Application of Artificial Intelligence in Predicting and Managing Financial Distress: A Case Study of Listed Companies in Iran

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ABSTRACT

Financial distress analysis is one of the essential and important topics in financial management, playing a vital role for investors, creditors, and other users of financial information. Predicting the likelihood of financial distress in companies before it occurs can provide valuable opportunities for managers in terms of risk management, as well as for investors and creditors in making better decisions. In this research, using data from manufacturing companies listed in Tehran Stock Exchange from 2011 to 2018 that have faced financial distress, the factors influencing financial distress were identified and, its prediction was examined using advanced Artificial Intelligence (AI) algorithms, including system dynamics and fuzzy logic. The results indicated that key variables such as production and demand played a decisive role in the occurrence of financial distress. These findings not only provided a tool for more accurate predictions of financial distress but also offered a framework for preventive policymaking in companies.

KEYWORDS

Artificial Intelligence (AI), Financial Distress, Fuzzy Logic, System Dynamics.

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Introduction

Since the 1950s, with the increase in the number of companies and business institutions and the complexity of economic and commercial relationships, the tasks of financial management have undergone significant changes. Governments' emphasis on economic growth has further contributed to the increase in the number of companies and institutions, making these tasks even more complex (Komeijani & Saadatfar, 2006). On the other hand, human access to new communication and information technologies has brought about environmental changes, which have accelerated the processes in the economy. The acceleration of activities and economic events has led to both positive and negative consequences. From among the most important negative outcomes, the most challenging ones are the intensification of competition for acquiring financial resources and the restricted access to profit by business units and economic enterprises. The limitation of access to profits and financial resources results in various consequences, the most significant of which is the increased probability of financial distress and bankruptcy in businesses and commercial units (Altman, 1968).

Bankruptcy of companies has always been one of the main concerns of investors, creditors, and governments. Timely identification of companies that are on the verge of bankruptcy can significantly reduce potential losses for stakeholders. The development of bankruptcy prediction models has always been a major topic of interest for both the academic community and economic enterprises (Moshaiehi & Ganji, 2014).

To appropriately seize investment opportunities and prevent resource wastage, one effective approach is to predict financial distress or bankruptcy. This can be achieved by first providing early warnings to companies about potential distress so that they can take necessary actions in response, and second, enabling investors to distinguish between favorable and unfavorable investment opportunities and allocate their resources accordingly. Predicting financial distress in companies has long been a significant topic in the fields of finance and economics. Therefore, this paper analyzes financial distress in production sector, emphasizing the role of macroeconomic, financial, managerial, and risk variables using AI algorithms.

Literature Review

Theoretical Foundations

Financial distress in banks, public, and private companies is a serious issue for the economic survival of countries. The individual and societal costs of financial distress have made predicting financial distress an important issue for many managers, banks, investors, policymakers, and auditors. Predicting financial distress is of significant importance to three groups of managers, creditors, and auditors. Managers, as agents of shareholders, must be proactive in activities that ensure the continuity and profitability of the company. Creditors, in evaluating a company's ability to repay its obligations, are interested in assessing the continuity of the business. Auditors, as another group, must express their opinion regarding the continuity of the company's operations and the

fairness of the financial information in reports. Therefore, they are interested in predicting financial distress or the continuity of a company's operations (Khoshtinat et al., 2005).

Given the development of companies, increased economic activities, heightened competition, and cycles of inflation and recession in recent decades, the number of companies experiencing financial distress and the significance of such distress have been increasing. The issue of bankruptcy and financial distress has always been a topic of concern. Therefore, studying the causes of financial distress and assessing the existing models is of high importance (Ahmadpour & Shahsavari, 2014).

Financial distress and bankruptcy of companies result in wasted resources and the inability to capitalize on investment opportunities. Predicting financial distress through the design of appropriate indicators and models can alert companies to the potential occurrence of financial distress and bankruptcy, allowing them to adopt appropriate policies in response to these warnings. On the other hand, market participants in both the capital and money markets need awareness and knowledge about the financial status and efficiency of the existing companies. One of the methods that can help ensure the efficient use of investment opportunities and better allocation of resources is the prediction of financial distress or bankruptcy. By providing the necessary warnings, companies can be alerted to potential financial distress, prompting them to take corrective actions. Additionally, investors and creditors can distinguish between desirable and undesirable investment opportunities and direct their resources towards the more favorable ones (Mehrani et al., 2004). Therefore, the prediction of financial distress and bankruptcy has always been a major subject for investors, creditors, and governments. Timely identification of companies nearing financial distress is highly desirable because it prevents investments in unproductive and inefficient opportunities for market participants.

From an economic perspective, financial distress can be interpreted as the company being in a loss-making position, meaning the company has failed to succeed. In this case, the company's return rate is lower than its cost of capital. Another form of financial distress occurs when a company fails to comply with one or more clauses in its debt agreements, such as maintaining the current ratio or the equity-to-total-assets ratio as stipulated in the contract. This situation is referred to as technical default. Other forms of financial distress include when the company's cash flows are insufficient to meet both principal and interest payments on debt or when the company's equity becomes negative (Weston et al., 1992).

Today, investors have a wide range of options when selecting areas for investment. Therefore, decision-making for investors is becoming increasingly complex and risky. The outcomes of these investments can have significant impacts on people's lives. Bankruptcy is an event that can challenge a country both socially and economically.

In this regard, changes in financial status of the companies serve as a useful guide for investors in making subsequent decisions (Altman, 1968). Financial distress and

ultimately the bankruptcy of economic units can result in significant losses at both the micro and macro levels.

At the macro level, financial distress in companies causes:

1. A reduction in GDP
2. An increase in unemployment
3. The waste of national resources and similar consequences.

At the micro level, it leads to substantial losses for stakeholders and economic entities such as shareholders, potential investors, creditors, managers, employees, suppliers, and customers. Therefore, to avoid the massive losses that arise from financial distress, it is necessary to conduct studies in this field. Thus, finding models to predict financial distress that occurs before bankruptcy is of great importance (Esmailzadeh Maghari & Shakeri, 2015).

