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# Comparison of Ant Colony Algorithm with Methods of Multiple Discriminant Analysis and LOGIT in Financial Distress Prediction

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## ABSTRACT

In this research, the Ant colony algorithm(ACA) was compared with two parametric models of multiple discriminant analysis (MDA) and LOGIT for predicting of financial distress, meanwhile, models were applied for data mining directed to superior variables in financial distress prediction. Data of 130 companies from 2005 to 2010 in form of two experiments were used.

The first experiment was based on distressed companies that fell under article 141, and non-distressed companies that did not fall article 141. This experiment included 130 year company and was done in two training and control samples each consisted 65 companies.

By studying the results of this experiment based on 15 variables with using data mining by each of three models, two superior variables of models were obtained including earnings before financial expenses and taxes to total assets and net worth to total assets.

Based on superior variables in the first experiment, the second experiment was performed that was based on a sample including all of companies in the first experiment in all years of study that were among domestic listed companies and included 718 year company.

The percent of financial distress prediction's success for ACA was 96.94% (distressed: 95.21%, non-distressed: 97.38%), for MDA was 95.82 (distressed: 82.88%, non-distressed: 99.13%) and for LOGIT was 97.08% (distressed: 88.36%,non-distressed:99.30%).

The results have shown that Ant Colony Algorithm in financial distress prediction is significantly superior than MDA (5%) and is significantly superior than LOGIT (9%).

**KEY WORDS**: Financial distress prediction, Ant colony algorithm, Ant colony optimization, MDA, LOGIT

## INTRODUCTION

In new attitudes to company as a socio-economic unit, companies have also major functionings in non-economic arenas such as labor market and employment capacity, environment and its preservation or destruction, generations and transfer of debt or capital to them, and many vital cases for community. Thus, due to fundamental non-economic consequences of companies and generally economic activities, financial distress and bankruptcy of companies or their health and efficiency have important effect on socio-economic indicators at macro or micro levels. Following these effects, naturally prediction of these situations can help very much in creating awareness to deal proportionately with potential future condition. This is mainly from two directions: from material and human capitals of actual investors in these units as well as decisions of potential investors rather than governance decisions to these units.

### Research Theoretical Basics

### 1. Definitions

According to study conducted by Outechava (2007) financial definitions can be categorized in three classes [1]:

1.1. Event-driven definition: According to Beaver (1966), it is disability in performing obligations in due date.

1.2. Process-driven definition: According to Gordon (1971), it is reduced profitability that leads to disability in performing obligations.

1.3. Technical definition: According to Whitaker (1999), it is reduced cash flows against financial costs of long-term debts and financial distress prediction models

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**2. Distress Procedures**

Distress procedures can be included hidden disability, cash deficit, relative disability to fulfill a commitment, complete disability and bankruptcy [2].

**3. Legal criteria**

In Article 141 of commercial code of Iran invite companies with accumulated losses of more than half the initial capital held extraordinary assembly to review the situation and generally in theoretical financial literature in Iran financial distress criterion has been considered.

**4. Financial Distress Theoretical Framework**

According to Outechava's (2007) study, theoretical framework of financial distress can be presented in three parts:

4.1. Early impairment: it is in companies' strategic level and refers to two cases which are lack of future realistic prediction and lack of appropriate variation proportionate to external changes that in this case company can perform its commitments and is non-distressed.

4.2. Financial distress: it is in operational level and includes deterioration of performance, failure, insolvency and default that in the former two cases company can perform its commitments and from profitability aspect is financial distressed. In the latter two cases company cannot perform its commitments and is also financial distressed from liquidity aspect.

**4.3. Bankruptcy:** it is legal confirmed situation of company default.

**5. Prediction models**

The types of models are theoretical models, statistics models and Artificially Intelligent Expert System Models (AIES) [3]. The basis of all kinds of predicted models is based on variables (indicators and ratios) i.e. variables that have better power to disaggregate non-distressed from distressed companies. But a question raised is that in which form of model these variables have more accurate disaggregation. Parametric models such as Multiple Discriminant Analysis (MDA), LOGIT and PROBIT etc or nonparametric models such as Data Envelopment Analysis (DEA) [8], Artificial Neural Networks (ANN) or methods and heuristic algorithms such as Ant Colony Algorithm etc. Studies have shown that nonparametric methods have not limitations of parametric methods such as normal data, etc. and on the other hand, they have more detection power and less error and furthermore, these models can also learn to find better detection power.

