	
7 – 12 months	860 mg	860 mg	
1 – 3 years	2 000 mg	2 000 mg	
4 – 8 years	2 300 mg	2 300 mg	
9 – 13 years	2 500 mg	2 300 mg	
14 – 18 years	3 000 mg	2 300 mg	2 600 mg
19 – 50 years	3 400 mg	2 600 mg	2 900 mg
51+ years	3 400 mg	2 600 mg	

3. Nutrient knowledge representation and data sets generation

3.1. Nutrient knowledge representation

Nutrient guidances were gathered based on nutrient resource materials; see for example [8, 9, 15]. These recommandations are presented using trapezoidal numbers denoted by $\langle a, b, c, d\rangle$ and geometricly presented by the function given in Fig. 1.

We build the trapezoidal numbers according to the experts' recommendations and the following rules:

— IF the nutrient is positive, THEN we prefer the upper border by overweighting it by 0.8 (goal: encouraging the eating of the positive nutrients);

— IF the nutrient is negative, THEN we prefer the lower limit by overweighting it by 0.8 (goal: limiting the consumption of the negative nutrients).

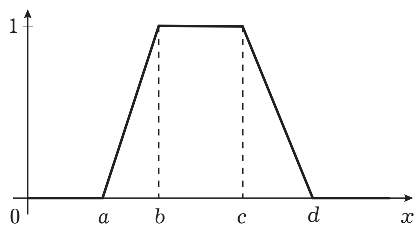

Fig. 1. Trapizoidal function of the support [a d].

Example 2. Cholesterol is a negative nutrient and the individuals requirement of ($9 \leqslant$) old is in the intervalle [200 230] mg. As $a = 200$, $d = 230$, then $b = 0.8 \cdot 200 + 0.2 \cdot 230 = 206$, and $c = 0.8 \cdot 206 + 0.2 \cdot 230 = 210.8$. The Cholesterol representation is given by $\langle 200, 206, 210, 8, 230\rangle$.

Applying the proposed rules to potassium and calcium, we derive the mapping given in Tables 2 and 3.

Table 2. Potassium trapezoidal number.

Gender	Potassium TN (mg/day)
Male (M)	$\langle 3000, 3800, 3960, 4000\rangle$
Female (F)	$\langle 2500, 2900, 2980, 3000\rangle$

Table 3. Triangular number of calcium.

Age (gendre)	Calcium TN (mg/day)
19 – 50 (F) OR 19 – 70 (M) OR 9 – 11 (M/F)	$\langle 800, 830.72, 836.86, 838.4\rangle$
> 70 (M) OR > 51 (F) OR 12 – 18 (M/F)	$\langle 1050, 1250, 1290, 1300\rangle$

Based on these representation models, we will build a huge data set in the next subsection.

3.2. Data sets generation

To built the data sets associated with different nutrients, first, we represent the requirement using triangular numbers. For example, Tables 4, 5, and 6 give different trapezoidal numbers of the potassium, phosphorus, and calcium requirements.

Table 4. Trapezoidal number of potassium daily requirements.

Gender	Age	Potassium TN (mg/day)
$G = 1$	$9 < A = \text{rand}(1000)$	$(3000, 3800, 3960, 4000, 1, .A)$
$G = 0$		$(2500, 2900, 2980, 3000, 0, .A)$

Table 5. Triangular number of Phosphorus daily requirements.

Gender	Age	Phosphorus TN (mg/day)
$G = \text{randBinary}(100)$	$9 \leqslant A = \text{rand}(1000) \leqslant 18$	$(1055, 1211, 1142.2, 1250, .G, .A)$
$G = 0$	$19 \leqslant A = \text{rand}(1000)$	$(600, 920, 984, 1000, .G, .A)$

Table 6. Triangular number of calsium dialy requirements.

