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Price Forecasting of Feed Raw Materials Used in Dairy Farming: A Methodological Comparison

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Abstract

Milk is a product of strategic importance for countries due to its nutritional value and its status as a priority foodstuff. Feed raw materials represent a critical input item within the dairy cattle sector. It is of great importance for producers to maintain their activities and profitability so that they ensure the balance of milk/feed parity. In countries such as Turkey, where inflationary effects are observed, the prices of feed raw materials are not stable. In an environment characterized by high price volatility, the ability to forecast feed raw material prices is of paramount importance for producers engaged in future planning. In this study, the price forecasting of 43 feed raw materials, which are extensively utilized in the ration preparation process within the dairy cattle sector, was conducted. The efficacy of 11 methods based on time series, statistics and grey system theory was evaluated. Following the assessment of model success criteria, it was determined that the DGM (1,1) method exhibited superior forecasting capabilities compared to exponential smoothing and regression models, as well as other grey forecasting models. Based on MAD, MSE and MAPE values, it can be posited that grey forecasting methods may serve as a viable alternative for price forecasting of feed ingredients.

Keywords Price Forecasting, Exponential Smoothing, Regression Analysis, Grey Forecasting

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Note

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1. Introduction

Milk is a liquid with a distinctive taste, smell, and colour that is secreted by the mammary glands of all mammals with the birth of their offspring and contains nutrients in quantities sufficient to meet the basic needs of the offspring . Milk and dairy products are an important food source for both humans and the offspring of animals. For this reason, the dairy sectors of goats, sheep, buffalo, and cattle continue to develop worldwide. Although production in the dairy sector is increasing, it is becoming increasingly difficult to produce enough products to meet the growing demand for existing livestock. For this reason, countries, especially the US and the EU, are trying to increase the amount of milk per animal by increasing productivity rather than increasing milk production by increasing the number of animals (Aydın et al., 2010).

Dairy animals need nutrients such as water, carbohydrates, proteins, fats, vitamins, and minerals to survive and produce high yields. To meet these requirements, all substances containing organic and inorganic nutrients that can be safely fed to animals are called feed. In the process of increasing yield, the proportional mixture of feeds fed to dairy animals is very important. The feed mixture that fully meets the nutrient requirements of an animal in its daily life is called a ration (Atıcı & Elen, 2024).

In an inflationary environment such as Türkiye, forecasting feed prices offers several benefits to dairy farmers. These benefits manifest themselves in areas such as cost management, production planning, and competitive advantage. Firstly, accurate forecasting of feed prices allows dairy farmers to manage their costs more effectively. In an inflationary environment, feed costs often fluctuate, and this can have a direct impact on farm profitability. By forecasting feed prices, businesses can better plan their budgets and take steps to manage cost increases. For example, companies can base their purchasing strategies on estimated feed prices, reducing the risk of being affected by sudden price increases. Secondly, forecasting feed prices plays an important role in production planning. By taking feed costs into account, dairy farms can set their production targets and use the resources needed to achieve these targets more efficiently. For example, if feed prices are forecast to rise, farms can minimize their costs by increasing their existing feed stocks or by using alternative feed sources. This situation helps companies to optimize their production processes. In addition, forecasting feed prices give farms a competitive advantage. In the dairy sector, keeping costs under control allows farms to adapt more quickly to market conditions. Accurate forecasting of feed prices helps businesses to determine their pricing strategies and remain competitive.

Forecasting is the conceptual name given to the process of using past and present data to form an idea of the probability of an event occurring in the future. For the forecasting process to be accurate, the characteristic structure of the data set to be used in the process of generating information about the future must first be accurately revealed. In the following process, the estimation method suitable for the characteristic structure of the data should be selected, and the estimation should be completed with appropriate computational tools.

In this study, the price of 43 feeds commonly used as nutrient ingredients in the dairy sector was estimated. In the estimation process, 11 estimation methods (4 exponential smoothing, 3 regression, 4 grey estimation) were used. The performance of the prediction results obtained as a result of these 11 methods was evaluated with the Mean Squared Error (MSE), Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE).

Among the methods used in the study, regression analysis, grey estimation, and exponential smoothing methods offer different advantages and disadvantages in the field of data analysis and forecasting. Regression analysis is a powerful tool for identifying relationships between variables; however, the accuracy of the model depends on ensuring the assumptions are met, and it carries the risk of overfitting (P. Vatcheva & Lee, 2016; Shrestha, 2020). Grey forecasting methods are notable for their ability to make effective predictions with little data, but the complexity and accuracy of the model can vary depending on the nature of the data (Chen et al., 2021). Exponential smoothing is effective in capturing trends and seasonality in time series data but has disadvantages such as over-reliance on historical data and insensitivity to sudden changes (Bocsi et al., 2022). As a result, while each method has strengths under certain conditions, it also has certain limitations. Therefore, which method to use depends on the characteristics of the data and the purpose of the forecast. This makes each estimation problem unique and has its dynamics.

The study is structured in six sections. The following section presents a review of the literature on the subject. In the third section, the 11 different forecasting models used in the study and the three methods used for success criteria for the forecasting model are presented in detail. In the fourth section, six-month price forecasts for the period between July 2023 and December 2023 are presented, based on 30 months of data on 43 different dairy cattle feeds in Türkiye. In the fifth section, the findings obtained from the empirical application are discussed, and the last section includes conclusions and recommendations.

2. Literature Review

This section comprises studies on the prices of agricultural products and studies utilizing the Grey Forecasting methodology. A separate literature review is conducted for each topic, and Table 1 presents the studies on price forecasts of agricultural products, while Table 2 presents the studies on the GM(1,1) model within the scope of the Grey Forecasting methodology. A review of the literature on price forecasts of agricultural products indicates that time series-based methods have been employed extensively. In some studies, these methods have been employed for comparative purposes. An analysis of time series-based methods employed in this field reveals the frequent utilization of ARIMA and VAR models with varying lag lengths and specifications. Additionally, studies have been conducted that account for seasonal effects and utilize the ARIMA model under varying seasonal factors. In studies comparing ARIMA, Exponential Smoothing Methods, and VAR models, it is observed that different methods tend to dominate depending on the structure of the data series and the cyclical situation. Following the advent of artificial intelligence (AI) methods that can be applied to time series, models such as recurrent neural networks (RNN) and artificial neural networks (ANN) have also begun to be employed in the forecasting process within this sector. Artificial intelligence forecasting methods, which do not require the fulfilment of preconditions such as stationarity and normality, are regarded as a preferred alternative to time series methods. These methods have been applied to price forecasts of agricultural and livestock products, including wheat (Bessler et al., 2003; Zou et al., 2007; Özdemir & Çılgın, 2022), corn (Xu & Zhang, 2021), milk and meat (Küçükoflaz et al., 2019), and strawberries (Akan & Baylan, 2022). A comprehensive overview of these studies can be found in Table 1.

