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# A Flexible Combination Forecast Method for Modeling Agricultural Commodity Prices: A Case Study Iran's Livestock and Poultry Meat Market

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## Abstract

In recent years, the fluctuation in agricultural commodity prices in Iran is increased and thus, accurate forecasting of price change is necessary. In this article, a flexible combined method in modeling monthly prices of beef, lamb and chicken from April 2001 to March 2021, was proposed. In this new method, three different approaches namely simple averaging, discounted and shrinkage methods were effectively used to combine the forecasting outputs of three hybrid methods (MLPANN-GA, MLPANN-PSO and MLPANN-ICA) together. In implementation stage of hybrid methods, based on test and error method, the optimal MLPANN structure was found with 3/2/4–6–1 architectures and the controlling parameters are carefully assigned. The results obtained from three hybrid methods indicate that, based on the RMSE statistical index, the MLPANN-ICA method performs the best when forecasting prices for beef, lamb, and chicken. The outputs of three combination approaches show that the shrinkage method, with a parameter value of K=0.25, achieves the highest prediction accuracy when forecasting prices for these three meats. In summary, the proposed method outperforms the other three hybrid methods overall.

**Keywords:** Agricultural commodity prices, Forecasting, Hybrid method, Meat

## Introduction

Price is a key factor in the financial and commercial activity of the agricultural sector, in such a way that the activists of the agricultural sector are always exposed to the risks associated by the fluctuation in the price of agricultural products (Hasan *et al.*, 2020). The price of agricultural products fluctuates a lot due to factors affecting the demand side and supply side ranging from climatic shocks to political, financial and market shocks. The continuous increase in food prices caused by the rapid increase in demand for food directly threatens more than 800 million people worldwide with chronic malnutrition. As a result, the price of agricultural commodities has attracted the attention of policymakers, academic researchers, and companies to predict the price of food products (Shao and Dai, 2018; Weng *et al.*, 2019).

As the share of food expenditure in household expenditure in developing countries is higher than in developed countries, the consequences of fluctuation in food prices are seriously pervasive in terms of food security in such coutries (Timmer, 2014). Recent decades, have witnessed an enormous increase and fluctuation in commodity prices. Volatility in the behavior of commodity prices is typically the result of the increase in the global demands,

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complex changes associated with cyclical, trend, and random factors and so on (Garganoa and Timmermann, 2013; Tomek and Kaiser, 2014; Chen, 2015). In recent years, the global economy has experienced an increase in the prices of many agricultural commodities. During the period 2006-mid 2008, World agricultural commodity prices considerably increased, so that the prices of commodity crops nearly doubled (Nazlioglu, 2011; Ajmera *et al*., 2012). As indicated by Fowowe (2016), prices of agricultural commodities particularly experienced enormous increase up to 64 percent in the period from 2001 to 2013. Also, Dreibus *et al.* (2014) found that in a past decade, food prices have increased by 2.8% per year on average. Ascendant trend in the prices of agricultural commodity can increase concern for countries that rely on food imports (Nazliogl and Soytas, 2011).

In recent years, the prices of agricultural goods have experienced significant increases due to multiple factors, including the global spread of Covid-19 and the ongoing conflict in Ukraine. This upward trend in agricultural prices has raised substantial concerns among countries that rely on food and agricultural imports, as noted by the FAO in 2022. Additionally, Asian economies, such as Iran, have also witnessed volatility and upward trends in the prices of agricultural commodities. For instance, Figure 1 illustrates the monthly price changes in various meat types in Iran from 2018 to 2021, clearly showing the presence of this volatility and upward trajectory. It is worth noting that a significant portion of the rise in agricultural commodity prices can be attributed to inflation, which, in turn, is a consequence of various factors, including governmental financial mismanagement, shifts in internal policies, chronic budget deficits, unregulated money creation by the banking sector, the discussions surrounding the Joint Comprehensive Plan of Action (JCPOA), the imposition of sanctions against Iran, the global impact of Covid-19, the ongoing conflict in Ukraine, and other related factors. The cumulative effect of these factors has resulted in a severe budget deficit within the Iranian government. Consequently, this budget deficit has become the primary driver of the expansion of the monetary base and a sharp increase in inflation, particularly in the prices of food items in Iran.

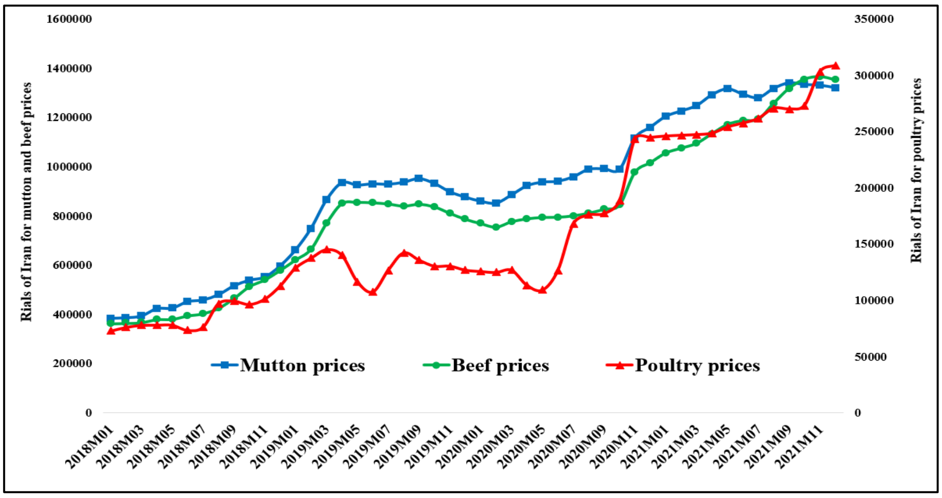



**Figure 1- The changes trend in prices of meat types in Iran (Agriculture Ministry of Iran, 2021)**

Price changes forecasting is a challenge in economic decision making, because the fluctuation of prices is affected by different factors (Wu *et al*., 2017). One of main targets of commodity price forecasting can be linking of between theory and practice, improving decision-making and risk management in industries that heavily reliant on commodity markets. This aims provides useful information to both policy makers and decision markers (No and Salassi, 2009; Mohamed and Al-Mualla, 2010). Also, because of price forecasts play a key role in public policy and are designed to influence human activity, are important (Allen *et al*., 2016).

The price forecasting of agricultural commodities is considered as an important and essential component in market management and decision planning, due to it can provide the simulated perspective of future, and identifying the balance in the supply and demand of agricultural commodities. In addition, agricultural commodity prices forecasting allowed producers to make better decisions, to help to optimize their commodity selling strategy, and to manage price risk. In the agricultural commodity market, the accurate forecasting of the price of agricultural commodities is challenging because of prices time series are very complex, highly volatile (Kantanantha *et al*., 2010; Mohamed and Al-Mualla, 2010; Xiong *et al*., 2015). Thus, an accurate forecasting method is needed for forecasting of the price of agricultural commodities which can avoid many disasters related to the demand and supply of agricultural commodities; and for farmers' production decision, consumers' low economic losses and government regulation (Ye *et al*., 2014; Yang *et al*., 2016).

Given the paramount importance of forecasts for both policymakers and decision-makers, extensive research has been conducted over the past decades to develop forecasting methods. These methods have evolved from simple models to more complex ones, as noted by Aiolfi and Timmermann in 2006. Currently, there exists a wide variety of models designed for forecasting agricultural commodity prices. In the study conducted by Wu *et al*. in 2017, the forecasting models for agricultural commodity prices were categorized into two main types: structural models and non-structural methods. Furthermore, short-term forecasting methods for agricultural commodity prices encompass a range of approaches, including time series methods such as the ARIMA model, regression methods like the vector auto-regression model, and machine learning methods, including neural networks. Although, traditional methods have extensively used to forecast the agricultural commodity prices, but these methods have contained weakness, as following:

1. Traditional methods that are applied to predict commodity prices, are based on the certain probability distribution, while this assumption may be unreasonable and non-rational (Atsalakis, 2014).

2. In most cases, time series for the price of agricultural commodities is nonlinear and non-stationary due to the intrinsic elaboration and volatility of these prices, thus the linear structure of traditional methods cannot properly forecast the nonlinear behaviors of time series of agricultural commodity prices (Xiong *et al*., 2015; Yang *et al*., 2016).

3. Time series methods (e.g. ARIMA model) are only based on observations of the same variable are collected and analyzed, (history prices of agricultural commodities) and random variables, therefore, these methods ignored other factors (not consider exogenous economic variables) that may affect agricultural commodity prices (Shahwan and Odening, 2007; Wu *et al*., 2017).

4. More current methods have focused on a single model and can only be applied in a small-scale data, consequently reduces the accuracy of the forecasting of agricultural commodity prices (Stock and Watson, 2004; Wu *et al*., 2017).

The early 1980s, artificial neural networks (ANN) have been suggested as an alternative technique to overcome the weaknesses of traditional models. Many researchers have started to apply ANN methods to forecast economic and financial applications due to the significant properties of handling nonlinear data with self-learning capabilities (Shahwan and Odening, 2007; Chen *et al*., 2010; Atsalakis, 2014). Also, there are a number of studies in which ANNs are used to develop forecasting models of agricultural commodity prices. More this studies demonstrate that ANN models can outperform the statistical forecasting techniques and can sometimes also outperform some other non-linear models (Das and Padhy, 2015; Pannakkong et al., 2016).

