Time-series Modelling and forecasting of traffic noise levels - A_IMA versus ANN approach

This chapter analyzes the long-term noise monitoring data using Autoregressive Integrated Moving Averages (ARIMA) modelling technique and ANN methodology. Box-Jenkins ARIMA and ANN approach has been utilized to simulate daily mean $L_{D_{ay}}$ (06-22h) and $L_{N_{ight}}$ (22-06h) in A and C weightings, Day-night average sound level (DNL) and $L_{A_{eq},24h}$ for a period of one year. The forecasting performance is ascertained using the statistical tests. The work draws a comparison of time-series ARIMA and ANN approach for ascertaining their suitability for traffic noise modeling and forecasting.

6.1 Background

A continuous long-term noise monitoring of ambient noise levels is cumbersome and quite expensive and in many cases the larger resources involved are not justified in terms of better accuracy than that achievable by cheaper and feasible temporal samplings [170]. The time-series analysis of ambient noise shall be thus instrumental in forecasting the future noise levels in addition to the continuous noise monitoring attributed to the stochastic nature of traffic noise. It can also serve as a suitable substitute to the continuous long-term noise monitoring provided the predicted data matches well with the actual measurement data. There have been very few studies reported so far on application of this approach to noise modelling [161-163,182]. Kumar et al. 1999 analyzed the short-term noise levels measured at 10 s intervals in the vicinity of a busy road carrying vehicular traffic using the ARIMA approach [182]. DeVor et al. 1979 used ARMA (Auto regressive moving average) model to assess the level of autocorrelation in the data via the Dynamic Data System approach to time-series analysis [163]. For reliable estimation of the mean level within a ± 5 dB range, it was recommended that the sample size in the range of 20-50 consecutive daily averages would be required. Schomer et al. 1983 simulations
demonstrate that non consecutive sampling strategies reduce the overall sampling requirements for non stationary data [164]. The exhaustive literature review reveals that ARIMA methodology has not been implemented so far for long-term noise monitoring, although it has been extensively used in air pollution predictions. The present work extends Kumar et al. 1999 work by analysis for long-term ambient sound levels forecasting using ARIMA approach. More recently, Artificial Neural Networks (ANN) have been suggested as an vital tool for the time-series forecasting. The main strength of the ANNs is their flexible nonlinear modeling capability [183]. The chapter also demonstrates the application of ANN methodology for time-series modelling and forecasting of traffic noise levels. A statistical comparison between the results observed from ARIMA and ANN approach is presented to ascertain their suitability for long-term noise modelling and forecasting. Although the developed ARIMA and ANN models are site-specific, yet the main objective behind the present work is to demonstrate their suitability and applicability for time-series modelling and forecasting which can be thus utilized for any site or location in general.

6.2 Long-term sound level data analysis

The long-term noise monitoring data analyzed in the present study is reported from CPCB noise monitoring station situated in Delhi city that comes under the commercial zone. The noise monitoring terminal is a standalone operating remote terminal sound-level meter consisting of a high quality microphone connected to an advanced acoustic signal-processing unit, which in turn is connected to an advanced high resolution data logger. The sound levels data are acquired locally, archived and communicated to a central station through an integrated GPRS modem [9]. The sound levels data considered in the present work is one-year (365 days) continuous noise
monitoring data taken from September 2013 to August, 2014 (http://www.cpcbnoise.com) at the CPCB noise monitoring station situated in the commercial area of East Arjun Nagar (77°17’ E, 28° 39’ N), New Delhi. The sound level parameters considered are daily mean $L_{\text{Day}}$ (06-22h) and $L_{\text{Night}}$ (22-06h) in A and C weightings, Day-night average sound level ($DNL$) and equivalent continuous sound pressure level in A-weighting for 24 hours, $L_{\text{eq,24h}}$ for a period of one year. It may be noted that $L_{\text{eq,24h}}$ data is from period of January, 2014 to December, 2014 for the CPCB site. The $DNL$ value is calculated from the $L_{\text{Day}}$ (06-22h) and $L_{\text{Night}}$ (22-06h) values as:

$$DNL = 10 \log \left[ \frac{1}{24} \left( 16 \times 10^{\frac{L_{\text{Day}}}{10}} \right) + 8 \times 10^{\frac{L_{\text{Night}} + 10}{10}} \right]$$ \quad (6.1)$$

Fig. 6.1 shows the time sequence plot of $L_{\text{Day}}$ (06-22h) in dB(A) for one year from September, 2013 to August, 2014. The average annual value of $L_{\text{Day}}$ (06-22h) is calculated to be 65.3 ± 1.4 dB(A). The monthly variation ranges from minimum value of 64.4 dB(A) in November, 2013 to maximum value of 66.3 dB(A) in August, 2014.
Fig. 6.2 shows the time sequence plot of $L_{\text{Night}}$ (22-06h) in dB(A) for one year from September 2013 to August, 2014. The monthly variation of $L_{\text{Night}}$ (22-06h) ranges from 57.7 dB(A) in January, 2014 to 59.5 dB(A) in February, 2014. The average annual value of $L_{\text{Night}}$ (22-06h) is calculated to be 58.9 ± 1.4 dB(A).