Table 1. Literature Review on Price Forecasting of Agricultural Products

Author(s)	Forecast Variable	Method
Brandt & Bessler (1984)	Pork Prices	ARIMA, VAR Models
Kling & Bessler (1985)	Fork, Oil, Corn Prices and Macroeconomic Indexes	AR, VAR, Exponential Smoothing Models
Kohzadi et al. (1996)	Timber Prices	RBF and MLP ANN, ARIMA, ETS, BATS, TBATS Models
Bessler et al. (2003)	Wheat Prices	VAR, Error Correction Models
Zou et al. (2007)	Wheat Prices	ARIMA and ANN Models
Shahwan & Odening (2017)	Fork and Canola Prices	ARIMA, ENN and Hybrid Models
Zong & Zhu (2012)	Rice, Oil, Soy Bean Oil, Flour, Sugar, Egg and Meat Prices	RBF and BP NN Models
Jha et al. (2013)	Soy Bean, Canola Oil Prices	ANN and ARIMA Models
Ahumada & Cornejo (2016)	Corn, Wheat and Soy Bean Prices	EqCM, DEqCM, Equilibrium Correction, Random Walking Models
Anggraeni et al. (2017)	Rice Price	ARIMAX, VAR Models
Gülerce & Ünal (2017)	Oil, Corn, Soybean, Wheat and Sugar Prices	ARMA, VARMA Models
Can & Gerşil (2018)	Cotton Prices	ANN and Time Series Methods
Küçükoflaz et al. (2019)	Milk, Meat Prices	ARMA Model
Weng et al. (2019)	Cucumber, tomato and Eggplant Prices	ARIMA and RNN Models
Yıldız & Atış (2019)	Dried Fig Export Prices	ARMA Model
Erdoğan (2021)	Peach Export Prices	Box-Jenkins Models
Xu & Zhang (2021)	Corn Prices	RNN Models
Akan & Baylan (2022)	Strawberry Prices	ARIMA Models
Özdemir & Çılgın (2022)	Wheat Prices	ARIMA, ANN and SVR Models
Akdemir & Çebi (2023)	Raisin and Fig Prices	ANN Model
Özden (2023)	Agricultural Input Prices	ARIMA, SARIMA, LSTM, CNN Models

In situations where there is ambiguity or a lack of comprehensive data regarding a given data set, grey forecasting models are among the most commonly employed techniques. Grey forecasting models, which are capable of utilizing a minimum of four observation values, can facilitate short-term forecasting in instances where access to a comprehensive data set is unavailable. The aforementioned capability renders grey forecasting models applicable to a plethora of fields, including finance, manufacturing, health, energy, logistics, and food. The model can be applied to data sets of any structure, whether univariate or multivariate. The diversity of grey forecasting models has led to a vast body of research literature. Grey forecasting models are frequently compared with their variations, as well as with forecasting models with disparate baselines. These models have been employed to forecast a range of economic variables, including vegetable prices (Jia, 2024), stock prices (Huang & Jane, 2009), USD-Euro parity (Kayacan et al., 2010), and housing prices (Liu & Li, 2019). The applications of grey forecasting models are numerous and diverse. They have been used to predict a range of variables, including economic growth rates (Wang & Le, 2019), cryptocurrency prices (Şahin & Bağcı, 2020), and credit risk (Aksoy & Gençtürk, 2024). For further details of these studies, please refer to Table 2.

Table 2. Literature Review on Studies Utilizing GM (1,1) Models

Author(s)	Forecast Variable	Method
Jia (2024)	Supermarket Vegetable Prices	GM (1,1) Grey Verhulst and Fourier Series Models
Huang & Jane (2009)	Stock Prices	ARX and GM (1,1) Models
Wu & Wang (2009)	Mean Absolute Percentage Error Minimization	DGM (1,1)
Kayacan et al. (2010)	USD-Euro Parity	GM (1,1), Grey Verhulst and Fourier Series Models
Yıldırım & Kesintürk (2015)	Credit Card Usage Statistics	Genetic Algorithm Based GM (1,1)
Fan et al. (2018)	Natural Gas Demand	EDGM (1,1)
Li et al. (2018)	Grain Yield Prediction	DGM (1,1)
Ömürbek et al. (2018)	Commercial, Investment and Islamic Banks Profitability	GM (1,1) Model
Yang et al. (2018)	Disease Incidence Trends	ODGM (1,1)
Javed et al. (2020)	Inbound and Outbound Tourism	EGM (1,1)
Liu & Li (2019)	Residence Prices	GM (1,1) Model
Rathnayaka & Seneviratna (2019)	Gold Price Demands	ODGM (1,1)
Wang & Le (2019)	Economic Growth Rate of Asian and African Countries	GM (1,1) Model
Wu et al. (2019)	Economic Indicators	ODGM (1,1)
Yu (2019)	Adaptive Variable Weight Accumulation Model	DGM (1,1)
Norouzi & Fani (2020)	Opet Cruel Oil	GM (1,1) Models
Şahin & Bağcı (2020)	BTC, IOTA, XRP and ETH Crypto Prices	GM (1,1) and Rolling GM (1,1) Models
Arsy (2021)	Demand Forecasting of Toyota Avanza Cars	EGM (1,1)
Zhao et al. (2021)	Agricultural Sustainability	EGM (1,1)
Zhou & Ding (2021)	Seasonal Time Series Forecasting	EDGM (1,1)
Li et al. (2023)	Cotton Exports	DGM (1,1)
Manickam et al. (2023)	Gold Prices	GM (1,1), Grey Verhulst and GM (2,1) Models
Singh et al. (2022)	BTC, Bionic, Cardano, Dogecoin, ETH, XRP Crypto Prices	GM (1,1) and EGM (1,1) Models
Tulkinov (2023)	Electricity Production from Coal and Renewables	EGM (1,1)
Xu et al. (2023)	Asset Price Forecasting	ODGM (1,1)
Aksoy & Gençtürk (2024)	Credit Risks of Banks in COVID-19 Term	GM (1,1) Model

Table 2 demonstrates the efficacy of grey forecasting models in price forecasting. A review of the literature on price forecasting of agricultural products and grey forecasting models reveals no studies in which grey forecasting methodology has been employed in the price forecasting of agricultural products. This study estimates the prices of agricultural products commonly used in animal feeding using both commonly used models and grey forecasting models. It represents a novel contribution to the literature in terms of estimating the prices of feed raw materials used in the dairy cattle sector with grey forecasting methods.

3. Methodology

The field of forecasting is divided into two main groups: qualitative forecasting and quantitative forecasting. The input data for quantitative approaches is typically collected at various time intervals. An effective analysis of the data is the foundation of these methods (Çuhadar, 2006). A time series is defined as a series of data points that represent the distribution of variables over a specified period, such as a day, week, month, season, or year. In the context of forecasting with time series, the number of observations and variables in the data set represents a crucial parameter in the selection of the most appropriate method. In the context of forecasting with small datasets, the utilization of methodologies that do not incorporate lag lengths or employ them to a lesser extent is preferable to circumvent the potential for information loss. Conversely, if a bidirectional or causal relationship exists between the variables in the data set, then estimation methods that allow for the use of multiple variable sets should be preferred. The estimation methods employed in the study are elucidated in the following sections.

3.1. Exponential Smoothing Methods

Exponential smoothing methods are a class of forecasting techniques that have gained prominence due to their simplicity, adaptability, and effectiveness in various applications. These methods use weighted averages of past observations, with the weights decreasing exponentially for older data points. The basic variants of exponential smoothing include single exponential smoothing (SES), double exponential smoothing (DES), and triple exponential smoothing (TES), each of which addresses different types of time series data based on their characteristics such as trends and seasonality (Bas et al., 2021; Ramadhan et al., 2023).

