The impact of COVID-19 on unemployment rate: An intelligent based unemployment rate prediction in selected countries of Europe

Muneeb Ahmad1 | Yousaf Ali Khan2 | Chonghui Jiang1 | Syed Jawad Haider Kazmi3 | Syed Zaheer Abbas4,5

1School of Finance, Jiangxi University of Finance and Economics, Nanchang, China
2School of Statistics, Jiangxi University of Finance and Economics, Nanchang, China
3Department of Management Sciences, University of Azad Jammu and Kashmir, Muzaffarabad, Pakistan
4Department of Mathematics and Statistics, Hazara University Mansehra, Pakistan
5School of Mathematics and Statistics, Beijing Institute of Technology, Beijing, China

Correspondence
Syed Zaheer Abbas, Department of Mathematics and Statistics, Hazara University Mansehra, Pakistan.
Email: zaheer@hu.edu.pk

Abstract
Unemployment remains a major cause for both developed and developing nations, due to which they lose their financial and economic impact as a whole. Unemployment rate prediction achieved researcher attention from a fast few years. The intention of doing our research is to examine the impact of the coronavirus on the unemployment rate. Accurately predicting the unemployment rate is a stimulating job for policymakers, which plays an imperative role in a country's financial and financial development planning. Classical time series models such as ARIMA models and advanced non-linear time series methods be previously hired for unemployment rate prediction. It is known to us that mostly these data sets are non-linear as well as non-stationary. Consequently, a random error can be produced by a distinct time series prediction model. Our research considers hybrid prediction approaches supported by linear and non-linear models to preserve forecast the unemployment rates much precisely. These hybrid approaches of the unemployment rate can advance their estimates by reproducing the unemployment ratio irregularity. These models’ appliance is exposed to six unemployment rate statistics sets from Europe's selected countries, specifically France, Spain, Belgium, Turkey, Italy and Germany. Among these hybrid models, the hybrid ARIMA-ARNN forecasting model performed well for France, Belgium, Turkey and Germany, whereas hybrid ARIMA-SVM performed outclass for Spain and Italy. Furthermore, these models are used for the best future prediction. Results show that the unemployment rate will be higher in the coming years, which is the consequence of the coronavirus, and it will take at least 5 years to overcome the impact of COVID-19 in these countries.

Keywords
artificial neural networks, corona virus, hybrid modeling approach, nonlinear, prediction, support vector machines, unemployment rate

Abbreviations: ACF, autocorrelation function; AIC, Akaike information criterion; ANN, artificial neural networks; ARIMA, autoregressive integrated moving average; ARNN, autoregressive neural network; BIC, Bayesian information criterion; MAE, mean absolute error; MAPE, mean absolute percent error; PACF, partial autocorrelation function; RMSE, root mean square error; SVM, support vector machine.
1 | INTRODUCTION

Investors use financial indicators like GDP with employment statistics to estimate monetary trends and select suitable investment strategies. Similarly, due to the association through the state production series as well as its effect on the fiscal strategy, the unemployment rate becomes a significant economic indicator for any country (Blanchard & Leigh, 2013). To cope with the socio-economic problems, a government always needs accurate forecasting for appropriate decision-making and formalizes a policy to cope with its socio-economic problems. From the mid of the 1990s research of the unemployment rate and macroeconomics, forecasting starts thriving. The estimation of macroeconomic variables has been analysed in numerous time series models (Milas & Rothman, 2008). One of the critical time-series suggestions of these activities illustrates its variation through linear data creates progression with reliability scattered improvements. The purpose of the research is to estimate the unemployment rate in some European countries after the spread of the novel COVID-19, usually known as coronavirus. The current catastrophic situation is utterly unexpected from the one that happened 10 years earlier. The last global disaster started in the budgetary division and sent to the rest of the economy more than a substantially stretched period by shrinking credit, business theory and absolute intrigue.

The COVID-19 crisis is the delayed state movement’s delayed consequence of battling the spread of lockdowns and social segregating. Versatile disorders, for example, the coronavirus, can pass on uncommon monetary and money related expenses on normal and generally economies (Anton Pak, 2020). For the most part, this plan addresses around 10% of the business; at any rate, there are fundamental separations by nation, with some Southern European (Ay şeygül, 2020). IMF evaluated that the overall advancement will decrease to $3% in 2020. GDP has contracted by 3.5% in the EU during the primary quarter (OECD, 2020). The hopeful conditions see unemployment in OECD countries extending from 5.4% before the epidemic to 9.2%. In any case, if the second surge of destructions hits overall budgetary and general prosperity structures, unemployment could considerably rise to 12.6%.

The monetary fall level in 2020 will be more confirmable than that of the currency-related crunch in 2009. According to the spring 2020 Financial Guess by the European Commission, the Gross domestic product will contract highly overall EU countries this year: by $7.5% for the EU when all is said in done and stretching out from $4% in Poland to more than $9% in Italy, France, and Spain. The COVID-19 secures some new issues, work and creation markets. As this catastrophe is progressing, the unemployment rate will increase, and the definite chain upset further. The everyday need for a relationship will be the prosperity to assure their agents and how to keep up business endeavours in the post-pandemic world (Omer Acikgoz, 2020). Unemployment over the entire European Union is dependent on to move to 9% in 2020, in the rouse of the Coronavirus pandemic and coming about lockdowns insisted by open governments. Among European countries, Greece is expected to suffer most, clearly at a horrible unemployment rate of 19.9%, next is Spain at 18.9%. In comparison, Germany is expected to have a minimum unemployment rate at 4%.