Artificial neural network model is an information processing system that was developed based on the structure of human brain neuron working (Atsalakis, 2014; Pannakkong *et al*., 2016). ANN model has considerable advantages into traditional statistical methods, such as self-learning, not making assumption of characteristic of the data, expressing highly non-linear relationship between the input and output data that can't be modeled in mathematics, generalizing at high speed, adapting and using only many parameters, and so on (Mollaiy-Berneti, 2015; Pannakkong *et al*., 2016). Notwithstanding above advantages, there are some problems for ANN model that many researchers criticize the performance of it. For example, the convergence in the training of ANN method is generally slow and the specification of ANN method carried out by trial and error technique. It is not able to determine the grade to which an input affects the output of the ANN model (Karimi and Yousefi, 2012; Amiri *et al*., 2015). When ANN model is specially used for forecasting the price of different agricultural commodities, its results cannot be ensured and overvaluing may happen. Thereupon, it may be some errors in the ANN method outputs (Wu *et al*., 2017).

Due to the complexity of real-world problems in nature and variety existence in characteristics of commodity prices such as seasonality, heteroskedasticity or a non-Gaussian error, using of a hybrid model can be a suitable alternative for forecasting commodity prices (Shahwan and Odening, 2007). The optimization of ANN model with evolutionary algorithms (ANN-EA) is the most important hybrid model that is used by researchers. In fact, one of suitable ways to overcome problems of ANN model and improve reliability of network, is usage of optimization methods such as evolutionary algorithms to optimize the network initial weights. Therefore, to reduce the weakness related to ANN methods, some evolutionary algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization algorithm (PSO) and Imperialist Competitive Algorithm (ICA) can be used for the optimization of the ANN structure. On the other hand, evolutionary algorithms can use to optimize linking weights and the obtained outputs of neural network (Ahmadi *et al*., 2015; Xiong *et al*., 2015; Kartheeswaran and Christopher Durairaj, 2017).

Commodity price forecasting using of the hybrid model of ANN-EA have problems. The choosing of the free parameters related to evolutionary algorithms in training the neural network using of evolutionary algorithms (e.g. PSO, GA, ICA), are typically based on cut and try, domain knowledge and ergodic search methods. Thus, the hybrid model of ANN-EA needs to determine controlling parameters and this task causes more complex. Therefore, variations to the controlling parameters alter the effectiveness of the optimization algorithm (Das and Padhy, 2015). Moreover, as indicated by Stock and Watson, (2004), the use of an individual model to forecast is rather unstable over time. Also, the results of this study show that the use of a type of the ANN-EA hybrid model cannot be appropriate to forecast different variables (agricultural commodities price). To overcome these limitations, combination methods can be used as an alternative to increase the accuracy of forecast models. Stock and Watson, (2004) found that the performance of the individual forecasts was unstable and most of the combination forecasts have lower mean squared forecast errors (MSFEs) than the individual models. Despite the formidable ability of hybrid methods, not unexpected that each of this hybrid methods still are not able to get desired results because of their drawbacks. Therefore, by considering the ability of each of this hybrid methods, the methodology and technique of the combination ways of hybrid models are necessity for the better forecasting of economic variables. Hybrid and combined methods have focus on different aspects. For instance, hybrid methods apply processes of noise reduction, seasonal adjustment and cluster on data, while ways of combination use of weight coefficients of individual methods (Rapach and Strauss, 2009; Yang *et al*., 2016). Thus, the hybrid models as individual methods can combine by combined methods. The obtained proportion coefficient of hybrid models can be adjusted in the combined method, so that the results can be the best (Aiolfi and Timmermann, 2006; Yang *et al*., 2016). To improve the accuracy of forecasting, some combined methods have been applied in several applications. For example, Stock and Watson, (2004) and Aiolfi and Timmermann (2006) used from three types of combination forecast methods, including simple averaging method, discounted method, shrinkage method. This three of combination forecast methods are considered in this study.

While numerous methods have been developed for forecasting agricultural commodity prices, the application of combination forecasting has not received extensive attention. Hence, this study aims to explore the forecasting accuracy of livestock and chicken meat prices by introducing a novel combination-hybrid prediction method. In this proposed method, we employ evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Imperialist Competitive Algorithm (ICA) to train Artificial Neural Network (ANN) models. Additionally, we assess whether the out-of-sample forecasts generated by this combination method exhibit greater accuracy and reliability compared to forecasts generated by individual hybrid methods, using various statistical indexes. It is important to note that there is limited existing research and infrequent scientific exploration into the forecasting capabilities of Iran's agricultural commodities market. Therefore, this research is expected to contribute significantly to filling this research gap.

Our experimental findings clearly demonstrate that the method proposed in this paper outperforms its individual components, yielding highly effective forecasts for agricultural commodities in the Iranian agricultural markets. Both error analysis and visual result analysis support the conclusion that the combination-hybrid model introduced in this paper achieves commendable forecasting outcomes. This combination-hybrid model not only enhances forecasting accuracy but also significantly improves efficiency when compared to other hybrid models comprised of its individual components. Additionally, the advantages of the method proposed in this paper can be summarized as follows:

1. Among agricultural commodities price forecasting methods, this method is flexible and has the great forecasting accuracy.
2. This method can be used to forecast many types of agricultural commodities with good performance.

The following sections provide a brief overview of the content covered in each sector: In Section 2, previous studies regarding commodity prices forecasting are surveyed. In Section 3, we delve into the intricacies of the data processing procedures and present the outcomes of our preliminary data analysis. Following that, in the fourth section, we provide a detailed illustration of the proposed combination-hybrid prediction method. Within this section, we expound upon the key components of our proposed method, which encompass Multilayer Perceptron Neural Networks (MLPNN), various evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Imperialist Competitive Algorithm (ICA), as well as the combination techniques applied to hybrid models. Each of these elements is described in depth, offering a comprehensive understanding of their roles and contributions to the overall methodology. Section 4 illustrates forecasting statistical criteria. In Sections 5, experimental results are discussed and a final section (Section 6) concludes this work.

## Background study

To date, some researchers have reported the use of traditional methods, the types of ANN models, and combination and hybrid methods for commodity prices modeling and forecasting. For example, Zou *et al.* (2007), Obe and Shangodoyin (2010), Pokterng and Kengpol (2013) and Pannakkong *et al.* (2016), for predicting agricultural commodity prices utilized ANN model. Several studies have yielded results indicating that Artificial Neural

Network (ANN) models tend to outperform well-established statistical forecasting methods. Additionally, when it comes to forecasting commodity prices, a variety of papers have explored the application of combination and hybrid methods, as exemplified below: In a study conducted by Wihartiko et al. (2021), an examination of models used for predicting the prices of agricultural products revealed that Artificial Intelligence, Data Mining, and Regression models were utilized at rates of 30%, 22%, and 18%, respectively. Moreover, for forecasting agricultural product prices, intelligent models were proposed, taking into account the concept of the supply chain. Raflesia et al. (2021) employed the PSO-RBFNN (Particle Swarm Optimization-Recurrent Neural Network) model in their research to predict agricultural commodity prices in Indonesia. The outcomes of this study demonstrated that the predictive accuracy of the PSO-RBFNN model surpassed that of competing models. In a study by Nosratabadi et al. (2020), it was shown that the combined ANN-GWO (Artificial Neural Network-Gray Wolf Optimization) model exhibited higher prediction accuracy when compared to the ANN-ICA (Artificial Neural Network-Imperialist Competitive Algorithm) model. These findings collectively underscore the effectiveness of ANN models and the potential benefits of combining them with various optimization algorithms for improved commodity price forecasting. Wang *et al.* (2018) used a hybrid model to forecast the monthly price of Chinese garlic during 2010-2017. Their proposed model consisted of an Autoregressive Integrated Moving Average (ARIMA) model as the linear part and the Support Vector Machine (SVM) model as the non-linear part of the proposed model. The results of this study showed that the hybrid ARIMA-SVM model has a better performance in predicting the price of garlic than the ARIMA and SVM models, and it can be used as an effective method for predicting the short-term price of garlic. Tian *et al.* (2017) developed a time-varying HAR model to forecast the realized volatility in the agricultural commodity futures markets of China. The authors used six agricultural commodity futures namely soybean, cotton, gluten wheat, corn, early Indica rice and palm futures and employed daily data of all sample periods. Their results showed that the proposed HAR model has better performance than both the simple HAR model and more sophisticated HAR-type models in almost all cases. Wu *et al.* (2017) proposed a mixed model, which combines ARIMA model and PLS regression method to forecast the weekly prices of agricultural commodity from January 2, 2014 to June 30, 2015 in Beijing. Their results displayed the proposed mixed model is more accurate in forecasting the prices of agricultural commodity than each single model does. Ahumadaa and Cornejo (2016) examined forecasting improvements of individual food price models by taking into account the cross-dependence of the commodities (including corn, soybeans and wheat) in the period 2008–2014. Their results indicated forecasting accuracies of models that include price interactions, can be improved. Das and Padhy (2015) developed a new hybrid SVM–TLBO method, that combines a support vector machine with teaching-learning-based optimization, to forecast commodity futures index (consist of futures prices of metals, energy, and agricultural commodities). Their experimental results illustrated that the proposed model outperforms the particle swarm optimization PSO-SVM hybrid and standard SVM models. Xiong *et al.* (2015) applied the combination method of vector error correction model with multi-output support vector regression (VECM–MSVR) to interval forecasting of agricultural commodity futures prices in China, and their results indicated the proposed method is a promising alternative for forecasting this futures prices. Atsalakis (2014) proposed a hybrid intelligent system called the Adaptive Neuro Fuzzy Inference System (ANFIS) to forecast monthly prices of four agricultural commodities (wheat, sugar, coffee, and cocoa). The experimental results of author's study showed that the neuro-fuzzy method outperforms the other feedforward such as neural network (NN), the two traditional methods AR and ARMA. Ye *et al.* (2014) used the optimal combination model to forecast vegetable price in Hainan. This proposed model included from three models are triple exponential smoothing model, simple linear regression model, and grey forecasting model. This study's forecasting results indicated the forecasting accuracy of the proposed combination model is better to each individual model and overcomes on of limitation of individual models. Garganoa and Timmermann (2013) examined the out-of-sample forecasting of commodity price indexes by means of macroeconomic and financial variables over the period 1947–2010. They found that the out-of-sample forecasting of commodity prices is strongest for industrials, metals, and the broad commodity index; while is weaker for fats/oils, foods, and livestock. Kantanantha *et al.* (2010) develop accurate yield and price forecasting models for stochastic crop decision planning. To overcome on existing difficulty, they developed Functional Principal Component Analysis (FPCA) and a futures-based model for yield and price forecasting and applied these methods to corn yield and its price for Hancock County in Illinois. They found that their forecasting results are more accurate in comparison to predictions based on existing methods. Ticlavilca *et al.* (2010) applied the Multivariate Relevance Vector Machine (MVRVM) model to forecast the prices of agricultural commodities. Authors used the monthly price data of cattle, hog and corn that were obtained for a period of 21 years (from 1989 to 2009). Also, proposed method is based on a Bayesian learning machine approach for regression. In their study, the efficiency and accuracy of the MVRVM model is compared with artificial neural network model. Shahwan and Odening (2007) used a hybrid model that combines a seasonal ARIMA model and an Elman neural network (ENN) to forecast agricultural commodity prices (including hog and canola prices from Germany). They employed a genetic algorithm (GA) to determine the optimal architecture of the ANNs. Their results showed that the out-of-sample forecasting be improved somewhat with the proposed hybrid method.

