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A Novel Machine Learning Model for Risk Management

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Abstract

This paper presents a novel machine learning model, called the "integrated model of ant colony optimization and support vector machine (ACO_SVM model)". It screens important project risk factors and gains an understanding of professional group to quantify the risk factors. The risk matrix questionnaire data, as established by the stakeholders of a large project, are imported into the new model for iterative computation. A few important risk factors and combinations are effectively and rapidly screened out among numerous project risk factors, and the feasibility of the model is preliminarily validated. In practice, the appropriate risk treatment/handling strategy can be constructed by concentrating on limited managerial resources of important risk factors, thus, reducing the overall risk occurrence rate and relevant loss in implementing projects in order to increase the success rate of projects.

Key words: *Ant colony optimization, machine learning, support vector machine, project risk factor, risk matrix*
JEL Classification: *C63, D81, G32, O22*

1. Introduction

Project risk management is a type of procedural management (Cooper et al., 2005) that includes risk identification, qualitative risk analysis, quantitative risk analysis, risk treatment/handling, etc. This study chooses quantitative risk analysis as the research focus, and cites and transforms the existing quantized data of risk factors (Steve Guanwei Jang, 2011). Moreover, it uses the integrated model of ant colony optimization (ACO) and support vector machine (SVM) to screen the important risk factors and combinations in order to build a new machine learning model. SVM is a very reliable statistical learning classifier, which is combined with ACO for exploration in a probable solution space. The existing solution is repeatedly improved until the characteristic of exploitation is achieved, and the most important risk factor combination that influences the project is determined from probable combinations of numerous risk factors. This study refers to the DoD 4245.7 template (1985), which uses the high risk and low risk categories of "Finance unavailable" of a project to recognize the success of a project. In other words, the important risk factors and combinations influencing "Finance unavailable" can be efficiently determined after iterative computation of the computational model proposed in this study for classification identification of SVM.

2. Literature Review

This study combines SVM with ACO, which crosses engineering and management fields, while attempting to solve the practical problems in project risk management: "what are important risk factors? What is the optimum simplified combination of risk factors?" If the exhaustive search method is used, there are 268, 435,455 (2^{28}-1) probable combinations of 28 risk factors, which requires 31 days to list all the combinations even though the computer lists one combination per 0.01 seconds, and matching of the optimum combination costs time, thus, mismatching time efficiency. The optimum combinations (approximately optimal solution) can be found within a few minutes using the ACO_SVM model, practicability is high, and relative basic theories are investigated and verified, as follows.

2.1 Project Risk

Risk is exposure to the consequences of uncertainty (Cooper et al., 2005). As risk certainly exists in the implementation of projects, all project stakeholders expect correct risk analysis results and appropriate risk handling strategies in order to reduce the probability of specific risk and loss, thus, the success rate of a project is increased accordingly. Therefore, it is very important to use finite resources to control a few very important risk factors from among numerous and complex risk factors.

Definition of project risk management: "Risk management refers to the culture, processes, and structures that are directed towards the effective management of potential opportunities and adverse effects. The risk management process involves the systematic application of managerial policies, processes, and procedures to the tasks of establishing the context, and identifying, analyzing, assessing, treating, monitoring, and communicating risk (Cooper et al., 2005)." Therefore, risk management aims at "effective management and control" of the probability and consequences of risk events, where the project risk factors are in complex correlation, rendering project management decision full of difficulties. This study intends to further identify the specific importance of risk factors in order to enhance the efficiency of project risk management.

As mentioned above, important factors are determined by the reduction of large set of project risk factors. Some literature combines the Rough Set Theory and SVM, using the rough sets to reduce number of indicators of risk factors, which reduces the dimensions of the input space. Dealing with redundant attributes improves the speed of SVM training (Zhengyuan et al., 2008), (Zehong and Weibo L, 2008). This paper uses ACO to search for important risk factors.

Another important topic is to determine the risk factors influencing the success or failure of a project. Some studies have integrated a neural network with SVM to establish a software project risk management model and intelligent risk prediction model, which uses relevant data and a software project questionnaire in the concept of using risk factors as the feature identification classification, in order to predict whether the software project is successful (Hu et al, 2007 and 2009). This study also uses SVM as a classifier, and regards risk factors as the features of analysis.

