A Levenberg-Marquardt Neural Network Model to predict employment status

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Abstract - A methodical, valid, and acceptable projection model can effectively embody the complex aspects of graduates' job data, as well as the nonlinear dynamic interplay of influencing components of graduates' work status. It has a robust and consistent distinctive knowledge power, allowing it to identify the most important factors that impact the change in graduate employment data. In this study, a data mining analysis model is created based on the situation reflected by students' employment, and it is used to anticipate the job status of graduates using a neural network architecture based on the levenberg-marquardt algorithm. In this paper, a prediction methodology of graduates' employment condition aligned using neural network is conceived using two different hidden layers and their performances are compared.

Keywords* —*Data Mining, Employability forecasting, Levenberg-marquardt, Neural network, Prediction, Root Mean Squared Error.

I. INTRODUCTION

Without a question, unemployment is one of the most damaging economic occurrences because of the effects it might have on a society's cohesiveness and stability. People above a certain age who are neither employed nor self-employed but who are currently available for work throughout the reference period are simply described as such. Unemployment is frequently caused by a discrepancy between the number of people looking for work and the number of positions available. This discrepancy might arise for a number of different causes. There is recurring (or Keynesian) unemployment when there is not adequate demand in the economy to supply employment for those who wants to work (e.g., the total number of job searchers exceeds the number of opportunities). A mismatch arises when the skills of the jobless workers are not in line with the skills required for available jobs and so structural unemployment emerges.

The state of the economy has a substantial impact on cyclical unemployment since it might reduce the number of job openings. Because of the multiple worldwide economic downturns, the twentieth century has come to be seen as a time when global unemployment first emerged. The first two recessions of the twentieth century, in 1915 and 1921, had relatively low unemployment rates. After the Great Depression of the 1930s, the number of unemployed people grew dramatically, reaching the greatest levels since World War I. A period of recovery and stability was followed by a period of practically zero growth and growing unemployment following the 1973 oil crisis. Countries affected by the 1980–1982 recession, which is often regarded as the worst since World War II, went through a period of high unemployment. Another significant downturn occurred in 1989, resulting in a recession that lasted from 1990 to 1991 and had ramifications that persisted until 1994. Another round of joblessness occurred in 2005 as the global economy continued to deteriorate and develop at a slower pace. The COVID-19 problem is now likely to have an impact on job prospects as well. In accordance with the findings of the Institute of Student Employers, 27% of employers plan to reduce hiring this year [1]. More than a quarter (27 percent) said they are unsure how the epidemic would affect their careers [2].

During the four industrial revolutions, major periods of structural unemployment were also encountered. The usage of steam engines during the First Industrial Revolution (1760-1840) facilitated the shift to new industrial techniques and away from manual labour. Also referred to as a technical revolution, Europe and the United States saw tremendous industrial growth during the Second Industrial Revolution, which made mass manufacturing possible through assembly line labour. The advent of industrial robots in factories ushered in the Third Industrial Revolution, which was sparked by advances in digital technology in the 1950s. During each of these technological revolutions, specialized knowledge was rendered obsolete in an instant, resulting in a surplus of unproductive employees and higher levels of unemployment. Companies have sought to address this issue by offering training

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programmes to prepare former employees and recent graduates for the workforce after graduation. As a result of these developments, universities have made significant efforts and attempts to close this gap by changing university structures, programmes provided, and the method for joint training [3]. This fourth revolution has been called Industry 4.0 because of the ongoing transformation of traditional practices due to the latest advances in artificial intelligence (AI), using IoT infrastructure to provide self-monitoring, and smart machines that can analyse and diagnose problems without the need for human involvement.

