Application of Dynamic Neural Networks with Exogenous Input to Industrial Conditional Monitoring

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Abstract— **Intelligent assessment of information gathered from industrial-grade data loggers for preemptive maintenance is one of the foremost areas of research in conditional monitoring. Due to the general operating environment, there exists a non-linear relationship between the input and output data gathered from these sensors. Moreover, the transmission of data from such dynamic environments is generally marred by a large SNR with substantial level of "false-noise" belonging to the normal movement pattern of the mechanical parts. Within this context, the goal of this paper is to explore, evaluate and develop an optimal, dynamic neural network to improve the fault prediction accuracy of condition monitoring systems.**

The training data for this research was obtained from a vibration and a thermal sensor connected mounted over a poly-phase induction motor. The objective was to identify any anomalies in the motor's fan-based cooling system. Moreover, the model presented a comparative analysis of a dynamic neural network (DNN) model against a non-linear autoregressive neural system (NARX) with exogenous input. The validation outcome presented a close regressive relationship of 0.9734 between observed and targeted outcomes over a 7-second delay with a NARX model giving a 4.56% and 5.23% classification accuracy. The best model system was evaluated against unseen anomaly data and demonstrated high prediction accuracy.

I. Introduction

TDVANCED data logging devices are now becoming an essential part of complex industrial machinery. These devices provide round-the-clock monitoring of safety critical systems for anomalies in temperature levels, voltage, current, vibration and other important parameters in order to demonstrate the normal operational pattern of mechanical system assemblies [1-3]. Timely identification of faults in industrial machinery, mainly induction motors is an extensively investigated domain as it plays an important role in cost and maintenance saving. Continued monitoring of such systems in industrial environments is highly crucial and is measured against a number of dependent and independent variables which make such systems highly nonlinear.

Multi-sensor data integration is considered an emerging technology that finds its applications in a wide range of domains including industrial equipment monitoring, fault detection and defect prevention in dynamic mechanical equipment. The advent of high-speed communication modes such as the GPRS and the broadband and robust computing and electronics hardware has made it possible to combine an array of loggers for remote condition monitoring and fault detection. Methodologies for the diagnosis of mechanical and electrical failures at their earlier stages have extensively been investigated [4-6]. These faults are generally of four types: bearing faults, stator-related faults, rotor-related defects and flaws related to temperature, electrical connectivity, terminal boxes and power-related failures [7]. Majority of these defects can be robustly detected based on the temperature, vibration, current or general power-related readings from the motor assemblies [8, 9]. Yet, these faults tend to "blend" in the generic roughness of the machinery producing a high SNR that generate a highly nonlinear input-output relationship. It is due to this nonlinear nature of the system and due to the highly complex nature of the underlying parametric machine data that makes time-series-based dynamic neural networks an ideal candidate for its modeling.

This work proposes a methodology for the time-series modeling of a nonlinear industrial system for the purpose of preemptive fault detection and prevention via dynamic neural networks. Within this scope, the domain of engine signature, signal and condition monitoring has largely been limited to wavelet packet and Fourier transforms based modeling due to their dimensionality reduction and noise removal capabilities [10-14]. However, FFT-based systems are generally less capable of resolving dynamic, time-based behaviors of temporal signals. Alternatively, Artificial intelligence (AI) techniques are widely used in the identification and classification of time-series-based condition monitoring systems [15-17]. Particularly, artificial neural networks (ANN) are well-known for their ability to generalize system training data in order to model noise-corrupted data.

Recently, the approach has shifted more to the use of dynamic and recurrent networks in condition monitoring [18-21]. Based on the recent developments, the

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methodologies investigated in this research present the implementation of a novel dynamic neural network based architecture for the identification of operational anomalies in machine motor behavior based on its vibration and temperature signature profiles. The paper reports on the developments as follows: Section 2 presents an overview of the application of ANN to the field of nonlinear condition monitoring. Section 2 describes the underlying model formulation and methodology. Section 3 presents a detailed system architecture and design of the underlying embedded system layout. Section 4 presents a detailed analysis of results and outcomes of the system before concluding the ongoing work in addition to any possible future directions.