Most countries show work advancement until 2019 and a critical inversion of the example in 2020, which adequately shows the current pandemic. For instance, a segment of the southern European countries, Spain and Greece, shows a higher unemployment rate diverged from various countries. Unemployment over European Affiliation is dependent upon to rise to 9% before the completion of 2020. Authorities have forewarned and kept on noticing that the Coronavirus illness will continue peaking to the peril to the lives of countless people with possibly huge interference to an organized world economy (Warwick, 2020). In Germany, the conclusion gauges extended unemployment in the short-run by $6,000 + 53,000 = 117,000 individuals (or +0.3 rate centres in the unemployment rate) In Germany, 60% of the astonishingly extended inflow into unemployment in April 2020 resulted from the conclusion.

The utilizing edge spoke to an extra 82% of the unemployment way from the parcel’s edge. Plainly, saving existing situations, for instance, by methods for a short period of work, is not adequate to prevent genuine work markets drop (Anja Bauer, 2020). One of the essential time-arrangement ramifications of such conduct is that it is conflicting with a piece of straight information producing measures with evenly circulated developments.

In preceding research, the autoregressive integrated moving average (ARIMA) model on unemployment ratio estimating for diverse industrial countries was useful for evaluating Germany and Spain’s unemployment data (Vicente, López-Menéndez, & Pérez, 2015). The classical linear ARIMA model’s usefulness and effectiveness were marked from the consequences attained, whereas utilizing different European unemployment rate expecting data sets (Dumićić, Čeh Časni, & Žmuk, 2015; Edlund & Karlsson, 1993) and out-of-sample anticipates for Canadian unemployment rates (Khan Jaffur, Sookia, Nunkoo Gonpot, & Seetanah, 2017). Yet, the circumstance was somewhat extraordinary on account of the unemployment rate-determining for the United States. The edge autoregressive (TAR) model, an old-style non-straight time
arrangement model, outflanked the direct time arrangement models for anticipating the USA unemployment rate informational index (Montgomery, Zarnowitz, Tsay, & Tiao, 1998). For transient estimating of occasionally changed month to month USA unemployment informational indexes, non-straight models outflank the direct models (Nagao, Takeda, & Tanaka, 2019; Proietti, 2003). The current advancement in the region of present-day measurements and AI has outfitted the forecasters with non-straight estimating devices, for example, fake neural organizations (ANN), profound learning and backing vector machines (SVM), among numerous others (Atsalakis, Ucenic, Skiadas, 2007; Katris, 2019). ANN is discovered to mainly precipitate in determining unemployment more than an uneven industrial phase for the United States, Canada, the United Kingdom, France and Japan (Moshiri & Brown, 2004; Peláez, 2006). The past outcomes show that the non-straight models are knowledgeable to hold onto the unemployment rate time arrangement's unevenness for long haul estimate skylines. All things considered, there stays an imbalance in unemployment rate-determining, and its end will undoubtedly be testing (Feuerriegel & Gordon, 2019).

The traditional ARIMA model is serious for gauging stochastic time arrangement, though non-straight ANN has delivered ideal outcomes in the many previous years. By the by, neural netting contains the obvious disadvantage, namely, resulting in the ‘ideal’ network engineering. The autoregressive neural organization model was proposed in the ongoing writing (Galbraith & Norden, 2019). Autoregressive neural network (ARNN) is a ‘white-box-like’ model to facilitate a feed-forward neural net containing one concealed layer to some point arrangement informational index through slackened estimations of the arrangement as data sources (Faraway & Chatfield, 1998). It has the upsides of less unpredictability and simple interpretability over ANN plan (Teräsvirta, Van Dijk, & Medeiros, 2005). The informational indexes close by containing direct and non-straight examples in the present issue of unemployment rate anticipating. It will be basic for politicians to choose a solitary model because one can see extraordinary alterations in the unemployment rates’ energetic conduct. By hybridizing direct and non-straight models, one can reduce the inclination and changes of segment models’ expectation mistakes. In this way, joining both the straight and non-direct models will favour precise models such as compound auto-correlation structures (Khashei & Bijari, 2011; Oliveira & Torgo, 2014). A few crossover models were applied in the past to take care of different anticipating issues that emerged in the securities exchange, monetary econometrics, power, the study of disease transmission and other applied zones (Aladag, Egrioglu, & Kadilar, 2009; Firmino, de Mattos Neto, & Ferreira, 2014; Pai & Lin, 2005; Zhang, 2003). Half and half ARIMA-ARNN is the most precise in gauging unemployment over the unbalanced business cycle for Canada, Germany, Japan, Sweden, Netherlands, New Zealand and Switzerland (Chakraborty & Ghosh, 2020). All these half and half models are demonstrated to help tackle genuine estimating issues.