In the midst of the Industry 4.0 revolution, educational institutions, particularly universities, must recognize (or even predict) the new requirements of the labour market as continuous developments have an influence on their requirements. In light of the COVID 19 crisis, firms are beginning to minimize costs by cutting out training candidates and seeking for highly educated graduates who can contribute immediately to the workplace once they are recruited. As a result, educational systems are under even more stress as their graduates' face increasingly difficult competition. Thus, it's critical to work on employability-enhancing technologies and approaches. Identifying important variables impacting employability, or the needs of the changing job market, for example, can be extremely beneficial to all parties. Having a clear understanding of one's skills and shortcomings might help students make more informed professional decisions. It is possible for instructors to concentrate on teaching students' skills that are in demand in quickly changing job markets. To create new competencies, programme managers may plan ahead and improve their curriculum. These improvements can be made for present and future employees. Together, all of these measures can help to reduce structural and cyclical unemployment by boosting people's employability and earning potential. In order to assure societal benefits while still benefitting from artificial intelligence's tremendous potential, these tools must include ethical and legal considerations into their design, training, and deployment [4]. According to research on the employability of recent graduates, scientists began grappling with this issue in the early 1980s. Using data from the National Assessment of Educational Progress (NAEP), which measures student progress across courses, together with economic trends and outlooks, the first research [5] sought to identify the challenges faced by students across the country. Graduates' abilities in arithmetic, reading, science, and writing were evaluated by professionals using a series of tasks. Results were compared to labour-market percentages to see how they stacked up. This procedure was time-consuming, labour-intensive, and expensive (because to the fact that it was vulnerable to human mistake). Figure 1 represents the total number of publications and its distribution from the year 1980-2020.

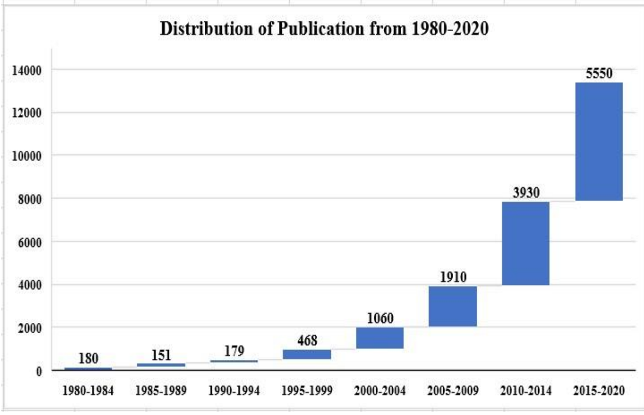

Figure 1 Distribution of Publication related to employability from the year 1980-2020

It can be observed that the studies on the employability of graduates in various fields have been carried out several times since the first publication, with an obvious uptick after 1990, when studies nearly quadrupled every five years.

II. Related Works

To identify and pick cryptic information from a data warehouse, a new technique is being used called data mining. You can use it with non-professionals because of the desktop location and support for random queries because of the data bank and data warehouse it uses [6]. Making a reliable and accurate projection of graduates' career prospects is now a time-consuming task with significant academic and practical implications. Accurately predicting post-graduation job opportunities is critical for formulating a reliable strategy and implementing effective dependability education activities [7]. Chen and Ren argue that a systematic, accurate model of graduates' employment information can capture the nonlinearity, nonstationarity, and series correlation inherent in graduates' employment data as well as the non-linear energetic interaction of persuading factors in their employment circumstances. Chen and Ren's model is based on this idea. As a third advantage, it is capable of extracting key impact information that influences changes in graduates' employment data [8]. A study by Rasjid et al. found that the use of feature fusion on the multi-cycle scale is a vital analysis in prediction of employment status. However, the majority of employment situation prediction methods employing an LSTM focus solely on one cycle, ignoring employment situation information across time scales [9]. Using class label credibility as the foundation, Dong et al. classified graduates' job condition and determined that class label credibility had a direct impact on the internal correlation between input and output data [10]. As observed, the LSTM neural network has greater forecast accuracy and successfully forecast both the (s-t):short-term and (l-t):long-term dynamic patterns of graduates' employment statistics, demonstrating its relevance and efficacy. Reconstruction of graduate employment data using wavelets improves

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generalization capabilities of LSTM forecast model as well as accuracy of forecasts for both long-term and short-term dynamic variations. Yang and Wang looked at the job situation for recent civil aviation aircraft graduates. Because of the complicated and irregular form of the curve, it's difficult for the single current model to provide the optimum forecast impact [11]. A hybrid approach using SSA and SVR was developed by Xu et al. By the hybrid method, defective feature components are extracted from the original dataset and the modelling and forecasting is done autonomously, yielding enhanced results [12]. Using multiscale feature fusion as an initial point, Wan et al. developed a method based on the tree structure for forecasting the noisy and nonlinear employment scenario. Their results show that this approach is more accurate than standard approaches in this case of neural network using LSTM training data [13]. An RBF-based and genetic algorithm-based approach for forecasting dependability was devised by researchers Liang et al. and it produced excellent results when the right parameters and network design were selected [14]. Using a neural network with an infinite impulse response, Munasypov et al. predicted component failures and system dependability using an IIR-LRNN. For the first time, dynamic modelling is being utilized for dependability forecasting. The prediction accuracy of this technique may be found to be greater when compared to other methods such as RBF, C-MLP and ARIMA [15].

