



A Hybrid Modified Orca Predation Algorithm with Backpropagation Neural Network Mathematical Modeling Approach for Time Series Forecasting: Comparative Analysis of Inflation and Export Data

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ABSTRACT

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Backpropagation, forecasting, mathematics modelling, macroeconomics, MOPA, neural network

Improving the accuracy and capabilities of long-term prediction models is an urgent need for supporting data-driven economic policy planning. This research aims to propose the integration of the Hybrid Modified Orca Predation Algorithm with Backpropagation Neural Network (MOPA-BPNN) as a predictive approach capable of capturing temporal dependencies in economic data. Additionally, this study emphasizes the importance of expanding the input dimensions by incorporating macroeconomic variables to enrich the predictive context. This research was conducted using a quantitative experimental approach and utilized 10 years of economic time series data from the West Nusa Tenggara Province, including inflation and export data. The proposed method is the hybrid MOPA-BPNN, which is evaluated comparatively against conventional BPNN and MOPA models. The results of the study indicate that the MOPA-BPNN approach consistently delivers the best performance, as evidenced by the lowest Mean Absolute Percentage Error (MAPE) values (3.14% for inflation and 18.18% for exports). This demonstrates a significant improvement in accuracy compared to using MOPA or BPNN separately. The implications of these findings suggest that the application of the MOPA-BPNN hybrid model can serve as a reliable technological foundation for early warning systems and the formulation of regional economic policies based on more accurate and adaptive predictions of long-term economic data dynamics.

1. INTRODUCTION

Artificial Intelligence (AI) is a rapidly growing field that focuses on developing systems capable of performing tasks that require human intelligence, such as pattern recognition, decision-making, and machine learning [1, 2]. The Backpropagation Neural Network (BPNN) algorithm is crucial for training neural networks and enabling them to learn from errors through the sequential propagation of error gradients. However, BPNN faces significant challenges, especially in deep networks, such as vanishing gradient problems and sequential update inefficiencies that hinder optimal convergence and increase computational costs [3, 4].

The BPNN algorithm optimizes predictions by adjusting weights and biases through a systematic error propagation process. This begins with the calculation of the gradient of the loss function, which is essential for updating the network parameters. The BPNN algorithm uses chain rules to propagate errors backward from the output layer to the input layer, effectively enabling the network to learn from its errors

by minimizing the loss function associated with each weight [5, 6]. In neural network training, BPNN performance can be enhanced through different activation functions or kernels such as radial basis function (RBF) and polynomial, which play an important role in improving model accuracy and efficiency [7].

Improvements in BPNN performance often involve the use of more efficient kernels in machine learning, such as RBF kernels and polynomial kernels. RBF has proven to be superior in various machine learning applications, including regression and support vector machine (SVM). This is due to its ability to improve accuracy and reduce classification errors compared to traditional kernels such as sigmoid and ReLU [8]. Additionally, the use of random kernels and non-overlapping learning strategies has shown significant progress in reducing sensitivity to outliers and overfitting, while improving model accuracy and efficiency [9]. The use of RBF network architectures and the development of alternative polynomial kernels also increase flexibility in handling various types of data and more complex applications [10].

The development of BPNN algorithms combined with other algorithms in machine learning has been widely conducted for both data forecasting and classification [11-16]. Suprajitno [15] constructed a hybrid Backpropagation-Relevance Vector Machine (BP-RVM) algorithm for hydro-climatological data prediction, and the training data yielded a MAPE value classified as an indication of high prediction accuracy ($< 10\%$). Xu et al. [16] developed a hybrid Grey Wolf Optimizer and Backpropagation Neural Networks Algorithm (GNNA) and found that the predictive performance of GNNA significantly improved compared to BPNN, which was significantly better than Generalized Boosting Model (GBM), Generalized Linear Model (GLM), maximum entropy (MaxEnt), and Random Forest (RF). Furthermore, Li et al. [12] also integrated a hybrid model between Backpropagation and Ensemble Empirical Mode Decomposition (EEMD) and obtained a coefficient of determination (R^2) value of 1.85% when simulating data. This value is smaller than that of EEMD-Long Short-Term Memory (LSTM) and BP-LSTM, which are 3.8% and 5.44%, respectively.

The combination of BPNN with other algorithms has been proven to improve accuracy performance during the training-testing process. However, the selection of components in the pre-processing stage is also a determining factor in recognizing data, especially in non-linear cases. One algorithm that is fast in the data convergence process is the Modified Orca Predation Algorithm (MOPA). In the data pre-processing stage, MOPA acts as an optimization algorithm that assists in the initial processing of data before it is used for model training. Several studies have shown that MOPA can be combined with neural networks. Kaladevi et al. [17] tested the combination of Convolutional Neural Network (CNN) with MOPA for breast cancer detection and classification. The research results found that the classification accuracy was 98.64%, specificity was 98.79%, and sensitivity was 98.82% compared to other methods.