This exploration utilized half-breed moves toward examining the connection between straight and non-direct segments of the unemployment rate time arrangement. The mixture system accepts an added substance connection among linear and non-direct models, expecting that various models can independently catch a period arrangement's straight and non-straight examples. At that point, the gauges can be consolidated. The half and half strategies are more proper for clarifying varieties of the unemployment rate within sight of non-fixed and nonlinearity in this time arrangement. In the crossbreed models' main period, an ARIMA model is applied to get the informational collection's direct examples. The remaining blunder estimations of the ARIMA model are determined and reestablished for additional demonstrating. In the following stage, non-straight ARNN, ANN and SVM models are applied to catch the non-direct patterns in the informational index utilizing ARIMA’s lingering esteems. We call this two-venture approach as ‘half breed displaying approach’. The crossover models' presentation on six unemployment rate informational indexes was tried through execution matric subtleties given in segment 3. It contrasted the outcomes with select the most suitable model for future expectations. This exploration sets up a suitable cross breed demonstrating approach for every nation and is utilized for future unemployment rate expectations.

The reaming of this research work is controlled. Section 2 describes the unemployment rate data sets, the Classical time series models and advanced non-linear time series techniques. The hybrid modelling approaches, along with algorithm representation, are discussed in Section 3. The application of the method on real-life data sets is presented in Section 4, while Section 5 concludes this research with economic consequences.

2 | METHODS

The unemployment rate speaks to the quantity of jobless as a level of the workforce. The gauging unemployment rate can be characterized as the extended incentive for the number of unemployed individuals at a workforce level. Six occasionally changed month to month
informational indexes on unemployment rates for France, Spain, Belgium, Turkey, Germany and Italy were used in this exploration, subtleties yielded (Area 3.2: Information, Codes and Computational climate) beneath. An abstract of such unemployment rate statistics sets is presented in Table 1. The schemes of the preparation figures for different countries are presented in Figure 1. The graphs of the data confirm the existence of non-stationary and nonlinearity in these unemployment rate data. We used a familiar linearity test, namely the New-F test since it covers the most extensive set of nonlinearity (Chakraborty & Ghosh, 2020). The said test rejects our hypothesis of linearity powerfully for all the seven unemployment rate data sets.

In our proposed research, we consider techniques for the assessment of univariate unemployment rate time arrangement. A blend of direct and non-straight methodologies that consider the specific qualities of information may offer more correct expectations. These informational indexes have some natural highlights of takeoff from ordinariness and nonlinearity of the information’s reliance structure, which is evident from prior investigations of these informational collections (Feuerriegel & Gordon, 2019; Katris, 2019; Nagao et al., 2019). To manage the non-fixed, the direct ARIMA model is viewed as first. Moreover, nonlinearity additionally exists. The neural organizations supported ARNN model appears appropriate in the second phase of the mixture model.

2.1 Methodology

This research engaged hybrid models based on ARIMA and ARNN, ANN, and SVM models to predict six countries’ unemployment rates.

2.1.1 ARIMA model

ARIMA is a linear time series model utilized for trailing linear propensity in stationary time series data. ARIMA model is symbolized by ARIMA \((p, d, q)\). The strictures \(p\) and \(q\) are the categorizes of the AR model and the MA model. Correspondingly, \(d\) is the level of distinction. ARIMA model can be accurately articulated as given below:

\[
x_t = \beta_0 + \sum_{i=1}^{p} \theta_i x_{t-i} + \epsilon_t + \sum_{j=1}^{q} \beta_j \epsilon_{t-j},
\]

where \(x_t\) indicates the genuine estimation of the variable viable at point \(t\), \(\epsilon_t\) is an irregular mistake at point \(t\), \(\theta_i\) and \(\beta_j\) are the model’s coefficients. The vital strides for the construction of ARIMA model for some random time arrangement informational collection are as per the following: model distinguishing proof of the model (accomplishing stationarity), assessment of model boundaries (the auto-correlation work (ACF), as well as the fractional auto-correlation work (PACF) plots, are utilized to choose the AR and Mama model boundaries, individually), and model analytical inspection (Teräsvirta et al., 2005).

2.1.2 Support vector machines

The support vector machines (SVMs) were suggested by Vapnik. Based on the structured risk minimization (SRM) principle, SVMs seek to reduce the generalization error’s upper bound as a substitute for the pragmatic inaccuracy as in additional neural arrangements. Furthermore, the SVMs models produce the retreat utility by pertaining a set of elevated measurement linear functions. The SVM regression function is prepared in the following way:

\[
z = w\phi(y) + a,
\]

Such as \(\phi(y)\) is identified as the characteristic, which is non-linear planned from the participation gap \(y\). The coefficients \(w\) and \(a\) are predictable by diminishing

| TABLE 1 | Representation of data sets for the unemployment rate |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | Italy | France | Belgium | Spain | Turkey | Germany |
| Observations   | 450   | 450    | 450     | 411   | 184    | 619    |
| Training data (80% of total available data) | 360   | 360    | 360     | 329   | 148    | 496    |
| Testing data (20% of total available data) | 90    | 90     | 90      | 82    | 36     | 123    |
| Maximum value  | 13.0  | 12.5   | 11.0    | 26.3  | 14.2   | 12.1   |
| Minimum value  | 5.8   | 7.2    | 5.0     | 7.9   | 7.8    | 0.5    |
\[ R(C) = C \frac{1}{N} \sum_{i=1}^{N} L_\varepsilon(d_i, z_i) + \frac{1}{2} ||w||^2, \quad (3) \]

