



Optimization of Financial Complexity of Iranian Listed Companies Using the Artificial Bee Colony Algorithm and a Fuzzy Multi-Criteria Decision-Making Approach

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Abstract

Financial complexity is one of the fundamental challenges faced by firms in the unstable environment of financial markets, which can lead to increased risk and reduced financial performance efficiency. The objective of this study is to optimize the financial complexity of companies listed on the Tehran Stock Exchange using the Artificial Bee Colony (ABC) algorithm and a fuzzy multi-criteria decision-making approach. This research is quantitative and applied in terms of methodology. In the first stage, the factors influencing financial complexity that had been previously identified were weighted and prioritized using the Fuzzy Step-wise Weight Assessment Ratio Analysis (Fuzzy SWARA) method. Subsequently, to optimize the level of financial complexity, the Artificial Bee Colony algorithm, as an artificial intelligence-based metaheuristic algorithm, was implemented on the financial data of 20 companies listed on the Tehran Stock Exchange. The optimization criterion was the minimization of the objective function value and the error level resulting from the algorithmic process. The results of the algorithm execution indicate that as the number of iterations increases, the objective function value decreases and the optimization process achieves satisfactory convergence. Specifically, in the fifth execution of the algorithm, after 1,550 iterations, the minimum objective function value of 1.3473 was obtained, representing the lowest optimization error level and the attainment of the most desirable financial complexity condition. The findings demonstrate that the Artificial Bee Colony algorithm, in combination with a fuzzy multi-criteria decision-making approach, constitutes an efficient tool for optimizing and managing the financial complexity of listed companies and can assist financial managers and capital market policymakers in making optimal decisions.

Keywords: Optimization; Fuzzy Multi-Criteria Decision Making; Artificial Bee Colony Algorithm; Listed Companies.

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1. Introduction

In contemporary financial systems, corporate performance and stability are increasingly shaped by the structure, behavior, and dynamics of financial complexity. Financial complexity emerges from the interaction of market participants, institutional structures, financial instruments, regulatory frameworks, technological infrastructures, and behavioral mechanisms, forming an adaptive system whose properties cannot be fully explained by linear or reductionist models [1, 2]. Modern corporations operate within such

complex environments, where uncertainty, feedback loops, and nonlinear relationships dominate decision-making processes. The growing sophistication of financial markets has transformed complexity from a secondary consideration into a core strategic variable affecting corporate risk exposure, investment behavior, pricing mechanisms, capital structure decisions, and systemic stability [3, 4].

Financial complexity directly influences market efficiency and corporate valuation through information asymmetry, strategic interaction, and the cognitive limits of market participants [5, 6]. Empirical evidence demonstrates



that increasing complexity in financial instruments and corporate disclosures alters investor behavior, slows market learning, amplifies mispricing, and heightens systemic vulnerability [7, 8]. These dynamics create an environment in which firms must continuously adapt their financial strategies to maintain competitiveness, resilience, and operational efficiency [9, 10]. Consequently, managing financial complexity has become a strategic priority for corporate governance, regulatory policy, and market design.

Theoretical research further demonstrates that financial complexity is not merely a byproduct of market development but a structural feature of modern financial capitalism. The growth of derivative instruments, algorithmic trading, fintech innovations, and global capital mobility has expanded the dimensionality of corporate financial decision spaces, generating new sources of risk and opportunity [8, 11]. Brunnermeier and Sannikov's macro-financial framework illustrates how interconnected balance sheets and feedback mechanisms propagate shocks across financial systems, magnifying instability when complexity exceeds institutional capacity for risk management [12]. In parallel, Gual et al. show that while financial complexity can stimulate economic growth, it also increases fragility when governance structures fail to align incentives with systemic stability [13].

Within capital markets, financial complexity manifests through intricate pricing structures, sophisticated trading strategies, heterogeneous investor expectations, and evolving regulatory regimes [3, 14]. Corporate managers must navigate this environment while balancing shareholder expectations, financing constraints, investment timing, and long-term growth objectives [15, 16]. Research on Iranian capital markets indicates that rising accounting information complexity significantly affects the speed of capital structure adjustment and the cost of financing, directly influencing corporate performance and strategic flexibility [16, 17]. Moreover, the growing participation of institutional investors and the increasing entropy of financial statements further amplify complexity in emerging markets such as Iran [18, 19].

Behavioral dimensions further intensify the challenge of financial complexity. Empirical studies on the Tehran Stock Exchange reveal pervasive herding behavior among investors, particularly during periods of heightened uncertainty, reinforcing nonlinear price dynamics and volatility clustering [20, 21]. Such behavior interacts with structural complexity to produce emergent market patterns that are difficult to forecast using traditional econometric

models [22]. Sornette's critical event theory demonstrates that market crashes often arise from endogenous instability rooted in complexity rather than from external shocks alone [2]. These findings underscore the necessity of advanced modeling frameworks capable of capturing adaptive behavior and nonlinear dependencies in financial systems.