The comprehensive review presented above suggests that combination and hybrid methods consistently outperform traditional methods and various types of Artificial Neural Network (ANN) models in the context of commodity price forecasting. Furthermore, it becomes evident that a method with the distinctive features of the proposed approach in this study, aimed at enhancing the prediction accuracy of hybrid methods involving neural networks and evolutionary algorithms through the use of individual combined techniques, has not been previously explored for predicting agricultural commodity prices. This underscores the novelty and potential significance of the approach outlined in this study, which seeks to advance the state of the art in commodity price forecasting by integrating the strengths of neural networks and evolutionary algorithms in a unique and promising manner.

## Materials and Methods

### The novel proposed method

There are several methods available for forecasting commodity prices, including time series methods, classical statistic methods, artificial neural networks methods and hybrid methods. To the best of authors' knowledge, there is no published work in the literature that is similar to the novel proposed method presented in this paper. This study takes advantage of different hybrid methods and combination approaches, and proposes a novel combined-hybrid method. This new method consists of two categories of individual methods and combination approaches. In this proposed method, combination approaches were used to adjust the weight coefficients and consequently to combine the forecasting outputs of individual methods and it should be assumed that the combination approaches able to recognize most of the seasonal, linear and nonlinear patterns. Individual methods included three hybrid methods of ANN-AE where MLPNN model combined with Genetic Algorithm (MLPNN-GA), Particle Swarm Optimization algorithm (MLPNN-PSO) and

Imperialist Competitive Algorithm (MLPNN-ICA). Combination approaches consist of simple averaging method, discounted method and shrinkage method. One of advantages of novel method is flexibility in increase (or decrease) of number of hybrid methods and combination approaches. Fig. 2 illustrates the details on combined method used in this study. According to Fig. 2, input data contains agricultural commodity prices (in this study including prices of beef, lamb and chicken).

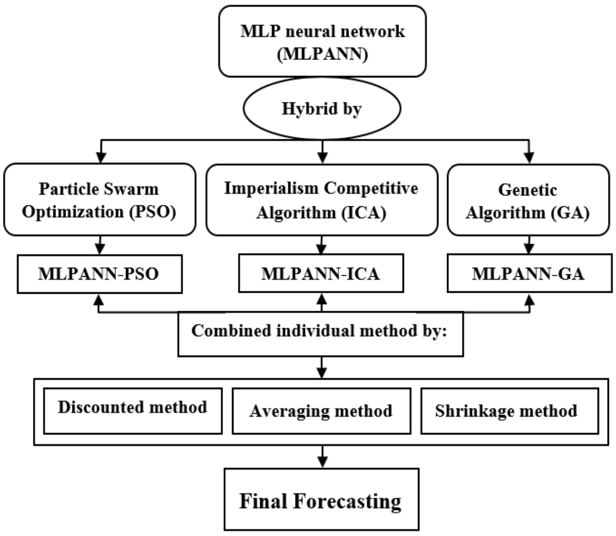



**Figure 2- Illustration of the proposed combination method**

There steps of performance of the proposed method are as below:

1) Inserting data to three hybrid methods of MLPANN-EA; after several times of training and testing, and then get the forecasted data from each of them separately.

2) Applying three combination approaches to adjust the weight coefficients between the three hybrid methods;

3) Comparing the proposed combined method with the other three individual using the criteria of Root Mean Square Error (RMSE).

## Hybrid methods of Multilayer Perceptron Neural Network with evolutionary algorithms

In order to overcome limitations related to ANN training, i.e. powerful technique for training, several different types of training algorithms are developed. Hybrid methods of combination ANNs with evolutionary algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) and imperialism competitive algorithm (ICA) are capable of adjusting the weight and bias of ANNs, moreover, these approaches have been widely used in the prediction of economic variables (Karimi and Yousefi, 2012; Amiri *et al*., 2015; Mollaiy-Berneti, 2015; Khandelwal *et al*., 2017; Jahed Armaghani *et al*., 2017).

In this study, three types of evolutionary algorithms, including GA, PSO and ICA are employed as a training algorithm for training multilayer perceptron neural network and updating the weights and biases.

## Multilayer Perceptron Neural Network (MLPNN)

The MLPNN is formed from a group of elements known as ‘neurons’ or ‘nodes’ that place at least in three types of layers including an input layer, a hidden layer and an output layer. The input layer contains the independent variables and the output layer receives the dependent variable. The number of neurons in the input and output layers shows the number of independent variables used for forecasting and a variable to be forecasted, respectively. The hidden layer is placed between the input and output layers and contains processing neuron. A hidden layer is enough to resolve similar or more complex problems. The most public method to determine the number of nodes per hidden layer is trial and error approach. The mathematical formulation of the relationship between the inputs ($x_i$) and the output (y) as follows:

$$y = f(b + \sum_{i=1}^{k} w_i x_i) \quad (1)$$

Where y is the output vector, $x_i$ the input vector, $w_i$ the weight of the neural model, b the bias, and f is the activation function. This activation function can take many forms. Suitable approach for the determination of activation functions of layers are through testing (Sangwan *et al*., 2015; Amiri *et al.*, 2015; Heddam, 2016; Johns and Burkes, 2017; Pham Dieu *et al.*, 2017; Mohammadi Ghahdarijani *et al*., 2017). In this work, the activation functions of both the input and hidden layers and the output layer are hyperbolic tangent sigmoid transfer function (tansig) and linear transfer function (purelin), respectively (Lazzus, 2011).

## Evolutionary Algorithms

### Genetic Algorithm (GA)

Genetic algorithm (GA) is one of the optimization methods, which is developed by Holland (1975). Genetic algorithm is a stochastic and heuristic search technique based on the biological evolution's process of in natural and imitates from the mechanic of natural genetics. This algorithm designed to solve complex problems of linear and non-linear optimization using the generation of potential solutions (Raikar *et al*., 2016; Kisi *et al*., 2017).

### Particle Swarm Optimization (PSO) Algorithm

The Particle Swarm Optimization (PSO) algorithm is a stochastic-population-based evolutionary computer algorithm is applied for the solution of complex and nonlinear optimization problems. PSO algorithm is inspired from social behavior of some animals such as fish schooling and bird flocking in nature. Some benefits of PSO algorithm are the ability of searching the spacious optimum with high convergence rate, simple and inexpensive coding, and the compatibility with the value change of the best group (Gaur *et al*., 2013; Chandrasekaran and Tamang, 2017)

### Imperialist Competitive Algorithm (ICA)

Imperialist Competitive Algorithm is a novel meta-heuristic evolutionary algorithm to solve various optimization problems that was developed by Atashpaz-Gargari and Lucas (2007). ICA, as a global search population-based technique, is inspired from the social-political behavior of human and uses the advantages of political, cultural and social evolution in optimization processes. ICA method is very similar to genetic algorithm and has upper ability to obtain the convergence rate and the optimal solution (Jahed Armaghani *et al*., 2017; Kisi *et al*., 2017)

## Combination Forecast Methods

The topic of combined forecasting method is the process of merging information related to the individual methods that can improve the forecast reliability of economic variables, such as prices. It is important to determine the weight coefficients of each single method in the combined method, so that with obtaining suitable weight coefficients can attain good forecasting outputs. The combined forecasting method states that if there exist three kinds of forecasting individual methods (hybrid methods) including MLPANN-GA, MLPANN-ICA and MLPANN-PSO, they can be added up as follows:

$$\begin{aligned}\hat{Y}_{combined(t)} &= \omega_1 \hat{Y}_{MLPANN-GA(t)} \\ &+ \omega_2 \hat{Y}_{MLPANN-PSO(t)} \\ &+ \omega_3 \hat{Y}_{MLPANN-ICA(t)}\end{aligned} \quad (2)$$

Where $\hat{Y}_{combined(t)}$, $\hat{Y}_{MLPANN-GA(t)}$, $\hat{Y}_{MLPANN-PSO(t)}$ and $\hat{Y}_{MLPANN-ICA(t)}$ are the forecasting outputs at period t by the combined method, MLPANN-GA, MLPANN-PSO and MLPANN-ICA, respectively, and $\omega_i$ (i = 1, 2, 3) is the weight coefficient allocated to MLPANN-GA, MLP-ANNPSO and

MLPANN-ICA methods at period t, respectively; with the assumption of $\sum_{i=1}^{3}\omega_i = 1$.Weight coefficient depends on the historical performance of each hybrid methods, thus, sample data divided into two periods. First period contains data that only are used for estimation and training of each hybrid methods: [1, T], and second data are used for computing weight coefficient and final forecasting: [T+1, …, n] (Stock and Watson, 2004; Rapach and Strauss, 2009; Yang *et al*., 2016). In the present paper, we consider out-of-sample combination forecasts of monthly price of meat types in Iran. For each hybrid methods, let $Y_t$ be the price of meat types (beef, lamb and chicken).

