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NEGOTIATION-BASED CAPACITY PLANNING WITH A LEARNING MECHANISM USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

In decentralized manufacturing environment with multiple factories that are scattered geographically, the complexity of production systems increases, and capacity planning and allocation of resources have become a significant concern that affects system performances. This study focuses on the development of an integrated framework to allocate limited budget in a multiple-factory environment. We develop a negotiation framework with learning mechanism to allocate autonomously finite budget provided by a headquarter and to facilitate the use of limited manufacturing resources that are scattered over individual factories. The outcome of the experiments shows good prediction of the opponent offers during negotiation, so it enables the reduction of negotiation time.

Keyword: Automated negotiation, capacity planning, learning mechanism, negotiation decision function

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CHAPTER 1
INTRODUCTION

Introduction chapter explains about research background, research objectives and procedure, benefits, research limitations, assumptions, and research outline.

1.1 Research Background and Motivation

Recently, there are more and more impacts of information technologies on the material processes in collaborative supply network. That is why it becomes a timely and crucial topic to consider supply networks as collaborative cyber-physical systems (Sokolov and Ivanov, 2015). Cyber-physical systems are characterized by decentralization and autonomous behavior of their elements. They incorporate elements from both information and material (physical) subsystems and processes (Zhuge, 2011). Most of the new factory concepts and supply networks on the cyber-physical principles share attributes of smart networking (Ivanov, Sokolov, and Kaeschel, 2010). Therefore, smart factories Industry 4.0 on the basis of collaborative cyber-physical systems represent a future form of industrial networks.

Industry 4.0 represents a smart manufacturing networking concept where machines and products interact with each other without human control. By this concern, the automated systems that able to provide the interactions, such like negotiations among several parties, is highly required to maintain the processes.

In decentralized manufacturing environment, the complexity of production systems increases, and capacity planning and allocation of resources have become a significant concern that affects system performances. However, profit-oriented attitudes make individual factory planners to acquire maximal resources from their headquarters by taking advantage of peer factories.

Imbalances in budget allocation will harm the overall performance of a firm. Thus, autonomous negotiation process among factories for the best budget and resource allocation is highly imperative.

1.2 Research Objectives

This study focus on the development of a negotiation framework with learning mechanism to allocate autonomously finite budget provided by a headquarters and to facilitate the use of limited manufacturing resources that are scattered over individual factories. A negotiation model is designed in the study to negotiate the budget allocation among factories. Motivated by the potential profits, an agent representing a factory exchanges a series of messages with other agents so that an appropriate local resources portfolio under market demand finally can be set. After receiving a budget allocation plan (i.e., an "offer") from its counterpart agent, an agent evaluates the influence of the plan based on the local capacity model and responses an offer. A Negotiation Decision Function (NDF) mechanism is employed herein to mimic the negotiation attitudes of a factory. The negotiation is ended either a deal is obtained or the time limit is reached.

1.3 Research Procedure

This research firstly try to determine the optimal resource portfolio plan for each local factory, and also determine the optimal allocation of tasks that specifies the optimal quantity of products produced in each time bucket. Next, after each factory able to get best profit for their local capacity planning model, they can use the model to evaluate the offer values from opponent during negotiation, so they can develop a mutually acceptable budget allocation plan for factories under an information asymmetry environment. Finally, from the experience of the negotiation result, a factory can use learning mechanism to predict the opponent next offer in negotiation.

1.4 Benefits

The benefits of this research are as follows :

- Provide recommendations about optimal capacity planning that will give best profit for factories that join negotiation.
- Understanding the predition of the next opponent offer during negotiation, so it will enable each factory to fasten their negotiation.
- To make new contribution on implementing a learning mechanism in the area of automated negotiation.

1.5 Research Limitations

As for some of the limitations as the scope for doing this research are:

a. There are only two parties who become participants of the negotiation.
b. The negotiation only consider one specific issue that become offering value between participants.

1.6 Assumptions

The Assumptions will be added at the model development stage.

1.7 Research Outline

As an outline, the systematic writing of this study is as follows :

CHAPTER 1 INTRODUCTION

This chapter gives a brief description about the content of the research. Specify research background, research objectives and procedure, research benefits, research limitations and assumptions, as well as the systematic writing for the final report.

CHAPTER 2 LITERATURE REVIEW

This chapter describes about the general description of literature relating to previous research as a references. The literature survey is regarding automated negotiation, negotiation decision function, and capacity planning.

CHAPTER 3 MATHEMATICAL MODEL AND METHOD

Chapter 3 describes the negotiation model among factories, local capacity planning model that is used by each factory to evaluate opponent offer during negotiation, and learning mechanism used for predicting the next opponent offer.

CHAPTER 4 NUMERICAL EXPERIMENTS

This chapter shows parameter setting and experiment results of the capacity planning model and implementation of the learning mechanism in the negotiation.

CHAPTER 5 CONCLUSIONS

This chapter explains the conclusions of the study along with the recommendations for the future study.

CHAPTER 2
LITERATURE REVIEW

Chapter 2 explains a review regarding research literatures in corresponding area. With literature review, this study can be justified scientifically.

2.1 Automated Negotiation with Learning Mechanism

Automated negotiation is a very challenging research field that is gaining momentum in the e-business domain. It is the process by which group of actors communicate with one another aiming to reach to a mutually acceptable agreement on some matter, where at least one of the actors is an autonomous software agent. There are three main categories of automated negotiations, classified according to the participating agent cardinality and the nature of their interaction (Jennings et al., 2001): the bilateral, where each agent negotiates with a single opponent, the multi-lateral which involves many providers and clients in an auction-like framework and the argumentation/persuasion-based models where the involving parties use more sophisticated arguments to establish an agreement.

In all these automated negotiation domains, several research efforts have focused on predicting the behavior of negotiating agents. This work can be classified in two main categories. The first is based on techniques that require strong a-priori knowledge concerning the behavior of the opponent agent in previous negotiation threads. The second uses learning mechanisms that perform well in single-instance negotiations. One quite popular tool that can support the latter case is Neural Networks.

In (Rau et al., 2006), the authors studied the negotiation process between a shipper and a forwarder using a learning-based approach, which employed a feedforward back-propagation neural network with two input data models and the negotiation decision functions. Issues of the negotiation were the shipping price, delay penalty, due date, and shipping quantity. (Papaioannou et al., 2006) designed and evaluated several single-issue bilateral negotiation approaches, where the Client agent is enhanced with Neural Networks. They compared the performance of MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function) Neural Networks towards the prediction of the Provider's offers at the last round.

Lee and Yang (2009) use Neural Networks approach in supplier selection negotiation process for forecasting the supplier's bid price. They include non-offer information such as inventory level, scheduled production plan, surplus capacity, and also offer information such as order quantity and due date as inputs for the Neural Networks predictive model. (Papaioannou et al., 2010) use Neural Networks that provide the means so that the agents can early detect the cases where agreements during negotiation are not achievable, thus supporting agent's decision to withdraw or not from the negotiation threads. (Tseng, 2012) also use Neural Networks as learning mechanism in distributed negotiation between planning sector and production sector in a factory of TFT-LCD Panel Manufacturing firm. However, this study will adopt adaptive Neural Networks based on Fuzzy Inference Systems as learning mechanism and try to implement it in automated negotiation between factories.

2.2 Negotiation Decision Functions

Multiple-agents negotiation by negotiation-decision-function (NDF) first proposed by Faratin et al. (1998), which are derived from bilateral negotiation functions, has showed a promising applications in intelligent, collaborative production control systems (Shen & Norrie, 1999; Parunak, 2000). Conventional negotiation models based on disclosure of information among agents (such as game theory) is limited to several real applications, but NDF-based negotiation is characterized by its autonomous (private) behavior, consideration of timing, and issues, and thus can be applied to numerous real world application domains, such as industry production planning and control. In addition, it provides a solid basis to build an incentive mechanism in which agents use certain negotiation parameters to achieve socially desirable outcomes.

