Development Industrial Interruption Cost Model by Adaptive Neuro-Fuzzy System Part I: Data Collecting and Model Development

P. Teansri, N. Uthathip, P. Bhasaputra, and W. Pattaraprakorn

Abstract— *This paper describes the development customer interruption cost model of industrial sector in Thailand by using adaptive neuro fuzzy inference system (ANFIS). In this study, the surveyed data set from food, beverage and tobacco industries is collected to demonstrate the concept of model development. To perform validating of the proposed model, the mean absolute percentage error is used as the predictive indicator. The study results show that the factor of industrial scale has a great significant impact to the interruption cost. For instance, the interruption cost at interruption duration of 60 minutes for small and large scale of food, beverage and tobacco industry can vary from 26,128.27 to 1,030,809.67 Baht per event. In addition, the interruption cost from ANFIS model compared with the interruption cost from customer survey is in an acceptable range. Under resources, time and financial support constraints, the electric utility planners can be applied the proposed model without performing customer survey. However, in order to apply in practical reliability investment planning, the evaluation interruption cost from ANFIS model can be improved the error to a lower range by increasing the training data set. In further study, the interruption cost model of other industrial groups according to Thailand Standard Industrial Classification (TSIC) will be presented in Part II: Evaluation interruption cost of high energy consumption industry.*

Keywords— **Interruption cost, Adaptive neuro-fuzzy inference system, Industrial customer.**

1. INTRODUCTION

Under situation of global and national economic growth, the electricity demand in Thailand, a key driven factor of country development, was rapid growing over a decade. In order to meet the customer load requirement, not only generation and transmission systems are required for improvement and expansion the existing system but the distribution system is also considered to deliver electricity to their customer with high level of customer service and satisfaction. However, the practical planning to construct new infrastructures in electrical power system is associated a large financial supports. In addition, the tasks of expansion transmission lines and improvement distribution systems are under complexity and several constraints. Therefore, reform the Thai Electricity Supply Industry (ESI) is one of the options to enhance planning objectives which the government can reduce investment burden of financing expensive in electricity infrastructure and hence enhance investing in other priority programs such as health, education and other social activities. The reform of ESI has been undergoing since the early 1990s especially in generation system. The private sector has opportunities to compete in electricity market. In 1992, Independent Power Producer (IPP) and Small Power Producer (SPP) programs with the aim to meet the growing demand for electricity are introduced in the initial phase of electricity reform. Furthermore, the Very Small Power Producer (VSPP) program which limits generation capacity of 10 MW has been launched in 2001. At the present, although EGAT is still the major player for power generation utility, the programs of electricity market competition from private sectors lead the country to have an improvement mechanism from tradition electricity authority. Sufficient reserve margin from several power producers and well management in transmission system imply that the electric power shortage problem is rarely occurring in Thailand.

Considering the distribution power systems, there are two electric utilities under natural monopoly structure response for delivering electricity to end-users: the Metropolitan Electricity Authority (MEA) supply electricity to 2,918,127 consumers in Bangkok and surrounding areas; and the Provincial Electricity Authority (PEA) responsible for electricity sale to 15,060,631 customers which accounting 99.9% of country's area. In the engineering point of view, the constraints of large service area and number of customers affect to the process of practical planning process especially for PEA. To serve adequacy electricity demand with improvement a quality of service, many concerned issues in Fig. 1 including availability, reliability and quality of power are sets of challenging optimization problems for utility planners [1]. The diversity of needs for power supply reliability and quality in the market tends to increase as well as the economic growth. Customer satisfaction is also extended along with the unit price of electricity. Under the competitive market environment, most of customers prefer to purchase the electricity from the electric utilities with lowest unit prices and high reliability of power supply. After the private sector can compete in

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electricity market, industrial customers especially in industrial estates have a chance of electricity services from public utilities and private suppliers. The image and service responsiveness are also attractive factors for customers to make a decision of service from which electric utility. Therefore, these subjects are often important part of utility business.

To justify with the effectiveness investment in large area on distribution system, the classification service area according to load patterns is one of the planning criteria for PEA. In general, the service area can be classified into five areas: industrial areas included industrial estates, industrial promotion zone, industrial park and etc., business area, town municipal area, district municipal area and rural area.

In each area, the reliability level, supply security and system stability are integrated in planning process which depends on impact levels during interruption to power systems and their customers. The benefits of improving system reliability and the cost of applying the optimal solution to enhance the system performance must be complied in the planning criteria. For instance, the most common reliability indices consisting of System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI), restoration time performance for industrial and business area are designed to be better than town municipal, district municipal and rural areas, respectively.

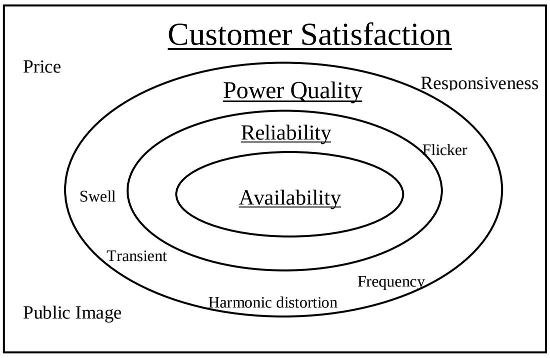

Fig. 1. Issues of customer satisfaction in power system.

