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MENU PLANNING WITH A DYNAMIC GOAL PROGRAMMING APPROACH

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Abstract

Dynamic Goal Programming (DGP) represents an extension of Goal Programming (GP). It is characterized by the importance of time factor in relation to its variables. As a complex decision making problem, Menu Planning Problem (MPP) requires the development of methodologies which are able to combine different and conflicting goals incorporating the dynamic characteristics. The article reviews some of the studies and approaches used in MPP. It deals with the Standard GP model of MPP. It provides a DGP formulation for solving the MPP. An MPP for the hemodialysis (HD) patient is an application that best exemplifies the proposed dynamic formulation.

Keywords: Goal Programming, Menu Planning Problem, Standard, Static/Dynamic Programming.

1 Introduction

The present paper is reconsiders the MPP with the DGP approach. Dynamic Programming (DP) is characterized by regarding the target values as a function of time. A target value appears on the accumulated value of the objective for each period of time within the planning period. This allows the Decision Maker (DM) to control the behavior of the objectives during the whole planning period, rather than only their final values. The achievement of goals at different periods in the day is

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restricted by DP. The proposed model can be simply adapted to plan the diet/menu of individuals in different health conditions. It can also analyze several other issues if the problem is dynamic in nature with respect to certain characteristics and constraints.

Various optimization approaches have been applied to solve the MPP, including linear programming (Smith, 1959, 1974; Bassi, 1976; Foytik, 1981; Silberberg, 1985; Westrich et al., 1998; Colavita and D`Orsi, 1990; Fletcher et al., 1994), integer programming (Balinfy, 1964; Leung et al., 1995), multistage multiple-choice programming algorithm (Balinfy, 1975), mixed integer programming (Armstrong and Sinha, 1974), bi-criteria mathematical programming (Benson and Morin, 1987), mixed integer linear programming (Sklan and Dariel, 1993; Valdez-Peña and Martĩnez-Alfaro, 2003) and GP (McCann-Rugg et al., 1983).

MPP is a scheduling problem whose objective is to find an optimal combination of meals that satisfy individual nutritional, structural and other requirements during a period of time. In MPP, multiple conflicting and diversified objectives are simultaneously taken into account, which is characteristic for typical Multi--Objective Decision Making (MODM) problems. These can be effectively solved by the GP approach. Thus the obtained solution represents the best compromise that can be achieved by the decision maker. The GP model is a distance function that tends to minimize unwanted positive and negative deviations from the achievement and aspiration levels.

To the best of our knowledge, little work has been undertaken on the solution of MPP by the GP approach. Indeed, applications of the GP approach to MPP differ from one research study to another. McCann-Rugg et al. (1983) used the GP approach interactively with the dietician who determined the availability of foods and their preference aspiration level. They aimed to compare the results of manual planning and of the GP approach of various dieticians. Ferguson et al. (2006) combined the use of linear programming and GP, seeking to improve complementary nutrition practices of young children to guarantee good conditions of their growth and health. Pasic et al. (2012) built a GP nutrition optimization model that intended to meet daily nutritional needs for women and men, thereby successfully overcoming budget constraint. Gerdessen and Vries (2015) studied the impact of the achievement functions in designing diet models based on GP. Their research enables the DM to use either a MinSum function or a MinMax function or a compromise between them.

In practice, the resolution of all healthcare problems and especially those related to nutrition should not be limited to the classical and static frame, but rather requires a dynamic one that considers the evolution of the decision making process over time. For example, in an everyday situation, if an individual had a dangerous health condition (cardiovascular, diabetic or end stage renal disease, etc.), he/she would have to choose among different meals available in order to satisfy their daily nutritional requirements. If he/she decides to eat a dish to gain more energy or protein, she/he will risk a simultaneous increase of potassium and sodium, taking into account the nutritional gain from the previously-eaten dishes. The decision made at each period must take into account its effects not only on the next period, but also on all subsequent periods. A dynamic problem can be divided into a number of stages (periods) or sub-problems, with an optimal decision required at each stage. DP is similar to a sequence of interrelated decisions, in which a decision made at each stage influences the decision to be taken in what follows.

