A Study of Using Artificial Neural Network in a Non-linear Centrifugal Compressor System

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***Abstract*—This study adopts the centrifugal compressor system which produces the nitric acid equipment in China Petrochemical Development Corporation's Plant. The system is non-linear and its manufacturing process is changeable, which the traditional PID (Proportional-Integral-Differential) control method is difficult to apply. This study is intended to apply the artificial neural network method to test and forecast the compressor performance. By means of collecting the PLC (Programmable Logic Controller) on-line data, the proposed method is applied to simulate the control system. According to the result of this study, the proposed method can reach the high accuracy, and make concrete contributions in promoting the safety of the centrifugal compressor system.**

Keywords-centrifugal compressor; PLC control system; artificial neural network

I. INTRODUCTION

Petrochemical industry has been one of the important industries in Taiwan. In 1980s, Taiwan's petrochemical industry ranked the fourth largest in the world, and the petrochemical industry has always been considered as a successful example of Taiwan's industrial and economic development. The level of correlation of the middle and lower reaches of the industrial chain is very high. Hence, petrochemical industry is the backbone of the basic industries of Taiwan's top priority for development, plays a key role in Taiwan's economic development, and has made considerable contributions. In 2009, the output value of Taiwan's petrochemical industry was 1318.6 billion NTD, accounting for 7.75% of the national gross industrial production [1].

However, petrochemical plants involve various equipment, lengthy process, large investment funds of relatively high level of system size and complexity. Regarding the complex and lengthy system facing large investments in the future, reliability, maintainability and validity are particularly important. Compressor, which is the key machine to mainly compress and transport various gases in chemical production, occupies an extremely important position [2].

Large compressor is a system of non-linearity with changing process links, and time delays will occur when fluids flow inside the channels or instrumental signals such as 4~20mA or 1~5V meter signals for signal transmission on the electric cable, the transmission of analogous signals from the on-site instruments to the traditional PLC controller. Hence, the accurate calculation of compressor performance is particularly important, and this is a problem that is that hard to overcome by most chemical plants. Previously, efforts have been made to establish the precise mathematical models for the compressor. Since the influencing factors are complex and numerous, most important parameters can only use experimental values or experiential formulas. Such experimental values and experiential formulas are hard to display by the non-linearity and variability of actual values regarding the performance of the compressor. The traditional PID control models have difficulties regarding these influencing factors. It is necessary to use new methods to carry out the simulated training of the compressor [3]. This study treated the centrifugal air compressor system of the specific equipment to produce nitric acid in the China Petrochemical Development Corp. (CPDC) Toufen Plant as the an example, and used the artificial neural network method to test the performance of the compressor by transmitting data from the traditional PLC controller to DCS monitoring system via Modbus communication protocol, in order to train the model for better prediction accuracy and performance enhancement [4].

Artificial neural network has a strong non-linearity response capability, and can clearly express any linear or non-linear response association as well as more conveniently conduct multivariate factor prediction. As it is closer to human thinking and linguistic expression as compared with the traditional PLC logic system, it can provide the method to access to system imprecision and approximate knowledge. In particular, when the internal pressure of the compressor rises to the critical point, the fluid field of the compressor may result in two unstable phenomena: anti-surge and rotating stall. Such unstable phenomena will lead to significant decline of pressure and reduce the working efficiency of the manufacturing process. This cannot be solved by the traditional programmable logic control system PLC PID. When the two non-linear phenomena occur at the same time, it will lead to wear and tear of the compressor to reduce the operating productivity [5]. In serious cases, the vibration of the compressor may result in structural damage and forced failure for maintenance. In January 2007, a rotating axis in CPDC Toufen Plant was seriously damaged by anti-surge. Although it did not cause industrial safety accident, the incident caused huge economic loss. The effective prevention of such events is the purpose and direction of this study, which aims to apply the artificial neural network with artificial intelligent forecasting capabilities to solve the complexity problem of the compressor system module. The design and configuration of the neural network provides a good mechanical failure diagnosis and predication method for the compressor system. This study attempts to use artificial neural network to test the performance of the compressor by collecting PLC online data via communications to conduct the simulated training of the system. This study also expects to make concrete contributions to the improvement of the operating safety of the centrifugal air compressor system.

