國 立 交 通 大 學

管理學院（資訊管理學程）碩士班

碩 士 論 文

利用蟻群最適化協助員工選擇課程

Use Ant Colony Optimization to Assist Employees in Selecting the Training Courses

研 究 生：謝育勳

指導教授：劉敦仁/林妙聰 博士

中 華 民 國 九 十 五 年 六 月

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摘　　要

在這資訊爆炸的時代裡，企業要如何維持其競爭力，不被市場所淘汰，這是現今企業最關心的議題。雖然不同的產業、市場定位，會有不同的競爭策略與方式，但所有的企業均會使其員工不斷的學習與成長，以因應不同的競爭環境。但在企業中，由於員工的時間與企業的預算是有限的，因此如何讓員工在有限的資源（時間與成本）下，參與最有價值的課程，是現今企業與員工最關心的課題。

本論文的主題是利用螞蟻演算法（Ant Colony Algorithm），協助員工做最適化的課程選擇。在所規劃之員工的課程集合中，必須考量企業所規定的訓練時間及預算下；另外，為了使員工不要只集中在某一個或兩個學習領域，因此也規定其所建議的訓練課程必須要涵蓋超過三個領域。本論文根據這些限制式及訓練課程資料，利用螞蟻演算法來產生最適化的課程建議，即求取『課程效用/(成本*時間)』之最大目標函數值。本論文亦將利用窮舉演算法(Exhaustive Algorithm)，以驗證本論文所提演算法的效能(Effectiveness)跟效率(Efficiency)。在效能方面，由於窮舉法可提供最佳解，因此其可以精準驗證近似演算法的效度。在效率方面，本演算法屬於近似法，因此所花費的時間將遠低於窮舉法所使用的時間。

本研究還是有很多可以改進的空間，例如：介面的設計、管理功能的加強、與其他訓練系統（訓練系統或線上訓練系統）的結合以及驗證效率演算法的選擇(例如選擇更有效率的 GA 演算法)，這些都是可以提供給未來研究者或是企業運用改良的方向。

關鍵字：螞蟻演算法、訓練課程規劃、決策支援、近似解法

Using Ant Colony Optimization to Assist Employees in Selecting the Training Courses

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ABSTRACT

In the information explosion era, the most critical issue for a company is how to keep its core competence and to prevent from losing the market shares. Companies in different industries and markets may deploy different strategies and methods to reinforce their competitiveness. Indeed, all companies will encourage their employees to continuously acquire new knowledge in the rapidly changing environment. Because there exist inevitable limitations in time and budget for preparing and selecting training courses, it is crucial to deploy some decision-aid mechanism to assist the employees to plan their training packages subject to the limited resources.

In this thesis, we use Ant Colony Optimization (ACO) to provide advice for employees. The courses planning process needs to abide the company's policies regarding training hours and costs. In order to avoid the courses of an employee are confined to only one or two areas, we stipulate that the selected training courses cover three or more areas. This study use ACO algorithm to generate packages of training courses for individual employees with the maximization of utility/(costs * hours) as the objective function values. Moreover, we also use an enumerate algorithm to verify the effectiveness and efficiency of our ACO algorithm. The two measurements are related to the solution quality and run time required by our algorithm.

There are a lot of parts that it can be improved in the future work, for example: design the fancy user interface, enhance the management functions, link the other training system or E-learning system, and select the verification algorithm that it can exactly prove the system efficiency.

Key Words: Ant Colony Optimization, Training Course Planning, Decision Support, Approximation Algorithm

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~ Acknowledgements ~

I am very glad I had the opportunity to join the Institute of Information Management (IIM) of National Chiao Tung University in 2004. In these two years, I learned theoretical knowledge from the professors. In addition, I can apply the theory to our work environment. Another, I make many good friends who are very outstanding and successful in their careers and willing to share experience and knowledge with one another. Therefore I am very proud that I could attend the Institute and enjoy a lot from the study process.

In these two years, I can smoothly finish the education of master. I have to express my thanks to my advisers, Dr. Liu and Dr. Lin. They gave me advice on my thesis and schoolwork. Although I was not familiar with the domain knowledge when I joined the Institute, they are willing to instruct me in many aspects. Moreover, I also appreciate the time with my classmates, who have encouraged and helped me to complete my study.

Chapter 1 Introduction

1.1 Research Background and Motivation

In 21st Century, all organizations need to face a lot of changes and challenges as shown in figure 1 [1]. Knowledge economy is one of the challenges for the organizations to acquire necessary knowledge and to gain advantages on competitions.

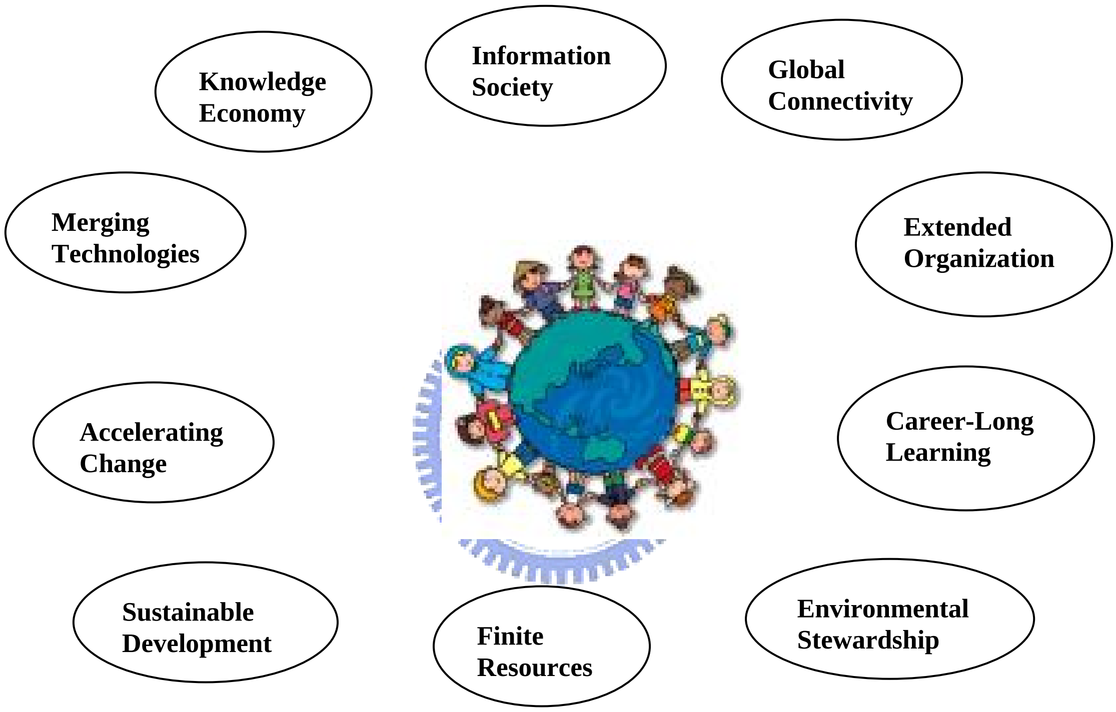

Figure 1：Changes at the dawn of the 21st Century
Data Source: [1]

To deal with the challenge of knowledge-economy, enterprises usually plan a lot of training courses for employees to enhance the strengths of their human capitals. Employees get professional knowledge from taking training courses to improve their own skill. Although the learning is important to employees, the trade-off between the learning time and working time is an issue. Consequently, an important problem for enterprises is how to determine optimal training courses for employees when there is restricted time and cost. And then to generate the maximal productivity of employees bases on the kind of knowledge and skill learned from the training courses.

This work investigates the problem of finding optimal training courses thus to provide the recommendation of suitable and useful training courses for employees. Because the problem of selecting the optimal training courses is similar to the traveling-salesman problem (TSP), it can be defined as a NP-hard problem. There are two kinds of heuristics to solve these problems: One is the ad-hoc heuristic such as the greedy method; another is the meta-heuristic which is usually applied in the natural or scientific areas. For example, Genetic Algorithms (GA) [15][17], Simulated Annealing [19][22], Tabu Search [13] [14], and Ant Colony Optimization (ACO) [8]. In this research, we adopt the method Ant Colony Optimization (ACO) to find optimal training courses.

1.2 Research Objective

In such highly competitive and knowledge-oriented era, companies have to keep their competitiveness in order to survive in the market. Through learning new knowledge and skill continuously, employees can contribute their knowledge to their jobs. However, there is conflict between the training time and working time of employees. The object of this research is to find the optimal training courses for employees under the limited cost and training time. The result of this research can be suggested to employees on selecting the suitable training courses, learning the valuable knowledge, and then contributing their knowledge in his/her work.

1.3 Research Process

The research mainly adopts an Ant Colony Optimization (ACO) algorithm to find optimal training courses. Figure 2 shows the research structure of this thesis. An overview of our research steps is illustrated as following:

1. **Problem Definition:** According to the motivation and object of our research, we want to develop a model of optimal training courses to be suggested to employees under the pre-defined training cost and time.
2. **Literature Review:** The literature review is separated into two parts: (1) the system model of training- a) Swanson’s training technology system [20]. There are five stages: analysis, design, development, practice, and evaluation; b) Goldstein’s training system model [3]: the stage of training requirement, the stage of training development, the stage of evaluation, the stage of training review; (2) the other part is algorithm. This work will focus on the concept of ACO (Ant Colony Optimization), and related study.

3. **Build the Model:** The problem of optimal training courses is a NP-hard problem. We use the ACO method to solve this problem.
4. **Construct the ACO Algorithm:** Based on the literature review and research model, we implement an ACO algorithm to find optimal training courses.
5. **Develop the System:** After constructing the ACO algorithm, we develop a recommendation system of selecting training course. The tool of development is the usage of Java.
6. **Verify the Effect and Efficiency:** The step is to verify the effect and efficiency of the system.
7. **Generate the Recommendation:** Employees can use the system to get the optimal recommendation of selecting training courses.

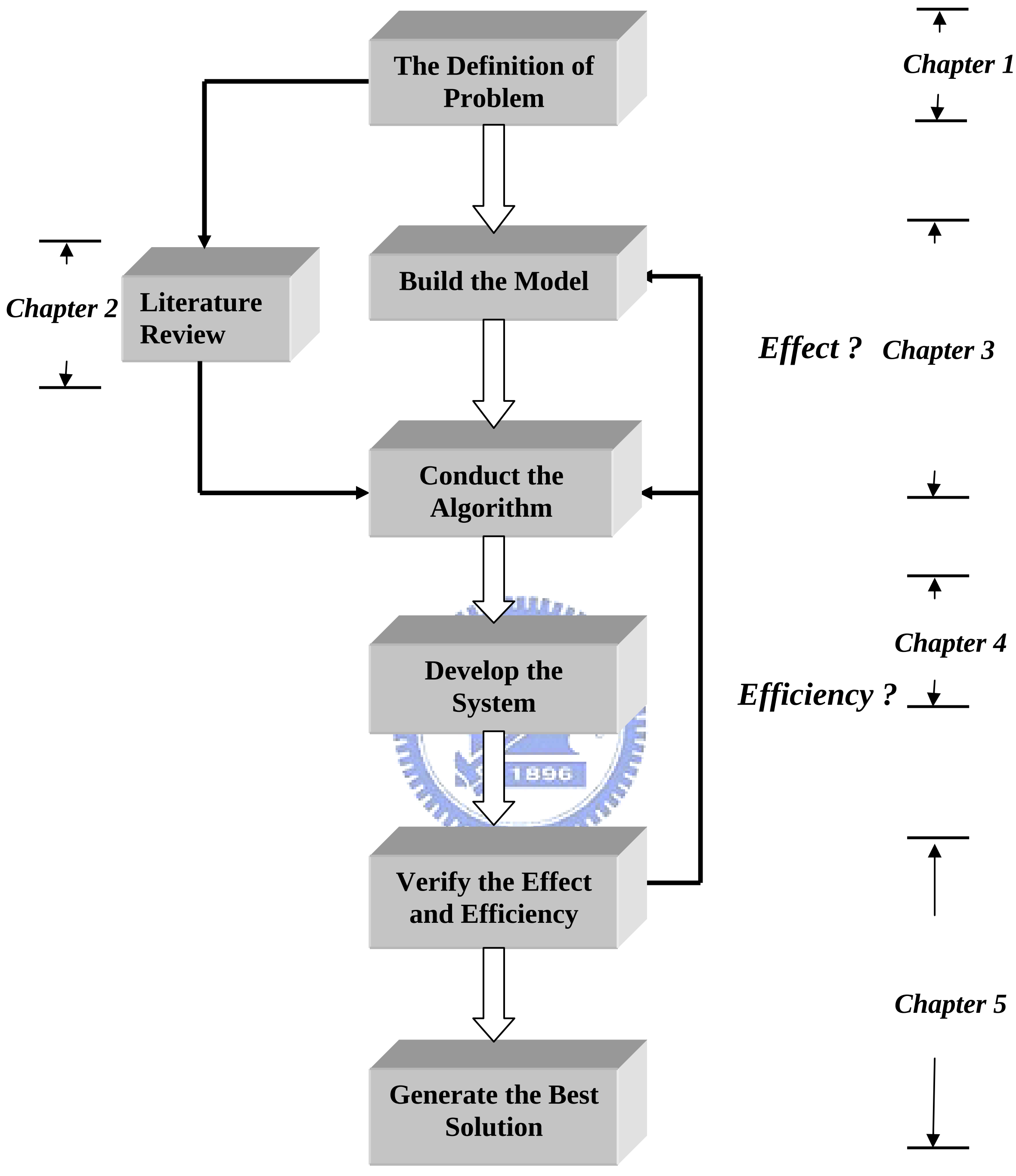

Figure 2：The research structure of thesis
Data Source: This Research

Chapter 2 Literature Review

There are two parts in the literature review: 1) Training Model: Because the development of the training-course recommendation system bases on the system model of training, we will describe the theory of training model; 2) ACO Algorithm: We will introduce the concept of ACO algorithm and the related study of ACO.