II. Overview

Electromechanical machines conventionally contain rolling ball-bearings that are considered a rudimentary part of rotation assemblies. These ball-bearings consist of two core inner and outer rings where rolling metallic balls are placed raceways within these rings to provide rotation. Defects within these rings and ball-bearings are a common cause of failure even in normal operating conditions.

A. Fault detection in dynamic mechanical units

According to Nandi et al. [5], almost half of all mechanical failures in industrial rotational assemblies are due to these bearing-related faults. Generally, fault occurrences in these parts are detected via vibration detection systems that calculate the following core parameters [1, 22]:

- The RMS velocity to detect imbalance and misalignment,
- RMS acceleration for high frequency fault and energy detection such as high-speed gear mesh, broken rotors or low bearing lubrication,
- True peak acceleration to detect bearing or gearbox related faults
- Crest factor (peak to RMS ratio) to indicate fault severity

Vibration signals in complex rotary systems exhibit a regular motion pattern along with noise that makes it difficult to find early failure symptoms of potential failures. Yu and Makis [23] utilized a time-synchronous averages wavelet transform based on a number of statistical measures to detect earlier system failures in planetary gearbox systems. The work reported a highly non-linear nature of signals in addition to high SNRs which played a dominant role in the modeling and detection of condition anomalies. Fault detection work has commonly focused on fault detection via signature analysis of motor power profiles [14, 24]. Further work by Yen & Lin utilized wavelet packet transforms to detect and classify machine anomalies via vibration signals[20]. Betta *et al*. [12] presented a DSP-based fault diagnosis architecture that utilized vibration spectrum with rule based isolation of faults to improve prediction accuracies in rotating machines.

B. Artificial neural networks in nonlinear dynamic systems

Artificial neural networks (ANNs) are well-known for their capability to address problems suffering from excessively high noise levels. Alguindigue's [19] initial work to model the behavior of rolling element bearings is regarded as one of the first attempts to utilize ANN in diagnostic vibration modeling. Recently, with the advent of efficient communication paradigms and computational hardware during the last decade, the focus has further shifted to remote and virtual condition monitoring via LAN and Wi-Fi-based connectivity[25] with attempts to include radio-frequency (RFID), Bluetooth and cellular GPRS networks as the primary modes of data transfer[26, 27]. Ballal et al. [18] implemented a dual-stage ANN classifier based on data accumulation via an ADXL330 accelerometer and a Jennic Wi-Fi module. Ling et al. [2] implemented Hilbert-Huang Transform (HHT) to eliminate low-energy vibration signals induced due to routine vibration signature which is considered a major source of training input distortion.

However, despite a considerable amount of research done in the area of ANN to nonlinear modeling, little effort is spent on the use of exogenous (support) training data and its role in the improvement of classification accuracies. As discussed earlier, mechanical equipment generally exhibit a wide range of features including voltage, current, temperature, torque and vibration that can be used to detect mechanical anomalies while complimenting each other. Based on this notion, the proposed work presents the application of vibration data along with the associated surface temperature outcomes to model an identification system in order to detect any potential defects. Section 3 describes a detailed architecture and the underlying proposed methodology used to implement a smart condition monitoring and data logging system.

III. Embedded System Architecture and Design

This section describes the underlying system architecture and development framework of ANN-based smart condition monitoring system capable of integrating multiple sensors. The system architecture develops a multi-tier and embedded client-server environment as follows (See Fig. 1):

1) *The smart sensor modules (SSM):* The test-bed is developed to host a set of sensor units termed as smart sensor modules (SSMs). These units operate on Netduino Plus 2/Arduino Uno R3 boards bearing Atmel Atmega 328 and STM32F405 Arm 7 microcontrollers to host the SEN-09198 Piezo vibration and MLX90614 IR temperature sensor respectively.
2) *The central controller unit (CCU):* The CCU is an IIS web-server hosting a TCP/IP socket application to bridge the serial data obtained from the SSM. The ANN-based anomaly detection logic is implemented at this layer primarily due to the lack of computational power and memory available on the SSM side.
3) *The remote client interface (RCI)*: The RCI units, also

termed as the ground-based units (GBUs) are generic handheld devices served via third-party web-domains that allow the CCUs to connect as web-services to provide remote access to the SSMs.