It is quite natural to rely upon dynamic characteristic of MPP in which any feasible solution provides a vector of meals satisfying nutritional, structural and other requirements. DP, a technique based on the optimality principle, was developed by Richard Bellman in the early 1950s. He stated that "an optimal policy has the property that, whatever the initial decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision". DP leads to optimal solutions, not only of the entire problem, but also of each of its sub-problems. For example, if we need to select projects for a 10-year program, DP gives the optimal solutions of the projects for the entire 10-year period as well as the optimal solution for any period of less than 10 years.

DGP represents an extension of classical GP in a context that assigns much importance to the dependence of its variables on time. To the best of our knowledge, although no research has investigated the use of the DGP approach to solve MPP, there are some work which has explored DGP. Trzaskalik (1997) discussed different aspects of the GP approach to multiple objectives DP. He described four approaches, namely: dynamic goal approach, dynamic hierarchical goal approach, dynamic period goal approach and dynamic hierarchical period approach. Trzaskalik (2003) applied period target values to hierarchical goal dynamic programming. A period backward approach is applied and a fixed single hierarchy of criteria is used. The proposed approach aimed to realize for the DM the possibility of interactive modeling the period backward fixed single hierarchy target goal structure of the final solution. Caballero et al. (1998) argued that most of the DGP approaches used goal values on the final value of their objective functions and developed a Lexicographic DGP (LDGP) algorithm using dynamic target values. In addition to the final values of the corresponding functions, they controlled their evolution along the planning periods. Pal and Moitra (2003) described the way of using preemptive priority-based GP to solve a class of Fuzzy Programming (FP) problems, with a set of linear and/or non-linear fuzzy goal objectives with the characteristics of DP. Hamalainen and Mantysaari (2002) developed a DGP approach, in which dynamic aspects arose from three factors; the house acts as heat storage, the price of electricity varies over time and the outdoor temperature changes during the day. Based on an

LDGP approach, Nha et al. (2013) developed a novel robust design optimization procedure that aims to implement time series based on multi-responses, unlike static responses implemented in the conventional experimental design formats and frameworks.

The remainder of the paper is organized into five sections. Section 2 presents the standard classical GP model of MP. The proposed DGP model is discussed in Section 3. Section 4 illustrates the dynamic approach through a specific example in the context of HD patient nutrition. Finally, section 5 concludes and outlines directions for future research.

2 Standard formulation of the MP model with Static GP

GP is an important method for MODM approaches. The GP model is a well--known approach for solving multi-objective programming problems which allows the DM to take into account several conflicting objectives simultaneously. Thus, the obtained solution represents the best compromise achievable. In general, the objective function of the GP model is a distance function that minimizes the unwanted positive and negative deviation. The standard and static GP model of MPP can be formulated as follows:

$$\text{Minimize} \sum_{i=1}^{N} (\delta_i^+ + \delta_i^-) \tag{1}$$

so that

$$\sum_{l=1}^{L} \sum_{j \in J_l} a_{ilj} x_{ljk} + \delta_i^- - \delta_i^+ = g_i \; \forall i = 1, \ldots, N, k = 1, \ldots, 7 \tag{2}$$

$$x_{ljk} \geq 0 \; with \; k = 1, \ldots, 7; \; l = 1, \ldots, L \; and \; j \in J_l \tag{3}$$

$$\delta_i^+ \geq 0, \delta_i^- \geq 0 \; for i = 1, \ldots, N \tag{4}$$

where

- i is the set of nutrients, i = energy, protein, potassium, sodium… N
- l is the type of recipe, j, $l = 1, \ldots, L$ (breakfast, snacks, lunch and dinner),
- J_l is the set of the j^{th} recipes of type l to be recommended,
- k is the k^{th}day in the week, $k = 1, \ldots, 7$,
- g_i is the i^{th} nutrient requirement per day,
- a_{ilj} is a coefficient indicating the quantity of i^{th} nutrient provided in 100 g in j^{th} recipe of type l,
- x_{ljk} is the quantity of j^{th} recipe of type l to be recommended in day k
- δ_i^-, δ_i^+ are negative and positive deviations from goal g_i.

3 Standard formulation of the MP model with Dynamic GP

The term "programming" is used in DP as a synonym of "optimization" and means "planning". It is basically a step-by-step search method used in optimization problems, whose solutions may be viewed as the result of a sequence of decisions (Bhowmik, 2010). As any other optimization models, in formulating the DGP model for solving MPP, we define the problem variables, determine the objective function and specify the constraints. In particular, in the process of formulating a DP model, a recursive relationship is developed, based on the principle of optimality, which keeps recurring as we move backward stage by stage.