![Fig. 6.2. Time sequence plot of $L_{\text{Night}}$ (22-06h) (in dB(A)) for September, 2013 to August, 2014.](image)

Figs. 6.3 & 6.4 shows the time sequence plot of $L_{\text{Day}}$ (06-22h) and $L_{\text{Night}}$ (22-06h) in dB(C) for a period of one year. The average value of $L_{\text{Day}}$ (06-22h) is calculated to be
71.3 ± 1.3 dB(C) and $L_{\text{Night}}$ (22-06h) is 66.1 ± 1.2 dB(C). Analysis of Day-night average sound levels, $DNL$ for a period of 365 days reveals that average $DNL$ value as 66.9 ± 1.2 dB(A).

**Fig 6.4. Time sequence plot of $L_{\text{Night}}$ (22-06h) (in dB(C)) for September, 2013 to August, 2014.**

Fig. 6.5 shows the time sequence plot of Day-night average sound level, $DNL$ value for a period of one year. This value ranges from minimum value of 66.2 dB (A) in January, 2014 to maximum value of 67.6 dB(A) in July, 2014.

**Fig 6.5. Time sequence plot of Day-night average sound level, $DNL$ (in dB(A)) for September, 2013 to August, 2014.**
Fig. 6.6 shows the time sequence plot of $L_{eq,24h}$ (in dB(A)) value for a period of one year from January, 2014 to December, 2014. The average annual value of $L_{eq,24h}$ is calculated to be $62.3 \pm 1.9$ dB(A). The value ranges from minimum value of 59.7 dB (A) in January, 2014 to maximum value of 65.1 dB(A) in November, 2014.

6.3 ARIMA Modelling approach

The ARIMA approach was first popularized by Box and Jenkins, and ARIMA models are often referred to as Box-Jenkins models [184]. In ARIMA modelling approach, a stationary time-series is made stationary by applying finite differencing of the data points. The mathematical formulation of the ARIMA ($p$, $d$, $q$) model using lag polynomials for a time-series data $Y_t$ where $t$ is an integer and $Y_t$ are real numbers [185,186]:

$$
(1 - \sum_{i=1}^{p} \phi_i L^i)(1-L)^d Y_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \epsilon_t
$$

(6.2)

where $p$, $d$ and $q$ are integers greater than or equal to zero and refer to the order of autoregressive, integrated and moving average parts of the model respectively. The
integer $d$ controls the level of differencing. When $d=0$, then it reduces to an ARMA $(p,q)$ model. ARIMA model is generalization of an ARMA model to include the case of non-stationarity as well. In equation (6.2), $L$ is the lag operator, $\phi_i$ are the parameters of the autoregressive part of the model, the $\theta_i$ are the parameters of the moving average part and the $e_t$ are error terms. In time-series analysis, an event occurring at time $t+k$ ($k > 0$) is said to lag behind an event occurring at time $t$, the extent of the lag being $k$. The error terms $e_t$ are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean. In practice, most economic or business time-series can be modelled with rather modest numbers of terms, $p$ and $q$, in the form of an Auto-regressive (AR), an Moving average (MA), or an ARMA model. In order to achieve parsimony, the forecaster's task is to identify the smallest numbers of terms, $p$ and $q$, to include within the model and still satisfactorily forecast the series. An ARIMA $(p,0,q)$ or ARMA $(p,q)$ is a model for time-series that depends on $p$ past values of itself and $q$ past random error terms $e_t$. This method has form of equation (6.3) as [187]:

$$Y_t = \theta_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \mu - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} + e_t$$

(6.3)

where $\theta_1, \theta_2, \ldots, \theta_q$ are the finite weights, $\mu$ is the mean of series, $Y_t$ is the forecasted output, $Y_{t-p}$ is observation at time $t-p$ and $\phi_1, \phi_2, \ldots, \phi_p$ is a set of finite parameters determined by linear regression and $e_t$ is error associated with the regression.

The ARIMA modeling involves three stages: identification stage, estimation stage and diagnostic checking stage. In identification stage, it is ensured that the time-series is sufficiently stationary (free from trend and seasonality) and to specify the appropriate number of autoregressive terms $p$ and moving average terms, $q$. The
estimation stage involves the estimation of parameters $p$ and $q$ of autoregressive moving average terms. The diagnostic stage ascertains whether the developed $ARIMA$ model fits well with the input time series data or not. Once it is ensured that the difference between the predicted and actual observations is sufficiently small, then the model can be utilized for forecasting. A model is considered adequate if low order autocorrelations are not significant even though significant autocorrelations of higher order still exist [187]. Seasonal patterns of the time-series can be examined via correlograms, which displays graphically and numerically the autocorrelation function ($ACF$) i.e. serial correlation coefficients and their standard errors for consecutive lags in a specified range of lags. The autocorrelation plots, $ACF$ shows the degree of correlation with the past values of the series as a function of number of periods (i.e lag) at which correlation is computed. The partial correlation plots, $PACF$ have the same form as the autocorrelation plots but displays partial autocorrelations values instead of autocorrelations and autocovariances. Although $ARIMA$ models are quite flexible in handling the time-series data and modeling, their major limitation is the pre-assumed linear form of the model [183]. Fig. 6.7 shows the flow chart depicting the $ARIMA$ methodology used in present study. The time-series has been analyzed using the SPSS software (Statistical Package for the Social Sciences), Version 17 [188]. The Time-Series Modeler procedure estimates exponential smoothing, univariate, Autoregressive Integrated Moving Average ($ARIMA$), and multivariate $ARIMA$ (or transfer function models) models for time-series, and produces forecasts. The procedure includes an Expert Modeler that automatically identifies and estimates, the best-fitting $ARIMA$ or exponential smoothing model for one or more dependent variable series, thus eliminating the need to identify an appropriate model through trial and error [188].
The characteristics of good ARIMA model are summarized [189] as follows:

- Stationary i.e. it has an AR term that satisfies some mathematic inequalities
- Invertible i.e. it has MA coefficient that satisfies some mathematic inequalities
- Parsimonious i.e. uses small number of coefficients to explain the available time-series data
- Statistically independent residuals
- Fits the available data sufficiently well

Fig. 6.7. Flow chart depicting the ARIMA methodology used.
- Root-mean squared error (RMSE) and Mean-absolute percent error (MAPE) is acceptable, sufficiently small forecast errors.