The value based reliability planning (VBRP) is one of the accepted approach from electric service providers in many countries. This tool attempts to establish a balance between the costs of improving service reliability for various types of customers with the benefits or value that these improvements bring to these customers. For better outstanding in the concept of VBRP, Fig. 2 shows the relationship between expected reliability level with respect to the costs of utility and customer perspective. The curve can be explained that the utility cost will generally increase as customers are provided with higher reliability. On the other hand, the customer costs associated with supply interruption will decrease as the reliability increases. The utility investment costs in distribution system which well known from historical data can be directly refered in term of capital cost, installation cost, operating cost and maintain facilities cost while the customer reliability cost is indirectly estimated from customer damage incurred during power interruption. Although trends of the customer interruption cost are similar in virtually all cases, the costs can vary over a wide range and depend on many factors such as location, type and size of customer. Under various activities in differrent customer sector, the interruption cost for each customer is also a constraint problem that utility necessary to appropriate manage during power system planning. Therefore, the issue of optimum system reliability improvement is a difficult and challenge tasks for utility. With the least cost planning strategy, determining optimal investment in different areas should consider the marginal customer cost of reliability equal to the marginal utility reliability cost. In this point, the societal cost will be minimized while the relaibility performance target of electric utility will also be achieved. The examples of some areas where customer interruption costs can be usefully applied to economic evaluation in electric transmission and distribution planning include:

- Transmission line expansion,
- Substation and distribution circuit design and rearrangement,
- Equipment rating design,
- Scheduling maintenance activities and
- Protection devices allocation.

The interruption cost normally is provided by direct customer survey and evaluated by average or approximation method [2]. However, there are some practical limitations. The interruption costs can vary on time; hence it needs to conduct new survey in every period that depends on utility planning process. Since a large number of customers and widely service area of PEA, it is very difficult to conduct the customer interview although the number of customer survey is calculated with statistical sampling method. The accuracy of interruption cost assessment also depends on time and available resources. Some utilities have a condition of resources limitation and the assessment in the service area may cover in specific networks. Hence, several literatures have been developed the alternative analytical techniques and interruption cost models to evaluate interruption cost for a wide service area. Main contributions of interruption cost evaluation with analytic techniques are reducing time, budget and human resources while the available data from customer survey and utility database is also utilized. Further, the development customer interruption cost models allow electric utility planners to estimate economic impact from power supply interruption in the view point of microeconomics and macroeconomics scale. Some techniques to apply in the interruption cost modeling from selected countries are reviewed in Table 1.

Table 1. Literatures for interruption cost model by several techniques

Methodology	Country	Summarized of details
The approximate methods	Canada [2]	Applied the available data (customer data, load data and interruption cost function) from most utilities to develop series of three alternative approximate methods and compare the accuracy with the based method for a widespread area.
Analytical method	Korea [3]	Presented the outage cost evaluation of generation and transmission system by combining the marginal outage cost function and Composite Power System Effective Load Duration Curve (CMELDC). The results of proposed method are demonstrated in IEEE Reliability Test System (RTS).
Fuzzy model	Thailand [4]	To cope the large deviation of the data which obtained from customer survey, the concept of fuzzy arithmetic was applied to model the Fuzzy Interrupted Energy Assessment Rate (FIEAR). The proposed method has been tested with a distribution system of which more than 40,000 actual interruptions were recorded. The results show that the FIEAR normally covers the IEAR.
A probability distribution approach	University of Saskatchewan, Canada [5]	Transformed the entire outage cost data set from surveyed specific interruption duration to a normal probability distribution function that can be used cooperate with practical power system reliability worth assessment.
Fuzzy linear regression model	Taiwan [6]	Described distribution and dispersed behaviors of interruption costs by applying regression analysis to predict distribution patterns for intermediate durations and using fuzzy to deal with uncertainty of actual distributions samples.
Multiple regression analysis	BC Hydro's service territory, Canada [7-8]	Used the impact of key drivers on the outage cost including outage duration, season of the year and time of day to develop multiple regression analysis of small business, medium business and residential customers. The regression coefficient value, the R-squared values adjusted for degrees of freedom, the statistics and the probability of F-distribution also presented in the article.
Multiple regression analysis	USA [9]	Surveyed the data from large commercial and industrial customers and identified regression models that allow reasonably accurate prediction of outage costs for customers who were not surveyed on-site from information that was readily available from utility customer representatives. The cost of obtaining outage cost estimated the customer basis was less than 20 percent of the cost that would be required to survey all customers on-site.
Linear regression	Finland [10]	Formulated outage cost models which impact from unplanned outage, planned outage, delayed and auto reclosing. The linear regression was applied to remove the discreteness of the questionnaires that were used to gather the data. The outage cost is a part of reliability calculation which proposes for regulation process when the Finnish electricity market is fully open.
Tobit regression	USA [11]	Applied the Tobit regression model to estimate the relative effects of various independent variables rather than normal orthogonal least square regression. The truncation of 0.05% of the highest values in the interruption cost distribution and the transformation of the interruption cost variable to a lognormal distribution were used. In this study, the Tobit regression was applied for commercial, industrial and residential customer. The independent variables in the study include customer and interruption characteristics.
Activity-based with Monte-Carlo technique	Sweden [12]	Applied the survey data in 2003-2005 to model the interruption cost of residential customers. The independent factors to model are interruption duration, activity patterns, outdoor temperature and daylight to describe the impact of different power interruptions. In this study, the worst case of customer interruption cost retrieved from survey was set to be the reference cost. This paper concludes that utility can analyze sensitivity factors that impact on residential customers without survey the cost in all cases of interruptions.
RBF Neural Network	Taiwan [13]	Proposed two interruption cost models including aggregated model (AAM) and probabilistic distribution model (PDM) by using the radial basis function (RBF) neural network with orthogonal least square learning method. A 11.4 kV distribution network with 5 feeders of the Taipower was used for tests. A Monte-Carlo time sequential simulation technique has also been to evaluate the interruption cost of individual load point, the system and the probability distribution of the cost indices. The results show that AAM could underestimate the reliability worth and PDM provides a more realistic approach.