\[ L_\varepsilon(d, z) = \begin{cases} |d - z| - \varepsilon |d - z| \geq \varepsilon, \\ 0 & \text{Others} \end{cases} \quad (4) \]

where both \( C \) and \( \varepsilon \) are prescribed parameters. The first term \( L_\varepsilon(d_i, z_i) \) is called the \( \varepsilon \)-intensive loss function. The \( d_i \) is the actual stock price in the \( i \)th period. This function indicates that errors below \( \varepsilon \) are not penalized. The term \( C \frac{1}{N} \sum_{i=1}^{N} L_\varepsilon(d_i, z_i) \) is the empirical error. In the second term, \( \frac{1}{2} ||w||^2 \), measures the flatness of the function. \( C \) evaluates the trade-off between the empirical risk and the flatness of the model. Introducing the positive slack variables \( \gamma \) and \( \gamma' \), which represent the distance from the actual values to the corresponding boundary values of \( \varepsilon \)-tube. Equation (3) is transformed into the following constrained formation:
2.2 | Minimize

\[ R(w, \gamma, \gamma^*) = \frac{1}{2}ww^T + C^* \left( \sum_{i=1}^{N} (\gamma_i + \gamma^*_i) \right) \]  \hspace{1cm} (5)

Subjected to

\[ \begin{align*}
    w\phi(z_i) + a_i - d_i &\leq \epsilon + \gamma^*_i, \\
    d_i - w\phi(z_i) - a_i &\leq \epsilon + \gamma_i
\end{align*} \hspace{1cm} (6) \]

Finally, introducing Lagrangian multipliers and maximizing the dual function of Equation (5) changes Equation (5) to the following form:

\[ R(\alpha_i - \alpha_i^*) = \sum_{i=1}^{N} d_i (a_i - \alpha_i^*) - \epsilon \sum_{i=1}^{N} \alpha_i - \alpha_i^* \]  \hspace{1cm} (8)
with the constraints
\[ 0 \leq \alpha_i \leq C. \quad (11) \]
\[
\sum_{i=1}^{N} (\alpha_i - \alpha_i^*) = 0 \quad (9)
\]
In Equation (8), \( \alpha_i \) and \( \alpha_i^* \) are called Lagrangian multipliers. They satisfy the equalities
\[ 0 \leq \alpha_i \leq C, \quad (10) \]
\[ \alpha_i + \alpha_i^* = 0. \]
Here, \( K(y, y_i) \) is called the kernel function. The value of the kernel is equal to the inner product of two vectors \( y_i \) and \( y_j \) in the feature space \( \phi(y_i) \) and \( \phi(y_j) \), such that:

\[
K(y, y) = \phi(y_i) * \phi(y_j).
\]

Any function that satisfying Mercer’s condition can be used as the Kernel function. The Gaussian kernel function

\[
K(y, y_i) = \exp\left(-\frac{|y_i - y_j|^2}{2\sigma^2}\right)
\]

is specified in this research. The SVMs were employed to estimate the non-linear behaviour of the forecasting data set because Gaussian kernels tend to give good performance under general smoothness assumptions.

### 2.2.1 Artificial neural networks

ANNs are elastic calculating structures for modelling an extensive series of non-linear problems. A substantial benefit of the ANN models over other classes of the non-linear model is that these are universal approximations, which may estimate a great group of functions through a high quantity of precision. They get authority from the input layer, that is, the info layer, concealed layer, and yield layer. The data starting with one layer then onto the next layer is passed utilizing loads chosen utilizing a danger minimization-based ‘learning calculation’. The ARNN model is an alteration of the neural organization model explicitly intended for the time-arrangement informational collection that utilizes a pre-determined figure of shrouded neurons in its engineering (Faraway & Chatfield, 1998). It utilizes slacked estimations of the time arrangement as contributions to the model. ARNN (\( p, k \)) is a non-direct feed-forward neural netting model among one shrouded coating (including \( p \) slacked data sources) and \( k \) concealed units in the shrouded layer. BIC is likewise utilized as a rule for the examination of various models made by ARNN. At this time \( z_t \) is calculated with preferred precedent inspections \( z_{t-p} \) as the participations. Therefore, the ARNN model through one concealed sheet can be illustrated by the subsequent arithmetical figure:

\[
\hat{z}_t = \theta_0 \left\{ w_{c_0} + \sum_{k} w_{c_k} \theta_k \left[ w_{i_k} + \sum_{j} w_{i_k} \hat{y}_{t-j} \right] \right\},
\]

where \( \{w_{c_k}\} \) indicates the concerning weights and \( \theta_1 \) is the creation task. Weights of the ARNN model are taught by means of an incline fall reverse broadcast algorithm (Faraway & Chatfield, 1998). The ARNN (\( p, k \)) model utilizes \( p \) as the figure of lags for an AR(p) model, and \( k \) is

\[
f(x) = \frac{1}{1 + \exp(-x)}.
\]

Hence, the ANN model of Equation (13), in fact, performs a non-linear functional mapping from the past observations \((z_{t-1}, z_{t-2},..., z_{t-p})\) to the future value \( z_t \), that is

\[
z_t = h(z_{t-1}, z_{t-2},..., z_{t-n}, w) + \epsilon_t.
\]
and can be symbolized as go behind data (Teräsvirta et al., 2005).

