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Analysis of ANN-Based Modelling Approach for Industrial Systems

Hamid Asgari, XiaoQi Chen, and Raazesh Sainudiin

Abstract—**A variety of analytical and experimental methods have been suggested so far for industrial system modelling. However, the need for optimized models for different objectives and applications is still a strong motivation for researchers to continue to work in this field. Artificial Neural Network (ANN) as a black-box approach has been playing a significant role in system identification and modelling of many industrial systems during recent decades. Using ANN for modelling purposes is a controversial issue among researchers in different scientific areas. This paper briefly discusses different arising challenges in using ANN-based models for industrial systems and describes advantages and disadvantages of this approach.**

Index Terms—**Analysis, modelling, system identification, artificial neural network, industrial systems.**

I. Introduction

Since artificial neural network was presented for the first time by Bernard Widrow from Stanford University in 1950's, it has been always a constant challenge for researchers to find optimal ANN-based solutions to design, manufacture, develop and operate new generations of industrial systems as efficiently, reliably and durably as possible. Getting enough information about the system which is to be modelled is the first step of system identification and modelling process. Besides, a clear statement of the modelling objectives is necessary for making an efficient model. Industrial systems may be modelled for condition monitoring, fault detection and diagnosis, sensor validation, system identification or design and optimization of control systems.

There are different approaches to model a system. Mathematical modelling is considered as a general methodology for system modelling. It uses mathematical language to describe and predict behaviour of a system. Mathematical models may be classified as "linear and nonlinear", "deterministic and stochastic (probabilistic)", "static and dynamic", or "discrete and continuous".

There are different ways to construct a mathematical model based on the prior information about the system. These approaches can be classified into three main categories including white-box, black-box, and gray-box models. A white-box model is used when there is enough knowledge about the physics of the system. In this case, mathematical equations regarding dynamics of the system are utilized to make a model. This type of model deals with dynamic equations of the system which are usually coupled and nonlinear. To simplify these equations in order to make a satisfactory model, making some assumptions based on ideal conditions and using different methods for linearization of the system is unavoidable. There are different software such as SIMULINK/MATLAB and MATHEMATICA which are really helpful in this case. A black-box model is used when no or a little information is available about the physics of the system. In this case, the aim is to disclose the relations between variables of the system using obtained operational input and output data from performance of the system. Artificial neural network (ANN) is one of the most significant methods in black-box modelling. The phrase gray-box is used when an empirical or black-box model is improved by utilizing a certain available level of insight about the system [1].

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II. Artificial Neural Network (ANN)

ANN is defined as a computing system which is made up of a number of simple, highly interconnected processing elements (neurons) with linear or nonlinear transfer functions [2]. These elements process information by their dynamic state response to external inputs [2]. Neurons are arranged in different layers including input layer, hidden layer(s) and output layer. The number of neurons and layers in an ANN model depends on the degree of complexity of the system dynamics. ANN learns the relation between inputs and outputs of the system through an iterative process called training. Each input into the neuron has its own associated weight. Weights are adjustable numbers which are determined during the training process. Fig. 1 shows the basic structure of a typical ANN with input, output and hidden layers [3].

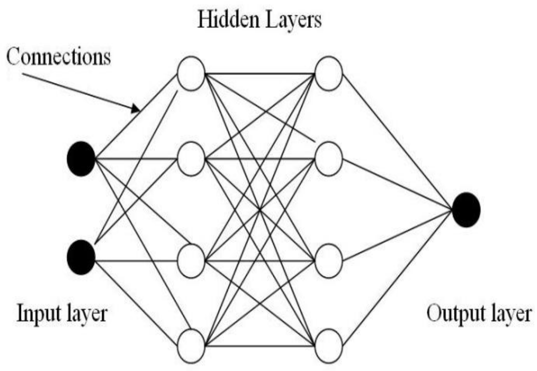

Fig. 1. Basic structure of a typical ANN with input, hidden and output layers [3].

ANN is a data-driven model. It has been considered as a suitable alternative to white-box models during the last few decades. ANN-based models can be created directly from operational data or simulated data from "original equipment manufacturers (OEM)" performance. Simulated data can be used when operational data are not available. The obtained data should cover the whole operational range of the system. All transient data during start or stop process should be removed from the collected data before the modelling process.

ANN has the power to solve many complex problems. It can be used for function fitting, approximation, pattern recognition, clustering, image matching, classification, feature extraction, noise reduction, extrapolation (based on historical data), dynamic modelling and prediction. ANN models can be created using different approaches based on the flexibility that ANN provides. This flexibility is based on the number of neurons, number of hidden layers, values of the weights and biases, type of the activation function, structure of the network, training styles and algorithms as well as data structure. The best structure will be the one which can predict behaviour of the system as accurately as possible.