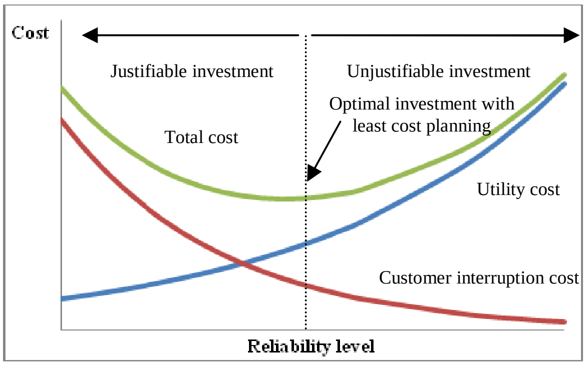

Fig. 2. Conceptual of reliability investment.

Several approachs for estimating the interruption cost of each customers group are employed from interruption cost models. Information relevant to the interruption cost is required to formulate the interruption cost model. Under development concept, the interruption cost can be estimated in the future without fully direct survey on all customers and some information is directly obtained from utility database. The benefits of interruption cost assessment using the customer damage model are minimizing internal resources, cost saving and less time consumption for interruption cost estimation in the future. In this paper, the principle of adaptive neuro-fuzzy inference system (ANFIS) is applied to develop customer interruption cost model at different scenario of distribution system performance. The article is divided into two parts. The first part organized as follows: an overview of methodology of interruption cost assessment is given in Section 2. The principles of ANFIS and conceptual of interruption cost model development are addressed in Section 3. Simulation results of customer interruption cost model provided from ANFIS model are presented in Section 4. Section 5 concludes the development concept of interruption cost by ANFIS.

In part I, the case study of development interruption cost model based ANFIS principle is demonstrated with the surveyed data of food, beverage and tobacco industries. Then, unreliability cost from large scale industrial customers represented in term of annual interruption cost is estimated in the part II. The analysis of reliability cost and worth is also compared with the value of gross domestic production in order to investigate macroeconomics impact from electric power interruption.

2. METHODOLOGY OF INTERRUPTION COST ASSESSMENT

Estimation of customer interruption cost can be obtained from several approaches. In general, it can be categorized into two methods which are direct assessment method and captive generation method. The direct assessment method or production-function approach estimates the cost of interruptions through lost service and production (industrial and commercial customers) or lost time (for households). This approach uses quantitative statistical information [14]. A drawback of direct assessment method is that some aspects such as restart time in processes or businesses are difficult to include in the estimation. Within this approach, several choices are possible. First, the lost production in each sector during an interruption can be estimated directly, and this can be aggregated to a macro-economy. Second, linkages between sectors can be included by manipulating input–output tables [15]. Captive generation method or market behavior method or indirect assessment method (revealed preferences) estimates interruption cost based on the expenditure in backup sources. Both the expenditures on backup facilities and the use of interruptible contracts can provide information on how commercial, industrial and household sectors value interruptions of the power supply. For example, expenditures on backup facilities show how much customers in each sector are willing to pay for a higher level of supply security than is currently provided by the network [16]. In this method, the scenarios of interruption durations per year are assumed for allowing customers to estimate the costs that they prefer to pay [17]. However, this method may not effectiveness for a country that the performance of electric networks is in high reliability level. For instance, a distribution area which is categorized in high reliability has an average about 30 minutes of supply interruptions a year, a backup generator would have to be used for only very short periods of time. Therefore, the capital cost per minute of operation would be so high that it is hardly ever attractive for firms or households to invest in backup technology. Therefore, in the countries with few interruptions, the expenditures on backup facilities most likely cannot be used to estimate an upper bound for the cost of interruptions. The two methods for estimating customer interruption cost both direct assessment method and captive generation method imply that most of the analytical data is provided from conducting the customer survey. In the practical assessment, customer survey requires several resources to estimate the customer interruption cost in different interruption scenarios. The survey-based approach is sometime not flexible for a distribution utility that responsible for large service area. To study covered all service areas, conducting the customer survey requires effectiveness of questionnaire, time, well trained surveyors, and customer database. In addition, the participation from customers is directly affected to the results of survey. Some respondents can be finished the survey within few hours while another customer may be returned the survey questionnaire in the next few months with some blank information. To cove the problem of conducting customer survey for large service areas, the data used to analyze and develop interruption cost model in this study is obtained from integrated method that includes direct customer survey-based approach, the phone interview, sending the questionnaire by post mail and e-mail. For the sending questionnaire by post mail and e-mail, the documents contained with question descriptions, the instruction and guideline, the example of answer and contact information are also attached in the survey questionnaire. To assessment macroeconomics impact of the industrial sector that is the major economic contributor, the interruption cost information of customers are collected to determine the cost per event of interruption that customer experienced during a year. In designing a sample, the data filled in questionnaire by industrial respondents is concerned as a simply survey. Some information is designed to appropriate interview between interviewer and respondents. The questionnaire is directly sent to the factory management level. It is expected that reliable of interruption cost and useful information will be obtained.

