ADAPTIVE PREDICTION MODEL FOR EFFECTIVE MAINTENANCE OF ELECTRICAL MACHINES

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Abstract

This work proposes a two stage prediction approach for the estimation of non-stationary machine variables through an optimum and generalized model imbibing real time data uncertainties. The prediction of machine speed and controller set point has been made using the proposed model for a three-phase induction motor operating on a single loop speed control with AC drive and PI controller. The trend of the machine variables has been extracted and added upon the Auto Regressive Moving Average (ARMA) time series prediction at stage one. ARMA prediction has been carried out using different combinations of Auto Regressive (AR) and Moving Average (MA) methods in order to obtain prediction results with less Mean Squared Error (MSE). The resulting prediction error indicates the inadequacy of the model to estimate the data characteristics which has been resolved at the subsequent stage by cascading an adaptive Least Mean Square (LMS) FIR filter to the time series model. The adaptive filter receives the predicted output including training data and iteratively adjusts its coefficients for zero error convergence. This has been tested for different parameter settings of step size and iterations at a specified filter length. The inclusion of adaptive filter in cascade also models the unknown real time factors influencing the system operation in an optimum and adaptive manner from the data available rather than the physical or fixed assumptions. The prediction accuracy of the model proposed has been compared with the existing technique of linear adaptive filter prediction using MSE as a comparison index. The wide difference in the MSE values of the prediction results obtained from the proposed and existing methods substantiates the efficiency of the proposed model in predicting time varying machine variables for better maintenance.

Key words: *Electrical Machine, Data Prediction Model, Time Series, Adaptive LMS, Predictive Maintenance.*

1. Introduction

Predictive maintenance employed in industries is focused to detect the problems of the system ahead to the occurrence of failures through data prediction so as to take corrective measures for prolonged life through prevention of unexpected process failures. The condition monitoring and predictive maintenance techniques, which entail continuous acquisition of physical and operational parameters and application of analysis techniques, have significant impacts in bringing out reliable machine maintenance in the industries. The condition of the electrical machines interpreted from the analysis is used to reduce the downtime and improve their performance. The predictive analysis applied for machine condition monitoring leads to assertive decision making in automation and control of processes in industrial applications and effective machine maintenance, which rely primarily on prediction accuracy. The prediction and analytics models in combination with data mining have high influence in the forecast of variables significant for preemptive and profitable enterprise decisions. NASA has listed the widely adopted predictive maintenance techniques for inferring the overall status of the system [1]. In this work, deriving an effective prediction model for univariate machine data of dynamic nature has been primarily focused. The precision in prediction enhances the probability of identifying the failures and deterioration and hence maximize the performance. This paper has been organized in sections of which the literature survey in Section 2 covers the aspects of predictive maintenance, predictive models and their applications in electrical machines. Section 3 introduces the proposed model for short term prediction of machine data. The experimental set up and procedure of data modeling have been explained in Section 4.

The prediction of machine data using ARMA (Auto Regressive Moving Average) model for different selection of AR and MA methods and orders has been illustrated with results in Section 5. The modeling of adaptive component using adaptive filtering technique and its effects on prediction accuracy have been discussed in Section 6 with a comparative analysis of adaptive linear prediction. The overall inference and scope of advantages that the componentized model can bring in predictive maintenance have been outlined in Section 7 as conclusion.

2. Literature Survey

Various hybrid models based on time series, mathematical transforms and artificial intelligence with supervised or unsupervised learning have been cited in literature for predictive modeling. It encompasses statistical, optimization, machine learning and data mining techniques based on the nature of data to develop predictive models. C.V. Apte et al. [2] have elaborated about data mining algorithms and specified that accurate determination of the functional relationship between explanatory variables and target variables is found to be a key challenge in the development of predictive models. Charles Nyce has stated that the predictive models need not always be 100 percent accurate and are prone to errors due to exclusion of significant factors or inclusion of insignificant factors or incorrect assumptions [3]. IBM has stated that predictive maintenance is widely replacing other methodologies used for Maintenance, Repair and Overhaul (MRO) in production industries. while designing a predictive maintenance application, the implementation of a mathematical model, continuous monitoring and control, selection of the best predictors for faults and accuracy validation have been identified as the important criteria [4]. Emerson Process Management has highlighted the methods of vibration analysis and infrared thermography for detection of impending failures and emphasized that the measurement of physical signals and information gathering through proper data interpretation methods have major role in health monitoring, priority fixation and predictive maintenance of electrical systems [5]. As cited by Frank Buytendijk and Lucie Trepanier, predictive analytics shall be carried out by modeling the system in three aspects: i) Predictive model, defining the relationship pattern between explanatory variables or events and predicted variables ii) Descriptive model, which segments the data based on observed characteristics and iii) Decision model, which provides solutions for optimal prediction [6]. Reza Askari Moghadam et al. [7] have used a hybrid model of linear ARIMA and non-linear neural network as prediction model in wireless sensor networks. The reduced data communication rate and power consumption have been highlighted as advantages resulting out of prediction. Mehdi Khashei et al. have combined SARIMA model with computational intelligence techniques for accurate forecast of non-linear data by overcoming the large input data requirements and linear dependence [8]. P.W.Tse et al. [9] have presented that the rate of machine deterioration can be determined by forecasting of non-stationary vibration signal using Recurrent Neural Networks (RNN). L.Karthikeyan et al. [10] have predicted the non-stationary time series by decomposing it into orthogonal components using the methods of Wavelet Transform and Empirical Mode Decomposition (EMD). The ARMA model is applied on the decomposed components independently to predict the results that have been compared to find the forecasting suitability of each method.