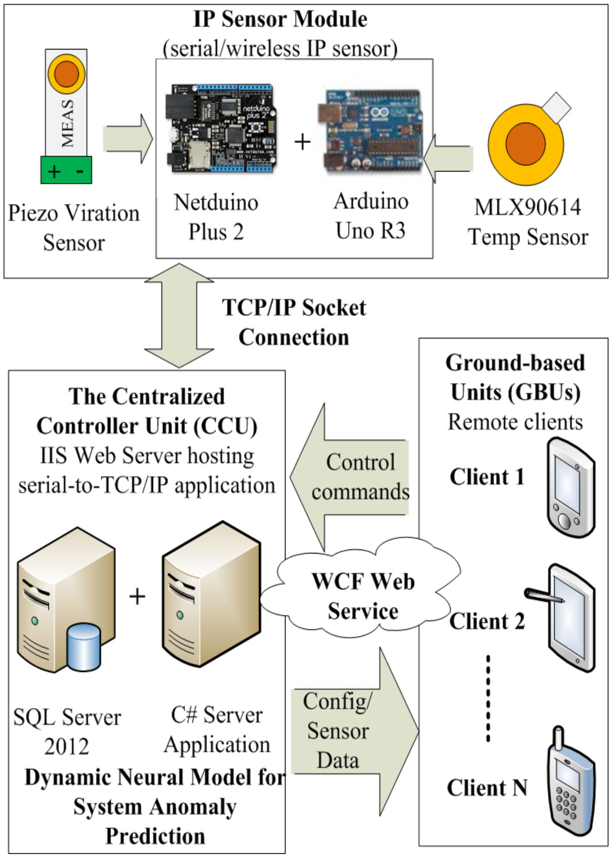


Fig. 1. The three-tier, embedded client-server architecture based on dynamic neural network modeling for condition monitoring

A. *Smart sensor unit (SSU) architecture*

The SSU module is designed to monitor faults in the induction motor fan of a cooling mechanism for a high temperature fluid-flow pipe-based industrial surface (See Fig. 2). The fan is controlled via a poly-phase induction motor and its speed is regulated via an existing embedded speed control unit that provides speed regulation based on the measured surface temperature. The main objective of the test-bed system is to preemptively identify possible cooling fan motor failures via the vibration and temperature data. The established behavior of this system is that any alteration in the temperature must be followed by an automated fan speed reduction/increment based on the existing control unit.

B. *The Central Controller Unit (CCU)*

The main objective of the CCU is to collate serial data byte streams from different SSMs, process it to standard feature vector data into the time series feature space and feed it to the ANN prediction/classification module. The hosting CCU machine runs over an IIS web server with a SQL Server 2012 database to store sensor data. The server application on the CCU is implemented as a C# .Net web-service to connect via the Windows Communication Foundation (WCF) platform. The client application is responsible for all the communication to and from the SSMs connected via TCP/IP connections thereby emulating a direct connection between the remote Ethernet application and the wireless/wired serial device.

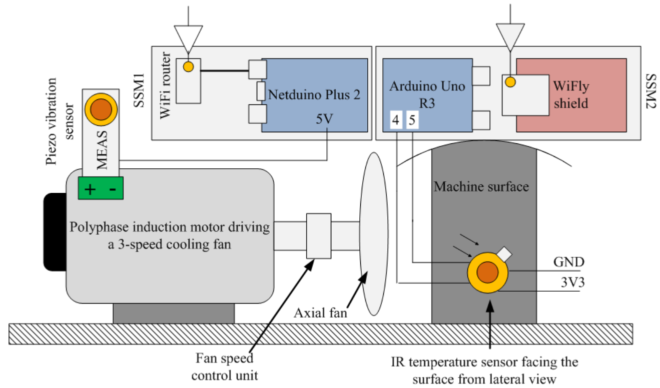


Fig. 2. Architecture of the mechanical test-bed based on two smart sensor modules measuring serial vibration and temperature data transmitted via a TCP/IP socket connection to the CCU