From a methodological perspective, traditional optimization and linear modeling approaches exhibit severe limitations when applied to complex financial environments. Rosenhead and Mingers argue that complex problem domains require systems thinking and modeling approaches that account for multiple interacting variables, uncertain information, and evolving system structures [23]. In financial contexts, this calls for the integration of artificial intelligence, metaheuristic algorithms, and fuzzy multi-criteria decision-making tools that can process high-dimensional, uncertain, and nonlinear data structures [24, 25]. Metaheuristic algorithms inspired by natural systems have demonstrated superior performance in navigating complex search spaces where conventional optimization methods fail [26].

Among these methods, the Artificial Bee Colony (ABC) algorithm has gained prominence as a robust optimization technique capable of efficiently exploring complex solution spaces and avoiding premature convergence [27, 28]. Its biologically inspired mechanisms of exploration, exploitation, and adaptive learning mirror the self-organizing behavior observed in financial markets, making it particularly suitable for financial optimization problems [24]. Empirical applications confirm the effectiveness of ABC in solving high-dimensional financial problems, including portfolio optimization, pricing models, risk management, and forecasting [26, 28].

However, optimization of financial complexity requires not only powerful search algorithms but also accurate weighting of decision variables under uncertainty. Fuzzy multi-criteria decision-making techniques provide a structured framework for integrating expert judgment with quantitative data, enabling precise prioritization of financial indicators when exact information is unavailable or imprecise [29]. The SWARA method, in particular, allows experts to express subjective evaluations linguistically, which are then transformed into quantitative weights through fuzzy logic, producing reliable decision-support structures for complex financial systems [29]. Combining fuzzy SWARA with metaheuristic optimization therefore offers a comprehensive approach to managing financial

complexity by simultaneously addressing uncertainty, multidimensionality, and nonlinear interactions.

In the Iranian context, financial markets exhibit distinct structural characteristics shaped by regulatory constraints, institutional development, macroeconomic volatility, and evolving technological infrastructure [15, 17]. These conditions intensify financial complexity for listed firms, making the development of adaptive optimization models particularly critical. The Tehran Stock Exchange, as a rapidly expanding emerging market, faces increasing challenges related to information asymmetry, pricing inefficiency, investor behavior, and capital allocation under uncertainty [20, 21]. Advanced forecasting models such as NARX neural networks further confirm the nonlinear and memory-dependent structure of market dynamics in Iran, reinforcing the need for intelligent optimization approaches [22].

Moreover, globalization and technological innovation continue to accelerate the pace at which financial complexity evolves. Fintech developments, algorithmic trading, and digital platforms are reshaping banking efficiency and risk transmission channels, amplifying both opportunities and systemic vulnerabilities [8, 11]. These transformations demand that corporate managers and policymakers adopt more sophisticated tools for monitoring, controlling, and optimizing financial complexity to ensure sustainable performance and systemic resilience [4, 9].

Despite the growing body of research on financial complexity, existing studies largely focus on descriptive analysis, risk assessment, or macro-level systemic effects [3, 13]. Limited attention has been devoted to the operational optimization of corporate financial complexity using integrated artificial intelligence and fuzzy decision-making frameworks, particularly in emerging markets. This gap restricts the practical applicability of complexity theory in corporate finance and leaves managers without actionable optimization models capable of guiding strategic financial decisions in uncertain environments [23, 24].

Accordingly, there is a pressing need for a comprehensive methodological framework that integrates expert knowledge, fuzzy logic, and metaheuristic optimization to manage financial complexity at the firm level. Such a framework must capture the multidimensional nature of financial systems, accommodate uncertainty, and produce implementable decision-support outputs aligned with corporate objectives and market conditions [27, 29]. By embedding these tools within the specific institutional context of the Tehran Stock Exchange, researchers can

generate insights that advance both theoretical understanding and practical financial management.

The aim of this study is to develop and apply an integrated fuzzy multi-criteria decision-making and Artificial Bee Colony optimization model to minimize and manage financial complexity in companies listed on the Tehran Stock Exchange.

2. Methodology

The present study is applied in terms of purpose and quantitative in nature with respect to its methodological approach. The overall research framework is based on modeling, optimization, and the application of artificial intelligence algorithms in the financial domain. The statistical population of the study consists of all companies listed on the Tehran Stock Exchange, from which 20 companies were selected as the statistical sample using purposive and convenience sampling. The criteria for selecting these firms were the availability of the required financial data and the continuity of their operations over the study period.

In this study, the variables influencing financial complexity that had been identified in the preliminary phase of the research were initially considered as the model inputs. To determine the weights and relative importance of these variables, the Fuzzy Step-wise Weight Assessment Ratio Analysis (Fuzzy SWARA) method was employed. This method, by incorporating expert judgment and fuzzy logic, enables more accurate prioritization of variables under conditions of uncertainty.