Single exponential smoothing is particularly useful for forecasting data without trends or seasonal patterns. It uses a smoothing constant called α, which ranges between 0 and 1, to determine the weight given to the most recent observation (Khairina et al., 2019; Sukardi et al., 2023). The choice of α is crucial, as it directly affects forecast accuracy; a higher α gives more weight to recent observations, making the model more responsive to changes, while a lower α results in a smoother forecast that may lag behind actual trends (Hasan & Dhali, 2017; Manalu et al., 2022). In contrast, double exponential smoothing extends SES by incorporating a trend component, making it suitable for data with a linear trend (Ramadhan et al., 2023; Taylor, 2003). This method adjusts both the level and the trend of the series, allowing for more accurate forecasts in the presence of trends.

Triple exponential smoothing, also known as the Holt-Winters method, further improves forecasting by accounting for seasonality in addition to trends (Bas et al., 2021; Yapar et al., 2019). This method is particularly useful for seasonal data, as it includes a seasonal index that adjusts the forecast based on the seasonal patterns observed in the historical data. The robustness of the exponential smoothing method has been demonstrated in various studies.

3.1.1. Simple Exponential Smoothing Method

The Simple Exponential Smoothing Method is used for forecasting with data that do not contain trend or seasonal patterns. In this method, future periods are found by using Eq. 1 with the averages of past values in an exponentially decreasing logic (Hanke & Wichern, 2014).

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y} \tag{1}$$

It's here;

- $\hat{Y}_{t+1}$: Estimated value for the next period
- Y_t: Actual value in period t
- $\hat{Y}_t$: Forecast value for period t
- α : Smoothing coefficient

is explained as.

3.1.2. Holt (Double) Exponential Smoothing Method

Two coefficients are used in the model. These are α, the smoothing coefficient, and β, the smoothing coefficient for trend estimation (Soysal & Ömürgönülşen, 2010). In the Holt method, the smoothed value (L_t), trend forecast value (T_t) and post-period p forecast value ($\hat{Y}_{t+p}$) are found using Eq. 2, Eq. 3 and Eq. 4, respectively.

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{2}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{3}$$

$$\hat{Y}_{t+p} = L_t + pT_t \tag{4}$$

It's here;

- L_t: Smoothing coefficient
- β: Smoothing coefficient for trend forecasting
- T_t: Trend forecast value
- P: Number of periods to be estimated
- $\hat{Y}_{t+p}$: p post-period forecast value

is explained as.

3.1.3. Multiplicative Holt-Winters Method

In this method, smoothing is performed by taking trend and seasonal factors into account. Calculations are made with 3 different parameters, α, β and γ. The smoothed value (L_t), the trend forecast value (T_t), the seasonality forecast (S_t) and the forecast value after p periods ($\hat{Y}_{t+p}$) are calculated using Eq. 5, Eq. 6, Eq. 7 and Eq. 8 respectively (Makridakis et al., 1998:161):

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{5}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{6}$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{7}$$

$$Y_{t+p} = (L_t + T_t p)S_{t-s+p} \tag{8}$$

It's here;

- s : Length of seasonality
- S_t : Estimation of seasonality
- γ : Smoothing coefficient for seasonality

is explained as.

3.1.4. Additive Holt-Winters Method

The only difference between this method from the previous one is that seasonal indices are added or subtracted in this method, whereas in the previous method, they are multiplied or proportioned (Temuçin & Temiz, 2016). The smoothed value (L_t), trend forecast value (T_t), seasonality forecast (S_t) and forecast value after p periods ($\hat{Y}_{t+p}$) are calculated by Eq. 9, Eq. 10, Eq. 11 and Eq. 12 respectively (Ferbar Tratar, 2015):

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{9}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{10}$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \tag{11}$$

$$F_{t+p} = (L_t + T_t p)S_{t-s+p} \tag{12}$$

3.2. Regression Models

3.2.1. Simple Linear Regression Method

Simple linear regression analysis is a regression model in which the relationship between a single independent variable (x) and the dependent variable (y) is expressed by a linear function. Eq. 13 expresses the time-dependent changes in the data (Beşel & Kayıkçı, 2016)

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 x + e \tag{13}$$

Here,

- $\widehat{\beta}_0$: Constant number
- $\hat{\beta}_1$: Slope of the time variable
- e : Error term
- x : Independent time variable

3.2.2. Polynomial Regression Model

Polynomial regression is a special case of multiple regression with only one independent variable "X". The univariate polynomial regression model is shown in Eq. 14 (Özen et al., 2021)

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 x_i + \hat{\beta}_2 x_i^2 + \hat{\beta}_3 x_i^3 + ... + \hat{\beta}_k x_i^k + e, i = 1, 2, ..., n \tag{14}$$

k is defined as the degree of the polynomial and the model (Ostertagová, 2012)

3.2.3. Linear Regression Model with Seasonal Dummy Variables

The dependent variable does not only depend on the independent variables that represent quantitative values (income, production, prices, etc.). It is also related to the quality of these variables. In other words, the independent variable's characteristics such as gender, race, color, belief, etc. affect the independent variable. For example, if two workers with the same characteristics earn different incomes due to their different genders or beliefs, we talk about a qualitative difference (Kutlar, 1998).

Dummy variables are used in linear regression models to express and estimate the seasonality effect in time series. If there are systematically similar changes in some periods of the time series under consideration, which again systematically affect the mean of the predicted value (the explained variable), then dummy variables can be included as explanatory variables in regression models. The seasonality effect can be tested through dummy variables. The dummy variable is inserted into the regression equation using Eq. 15 (Yamak & Erkan, 2021)

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 D_{it} + e \tag{15}$$

The positioning of the dummy variable in the model is carried out according to the definition shown in Eq. 16

$$D = \begin{cases} 1 \text{ if there is a seasonality effect in period t} \\ 0 \text{ otherwise} \end{cases} \tag{16}$$

By testing whether the coefficient $\hat{\beta}_1$ is statistically significant, the effect of the dummy variable, i.e. the seasonality effect, on the explained variable effect is determined.

3.3. Grey Forecasting Models

Grey system theory refers to an interdisciplinary approach that was introduced by Deng in the early 1980s as an alternative method for quantifying uncertainty (Ju-Long, 1982). Grey theory works with systems characterized by incomplete information and provides effective results in solving problems with small samples and incomplete data (Lin & Liu, n.d.; Şahin & Kılınç, 2022). As noted by Aydemir & Turhan (2022), "Grey relational analysis (GRA), also called grey incidence analysis (GIA), is an important part of grey system theory," which helps in determining the primary and secondary relationships between various factors by calculating the grey relational degree (GRD).