Wang and Chou (2004) investigate the properties of the NDF mechanism in an agent-based system. In Lin (2009) NDF-based negotiation can generate a mutual acceptable capacity plan via the negotiation among planning and production sectors in TFT-LCD industry, and in Wang and Wang (2012) NDF-based negotiation is firstly been used to deals with the conflicts among multiple factories about capacity planning. This study will adopt this type of negotiation mechanism and also implement it in capacity planning model that have been used by each factory to evaluate the budget allocation offers during negotiation.

2.3 Solving Stochastic Capacity Planning Problem using Genetic Algorithm (GA)

Stochastic resource planning and capacity allocation deals with the problem of how to find an optimal resource portfolio under uncertain demands. Such a portfolio planning has been explored in high-tech manufacturing industries due to intensive capital and technology involvement as well as risky market demands and short product/equipment life cycle (Neslihan, 2002).

Soft computing methodology has been employed increasingly in solving local resource-planning problems, as compared with conventional linear and mixed linear programming. Holland (1975) first proposed a simple Genetic Algorithm (GA). Major concerns for using GA include when a GA methodology should be used, the representation of a chromosome structure and the design of an initial population, population size, selection probabilities, genetic operators, and termination conditions. Numerous studies have surveyed GA and can found in (Mitsuo & Runwei, 2000).

Wang and Lin (2002) addressed a capacity expansion and allocation problem for a high-tech manufacturing with a constrained budget using GA. Wang and Hou (2003) also solved the problem of capacity expansion and allocation in the semiconductor testing industry using GA. Pongcharoen et al. (2004) proposed a GA based scheduling tool that token into account multiple-resources constraints and multiple-levels of product structure. Other notable research on the applications of GA in production and operations management have also been reviewed by Chaundry and Luo (2005). This study uses GA to solve individual factory capacity-planning model proposed by Wang et al. (2008), with the addition of a budget constraint, to evaluate the potential benefit of a received offer.

CHAPTER 3
MATHEMATICAL MODEL AND METHOD

This chapter explains about model development starting from description of the negotiation model among factories, local capacity planning model that is used by each factory to evaluate opponent offer during negotiation, and learning mechanism used for predicting the next opponent offer.

3.1 Problem Formulation

3.1.1 Negotiation Model for Resource Planning among Factories

Budget allocation becomes major negotiable issue among factories since they are profit-centered agents. Having local demand information, they intend to maximize local profits given the resources are limited by finite budget provided by the headquarters.

In the model, we allow each agent/factory to propose budget usage plans as offers to its opponents. The negotiation attitude of a factory is represented by an NDF mechanism. Agents who receive an offer from other agents then calculate its own potential benefit using the local capacity planning model and determine whether to accept a deal. The agent then generates a counter offer to its negotiating opponents by using NDF mechanism. The potential profit of such an offer is compared to the profit of the previous received offer. If the newly received offer can produce a higher potential profit than the potential profit that the offer is preparing to send back to the offer provider, the received offer is accepted as a compromised plan.

The negotiation procedure with NDF mechanism and local capacity planning model among the agents is presented in Figure 3.1 and described as follows:

Step 1. The negotiation starter, say Factory 1, generates an offer (i.e., the budget in real number) by using NDF-based negotiation tactic to reflect its attitude during the negotiations.

Step 2. Each of the offer receivers, say Factory 2, first checks the negotiation time. If the negotiation time is expired, the factory sends a negotiation-failure message to the offer provider and goes to *step 5*. Otherwise, the offer receiver uses its local capacity-planning model to calculate a potential profits V_I^1 on the basis of local demands and the offer content (i.e., budget-allocation plan) provided from its counter party.

Step 3. Factory 2 compares the potential profit obtained from *step 2* with the value V_I^2 resulting from its local capacity planning model on the basis of a new offer (budget), which is generated according to negotiation tactic. If the received offer results in a higher potential profit than the local generated one, Factory 2 sends a deal message back to Factory 1 and goes to *step 5*. Otherwise, Factory 2 sends its local offer value to Factory 1.

Step 4. After receiving the offer from Factory 2, Factory 1 conducts the same procedure as *steps 2* and *3*.

Step 5. Negotiations are over, and the budget plan is output. Once the compromised version of the budget-allocation plan is obtained after a negotiation process, each factory can develop its resulting resource-investment portfolio and capacity-allocation plan.

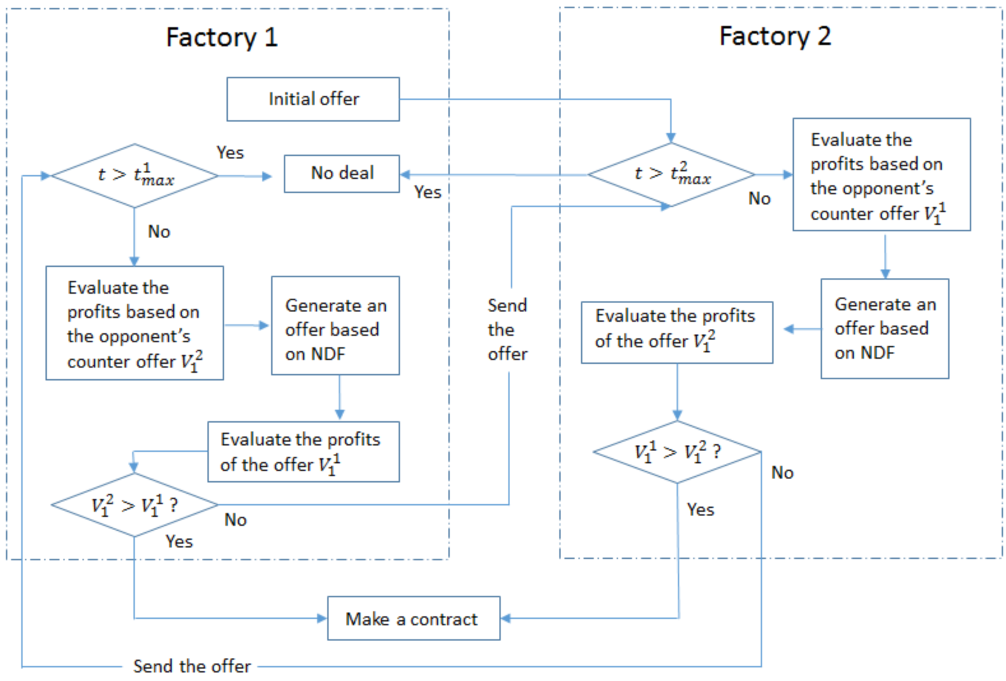

Figure 3.1 Negotiation procedure

3.1.2 Time-Dependent Tactic based on Negotiation Decision Function (NDF)

Multilateral negotiation functions are the foundations of NDF model. It is composed of the following factors:

Parties: One side of the negotiators, i.e. agent.

Issue: Subject of the negotiation, ex: price or quantity.

Offer/Counter Offer: Offer value is the opinion proposed by the agent against the issue of negotiation. At time *t*, agent *a* proposes an offer value $x^t_{a\to b}[j]$ against issue *j* to agent *b*. Counter-offer is the value proposed by the agent after conducting evaluation and adjustment. At time *t'*, against issue *j*, agent *b* proposes counter-offer value $x^{t'}_{b\to a}[j]$ back to agent *a*.

Negotiation thread: Records of all the offers proposed by the agent during the negotiation. Within a limited time t_n, the negotiation threads of agent *a* and *b*, $X^{t_n}_{a\leftrightarrow b}$ are vectors of limited length *n*, $\left(x^{t_1}_{a\to b}, x^{t_2}_{b\to a}, x^{t_3}_{a\to b}, x^{t_4}_{b\to a}, x^{t_5}_{a\to b}, \cdots\right)$. The last line of negotiation thread is the result of negotiation, ―Accept" or ―Reject".