In the subsequent stage, in order to optimize the level of financial complexity of firms, the Artificial Bee Colony (ABC) algorithm was applied as an artificial intelligence-based metaheuristic optimization technique. In this algorithm, the objective function was defined such that its minimization represents a reduction in the error level and the achievement of the optimal state of financial complexity. The algorithm was implemented on the financial data of the selected companies by specifying the initial parameters, including population size, the number of employed bees, onlooker bees, and scout bees, as well as the number of iterations.

To evaluate the performance of the algorithm, several independent runs were conducted, and the objective function values and the number of iterations in each run were analyzed. The main evaluation criterion was the convergence behavior of the algorithm and its ability to

reach the minimum objective function value. All quantitative analyses were performed using specialized data analysis software and computational environments associated with artificial intelligence algorithms.

3. Findings and Results

The algorithm of this technique is conceptually identical to the standard SWARA method, with the difference that it is implemented in a fuzzy environment. Accordingly, it holds particular significance because applying this method within a fuzzy framework eliminates the ambiguity inherent

in respondents' linguistic judgments and leads to more precise results.

Step 1.

The research factors are arranged in descending order according to their importance.

Step 2.

Based on the scale presented in Table 1, the relative importance of factor j compared to factor $j - 1$, which has higher importance, is determined until the last factor is reached. After determining all relative importance scores provided by the experts, the geometric mean of the corresponding scores is computed in order to aggregate their judgments. The output of this step is the computation of $\tilde{S}_j$.

Table 1. Linguistic Terms and Fuzzy SWARA Numbers

Linguistic Term	Triangular Fuzzy Number
Equal importance	(1, 1, 1)
Slightly less important	(1.5, 1, 0.67)
Less important	(0.67, 0.5, 0.4)
Much less important	(0.4, 0.33, 0.286)
Very much less important	(0.286, 0.25, 0.22)

Step 3. Calculation of coefficient $\tilde{K}_j$

This coefficient is calculated using Equation (1):

$$\tilde{K}_j = \begin{cases} 1, & j = 1 \\ \tilde{S}_j + 1, & j > 1 \end{cases}$$

Step 4. Calculation of fuzzy weights $\tilde{q}_j$

The fuzzy weights are obtained from Equation (2):

$$\tilde{q}_j = \begin{cases} 1, & j = 1 \\ \frac{\tilde{q}_{j-1}}{\tilde{K}_j}, & j > 1 \end{cases}$$

Step 5. Calculation of relative weights

$$\tilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^n \tilde{q}_k}$$

The output of this step is the fuzzy relative weights in the form (w_j^l, w_j^m, w_j^u) . To convert these fuzzy weights into crisp values, Equation (4) is applied:

$$W_{\text{crisp}} = \frac{(w_j^m - w_j^l) + (w_j^u - w_j^l)}{3} + w_j^l$$

The Artificial Bee Colony (ABC) algorithm is an optimization method that simulates the foraging behavior of a honey bee colony and was first proposed in 2005 by Karaboga for real-parameter optimization. In this mathematical model, the artificial bee colony consists of three types of bees. Employed bees are responsible for exploiting specific food sources and bringing nectar back to the hive. Onlooker bees observe the employed bees and decide whether a particular food source is still worth exploiting. Finally, scout bees are responsible for discovering new food sources. In the ABC algorithm, a food source is defined as a state in the search space (i.e., a candidate solution to the optimization problem), and the number of food sources is initially equal to the number of bees in the colony. The quality of a food source is determined by the value of the objective function at that position, which represents the fitness value.

The first step of the SWARA method involves ranking the factors by experts. Accordingly, 29 criteria were provided to 14 experts who were fully familiar with this method, and they were asked to assign ranks from 1 to 29 to the indicators. This ranking is presented in Table 2.