Although industry classified in the similar category was assumed that interruption costs in each industrial scale are not widely different. The relevant factors expressed in term of percentage of customer interruption cost are filled in the customer questionnaire that includes:

- Costs of idle and overtime of employees;
- Costs of machine and equipment damages;
- Costs of production lost or lower productivity;
- Costs of damaged raw material and products;
- Costs of re-start production and
- Cost of standby power supply operation.

These factors are also used to verify the reliability and quality of information from customer survey responses. The interruption characteristics including interruption frequency, interruption duration, season of interruption and time of a day are also included in the customer interviews. Furthermore, information about industrial characteristics, energy consumption, production rate, raw material consumption and process operation hours is gathered. After conducting customer survey, the data set of selected industry comprising industrial type, electrical energy consumption, process characteristic, interruption duration and process recovery time is assigned to be the input variables of ANFIS. In this paper, the customer data from food, beverage and tobacco industries in Thailand is used to illustrate the interruption cost model development by ANFIS approach. The data of other industrial sectors collected from customer survey is also used to develop interruption cost models with similar concept.

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The nature of data set obtained from survey approach contains uncertainty and variety of pattern. Although similarity of firms or manufacturing processes, different customers or respondents may estimate the interruption cost in their perspective and past experiences. This is called "human reasoning processes". The input-output data set which used to develop customer interruption cost model is then assumed as non-linear relationship system. The uncertainty of survey data provides the fuzzy approach to develop interruption cost model by performing relationship between input variables and output variable based on if-then rules. The formulation fuzzy rules can be called as "knowledge-based technique". However, fuzzy approach may complicate to set fuzzy rules and influenced parameters when a large input-output data set is collected from customer survey. Therefore, artificial neural networks (ANNs) have been used as computational tools for pattern classification. In neural networks, the relations are not explicitly given, but are 'coded' in the network and its parameters. In contrast to knowledge-based techniques, no explicit knowledge is needed for the application of neural networks. For this reason, the ANFIS approach which combines the concept of fuzzy logic and neural network is introduced to deal with the customer survey data. The basic idea of ANFIS approach in this article is to provide a method for the fuzzy modeling procedure to learn information about data set, in order to automatically compute the membership function parameters. These parameters are tuned using a combination of least square estimation and back propagation algorithm. The learning process of parameters tuning will change in similar to a neural network. Their adjustment is facilitated by a gradient vector which provides a measure of how well the fuzzy inference system is modeling the input-output data for a given set of parameters. Once the gradient vector is obtained, several optimization routines could be applied in order to adjust the parameters until the error between the actual and desired outputs is minimized. This approach has the advantage over the fuzzy approach that need human expert to tune the system parameter by adjusting the bounds of the membership functions.

3.1 Architecture of ANFIS

The ANFIS principle gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership function parameters which are extracted from a data set according to a given error criterion [18]. In general, ANFIS architecture of five layers for constructing inference system can be described as shown in Fig. 3. Each layer consists of several nodes described by the node function. The rule base of ANFIS contains fuzzy if-then rules of Sugeno type [19]. For a first order two-rule Sugeno fuzzy inference system, the two rules may be stated as from the nodes in the previous layers. To illustrate the procedures of an ANFIS, for simplicity, it is assumed those two inputs (x, y) and one output (f_i) are used in this system. The rule base of ANFIS contains fuzzy if-then rules of Sugeno type. For a first order two-rule Sugeno fuzzy inference system, a common rule set with the two fuzzy if-then rules is the following [20].

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

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

where x and y are the inputs of ANFIS, A and B are the fuzzy sets, f_i (x, y) is a first order polynomial and represents the outputs of the first order Sugeno fuzzy inference system, p_i, q_i and r_i are the design parameters determined during the training process. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system.

- *Layer 1: all the nodes are adaptive nodes. The output* of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_{1,i} = \mu_{A_i}(x) \qquad i = 1, 2 \tag{1}$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad i = 3, 4 \tag{2}$$

where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership functions. For instance, if the bell shaped membership function is employed, $\mu_{A_i}(x)$ is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left(\frac{x - c_i}{a_i} \right)^2 \right\}^{b_i}} \tag{3}$$

where a_i, b_i and c_i are the parameters of membership function, governing the bell shaped function accordingly.