The aim of this section is to apply DP to MPP. To this end, let us consider the following DGP model:

$$\text{Minimize} \sum_{i=1}^{N} \sum_{t \in t_k} \delta_{it}^{+} + \delta_{it}^{-} \tag{5}$$

so that

$$\delta_{it-1}^{-} - \delta_{it-1}^{+} + \delta_{it}^{-} - \delta_{it}^{+} + \sum_{l=1}^{L} \sum_{j \in J_l} a_{ilj} x_{ljt} = g_{it}$$
$$\forall\, i = 1, \dots, N;\ k = 1, \dots, 7 \ and \ t \in t_k \tag{6}$$

$$\sum\nolimits_{j \in J_l} \sum\nolimits_{t \in t_k} y_{ljt} = 1 \ \forall\, t \in t_k \ and \ l = 1, \dots, 5 \tag{7}$$

$$\delta_{it}^{+} \geq 0, \delta_{it}^{-} \geq 0 \ for \ i = 1, \dots, N \ and \ t \in t_k \tag{8}$$

$$x_{ljt} \geq 0 \ with \ k = 1, \dots, 7;\ l = 1, \dots, L;\ j \in J_l and \ t \in t_k \tag{9}$$

where

- i is the set of nutrients, i = energy, protein, potassium, sodium… N
- l is the type of recipe, $l = 1, \dots, L$ (breakfast, snacks, lunch, and dinner),
- J_l is the set of j^{th} recipes of type l to be recommended,
- k is the k^{th}day in the week, $k = 1, \dots, 7$,
- t_k is the period t in day k, $t = 1, \dots, T \in t_k$and $k = 1, \dots, 7$, which are the time slots used in DP,
- g_{it} is the i^{th} nutrient requirement (goal) per period t,
- a_{ilj} is a coefficient indicating the quantity of i^{th} nutrient provided in 100 grams from j^{th} recipe of type l,

- x_{ljt} is the quantity of j^{th}recipe of type l to be recommended in the period t of day k,
- y_{ljt} is a binary variable to decide whether the recipe j of type l is included or not in period t of day k,
  $\begin{cases} y_{ljt} = 1 \text{ If the recipe is included} \\ \qquad else\ 0 \end{cases}$
- $\delta_{it}^{-}, \delta_{it}^{+}$ are the negative and positive deviations from i^{th} nutrient goal in period t.

The sixth constraint above defines the following recursive relationship between the solutions of the sub-problems: It identifies the optimal solution for period t when the optimal solution given in the period $t - 1$ is taken into account.

4 An illustrative example: A hemodialysis patient diet

To illustrate the application of the DGP model for solving MPP, a specific group of patients with chronic illness was chosen. A non-diabetic HD patient with the level of Glomerular Filtration Rate (GFR) < 15 ml/min, with age less than 60 years, Ideal Body Weight (IBW) = 70kg and a Body Mass Index (BMI) between 22 and 25. The nutritional requirements for HD patients are based on the daily intake as presented in the table below:

Table 1: Recommended daily intake of nutrients for a clinically stable HD patient

Nutrients	Daily Requirements
Energy	35 Kcal/ Kg IBW
Protein	1,2g/ Kg IBW
Sodium	80 mmol
Potassium	1 mmol/ Kg IBW

We consider a Database (DB) of 66 different Tunisian recipes classified into five different types: breakfast, morning snack, lunch, afternoon snack and dinner. The DB could be enlarged to include more ingredients and recipes and help in calculating the nutritional values of all the recipes. The recipes are listed in the following table:

Table 2: Recipes and their nutritional components

Recipes /Nutrients per 100 g	Energy (kcal)	Protein (g)	Potassium (mmol)	Sodium (mmol)	Type of recipe
Barquette tuna	147.68	11.36	121.16	216.5	2 and 4
Borghol with meat	778.26	32.1	777.9	115.85	3 and 5
Lemon cake	1151.32	18.84	79.95	1015.22	1 and 2
Four quarts cake	729.18	10.61	78.68	393.6	1,2 and 4
Cannelloni with ricotta	305.13	26.2	1016.68	365.15	5
Cannelloni with spinach and ricotta	824.49	30.82	449.74	710.67	3 and 5
Chakchouka with peppers	516.72	4.71	114.12	49.74	3,5 and 2
Coca Cola	93.6	0	0	8.68	4
Chicken couscous	1169.96	35.65	902.33	151.1	3 and 5
Couscous with turkey	555.98	34.49	829.38	99.24	3 and 5
Couscous with fish	757.57	23.72	530.56	471.35	3 and 5
Fondant potatoes	596.59	11.55	110.84	398.25	4 and 1
Chocolate cake	794.1	14.33	349.15	548.68	1,2 and 4
Peach juice	19.5	0.45	95	0.6	1 and 2
Pear juice	58	0.38	119	1	1,2 and 4
Apple juice	43	0.3	75	2	1,2 and 4
Orange juice	46	0.7	169	0	1,2 and 4
Orange juice, peach and banana	147.8	4.04	349.4	55.2	2 and 4
Macaroni with chicken	932.66	43.5	1953.32	235.29	3 and 5
Mini blown escalope	253.76	5.3	71.86	437.84	2
Ojjatuna	193.67	9.75	113.02	121.62	3 and 5
Fruit paste	107	0.5	45	0.5	4 and 2
Chicken rice	968.72	35.13	542.29	121.74	3 and 5
Summer salad	93.09	0.08	19.54	4.3	3 and 5
Salad ommekhourya	205.23	0.66	161.93	39.16	3 and 5
Salt samsa	253.76	5.3	71.86	437.84	4
Grenadine syrup	79.8	0	8.4	12.9	4
Sorbet granite	92	0.5	100	8	4
Bird tongues soup	292.26	16.98	380.06	71.69	3 and 5
Spinach and ricotta tajine	305.13	26.2	1016.68	365.15	3
Tea	0.5	0	18.5	5.5	4
Coffee	2	0.07	24	5.3	4
Flavored yogurt	101	4.84	215.09	64.54	4
Fruit yogurt	113	3.5	206	55	2 and 4

To solve the MP of the HD patient problem, we used AMPL (A Modeling Language for Mathematical Programming) which applies optimization solvers such as CPLEX. AMPL is a modern modeling environment which contains an advanced architecture providing much flexibility as compared to other modeling systems. We used it for the following purposes: reading a model, analyzing data, solving/optimizing the model using CPLEX, and generating the results of the optimization.

Suppose that the day is divided into five periods (T = 5). Accordingly, the MPP will consist of five sub-problems and in each stage only one decision must be taken. The DGP model of the HD patient diet problem can be formulated as follows:

The objective function:

$$\text{Minimize} \sum_{i=1}^{4} \sum_{t \in t_k} \delta_{it}^{+} + \delta_{it}^{-} \tag{10}$$

so that

$$\delta_{it-1}^{-} - \delta_{it-1}^{+} + \delta_{it}^{-} - \delta_{it}^{+} + \sum_{l=1}^{5} \sum_{j \in J_l} a_{ilj} x_{ljt} = g_{it}$$
$$\forall\, i = 1, \dots, 4;\ k = 1, \dots, 7 \ and\ t \in t_k \tag{11}$$

$$100 y_{ljt} \le x_{ljt} \le 200 y_{ljt}\ \forall\, t \in t_k;\ l = 1, \dots, 5\ and\ j \in J_l \tag{12}$$

$$\sum_{j \in J_l} \sum_{t \in t_k} y_{ljt} = 1\ \ \forall\, k = 1, \dots, 7\ and\ l = 1, \dots, 5 \tag{13}$$

$$y_{ljt} \in \{0, 1\}\ \forall\, l = 1, \dots, 5;\ j \in J_l\ and\ t \in t_k \tag{14}$$

$$\delta_{i0}^{+} = \delta_{i0}^{-} = 0 \tag{15}$$

$$\delta_{it}^{+} \ge 0, \delta_{it}^{-} \ge 0\ for\ i = 1, \dots, 4\ and\ t \in t_k \tag{16}$$

$$x_{ljt} \ge 0\ with\ l = 1, \dots, 5, ; j \in J_l and\ t \in t_k \tag{17}$$

where:

- i is the set of nutrients, i is energy, protein, potassium or sodium,
- l is the type of recipe, l = 1 (breakfast), 2 (morning snack), 3 (lunch), 4 (afternoon snack), 5 (dinner),
- j_l is the set of the j^{th} recipes of type l to be recommended, $l = 1, \dots, 5$,
- k is the k^{th} day in the week, $k = 1, \dots, 7$,
- t_k is the period t in day k , $t = 1, \dots, T \in t_k$ and k = 1, ..., 7, which are the time slots used in DP,
- g_{it} is the i^{th} nutrient requirement per period t of day k,