2.1 Problem Formulation of Training Course Planning

2.1.1 Swanson's training technology system [10]

Swanson delivered the training technology system in 1987, and it was the function to design the course and process the training. The system separated the training into five stages: analysis, design, development, practice, and evaluation. The detailed description is as below:

1. **Analysis Stage:** When any systems are developed, the first step must be the analysis of system. The development of training system follows also this procedure, and it is the most important stages in the process of development. The main task of this stage is to get the requirements of training and to analyze the requirements. The requirements can be discriminated into three dimensions: organization analysis, task analysis, and performance analysis.

   (1) Organization Analysis: The object of organization analysis is to analyze the gap between the achievement of business and the supply of inner-organization human resource. Further, to design the training policy and activities makes up the gap. So the tasks emphasize the verification of organization's object, the condition of human resource in the organization, and the strategy of human resource.

   (2) Task Analysis: The analysis is based on the scientific and systematic methods, and it determines the task items and what kinds of knowledge, technology, and ability can fit the working task. One of the suitable tools to proceed the task analysis is the 'task analysis record form'. This form includes six data: (a) Task List: List the main and second task; (b) The performed frequency : Describe the frequency of implementing main and second task; (c) The Quantity and Quality Standards: Explain the performance of main and second task; (d) Performance Conditions: Point out the environment of main and second task;(e) Skill Required: List all the required knowledge and skill of main and second task;(f) The Best

Learning Place: Illustrate the best place of learning task [3].

(3)Performance Analysis: To determine if the performance is good or bad. If the performance of employee is poor, HR member has to analyze the reason that causes the poor performance of the employee. Then to select the suitable training courses For employee to improve his/her performance.

2. **Design Stage:** Design the complete training courses according to the result of analysis. We can use the 5W1H module as the thinking point of design. (1) Whom: the trainees can be classified according to the vertical model and horizontal model. The vertical model is to deliver the different training courses according to the different positions. The horizontal model bases on the different functionality of job. And the company provides applicable training courses; (2) Who: There are two sources of trainers: one is Inner-Trainers→ the roles are played by the inner-employees. It implied lower cost but also lower quality. Another is Outer-Trainers→ the company has to employ or invite the instructors. It implied higher cost but with higher quality; (3) What: To determine the content of training has to verify the requirements and object of training; (4) When: The training time has to be the balance between employee's working time and private time; (5) Where: Determine the place of training according to the content of training, the conduct method, and the physical training space; (6) How: According to different property of training courses, apply the different methods of training. There are a lot of different methods that the trainers can adopt: for example, coaching, lecture, team communication, case study, and role play, etc.
3. **Development Stage:** Prepare the material of training courses and simulate the process of training. Verify all the preparation for what is being described above, such as verifying the training contents, instructors list, training place and training time.
4. **Practice Stage:** It is the real time to implement the training activities.
5. **Evaluation Stage:** To evaluate the result of training by the performance of employees in the training courses. And the evaluation will provide the references to the training department. Furthermore, it can improve training activities next time.

2.1.2 Goldstein's training process model [16]

Goldstein delivered the model to emphasize each component of a project, and the relationship of every component. There are four phases in this model: Requirement Phase, Training Development Phase, Evaluation Phase, and Review Training Object Phase.

1. **Requirement Phase:** (1) The evaluation of training requirement: this phase in the process of training is to provide the all required information. (2) The object of training: Develop the training object from the evaluation of training requirement, And the training objects will be guided to the training design.
2. **Training Development Phase:** (1) The design of training environment: Design the training environment after verifying the task, KSAs, and objects. (2) The policy of learning: Use the effective learning policy, then apply this knowledge from training process to the work.
3. **Evaluation Phase:** (1) Deliver the standard of evaluation: the standard of evaluation comes from the requirement and object of training activities. (2) The application of evaluation model: Develop the highly valid and credible evaluation forms, and use this form to evaluate the result of training.
4. **Review Training Object Phase:** Reviewing the outcomes of training, the initial training objects and the feedback can amend the training process. Furthermore, it can improve following training activities.

The figure 3 shows the whole picture of this model [16]:

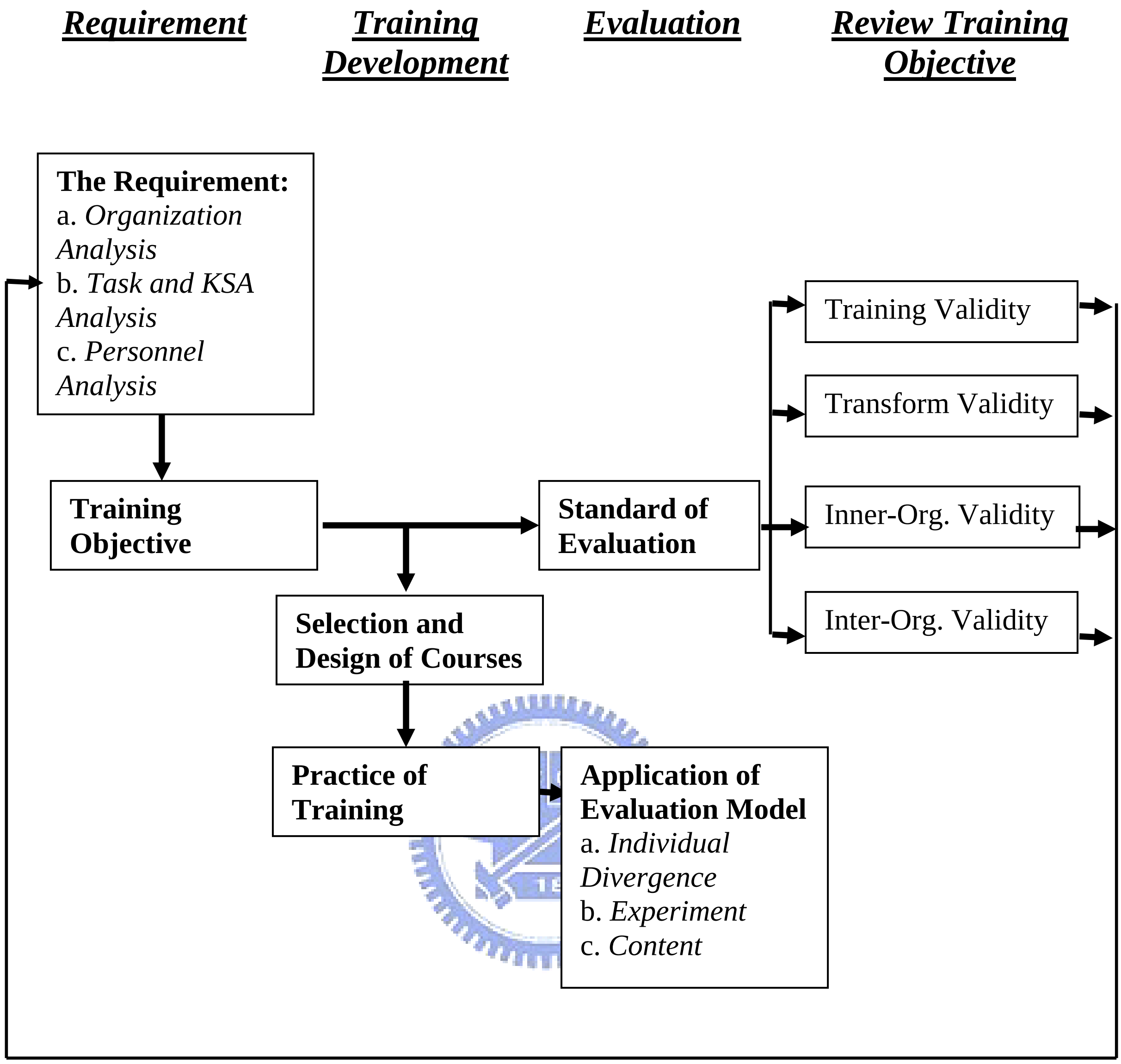

Figure 3：Goldstein's training process model
Data Source: [16]

2.2 Ant Colony Optimization (ACO)

2.2.1 Concept of Ant Colony Optimization

Ant Colony Optimization is a novel approach for solving combinatorial optimization problems [5]. This approach imitates the method how ants find out food: When the ants search for the food, they would leave the chemical composition (Pheromone). The pheromone reveals the processing information of finding food. The shorter the path of finding food is, the mores pheromone consists. Finally, according to the positive feedback, all ants would follow the path which consists most pheromone to find out food [10]. The following figure is the behavioral process of ants' finding food.

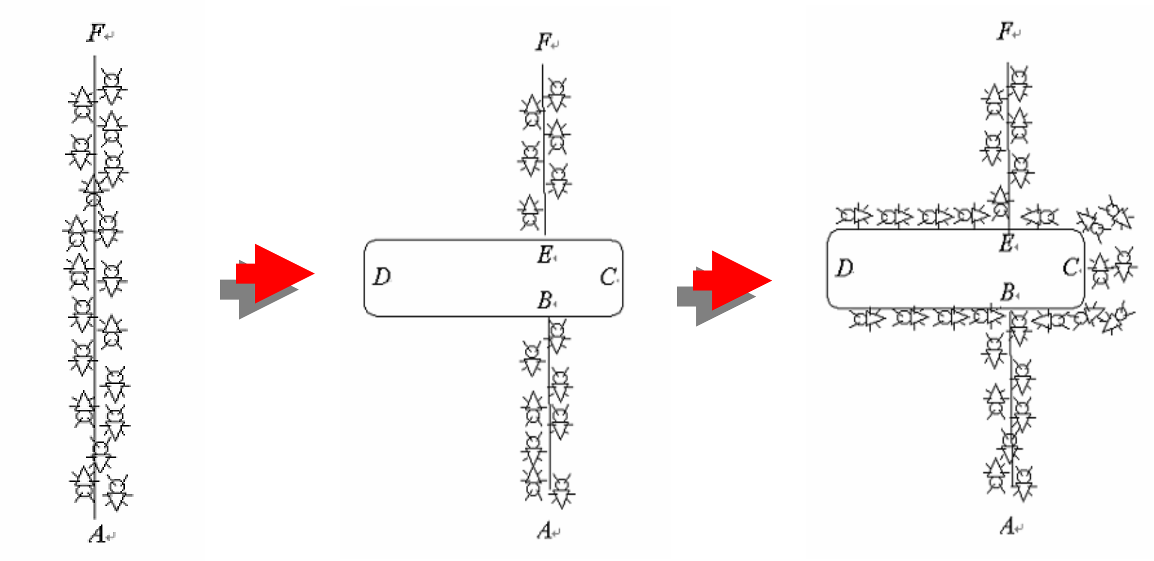

Figure 4：The behavioral process of ants' finding food
Data Source: [15]

The ant colony optimization (ACO) was based on the concept of real ants to develop the artificial ants in the system. It takes advantage of the powerful function how ants search for food, so the artificial ants keep the three key features of real ants [7]:

1. Ants prefer to select the trail with higher pheromone.
2. The shorter distance of path, the more pheromone would be left behind.
3. Ants communicate with each other via pheromone to achieve the effect of indirect communication.

Although the artificial ants imitate the real ants, there are some different behaviors. Because the artificial ants are used to find out the best solution in short time, some shortcomings have to be eliminated. There are some difference between artificial ants and real ants: Artificial ants have some memory for knowledge-sharing.

1. Artificial ants are not completely blind, and they can be led by other physical information.
2. The artificial ants live in the environment where the time is not continuous.