Table 2. Ranking of Research Factors by Experts

Code	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12	Expert 13	Expert 14
C1	3	18	16	17	16	3	16	19	3	16	13	15	17	16
C2	5	4	5	4	6	4	6	4	4	5	5	5	3	6
C3	1	1	2	2	1	1	1	1	2	2	2	1	2	1
C4	7	8	7	14	7	6	7	7	15	7	7	7	8	7
C5	14	7	8	13	9	14	9	8	13	8	14	8	7	9
C6	16	2	17	3	18	16	18	6	1	17	16	17	1	19
C7	17	12	18	10	21	17	21	2	16	18	17	19	12	21
C8	18	21	19	18	3	18	3	11	10	19	18	18	4	2
C9	19	14	20	20	16	19	16	15	18	20	19	20	13	17
C10	20	15	21	19	19	20	19	14	20	21	20	21	16	18
C11	10	16	9	12	11	10	11	16	12	9	12	9	15	11
C12	12	17	10	11	13	12	13	17	11	10	11	10	18	13
C13	4	3	4	5	4	5	4	3	5	4	4	3	17	4
C14	11	9	14	7	8	11	8	10	7	14	10	14	9	8
C15	8	10	13	8	10	8	10	9	8	13	8	12	10	10
C16	9	11	12	9	12	9	12	12	9	12	9	13	11	12
C17	6	5	11	6	5	7	5	5	6	5	6	5	6	5
C18	21	19	6	1	2	21	14	18	19	6	1	2	19	16
C19	2	6	1	21	12	2	2	6	21	1	21	6	5	3
C20	15	13	15	15	15	15	15	13	14	15	15	16	14	15
C21	13	20	3	16	17	13	17	20	17	3	3	4	20	14
C22	25	22	26	22	29	25	24	23	22	28	27	25	24	22
C23	28	27	25	26	22	23	28	27	26	22	24	27	23	27
C24	27	25	29	23	28	26	25	24	23	27	28	24	27	25
C25	22	29	24	27	23	24	29	28	27	23	22	22	25	29
C26	23	23	28	24	27	27	26	25	24	26	29	26	26	24
C27	24	26	27	28	24	22	23	29	28	24	23	23	29	28
C28	26	24	23	25	26	28	27	26	25	25	25	29	28	23
C29	27	26	22	29	25	29	22	22	29	29	26	28	22	26

In the second step, the criteria were arranged in descending order for each of the 14 experts (with the criterion ranked 1 placed at the top and the criterion ranked 29 placed at the bottom). Then, the relative importance of

each criterion j with respect to criterion $j - 1$ was expressed based on the scale presented in Table 1. The output of this step is the set of S_j values. Table 3 presents the judgments of the first expert as an illustrative example.

Table 3. Calculation of S_j Values for the Experts (Example: Expert 1)

Code	S_j
C3	—
C1	(0.22, 0.25, 0.286)
C2	(0.4, 0.5, 0.67)
C13	(0.286, 0.33, 0.4)
C17	(0.67, 1, 1.5)
C4	(0.4, 0.5, 0.67)
C15	(0.4, 0.5, 0.67)
C16	(0.4, 0.5, 0.67)
C11	(0.22, 0.25, 0.286)
C14	(0.22, 0.25, 0.286)
C12	(0.4, 0.5, 0.67)
C5	(0.4, 0.5, 0.67)
C20	(0.22, 0.25, 0.286)
C6	(0.4, 0.5, 0.67)
C7	(0.4, 0.5, 0.67)
C8	(0.286, 0.33, 0.4)
C9	(0.22, 0.25, 0.286)

C10	(0.286, 0.33, 0.4)
C18	(0.286, 0.33, 0.4)
C19	(0.286, 0.33, 0.4)
C21	(0.22, 0.25, 0.286)
C22	(0.22, 0.25, 0.286)
C23	(0.4, 0.5, 0.67)
C24	(0.4, 0.5, 0.67)
C25	(0.22, 0.25, 0.286)
C26	(0.22, 0.25, 0.286)
C27	(0.4, 0.5, 0.67)
C28	(0.22, 0.25, 0.286)
C29	(0.4, 0.5, 0.67)

In the next step, the weights of the criteria were calculated based on the judgments of Expert 1. The results are reported in Table 4. The column W_j represents the weight of each criterion. For example, for criterion C_{21} , the values were computed as follows:

$$\begin{aligned}
 K_{C_{21}} &= (1,1,1) + S_{C_{21}} = (1.22, 1.25, 1.286) \\
 q_{C_{21}} &= \frac{q_{j-1}}{K_j} = \frac{q_{C_{21}}}{K_{C_{21}}} = \frac{(1, 1, 1)}{(1.22, 1.25, 1.286)} \\
 &= (0.778, 0.800, 0.820) \\
 W_{C_{21}} &= \frac{q_j}{\sum q_j} = \frac{q_{C_{21}}}{\sum q_j} = \frac{(0.778, 0.800, 0.820)}{(3.116, 3.587, 4.103)} \\
 &= (0.190, 0.223, 0.263)
 \end{aligned}$$

Moreover, the non-fuzzy (crisp) weight was calculated using the following equation:

$$\begin{aligned}
 W_{\text{crisp}} &= \frac{(w_j^m - w_j^l) + (w_j^u - w_j^l)}{3} + w_j^l \\
 &= \frac{(0.223 - 0.190) + (0.263 - 0.190)}{3} \\
 &\quad + 0.190 = 0.01063
 \end{aligned}$$

The final weight of each criterion, obtained by aggregating the experts' judgments, is presented in Table 4. This table integrates the opinions of all experts using the aforementioned fuzzy relations and determines the weight of each criterion.