One of the ways to effectively utilize investment opportunities and allocate resources better is by evaluating financial distress. Through financial distress evaluation, the financial situation of companies is clarified, and their distress is examined so that shareholders and managers can take measures to prevent distress or make changes to the company's structure. By taking the right and timely actions, they can potentially prevent the company from heading toward bankruptcy.

Therefore, evaluating the financial distress of companies has always been a topic of interest for investors, creditors, and governments. Timely identification of companies that are on the verge of financial distress is highly desirable (Rostami et al., 2011).

With the increasing expansion of joint-stock companies and the emergence of severe financial crises at both the micro and macroeconomic levels, owners and stakeholders of businesses have sought to create protection against such risks. This has made them more sensitive and aware of using appropriate predictive models to evaluate the financial capability of companies (Kurdistani et al., 2011).

One of the most important pieces of information that can assist economic decision-makers in making optimal resource allocation decisions is identifying the variables for predicting bankruptcy and financial distress in companies. Therefore, finding financial warning indicators has always been one of the most popular areas of research in the field of finance.

Financial distress in a company is usually determined by various interconnected factors; hence, accurately identifying the causes of financial distress in each case is not always easy. Generally, the factors of financial distress include both external and internal factors. External factors are those that cannot be controlled by the company but create financial problems for it. These include changes in economic structures, business fluctuations (such as mismatches between production and consumption, sales decline, inflation, price drops, and rising interest rates), issues related to financing, natural disasters, and increased competition. Internal factors include instances where managers have made mistakes or failed to take necessary actions in past management decisions. Examples include excessive credit sales, poor management (lack of training, experience, ability, and innovation in management, competition, technology, resources, and

management errors), inability to effectively manage capital, fraud, and embezzlement (Komeijani & Sadatfar, 2006).

The most important reasons for bankruptcy in Iran can be attributed to economic fluctuations as an external factor and higher production costs, interest expenses, and the improper determination of capital structure as internal factors. Liquidity problems are considered one of the major factors affecting the financial crises of companies (Weston et al., 1992).

Decision-making in financial matters has always been associated with risk and uncertainty. One way to assist investors is to provide predictive models about the overall outlook of a company.

The closer the predictions are to reality, the more reliable and complete the basis for making decisions will be. Beaver states, "prediction can be made without decision-making, but no decision, however small, can be made without prediction" (Mehrani et al., 2005).

Numerous efforts have been made to develop predictive models for the overall outlook of companies, particularly in the area of financial distress and bankruptcy. The result of these efforts has been the creation of various models that now accurately predict the likelihood of such events.

Studies show that although statistical models have been able to provide good predictions regarding financial distress or bankruptcy in companies, some of the restrictive assumptions of these models, such as linearity, normality, and the independence of the predicting variables, have affected the effectiveness of these methods. Therefore, over time, other methods have been introduced to overcome some or all of these limitations and improve prediction performance. For example, artificial neural networks, genetic algorithms, and support vector machines can be mentioned (Raaei & Fallahpour, 2008).

Research Background

Numerous studies have been conducted regarding the ability of financial statements to predict financial distress. Some of the most important and relevant studies to this research are outlined below:

In 1942, Charles Merwin conducted a study in which he examined financial ratios for bankrupt and non-bankrupt companies over a six-year period. He stated that the ratios of working capital to total assets, equity to total liabilities, and the current ratio were good predictors of bankruptcy. Merwin concluded that the ratio of working capital to total assets was the best indicator of the bankruptcy (Horrigan, 1968).

The first person to use univariate analysis for predicting financial distress in companies was Beaver. He selected 79 bankrupt and 79 non-bankrupt companies and, out of 30 financial ratios, identified 6 with the lowest error rates, such as the ratio of cash flow to total assets, the ratio of net profit to total assets, the ratio of total liabilities to total assets, the ratio of working capital to total assets, current ratio, and the uncertainty ratio. Beaver's findings showed that the ratio of cash flow to total debt had the highest predictive power (Beaver, 1966).

Edward Altman, in 1968, for the first time examined the effect of various financial ratios in predicting financial distress in companies. Altman used Multiple Discriminant Analysis (MDA) in his study. The model he developed, known as the Z-Score, is still widely used as an indicator of a company's financial health. Altman's theory was that his bankruptcy prediction model, which consists of 5 financial ratios, could distinguish between bankrupt and non-bankrupt companies. He suggested that his model could be used for evaluating business loans, internal control processes, and investment options (Altman, 1968).

Elson (1980) developed a model using logistic regression and data from 105 bankrupt and 205 non-bankrupt companies from 1970 to 1976. He incorporated 9 financial ratios as independent variables, 5 of which had been used in previous studies (Elson, 1980).

Another study used financial ratios based on cash flow statements and balance sheets to identify bankrupt companies. The study, which covered a 5-year period and used data from 60 bankrupt and 230 non-bankrupt companies, concluded that cash flow ratios were more effective than balance sheet and profit-loss ratios in predicting financial distress (Kazi, 1984).

Wallace used artificial neural networks to design his model. The 5 financial ratios used in his model included: working capital to total assets, cash flows to total liabilities, net profit to total assets, total liabilities to total assets, and current assets to current liabilities. Wallace's model had an overall prediction accuracy of 34% (Wallace, 2004).

Wanda tested a model using neural networks for predicting financial distress. This model used key financial ratios reported in previous studies as the best predictors, including working capital to total assets, cash flow to total assets, net profit to total assets, total liabilities to total assets, current ratio, and the quick ratio. Wanda's model, which tested 65 different financial ratios from past studies, achieved an impressive 94% prediction accuracy for financial distress (Wanda, 2004).

Benjamin and colleagues focused on predicting financial distress in high-tech industries listed on the New York Stock Exchange. They used 6 financial ratios, including 2 cash-related and 4 balance sheet and profit-loss ratios, employing logistic regression to study data from 60 bankrupt and 60 non-bankrupt companies from 2000 to 2002. Their composite model achieved 85% prediction accuracy for both bankrupt and non-bankrupt companies (Benjamin et al., 2005).

Khoshtaynat and Qasuri, in their study, estimated the case sample and analyzed nine financial ratios from cash flow and balance sheet items. Their results, based on the multiple discriminant analysis model, showed that a combination of financial ratios from the cash flow statement, balance sheet and profit-loss items were more effective than balance sheet and profit-loss ratios alone in predicting financial distress (Khoshtinat & Qasuri, 2005).