2.2.2 Structures of ACO

In 1991, Dorigo, Colorni, Maniezzo imitated the real ants to develop the system which can find out the optimal solution. This solution is called ant system (AS). Then in 1995, Gambardella and Dorigo, etc. brought up the theory of Ant-Q[6]. This theory is that according to the ants who find out the shortest distance for food , then the following ants can also find this shortest path through the pheromone($\triangle$AQ(r,s)) left by the ants who find the shortest path first. The $\triangle$AQ(r,s) means that the ants leave pheromone from city r to city s, and use the α value to measure the collaborative learning. The parameter is extended to be $\triangle$AQ(r,s) $^{\alpha}$. The effect which use the positive feedback of $\triangle$AQ(r,s) $^{\alpha}$ to find out the shortest path is called Q-value. To be the first, Dorigo and Gambardella combined the definition of AS and Ant-Q to develop a new approach called ant colony optimization (ACO) [7].We will simply introduce these three algorithms:

1. Ant System (AS) Algorithm Model:

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum\limits_{k\in allowed_k}[\tau_{ik}(t)]^{\alpha}[\eta_{ik}(t)]^{\beta}} & j\in allowed_k \\ 0 & otherwise\end{cases} \qquad (2.1)$$

$P_{ij}^{k}(t)$ → It means the function of the probability that ants go through from the City i to the next City j in the time (t). This function is calculated from pheromone (τ_{ik}) and the distance of cities (η_{ij}). Use the α value and β value to set the weight.

Allowed$_k$ → The area k is allowed for ants.

$$\tau_{ij}(t+1)=\rho*\tau_{ij}(t)+\Delta\tau_{ij}(t,t+1) \qquad (2.2)$$

$$\Delta\tau^{k}{}_{ij}(t,t+1)=\sum_{k=1}^{m}\Delta\tau^{k}{}_{ij}(t,t+1) \qquad (2.3)$$

The equation 2.2 means the continuous movement of ants' finding food, and it would cause the continuous accumulation of pheromone. The factors of time and distance would cause the evaporation of pheromone, so we can use the symbol ρ to present the weight of evaporation. The value ρ is between 0 and 1.

The equation 2.3 means the total amount of pheromone left by ants (From k=1 to m). The time is from t to t+1, and the distance is from City i to City j.

2. Ant-Q Algorithm Model:

Ant-Q algorithm model is extended from AS algorithm model, and the key point of Ant-Q is that the ants can reduce their time of food searching according to the transmission of inter-ants' pheromones (The model has the characteristics of learning, so Ant-Q is also called Q-learning). The Ant Q in the Q-learning exactly means △AQ(r,s). On the other hand, the ants from city i to city j transmit the message of the shortest path to each other through the pheromone left. This method is called positive feedback [6].

$$s = \begin{cases} \arg \max\limits_{u \in J_k(r)} \{[AQ(r,s)]^{\alpha} * [HE(r,s)]^{\beta}\} \; if \;\; q \leq q_0 \\ P_{ij}^{k}(t) \qquad\qquad\qquad\qquad otherwise \end{cases} \qquad (2.4)$$

From the equation 2.4, when ants select the next city s, they will calculate the probability of every path and use the random value to determine which city is actually visited. △AQ(r,s)→ The pheromone of ants which is left from city r to city s; HE(r,s)→ The reciprocal of distance is from city r to city s; the value of α and β are set for the important coefficient before two parameters(△AQ(r,s) and HE(r,s)). The parameter of q_0 is the threshold, and the value is between 0 and 1($0 \leqq q_0 \leqq 1$). The parameter q is a random value, and this value is located between 0 and 1. If the value q is less or equal than q_0, the ants will select the next city based on the maximum value of $\{[AQ(r,s)]^{\alpha} * [HE(r,s)]^{\beta}\}$. How would the ants make the decision about where to go? The higher value of the result is, the more probability will this city be selected. Another, if the value q is bigger than q_0, the decision of selecting will be based on $P_{ij}^{k}(t)$. The value of $P_{ij}^{k}(t)$ is calculated from equation 2.1. Ant Q-learning provided the status (transition rule) to control the degree of convergence and exploration. In equation 2.4, if the value of q_0 is set bigger, the probability of $q \leqq q_0$ would be bigger. Then the probability that the next ant follows the previous ant's path and to generate better solution will be higher. So it will speed up the convergence, and reduce the hazard of stop. For this reason, the better solution will be gotten when the value of q_0 is set for the suitable value.

3. Ant Colony Optimization Model (ACO Model):

The algorithm of ACO is combined of the algorithms of AS and Ant-Q, and it differs from AS in three main parts: First, the experience of search which is accumulated by ants (ACO) is stronger than the usage of Ant System (AS); Second, the evaporation and deposit of pheromone tale place only on the arcs belonging to the best-so-far tour; Third, an ant uses an arc (i,j) to move from city i to j each time, and it removes some pheromone from the arc to increase the exploration of alternative paths [9]. Another, the equation 2.5 presents the ACO, and equation 2.6 describes the result of pheromone.

$$s = \begin{cases} \arg \max\limits_{u \in J_k(r)} \{[\tau_{ij}(t)] * [\eta_{ij}(t)]^{\beta}\} \; if \;\; q \le q_0 \\ P_{ij}^{k}(t) \qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \qquad (2.5)$$

$$\tau_{ij}(t)^{new} = \rho * \tau_{ij}(t)^{old} + \sum_{k=1}^{m} \Delta \tau_{ij}^{k}(t, t+1) \qquad (2.6)$$

The equation 2.5 is similar to the equation 2.4, the only difference is that the pheromone τ_{ij} is not given the weight α. The equation 2.6 means that the accumulative condition of new pheromone is based on the old one in the process of ants' finding the path. The new pheromone is equal to the remainder of old pheromone plus the total amounts of pheromone from city i to city j in the restricted time (t to t+1).

(1) The Features and Procedure of ACO

① The features of ACO [8]:

Ⅰ. The positive feedback: The positive feedback is the autocatalytic behavior .The ants can speed up transiting messages to each other through the pheromone left by other ants.

Ⅱ. The distributed calculating method: It means the model of multi-point search. We can look for a new solution in the known area, and then it can avoid premature convergence.

Ⅲ. Use the greedy algorithm: When the initial solution is generated, we can use the greedy algorithm to speed up finding out the acceptable solution. Then this method can avert from wasting time on invalid searching.

② The procedure of ACO:

We present the pseudo-code to describe the procedure of ACO [11]:

● **INITIALIZE**

○ Set the parameters and initial pheromone on each connection

● **LOOP** */* Each loop is called an <u>Iteration</u> at this level*/*

○ Each ant is positioned on a starting node

○ **LOOP (Sub-loop)** */* Each loop is called a <u>Step</u> at this level */*

⊙ Apply the <u>State Transition Rule</u> to construct the solution

⊙ Proceed the immediate <u>Local Pheromone Update Rule</u>

○ **UNTIL** all ants have built complete solutions

○ A <u>Global Pheromone Update Rule</u> is applied.

● **UNTIL** achieving the previous setting stop target

(2) The Setting of Parameters and Initial Pheromone

① The Setting of Parameters: It is so important to set the parameters, because the setting of parameters will directly impact the quality and efficiency of the solution. If we can set the suitable parameters, we can find the acceptable solution more quickly; on the contrary, if the parameters are set unsuitably, we may get the solution which is restricted in the local best solution. Furthermore, we have to decide how many ants to be selected from the ants' population and the number of iteration.

② The Setting of Initial Pheromone: The initial pheromone can be directly given a constant, and it also can be gotten via formula. Normally, the initial pheromone τ_{ij} (From city i to city j) is given a non-zero constant.

(3) State Transition Rule: The rule is constructed by the consistency of pheromone (τ_{ij}) and local heuristic function (η_{ij}). And this rule guides the ants to determine the next city to go. In order to construct the solution, we will randomly generate the numeral q ($0<q<1$) and set the constant q_0 ($0<q_0<1$). If $q \leqq q_0$, we will do the 'Exploitation' to construct the solution; otherwise, if $q>q_0$, we will do the 'Exploration' to construct the solution [7].

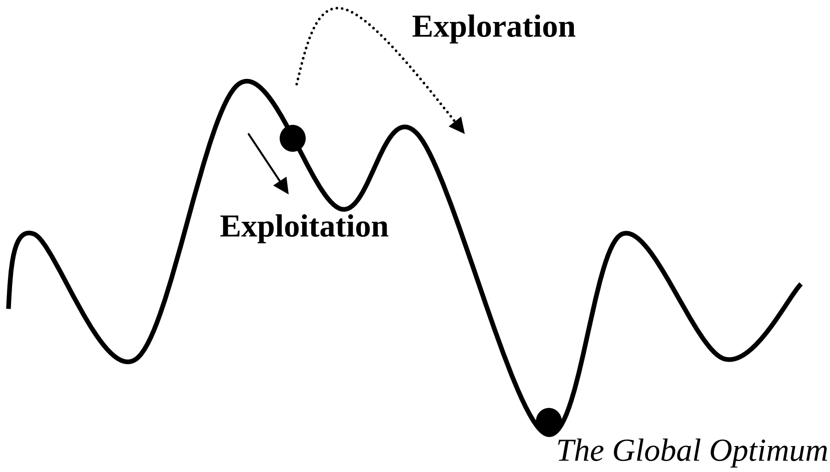

Figure 5：The concept of Exploitation and Exploration
Data Source: [12]

① Exploitation: The equation 2.7 presents the method how ants select next city:

$$v = \begin{cases} \arg\max\limits_{l \in U}[(\tau_{il})^{\alpha} * (\eta_{il})^{\beta}] & q \le q_0 \\ V & otherwise \end{cases} \quad (2.7)$$

The parameters are described in the following:

- i : The current city
- ν : The next city
- l : The candidate city
- U : The set of all candidate city
- V : Use the roulette wheel selection strategy to select the candidate city from U
- τ_{il} : The pheromone in the path (i,*l*)
- η_{il} : The visibility in the path (i,*l*). It is the inverse of distance (i,*l*)

② Exploration: The purpose is to find out the global optimum, In the process of constructing the solution, the probability of selecting the candidate city is shown in the equation 2.8: P_{iv} : The transit probability from city *i* to city *v*.

$$P_{iv} = \frac{(\tau_{iv})^{\alpha}(\eta_{iv})^{\beta}}{\sum\limits_{l \in U}(\tau_{il})^{\alpha}(\eta_{il})^{\beta}} \quad (2.8)$$

(4) Local Pheromone Update Rule: The purpose of local pheromone update rule is to reduce the value of used path, and then it makes the following ants have more

opportunity to find out the other solution. The method can achieve the effect of diversification. When ants construct the solution, the pheromone level on each edge (*i*, *j*) visited by the ant is updated in the following [7] :

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\tau_0 \quad (2.9)$$

ρ : It is the coefficient of evaporation rate between 0 and 1.

τ_0: The initial pheromone

The previous scholars provided the two models to implement the local pheromone update [4]:

① Ant Density Model: The following ants decide which the next city is according to the pheromone amounts left by the previous ants.

$$\Delta\tau_{ij}^{k}(t,t+1) = Q \quad (2.10)$$

Q: It means the pheromone left by ants from city *i* to city *j* between time t and t+1. According to the previous literatures, the Q is usually set to be a constant and the type is an integer (for example: 1, 10, and 100).

② Ant Quality Model: The following ants decide which the next city is according to the distance between cities.

$$\Delta\tau_{ij}^{k}(t,t+1) = \frac{Q}{d_{ij}} \quad (2.11)$$

Q/d_{ij}: The accumulation of pheromone / the distance of city *i* and city *j*

(5) Global Pheromone Update Rule: After all the ants construct the solution, all the pheromone in the whole system will be updated (the global update or offline update). The main purpose is to favor the best solution found by the ants by putting more pheromone on its edges. Then it leads to an intensification of the search around that solution [12]. There are a lot of methods of global pheromone update rule, and we introduce some methods for global pheromone update:

① Global-Best Update Model: We update the pheromone according to the shortest path of K_{th} ant's passing through [6].

$$\Delta AQ(r,s) = \frac{W}{L_{K_{gb}}} \quad (2.12)$$

The notation of the parameters:

W: The accumulation of pheromone

L_K: The total amount of pheromone for K_{th} left by ants.

$\frac{W}{L_{K_{gb}}}$: The pheromone of K_{th} left by ants from city r to city s.

② The Elitist Ants Update Model: The update rule is according to the pheromone left by elite ants [2].

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\Delta\tau_{ij}^{e} \quad (2.13)$$

$\Delta\tau_{ij}^{e}$: The elite ants leave the pheromone between city *i* and city *j*.