Accept means the two parties have an agreement. Reject means the negotiation is failed. In case of the last line is not showing –Accept" or –Reject", which means the negotiation is still –Active".

Scoring function: $x_j^i \in [\min_j^i, \max_j^i]$ means the acceptable value range for agent *i* against issue *j*, ($i \in \{a,b\}$, $j \in \{1,...,n\}$). In the practical world, the number of issue is finite, $V_j^i : [\min_j^i, \max_j^i] \to [0,1]$ indicates the score of agent *i* against issue *j* is between 0 and 1. $V_j^i(x_j)$ represents the score when agent *i* proposes an offer x_j against issue *j*. For comparison, the following is the standard form of scoring function:

$$V_j^i(x_j) = \begin{cases} \dfrac{\max_j^i - x_j}{\max_j^i - \min_j^i} & \text{if } x_j \text{ decreasing} \\ \dfrac{x_j - \min_j^i}{\max_j^i - \min_j^i} & \text{if } x_j \text{ increasing} \end{cases} \tag{3.1}$$

Decision function: The function used by agent to judge the opponent offer and determine the next step. The definition of this function is as following:

$$I^a(t', x_{b\to a}^t) = \begin{cases} reject & \text{if } t' > t_{\max}^a \\ accept & \text{if } V^a(x_{b\to a}^t) \geq V^a(x_{a\to b}^{t'}), t' > t \\ x_{a\to b}^{t'} & \text{otherwise} \end{cases} \tag{3.2}$$

Agent *a* determines $x_{b\to a}^t$, which is the opponent offer at time *t*. If *t'* exceeds the maximum acceptable negotiation time for agent *a*, $t_{\max}^a$, this term of negotiation is rejected. Otherwise, the agent conducts comparison between the scores of the offer, $x_{b\to a}^t$ and counter-offer, $x_{a\to b}^{t'}$. If the offer from opponent is higher, then agent accepts this offer and makes an agreement. If the counter-offer is higher, then agent sends the counter-offer back to the opponent and continues the negotiation.

When agent a received the offer from agent b, the offer value becomes the last line of negotiation thread. If this offer is not satisfied by agent a, agent a needs to generate a counter-offer. When generating the counter-offer, agent using tactic to calculate the value. In this study, time-dependent tactic is used during negotiation.

Time-dependent tactics change offer values depending on negotiation time remained. In equation (3.3) below, agent a and agent b represent the factories that become negotiation attendants, *Bu* represents the negotiable budget plan, and *t* is the current time, upb^a and lob^a are the expected upper bound and lower bound of budget of agent a.

$$xc_t^{a \to b}[Bu] = upb^a - \alpha^a(t)(upb^a - lob^a) \tag{3.3}$$

The offer value that changes according to the time function $\alpha^a(t)$ is formulated in equation (3.4) as follow:

$$\alpha^a(t) = reon^a + (1 + reon^a)\left(\frac{min(t, t_{max}^a)}{t_{max}^a}\right)^{\frac{1}{\beta}} \tag{3.4}$$

Here t_{max}^a represents the negotiation time limit of the agent a, $0 \le t \le t_{max}^a$. Note that the ratio $\alpha^a(t)$ is bounded to the acceptable budget range $0 \le \alpha^a(t) \le 1$, and $\alpha^a(t_{max}^a) = 1$ represents the budget deadline of concession of agent a. The $reon$ represents the reservation ratio of the budget offer value ranged from 0 to 1. β parameter can be valued as $\beta < 1$ for Boulware tactic, $\beta = 1$ for linear tactic, and $\beta > 1$ for conceder tactic.

3.1.3 Capacity Planning Model of Individual Factories

The capacity-planning model and corresponding algorithm for an individual factory is used in two situations:

(1) Calculate the potential profit under the proposed offer (budget allocation plan) based on the local resources and demands.
(2) Evaluate if the received offer sent by peer factory is acceptable.

The current study will use the individual-factory resource-planning and capacity-allocation model based on Wang et all (2008) and adds to it a budget constraint to evaluate the potential benefit of the proposed offer, as well as to determine whether a received offer should be accepted. Capacity planning herein considers the variance of different demands and expected return in long-term planning horizon. A decision-maker must adjust the level of resources through alternatives such as renting and transferring by outsourcing.

Both make-to-stock and make-to-order types of production are considered in the model. The former needs to be completely fulfilled in the span of production horizon, while the latter are done selectively. Furthermore, owing to its potential profitability, capital can be easily gathered from the monetary market. Residual capital/assets in earlier periods, which is regarded as liquidity, can be used in subsequent planning periods. Several assumptions that needed are presented as follows:

1) Demand are presented as a set in which each demand consists of several types of products. Moreover, the each demand was presented in a discrete-time base.
2) Resource procurement occurs only in the initial period, whereas resource capacity can be adjusted in the intermediate periods through renting or transferring from other plants.
3) The target utilization and throughput rate of resource for individual products are known.
4) There are finite resource configurations to confine the technological feasibility for producing a product. Furthermore, an auxiliary resource can only work with a specified main resource and a product can thus only be performed by certain feasible resource configurations.

The objective of the optimal simultaneous planning decision for level of capacity is to maximize the net profit in long-term periods and can be expressed formally as follows:

$$Max : (1-\lambda)\sum_{\varsigma}\left(\frac{\theta^{\varsigma}}{\eta}\right) - \lambda\left(\frac{\sum_{\varsigma}\left|\theta^{\varsigma}-\overline{\theta^{\varsigma}}\right|}{\eta}\right) \tag{3.5}$$

Where, λ is the tradeoff parameter of risk. We can see the tradeoff between the expected profits $\sum_{\varsigma}\left(\frac{\theta^{\varsigma}}{\eta}\right)$ in all realized demands and its risk that is modeled as the mean absolute deviation (MAD) of profits in equation (3.5) above.

Constraints that included in this model are presented as follows:

Constraint 1: Required number of resources

The number of existing resources must be equal or larger than the allocated capacity (in machine quantity) to fulfill the promised orders.

$$K_m + \sum_z X_{p,m,z} \geq \sum_j \frac{c_{m,j}Q_{p,m,j}}{r_{m,j}w_{p,m}y_{p,m}} \ , \forall p,\ m \in M \tag{3.6}$$

$X_{p,m,z}$ = number of resource type m associated with resource acquisition alternative z in period p

$c_{m,j}$ = product-resource capabilities for product j associated with main resource type-m.

$c_{m,j}$= 1, if main resource type m can conduct product ;

$c_{m,j}$= 0, otherwise

$Q_{p,m,j}$= quantity of product j produced by main resource type m in period p

$r_{m,j}$= theoretical throughput of product j conducted by resource type m

$w_{p,m}$= working hours of resource type m in period p

$y_{p,m}$= target utilization of resource type m in period p

Constraint 2: Configurations constraints among resources

Main resource $(m \in M)$ must be associated with auxiliary resources $(m_2 \in H)$ to conduct promised product type j. Hence, the quantities of products that are produced using main resources must be equal to the quantities of products supported by auxiliary resources.

$$\sum_{m_2 \in H} c_{m,m_2} Q_{p,m_2,j} = Q_{p,m,j} \ , \forall p, j, m \in M \tag{3.7}$$

c_{m,m_2}= resource configuration capabilities regarded with auxiliary resource type m_2.

c_{m,m_2}= 1, if auxiliary resource type m_2 can cooperate with main resource m

c_{m,m_2}= 0, otherwise

$Q_{p,m_2,j}$= quantity of product j produced by auxiliary resource type m_2 in period p