Each CCU instance is capable of handling 30 simultaneous client (SSM) connections which are identified via configuration tables transmitted while the SSMs attempt their initial connections with the CCU. It must be noted that, these Ethernet-enabled SSM are also capable to act as dumb IP-based web-servers without the need of a CCU for direct remote logging purposes. However, due to onboard processing and memory limitations, it is not feasible for the SSM microcontrollers to host an AI application which, in the current scenario, is the core of this application that enable smart anomaly detection based on the data transmitted by these data loggers.

C. *The remote client interface (RCI)*

The RCI or ground-based unit is primarily a third-party web-server that provides a service-oriented architecture to provide user registered to it via various computing devices to have real-time updates on the status of the sensor networks being monitored. These remote clients are capable of raising soft-alarms based on the identification outcome provided by the AI routines installed on the respective CCUs. The underlying smart logic implemented in these AI-routines is further elaborated in the next section.

IV. A Dynamic Neural Network-based Prediction Methodology in Motors for Real-time Condition Monitoring

Time-series-based identification in condition monitoring via ANNs started in early 1990s with the work of Peng *et al.* to predict electrical load prediction [28]. Further work by Chen *et al.* and Djukanovic *et al.* used separate ANN approaches to employ multiple input parameters including load demand, time and temperature to predict overload conditions via static feed-forward neural networks [29-31]. Papalexopoulos *et al.* [32] incorporated additional parameters including direct/indirect temperature, cooling/heating measures and historic load data within a single neural network to predict load conditions. Lately, work in dynamic neural networks is also done by Chogumaira *et al*. and Wang *et al*. by utilizing evolutionary optimization routines to adjust and improve the optimal number of generator and line branches feeding the system [33, 34].

Yet, the above-mentioned work predominantly employs nonlinear time-series approaches and assumes the output is dependent upon variables independent and dependent of the underlying temperature of the system. Within the context of the proposed application area of condition monitoring, majority of input variables such as voltage, current and power are termed as dependent variables whose values generate the resultant system temperature. However, the temperature-dependent-load is often estimated through vibration variables such as ventilation (wind speed), humidity (relative evaporation due to heat) and even the sound signature from the machine itself. As of yet, these neural network-based system diagnostic techniques have generally focused on dynamic training values as inputs or as standard feed-forward networks.

Non-linear autoregressive networks are a special category of recurrent dynamic networks with a large number of network layers connected via feedback connections in the form of a recurrent dynamic network supported by an external (exogenous) input to improve calibration. These so-called NARX models are primarily based on linear autoregressive exogenous models used in time-series modeling defined as:

A large number of these earlier condition monitoring systems were regarded as non-stationary time series systems which made it difficult to accurately forecast outcomes [28-32]. These systems can roughly be summarized as follows as dynamic feed-forward systems (1):

$$y(t) = f\left(y_{t-1}, \dots, y_{t-n_y}, u_{t-1}, \dots, u_{t-n_u}\right) + e_t \tag{1}$$

Moreover, the dynamic feed-forward neural network with exogenous input is given in (2):

$$y(t) = f\left(u_{t-1}, \dots, u_{t-n_u}, e_{t-1}, \dots, e_{t-n_k}\right) + e_t \tag{2}$$

In (1) and (2), $y(t)$ is the temperature outcome, u_{t-1} is the available vibration information, u_t is the vibration forecasted and e_t is the noise residual at time t modeled as a Gaussian zero-mean-process with variance σ. Moreover, n_y, n_u *and* n_k represents the time-delays for each respective model.