Jebur et al. [18] proposed a new approach that combines deep hybrid learning with the Self-Improved Orca Predation Algorithm (SI-OPA) for image denoising. The study found that the proposed approach demonstrated superior performance in all aspects, and this hybrid model showcased the benefits of combining Bi-LSTM, an optimized CNN, and SI-OPA for advanced image denoising applications. Furthermore, Yan et al. [19] used MOPA to predict electricity load in North Korea and found that the MOPA model had an average Mean Absolute Percentage Difference (MAPD) of 365 in the northern region; 12.8 in the southern region; 8.6 in the central region; and 30.8 in the eastern region. These results provide the best fit and outperform other techniques in terms of MAPD index with lower values for all regions and years.

The results of the study described above show that MOPA has never been combined with BPNN in data forecasting. Hybrid MOPA-BPNN has good potential because BPNN has limitations such as slow convergence, the risk of getting stuck in local minima, and sensitivity to initial parameters, so more efficient optimization is needed to improve its performance. MOPA, as a metaheuristic algorithm based on orca behavior, can be used to address these issues by enhancing exploration and exploitation in the search for optimal solutions. The MOPA-BPNN hybrid enables more optimal weight initialization, more adaptive parameter settings, and accelerated convergence, thereby reducing prediction errors. Therefore, this study aims to evaluate the effectiveness of the hybrid MOPA-BPNN in improving prediction performance

compared to conventional BPNN by testing this model on various economic datasets such as inflation and exports, thereby providing deeper insights into the role of metaheuristic-based optimization in enhancing the accuracy and efficiency of economic data forecasting models.

2. RESEARCH METHOD

This study uses an experimental quantitative approach with the aim of evaluating the performance of the combination of the MOPA and BPNN in economic data forecasting. The dataset consists of economic time series data on monthly inflation and export values. In the implementation stage, MOPA is used to optimize the initial weights of BPNN, while BPNN is trained with the optimized parameters. The results obtained from the MOPA-BPNN combination were then compared with conventional BPNN and MOPA methods to evaluate the effectiveness of the proposed method in improving the accuracy of economic data forecasting. The stages in conducting this research are shown in Figure 1.

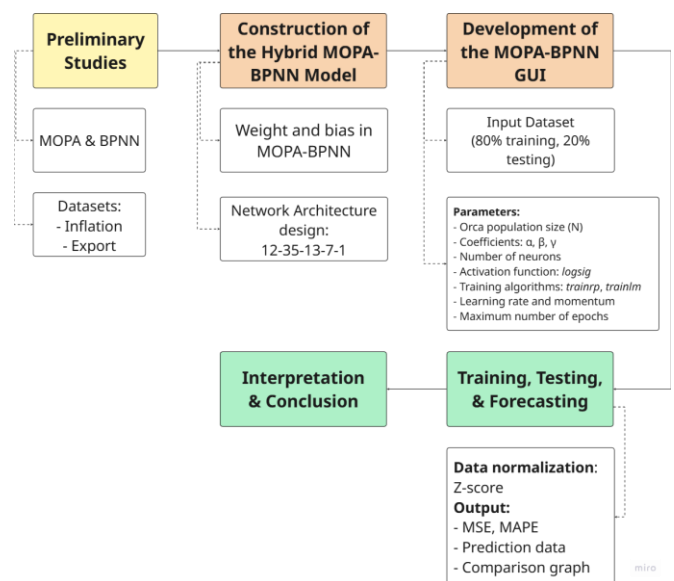


Figure 1. Research procedures

Based on Figure 1, there are six stages in this study, as follows:

a. Conducting a literature study on MOPA and BPNN Algorithms. This stage aims to gain an in-depth understanding of the MOPA and BPNN, including the working principles, advantages, and disadvantages of each algorithm. The literature used includes scientific journals, books, and other reliable sources that discuss the implementation and application of these algorithms in the field of economic data forecasting.

b. Constructing a hybrid MOPA-BPNN algorithm. In this stage, MOPA is designed and integrated into BPNN to build a hybrid model. MOPA is used to optimize the initial weights of the artificial neural network before training with BPNN begins. This process includes designing the neural network architecture, selecting the number of hidden layers, and determining the appropriate optimization parameters to improve the performance of economic data prediction.

c. Developing a GUI for data simulation. After the hybrid model is formed, the research team then develops a MATLAB-based Graphical User Interface (GUI) to facilitate

users in performing data simulation and analysis. This GUI will be designed to accept inputs such as activation functions, training functions, learning rates, the number of neurons per hidden layer, momentum, and other parameters. Additionally, the system displays prediction results, model accuracy metrics (Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE)), and comparison graphs of actual versus predicted data.

$$MSE = \frac{\sum_{t=1}^n (A_t - F_t)^2}{n} \quad (1)$$

$$MAPE = \frac{\sum_{t=1}^n \left(\frac{A_t - F_t}{A_t} \right) \times 100}{n} \quad (2)$$

with n is the number of observations, A_t are represents the actual value at time t , and F_t is the predicted value at time t .