This paper uses a 5×5 risk matrix as the basis of researching data type, where the 25-point-scale data are generated based on an expert group's understanding of individual risk factors (including cost, time, and quality), and considers the likelihood and impact of different risk factors. At present, there is no study of the same data type in ACO or SVM. This study conducts preliminary verification analysis as an application of the semi- quantitative risk analysis approach (Kerzner, 2003).

2.2 Support Vector Machine (SVM)

It is an extensively used classification method and type of supervised learning, where the searched "Support Vectors" are used to establish a hyper plane to distinguish class. Vapnik proposed the theoretical book of statistical learning in 1995 (Vapnik, 1999), and relevant studies were applied to text categorization (Joachims, 1998), object recognition (Pontil and Verri, 1998), handwriting recognition (Vapnik, 1999), and Biotechnology (Brown et al., 1999).

Table 1: Parameters of SVM (Vapnik, 1999)

$\mathbf{x}$	input
y	class, output
$\mathbf{w}$	weight vector or normal vector
α	dual vector or Lagrange multipliers
b	bias
L_P	primal Lagrangian
L_D	dual Lagrangian
$\langle \mathbf{x} \cdot \mathbf{z} \rangle$	inner product between x and z
$\mathrm{K}(\mathbf{x},\mathbf{z})$	kernel $\langle \Phi(\mathbf{x}) \cdot \Phi(\mathbf{z}) \rangle$
ξ	slack variable

The SVM can handle linearly separable and linearly inseparable classification problems. There are as many as 28 risk factors in this paper, which is higher dimensional data set, and only Linearly Inseparable is considered. For relevant parameters see Table 1, and the basic calculation procedure of SVM is described, as follows (Vapnik, 1999).

Linearly inseparable must allow misclassification, which should be minimized as possible, and a hyper plane of least misrecognition is established. Slack variables shall be imported into this type of problem. $\xi_i \geq 0$, i=1, 2, …m.

$$\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b \geq +1 - \xi_i \qquad for \quad y_i = +1 \tag{1}$$

$$\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b \leq -1 + \xi_i \qquad for \quad y_i = -1 \tag{2}$$

where ,y_i = +1 or -1, i = 1,2,…m, the least errors of hyper plane for training, described as follows:

$$\begin{aligned} &\underset{w,b,\xi}{Min} \quad (1/2)\langle \mathbf{w}^{\mathbf{T}} \cdot \mathbf{w} \rangle + \mathrm{C}\sum_{i=1}^{m} \xi_i \\ &subject \quad to \quad y_i\left(\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b\right) + \xi_i \geq 1 \\ &\qquad\qquad \xi_i \geq 0, \qquad\qquad i = 1,2,\ldots m \end{aligned} \tag{3}$$

C is a Penalty parameter. In the same way, (3) can be optimized and solved by using Lagrangian, expressed as (4):

$$\begin{aligned} L_P(\mathbf{w}, b, \xi, \boldsymbol{\alpha}, \mathbf{r}) = (1/2)\langle \mathbf{w}^{\mathbf{T}} \cdot \mathbf{w} \rangle + C\sum_{i=1}^{m} \xi_i \\ - \sum_{i=1}^{m} \alpha_i \left[y_i\left(\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b\right) - 1 + \xi_i \right] - \sum_{i=1}^{m} r_i \xi_i \end{aligned} \tag{4}$$

$\alpha_i \geq 0$ and $\gamma_i \geq 0$ are the first two terms that minimize the objective function, the third term represents the inequality constraint with a slack variable, and the last term is the result when ξ_i is nonnegative.

L_p is minimized in order to obtain variables **w**, ξ and b; let the first order derivative of L_p to **w**, ξ and b be 0, thus, (5) (6) (7) can be obtained:

$$\partial L_P(\mathbf{w}, b, \xi, \boldsymbol{\alpha}, \mathbf{r}) / \partial \mathbf{w} = \mathbf{w} - \sum_{i=1}^{m} y_i \alpha_i \mathbf{x}_i = 0, \quad \mathbf{w} = \sum_{i=1}^{m} y_i \alpha_i \mathbf{x}_i \tag{5}$$

$$\partial L_P(\mathbf{w}, b, \xi, \boldsymbol{\alpha}, \mathbf{r}) / \partial \xi_i = C - \alpha_i - r_i = 0, \quad C = \alpha_i + r_i \tag{6}$$

$$\partial L_P(\mathbf{w}, b, \xi, \boldsymbol{\alpha}, \mathbf{r}) / \partial b = \sum_{i=1}^{m} y_i \alpha_i = 0, \quad \sum_{i=1}^{m} y_i \alpha_i = 0 \tag{7}$$