The mathematical model of a system is generally derived from the system dynamic equations or from the stochastic model using the probabilistic distribution of the input and output parameters. This requires deep insight of system mechanics, environmental factors and inclusion of all the necessary conditions as predictors in the forecast model. However, the mathematical equations of system mechanics and type of disturbances are often unknown in the field implementation. In such case, predictive models derived from the experimental data will be an effective solution in real time and such a model has been proposed for the estimation of future states of non-stationary real time machine data. At stage one, the short term prediction results are estimated as addition of trend and time series prediction. The mismatch in the data prediction is minimized by cascading of adaptive FIR filter, which acts as an adaptive component that adjusts the disparity in the time series prediction.

3. Proposed Prediction Model

A generalized short-term prediction model using time series analysis with additive trend and cascaded adaptive filter, which encompasses significant prediction factors for optimum online prediction of the machine variables, has been proposed. In this work, development of a reliable prediction model that gives more accuracy and suits the practical conditions has been instigated for non-stationary data of three phase induction motor. The proposed data prediction model shown in Figure 1 converts the non-stationary data into stationary data through the process of data detrending.

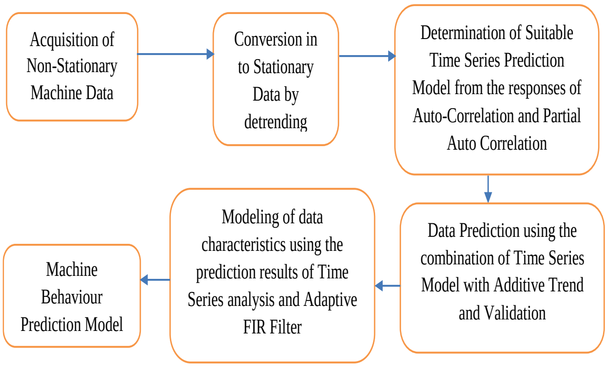

Fig. 1. Proposed Prediction Model for Non-Stationary Z Machine Data

The type of time series suitable for the representation of detrended data has been identified from the auto correlation and partial auto correlation responses. The stage one uses the combination of additive trend and linear time series for prediction. The adaptive model proposed in stage two receives the predicted time series and training data for iterative adjustment of its coefficients for zero error convergence at different parameter settings. The model has been tested on the three-phase induction motor operating on a single loop speed control with AC drive and PI controller for prediction of speed and controller set point data behaviour. Since the acquired data fits for Auto Regressive Moving Average (ARMA) model, the prediction has been made for different combination of Auto Regressive (AR) and Moving Average (MA) algorithms to perceive the accuracy of the predicted results. The model proposed, by cascading of adaptive FIR filter, uses Least Mean Square algorithm for error minimization and has been experimented to analyze the prediction behavior of adaptive component.

4. Experimental Set up and Modeling Procedure

The layout of experimental setup shown in Figure 2 consists of a PI controller, three phase AC drive, three phase squirrel cage induction motor and a data acquisition system (compact RIO – cRIO9068) operating in a closed loop. The reference speed of the induction motor has been set as a continuously varying pattern (as given in the pseudocode shown in Figure 3) by generating analog reference voltage of (4-10)V through analog output module NI9263 connected to cRIO9068.