Gender	Age	Calsium TN (mg/day)
$G = 0$	$19 \leqslant A = \text{rand}(1000) \leqslant 50$	$(800, 830.72, 836.86, 838.4, 0, .A)$
$G = 1$	$19 \leqslant A = \text{rand}(1000) \leqslant 70$	$(800, 830.72, 836.86, 838.4, 1, .A)$
$G = \text{randBenary}(100)$	$9 \leqslant A = \text{rand}(1000) \leqslant 11$	$(800, 830.72, 836.86, 838.4, .G, .A)$
$G = 1$	$70 \leqslant A = \text{rand}(1000)$	$(1050, 1250, 1290, 1300, 1, .A)$
$G = 0$	$51 \leqslant A = \text{rand}(1000)$	$(1050, 1250, 1290, 1300, 0, .A)$
$G = \text{randBenary}(100)$	$12 \leqslant A = \text{rand}(1000) \leqslant 18$	$(1050, 1250, 1290, 1300, .G, .A)$

Example 3. Lets us show how to built the data set associated with potassium nutrient.
(a) we fixe the gender to 0 then we generate 1000 age great than 9 years. Thus we get 1000 samples such as the first four components are given by $(3000, 3800, 3960, 4000, 1)$.
(b) we fixe the gender to 0 then we generate 1000 age great than 9 years. Thus we get 1000 samples such as the first four components are given by $(2500, 2900, 2980, 3000, 0)$. The data sets associated with all the considred nutrients are generated following the same procedure.

4. Nutrients crisp representation using optimal auto-encoder

In this work, we use a deep multilayer neural network (called auto-encoder) to convert the trapezoidal numbers into crisp output. The auto-encoder is a deep neural network composed of two principal sections: the encoder (box of neurons) and the decoder (box of neurons). The intermediate layer provides the coded information.

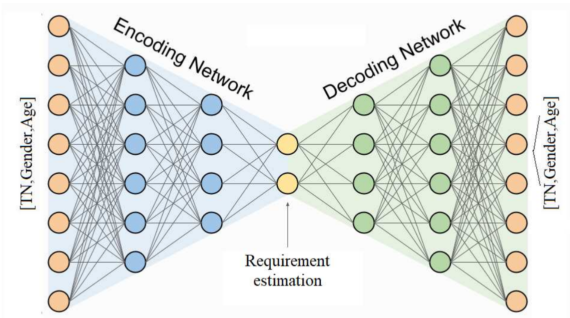

Fig. 2. Auto-encoder with random architecture.

We first consider an auto-encoder that has a random architecture; see Fig. 2. In our case, the interlayer is a single unit which delivers the coded information that represents the predicted need for nutrients.

To optimize the used auto-encoder, we propose a new regulation function and we use a fuzzy genetic algorithm based on the generated data.

The adjustment of the parameters of the auto-encoder Ω consists of minimizing a cost function $E(\Omega)$ given by Eq. (2),

$$E(\Omega) = \text{MSE}(\Omega) + \sigma \cdot \psi(\Omega) + \mu \cdot \phi(\Omega). \tag{2}$$

Where $\text{MSE}(\Omega)$ is the global reconstruction error, $\psi(\Omega)$ is the regulation function [16], and $\phi(\Omega)$ is the the sparsity term [17]. Regrettably, this expression does not make a difference between various units and does not control the number of units. In this work, we propose a new control term that take into a count all these aspects (see Eq. (3)),

$$\psi(\Omega) = \sum_{l,i} P_{l,i}^{Enc} \|\Omega_{l,i}^{Enc}\|^2 + \sum_{l,i} P_{l,i}^{Dec} \|\Omega_{l,i}^{Dec}\|^2. \tag{3}$$

Where $P_{l,i}^{Enc}$ (resp. $P_{l,i}^{Dec}$) is the penality parameters that permit to control the sparsity loss of the neuron i of the layer l of the encoder (resp. Decoder).

IF the neurons i and j are in the same hidden layer l, and if $i < j$, THEN $P_{l,i}^{Enc} < P_{l,j}^{Enc}$; compared to the neuron j, the neuron i has a very high chance of remaining in the layer l.

For a given layers l and k, IF $l < k$, THEN $\max_i |P_{l,i}^{Enc}| < \min_j |P_{k,j}^{Enc}|$. In contrast to the k layer, l has a large chance of staying in the neural network. We comment the decoder sparsity part.

To minimize the cost function E, we can utilize a recurrent network [18–20]. We can also use evolutionary heuristic methods such as: firefly optimization [21], genetic algorithm [23], particle swarm algorithm, stochastic fractal search with specific operators [2], etc. In our case, we employ the fuzzy genetic algorithm to take advantage of the evolutionary approaches to generating highquality decisions and the capacity of fuzzy logic to operate in stochastic environments.