There are several index used to identify the best model such as Bayesian Information Criterion (BIC) as [187]:

\[
BIC = n \log (SSE) + m \log (n)
\]

(6.4)

where \( m \) is the number of parameters of the model for time-series of length \( n \) and \( SSE \) is the Sum of squared errors. In this equation, the first term measures the goodness-of-fit of the model, while the second term penalizes the number of model parameters. Given any two estimated models, the model with the lower value of BIC is the one to be preferred. In order to chose the best ARIMA \((p,d,q)\) model for each time-series, Akaike Information Criterion (AIC) was applied in the model selection procedure. For a fitted ARIMA time-series of length \( n \), the AIC is defined as [190]:

\[
AIC = \ln \left( \hat{\sigma}_{p,q}^2 \right) + 2(p+q)/n
\]

(6.5)

where \( \hat{\sigma}_{p,q}^2 \) is the residual error variance from the fitted model. When comparing the fitted model, the model with smallest AIC value is chosen [191].

### 6.4 Time-series analysis using ARIMA approach

The input series for ARIMA needs to be stationary i.e. it should have a constant mean, variance and autocorrelation through time. So, the series first needs to be differenced until it is stationary. The number of times the series needs to be differenced to achieve stationarity is represented by parameter \( d \). Seasonal patterns of the time-series can be examined via correlograms, which displays graphically and numerically the autocorrelation function (ACF) i.e. serial correlation coefficients and their standard errors for consecutive lags in a specified range of lags [187]. The autocorrelation
plots, ACF shows the degree of correlation with the past values of the series as a function of number of periods (i.e. lag) at which correlation is computed. The partial correlation plots, PACF have the same form as the autocorrelation plots but display partial autocorrelations values instead of autocorrelations and autocovariances. Figs. 6.8 (a) to (f) illustrates the ACF and PACF for the daily mean time series data of \( L_{\text{Day}} \) (06-22h) and \( L_{\text{Night}} \) (22-06h) in A and C weightings, \( DNL \) and \( L_{\text{eq},24h} \) values. The two vertical lines in the ACF and PACF plots designate the 95% confidence intervals for the estimated autocorrelation and partial autocorrelation coefficients. The y axis of the ACF and PACF plots indicates the lag at which the autocorrelation is computed; the x axis indicates the value of the correlation (between \(-1\) and \(1\)). Large or frequent excursions from the bounds suggest the requirement of a model for explanation of the dependence.
Fig. 6.8 (a) to (f). Auto Correlation Functions (ACF) and Partial Auto Correlation Functions (PACFs) residuals for \( L_{\text{Day}} \) (in dB(A)), \( L_{\text{Night}} \) (in dB(A)), \( L_{\text{Day}} \) (in dB(C)), \( L_{\text{Night}} \) (in dB(C)) and Day-night average sound level, \( DNL \) (in dB(A)) and \( L_{\text{eq,24h}} \) in dB(A). The vertical lines indicate the upper and lower confidence limits.

The ACF plots shown in Fig. 6.8 of \( L_{\text{Day}} \), \( DNL \) and \( L_{\text{eq,24h}} \) indicate the presence of weekly periodicity in time-series. The Expert Modeller within the software tool SPSS considers both experimental smoothing and ARIMA models and model variables are transformed where appropriate using a differencing or a square root or natural log transformation. A model with no orders of differencing assumes expert modeller automatically finds the best fitting model for each dependent series. A positive correlation indicates that large current values correspond to large values at the specified lag and a negative correlation indicates that large current values correspond to small values at the specified lag. The confidence limits are provided to display when ACF or PACF are significantly different from zero, suggesting that the lags having values outside these limits should be considered to have significant correlation. Visual inspection of Fig. 6.8 shows significant deviations from zero. The interpretation suggests that the all ACF and PACF values are correlated to each other during the successive days.
Fig. 6.9. (a) to (f). Comparison of ARIMA model simulations (blue line) and observations (red line) of $L_{\text{Day}}$ (in dB(A)), $L_{\text{Night}}$ (in dB(A)), $L_{\text{Day}}$ (in dB(C)), $L_{\text{Night}}$ (in dB(C)) and Day-night average sound level, $DNL$ (in dB(A)) and $L_{\text{eq,24h}}$ in dB(A).

