

Article

A Hybrid Fuzzy Cognitive Map and Genetic Algorithm Approach with Least-Influence Weighting for Decision-Support Forecasting

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Abstract

We propose a hybrid intelligent methodology for forecasting outcomes in complex human-centered systems characterized by uncertainty and reliance on expert knowledge. The framework integrates fuzzy cognitive maps (FCMs), a novel Least-Influence Method for estimating causal arc weights, and genetic algorithms for model tuning. The proposed influence comparison method simplifies expert elicitation by reducing the cognitive load of direct weight estimation, while the genetic algorithm ensures alignment of forecasts with observed or expert-derived data. A forecasting algorithm based on incremental changes in concept levels enhances the sensitivity of the output variable to factor variations. To illustrate the applicability of the framework, we construct a decision-support model for predicting weight-loss success under diverse psychological, behavioral, and environmental conditions. Simulation results demonstrate how factor ranking, scenario modeling, and paired influence analysis provide actionable insights for decision-making. Beyond the weight-loss domain, the approach is generalizable to a wide range of knowledge-based systems requiring robust integration of expert judgment, fuzzy reasoning, and evolutionary optimization.

Keywords: fuzzy cognitive mapping; genetic algorithms; hybrid intelligent systems; influence estimation; factor ranking; decision-support; scenario modeling

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1. Introduction

Obesity is one of the most pressing global health concerns, contributing to increased morbidity, reduced life expectancy, and substantial healthcare costs. It is generally defined as a condition of excessive fat accumulation that adversely affects physical and metabolic health, with body mass index (BMI) values above 30 kg/m² serving as the standard diagnostic threshold [1]. Over the past two decades, the prevalence of obesity has risen dramatically, driven by sedentary lifestyles, calorie-dense diets, and limited opportunities for sustained physical activity, a trend that further intensified during the COVID-19 pan-

demic due to prolonged home confinement and reduced mobility. Recent estimates indicate that by 2035, more than four billion people, over half of the global population, will be overweight or obese [2]. Particularly alarming is the accelerating growth of obesity among children and adolescents, which poses significant long-term risks to individual health and socio-economic stability. These patterns highlight an urgent need for improved computational methods of forecasting and intervention that can integrate diverse behavioral, psychological, and environmental factors to support personalized decision-making in weight-management contexts.

Efforts to promote weight reduction increasingly rely on technologies that support behavioral change and individualized decision-making, including mobile applications, wearable sensors, and online health platforms that continuously collect nutritional, physiological, and activity-related data. From a decision-analytic perspective, successful weight management depends on how individuals adjust controllable factors such as dietary habits, physical activity, and stress-management strategies within a dynamic human-centered system. Consequently, predictive models that capture causal relationships among these factors are essential for the development of effective decision-support tools. Two forecasting questions are particularly important: (1) what level of weight-loss success can be expected under a given combination of influencing factors, and (2) which factors should be modified to improve the probability of success? Reliable answers to these questions can facilitate personalized intervention planning and enhance the transparency and adaptability of intelligent weight-management systems.

Modeling the relationship between multiple determinants of weight-loss outcomes requires an approach capable of integrating both quantitative information and expert knowledge, particularly in domains where behavioral and psychological influences are difficult to measure precisely. Multivariate regression analysis has traditionally been used to estimate the dependence of an outcome variable on multiple predictors using least-squares techniques [3,4] and has proven valuable in a wide range of decision-support applications [5,6]. Nevertheless, regression-based approaches face important challenges when applied to complex human-centered systems. They generally require well-defined quantitative variables, provide limited support for linguistic expert knowledge, and often struggle to represent intricate feedback relationships among interacting factors. Furthermore, as model complexity increases, interpretation of higher-order nonlinear relationships becomes increasingly difficult. These limitations motivate the exploration of alternative modeling frameworks capable of representing uncertainty, expert judgment, and dynamic causal interactions.

To address these limitations, fuzzy set theory [7] enabled the representation of uncertainty and linguistic reasoning, allowing complex nonlinear relationships to be described using natural language if-then rules [8]. Early fuzzy rule-based implementations [9,10] demonstrated that fuzzy logic could be effectively integrated with computational intelligence methods, such as genetic algorithms and neural networks, to model nonlinear dependencies [11,12]. While fuzzy models allow expert assessments to be represented mathematically through membership functions, adding new variables requires restructuring the entire rule base, and they fail to depict how variable values evolve over time. These limitations contributed to the emergence of fuzzy cognitive maps (FCMs) as a flexible framework for representing complex causal systems. FCMs represent systems as directed graphs [13,14] where nodes correspond to variables (concepts) and weighted connections reflect the strength and direction of causal influence. Unlike classical fuzzy inference, FCMs employ a recursive updating mechanism inspired by neural networks, allowing them to trace how shifts in variables propagate through the network and eventually stabilize at an equilibrium state.

Over the past three decades, FCMs have been successfully applied to a wide range of complex decision domains, including pattern recognition [15], risk and crisis management [16], political and policy analysis [17], defense and conflict forecasting [18], environmental and socio-economic planning [19], medical decision-support [20], and artificial intelligence research [21]. They have also been used to explore behavioral processes such as the cognitive conflicts that impede the adoption of healthy habits [22]. FCMs offer two key advantages over both regression models and fuzzy if-then rules: new variables can be incorporated easily by adding additional nodes to the graph without restructuring the model, and the inclusion of feedback loops enables explicit examination of how variable values change over time due to mutual influence. Despite these advantages, the practical effectiveness of FCMs depends critically on the specification of connection weights, which strongly influence forecasting accuracy and simulation outcomes.

1.1. Literature Review and Research Gaps

While the evolution from classical regression analysis to fuzzy systems has expanded modeling capabilities in human-centered domains, a systematic analysis of current FCM methodologies identifies three methodological challenges that remain unresolved. The first concerns the complexity of expert weight elicitation: standard FCM implementations rely heavily on direct numerical assignment of causal weights, which imposes a severe cognitive burden on experts and compromises structural consistency. The second concerns limited sensitivity to incremental state changes, since conventional recurrence mechanisms often fail to capture subtle, incremental fluctuations in interconnected psychological and behavioral concept levels over time. The third concerns the limited integration of expert knowledge with data-driven optimization, as there remains a shortage of streamlined frameworks that bridge qualitative expert pairwise matrices with automated optimization algorithms.

To address these gaps, the objective of this study is to develop a comprehensive methodology for designing and tuning FCMs to forecast weight-loss success based on multiple influencing factors. Toward this objective, this study makes four principal contributions: a Least-Influence Method for estimating FCM connection weights through relative comparisons with a baseline causal influence, which reduces the burden of direct numerical elicitation; a constrained genetic algorithm optimization procedure that refines expert-derived weights while preserving the qualitative structure of the cognitive map; an incremental-change recurrence mechanism for modeling variations in concept levels and propagating causal effects through the network; and a proof-of-concept application to weight-loss forecasting that demonstrates the framework's utility for scenario analysis, factor ranking, and evaluation of joint causal influences.

1.2. Positioning of the Proposed Framework Within FCM Elicitation and Learning Literature

To clarify the methodological novelty of the proposed hybrid approach, it is essential to distinguish it from established paradigms in FCM parameterization. Existing weight-determination techniques generally fall into two broad categories: expert-driven elicitation and data-driven learning.

1.2.1. Expert-Driven Elicitation vs. Least-Influence Method

Traditional expert parameterization typically relies on direct numerical assignment or direct linguistic mapping using fuzzy membership functions [23]. While simple, these methods impose a high cognitive load when scaling, as experts must maintain global structural consistency across all connected edges.

In contrast, hierarchical and matrix-based pairwise comparison approaches, such as those derived from Saaty's analytic hierarchy process (AHP) [24], reduce cognitive strain

by focusing on relative ratios. However, standard AHP approaches require full reciprocity matrices which can become prohibitively complex for sparse networks.

The proposed Least-Influence Method introduces methodological simplification. Instead of evaluating every possible pair, experts only identify the single weakest causal link and benchmark other active links against this single baseline using intuitive scale increments. This explicitly preserves the sign of the edge and isolates the elicitation to active connections, substantially reducing the number of required judgments compared to full pairwise matrices [25].

1.2.2. Data-Driven Learning and Optimization Tactics

Data-driven FCM refinement has been extensively studied using both local and global search algorithms. Among local methods, Hebbian and nonlinear Hebbian learning (NHL) are unsupervised, localized algorithms that iteratively update weights based on the co-activation of adjacent concepts [26]. While computationally efficient, Hebbian learning is highly sensitive to initial conditions and can corrupt the structural knowledge originally embedded by experts, sometimes altering the intended semantic direction of causal loops. Among global methods, metaheuristics such as real-coded genetic algorithms (RCGAs), particle swarm optimization (PSO), and differential evolution (DE) treat weight discovery as a continuous optimization problem aimed at minimizing prediction error across sequential data states [27–29].

1.2.3. Methodological Novelty of the Proposed Hybrid Architecture

The primary novelty of our framework lies not in the isolated invention of a new metaheuristic but in the hybrid operational pipeline that bridges qualitative human insight with global evolutionary tuning. This pipeline extends an approach previously applied by the authors to defense and security forecasting [18], adapted here with a new weight-elicitation procedure (the Least-Influence Method) and a domain-specific concept structure for weight-loss behavior. First, unlike standard evolutionary approaches that search the full continuous parameter space without prior structure, our genetic algorithm uses the baseline outputs of the Least-Influence Method to bound the search space to narrow intervals around the expert baseline (a half-width of ± 0.25), which constrains the optimization to a much smaller region than an unconstrained search would explore. Second, because optimization is restricted to these narrow, expert-centered intervals, the procedure is designed to preserve the qualitative causal structure of the map and reduce the likelihood of sign reversals during tuning. Third, the optimization operates on a novel incremental-change recurrence relation (Equation (11)) rather than standard sigmoidal transformation functions, which provides greater sensitivity to incremental changes in psychological and behavioral variables.