Selecting the right parameters as inputs and outputs of ANN is very important for making an accurate and reliable model. The availability of data for the selected parameters, system knowledge for identification of interconnections between different parameters and the objectives for making a model are basic factors in choosing appropriate inputs and outputs. Accuracy of the selected output parameters can be examined by sensitivity analysis.

Many issues should be considered when a comparison is made between ANN and any of the conventional modelling techniques. However, major applications of ANN in industrial systems as well as positive and negative aspects of this methodology, can be presented on the basis of research activities that have been carried out so far in the field of gas turbines; an exemplar of modern and advanced industrial systems [4].

III. ANN Applications To Industrial Systems

Artificial neural network has many advantages to conventional modelling approaches. These advantages are due to the special structure and algorithm of the network. ANN methodology can be a suitable alternative to classical statistical modelling techniques when obtained data sets indicate nonlinearities in the system [5]. ANN and specially the Hopfield model have a demonstrated capability to solve combinational optimization problems in industrial plants [6]. ANN models can be used online on industrial sites for condition monitoring, sensor validation, fault diagnosis, system identification or control.

ANN offers a cost-effective and reliable approach to condition monitoring. It reduces the number of wrong decisions, minimizes the demand for spare parts and reduces maintenance costs. The collected data related to the condition of the system can be classified and trained by using artificial neural networks in order to generalize a method for data analysis at any time of the measurement. Magnus Fast et al. used simulation data and applied ANN to examine condition-based maintenance of gas turbines [7]. They also utilized a combination of ANN method and "cumulative sum (CUSMUS)" for condition monitoring and detection of anomalies in the performance of gas turbines [8].

Since ANN is adaptable to continuously varying data, it is replacing the traditional methods and systems for fault diagnosis. Fault diagnosis plays a significant role for owners of industrial systems to shift from preventive maintenance to predictive maintenance in order to reduce the maintenance costs [9]. Application of ANN to diagnosis and condition monitoring of a combined heat and power plant was discussed by Fast et al. [10]. Bettocchi et al. developed a "multiple-input and multiple-output (MIMO)" neural network approach for diagnosis of single-shaft gas turbine engines [11]. They observed that ANN can be very useful for the real time simulation especially when there were not enough information about the system dynamics. Simani et al. carried out a study to detect and isolate faults on an industrial gas turbine prototype [12]. They suggested exploiting an identified linear model in order to avoid nonlinear complexity of the system. For this purpose, black-box modelling and output estimation approaches were applied.

ANN was applied for fault diagnosis of a medium-size industrial gas turbine by Arriagada et al. [13]. They obtained a comprehensive data set and trained them using ANN. The trained network was able to make a diagnosis about the gas turbine's condition when a new data set was presented to it. The results proved that ANN could identify the faults and generate warnings at early stages with high reliability. Fig. 2 shows a schematic drawing of the ANN and the interpretation of the outputs in a graphical display [13]. The ANN can be named 14-H-28 according to its structure. The inputs correspond to the 14 measured parameters of the system. The desired outputs from the ANN are unique combinations of 28 binary numbers arranged in a graphical display [13]. The training process of the ANN stopped when it showed the best performance based on a selected number of hidden neurons and weights for the network [13].

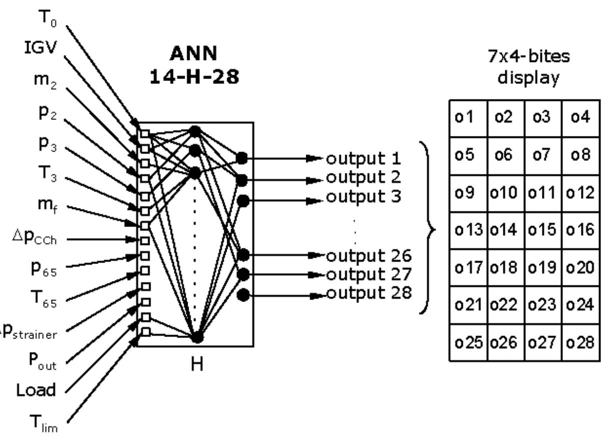

Fig. 2. Schematic drawing of the ANN and the interpretation of the outputs in a graphical display [13]

Using ANN for sensor validation leads to more cost-effective maintenance and can increase availability as well as reliability of industrial systems. It has a considerable effect in increasing system's lifetime and assuring its reliable performance. It can also strengthen automation of the system by providing valid data for diagnostic and monitoring systems. Palme et al. developed an ANN-based methodology in gas turbines to minimize the need for calibration of sensors and to decrease the percentage of shutdowns due to sensor failure [14]. Fast also applied different ANN approaches for gas turbine condition monitoring, sensor validation and diagnosis [15].