Grey theory is commonly applied in system analysis, data processing, forecasting, decision-making, and system control (Es, 2020; Şahin & Aydemir, 2019). The main purpose of the theory is to analyze the dynamics of uncertain systems that cannot be determined by stochastic or fuzzy methods, utilizing a small amount of data (Liu & Forrest, 2010). Aydemir & Turhan (2022) further emphasize that "GIA models are considered primary components of modern grey system theory," highlighting their significance in contemporary applications. Grey forecasting, a sub-field of grey theory, includes various forecasting methods based on time series and causal relationships. While GM (1,1) and Grey Verhulst models refer to models with one type of data, GM (0,N) and GM (1,N) refer to grey models with N-1 independent variables (Es, 2020)). As stated by Zhang & Luo (2022), "scholars have built the grey relational degree calculation method from various angles, enriching the system of grey relational analysis theory." The forecasting models operating within the Grey System are summarized as follows (Kuzu Yıldırım, 2021).

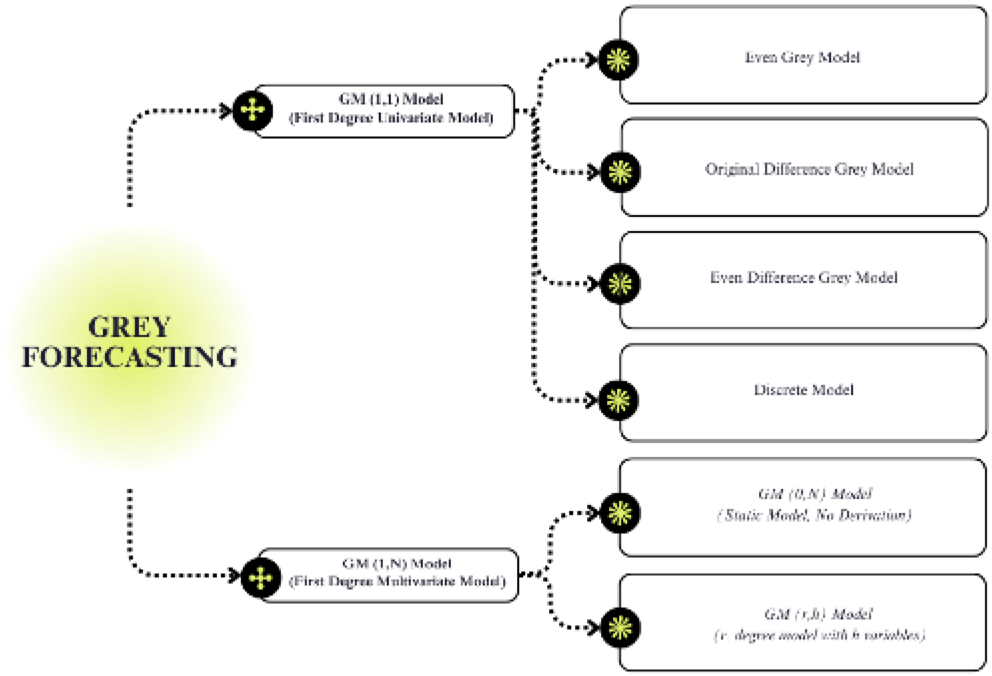

Figure 1. Forecasting Models Based on Grey System Theory

3.3.1. DGM (1,1) Model

The formulation of the DGM (1,1) model, which is the discrete form of the GM (1,1) model, is as follows (Dong & Sun, 2011):

Step 1: The non-negative raw data sequence specified in Eq. 17 is constructed.

$$x^{(0)}(k) \geq 0 \quad (k = 1, 2, ..., n) \tag{17}$$

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\right) \tag{18}$$

Step 2: A cumulative accumulation sequence $X^{(0)}$ of the raw data sequence $X^{(1)}$, called AGO, is constructed.

$$X^{(0)}, X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)\right) \tag{19}$$

Step 3: The DGM difference equation with the estimated parameters β_1 and β_2 is generated.

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2 \tag{20}$$

Step 4: The parameter vector $\hat{\beta} = (\beta_1, \beta_2)^T$ and the matrices B and Y to be used in the process of estimating the parameters are generated:

$$B = \begin{bmatrix} x^{(1)}(1) & \dots & 1 \\ x^{(1)}(2) & \dots & 1 \\ \vdots & \ddots & \vdots \\ x^{(1)}(n-1) & \dots & 1 \end{bmatrix} \tag{21}$$

$$Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix} \tag{22}$$

Step 5: With the help of matrices B and Y, parameters are estimated using Eq. 23 and the least squares method.

$$\hat{\beta} = (B^T B)^{-1} B^T Y \tag{23}$$

3.3.2. Original Difference Grey Forecast ODGM (1,1) Model

The model based on the original difference form of the GM (1,1) model and Eq. 23 is called the ODGM, the original difference model. The estimates of the parameters β_1 and β_2 and the calculation of the matrices B and Y are the same as the GM (1,1) model. The original difference equation is shown in Eq. 24 (Liu & Yang, 2017):

$$x^{(0)}(k) + a x^{(1)}(k) = b \tag{24}$$

3.3.3. Basic Form Grey Forecast EGM (1,1) Model

A "Z series" is defined for EGM (1,1), which is known as the basic form of the grey model. The steps of the model that differ from GM (1,1) are summarized below (Kuzu Yıldırım, 2021)):

Step 1: $Z^{(1)} = \left(z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\right)$ is a series whose values are determined by Eq. 25.

$$z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right) \tag{25}$$

Step 2: The EGM (1,1) model to be used for estimating the parameter vector is constructed by Eq. 26.

$$x^{(0)}(k) + a z^{(1)}(k) = b \tag{26}$$

Step 3: The Y matrix to be used for parameter estimation is the same as the ODGM (1,1) and GM (1,1) matrices. The construction of matrix B is as in Eq. 27.

$$B = \begin{bmatrix} -z^{(1)}(2) & \dots & 1 \\ -z^{(1)}(3) & \dots & 1 \\ \vdots & \ddots & \vdots \\ -z^{(1)}(n) & \dots & 1 \end{bmatrix} \tag{27}$$

Step 4: Estimation of parameters using the Least Squares Method.

3.3.4. Basic Difference Grey Forecasting EDGM (1,1) Model

In this model, forecasts are made using Eq. 28 when based on the cumulative series and Eq. 29 when based on the original observations (Kuzu Yıldırım, 2021):

$$x^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)\left(\frac{1-0.5a}{1+0.5a}\right)^k + \frac{b}{a} \tag{28}$$

$$x\hat{}^{(0)}(k) = \left(\frac{-a}{1-0.5a}\right)\left(x^{(0)}(1) - \frac{b}{a}\right)\left(\frac{1-0.5a}{1+0.5a}\right)^k \tag{29}$$

3.4. Performance Criteria for the Forecasting Model

Performance measures of forecasting models are frequently used in the literature. In this study, the Squared Mean Squared Error (MSE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) are used. The equations related to the criteria used are shown in Eq. 30, Eq. 31 and Eq. 32 respectively (Groebner et al., 2018).

$$\mathrm{MSE} = \frac{1}{N}\sum(y_t - \hat{y}_t)^2 \tag{30}$$

$$\mathrm{MAD} = \frac{1}{N}\sum|y_t - \hat{y}_t\ | \tag{31}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum\frac{|y_t - \hat{y}_t\ |}{y_t} \tag{32}$$

Where y_t is the actual value, $\hat{y}_t$ is the predicted value and N is the number of observations.

4. Application

In this study, future prices of feed raw materials, which are frequently used for cattle feeding in the livestock sector, are forecasted. Exponential smoothing techniques, regression models and grey forecasting models were used in the forecasting process. For each feed, univariate models were constructed separately. At the end of the forecasting, the performance measures of the forecasting models were calculated and the model with the least error was analyzed.