1.3. Article Structure

The remainder of the article is structured as follows: Section 2 describes the models and algorithms used for constructing and tuning FCMs for multivariate forecasting. Section 3 presents the application of the approach to predicting weight-loss outcomes. Discussion and summary are presented in Sections 4 and 5, respectively. Finally, the genetic optimization algorithm used for parameter tuning is detailed in Appendix A, and Appendix B defines the computational parameters and implementation of the genetic algorithm.

2. Fuzzy Cognitive Maps in Forecasting

The proposed hybrid computational framework is executed in four sequential phases. In the first phase, expert knowledge elicitation, qualitative pairwise comparisons of concept influences are gathered and processed using the Least-Influence Method to establish a consistent baseline causal weight matrix (W_0). In the second phase, dynamic forecasting simulation, an initial state vector (A_0) is introduced, and the model executes an iterative, incremental-change recurrence relation to simulate how system variables propagate and evolve over discrete time steps. In the third phase, model calibration and optimization, a genetic algorithm evaluates the discrepancy between simulated predictions and empirical data, once the recurrence relation has reached a stable equilibrium, in order to fine-tune the connection weights within constrained intervals. In the fourth phase, post-stabilization analysis, the optimized model is used to rank the behavioral and psychological concepts according to their total systemic impact on weight-loss outcomes.

2.1. Theoretical Foundations and Model Notions

An FCM is defined as a directed graph [13] in which vertices represent *concepts*, or variables describing system characteristics, and weighted edges denote the causal influence of one concept on another. Each edge weight w_{ij} reflects the magnitude and direction of the effect of concept C_i and concept C_j . The model therefore captures both positive and negative relationships among variables in a form suitable for iterative computation.

In this context, the term *cognitive* is used to indicate the involvement of subjective human judgment regarding the directional relationship between the variables. Furthermore, the term *fuzzy* translates descriptive words on the intensity of the association into discrete numbers in the ranges of $[0, 1]$ and $[-1, 0]$.

Let $C = \{C_1, C_2, \dots, C_n\}$ denote the complete set of concepts included in the model. Each concept C_i represents a variable that characterizes an element, process, or condition within the system under study. The quantitative state of each concept is expressed by a value $A_i \in [-1, +1]$, which indicates the concept's relative level at a given time step.

For practical interpretation, the scale can be viewed as symmetric around zero: values near +1 correspond to the highest or most favorable levels of a factor, values near −1 represent the lowest or least desirable levels, and values close to 0 reflect an average or neutral state. When expert evaluation is used instead of direct measurement, qualitative assessments such as *very low*, *low*, *medium*, *high*, or *very high* can be converted into numerical form using fuzzy membership functions.

To facilitate such expert-to-numeric transformation, a “thermometer” scale, as presented in Table 1, may be applied, assigning specific numerical values to linguistic categories; for example, −1 = minimum level, 0 = average, +1 = maximum. This mapping allows consistent quantification of subjective inputs and provides a uniform representation of all concepts within the computational framework of the FCM.

The relationships among concepts in a fuzzy cognitive map are expressed through weighted connections that quantify the influence of one concept on another. The weight w_{ij} assigned to the directed edge from concept C_i to concept C_j represents the strength and direction of this causal effect. In general:

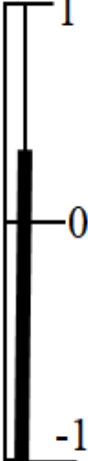
- $w_{ij} > 0$ indicates a *direct* (positive) influence, meaning that an increase in C_i tends to increase C_j ;
- $w_{ij} < 0$ indicates an *inverse* (negative) influence, meaning that an increase in C_i tends to decrease C_j ;
- $w_{ij} = 0$ indicates no measurable influence between the two concepts.

In practice, the numerical estimation of w_{ij} can be based on empirical data or expert judgment. When experimental or observational data are available, the derivative $w_{ij} = \frac{dx_j}{dx_i}$

can be used to approximate the sensitivity of one variable to changes in another. In cases where data are sparse or unavailable, expert evaluation provides a practical alternative. Experts can assign influence values using qualitative terms, such as *weak*, *moderate*, or *strong*, which are then converted into numerical values within the interval $[-1, +1]$.

When multiple experts contribute, their individual assessments can be aggregated using weighted averaging to produce a composite estimate of each w_{ij} . This process leverages human expertise in identifying causal dependencies while maintaining internal consistency within the model's quantitative framework.

Table 1. Assessment of the degree of influence.

Thermometer Scale	Linguistic Estimation	Quantitative Estimation
	Positive maximum	1
	Positive above average	0.75
	Positive average	0.5
	Positive below average	0.25
	Neutral or average	0
	Negative below average	-0.25
	Negative average	-0.5
	Negative above average	-0.75
	Negative maximum	-1

2.2. Causal Weight Estimation and Forecasting Algorithm

This section introduces a new procedure for estimating the relative strengths of influence among concepts, referred to as the *Least-Influence Method*, which draws on the pairwise comparison approach [30]. Unlike traditional direct assessment methods that require experts to assign numerical values to each causal link, the present method relies on comparative judgments between pairs of influences. This simplifies the elicitation process and reduces the cognitive effort required from experts.

The approach assumes that the directed graph of the FCM distinguishes between positive and negative influences, and that the smallest positive and negative influence magnitudes are known. Let

$$\{w_1, w_2, \dots, w_{min}, \dots, w_n\}$$

represent a set of influences of the same sign, where w_{min} corresponds to the least (smallest) influence. For each influence w_i , a corresponding rank value r_i is assigned such that the relation “greater w_i ” implies “greater r_i ”. The proportionality between influence magnitudes and their ranks is therefore expressed as follows:

$$\frac{w'_1}{r_1} = \frac{w'_2}{r_2} = \dots = \frac{w'_{min}}{r_{min}} = \dots = \frac{w'_n}{r_n}, \quad (1)$$

From Equation (1), all influences can be determined in terms of the least influence w_{min} :

$$w'_1 = w'_{min} \cdot \frac{r_1}{r_{min}}, \quad w'_2 = w'_{min} \cdot \frac{r_2}{r_{min}}, \quad \dots, \quad w'_n = w'_{min} \cdot \frac{r_n}{r_{min}} \quad (2)$$

To ensure normalization of the influence magnitudes, the following condition is imposed:

$$w'_1 + w'_2 + \dots + w'_n = 1.$$

Then, for the least-influence strength, we obtain:

$$w'_{min} = \frac{1}{\frac{r_1}{r_{min}} + \frac{r_2}{r_{min}} + \dots + \frac{r_n}{r_{min}}} \quad (3)$$

The rank ratios $\frac{r_i}{r_{min}}$ are determined according to the scale of pairwise comparisons [24]:

$$\frac{r_i}{r_{min}} = \begin{cases} 1, & \text{if } w_i \text{ is the same as } w_{min} \\ 3, & \text{if } w_i \text{ is a little bit more than } w_{min} \\ 5, & \text{if } w_i \text{ is more than } w_{min} \\ 7, & \text{if } w_i \text{ is significantly more than } w_{min} \\ 9, & \text{if } w_i \text{ is absolutely more than } w_{min} \end{cases}$$

Once the rank ratios are obtained, the intermediate influence strengths (denoted here as $w'_1, w'_2, \dots, w'_n$) are calculated using Equations (2) and (3), satisfying the strict mathematical sum-to-one condition ($\sum w'_i = 1$).

To map these proportions into a standard fuzzy continuous range of [0, 1] where the strongest active causal link reaches peak operational intensity, a final bounds transformation is executed. Each intermediate weight is divided by the maximum observed proportional weight (w'_{max}) within its respective reference sign set:

$$w_i = \frac{w'_i}{\max(w'_1, w'_2, \dots, w'_n)}$$

Following this bounds transformation, the final assigned weights (w_i) naturally no longer sum to one. Instead, they are bounded within the interval [0, 1], where the maximum causal edge is anchored precisely at $w_{max} = 1.0$. This two-stage calculation pipeline successfully preserves the relative proportions dictated by the expert's comparative judgments while shifting the final network connections into a highly sensitive operational scale for the FCM weight matrix W_0 .

The dynamic behavior of a fuzzy cognitive map can be represented through a recurrence relation that updates concept values over successive time steps. Let the matrix of concept influences be defined as follows:

$$W_0 = \begin{bmatrix} 0 & w_{12} & \dots & w_{1n} \\ w_{21} & 0 & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & 0 \end{bmatrix} \quad (4)$$

where the diagonal elements are set to zero, indicating that no concept directly influences itself. The initial state of the system is expressed by the following vector:

$$A^0 = [A_1^0, A_2^0, \dots, A_n^0], \quad (5)$$

which represents the activation levels of all concepts at the time step $k = 0$. After repeated interactions among concepts, the system reaches a stationary state characterized by the following vector:

$$A^l = [A_1^l, A_2^l, \dots, A_n^l] \quad (6)$$

where changes between consecutive iterations become negligibly small, i.e., $|A_i^l - A_i^{l-1}| < \varepsilon$ holds for all $i = 1, 2, \dots, n$. The parameter ε denotes a small positive threshold that defines convergence.

The questions of convergence and stability have been discussed in prior research [13,31,32]. For the purposes of this study, it is assumed that the process converges to a stable equilibrium or attractor within a finite number of iterations.