The first researchers to use both system dynamics and fuzzy logic together were Pankaj, Set, and Sushil in 1994. They developed a model for qualitative analysis of causal loops using fuzzy linguistic uncertainties to align the understanding of modelers. Most

studies combining system dynamics and fuzzy logic aimed at describing fuzzy variables when data was unavailable (Kunsch & Springael, 2008).

Pirayesh and colleagues focused on liquidity ratios from the cash flow statement to predict financial distress. Their study used a sample of 40 bankrupt and 40 non-bankrupt companies from 2004 to 2006. The results showed that their model had prediction accuracies of 93.75% and 78.75% for one and two years before bankruptcy, respectively (Pirayesh et al., 2009).

Saidi and Aghai, in their paper titled "Predicting Financial Distress of Tehran Stock Exchange-listed Companies Using Bayesian Networks," proposed a prediction model using Bayesian networks. Their findings showed that discretizing categories from two to four improved the model's performance, but increasing the categories to five reduced the model's accuracy (Saidi & Aghai, 2009).

Mesaki, in his study, used logistic regression to examine 53 bankrupt and 53 non-bankrupt companies in Japan between 1973 and 1997. He tested 32 accounting variables (including 5 from the cash flow statement and 27 from the balance sheet and income statement), normalizing them by total assets, total liabilities, and total sales. The results showed that the normalized variables achieved prediction accuracies of 81.1%, 87.7%, and 78.3% for predicting financial distress based on total assets, total liabilities, and total sales, respectively (Mesaki, 2010).

Camposano et al. (2010) used system dynamics and fuzzy logic to strengthen supply chain management by simulating supply chain dynamics using fuzzy demand estimation.

Mousavi Shiri and Tabrizani used Data Envelopment Analysis (DEA) in their study and examined the role of efficiency in predicting financial distress in companies. They studied 60 companies listed in Tehran Stock Exchange from 2000 to 2010 and confirmed their results with the MDA technique. The findings revealed that efficiency plays a crucial role in predicting financial distress, as it can signal impending bankruptcy up to two years in advance (Mousavi Shiri & Tabrizani, 2012).

Mohseni and colleagues developed a model to predict financial distress in Tehran Stock Exchange-listed companies. They used efficiency alongside financial ratios as a predictor to improve prediction accuracy. Their findings indicated that efficiency significantly enhanced the model's prediction power (Mohseni et al., 2013).

Orji and Wei developed a modeling theory for supplier behavior in fuzzy environments using system dynamics, leading to more realistic supplier selection decisions (Orji & Wei, 2015).

Nasirzadeh and colleagues applied integrated system dynamics and fuzzy logic to evaluate the economic feasibility of BOT projects, using fuzzy numbers to estimate uncertain parameters and simulate project's Net Present Value (NPV) (Nasirzadeh et al., 2015).

Ahmadpour and Shahsavari investigated how managers' discretion in companies listed in Tehran Stock Exchange influenced the three stages of financial distress, using the Altman bankruptcy prediction model. Their study, based on panel data techniques,

showed that managers manipulated accounting profits to portray a better financial position as companies approached bankruptcy (Ahmadpour & Shahsavari, 2014).

Other researchers, such as Sang and Zhang (2015) and Orji and Wei (2015), applied system dynamics models to simulate secondary scenarios and subsequently ranked them using multi-criteria decision-making techniques.

Desalles and colleagues explored the application of fuzzy logic in system dynamics to better model decision-making policies, particularly regarding uncertainty in model variables (Desalles et al., 2016).

Sterman and colleagues examined the use of System Dynamics modeling in the process of AI adoption in the financial services industry. The authors' model included various factors such as organizational readiness, costs, and feedback resulting from AI adoption (Sterman, et al., 2020).

Zhang and colleagues explored the complexities of Artificial Intelligence (AI) adoption in the financial sector using System Dynamics models, identified factors that affect the speed and success of this process (Zhang, et al., 2020).

Aini Zadeh and Gharib investigated the impact of financial ratios and ownership structure in predicting financial distress in companies. Using logistic regression to test hypotheses, their study covered 134 companies listed in Tehran Stock Exchange from 2014 to 2019. They found that the ratios of fixed asset turnover and total asset turnover negatively influenced financial distress, while inventory turnover and ownership structure had no effect (Aini Zadeh & Gharib, 2021).

Brown and colleagues used a System Dynamics approach to model the technology adoption process in the financial services industry, focusing specifically on AI. It simulates various interactions within the financial system (Brown, et al., 2021).

Noor and colleagues reviewd and analyzed various studies on the adoption of AI in financial institutions and explored different models, including System Dynamics models, used for analyzing AI adoption (Noor et al., 2021).

Shokhzadeh and Zafari explored the prediction of financial distress in Tehran Stock Exchange-listed companies using artificial neural networks, achieving prediction accuracy of 86%, 86%, and 90% for one, two, and three years before bankruptcy, respectively. Their study is distinct in analyzing financial distress from macroeconomic, financial, managerial, and risk perspectives and validating the use of both system dynamics and fuzzy logic algorithms (Shokohzadeh & Zafari, 2021).

Taghavib and colleagues used a System Dynamics approach to analyze AI adoption in banks, providing a case study of several large banks that have implemented AI (Taghavi, et al., 2024).

Nguyen and colleagues investigated the role of System Dynamics modeling in financial system innovations and its application in adopting new technologies such as AI (Nguyen, et al., 2022).

Zhang and colleagues evaluated the impact of AI on financial risk management using System Dynamics models (Zhang et al., 2023).

Farazi, in his study, analyzed the role of AI in managing emerging risks by comparing

traditional approaches with machine learning (ML) and artificial neural networks (ANN). His study demonstrated that ANN and deep neural networks (DNN) outperformed traditional approaches by enhancing flexibility and performance under multiple risk factors (Farazi, 2024).

Mehrabi and colleagues proposed a hybrid model combining artificial immune systems (AIS) and neural networks (WNN) to predict financial problems. Their findings showed that the AIS-WNN hybrid model outperformed traditional methods in terms of prediction accuracy, sensitivity, and robustness (Mehrabi, 2024).