The model results for sound level parameters $L_{\text{Day}}$ (in dB(A)), $L_{\text{Night}}$ (in dB(A)), $L_{\text{Day}}$ (in dB(C)), $L_{\text{Night}}$ (in dB(C)) and $DNL$ (in dB(A)) and $L_{\text{eq,24h}}$ in dB(A) are shown in Figs. 6.9 (a) to (f). The best fit ARIMA model was adjudged based on the model...
selection criteria such as minimum value of Mean squared error, \(MSE\) and \(AIC\). The \(ARIMA\) models, namely \(ARIMA(0,0,14)\), \(ARIMA(0,0,7)\), \(ARIMA(0,0,14)\), simple, \(ARIMA(1,0,7)\) and \(ARIMA(0,1,9)\) have been observed as the most suitable using the expert modeller for simulating and forecasting the daily mean \(L_{\text{Day}}\) (in dB(A)), \(L_{\text{Night}}\) (in dB(A)), \(L_{\text{Day}}\) (in dB(C)), \(L_{\text{Night}}\) (in dB(C)) and \(DNL\) (in dB(A)) and \(L_{\text{eq},24\text{h}}\) in dB(A) respectively. Table 6.1 represents the \(AIC\) values corresponding to the \(ARIMA\) models developed for each parameters. It also represents the statistical tests for ascertaining the performance of \(ARIMA\) models developed for each site. An autoregressive order of 1 specifies that the value of series one time periods in the past is used to predict the current value. Moving-average order of 7 specifies that deviations from the mean value of the series from each of the last seven time periods be considered when predicting the current value of the series. The analysis for \(L_{\text{Night}}\) (in dB(C)) time-series reveals that a simple exponential smoothing model is best fit for the data. It is equivalent to zero orders of autoregression, one order of differencing and one order of moving average and no constant [188]. These models are parsimonious amongst all the other possibilities especially when no suitable model can be found with the available methodology [185,192]. These results also suggest that the model forecasted values are following the observed trend quite well. Consequently, the model gives satisfactory results and can be used as a reliable predictive tool. Several measures of accuracy were applied to ascertain the performance of the \(ARIMA\) models so developed, such as stationary \(R\)-squared, \(R\)-squared, Root Mean Squared Error (\(RMSE\)), Mean Absolute Percentage Error (\(MAPE\)) and Normalized \(BIC\) (Bayesian Information Criterion). Lower value of \(BIC\), \(RMSE\) were preferable. The low \(RMSE\) values observed indicates that the dependent series is closest with the model predicted levels and thus the predictive model is useful at 95 % confidence limits [193,194].
The observed low RMSE values (≤ 1.5 dB(A)) validates the ARIMA models so developed although the $R$-squared value is low for each parameter except that for $L_{eq,24h}$. The Ljung-Box statistic, also known as the modified Box-Pierce statistic, provides an indication of whether the model is correctly specified. A significance value less than 0.05 implies that there is structure in the observed series which is not accounted for by the model [188]. Using Ljung-Box model, value of statistics lies between 15.08 to 67.67, significance level varies from 0.09 to 0.59 for all ARIMA models, which validates the model compatibility [194].

### Table 6.1. ARIMA Models Statistics.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$RMSE$</th>
<th>$MAPE$</th>
<th>Normalized $BIC$</th>
<th>Model Fit statistics</th>
<th>$AIC$</th>
<th>Ljung-Box $Q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_{Day}$ dB(A)</td>
<td>1.2</td>
<td>1.4</td>
<td>0.5</td>
<td>Stationary $R$-squared</td>
<td>0.2</td>
<td>0.7</td>
</tr>
<tr>
<td>$L_{Night}$ dB(A)</td>
<td>1.2</td>
<td>1.2</td>
<td>0.4</td>
<td>Stationary $R$-squared</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>$L_{Day}$ dB (C)</td>
<td>1.1</td>
<td>1.2</td>
<td>0.3</td>
<td>Stationary $R$-squared</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>$L_{Night}$ dB (C)</td>
<td>1.2</td>
<td>1.0</td>
<td>0.3</td>
<td>Stationary $R$-squared</td>
<td>0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>$DNL$ dB(A)</td>
<td>1.1</td>
<td>1.1</td>
<td>0.2</td>
<td>Stationary $R$-squared</td>
<td>0.4</td>
<td>0.12</td>
</tr>
<tr>
<td>$L_{eq,24h}$ dB(A)</td>
<td>1.0</td>
<td>1.1</td>
<td>-0.1</td>
<td>Stationary $R$-squared</td>
<td>0.4</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

Normalized $BIC$ is a general measure of the overall fit of a model and has been widely used for model identification in time series and linear regression analysis. Negative values of $BIC$ for $L_{eq,24h}$ indicate a higher accuracy in the model so developed. On the basis of the above discussion, it can be concluded that the model performance is satisfactory for all the sound level parameters. The relative success of statistical models in reproducing the measured time-series can also be measured in terms of
residuals of error. The frequency distributions of the residuals of the ARIMA models for all noise metrics are presented in Figs. 6.10.

![Histograms of residuals for different noise metrics](image)

**Figs. 6.10.** (a) to (f). Standardized Residual analysis of ARIMA model for $L_{\text{Day}}$ (in dB(A)), $L_{\text{Night}}$ (in dB(A)), $L_{\text{Day}}$ (in dB(C)), $L_{\text{Night}}$ (in dB(C)) and DNL (in dB(A)) and $L_{\text{eq,24h}}$ in dB(A). $X$-axis denotes the residual error in dB(A) or dB(C), $Y$-axis denotes the frequency of occurrence.

The study of residuals is very essential in deciding the appropriateness of the statistical model. The histogram distribution pattern (Figs. 6.10 (a) to (f)) displays that
the residuals are, in general, distributed equally around zero approaching the Gaussian distribution, which again validates the suitability of the statistical models developed in the present study.