5. Fuzzy gentic algorithm

We use Fuzzy Genetic Algorithm (FGA) to optimize the architecture of the auto-encoder and to solve the optimal diet problem. To this end, we adopt random convex-combination crossover, multi chromosomes mutation, and permutation selection operators.

To update, in each iteration, the mutation probability, crossover probability, and the number of individual in the population we implement a fuzzy system that have iteration, best fitness, variation fitness, and mean fitness as input; the outputs of our system are mutation probability, crossover probability, and the number of individual in the population. The figure 3 give the architecture of the proposed system that implement the madani inference to transform inputs; the number of rules is nine.

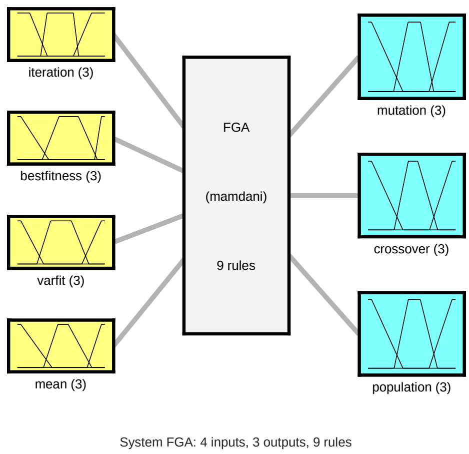

Fig. 3. Fuzzy genetic system.

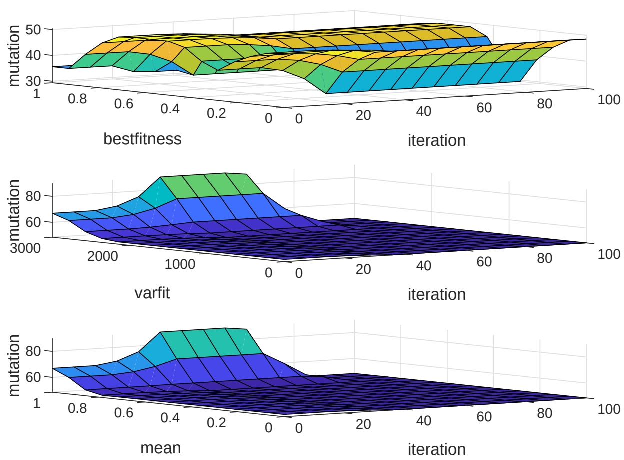

Fig. 4. Fuzzy genetic system.

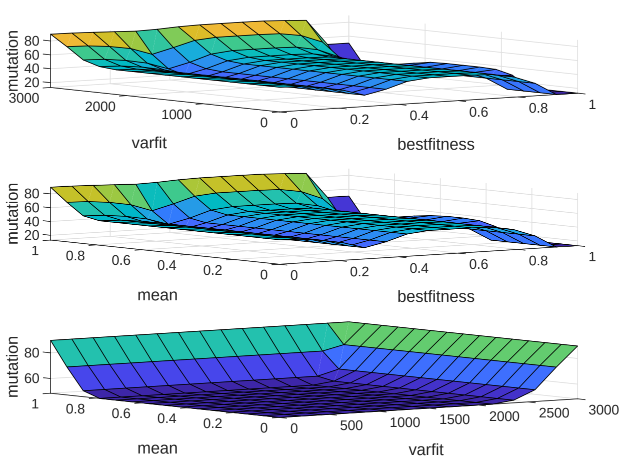

Fig. 5. Fuzzy genetic system.

The mumbership function associated with the mutation probability is based on six function. These functions are presented by Figs. 4 and 5. In this sense, if the variable fitness is low and the number of iteration is low the mutation probability must be low too; if the mean cost and the number of iteration is hight, then the probability of mutation must be hight.

6. Experimentation

Several tests and experiments have been realized with various configurations under a compatible HP, Intel (R) Core (TM) i5 – 4210U CPU@ 1.70GHz, 2.40 GHz, and 6.00Go GB of RAM through Matlab.