To describe the updating process, we consider that the value of each concept C_i at step $(k + 1)$ depends on the levels of all other concepts C_j at step k . The dependence can be noted as follows:

$$A_i^{k+1} = \Psi(A_1^k, \dots, A_j^k, \dots, A_n^k). \quad (7)$$

Taking the differential form of this expression yields the relationship between incremental changes at successive steps:

$$\Delta A_i^{k+1} = \frac{\partial A_i^{k+1}}{\partial A_1^k} \Delta A_1^k + \dots + \frac{\partial A_i^{k+1}}{\partial A_j^k} \Delta A_j^k + \dots + \frac{\partial A_i^{k+1}}{\partial A_n^k} \Delta A_n^k. \quad (8)$$

Because each partial derivative $\frac{\partial A_i^{k+1}}{\partial A_j^k}$ corresponds to the influence weight w_{ji} , the equation becomes

$$\Delta A_i^{k+1} = \sum_{j=1}^n \Delta A_j^k w_{ji}, \quad i = 1, 2, \dots, n, \quad (9)$$

where

$$\Delta A_i^{k+1} = A_i^{k+1} - A_i^k, \quad \Delta A_i^k = A_i^k - A_i^{k-1}. \quad (10)$$

Combining these relations gives the iterative update rule for the FCM:

$$A_i^{k+1} = A_i^k + \sum_{j=1}^n (A_j^k - A_j^{k-1}) w_{ji}. \quad (11)$$

In matrix form, Equation (10) can be written compactly as follows:

$$\mathbf{A}^{k+1} = \mathbf{A}^k + (\mathbf{A}^k - \mathbf{A}^{k-1}) \mathbf{W}_0, \quad (12)$$

For the initial iteration ($k = 0$), the relation simplifies to the following:

$$\mathbf{A}^1 = \mathbf{A}^0 + \mathbf{A}^0 \mathbf{W}_0.$$

This follows from the initialization assumption $\mathbf{A}^{-1} = 0$, meaning the system is assumed to have been at a neutral state prior to the introduction of the initial condition $\mathbf{A}^0$. The first iteration therefore treats $\mathbf{A}^0$ itself as the incremental departure from this prior resting state. The above formulation provides the basis for simulating the step-by-step evolution of concept levels and forms the foundation for the forecasting algorithm presented in the following section.

The fuzzy cognitive map described in the previous section can be used to forecast the value of an output concept based on the initial conditions of several influencing factors. Let the system consist of n concepts, where C_n denotes the target (output) variable and $C_1, C_2, \dots, C_{n-1}$ represent the input variables that interact with one another.

The forecasting procedure can be summarized as follows:

Step 1. Initialization.

Set the initial vector

$$\mathbf{A}^0 = [A_1^0, A_2^0, \dots, A_{n-1}^0, A_n^0 = 0], \quad (13)$$

where each of $A_i^0 \in [-1, +1]$, defines the level of the corresponding input concept at the starting point.

Step 2. Simulation.

Using the recurrence relation (Equation (11)), compute the steady-state vector $\mathbf{A}^l$ whose elements represent the equilibrium values of all concepts after iterative updates. The final value of the output concept A_n^l is recorded as the forecasted outcome.

Step 3. Normalization.

Identify the maximum and minimum steady state of the output concept, denoted as $(\bar{A}_n)$ and $(\underline{A}_n)$, respectively. These represent the extreme attainable levels of the output variable.

Step 4. Output estimation.

Normalize the equilibrium value A_n^l obtained in step 2 using the following:

$$\hat{A}_n^l = \hat{A}_n = \begin{cases} \frac{A_n^l}{\bar{A}_n}, & \text{if } A_n^l \geq 0 \\ -\frac{A_n^l}{\underline{A}_n}, & \text{if } A_n^l < 0 \end{cases} \quad (14)$$

where $\hat{A}_n$ represents the scaled prediction of the output variable corresponding to the given output configuration.

Normalization ensures that all predicted values remain within the interval $[-1, +1]$ and compensates for the absence of an explicit threshold function in Equation (11). The resulting normalized value A_n^l can be interpreted as the expected degree of achievement of the target outcome given the specified levels of the input factors.

2.3. Model Tuning, Optimization and Concept Ranking

To ensure that the FCM produces accurate forecasts, the initial weights estimated through the Least-Influence Method must be fine-tuned against empirical or expert-derived data. The purpose of the tuning procedure is to adjust the connection weights so that the simulated output values generated by the model correspond as closely as possible to the known or expected results. This adjustment is accomplished through an optimization process that minimizes the discrepancy between the model's predictions and reference data.

Assume that, via observations, it is possible to collect the data presented in Table 2, where $A_{ip} \in [-1, 1]$ is the level of the concept C_i in observation p , $i = 1, 2, \dots, n$, $p = 1, 2, \dots, N$, and N is the number of observations. It is assumed that the values A_{ip} in Table 2 can be obtained in two ways: experimentally or by expert assessment. For the implementation presented in Section 3, these values were derived entirely as expert-defined qualitative scenarios.

Table 2. Observations “input-output”.

№	Inputs				Output
	C_1	C_2	...	C_{n-1}	C_n
1	A_{11}	A_{21}	...	$A_{n-1,1}$	A_{n1}
$\vdots$		$\vdots$	...	$\vdots$	$\vdots$
P	A_{1p}	A_{2p}	...	$A_{n-1,p}$	A_{np}
$\vdots$		$\vdots$	...	$\vdots$	$\vdots$
N	A_{1N}	A_{2N}	...	$A_{n-1,N}$	A_{nN}

The experimental method provides the possibility of precise measurement of the parameter x_{ip} , associated with the concept C_i , and transformation x_{ip} into the level $A_{ip} \in [-1, 1]$. The expert method uses qualitative assessments of A_{ip} levels in the form of linguistic (fuzzy) terms, which correspond to numerical values (Table 1).

The FCM parameters that are adjusted based on the observation results are the arc weights $w_{ij} \in [\underline{w}_{ij}, \bar{w}_{ij}]$, where $\underline{w}_{ij} \in (\bar{w}_{ij})$ is the lower (upper) limit of the interval of acceptable values w_{ij} . When choosing intervals $[\underline{w}_{ij}, \bar{w}_{ij}]$, we will proceed with the following assumptions:

- The type of influence $w_{ij} > 0$, $w_{ij} < 0$, or $w_{ij} = 0$ is determined by experts and does not change when adjusting the FCM;
- The strength of influence w_{ij} is estimated by an expert with an accuracy of up to one linguistic term (see Table 1), i.e., ± 0.25 ;
- The strengths of positive $w_{ij} > 0$ and negative $w_{ij} < 0$ influences change in the intervals $[0.05, 0.95]$ and $[-0.95, -0.05]$, respectively.

Taking these assumptions into account, the intervals of the FCM arc weights are chosen as in the following examples:

$$0.3 \in [0.1, 0.5], -0.3 \in [-0.5, -0.1],$$

$$0.1 \in [0.05, 0.3], -0.1 \in [-0.3, -0.05],$$

$$0.8 \in [0.6, 0.95], -0.8 \in [-0.95, -0.6].$$

Let $\hat{A}_n = F(\mathbf{A}_0, \mathbf{W}_0)$ be the input–output dependence model, which corresponds to the forecasting algorithm from Section 2.2. Using this model and Table 2, we find the following deviations:

$$\varepsilon_p = A_{np} - \hat{A}_{np}, p = 1, 2, \dots, N, \quad (15)$$

where A_{np} is the output value in the p -th observation, and $\hat{A}_{np}$ is the output forecast for the input values from the p -th observation, i.e.,:

$$\hat{A}_{np} = F(A_{1p}, A_{2p}, \dots, A_{n-1,p}, A_{np} = 0, \mathbf{W}_0).$$

Following the least-squares method adopted in regression analysis, we formulate the problem of the FCM adjustment based on observations as follows: find a matrix of influence strength $\mathbf{W}_0 = [w_{ij}, i = 1, 2, \dots, n, j = 1, 2, \dots, n]$, whose elements satisfy the constraints $w_{ij} \in [\underline{w}_{ij}, \bar{w}_{ij}]$ and minimize the sum of squares of deviations (15), i.e.,:

$$S(\mathbf{W}_0) = \sum_{p=1}^N [A_{np} - F(\mathbf{A}_p, \mathbf{W}_0)]^2 \xrightarrow{\mathbf{W}_0} \min \quad (16)$$

where $\mathbf{A}_p = [A_{1p}, A_{2p}, \dots, A_{n-1,p}, A_{np} = 0]$, $p = 1, 2, \dots, N$.

To solve the nonlinear optimization problem in Equation (16), a genetic algorithm is used [33], and is presented in Appendix A.

The ranks of input concepts characterize their importance in terms of influencing the output concept [34]. The importance index of the input concept C_j corresponds to the value $\hat{A}_n$ obtained for the vector Equation (13), in which the value of the concept C_j is set at the upper level ($A_j = 1$) and the remaining input concepts are set at the lower levels, i.e., $A_i = -1$ ($i \neq j$). Similarly, the indices of the joint influence of several input concepts are calculated.

The ranks of concepts can be used to solve the synthesis problem, that is, to answer the question: how can the levels of input concepts be changed to increase or decrease the level of output concept? It is appropriate to recall that the ranking of elements is an important part of modeling and decision-making in the early stages of system design [35,36].

3. Simulation Results

3.1. FCM Construction

Construction of the FCM as a model of the relationship “influencing factors—success of weight loss” must begin with the classification of influencing factors.

A person who wants to lose weight can be considered as a generalized dynamic system, which is a set of objects and processes that change over time [37]. The model used to manage such a system should reflect the *structure* and *behavior* of the system and the *goal* and *resources* for management. These components of the model serve as the basis for classifying the factors that influence the success of weight loss (Figure 1):

- The only element of the system structure is a person with his or her medical and psychological indicators;
- The behavior is a process of fighting excess weight, which occurs in a given environment;
- The goal is weight loss, which is assessed by the level of success;
- Resources are financial support for a person in the process of losing weight.