- *Layer 2:* every node in this layer is a fixed node, marked by a circle and labeled Π, with the node function to be multiplied by input signals to serve as output

$$O_{2,i} = \omega_i = \mu_{A_i}(x).\mu_{B_i}(y) \qquad for \quad i = 1, 2 \tag{4}$$

- *Layer 3:* every node in this layer is a fixed node, marked by a circle and labeled N. The node function normalizes the firing strength by calculating the ratio of the i^{th} node firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \varpi_i = \frac{\omega_i}{\sum \varpi_i} = \frac{\omega_i}{\omega_1 + \omega_2} \qquad for \quad i = 1, 2 \tag{5}$$

- *Layer 4:* every node in this layer is adaptive node, marked by a square, the output of each node in this layer is simply the product of normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by:

$$O_{4,i} = \varpi_i \cdot f_i = \varpi_i (p_i x + q_i y + r_i) \qquad for \quad i = 1, 2 \tag{6}$$

- *Layer 5:* every node in this layer is the fixed node. The node performs the summation of all incoming signals. Hence, the output of this model is computed by:

$$O_{5,i} = f_{out} = \sum_i \varpi_i \cdot f_i = \frac{\sum_{i=1}^{2} \omega_i f_i}{\omega_1 + \omega_2} = overall \quad output \tag{7}$$

It can be observed that there are two adaptive layers in the ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters {a_i, b_i and c_i }, which are related to the input membership functions. These parameters are also called "premise parameters". In the fourth layer, there are also three modifiable parameters {p_i, q_i and r_i }, pertaining to the first order polynomial. These parameters are also referred to the consequent parameters.

3.2 Learning algorithm of ANFIS

The task of learning algorithm for ANFIS architecture is to adjust all the modifiable parameters, namely {a_i, b_i, c_i} and {p_i, q_i, r_i}, to make the ANFIS output match the training data. When the premise parameters a_i, b_i,and c_i of the membership function are fixed, the output of the ANFIS model can be written as:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \tag{8}$$

Substituting Eq. (5) into Eq. (8) yields:

$$f = \varpi_1 f_1 + \varpi_2 f_2 \tag{9}$$

Substituting the fuzzy if-then rules into Eq. (9), it becomes:

$$f = \varpi_1 (p_1 x + q_1 y + r_1) + \varpi_2 (p_2 x + q_2 y + r_2) \tag{10}$$

After rearrangement, the output can be expresses as:

$$f = (\varpi_1 x) p_1 + (\varpi_1 y) q_1 + (\varpi_1) r_1 + (\varpi_2 x) p_2 + (\varpi_2 y) q_2 + (\varpi_2) r_2 \tag{11}$$

The output in eq. (11) is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. Table 2 summarizes the activities in each pass. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [21].

Table 2. Two passes in the hybrid learning procedure

Parameters	Forward Pass	Backward Pass
Premise parameters	Fixed	Gradient Descent
Consequent Parameters	Least Square Estimation	Fixed
Signals	Node Outputs	Error rate

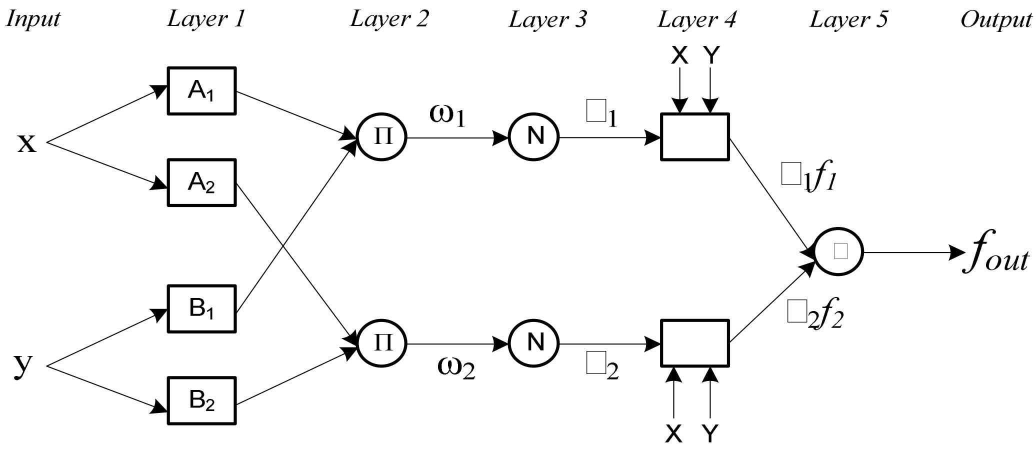

Fig. 3. ANFIS architecture.

3.3 Interruption cost model from ANFIS architecture

In this study, interruption cost model by ANFIS principle is demonstrated. The inputs-output data set is provided from the manufacturing related to food, beverage and tobacco industry. Four variables in each industry including electrical energy consumption, process characteristics, interruption duration and process recovery time are collected and assigned to be the input variables while the interruption cost is the output variable. Each input to construct the model can be described as follows:

- *Electrical energy consumption:* this variable refers to the average of electricity utilization in manufacturing process for each sampled industry (kWh/month). Main assumption of this variable is that the interruption cost of industry consumed large amount of electricity should greater than the interruption cost observed by industry with less electricity consumption. The information implies the plant capacity which is provided from billing database of electric utility. Therefore, this variable can be automatically extracted from the database for performing the reliability cost worth assessment in the future.