ANNs can be used to model a wide class of industrial systems in many applications. They are powerful tools in system identification and modelling, because of their excellent ability to approximate uncertain nonlinearity to a high degree of accuracy. The main steps for identification and modelling of a dynamic system are data collection, model structure selection, model estimation using appropriate software, and model validation [1]. They can perform implicit nonlinear modelling and filtering of system data [6] and detect coupled nonlinear relations between independent and dependent variables without any need for dynamic equations [16, 17]. Chiras et al. employed a nonparametric analysis in time and frequency domains to determine the order and nature of nonlinearity of aero gas turbine [18]. They also explored the nonlinear relationship between dynamics of shaft rotational speed and the fuel flow and observed that the results could be matched with the results from a previously estimated model. [19].

ANN has been considered as an acceptable solution to many outstanding problems in modelling and control of nonlinear systems. Fast et al. used real data obtained from an industrial gas turbine working under full load to develop a simple ANN model of the system with very high prediction accuracy [20].

In control design process, a neural network may directly implement the controller (direct design). In this case, a neural network will be trained as a controller based on some specified criteria. It is also possible to design a conventional controller for an available ANN model (indirect design). In this approach, the controller is not itself a neural network.

Investigation for the practical use of artificial neural networks to control complex and nonlinear systems was carried out by Nabney and Cressy [21]. They utilized multiple ANN controllers to maintain the level of thrust for aero gas turbines and to control system variables for a twin-shaft aircraft gas turbine engine in desirable and safe operational regions. The main idea behind the research was to minimize fuel consumption and to increase the engine life. They aimed to improve the performance of control system by using the capability of ANN in nonlinear mapping instead of using varieties of linear controllers. They applied a reference model as an input to the ANN controller. The results showed that performance of the applied ANN controllers was better than conventional ones; but they could not track the reference models as closely as was expected.

Ogaji et al. explored three different architectures of ANN for multi-sensor fault diagnosis of a gas turbine and showed that ANN can be used as a high-speed powerful tool for real-time control problems [22]. Dodd and Martin proposed an ANN-based adaptive technique to model and control an aero gas turbine engine and to maintain thrust at desired level while minimizing fuel consumption in the engine. They suggested a technique which consequently could lead to maximizing thrust for a specified fuel, lowering the critical temperature of the turbine blades and increasing the engine life [23]. The simplicity and differentiability of the neural network helped the researchers to calculate necessary changes to controllable parameters of the engine and consequently to maintain the level of the thrust in a targeted point.

Mu and Rees investigated nonlinear modelling and control of a gas turbine using ANN to identify the engine dynamics under different operational conditions [24]. An "approximate model predictive control (AMPC)" was applied in order to control shaft rotational speed. The results proved that the performance of AMPC as a global nonlinear controller was much better than gain-scheduling PID ones. AMPC showed optimal performance for both small and large random step changes as well as against disturbances, uncertainties and model mismatch. AMPC showed better performance against disturbances and uncertainties.

Balamurugan et al. employed Ziegler-Nichols method to tune PID controller parameters for a gas turbine [25]. They also trained an ANN controller to control the speed of the system. The response of the system with the ANN controller was simulated with a step load disturbance. The simulation results showed that the time domain response of ANN controller was well damped [25]. As Fig. 3 shows, ANN controller performed better than the PID controller [25].

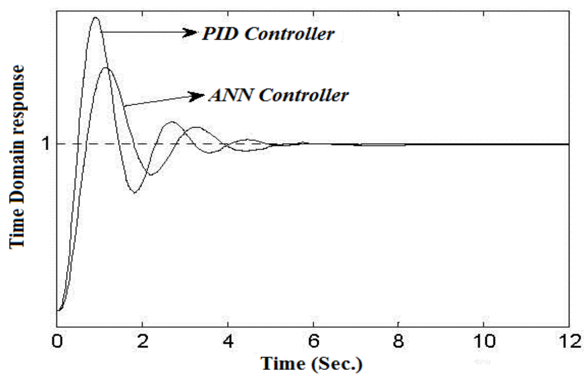

Fig. 3. A comparison of gas turbine plant response with PID and ANN controllers [25]

In many cases, the obtained data from the systems located on industrial factories and plants may include noisy data. Besides, some sorts of data may be inaccurate or incomplete due to faulty sensors. These especially happen when the system is old and/or maintenance is poor. ANN has the capability to work considerably well even when the data sets are noisy or incomplete. It can learn from incomplete and noisy data [26].

ANN requires less formal statistical training to be developed [27]. Training ANN is simple and does not need professional statistical knowledge. If the data sets and appropriate software are available, then even newcomers to the field can handle the training process. However, experience and statistical background can still be very useful and effective during the whole performance. ANN with hidden layer(s) has the ability to predict all interrelationships or interactions between all input variables [27]. It has the capability to be developed using different training algorithms [27]. There are varieties of training algorithms which can be used during the learning process. ANN also has the capability of dealing with stochastic variations of the scheduled operating point with increasing data [6]. It is very fast and can be used for on-line processing and classification [6].

