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Time Series Statistical Analysis by Using Artificial Neural Network techniques

Case study: Forecasting Models

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A B S T R A C T

Artificial Intelligent is regarded as a novel tool for future statistical data estimation. As an important issue. Also, an important issue on how to evaluate weather forecasting. In this context, numerous papers are available to describe methodologies similar to neural networks (NN) regression for weather prediction (time-series application). The next study is a review about nonetheless, to perform ranking as this model is complex due to the variety of the forecasting horizon, time step, data set and performance indication. Also, the accurateness of these models is dependent on input parameters and architecture type algorithms utilized. This leads to a better understanding of the contributions to be expected from analytics. Real data from different country sites will be used while developing the model. The advance of the forecasting is proposed to support countries, future stakeholders, and engineers to select sites of weather systems to evaluate the techno-economic merits of large-scale weather 'data integration the Objective of this work is to investigate and assess the forecasting statistical models using artificial intelligence techniques .The results indicated that ANN realized enhanced in predicting the advanced casing of the weather forecasting.

1. Introduction

Several statistical techniques are related to independent data, or the slightest uncorrelated [1]. There are various practical positions where data influence correlation [2]. This is mainly so where repetitive observations on a certain system are completed in sequence time [3]. Data assembled in sequence time were known as a time series. This is one of the types that distinguish time-series data from cross-sectional data. Time series 'data could be found in, Engineering, social sciences, finance, epidemiology, economics, physical sciences and Environmental Modeling [4]. The simple formula of data is a long-ish series of persistent measurements which are equal in space-time points [5]:

• Observations are completed at separate points in time, his time is the presence of equal points 'space.

• Observations formed as continuous distribution. The 4 sets of the time series components are Random, Cyclic Variations Seasonal Variations, and Trend or Irregular movements. [6]. Time series was categories of 4 varieties of inconstancy [7]:

- A "long-term tendency"
- "Cyclical movements" covered the "long-term trend", the cycles seem to influence the heights point throughout stages of industrial richness.
- "Seasonal Movement" inside every year, the nature of which is based on the series natural. "Residual variations" during the changes affecting individual variables or other main actions.
- "Traditionally", the 4 differences had been supposed to be commonly individual of one to extra and identified by resources of an extra decomposition form:

$$y_t = T_t + C_t + S_t + I_t, \quad t = 1, \dots n \quad (1)$$

Where,
y_t: "observed series at time t",
T_t : "long-term trend",
C_t : "business cycle",
S_t : "seasonality",
I_t: "irregulars".
If there are components, this relationship is definite as:

$$y_t = T_t \times C_t \times S_t \times I_t, \quad t = 1, \dots n \quad (2)$$

Where now S_t and I_t can be expressed in a part of trend-cycle $T_t \times C_t$.In selected suitcases, "mixed additive–multiplicative" models were important. Weather data, it is a seasonality that gives verity, those specific months are extra significant in the relation of action. This part is definite to stop ended of 12 repeated months or additional mostly ended at 365 repeated days, annual series cannot be cover seasonality. Stream series could be influenced by extra differences related to the confirmation of the calendar. The greatest significant was the "*trading day"* variants, which were indicated the verity that the action in specific days of the week is additional significant than others. Months with 5 of the greatest significant days record an additional of action "*ceteris paribus*" in evaluation 2 months or 4 such days. on the contrary, months with 5 of the minimum significant days record a shortfall of action. The length-of-month variant is regularly allocated to the seasonal element. The trading day element is frequently assessed as insignificant in quarterly series and even extra so in yearly data. An additional significant calendar variant is the "*moving holiday"* element. That element was related to holidays which have a variant date from one year to a new year.
The models (1) and (2), the trading day elements were indirectly elements of the asymmetrical. To guess trading day variants which were combined in the X11 technique of "seasonal adjustment" [8] also it's following varieties, the X11ARIMA [9] also X12ARIMA methodologies [10]. The last 2 varieties furthermore contain models to assess "moving holidays. If the new modules are existing, the seasoning decay model converts to:

$$y_t = T_t + C_t + S_t + D_t + H_t + I_t \quad (3)$$

Where:
D_t: trading day
H_t: moving holiday elements, individually. Correspondingly,
S_t: Seasonal adjustment
I_t: "irregulars".
"Multiplicative decomposition" model converts to:

$$y_t = T_t \times C_t \times S_t \times D_t \times H_t \times I_t \quad (4)$$

Where the elements St, D_t, H_t, and I_t are relational to the "trend-cycle". Models (3) and (4) are charity usually by techniques of "seasonal adjustment". Extra fewer used "decomposition models" are the "log-additive and the mixed models". "Seasonal adjustment" really involves the assessment of wholly the time series elements or components and the elimination of holiday, seasonality and trading day actions from the detected series. The justification was that these modules which were reasonably foreseeable conceal the existing phase of the "business cycle" which is serious for a plan and make the decision. There are additional types of time series breakdown frequently used for modeling and predicting "univariate ARIMA time series":

$$y_t = \eta_t + e_t \quad (5)$$

Where η_t and e_t are stated to like the *noise* and the *signal*, according to the electrical engineering terms. The signal _t includes all the logical constituents of models (1) and (4), i.e., T_t, C_t, S_t, D_t, and H_t. Model (5) is traditional in extraction 'signal where the difficult is to discover the greatest assessments of the signal η_t assumed the observations y_t dishonored by noise e_t. The top assessments are generally definite as reducing the "Mean Square Error". As a final point, it assumed its major basic to optimize and recognized "decomposition theory" according to [11]. A stochastic procedure $\{Y_t\}$ is *2nd order stationary* if the 1st two moments did not depend on time, the variance & mean were constant, and also the "Auto Covariance Function" built on the time lag and not on the original time [12]:

$$E(Y_t) = \mu \quad (6)$$

$$E(Y_t - \mu)^2 = \sigma_Y^2 < \infty \quad (7)$$

$$E[(Y_t - \mu)(Y_{t+k} - \mu)] = \gamma_k \quad (8)$$

where $k = 0, 1, 2, \dots$, signifies of the time lag, Every stochastic procedure, stationary to the second-order, could be analysis into 2 commonly uncorrelated procedures and, such that: $\{Z_t\}$ and $\{V_t\}$:

$$Y_t = Z_t + V_t \quad (9)$$

Where,

$$Z_t = \sum_{j=0}^{\infty} \psi_j a_{t-j}, \quad \psi_0 = 1, \sum_{j=1}^{\infty} \psi_j^2 < \infty \quad with \langle a_t \rangle \sim WN(0, \sigma_a^2) \quad (10)$$

The element
$\{Z_t\}$: "Convergent Infinite Linear Combination" a_t's,
WN : "white noise process with zero mean",
σ_a^2: "constant variance, and zero auto covariance".
Model (10) was recognized as an
$MA(\infty)$: "infinite moving average", and the a_t's were the innovations.
$\{Z_t\}$: "Nondeterministic since only one realization" of the progression is not enough to govern coming values $\{Z_{t+l}\}$, $l > 0$,
The element $\{V_t\}$ could be signified by [12].

$$V_t = \mu + \sum_{j=1}^{\infty} [\alpha_j \sin(\lambda_j t) + \beta_j \cos(\lambda_j t)], \quad -\pi < \lambda < \pi, \quad (11)$$

Wherever:
μ = constant mean of a process

$\{Y_t\}$ and $\{\alpha_t\}$, $\{\beta_t\}$ were commonly uncorrelated "White Noise Processes". $\{V_t\}$ was known as a deterministic method so, it could be forecast in the coming without error.

"Wold theorem" determines that the advantage of stationary was powerfully concerning to the linearity. It delivers a validation for "Autoregressive Moving Average" (ARMA) models [13].

2. Time Series Analysis

Time series analysis was a statistical method that covenants with "Time Series" data, or "Trend Analysis". The data is considered in three types [14]:

Time series data, Cross-sectional data, and Pooled data. In continuation an appropriate model was formfitting to a specified "Time Series" and the consistent factors were assessed and use the recognized values of data. The process to fit a suitable model was called "analysis of time series" [15]. It includes techniques that are a challenge to realize the series natural and is frequently beneficial for coming simulation and predicting. Collecting previous observations must be analyzed to take the original data generation' as a procedure for the series [16]. The coming actions were then forecast and use a model. This methodology was mainly beneficial when there was not considerable information that is tracked by the sequential observations or a suitable descriptive model was deficient. Time series predicting has significant uses in several fields. Often valued for making decisions in the strategic plan and preventive actions are available depends on the prediction results. In the past several periods' several efforts had been prepared by investigators for the development of the appropriate time series predicting models [17].