Another, the equation 2.14 shows: $\Delta\tau_{ij}^{e}$ = the amount of elite ants * the accumulation of pheromone / the total amount of pheromone left by elite ants.

$$\Delta\tau_{ij}^{e} = \sigma * \frac{Q}{L^{e}} \quad (2.14)$$

③ The Max-Min Update Model: The model is used to set up the minimal and maximal value for the pheromone left by ants, and the purpose is to avoid the early stagnation or early convergence (The more pheromone will make the early stagnation situation; The less pheromone will make the early convergence) [21].

$$\tau_{ij}(t+1) => \tau_{\min} \le \tau_{ij}(t+1) \le \tau_{Max} \quad (2.15)$$

$\tau_{\min}$: Set the pheromone to be a lower bound: if the pheromone is less or equal to the lower bound between time t and t+1, the τ_{ij} will equal to the lower bound.

τ_{Max} : Set the pheromone to be an upper bound: if the pheromone is more or equal to the upper bound between time t and t+1, the τ_{ij} will equal to the upper bound.

Chapter 3 Model Design and ACO Algorithm

There are two parts in this chapter: build the model of selecting training courses and construct the ACO algorithm. The model is defined as the training courses design, selecting courses objective function, and restriction. We develop the ACO algorithm, including defining the parameters, stating transition rule, and updating the pheromone which are based on the training model and the theory of ACO (Ant Colony Optimization). The conceptual structure of proposed model and ACO algorithm is shown in figure 6.

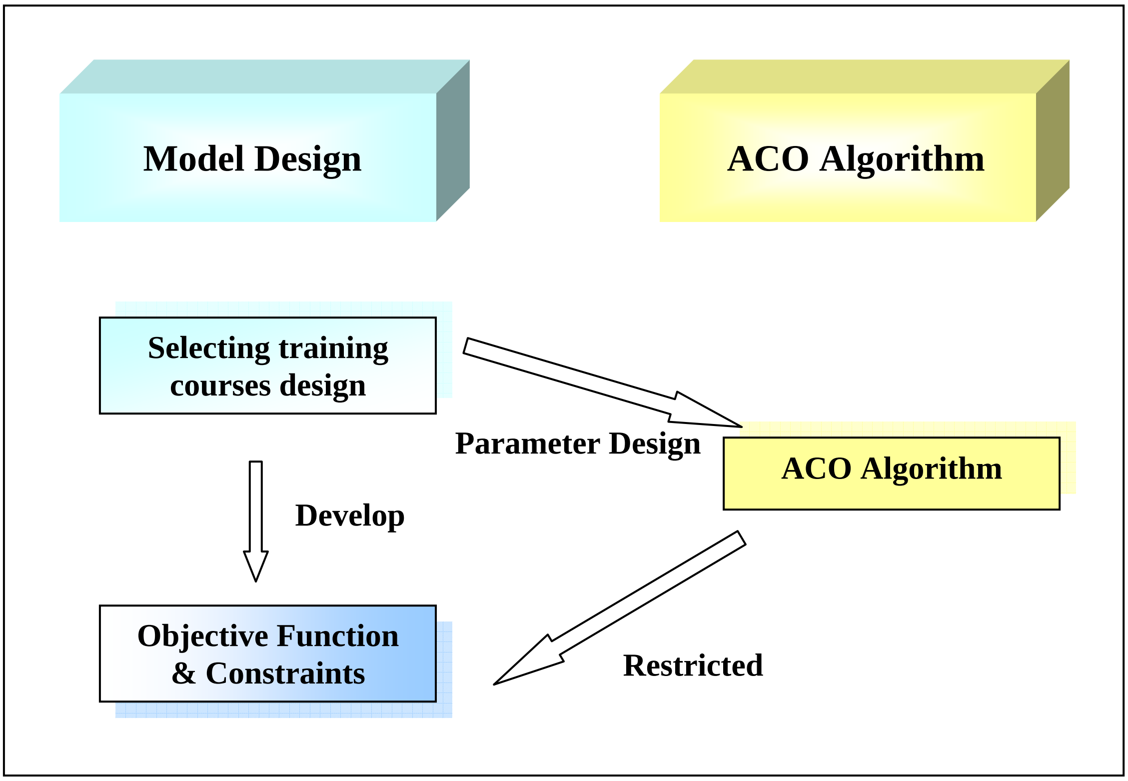

Figure 6：The concept design structure of this chapter
Data Source: This Research

3.1 Model Design

3.1.1 Design of Training Course Planning

Although many scholars provided different training models, the process of designing training courses and arranging training courses is essential. We adopt the Goldstein’s training process model to design and plan training courses. From the concept of ‘Requirement Phase’ to ‘Training Development Phase’, we are according as certain company’s training model to select and design the training courses. There are many training courses delivered by this company based on the ‘requirement phase’ (Organization Analysis, Task and KSA Analysis, and Personnel Analysis), but we select only 25 training courses in this thesis for the sake of simply research. Although the company provides a lot of training courses for its employees, it is impossible for employees to attend all of the training courses. It should achieve the company’s defined training objective and be restricted some constraints (It will be described in 3.1.2). Furthermore, each training course has its properties, and we will list these properties of the selected training courses in the table 1.

Table 1: The selected training courses and properties

No.	Course Text	Dimension	Hours	Cost	Utility
G1	Conflict Management	General knowledge course(1)	6	8	400
G2	Network Overview	MIS(2)	4	7	600
G3	Financial Management	Finance(3)	5	6	800
G4	Management Strategy	Management(4)	6	5	400
G5	TQM	Industrial Management(5)	8	9	600
G6	Communication Skill	General knowledge course(1)	9	10	700
G7	Electronic Commerce	MIS(2)	3	5	800
G8	Investment	Finance(3)	7	4	200
G9	Performance Interview	Management(4)	10	8	700
G10	Six Sigma	Industrial Management(5)	5	6	600
G11	Relationship	General knowledge course(1)	6	5	500
G12	KM	MIS(2)	9	7	900
G13	Financial Statement	Finance(3)	4	6	400
G14	Leadership	Management(4)	8	8	500
G15	Operation Research	Industrial Management(5)	10	7	700
G16	Negotiation Skill	General knowledge course(1)	3	4	200
G17	ERP Concept	MIS(2)	7	9	900
G18	Financial Accounting	Finance(3)	8	4	300
G19	Project Management	Management(4)	9	9	1000
G20	Industry Safety	Industrial Management(5)	5	10	1000
G21	Presentation Skill	General knowledge course(1)	6	7	500

G22	MS Office	MIS(2)	4	6	600
G23	Stock Option	Finance(3)	8	6	700
G24	Business Strategy	Management(4)	9	5	600
G25	Scheduling	Industrial Management(5)	8	9	900

Data Source: This Research

3.1.2 Objective Function and Constraints

According to the training courses designed and the corporate training strategy, we can build the objective function and constraints for the employees to select their training courses.

1. Objective Function：

$$Max \sum_{i=1}^{n} U_i * \frac{1}{C_i} * \frac{1}{H_i} * G_i \quad (3.1)$$

The notation of parameters:

U_i ： The coefficient of the utility of the training course (The value is evaluated by training administrators)

C_i ： The costs of training course (10 Thousand Dollars) [Because the objective function is set to get the maximum, the training cost will be set inverse value C^{-1}]

H_i ： The time of training course (hours) [Because the objective function is set to get the maximum, the training time will be set inverse value H^{-1}]

G_i ： The Course is selected or not (1: Selected; 0: not selected)

2. Constraints:

(1) The limitation of employee's training time (The company sets the training time under 50 hours for each employee)

$$\sum_{i=1}^{n} H_i * G_i \le Max\,T \quad (3.2)$$

The notation of parameters:

Max T：The upper bound of employee's training time (50 Hours)

(2) The limitation of employee's training cost (The company sets the training cost under 45 (10 thousands dollars) for each employee.

$$\sum_{i=1}^{n} C_i * G_i \leq Max\ M \quad (3.3)$$

The notation of parameters:

Max M：The upper bound of employee's training cost (45 [10 thousands dollars])

(3) The lower bound of course dimensions D≧ 3 （To avoid the employee concentrating on only one or two dimensions）

$$Min\ DI \leq Total\ \ N\ of\ \ D_i \quad (3.4)$$

The notation of parameters:

Min DI: The lower bound of course domains (3 dimensions)

D_i ：Category of domains

Total N of D_i: The total numbers of selected domain

3.2 ACO Algorithm

3.2.1 ACO Design Concept for Selecting Training Courses

According to the previous literatures, we can find out the ACO can solve many kinds of problems, like Traveling Salesman Problem (TSP), Scheduling Problem, Vehicle Routing Problem (VRP), and Quadratic Assignment Problem (QAP). In this thesis, we will imitate the method of ACO algorithm to solve the Traveling Salesman Problem. In the following figure, we will compare the concept of TSP and selecting training courses.

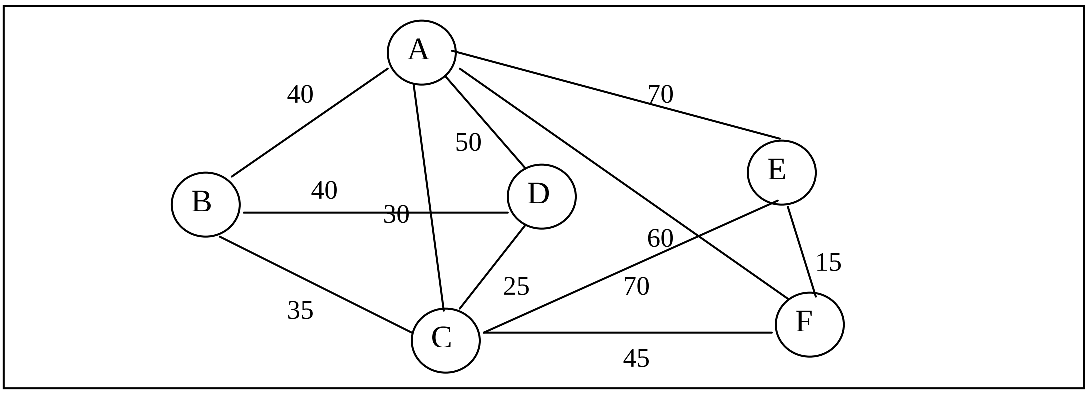

Figure 7：The Diagram of TSP
Data Source: This Research

In Traveling Salesman Problem, salesman starts from point A and visit the neighbor point by the shortest distance. After ants' visiting all these points (without repeating visiting the same point), the salesman finally comes back to the start point A. This model is to seek for the shortest distance of visiting all points. It emphasizes the total shortest distances (the key point is the distance between neighbor points) and all points have to be selected without repetition. In our research, we will imitate the TSP solution, but there are some differences between TSP and selecting training course: (1) we don't care the relation of the neighbor point, and we set the score (Utility*1/Cost*1/Time) in each point; (2) we don't need all courses to be selected. The following chart will show the concept of selecting training courses.

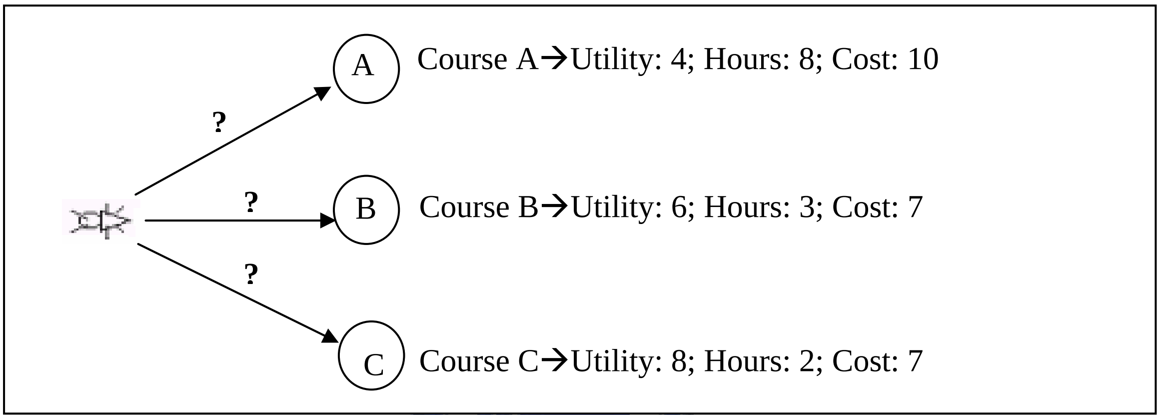

Figure 8：The Diagram for the concept of selecting training courses
Data Source: This Research

3.2.2 Procedure of ACO for Selecting Training Courses

According to the description of pseudo-code of ACO in the literature review, we develop the procedure of ACO for Selecting Training Courses. The flow chart of ACO is shown in the following figure.