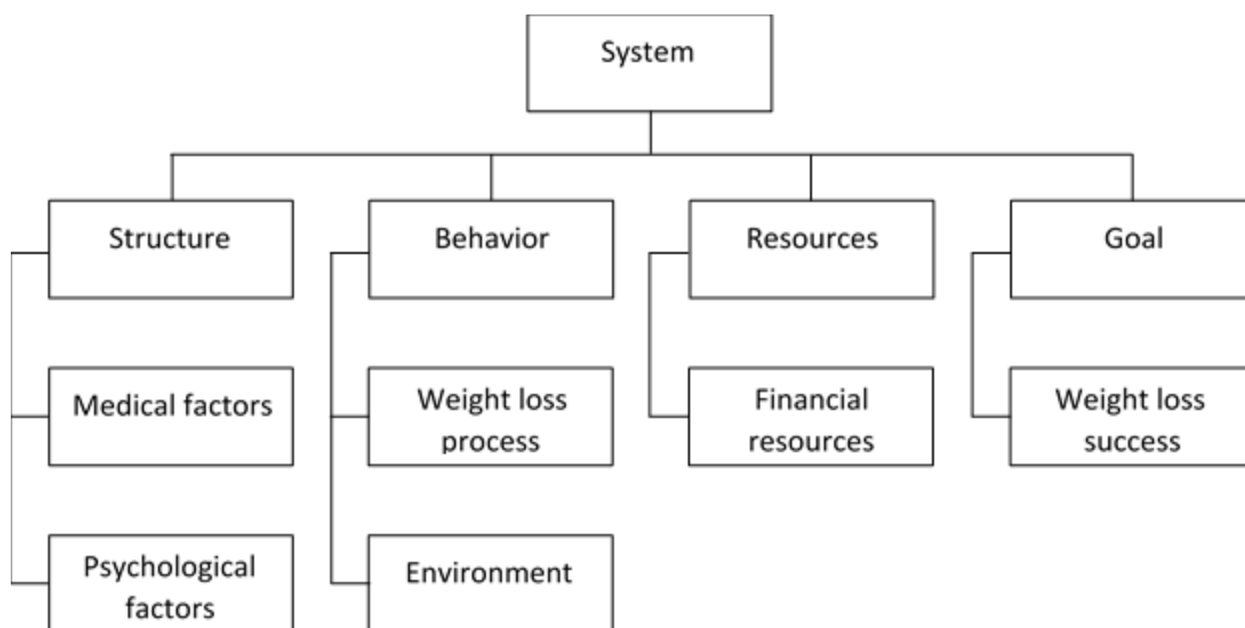


Figure 1. Components of the system model of the weight-loss process.

The taxonomy structure of “classes” (the left column of Table 3) is fixed, but the factors (or items) within each of these classes can be expanded or adjusted as needed. This article focuses on psychological factors and does not consider medical factors.

Based on the classification of influencing factors from Table 3, an FCM was constructed and is presented in Figure 2 and Table 4.

The numbers in the interval $[-1, +1]$, which are used to evaluate the concepts in Table 4, can be interpreted in the following terms: -1 (definitely not), -0.8 (almost certainly not), -0.6 (probably not), -0.4 (maybe not), -0.2 to $+0.2$ (unknown), $+0.4$ (maybe), $+0.6$ (probably), $+0.8$ (almost certainly), $+1$ (definitely). The signs of the influence of concepts on each other were obtained expertly.

Table 3. Factors affecting weight-loss success.

Class	Factors
Medical	• Health
	• Genetic predisposition
Psychological	• Tendency to overeat
	• Desire to change oneself
	• Strictness towards oneself
	• Willpower
	• Self-control
	• Discipline
	• Laziness
	• Stability
Weight-loss process	• Stress resistance
	• Proper nutrition
	• Physical exercise
Environment	• Supervision by a trainer
	• Busyness at work
	• Stress
Financial resources	• Temptations to break the diet
	• Payment for healthy food

- Payment for the gym
- Payment for the trainer

Table 4. Concepts of forecasting model with intervals, definitions and sources.

Concept	Content	Interval for Esti-Operational mation	Definition (Weight-Loss Context)	Source
C_1	Willpower	$[-1, +1]$	Intrinsic motivation to sustain behavioral tracking.	[38–41]
C_2	Constancy/ability to play a long game	$[-1, +1]$	Behavioral grit and continuous dietary adherence.	[38]
C_3	Laziness	$[-1, +1]$	Inclination toward physically inactive states.	[42]
C_4	Self-confidence	$[-1, +1]$	Perceived self-efficacy to resist cravings.	[22,40,41]
C_5	Stress resistance	$[-1, +1]$	Capacity to process environmental pressure.	[43]
C_6	Overeating	$[-1, +1]$	Consumption driven by hedonic/emotional cues.	[44,45]
C_7	Sports activity	$[-1, +1]$	Structured execution of physical exercise.	[42]
C_8	Unbalanced diet	$[-1, +1]$	Poor macronutrient or high glycemic load.	[44,45]
C_9	Stress	$[-1, +1]$	Chronic tension disrupting metabolic balance.	[43]
C_{10}	Temptation of the external environment	$[-1, +1]$	Environmental cues presenting dense calories.	[22]
C_{11}	Knowledge of healthy eating	$[-1, +1]$	Literacy regarding nutritional mechanics.	[46]
C_{12}	Financial resources	$[-1, +1]$	Socio-economic capacity to afford healthy diets.	[47]
C_{13}	Success of weight loss	$[-1, +1]$	Stable reduction in baseline body mass index.	[39,48]

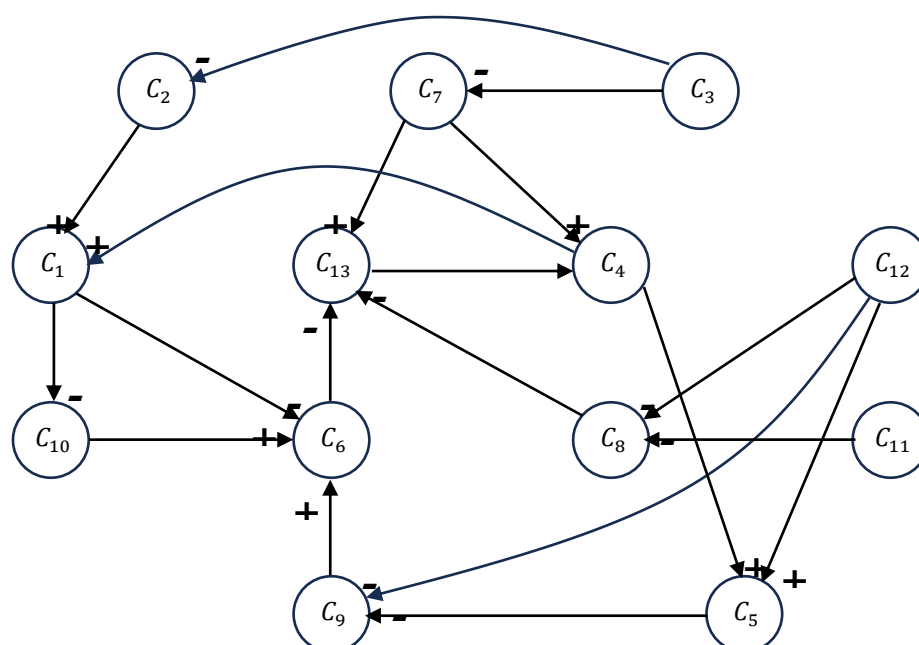


Figure 2. Fuzzy cognitive map for predicting weight-loss success. See also the matrix layout for clarification (Matrix 17).

3.2. Concepts Influence Valuation

To evaluate the strength of the concepts' influence on each other on the FCM graph (arc weights), the Least-Influence Method proposed in Section 2.2 is used.

3.2.1. Positive Influences

The weights of positive influences on the FCM graph (Figure 2) are determined by the following set:

$$\{w_{2,1}, w_{4,1}, w_{4,5}, w_{7,4}, w_{7,13}, w_{9,6}, w_{10,6}, w_{12,5}, w_{13,4}\}.$$

It is assumed that the weight of the least positive influence is the following:

$$w_{10,6} = w(C_{10} \rightarrow C_6).$$

Comparisons of the strengths of positive influences with the least of them are presented in Table 5.

Table 5. Expert linguistic comparisons, intermediate proportions, and final operational weights for positive causal influences.

Causal Link	Expert Linguistic Comparison	Assigned Rank Ratio $\left(\frac{r_i}{r_{10,6}}\right)$	Weight Before Normalization (w'_i)	Normalized Final Weight (w_i)
$C_2 \rightarrow C_1$	A little bit more than w_{min}	3	$\frac{3}{32}$	≈ 0.43
$C_4 \rightarrow C_1$	The same as w_{min}	1	$\frac{1}{32}$	≈ 0.14
$C_4 \rightarrow C_5$	Between “the same” and “a little more”	2	$\frac{2}{32}$	≈ 0.29
$C_7 \rightarrow C_4$	More than w_{min}	5	$\frac{5}{32}$	≈ 0.71
$C_7 \rightarrow C_{13}$	Significantly more than w_{min}	7	$\frac{7}{32}$	1.00 (Maximum Ceiling)
$C_9 \rightarrow C_6$	A little bit more than w_{min}	3	$\frac{3}{32}$	≈ 0.43
$C_{10} \rightarrow C_6$	The same as w_{min} (Baseline Baseline)	1	$\frac{1}{32}$	≈ 0.14
$C_{12} \rightarrow C_5$	More than w_{min}	5	$\frac{5}{32}$	≈ 0.71
$C_{13} \rightarrow C_4$	More than w_{min}	5	$\frac{5}{32}$	≈ 0.71

Note: Intermediate proportions (w'_i) are calculated using a strict sum-to-one constraint ($\sum w'_i = 1$) to isolate pure relative expert ratios (Equations (2) and (3)). Final weights (w_i) are scaled against the maximum observed magnitude ($w'_{7,13} = \frac{7}{32}$) to anchor the peak operational causal intensity at 1.0; consequently, the final column naturally does not sum to unity.

Substituting the rank ratios from Table 5 into Equation (3), we obtain the strength of least positive influence:

$$w_{10,6} = \frac{1}{r_{2,1}/r_{10,6} + r_{4,1}/r_{10,6} + \dots + r_{13,4}/r_{10,6}} = \frac{1}{3+1+2+5+7+3+1+5+5} = \frac{1}{32}.$$

The remaining influence strengths are calculated using Equation (2) and presented in column four of Table 5 (Weight Before Normalization). To obtain normalized values, it is necessary to divide the numbers in the second row by the maximum value ($w'_{7,13}$). Final weights, scaled against the maximum observed magnitude to establish a maximum ceiling of 1.0, appear in the rightmost column of Table 5.

3.2.2. Negative Influences

The weights of negative influences on the FCM graph (Figure 2) are determined by the following set:

$$\{w_{1,6}, w_{1,10}, w_{3,2}, w_{3,7}, w_{5,9}, w_{6,13}, w_{8,13}, w_{11,8}, w_{12,8}, w_{12,9}\}.$$

It is assumed that the weight of the least negative influence is the following:

$$w_{12,9} = w(C_{12} \rightarrow C_9).$$

Comparisons of the strengths of negative influences with the least of them are presented in Table 6.