3. Time Series Forecasting Using Stochastic Models

The choice of an appropriate model was significant as it replicates the original construction of the series and this formfitting model in chance was a charity for coming predicting. A model of time series was supposed to be non-linear otherwise linear based on previous data to present an assessment of the series is a historical observation. Overall time series models for data could have several formulas and characterize many stochastic procedures. There were two commonly charity "Linear Time Series Models" "Autoregressive" *(AR)* [18] and "Moving Average" *(MA)* [19] models. Relating these 2, the "Autoregressive Moving Average" *(ARMA)* [20] and "Autoregressive Integrated Moving Average" *(ARIMA)* [21] modeling had been suggesting in many works. The "Autoregressive Fractionally Integrated Moving Average" *(ARFIMA)* [22] modeling specifies ARMA and ARIMA modeling. For seasonal time series forecasting, a difference of ARIMA, viz. the "Seasonal Autoregressive Integrated Moving Average" *(SARIMA)* [23] model was used. ARIMA model and its altered disparities were dependent on the well-known Box-Jenkins standard [24] and so these are moreover approximately identified according to Box-Jenkins techniques. Linear models had towed much consideration during their relative straightforwardness inconsiderate and application. However, several applied time series demonstrate non-linear forms. Specific of them were the well-known "Autoregressive Conditional Heteroskedasticity" *(ARCH)* [25] model and its differences similar *"Generalized ARCH" (GARCH)* [26], *"Exponential Generalized ARCH" (EGARCH)* [27], etc., the "Threshold Autoregressive" *(TAR)* [28] model, the "Non-linear Autoregressive" *(NAR)* [29] model, the "Nonlinear Moving Average" *(NMA)* [30].

4. The "Autoregressive Moving Average (ARMA)" Models [31]

An ARMA (*p*, *q*) model was a mixture of AR(*p*) and MA(*q*) models and was appropriate for "Univariate Time Series Modeling". In an AR(*p*) model the coming assessment of a variable was supposed to be a linear mixture of *p* historical observations and a random error collected with a constant term. As a Mathematical form, the AR(*p*) model could be specified as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots\dots\dots + \varphi_p y_{t-p} + \varepsilon_t \qquad (12)$$

models' parameters are:

y_t = Actual value and t

ε_t = Random shock,

φ_i = Modes

at time period t : $\O_i$ (i 1,2,..., p)

c = Constant.

p = Integer constant was recognized according to model order occasionally the constant term is lost at a simple model.

The MA (*q*) model was specified by:

$$y_t = \mu + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t = \mu + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots\dots\dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (13)$$

Here μ = "mean of the series",

θ_j (j 1,2,...,q) = model' parameters

q = Model 'order.

(AR)" and (MA)" \ could be powerfully collective to formulate as an overall and valuable class of time series models, recognized as the ARMA models. To put in Mathematical expression an ARMA (*p*, *q*) form was characterized as:

$$y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (14)$$

Now the orders of model *p*,*q*. Regularly, ARMA is influenced by the Lag operative [21 to 23] symbolization. The Lag or backshift operator was clear $Ly_t = y_{t-1}$. Polynomials of Lag operator or Lag polynomials were charity to signify ARMA models as:

$AR(p) model: \varepsilon_t - \varphi(L) y_t$

$MA\ (q)\ model$: $y_t = \theta(L)\varepsilon_t$.
$ARMA\ (\rho,q)\ model$: $\varphi(L)y_t = \theta(L)\varepsilon_t$.

$$Here\ \varphi(L) = 1 - \sum_{i=1}^{p} \varphi_i L^i \ \ and\ \ \theta(L) = 1 + \sum_{j=1}^{q} \theta_j L_j \quad (15)$$

5. Stationary Analysis [32]

When an **AR (*p*)** procedure was characterized as $\boldsymbol{\varepsilon_t = \phi\ (L)\ y}$, then $\phi\ (L) = 0$ was identified as the specific equation for the procedure. It is verified by a technique that an essential and satisfactory condition for the **AR (*p*).** The AR (1) model $y_t = c + \varphi y_{t-1} + \varepsilon_t$ was stationary when $|\emptyset_1| < 1$ with a constant mean:

$$\mu = \frac{c}{1-\varphi_1}$$

and constant variance.

$$\gamma_0 = \frac{\sigma^2}{1-\varphi_1^2}$$

An MA (*q*) process was always stationary, regardless of the values of the MA parameters.