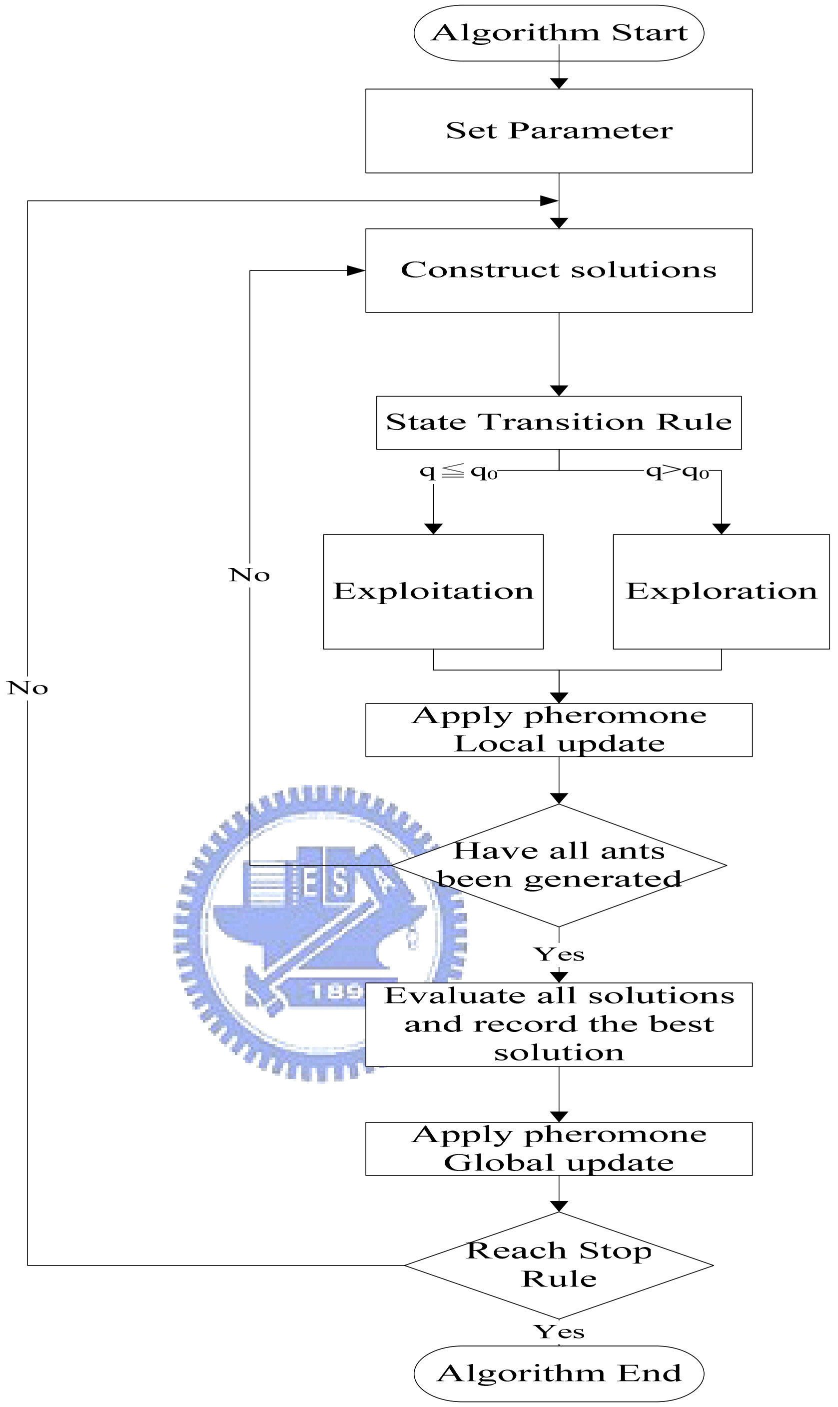

Figure 9：The Procedure of ACO for Selecting Training Courses
Data Source: This Research

3.2.3 Algorithm of ACO for Selecting Training Courses

According to the description of literature review, there are some components we have to define first: Setting the parameters, stating transition rule, local pheromone update rule, and global update rule. We will introduce them in the following:

1. Setting the Parameters:

(1) The initial Pheromone (τ_0): When each ant starts the search, it exist the pheromone on the selected courses. In previous literature, it is usually a constant value or an emphasized coefficient. In this thesis, we apply the method of emphasized coefficient to set our initial pheromone because it can reduce the bias of subjective judgment, and it also can increase the weight of influence for our concerned key factors. In this thesis, the most important factors are the utility and cost of training courses. The initial Pheromone value is based on the following equation

$$\tau_0 = \frac{\sum_{i=1}^{nodes} \left(\frac{Utility_i}{Cost_i} \right)}{(The\ \ Number\ \ of\ \ Nodes\ \ * 10)} \qquad (3.5)$$

(2) The amount of ants (ants): Because the amount of ants will impact the quality and performance, we will refer the previous research to set the suitable amount of ants (40 ants).

(3) Parameters (α, β): α → Determine the relative influence of the pheromone trail; β → Determine the relative influence of the heuristic information. If the parameters are set suitably, we can get the ideal solution faster. In the other hand, if we don't set the right parameters, we will involve the local best solution instead of the really ideal solution. According to the previous experience of other research, we apply α value =1 and β value = 2.

(4) The coefficient of pheromone evaporation (ρ): The value is located between 0 and 1, and we will set the value to 0.1 in our research.

2. Construct Solutions

Before running the Stating Transition Rule, we have to eliminate the courses which are beyond the restrictions in every iteration. The purpose is to ensure the following candidate courses are under our defined policy, and then we won't waste a lot of time to generate solutions having no effect. The selecting courses have to fit the equation 3.1, 3.2, and 3.3.

3. Stating Transition Rule:

In this rule, we have to define the critical value q_0 to differentiate between 'Exploration Rule' and 'Exploitation Rule'. In this research, we set the value to be 0.9.

(1) Exploitation Rule: In this research, we will define the strategy of selecting the next courses:

$$\nu = \begin{cases} \arg\max_{l \in U} [(\tau_l)^{\alpha} * (\eta_l)^{\beta}] & q \le q_0 \\ V & otherwise \end{cases} \quad (3.6)$$

The notations of parameters are described in the following:

l: The candidate course (The course hasn't been selected)

U: The set of all candidate courses

ν : The next selecting course

V: Use the roulette wheel selection strategy to select the candidate course from U

τ_l: The pheromone value of course l. The value is: $U_l * \frac{1}{C_l}$

η_l: The value of predefined objective function $U_l * \frac{1}{C_l} * \frac{1}{H_l}$

(2) Exploration Rule: If the random generated value q is bigger than q_0, the transit probability of selecting course l is shown in the equation 3.7.

$$P_l = \frac{(\tau_l)^{\alpha} (\eta_l)^{\beta}}{\sum_{l \in U} (\tau_l)^{\alpha} (\eta_l)^{\beta}} \quad (3.7)$$

For example, there remains three allowed courses [U: The set of all candidate courses] (8, 9, 10) that we can select them in the next run. Then each probability is in the following equation:

$$P_8 = \frac{(\frac{200}{4*10})^1 (\frac{200}{7*4})^2}{(\frac{200}{4*10})^1 (\frac{200}{7*4})^2 + (\frac{700}{8*10})^1 (\frac{700}{10*8})^2 + (\frac{600}{5*10})^1 (\frac{600}{5*6})^2} = 0.097 \quad (3.8)$$

$$P_9 = \frac{(\frac{700}{8*10})^1 (\frac{700}{10*8})^2}{(\frac{200}{4*10})^1 (\frac{200}{7*4})^2 + (\frac{700}{8*10})^1 (\frac{700}{10*8})^2 + (\frac{600}{5*10})^1 (\frac{600}{5*6})^2} = 0.145 \quad (3.9)$$

$$P_{10} = \frac{(\frac{600}{5*10})^1 (\frac{600}{5*6})^2}{(\frac{200}{4*10})^1 (\frac{200}{7*4})^2 + (\frac{700}{8*10})^1 (\frac{700}{10*8})^2 + (\frac{600}{5*10})^1 (\frac{600}{5*6})^2} = 0.758 \quad (3.10)$$

According to the roulette wheel selection strategy, we can generate the random value (between 0 and 1) to decide which course we can select in this run. The concept is shown in the figure11. So if the random value is located in [0, 0.097], the course 8 will be selected; if the random value is located in [0.097, 0.242], the course 9 will be selected; if the random value is located in [0.242, 1.000], the course 10 will be selected.

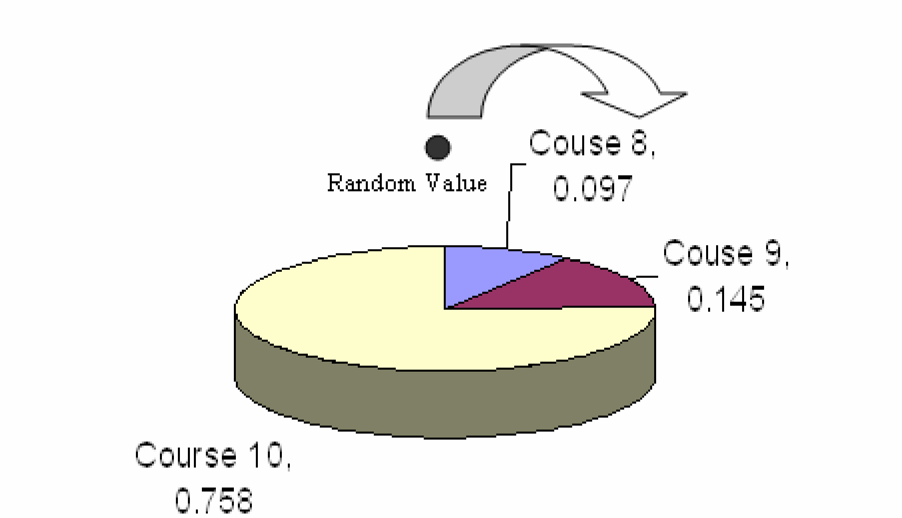

Figure 10：The Concept of Roulette Wheel Selection Strategy
Data Source: This Research

4. Local Pheromone Update Rule:

The purpose of local pheromone update is to improve the opportunity of finding another solution. In this research, we also apply this method to find out another acceptable solution.

$$\tau_l^{new} = (1-\rho)\tau_l^{old} + \rho\tau_0 \quad (3.11)$$

ρ : It is the coefficient of evaporation rate between 0 and 1. In this thesis, we set the value is 0.1.

τ_0 : The initial pheromone

τ_l^{new} : The updated pheromone in the local update rule

5. Global Pheromone Update Rule:

According to the literature review, there are many global pheromone update methods. In our research, we apply the Elitist Ants Update Model to be our global pheromone update rule. We use the elite ants to get the maximal objective function value to follow the global pheromone update rule.

$$\tau_{jl}^{new} = \gamma^{e} * \tau^{e} \quad (3.12)$$

$$\gamma^{e} = \frac{\eta^{e}}{(\sum_{m=1}^{nodes} \eta / nodes)} \quad (3.13)$$

τ^{e}: The pheromone of elite ants

η^{e} : The Eta Value of elite ants = the courses are selected by elite ants (Utility / (Cost * Hours))

$(\sum_{m=1}^{nodes} \eta / nodes)$: The average Eta Value

Chapter 4 System Development

4.1 Development Tool & System Structure

4.1.1 Development Tool

We apply Java to be our development environment, because it can cross every platform (Windows, UNIX, and Linux). A lot of strengths of Java is why we determine to use it to develop our system:

1.Java has the specialty of fast, safe, and efficient development, so it can improve your efficiency of work.