a. Data collection. The data used in this study is sourced from official sources such as the World Bank, the Central Statistics Agency (BPS), and Yahoo Finance, covering the past 10 years (2015–2024). The collected data includes two types of economic patterns: (1) dynamic data (monthly inflation); (2) seasonal data (export data).

b. Data training and testing. After the data was collected, a preprocessing process was carried out, including normalization and division of the dataset into two groups, namely 80% for training and 20% for testing, to evaluate the model's performance in predicting previously unseen data.

c. Interpretation and conclusions. The simulation results and model performance evaluation are analyzed based on prediction accuracy using the MSE and MAPE metrics. Actual data is compared with prediction results to assess the effectiveness of the MOPA-BPNN combination in economic forecasting. The conclusions drawn include the advantages of this hybrid method over conventional methods (BPNN), as well as recommendations for further research in developing optimized economic data forecasting models.

3. RESULT AND DISCUSSION

3.1 Construction of the MOPA-BPNN algorithm

The MOPA is an optimization algorithm inspired by the hunting behavior of orca whales. This algorithm is an extension of the Orca Predation Algorithm (OPA) with modifications to the exploration and exploitation mechanisms, thereby enhancing the efficiency of finding optimal solutions in various optimization problems [20]. In the context of data forecasting, MOPA can be used to optimize weights and biases in BPNN to improve prediction accuracy. MOPA uses a series of mathematical equation to represent the predatory behavior of orcas in finding optimal solutions.

The MOPA optimization process can be described in three main predation stages. The first stage, chasing or encircling prey, models the exploration ability of predators to identify and surround potential solutions in a wide search space. The second stage, cooperative hunting, represents the balance between exploration and exploitation, where multiple predators share information to improve the search process and converge toward promising regions. Finally, the third stage, attacking prey, emphasizes exploitation, in which predators focus on intensively refining the best candidate solutions until

convergence is reached. These three stages enable MOPA to maintain a dynamic balance between global exploration and local exploitation, which is essential for solving complex forecasting and optimization problems. Here are some of the main formulas in the MOPA algorithm:

3.1.1 Orca agent position

The position of the orca agent is updated using Eq. (3):

$$X_i(t+1) = X_i(t) + A \cdot D \quad (3)$$

with $X_i(t+1)$ is the new position of the orca agent in iteration $t+1$, $X_i(t)$ is the current position of the Orca agent, A is a factor accelerating the hunt, and D is the distance between the orca agent and its prey.

3.1.2 Exploration and exploitation mechanisms

Exploration and exploitation are controlled by probability parameters according to Eq. (4).

$$X_i(t+1) = X_{best}(t) + C \cdot (X_{rand}(t) - X_i(t)) \quad (4)$$

with X_{best} is the best position found, C is a factor of movement, X_{rand} is the position of another randomly selected orca agent.

3.1.3 Convergence towards optimal solutions

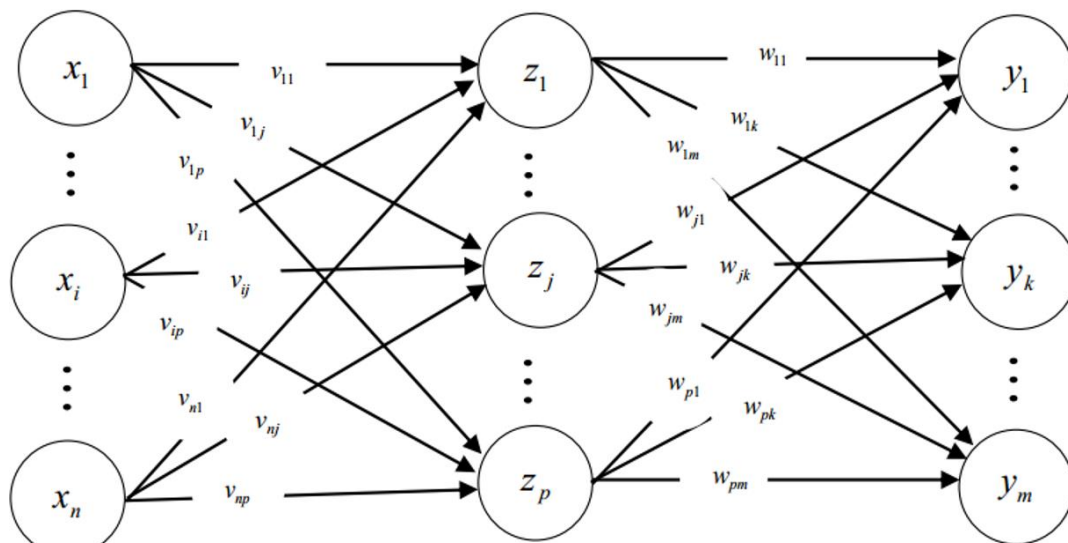
MOPA convergence is controlled by dynamic weighting parameters according to Eq. (5).

$$V_i(t+1) = w \cdot V_i(t) + r \cdot (X_{best}(t) - X_i(t)) \quad (5)$$

with $V_i(t+1)$ is the speed of movement of the orca agent, w is the inertia factor, r is the randomization factor.