**6. Ant Colony Algorithm**

About ant colony algorithm which is one of the models of this study it should be said that at first it was introduced in 1992 by Dorigo [4] based on tracking the shorter path by ants to find food by following the trace that other ants making trails by leaving a substance called "pheromone". This substance remains on track for a while and will gradually evaporate. Ants with their sense of smell find that a path with more pheromone means the more probability they can achieve food. So, the reception of a path depends on two factors, the length of the path and the number of ants passing that path. The shorter length and the more number of ants passing through a path imply that the path will be more successful. In mathematical algorithm implementation these two factors are considered as two functions include:

6.1. Heuristic function that is dependent on the length of each path.

$$\eta_{ij} = \frac{1}{d_{ij}}$$

6.2 . Pheromone function is dependent on each ant secretion.

$$\Delta \tau_{ij}^{k}(t, t+1) = Q / d_{ij}$$

$$\Delta \tau_{ij}(t, t+1) = \sum_{k=1}^{m} \Delta \tau_{ij}^{k}(t, t+1)$$

In the first relationship the amount of pheromone of ant kth is calculated on the edge dij and in the second relationship the total pheromone is calculated on that edge by passing m ants

6.3. Probability Function

$$\frac{\tau_{ij}^{a} . \eta_{ij}^{b}}{\sum_{l \in C_i^k} \tau_{il}^{a} . \eta_{il}^{b}}$$

This function determines the probability of selecting the next city and it is calculated for all cities that the ant k has a choice from city i and based on the maximum value for this function from i to selected city the movement will continue based on the value of this function.

6.4. Updating Function

After choosing the next city, and before beginning the next step to detect the next possible city on the path, the pheromone function is updated for some of the pheromone evaporation that occurs over time and to avoid rapid convergence of algorithm.

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}$$

In above relationship the amount of pheromone is calculated at time t +1. This relationship consists of two components:

. $\Delta \tau_{ij}$

This part includes the total amount of pheromone secreted in distance (t, t +1).

. $(1-\rho).\tau_{ij}(t)$

Because over time some part of pheromone evaporates, in this part of the relationship, the amount of pheromone at time t occurs with coefficient (1-ρ) and so in whole relationship the net amount of pheromone at time t +1 will be calculated.

**7. Application of ant colony in financial distress prediction**

But what relationship do this algorithm and its defined mathematical functions have with bankruptcy prediction?

7.1. Extraction Function(R)

If the defined variables of model for tested companies are smaller than tested critical numbers of each variable in each path, the company will suffer financial crisis.

$$R = \{C_{x1}, C_{x2}, C_{x3}, C_{x4}, C_{x5}\},$$

$$X_{ki} \leq C_{xi}, i \in \{1,2,3,4,5\};$$

7.2. Pheromone Function (FIT=τ)

The "number" of companies that in control group have been detected correctly (non-distressed or distressed) by extraction function for each path (from beginning to current passing), in other words there is conformity between detection and reality.

$$FIT_{Rk} = B_{Rk}{}^{+} + NB_{Rk}{}^{+}$$

This function is updated from the second stage and is used in probability function.

$$\tau_{,j}(t+1) = (1-\rho)\tau_{,j}(t) + \Delta\tau_{,j}(t)$$

Where Δ is the difference of pheromone in two stages and the previous pheromone will be adjusted by coefficient (1-ρ).

7.3. Heuristic Function (D= η)

It is the "number" of companies that have been correctly detected (non-distressed or distressed) by extraction function for "two variables current nodes."

$$D_{Cim,Cjn} = B_{Cim,Cjn}{}^{+} + NB_{Cim,Cjn}{}^{+}$$

7.4. Probabilistic Function

$$p_{,j}(t) = \frac{[\tau_{,j}(t)]^{\alpha}[\eta_{,j}(t)]^{\beta}}{\sum_{l \in V_k(i)} [\tau_{il}(t)]^{\alpha}[\eta_{il}(t)]^{\beta}}$$

## RESEARCH LITERATURE

1. Milea Study (2005) [5]

Milea achieved the success of 86.3%, 86.9% and 80.5%, respectively by using extraction function of "conjunction of several propositions with smaller operators" and using the criterion "the number of correct detection" in algorithm functions and 5 variables of Altman (1968), in the first experiment based on total data in the form of 55 distressed and 55 non- distressed companies and in the second experiment based on training group with 70 cases and control group with 40 cases, that these results have been better compared to performance of linear regression model with success of 80%, 77.1% and 70%.