Wardhini et al. (2024) applied AI in a metamodel control system to manage crises, covering data collection, preprocessing, model monitoring, and optimizati.

Abdallavi and colleagues presented an innovative approach for predicting financial distress using weighted neutrosophic value distances, aiming to estimate the likelihood of financial distress for any company or organization (Abdallavi et al., 2025).

Methodology

System dynamics is a powerful methodology for gaining insights into issues with dynamic complexity and resistance to policymaking (Georgiadis & Bessou, 2008). It is a computer-based approach used to analyze and solve complex problems with a focus on policy analysis and design. Simulation using system dynamics models is highly useful for learning about the dynamic complexities of systems. It is also an essential tool for identifying optimal policies within existing systems, improving system behavior by changing parameters, and making structural changes. This approach has been applied across diverse fields, from production-distribution systems to ecosystems (Falo Lebsanev, 1999).

Steps of System Dynamics Modeling can be described as follows:

1. *Problem Definition*: This step involves clarifying the goal of the model. Clear articulation of the model's goal is essential for effective model development. Having a clear problem in mind facilitates the development of models that are practically suitable for the issue at hand.

2. *Variable Identification*: This involves identifying key variables that need to be included in the model to correctly represent the problem being examined. It is helpful to list all variables first, and then prioritize them.

3. *Reference Modes*: A reference mode is a pattern of behavior over time. Reference modes are depicted as charts of key variables over time. However, these charts do not necessarily represent observed behavior; they can reflect past or future behavior.

4. *Reality Checking*: This step defines certain scenarios for reality checking, concerning how variables are interrelated. Essentially, it involves understanding the reality and the relationships between factors. Changes in certain variables may have significant effects on other variables. Information on reality checking is often recorded as notes about the necessary relationships and is based on the knowledge the researcher has about the system under study.

5. *Dynamic Hypotheses*: A dynamic hypothesis is a theory about the structure that exists

and provides reference modes. A dynamic hypothesis can be presented in textual form, causal-loop diagrams, or flowcharts. Dynamic hypotheses can specify what is retained in the model and what is excluded. Like all hypotheses, dynamic hypotheses are not always correct, and revision is an essential part of developing a good model.

6. *Simulation Model*: A simulation model is a set of hypotheses expressed through a clear set of mathematical relationships. Simulation models generate behavior through simulation. A simulation model serves as an experimental environment where different structural elements that determine behavior can be tested and understood.

This process is iterative and flexible. As work progresses on a particular issue, an understanding of the problem may emerge that changes how the components are considered. Defining clear boundaries between the system under study and its external environment is a necessary step in the system dynamics approach (Georgiadis et al., 2005).

Studies conducted so far on financial distress have primarily focused on financial ratios, and none of them have considered the factors and variables affecting financial distress, which interact in a complex manner with each other. Moreover, the risks and uncertainties present in the systems have not been taken into account in most previous studies. This research aims to introduce an appropriate model for predicting financial distress in companies by using theoretical foundations and empirical evidence, integrating system dynamics simulation methods and fuzzy logic. This approach will address the aforementioned shortcomings and improve the accuracy of financial distress prediction.

In addition to key financial ratios for predicting financial distress, the goal is that the use of other variables as predictors can enhance the prediction accuracy and power of the model. Some of the factors to be examined in this study include external factors such as business fluctuations, competition, changes in economic structures, fraud, and economic volatility, and internal factors such as excessive credit sales, poor management, net profit, company performance score, debt quantity and quality, debt repayment capacity, production costs, interest expenses, and improper capital structure determination.

In this context, the system dynamics simulation method will be used to simulate the various parameters affecting financial distress and their interrelationships, as well as the specific project under consideration. Additionally, fuzzy logic will be used to account for the impact of qualitative factors on the project. To achieve this, all influencing factors on financial distress will first be identified, and a qualitative model of the project will be developed using causal feedback loops. Then, the mathematical relationships between the variables will be determined, and quantitative modeling will be carried out to assess the financial distress of the project. Finally, by using the developed quantitative model, the likelihood of financial distress, based on fuzzy input values, will be determined for the project, and the conditions of non-financial distress will be established by comparing different options under consideration.

Research Hypotheses

Based on the theoretical foundations presented and the objective of the research, the following hypotheses have been formulated:

1. First Hypothesis: What are the external factors influencing financial distress?
2. Second Hypothesis: What are the internal factors influencing financial distress?
3. Third Hypothesis: What is the model for the factors influencing financial distress?
4. Fourth Hypothesis: What are the scenarios for reducing financial distress?

Research Variables

1. Dependent Variable

Financial Distress

Financial distress refers to the inability of a company to meet its financial obligations. In this study, Article 141 of the Commercial Code is used as the criterion for identifying financial distress. Companies that fall under Article 141 of the Commercial Code are classified as financially distressed companies.

2. Independent Variables

To determine the independent variables, a review of the literature and previous research studies was conducted using library resources and interviews with specialists, experts, and professionals in the field of financial distress. Through the literature review and the Delphi method, the factors influencing financial distress were identified. After three stages of the Delphi technique, the following final criteria were selected.

Table 1.
Final Criteria for Financial Distress Based on Delphi Technique Results

No	Variable
1	Unemployment Rate
2	Debt Repayment Ability
3	Gross Domestic Product (GDP)
4	National Resources
5	Competition
6	Inflation
7	Export and Import Levels
8	Net Profit Level
9	Quantity and Quality of Debt
10	Excessive Credit Sales
11	Company Efficiency Score
12	Wage Increase Rate
13	Debt Service Coverage Ratio
14	Asset Coverage Ratio
15	Bank Debt to Debt Ratio
16	Production Costs
17	Payable Interest Costs
18	Inappropriate Capital Structure Determination
19	Ineffective Management
20	Fraud

(Source: Researcher's Findings)

Findings

In the system dynamics method, the first step is to understand the existing problem, and then, through discussions and consultations with experts, a causal-loop diagram is developed. After the causal-loop diagram is prepared, a flow diagram is created. At each stage of this process, revisions may be made to previous steps.