6.5 **ANN approach for time-series modelling**

Artificial Neural Networks (ANN) are flexible computing frameworks for modeling a broad range of non linear problems. One of the most significant advantages of the ANN models over other classes of nonlinear models is that ANNs are universal operators that can approximate a large class of functions with a high degree of accuracy [195-197]. Single hidden layer feed forward network is the most widely used model for the time series modeling and forecasting [197]. The model is characterized by a network of three layers of simple processing units connected by acyclic links as shown in Fig. 6.11. The relationship between the output \( y_t \) and the inputs \( (y_{t-1}, \ldots, y_{t-p}) \) has the following mathematical representation [197]:

\[
y_t = w_0 + \sum_{j=1}^{q} w_{j} g \left( w_{0,j} + \sum_{i=1}^{p} w_{i,j} y_{t-i} \right) + \epsilon_t
\]  

(6.6)

where \( w_{i,j} (i=0,1,2,\ldots,p, j=1,2,\ldots,q) \) and \( w_{j} (j=1,2,\ldots,q) \) are the modal parameters called connection weights; \( p \) is the number of input nodes; and \( q \) is the number of hidden nodes. ANN model performs a non linear functional mapping from the past observations to the future value \( y_t \) i.e

\[
y_t = f (y_{t-1}, \ldots, y_{t-p}, w) + \epsilon_t
\]  

(6.7)

where \( w \) is a vector of all parameters and \( f () \) is a function determined by the network structure and connection weights. Thus, the neural network is equivalent to a non linear autoregressive model. The logistic function is often used as the hidden layer transfer function. In practice, simple network structure that has a smaller number of
hidden nodes often works well. This may be attributed due to the overfitting effect typically found in neural network modeling process. An overfitted model has a good fit to sample used for model building but has poor generalization ability. The choice of $q$ i.e. number of hidden layer neurons is data-dependent and there is no systematic rule in deciding this parameter. In addition to choosing an appropriate number of hidden nodes, another important task of ANN modeling of time-series is the selection of the number of lagged observations, $p$, the dimensions of the input vector [197]. However, there is no theory that can be used to guide the selection of $p$. The shot-gun (trial-and-error) methodology for specific problems is typically adopted by the most researchers which is the primary reason for inconsistencies in literature [104]. Once a network structure ($p$, $q$) is specified, the network is ready for training a process of parameter estimation. Because of the potential overfitting effect with the model, parsimony is the guiding principle in choosing an appropriate model for forecasting. The parameters are estimated such that the cost function of neural network is minimized. Cost function is an overall accuracy criterion such as the following mean squared error is minimum [197]:

$$ E = \frac{1}{N} \sum_{n=1}^{N} e_i^2 $$  \hspace{1cm} (6.8)

$$ E = \frac{1}{N} \sum_{n=1}^{N} \left( y_t - \left( w_0 + \sum_{j=1}^{q} w_j g \left( \sum_{i=1}^{p} w_{i,j} y_{t-i} \right) \right) \right)^2 $$ \hspace{1cm} (6.9)

where $e_i$ is the error between the values calculated by neural network for each input and expected response or target and $N$ is the number of training samples.
6.6 Time-series analysis using ANN approach

Training a network is an essential factor for the success of the neural networks. Amongst the several learning algorithms available, back-propagation has been the most popular, most widely implemented learning algorithm of all neural networks paradigms. It is based on a multilayered, feed forward topology, with supervised learning. That is, the network is trained in what response it makes to each input it receives. The weights in a network are adjusted by comparing the actual response with the target response in such a way to minimize the mean squared error. ANN belong to the data-driven approach, i.e. the analysis depends on the available data, with little a priori rationalization about relationships between variables and about the models [104]. The creation of the ANN predictive model (in Matlab software) for involves the following: (i) Creating the network topology which involves the selection of the number of input neurons, the number of hidden layers, the number of hidden neurons in the hidden layer and the number of output neurons; (ii) Training the network that involves selecting the network type/training algorithm, (feed-forward back-propagation algorithm in present case), feeding the training and target data, selecting the training function (TRAINGDM), selecting the adaptation learning function (LEARNNGDM), selecting the performance function (MSE), and selecting the
transfer function \((TANSIG)\). To determine the best performing model, simulation experiment were conducted on different ANN model configurations. The sound level data set for a period of one year was divided into training data (70%), testing data (15%) and validation data (15%).

Fig. 6.12. Flow Chart of methodology for development of an ANN Model.

Fig. 6.12 shows the flow chart of methodology for the development of an ANN model. Extensive simulations were performed to determine the best combination of
parameters involving the network architecture and other parameters such as: learning rate, momentum constant, number of hidden neurons, learning algorithm and activation function. The network was trained with selecting different values of $p$ and $q$ each time, where $p$ is the number of lagged observations and $q$ is the number of hidden layers neurons and each time the $MSE$ and $R$ between the measured and predicted data was analyzed. The network structure that returns the smallest $MSE$ and highest value of $R$ was adjudged to be the best models. This methodology is thus applied to the sound level parameters under consideration for a period of one year. Fig. 6.13 shows the time sequence plot of measured and predicted $L_{\text{Day}}$ (in dB(A)) from ANN approach.