2. Wang Study (2009) [6]

Wang achieved the success of 79.1% and 76.3% by using extraction function of "conjunction of several propositions with operator between maximum and minimum" and with criterion "the correct detection ratio" in algorithm functions and 5 variables of net income to equity ratio, quick ratio, accumulated profit and loss to total assets, equity to assets and financial costs to total sales that obtained from data mining with statistical t-student test and updating function $T(t+1)=(1-p)\times[T(t)+\Delta]$ (for the best path in each round: $Q = \Delta$ and the other paths of that round $\Delta = 0$), in training group with 180 cases and in control group with 20 cases.

## MATERIALS AND METHODS

### 1. Research Hypotheses

1.1. The accuracy of financial distress prediction by using ant colony algorithm is more than multiple discriminant analysis method.

1.2. The accuracy of financial distress prediction by using ant colony algorithm is more than Logit.

### 2. Community and Statistical Sample

2.1. Research community is companies in Tehran Stock Exchange that have had below conditions:

They have published their financial data and these data are available in rdis.ir.

They have not changed their financial year.

They have not belonged to investment, leasing, banking and insurance companies.

2.2. Research sample includes 130 companies from community in the period 2005 - 2010 which will be described below.

2.2.1. The first test samples (training and control)

The sample consisted of 130 year Company that have been basis of selection of superior variables in three models, includes two groups of training sample and control sample that each sample consists of two parts of distressed and non-distressed companies.

2.2.2. The second test sample

This sample consists of all 130 companies during 6 years that must be consisted of 780 year company, but due to exit of some distressed companies after several years since the first year that fell under Article 141 and entering of some companies during years of investigation 718 year company were placed in this sample that extracted models based on training sample were applied for it to test the accuracy of models in maximum spectrum of year companies.

### 3. Study Variables

Table 1: Study Variables

| **classical variables** | **indicator** |
|---|---|
| current ratio: current asset to current liability | CR |
| working capital to total assets | WCA |
| retained earnings to total assets | REA |
| earnings before interest (financial cost) and tax to total assets | EBITA |
| sales to total asset | SA |
| equity to total assets | EA |
| equity book value to total debt | BEBL |
| asset to financial cost | AFC |
| **variables based on cash flows statement** | |
| net operating cash flow to total assets | CFOA |
| net operating cash flow to total liabilities | CFOL |
| net operating cash flow to total sales | CFOS |
| net operating cash flow to current liability | CFOCL |
| net operating cash to operating profit: earnings quality | CFOP |
| **size** | |
| company size (logarithm of total asset) | SZA |
| company size (logarithm of total net sales) | SZS |

In this study according to theoretical literature on this subject inside and outside Iran, 15 variables were considered as primary variables (table 1). Many variables are from classical variables in distress prediction with many applications and some are selected based on feedback in internal studies and the importance of cash flows and two variables for company size.

4. Average significant difference of variables between distressed and non- distressed companies.

This review is used for parametric models and by using the first sample 130 companies' data by Eviews software it was examined based on four tests that in following table 2 the summary of tests implementation is seen:

Table 2: Significant difference between variables

| H0 : Equality of mean | AFC | BEBL | CACL | CFOA | CFOCL |
|---|---|---|---|---|---|
| t-test | 0.1987 | 0 | 0 | 0.6077 | 0.612 |
| Satterthwaite-Welch t-test | 0.0553 | 0 | 0 | 0.5109 | 0.4508 |
| ANOVA F-test | 0.1987 | 0 | 0 | 0.6077 | 0.612 |
| Welch F-test | 0.0553 | 0 | 0 | 0.5109 | 0.4508 |
| Result | | Different | Different | | |
| | REA | SA | SZA | SZS | WCA |
| t-test | 0.0001 | 0.0321 | 0.0083 | 0.0000 | 0 |
| Satterthwaite-Welch t-test | 0.0114 | 0.0055 | 0.008 | 0.0000 | 0.0069 |
| ANOVA F-test | 0.0001 | 0.0321 | 0.0083 | 0.0000 | 0 |
| Welch F-test | 0.0114 | 0.0055 | 0.008 | 0.0000 | 0.0069 |
| Result | Different | Different | Different | Different | Different |
| | CFOL | CFOP | CFOS | EA | EBITA |
| t-test | 0.6694 | 0.1465 | 0.4512 | 0 | 0 |
| Satterthwaite-Welch t-test | 0.5252 | 0.3381 | 0.6082 | 0.0026 | 0 |
| ANOVA F-test | 0.6694 | 0.1465 | 0.4512 | 0 | 0 |
| Welch F-test | 0.5252 | 0.3381 | 0.6082 | 0.0026 | 0 |
| Result | | | | Different | Different |