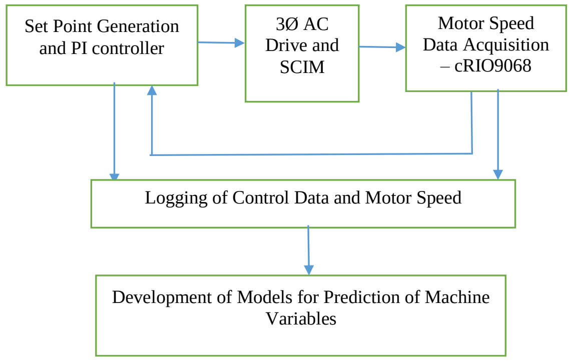

Fig.2. Experimental set up

The PI controller compares the set point with motor speed and generates control output that acts on the AC drive to achieve the speed as specified by the set point. The PowerFlex70 AC drive takes the speed reference as control input and actuates the induction motor by generating variable voltage and frequency corresponding to the PI controller output. The speed developed by the motor in response to the stimulus signal of the controller set point is measured by acquiring the speed feedback reference value from the AC drive through universal analog input module NI9219 interfaced with cRIO.

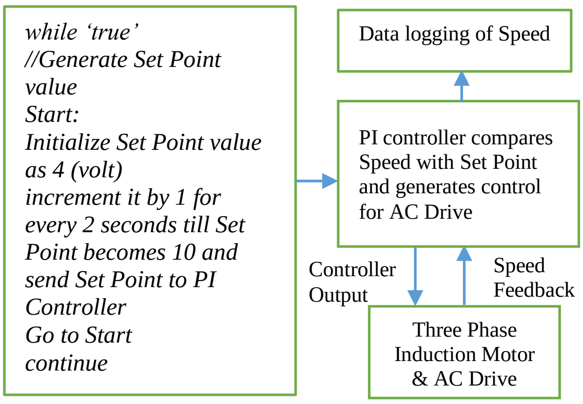

Fig.3. Functional Block Diagram of Experimental Setup

The values of speed references generated as controller set points, the corresponding speed developed in the induction motor and output of the PI controller are logged in real time controller of cRIO9068 and plots of all the specified variables are as shown in Figure 4. A set of 630 samples of controller set points is generated at the sampling interval of 2 seconds and the values of corresponding motor speed and controller output have been logged in the spread sheet.

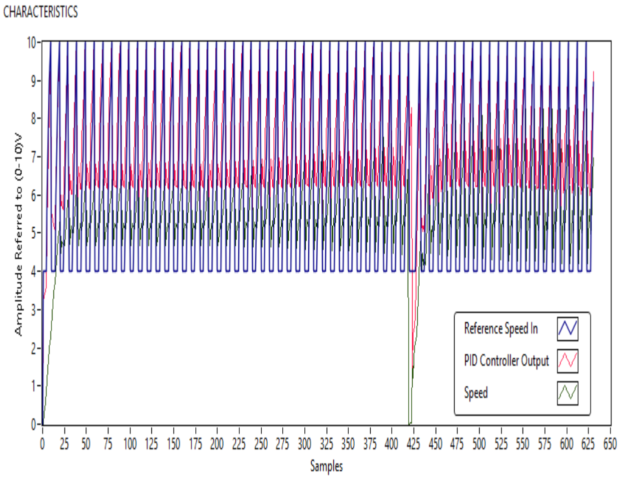

Fig.4. Data Characteristics (Actual Speed, Reference Speed, Controller Output)

A subset of 420 values from the recorded data set of 630 samples has been extracted to form the univariate time series of Set Point and Speed. These are taken as in-sample data for the prediction of subsequent unknown values. Time Series analysis widely used in economical, statistical, biological and environmental studies has been applied in this work to build a dynamic model that predicts the operational parameters of a three phase induction motor. The distribution of a physical variable using time series demands the stationarity of the series. Hence the logged univariate time series of speed and set point are tested for stationarity by mean and variance. A time series can possess deterministic or stochastic periodicity and trend. The trends of deterministic and stochastic nature can be represented as linear, exponential, cyclic, quadratic, cubic or polynomial expression. Since both the time series of speed and set point did not meet the stationarity conditions, the time series is preprocessed by removing the trend identified as cubic nature. The detrended time series having satisfied the stationarity conditions, their auto-correlation and partial auto correlation plots are obtained for a lag of 105 (Figures 5 and 6).