2. Java can be implemented in different platforms, so it is not limited in only one environment.

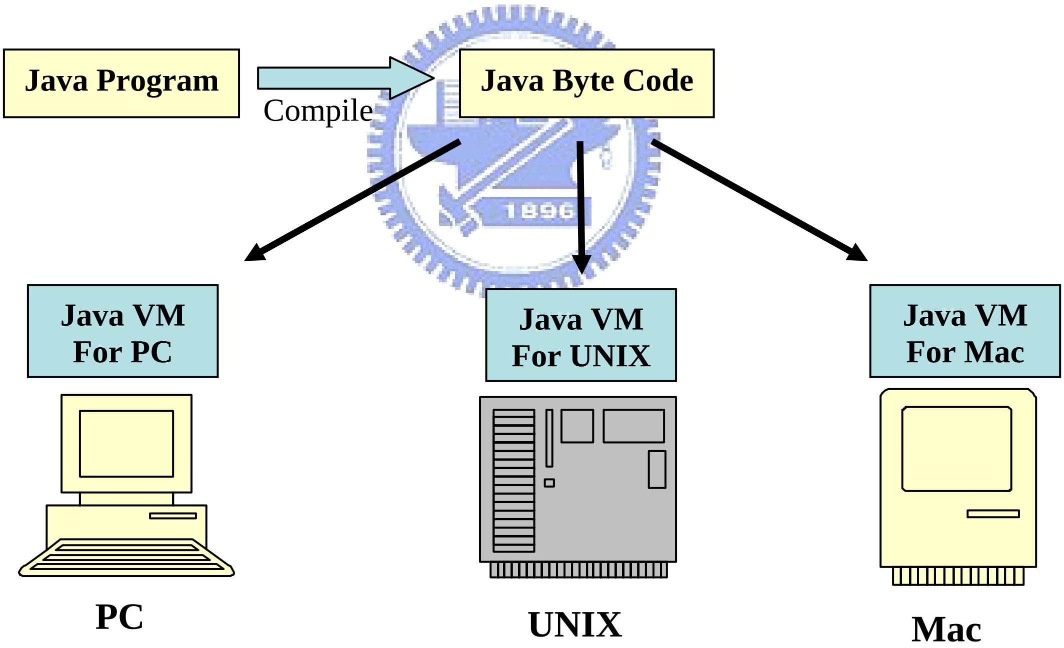

Figure 11：Java for the different platform
Data Source: This Research

3. Java possesses the property of OOP (Object-Oriented Programming), so it can be reused and be easy maintained.

4. Java can support any kinds of database (SQL, Oracle, Access), and it also supports to implement the java code in the web environment.

According to the above description, we determine to use Java program to implement our system. There are a lot of java development tools (NetBean, Eclipse, JBuilder) to edit Java programs. We use Borland JBuilder 2006 Enterprise to be our development tool, because there are some advantages for this tool: (1). It uses the two-way visional development interface, so it makes us edit java program easily; (2) It also can improve the efficient development of EJB, XML, Web Services and Database Application Program; (3) JBuilder also provides the embedded database management tool (JDataStore Explorer), and it doesn't require to use JDBC to connect the database.

4.1.2 System Structure

In this thesis, the research of ACO algorithm is our main topic. So we will focus on implementing ACO algorithm in the system design. We don't do a lot of effort to develop the UI (User Interface) and the other assistant functions. The following figure is our designed system structure.

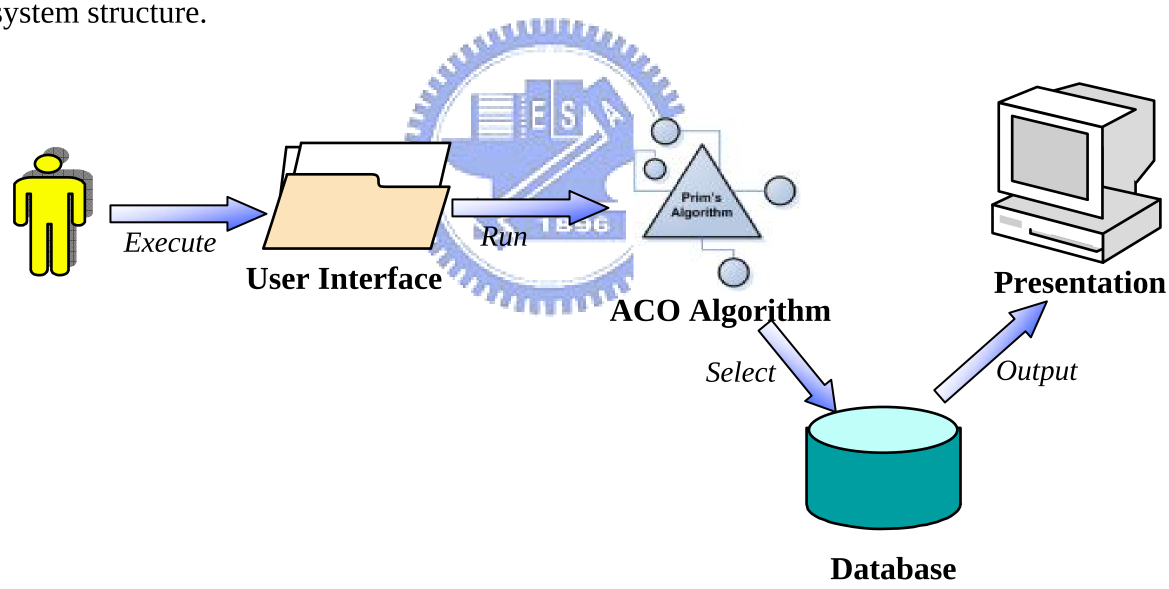

Figure 12：The System Structure
Data Source: This Research

We can execute the system via the simple user interface, and the user interface will trigger the main program of ACO algorithm (The detail ACO Algorithm will be described in next section). After running the ACO algorithm, we will get the generated results (The recommended training course numbers). The provided training course numbers are the criteria of selecting the raw records (The courses attributes: no., description, utility, costs, and hours) from the database, and then the complete recommended courses information will be presented in the screen. The designed structure of Database is shown in the following table:

Table 2: The Structure of Database

Item	Data Type	Length	Description
NUMBER	INT	3	Training Course Number
DESCRIPTION	STRING	30	Course Description
HOURS	INT	3	Training Hours
COST	INT	5	Training Costs(1000 Dollars)
UTILITY	INT	4	Training Course Utility
DIMENSION	STRING	30	Course Dimensions

Data Source: This Research

4.2 Program Design Logic of ACO Algorithm

According as the Figure 9 (the procedure of ACO for selecting training course) and the ACO mathematical model, we design the structure for the ACO algorithm of this thesis. The structure is shown in Figure 13.

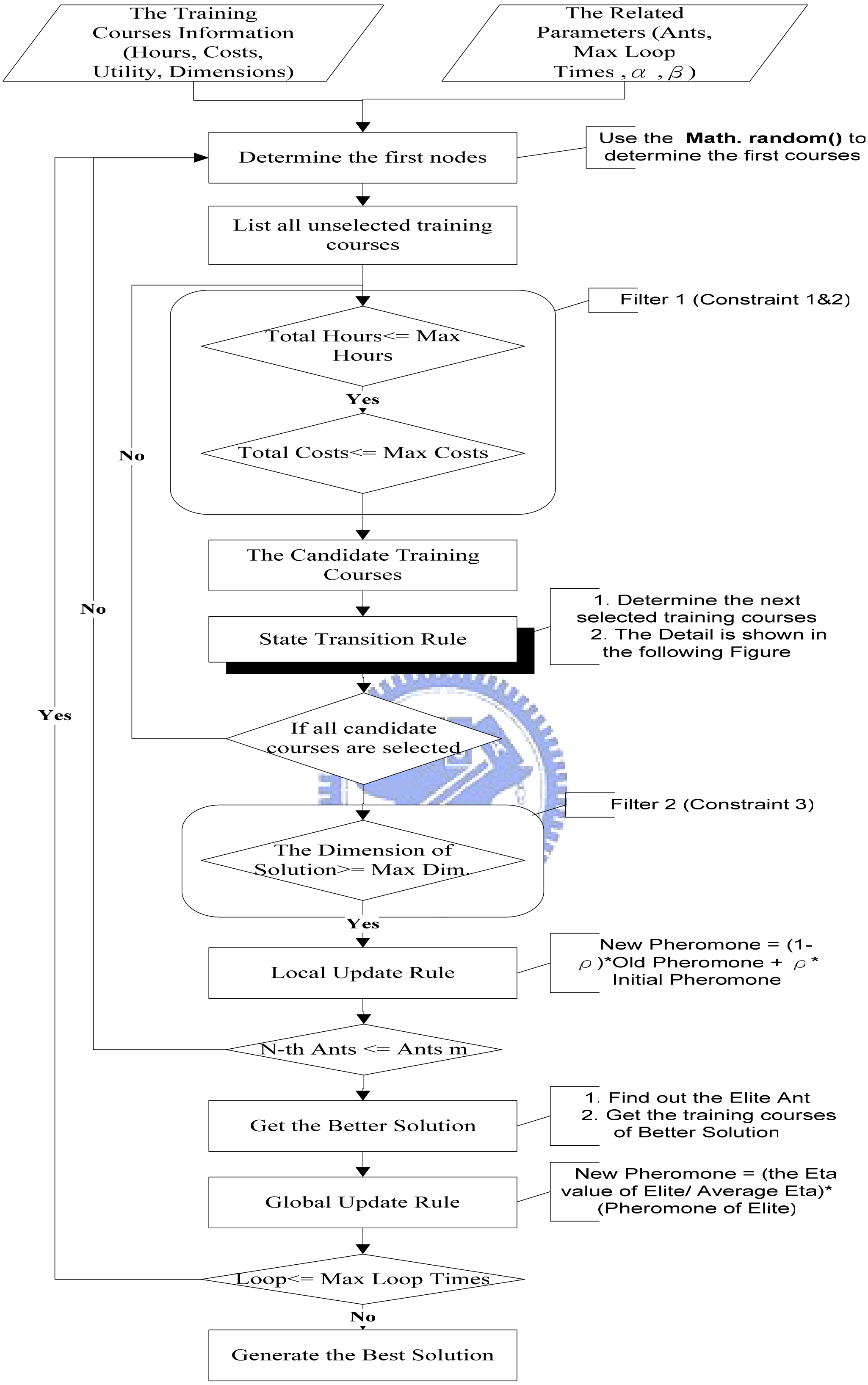

Figure 13：The Structure of Program Design Logic for ACO
Data Source: This Research

1. Training Courses Attributes and Set the Parameters:

(1) Training Courses Attributes: We use the two-dimension array (int[][] data) to store the training course attributes. The size of training courses array: The number of training courses * the number of attributes (data[training courses][attributes]). In this thesis, we set the five attributes and an additional marks in this array: training course number, training hours, training costs, training utility, training dimension, and the mark of selection (0: hasn't been selected; -1: has been selected). The examples of data are shown in the following table:

Table 3: The Examples of Data Array

Courses No. Data[i][0]	Hours Data[i][1]	Cost Data[i][2]	Utility Data[i][3]	Dimension Data[i][4]	Selected Mark Data[i][5]
1	6	8	400	1	0
2	4	7	600	2	0
3	5	6	800	3	0
4	6	5	400	4	0
5	8	9	600	5	0
6	9	10	700	1	0
7	3	5	800	2	0
8	7	4	200	3	0
9	10	8	700	4	0
10	5	6	600	5	0
11	6	5	500	1	0
12	9	7	900	2	0
13	4	6	400	3	0
14	8	8	500	4	0
15	10	7	700	5	0
16	3	4	200	1	0
17	7	9	900	2	0
18	8	4	300	3	0
19	9	9	1000	4	0
20	5	10	1000	5	0
21	6	7	500	1	0

22	4	6	600	2	0
23	8	6	700	3	0
24	9	5	600	4	0
25	8	9	900	5	0

Data Source: This Research

(2) Set the Parameters: We set some required parameters in the beginning of executing algorithm.

① The amounts of ants: int ants = 40.

② The parameters of α, β : int alpha = 1; int beta = 2.

③ The critical point of transition rule(q_0): double lambda = 0.9.

④ The evaporation of Pheromone(ρ): double rho = 0.1.

⑤ The limitation of iteration: int loop_lmt = 10.

2. Determine the first nodes: We use a random value (Nodes * Math. random () [the value is between 0 and 1]) to determine which training course we have to select it at the start point.

3. Filter 1: According to the constraint 1 and 2 (The total training hours of selected training courses are less than the maximum training hours, and the total training costs of selected training courses are less than the maximum training costs we defined).

4. State Transition Rule: There are two rules in the transition rule: One is Exploitation Rule, and another is Exploration Rule. When the random value (Math. random ()) is equal or less than q_0 (We set the value to be 0.9), we apply the exploitation; otherwise, if the random value is bigger than q_0, the exploration is applied to escape from the local best solution. It may find out the global best solution.

(1) Exploitation Rule: The next training course which will be selected is based on the maximum ν ($(\tau_l)^\alpha * (\eta_l)^\beta$). So we can ensure that more valuable training courses will be picked up in this rule.

(2) Exploration Rule: We calculate the weight of every unselected training course, and use the roulette wheel selection strategy to determine the cumulated ordering. Then we also use a random value to determine which section it is located in, and in advanced we select the training courses which are located in this section.