Table 6. Expert linguistic comparisons, intermediate proportions, and final operational weights for negative causal influences.

Causal Link	Expert Linguistic Comparison	Assigned Rank Ratio $\left(\frac{r_i}{r_{12,9}}\right)$	Weight Before Normalization (w'_j)	Normalized Final Weight (w_j)
$C_1 \rightarrow C_6$	Significantly more than w_{min}	7	$\frac{7}{51}$	≈ 0.78
$C_1 \rightarrow C_{10}$	More than w_{min}	5	$\frac{5}{51}$	≈ 0.56
$C_3 \rightarrow C_2$	A little bit more than w_{min}	3	$\frac{3}{51}$	≈ 0.33
$C_3 \rightarrow C_7$	Absolutely more than w_{min}	9	$\frac{9}{51}$	1.00
$C_5 \rightarrow C_9$	A little more than w_{min}	3	$\frac{3}{51}$	≈ 0.33
$C_6 \rightarrow C_{13}$	Absolutely more than w_{min}	9	$\frac{9}{51}$	1.00
$C_8 \rightarrow C_{13}$	Significantly more than w_{min}	7	$\frac{7}{51}$	≈ 0.78
$C_{11} \rightarrow C_8$	A little more than w_{min}	3	$\frac{3}{51}$	≈ 0.33
$C_{12} \rightarrow C_8$	Between the same and a little more than w_{min}	4	$\frac{4}{51}$	≈ 0.44
$C_{12} \rightarrow C_9$	The same as w_{min}	1	$\frac{1}{51}$	≈ 0.11

Note: Intermediate proportions (w'_j) reflect the relative expert ranking weights (Equations (2) and (3)). Final weights (w_j) are dynamically normalized by dividing all entries by the absolute maximum observed value $(w'_{3,7} = \frac{9}{51})$ to map the highest operational negative feedback mechanism at precisely -1.00 (as detailed in Section 2.2).

Substituting the rank ratios from Table 6 into Equation (3), we obtain the strength of least negative influence:

$$w_{12,9} = \frac{1}{r_{1,6}/r_{12,9} + r_{1,10}/r_{12,9} + \dots + r_{12,9}/r_{12,9}} = \frac{1}{7 + 5 + 3 + 9 + 3 + 9 + 7 + 3 + 4 + 1} = \frac{1}{51}$$

The remaining influence strengths are calculated using Equation (2) and presented in the fourth column of Table 6. To obtain normalized values, it is necessary to divide the numbers in the second row by the maximum value $(9/51)$, which corresponds to the largest negative weight before normalization.

Final weights, scaled against the maximum observed magnitude to establish a maximum ceiling of 1.0, appear in the rightmost column.

The results of Tables 5 and 6 are presented in the matrix of the influences of concepts (4), which has the following form:

$$W_0 = \begin{bmatrix}
0 & 0 & 0 & 0 & 0 & -0.78 & 0 & 0 & 0 & -0.56 & 0 & 0 & 0 \\
0.43 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.33 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.14 & 0 & 0 & 0 & 0.29 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.33 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 \\
0 & 0 & 0 & 0.71 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.78 \\
0 & 0 & 0 & 0 & 0 & 0.43 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0.14 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.33 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.71 & 0 & 0 & -0.44 & -0.11 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.71 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \quad (17)$$

3.2.3. Convergence Stability and Normalization Mechanics

A defining structural characteristic of this incremental framework is the deliberate omission of traditional stepwise nonlinear activation functions (such as Sigmoid or Tanh) during intermediate recurrence steps. Instead, the model relies on the incremental recurrence propagation defined in Equation (11), applying a global normalization function exclusively upon reaching a steady-state condition. The mathematical validity and stability of this design are governed by three explicit properties:

1. **Contractive Mapping and Bounded Search Space:** In traditional linear recurrence systems, the state vector risks infinite divergence if the spectral radius (the largest absolute eigenvalue, $\rho(W)$) of the weight matrix exceeds unity ($\rho(W) > 1$). In our architecture, this instability is structurally bypassed. Because the search space for the optimization framework is tightly constrained by the baseline parameters derived from the Least-Influence Method, the upper bounds enforced by the evolutionary algorithm guarantee that the maximum absolute row sum norm (the L_∞ norm) of the weight matrix is contractive:

$$||W||_\infty = \max_{1 \leq i \leq n} \sum_{j=1}^n |w_{ij}| < 1$$

Because $\rho(W) \leq ||W||_\infty$, this bounding ensures $\rho(W) < 1$. The recurrence relation therefore acts as a contractive mapping, which guarantees convergence to a stable, unique fixed-point attractor and rules out divergence.

2. **Conservation of Cognitive Interpretation:** Standard FCM architectures apply squashing functions at every discrete iteration step to keep concept values strictly mapped within artificial intervals. While computationally convenient, this stepwise

transformation distorts the raw accumulation of concept-level changes during propagation. By allowing unhindered, linear propagation throughout the recurrence phase, the matrix explicitly preserves the cumulative magnitude of conceptual shifts. Post-convergence normalization ensures that the final values are perfectly mapped back to interpretable cognitive scales without introducing mathematical artifacts during intermediate causal loops.

3. **Preservation of Superposition and Gradient Clarity:** Maintaining a linear operational path through the recurrence phase guarantees a smooth, well-defined error surface for the genetic algorithm described in Appendix A. Traditional sigmoidal updates can introduce vanishing gradient effects and additional local minima across the search space. Avoiding stepwise thresholding keeps the optimization landscape continuous, which supports more reliable convergence of the genetic algorithm.

3.3. FCM Tuning Results

To tune the initial version of the FCM, which is determined by matrix (17), the training data “influencing factors—success of weight loss” from the Table 7 were used.

Table 7. Training data for the FCM tuning.

No	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
1	−1	−1	1	−1	−1	1	−1	1	1	1	−1	−1	−1
2	−0.75	−0.8	0.75	−0.8	−0.75	0.8	−0.8	0.75	0.7	0.8	−0.75	−0.8	−0.75
3	−0.5	−0.5	0.5	−0.55	−0.5	0.5	−0.55	0.55	0.5	0.6	−0.5	−0.55	−0.5
4	−0.25	−0.3	0.3	−0.2	−0.1	0.25	−0.15	0.25	0.2	0.3	−0.15	−0.25	−0.25
5	0.05	−0.1	0.15	−0.1	0.1	0.2	0.05	0.15	0.1	0.15	0.05	0.1	0
6	0.25	0.3	−0.1	0.2	0.3	−0.2	0.3	−0.1	−0.2	−0.1	0.1	0.2	0.25
7	0.5	0.5	−0.45	0.6	0.4	−0.25	0.5	−0.2	−0.5	−0.3	0.3	0.5	0.5
8	0.8	0.6	−0.8	0.8	0.8	−0.65	0.8	−0.6	−0.6	−0.7	0.8	0.8	0.75
9	1	1	−1	1	1	−1	1	−1	−1	−1	1	1	1

These scenarios were constructed through expert elicitation using the linguistic assessment framework defined in Table 1 and then transformed into numerical values. As a result of using the algorithm of prediction (Section 2) and solving the optimization problem in Equation (16), the weights of the FCM graph arcs after tuning are obtained and presented in Table 8 (together with the arc weights before tuning and intervals of acceptable arc weight values). The dynamics of the criterion in Equation (16) changes with an increase in the number of iterations M of the genetic algorithm of optimization, which is shown in Figure 3. The optimization process was executed within a MATLAB R2018a environment using a population size of 200 chromosomes over approximately 4000 generations until convergence (see Appendix B).

Table 8. Arc weights before and after tuning.

w_{ij}	Before Tuning	Interval		After Tuning
		$\underline{w}_{ij}$	$\overline{w}_{ij}$	
$w_{2,1}$	0.43	0.2	0.6	0.217
$w_{4,1}$	0.14	0.05	0.3	0.255
$w_{3,2}$	−0.33	−0.5	−0.1	−0.493
$w_{7,4}$	0.71	0.5	0.9	0.898
$w_{13,4}$	0.71	0.5	0.9	0.502
$w_{4,5}$	0.29	0.1	0.5	0.270

$w_{12,5}$	0.71	0.5	0.9	0.672
$w_{1,6}$	-0.78	-0.95	-0.6	-0.924
$w_{9,6}$	0.43	0.2	0.6	0.598
$w_{10,6}$	0.14	0.05	0.3	0.167
$w_{3,7}$	-1	-1.00	-0.75	-0.942
$w_{11,8}$	-0.33	-0.5	-0.1	-0.330
$w_{12,8}$	-0.44	-0.6	-0.2	-0.439
$w_{5,9}$	-0.33	-0.5	-0.1	-0.381
$w_{12,9}$	-0.11	-0.3	-0.05	-0.053
$w_{1,10}$	-0.56	-0.7	-0.3	-0.676
$w_{6,13}$	-1	-1.0	-0.75	-0.948
$w_{7,13}$	1	0.8	0.95	0.950
$w_{8,13}$	-0.78	-0.95	-0.6	-0.603

Table 9 contains a comparison of expert values of the weight-loss success (A_{13} from Table 7) and simulation results ($\hat{A}_{13}$) before and after the FCM tuning. To perform normalization according to Equation (14), the following values were used:

$\underline{A}_{13} = -7.883$, $\bar{A}_{13} = 7.883$ (before tuning), $\underline{A}_{13} = -8.255$, $\bar{A}_{13} = 8.255$ (after tuning).

The mean absolute deviation (MAD) and the mean square error (MSE) are as follows:

$$\text{MAD} = \frac{1}{9} \sum_{p=1}^9 |A_{13,p} - \hat{A}_{13,p}| = \begin{cases} 0.031, & \text{before tuning} \\ 0.028, & \text{after tuning} \end{cases}$$

$$\text{MSE} = \frac{1}{9} \sum_{p=1}^9 (A_{13,p} - \hat{A}_{13,p})^2 = \begin{cases} 0.002, & \text{before tuning} \\ 0.001, & \text{after tuning} \end{cases}.$$

The modest reduction in MAD and MSE suggests that the initial expert-derived weights were already broadly consistent with the elicited scenarios, while the genetic algorithm provided a limited additional calibration benefit.