II. LITERATURE REVIEW

In this study, the most widely used back-propagation neural (BPN) network is employed to construct the forecasting model, which is of the feed-forward network architecture and a type of monitoring learning network. BPN network trains the network by using the input vectors and their corresponding target vectors. With the learning and filtering capabilities of the network, the network results will be approximate before classifying the input variables by the transformation function. The characteristic of the BPN network is the generalization of the network. It requires representative input values and target values as the training data set to train the network and can obtain satisfactory output results for input outside the training data set. From the point of view of the curve approximate value, the BPN network has considerably good accuracy in the numerical interpolation approximation function. BPN network back-propagates the output layer unit errors to various layers gradually, and then obtains the reference errors of various layers to adjust the corresponding linkage weighted values to minimize by convergence the error between the inferred output values and the target output values [6].

The basic principle of BPN model uses the concept of the steepest descent method of the optimization methods to minimize the error function. The purpose is to reduce the gap between the network prediction value and the actual target value. In general, the learning quality is represented by mean square sum error, and a smaller value represents higher learning quality. In the learning process of the BPN network algorithm, the repeated learning of simulated training can continuously modify the model until convergence. The multiple-layer feed forward network may use different transformation functions in different cases. The more commonly used transformation functions include the logarithmic double bending curve with output values in the range of 0 to 1, the tangent double bending transfer function with output value in the range of -1 to 1 and the linear transformation function with values outside of the range of -1 to 1. This study uses the linear transformation function with characteristics as follows [7]:

Effective samples should be obtained and programming tools should be selected prior to the forecasting of abnormal trend by using the artificial neural network. The function value obtained after training and learning can be used for simulation. This study uses Alyuda NeuroIntelligence software for learning training. Since the Alyuda NeuroIntelligence has perfect operating interface and simple programming instructions, its use is very convenient and accurate.

The main factors include learning rate, momentum and training times. Too large or small of a learning rate is adverse to the convergence of the network. Greater learning rate will lead to greater modification of the network weighted value and more rapid approach to the function minimum values to speed up the learning and make the network very unstable. Relatively, if the learning rate is too small, the convergence speed will be slow and it is vulnerable to local minimum value. The sample model is adopted in the learning process. In the learning process, the training is conducted by one training sample at one time. The error is calculated upon input of each sample and the weighted value is updated along. Until the completion of the learning of all samples, it is called as a learning cycle. The present value is 0.01, and amplitude adjustment will be made depending on the situation of network learning.

Momentum can improve the swing phenomenon during the convergence process and speed up the rate of convergence. Its role is like a low-pass filter to allow the network to neglect the extremely tiny change in the error curve and respond to the trends of the latest changes. Hence, momentum reduces the sensitivity of the network regarding the change in the local gradient of the error curve, and thus effectively prevents the network from falling into the local extreme value.

Training times is the times of the simulation training cycle. The learning of all data input into the network is called a cycle. Appropriate learning times can lead to relatively good summarization capability of the network to allow the network to accurately forecast the result in case of samples without learning in the test process. Excessive training times will result in over-learning of the BPN model and possibly lead to inaccurate forecasting results of new data without learning in the testing process. The solution to this problem is the determination of the reasonable training times. Methods to determine the BPN model learning level can be mainly divided into two types. One is to determine the learning times to stop the BPN model learning after given times of learning. However, this may easily lead to the failure of convergence of the network model. The other method is to determine the BPN model convergence range until the network model error is smaller than the set error value. In this way, it can ensure that the network model is at the convergence state when it stops learning. It is noteworthy that, the pursuit of minimized error can probably lead to the problem of over-training. As a result, the BPN model learning error will be extremely small; however, the testing results will have very large error values [8]. This study determines 10,000 times as the cycling times. For the consideration of the inability to converge by the network as a result of over-training, it needs repeated tests to select the best one.

III. RESEARCH METHODOLOGY

The research subject of this study is the centrifugal air compressor system for the production of nitric acid in the CPDC Toufen Plant. Using Modbus communication protocol, this study acquired 18 points of the compressor system from the traditional PLC controller to DCS system database different analogous signals during the period of 2010.01.01 to 2011.02.28. It collected 10050 sample data, and repeatedly trained these sample data for 10 times with correlation and R-squared values as the assessment results.