6.1. Estimation of nutrients requirements

Based on the data sets built at the precedent section, we use genetic algorithm, based on the system presented in Fig. 3, to optimize the architecture of the neural network.

The Fig. 6 presents the performance curve of genetic algorithm during the optimization procedure of the auto-encoder architecture based on the proposed loss function. The overage cost becomes early stable (at the generation 10).

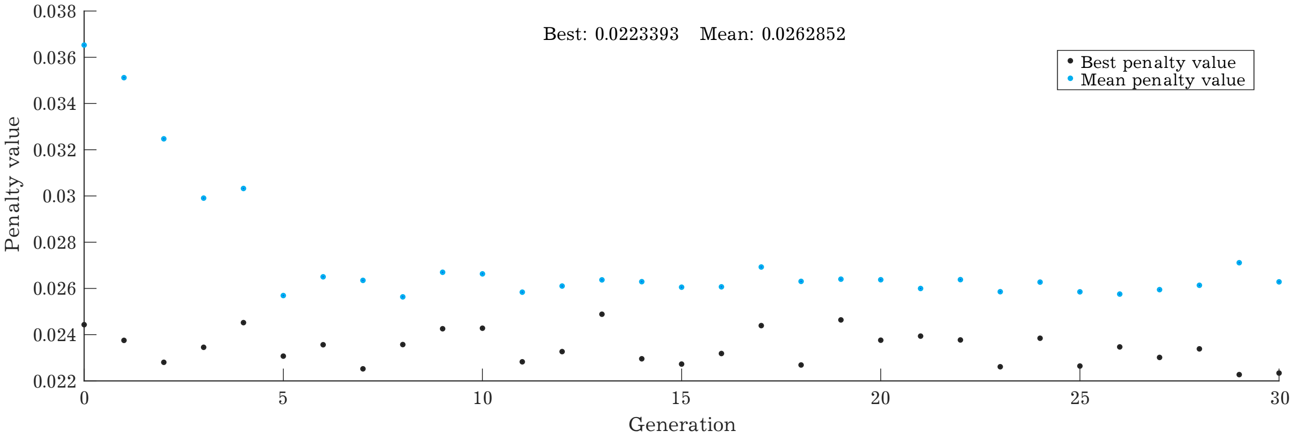

Fig. 6. The performance curve of genetic algorithm for neural network optimization.

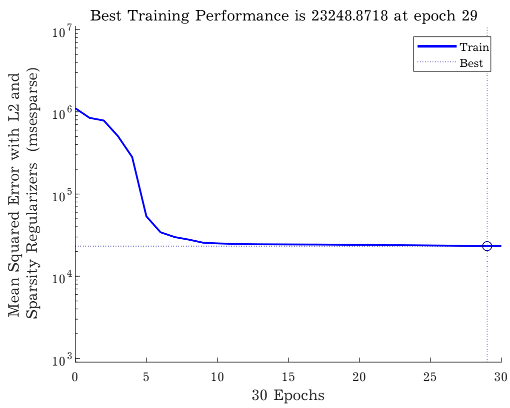

Fig. 7. The performance curve of the optimal neural network.

The minimum loss is associated with the artificial neural network of five neurons in the encoder part and five neurons in the decoder part.

Figure 7 gives the performance curve of the optimal auto-encoder on the test data set.

The value of the loss function of the optimal auto-encoder is very small (almost 0.0016). Thus, the built neural network is capable to generalize its experience to test samples (unseen samples). As consequence, our system can predict appropriate daily nutrients requirements based on the individual age and gender. We will use the optimal neural network to estimate the nutrients requirements in the next section.

6.2. Optimal Morocco diet

To determine an optimal diet for a given individual, we process it in three steps:

(a) Specify the age and gender of the individual concerned;

(b) Represent the requirements in different nutrients via "trapizoidal numbers" model;

(c) Present the representation found in (b) to the auto-encoder we have already trained;

(d) Use fuzzy genetic algorithm to solve the model described in Section 2.