- *Process characteristics:* the manufacturing processes are generally defined into two categorizes; I) continuous process and II) batch process. In this study, the manufacturing of factory operated with continuous process means all raw material and production processes are definitely interrupted during sustain interruption occurred. The iron and steel manufacturing, cement manufacturing, pulp and paper manufacturing can be defined as the factory operated with continuous process. In addition, some processes may sensitive to power quality problem which can quickly lead to a cascading shutdown of the entire process. In contrast, a factory operated with batch process or non-continuous process means that the production system is divided into several sub-sections. The material and process flow is not directly transfer to another sub-process. Therefore, some processes can be restarted production lines after interruption event is corrected. The food, beverage and tobacco manufacturing, the wood and furniture manufacturing and some of the electric and electronic manufacturing are classified in the batch process. From the onsite customer survey, the assumption of this variable can be defined that the industry operated with continuous process has a possibility of higher impact from sustain interruption than the industry operated with a batch process.

- *Interruption duration:* in the study, interruption duration is defined as the time of a power supply out of service that industry had experienced during one year. In general, interruption duration from industrial perspective is longer than the time recorded from electric utility. In a case of critical components, major equipment or devices in power supply systems are out of service, failure and customers do not have a redundant circuit, interruption duration time is normally longer than the interruption caused by animals or extreme weather. The industrial customer damage from power system components failure and is typically larger than the interruption caused by animal and weather.

- *Process recovery time:* when power supply is out of service, most of manufactures require time for managing processes and activities. Process recovery time refers to the duration time which industry needs to deal with the production lines. The performed procedures after power supply interruption include resetting interrupted machines and equipment, extraction material damage or blockage, re-checking all emergency and safety systems, re-starting the manufacturing processes and feeding a raw material until the production capacity reaches to normal operation. Recovery time can vary from a minute to a day depending on interruption duration, characteristic of process and plant operation. In the survey, the steel products manufacturing often integrated electric motors of different ratings and specifications in one controlled system. A loss of control of one motor caused by unexpected and sudden power interruption can upset the general control and lead to complete standstill of the whole production system. The processes require at least 45 minute for voltage dip problem and 6-8 hours for interruption event of 15 minutes. The relationship of interruption duration and process recovery time from customer survey is illustrated in Fig. 4. Like an interruption duration, the assumption of this variable is that an industry which requires long recovery time to deal interrupted processes has a damage cost higher than the industry which require a short recovery time or not sensitive to the power quality event.

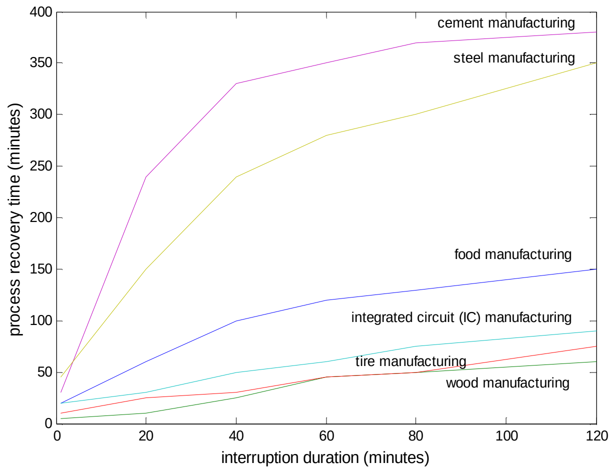

Fig. 4. Process recovery time and interruption duration of selected manufacturing industries.

In order to demonstrate the interruption cost model from ANFIS, the data provided from 325 food, beverage and tobacco industries in Table 3 including small scale, medium scale and large scale industries is used as the case study. The data is divided into two separate data sets. During data training process, the 260 data set is selected to learn a non-linear relationship between input-output variables while the 65 data set is assigned to be the testing data. According to the survey questionnaire, the number of membership function for each input and output is defined as shown in Table 4. The architecture and training parameters of ANFIS model are displayed in Table 5. In the ANFIS model, least square estimation and gradient descent algorithm are applied in the hybrid learning rules.

Table 3. Number of sampled industries

Industrial size	Number of industry	Electrical energy consumption (kWh/month)
Small	60	<100,000
Medium	78	100,000-250,000
Large	187	>250,000

Table 4. Number of membership function for input/output variables of ANFIS

Variable	Description	No. of MF	Range
Input 1	Electrical energy consumption	3	10,000-16,500,000 kWh/month
Input 2	Process types	2	Continuous/Batch
Input 3	Interruption duration	8	1-60 min.
Input 4	Recovery time	9	15 min.-24 hrs.
Output 1	interruption cost	10	5,000-10,000,000 Baht/event

Table 5. ANFIS architecture and training parameters

Number of layer	5
Size of input/output data set	325
Number of input	4
Number of output	1
Membership function	Gauss
Learning rules	Least square estimation Gradient descent algorithm
Momentum constant	0.9
Number of epoch	100

4. SIMULATION EXAMPLES

In this study, the ANFIS model has been developed to estimate interruption cost of food, beverage and tobacco industries. The ANFIS system with four inputs using gauss-shaped membership functions is shown in Fig. 5. The number of fuzzy rules is set to 432 rules according multiplication number of membership functions for each input. The output is comprised of a linear combination of the inputs multiplied by the normalized firing strength.