According to the results of four tests it can be seen that most different variables are SZA, BEBL, CACL, SA WCA, REA, SZS, SZA, EA, and EBITA. As it can be seen in this table, the company size in terms of sales and asset has a significant difference.

## 5. Research Models

### 5.1. Implementation of parametric models

Based on variables that have significant difference, the model was estimated by using Eviews software and three methods were used to find the best variables (table 3).

5.1.1. Forward Regression Method

In this method all of variables are imported to software and by increase of each variable to find the maximum variable for optimality a model is developed which is given below.

5.1.2. Backward Regression Method

In this method of the linear regression implementation, one by one the total variables and the least important variables will be reduced and finally the optimum combination is introduced by maximum removal.

5.1.3. Combinatorial Method

In this method, the researcher will search a number of superior variables as discriminant regressor.

Table 3: comparison of research parametric models

| Model | Results |
|---|---|
| **OLS**<br>Forward | **Prob. F 0**   **R-squared 0.745783**<br>**variable**: EA, EBITA, BEBL, SA, REA, SZS<br>**p-value T**: 0.00, 0.00, 0.02, 0.14, 0.15, 0.43<br>**SIG. 5%**: EA, EBITA, BEBL |
| **OLS**<br>Backward | **Prob. F 0**   **Durbin-Watson 1.422**   **R-squared 0.754233**<br>**variable**: EA, EBITA, BEBL, SA, REA, SZS, CACL, WCA<br>**p-value (T)**: 0.00, 0.00, 0.01, 0.13, 0.33, 0.44, 0.18, 0.19<br>**SIG. 5%**: EA, EBITA, BEBL |
| **OLS**<br>Combinatorial<br>The first Superior | **Prob. F 0**   **R-squared 0.623345**<br>**variable**: EA<br>**p-value (T)**: 0.00<br>**SIG. 5%**: EA |
| **OLS**<br>Combinatorial<br>The second superior | **Prob. F 0**   **R-squared 0.704447**<br>**variable**: EA, EBITA<br>**p-value (T)**: 0.00, 0.00<br>**SIG. 5%**: EA, EBITA |
| **OLS**<br>Combinatorial<br>The third superior | **Prob. F 0**   **R-squared 0.724646**<br>**variable**: EA, EBITA, BEBL<br>**p-value (T)**: 0.00, 0.00, 0.04<br>**SIG. 5%**: EA, EBITA, BEBL |
| **LOGIT**<br>The first superior | **Prob. LR 0**   **McFadden R-squared 0.932467**<br>**variable**: EA<br>**p-value (Z)**: 0.04<br>**SIG. 5%**: EA |
| **LOGIT**<br>The second superior | **Prob. LR 0**   **McFadden R-squared 1.000000**<br>**variable**: EA, EBITA<br>**p-value (Z)**: 1.00, 1.00<br>**SIG. 5%** |
| **LOGIT**<br>The third superior | **Prob. LR 0**   **McFadden R-squared 1.000000**<br>**variable**: EA, EBITA, BEBL<br>**p-value (Z)**: 1.00, 1.00, 1.00<br>**SIG. 5%** |

### 5.2. Fitness test for parametric models

In this section, to review the study's two variables model, several tests will be conducted.

#### 5.2.1. Test of redundant variable of two variables model of study

Model variables elimination is from coefficient tests to investigate justifiability (table 4).

Table 4: Redundant Test

| EBITA elimination | | EA elimination | | Null Hypothesis: justifiability of elimination |
|---|---|---|---|---|
| interpretation | Prob. F | interpretation | Prob. F | |
| No- elimination | 0.0000 | No- elimination | 0.0000 | discriminant analysis |

#### 5.2.2. Arch Test

Discriminant analysis model is from residual tests of model to review homogeneity of variance (table 5).