A. A DNN classifier for nonlinear output classification without exogenous data

A dynamic neural model (DNN) is used to nonlinearly approximate function f as shown in Fig. 3 (a) where the next value of the dependent $y(t)$ output signal is regressed on the basis of an independent exogenous signal $(u_{t-1}, \dots, u_{t-n_u})$ which is the temperature series in the current case in addition to the previous values of the original vibration signal $(y_{t-1}, \dots, y_{t-n_y})$. The NARX model can be implemented using a two-layer recurrent dynamic feed-forward neural network to approximate the function f.

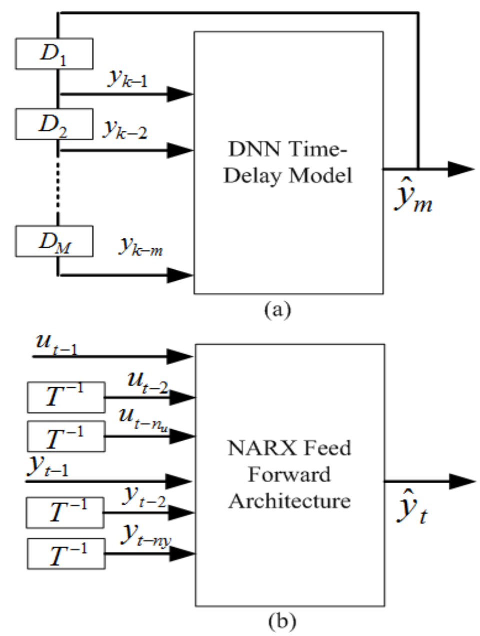


Fig. 3. (a) A DNN network without exogenous data and (b) a series-parallel NARX architecture where - u is the exogenous (temperature) input and y is the autoregressive vibration variable and $\hat{y}$ corresponds to the classification of the autoregressive variable

B. A nonlinear autoregressive classifier for classification with exogenous data (NARX)

It can be observed from Fig. 3 (b) that, with the availability of additional sensor variables, basic series-parallel prediction method is enough to provide a classification function estimator. In the current scenario, the system takes the following two training input sequences for the NARX classifier (Fig. 3(b)):

- Experimental vibration data for the autoregressive variables from $t-1$ to $t-n_y$ where n is the order of the system model
- Experimental temperature data of a single, "critical-point" on the mechanical surface from $t-1$ to $t-n_u$ for the exogenous variables

As output the system generates:

- Experimental data of the autoregressive variables at a later time t to predict the modeled vibration value

V. Model Training Outcome and Analysis

The test-bed was created to evaluate the underlying industrial condition against the vibration signature profile variable obtained from a piezo-electric vibration sensor as a direct function of current/torque produced in the system. The system also recorded the respective temperature of the surface being monitored as an independent variable which was to be objectively monitored to preemptively monitor the immediate operating environment of the industrial unit. The system was evaluated against two neural network genres including a standard DNN technique and a nonlinear autoregressive system support by an external input (NARX) with two 7- and 14-second delays.

The data used in this research was gathered from a NEMA Design B three-speed polyphase induction motor driving a low performance fan load with a 30cm axial-flow wingspan used for cooling heavy electro-mechanical equipment and surfaces. Despite the steady-speed operation of the industrial requirement, the variable speed fan was chosen for the test-bed to emulate the following commonly available operating anomalies in the underlying induction motor.

For the exogenous time series temperature input logging, the SSM-2 uses the MLX90614 infrared temperature module for non-contact temperature measurement. The sensor is used due to its high-resolution capability to read surface temperature measurement via a 10-bit PWM and an output resolution accuracy of $0.14°C$. Due to the comparatively lightweight computational requirement of the "non-video" IR module, an 8 bit Arduino Uno R3 microcontroller board was used with an MLX90614 temperature sensor. The main vibration data is captured via a high sensitivity piezoelectric film-based vibration sensor with an operating frequency of 0.001 to 10^9 Hz and a dynamic range of 10^{-8} to 10^6 psi. This vibration-to-voltage transducer produces a large voltage +/- 90V when the piezoelectric film moves in horizontal direction which is lowered down to ADC level via a $1\ m\Omega$ resistor.