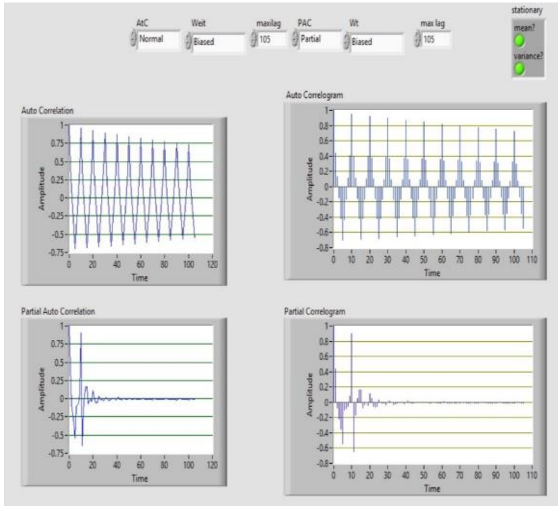

Fig. 5. Data Preprocessing of Speed

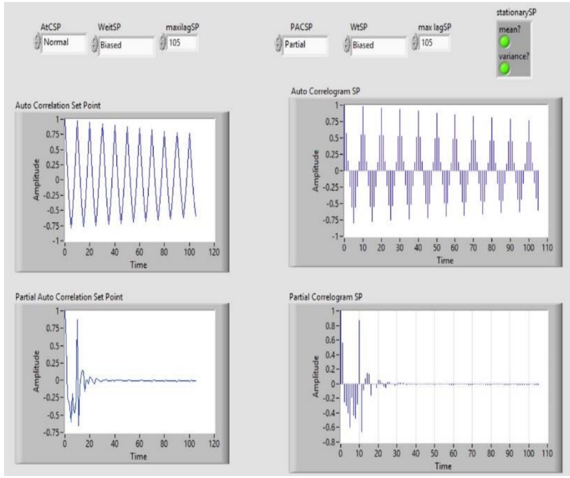

Fig. 6. Data Preprocessing of Set Point

The auto-correlation and partial auto-correlation plots of the detrended time series of speed and controller set point show a decaying pattern after certain lags. As per the model selection criteria specified by NIST, the type of time series is found to be Auto-Regression and Moving Average (L, N). The procedure of implementing the proposed model for prediction of non-stationary speed and set point using LabVIEW platform has been illustrated in the flow chart given in Figure 7.