Table 5: Arch Test

| interpretation | Prob. | Null Hypothesis: variance equality |
|---|---|---|
| equality | 0.4880 | F-test |
| equality | 0.4801 | $\chi 2$ test |

#### 5.2.3. Ramsey Test

Discriminant analysis model is from structural stability tests to review explanation error (table 6).

Table 6: Ramsy Test

| interpretation | Prob. | Null Hypothesis: no error explanation in model |
|---|---|---|
| no error explanation | 0.2840 | F-test |
| no error explanation | 0.2668 | $\chi$2 test |

### 5.2.4. Hosmer – Lemeshow Test

This test is to review suitability and total fitness of Logit model (table 7).

Table 7: Hosmer – Lemeshow Test

| interpretation | Prob. | H0: Goodness of fit |
|---|---|---|
| Goodness of fit | 0.9473 | $\chi$2 test |

### 5.3. Implementation of ant colony model

The aim of the model in this study is to find superior variables (table 8) based on data mining through ant colony optimization (ACO) that in applying this model to predict financial distress, no record has been found for it. Studies done by Milea (2005) and Khodadadi (2010) according to data mining based on ant colony optimization have not conducted to find superior variables and Wang's study by data mining has been based on T-test statistical test.

Table 8: Results of implementation of ant colony model

| Initial variables: 15 | 1=a 2=b 0.05=r | Research method: Ant Colony |
|---|---|---|
| | EA, EBITA, SZS | superior variables |
| Merit coefficient: 0.83129 | EA, EBITA | effective variables selection of algorithm |

### 5.4. Disaggregation power test of ant colony model

In classifying the companies and creating rules for detection, all data in training sample in some distances called rules are properly detected by Weka software. Thus, according to Tables 3 & 8 and the highest power of all three models, final variables were chosen to compare three methods by two varying variable EA (equity to total assets) and EBITA (earnings before interest and taxes to total assets).

5.6. Summary of research final models

The models based on their coordinates for control samples and the second experiment were implemented and extracted functions of models and critical numbers for discriminant analysis model regression function and Logit model exponential function and ant colony model two variables were obtained by observing data and chart analysis and trial and error, that the results are shown on the table 9.

Table 9: Final extraction functions of study models

| **Function** | **Model** |
|---|---|
| Z = ( 0.528800620439 + 0.630019165658*EA + 1.31678388539*EBITA<br>If Z < 0.57 then distressed | **OLS** |
| Z = ( 44.09 * EA - 1.538 )<br>If [(EZ/(1+EZ)] <0.7 then distressed | **LOGIT** |
| If ( EA< 0.082 AND EBITA < O.41 ) then distressed | **ACA** |

## 6. Research findings

6.1. Findings of models implementation for the first experiment sample

All three models have equal power as shown on table 10 and there is only one mistake in training sample for ant colony algorithm and logit. So, to measure superiority of models with the same coefficients and functions, the second sample was used.

Table 10: Findings of model implementation for data of the first experiment (D: Distressed, ND: Non- Distressed)

| | **Training dataset** | | **Control dataset** | |
|---|---|---|---|---|
| | **Total years of research period** | | **Total years of research period** | |
| | D | ND | D | ND |
| **OLS - Model error no.** | 0 | 0 | 0 | 0 |
| **Actual no.** | 20 | 45 | 20 | 45 |
| **Success percent** | 100.00 | 100.00 | 100.00 | 100.00 |
| **LOGIT- Model error no.** | 0 | 1 | 0 | 0 |
| **Actual no.** | 20 | 45 | 20 | 45 |
| **Success percent** | 100.00 | 97.78 | 100.00 | 100.00 |
| **ACA- Model error no.** | 0 | 1 | 0 | 0 |
| **Actual no.** | 20 | 45 | 20 | 45 |
| **Success percent** | 100.00 | 97.78 | 100.00 | 100.00 |

6.2. Findings of models' implementation for comprehensive sample of the second experiment

Obviously, based on table 11, disaggregatability power of ant colony algorithm in detection distressed companies is more than parametric methods. The result of comparison of models' results based on two tests has obtained by using Eviews that confirms both hypotheses of research based on that the accuracy of ant colony algorithm to predict distress even in 5% level or lower than that is significantly more than two models of discriminant analysis and logit (table 12).