There is a favorable correlation between graduate employment, enrollment, and education management based on recent studies. This research employs the neural network model to create an efficient model to forecast the job condition of graduates based on the situation embodied by students' employment. The comparison of error and hidden layers demonstrates that the neural networks are well suited than traditional models for projecting the current unemployment rate of college graduates. A graduate employment prediction approach based on the levenberg-marquardt algorithm is proposed in this research, encompassing network structure design, network training, and prediction procedure. The execution for 5 and 10 hidden layers is carried out, and their performances are compared.

III. Materials and Methods

This paper expounds the levenberg-marquardt algorithm based neural network constituting various numbers of hidden layers. This paper explores the theoretical basis of levenberg-marquardt algorithm based on graduate employment data. Since its inception, Levenberg-Marquardt has been used to address nonlinear least squares issues. Problems with least squares occur when trying to fit a scientific model to a collection of data by minimalizing a goal represented as the addition of squares of the errors between the function's model and the data points. The least square's goal has parameters that are quadratic if the model is linear. This goal may be achieved in a single step by solving a linear matrix equation with regard to the parameters. Iterative algorithms are required to solve the least squares issue if the fit function has nonlinear parameters. Model function and data point error sums are reduced by such algorithms by making well-chosen changes to model parameter values at regular intervals. Figure 2 represents the basic neural network architecture.

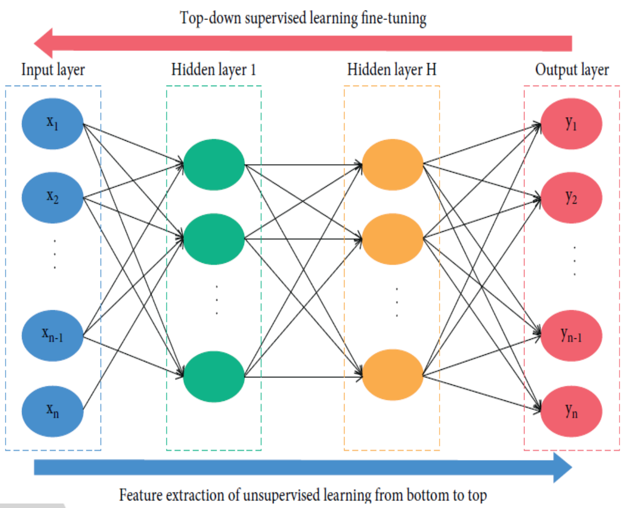

Figure 2 Basic architecture of a neural network model

It is conventional and useful to minimize the sum of the weighted squares of the errors (or weighted residuals) between the data and the curve-fit function $\hat{y}(t,p)$, when fitting a model function, comprising an independent variable 't' and a vector of 'n' parameters 'p' to a collection of 'm' data points.

$$\chi^2(p) = \sum_{i=1}^{m}\left[\frac{y(t_i)-\hat{y}(t_i;p)}{\sigma_{y_i}}\right]^2 \quad (1)$$

$$= (y-\hat{y}(p))^T W (y-\hat{y}(p)) \quad (2)$$

$$= y^T W_y - 2y^T W\hat{y} + \hat{y}^T W\hat{y} \quad (3)$$

Where σ_{y_i} is the measurement error of datum $y(t_i)$. Typically, the weighting matrix 'W' is diagonal with $W_u = \frac{1}{\sigma_{y_i}^2}$. More formally, W can be set to the inverse of measurement error covariance matrix, in the unusual case that is known. In general, the weights W_u can be adjusted to achieve alternative curve-fitting objectives. Since the sum of the squares of normally distributed variables is distributed as the chi-squared distribution, this scalar-valued goodness-of-fit measure is called the chi-squared error criteria. If the function $\hat{y}(t,p)$ is nonlinear in the model parameters p, then the minimization of χ^2 with respect to the parameters must be done recursively. Each iteration's

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purpose is to identify a 'h' perturbation to the parameters that decreases the number of iterations (χ^2). Figure 3 portrays the flowchart of the Levenberg-Marquardt algorithm.