The inequality constraints handling method is to convert them into equality constraints, where KKT conditions must be met:

Equations (5), (6), and (7) are substituted in Eq. (4), and L_p can be reduced to Eq. (10);

$$\alpha_i \left[y_i \left(\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b \right) - 1 + \xi_i \right] = 0, \quad \forall i = 1, \ldots, m \tag{8}$$

$$\xi_i (\alpha_i - C) = 0, \quad \forall i = 1, \ldots, m \tag{9}$$

$$\begin{aligned} L_P(\mathbf{w}, b, \xi, \boldsymbol{\alpha}, \mathbf{r}) &= (1/2) \langle \mathbf{w}^{\mathbf{T}} \cdot \mathbf{w} \rangle + C \sum_{i=1}^{m} \xi_i \\ &\quad - \sum_{i=1}^{m} \alpha_i \left[y_i \left(\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b \right) - 1 + \xi_i \right] - \sum_{i=1}^{m} r_i \xi_i \\ &= \sum_{i=1}^{m} \alpha_i - (1/2) \sum_{i,j=1}^{m} y_i y_j \alpha_i \alpha_j \langle \mathbf{x}_i \cdot \mathbf{x}_j \rangle \end{aligned} \tag{10}$$

In order to determine the optimal hyper plane, $\boldsymbol{\alpha}$ of the Dual problem must be maximized, thus, the original problem $L_p(\mathbf{w}, b, \xi, \boldsymbol{\alpha}, \mathbf{r})$ is converted into dual problem $L_D(\boldsymbol{\alpha})$, and expressed as Eq. (11):

$$\begin{aligned} &\underset{\alpha}{Max} \quad L_D(\boldsymbol{\alpha}) = \sum_{i=1}^{m} \alpha_i - (1/2) \sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j \langle \mathbf{x}_i \cdot \mathbf{x}_j \rangle \\ &subject \quad to \quad \sum_{i=1}^{m} \alpha_i y_i = 0 \\ &\qquad\qquad\qquad 0 \leq \alpha_i \leq \mathrm{C}, \quad i = 1, 2 \ldots m \end{aligned} \tag{11}$$

where α_i is limited to C, parameter C is the upper value of α_i, and the C value is user-specified. Finally, the best decision hyper plane is computed.

Another method is to use mapping function Φ to convert the training sample from an input space into a feature space, also known as a kernel function. In Dual Lagrange (11), the inner product is replaced by a kernel function (12), and the Dual Lagrange L_D (**α**) (1) (3) of the nonlinear SVM are similar to (11).

$$\mathrm{K}(\mathbf{x}_i, \mathbf{x}_j) = \left\langle \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j) \right\rangle \tag{12}$$

$$\begin{aligned} &\underset{\alpha}{Max} \quad \mathrm{L}_D(\alpha) = \sum_{i=1}^{m} \alpha_i - (1/2) \sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j \mathrm{K}(\mathbf{x}_i, \mathbf{x}_j) \\ &subject \quad to \quad \sum_{i=1}^{m} \alpha_i y_i = 0 \\ &\qquad\qquad 0 \le \alpha_i \le \mathrm{C}, \quad i = 1,2 \ldots m \end{aligned} \tag{13}$$

The linearly separable solution method is used (13), and the optimal hyper plane is obtained, expressed as (14). According to the application of the kernel function, offset b is implied in the kernel function. Therefore, if the offset can be adjusted in the kernel function, the nonlinear SVM can be expressed as (15).

$$\begin{aligned} f\left(\mathbf{z}, \boldsymbol{\alpha}^*, b^*\right) &= \sum_{i=1}^{m} y_i \alpha_i^* \left\langle \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{z}) \right\rangle + b^* \\ &= \sum_{i=1}^{m} y_i \alpha_i^* \mathrm{K}(\mathbf{x}_i, \mathbf{z}) + b^* \end{aligned} \tag{14}$$

$$f\left(\mathbf{z}, \boldsymbol{\alpha}^*, b^*\right) = \sum_{i \in sv} y_i \alpha_i^* \left\langle \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{z}) \right\rangle = \sum_{i \in sv} y_i \alpha_i^* \mathrm{K}(\mathbf{x}_i, \mathbf{z}) \tag{15}$$

z is the test data vector and $\boldsymbol{\alpha}^*$ and b^* are the solution to the offset and Lagrange multipliers, respectively.