4.1. Data Set and Characteristics of the Data Set

Data set used in the study; monthly prices for 6 roughage, 33 concentrate feeds and 4 by-products between January 2021 and June 2023. For each feed raw material, a time series of 30 months of price data was collected. The number of observations in the dataset, which consists of 43 columns and 30 rows, is 1290.

The prices of feed raw materials were obtained from the monthly press releases of the Afyonkarahisar, Antalya, Burdur, Denizli, Erzurum, Isparta and Konya Commodity Exchanges and the database of the Turkish Feed Industrialists' Association.

Minimum, maximum, mean, standard deviation, variance, skewness and kurtosis statistics were used to understand the characteristic structure of the data set and to prepare it for forecasting models. The descriptive statistics obtained using the R Studio software are presented in Table 3.

The descriptive statistics of the dataset, including skewness and kurtosis, indicate that imported sunflower meal, wheat straw, wet beet pulp, beetroot, rape, carrot, and barley do not have a balanced distribution; they are clustered in the right/left tails or exhibit a skewed distribution. To prepare these datasets for regression analysis, a series of visual inspections were conducted. Linear and polynomial curves, as well as dummy variables, were added to the months in which price fluctuations were observed to obtain the most appropriate curve. R Studio was used to analyze the regression and grey forecasting models, while EViews 10 was employed to apply the exponential smoothing models. The results are presented in detail below.

Table 3. Descriptive Statistics of the Data Set Used for Feed Price Forecasting

Feed Raw Materials	Minimum	Maximum	Mean	Std. Dev.	Variance	Skewness	Kurtosis
Barley	1485	5943	3074	1385	1919	0,877	−0,356
Imported Barley	1441	6665	2445	1458	2126	2411	5244
Sunflower Meal	1769	31605	4617	6485	42051	4182	18151
Bonkalite	1578	6460	3232	1489	2216	0,979	−0,107
Wheat	1980	7452	3611	1661	2759	1249	0,632
Wheat Flakes	3432	11908	6157	2998	8987	0,778	−0,940
Imported Wheat	1988	7300	3458	1648	2716	1372	0,877
Wheat Hay	0,770	2521	1182	0,465	0,216	1658	2402
Wheat Flour	2786	10597	4933	2331	5433	1096	0,288
Rye	1560	6068	3177	1472	2167	0,926	−0,547
DDGS	2694	8160	4607	2004	4017	0,676	−1250
Hazelnut Meal	1335	4062	2415	0,963	0,928	0,572	−1195
Vetch	1300	7700	4572	1797	3230	−0,359	−0,372
Full Full-Fat Soy	4467	12982	7821	3012	9071	0,467	−1550
Carrot	1112	18319	3958	4355	18967	2759	7159
Thin Wheat Bran	1687	4181	2619	0,900	0,810	0,612	−1282
Rough Wheat Bran	1870	4925	3006	0,964	0,929	0,704	−0,593
Blackened Chickpeas	2100	8716	4616	2108	4445	0,463	−0,916
Canola	4725	13124	6064	1897	3597	3253	11012
Bran	1409	4727	2657	0,996	0,993	0,830	−0,381
Fractured Wheat	1609	6093	3177	1322	1747	0,859	−0,224
Molasses	1250	6320	2799	1750	3063	0,878	−0,730
Corn	1760	6339	3450	1444	2086	0,739	−0,856
Corn Grits	3973	7140	4818	0,842	0,709	1330	1488
Corn Imported	1822	6449	3574	1598	2553	0,595	−1156
Corn Bran	2001	5950	3570	1394	1943	0,561	−1246
Corn on the Cob	0,300	3000	1191	1051	1104	0,578	−1600
Corn Silage	0,306	0,923	0,588	0,193	0,037	0,517	−0,916
Cottonseed Meal	2400	6025	3861	1257	1581	0,563	−1258
Beetroot	0,342	5618	3322	1560	2434	−0,168	−1030
Beetroot Meal	1125	6059	3263	1408	1983	0,667	−0,616
Potato	1034	6549	2685	1744	3040	1202	0,294
Rasmol	1745	4583	2872	1024	1049	0,630	−1289
Moist Corn	1501	5634	2737	1280	1639	1045	0,164
Soy	4688	13380	8176	3338	11144	0,511	−1572

Feed Raw Materials	Minimum	Maximum	Mean	Std. Dev.	Variance	Skewness	Kurtosis
Soy Meal	4026	11855	6877	2716	7378	0,542	-1302
Triticale	1480	5909	2963	1353	1830	0,995	0,160
Wet Beet Pulp	0,368	5330	0,869	1067	1139	4240	18540
Clover	1121	3646	2047	0,803	0,645	0,686	-0,900
Clover Hay	0,495	1905	1050	0,392	0,154	0,712	0,063
Oats	1762	4824	2862	0,920	0,847	0,748	-0,675
Oatmeal	4214	15634	8067	3009	9052	1267	0,938
Soft Wheat	1775	6670	3370	1586	2517	0,964	-0,290

4.2. Forecasting of Feed Raw Material Prices

When the prediction studies were analysed, it was found that the training and test groups were divided in different proportions. Petmezas et al. (2022) determined the ratios of training and test groups as 60%:40% in the study using the CNN-LSTM network method, Oladipo et al. (2023) determined the ratios of training and test groups as 60%:40%, 70%:30% in the study using the Neuro-Fuzzy Inference System method, Cahyo et al. (2024) determined the ratios of training and test groups as 80%:20%, 70%:30%, 60%:40% in the study using regression analysis. When the studies were analysed in detail, it was found that no optimal standard ratio was achieved and that these ratios varied depending on the structure of the problem and the data set.

In this study, the forecasting of feed raw materials was conducted using a data set comprising 20 months of observations between January 2021 and August 2022. This data set was divided into two groups: the first group, comprising 66.6% of the data set, was designated as the training data, while the second group, comprising the remaining 10 months of observations (33.3% of the data set), was designated as the test group. In the regression analysis phase, the movements of feed prices over time were analysed, and the most accurate regression curve was determined. It should be noted that changes in feed prices against the independent variable of time are not always linear. The following figures present the movements of wheat hay and wheat flakes feed prices over time in graphical form:

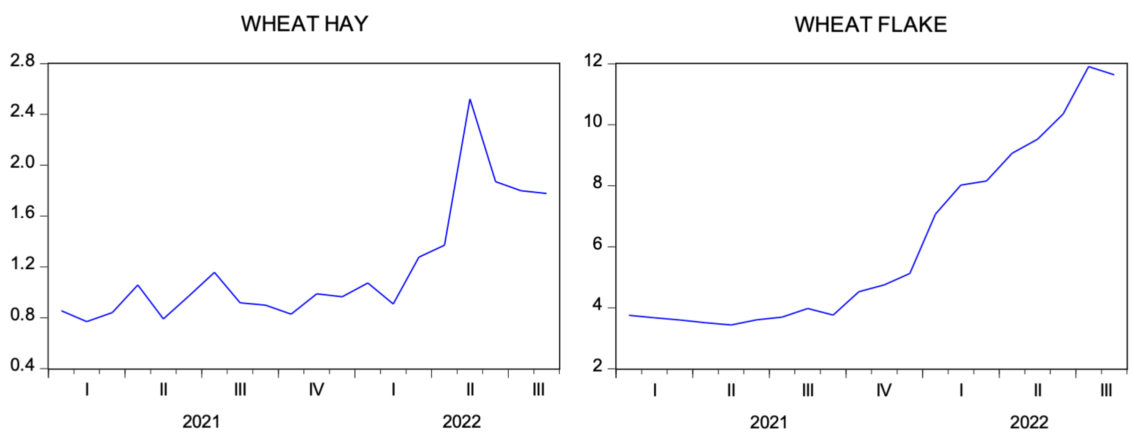

Figure 2. Graphical Distribution of Wheat Hay and Wheat Flake Feed Prices

As demonstrated in the accompanying graphs, the application of a linear curve to forecast the prices of these two feeds will result in inaccurate predictions. This is because the distribution of feeds exhibits a greater resemblance to a polynomial function. To accommodate this phenomenon, quadratic and cubic regression models have been developed for feeds exhibiting such characteristics.

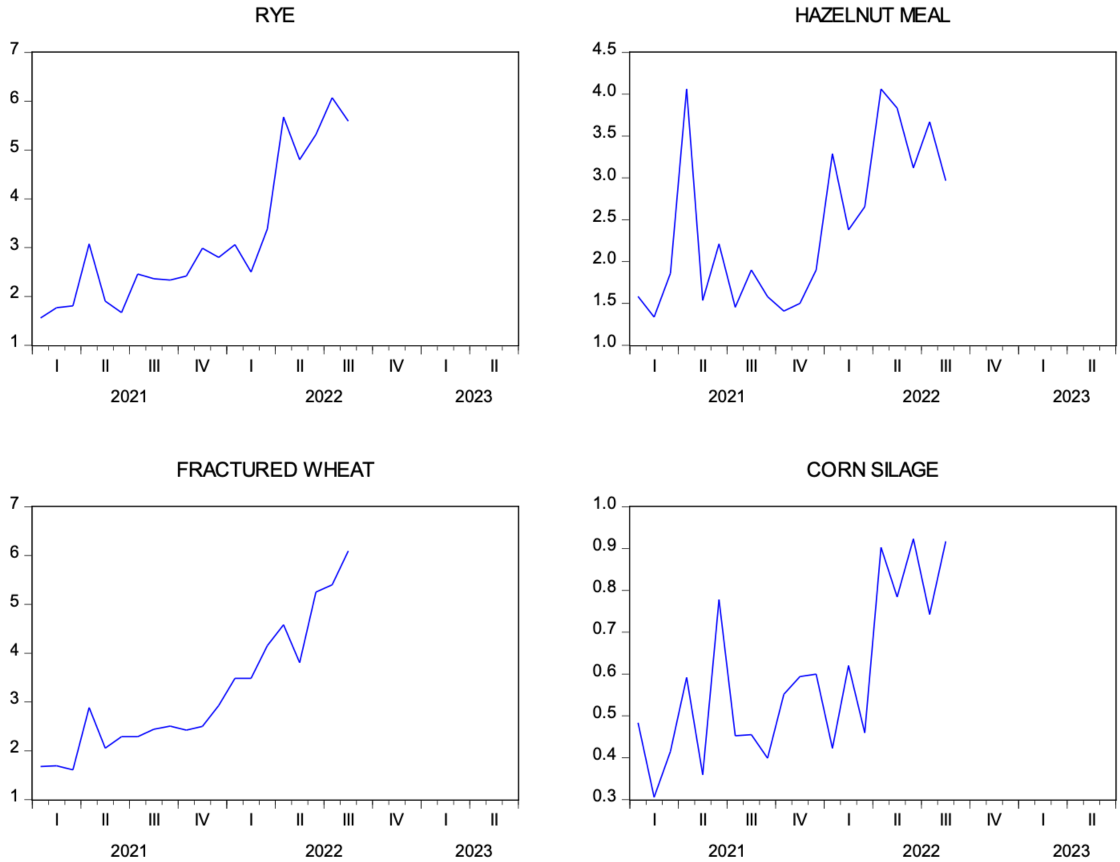

Figure 3. Graphs of Feeds with Seasonality Observed

Conversely, an examination of the graphs reveals a sudden increase in the prices of fractured wheat, corn silage and rye feeds in the fourth month of the year, with a similar trend observed in the sixth month for corn silage feed. Regression models were constructed by incorporating a dummy variable to represent the months of increase observed in the feed groups exhibiting analogous trends to those illustrated in the aforementioned graphical examples. The regression model with a dummy variable is formulated as follows:

$$\hat{Y}(\text{feed price}) = \hat{\beta}_0 + \hat{\beta}_1(\text{dummy})_1 + \hat{e}$$
$$\text{dummy}_i = \begin{cases} 1 \text{ for } i. \text{ month} \\ 0 \text{ for other months} \end{cases} \tag{33}$$

According to this formulation, the months that are considered to affect the dependent variable, i.e. the feed price, are taken as 1 and the other months are taken as 0. In the models formed, the April and June months of the year were added to the model as dummy variables. The results and model parameters of the regression models constructed in line with the above information are shown in Table 4.

Table 4. Results of Regression Analyses for Feed Prices

Depented Variable	Model				B_0			Indepented		
	Type	F-Val.	p-Val.	R^2	Coef.	t-Value	p-Value	Coef.	t-Value	p-Value
Barley Imported	Pol. Reg.	35967	0,000	0,871	0,447	0,716	0,484	Month:0,630	2512	0,023
								Month²:−0,084	−3053	0,008
								Month³: 0,003	3900	0,001
Wheat Hay	Pol. Reg.	18179	0,000	0,681	0,979	4746	0,000	Month:−0,054	−1194	0,249
								Month 2: 0,005	2565	0,020
Corn Grits	LR	11209	0,000	0,384	1381	22726	0,000	Month: 0,017	3348	0,004
Barley	LR	163756	0,000	0,901	0,741	3560	0,002	Month: 0,222	12797	0,000
Sunflower Meal	Pol. Reg.	13683	0,000	0,720	2434	2956	0,009	Month:−0,191	−0,578	0,572
								Month²:0,028	0,777	0,449
								Month³: −0,001	−0,497	0,626
Bonkalite	LR	98711	0,000	0,846	0,802	2876	0,010	Month: 0,231	9935	0,000
Wheat	LR	77672	0,000	0,812	0,955	2776	0,012	Month: 0,253	8813	0,000
Wheat Flake	Pol. Reg.	298323	0,000	0,982	4689	9915	0,000	Month:−0,659	−3462	0,003
								Month²:0,081	3904	0,001
								Month³:−0,001	'−2,269	0,037
Wheat Imported	LR	58628	0,000	0,765	0,899	2359	0,030	Month:0,244	7657	0,000
Wheat Flour	LR	35634	0,000	0,664	1561	2422	0,026	Month:0,321	5969	0,000
Rye	LR (Dummy)	46755	0,000	0,846	1452	2565	0,020	Month:0,218	9217	0,000
								Dummy (April):1,452	3189	0,005
DDGS	LR	93262	0,000	0,838	1351	3511	0,002	Month:0,310	9657	0,000
Hazelnut Meal	LR (Dummy)	21115	0,000	0,713	1185	4596	0,000	Month:0,099	4688	0,000
								Dummy (April):1,885	4633	0,000
Vetch	Pol. Reg.	26849	0,000	0,826	-	-	-	Month:1,811	4361	0,000
								Month²:−0,194	−3080	0,007
								Month 3:0,006	2618	0,018
Full-Fat Soy	LR	151239	0,000	0,894	2768	5904	0,000	Month:0,481	12298	0,000
Carrot	Pol. Reg.	4861	0,14	0,477	−3552	−0,947	0,358	Month:3,264	2163	0,046
								Month²:−0,402	−2437	0,027
								Month³: 0,014	2709	0,015
Thin Wheat Bran	LR	136732	0,000	0,884	1118	7635	0,000	Month:0,143	11693	0,000
Rough Wheat Bran	LR	57420	0,000	0,761	1513	6734	0,000	Month:0,142	7578	0,000
Blackened Chickpeas	LR	90561	0,000	0,834	1198	2924	0,009	Month:0,325	9516	0,000
Canola	Pol. Reg.	20054	0,000	0,790	3852	3722	0,002	Month:1,222	2934	0,010
								Month²:−0,179	−3925	0,001
								Month³: 0,007	4772	0,000
Bran	LR (Dummy)	58832	0,000	0,874	0,936	3992	0,001	Month:0,206	10717	0,000
								Dummy (April):0,735	1985	0,044
Fractured Wheat	LR	100682	0,000	0,848	−0,062	−0,191	0,851	Month:0,227	10034	0,000