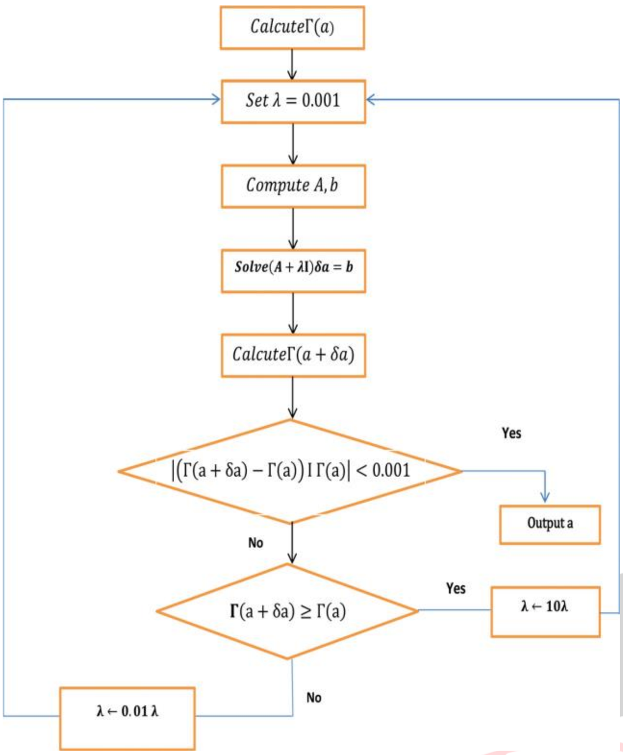

Figure 3 Flowchart of Levenberg-Marquardt algorithm

IV. DATA COLLECTION AND PREPARATION

For the purpose of analysis, the data has been collected from the students studying various departments in PSG Polytechnic College, Coimbatore. A total of 1260 instances were collected by considering various factors. The following are the departments from which the information was collected: EEE, ECE, IT, Computer Engineering, Computer Networking, Mechanical Engineering, Mechatronics, Automobile Engineering and Foundry Technology. The dataset has been collected by considering various factors that determines the students' eligibility for getting employed or unemployed. The factors and its corresponding values are specified in table 1.

Table 1 Parameters and its numerical values

S. No.	Feature Label	Range	Numeric Values
01	CGPA	0-10	0-10
02	Backlogs	0-54	0-54
03	Nature of Job	Core	1
		Software	2
		Government	3
		Higher Studies	4
		BPO	5
04	Laziness	Yes	1
		No	0
05	Clarity	High	1
		Moderate	2
		Low	3
		No	0
06	Team Work	Supportive	1
		Non-Supportive	0
07	Communication Skills	Beginner	1
		Intermediate	2
		Fluent	3
08	Analytical Skills	Bad	1
		Medium	2
		Good	3
09	Technical Skills	Bad	1
		Medium	2
		Good	3
10	Attitude	Good	1
		Bad	0
11	Computer Skills	High	1
		Moderate	2
		Low	3
		No	0
12	Confidence Level	High	1
		Low	0
13	Status of Employment	Employed	1
		Unemployed	0

V. IMPLEMENTATION

The Levenberg-Marquardt algorithm based Neural Network model is chosen for evaluation using MATLAB 2019. Out of the parameters chosen, there are 12 inputs (various factors) and 1 target (status of employment). In MATLAB, the inputs and outputs are mapped using a specific procedure. The segregation of dataset for the purpose testing, training and the validation are done through dedicated GUI in the neural network toolbox. In this work, 75% of the dataset is used for testing, 15% is used for testing and the remaining 15% is used for validation.

VI. RESULTS AND DISCUSSION

As this research work mainly focusses on the performance evaluation of the number of hidden layers in the neural network model, 5 and 10 hidden layers have been chosen. The forecast results obtained are presented in table 2 and table 3. From the results it is observed that the Levenberg-Marquardt based neural network model has better forecasting ability than the other techniques (MLP – Multi-Layer Perceptron; SVM – Support Vector Machines; GARCH – Generalized AutoRegressive Conditional Heteroskedasticity) reported.

Table 2 Forecast effect comparison for 5 hidden layers

	TrS		TS		VS	
	T	M	T	M	T	M
LM-NN	0.00060	0.00120	0.00050	0.00100	0.00040	0.00080
MLP	0.00610	0.00310	0.01470	0.02780	0.00820	0.01390
SVM	0.00630	0.01120	0.00980	0.01930	0.00430	0.00780
GARCH	0.00790	0.00990	0.04030	0.06220	-	-

* TrS-Training Set *TS-Test Set * VS-Validation Set

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Table 3 Forecast effect comparison for 10 hidden layers