The kernel function selected in this paper is a radial basis function (RBF) (17) (Huang and Wang, 2006), where the parameter γ must be appropriately set in order to increase classification accuracy. This paper uses a grid algorithm to seek the optimum parameter combination of (C, γ).

$$\mathrm{RBF} : \mathrm{K}(\mathbf{x}_i, \mathbf{x}_j) = \exp[\left\| \mathbf{x}_i - \mathbf{x}_j \right\|^2 / \gamma], \quad \gamma \in R \tag{17}$$

2.3 Ant Colony Optimization (ACO)

The ACO was first proposed by Dorigo et al. in 1992. It is the heuristic algorithm established by simulating an ant colony hunting for food. The theory of ACO is usually applied to traveling salesman problems (TSP)(Dorigo and Gambardella, 1997), and to feature selection (Bello et al., 2006)(Sivagaminathan and Ramakrishnan, 2007)(Zhang and Hu, 2005). This study regards individual “risk factors” as different “features”, which uses the logic sum concept to solve TSP in iterative selection of the features (risk factors) of ACO. A combination of features (risk factors) is selected by different ant colonies in order to determine the combination with the shortest path nodes equivalent to TSP. The concept of the 0/1 Knapsack Problem (KP) (Shi, 2006) is imported to seek the optimal recognition rate of the least risk factors, which view is applied to project risk analysis, and the success or failure of a project is identified by the combination of optimal and least risk factors. The ACO solving process is described, as follows, by taking the feature selection as an example.

The concept of ACO is to use existing experience to search for new exploration in the probable solution space, repeatedly improving the existing solution until exploitation. The principle is that an ant hunts for a food "pheromone" along a path, i.e. a marked path for subsequent ants to follow the pheromone. Higher pheromone concentration is more likely to attract ants, and vice versa. ACO simulates this foraging behavior. In the "solution" search space, each state represents a feature subset, and all feature selection methods contain two important components (Bello et al., 2006):

1. An evaluation function used to evaluate a candidate feature subset.
2. A search algorithm to search the feature space.

Table 2: Parameters of ACO (Dorigo and Gambardella, 1997)

τ	Pheromone trail of combination
η	Local heuristic of combination
P	Transition probability of combination
α	Relative importance of the pheromone
β	Relative importance of local heuristic
q_0	Determines the relative importance of Exploitation versus Exploration
ρ	Trail persistence

Search strategies are important because the feature selection process may be time consuming and require an exhaustive search for the "optimal" subset, thus, it is impractical for even moderate sized problems (Zhang and Sun, 2002). The search for the best subset of features can be rapidly and effectively completed, as based on the state transition rule, local updating rule, global updating rule, and local search of ACO. The major parameters of ACO (see Table 2) are briefly described, as follows (Dorigo and Gambardella, 1997).

(1) State transition rule

In the ant colony system (ACS), as probability value *p* is an important indicator that determines the next feature, ant *k* selects next feature *j*, expressed as (18):

$$j = \begin{cases} \arg \max_{k \in US} \left[(\tau_k)^{\alpha} (\eta_k)^{\beta} \right] & q \le q_0 \quad Exploitation \\ J & q > q_0 \quad Exploration \end{cases}$$
$$P_j = (\tau_j)^{\alpha} (\eta_j)^{\beta} \Big/ \left[\sum_{k \in US} (\tau_k)^{\alpha} (\eta_k)^{\beta} \right] \tag{18}$$

where *US* is the feature set ant *k* has not yet visited; *j* is the selected next feature; *j* is the probability value of selecting next feature *j*; *q* is the value between 0 and 1 generated by system at random; q_0 is also a value between 0 and 1, as defined by the user; τ is the pheromone trail of combination with time t. This paper uses the method of Golub et al. (1999)and Ressom et al. (2007) as local heuristic of combination (η), i.e. the Pearson method (19), as well as an Evaluation function (Bello et al., 2006); where parameters α and β are the influential degree determining pheromone quantity and heuristic information.