BPNN is a supervised learning algorithm and is typically used by perceptrons with multiple layers to modify the weights connected to the neurons in its hidden layer [21]. In a BPNN network, each unit in the input layer is connected to every unit in the hidden layer, and each unit in the hidden layer is connected to every unit in the output layer [22]. The architecture resulting from training with the smallest error is the architecture used for prediction or pattern recognition. The architecture of an artificial neural network consists of an input layer, a hidden layer, and an output layer. The architecture of the artificial neural network is shown in Figure 2.

The activation function used by BPNN must meet several requirements, namely continuity, differentiability [23], and non-decreasing [24]. Functions that meet these three criteria include the identity function (purelin), the binary sigmoid function (logsig), the bipolar sigmoid function (tansig), and the hyperbolic tangent function. The hidden layer and output layer in a BP network play a crucial role in data pattern recognition. Changes in the weights of the input layer, hidden layer, and output layer are manipulated using activation functions and training functions placed at each hidden layer. An activation function is a function used in neural networks to activate or deactivate neurons [25]. Activation functions in NNs include threshold, linear functions (purelin), and sigmoid functions (logsig, tansig, tan-hyperbolic). However, in BPNN, only linear and sigmoid functions are used. Combinations of activation functions in the hidden layer and output layer have been widely used, such as the tansig function in the hidden layer and purelin in the output layer [26, 27], and the logsig function in each layer [28]. The data forecasting mechanism is shown in Figure 3.



Note: x_n : Layer input; v_{np} : Hidden layer weight matrix; z_p : Hidden layer; w_{pm} : Output layer weight matrix; y_m : Output layer