Table 4. Criteria Weights Based on Experts' Judgments

Code	S_j	K_j	q_j	Fuzzy w_j	Crisp w_j
C3	—	(1,1,1)	(1,1,1)	(0.244, 0.279, 0.321)	0.281115
C13	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.333,0.401,0.455)	(0.081,0.112,0.146)	0.112975
C2	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.259,0.321,0.373)	(0.063,0.089,0.120)	0.090733
C17	(0.67,1,1.5)	(1.67,2,2.5)	(0.103,0.160,0.223)	(0.025,0.045,0.072)	0.047209
C4	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.062,0.107,0.160)	(0.015,0.030,0.051)	0.032041
C15	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.037,0.071,0.114)	(0.009,0.020,0.037)	0.021832
C16	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.022,0.048,0.081)	(0.005,0.013,0.026)	0.014931
C11	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.017,0.038,0.067)	(0.004,0.011,0.021)	0.012076
C14	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.013,0.030,0.055)	(0.003,0.008,0.018)	0.009769
C12	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.008,0.020,0.039)	(0.002,0.006,0.013)	0.006718
C5	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.004,0.011,0.023)	(0.001,0.003,0.007)	0.003756
C20	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.003,0.009,0.019)	(0.001,0.002,0.006)	0.003047
C6	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.002,0.006,0.013)	(0.0002,0.004)	0.002110
C7	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.001,0.004,0.010)	(0.001,0.003)	0.001466
C8	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.001,0.003,0.007)	(0.001,0.002)	0.001125
C9	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.001,0.002,0.006)	(0.001,0.002)	0.000914
C10	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.002,0.005)	(0.0,0.002)	0.000703
C18	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.001,0.004)	(0.0,0.001)	0.000540
C19	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.001,0.003)	(0.0,0.001)	0.000415
C21	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.001,0.002)	(0.0,0.001)	0.01063
C1	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.0,0.001)	(0.0,0)	0.000114
C22	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.003,0.009,0.019)	(0.001,0.002,0.006)	0.000116
C23	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.004,0.011,0.023)	(0.001,0.003,0.007)	0.000121
C25	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.003,0.009,0.019)	(0.001,0.002,0.006)	0.000124
C29	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.003,0.009,0.019)	(0.001,0.002,0.006)	0.000217
C24	(0.286,0.33,0.4)	(1.286,1.33,1.4)	(0.001,0.003,0.007)	(0.001,0.002)	0.000226
C28	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.003,0.009,0.019)	(0.001,0.002,0.006)	0.000231
C26	(0.4,0.5,0.67)	(1.4,1.5,1.67)	(0.004,0.011,0.023)	(0.001,0.003,0.007)	0.000224
C27	(0.22,0.25,0.286)	(1.22,1.25,1.286)	(0.003,0.009,0.019)	(0.001,0.002,0.006)	0.000126