$$\eta_i = \left|\mu_i^1 - \mu_i^2\right| \Big/ (\sigma_i^1 + \sigma_i^2) \tag{19}$$

First, class 1 and 2 (superscript) are grouped, and the mean μ and standard deviation σ of feature *i* (subscript) in class 1 and class 2 are calculated, respectively. The larger the value, the better is the feature recognition capability. In addition, parameter β has considerable importance. For example, when $\beta = 0$, it means all features are unrelated to their recognition capability; contrarily when $\beta = 1$, it means all features are of equal importance.

Equation (18) consists of exploitation and exploration. Exploitation is the information obtained from previous experience and heuristic, thus, the feature will be selected for stronger pheromone (τ) and higher identifiability (η), thus, exploration is any feature selected randomly by the probability value.

(2) Local updating rule

By continuously using the state transition rule, each ant is able to establish travel. As an ant forms its travel, the ant corrects the pheromone quantity on the selected feature, thus, the pheromone quantity of a selected feature is corrected by the local updating rule.

A solution of TSP is established, the ants select a feature and change their pheromone level, as based on the local updating rule, and expressed as (20):

$$\tau_i^{new} = \rho \times \tau_i^{old} + (1-\rho) \times \tau_0 \tag{20}$$

τ_i^{new} is the new pheromone concentration of feature *i*; τ_i^{old} is the previous pheromone concentration of feature *i*; ρ ($0 < \rho < 1$) is called trail persistence of pheromone, 1-ρ is the evaporation rate of pheromone, and τ_0 is the initial pheromone level of the problem. The local updating rule not only reduces the importance of unrelated features, but also helps ants select unexplored features.

(3) Global updating rule

When all the ants stop selecting, the pheromone quantity is corrected again, as based on the global updating rule. In ACS, the best ant is allowed to leave pheromone again before the next iteration. The global updating rule is used after all ants have completed their selection. The pheromone level is updated by the updating rule, as in (21):

$$\tau_i^{new} = \rho \times \tau_i^{old} + (1-\rho) \times \Delta\tau_i^e \tag{21}$$

$\Delta\tau_i^e$ is the ant with the minimum misrecognition rate. The pheromone of the feature selected by the best ant is strengthened again by the Global Updating Rule, rendering that feature more attractive and it guides the next generation ant to select again. Which is to say, when a solution is created, these features are more likely to be selected in the future.

(4) Local search

Local search enhances local search capability, and the “solution” usually falls into the local optima, which local optimal solution can be effectively escaped by a local search, which enlarges the search area and increases the probability of an optimal solution (or better solution).

3. Experiment and Analysis

The most striking aspect of the results is the change in the causality relation between the two markets after the break in September 2008. It is found that prior to break point, spot market seems to have a causal effect on futures market. However, after the break, dynamics change and futures market becomes a significant leading factor in spot market. Block-exogeneity test results show the strong unidirectional causal relationship from futures to spot market in the post break period.

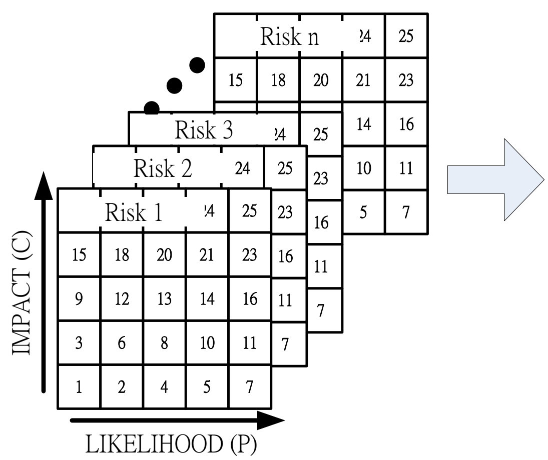
The modular heuristic algorithm (ACO) and machine learning (SVM) are merged into a project risk management process, regardless of the type and stage of a project, the data type meeting classification identification is applicable. The devoted information source is the risk information of the project construction phase to the project’s stakeholders, via a questionnaire of risk matrix (Steve Guanwei Jang, 2011), which includes costs, time and quality information, the probability and impact of risk, and multiple group information, where the most important and optimum risk factor combination is screened out by the calculation of the ACO_SVM model.