Figure 2. Backpropagation neural network architecture

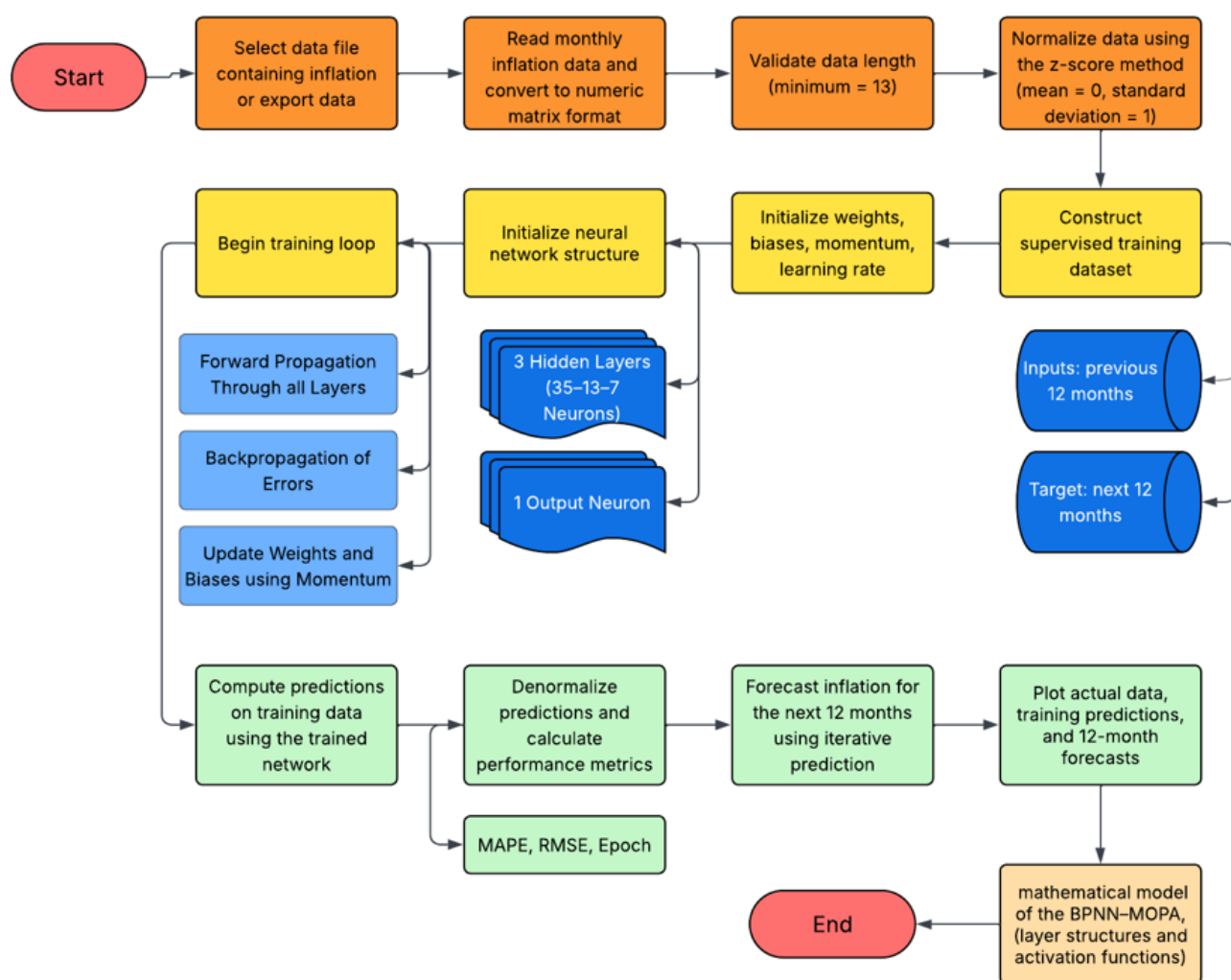


Figure 3. Flowchart of the MOPA-BPNN computational algorithm

In Figure 3, the MOPA-BPNN computational algorithm begins with the process of selecting an Excel file containing monthly inflation data as the database for training and prediction. The data is read and converted into a numerical matrix format so that it can be processed by the system. Thus, the data length is validated to ensure that the data has a minimum of 13 entries, as 12 months of data are required as

input and 1 month as the target output in each training sample. The validated data is then normalized using the z-score method, which sets the mean to zero and the standard deviation to one, to improve the efficiency of the neural network training process.

After that, a supervised dataset is formed where the last 12 months are used as input and the 13th month as the target

output. The artificial neural network (BPNN) structure is then initialized with three hidden layers consisting of 35, 13, and 7 neurons in sequence, as well as one neuron in the output layer. The initial weights and biases of the network are determined randomly, and the values of the momentum and learning rate parameters are also set. The training process begins with forward propagation from the input to the output through all layers of the network, followed by Backpropagation to calculate the error and update the weights and biases using the momentum technique.

After the training is complete, the trained network is used to generate predictions for the training data. The prediction results are then normalized back to their original scale and evaluated using several performance metrics, namely MSE and MAPE. Furthermore, the system displays the inflation prediction values for the next 12 months and performs an iterative prediction process with the prediction results are used as input for the next month's prediction. These prediction results are then visualized in the form of a graph showing actual data, training results, and predictions for the next 12

months. In the final stage, the system generates a mathematical model of the artificial neural network, including the layer structure and activation functions used, and the computational process is declared complete.

3.2 Comparison of data prediction accuracy using MOPA-BPNN

The performance evaluation of the MOPA-BPNN hybrid model in predicting economic data was carried out through a training and testing process on two types of data, namely inflation and exports. The evaluation was carried out by comparing the model's prediction results with actual data using several predictive accuracy indicators such as MSE and MAPE. This comparison aims to demonstrate the effectiveness of MOPA-BPNN in capturing time series data patterns and improving the accuracy of prediction results. The prediction results for inflation and export data are presented in Table 1.

Table 1. Predicted data results of inflation and exports

Data	MOPA		BPNN		MOPA-BPNN	
	MSE	MAPE	MSE	MAPE	MSE	MAPE
Inflation	0.210	127.89%	0.141	182.13%	0.026	93.14%
Exports	292,855.402	23.70%	599,845.064	25.07%	112,091.233	18.18%