This study used the artificial neural network software to address the problems including the prediction of the compressor system current status, classification and function approximate values, in order to forecast the compressor inlet flow rate and prevent it from approaching the curve of anti-surge. The system flow rate was controlled by changing the level of openness of the control valve to reduce compressor inlet pressure and prevent the compressor anti-surge. This study also simulated the prediction module by empirical study to validate the proposed the effectiveness and feasibility of the prediction of the inlet flow rate of the compressor, and thus, provide a good mechanical failure diagnosis prediction method. That is, this study applied the neural network software named Alyuda NeuroIntelligence as the empirical study tool.

IV. DATA ANALYSIS

A. Sample Data Collection and Analysis

According to the available 10050 sample data of the compressor PLC system in CPDC Toufen Plant in operation, this study removed 728 invalid data samples and effectively acquired 6340 data samples as the training data (about 68.01%), and 1491 data samples as the validation data (about 15.99%). Finally, it selected 1491 data samples as the testing data (about 15.99%).

Since the data of the compressor PLC system in CPDC Toufen Plant were collected in time sequence from the period from January 1, 2010 to February 28, 2011, this study listed in the segmented items of “training data”, “validation data”, and “testing data”, and manually set the “control valve FHV-611” as an independent variable and the rest 17 influencing factors as the dependent variables.

B. Sample Data Pre-processing

According to the above sample data, the Alyuda NeuroIntelligence software will automatically implement proportional classification and encoding program to map the 17 dependent variables on the input layer into the range of [-1,1] and the independent variable of “control valve FHV-611” at the output layer is mapped to the range of [0,1].

C. Artificial Neural Network Architecture

In the design unit, this study implemented the search of the network architecture. After the completion of the implementation, the IDs in the table in 11 categories of classified network layers for the selection of users. This study used the optimal value of the search net architecture, namely, the number of the artificial neural network layer (17-3-1) as the setting value as shown in Fig. 1.