3.1 Data type and source of data

In terms of risk identification, when preliminary risk factor screening is completed, the risk factors are regarded as feature eigenvectors, which are different from pattern and signal recognition, in that they can directly use quantized eigenvector, thus, each project is unique. The likelihood and impact of risk factors are judged by experts (stakeholders), and as such judgment is subjective, it is “qualitative risk analysis”. Considering the required data type for the algorithm proposed in this study, the qualitative and quantitative risk analyses are integrated, and the judgment of linguistic terms of expert group is converted into quantized data for a related algorithm to recognize, i.e. “semi-quantitative risk assessment” (Cooper et al., 2005). In order to validate the feasibility of a model in advance, the open project risk data, and related literature, should be applied, as project management data and data of public and private organizations are confidential, thus, there is no open information.

This study cites the questionnaire data of Steve Guanwei Jang (2011), and the research target is the Taiwan High Speed Rail (THSR) project. The questionnaire is designed based on a risk matrix, which is different from a general questionnaire, and is displayed in the matrix mode. The likelihood of individual risk factors and their impact on a project are simultaneously considered, and there are 25 scales. This paper only uses 37 questionnaire data of the 28 risk factors (not listed item by item due to limited length) as the input data source of ACO_SVM, and output uses the risk level of "Finance unavailable" in project management as classification recognition (Figure 1). When the maximum recognition accuracy rate is obtained by importing the risk factor combination screened by the iterative calculation of ACO into SVM, this combination is of high importance.

Figure 1: Data type of questionnaire



Risk / Sample	Risk 1	Risk 2	Risk 3	...	Risk 28	Class
Sample 1	17	18	11	...	9	-1
Sample 2	20	24	22	...	10	+1
Sample 3	22	20	9	...	9	+1
Sample 4	21	10	19	...	12	+1
Sample 5	23	16	11	...	10	-1
Sample 6	19	12	19	...	8	-1
Sample 7	19	19	17	...	11	-1
...	...	...	...	...	...	...
Sample 37	20	23	23	...	8	-1

Class -1: lower risk of "Finance unavailable"

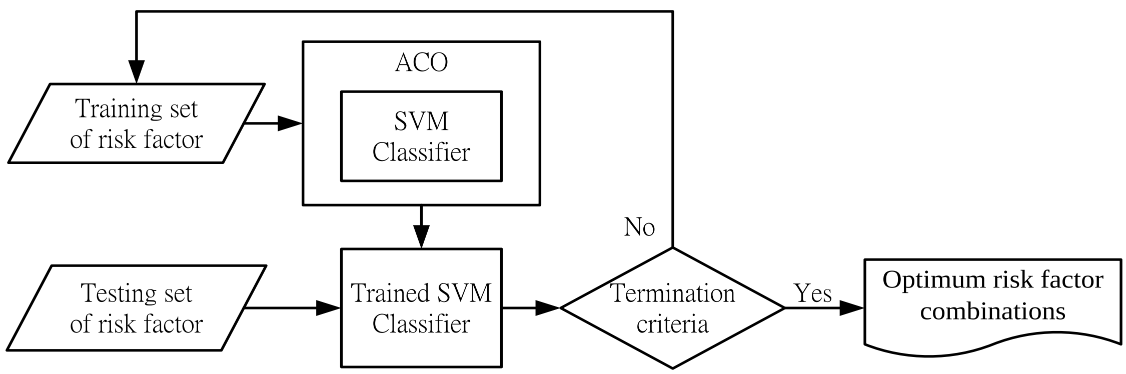
Class +1: higher risk of "Finance unavailable"

3.2 Computational process of ACO_SVM

This study uses Matlab to compose the ACO program, sets 10 ants, iterations of 100 times, and combined with libsvm (Chang and Lin, 2014) to construct the ACO_SVM model. Before related data are formally imported into the ACO_SVM model, data scaling of the 37 risk factor questionnaires is conducted, and bootstrapped 2,000 times, with 80% of data as the training set, and 20% of data as the testing set. For recognition of SVM, the optimum parameter combination of the RBF kernel function (for SVM) in the training set is searched using a grid algorithm, and parameter combination (C=8, γ =0.0078125) is used to set the ACO_SVM model for training and testing, the optimal risk factor combination is obtained, the most important individual risk factor is confirmed, and the best and simplest risk factor combination is screened out.