For example, if an individual is a man of 38 old, the auto-encoder produces the following estimation: Calories (2400 kcal), Calcium (1004.8 mg), Phosphorus (700.001 mg), Potassium (3400 mg), Sodium (1500 mg), Zinc (11 mg), Iron (9 mg), Protein (91 g), Carbohydrate (271.3 g), Magnesium (384.7 mg), Vitamin b6 (2.4 mg), Vitamin b12 (8.3 μg), Vitamin C (155 mg), Vitamin A (1052.67 μg), Vitamin E

(9.5 mg), Satured fat (20.03 g), Total fat (65.1 g), and Cholesterol (230 mg). The predicted requirements almost the same recommanded by the experts for male individual of 38 old [8, 9, 15].

The figure 8 gives different performance index of fuzzy GA applied to the problem 1. We remark that the optimization process converges very early.

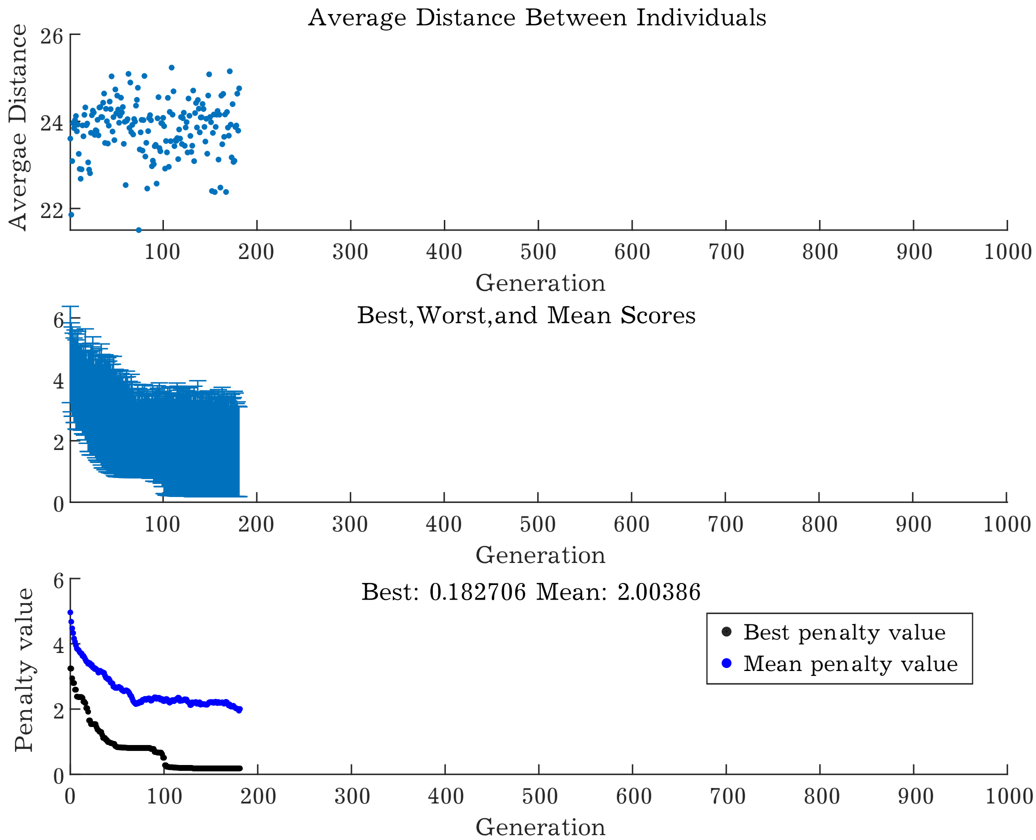

Fig. 8. Performance index of fuzzy GA applied to the problem 1.

Table 7 gives total glycemic load and total unfavorable nutrients excess of the diets produced by FGA for different population size and three nominal nutrients glycemic load are considered: min, mean, and max. Where FGA is fuzzy genetic algorithm, Pop. is the the population size of FGA, TGL is total glycemic load, and TUNG is Total unfavorable nutrients gap.

Table 7. Total glycemic load, and Total unfavorable nutrients excess of daily diets produced by FGA for different population size. Three nominal nutrients glycemic load are considred: min, mean, and max.