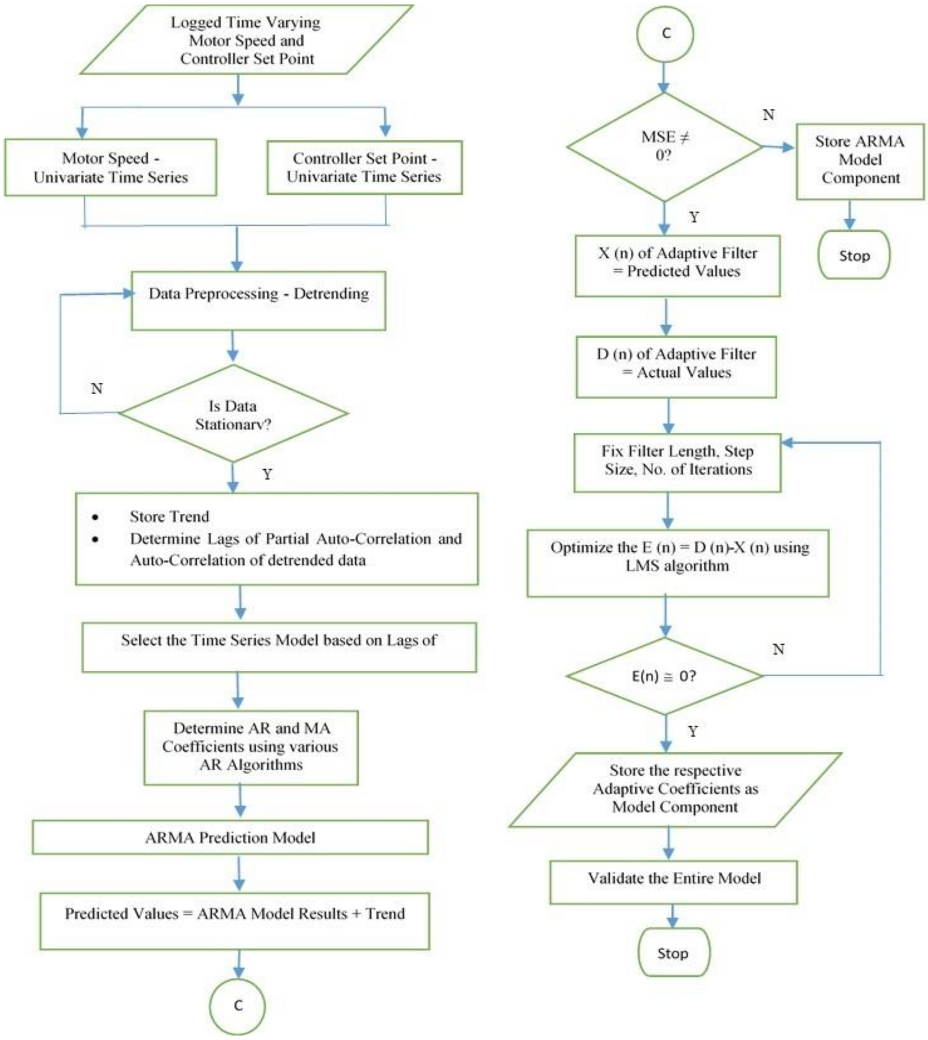

Fig. 7. Procedure for Prediction of Univariate Non-Stationary Machine Variables

5. Time Series Prediction of Machine Data

In order to develop the time series of machine data, ARMA(L,N) model has been constructed with the values of the machine physical variables, speed and controller set point (X_k) with respect to time sequence k, as represented by equation 1. The Auto Regression model coefficients up to the order L i.e., ρ^1 to ρ^L are computed using various AR methods namely Yule-Walker, Burg-Lattice, Least-Squares and Forward Backward. The Moving Average model coefficients of order N, θ^1 to θ^N are calculated using Yule-Walker method.

$$X_K = \sum_{O=1}^{O=L} \rho^O \, X_{K-O} + \sum_{m=0}^{m=N} \theta^m \, \varepsilon_{K-m} \qquad (1)$$

where ε_K is zero-mean white noise coefficient and $\theta^0 = 1$. The values of the ARMA time series X_k are evaluated as weighted summation of L recent values of X and N recent values of white noise. The values of L and N are empirically chosen from lag values of partial auto correlation and auto correlation of the stationary speed and set point data. The prediction models for set point and speed are developed in LabVIEW using time series ARMA prediction model as described above. The estimated AR and MA model coefficients are used for data prediction of subsequent 50 to 250 steps with the time duration of 2 seconds per step. The Trend causing non-stationarity in the data, identified as cubic nature has been added to the linear ARMA prediction values. As a measure of assessing the goodness of fit of ARMA and trend combination, the prediction results are compared with the actual data using the error metric of Mean Square Error. The MSE values obtained for various AR and MA methods and orders used in the prediction of set point and speed have been furnished in Tables 1 and 2.

Table 1. Prediction Error for Set Point (Stage 1)

AR Method	AR Order	MA Method	MA Order	MSE
Least-Squares	12	Yule -Walker	22	4.32
Yule-Walker	10	Yule-Walker	7	3.86
Forward Backward	10	Yule-Walker	22	3.79
Yule-Walker	10	Yule-Walker	22	3.57
Yule-Walker	10	Yule-Walker	9	3.37
Yule-Walker	10	Yule-Walker	27	2.96
Yule-Walker	12	Yule-Walker	8	2.71
Yule-Walker	14	Yule-Walker	8	2.69
Yule-Walker	15	Yule-Walker	8	2.65
Forward Backward	7	Yule-Walker	72	2.56

Table 2. Prediction Error for Speed (Stage 1)

AR Method	AR Order	MA Method	MA Order	MSE
Least -Squares	16	Yule -Walker	45	3.60
Yule-Walker	10	Yule -Walker	47	3.34
Forward Backward	12	Yule -Walker	81	3.28
Yule-Walker	12	Yule -Walker	14	2.94
Yule-Walker	12	Yule -Walker	10	2.91
Yule-Walker	14	Yule -Walker	91	2.82
Burg Lattice	18	Yule -Walker	91	2.76
Yule-Walker	12	Yule -Walker	39	2.71
Yule-Walker	14	Yule -Walker	102	2.67
Least-Squares	5	Yule -Walker	102	2.41
Least-Squares	4	Yule -Walker	91	2.07

The tabulated results thus obtained with ARMA and additive trend show that the methods of Yule-Walker, Forward Backward and Least Squares fit more appropriately in the determination of AR model coefficients. The predicted data of controller set point and speed have the lowest values of MSE as 2.56 and 2.07 respectively.

The plots of predicted results and actual data of the Set Point and Speed for lower values of MSE are shown in the Figure 8. For the machine data that has been considered, the estimated trend component represents the operational variations encountered by the machine and the ARMA prediction result shows the linear machine response characteristics. The error obtained in the prediction results reveals the data characteristics that could not be modeled by time series predication.

6. Application of Adaptive Filter for Identification of Adaptive Component

An adaptive filter iteratively computes the filter coefficients to obtain the relationship between the input and output digital sequences, either as Finite Impulse Response (FIR) / Infinite Impulse Response (IIR) in case of linear systems or Volterra / bilinear filters with respect to non-linear systems. The filter uses adaptive algorithms to adjust its coefficients as per the system configuration [11].