* Regression models were analyzed with a significance coefficient of 0.05.

Depented Variable	Model				B_0			Indepented		
	Type	F-Val.	p-Val.	R^2	Coef.	t-Value	p-Value	Coef.	t-Value	p-Value
Molasses	LR	112393	0,000	0,862	1070	4179	0,001	Month:0,227	10602	0,000
Corn	LR	197041	0,000	0,916	0,860	3897	0,001	Month:0,259	14037	0,000
Corn Grits	LR	172028	0,000	0,905	0,224	5940	0,000	Month:0,224	13116	0,000
Corn Imported	LR	52459	0,000	0,745	−0,419	−1652	0,116	Month:0,153	7243	0,000
Corn Bran	LR (Dummy)	16439	0,000	0,659	0,333	5995	0,000	Month:0,022	4,70	0,000
								Dummy (June):0,256	2864	0,011
Corn on the Cob	LR	165049	0,000	0,902	1742	9257	0,000	Month:0,202	12847	0,000
Beetroot	Pol. Reg.	23911	0,000	0,818	2214	2792	0,013	Month:−0,365	−1145	0,269
								Month²:0,063	1808	0,089
								Month³: −0,002	−1700	0,108
Beetroot Meal	LR (Dummy)	24270	0,000	0,741	1070	2987	0,008	Month:0,181	6747	0,000
								Dummy (April):1,094	4165	0,047
Potato	LR	66745	0,000	0,788	−0,062	−0,162	0,873	Month:0,262	8170	0,000
Rasmol	LR	118097	0,000	0,868	1179	6635	0,000	Month:0,161	10867	0,000
Moist Corn	LR (Dummy)	31445	0,000	0,787	0,600	2002	0,048	Month:0,181	7358	0,000
								Dummy (June):1,094	2310	0,034
Soy	LR	122124	0,000	0,934	2645	4632	0,000	Month:0,527	11051	0,000
Soy Meal	LR (Dummy)	51145	0,000	0,857	2342	4572	0,000	Month:0,022	9,69	0,000
								Dummy (April):0,315	3177	0,006
Triticale	LR	88437	0,000	0,831	0,775	2918	0,009	Month: 0,208	9404	0,000
Wet Beet Pulp	Pol. Reg.	6037	0,006	0,531	0,408	2537	0,022	Month:0,501	0,781	0,446
								Month²:−0,006	−0,862	0,402
								Month³: 0,000	1141	0,271
Clover	LR (Dummy)	13624	0,000	0,616	0,9	3581	0,002	Month:0,097	4708	0,000
								Dummy (Feb.): 1,154	2910	0,010
Clover Hay	LR	30363	0,000	0,328	0,499	4366	0,000	Month:0,499	5510	0,000
Oats	LR	44868	0,000	0,714	1482	6309	0,000	Month:0,131	6698	0,000
Oatmeal	LR	50491	0,000	0,737	3482	4730	0,000	Month:0,437	7106	0,000
Soft Wheat	LR	107059	0,000	0,856	0,765	0,664	0,016	Month:0,248	10347	0,000

* Regression models were analyzed with a significance coefficient of 0.05.

Upon analysis of the F statistic values and p-values associated with the models, it becomes evident that the models exhibit a statistically significant outcome. Upon analysis of the regression models utilising seasonal dummy variables, it was observed that the F statistic values and p-values of all models exhibited statistical significance. Additionally, the t-statistic values and p-values of the dummy variables indicated that the dummy variable was statistically significant in forecasting prices. Price forecasts were generated using the coefficients obtained from the regression models. Subsequently, exponential smoothing methods were employed for forecasting purposes, following the regression forecasting stage. The parameters of the exponential smoothing methods obtained through the Eviews 10 package are presented in Table 5.