A network architecture 8-3-1 was found to be optimum. The $MSE$ in training was observed to be $1.67 \text{ dB(A)}^2$ and $0.67 \text{ dB(A)}^2$ in testing whereby the correlation coefficient, $R$ was observed to be 0.66 in training and 0.74 in testing. It may be noted here that there is no theory that can be used to guide the selection of $p$ and $q$. Hence, experiments are often the best possible way to select appropriate value of $p$ and $q$. 

Fig. 6.13. Time sequence plot of measured and predicted $L_{\text{Day}}$ (06-22h) (in dB(A)) from ANN approach for September, 2013 to August, 2014.
[183]. A similar analysis was performed for the other parameters as well. Fig. 6.14 shows the time sequence plot of measured and predicted $L_{\text{Night}}$ (22-06h) (in dB(A)) from ANN approach. A network architecture 10-6-1 was adjudged to be the optimum for the $L_{\text{Night}}$ (22-06h) parameter. The $MSE$ observed in training was 1.60 dB(A)$^2$ and 0.73 dB(A)$^2$ while testing. The correlation coefficient, $R$ was observed to be 0.60 in training and 0.61 in testing.

Fig. 6.14. Time sequence plot of measured and predicted $L_{\text{Night}}$ (22-06h) (in dB(A)) from ANN approach for September, 2013 to August, 2014.

Fig. 6.15 shows the time sequence plot of measured and predicted $L_{\text{Day}}$ (06-22h) (in dB(C)) from the ANN approach. In this case, a network architecture 8-4-1 was adjudged to be optimum. The $MSE$ observed in training was 1.34 dB(A)$^2$ and 1.09 dB(A)$^2$ while testing. The correlation coefficient, $R$ was observed to be 0.62 in training and 0.62 in testing. Similarly, for the $L_{\text{Night}}$ (22-06h) (in dB(C)) parameter shown in Fig. 6.16, a network architecture 10-7-1 was adjudged to be optimum.
Fig 6.15. Time sequence plot of measured and predicted $L_{\text{day}}$ (06-22h) (in dB(C)) from ANN approach for September, 2013 to August, 2014.

The $MSE$ observed in training was 1.34 dB(A)$^2$ and 1.09 dB(A)$^2$ while testing. The correlation coefficient, $R$ was observed to be 0.62 in training and 0.62 in testing.

Fig 6.16. Time sequence plot of measured and predicted $L_{\text{night}}$ (22-06h) (in dB(C)) from ANN approach for September, 2013 to August, 2014.

For the $DNL$ (in dB(A)) parameter shown in Fig. 6.17, a network architecture 10-5-1 was adjudged to be optimum.
Fig 6.17. Time sequence plot of measured and predicted \(DNL\) (in dB\((A)\)) from ANN approach for September, 2013 to August, 2014.

The \(MSE\) observed in training was 1.34 dB\((A)^2\) and 1.09 dB\((A)^2\) while testing. The correlation coefficient, \(R\) was observed to be 0.62 in training and 0.62 in testing. Fig 6.18 shows the time sequence plot of measured and predicted \(L_{eq,24h}\) (in dB\((A)\)) from the ANN approach. The sound level parameter, \(L_{eq,24h}\) (in dB\((A)\)) data was available for a period of January, 2014 to December, 2014 for the CPCB site. So, the ANN model utilized 11 months data for training and December month data was fed as the test dataset as illustrated in flow chart in Fig. 6.12. A network architecture 6-3-1 was adjudged to be optimum. The \(MSE\) observed in training was 0.99 dB\((A)^2\) and 0.81 dB\((A)^2\) while testing. The correlation coefficient, \(R\) was observed to be 0.85 in training and 0.81 in testing.
Fig 6.18. Time sequence plot of measured and predicted $L_{eq,24h}$ (in dB(A)) from ANN approach for January, 2014 to December, 2014.

6.7 Comparison of ANN and ARIMA approach

Autoregressive Integrated Moving Average (ARIMA) and the Multiple linear regression (MLR) models have been widely used for air quality forecasting in urban areas, but they are of variable accuracy owing to their linear representation of non-linear systems [111]. ARIMA is better to capture the linear pattern of a time-series and is better for seasonal patterns, while ANN is better to capture the non-linear pattern of a time series and are better to capture noise and extreme values. Table 6.2 shows the comparison of errors associated with time-series modelling of sound level parameters using ARIMA and ANN approach for a period of one year. The mean squared error, MSE observed for the training and validation data is quite low for both the ARIMA and ANN models so developed. It can be also observed that that the MSE is low for each sound level parameter for the time-series model so developed using ANN approach. The coefficient of determination, $R^2$ is also higher for each sound level parameter for the time-series model developed using ANN approach.
Table 6.2. Statistical comparison of the errors associated with time-series modelling of sound level parameters using ARIMA and ANN approach for a period of one year.