Next subsection describes four types of combined methods that are considered in this paper. The difference between these methods lies in how historical information is used to compute the combination forecast.

**Simple averaging method**

The first class of combined methods is simple averaging schemes. This method divides to three categories: the mean, median, and trimmed mean. The mean method is equally distributing the weight coefficients in the combined method, so that in Eq. 2 $\omega_1 = \omega_2 = \omega_3 = 1/3$ is allocated. In most cases, the equal weight coefficients may not have the appropriate forecasting outputs. The median method is the set median of $\hat{Y}_{MLPANN-GA(t)}$, $\hat{Y}_{MLPANN-PSO(t)}$ and $\hat{Y}_{MLPANN-ICA(t)}$. In the trimmed mean method, through $\hat{Y}_{MLPANN-GA(t)}$, $\hat{Y}_{MLPANN-PSO(t)}$ and $\hat{Y}_{MLPANN-ICA(t)}$, for each other with the smallest and largest values, the set of $\omega_i = 0$. Whereas there exist three hybrid methods, the results of both median method and trimmed mean method is similar (Stock and Watson, 2004; Rapach and Strauss, 2009; Yang *et al*., 2016).

**Discounted method**

According to the basic framework of Stock and Watson (2004), the discounted method uses the following weight coefficients:

$$\omega_i = n_i^{-1} / \sum_{j=1}^{3} n_j^{-1} \quad (3)$$

$$n_i^{-1} = \sum_{s=T+1}^{T+n} \gamma^{T+n-s} (Y_s - \hat{Y}_{i.s})^2 \quad (4)$$

Where $\gamma$ is a discount factor, $Y_s$ is actual values of out-of-sample and $\hat{Y}_{i.s}$ is forecasting values of out-of-sample for each hybrid method. In this method, greater weights are allocated to hybrid methods that have lower RMSE values (Stock and Watson, 2004; Rapach and Strauss, 2009; Costantini and Pappalardo, 2010). By following from Stock and Watson, (2004), we consider values of .9, 0.95 and 1.0 for discount factor.

**Shrinkage method**

The weight coefficients of shrinkage method are based on the average of the OLS estimator of the weights. Shrinkage method takes the form:

$$\omega_i = \mu\hat{\beta}_i + (1-\mu)(1/m) \quad (5)$$

$$\mu = \max\{0.1 - k[m/(t-(T+1))]\} \quad (6)$$

Where $\hat{\beta}_i$ is the ith estimated coefficient from OLS regression of $Y_s$ on $\hat{Y}_{MLPANN-GA(t)}$, $\hat{Y}_{MLPANN-PSO(t)}$ and $\hat{Y}_{MLPANN-ICA(t)}$, imposing an intercept of zero (no intercept). In Eq. 6, m is the number of hybrid methods (m=3) and k is a constant amount that conducts shrinkage method towards same weighting (Stock and Watson, 2004). By following from Stock and Watson (2004) for k is consider amounts of 0.25, 0.5, 0.75 and 1.0.

**Forecasting criteria**

Forecasting combination methods are typically assessed using standard statistical. In this study, Root Mean Square Error (RMSE) was used. This criteria measure the deviation between the actual and forecasted data, so that the model with the lowest value of RMSE is denoted as the best model. Detailed descriptions and definitions of this performance criteria is can be calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (7)$$

Where, $Y_i$ is the actual value, $\hat{Y}_i$ is the forecasted value, $\bar{Y}_i$ is the mean of the actual value and n represents the time period of forecasting (Das and Padhy, 2015; Yang *et al*., 2016; Jahed Armaghani *et al*., 2017). To obtain the results of the applied methods, this study utilized MATLAB software.

## Dataset

In this study, the data required for analysis consists of both dependent and independent variables. The dependent variable under investigation pertains to the prices of agricultural goods, specifically focusing on the prices of various meat types in Iran. On the other hand, the independent variables comprise lagged prices, which exert an influence on the prices of agricultural commodities. To identify these lagged prices, an Autoregressive model (AR) was employed. For the monthly price data of beef, lamb, and chicken, the optimal lag lengths were determined as follows: a lag of 3 months for beef, a lag of 2 months for lamb, and a lag of 4 months for chicken. The dataset used in this study encompasses monthly price observations for these meat types, spanning the time period from April 2001 to March 2021. The data of prices of meat type for this study consist of beef, lamb and chicken in agricultural market and these data were collected from Ministry of Agriculture in Iran (2021). The statistical descriptions of three agricultural commodity prices are shown in Table 1. This table describes the data set of prices in terms of mean, maximum, minimum, standard deviation, kurtosis (measure of flatness of the distribution), and skewness (degree of asymmetry of a distribution near its mean). Examining the minimum and maximum of prices indicate a big difference between them. Also, the mean, standard deviation, skewness and kurtosis show that prices demonstrate high fluctuation. In totality, the data description in Table 1 present the data have high variation.

**Table 1- The statistical descriptions of real prices of beef, lamb and chicken**

| Parameter | Beef | Lamb | Chicken |
|---|---|---|---|
| Mean | 277295.6 | 296770.2 | 62434.67 |
| Median | 111845.5 | 143985.5 | 33722.5 |
| Maximum | 1440806 | 1458052 | 308717 |
| Minimum | 21389 | 21368 | 8943 |
| Std. Dev. | 337085.4 | 363096.8 | 66963.78 |
| Skewness | 1.79 | 1.71 | 2.1 |
| Kurtosis | 5.42 | 4.84 | 7.04 |
| Jarque-Bera | 195.56 (0.00) | 158.77 (0.00) | 356.74 (0.00) |

Source: Research findings

Note: Value of prices are expressed in Iranian Rials

For assessing the forecasting performance of new proposed method, respectively, 80 and 20 percent of data was distributed to training and testing sets. Also, the normalization of data to ensure the variation uniform of input variables and prevent variable scattering was followed as Equation 8: (Hooshyaripor *et al*., 2015; Shojaie *et al*., 2016):

$$Z_i = \frac{2(Y_i - Y_{min})}{(Y_{max} - Y_{min})} - 1 \qquad (8)$$

## Results

### The forecasting results of hybrid methods

Hybrid methods structure due to its impacts on the estimated values, is an important topic that needs consideration. In this study, the determination of hybrid methods structure simultaneously performs in two aspects: MLPNN structure and evolutionary algorithm structure. In current study, prices of meat types (beef, lamb and chicken) were modeled using three different hybrid methods, MLPANN-GA, MLPANN-PSO and MLPANN-ICA. In this work, the evolutionary algorithms of GA, PSO and ICA were used to optimize the connection weights of the MLPANN. In fact, The MPLANN model was trained and optimized by GA, PSO and ICA algorithms to estimate prices of meat type by using of input parameters (the price lag of meat type). Various settings in adjustment of the optimization parameters of these methods (Initializing parameters) is represented in Table 2.

Indeed, the number of neurons in the input and output layers of a Multilayer Perceptron Artificial Neural Network (MLPANN) model corresponds to the number of input and output variables, respectively. However, determining the optimal number of hidden layers and neurons within those layers is a task that depends on the complexity of the problem at hand, and there is no one-size-fits-all method for determining them. Several studies, such as Hornik et al. (1989) and Ahmadi et al. (2015), have demonstrated that a single hidden layer with an adequate number of neurons can often yield favorable accuracy in MLPANN models. In your study, you explored various architectures, specifically 3/2/4-x-1 architectures, with one hidden layer and a varying number of neurons (x ranging from 1 to 10). Here, the 3/2/4 inputs represent the number of effective lag observations for each meat type, namely beef, lamb, and chicken, respectively. The network has one output for each of these meat types, representing their respective prices. After conducting multiple experiments and testing different configurations, it was determined that setting the number of hidden layer neurons to 6 yielded the best results. Through a trial-and-error approach, it was further confirmed that the MLPANN architecture with 3/2/4–6–1 (3/2/4 input units, 6 hidden neurons, and 1 output neuron) produced superior results compared to other parameter values, demonstrating its effectiveness in addressing the problem at hand.

**Table 2- Parameters used in structure of the optimized MLPANN-GA, MLPANN-PSO and MLPANN-ICA**

| The type of method | The type of parameter | Value |
|---|---|---|
| MLPANN | Number of input neurons | Beef: 3/Lamb: 2/Chicken: 4 |
| | Number of hidden neurons | 6 |
| | Number of output neurons | 1 |
| | Training algorithm | GA, PSO and ICA |
| GA | Population size | 150 |
| | Max number of generation | 20 |
| | Recombination rate | 0.15 |
| | Crossover rate | 0.5 |
| | Mutation rate | 0.35 |
| PSO | Number of particles (Swarm size) | 20 |
| | Number of max iteration | 20 |
| | $C_1$ and $C_2$ in Eq. 2 | 2 |
| ICA | Number of initial countries | 20 |
| | Number of initial imperialists | 30 |
| | Number of decades | 20 |
| | Revolution rate | 0.3 |
| | $\xi$ (Zeta) | 0.02 |

Source: Research findings

After determining optimal values of parameter's hybrid methods, three these methods were trained for prices of beef, lamb and chicken. Predicted prices of beef, lamb and chicken in training stage of MLPANN-GA, MLPANN-PSO and MLPANN-ICA methods is shown in Fig. 3, 4 and 5. Also the extent of the match between the observed prices and predicted prices of these meat is shown in Figs. 6, 7 and 8, According to the few number of training data (about 252 observations for each type of meat), can be seen in Figs. 3 to 8 that these hybrid methods institute an acceptable relationship between observed prices and predicted prices and well approximate corresponding prices data. This relationship shows that hybrid methods of MLPANN with evolutionary algorithm has a successful implementation to map the nonlinear behavior of prices (output). Also, from the scatterplots of the simulations are given in Figs. 6, 7 and 8, it is clear that the simulation of three methods for beef prices is better than lamb and chicken prices. In addition, for all three types of meat, the MLPANN-ICA method is better than two other methods in simulation of prices.