<u>Constraint 3: Production balance from market demand</u>

Treats demand type make to order (MTO)

$$\sum_{m \in M} c_{m,j} Q_{p,m,j} = o_{p,j} \tag{3.8}$$

Where, $j \in MTO$

$o_{p,j}$= market demands for product j in period p

<u>Constraint 4: Inventory balance from market demand</u>

Treats demand type make to stock (MTS)

$$V_{p,j} - S_{p,j} = V_{p-1,j} - S_{p-1,j} + \sum_{m \in M} c_{m,j} Q_{p,m,j} - o_{p,j} \ , \forall p \tag{3.9}$$

Where, $j \in MTS$

$V_{p,j}$= the excess production quantity of product j in period p

$S_{p,j}$= capacity lack quantity of product j in the end of period p

$V_{p-1,j}$ and $S_{p-1,j}$ are the net inventory and the net backorder according to the gap between the production and market demand in product type j from period $p-1$ to period p

Constraint 5: Capital balance equation

The profit in period p is computed by adding the remaining budget and the incomes of production profit, and subtracting the outsourcing cost of resources and inventory cost.

$$F_p = F_{p-1}(1+I_p) - \sum_{m\in M\cup H,z}(u_{p,m,z}X_{p,m,z}) - \sum_j(a_{p,j}V_{p,j} + l_{p,j}S_{p,j}) + \sum_{j\in MTS} b_{p,j}o_{p,j} + \sum_{j\in MTO} b_{p,j}Q_{p,m,j} \quad (3.10)$$

Where,

$u_{p,m,z}$= unit cost of resource type m obtained by outsourcing alternative z in period p

$a_{p,j}$= the unit excess production cost of product j in period p

$l_{p,j}$= the unit lack production cost of product j in period p

$b_{p,j}$= unit profits of a product j produced in period p

Constraint 6: Profit of demand scenario

The profits of demand ς is calculated by net profits from period 1 to period p^{end}

$$\theta^{\varsigma} = \frac{F_{p^{end}}}{\Pi_p(1+I_p)} - \sum_{m\in M}(e_m - d_m)(K_m - K_{0,m}) \quad (3.11)$$

Where,

F_p= capital in the end of period p

I_p= capital interest rate in period p

e_m= unit cost of purchasing a resource type m

d_m= unit salvage value of phasing out a resource type m

K_m= number of in-house resource type m during the planning horizon

$K_{0,m}$= number of resource type m in the initial period

<u>Constraint 7: Limited budget of negotiation</u>

The budget provided by the headquarters is limited because of the content of the negotiation.

$$\sum_{m\in M} e_m \left(K_m - K_{0,m}\right) \leq xc \tag{3.12}$$

Here, xc is the offer value (budget) that the factory wants to evaluate.

In order to solve this local capacity planning problem, a systematic searching tool, i.e., Genetic Algorithm is served to perform reproduction, crossover, and mutation of chromosomes between generations. The following outline summarizes how the genetic algorithm works.

1. The algorithm begins by creating a random initial population.
2. The algorithm then creates a sequence of new populations. At each step, the algorithm uses the individuals in the current generation to create the next population. To create the new population, the algorithm performs the following steps:
    a. Scores each member of the current population by computing its fitness value.
    b. Scales the raw fitness scores to convert them into a more usable range of values.
    c. Selects members, called parents, based on their fitness.
    d. Some of the individuals in the current population that have lower fitness are chosen as *elite*. These elite individuals are passed to the next population.
    e. Produces children from the parents. Children are produced either by making random changes to a single parent, which is known as *mutation*, or by combining the vector entries of a pair of parents, which is known as *crossover*.

f. Replaces the current population with the children to form the next generation.

3. The algorithm stops when one of the stopping criteria is met.
   a. Generations: The algorithm stops when the number of generations reaches the value of ***Generations***.
   b. Time limit: The algorithm stops after running for an amount of time in seconds equal to ***Time limit***.
   c. Fitness limit: The algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to ***Fitness limit***.
   d. Stall generations: The algorithm stops when the weighted average change in the fitness function value over ***Stall generations*** is less than ***Function tolerance***.
   e. Stall time limit: The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to ***Stall time limit***.
   f. Function tolerance: The algorithm runs until the weighted average relative change in the fitness function value over ***Stall generations*** is less than ***Function tolerance***. The weighting function is $1/2^n$, where n is the number of generations prior to the current.

3.2 Learning Mechanism using Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a multilayer feed forwards network-based neural fuzzy system. To perform desired input–output characteristics, adaptive learning parameters are updated based on gradient learning rules. In order to describe Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture, for simplicity, we assume that the fuzzy inference system under consideration has two inputs x and y and one output z. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following (Jang et all, 1997):

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

Figure 3.2 illustrates the reasoning mechanism for this Sugeno model:

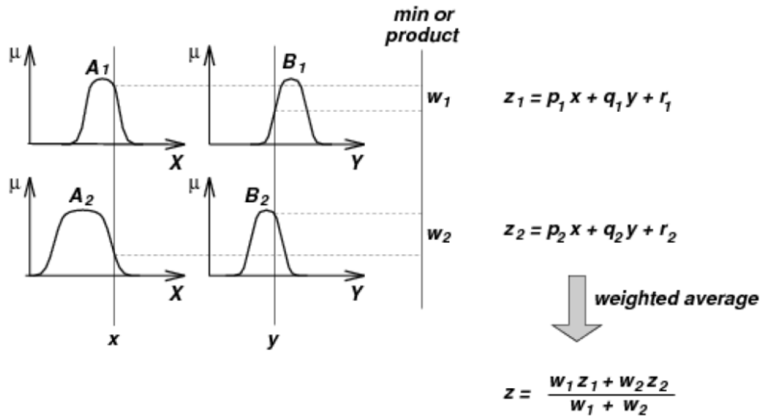

Figure 3.2 A two input first order Sugeno fuzzy model with two rules

Fuzzy inference systems consist of five layers of adaptive networks; two inputs (x and y) and one output is illustrated in Figure 3.3 below:

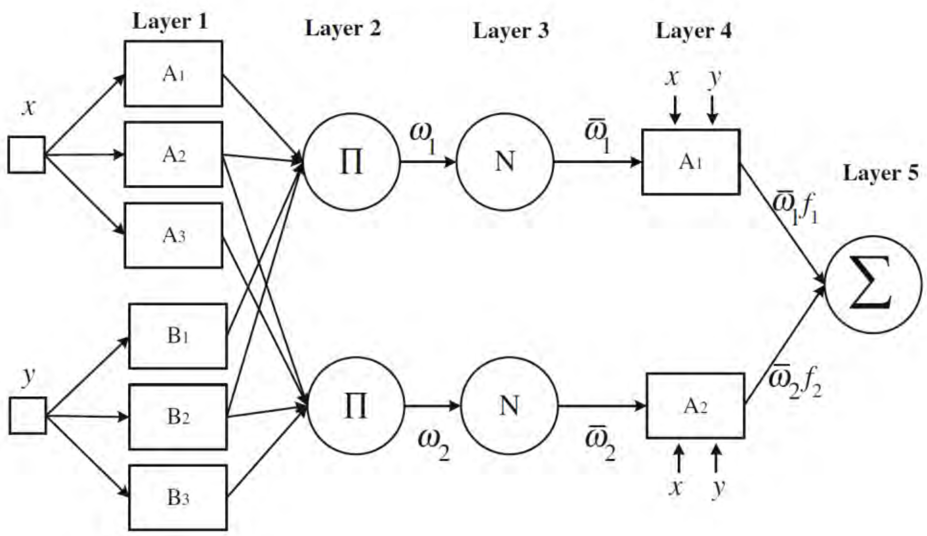

Figure 3.3 ANFIS model architecture

The entire system architecture consists of five layers is explained as follows:

Layer 1: The first layer, named the fuzzification layer, is the input layer whose neurons transmit external crisp signals directly to the next layer as:

$$O_{1,i} = \mu A_i(x), \quad i = 1,2,3$$
$$O_{1,i} = \mu B_{j-3}(x), \quad j = 4,5,6 \tag{3.13}$$

where x is input to node i and A_i is a linguistic label associated with this node function. $O_{1,i}$ is the membership function of A_i. Gaussian parameterized membership function is usually performed as an input membership function guaranteeing a smooth transition between 0 and 1.

$$\mu A(X) = exp\left\{-\left(\frac{x-c_i}{\alpha_i}\right)^2\right\} \tag{3.14}$$

where $\{\alpha_i, c_i\}$ is the parameter set.