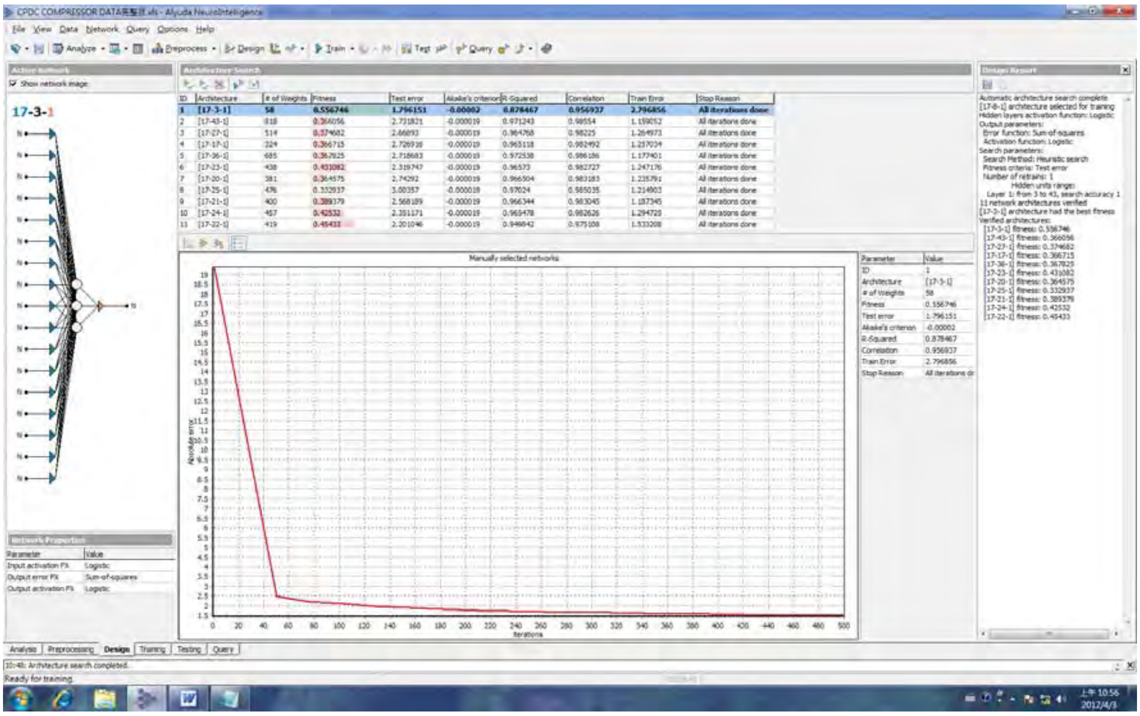

Figure 1. Artificial neural network architecture

D. *Simulation Training*

According to the number of layers of the artificial neural network (17-3-1) selected in the design unit, this study conducted the simulation training. The simulation training of the Alyuda NeuroIntelligence software has 7 options of algorithms. After multiple simulation trainings, this study selected the Levenberg-Marquardt algorithm with the rest functions set with the default values. By using this Levenberg-Marquardt algorithm, the output values and the error correction rate can be determined to maximize the convergence effect, as shown in Fig. 2.

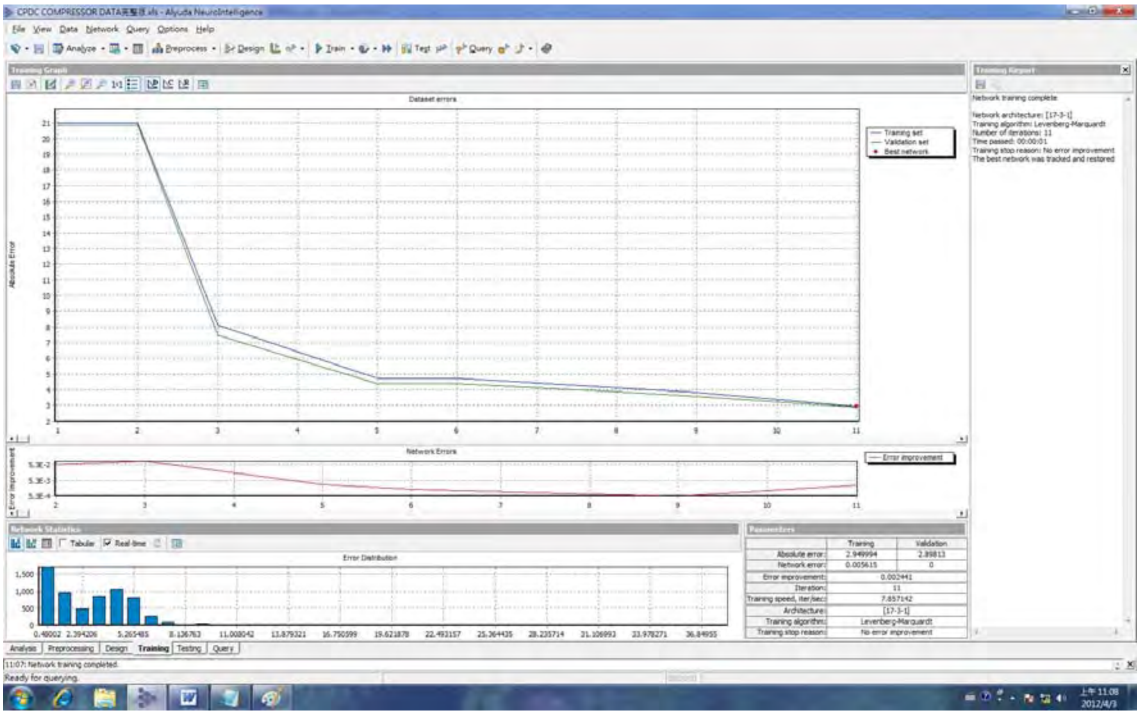

Figure 2. Simulation training

E. *Forecasting Results and Assessments*

According to the Levenberg-Marquardt algorithm selected in the simulation training unit, the results can be clearly displayed in the testing unit. With Correlation and R-squared values as the assessment results, the contents include the training block’s Correlation and R-squared values, the validation block’s Correlation and R-squared values, and the testing block’s Correlation and R-squared values. The Correlation and R-squared values of all blocks are as shown in Table 1 and Fig. 3.