In order to compare the performance of three hybrid methods together, the new data sets (remainder 20% which were not used for the training stage) are used as the testing sets. Fig. 9 demonstrate the results of forecasting values of MLPANN-GA, MLPANN-PSO and MLPANN-ICA methods for data of observed prices in test period. It is noted that, considering the 3/2/4 lag of prices of each beef, lamb and chicken as independent variable, 3/2/4 of forecasting values of these methods is cut and 47, 48 and 46 predicted values is remained.

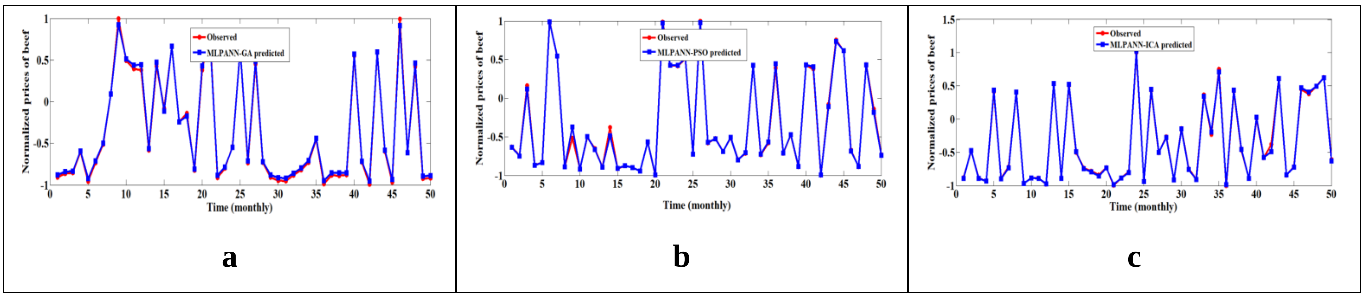



**Figure 3- Graphs of the observed and predicted prices of beef by MLPANN-GA (a), MLPANN-PSO (b) and MLPANN-ICA (c) methods in training period**

Source: Research findings

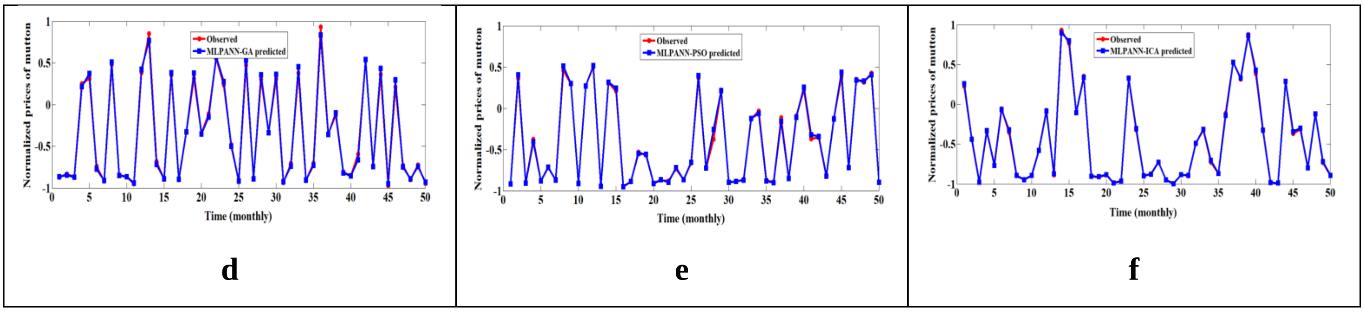



**Figure 4- Graphs of the observed and predicted prices of lamb by MLPANN-GA (d), MLPANN-PSO (e) and MLPANN-ICA (f) methods in training period**

Source: Research findings

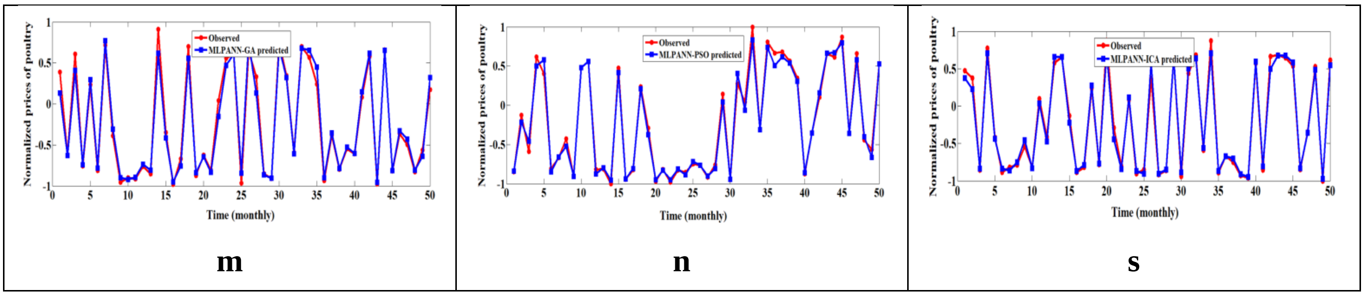



**Figure 5- Graphs of the observed and predicted prices of chicken by MLPANN-GA (m), MLPANN-PSO (n) and MLPANN-ICA (s) methods in training period**

Source: Research findings

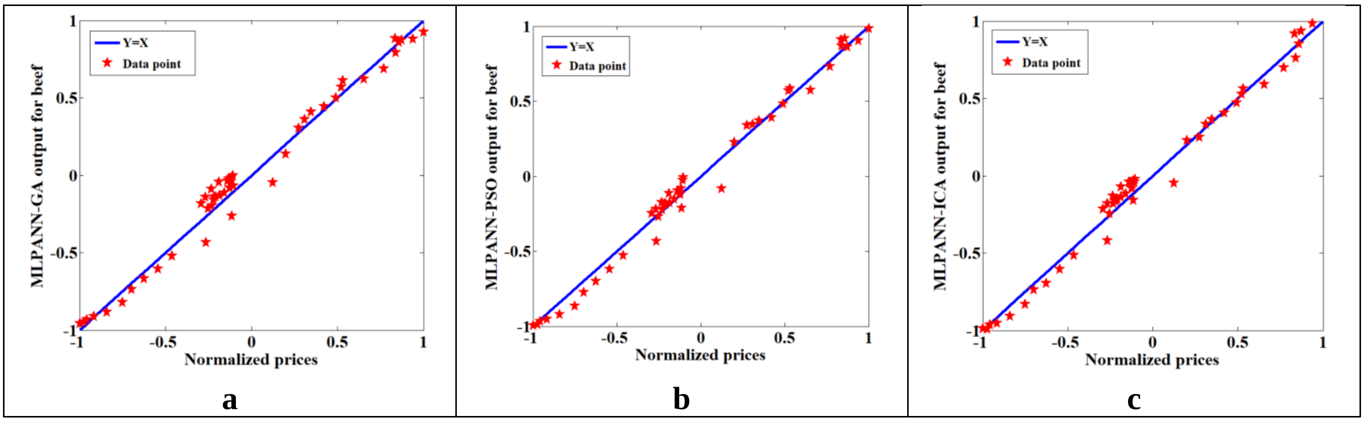



**Figure 6- The performance of predicted prices of beef versus the observed prices by MLPANN-GA (a), MLPANN-PSO (b) and MLPANN-ICA (c) methods in training period**

Source: Research findings

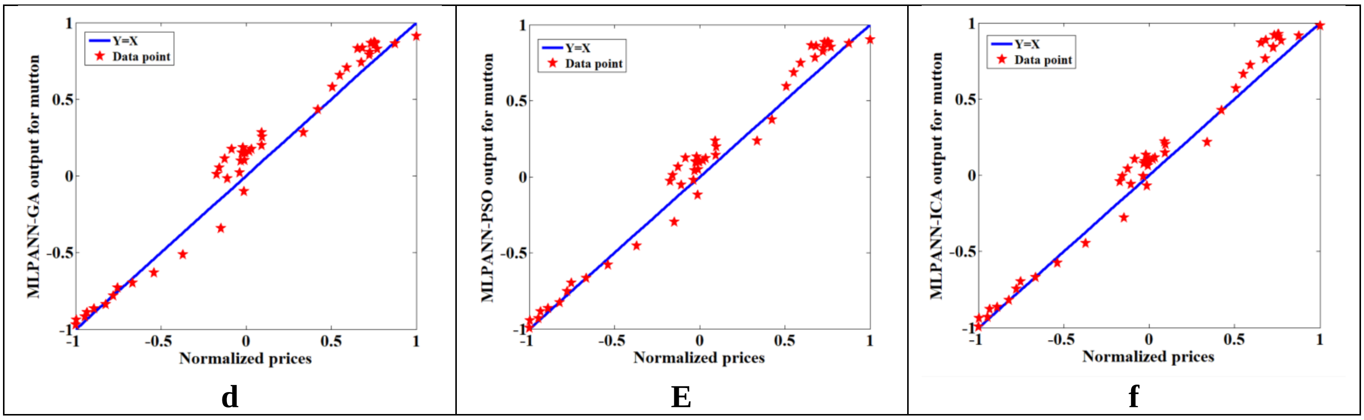



**Figure 7- The performance of predicted prices of lamb versus the observed prices by MLPANN-GA (d), MLPANN-PSO (e) and MLPANN-ICA (f) methods in training period**