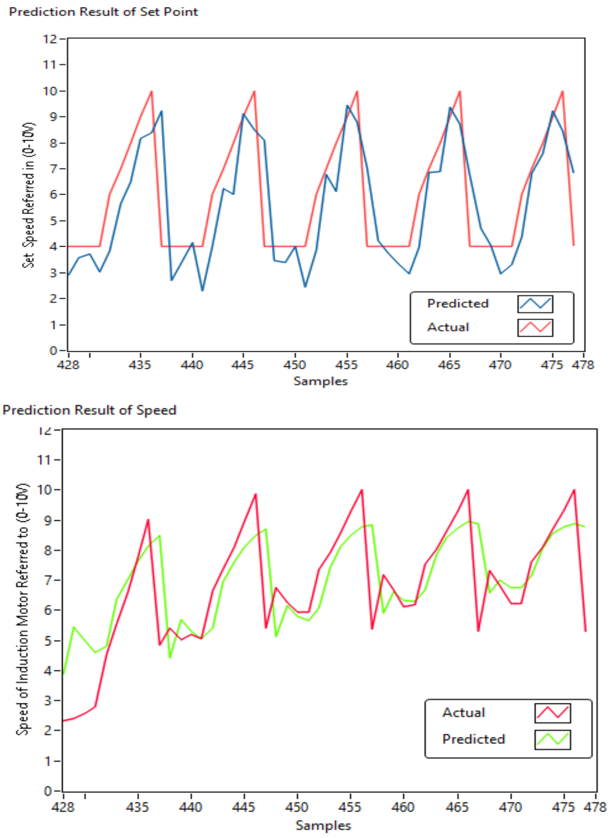

Fig. 8. Prediction Results of Set Point (MSE-2.56) and Speed (MSE–2.07)

In the model proposed, an adaptive filter structure has been used to identify the adaptive component to achieve high accuracy in prediction. The adaptive FIR filter configuration shown in Figure 9 will identify the adaptive component of the prediction model using the time series predicted values as X(n) and actual data as D(n). The adaptive component that is identified and cascaded with time series prediction includes the unincorporated data characteristics and subsides the factors causing modeling error, thus yielding higher accuracy.

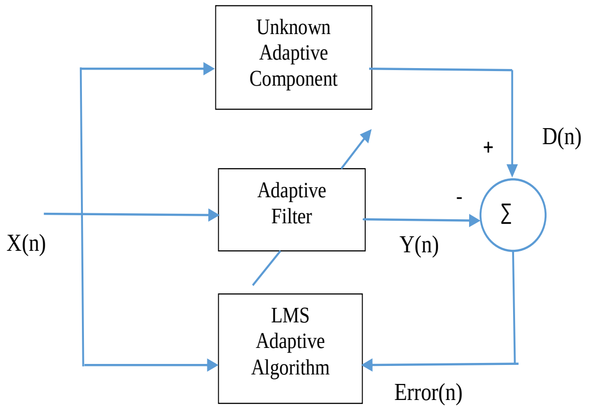

Fig. 9. Adaptive Filter Structure for Identification of Adaptive Component

The convergence of the error, Error(n) in equation 2 to zero is achieved through minimization of error between the known system output D(n) and adaptive filter output Y(n) with optimized filter coefficients obtained by the iterative adjustment of the coefficients using adaptive LMS algorithm.

$$\text{Error}(n) = D(n) - Y(n) \tag{2}$$

The output Y(n) of the linear adaptive Finite Impulse Response (FIR) filter is computed using equation 3.

$$Y(n) = \sum_{i=0}^{i=L-1} w_i(n)\, x(n-i) \tag{3}$$

where $\{w_i(n)\}$ are the coefficients of the adaptive filter, $\{x(n-i)\}$ are the input sequences and Y(n) is the output of the adaptive filter.

6.1 Least Mean Square Adaptive Algorithm for FIR Filter

The $\text{Error}(n)_{MSE}$ has been estimated as an average of the expected value of quadratic error signal as shown in equation 4. The coefficients of the adaptive filter given in equation 3 are modified such that the output of the filter gives minimized value of $\text{Error}(n)_{MSE}$ [11].

$$\text{Error}(n)_{MSE} = (1/2) * \int_{-\alpha}^{\alpha} e^2(n)\, p_n\, [e(n)] d[e(n)]$$
$$= (1/2) * E\{e^2(n)\} \tag{4}$$

where p_n [$e(n)$] is the Probability Density Function of the error at time n.