3 | HYBRID MODELLING APPROACHES

The hybrid modelling approach of time series data is a two-steps approach. Here in the first step, the linear components of time series are modelled with the help of the classical ARIMA \( (p, d, q) \) model, and in the second step, the ANN, SVM or ARNN model is adjusted on the residuals obtained from ARIMA model in the first step and subsequently capture the non-linear components of the time series data. To get the final results, that is (hybrid modelling forecast), both the steps are combined. The hybrid modelling approach operates the distinctive attribute and the power of the ARIMA model and ANN, SVM and ARNN models in determining various patterns.

This research considered hybrid ARIMA-ANN, hybrid ARIMA-ARNN and hybrid ARIMA-SVM models for forecasting the unemployment rate in selected countries of Europe.

3.1 | Hybrid ARIMA–ARNN model

We suggest an amalgam ARIMA–ARNN model, which is a two-step channel move towards. Firstly, to model the linear elements of the time series, an ARIMA model is constructed, and a series of predictions is created. Secondarily, the ARIMA outstandings are modelled with a non-linear ARNN model. The preparation of the planned mixture ARIMA–ARNN model \( (M_t) \) can be officially symbolized is given as:

\[
M_t = X_t + W_t, \tag{17}
\]

where \( X_t \) is the linear fraction, and \( N_t \) is the non-linear element of the amalgam model. We can estimate together \( X_t \) and \( W_t \) from the preparation statistics set. Let, \( \tilde{X}_t \) be the anticipated cost of the ARIMA model at time \( t \) plus \( \varepsilon_t \) stands for the error outstandings at point \( t \), found from the ARIMA model. We can after that mark

\[
\varepsilon_t = M_t - \tilde{X}_t. \tag{18}
\]

The outstandings are molded by the ARNN model and can be symbolized as go behind

\[
\varepsilon_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, ..., \varepsilon_{t-n}) + \gamma_t,
\]

for \( n \) observation.

Where \( h \) is a non-linear function of the ARNN model as well as \( \gamma_t \) is the casual upsets.

Consequently, we can inscribe the mutual estimation like as:

\[
\hat{M}_t = \tilde{X}_t + \hat{W}_t, \tag{19}
\]

where \( \hat{W}_t \) is the estimated rate of the ARNN model. ARNN models the available auto-correlations in the outstandings that ARIMA could not model. This is noteworthy since the linear ARIMA model cannot create white noise movements in the forecast excellent due to the model neglect requirements and disorders in the unemployment rate time series. Therefore, if the error series is modelled again, the unusual predictors' performance can be enhanced, still although slightly at period.

Likewise, the same two-step procedure is adopted for hybrid ARIMA-ANN and hybrid ARIMA-SVM. The algorithmic demonstration of the hybrid prediction modelling move towards is well explaining in the Algorithm given below:

3.2 | Data, codes and computational environment

The data used in this research are taken from FRED Economic Data sets, which is an open-access data repository and is online available at https://fred.stlouisfed.org. All results reported in this research are carried out in R-studio statistical software, user-friendly and freely available online software. With the ‘forecast’ package’s help, we fitted classical ARIMA \( (p, d, q) \) to the data sets. For the SVM implementation in the R-environment, we use the ‘e1071’ R package. ARNN was implemented with the help of the ‘nnfor’ R package using ‘nnetar’ function and utilized ‘caret’ package of R with ‘mlp’ function for the ANN model. One secreted sheet through the integer of concealed neurons \( k \approx \sqrt{n} \), wherever \( n \) is the exercised section size for all the tests through the ANN model.

3.3 | Performance evaluation metrics of the models

Different forecasting models are estimated supported on signifying complete inaccuracy (MAE) and mean absolute percent error (MAPE) with the root means square error (RMSE) for the unemployment rate data sets (Zhang, 2003). The arithmetic appearance of these presentation assessment metrics.
Algorithm for Machine based unemployment rate prediction model

**Step-1 Initiate**

- **Partition of Sample data:** Input: {Training Data} → Output: {Testing Data}

**Step-2 Performed:** Perform and determine optimal ARIMA (p, d, q) by means of training data

- Parameters p, d, and q of the ARIMA model are preferred utilizing information criteria (AIC, BIC, etc.)
- Obtained ARIMA (p, d, q) model prediction using the training data set.
- Obtain residuals (\( \hat{\epsilon} \)) by using ARIMA prediction

**Step-3 Performed:** Obtain best ARNN (p, k) model from training data set residuals

- Performed lag selection on training data set residuals and then apply ARNN model with p selected lagged input from residuals and k hidden units.
- Obtain prediction of residuals using ARNN model

**Step-4 Prediction of the unemployment rate (\( \hat{M}_i \)):** Combine predictions of ARIMA with predictions of ARNN to obtain the final prediction.

**Step-5 Repetition:** Repeat step 3-4 by inducting SVM and ANN.

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} | m_i - \hat{m}_i |, \quad (20)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (m_i - \hat{m}_i)^2}, \quad (21)
\]

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{m_i - \hat{m}_i}{m_i} \right|, \quad (22)
\]

where \( m_i \) is the concrete output, \( \hat{m}_i \) is the forecasted output and \( n \) signifies the number of statistics ends. The following estimating model’s performance is better in that we decrease the value of these performance metrics.