	TrS		TS		VS	
	T	M	T	M	T	M
LM-NN	0.00040	0.00800	0.00030	0.00060	0.00020	0.00050
MLP	0.00710	0.00410	0.01670	0.02980	0.00920	0.01590
SVM	0.00730	0.02120	0.00990	0.02930	0.00630	0.00890
GARCH	0.00890	0.00890	0.04530	0.06420	-	-

* TrS-Training Set *TS-Test Set * VS-Validation Set

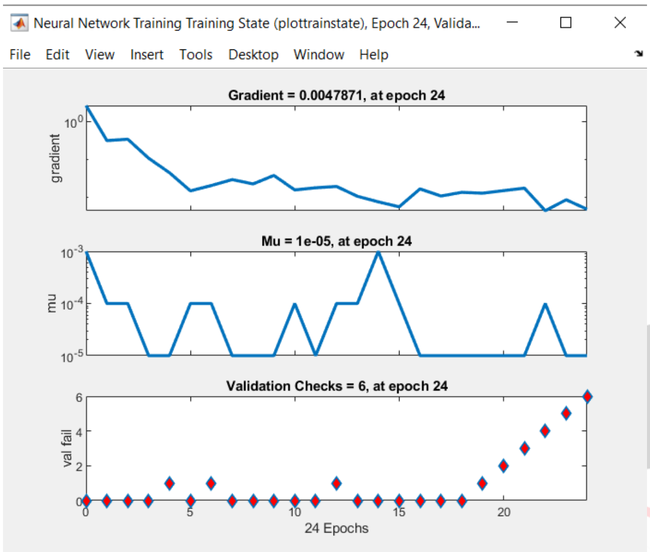

Figure 4 Performance of Training state at epoch 24 (5 hidden layer)

From figure 4, it is observed that the training state of a 5 hidden layer provides the best result at iteration/epoch at 24 with a gradient value of 0.0047871, Mu at 1e-05 and validation check at 6.

From figure 5, it is noticed that the error value gets settled at 0.02103, considering zero error line. From figure 6, it is observed that the training state of a 10 hidden layer provides the best result at iteration/epoch at 11 with a gradient value of 0.019812, Mu at 0.0001 and validation check at 6.

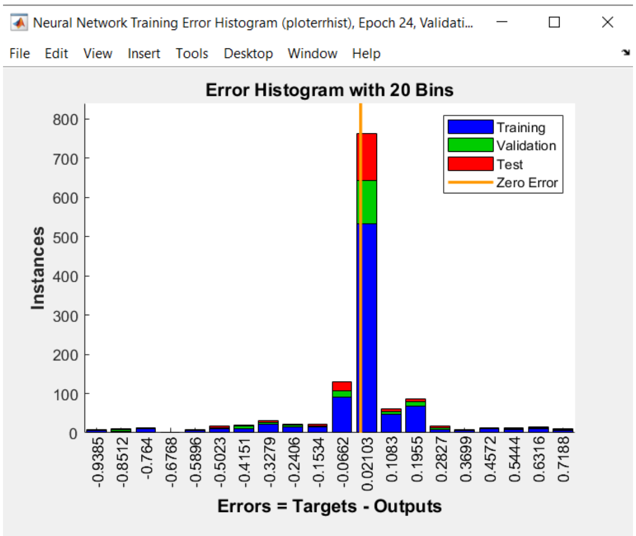

Figure 5 Error representation for all cases (5 hidden layer)

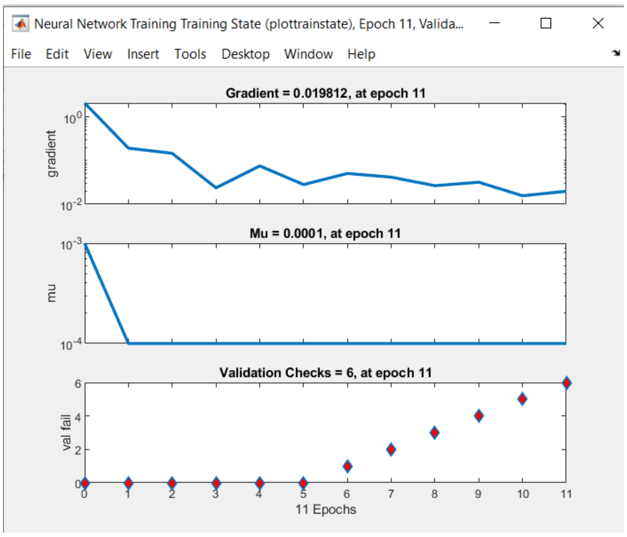

Figure 6 Performance of Training state at epoch 24 (10 hidden layer)