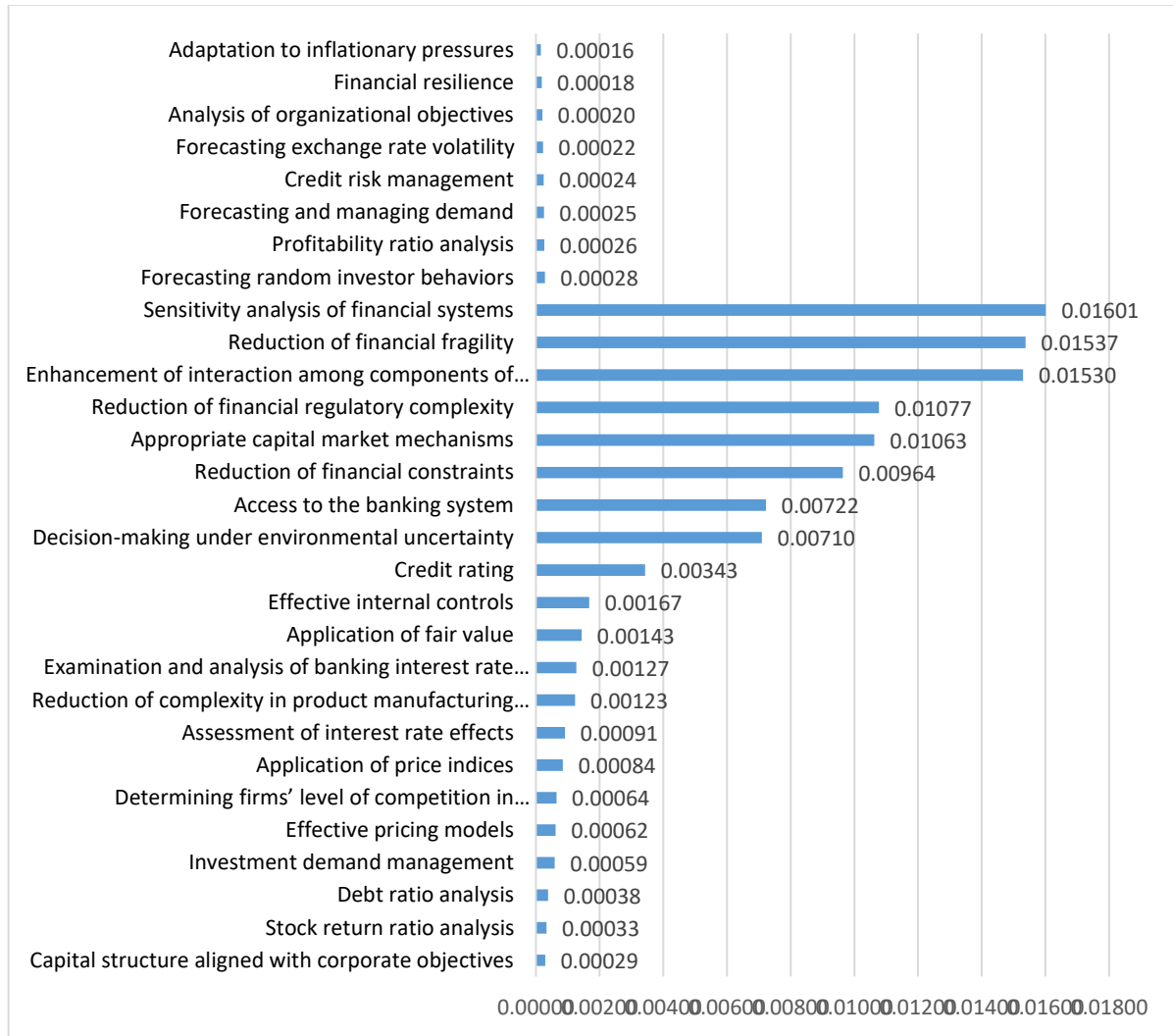


Figure 1. Final Weights of the Criteria

As can be observed, the objective function in the present study for optimizing financial complexity using the Artificial Bee Colony (ABC) algorithm is formulated as a minimization problem. That is, the optimal state is achieved when the level of financial complexity attains its minimum possible value.

$$\min f(x) \text{ (Equation 1)}$$

$$x \in X, x = 1, 2, \dots, n$$

where X denotes the set of variables identified in the qualitative phase of the study.

$$\min W(x) = \sum_{i=1}^n m \phi_i l_i x_i \text{ (Equation 2)}$$

where W represents the weight (magnitude) of financial complexity under different conditions based on the values of x , which correspond to the study variables.

ϕ_i also denotes the degree of influence of each variable on financial complexity, considering the weights of the variables.

l_i denotes the persistence (durability) of the influence of each variable on financial complexity, considering the weights of the variables.

x_i denotes the study variables.

Subject to:

$$g_j(x) \leq 0, j = 1, 2, \dots, n \text{ (Equation 3)}$$

g_j denotes the model constraints with respect to its variables. These constraints may include more than one restriction.

$$D_i = \{x_i \mid x_i \in [x_{i,\min}, x_{i,\max}]\} \text{ (Equation 4)}$$

$$D_i = \{d_{i,1}, d_{i,2}, \dots, d_{i,r}\} \text{ (Equation 5)}$$

D_i can be considered as either a continuous or a discrete set.

$x_{i,\min}$ and $x_{i,\max}$ define the lower and upper bounds of the interval that a variable related to financial complexity can assume. To reduce error within the constraints, a penalty approach is applied. In this approach, the objective of optimizing financial complexity is defined more precisely by introducing a penalty function:

$$f_{\text{penalty}}(x) = (1 + \varepsilon_1 v)^{\varepsilon_2} \times W(x) \text{ (Equation 6)}$$

$$v = \sum_{i=1}^n \max(0, g_{i,\max}) \text{ (Equation 7)}$$

where v is the sum of errors for each variable. Moreover, ε_1 indicates the error magnitude for each variable at point 1. To further improve error reduction, the following function is also formulated:

$$f(x) = \begin{cases} \sigma_i^+ = f_y, & \sigma_i \geq 0 \\ \sigma_i^-, & \sigma_i < 0 \end{cases} \text{ (Equation 8)}$$

σ is computed according to the degree of error reduction. f_y denotes the level of conformity between the standard error and the actual error.

$$\begin{cases} \left(\left(\frac{\lambda}{C_c} \right) - \left(\frac{\lambda}{C_c} \right)^i \right) \lambda_i < C_c, \lambda \geq C_c \\ \frac{\pi^2 E}{\lambda^2} \end{cases} \lambda_i < C_c, \lambda \geq C_c \text{ (Equation 9)}$$

$$\delta_i \leq \delta_i^u \leq E_{\max}, i = 1, 2, \dots, n$$

C_c denotes the error reduction rate of each variable relative to the other variables.

λ denotes the increasing or decreasing rate of the errors of each variable relative to the other errors.

E denotes the response level of the financial complexity reduction objective function to error reductions.

σ_i indicates the level of deviation of errors from the normal state.

Constraint conditions for financial complexity are as follows:

$$\frac{\Delta_T}{H} \leq R \text{ (Equation 10)}$$

Δ_T denotes the maximum displacement and changes in the value of each variable from one point to another improvement point.

H denotes the maximum allowable increase for each variable.