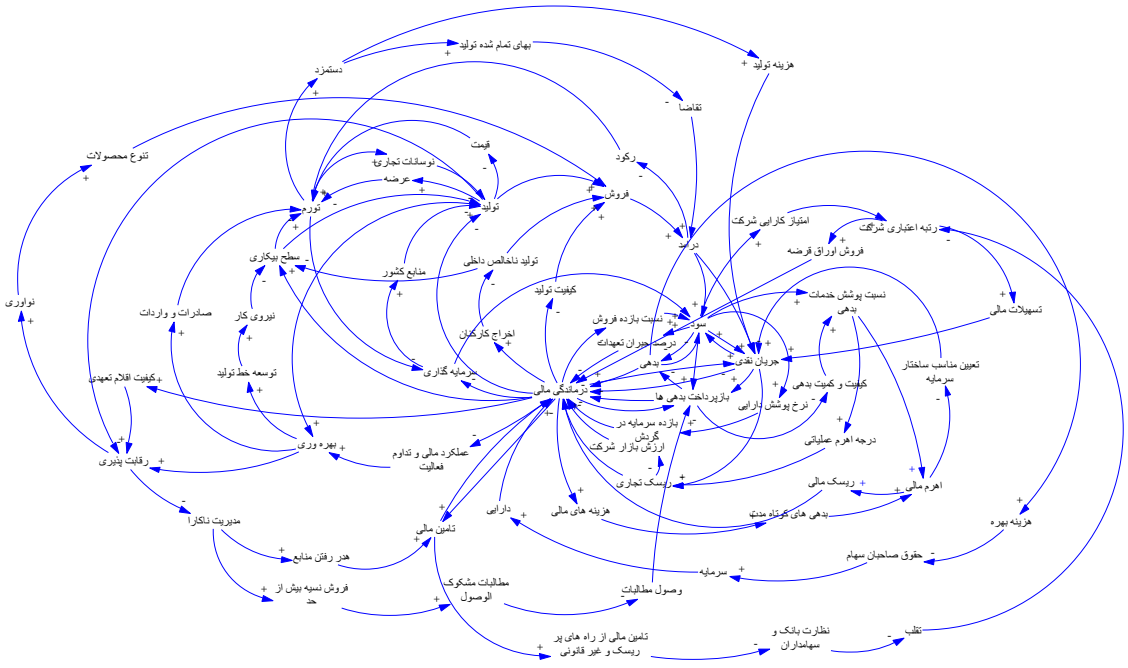
Using the causal-loop diagram, the relationships between variables are clearly illustrated. The causal-loop diagram for financial distress is shown in Figure 1. This model demonstrates that financial distress consists of various components, each of which is influenced by different factors. These influences may not be linear and could instead form a circular or feedback loop structure.

All the loops in this model are reinforcing, and some of the most important loops are described below.

For example, as the profit of an organization increases, its debts decrease, and with the reduction of debts, the organization faces less financial distress. With reduced financial distress, the organization can focus more on production and improve the quality of its products. As the quality of production improves, sales also increase, which in turn leads to higher revenue and profit for the organization.

Additionally, as the organization has more resources available, it can increase its production, which in turn leads to higher revenue. With increased revenue, the organization's profit also grows. As a result, the organization faces less financial distress and can make more investments, securing additional resources for the organization from the country.

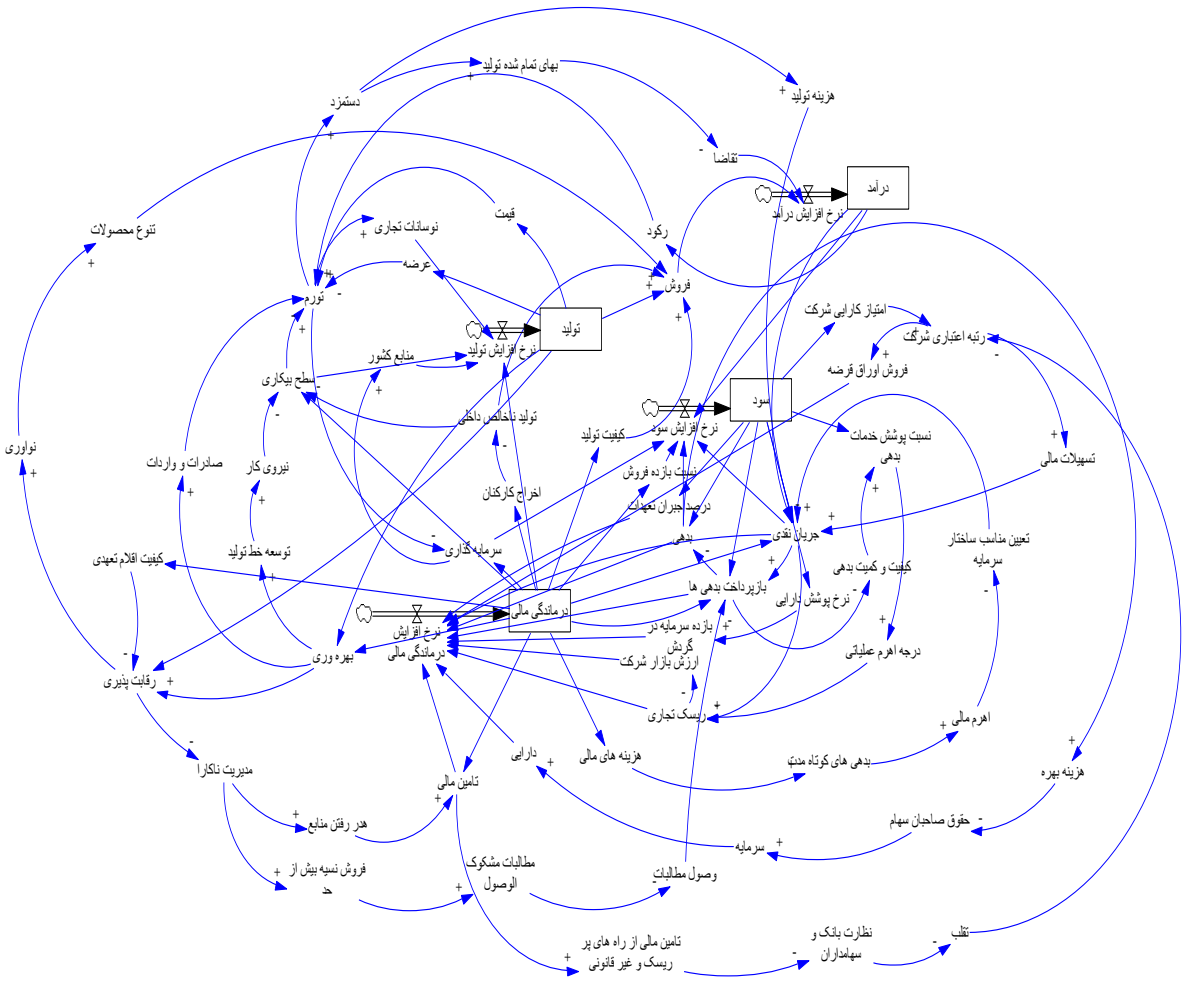
Figure 1.
Causal-Loop Model of Financial Distress