6. "Autocorrelation and Partial Autocorrelation Functions" "ACF and PACF" [33]

To govern a suitable form for a specified data of time series, it was essential to transfer the "ACF" and "PACF" investigation. To defining the order of AR and MA terms as follow:
At a time, series **{*x* (*t*), *t* = 0, 1, 2...}** the *"Auto covariance"* at lag *k* is given by:

$$\gamma_k = Cov(x_t, x_{t+k}) = E[(x_t - \mu)(x_{t+k} - \mu)] \quad (16)$$

The "*Autocorrelation Coefficient"* at Lag *k* is given by:

$$\rho_k = \frac{\gamma_k}{\gamma_0} \quad (17)$$

Now μ: "Mean of The Time Series", I .e. $\mu = E[x_t]$
The auto covariance at lag
zero i.e. γ_0: "Variance of The Time Series".
From the classification it was strong to clear that:
ρ_k: "Autocorrelation Coefficient" is dimensionless
$-1 \le \rho_k \le 1$ Statisticians Box and Jenkins
γ_k: *"Theoretical Auto covariance Function (ACVF)"*
ρ_k: "Theoretical Autocorrelation Function *(ACF)"*.
An additional measure, identified as the "Partial Autocorrelation Function" *(PACF)*, *k* period ago and the present observation. The greatest suitable example guess for the ACVF at lag *k* was:

$$c_k = \frac{1}{n}\sum_{t=1}^{n-k}(x_t - \mu)(x_{t+k} - \mu) \quad (18)$$

To guess the example of ACF at lag *k* can be specified by:

$$r_k = \frac{c_k}{c_0} \quad (19)$$

Here **{*x* (*t*),*t* = 0,1,2,.......}** = the size training series equal n with mean μ .

7. "Autoregressive Integrated Moving Average (ARIMA)" Models [34]

In "ARIMA" models a non-stationary time series was prepared stationary by finite different applications of the data points. The mathematical forms of the ARIMA (*p*, *d*,*q*) model by using lag polynomials was specified as follow:

$$\varphi(L)(1-L))^d y_t = \theta(L)\varepsilon_t, i.e.$$
$$\left(1 - \sum_{i=1}^{p}\varphi_i L^i\right)(1-L)^d y_t = \left(1 + \sum_{j=1}^{q}\theta_j L^j\right)\varepsilon_t \quad (20)$$

Now,
p, *d*, and *q*: integers > or = to zero and denote to the order of the "Autoregressive, Integrated, and Moving Average" are parts of the models one-to-one.

8. "Seasonal Autoregressive Integrated Moving Average (SARIMA)" Models [35]

The "ARIMA" models (20) are presented a non-seasonal and non-stationary data. Their future model was recognized as the Seasonal ARIMA (SARIMA) model. In this model, seasonal differencing of suitable order was a benefit to eliminating now-

s = 4. This model was usually expressed as the SARIMA (*p*, *d*,*q*)× (*P*, *D*, *Q*)^s model.
Scientific mathematical formula of a SARIMA (*p*, *d*,*q*)× (*P*, *D*, *Q*)*s* form in expressions of lag polynomials was specified as follow:

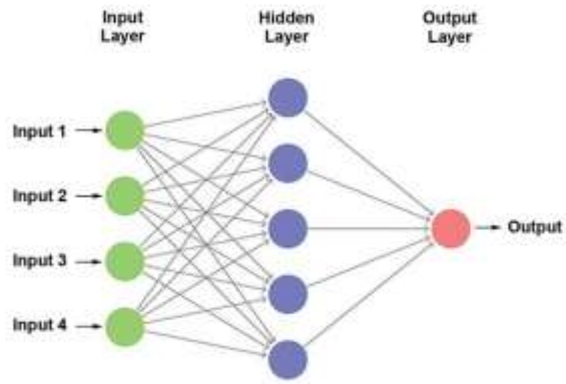
$$\Phi_p(L^s)\varphi_p(L)(1-L)^d(1-L^s)^D y_t = \Theta_Q(L^s)\theta_q(L)\varepsilon_t\ ,$$
$$i.e. \Phi_p(L^s)\varphi_p(L)z_t = \Theta_Q(L^s)\theta_q(L)\varepsilon_t. \quad (21)$$

Here $\boldsymbol{z_t}$: the "Seasonally Differenced Series".