FGA	TGL			TUNG(mg)		
Pop. Size	Min Glyc.	Mean Glyc.	Max Glyc.	Min Glyc.	Mean Glyc.	Max glyc.
100	2.7e+3	2.9e+3	3.0e+3	3.9e+4	3.6e+4	3.0e+4
150	2.2e+3	2.0e+3	2.2e+3	2.0e+4	2.8e+4	2.6e+4
200	612.40	818.37	562.08	2.4e+3	2.9e+3	2.7e+3
250	23.97	13.92	11.65	41.42	53.91	65.80
300	12.09	8.82	13.32	50.17	18.85	51.43
350	18.44	11.42	12.19	42.04	56.84	71.66
400	11.34	13.88	8.62	60.47	68.25	53.92

The diets associated to population size less or equals 200 are rejected because of their total glycemic load (almost 562.08–2.9e+3). The total unfavorable nutrients excess is very large (almost 2.4e+3–3.6e+4 mg). Diets corresponding to a population size between 250 and 400 are acceptable and can be recommended to people with diabetes, cholesterol, etc.

7. Conclusion

In this work, we have solved a rather challenging problem in the field of nutrition – the problem of designing systems to produce personalized diets. To this end, we used a model of representation of knowledge about nutrient requirements that trapezoidal numbers. This allowed us to generate a vast database that we used to educate an optimized auto-encoder based on an original control function that we minimized by a fuzzy genetic algorithm. The estimates produced are subsequently used to train customized diets to test individuals. The suggested system proved to have a very high capability to forecast the daily requirements of various individuals and was able to elaborate diets of very high-quality diets.

Despite its good performance, the use of a single neural network produces good estimates of the needs of some nutrients at the expense of some others that have very small values, for example, some vitamins.

To remedy this problem, we will divide the different nutrients into subgroups using clustering methods, and we will build a deep neural network for each group.

[1] Bas E. A robust optimization approach to diet problem with overall glycemic load as objective function. Applied Mathematical Modelling. **38** (19–20), 4926–4940 (2014).

[2] El Moutaouakil K., Cheggour M. Chellak S., Baizri H. Metaheuristics Optimiza-tion Algorithm to an Optimal Moroccan Diet. 2021 7th Annual International Conference on Network and Information Systems for Computers (ICNISC). 364–368 (2021).

[3] Bas E. 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. Food Research International. **83**, 1–13 (2016).

[4] Amin S. H., Mulligan-Gow S., Zhang G. Food selection for a feeding problem using a multi-objective approach under uncertainty. Application of decision science to business and management. 181 (2019).

[5] Khan M. A., Haq A. L., Ahmed A. Modele multi-objectifs pour la planification de l'alimentation quotidienne. Fiabilite: theorie et applications. **16** (1), 61 (2021).

[6] You A. Dietary guidelines for Americans. US Department of Health and Human Services and US Department of Agriculture (2015).

[7] National Academies of Sciences, Engineering, and Medicine. Dietary reference intakes for sodium and potassium (2019).

[8] Morris R. C. (Jr), Sebastian A., Forman A., Tanaka M., Schmidlin O. Normotensive salt sensitivity: effects of race and dietary potassium. Hypertension. **33** (1), 18–23 (1999).

[9] Lind T., Lonnerdal B., Stenlund H., Ismail D., Seswandhana R., Ekstrom E.-C., Persson L.-A. A community-based, randomized controlled trial of iron and/or zinc supplementation of Indonesian infants — interactions between iron and zinc. The American Journal of Clinical Nutrition. **77** (4), 883–890 (2004).

[10] O'Brien K. O., Zavaleta N., Caulfield L. E., Wen J., Abrams S. A. Prenatal Iron Supplements Impair Zinc Absorption in Pregnant Peruvian Women. The Journal of Nutrition. **130** (9), 2251–2255 (2000).

[11] Weaver C. M., Gordon C. M., Janz K. F., Kalkwarf H. J., Lappe J. M., Lewis R., Zemel B. S. The National Osteoporosis Foundation's position statement on peak bone mass development and lifestyle factors: a systematic review and implementation recommendations. Osteoporosis international. **27** (4), 1281–1386 (2016).

[12] D'Odorico P., Davis K. F., Rosa L., Carr J. A., Chiarelli D., Dell'Angelo J., Gephart J., MacDonald G. K., Seekell D. A., Suweis S., Rulli M. C. The global food–energy–water nexus. Reviews of Geophysics. **56** (3), 456–531 (2018).