Layer 2: In the second layer, called the product layer, every node is a circle node labelled Π, which multiplies incoming signals and sends the product out; each node output represents the igniting strength of a rule.

$$O_{2,i} = \omega = \mu A_i(x) \times \mu B_i(y), \quad i = 1,2,3, \dots, N \tag{3.15}$$

Layer 3: The outputs of the third layer, called the normalized layer, are the normalization of incoming firing strengths. Every node in the third layer is a circle node labelled N. The ith node is calculated as:

$$\overline{\omega} = \frac{\omega_i}{\omega_1+\omega_2+\cdots+\omega_N}, \quad i = 1,2, \dots, N \tag{3.16}$$

Layer 4: In contrast to the first layer, the fourth layer is defuzzification layer where every node i is an adaptive node labelled as a square; each node function is calculated as:

$$O_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_i y + \cdots + r_i), \quad i = 1,2,3, \dots, N \tag{3.17}$$

where $\overline{\omega}_i$ is the output of third layer and $\{p_i, q_i, r_i\}$ is the parameter set. Linear parameters in this layer are referred to as consequent parameters.

Layer 5: The last layer is total output layer. The single node in this layer is a circle node that is labelled Σ and computes the overall output of ANFIS as the summation of all incoming signals:

$$O_i^5 = Overall\ input = \sum_i \overline{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{3.18}$$

There are two adaptive layers (the first and the fourth one) with square nodes in this ANFIS architecture. In the fuzzification layer—the first layer—there are two modifiable parameters $\{\alpha_i, c_i\}$ that are related to input membership functions and are known as premise parameters. And in the fourth defuzzification layer, there are three more modifiable parameters $\{p_i, q_i, r_i\}$ having to do with the first-order polynomial and so-called consequent parameters.

CHAPTER 4
EXPERIMENTS RESULTS

This chapter shows the result of numerical experiment in orer to test whether the models that have been developed can be used properly and can represent real conditions.

4.1 Solving Local Capacity Planning Model using Genetic Algorithm

An application in semiconductor testing industry is given below to illustrate the implementation of local capacity planning model. The semiconductor testing industry constantly struggles for resource planning with constrained budget to invest, limited capacity of resources and lumpy demands. In the industry, simultaneous resources for processing an order are commonly considered. Testers are the main resource for testing semiconductor chips. Many other kinds of resources (such as handlers, load boards, tools, and testing programs) work simultaneously to conduct the test for a wafer/chip. Each resource may have several types resulting from different functionalities and processing precisions. A tester performs the functional test and a handler feeds a wafer/chip material into the tester. Each testing task requires a specific temperature setting for the handlers. The equipment costs of a tester set usually range from three hundred thousand to two million US dollars. The cost of a handler is around one-tenth of a tester. Slight improvements of capacity investment and utilization can thus result in gains of millions of dollars.

The data that have been used for illustration is based on the following case condition:

(1) Three types of main resource, named semiconductor-chip testers #1, 2 and 3;

(2) Four types of auxiliary resource, named semiconductor-chip handlers #1, 2, 3, and 4;

(3) Demands are represented by three products over eight quarters. Product 1 is of make-to-stock type and products 2 and 3 are of make-to-order type;

(4) The initial budget is 10 million, with 1.02% interest rate and 80% target utility,

(5) 1800 available operating hours in each period per year.

The other data that have been used is given in Appendix A.

Genetic Algorithm (GA) solve local capacity planning model and gave optimal profit as shown in Figure 4.1.

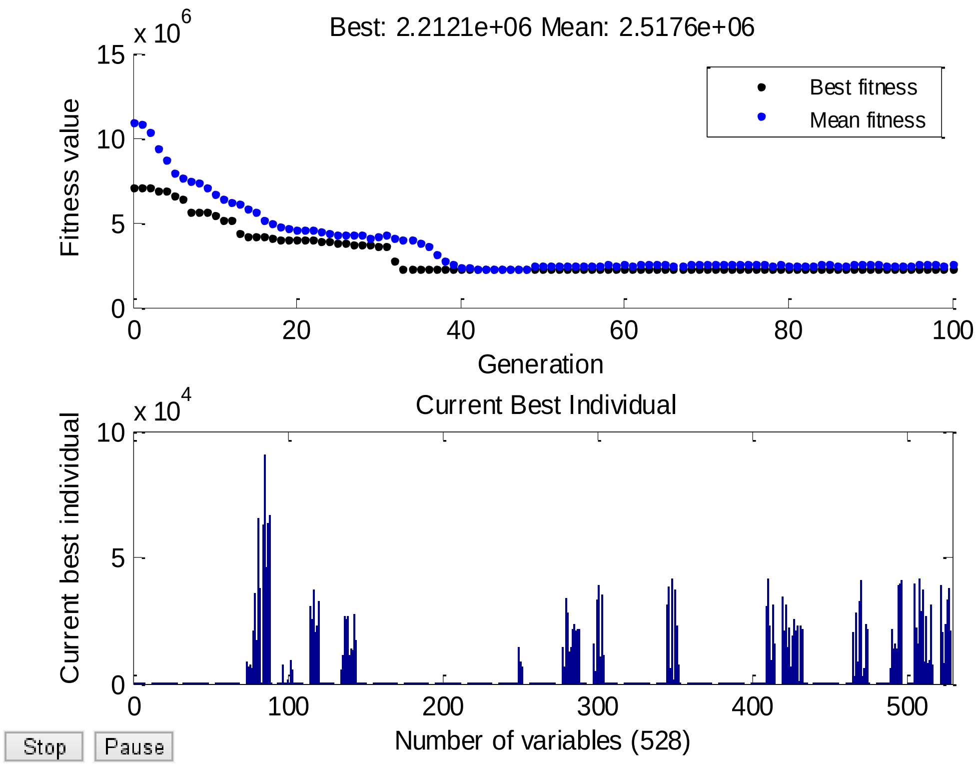

Figure 4.1 Optimal profit of the capacity planning model

Figure 4-1 shows that since generation 40, the GA is already start to give convergent result for the optimal profit that factory will get. The best profit is about 2.2×10^6 US Dollar. The following also listed the results of optimal capacity planning that generated by utilizing Genetic Algorithm. Table 4-1 and Table 4-2 show the optimal number of main resource and auxiliary resource respectively during eight future periods. The optimal number of each three products that can be produced by main resource is shown in Table 4-3. While Table 4-4 shows the optimal number of those three products that can be produced by auxiliary resource associated with main resource.