Source: Research findings

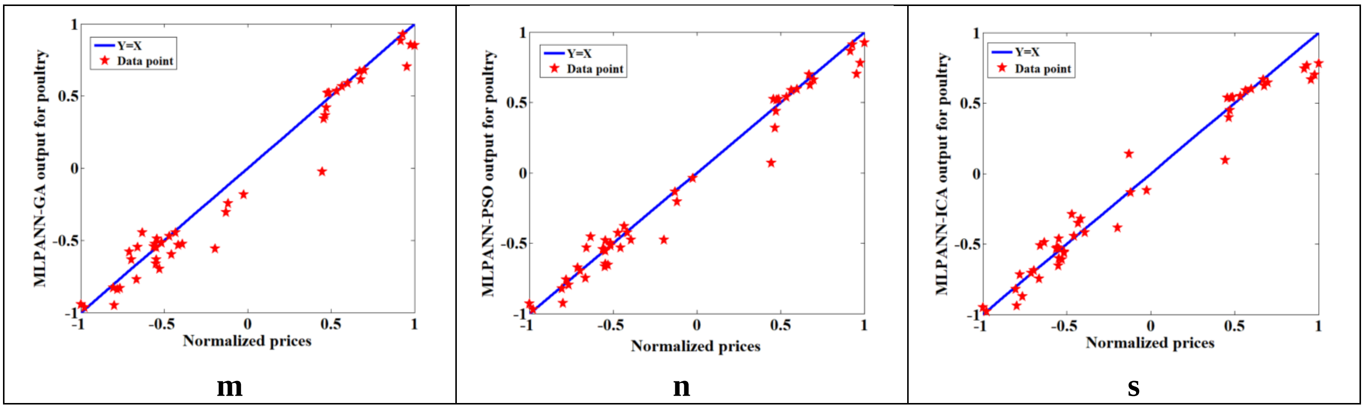
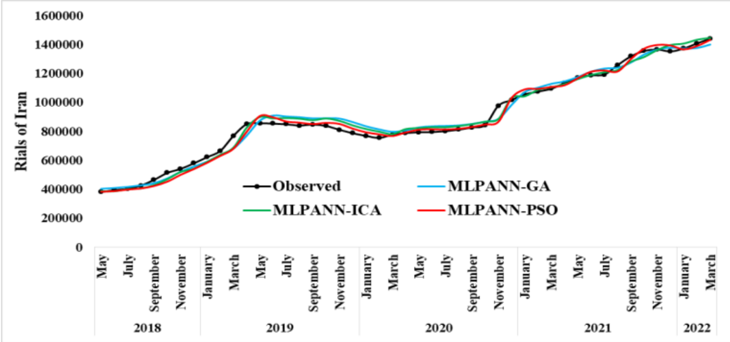


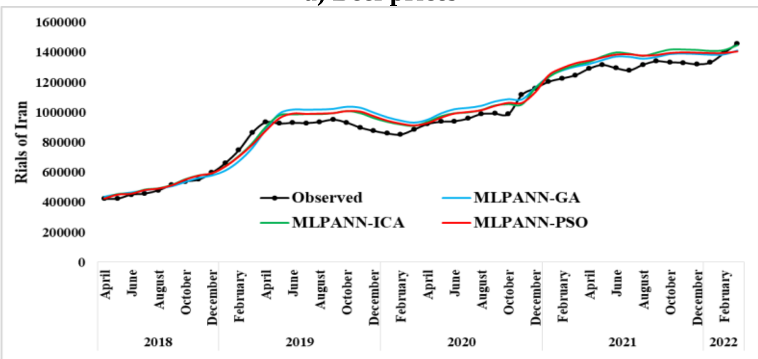

**Figure 8- The performance of predicted prices of chicken versus the observed real prices by MLPANN-GA (m), MLPANN-PSO (n) and MLPANN-ICA (s) methods in training period**

Source: Research findings

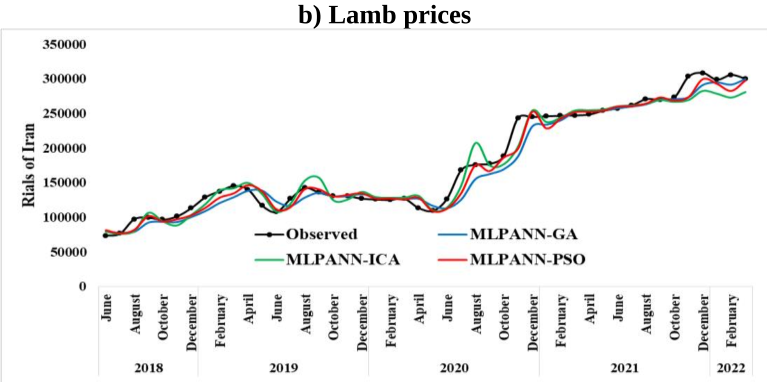
The implementation and accuracy of each hybrid methods were evaluated based on the statistical index of Root Mean Square Error (RMSE). This statistical index is indicated in Table 3. Generally, the results of Fig. 9 and Table 3 indicate all three methods provide fitting estimates for the price of beef, lamb and chicken. Also, it can be seen for beef, based on statistical index of RMSE, the MLPANN-ICA method has the best accuracy in forecasting prices compared with MLPANN-PSO and MLPANN-GA methods. In overall, the use of a type of three these hybrid methods cannot be appropriate to forecast agricultural commodities price, therefore usage of combination method can be suitable.




**a) Beef prices**




**b) Lamb prices**




**c) Chicken prices**

**Figure 9- The results of observed and forecasted values of MLPANN-GA, MLPANN-PSO and MLPANN-ICA methods for prices of beef, lamb and chicken in test period.**

Source: Research findings

**Table 3- The results of accuracy comparison between each hybrid methods using of statistical index of RMSE**

| **Commodity** | Method | RMSE |
|---|---|---|
| Beef | MLPANN-GA | 41410.6 |
| | MLPANN-PSO | 35353.6 |
| | MLPANN-ICA | 34022.5 |
| Lamb | MLPANN-GA | 64452 |
| | MLPANN-PSO | 56211.7 |
| | MLPANN-ICA | 56065.3 |
| Chicken | MLPANN-GA | 15336 |
| | MLPANN-PSO | 14525.6 |
| | MLPANN-ICA | 12496.1 |

Source: Research findings

## The forecasting results of proposed combination methods

In this section, the empirical performance of the combination methods is examined using the testing data set. In fact, combination methods of prices of beef, lamb and chicken for three hybrid methods are analyzed. Used combination methods in this study contain simple averaging method, discounted method and shrinkage method. Simple averaging method consists of two the mean and median methods. Discounted method performs for values of .9, 0.95 and 1.0 for discount factor (γ). In shrinkage method, values of 0.25, 0.5, 0.75 and 1.0 is considered for constant parameter k. Thus, all in all, 9 type of combination methods is utilized. The results of these combination methods for forecasting the prices of beef, lamb, and chicken during the test period are visualized in Fig. 10, 11, and 12.