4 | APPLICATION OF THE METHODOLOGY ON REAL-LIFE DATA SETS AND DISCUSSION

Data set of six selected countries on the unemployment rate are partition into two groups of statistics, as presented in Table 1. These time-varying data sets are non-linear in nature and have trends confirmed by statistical tests (see Section 2.1). The graphical display of these data sets presented in Figure 1 makes it clearer that the data sets are non-linear in natural and non-stationary. We applied ARIMA, ANN, SVM, ARNN model, testing appraise the presentations of ARIMA, ANN, SVM, ARNN, Hybrid ARIMA-ANN model of (Zhang, 2003), Hybrid ARIMA-SVM model of (Pai & Lin, 2005) and Hybrid ARIMA–ARNN model of (Chakraborty, Chakraborty, Biswas, Banerjee, & Bhattacharya, 2020) to all the six data sets for performance evaluation purpose.

We started from the classical ARIMA (p, d, q) model and fit the ARIMA model with the ‘forecast’ package of R-programming software. For this purpose, we need to specify the value of p, d and q (the model) first. With ACF and PACF plots’ help, we decided the model’s orders that best fit the data. In contrast, the value of d in the ARIMA model was obtained through the ADF test for a stationary test for the model. The most appropriate ARIMA model is then selected using the Akaike Information Criteria (AIC) importance for every country using the training data set. Next, using the fitted ARIMA model, forecasts for 2-year as well as 5-year time steps were generated. Additionally, we calculated residual errors using training data predicted values.

We modelled residuals obtained from ARIMA with ARNN (p, k) model in the second step. To make the forecast values positive, we set pre-distinct the Box-Cox alteration \( \lambda = 0 \). The assessments of p and k are found by preparing the network, which is a statistics reliant move toward (Teräsvirta et al., 2005). Further, to get the final forecasts, we added the linear forecast of ARIMA and non-linear forecasts of ARNN altogether. Furthermore, simple support vector machines (SVM) and their hybrid version were also implemented in this research. For the ANN model’s computation simplicity, we employed one hidden layer anywhere the numeral of hidden neurons \( k \approx \sqrt{n} \), where \( n \) is the section volume of the training data set.

ARIMA (2,1,2) model is best built-in to France unemployment training data set with AIC and log-likelihood values as −155.28 and 85.67. Next, the ARNN (4,2)
model, with a mean of 18 networks, was turned on the residuals obtained from ARIMA (2,1,2).

We then obtained prediction using the testing data set, using the hybrid ARIMA-ANN, hybrid ARIMA-SVM and hybrid ARIMA–ARNN model and evaluated its result with authentic values. The performance metrics for the 2-year and 5-year forecasts of France for all computed models are presented in Table 2.

Similarly, ARIMA (2, 1, 2) model best fixed to Turkey training data set, including AIC = −564.05 and log-likelihood L = 350.03. An ARNN (2,1) model, through 18 networks, each having three weights, was tuned on training data set outstandings to obtain from ARIMA (2,1,2). The predicted consequences of ARIMA and ARNN are further added to obtain the concluding estimating from which MAE, MAPE and RMSE assessments are calculated. Performance evaluation matrices for Turkey are presented in Table 3.

For Spain, the ARIMA (2,1,3) model best fixed to training data set containing AIC = −788.11 as well as log-likelihood (L) assessment as 451.05. Additionally, the ARNN (22,11) model by means of 18 networks was tuned on outstandings attained from the ARIMA model in step one, a 22–11–1 network through 349 weights. To conclude, the estimate of ARIMA and ARNN are further jointly to acquire the ultimate anticipate. We calculate RMSE, MAE and MAPE based on the final forecasted value and present them in Table 4.

Likewise, we applied all the forecasting models for Belgium and Italy data sets and presented Tables 5 and 6. ARIMA (2,1,2) with AIC = −581.71 and log-likelihood = 342.54 was first fitted to Belgium's monthly unemployment data set.

The ARIMA model outstandings are further modelled among an ARNN (18,4) model with a middling of 18 networks. For the Italy monthly data, we robust an ARIMA (2,2,1) harmony ARNN (12,6) model on remainings found from ARIMA (2,2,1). Finally, we fitted ARIMA (2,1,2) model for Germany data with AIC = −745.46, and log-likelihood (L) equals 577.73. ARNN (3,2) model through the usual of 18 networks, every of that is a 3–2–1 association with nine weights, was then tuned on residuals of the ARIMA model and obtained the resulting residuals of ARNN (3,2). Finally, the fitted ARIMA forecast and the forecast of tuned ARNN on the ARIMA model's residuals are further jointly to find the final estimated assessments. The concert determined are then computed with RMSE, MAE and MAPE values, and the results are presented in Table 7.

We particularly ARIMA, ANN, ARNN, SVM, the length using hybrid ARIMA–ANN of (Zhang, 2003), hybrid ARIMA–SVM model of (Pai & Lin, 2005) and hybrid ARIMA-ARNN model of (Chakraborty et al., 2020) applied on unemployment data sets of these selected countries of Europe and compared the results. All the computed results are presented in Tables 2–7. The estimated forecasts for the testing data sets of the best hybrid model for six data sets, the length of among real principles, are intrigued and presented in Figures 2–7.