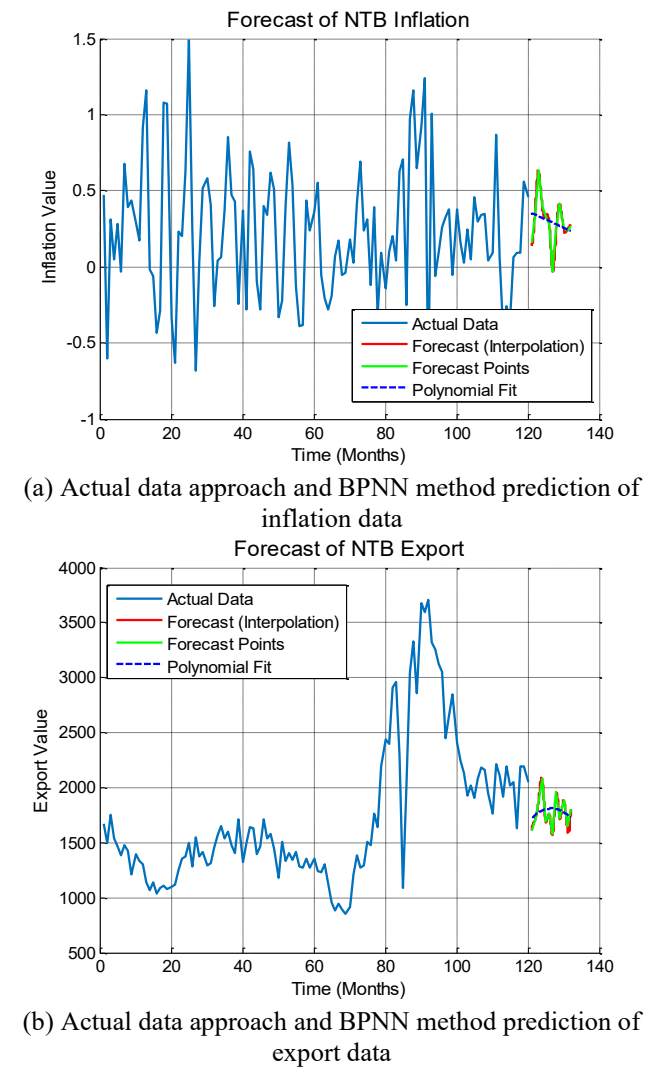


Figure 4. Prediction results using the BPPN algorithm

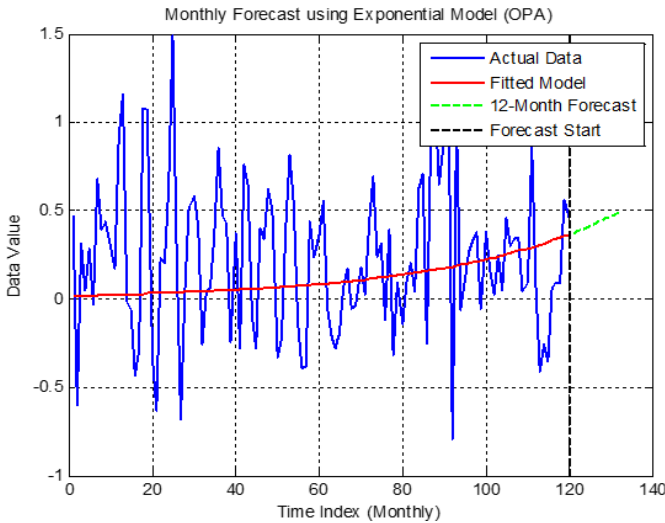
Table 1 presents a comparison of the accuracy levels of inflation and export data predictions obtained through three modeling methods. Model performance was evaluated using two main indicators, namely MSE and MAPE. For inflation data, the MOPA method produced an MSE value of 0.210 with a MAPE of 127.89%. The BPNN method showed a decrease in MSE to 0.141, but was accompanied by an increase in MAPE to 182.13%. Meanwhile, the MOPA-BPNN method recorded the best performance with a very low MSE of 0.026 and a MAPE of 93.14%. In the export data, the MOPA method showed an MSE value of 292,835.402 and a MAPE of 23.70%. BPNN produced a higher MSE value of 599,845.064 with a MAPE of 25.07%. Conversely, MOPA-BPNN produced an MSE value of 112,091,223 with the lowest MAPE value of 18.18%. These results indicate that MOPA-BPNN is capable of providing estimates that are closer to actual values compared to the other two methods. Although the MSE value of MOPA-BPNN in export predictions is slightly higher than MOPA, the lowest MAPE value of 18.18% indicates that this method has a smaller relative error, making its predictions proportionally more accurate.

Figure 4 presents the results of inflation data predictions for the province of Nusa Tenggara Barat (NTB) using the BPNN method, with actual data displayed as a blue line, BPNN predictions shown by a red line, prediction points displayed as a purple line, and the polynomial fit shown as a dotted green line. The prediction curve follows the historical trend, reflecting the dynamics of the economy. The inflation graph shows more stable fluctuations than the sharper export graph. This indicates that export-import data is more sensitive to external factors. This model is relatively simple but capable of describing general trends. The accuracy of the prediction depends on the optimal weight training of the neural network. The mathematical models obtained from training the BPNN artificial neural network on inflation and export data are represented in the form of quadratic equations as shown in Eqs. (6) and (7).

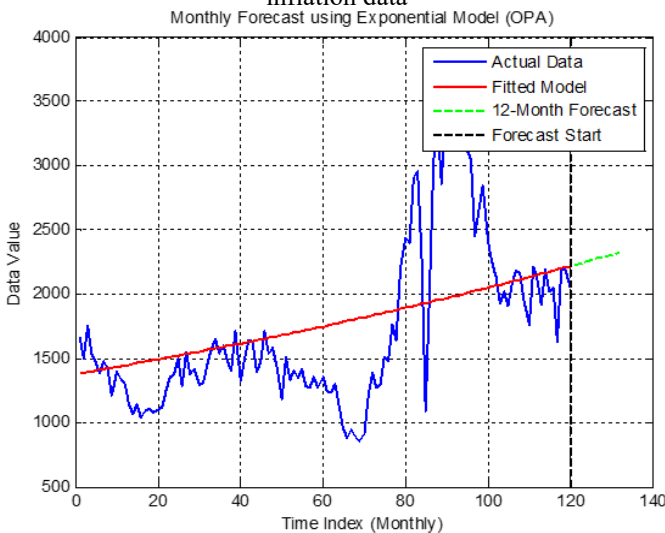
$$F_{Inf}(t) = (-0.0001) \times t^2 + 0.0032 \times t + 0.7690 \quad (6)$$

$$F_{Exp}(t) = (-2.9121) \times t^2 + 738.2842 \times t + (-44981.3860) \quad (7)$$