<table>
<thead>
<tr>
<th>Statistical Parameter</th>
<th>$L_{\text{Day}}$ dB(A)</th>
<th>$L_{\text{Night}}$ dB(A)</th>
<th>$L_{\text{Day}}$ dB(C)</th>
<th>$L_{\text{Night}}$ dB(C)</th>
<th>$\text{DNL}$ dB(A)</th>
<th>$L_{\text{eq},24h}$ dB(A)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANN</td>
<td>ARIMA</td>
<td>ANN</td>
<td>ARIMA</td>
<td>ANN</td>
<td>ARIMA</td>
</tr>
<tr>
<td>Model Topology</td>
<td>8-3-1</td>
<td>(0,0,14)</td>
<td>10-6-1</td>
<td>(0,0,7)</td>
<td>8-4-1</td>
<td>(0,0,14)</td>
</tr>
<tr>
<td>$\text{MSE in dB(A)}^2$</td>
<td>1.3</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>0.9</td>
<td>1.3</td>
</tr>
<tr>
<td>$\text{RMSE in dB(A)}$</td>
<td>1.1</td>
<td>1.2</td>
<td>1.2</td>
<td>1.2</td>
<td>1.0</td>
<td>1.1</td>
</tr>
<tr>
<td>$\text{MAE in dB(A)}$</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Maximum Error in dB(A)</td>
<td>3.6</td>
<td>4.7</td>
<td>9.2</td>
<td>10.3</td>
<td>1.7</td>
<td>5.1</td>
</tr>
<tr>
<td>Minimum Error in dB(A)</td>
<td>-4.9</td>
<td>-4.7</td>
<td>-3.2</td>
<td>-2.9</td>
<td>-4.8</td>
<td>-5.1</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.4</td>
<td>0.2</td>
<td>0.3</td>
<td>0.2</td>
<td>0.4</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Table 6.3 shows the comparison of the forecast from both the models with respect to the measured value. The measured value is the monthly average sound levels for period of September, 2014 for the CPCB site in case of sound level parameters, $L_{\text{Day}}$, $L_{\text{Night}}$ and $\text{DNL}$ and that of December, 2014 for $L_{\text{eq},24h}$ parameter. The forecast error (in %) is calculated as: \[
\text{difference} \times \frac{100}{\text{Measured}\text{Level}},
\] where difference is calculated as (Measured - Predicted Level) in dB(A). It can be observed that both the models achieved good forecast performance as is evident from the low value of forecast error ($\leq 2.1\%$) for
both the models. However, the performance of ANN models is better than the ARIMA model for the time-series prediction of traffic noise levels.

**Table 6.3. Statistical comparison of the forecasted value of sound level parameters for the next month ANN models developed.**

<table>
<thead>
<tr>
<th>Comparison of Forecasted Value with respect to Measured Value</th>
<th>$L_{\text{Day}}$ dB(A)</th>
<th>$L_{\text{Night}}$ dB(A)</th>
<th>$L_{\text{Day}}$ dB(C)</th>
<th>$L_{\text{Night}}$ dB(C)</th>
<th>DNL dB(A)</th>
<th>$L_{\text{eq,24h}}$ dB(A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured value for next month in dB(A)</td>
<td>66.8 ± 2.7</td>
<td>58.6 ± 2.0</td>
<td>71.6 ± 1.5</td>
<td>67.7 ± 2.2</td>
<td>68.5 ± 2.3</td>
<td>64.8 ± 1.1</td>
</tr>
<tr>
<td><strong>ANN Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecasted Value in dB(A)</td>
<td>66.3 ± 1.4</td>
<td>59.4 ± 1.4</td>
<td>71.4 ± 0.9</td>
<td>67.1 ± 1.3</td>
<td>68.1 ± 1.5</td>
<td>64.7 ± 0.4</td>
</tr>
<tr>
<td>Forecast Error (in %)</td>
<td>0.8</td>
<td>1.4</td>
<td>0.2</td>
<td>-0.8</td>
<td>-0.5</td>
<td>-0.1</td>
</tr>
<tr>
<td><strong>ARIMA Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecasted Value in dB(A)</td>
<td>66.1 ± 2.7</td>
<td>59.4 ± 2.4</td>
<td>71.1 ± 2.2</td>
<td>66.2 ± 2.3</td>
<td>67.5 ± 2.1</td>
<td>64.1 ± 1.9</td>
</tr>
<tr>
<td>Forecast Error (in %)</td>
<td>-1.2</td>
<td>1.4</td>
<td>-0.7</td>
<td>-2.1</td>
<td>-1.4</td>
<td>-1.1</td>
</tr>
</tbody>
</table>

The present observations also reveal that the pattern of ARIMA model is directional which is accounted for the linear pattern observed in plots of Figs. 6.9 (a) to (f), while the ANN model is towards value forecasting. This finding agrees with the previously reported work of Adebiyi *et al.*, 2014 [198]. The primary difference of ANN from most of the statistical techniques is the absence of any statistical inference tests and construction of confidence bounds for model weights of the overall fit [199]. ANN have proved to be a wide class of flexible modelling algorithm and robust to the problems such as non-gaussian distributions, non-linear relationships, outliers and
noise presented in the data. However, as enunciated by Sivaram et al., 2014 [199], ANN technology will not replace traditional quantitative techniques completely but it does offer an alternative to traditional quantitative techniques. Furthermore, the statistical analysis of the predicted sound level parameters viz., \( L_{\text{Day}} \) and \( L_{\text{Night}} \) in A and C weightings, \( DNL \) for September, 2014 and \( L_{\text{eq,24h}} \) for December, 2014 is conducted in table 6.4. The \( t \)-stat value is less than the \( t \)-critical value of \( \pm 2.04 \) for the developed model. This implies that the predicted traffic noise levels using ANN model fits well with the field data at 5 % significance level [114, 115].

### Table 6.4. Statistical comparison of errors associated with time-series modelling of sound level parameters using ANN approach for the test data set for period of one month.