Thus, to determine the minimum filter coefficients, the cost function $\text{Error}(n)_{MSE}$ is differentiated with respect to its coefficient parameters and has been equated to zero, by optimization theory. Hence it becomes,

$$\frac{\partial\, \text{Error}(n)_{MSE}}{\partial w_i(n)} = 0 \tag{5}$$

The Least Mean Square algorithm takes the $\text{Err}(n)_{LMS}$ given in equation 6 as cost function using the current value of the error function instead of probabilistic values $\text{Error}(n)_{MSE}$.

$$\text{Err}(n)_{LMS} = (1/2) * e^2(n) \tag{6}$$

According to the method of steepest descent algorithm, the filter coefficients of a particular iteration, $w_i(n)$ are modified according to the derivative of the $\text{Err}(n)_{LMS}$ function with respect to the coefficient by itself as shown in equation 7.

$$w_i(n+1) = w_i(n) - \mu(n) \frac{\partial\, \text{Err}(n)_{LMS}}{\partial w_i(n)} \tag{7}$$

where $\mu(n)$ is defined as the step size.

Thus appropriate selection of step size and number of iterations could bring faster convergence of error to zero and identifies the model of the unknown machine data characteristics that are not estimated from time series prediction. To identify the adaptive model component that makes the time series prediction results to merge with the actual training data, the data predicted by the time series model X(n) and the actual training data D(n) are fed as inputs to adaptive FIR filter to obtain optimum prediction solution. An analysis has been made for different number of iterations and step sizes for the adaptive filter length of 50. The prediction accuracy and processing time of adaptive filter for different step sizes and iterations are highlighted in Tables 3 and 4. The tabulated results show the rate of convergence of the MSE pertaining to the specific time series model for different step sizes and number of iterations of the filter. The significant convergence of the prediction error up to the order of 10^{-6} and 10^{-5} have been observed for set point and speed respectively at higher iterations.

Table 3. Error Convergence of Speed Prediction using proposed model

ARMA Prediction Model for Speed	**No. of Iterations**	**Step Size = 0.0003**		**Step Size = 0.00035**	
		MSE	**Time (s)**	**MSE**	**Time (s)**
AR Method – Burg Lattice MA Method – Yule Walker AR Order = 18, MA Order =91 MSE = 2.76	50	0.372	0.0020	0.3675	0.0020
	500	0.2663	0.0180	0.2841	0.0160
	5000	0.18031	0.1741	0.18618	0.1741
	10000	0.13811	0.3332	0.137945	0.3482
	20000	0.089796	0.7024	0.085288	0.5893
	40000	0.047418	1.3959	0.042546	1.3168

Table 4. Error Convergence of Set Point using proposed model

ARMA Prediction Model for Set Point	**No. of Iterations**	**Step Size = 0.0003**		**Step Size = 0.00035**	
		MSE	**Time (s)**	**MSE**	**Time (s)**
AR Method – Yule Walker MA Method – Yule Walker AR Order = 12, MA Order = 08 MSE = 2.71	50	0.00837	0.0020	0.0057	0.0020
	500	0.001348	0.0190	0.001365	0.0180
	5000	3.837E-5	0.1721	5.005E-5	0.1731
	10000	1.892E-6	0.2982	3.007E-6	0.2961

It is observed that for a specified number of iterations, better zero convergence happens either with increase or decrease of step size, whereas for a fixed step size, the increase in the number of iterations brings closer error convergence consistently. In order to evaluate the performance of the adaptive model component, a comparative study has been made by considering the time series speed prediction with MSE lesser by 0.69 and the corresponding results are shown in Table 5.

Table 5. Error Convergence of Speed with proposed model (MSE = 2.07)

ARMA Prediction Model for Speed	**No. of Iterations**	**Step Size = 0.0003**		**Step Size = 0.00035**	
		MSE	**Time (s)**	**MSE**	**Time (s)**
AR Method – Least Square MA Method – Yule Walker AR Order = 4, MA Order =91	50	0.354	0.0019	0.333	0.0010
	500	0.1214	0.0160	0.1134	0.0130
	5000	0.0079	0.1611	0.0077	0.1741
	10000	2.8E-3	0.3332	2.9E-3	0.2951
	20000	5.199E-4	0.5954	6.2175E-4	0.5954
	40000	1.833E-5	1.1860	3.0537E-5	1.9280

The prediction results obtained for machine speed and controller set point after inclusion of the Adaptive FIR Filter working on LMS algorithm have been illustrated in Figures 10 and 11 respectively along with the minimization of MSE.