(Source: Researcher's Findings)

The state and flow diagram corresponding to the final causal-loop diagram is shown below. In this diagram, the variables of production, income, profit, and financial distress are considered as state variables, while other variables are treated as flow variables.

Figure 2.
State-Flow Diagram of the Model

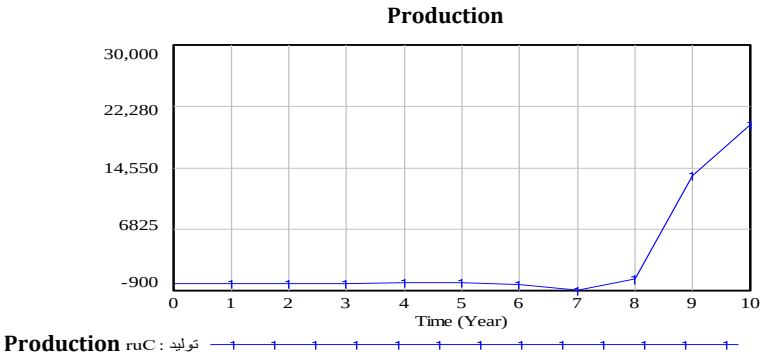


(Source: Researcher's Findings)

In the following, the initial behavior of some state and flow variables is shown in the figures below over a simulation period of 10 years. These results were obtained from simulating the state-flow diagram in Vensim software over a 10-year period.

1. The organization’s production over the ten-year simulation period shows an upward trend.

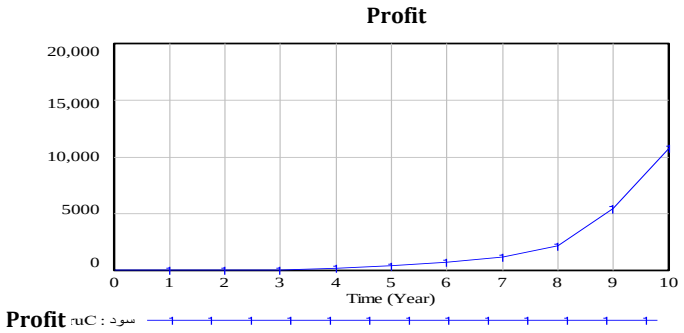
Figure 3.
Behavior of the Production Variable



(Source: Researcher's Findings)

2. The organization's profit shows an upward trend over the ten-year simulation period.

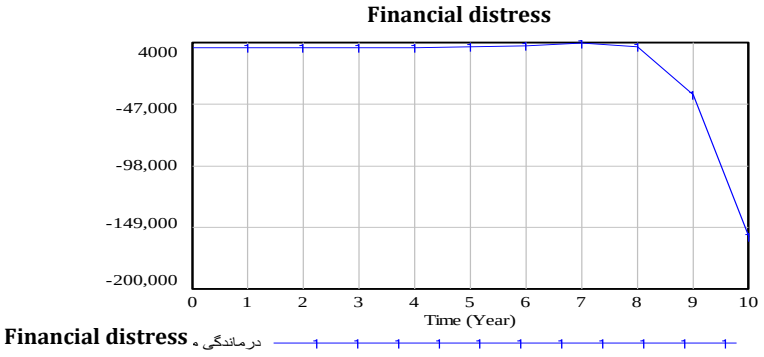
Figure 4.
Behavior of the Profit Variable



(Source: Researcher's Findings)

3. The financial distress of the organization shows a downward trend over the ten-year simulation period.

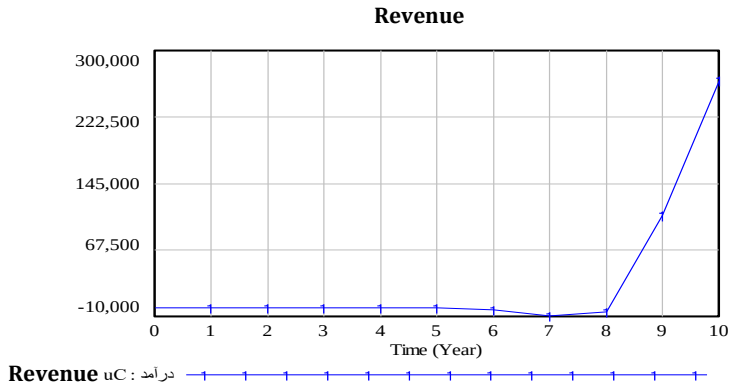
Figure 5.
Behavior of the Financial Distress Variable



(Source: Researcher's Findings)

4. The organization's revenue follows an upward trend over the 10-year simulation period.

Figure 6.
Behavior of the Revenue Variable



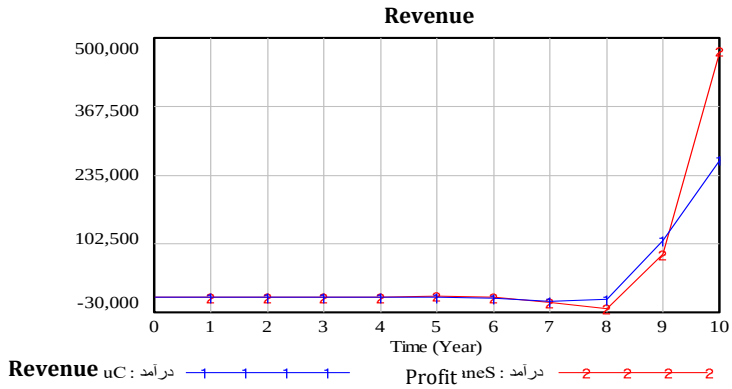
(Source: Researcher's Findings)