The procedure of exploitation and exploration is shown in the following figure:

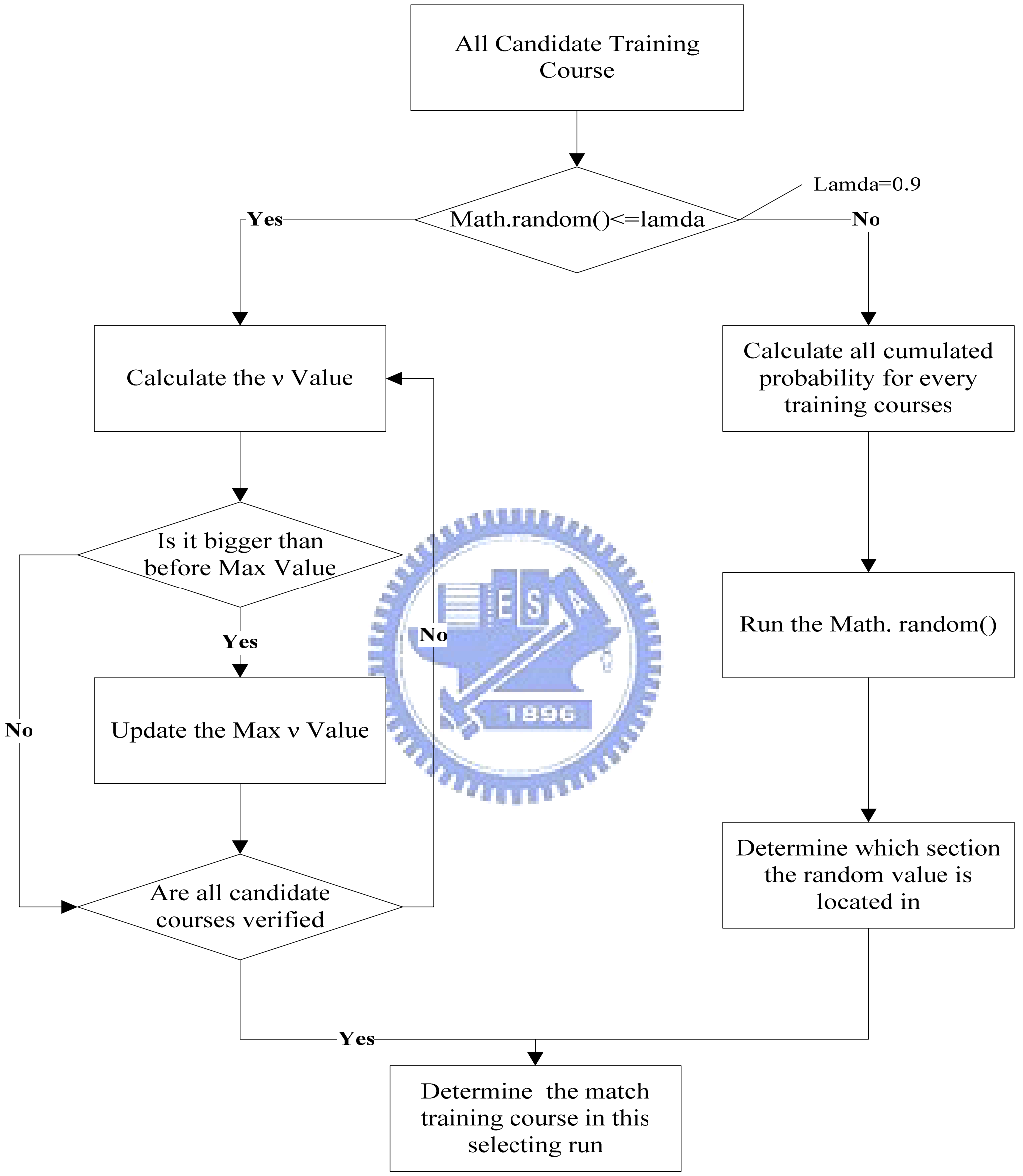

Figure 14：The Procedure of State Transition Rule
Data Source: This Research

5. Filter 2: Because the filter is based on the constraint 3 (The selected training courses have to be located in at least three dimensions), we have to determine if the solution can be accepted until at the end each ant has found the solution. If the solution found is not satisfied by this constraint, the result will be eliminated. On the other hand, if the

dimensions of selected training courses are more than or equal to three dimensions, the solution will be kept and in advance it will provide the related pheromone of the solution found to update local pheromone.

6. Local Update Pheromone: The new pheromone = (1- ρ) * the pheromone in this run + ρ * the initial pheromone.

7. Get the better solution: After all ants (we set 40 ants) process the procedure, we can get the elite ant (which can generate the maximum value of objective function) in this run. The set of training courses of the elite ant's visiting is a better solution and it contributes a better beneficial result.

8. Global Update Rule: Because we get the elite ant in the last step, we can use the pheromone of this elite ant to enhance the consistency of pheromone. The purpose is to speed up the convergence of finding solution. The new pheromone = (the η value of elite / the average of η) * the pheromone of elite ant.

9. Generate the Best Solution: After finishing the loop times (we set 10 times), compare the solutions which are provided by each elite ant. Then the best solution will be generated in the end of executing algorithm.

Chapter 5 Computational Experiments

In this chapter, we will introduce the verified method and the result of verification. We use the enumeration algorithm to verify the effect and efficiency. There are three parts in this chapter: In the first part, we will introduce the verified algorithm: Enumeration Algorithm; in the second part, we will use the data samples to execute our ACO Algorithm and generate the result; in the third part, we will provide the conclusion of these two results after comparison.

We used the sample of training courses which is listed in chapter 3 to be our contents for analyzing. We could find out the max objective function for selecting training courses (The maximum of utility/hour/cost). But the selected training courses have to follow the rules of constraints (The total hours of selected training courses <= Maximum Hours which we defined; the total costs of selected training courses <= Maximum Costs which we defined; the total dimensions of selected training courses >= 3). We use Enumeration Algorithm to verify the effect and efficiency of our ACO algorithm. Because the enumeration algorithm will visit all the solutions and get the best solution from the solution sets, we can get the best solution for our objective function. Another, even it is not efficient to find out the solution in the enumeration algorithm, the used time of ACO is much less than the spending time of that. We also can say it is not bad efficiency to find out the solution.

5.1 Results of Enumeration Algorithm

The concept of Enumeration algorithm is to list all the acceptable solutions which fit in with the constraints), then to select the maximum objective function from the list. The logic of Enumeration algorithm is shown in the following figure:

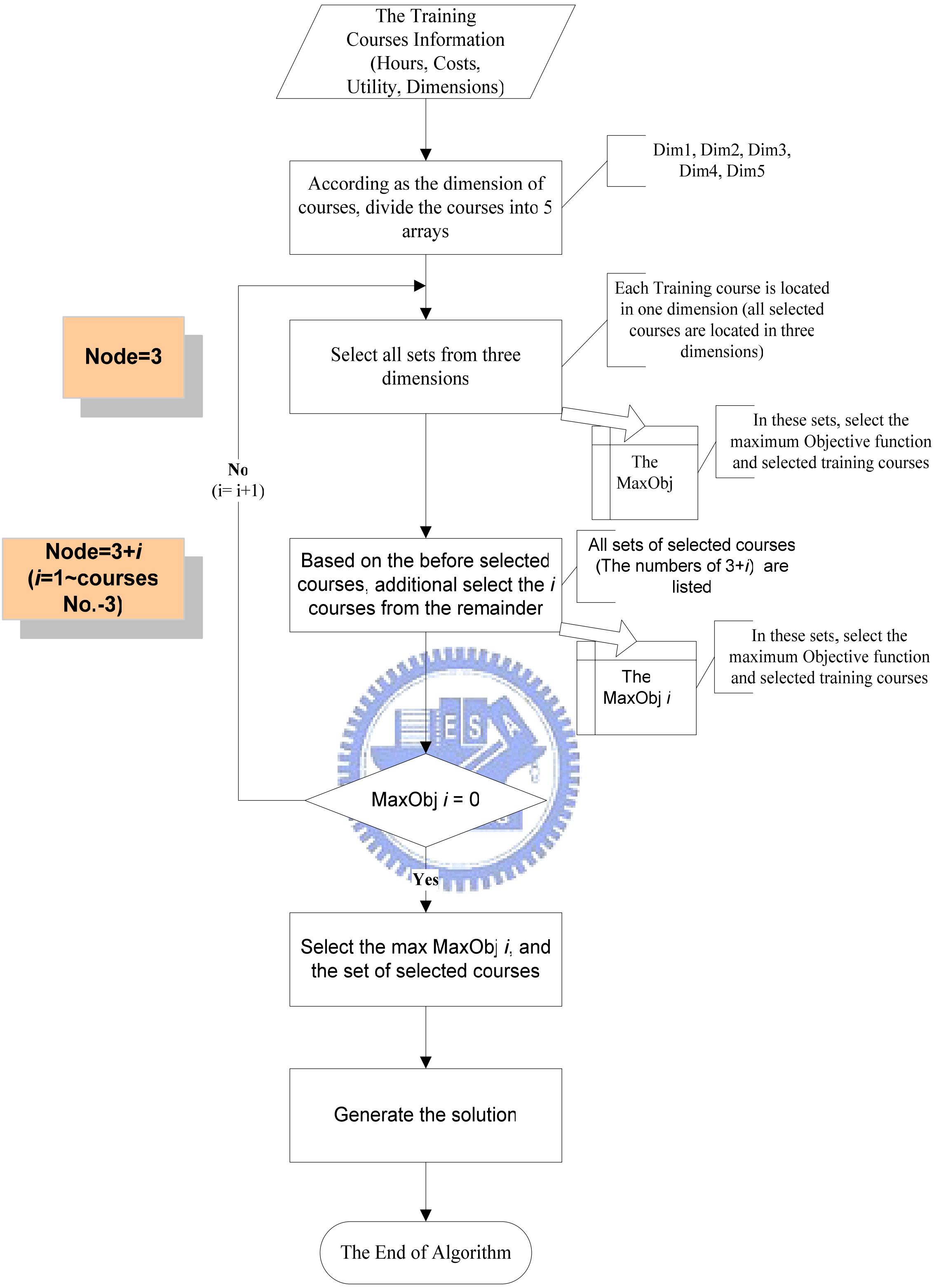

Figure 15：The Procedure of Enumeration Algorithm
Data Source: This Research

1. The training courses information: The data sources are the same as we designed for ACO Algorithm Program (In this case, we provide 25 training courses as testing sample. The

designed structure of data is also the same as we designed for ACO Algorithm Program (data [][]: course number, hours, costs, utility, dimension, and selected mark).

2. According to the dimensions, we can group the training courses into 5 types: The main purpose is to select the training courses easily from the different dimension containers.

3. Select all sets from three dimensions: Because we set this constraint that the selected training courses have to be located in minimum three dimensions, the minimum numbers of selected training courses are three, and they have to come from three different dimension containers. The numbers of possible solutions are $C_2^5 * 5 * 5 * 5 = 1250$, but the solution sets have to fit the constraints 1 and 2. While the solution sets are generated, the value of each objective function is also calculated. From these possible solutions which satisfy with the constraints 1, 2, and 3, we can compare the value of objective function and get the better solution (In this iteration, the solution has the maximum objective function.).

4. In each loop, add *i* (*i*=1 to (maximum training courses-3)) training course: According to the generated possible solutions in last step (The solution sets don't focus only on the last better solution, because the best solution is not only the set of all maximum objective function. It also has to satisfy with the constraints.), we have to add one training course in each loop. The first run in this iteration, we add one training course from the remainder containers (Excluding the selected training courses in the last step), and judge if each solution satisfy with the constraints. After this run, we can get the value of maximum objective function and better solution. When this cycle finishes, we will add the next training course. In the iteration, the numbers of selecting times are $C_2^5 * 5 * 5 * 5 * C_i^{22} = 1250 * C_i^{22} \quad i = 1\, to\, (courses - 3)$. The loop run will stop until the value of maximum objective function is 0 in the *i-th* times.

5. Compare the value of maximum objective function of each solution set, then we select the maximum one. The solution set which has the value of maximum objective function is our final solution.

The development tool is the same as our ACO algorithm. In the system simulation run, we use the Pentium M 1.6G, 1GB RAM, and Win XP to be our implementing environment.