Table 9. Expert assessments and simulation results.

№	A_{13}	Before Tuning			After Tuning		
		A_{13}^l	$\hat{A}_{13}^l$	$ A_{13} - \hat{A}_{13}^l $	A_{13}^l	$\hat{A}_{13}^l$	$ A_{13} - \hat{A}_{13}^l $
1	-1	-7.883	-1	0.000	-8.255	-1	0.000
2	-0.75	-6.073	-0.770	0.020	-6.349	-0.769	0.019
3	-0.5	-4.101	-0.520	0.020	-4.296	-0.520	0.020
4	-0.25	-1.857	-0.236	0.014	-1.904	-0.231	0.019
5	0	-0.502	-0.064	0.064	-0.481	-0.058	0.058
6	0.25	1.536	0.195	0.055	1.640	0.199	0.051
7	0.5	3.238	0.411	0.089	3.497	0.424	0.076
8	0.75	5.765	0.731	0.019	6.102	0.739	0.011
9	1	7.883	1	0.000	8.255	1	0.000

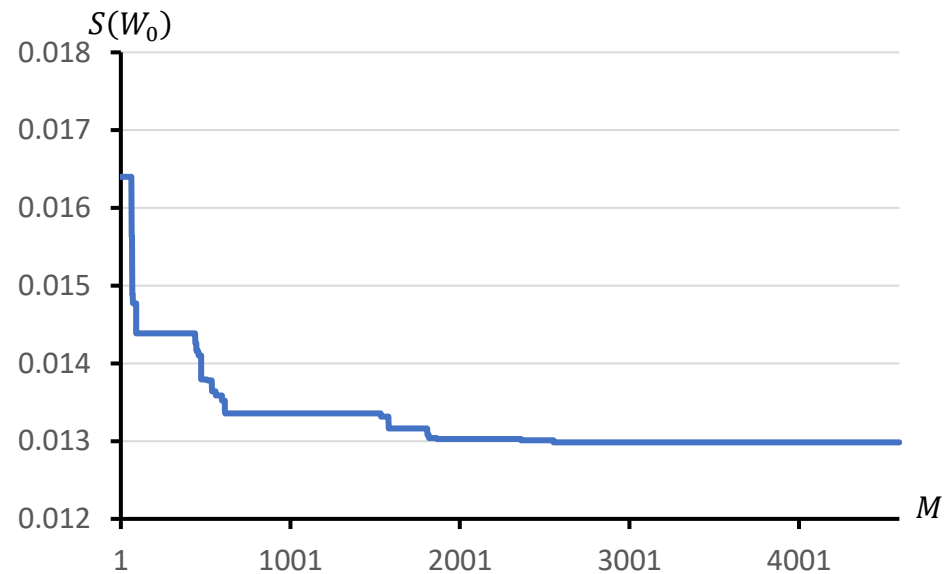


Figure 3. Convergence behavior of the genetic algorithm optimization criterion over iterations.

To evaluate the structural sensitivity and robustness of the tuned FCM under a compact observation framework ($N = 9$), an analytical sensitivity assessment was performed based on the weight variance intervals in Table 8. As established by the contractive matrix mapping property detailed in Section 3.2.3, the system enforces a strict operational ceiling where $\|W\|_{\infty} < 1$. This mathematical property implies that bounded variations or noise within the expert linguistic threshold (± 0.25) tend to be damped during the recurrence cycles. The fact that the genetic algorithm produced only marginal adjustments to the overall system error suggests that the network is relatively insensitive to localized parameter fluctuations, which may reduce the overfitting risk associated with traditional regression analysis on small samples.

3.4. Modeling Weight-Loss Scenarios

A scenario is a vector of factor values (level concepts $C_1, C_2, \dots, C_{12}$) that determines the success of weight loss (level of concept C_{13}) for a specific person. Scenario modeling is intended to answer the question: what will happen, if? Examples of linguistic descriptions of seven scenarios are given in Table 10. Numerical values ($A_1, A_2, \dots, A_{12}$) of concept $C_1, C_2, \dots, C_{12}$ levels for these scenarios are given in Table 11. The forecast of weight-loss success ($\hat{A}_{13}$) in each of the scenarios and its interpretation on the thermometer scale are shown in Table 12.

Table 10. Description of scenarios.

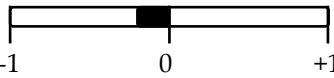
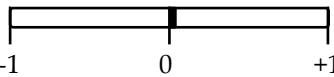
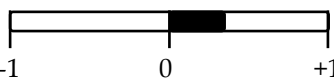
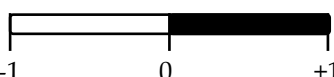
Scenario	Description
S_1	An ordinary person: weak willpower (C_1), considerate laziness (C_3), and many other negative factor values.
S_2	The person made minimal efforts toward behavior change—more or less constantly (C_2), reduced overeating (C_6), reduced nutritional imbalance (C_8), began to study the basics of a healthy lifestyle (C_{11}).
S_3	More substantial efforts: increased willpower (C_1), started engaging in sports (C_7).
S_4	The individual intensified efforts toward self-regulation: started monitoring the consistency of events (C_2), started seriously studying healthy eating (C_{11}), started investing money in the process (C_{12}).
S_5	Substantially reduced negative behavioral factors: significantly reduced laziness (C_3), overeating (C_6) and unbalanced diet (C_8).

S_6	Already moved to a professional level: significant improvements in willpower (C_1), decreased laziness (C_3), increased self-confidence (C_4), noticeable decrease in overeating (C_6) and increase in exercise (C_7), decrease in nutritional imbalance (C_8) and reduction in environmental temptations (C_{10}).
S_7	The ideal level of all factors.

Table 11. Levels of concepts in different scenarios.

Scenario	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
S_1	−0.25	0.25	0.5	0.25	0.75	0.5	−0.25	0.5	0.5	0.75	0.25	0.25
S_2	−0.25	0.5	0.5	0.25	0.75	0.25	−0.25	0.25	0.5	0.75	0.5	0.25
S_3	0.5	0.5	0.5	0.25	0.75	0.25	0.5	0.25	0.5	0.75	0.5	0.25
S_4	0.5	0.75	0.5	0.25	0.75	0.25	0.5	0.25	0.5	0.75	0.75	0.75
S_5	0.5	0.75	−0.25	0.25	0.75	−0.25	0.5	−0.5	0.5	0.75	0.75	0.75
S_6	0.75	0.75	−0.75	0.75	0.75	−0.5	0.75	−0.75	0.5	0.25	0.75	0.75
S_7	1	1	−1	1	1	−1	1	−1	−1	−1	1	1

Table 12. Weight–loss success in different scenarios.

Scenario	$\hat{A}_{13}$	weight
		gain loss
		−1 0 +1
S_1	−0.268	
S_2	−0.199	
S_3	0.033	
S_4	0.079	
S_5	0.343	
S_6	0.597	
S_7	1.000	

3.5. Ranking of Factors Influencing the Success of Weight Loss

The importance indices of concepts $C_1, C_2, \dots, C_{12}$ in terms of their influence on the concept C_{13} coincide with the values of $\hat{A}_{13}$, which are calculated using the algorithm from Section 2.2 when the initial vectors (13), i.e.,

$$A^0 = [A_1^0, A_2^0, A_3^0, \dots, A_{11}^0, A_{12}^0, A_{13}^0]$$

have the following form:

$A^0 = [+1, -1, -1 \dots, -1, -1, 0]$ – for the influence of concepts C_1 ;

$A^0 = [-1, +1, -1 \dots, -1, -1, 0]$ – for the influence of the concept $C_2 \dots$;

$A^0 = [-1, -1, -1 \dots, -1, +1, 0]$ – for the influence of the concept C_{12} .

Figure 4 shows an example of step-by-step change in the values of the C_{13} concept before entering the stationary mode, where $I(C_i)$ is the importance index of factor C_i . The obtained values of $\hat{A}_{13}$ are presented in Figure 5 in the form of a diagram that shows the relative importance of factors ($C_1, C_2, \dots, C_{12}$), affecting the level of weight-loss success (C_{13}). Figure 5 shows that the greatest increase in weight-loss success is associated with an increase in willpower (C_1) and sport activity (C_7), and the greatest decrease in this success is caused by laziness (C_3) and overeating (C_6).

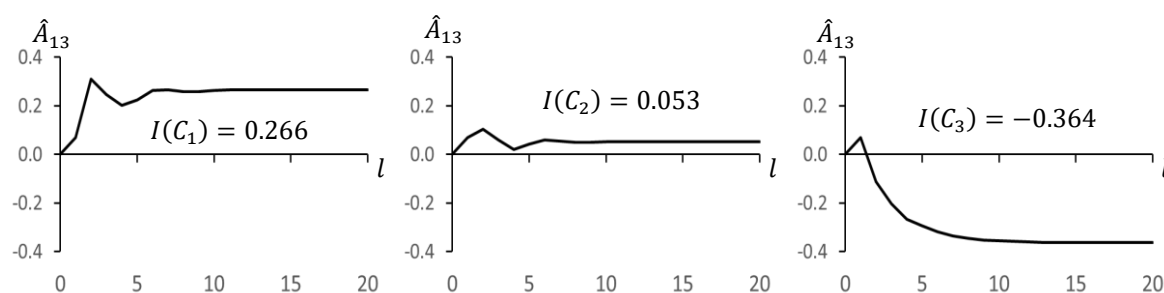


Figure 4. Step-by-step change in the value of the concept C_{13} when calculating the indices of the importance of concept C_1, C_2, C_3 .

To evaluate the paired effects of factors on the concept C_{13} , initial vectors of the following type were used:

$A^0 = [+1, +1, -1, \dots, -1, -1, 0]$ – for joint influence of C_1 and C_2 ;

$A^0 = [-1, +1, +1, \dots, -1, -1, 0]$ – for joint influence of C_2 and $C_3, \dots$;

$A^0 = [-1, -1, -1, \dots, +1, +1, 0]$ – for joint influence of C_{11} and C_{12} .