Table 11: Findings of implementation for the second test data (D: Distressed, ND: Non-Distressed)

| Year | Period of Research | | | 2010 | | | 2009 | | | 2008 | | | 2007 | | | 2006 | | | 2005 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Situation | ND | D | SUM | ND | D | SUM | ND | D | SUM | ND | D | SUM | ND | D | SUM | D | D | SUM | ND | D | SUM |
| OLS | | | | | | | | | | | | | | | | | | | | | |
| Model Error No. | 5 | 25 | 30 | 2 | 6 | 8 | 0 | 3 | 3 | 0 | 5 | 5 | 2 | 6 | 8 | 1 | 3 | 4 | 0 | 2 | 2 |
| Actual No. | 572 | 146 | 718 | 82 | 26 | 108 | 86 | 26 | 112 | 94 | 22 | 116 | 100 | 25 | 125 | 105 | 24 | 129 | 105 | 23 | 128 |
| Success Percent | 99.13 | 82.88 | 95.82 | 97.56 | 76.92 | 92.59 | 100.00 | 88.46 | 97.32 | 100.00 | 77.27 | 95.69 | 98.00 | 76.00 | 93.60 | 99.05 | 87.50 | 96.90 | 100.00 | 91.30 | 98.44 |
| LOGIT | | | | | | | | | | | | | | | | | | | | | |
| Model Error No. | 4 | 17 | 21 | 2 | 5 | 7 | 1 | 3 | 4 | 0 | 4 | 4 | 1 | 1 | 2 | 0 | 2 | 2 | 0 | 2 | 2 |
| Actual No. | 572 | 146 | 718 | 82 | 26 | 108 | 86 | 26 | 112 | 94 | 22 | 116 | 100 | 25 | 125 | 105 | 24 | 129 | 105 | 23 | 128 |
| Success Percent | 99.30 | 88.36 | 97.08 | 97.56 | 80.77 | 93.52 | 98.84 | 88.46 | 96.43 | 100.00 | 81.82 | 96.55 | 99.00 | 96.00 | 98.40 | 100.00 | 91.67 | 98.45 | 100.00 | 91.30 | 98.44 |
| ACA | | | | | | | | | | | | | | | | | | | | | |
| Model Error No. | 15 | 7 | 22 | 3 | 3 | 6 | 4 | 1 | 5 | 3 | 3 | 6 | 3 | 0 | 3 | 2 | 0 | 2 | 0 | 0 | 0 |
| Actual No. | 572 | 146 | 718 | 82 | 26 | 108 | 86 | 26 | 112 | 94 | 22 | 116 | 100 | 25 | 125 | 105 | 24 | 129 | 105 | 23 | 128 |
| Success Percent | 97.38 | 95.21 | 96.94 | 96.34 | 88.46 | 94.44 | 95.35 | 96.15 | 95.54 | 96.81 | 86.36 | 94.83 | 97.00 | 100.00 | 97.60 | 98.10 | 100.00 | 98.45 | 100.00 | 100.00 | 100.00 |

Table 12: Significant differences in results of models implementation

| H 0: Equality of Mean | OLS- LOGIT | OLS- ACA | LOGIT- ACA |
|---|---|---|---|
| t-test | 0.87 | 0.052 | 0.088 |
| ANOVA F-test | 0.87 | 0.052 | 0.088 |
| Result | | Different(5%) | Different(9%) |

## 7. Results related to hypotheses

The results have shown that Ant Colony Algorithm in financial distress prediction is significantly superior to MDA (5%) and is significantly superior to LOGIT (9%) and the result confirmed the first research hypothesis (5%).

**Study Limitations**

There are not enough companies in different industries that through emphasizing on specific industries can have sufficient data to perform or compare the industries. Certainly, this leads to select different industries in this study that develop model's capability and application for various industries.

**Suggestions for future researches**

Regarding the significant difference in distress detection by ant colony algorithm performing the following works is appropriate:

Implementing three models and finding extracted functions by data of earlier years to predict the current state of companies

- This algorithm will be also designed and implemented as fuzzy
- Design and implementing ant colony algorithm by genetic algorithm
- Model implementation for non-manufacturing firms (banks and insurance, etc.)

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