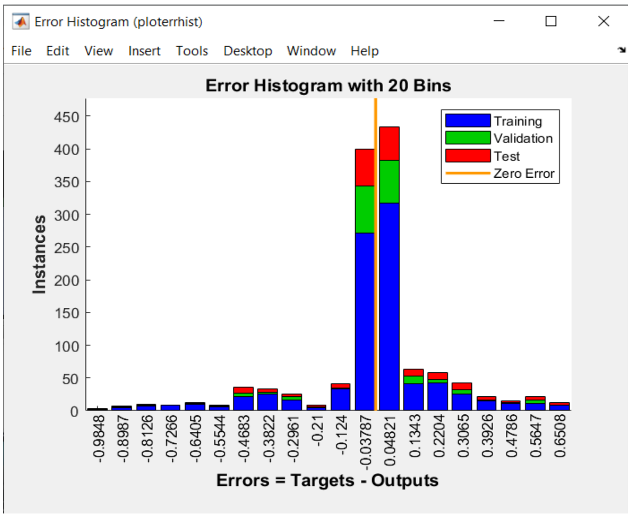

Figure 7 Error representation for all cases (10 hidden layer)

From figure 7, it is noticed that the error value gets settled at 0.04821, considering zero error line. Figure 8 portrays the sum of squared errors of a function.

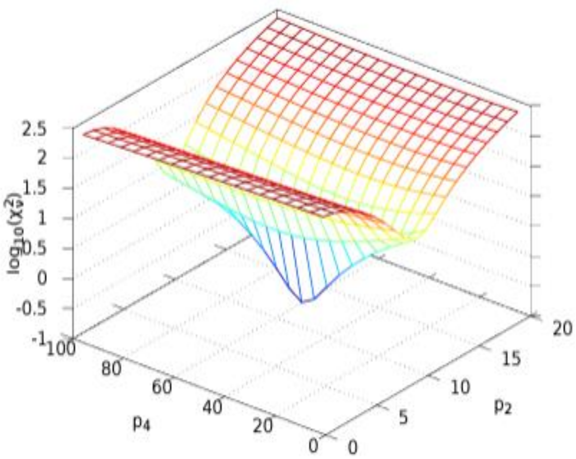

Figure 8 Sum of squared errors of a function

However, in both the training and test sets, the GARCH model, a classic econometric technique, failed to produce good forecast results. The following are some plausible

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explanations: To begin, the GARCH model is a linear model that is unable to capture the nonlinear dynamic link between fiscal determinants and so cannot accurately explain the nonlinear features of graduates' job data. Compressible data is required for the development of GARCH and other job status models. In most circumstances, differential or logarithmic differential processing is required, resulting in the employment data loss. Levenberg-Marquardt Neural Network may efficiently dispose the information related to original data and holds the interaction between variables, thereby capturing the dynamic features of the available data. The use of LM-NN not only eliminates the traditional econometric model's dependency on index selection in the modelling process, but it also solves the fault that cannot be described by the linear models. Simultaneously, it solves the limitations of shallow machine learning algorithms. As a result, LM-NN obtains the nonlinear dynamic qualities, incorporates its nonstationary cum time-dependent features more systematically than other models, resulting in a stronger forecast effect.

VII. CONCLUSIONS

According to the forecast results, the employment rate of graduates has an unchanging tendency, with very little increase and drop tendencies. Because of the vast population base and quick expansion, the overall population and number of college graduates will continue to rise in the coming years. To determine correctness, the test data are further added to the trees for classification and the difference between the predicted employment rate and the actual employment rate are displayed. This study advances a system-level forecasting technique on employment based on the Levenberg-Marquardt neural network, which consists of training, forecasting and optimization. This research article envisions the speculative foundation and the practical application of LM-neural network applied to the real-time dataset to decompose and reconstruct graduates' employment data, thereby eliminating the impact of (s-t):short-term random noise and improving the model's forecast resulting in enhanced capability. The LM-neural network not only eliminates the traditional econometric model's dependency on index selection in the modelling process, but it also eliminates the fault that linear econometric methods cannot describe nonlinear interaction of factors. Simultaneously, it overrides the problems that other machine learning algorithms cannot represent, resulting in easy over fitting. As a result, the LM-neural network procures the nonlinear dynamic qualities and includes its nonstationary and time-dependent features little deeper than earlier models, resulting in a stronger forecast effect.

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