The final results generated are in the bellow table:

Table 4: The Selected training courses of Enumeration Algorithm

Courses No.	Hours	Cost	Utility	Dimension	Objective Function
16	3	4	200	1	16
22	4	6	600	2	25
13	4	6	400	3	16
2	4	7	600	2	21
3	5	6	800	3	26
7	3	5	800	2	53
10	5	6	600	5	20
11	6	5	500	1	16
Total	**34**	**45**			**193**

Data Source: This Research

Table 5: The Performance of Enumeration Algorithm

Item	Value
Objective Function	193
Spending Time	505357 Milliseconds ≒ 505 seconds

Data Source: This Research

5.2 Results of ACO Algorithm in this thesis

In the system simulation run, we apply the same environment with the run of Enumeration algorithm. Because we maybe get different solution set in each run, we will run 8 times and list all the solutions in the following table:

Table 6: The Selected Training courses of ACO Algorithm

Times	Selected Courses List	Total Hours	Total Costs	Total Dimension	Objective Function	Spending Time *(Millisecond)*
1	16,11,2,22,10,3,7,13	34	45	4	193	130
2	16,11,10,2,22,3,7,13	34	45	4	193	90
3	16,11,10,2,13,22,7,3	34	45	4	193	70
4	16,11,10,2,22,3,7,13	34	45	4	193	80
5	16,11,10,22,3,7,2,13	34	45	4	193	70
6	16,10,13,2,22,3,7,11	34	45	4	193	80
7	16,11,10,2,22,3,7,13	34	45	4	193	80
8	16,11,10,2,22,3,7,13	34	45	4	193	80
Ave.					**193**	**85**

Data Source: This Research

5.3 Discussion

According to table 6, we can see that the recommendations are the same in each executed ACO Program. It is the stable status for finding solution, and the time spent for each run is almost the same [It is around 80 milliseconds]. It takes short time to get the solution, so the time spent can be easily accepted by the users.

Moreover, after comparing table 6 with table 5, we can find out the best solution of objective function is the same. Then we can prove the ACO algorithm can help us to find out the best solution or nearby the best solution. Furthermore, according to the time spent for these two algorithms (Enumeration Algorithm spent 505357 Milliseconds; but the ACO only uses 85 Milliseconds), Enumeration Algorithm uses 6000 times more of time than ACO algorithm does. There is huge gap between these two algorithms regarding the time they spend. The final generated best solution of ACO program is shown in the following figure, and the selected training courses can be recommended to employees as they select the training courses.

Sample Database Application

Find

	NUMBER	DESCRIPTION	HOURS	COST	UTILITY	DIMENSION
1	1	Conflict Management	6	8	400	General knowledge course
2	2	Network Overview	4	7	600	MIS
3	3	Financial Management	5	6	800	Finance
4	7	Electronic Commerce	3	5	800	MIS
5	10	Six Sigma	5	6	600	Industrial Management
6	11	Relationship	6	5	500	General knowledge course
7	16	Negotiation Skill	3	4	200	General knowledge course
8	22	MS Office	4	6	600	MIS

Figure 16：The executing result of ACO Algorithm
Data Source: This Research

Chapter 6 Conclusion and Future Work

6.1 Conclusion

It is very important for employees to continuously learn new knowledge in the world of knowledge economy, because the technology is developing in high-speed. In addition, such rapid development leads to the uncertain environment and high competition. In this challenging market, if the company wants to keep its power of competition, it has to enhance the professional knowledge and skills of employees through training courses. Accordingly, the company will deliver more and more training courses for its employees. However, there are restrictions of each employee's training time and cost. Thus, selecting the suitable training courses under the limited training hours and costs is an important issue. In this thesis, in order to help the employees do the selection, we use ACO algorithm to provide the recommendation of optimal training courses. The proposed system can assist employees to select more valuable training courses under the limited training costs and time.

We will use the following figure to describe the result of this thesis.

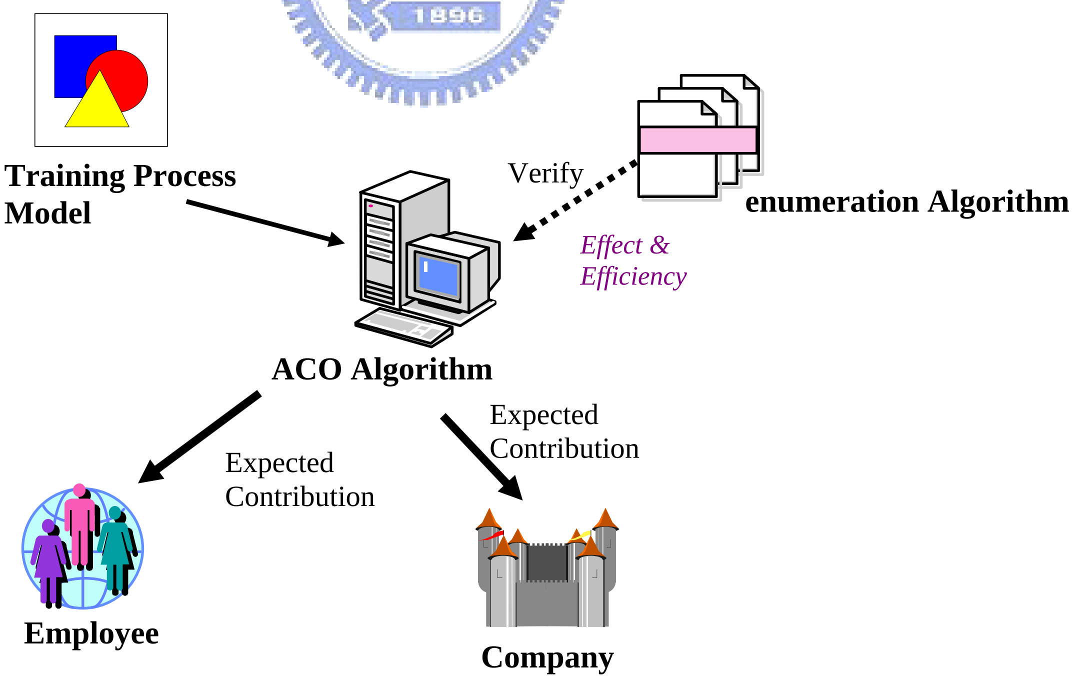

Figure 17 Result of research

1. Training Process Model: The development of selected training courses system is based on the concept of training process model. There are four key steps in Goldstein's training process model (Requirement, Training Development, Evaluation, and Review Training Object). Our system provides the reference for the selection and design of courses in the training development step.

2. ACO Algorithm:

(1) Use the ACO Algorithm to provide the solution for selecting the valuable training courses. Since the training costs and time of employees are restricted, we have to assist employees to select the worthy courses under the limitation of stipulated costs and time. In addition, the diversification of training is necessary; thus we request that the selected training courses need to belong to more than three dimensions.

(2) We used the property of ants' leaving pheromone to find out the solution, and the method can really help us to find out the solution of maximum objective function (The objective function is defined as Utility/(Costs*Hours)) in the short time.

3. The comparison - Enumeration Algorithm: Although the efficiency of Enumeration algorithm is poor, the best solution can be found out by this algorithm. So we can compare the solutions generated by these two algorithms. Our verification shows that we could get the nearly best solution via ACO Algorithm. Moreover, the running time of ACO algorithm is faster than that of Enumeration algorithm.

4. The Expected Contribution for Employees: The system can assist the employees to select the valuable training courses under the limitation of constraints (Time and Cost). On the other hand, the employees will not waste a lot of time to take the useless courses, and they can deliver the knowledge from the training courses to contribute to their tasks.

5. The Expected Contribution for Company: The generated results can help the training administrators plan future training courses. Because the results can help the administrators determine which courses are useless and which courses are valuable, they will not waste the training costs to deliver useless courses. In addition, the system can help employees select the right course and get the useful knowledge, so the employees can provide more contribution to their company.

6.2 Future Work

Because there are a few prior literatures or design for assisting employees to select the valuable training courses, we don't have the plentiful information to refer. So there are still a lot of parts that we can improve it:

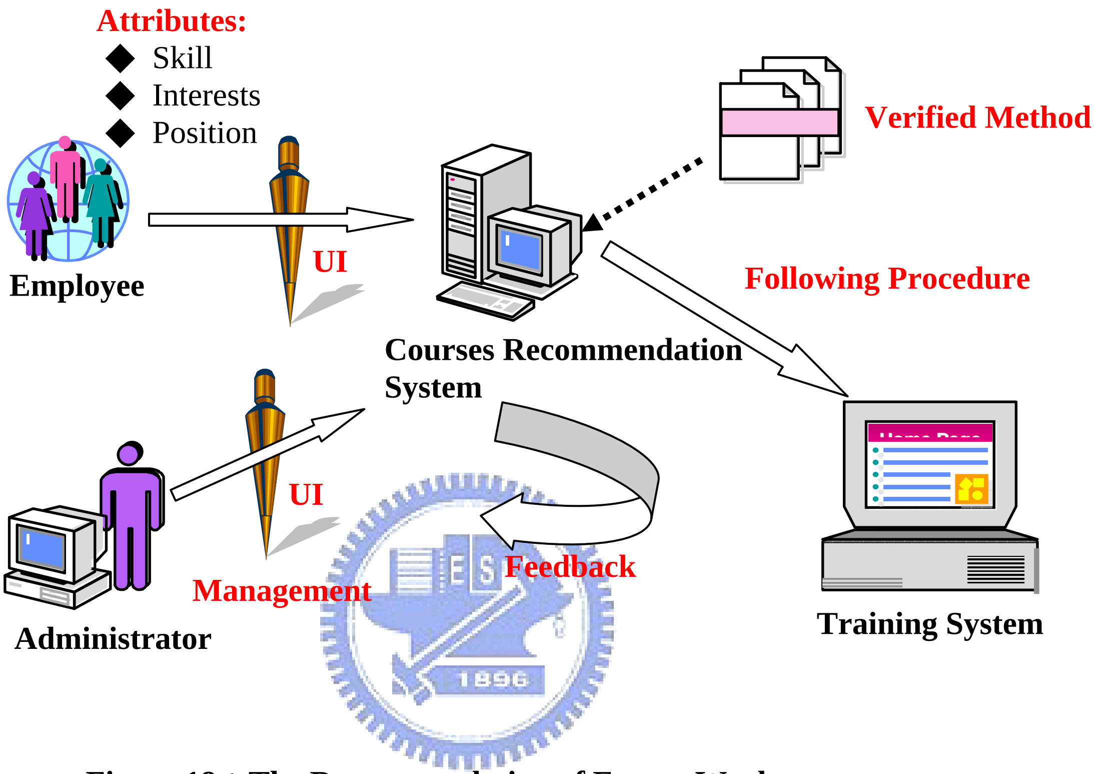

Figure 18：The Recommendation of Future Work
Data Source: This Research

1. Attributes: Because every employee has specific attribute, it is impossible to recommend the same training courses for each employee. The better design for the training system is that the recommendation can provide more suitable proposals according to the employee' attributes. There are three main attributes which we suggest to be the reference in the future system design:
    (1) Skill: Because every employee has his/her specific skills, it is not reasonable to force the employee to attend the training course which he/she knows well. For this reason, we can build the employees' skill bank first, then the recommended

training courses can exclude what the employee has already known well. Thus the recommended courses could increase the knowledge of the employee.

(2) Interests: We can design the parameters for the employee's interests, and set the weights for each dimension or course. Then the recommended courses will trend to the heavy weights of employees' setting. It means the selected courses will fit the trainee's expectation more.

(3) Position: Different positions need different skills or knowledge, so the employee will need some required courses for what he/she lacks while he/she is occupying certain position. For the purpose, we can do the job analysis first, then we can define the required skill or knowledge of each position. Furthermore, we can compare the employee's skill bank and the result of job analysis, so we can find out the skill gap for each employee. The recommended courses system can provide the employee's necessary courses according to above information.

2. Management: In this thesis, we don't do the effort to construct the managing function for this system, because it is not the main topic for this research. But the complete system design will include the management function. So we recommend the future work to add the management function which can allow the administrators to set the parameters, to increase or modify the training courses in the database, and to modify the weights. This will strengthen the effectiveness of system.

3. UI (User Interface): In this thesis, we don't develop the user interface for the employees and administrator, because we focus on the main point in ACO algorithm. It is the insufficient part for our design, because the user interface is very important for the development of system. So we give this recommendation and expect it can be improved in next system design.

4. Verified Method: In this thesis, we use Enumeration algorithm to do our verification. But Enumeration algorithm can only prove if the effect is good or not. Regarding the efficiency: Enumeration algorithm is not a useful method for comparison, because it works inefficiently. So if we want to prove the efficiency of our designed algorithm, we have to use a more efficient algorithm (for example: Genetic Algorithm [GA]) to do the verification of efficiency.

5. Following Procedure: After recommending the training courses, if we can link the training system to book the training courses, it will be more convenient for the employees. The employees can use the single way to book the training courses or get all information of training courses, and they don't need to operate another system. Furthermore, if E-Learning is embedded in the training system, the employees can directly conduct the training via internet or intranet.

6. Feedback: The generated results of recommended training courses can provide the reference for the planning of next training courses. The planning will be improved in every feedback run, and it will retain the more useful courses and eliminate the useless courses. Then it will not only reduce the ineffective training costs and hours, but also increase the competition of company.

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