Table 4.1 Number of Main Resource

Main resource	Main resource quantity by	Period							
		1	2	3	4	5	6	7	8
Tester 1	In house	1	1	0	1	1	1	1	0
	Transfer	1	1	1	1	1	1	1	1
	Rent	1	0	0	1	1	1	1	1
Tester 2	In house	3	1	2	4	5	3	3	4
	Transfer	3	2	2	4	5	3	3	4
	Rent	3	1	2	4	5	3	3	4
Tester 3	In house	2	2	2	1	2	1	1	2
	Transfer	2	2	2	1	2	1	2	2
	Rent	2	2	2	1	2	1	1	2

Table 4.2 Number of Auxiliary Resource

Auxiliary resource	Auxiliary resource quantity by	Period							
		1	2	3	4	5	6	7	8
Handler 1	In house	2	1	2	1	3	3	1	2
	Transfer	2	1	3	1	3	3	1	2
	Rent	2	1	2	1	3	3	1	2
Handler 2	In house	6	5	2	6	4	6	3	4
	Transfer	6	5	2	6	5	7	3	5
	Rent	6	5	2	6	4	6	4	4
Handler 3	In house	1	1	2	1	1	2	1	1
	Transfer	1	2	2	1	1	2	1	1
	Rent	1	1	2	2	1	2	1	1
Handler 4	In house	2	3	2	3	4	3	5	3
	Transfer	3	3	2	3	4	3	5	3
	Rent	2	4	2	3	4	3	5	4

Table 4.3 Number of Product Produced by Main Resource

Period	Tester 1			Tester 2			Tester 3		
	Product 1	Product 2	Product 3	Product 1	Product 2	Product 3	Product 1	Product 2	Product 3
1	14352	65437	1	7348	2	24640	1	0	26608
2	8430	37766	1	0	1	29427	1	1018	25390
3	6927	0	1	0	1	30815	1	2147	26822
4	7511	62599	1	1786	1	25353	1	21063	11241
5	5908	90922	1	0	1	37105	1	18487	13943
6	20927	45842	1	9146	2	20362	1	16310	13186
7	36022	63459	1	5596	1	23078	1	5782	27222
8	17238	67064	1	0	1	32686	1	11557	17184

Table 4.4 Number of Product Produced by Auxiliary Resource Associated with Main Resource

Period			1	2	3	4	5	6	7	8
Tester 1	Product 1	Handler 1	1	1	1	1	1	1	1	1
		Handler 2	14348	8426	6923	7507	5904	20923	36018	17234
		Handler 3	1	1	1	1	1	1	1	1
		Handler 4	1	1	1	1	1	1	1	1
	Product 2	Handler 1	25861	9524	30041	7636	28250	14669	6510	33794
		Handler 2	28191	12637	14362	21521	23809	20702	21853	21750
		Handler 3	2	1	1	1	2	1	1	1
		Handler 4	11382	15603	4821	33440	38862	10469	35094	11518
	Product 3	Handler 1	1	1	2	1	1	1	1	1
		Handler 2	1	1	1	1	1	2	1	1
		Handler 3	2	1	1	1	1	1	1	1
		Handler 4	1	1	1	2	1	2	1	1

Table 4.4 Number of Product Produced by Auxiliary Resource Associated with Main Resource *(Continue)*

Period			1	2	3	4	5	6	7	8
Tester 2	Product 1	Handler 1	1	1	1	1	1	1	1	2
		Handler 2	31357	38610	5949	41636	1342	37110	22828	7375
		Handler 3	2	1	1	1	2	1	1	1
		Handler 4	2	1	1	1	1	1	1	1
	Product 2	Handler 1	1	1	1	1	2	1	1	1
		Handler 2	2	1	1	1	1	1	1	2
		Handler 3	1	1	1	1	1	1	1	1
		Handler 4	1	1	1	1	1	1	1	1
	Product 3	Handler 1	1	1	1	1	1	1	1	1
		Handler 2	30639	41367	22947	9662	31611	15963	2816	32945
		Handler 3	11093	23894	39861	34325	20962	31339	14503	22346
		Handler 4	6920	19199	25783	21219	22714	1026	22993	21792

Table 4.4 Number of Product Produced by Auxiliary Resource Associated with Main Resource *(Continue)*

Period			1	2	3	4	5	6	7	8
Tester 3	Product 1	Handler 1	1	2	1	1	1	2	1	1
		Handler 2	1	1	1	1	1	1	1	1
		Handler 3	1	1	1	1	1	1	1	1
		Handler 4	1	1	1	1	1	1	1	2
	Product 2	Handler 1	20016	2815	28245	8869	32687	40659	3083	6035
		Handler 2	23455	21871	610	42095	29256	30042	5959	1075
		Handler 3	1	2	1	1	1	1	1	1
		Handler 4	6241	21294	13662	15842	13839	39264	39910	40688
	Product 3	Handler 1	1	1	1	1	1	1	1	1
		Handler 2	39371	21937	15661	41892	28892	37318	8768	26853
		Handler 3	7968	9389	31289	7128	18557	36540	24039	5601
		Handler 4	33651	39027	20241	7964	23789	32983	37586	20971

4.2 Predicting Opponent Offer by Utilizing Adaptive Neuro-Fuzzy Inference System (ANFIS) as Learning Mechanism

As each factory able to generate their best profit from their own local capacity planning model, now they try to have bilateral negotiation each other given a limited budget provided by headquarter. Using Time-Dependent tactics which change offer values depending on negotiation time remained, we get some negotiation data. These data we utilize to implement Adaptive Neuro-Fuzzy Inference System (ANFIS) in order to predict opponent offer for the next negotiation.

As we started the ANFIS, it would record the first 3 offers proposed by the opponent and utilize a score function to calculate the scores of these 3 offers as the input values (X_1, X_2, and X_3). The computed sum of speculated weight values and 3 scores was set to be the output of this model. After that, as the same technique, we used the opponent score function and opponent weight values to calculate a total score value and set it as the target.

Parameter setting for the time-dependent tactic is given in Appendix A. After gathering threads of several negotiations, then by utilizing score function, we obtain some input values and their target values that represent the next opponent offer. Table 4.5 and Table 4.6 below show the training data and checking data that we have been used:

Table 4.5 Training Data

X1	X2	X3	Target
0.1136	0.5564	0.1886	0.59594
0.2641	0.6356	0.3375	0.67364
0.58442	0.7544	0.65898	0.7962
0.7412	0.83882	0.8216	0.8782
0.9046	0.9196	0.9886	0.9592
1	0.9978	1	1
1	1	1	1
0.188	0.64626	0.2644	0.6847
0.3406	0.7262	0.4152	0.7652
0.4926	0.8064	0.5646	0.8492
0.644	0.8916	0.7262	0.93136
0.8	0.9746	0.8824	1
0.9566	1	1	1

Table 4.6 Checking Data

X1	X2	X3	Target
0.129	0.5418	0.2042	0.58206
0.27878	0.6228	0.35166	0.66046
0.57292	0.7638	0.64688	0.805
0.7298	0.8488	0.8108	0.8902
0.8936	0.9304	0.9772	0.9712
1	1	1	1
1	1	1	1
0.2126	0.62002	0.289	0.6592
0.36632	0.7006	0.4416	0.7394
0.5194	0.781	0.5916	0.8238
0.6714	0.8915	0.74414	0.933
0.822	0.973	0.8986	1
0.9758	1	1	1

The experiment giving prediction result of the next opponent offer that given in Table 4.7.

Table 4.7 Comparison of Prediction and Desired Output

Prediction Output	Desired Output	Difference
0.595931909	0.58206	0.013871909
0.673668919	0.66046	0.013208919
0.796198794	0.805	0.008801206
0.878200413	0.8902	0.011999587
0.959199409	0.9712	0.012000591
0.999856984	1	0.000143016
1.000143859	1	0.000143859
0.684698765	0.6592	0.025498765
0.765177274	0.7394	0.025777274
0.849204026	0.8238	0.025404026
0.931358234	0.933	0.001641766
1.000000999	1	9.99112E-07
0.999998773	1	1.22744E-06

Root-mean squared error (RMSE) that represents the sample standard deviation of the differences between predicted value and desired value is shown in Figure 4.2.