Table 1. Correlation and R-squared values

	Target	**Output**	**AE**
Mean:	43.501487	43.121819	2.235158
Std Dev:	9.600928	8.717931	2.061895
Min:	0	1.580225	0.000121
Max:	51.07942	48.670216	43.116815
Correlation: 0.950278 **R-squared: 0.878328**			

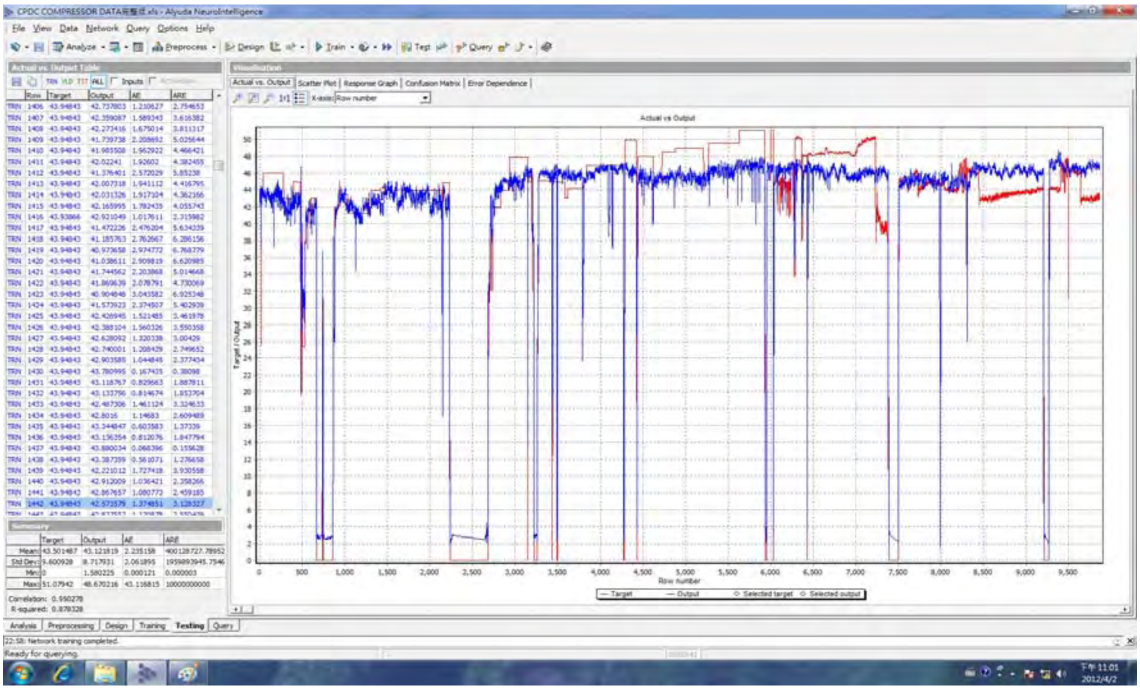

Figure 3. Forecasting results

F. Comparison of the Predicted Values and the Actual Values

After 10 times of repeated simulation training, this study found 10 groups of validation data for Correlation and R-squared values, as shown in Table 2. Under the same conditions, the training results are total different in various times because the network will start to converge from different locations after each random initialization of the initial weight value of the network, and finally, converge to different locations. However, the 10 group of data indicate that the model’s average correlation, R-squared average values are up to 0.9396785 and 0.8224103 respectively, proving that the level of correlation is high and positive.

This study compared and validated the predicted data of the case simulation and the data of the actual compressor system data. The comparison results between the predicted values of Correlation and R-squared and the actual values of Correlation and R-squared have proved the accuracy and feasibility of the artificial neural network model.