This paper combines the characteristics of ACO with the reliable classification capacity of SVM in order to select risk factors, and the optimum risk factor subset is searched by iterative calculation. The SVM is used as a classification function, and the subset is selected by Filter and Wrapper (John, 1994), (Kohavi and John, 1997). The difference is whether the "classification function" is used or not. As a Wrapper has better classification recognition capability, this study uses Wrapper integrated SVM directly into ACO in order to establish the computational process, as shown in Figure 2. The ACO_SVM model can rapidly and effectively search the important risk factors and combinations from the 28 risk factors.

Figure 2: Computational process of ACO_SVM model



3.3 Experimental results and analysis

The scale data of risk factors (1~25) are used as risk effect imported into the ACO_SVM model, and the important risk factors and combinations are determined according to the SVM recognition (prediction) accuracy rate. The higher the accuracy rate, the more important the combination of risk factors selected by ACO (see Table 3).

Taking ant colonies 3 and 4 in Table 3 as examples; after calculation search of ant colony 3, the combination of 100% recognition rate of SVM has 10 risk factors: 6, 7, 14, 15, 17, 18, 19, 20, 24, and 28. The combination of ant colony 4 is 9, 15, 19, 20, 24, and 28, and there are six risk factors. Although ant colonies 3 and 4 have different risk factor combinations, the recognition rate is 100%, and risk factors 15, 19, 20, 24, and 28 are repeated in two different combinations, meaning the five factors have relatively higher importance in specific management situations, and can be further analyzed. Meaning after the calculation of the ACO_SVM model, the complex group opinion can be "transferred" to easily analyzed information.

Table 3: Experimental results

Ant Colony	SVM Recognition rate (%)	No. of risk factor selected										risk factor statistics of times of selection					
												No.	Times	No.	Times	No.	Times
1	100	6	9	19	20	24	25	27	28			1	2	11	0	21	0
2	100	1	9	12	14	15	19	23	24	27		2	0	12	1	22	1
3	100	6	7	14	15	17	18	19	20	24	28	3	1	13	0	23	2
4	100	9	15	19	20	24	28					4	1	14	4	24	10
5	100	6	9	15	19	20	24	28				5	0	15	8	25	1
6	100	1	7	9	19	22	24					6	5	16	2	26	0
7	100	8	9	14	15	19	20	24	28			7	3	17	1	27	2
8	100	4	9	14	15	16	19	20	23	24	28	8	1	18	1	28	8
9	100	6	7	9	15	16	19	20	24	28		9	9	19	10		
10	100	3	6	9	15	19	20	24	28			10	0	20	8		

Four core messages are listed as the principal axis of analysis (see Table 3):

1. Confirm the combination of the least risk factors: there are numerous risk factors influencing implementation of a project, and to promote the success of a project, subjective determination shall be avoided and resources shall be centralized in order to reduce interference and interaction by unnecessary risk factors. The ACO_SVM model, as proposed in this study, can effectively select only 6 risk factors from the 28 factors, thus, the management team must reduce the category for more efficient management activity. The combinations of least risk factors selected by ant colonies 4 and 6 are sorted according to Table 3 (name of risk factor _number);