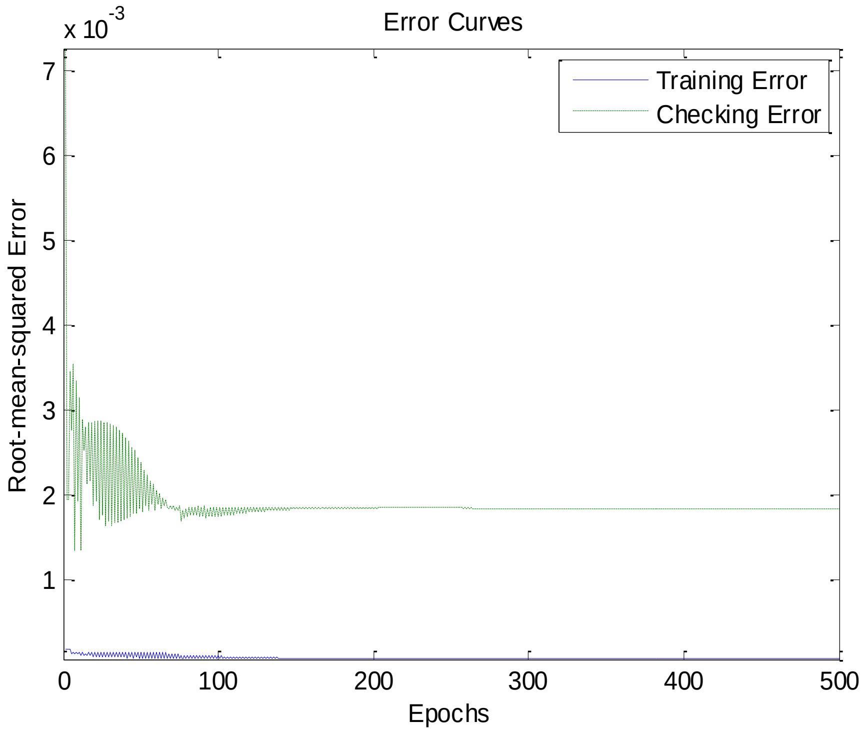

Figure 4.2 RMSE of the differences

As shown in Figure 4-2, the RMSE is converge to only 1.8×10^{-3} since 150^{th} epoch. Therefore, the learning mechanism using ANFIS give good prediction of the opponent's next offer. So then, it will helps each of negotiation attendant to fastly decide their next move, so then it will reduce their negotiation time.

APPENDIX A

Parameter Setting

Table A.1 Unit Profits of Three Products Produced in Eight Periods

	Product 1	Product 2	Product 3
Period 1	200	150	180
Period 2	200	150	180
Period 3	200	150	180
Period 4	190	140	170
Period 5	190	140	170
Period 6	190	140	170
Period 7	180	130	160
Period 8	180	130	160

Table A.2 Resource Configuration Capabilities

	Handler 1	Handler 2	Handler 3	Handler 4
Tester 1	0	1	0	0
Tester 2	1	1	0	1
Tester 3	0	1	1	1

Table A.3 Product-Resource Capabilities

	Product 1	Product 2	Product 3
Tester 1	1	1	0
Tester 2	1	0	1
Tester 3	0	1	1

Table A.4 Unit Salvage Value and Unit Cost of Purchasing for Three Main Resource

Main resource	Unit salvage value	Unit cost of purchasing
Tester 1	1300000	3900000
Tester 2	650000	1350000
Tester 3	980000	2840000

Table A.5 Unit Salvage Value and Unit Cost of Purchasing for Four Auxiliary Resource

Auxiliary resource	Unit salvage value	Unit cost of purchasing
Handler 1	100000	300000
Handler 2	70000	210000
Handler 3	130000	420000
Handler 4	160000	480000