The mathematical model in Eq. (6) describes the quadratic relationship between time t and the predicted inflation rate. The negative coefficient of t^2 indicates that the inflation trend tends to slow down or decline after a certain point. Thus, this model not only captures linear patterns but also represents changes in the rate of inflation growth over time. Meanwhile, Eq. (7) represents a prediction model for export data, which also shows a quadratic relationship between time t and the predicted export value. The quadratic coefficient, which is larger in absolute terms than in Eq. (4), indicates that the variation or fluctuation in export values over time is more pronounced. The relatively large linear coefficient indicates a growth trend in the early period, but the negative quadratic coefficient implies that this trend will reach a maximum point and then decline over time. Both models demonstrate that BPNN can generate non-linear approximation functions for historical data, thereby providing a more realistic picture of inflation and export dynamics during the analyzed period. The graph of the MOPA method results can be seen in Figure 5.



(a) Actual data approach and MOPA method prediction of inflation data



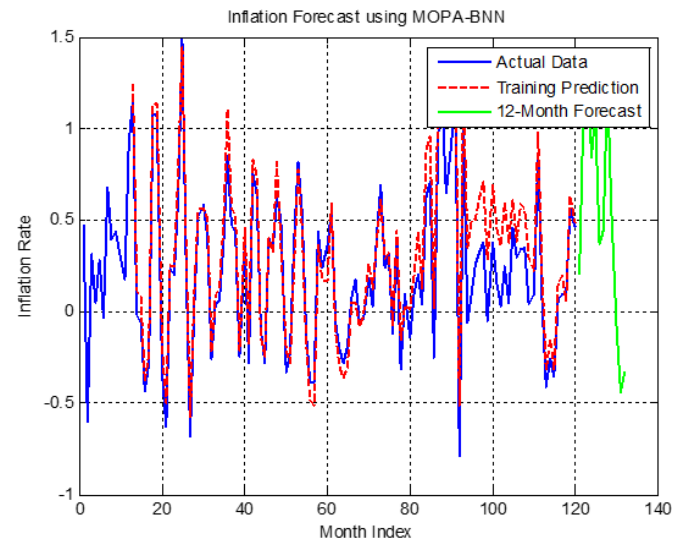
(b) Actual data approach and MOPA method prediction of export data

Figure 5 shows a visual representation of the results of inflation and export data predictions for NTB Province using the MOPA method. The figure presents the results of inflation data predictions for NTB Province using the MOPA method. In the graph, the blue line represents actual data, the red line shows the MOPA method's estimation results on historical data, and the green line displays projections for the next 12 months. The graph shows a slow but consistent growth trend. Inflation predictions indicate a gradual increase over time with a smooth pattern. Meanwhile, the export prediction shows more significant long-term growth. This model is suitable for data with exponential patterns or natural growth. MOPA provides optimal solutions to model parameters through an evolutionary approach. The modeling results using MOPA on inflation data and export data produce a mathematical model in the form of an exponential function, as shown in Eqs. (8) and (9).

$$y(t) = 0.0195e^{0.0244 \times t} \quad (8)$$

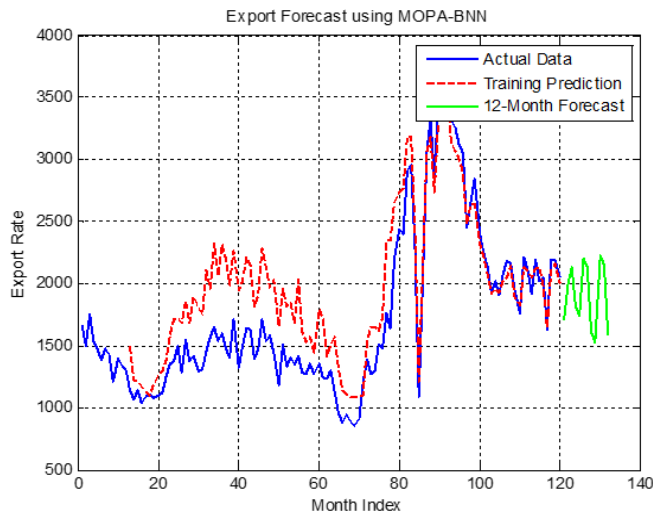
$$y(t) = 01377.7157e^{0.0040 \times t} \quad (9)$$

The mathematical model in Eq. (8) represents the exponential relationship between time t and the predicted inflation rate. The exponential coefficient of 0.024 indicates that the inflation rate is expected to increase consistently over time at a growth rate of 2.44% per unit of time. Meanwhile, the initial constant of 0.019 represents the estimated inflation value at the starting point of observation. This exponential growth pattern reflects the long-term trend of rising inflation. Meanwhile, the model for export data is shown in Eq. (9), which also shows exponential growth characteristics with a growth rate of 0.40% per unit of time. The initial coefficient of 1377.715 indicates the initial estimated value of export activity at time $t = 0$. The relatively smaller growth rate compared to the inflation model indicates that exports experienced slower but stable growth over the observed period. In general, both models show that the MOPA approach is capable of capturing the natural growth patterns of non-linear economic data. The resulting exponential function reflects the potential for positive development in inflation and international trade, and can be used as a basis for reliable long-term projections. The graph of the MOPA-BPNN method results can be seen in Figure 6.