Among all the forecasting models, the performances of the hybrid ARIMA–ARNN model (Chakraborty et al., 2020) is better compared to all other individuals and hybrid models for France, Belgium, Turkey and Germany. In contrast to hybrid models, hybrid ARIMA-SVM and hybrid ARIMA-ANN’s performance is somewhat similar for most countries. But for the Italy and Spain unemployment data sets, the hybrid ARIMA-SVM model of (Atsalakis et al., 2007) outperformed.

The reason behind this is; as we know, the ARIMA component of both models are the same and serve for the same object. Support vector machine (SVM) assigns an additional penalty for optimizing the results, whereas Auto-Regressive Neural Networks use their lags data for tuning networks. Both are advanced hybrid techniques used for predictions. In Italy and Spain, ARIMA-SVM performed outclass because shocks in the unemployment

### Table 2: The France unemployment rate data set performance metrics of different forecasting models

| Model                  | 2-Years ahead forecast | 5-Year ahead forecast |
|------------------------|------------------------|-----------------------|
|                        | MAE        | MAPE      | RMSE     | MAE        | MAPE      | RMSE     |
| ARIMA                  | 0.091      | 1.590     | 0.096    | 0.401      | 4.187     | 0.381    |
| ARNN                   | 0.101      | 6.873     | 0.107    | 0.633      | 5.465     | 0.659    |
| ANN                    | 0.125      | 4.391     | 1.37     | 0.605      | 7.483     | 0.645    |
| SVM                    | 0.095      | 1.601     | 0.105    | 0.609      | 5.192     | 0.665    |
| Hybrid ARIMA-ARNN      | **0.078**  | **1.071** | **0.087**| **0.310**  | **4.165** | **0.325**|
| Hybrid ARIMA-ANN       | 0.094      | 1.563     | 0.095    | 0.357      | 4.443     | 0.331    |
| Hybrid ARIMA-SVM       | 0.091      | 1.547     | 0.092    | 0.324      | 5.120     | 0.385    |

Note: Bold values indicate the best results produces by the corresponding method.
data are enormous. Consequently, the variation in residuals obtained from the fitted ARIMA model is sufficiently large, which is efficiently modelled by SVM and, as a result, gives better prediction performance.

Based on the best forecasting models, the 2-years and 5-years ahead point forecast has been computed for all the six countries and is presented in Table 8. The point forecast clearly shows that the unemployment rate remains a bit higher in the coming 2 years, which starts decaying from the third year and after 5 years it will be more stable.

## 5 Conclusion and Economic Consequences

Forecasting the unemployment charge could be essential for monetary market contributors and is a dependable indicator of employment marketplace circumstances. The discharge of the month-to-month unemployment fee for a rustic is one of the maximum critical normal monetary occasions for the marketplace members. The impact of the unemployment news on inventory returns is not so trustworthy due to the comparative significance of

### Table 3 Turkey monthly unemployment rate data performance metrics for different forecasting models

| Model          | 2-Years ahead forecast 2022 | 5-Year ahead forecast 2025 |
|----------------|-----------------------------|---------------------------|
|                | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| ARIMA          | 0.119 | 2.690 | 0.109 | 0.297 | 4.177 | 0.221 |
| ARNN           | 0.120 | 5.295 | 0.137 | 0.405 | 6.394 | 0.464 |
| ANN            | 0.109 | 7.783 | 0.114 | 0.433 | 5.365 | 0.469 |
| SVM            | 0.099 | 2.594 | 0.111 | 0.409 | 5.272 | 0.466 |
| Hybrid ARIMA-ARNN | 0.078 | 2.068 | 0.110 | 0.255 | 4.120 | 0.290 |
| Hybrid ARIMA-ANN | 0.097 | 2.558 | 0.119 | 0.305 | 4.120 | 0.335 |
| Hybrid ARIMA-SVM | 0.101 | 2.537 | 0.127 | 0.291 | 3.156 | 0.330 |

### Table 4 The Spain monthly unemployment rate data performance metrics of forecasting models

| Model          | 2-Years ahead forecast | 5-Year ahead forecast |
|----------------|------------------------|------------------------|
|                | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| ARIMA          | 0.175 | 2.623 | 0.183 | 0.685 | 7.708 | 0.647 |
| ARNN           | 0.167 | 2.095 | 0.189 | 0.614 | 7.365 | 0.637 |
| ANN            | 0.173 | 2.084 | 0.191 | 0.613 | 7.247 | 0.651 |
| SVM            | 0.268 | 2.915 | 0.373 | 0.740 | 8.92  | 0.798 |
| Hybrid ARIMA-ARNN | 0.198 | 2.183 | 0.205 | 0.601 | 7.017 | 0.727 |
| Hybrid ARIMA-ANN | 0.198 | 2.217 | 0.218 | 0.615 | 7.387 | 0.738 |
| Hybrid ARIMA-SVM | 0.185 | 2.135 | 0.165 | 0.601 | 7.017 | 0.635 |