Table A.6 Parameter Setting for Time Dependent Tactic

t_{max}	3600 seconds
upb	10000000
lob	5000000
$reon$	0.25
β	0.2

APPENDIX B

Source code in MATLAB (Negotiation procedure)

```
%% TCP/IP Sender (Machine A)

% Clear console and workspace
clc;
clear all;
close all;


%==================================================================
% t = cputime;
% set_time = t;
% t_max = 50;
%==================================================================

t = cputime;
t_max = 2000;
upb = 10000000;
lob = 5000000;
reon = 0.25;
beta = 0.2;

%==================================================================
%budget that the factory wants to evaluate
xc = 10000000;

%unit profits of 3 products (t) produced in 8 periods (p)
Bpt = [200 150 180;
    200 150 180;
    200 150 180;
    190 140 170;
    190 140 170;
    190 140 170;
    180 130 160;
    180 130 160];


%------------------------------------------------------------------
%resource configuration capabilities for a product t regarded with
3 MR (m)
%and 4 AR (a)
Cma = [0 1 0 0;
    1 1 0 1;
    0 1 1 1];

%product-resource capabilities for 3 products (t) associated with
3 MR (m)
Cmt = [1 1 0;
    1 0 1;
    0 1 1];
```

```
%resource configuration capabilities for 3 products (t) regarded
%with 3 MR (m)
%and 4 AR (a)
for m=1:3
    for a=1:4
        for t=1:3
            Cmat(m,a,t) = Cma(m,a)*Cmt(m,t);
        end
    end
end
%------------------------------------------------------------------


%---------------------------------
%unit salvage value for  4 AR (a)
Da = [100000 70000 130000 160000];

%unit salvage value for 3 MR (m)
Dm = [1300000 650000 980000];
%---------------------------------


%---------------------------------
%unit cost of purchasing 4 AR (a)
Ea = [300000 210000 420000 480000];

%unit cost of purchasing 3 MR (m)
Em = [3900000 1350000 2840000];
%---------------------------------


%capital interest rate in period p
Ip = 1.02;


%---------------------------------------------------------------
%unit excess production cost of 3 products (t) in 8 periods (p)
Jpt = .1*Bpt;

%unit lack production cost of 3 products (t) in 8 periods (p)
Lpt = .2*Bpt;
%---------------------------------------------------------------


%-----------------------------------------
%number of 4 AR (a) in the initial period
K0a = [2 3 3 2];

%number of 3 MR (m) in the initial period
K0m = [2 1 1];
%-----------------------------------------
```

```
%market demands for 3 products (t) in 8 periods (p)
for n=1:50
    %Normal Distribution with sigma 3500 (for 1 period)
        %Opt=[3500.*randn(1,1,n)+35700 3500.*randn(1,1,n)+30240
3500.*randn(1,1,n)+31500];
    %Normal Distribution with sigma 3500
        %Opt=[3500.*randn(8,1,n)+35700 3500.*randn(8,1,n)+30240
3500.*randn(8,1,n)+31500];
    %Uniform Distribution with sigma 3500
        Opt=[29638+(41762-29638).*rand(8,1,n) 24178+(36302-
24178).*rand(8,1,n) 25438+(37562-25438).*rand(8,1,n)];
end


%------------------------------------------------------------------
%throughput of 3 products (t) conducted by 4 AR (a) associated
with MR (m)
Rma=[8 8 8 8;5 5 5 5;7 7 7 7];

%throughput of 3 products (t) conducted by 3 MR (m)
Rmt=[8 8 8;5 5 5;7 7 7];
%------------------------------------------------------------------



%------------------------------------------------------------------
%unit cost of 3 MR (m) obtained by 2 kinds outsourcing alternative
z in period p
Umz=[600000 1800000;300000 900000;450000 1350000];

%unit cost of 4 AR (m) obtained by 2 kinds outsourcing alternative
z in period p
Uaz=[60000 150000;30000 90000;60000 180000;90000 240000];
%------------------------------------------------------------------



%------------------------------------
%working hours of AR (a) in period p
Wpa=1800;

%working hours of MR (m) in period p
Wpm=1800;
%------------------------------------



%-----------------------------------------
%target utilization of AR (a) in period p
Ypa=.8;

%target utilization of MR (m) in period p
Ypm=.8;
%-----------------------------------------


[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);
```

```
%=================================================================
% Configuration and connection
con = tcpip('192.168.0.169',4013);

% Open socket and wait before sending data
fopen(con);
pause(0.5);

%=================================================================
% Send data every 200ms  (First offer)
    DataToSend=[xc y]
    fwrite(con,DataToSend);
    pause(300);

% Read data from the socket
  DataReceived=fread(con,2);

  xc=DataReceived(1);

[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);

% Negotiation
while DataReceived(2)<=y % If this stopping condition is still
false, increasing "DataReceived", then send to MAchine B
    alpha=reon+(1-reon)*((min((cputime-t),t_max)/t_max));
    xc=upb-alpha*(upb-lob);

[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);
    DataToSend=[xc y]
    fwrite(con,DataToSend);
    pause(300);
    DataReceived=fread(con,2);
    xc=DataReceived(1);

[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);
end

%set_time = cputime - set_time

if DataReceived(2)>y
    fwrite(con,DataReceived)
end


%
%=================================================================
% % Close and delete connection
% fclose(con);
% delete(con);
```

```
%% TCP/IP Receiver (Machine B)

% Clear console and workspace
clc;
clear all;
close all;

% Configuration and connection
con=tcpip('192.168.0.169', 4013,'NetworkRole','server');

% Wait for connection
disp('Waiting for connection');
fopen(con);
disp('Connection OK');

t = cputime;
%y_local = 13500000; %initial
% t_max = 20;
t_max = 2000;
upb = 15000000;
lob = 5000000;
reon = 0.30;
beta = 0.2;

% Read data from the socket
 DataReceived=fread(con,2);

%=================================================================
%budget that the factory wants to evaluate
xc = DataReceived(1);

%unit profits of 3 products (t) produced in 8 periods (p)
Bpt = [200 150 180;
    200 150 180;
    200 150 180;
    190 140 170;
    190 140 170;
    190 140 170;
    180 130 160;
    180 130 160];
% Bpt = [200 150 180];



%-----------------------------------------------------------------
%resource configuration capabilities for a product t regarded with
%3 MR (m)
%and 4 AR (a)
Cma = [0 1 0 0;
    1 1 0 1;
    0 1 1 1];
```

```
%product-resource capabilities for 3 products (t) associated with
3 MR (m)
Cmt = [1 1 0;
    1 0 1;
    0 1 1];

%resource configuration capabilities for 3 products (t) regarded
%with 3 MR (m)
%and 4 AR (a)
for m=1:3
    for a=1:4
        for t=1:3
            Cmat(m,a,t) = Cma(m,a)*Cmt(m,t);
        end
    end
end
%------------------------------------------------------------------


%---------------------------------
%unit salvage value for  4 AR (a)
Da = [100000 70000 130000 160000];

%unit salvage value for 3 MR (m)
Dm = [1300000 650000 980000];
%---------------------------------


%---------------------------------
%unit cost of purchasing 4 AR (a)
Ea = [300000 210000 420000 480000];

%unit cost of purchasing 3 MR (m)
Em = [3900000 1350000 2840000];
%---------------------------------


%capital interest rate in period p
Ip = 1.02;


%-------------------------------------------------------------
%unit excess production cost of 3 products (t) in 8 periods (p)
Jpt = .1*Bpt;

%unit lack production cost of 3 products (t) in 8 periods (p)
Lpt = .2*Bpt;
%-------------------------------------------------------------


%-----------------------------------------
%number of 4 AR (a) in the initial period
K0a = [2 3 3 2];

%number of 3 MR (m) in the initial period
```

```
K0m = [2 1 1];
%-----------------------------------------


%market demands for 3 products (t) in 8 periods (p)
for n=1:50
    %Normal Distribution with sigma 3500 (for 1 period)
        %Opt=[3500.*randn(1,1,n)+35700 3500.*randn(1,1,n)+30240
3500.*randn(1,1,n)+31500];
    %Normal Distribution with sigma 3500
        %Opt=[3500.*randn(8,1,n)+35700 3500.*randn(8,1,n)+30240
3500.*randn(8,1,n)+31500];
    %Uniform Distribution with sigma 3500
        Opt=[29638+(41762-29638).*rand(8,1,n) 24178+(36302-
24178).*rand(8,1,n) 25438+(37562-25438).*rand(8,1,n)];
end


%-----------------------------------------------------------------
%throughput of 3 products (t) conducted by 4 AR (a) associated
with MR (m)
Rma=[8 8 8 8;5 5 5 5;7 7 7 7];

%throughput of 3 products (t) conducted by 3 MR (m)
Rmt=[8 8 8;5 5 5;7 7 7];
%-----------------------------------------------------------------


%-----------------------------------------------------------------
%unit cost of 3 MR (m) obtained by 2 kinds outsourcing alternative
z in period p
Umz=[600000 1800000;300000 900000;450000 1350000];

%unit cost of 4 AR (m) obtained by 2 kinds outsourcing alternative
z in period p
Uaz=[60000 150000;30000 90000;60000 180000;90000 240000];
%-----------------------------------------------------------------


%------------------------------------
%working hours of AR (a) in period p
Wpa=1800;

%working hours of MR (m) in period p
Wpm=1800;
%------------------------------------


%-----------------------------------------
%target utilization of AR (a) in period p
Ypa=.8;

%target utilization of MR (m) in period p
Ypm=.8;
%-----------------------------------------
```

```
[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);
%=================================================================
=========


% Negotiation
while DataReceived(2)<=y   % If this stopping condition is still
false, increasing "DataReceived", then send to MAchine A
    alpha=reon+(1-reon)*((min((cputime-t),t_max)/t_max));
    xc=upb-alpha*(upb-lob);

[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);
    DataToSend=[xc y]
    fwrite(con,DataToSend);
    pause(300);
    DataReceived=fread(con,2);
    xc=DataReceived(1);

[x,y]=GA(Cmt,Rmt,Wpm,Ypm,Cmat,Rma,Wpa,Ypa,Opt,Jpt,Lpt,Ip,Umz,Uaz,B
pt,Em,Dm,K0m,Ea,Da,K0a,xc);
end

%set_time = cputime - set_time

if DataReceived(2)>y
    fwrite(con,DataReceived)
end


%
%=================================================================
% % Close and delete connection
% fclose(con);
% delete(con);
```

CHAPTER 5
CONCLUSION AND FUTURE RESEARCH

This section explains research conclusions obtained from the results and some additional recommendations to improve this research.

5.1 Conclusion

This study develops a learning mechanism using Adaptive Neuro-Fuzzy Inference System (ANFIS), and it is successfully implemented into automated negotiation system between two factories that negotiating budget allocation regarded to their own local capacity planning. The learning-based negotiation model can be applied to support negotiation parties with useful information for predicting opponent's offer during negotiation.

The results of experiments show us that each factory able to obtain best profit from their local capacity planning model, and then they can use the model to evaluate the offer values from opponent during negotiation. If the budget that offered brings better profit, then the negotiation will be compromised. From the experience of the negotiation result, a factory can learn about the opponent move and predict their next offer. The learning mechanism that have been used gives very good prediction of the opponent's offer, so then it will enables them to reduce the negotiation time.

5.2 Recommendation for Future Research

From a comprehensive perspective on the results of this study, the further research can be developed towards the several directions in the future.

1. In this study we utilize time-dependent tactic for doing negotiation experiments. The future research should be able to implement other kinds of tactics into negotiation-based capacity planning and then also integrate

it with the learning mechanism. The integration should also give good prediction of the opponent's next offer.

2. The structure of this study is engaged in the situation on one to one (bilateral negotiation). In the future, we can extend the framework to involve more factories to become participants of negotiation (multilateral negotiation).
3. This study investigated a specific issue of negotiation which is budget allocation. In the future, we can consider other issues that possible to become offering value, and these issues also related to the optimal profit evaluation of capacity planning for each factories that participate the negotiation.

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