(a) Actual data approach and MOPA-BPNN method prediction of inflation data

Figure 5. Prediction results using the MOPA algorithm



(b) Actual data approach and MOPA-BPNN method prediction of export data

Figure 6. Actual data approach and MOPA-BPNN method prediction

Figure 6 shows the blue line as actual data, the red dotted line as the model's training results on historical data, and the green line as the prediction results for the next 12 months. The combination of these two methods appears to successfully integrate the strengths of each approach in capturing complex data patterns. Figure 6 shows predictions that are more adaptive to fluctuating patterns. The model was trained with the last 12 months of input to produce more accurate outputs. Both inflation and export predictions demonstrate the model's ability to capture complex nonlinear patterns in economic data. The combination of optimization and deep learning significantly improves model performance. The graph results display a smoother and more realistic prediction approach. The mathematical model generated through the combination of MOPA-BPNN on inflation and export data is represented in the form of a layered neural network structure. The training process for weights and biases is performed adaptively using the MOPA approach, which acts as a population-based optimization algorithm to improve convergence quality and avoid local minimum traps during the network training process. This model is capable of learning complex feature representations and capturing non-linear relationships in economic time series data, both for inflation and export-import predictions. The main advantage of this approach lies in its ability to combine the exploratory power of MOPA with the generalization capability of BPNN, resulting in a more accurate and stable prediction model against historical data dynamics.

Based on these findings, the combined MOPA-BPNN method showed the best predictive performance in estimating inflation and export data when compared to the use of MOPA or BPNN methods separately. This superiority is reflected in the lowest MSE and MAPE values, particularly in inflation data with an MSE value of 0.026 and a MAPE value of 93.14%, which are significantly better than the other two methods. Meanwhile, in export data prediction, although the MSE of the MOPA method is smaller, the lowest MAPE value of 18.18% obtained by MOPA-BPNN indicates relatively higher accuracy. The graphical visualization in Figure 6 shows that the MOPA-BPNN model has a high adaptive ability in capturing complex and fluctuating data patterns. The multi-

layer neural network architecture used, along with the training process based on population optimization algorithms, enables the model to avoid local minimum traps and generate accurate representations of non-linear patterns in economic time series data. Therefore, the MOPA-BPNN approach is worth considering as a strategic alternative in predictive modeling, given its ability to integrate global exploration strength with nonlinear modeling effectiveness.

Research in various previous studies supports the effectiveness of the BPNN and MOPA methods in the context of prediction and optimization. Research by Alsaawy et al. [29] shows that BPNN consistently provides better results than regression models in predicting bank financial strength. Aslam et al. [30] also note a significant improvement in the accuracy of short-term load predictions with BPNN, achieving MAPE improvements of up to 99.32% and 38.1%. Meanwhile, Azizah et al. [31] demonstrated that BPNN can achieve a low MAPE of 2.063% in predicting seawater salinity, reinforcing the claim that this method excels in handling complex and non-linear data relationships. Lyu et al. [32] also demonstrated that BPNN optimized with genetic algorithms and K-fold cross-validation produces more consistent predictions of concrete structure strength compared to empirical formulas.

On the other hand, the ability of the MOPA algorithm to perform global search and avoid local stagnation has been demonstrated by Olivares et al. [33] through its integration with deep Q-learning for feature selection in high-dimensional data. The advantages of the MOPA approach are also highlighted in a study by Yan et al. [19] which shows the superior performance of the LSV/MOPA model in electricity load forecasting with lower MAPD values compared to other methods. Additionally, Emam et al. [20] demonstrate that MOPA excels in terms of computational speed and efficiency in the design of hybrid energy systems. Based on the findings, the main advantage of the MOPA-BPNN method lies in its ability to combine the global exploration of MOPA and the generalization of BPNN, enabling it to produce more accurate and stable predictions, especially for complex and fluctuating data such as inflation and exports. However, its drawback is that although it is relatively accurate (low MAPE), this model does not always produce the smallest MSE value for all types of data, as seen in export predictions where the MOPA method recorded a lower MSE.

4. CONCLUSIONS

The MOPA-BPNN hybrid method is an effective approach for predicting inflation and export data. This hybrid method produces higher accuracy than using MOPA or BPNN individually, as demonstrated by the lowest MSE and MAPE values for both types of data. The advantage of MOPA-BPNN lies in its ability to combine the global exploration capabilities of MOPA with the non-linear learning capabilities of BPNN, resulting in a model that is more adaptive to fluctuations and complex patterns in economic time series data. Thus, MOPA-BPNN can be used as a reliable approach in forecasting dynamic and non-linear economic data. Further research is recommended to explore the development of predictive models by integrating the MOPA-BPNN method with other machine learning or deep learning techniques, such as LSTM networks or Transformer models, which excel at capturing long-term patterns and complex temporal dynamics.

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