9. Time Series Forecasting Using "Artificial Neural Networks" Ann

9.1 Artificial Intelligence Systems

The neural network method had been used to consider consistency, availability, reliability, forecasting and maintainability systems. The neural network input was trained and layer had been inclusive 80 or 100 neurons in the 1st hidden layer, 10 neurons in the 2nd hidden layer and one neuron in the output layer. The optional network had been a charity to reflect the effect of separate input parameters and gatherings of input parameters on the compound output parameter. These need an advanced tool to forecast load profile built on previous weather history, and ANN proposal powerful choice for this purpose as shown in figure (1).



Figure(1) "General scheme for an artificial neural network (ANN) model technique"

9.2 Artificial Neural Network Modeling

ANN model is appropriate obtainable in 4 situations as:

- Extract calculations result from weather data
- Taking network and using values of theoretical prediction
- A set of data which was not controlled by training as network testing with data.
- Identify the maximum network structure based on statistical realization' data.

Artificial neural networks (ANN) replicate the brain works by programming techniques by saving the "Machine Learning" as the built-on performance of the humanoid.

Model of the output had been stated as follow:

$$Y_t = \alpha_o + \sum_{i-1}^{q} \alpha_j\, g\left(\beta_{oj} + \sum_{i=1}^{p} \beta_{ij}\, y_{t-i}\right) + \varepsilon_t, \forall t \qquad (22)$$

Where $\boldsymbol{Y_{t-i}(i = 1, 2, \dots\dots, p)}$

P input, $\mathbf{y_t}$ output

The digits p, q is the integer of hidden and input nodes.

Connection weights are:

$\alpha_j (j = 0,1,2, \dots\dots\dots, q)$,

$\beta_{ij}\ (i = 0,1,2, \dots, p; j = 0,1,2, \dots\dots q)$

$\boldsymbol{\varepsilon_t}$ Random shock

$\boldsymbol{\alpha_o}, \boldsymbol{\beta_{oj}}$ support form is:

Frequently, the logistic sigmoid function:

$$g(x) = \frac{1}{1+e^{-x}} \qquad (23)$$

The nonlinear activation function is applied such as Gaussian and linear has been held.

THE Feedforward ANN model in real realizes a mapping of non-linear functional from the historic time-series data to the next value.

$$y_t = f(y_{t-1}, y_{t-2}, \dots\dots y_{t-p,W)+\varepsilon_t} \qquad (24)$$

w was an all vector parameters

f was a function resolved by the connection weights and structure of a network.

processes were held, which were based on the error function minimization:

$$F(\varphi) = \sum_t e_t^2 = \sum_t (y_t - \hat{y}_t)^2 \qquad (25)$$

Here $\boldsymbol{\varphi}$ was the space of all connection weights. To minimize an error optimization function method is handled are mentioned as "*Learning Rules*". *Generalized Delta Rule and Backpropagation* was the best-known learning rule.

9.3 Network Parameters Selection

The parameters similar to an input' neurons, output, and hidden layers, transfer function, network construction, learning algorithm, learning rate, and momentum verity or are designated to improve the artificial neural networks model. The input neurons' number in the input layer was equivalent to several verities or that give effects on the performance of the system. A neuron's processing layer that was between the input and output layer was termed a hidden layer. The number of hidden layers and an optimal number of hidden neurons may differ reliant on the precision requisite. All verity or optimization by trial-and-error technique to reach results with moral precision. The number of neurons in the output layer was equal to several verities or chosen for forecasting the system's performance.

- ➢ The input-output dataset removed from trials were separated 2 sets "training input-output data & testing output data".
- ➢ Improve an Artificial neural networks model and describe the inputs and outputs.
- ➢ Optimization of I/O both in the ranged between 0 and 1 or between −1 and 1.
- ➢ MATLAB-neural network toolbox, Train the NN with standardized input & output Data.
- ➢ The data set which was not used in the training of NN it's used as a testing input-output data.
- ➢ Compute the performance of statistical information.
- ➢ Choice the top NN construction built on historical data.