R denotes the range of variable changes under maximum conditions.

$$\frac{d_i}{h_i} \leq R_i \text{ (Equation 11)}$$

d_i denotes the magnitude of change in each variable in the previous functions.

h_i denotes the maximum allowable increase for each variable.

R_i denotes the range of change of each variable under maximum conditions.

$$\frac{p_r}{\phi_t p_n} \geq \frac{p_r}{\phi_t p_n} + \left(\frac{M_{rx}}{\phi_t M_{rx}} + \frac{M_{ry}}{\phi_t M_{ry}} \right) \leq 1 \text{ (Equation 12)}$$

p_n denotes the normal influence power of each variable.

ϕ_t denotes the minimum degree of financial complexity reduction per change in the value of each variable.

p_r denotes the actual influence power of each variable.

M_{rx} denotes the magnitude of linear changes in variable x across the change range r for each variable.

M_{ry} denotes the magnitude of nonlinear changes in variable y across the change range r for each variable.

The above relations were coded in MATLAB; an illustrative example of the coding procedure is provided below.

1. Initialise population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met)
4. // Forming new population.
5. Select sites for neighbourhood search.
6. Recruit bees for selected sites (more bees for best sites) and evaluate fitnesses.
7. Select the fittest bee from each patch.
8. Assign remaining bees to search randomly and evaluate their fitnesses.
9. End While.

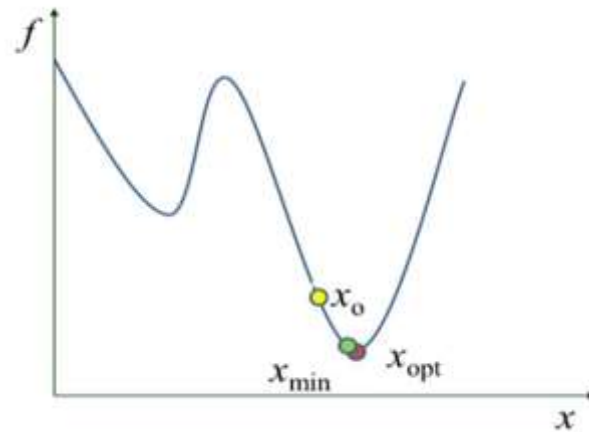


Figure 2. Plot of Minimization of Financial Complexity in the Artificial Bee Colony Algorithm

The results from five runs of the ABC algorithm, based on the optimal parameter values presented in the preceding tables, are shown in Table 5. The stopping criterion for executing the algorithm was defined such that if, over 50

consecutive iterations, the objective function value did not change by more than 0.1 (i.e., it did not decrease), the program execution would be terminated.

Table 5. Results from Five Runs of the Artificial Bee Colony (ABC) Algorithm

Run No.	1	2	3	4	5
Number of iterations	1340	1356	1371	1400	1550
Objective function value	2.7235	2.5957	1.9271	1.4040	1.3473

As shown in Table 5, the results of five executions of the ABC algorithm are presented. In the first run, with 1,340 iterations, the objective function value was 2.7235, indicating the corresponding level of financial complexity. This pattern continues until the fifth run, in which the number of iterations reached 1,550 and the minimum financial complexity level (objective function value) was

1.3473. As indicated, the fifth run produced a smaller and superior objective function value compared with the other runs. As also reflected in the following table, the optimal state of financial complexity is achieved when the error level is minimized; in this case, the minimum error value is 1.3473, and consequently, financial complexity reaches its minimum possible level.

Table 6. Descriptive Statistics of Artificial Bee Colony Algorithm Performance Across Five Runs

Mean objective function value	Best objective function value	Worst objective function value
1.7468	1.3473	2.7235

4. Discussion and Conclusion

The findings of the present study provide strong empirical support for the effectiveness of integrating fuzzy multi-criteria decision-making with the Artificial Bee Colony (ABC) algorithm for optimizing financial complexity in listed firms. The convergence behavior of the ABC algorithm, as demonstrated by the progressive decline in the objective function values across successive iterations and executions, confirms the algorithm's capacity to efficiently explore the high-dimensional and nonlinear solution space

of financial complexity. This performance is consistent with the theoretical foundations of the ABC algorithm as a robust metaheuristic optimization method capable of balancing global exploration and local exploitation in complex problem domains [26-28]. The observed improvement in optimization quality from the first to the fifth execution indicates that the adaptive learning mechanisms embedded in the algorithm effectively capture the intricate interactions among financial variables.

The results further demonstrate that financial complexity is highly sensitive to the relative weights assigned to key

financial indicators. The fuzzy SWARA procedure enabled the study to account for expert judgment uncertainty while maintaining quantitative rigor, leading to a prioritized structure of financial complexity drivers. This outcome aligns closely with the argument that financial complexity cannot be adequately managed through purely statistical or mechanistic approaches, but rather requires hybrid frameworks that integrate human expertise and computational intelligence [23, 29]. By incorporating expert-derived fuzzy weights, the model reflects the practical realities of financial decision-making in emerging markets, where incomplete information and institutional constraints shape managerial behavior.