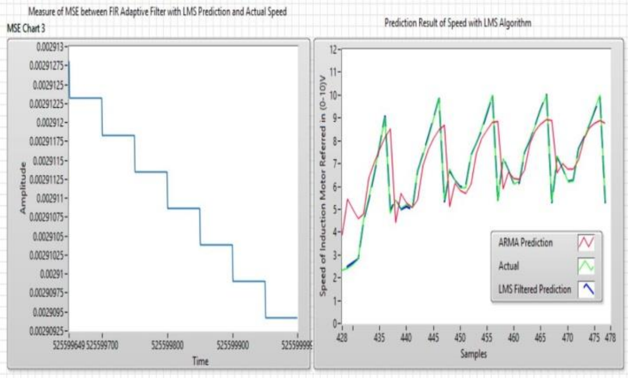

Fig.10. Minimization of Prediction Error with Adaptive LMS Algorithm (Speed)

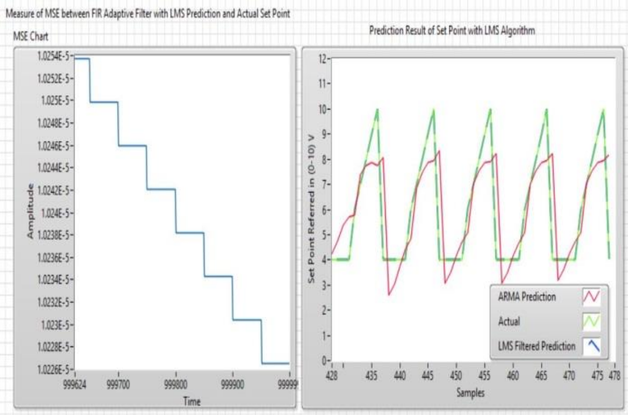

Fig.11. Minimization of Prediction Error with Adaptive LMS Algorithm (Set Point)

The results of comparative analysis given in Tables 3 and 5 reveal that for the same number of iterations, the adaptive component of the proposed model gives better performance with huge margin of error convergence in a shorter duration even for the marginal optimization of the prediction results of the time series model. The duration taken could be further minimized by executing the model in a dedicated and deterministic real-time processor. The adaptive filter shown in Figure 12 is used for estimation of the future values of the signal X(n) from the actual and delayed set of samples of X(n). The adaptive filter performs AR model estimation by iterative adjustment of its coefficients in online mode based on the Error(n).

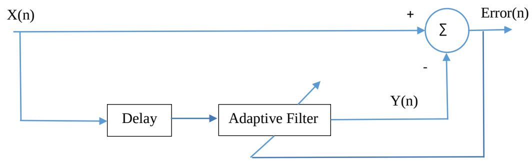

Fig. 12. Adaptive Filter Structure for Prediction

The efficiency of the proposed model in predicting the non-stationary machine variables is evaluated by comparing the prediction accuracy of the proposed model (Table 4) with that of adaptive filter prediction (Table 6). The non-stationary machine variable predicted using adaptive linear prediction for various filter lengths and step sizes estimates the signal with Mean Square Error (MSE) ranging from 2.20 to 2.86 and 2.13 to 2.99 for step size of 0.0003 and 0.00035 respectively. In contrast to this, the results obtained from the proposed model show better prediction accuracy with MSE varying from 1.892E-6 to 0.00837 and 3.007E-6 to 0.0057 for step sizes of 0.0003 and 0.00035 respectively.

Table 6. Error Convergence of Set Point with Adaptive Prediction

Filter Length	Step Size = 0.0003		Step Size = 0.00035	
	MSE	Time (s)	MSE	Time (s)
128	2.58	2.00	2.99	0.99
64	2.25	2.00	2.20	1.00
50	2.20	0.999	2.13	1.00
32	2.32	1.00	2.23	1.99
16	2.86	0.3332	2.72	1.59

This combination of trend, time series and adaptive system identification gives a simple and generalized prediction model design that improves prediction accuracy by facilitating the inclusion of relevant and unknown predictors in online through adaptive filter. In addition to achieving better accuracy, the model also characterizes the trend of the data pattern which is a widely used diagnostic parameter in condition monitoring.

7. Conclusion

The effectiveness of predictive maintenance strategies adopted for machine maintenance depends on the optimal nature of the prediction model deigned. The advanced diagnostic capabilities encompassing new algorithms and methodologies ease data driven analysis of the machine's physical and operational parameters influential in condition monitoring and predictive maintenance of electrical machines. The proposed machine data prediction model is making machine failure prognosis at three independent levels namely Trend, Linear Response and Adaptive variations. The onset of machine failures inherently evident in the signals acquired, on processing with precisely designed model will disclose the extent of failure development in the system. When failure predictions have been made using componentized model, the impacts on individual model component will be clearly distinct. Such variations observed in the discrete components enable adoption of appropriate predictive maintenance decisions leading to an enhanced process coordination and fault tolerance in industrial environment.

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