Table 2. Average of Correlation and R-squared values

	Training Correlation	Training R-squared	Validation Correlation	Validation R-squared	Testing Correlation	Testing R-squared	All data Correlation	All data R-squared
01	0.964103	0.810058	0.744965	0.283085	0.922058	0.804383	0.942903	0.777209
02	0.966489	0.829918	0.758733	0.268469	0.920382	0.822575	0.946825	0.795142
03	0.96017	0.837792	0.735378	0.3735	0.906746	0.729306	0.937049	0.804076
04	0.976473	0.92067	0.755589	0.480197	0.918597	0.62623	0.950278	0.878328
05	0.924807	0.821027	0.735256	0.462219	0.923564	0.693879	0.909847	0.79225
06	0.979468	0.956339	0.780965	0.562586	0.914652	0.33814	0.952879	0.901127
07	0.964971	0.920646	0.762341	0.505161	0.920132	0.623449	0.946231	0.88156
08	0.964746	0.904809	0.74248	0.473053	0.911761	0.428382	0.934132	0.853139
09	0.967512	0.854896	0.739226	0.40565	0.919064	0.759821	0.943221	0.822263
10	0.948405	0.745133	0.765967	0.264223	0.93191	0.801563	0.93342	0.719009
Average	0.9617144	0.8601288	0.75209	0.4078143	0.9188866	0.6627728	0.9396785	0.8224103

V. CONCLUSION

The centrifugal air compressor system of the equipment specializing in the production of nitric acid in CPDC Toufen Plant is a system of non-linearity with changing process links. It is relatively difficult for traditional PID control models to process such factors. Therefore, in this study, we use the neural network to predict the performance curve of the compressor system. By using the neural network, we acquire the historical data of analogous signals at 18 points of the compressor PLC system by using the neural network. A total of 10050 data samples dated in the period of 2010.01.01~2011.02.28 were used as the input samples of the artificial neural network for analysis of learning, simulation and training.

Regarding the anti-surge prevention and rotating stall control of the centrifugal air compressor in zone 20 of the CPDC Toufen Plant, this study applied the Alyuda NeuroIntelligence software for simulation and training to realize more sensitive control of the ventilation control valve, thus providing more protection of the centrifugal air compressor. The contributions of this study are as follows:

First, this study elaborated on the current status of the flow process of zone 20 of the CPDC Toufen Plant, and explained in detail the harm of anti-surge and the cause of rotating stall of the centrifugal air compressor in operation.

Second, this study elaborated on the principle and model of the artificial neural network as well as its applications and processing means.

Third, Alyuda NeuroIntelligence neural network is an expert-level artificial neural network software, and this study conducted in-depth study and introduction of this software for simulation training. Problems such as the prediction, classification and function approximate value were solved. The software has advantages such as being intelligent, rapid and easy to use.

Fourth, Alyuda NeuroIntelligence software was applied in the design unit to search for the optimal value of the network architecture: with number of layers of network (17-3-1) as the neural architecture, the training unit provided 7 types of algorithms for continuous, repeated simulation training. This study found that Levenberg-Marquardt algorithm can obtain the optimal convergence and prediction effects. A prediction system was designed based on this algorithm to cross-validate the current PLC control system to realize more intelligent control requirements. The results are consistent with the requirements of protecting the compressor and saving energy.

In summary, the artificial neural network with artificial intelligent prediction capability can solve the complex problems of the compressor system module. The design and establishment provides a very good method for the compressor system. By the simulation of the prediction model through empirical analysis, this study proved that the effectiveness and feasibility of the proposed compressor system failure diagnosis prediction model. The findings suggested that the compressor system failure diagnosis prediction model developed by the artificial neural network has scientific, practical and effective prediction method, and is capable of effectively forecasting satisfactory prediction results.

Regarding the compressor system of CPDC Toufen Plant compressor system, this study added an intelligent prediction analysis condition to solve the problem of inability to deal with the non-linear problems by the traditional programmable logic controller PLC system through integration of practice and theory. The strength enhancement and feasibility of the prediction model were confirmed, and provided the compressor with another layer of protection. This approach can effectively issue the warning message in real time and identify the true causes of the abnormal conditions to help maintenance or the operating personnel to take the most appropriate control method for economic benefits and prevention of industrial safety accidents. It can be widely inferred in the future. The compressor system failure diagnosis prediction module can be applied in the study of CPDC Toufen Plant, and this module can be applied in other different fields for further extensions.

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