From a theoretical perspective, the results reinforce the notion that financial complexity is not a static attribute but an evolving systemic phenomenon shaped by feedback loops, behavioral interactions, and institutional dynamics [1, 10]. The model's capacity to minimize complexity through coordinated adjustment of multiple financial variables confirms Carlin's argument that strategic financial behavior must explicitly account for complexity as a core decision variable rather than a secondary outcome [3]. Moreover, the reduction in the optimization error achieved by the integrated model reflects the feasibility of translating abstract complexity theory into operational financial management tools.

The study's findings also provide important insights for understanding the structural sources of financial fragility. The results indicate that when financial complexity exceeds the adaptive capacity of firms, inefficiencies and vulnerabilities intensify, supporting the macro-financial framework proposed by Brunnermeier and Sannikov, which emphasizes the destabilizing effects of interconnected balance sheets and nonlinear amplification mechanisms [12]. The ability of the proposed model to dampen complexity through optimization suggests that firm-level interventions can contribute to broader systemic stability, particularly in markets characterized by high volatility and institutional uncertainty such as the Tehran Stock Exchange.

Behavioral factors further explain the significance of the results. The optimization process captured the underlying nonlinearities associated with investor behavior, which previous studies have identified as a key driver of price instability and market inefficiency [20, 21]. By minimizing complexity, the model indirectly reduces the cognitive and informational burdens placed on market participants, which aligns with evidence that excessive complexity exacerbates herding behavior, mispricing, and volatility clustering [2, 7].

Consequently, the findings support the argument that effective complexity management enhances market transparency and informational efficiency.

The results also complement research on accounting and information complexity. Mohammadi and Pendar demonstrated that higher accounting information complexity slows capital structure adjustment and increases financing costs [16]. The present study's optimization framework addresses this challenge by identifying and weighting the most influential financial variables, thereby providing a mechanism for simplifying financial decision structures without sacrificing informational content. Similarly, Soltani Pour Sardou's findings on financial statement entropy and stock returns highlight the destabilizing effects of excessive disclosure complexity, which the proposed model mitigates through systematic variable optimization [18].

In the context of Iranian capital markets, the study's findings carry particular relevance. Structural constraints, regulatory uncertainty, and macroeconomic volatility create an environment in which financial complexity rapidly escalates [15, 17]. The superior performance of the ABC-fuzzy model demonstrates its suitability for such environments, where traditional linear optimization techniques often fail to capture market dynamics [24, 25]. The integration of intelligent algorithms with fuzzy decision systems offers a practical solution to the challenges identified in studies on fintech development, banking efficiency, and systemic risk in Iran's financial sector [4, 11].

Furthermore, the results contribute to the growing literature on intelligent financial modeling. The consistency between the present findings and those reported in studies employing neural networks and adaptive forecasting models in the Tehran Stock Exchange underscores the importance of nonlinear, learning-based methods in modern financial analysis [22]. By extending this line of research into the domain of financial complexity optimization, the study provides a novel contribution that bridges predictive analytics and strategic financial management.

From a policy standpoint, the findings support Awrey's argument that effective regulation must account for the interaction between financial innovation and complexity [8]. The proposed optimization framework offers regulators and policymakers a quantitative tool for assessing and controlling complexity at the firm level, complementing macro-prudential oversight mechanisms. Moreover, the model aligns with Gual et al.'s conclusion that financial complexity, while potentially growth-enhancing, requires

deliberate governance structures to prevent systemic fragility [13].

In summary, the study demonstrates that financial complexity is not an unavoidable byproduct of market development but a manageable construct that can be systematically optimized using intelligent hybrid models. By integrating fuzzy expert judgment with metaheuristic optimization, the research advances both theoretical understanding and practical application of financial complexity management, offering a scalable framework for corporate decision-makers operating in uncertain and dynamic financial environments.

This study was limited by the sample size and the exclusive focus on firms listed on the Tehran Stock Exchange, which may restrict the generalizability of the findings to other markets or institutional contexts. Additionally, the model relies on expert judgments that, despite being processed through fuzzy logic, may still reflect subjective biases. Computational constraints also limited the exploration of alternative algorithm configurations and parameter sensitivity.

Future studies should extend the proposed framework to comparative analyses across different capital markets and economic systems. Researchers may also explore hybridization with additional artificial intelligence techniques such as deep learning or reinforcement learning. Longitudinal designs could further investigate the stability of financial complexity optimization over different economic cycles and crisis periods.

Financial managers should adopt intelligent optimization frameworks to continuously monitor and adjust corporate financial structures. Organizations are encouraged to integrate expert-driven fuzzy systems into their strategic planning processes. Policymakers and regulators can utilize similar models to design early-warning systems and enhance financial stability oversight mechanisms.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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