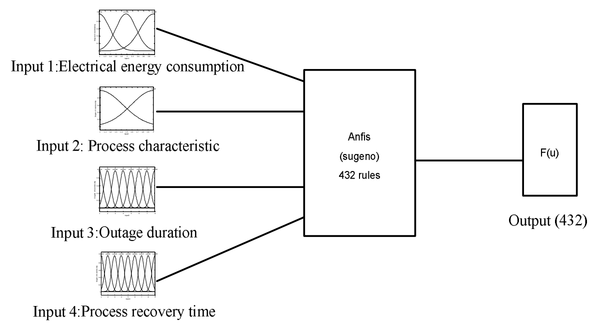

Fig. 5. ANFIS system: 4 inputs, 1 output, 432 rules

According to the electricity rate in PEA' tariff, the electrical energy consumption referred to the scale of industry is divided into three categories which are small scale, medium scale and large scale industry. To present the adjusted membership function parameters from data training process, the example of three membership functions of electrical energy consumption is plotted in Fig. 6. To normalize the range of this input, the actual electrical energy consumption from 10,000-16,500,000 kWh/month is converted to an appropriate range as well as the other input and output variables. After the process of data training is finished, input membership functions of electrical energy consumption are adjusted to obtain least square error. The results of data training illustrate that membership parameters of large scale industries (in1mf3) are the most adjusted parameters. In addition, the trend of mean square error (MSE) during data training process in Fig. 7 is decreased from initial state and remained constant after training epochs of 55. The final convergence value of MSE is 4.0515×10^{-6} with 0.1 step size. It can indicate that 432 fuzzy rules impact to a large scale of industry that is the results of the highest number of customer survey data.

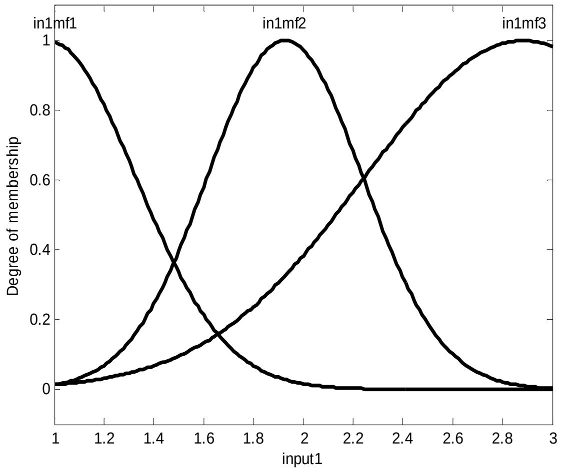

Fig. 6. Membership functions of electrical energy consumption after training data is obtained.

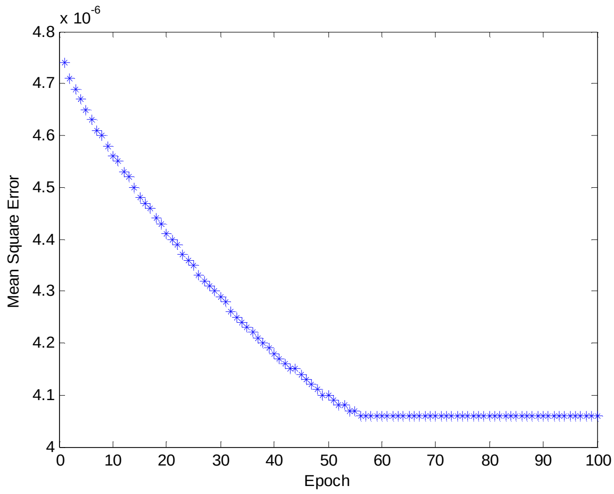

Fig. 7. The curve of network error convergence during data training for interruption cost model of TSIC 31.

Furthermore, to evaluate the reliability of ANFIS model, the 65 testing data set excluded from the data training is used to validate the performance of the model. The error range and the average absoulute error of the ANFIS model with testing data set is summarized in Table 6. The results show that the interruption cost from ANFIS model provides the error of 8.6% for small scale industry when compared with the interruption cost from survey questionnaire while the medium scale industry and large scale industry have the average error of 8.1% and 9.5%, respectively. The errors provided by model validation show that the concept of interruption cost evaluated from ANFIS model can be used instead of collecting new data from the customer survey approach.

Table 6. Performance validating of ANFIS model

Industrial scale	Number of testing data	Error range (%)	Average error (%)
Small scale	13	6.3-9.8	8.6
Medium scale	15	7.5-9.2	8.1
Large scale	37	8.2-11.5	9.5

After performing data training process, the customer interruption cost by ANFIS can be generated with optimal system parameters. The model is varied with the interruption duration in order to provide customer damage function. Because of output from ANFIS model is the fuzzy number, therefore, the defuzzification process to convert the fuzzy number to the real value of customer interruption cost can be performed by using Eq. (12). The relationship between fuzzy output level and actual interruption cost is also illustrated in Fig. 8.

$$cic_{avg} = 847 \times \exp^{(0.9709 \times f_o)} \tag{12}$$

where cic_{avg} is the average customer interruption cost expressed in (Baht) and f_o is the fuzzy output number, which obtained from the ANFIS model under specific input data set. If the four input variables of the industry produced frozen food are known. For instance, the industry operates with the average of electrical energy consumption of 5,370,000 kWh/month, 24 operating hours with continuous process, approximately 45-60 minutes required recovering production lines until reaching the normal capacity. If the interruption occurred with 15 minutes, the ANFIS model can estimate customer interruption cost with the fuzzy output level of 5.8. Then, the actual interruption cost can be evaluated using Eq. (12) that is 236,314.9 Baht/event. In addition, this model can be used as the reliability cost and reliability worth evaluation tool under the different scenario of interruption or customers if the four input variables are available.