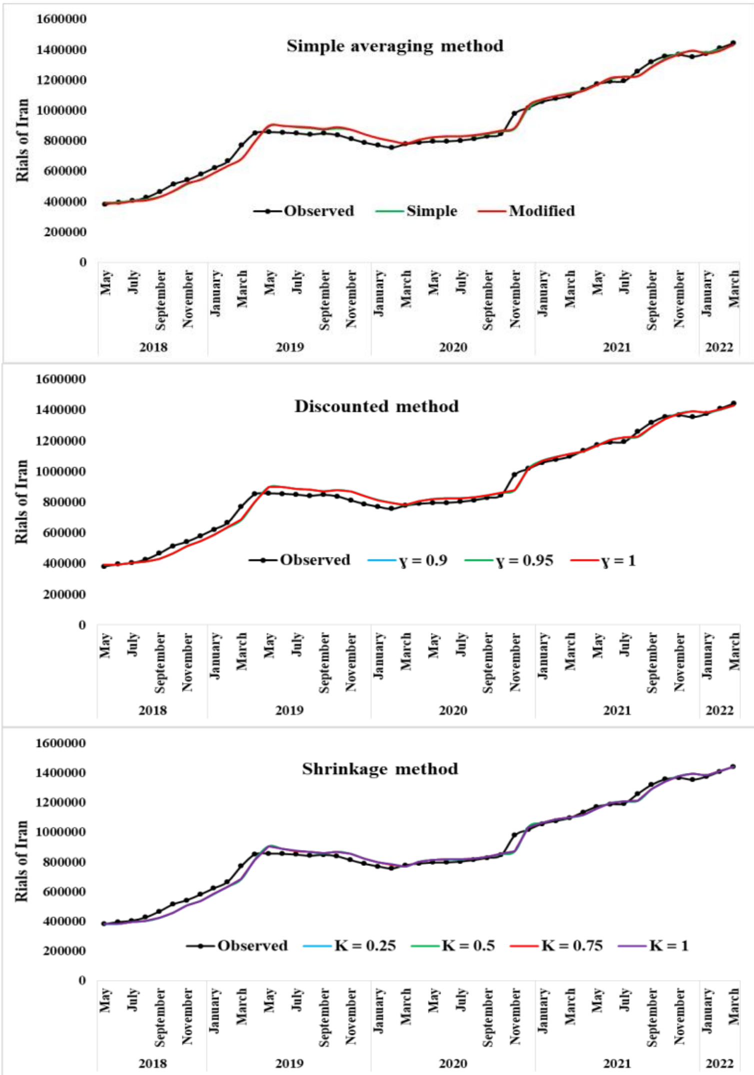



**Figure 10- Final forecasted values for beef price by three combination methods**

Source: Research findings

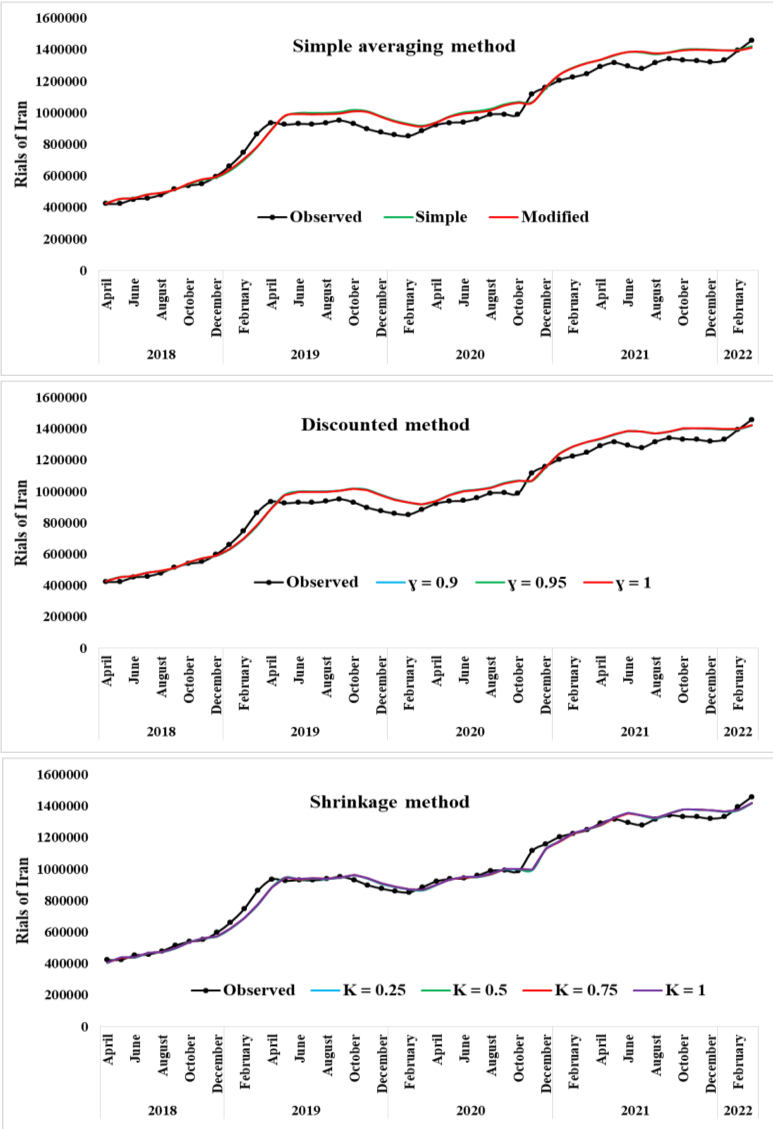



**Figure 11- Final forecasted values for lamb prices by three combination methods**

Source: Research findings

Additionally, Table 4 provides the calculated values of the root mean square error (RMSE) statistical index for the three combination methods. This statistical index helps assess the accuracy and performance of the combination methods in forecasting agricultural commodity prices. Upon observing Fig. 10, 11, and 12, it is evident that the curves generated by the three combination methods closely resemble each other. An accuracy comparison of these three combination methods in Table 4 reveals that, based on the lowest RMSE values, the shrinkage method with K = 0.25 emerges as the most effective combination method for forecasting beef, lamb, and chicken prices. In summary, the shrinkage method outperforms both the simple averaging and discounted methods when it comes to forecasting meat prices

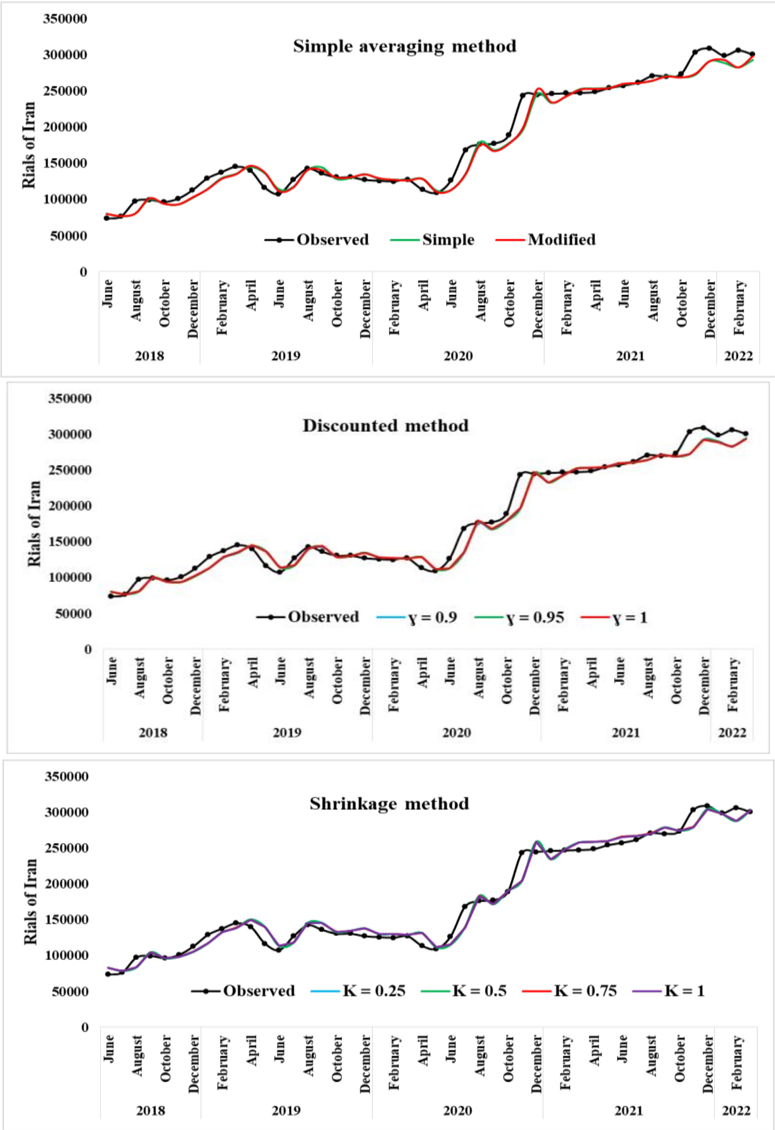



**Figure 12- Final forecasted values for chicken prices by three combination methods**
Source: Research findings

**Table 4- The statistical index of RMSE for three combination methods for beef, lamb and chicken prices**

| Method | Beef | Lamb | Chicken |
|---|---|---|---|
| Simple averaging: The mean method | 34673.9 | 57937.4 | 13007.6 |
| Simple averaging: The median method | 36393.6 | 55946.1 | 12778.9 |
| Discounted method:γ = 0.9 | 34275.7 | 58363.2 | 13038.2 |
| Discounted method :γ = 0.95 | 34198.6 | 57942.8 | 12943.9 |
| Discounted method :γ = 1.0 | 34168.4 | 57504.0 | 12892.5 |
| Shrinkage method:K = 0.25 | 32527.6 | 34909.5 | 11622.1 |
| Shrinkage method:K = 0.5 | 32529.5 | 34935.0 | 11623.4 |
| Shrinkage method:K = 0.75 | 32532.8 | 34977.5 | 11625.7 |
| Shrinkage method:K = 1.0 | 32537.3 | 35036.9 | 11628.8 |

Source: Research findings

## The comparison of results of the proposed combined methods with hybrid methods

To achieve accurate results, the forecasting ability of the combined methods was compared with three hybrid methods. In the more accurate term, the forecasting accurate and ability of three combination methods were compared with each MLPANN-GA, MLPANN-PSO and MLPANN-ICA methods. The results of this comparison are displayed in Fig. 13, 14 and 15; and Table 5. In Fig. 13, 14 and 15, the scattering plot of the best combination method is mapped versus the plot of three hybrid methods. Also, based on the statistical index of RMSE, the forecasting ability of all combination and hybrid methods were ranked in Table 5.

From Fig. 13, 14 and 15, it can be seen that the curves of combination methods were closer to the curve of actual data. That demonstrated that the combined methods outperformed the other hybrid methods.

The results presented in Table 5 reveal that only four of the shrinkage methods exhibit superior accuracy and forecasting capability across all hybrid methods when it comes to predicting prices for beef, lamb, and chicken, as indicated by the RMSE statistical index. Additionally, the ranking of forecasting accuracy for the MLPANN-ICA method surpasses that of the combined methods of simple averaging and discounted methods for beef and chicken prices, while the Simple Averaging (median) method outperforms for lamb prices. Furthermore, in the case of beef and chicken prices, the forecasting performance of two combination methods, simple averaging and discounted methods, exceeds that of the individual methods MLPANN-PSO and MLPANN-GA methods. Finally, MLPANN-GA method has the lowest rank between all the forecasting methods that are used to forecast prices of beef, lamb and chicken. On overall, the new proposed combined method has lower RMSE into MLPANN-GA, MLPANN-PSO and MLPANN-ICA methods. In a nutshell, the aforementioned comparison results confirm that the proposed combined method outperformed the other three hybrid methods as individual methods.

The review of forecasting studies; such as Wihartiko *et al.* (2021), Raflesia *et al.* (2021), Wang *et al*. (2018), Das and Padhy (2015) and Xiong *et al.* (2015); demonstrate that combination and hybrid methods have better performance than traditional methods and the types of ANN models. The comparison of the present paper with the above studies shows that the results of the present paper is consistent with the results of the aforementioned studies regarding the increase in forecasting accuracy when using combined or hybrid models.