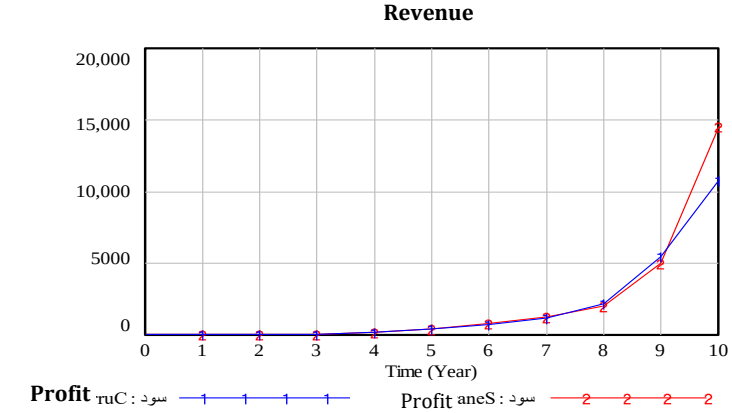
Then, scenarios related to the model were presented, which are outlined below:

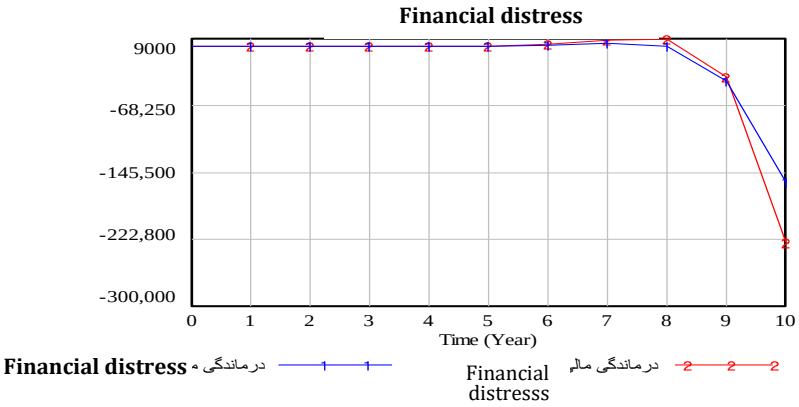
Scenario 1: Doubling Production

In this scenario, the increase in production is examined to evaluate the idea that by increasing production, revenue and profit can be raised, and financial distress can be reduced.

Figure 7.
Behavior of the variables income, profit, and financial distress with respect to the increase in production







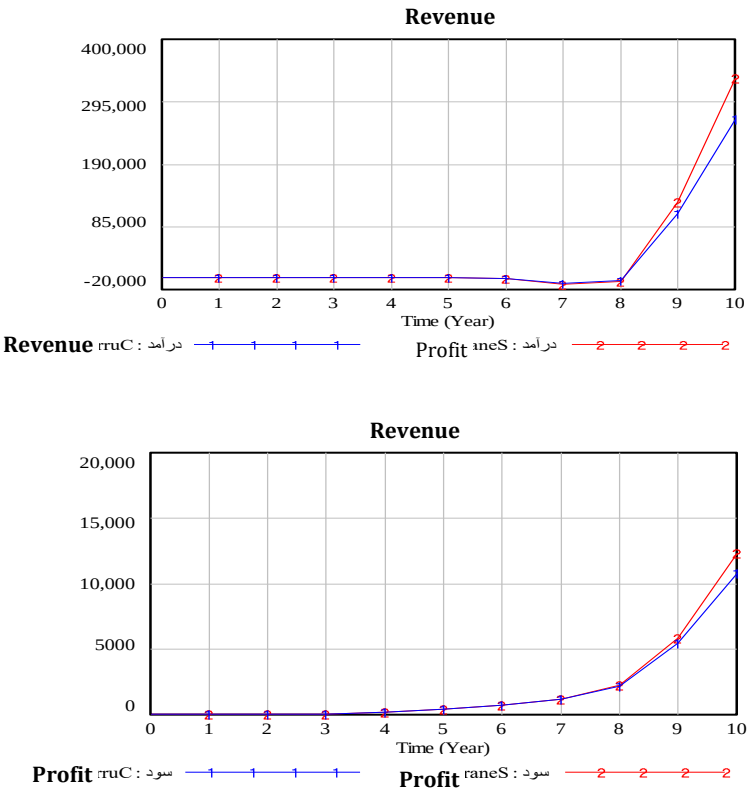
(Source: Researcher's Findings)

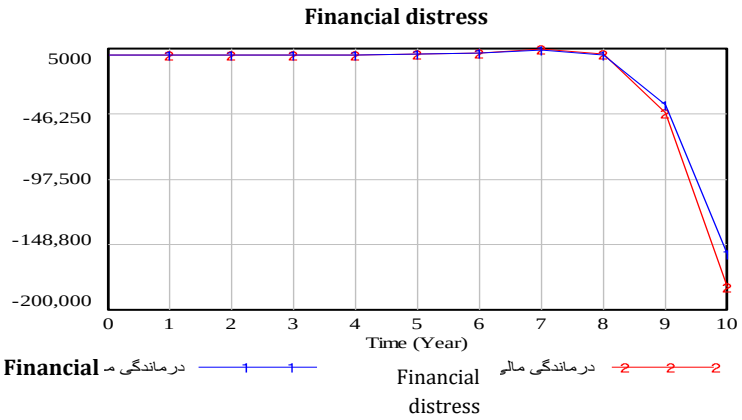
As seen in the above figures, this scenario produces our desired results, as ultimately, income and profit increase while financial distress decreases. Therefore, this scenario could lead to an improvement in the organization's situation in this case.