The diagram of the most important paired influences is shown in Figure 6, from which it can be seen that the greatest increase in weight-loss success is due to the joint influence of willpower (C_1) and sport activity (C_7) and also sport activity (C_7) with a knowledge of healthy eating (C_{11}). The greatest decrease in success is caused by the joint influence of laziness (C_3) and overeating (C_6) and also laziness (C_3) and an unbalanced diet (C_8).

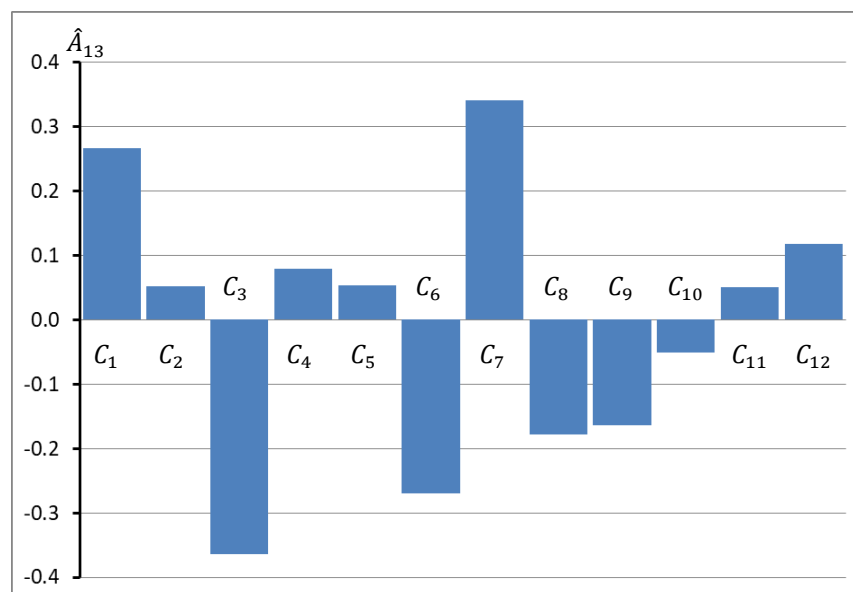


Figure 5. Diagram of influences on the C_{13} concept.

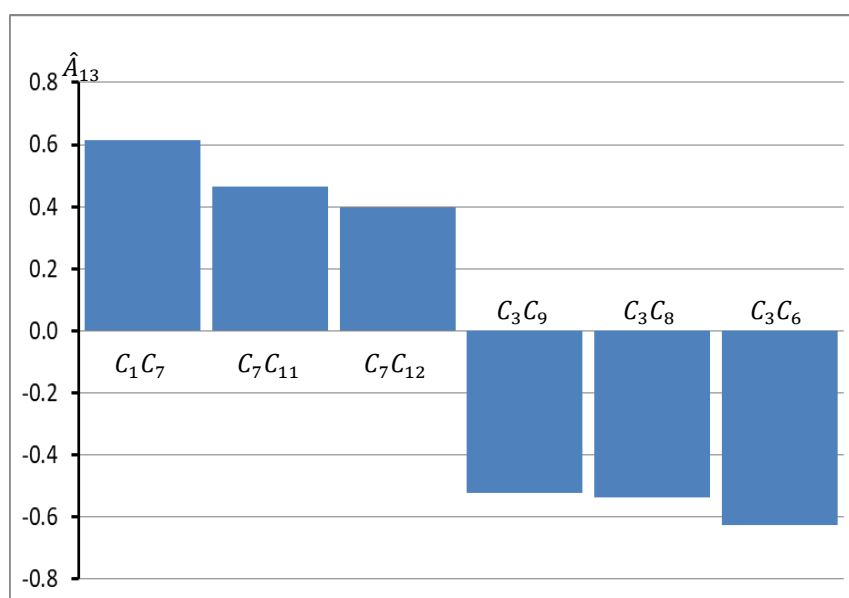


Figure 6. Diagram of paired influences on the C_{13} concept.

3.6. The Impact of Self-Control on Weight-Loss Success

Self-control has the most powerful influence on an individual's ability to manage his or her behavior, interrupt actions that lead to undesirable results and thereby help to achieve a goal [40,41]. To take into account the impact of self-control on the correctness of task execution, probabilistic models of algorithms with control and correction are used in the theory of the reliability of human-machine systems [5]. The purpose of this section is to show the application of FCM to assess the impact of self-control on weight-loss success.

Let C_0 be a concept that corresponds to a person's self-control in the weight-loss process. In relation to the FCM in Figure 2, self-control (C_0) enhances constancy (C_2) and sports activity (C_7) but weakens laziness (C_3) and overeating (C_6). Knowledge of healthy eating (C_{11}) can have a positive effect on self-control (C_0).

We will assume that the following influence strengths $w_{i,j} = w(C_i \rightarrow C_j)$ have been established by experts:

$$w_{0,2} = 0.75, w_{0,3} = -0.75, w_{0,6} = -0.75, w_{0,7} = 0.75, w_{11,0} = 0.5.$$

The matrix of arc weights of the FCM graph taking into account self-control (C_0) is based on the matrix in Equation (17), to which one row with elements $w_{0,2}$, $w_{0,3}$, $w_{0,6}$, $w_{0,7}$ is added, and one column with element $w_{11,0}$ is added as well. Applying this matrix in the forecasting algorithm (Section 2.2) yields the dependence of weight-loss success ($\hat{A}_{13}$) on the level of self-control (A_0) across various scenarios, as shown in Figure 7.

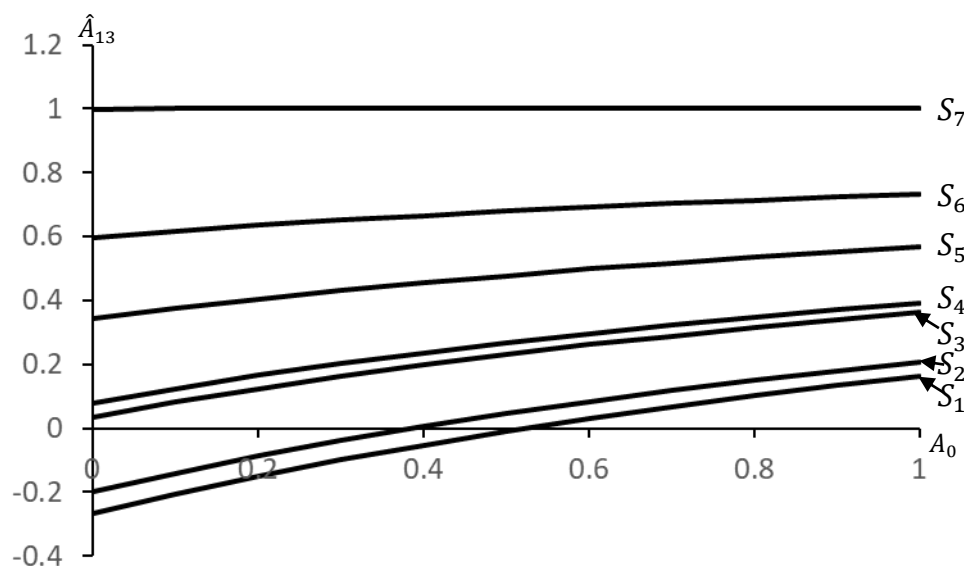


Figure 7. Weight-loss success ($\hat{A}_{13}$) as a function of self-control level (A_0) under various scenarios.

4. Discussion

The simulation results and factor analysis presented in this study offer several key insights into the modeling of weight-loss success and the utility of hybrid intelligent systems. The findings validate our primary hypothesis that combining expert-derived pairwise comparisons with evolutionary tuning produces a sensitive and accurate forecasting model for complex, human-centered systems. Specifically, the Least-Influence Method successfully addresses the cognitive burden and subjective inconsistency typically associated with direct weight estimation in fuzzy cognitive maps [13]. The relatively small improvement in MAD and MSE after genetic tuning is consistent with the initial expert estimates already being broadly accurate. This suggests that structured pairwise comparisons can provide a reasonable computational foundation for capturing complex causal relationships, though further validation on independent data would strengthen this conclusion.

From a theoretical perspective, this study moves beyond simple statistical correlation by explicitly quantifying the dynamic, paired feedback effects of interconnected psychological and behavioral variables. Consistent with traditional behavioral research [1], our factor ranking identifies willpower (C_1) and sport activity (C_7) as the most significant positive drivers for weight loss, while laziness (C_3) and overeating (C_6) act as the primary systemic inhibitors. However, unlike traditional linear regression models which fail to handle qualitative or linguistic variables [8], our framework captures complex multi-modal interactions. For instance, the joint influence of sport activity and knowledge of healthy eating ($C_7 \bullet C_{11}$) illustrates a synergistic effect that standard linear approximations overlook. Furthermore, the inclusion of self-control (C_0) as a governing concept demonstrates the theoretical flexibility of our computational architecture; the model effectively

simulates how a high-level psychological governor can simultaneously dampen negative factors and amplify positive ones across diverse, nonlinear forecasting scenarios.

From a structural standpoint, the proposed FCM operates as a multiple-input–single-output system where connection arcs represent explicitly interpretable causal pathways. Traditional empirical frameworks like multivariate regression or neural networks treat parameters as uninterpretable, requiring massive data arrays to prevent distortion. In contrast, a primary advantage of the hybrid framework is its capacity to function reliably as a “pure expert system”. By initializing the map with disciplined pairwise proportions via the Least-Influence Method, the reliance on dense physical observation tables is reduced. However, the exclusion of multi-seed stochastic permutations and holdout cross-validation sets bounds the immediate generalization of these specific coefficients. Future research extensions will focus on validating these optimization landscapes against continuous biometric streams.

From a practical standpoint, these findings offer guidance for health program administrators, wellness managers, and public health policymakers interested in designing optimized intervention strategies. Rather than relying solely on uniform lifestyle recommendations, policymakers could use this simulation framework as a decision-support tool to explore the likely effects of targeted policies before implementation. For example, because the model captures the ripple effects of psychological variables on behavioral outputs, practitioners can simulate personalized scenarios to determine whether a specific patient requires interventions focused on stress reduction or behavioral coaching to overcome structural inhibitors like laziness, thereby maximizing long-term intervention compliance and resource efficiency.