9.4 Different Prediction Models

Enactment actions and their important appearances will be considered. In each of the upcoming characteristics, y_t was the confident value, $_{it}$ was the forecasted value, $e_t = y_t - f_t$ was the forecasting error and n is the equal size of the test data. Also,

"Test mean" $\bar{y} = \frac{1}{n}\sum_{t=1}^{n} y_t$ (26)

"Test variance" $\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n} (y_t - \bar{y})^2$ (27)

The Mean Forecast Error (MFE)

To measure MPE

$$MFE = \frac{1}{n}\sum_{t=1}^{n} e_t \qquad (28)$$

The Mean Absolute Error (MAE)

To measure MAE

$$MAE = \frac{1}{n}\sum_{t}^{n} |e_t| \qquad (29)$$

The Mean Absolute Percentage Error (MAPE)

To measure MAPE

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| x100 \quad (30)$$

The Mean Percentage Error (MPE)
To measure MPE

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\left\{\frac{e_t}{y_t}\right\} x100 \quad (31)$$

The Mean Squared Error (MSE)
To measure MSE

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \quad (32)$$

The Sum of Squared Error (SSE)
To measure SSE

$$SSE = \sum_{t=1}^{n} e_t^2 \quad (33)$$

The Signed Mean Squared Error (SMSE)
To measure SSE

$$SMSE = \frac{1}{n}\sum_{t=1}^{n}\left\{\frac{e_t}{|e_t|}\right\} e_t^2 \quad (34)$$

the Root Mean Squared Error (RMSE)
To measure RMSE

$$\sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \quad (35)$$

The Normalized Mean Squared Error (NMSE)
To measure NMSE

$$NMSE = \frac{MSE}{\sigma^2} = \frac{1}{\sigma^2 n}\sum_{t=1}^{n} e_t^2 \quad (36)$$

Forecasting is the use of recognized calculating weather data on the detected relationship between a dependent variable (e.g., simulation output) and an independent variable (e.g., simulation input) to the assessment of other values of the independent variable from new clarifications of the dependent variable.

10. Conclusions and Recommendation

10.1 Conclusions

- The time series is used for a set of measurements that are present for one or more variables (such as previous temperatures) arranged according to their occurrence in time and give specific phenomenon values that the first n of this view is: x1, x2, x3, ..., xn.) Time series is one of the most important prediction methods for the future through the facts of yesterday and today.
- Mathematically: we say that the independent time variable (t) and the corresponding values have the dependent variable (y) and that each value in time t is offset by the values of the dependent variable y then y is a function of time t.
- The model is set: this is done by drawing the time series in what is called Time Plot where the horizontal coordinate is time (and the vertical coordinate is the phenomenon previous observations (temperature)) and then choosing a mathematical model based on some statistical measures that distinguish a model from another and on the experience derived from data Previous weather data.
- The model has been applied: After nominating a general model and the solution in a suitable and appropriate feed-forward method to describe the observed series, we estimate the parameters of this model from the observational data using statistical estimation methods for time series and this candidate model is taken as a prototype that can be modified later.
- Model Diagnostics and Testing: Perform screening tests on Fitting Errors to see how well the views match the values calculated from the candidate model and the validity of the model's assumptions. If the nominated model passes these tests, we are accustomed to it as the final model and used to generate forecasts for future values, otherwise, we return to the first step to assigning a new model.
- Forecast Generation: The final model is used to generate forecasts for future values and then calculate Forecast Errors whenever new values are seen from the time series and monitor these errors in which are set to accept a certain error rate if the forecast errors exceed it. The form is reviewed and the cycle is repeated to select another candidate model.
- For evaluating the forecasting method as one of the methods used to study the unstable state procedures. The peak time of temperature raises occurs between 7 am to 5 pm. The outdoor states furthermore various significantly through the day as an effect of Weather. Weather prediction had been a significant result to decide by evaluating the forthcoming from historic data. This learning in comparison to the enactment of the most -charity “Feed-Forward Back” ANN with the random forecast, for predicting the weather. The default recognition feed-forward networks function which is created by “Mean Square Error” MSE, among the outputs of network and the target outputs. It was discovered “Training Regression Models” with the various grade that R nearby 1 in various situations (if lower RMSE then the greater R **assessments**). “MSE is the average squared various between outputs and targets. Lower values are better”. Correlation among the target and output) standards for in cooperation the training and validation, produced in MATLAB software. In cooperation, the training and validation are shown necessary coefficients of correlation (R assessment). ANN realized enhanced in predicting the advanced casing of the weather forecasting.

10.2 Recommendation

In the simulation, we have used ANN to forecast It can be extended further by incorporating multiple application scenarios within the health applications.