- a_{ilj} is a coefficient indicating the quantity of i^{th}nutrient provided in 100 g of j^{th} recipe of type l,
- x_{ljt} is the quantity of j^{th} recipe of type l to be recommended in period t of day k,
- y_{ljt} is a binary variable to decide whether recipe j of type l is included or not in period t of day k,
  $\begin{cases} y_{ljt} = 1 \text{ If the recipe is included} \\ \qquad\qquad else\ 0 \end{cases}$
- δ_{it}^{-},δ_{it}^{+} are negative and positive deviations from i^{th} nutrient goal in period t of day k.

The formulation of the MPP of an HD patient using DGP is expressed by the objective function in equation (10) subject to constraints from equations (11) to (17). The objective of the model is to minimize the positive and negative deviations over all periods in each day of one week. Moreover, goals have to be satisfied for the four nutrients (protein, energy, sodium and potassium). In each period of the day, the patient can have various products but one recipe from each type (breakfast, morning snack, lunch, afternoon snack, and dinner) must be chosen as defined in equation (11). It follows from constraint (12) that the quantity of each recipe included in each period must be between 100 and 200 grams. Constraint (13) implies that the binary variable y_{ljt} is used to decide whether the recipe j with type l is included in each period t of the day. The initial state of the positive and negative deviations included constraint (15) is zero. Non-negativity constraints are described by (16) and (17).

In MPP, we are faced with the incommensurability problem when objectives are expressed in different measurement units (Kcal, mmol, g, etc.). Several studies have explicitly treated this problem; worth noting here is the methodology of Kettani et al. (2004). They have indicated that a commonly used method of performing the normalization is to convert the deviations to a Euclidean distance which normalizes the positive and negative deviation variables. It is realized through assigning a set of weight coefficients to the deviations of the objective function, with the importance factor and the normalization constant (factor) mixed and aggregated together as a weight coefficient. The importance factor should be equal to 1 because all goals are supposed to be of equal importance (implicit weighting is appropriate only if the goals are of extreme importance). The normalization constant is used to allow the conversion from one scale to an equivalent one. A normalization procedure is the process of scaling a vector so that each row vector of the decision matrix is divided by its norm. This can be carried out for any norm. The normalization procedure is used to reduce the impact of large-valued features specified on a different scale (mmol, g, Kcal …) and to allow small-valued features to equally contribute to the optimization of an objective function. The advantages of the normalization factor $\frac{1}{\|a_i\|}$ are numerous. First, all criteria are measured in dimensionless units, which facilitates comparisons between the attributes. Second, the relative proportions of a_i components remain unchanged because their normalization consists in dividing them by the same constant. Third, the choice of the scale for a given objective, from among equivalent scales (ratio level), does not affect the global measure of distance due to the property: $b\|a_i\| = \|ba_i\|$.

To formulate the Normalized GP (NGP) model, we have as an objective function:

$$\text{Minimize} \sum_{i=1}^{n} \frac{1}{\|a_i\|}(\delta_i^+ + \delta_i^-) \quad (18)$$

where:

$$\|a_i\| = \sqrt{\sum_{i=1}^{n} x_i^2}$$

and x is the norm of a vector.

In order to solve the problem given above, we used an ACCESS DB with the 66 recipes presented previously. The data used to build this DB was extracted from the official DB of the Tunisian Institute of Nutrition. An optimization environment with AMPL for solving the relevant optimization problem has been established.

The proposed GP model was implemented with AMPL, and computational tests were run on a system with an Intel® Core™ i5-5200U CPU with base frequency 2.20GHz, 4GB RAM and a 64-bit operating system. The model was verified and validated in accordance with many instructions from diet experts specializing in HD patients. All the guidelines to make a balanced MP model were followed.

Different recipes for the week were obtained, and the results of the DGP model showed that the best dishes from the 66 proposed are those shown in Table 3.

Table 3: Computational results

Recipe Number	**Recipe type**	**Period of the day**	**Day 1**
1	*2*	*3*	*4*
7	Breakfast	1	100 g
34	Morning Snack	2	100 g
16	Lunch	3	194 g
21	Afternoon Snack	4	100 g
41	Dinner	5	100 g

Table 3 cont.