A. *Model training data*

Data for model training was obtained as readings from both the SSUs with the fan operated in a variable speed mode against a steady/increasing/decreasing temperature pattern (See grayed row in Table I representing normal fan operation). In order to induce the actual operating behavior of the fan assembly, artificial temperature changes were induced on the test-bed application surface with an additional heat source (See Fig. 1). In normal circumstances, the fan's temperature sensing unit was expected to increase motor speed to reduce the temperature resulting in an increased vibration signature from the fan control unit (See Fig 4). The system was trained against a standard 70, 15, 15 percent data division for a total of 6587 training, 1411 validation and testing frames respectively. Each sample represented data values recorded on per second-basis from the sensors for an approximate total of 156 minutes. The underlying network was trained based on the parameters given in Table II where 7 and 14 second delays in training were induced to compensate for the observed maximum and minimum time required by vibration/motor speed adjustment mechanism to kick-off against abrupt or gradual temperature changes. The system was evaluated using DNN and NARX models with a 10-consecutive-validation-failure set as a stopping criterion to ensure an efficient input convergence and prevent the network from converging over an outlier-based premature validation failure criterion.

B. *Network evaluation outcomes for DNN and NARX models*

The sensor input data was obtained from test-bed lab conditions emulating the case of a fan-based surface cooling system with the sensor inputs recorded at one-second intervals. The data preprocessing involved dividing the data into three core categories with each further divided into two groups with one used for training and the other for evaluation purposes.

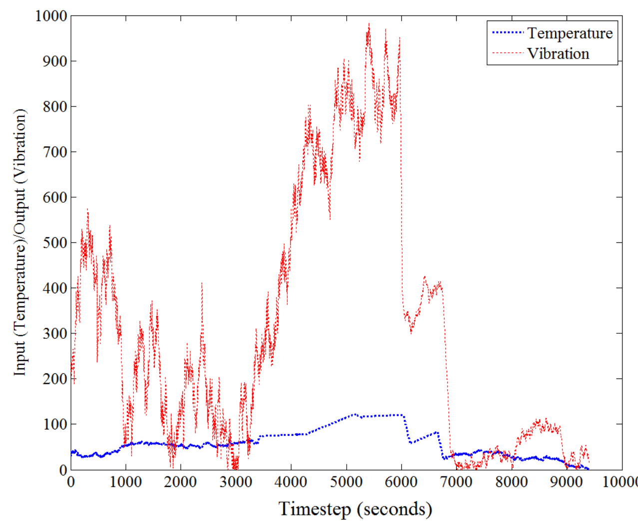


Fig. 4. Training data representing the time-series response showing outcome vibration pattern against artificially induced temperature changes (temperature shown as the lower data with changes induced from frame 3000 – 6500

TABLE I. EXPECTED SYSTEM FAN OPERATING BEHAVIOR BASED ON SENSOR-BASED DATA

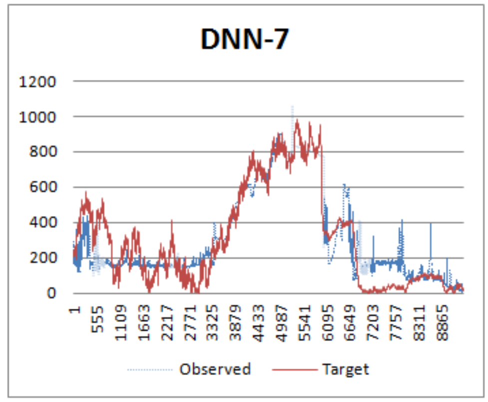
	Temperature (T°C)	Fan speed (Vibration)	Operating condition
(a)	Increasing /steady	Steady	Normal
(b)	Increasing /steady	Increasing	Normal: (Automated temperature-based fan control system triggered)
(c)	Increasing /steady	Reducing	Anomalous: possible motor/control system failure
(d)	Reducing	Steady /increasing	Possible over-current/heating/torque situation with motor/control system failure

Fig. 5 presents the validation outcome comparing the modeled (observed) outcome (shown as a dotted pattern) with the actual outcomes (shown as a solid line) with (a) and (b) representing models trained at 7- and 14-second intervals. Various network delay combinations were evaluated ranging from 5 – 20 second delays and the number of hidden neurons was fixed to 10 due to their minimum role in the network performance efficiency.