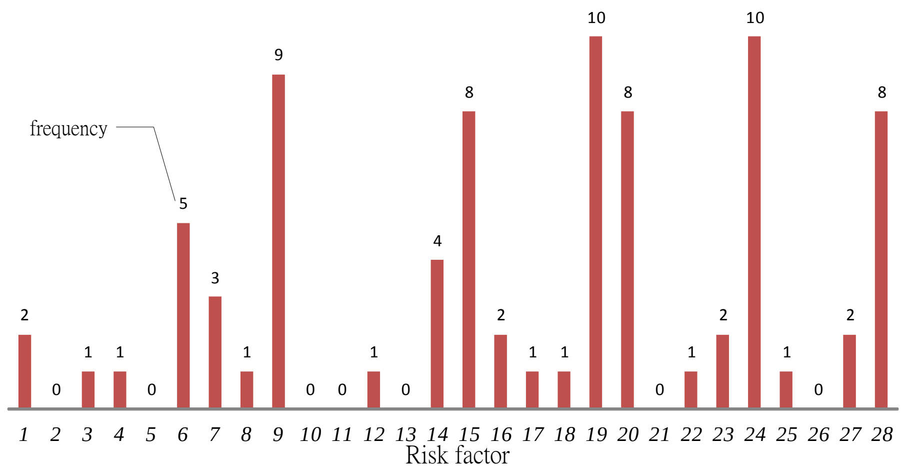
Combination 1: Resource unavailable _9, Complex system interface/integration _15, Insolvency of contractor _19, Contract breach _24, Industrial disputes _28;

Combination 2: Default of subcontractor _1, Force Majeure _7, Resource unavailable _9, Insolvency of contractor _19, Inflexible contract arrangement _22, Contract breach _24.

2. Risk factor selected the most: according to the parameter conditions set by the ACO_SVM model, and taking the risk factors selected by 10 ants as an example, there are Insolvency of contractor_19 and Contract breach_24; according to this result, besides routine work, a risk handling strategy can be proposed; e.g. “adjust the staffing organization of project”, “strengthen management, and evaluation and audit of contractor”, “give contractor more assistance, and study alternative schemes timely”.

3. Risk factor not selected: there are seven factors, including 2, 5, 10, 11, 13, 21, and 26, which have not been selected by ant colony during any iterative calculation screening process of the ACO_SVM model, meaning the importance of the 7 risk factors is very low. In terms of project team, the original management resources (labor force, materials, and finance) of the 7 risk factors can be adjusted, relevant administrative procedures can be reduced, and activities related to the 7 factors can be directly removed to avoid unnecessary interference.

Figure 3: Bar chart of number of selections of risk factor



4. Ordering of importance of individual risk factors: according to the process of ACO, the number of selections of individual risk factors implies a difference in importance, and importance can be preliminarily determined according to how many times the risk factor is selected (Figure 3). The length of the vertical bar represents the number of selections (horizontal axis represents 28 different risk factors), the larger number of selections represents higher importance, and ordering provides reference for decision making. The problem in resource selection can be solved by the importance of individual risk factors in the experimental results of the ACO_SVM model. For example, factor 1 (selected 2 times), factor 9 (selected 9 times), when there is conflict of resource application, the demand of factor 9 shall have priority.

To sum up the aforesaid analyses, the experimental results of the ACO_SVM model show that, the Insolvency of contractor_19 and Contract breach_24 are selected the most by the ant colony, as compared with the System Dynamics and interview of Steve Guanwei Jang (2011) to correct the results (Figure 4), the Insolvency of contractor_19, Contract breach_24 and Finance unavailable are highly correlated. Different methods with the same data source have the same findings, proving the feasibility of the ACO_SVM model, and providing more valuable analytic information. At the project meeting of key milestones, the communication between project manager and stakeholders will be smoother, and can focus on the really important issues.

Figure 4: The modified direct cause and consequence for “insolvency of contractor”

(Steve Guanwei Jang, 2011)

4. Conclusions and Recommendations

The process of project risk management is classic group decision making, where milestone decisions are not determined by personal or a few persons' subjective consciousness; project management requires a labor force with professional knowledge and experience, and each stakeholder has different perceptions, attitudes, motivations, and personalities (F. Herrera, 1995)regarding how to fuse group opinions effectively. This study proposes a new method for integrating group opinions, where quantitative information is obtained by a risk matrix and imported into the ACO_SVM model for calculation, optimal and least combinations of risk factor can be obtained, while unimportant risk factors can be screened out, and the importance of each risk factor can be identified in order to reduce the probability of overall project decision-making mistakes, thus, increasing the success rate of a project.

The cases presented in this study are preliminarily validated by the ACO_SVM model, where two optimum simplified risk factor combinations are searched, which can be used as a reference frame for project resource scheduling and organizational adjustment. The Insolvency of a contractor and contract breach factors are proved most influential to the success of a project, highlighting the importance of “finance management” and “contract management” of a large project, which require the proposal of appropriate management strategies, precise evaluations, and planning.

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