### Table 5 The Belgium monthly unemployment rate data performance metrics for different forecasting models

| Model          | 2-Years ahead forecast (2022) | 5-Year ahead forecast (2025) |
|----------------|--------------------------------|-------------------------------|
|                | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| ARIMA          | 0.219 | 3.003 | 0.244 | 0.206 | 0.230 | 4.671 |
| ARNN           | 0.274 | 3.906 | 0.328 | 1.204 | 0.848 | 12.935 |
| ANN            | 0.292 | 4.177 | 0.349 | 0.738 | 0.584 | 11.518 |
| SVM            | 0.274 | 3.906 | 0.328 | 1.204 | 0.978 | 15.935 |
| Hybrid ARIMA-ARNN | 0.214 | 2.192 | 0.235 | 0.197 | 0.234 | 4.529 |
| Hybrid ARIMA-ANN | 0.218 | 3.002 | 0.243 | 0.206 | 0.255 | 4.668 |
| Hybrid ARIMA-SVM | 0.220 | 3.023 | 0.245 | 0.208 | 0.262 | 4.706 |
records on exertions market circumstances and financial strategy modifications over the years, depends upon the country’s economy. Considering the complexity in forecasting marketplace response, calculating the unemployment charge correctly is pretty beneficial for buyers to evade the marketplace danger from the unpredicted interchange in project circumstances and economical treatment.

In this research, we hired hybrid modelling tactics in decided on Europe (i.e., France, Turkey, Spain, Belgium, Italy and Germany) to research coronavirus’s effect on the unemployment rate. Those hybrid versions filter linearity through the Arima model and predict nonlinearities in attendance inside the inaccuracy outstandings among an ARNN, ANN and SVM models. The hybrid ARIMA-ARNN model properly explained the linear and nonlinear inclination gift inside the unemployment price facts sets of France, Belgium, Turkey and Germany better than the conventional unmarried and hybrid models. Whereas, hybrid ARIMA-SVM accomplished an outclass for Italy and Spain. It also creates higher anticipate precision than a variety of particular models for a maximum of the information sets taken into consideration. This looks at the hybrid modelling method that could be helpful for monetary and politicians in preference and strategy manufactures. Even though some econometric phenomenon can range close to a variety of external aspects, those instabilities are commonly tough to be appropriately captured for correct projecting. But, these hybrid models might also still expect higher accuracy.

Philosophy and data agree on several investigative results: (a) More than the previous several years, the unemployment rate for almost all the countries intentional in this research had no reliable tendency at all as well as has unequal recurring associations; (b) The hybrid modelling approach improved short-term and long-term anticipations as measured up to further insistent individual univariate forecasting techniques.

### 5.1 Limitations and future research work

For similar research, there are several limitations for the implementation of these hybrid intelligent based prediction procedures. As hybrid procedures involved two steps and Hybrid ARIMA-SVM, ARIMA-ARNN and ARIMA-ANN are iterative based procedures that used prior information for tunning parameters/networks. Therefore, we need a sufficiently large sample size to get appropriate data for training networks/optimization of parameters and testing purposes. Furthermore, these
procedures work well when the time series is non-linear, and residuals obtained from the linear component are highly variant.

There are several exciting points one should consider for future research work; (a) one should apply these hybrid methods to other regions of the world (i.e., Africa and Asian countries) data sets and validate these approaches and compare the results with one achieved for Europe, another topic of consideration is one may include additional potential variables (i.e., Duration of COVID-19 and Lockdown, Size of Population, Economic Conditions, Government Policies and Dependency of the

FIGURE 2  Forecasted estimations for the unemployment rate data sets of France based on the selected hybrid model [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 3  Forecasted estimations for the unemployment rate data sets of Italy based on the selected hybrid model [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 4  Forecasted estimations for the unemployment rate data sets of Spain based on the selected hybrid model [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 5  Forecasted estimations for the unemployment rate data sets of Belgium based on the selected hybrid model [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 6  Forecasted estimations for the unemployment rate data sets of Turkey based on the selected hybrid model [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 7  Forecasted estimations for the unemployment rate data sets of Germany based on the selected hybrid model [Colour figure can be viewed at wileyonlinelibrary.com]
country on Import/Export, etc.) for Asia and Africa to predict unemployment rate more precisely; (b) Another possible extension of the work should be the expansion of these hybrid approaches to hybrid vector autoregressive integrated moving average with the combination of ANN, ARNN and SVM for multivariate forecasting problems that arise in numerous practical fields.

CONFLICT OF INTEREST
The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT
Data used in this research is available online at FRED Economic Data. https://fred.stlouisfed.org.

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ORCID
Muneeb Ahmad https://orcid.org/0000-0002-0606-0982
Syed Zaheer Abbas https://orcid.org/0000-0003-1502-020X

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TABLE 8  Two years and 5 years ahead point forecasts based on the best hybrid model

| Country  | Method                | 2-Years ahead forecast | 5-Years ahead forecast |
|----------|-----------------------|------------------------|------------------------|
| France   | Hybrid ARIMA-ARNN     | 7.9                    | 6.4                    |
| Italy    | Hybrid ARIMA-SVM      | 9.2                    | 7.3                    |
| Belgium  | Hybrid ARIMA-ARNN     | 5.8                    | 4.7                    |
| Turkey   | Hybrid ARIMA-ARNN     | 13.5                   | 9.2                    |
| Spain    | Hybrid ARIMA-SVM      | 15.8                   | 11.5                   |
| Germany  | Hybrid ARIMA-ARNN     | 6.7                    | 5.5                    |

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