References

1. Tariq Usman Saeed, Thomas Hall, Hiba Baroud, Matthew J. Volovski "Analyzing road crash frequencies with uncorrelated and correlated random-parameters count models: An empirical assessment of multilane highways" Analytic Methods in Accident Research,(23), pp. 1-17, 2019. https://doi.org/10.1016/j.amar.2019.100101

2. Alejandro Ramírez-Rojas, Leonardo Di G, SigalottiElsa LeticiaFlores Márquez, OttoRendón "Chapter 7 - Multiscale analysis in time series" Time Series Analysis in Seismology Practical Applications ,Pages 251-274, 2019. https://doi.org/10.1016/B978-0-12-814901-0.00015-8

3. Svetlozar Nestorova, Boris Jukićb, Nenad Jukića, Abhishek Sharmaa, Sippo Rossi "Generating insights through data preparation, visualization, and analysis: Framework for combining clustering and data visualization techniques for low-cardinality sequential data" Decision Support Systems Volume 125, October , pp. 1-17 , 2019. https://doi.org/10.1016/j.dss.2019.113119

4. G. C. Tiao & G. E. P. Box "Modeling Multiple Time Series with Applications Journal of the American Statistical Association Volume 76, Issue 376, pp.802-816, 1981. https://doi.org/10.1080/01621459.1981.10477728

5. Samaneh Aminikhanghahi and Diane J. Cook "A Survey of Methods for Time Series Change Point Detection" Knowl Inf Syst.; 51(2): 339–367, May, 2017.. DOI: 10.1007/s10115-016-0987-z

6. Kim, C. J., & Nelson, C. R. State-space models with regime-switching. Cambridge, MA: MIT Press , 1999.

7. CLEVELAND, W.P., TIAO, G.C. : "Decomposition of Seasonal Time Series: a Model for Census X11 Program", Journal of the American Statistical Association, 71, pp. 581-587, 1976..

8. Gian Luigi Mazzi, Dominique Ladiray and Dan A. Rieser "Handbook on Seasonal Adjustment" , 2018.

9. Erika Foldesi, Peter Bauer Beata and Horvath Beata Urr "SEASONAL ADJUSTMENT METHODS AND PRACTICES" project report, ,2007.

10. David F. FINDLEY, Brian C. MONSELL, William R. BELL, Mark C. OTTO and Bor-Chung CH "New Capabilities and Methods of the X-1 2-ARIMA Seasonal-Adjustment Program" Journal of Business & Economic Statistics, Vol. 16, No. 2 (Apr. 1998), pp. 127-152 Published by Taylor & Francis, Ltd. on behalf of American Statistical Association Stable URL: http://www.jstor.org/stable/1392565

11. Robert H. Shumway • David S. Stoffer "Time Series Analysis and Its Applications" With R Examples"2011. DOI 10.1007/978-1-4419-7865-3

12. Charles Gauvin, Erick Delage and Michel Gendreau "A stochastic program with time series and affine decision rules for the reservoir management problem" European Journal of Operational Research Volume 267, 2, PP. 716-732 June 2018. https://doi.org/10.1016/j.ejor.2017.12.007.

13. EricGhysels, Denise R.Osborn and Paulo M.M.Rodrigues "Chapter 13 Forecasting Seasonal Time Series" Handbook of Economic Forecasting, Volume 1, PP. 659-711., 2006. https://doi.org/10.1016/S1574-0706(05)01013-X

14. Felipe S.L.G. Duarte, Ricardo A. Rios, Eduardo R. Hruschka and Rodrigo F. de Mello "Decomposing time series into deterministic and stochastic influences: A survey" Digital Signal Processing Volume 95, December 2019. https://doi.org/10.1016/j.dsp.2019.102582

15. Rajendra J. Bhansali "Model specification and selection for multivariate time series" Journal of Multivariate Analysis Volume 175, pp.1-19, , January 2020. https://doi.org/10.1016/j.jmva.2019.104539

16. John C. Brocklebank, David A. Dickey and Bong S. Choi "SAS® for Forecasting Time Series"2018.

17. Ravi Mahendra Gor "Forecasting Techniques: Chapter 5" Industrial Statistics And Operational Management, 2009.

18. Alimorad Mahmoudi, Mahmood Karimi and Hamidreza Amindavar "Parameter estimation of autoregressive signals in presence of colored AR(1) noise as a quadratic eigenvalue problem" Signal Processing, Volume 92, Issue 4, April 2012, PP. 1151-1156. https://doi.org/10.1016/j.sigpro.2011.11.015

19. Carl Chiarella, Xue-Zhong Hea and Cars Hommes "Moving average rules as a source of market instability" Physica A 370 pp.12–17, 2006.