Despite the model’s accuracy, several limitations remain that point to fruitful future research directions. First, regarding factor selection, this study focused primarily on psychological, behavioral, and environmental variables; the exclusion of explicit medical constraints and genetic predispositions may limit the model’s predictive power in highly specialized clinical settings. Second, while the Least-Influence Method reduces cognitive load, the initial matrix still relies on the subjective judgments of the participating experts. Future research should focus on expanding the factor set to incorporate biological markers and real-time streams from wearable fitness sensors and smart devices. Additionally, applying this unified, evolutionary computational methodology to other complex, data-scarce macro-domains, such as financial risk assessment or public policy evaluation, would further test its generalizability as a robust intelligent decision-support tool.

5. Conclusions

This study successfully introduced a hybrid intelligent framework that integrates a qualitative Least-Influence Method with automated genetic algorithm optimization to enhance the forecasting accuracy of fuzzy cognitive maps (FCMs). Applied to a comprehensive weight-loss forecasting case study, the proposed methodology demonstrated structural consistency, reduced the cognitive load on domain experts, and captured nonlinear behavioral feedback loops with a higher degree of sensitivity when compared to traditional linear approaches.

However, the efficacy of the current framework is bound by specific assumptions and limitations that must be acknowledged. First, the model operates under the assumption that the selected behavioral, psychological, and environmental factors are sufficient to capture the dynamics of weight stabilization, omitting critical biological mechanisms and genetic predispositions that influence clinical outcomes. Second, despite the evolutionary tuning phase, the baseline structure of the system still relies fundamentally on the subjective initial assessments provided by participating experts.

To address these limitations, future research directions will focus on expanding the model's architectural boundaries. A primary objective is to incorporate objective physiological metrics and real-time data streams generated by wearable biometric sensors, thereby reducing reliance on qualitative expert elicitation. Additionally, future work will explore the generalizability of this hybrid FCM-GA framework by applying it to other complex, data-scarce decision-making domains, such as socio-economic risk management and broad-scale public policy modeling.

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Appendix A

The genetic algorithm.

To solve the nonlinear optimization problem in Equation (16), a genetic algorithm is proposed based on the following concepts and operations [49]: *chromosome* is a coded solution; *population* is an initial set of solutions; *fitness function* is a criterion for selecting parents; *crossover* is the operation of generating offspring chromosomes from the parent chromosomes; *mutation* is a random change in the elements of the chromosome.

If $P(t)$ are the parent chromosomes, and $C(t)$ are the offspring chromosomes at the t -th iteration, the general structure of the genetic algorithm has the following form:

```

begin
     $t := 0$ ; to set the initial value of  $P(t)$ ;
    to evaluate  $P(t)$  using the fitness function;
    while (until the completion conditions are met) do
        to perform crossover operation on selected parents  $P(t)$ , in order to get  $C(t)$ ;
        to perform mutation operation on offspring  $C(t)$ ;
        to evaluate  $C(t)$  using the fitness function;
        to choose  $P(t+1)$  from  $P(t)$  and  $C(t)$ ;  $t := t+1$ ;
    end
end.
```

A chromosome is defined as a vector of nonzero matrix elements:

$$W_0 = [w_{ij}], w_{ij} = R[\underline{w}_{ij}, \overline{w}_{ij}],$$

where $R[\underline{x}, \overline{x}]$ is the operation of finding a random number randomly distributed over an interval $[\underline{x}, \overline{x}]$. For example, for the FCM in Figure 2, the generator of the initial population of chromosomes is a vector as follows:

$$[w_{2,1}, w_{4,1}, w_{3,2}, w_{7,4}, w_{13,4}, w_{4,5}, w_{12,5}, w_{1,6}, w_{9,6}, w_{10,6}, w_{3,7}, w_{11,8}, w_{12,8}, w_{5,9}, w_{12,9}, w_{1,10}, w_{6,13}, w_{7,13}, w_{8,13}]$$

where $w_{2.1} = R[0.2, 0.6]$, $w_{4.1} = R[0.05, 0.3]$, $w_{3.2} = R[-0.5, -0.1]$, $w_{7.4} = R[0.5, 0.9]$, $w_{13.4} = R[0.5, 0.9]$, $w_{4.5} = R[0.1, 0.5]$, $w_{12.5} = R[0.5, 0.9]$, $w_{1.6} = R[-0.95, -0.6]$, $w_{9.6} = R[0.2, 0.6]$, $w_{10.6} = R[0.05, 0.3]$, $w_{3.7} = R[-1.00, -0.75]$, $w_{11.8} = R[-0.5, -0.1]$, $w_{12.8} = R[-0.6, -0.2]$, $w_{5.9} = R[-0.5, -0.1]$, $w_{12.9} = R[-0.3, -0.05]$, $w_{1.10} = R[-0.7, -0.3]$, $w_{6.13} = R[-1.00, -0.75]$, $w_{7.13} = R[0.8, 0.95]$, $w_{8.13} = R[-0.95, -0.6]$.

Hence, the following examples of chromosomes:

$$\begin{aligned} &[0.522, 0.244, -0.261, 0.619, 0.716, 0.494, 0.611, -0.943, 0.504, \\ &0.071, -0.854, -0.322, -0.473, -0.335, -0.227, -0.352, -0.933, 0.877, -0.603], \end{aligned} \quad (A1)$$

$$\begin{aligned} &[0.212, 0.246, -0.232, 0.854, 0.869, 0.336, 0.523, -0.882, 0.382, \\ &0.084, -0.911, -0.385, -0.406, -0.137, -0.198, -0.418, -0.826, 0.905, -0.620]. \end{aligned} \quad (A2)$$

The crossing of a pair of parent chromosomes generates an offspring chromosome. The crossing operation is performed by a random exchange of genes (elements) of the parent chromosomes. To do this, a random number is assigned to each gene of the off-

spring chromosome $\xi_1 = R[1, 0]$. If $\xi_1 \leq 0.5$, this gene is taken from the first parent; otherwise, the gene is taken from the second parent. Let the parent chromosomes be given by strings from Equations (A1) and (A2), and random numbers ξ_1 correspond to the following vector:

$$\begin{aligned} &[0.01, 0.61, 0.66, 0.69, 0.73, 0.19, 0.62, 0.47, 0.44, \\ &0.51, 0.26, 0.65, 0.01, 0.30, 0.85, 0.83, 0.50, 0.32, 0.55]. \end{aligned}$$

Then, as a result of crossing Equations (A1) and (A2), we get the offspring chromosome:

$$\begin{aligned} &[0.522, 0.246, -0.232, 0.854, 0.869, 0.494, 0.523, -0.943, 0.504, \\ &0.084, -0.854, -0.385, -0.473, -0.335, -0.198, -0.418, -0.933, 0.877, -0.620]. \end{aligned} \quad (A3)$$

Each gene in Equation (A3) can undergo mutation. To do this, a random number $\xi_2 = R[0, 1]$ is assigned to each gene, and the mutation coefficient q is set (in this case, $q = 0.1$). If $\xi_2 \leq q$, this gene is replaced by a random number from the range of acceptable values.

Let a vector of random numbers ξ_2 have the following form:

$$\begin{aligned} &[0.55, 0.66, 0.11, 0.73, 0.77, 0.08, 0.24, 0.13, 0.55, \\ &0.15, 0.89, 0.64, 0.05, 0.41, 0.81, 0.43, 0.24, 0.19, 0.68]. \end{aligned}$$

Therefore, only the sixth and the thirteenth genes are mutated in the chromosome in Equation (A3), and after that the offspring chromosome takes the following form:

$$\begin{aligned} &[0.522, 0.246, -0.232, 0.854, 0.869, 0.273, 0.523, -0.943, 0.504, \\ &0.084, -0.854, -0.385, -0.430, -0.335, -0.198, -0.418, -0.933, 0.877, -0.620], \end{aligned}$$

where $0.273 = R[0.1, 0.5]$, $-0.430 = R[-0.6, -0.2]$.

The fitness function is the criterion in Equation (16) with a minus sign, i.e., the better the chromosome meets the optimization criterion, the greater the fitness function.

The selection of parent chromosomes for the crossing operation is not accidental. Priority is given to the best solutions. The larger the fitness function, the greater the probability that a given chromosome will produce offspring [49]. When the genetic algorithm is executed, the population size remains constant. Therefore, after crossing operations and mutations, it is necessary to remove chromosomes from the resulting population that has the worst value of the matching function.

Appendix B

Computational Parameters and Implementation of the Genetic Algorithm.

To guarantee complete reproducibility of the optimization curves shown in Figure 3, the structural execution parameters for the real-coded genetic algorithm are defined as follows:

- **Population Size (*pop_size*):** 200 chromosomes;
- **Generations to Convergence:** ≈ 4000 generations;
- **Termination Criteria:** The algorithm terminates if the absolute generation ceiling (*max_gen*) is reached, if the objective function value drops below the accuracy threshold ($\gamma = 0.0001$), or if the improvement delta $|S(W_0)_L - S(W_0)_{L-1}|$ drops below 10^{-4} ;
- **Selection Framework:** Performance-weighted roulette-wheel selection. Probabilities are dynamically scaled against the maximum error boundaries via $p_k = \frac{FF_{gen}[k] - \min FF_{gen}}{\sum (FF_{gen}[j] - \min FF_{gen})}$;
- **Mutation Operator Rate (*q*):** 0.10 uniform gene mutation probability;
- **Elitism and Survival Strategy:** A total-pool ($\mu + \lambda$) selection mechanism is utilized. A set of *crossovers_number* offspring are merged directly into the parent population pool of size *pop_size*, after which only the top 200 highest-performing individuals across both generations are selected to survive;
- **Randomization Framework and Environment:** All stochastic initialization matrices, uniform crossovers, and continuous mutation operations rely strictly on the native, built-in pseudorandom execution streams of the **MATLAB** R2018a numerical computing environment.

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