[13] Zimmermann M. B., Chassard C., Rohner F., N'goran E. K., Nindjin C., Dostal A., Hurrell R. F. The effects of iron fortification on the gut microbiota in African children: a randomized controlled trial in Cote d'Ivoire. The American Journal of Clinical Nutrition. **92** (6), 1406–1415 (2010).

[14] Meschia J. F., Bushnell C., Boden-Albala B., Braun L. T., Bravata D. M., Chaturvedi S., Wilson J. A. Guidelines for the primary prevention of stroke: a statement for healthcare professionals from the American Heart Association/American Stroke Association. Stroke. **45** (12), 3754–3832 (2014).

[15] Donati M., Menozzi D., Zighetti C., Rosi A., Zinetti A., Scazzina F. Towards a sustainable diet combining economic, environmental and nutritional objectives. Appetite. **106**, 48-57 (2016).

[16] Møller M. F. A scaled conjugate gradient algorithm for fast supervised learning. Neural networks. **6** (4), 525–533 (1993).

[17] Olshausen B. A., Field D. J. Sparse coding with an overcomplete basis set: A strategy employed by V1? Vision Research. **37** (23), 3311–3325 (1997).

[18] El Moutaouakil K., Touhafi A. A New Recurrent Neural Network Fuzzy Mean Square Clustering Method. 2020 5th International Conference on Cloud Computing and Artificial Intelligence: Technologies and Applications (CloudTech). 1–5 (2020).

[19] Haddouch K., El Moutaouakil K. New Starting Point of the Continuous Hopfield Network. International Conference on Big Data, Cloud and Applications. 379–389 (2018).

[20] El Ouissari A., El Moutaouakil K. Density based fuzzy support vector machine: application to diabetes dataset. Mathematical Modeling and Computing. **8** (4), 747–760 (2021).

[21] Yang X. S. Nature-Inspired Metaheuristic Algorithms. Luniver Press (2008).

[22] Jang J. S. R., Sun C. T., Mizutani E. Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]. IEEE Transactions on Automatic Control. **42** (10), 1482–1484 (1997).

[23] Civicioglu P. Transforming geocentric cartesian coordinates to geodetic coordinates by using differential search algorithm. Computers and Geosciences. **46**, 229–247 (2012).

Оптимальне нечітке глибоке представлення добових потреб у поживних речовинах: застосування до оптимальної проблеми дієти Марокко

Ель Мутауакіл К.[1], Саліха С.[2], Хічам Б.[3]

[1] *Інженерно-наукова лабораторія (LSI), Полідисциплінарний факультет Таза, USMBA, Марокко*
[2] *Дослідницька лабораторія MorphoSciences, Факультет медицини та фармації, CAU, Марокко*
[3] *Лабораторія біонаук і здоров'я, Факультет медицини та фармації, CAU, Марокко*

Вирішення проблеми оптимального харчування обов'язково передбачає оцінку добової потреби в позитивних і негативних поживних речовинах. Більшість підходів, запропонованих у літературі, засновані на стандартних номінальних оцінках, які можуть викликати дефіцит в одних і передозування в інших нутрієнтах. Підхід, запропонований у цій роботі, полягає в персоналізації цих потреб на основі інтелектуальної системи. На початку подаємо потреби, отримані з рекомендацій експертів у галузі харчування, трапецієподібними числами. На основі цієї моделі створюємо велику базу даних. Остання використовується для навчання глибокої нейронної мережі, архітектуру якої оптимізуємо за допомогою методу нечіткого генетичного алгоритму, приймаючи індивідуальну умову регулювання. Наша система оцінює потреби в поживних речовинах лише на основі статі та віку. Ці оцінки інтегровані в математичну модель, яку ми використовували в нашій попередній роботі. Потім ми знову використовуємо нечіткий генетичний алгоритм для складання персоналізованих дієт. Запропонована система показала дуже високу здатність прогнозування потреб різних за віком та статтю людей і дозволила складати дуже корисні раціони харчування.

Ключові слова: *глибока нейронна мережа, потреби в поживних речовинах, оптимальна дієта, генетичний алгоритм, алгоритм світлячка, нечітке квадратичне програмування, трикутні нечіткі числа.*