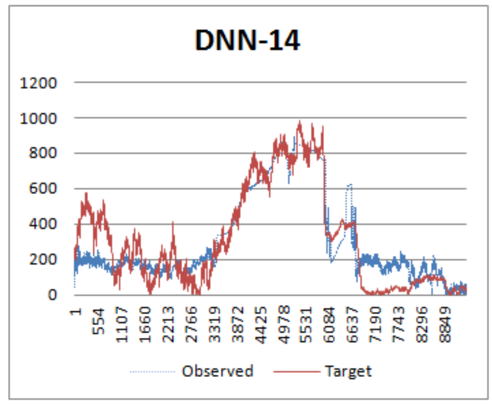
Performance accuracy and stability of both the DNN and NARX models is presented in Table II. The accuracies are based upon conditions (c) and (d) from Table I demonstrating two well-known operational cases in condition monitoring. The case, shown in Table I demonstrate (c) an increase in temperature with a reduction in the underlying temperature which is possibly due to surface overheating and (d) of motor speed increase with a fall in temperature over extended periods of time due to excess current drawn by the motor which could eventually result into the overheating of the fan itself.

TABLE II. PERFORMANCE FOR SELECTED DNN/NARX MODELS TESTING OVER 100-MINUTE UNSEEN DATASETS

Model/Delay	DNN (7-sec)	DNN (14-sec)	NARX (7-sec)	NARX (14-sec)
Training time	25	18	9	7
Testing % error (Table I Case (c))	9.34%	8.76%	4.56%	4.84%
Testing % error (Table I Case (d))	6.11%	5.95%	5.23%	5.56%



(a)



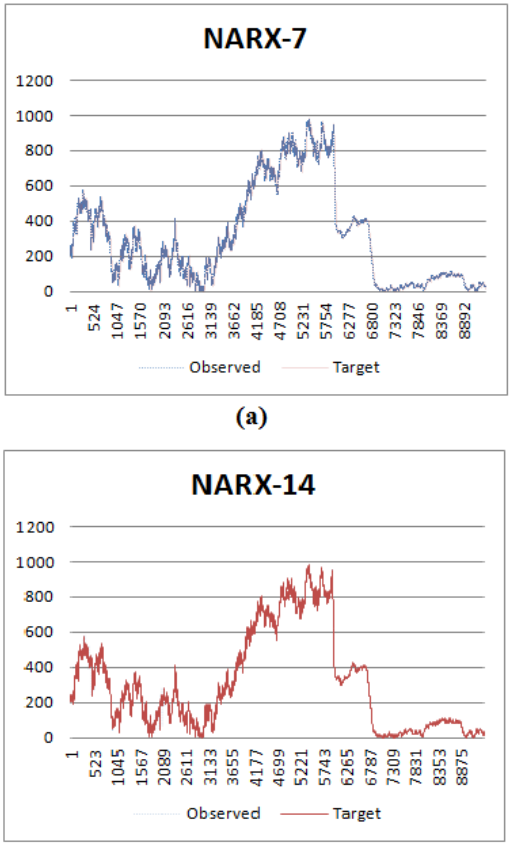
(b)

Fig. 5. Prediction performance of DNN model with a (a) 7- and (b) 14-second delay trained against 9409 training vectors

Fig. 5 and Fig. 6 present a comparison of targeted and observed vibration predictions against trained DNN and NARX classification models. A close comparison shows a marked reduction in classification error when moving from DNN to NARX models, particularly with training done with a 7-second delay. The outcome presented in Fig. 6 thereby makes NARX-7 to be the most efficient model in terms of classification error. Moreover, Table II further demonstrates minimal error statistics for the anomaly cases presented in Table I (c) and (d) with a training convergence time of 9 seconds only. It must be noted that attempts were made to improve the accuracy of DNN-7 and DNN-14 framework by increasing the number of neurons. However, the change did not improve the accuracy to a substantial level at the cost of training computational complexity.