<table>
<thead>
<tr>
<th>Statistical Parameter</th>
<th>( L_{\text{Day}} ) dB(A)</th>
<th>( L_{\text{Night}} ) dB(A)</th>
<th>( L_{\text{Day}} ) dB(C)</th>
<th>( L_{\text{Night}} ) dB(C)</th>
<th>( DNL ) dB(A)</th>
<th>( L_{\text{eq,24h}} ) dB(A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( MSE ) in dB(A)(^2)</td>
<td>4.1</td>
<td>1.8</td>
<td>1.5</td>
<td>2.4</td>
<td>2.4</td>
<td>1.0</td>
</tr>
<tr>
<td>( RMSE ) in dB(A)</td>
<td>2.0</td>
<td>1.3</td>
<td>1.2</td>
<td>1.5</td>
<td>1.5</td>
<td>1.0</td>
</tr>
<tr>
<td>( MAE ) in dB(A)</td>
<td>0.6</td>
<td>0.4</td>
<td>0.2</td>
<td>0.5</td>
<td>0.4</td>
<td>0.1</td>
</tr>
<tr>
<td>Maximum Error in dB(A)</td>
<td>6.5</td>
<td>4.3</td>
<td>2.0</td>
<td>4.2</td>
<td>4.5</td>
<td>1.6</td>
</tr>
<tr>
<td>Minimum Error in dB(A)</td>
<td>-2.5</td>
<td>-1.5</td>
<td>-2.1</td>
<td>-1.5</td>
<td>-1.6</td>
<td>-2.9</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.5</td>
<td>0.6</td>
<td>0.3</td>
<td>0.6</td>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>( t )-stat</td>
<td>1.6</td>
<td>1.8</td>
<td>0.7</td>
<td>1.9</td>
<td>1.4</td>
<td>0.2</td>
</tr>
<tr>
<td>( t )-critical</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
</tr>
</tbody>
</table>

### 6.8 Conclusions

The study focused on a statistical analysis of one year continuous noise monitoring data using a conventional \( \text{ARIMA} \) approach and ANN approach, covering the period from September, 2013 to August, 2014 for one sample site in Delhi city. In
this respect, daily mean $L_{\text{Day}}$, $L_{\text{Night}}$ in A and C-weightings, Day-night average sound level ($DNL$) and $L_{\text{Aeq,24h}}$ were used. The ARIMA models, namely $ARIMA(0,0,14)$, $ARIMA(0,0,7)$, $ARIMA(0,0,14)$, simple, $ARIMA(1,0,7)$ and $ARIMA(0,1,9)$ have been developed as the most suitable for simulating and forecasting the daily mean $L_{\text{Day}}$, $L_{\text{Night}}$ in A and C-weightings, $DNL$ and $L_{\text{Aeq,24h}}$ levels respectively. The ANN models with architecture: 8-3-1, 10-6-1, 8-4-1, 10-7-1, 10-5-1, and 6-3-1 have been developed as the most suitable for simulating and forecasting the daily mean $L_{\text{Day}}$, $L_{\text{Night}}$ in A and C-weightings, Day-night average sound level ($DNL$) and $L_{\text{Aeq,24h}}$ levels respectively. The validation and suitability of the developed ARIMA and ANN model is ascertained at various stages. The observed and predicted values have been found to match well. The statistical parameters: stationary $R$ squared, $R$ squared, Root Mean Squared Error ($RMSE$), Mean Absolute Error ($MAE$) were used to test the validity and applicability of the developed ARIMA and ANN models indicating that the models fits reasonably well with the observed data series.

Furthermore the results of the present study suggest that it is possible to predict the sound levels using statistical analysis of the present and historical time-series data sets obtained from continuous long-term noise monitoring. Both the models can achieve good forecast in application to time-series modelling and forecasting of traffic noise levels. The ARIMA and ANN methodology demonstrated in the present work can thus serve as a suitable substitute to the long-term noise monitoring and is thus indispensable for saving costs and time incurred on continuous noise monitoring. However, the ARIMA and ANN models so developed for sound level descriptors are adequate for the particular site in commercial area of Delhi region and can’t be generalized for the other sites as well. It is obvious that for other
sites, these models can be developed afresh with different $p$, $d$, $q$ values in case of ARIMA and different $p$ and $q$ values in case of ANN approach.

The present work also compared the performance of ANN predictive model in comparison to the conventional Box Jenkins ARIMA model, which has been widely used for time-series forecasting. The findings revealed that the Artificial Neural Network (ANN) models out-perform the ARIMA model so developed. It is observed that the pattern of ARIMA forecasting models is directional and as such the time-series predictive model utilizing ANN approach is demonstrated superior performance over the ARIMA model. The unique characteristics of ANNs - adaptability, non linearity, arbitrary function mapping ability thus make them useful for forecasting tasks. However, as enunciated by Zhang et al. (1998), the shot-gun (trial-and-error) methodology for specific problems is typically adopted by many researchers, which is the primary reason for inconsistencies in the literature. Construction of an ANN model is time consuming and depends on the size of training data and network structure. Also, it is sometimes like a black-box wherein one can’t adjudge the weights and biases developed while training the network. However, inspite of these shortcomings, ANN can serve as vital substitute to the cumbersome and expensive long-term traffic noise monitoring in Delhi city. Previous research investigations conducted by Zhang et al., 2003 [183] reveals that although both ARIMA and ANNs have the flexibility in modelling a variety of problems, yet none of them is the universal best model that can be used indiscriminately in every forecasting situation. Thus, future studies can further explore the potential of hybrid linear-nonlinear models in accurate forecasting of sound levels when applied to the dynamic time-series database.