1	*2*	*3*	*4*
Recipe Number	**Recipe type**	**Period of the day**	**Day 2**
1	Breakfast	1	100 g
34	Morning Snack	2	100 g
5	Lunch	3	100 g
21	Afternoon Snack	4	100 g
42	Dinner	5	100 g
Recipe Number	**Recipe type**	**Period of the day**	**Day 3**
2	Breakfast	1	100 g
34	Morning Snack	2	100 g
5	Lunch	3	173 g
21	Afternoon Snack	4	100 g
51	Dinner	5	100 g
Recipe Number	**Recipe type**	**Period of the day**	**Day 4**
1	Breakfast	1	100 g
22	Morning Snack	2	100 g
6	Lunch	3	100 g
35	Afternoon Snack	4	100 g
44	Dinner	5	100 g
Recipe Number	**Recipe type**	**Period of the day**	**Day 5**
2	Breakfast	1	100 g
22	Morning Snack	2	100 g
11	Lunch	3	100 g
20	Afternoon Snack	4	125 g
37	Dinner	5	100 g
Recipe Number	**Recipe type**	**Period of the day**	**Day 6**
1	Breakfast	1	100 g
34	Morning Snack	2	100 g
12	Lunch	3	100 g
20	Afternoon Snack	4	125 g
46	Dinner	5	100 g
Recipe Number	**Recipe type**	**Period of the day**	**Day 7**
2	Breakfast	1	100 g
34	Morning Snack	2	100 g
13	Lunch	3	100 g
10	Afternoon Snack	4	123 g
39	Dinner	5	100 g

By choosing these different dishes, the patient guarantees that all his/her requirements in energy, protein, sodium and potassium are satisfied.

Applying the DGP entails taking into consideration its most important features. In other words, the MPP has to be divided into a number of sub-problems or periods t, and an optimal decision must be taken in each period regarding the correlation between these decisions.

In so doing, the best dish is scheduled in each period of the day and the daily menu consists of the chosen dishes. Decisions are interrelated in the sense that a decision taken to eat an amount of food in any period t is influenced by the quantity eaten previously (in the period $t-1$) and so on to the amount of food to be eaten next (in the period $t+1$). Due to the interrelation of the decisions, the findings of the DGP show that the amount of the chosen recipes is around 200 grams in period 3 (lunch) of the first and the third days and is superior to 100 grams in period 4 (afternoon snack) of the fifth, sixth and seventh days. In this case, the best dishes are chosen with different amounts to satisfy the main constraint of the MPP related to nutritional requirements.

We assume that the smallest unit of each dish is 100 grams. The DGP tends to simultaneously take 100 grams from each of the recipe type and take a long step in one of the recipes to complete the solution which satisfies the nutritional requirements of the day. Hence the program can give multiple solutions for each day. Moreover, swapping the daily menus between any two days of the week is possible without loss of optimality. Our future research will include a cost function which can reduce the number of multiple solutions. In addition, we have no under- or over-achievement in a real-world case which satisfies all goals related to the four nutrient requirements. Positive and negative deviations are zero in the latest periods of each day of the week for all nutrients ($\delta_{i5}^{-} = \delta_{i5}^{+} = 0$ for $\forall$ $k = 1, \dots, 7$).

While an experienced dietician needs from a couple of minutes to a number of hours to plan manually a daily menu for an HD patient, a computer needs less than a second (0.041 second) to solve the problem and display the results of planning a weekly menu divided into five periods per day thanks to using the DGP model. For both static and dynamic models, menus are displayed for a week. In a nutshell, the longer the period and the less redundant the meals between days and periods of the day, the more obvious the importance of the DGP.

5 Conclusion

In this paper, we have presented the classical GP approach in MPP and we have underscored the importance of DGP as a better alternative. We have also presented an illustrative example focusing on a critical health condition, which is that of a patient undergoing HD. Our research has clearly shown that the proposed approach can be implemented even if in more complex and sensitive situations. It has been demonstrated that the MPP is modeled as dynamic problem and the solutions describes states that occur over time.

Based on the promising results presented in this paper, it will be interesting to assign weights to all periods of the day. Fuzzy logic can be used in further research, providing healthier intake of nutrients through food suggestion and nutritional analysis. The cost is one of the most important objectives in any MPP. In future research, we can consider the cost as a decision criterion even though the cost of a dish represents a secondary problem for patients undergoing HD or suffering from any other chronic illness.

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