C. *Best model evaluation with unseen machine data*

The NARX-7 model thus obtained was evaluated against unseen data gathered under conditions described in Table I (c) and (d) with the results demonstrated in Fig. 7 and Fig. 8 with '+' sign represents output and '.' sign represent the intended target. The lower dashed line represents the underlying temperature change pattern. The outcomes presented in



(a)

(b)

Fig. 6. Prediction performance of NARX model with a (a) 7- and (b) 14-second delay trained against 9409 training vectors and previous temperature profile as the exogenous data shown in (c) and (d)

Fig. 7 and 8 presented a substantial level of classification accuracy in the prediction of output vibration which can primarily be attributed to the introduction of exogenous data in the form of temperature series. The outcome demonstrates the suitability of exogenous sensor data on nonlinear autoregressive systems which can ultimately be utilized in the modeling of highly stable condition monitoring systems.

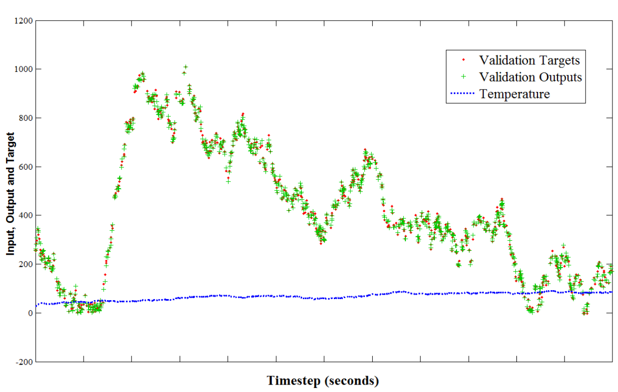


Fig. 7. Prediction outcome of best-performance NARX model with a 7-second delay input data taken from situation given in Table I (d) representing an erratic (induced) fan failure condition

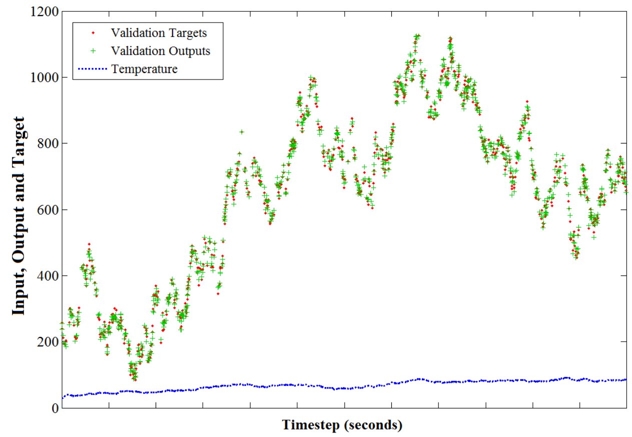


Fig. 8. Prediction performance of best-performance NARX model with a 7-second delay input data from Table I (c) representing an induction motor/surface overheating situation

VI. Conclusion

The work presented the evaluation of a nonlinear condition monitoring system that emulated an industrial environment in controlled lab environment. The research work objectively evaluated two unique neural network paradigms with a combination of parameters to obtain optimal ANN combination to improve the prediction accuracy. Overall, the NARX system with 7-second delay presented the lowest error rate and highest prediction accuracy. Yet, it was observed that despite an exceptionally high output-to-target relationship for the NARX-based systems, it was extremely difficult to gather reliable exogenous data in real industrial environments especially when the temperature got beyond the advised operating range of -20 to 120 C°. This limitation is envisaged to be catered as a possible future extension of this project to employ remote sensing devices such as vision sensors, sound monitors and non-invasive current measurement units where the data can be used as input feature matrix to improve the prediction under hazardous (high-temperature/power) environments.

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