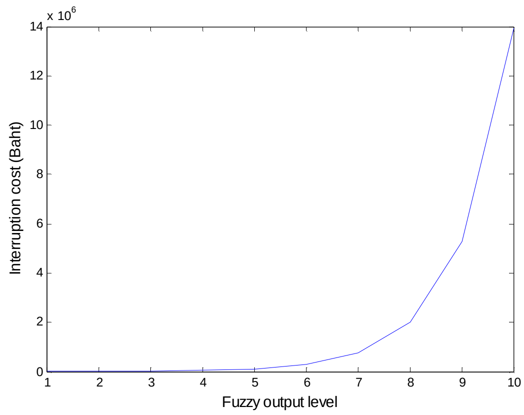

Fig. 8. Defuzzification fuzzy output to the actual cost.

Based on training data set provided from survey approach, the interruption cost at different interruption duration from the output of ANFIS model after defuzzification can be plotted in Fig. 9. For the interruption duration of 1 minute till 60 minutes, interruption cost of small scale industry and medium scale industry can vary from 4,493.43-26,128.27 Baht/event and 23,632.11-111,187.67 Baht/event, respectively. In addition, interruption cost model for the large scale industry at duration of 1 minute is 232,087.94 Baht/event while the interruption cost at 60 minutes can reaches to 1,030,809.67 Baht/event. The interruption cost evaluated from ANFIS model for small, medium and large scale industry is also presented in Table 7. Major findings of this study can be concluded that the utility planners should be addressed the factors that relate to the customer interruption cost in each sector. The results of interruption cost based on survey data without performing data analysis may not appropriate to apply in the practical planning. In this study, not only the interruption duration is analysed, the factors of electrical energy consumption and manufacturing characteristics are also investgiated. However, the developed model in this study is employed by random sampling data from survey approach which may not cover all processes under food, beverage and tobacco industry. In order to utilize the developed interruption cost model in practical assessment, the training and testing data set should be increased covering most of sub-category industry. The reliability of the model for practical implementation is also improved when a large amount of data has collected. Under the restriction of time and resources for conducting customer survey, the concept of customer interruption cost evalaution by using ANFIS model can be applied as an economic computation tool for distribution utility to assess relaibility cost-worth in the network improvement and expansion projects.

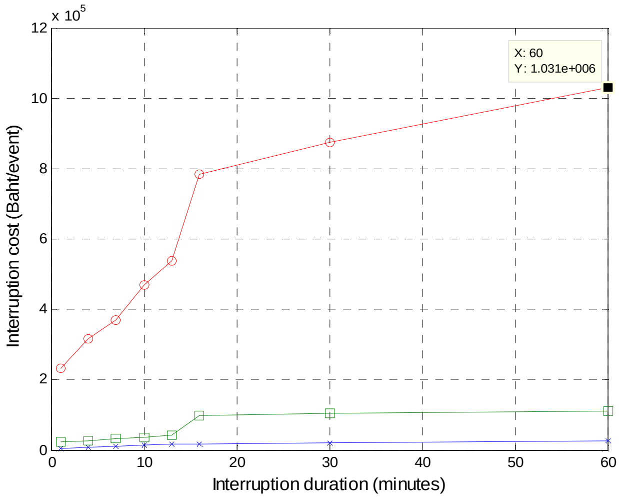

Fig. 9. Individual customer damage function for food beverage and tobacco industry from ANFIS model.

Table 7. Average interruption cost of food, beverage and tobacco industry from the proposed model

Interruption duration	Interruption cost (Baht/event)		
	Small scale	Medium scale	Large scale
1 minute	4,493.43	23,632.11	232,087.94
10 minutes	13,256.35	36,946.25	467,532.59
16 minutes	18,454.08	97,957.88	784,121.25
30 minutes	21,810.02	103,157.52	872,878.80
60 minutes	26,128.27	111,187.67	1,030,809.67

5. CONCLUSIONS

Reliability cost-worth assessment is more important issue of value based reliability planning in power distribution system. Most of the assessment is employed by customer perspectives based on customer survey. However, the constraints of interruption cost assessment including resources requirement, available budget, time consuming are the factors which push some researches and planners propose new analytical methods for the interruption cost assessment. In addition, using the customer interruption cost from survey without performing data analysis may result in under or over estimation. This paper develops the customer interruption cost model by using ANFIS approach which can deal the data associated the high uncertainty from customer survey. To demonstrate the steps of development, the data set from selected samples covered with small, medium and large scale of food, beverage and tobacco industries in Thailand is surveyed. From survey questionnaire, the data of each industry including electrical energy consumption, process characteristic, interruption duration and process recovery time is assigned to be input variables of ANFIS model. In fuzzy inference system, 432 fuzzy rules are employed from the four input variables to calculate the fuzzy output which represents the damage cost level. The results show that ANFIS architecture can deal with the large and uncertainty of data set from customer survey. Under the restrictions of resources and time requirement to perform the direct interruption cost assessment from customer survey, this paper proposes the ANFIS approach to develop the interruption cost model and use to evaluate the customer damage cost in the practical distribution system design and planning. Moreover, further study will be presented the interruption cost model with the data set from other industrial groups. Finally, this concept requires improving the precision and reliability of ANFIS model before using in practical planning for reliability assessment of distribution system.

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