In addition to the mentioned applications of ANN to industrial systems, they have many other common advantages such as simple processing elements, fast processing time, easy training process, high computational speed, capturing any kind of relation and association, exploring regularities within a set of patterns and having the capability to be used for very large number and/or diversity of data and variables. It provides high degree of adaptive interconnections between elements. It can be used where the relations between different parameters of the system are difficult to uncover with conventional approaches.

ANN can be used to model the whole or part of a system or process which is unidentified or difficult to be identified through traditional methods. ANN is not restricted by variety of assumptions such as linearity, normality and variable independence, as conventional techniques are. It even has the ability to generalize the situations for which it has not been previously trained.

Generally, it is believed that the ability of ANN to model a wide class of systems in variety of applications can decrease the required time on model development and leads to a better performance compared with conventional techniques [1].

IV. ANN Limitations

As any modelling technique, artificial neural network has its own limitations on the basis of the particular application and methodology under consideration. The basic challenges to be resolved include training time, upgrading of trained neural nets, selection of the training vector and integration of technologies in the problem domain [6]. Despite all investigations carried out so far, ANN as a black-box technique is still restricted to clearly identify the importance of every single input parameter during training process [27]. There is little intuitive information about what actually happens inside the network during learning process and one can hardly intuitively interpret the internal workings of an ANN.

There are remarkable difficulties for using ANN models on industrial sites [27]. Compared with other conventional models, ANN models may be more difficult to use on operational fields. Special software and hardware is required to implement the model. The correct Interpretation of the output is not also easy [27]. To implement an ANN model, sometimes many computational resources such as mainframes, minicomputers, and processors are needed. For more complicated systems, more resources are required.

To train, validate and test an ANN, usually large amount of data sets are required. There is no fixed number of data sets for an optimal training process. It may differ case by case for different industrial systems. However, the amount of the obtained data should be large enough to disclose underlying structure of the system as accurately as possible and to provide sufficient understanding of the system dynamics.

The data sets may be on-site operational data or simulated data by a previously confirmed model. Data acquisition especially on operational sites may be a difficult and time-consuming process. New data sets cannot be fed directly to the trained ANN to improve its performance and it is needed to be trained again against all of the available data sets. Manipulating time series data in ANN is also a complicated issue.

ANN relies on empirical development. It is a nearly new technique and still needs to be developed based on the practical implementations and experiments gained by researchers. There are many issues in terms of methodology which need to be resolved [27]. A unique ANN model is trained to solve just a specific problem. It means getting good results from an ANN model for a problem, does not guarantee to solve other problems.

ANN has the potential tendency to overfit during training process. Overfitting can occur during training process when the ANN gets too specialized to fit the training data extremely well, but at the expense of reasonably fitting the validation data. Overfitting is reflected by the steady increase in the validation error accompanied by a concomitant steady decrease in the training error. Poor performance due to overfitting is one of the most common hurdles to successfully using ANNs. It can be overcome by using cross-validation method, decreasing the number of neurons in hidden layer(s), or by adding a penalty term to the objective function for large weights. Fig. 4 shows a simple example of overfitting problem [28].

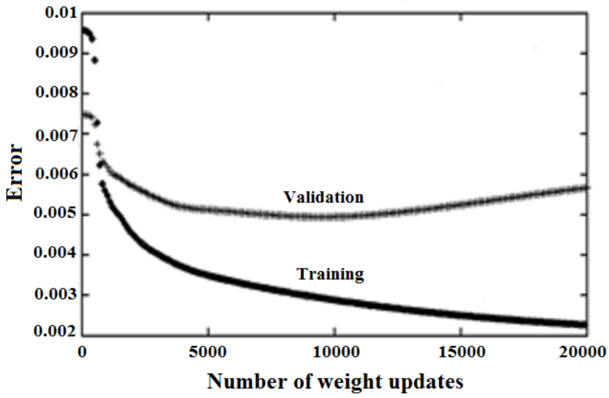

Fig. 4. Overfitting; error versus number of weight updates [28]

V. Conclusion

There are different approaches and methodologies in system identification and modelling of industrial systems. Artificial neural network has been considered as a suitable alternative to white-box models during the last few decades. The nature and strength of the interrelations of system variables as well as the nature of applications are vital criteria for training a neural network with sufficiently rich empirical data. It is important to notice that approximation and error are inseparable parts of any system identification method and ANN is not an exception. In this paper, applications and limitations of ANN approach for system identification and modelling were briefly discussed. It was shown that despite all the limitations, using ANN can still lead to remarkable enhancements in the process of industrial system modelling.

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