20. S. Dillinger and B.J. MacVicar "Cleaning high-frequency velocity profile data with autoregressive moving average (ARMA) models"Flow Measurement and Instrumentation Volume 54, PP. 68-81, April 2017 . https://doi.org/10.1016/j.flowmeasinst.2016.12.005

21. Mehdi Khashei, Mehdi Bijari and Gholam Ali Raissi Ardali "Hybridization of the autoregressive integrated moving average (ARIMA) with probabilistic neural networks (PNNs)" Computers & Industrial Engineering Volume 63, Issue 1, PP. 37-45. August 2012. https://doi.org/10.1016/j.cie.2012.01.017

22. Mahdi Saleh, Eric Grivel, Samir-Mohamad Omar "Jeffrey's divergence between ARFIMA processes" Digital Signal Processing Volume 82, PP. 175-186, November 2018. https://doi.org/10.1016/j.dsp.2018.06.013

23. Nari Sivanandam Arunraj and Diane Ahrens "A hybrid seasonal autoregressive integrated moving average and quantile

regression for daily food sales forecasting"International Journal of Production Economics Volume 170, Part A, 2015, PP..321-335, https://doi.org/10.1016/j.ijpe.2015.09.039

24. Yucai Zhua and Håkan Hjalmarsson "The Box–Jenkins Steiglitz–McBride algorithm" Automatica Volume 65, PP. 170-182., March 2016. https://doi.org/10.1016/j.automatica.2015.12.001

25. Maddalena Cavicchioli "On mixture autoregressive conditional heteroskedasticity" Journal of Statistical Planning and Inference Volume 197, PP. 35-50, December 2018. https://doi.org/10.1016/j.jspi.2017.12.002

26. Farshad Fathiana, Ahmad Fakheri Fardb, Taha B.M.J. Ouardac and Yagob Dinpashohb "Modeling streamflow time series using nonlinear SETAR-GARCH models"Journal of Hydrology Volume 573, PP. 82-97, June 2019. https://doi.org/10.1016/j.jhydrol.2019.03.072

27. Song-Zan Chiou-Wei, Zhen Zhu, Sheng-Hung Chen and Sheng-Pin Hsueh "Controlling for relevant variables: Energy consumption and economic growth nexus revisited in an EGARCH-M (Exponential GARCH-in mean) mode"Energy Volume 109, 15, PP. 391-399 August 2016.. https://doi.org/10.1016/j.energy.2016.04.068

28. Yaxing Yang and Shiqing Ling "Self-weighted LAD-based inference for heavy-tailed threshold autoregressive models"Journal of Econometrics Volume 197, Issue 2, PP. 368-381. April 2017. https://doi.org/10.1016/j.jeconom.2016.11.009

29. Rafael F. Santos, Guilherme A.S. Pereira and L.A. Aguirre "Learning robot reaching motions by demonstration using nonlinear autoregressive models" Robotics and Autonomous Systems Volume 107, Pages 182-195, September 2018. https://doi.org/10.1016/j.robot.2018.06.006

30. H_ Wakamatsu "Model Reference Nonlinear Adaptive Control System Using Nonlinear Autoregressive Moving Average Model Derived From Volterra Series And Its Application To Control Of Respiration" Volumes 20, Issue 5, Part 10 PP. 191-196, July 1987.

31. MassimoGuidolin and ManuelaPedio "Chapter 2 - Autoregressive Moving Average (ARMA) Models and Their Practical Applications "Essentials of Time Series for Financial Applications, PP. 41-76, 2018.. https://doi.org/10.1016/B978-0-12-813409-2.00002-9.

32. Abdul Jalil and Nasir Hamid Rao "Chapter 8: Time Series Analysis (Stationarity, Cointegration, and Causality) Environmental Kuznets Curve (EKC)A Manual,2019. https://doi.org/10.1016/B978-0-12-816797-7.00008-4

33. Terence C.Mills "Chapter 3 - ARMA Models for Stationary Time Series" Applied Time Series AnalysisA Practical Guide to Modeling and Forecasting 2019, https://doi.org/10.1016/B978-0-12-813117-6.00003-X

34. ARIMA modeling in R | texts. www. otexts. org. Retrieved 2016-05-12.

35. Wire, Leneenadogo & Isaac Didi Essi "Seasonal Autoregressive Integrated Moving Average (SARIMA) Modelling and Forecasting of Inflation Rates in Nigerian (2003- 2016)" International Journal of Applied Science and Mathematical Theory ISSN 2489-009X Vol. 4 No. 1, 2018.