Scenario 2: Doubling the Demand

Next, the scenario of increasing demand is examined to improve the organization's situation through this scenario. The results of this scenario are presented below.

Figure 8.
Behavior of the variables income, profit, and financial distress with respect to the increase in demand





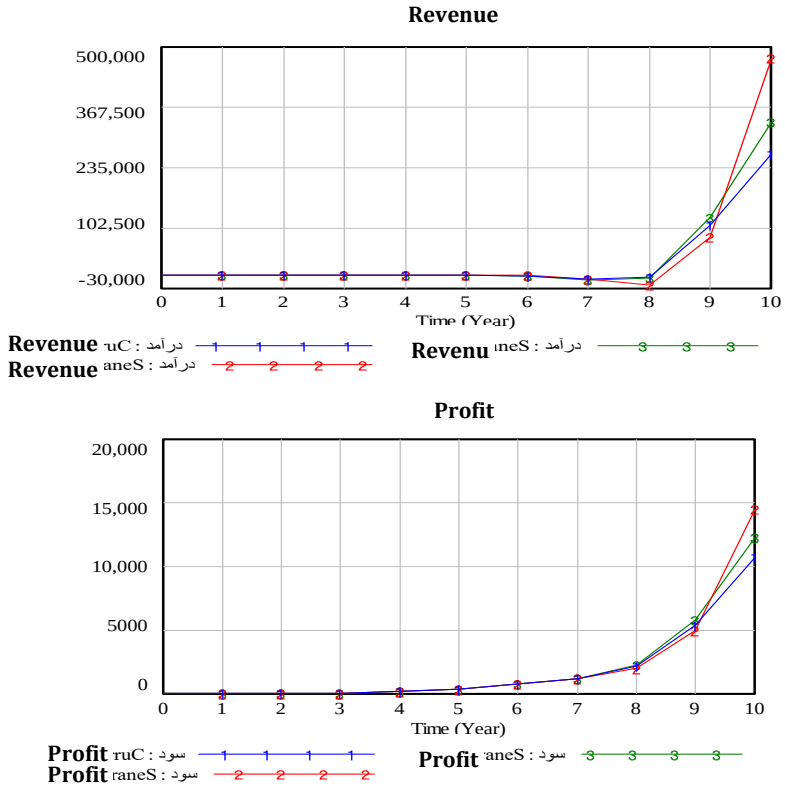
(Source: Researcher's Findings)

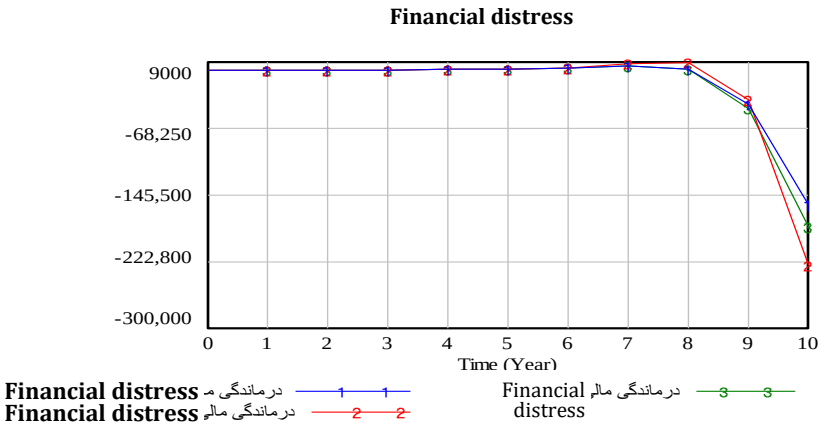
As shown in the above figures, this scenario also delivers the desired results, as it leads to an increase in income and profit, as well as a decrease in financial distress. Therefore, it can be considered as a solution for improving the organization's situation. However, to choose the best scenario, a comparison in terms of financial distress between them should be conducted, as detailed below.

Research Results

As shown in the figures below, Scenario 1 (doubling production) has resulted in the greatest reduction in the company's financial distress, as well as the highest increase in income and profit. Therefore, it can be selected as the best scenario.

Figure 9.
Result of the Best Scenario





(Source: Researcher's Findings)

Discussion and Conclusion

Given the development of companies, the increase in economic activities, intensifying competition, and the cycles of inflation and recession in recent decades, the number of financially distressed companies and the importance of financial distress have been rising. The issue of bankruptcy and financial distress has always been a significant concern. Financial distress and bankruptcy lead to the waste of resources and missed investment opportunities. Predicting financial distress by designing appropriate indicators and models can alert companies to the occurrence of financial distress and bankruptcy, allowing them to take appropriate measures in response.

Moreover, market participants, such as investors and financial institutions, need to be aware of the financial status and efficiency of existing companies. One method that can help in appropriately utilizing investment opportunities and better resource allocation is predicting financial distress or bankruptcy in companies. This way, companies can be alerted to financial distress, prompting them to take necessary actions, and investors and creditors can distinguish between favorable and unfavorable investment opportunities, channeling their resources into suitable investments. Thus, predicting financial distress and bankruptcy has always been a topic of interest to investors, creditors, and governments. Timely identification of companies facing financial distress is highly valuable, as it prevents investment in wrong or inefficient opportunities in the market.

Since this research uses a simulation model to provide solutions to prevent financial distress, it offers the advantage of changing various model variables in different combinations (which could encompass a large number of scenarios) without any cost. It allows for the observation of the behaviors resulting from policy changes and helps in selecting the best approach. It's important to note that evaluating policies in the real world through experience requires significant costs and time, leading to resource wastage. In contrast, simulation enables the evaluation of numerous policies with minimal time and cost.

It is also noteworthy that in previous research studies on financial distress, systems have mostly been studied in static environments or have only addressed the linear impact

of a single factor on financial distress. However, the model presented in this study is a dynamic model that incorporates a large number of factors affecting financial distress and is time-dependent, showing the effects of changes over time. Additionally, since the model is a simulation of reality, it allows for observing, calculating, and analyzing the changes in various aspects of financial distress. In contrast, in previously proposed models, changes need to be made, and one must wait for the effects, which could potentially result in negative consequences if those changes are incorrect. Therefore, it can be stated that the model presented in this research has a particular advantage over previous models.

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