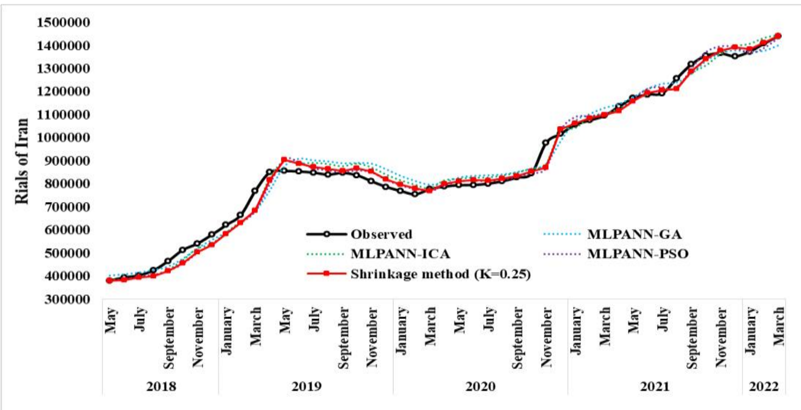



**Figure 13- The comparison of the forecasting ability of shrinkage method with three hybrid methods for beef prices**

Source: Research findings

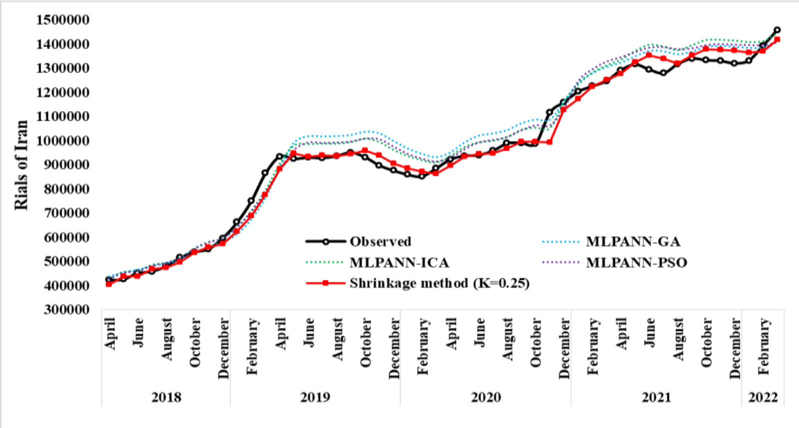



**Figure 14- The comparison of the forecasting ability of shrinkage method with three hybrid methods for lamb prices**

Source: Research findings

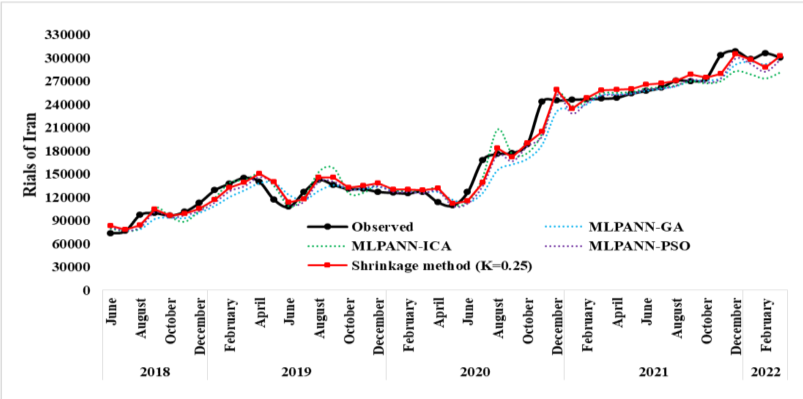



**Figure 15- The comparison of the forecasting ability of shrinkage method with three hybrid methods for chicken prices**

Source: Research findings

**Table 5- Ranking the forecasting ability of combination and three hybrid methods for prices of beef, lamb and chicken**

| Method | | Beef | Lamb | Chicken |
|---|---|---|---|---|
| Combination methods | Simple averaging: The mean method | 9 | 9 | 9 |
| | Simple averaging: The median method | 11 | 5 | 6 |
| | Discounted method:γ = 0.9 | 8 | 11 | 10 |
| | Discounted method :γ = 0.95 | 7 | 10 | 8 |
| | Discounted method :γ = 1.0 | 6 | 8 | 7 |
| | Shrinkage method:K = 0.25 | 1 | 1 | 1 |
| | Shrinkage method:K = 0.5 | 2 | 2 | 2 |
| | Shrinkage method:K = 0.75 | 3 | 3 | 3 |
| | Shrinkage method:K = 1.0 | 4 | 4 | 4 |
| Hybrid methods | MLPANN-GA | 12 | 12 | 12 |
| | MLPANN-PSO | 10 | 7 | 11 |
| | MLPANN-ICA | 5 | 6 | 5 |

Source: Research findings

## Conclusion

In recent years, economic researchers have increasingly focused on forecasting techniques for agricultural commodity prices, aiming to achieve high accuracy and effectiveness. Effective forecasting methods are instrumental in mitigating price risks and fluctuations. This study sought to evaluate the efficacy of a newly proposed combined method for modeling the prices of agricultural commodities, specifically meat types. In this research, various hybrid and combination methods were employed. The study introduced a novel combined-hybrid method comprising six distinct approaches: three hybrid methods functioning as individual models and three strategies for combining these individual methods. Three hybrid methods included MLPNN-GA, MLPNN-PSO and MLPNN-ICA, and three approaches consisted of simple averaging, discounted and shrinkage methods. In fact, in this new method, three different approaches were effectively used to combine the forecasting outputs of MLPANN-GA, MLPANN-PSO and MLPANN-ICA methods together. The combined method can improve hybrid methods' forecasting accuracy and incorporate in their output. Also, because of the combination of the three hybrid methods, the new combined method can effectively forecast prices. The results obtained from three hybrid methods for forecasting the prices of beef, lamb and chicken in Iran show that all three methods provide fitting estimates for prices of beef, lamb and chicken. Also, based on the statistical index of RMSE, the MLPANN-ICA method has the best performance in forecasting prices of beef, lamb and chicken. In overall, the usage of a type of three these hybrid methods cannot be appropriate to forecast agricultural commodities price, therefore usage of combination method can be suitable. The outputs of three combination approach indicated that shrinkage method (with K=0.25) has the highest forecasting accuracy for forecasting prices of beef, lamb and chicken. Finally, by using the same experimental data, the performance of the proposed method was compared with other three hybrid methods. Based on RMSE statistical measure, for beef, lamb and chicken, shrinkage method has higher rank into three hybrid method in forecasting prices. The proposed method has demonstrated its superiority over the other three hybrid approaches. This method exhibits versatility, making it suitable for various cases involving different variables, without necessitating complex adjustments to the combined model. Another noteworthy advantage of this novel combined method is its ability to assign weight coefficients to each individual hybrid method through the utilization of the three aforementioned approaches. However, it is important to acknowledge a significant limitation of this study, which is the scarcity of time series data pertaining to agricultural commodity prices in Iran. With access to a more extensive dataset encompassing a broader range of price data, the results obtained from the novel proposed combination method could potentially be further refined and rendered more accurate.

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# ارائه یک مدل ترکیبی انعطاف‌پذیر برای پیش‌بینی قیمت محصولات کشاورزی؛ مطالعه موردی بازار گوشت ایران

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## چکیده

موضوع قیمت یک عامل کلیدی در فعالیت مالی و تجاری مرتبط با بخش کشاورزی است، به گونه‌ای که همواره فعالان بخش کشاورزی در معرض ریسک‌های ناشی از نوسان قیمت محصولات کشاورزی قرار دارند. این مسئله نه تنها منجر به تصمیم‌گیری نادرست در زمینه تولید بهینه محصولات در سال جاری می‌شود، بلکه می‌تواند اجرای تعهدهای مالی آنان را در سال‌های آتی با خطر روبه‌رو سازد. در سال‌های اخیر، نوسانات قیمت محصولات کشاورزی در ایران افزایش یافته است و لذا پیش‌بینی دقیق تغییرات قیمت ضروری به نظر می‌رسد. در مطالعه حاضر، یک رویکرد ترکیبی انعطاف‌پذیر در پیش‌بینی قیمت ماهیانه گوشت گاو، گوشت گوسفند و مرغ از آوریل ۲۰۰۱ تا مارس ۲۰۲۱ ارائه شده است. در این روش جدید، سه روش ترکیب انفرادی مختلف شامل روش میانگین‌گیری، روش تنزیل شده و روش انقباض برای ترکیب خروجی‌های پیش‌بینی مربوط به سه مدل ترکیبی متشکل از شبکه عصبی پرسپترون (MLPANN) و الگوریتم‌های تکاملی (الگوریتم ژنتیک GA، الگوریتم ازدحام ذرات PSO و الگوریتم رقابت استعماری ICA) مورد استفاده قرار گرفتند. نتایج حاصل از این مطالعه نشان داد که بر اساس شاخص آماری RMSE، مدل ترکیبی پرسپترون- الگوریتم رقابت استعماری (MLPANN-GA) و روش انفرادی انقباضی با (K=0.25) دارای بالاترین دقت در پیش‌بینی قیمت گوشت گاو، گوسفند و مرغ است. همچنین عملکرد مدل پیشنهادی از اجزای آن (مدل‌های ترکیبی) بهتر است. روش پیشنهادی برای پیش‌بینی از نظر نوع محصول یا جایگزینی اجزای تشکیل‌دهنده دارای انعطاف‌پذیری است.

**واژه‌های کلیدی:** پیش‌بینی، قیمت محصولات کشاورزی، گوشت، مدل هیبریدی

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