Table 5. Parameters Results from Exponential Smoothing Models

Price Estimated Feed	Simple Exponential Smoothing Parameter	Holt (Double) Exponential Smoothing Method Parameter	HW- Additive Exponential Smoothing Parameters	HW- Multiplicative Exponential Smoothing Parameters
Barley	α : 0,999	α : 0,474	α: 0,84,β: 0,12,ɣ: 0,10	α: 0,17,β: 1,00,ɣ: 0,07
Imported Barley	α : 0,720	α : 0,658	α: 0,10,β: 0,11,ɣ: 0,05	α: 0,34,β: 0,03,ɣ: 0,17
Sunflower Meal	α : 0,134	α : 0,056	α: 0,13,β: 0,00,ɣ: 0,10	α: 0,15,β: 0,00,ɣ:0,10
Bonkalite	α : 0,999	α : 0,372	α: 0,44,β: 0,39,ɣ: 0,09	α: 0,39,β: 0,18,ɣ: 0,11
Wheat	α : 0,999	α : 0,392	α: 0,85,β: 0,10,ɣ: 0,10	α: 0,69,β: 0,06,ɣ: 0,09
Wheat Flakes	α : 0,999	α : 0,528	α: 1,00,β: 0,16,ɣ: 0,00	α: 0,95,β: 0,14,ɣ: 0,18
Imported Wheat	α : 0,999	α : 0,386	α: 0,32,β: 1,00,ɣ: 0,10	α: 0,29,β: 1,00,ɣ: 0,11
Wheat Hay	α : 0,654	α : 0,230	α: 0,47,β: 0,03,ɣ: 0,10	α: 0,31,β: 0,04,ɣ:0,12
Wheat Flour	α : 0,524	α : 0,178	α: 0,19,β:0,349,ɣ:0,08	α: 0,22,β: 0,220,ɣ:0,10
Rye	α : 0,730	α : 0,254	α: 0,81,β: 0,14,ɣ: 0,10	α: 0,64,β: 0,00,ɣ: 0,10
DDGS	α : 0,999	α : 0,710	α: 0,65,β: 0,97,ɣ: 0,15	α: 1,00,β: 0,09,ɣ: 0,00
Hazelnut Meal	α : 0,398	α : 0,194	α: 0,14,β: 0,57,ɣ: 0,10	α: 0,08,β: 0,45,ɣ: 0,06
Vetch	α : 0,001	α : 0,120	α: 0,23,β: 1,00,ɣ: 0,02	α: 0,13,β: 1,00,ɣ: 0,10
Full Fat Soy	α : 0,999	α : 0,60	α: 1,00,β: 0,08,ɣ: 0,00	α: 1,00,β: 0,04,ɣ: 0,00
Carrot	α : 0,060	α : 0,001	α: 0,03,β: 1,00,ɣ: 0,12	α: 0,00,β: 0,00,ɣ: 0,10
Thin Wheat Bran	α : 0,999	α : 0,512	α: 0,59,β: 0,99,ɣ: 0,10	α: 0,89,β: 0,00,ɣ:0,06
Rough Wheat Bran	α : 0,999	α : 0,999	α: 1,00,β: 0,00,ɣ: 0,00	α: 1,00,β: 0,00,ɣ: 0,00
Black. Chick.	α : 0,999	α : 0,590	α: 1,00,β: 0,27,ɣ: 0,00	α: 1,00,β: 0,3,ɣ: 0,00
Canola	α : 0,632	α : 0,152	α: 0,74,β: 0,05,ɣ: 0,10	α: 0,27,β: 0,00,ɣ: 0,10
Bran	α : 0,752	α : 0,222	α: 0,68,β: 0,01,ɣ: 0,10	α: 0,56,β: 0,00,ɣ: 0,06
Fractured Wheat	α : 0,742	α : 0,266	α: 0,78,β: 0,06,ɣ: 0,10	α: 0,30,β: 0,10,ɣ: 0,08
Molasses	α : 0,999	α : 0,852	α: 1,00,β: 0,02,ɣ: 0,00	α: 1,00,β: 0,01,ɣ: 0,00
Corn	α : 0,999	α : 0,422	α: 1,00,β: 0,45,ɣ: 0,00	α: 0,97,β: 0,00,ɣ: 0,02
Corn Grits	α : 0,274	α : 0,001	α: 0,94,β: 0,01,ɣ: 0,10	α: 0,85,β: 0,02,ɣ: 0,11
Corn Imported	α : 0,862	α : 0,302	α: 0,81,β: 0,04,ɣ: 0,10	α: 0,76,β: 0,00,ɣ: 0,22
Corn Bran	α : 0,999	α : 0,700	α: 1,00,β: 0,05,ɣ: 0,00	α: 1,00,β: 0,02,ɣ: 0,00
Corn on the Cob	α : 0,598	α : 0,276	α: 0,68,β: 0,12,ɣ: 0,10	α: 0,87,β: 0,13,ɣ: 0,09
Corn Silage	α : 0,486	α : 0,212	α: 0,15,β: 1,00,ɣ: 0,10	α: 0,09,β: 1,00,ɣ: 0,26
Clover Hay	α : 0,474	α : 0,017	α: 0,13,β: 0,99,ɣ: 0,14	α: 0,10,β: 0,65,ɣ: 0,11
Oats	α : 0,608	α : 0,270	α: 1,00,β: 0,20,ɣ: 0,00	α: 0,63,β: 0,10,ɣ: 0,28
Oatmeal	α : 0,999	α : 0,448	α: 0,30,β: 1,00,ɣ: 0,11	α: 0,26,β: 0,62,ɣ: 0,10
Soft Wheat	α : 0,830	α : 0,312	α: 0,66,β: 0,16,ɣ: 0,10	α: 0,78,β: 0,02,ɣ: 0,14

* Exponential Smoothing Models were analyzed with a significance coefficient of 0.05.

After the exponential smoothing methods, the estimation phase proceeded with ODGM (1,1), EGM (1,1), EDGM (1,1) and DGM (1,1) methods, which are GM (1,1) estimation methods. The parameter values obtained as a result of the prediction models generated using R Studio are presented in Table 6.

Table 6. Parameters Estimated by GM (1,1) Forecasting Models

Feed Raw Materials	ODGM(1,1)	EGM(1,1)	EDGM(1,1)	DGM(1,1)
Wheat	β_0 = −0,0460	β_0 = −0,0469	β_0 = −0,0469	β_0 = 1,0479
	β_1 = 2,1931	β_1 = 2,2543	β_1 = 2,2543	β_1 = 2,3186
Fractured Wheat	β_0 = −0,0370	β_0 = −0,0374	β_0 = −0,0374	β_0 = 1,0378
	β_1 = 2,1503	β_1 = 2,2017	β_1 = 2,2017	β_1 = 2,2549
Barley	β_0 = −0,0424	β_0 = −0,0432	β_0 = −0,0432	β_0 = 1,0440
	β_1 = 1,9888	β_1 = 0,04	β_1 = 0,04	β_1 = 2,0935
Corn	β_0 = −0,0980	β_0 = −0,0385	β_0 = −0,0385	β_0 = 1,0440
	β_1 = 2,218	β_1 = 2,2687	β_1 = 2,2687	β_1 = 2,0935
Barley FLour	β_0 = −0,0389	β_0 = −0,0393	β_0 = −0,0393	β_0 = 1,0398
	β_1 = 3,2975	β_1 = 3,3881	β_1 = 3,3881	β_1 = 3,4823
Bonkalite	β_0 = −0,0392	β_0 = −0,0398	β_0 = −0,0398	β_0 = 1,0403
	β_1 = 2,1479	β_1 = 2,2024	β_1 = 2,2024	β_1 = 2,2591
Bran	β_0 = −0,0451	β_0 = −0,0448	β_0 = −0,0448	β_0 = 1,0443
	β_1 = 1,6712	β_1 = 1,7663	β_1 = 1,7663	β_1 = 1,8660
Rasmol	β_0 = −0,0394	β_0 = −0,0401	β_0 = −0,0401	β_0 = 1,0409
	β_1 = 1,8517	β_1 = 1,8924	β_1 = 1,8924	β_1 = 1,9347
Sunflower Meal	β_0 = −0,0292	β_0 = −0,0230	β_0 = −0,0230	β_0 = 1,0164
	β_1 = 2,8774	β_1 = 3,3183	β_1 = 3,3183	β_1 = 3,7563
Soy Meal	β_0 = 0,0377	β_0 = −0,0382	β_0 = −0,0382	β_0 = 1,0387
	β_1 = 4,4476	β_1 = 4,5543	β_1 = 4,5543	β_1 = 4,6650
Hazelnut Meal	β_0 = −0,0226	β_0 = −0,0223	β_0 = −0,0223	β_0 = 1,0220
	β_1 = 1,8635	β_1 = 1,9043	β_1 = 1,9043	β_1 = 1,9455
Beetroot Meal	β_0 = −0,0359	β_0 = −0,0359	β_0 = −0,0469	β_0 = 1,0361
	β_1 = 2,3348	β_1 = 2,4	β_1 = 2,2543	β_1 = 2,4691
Potato	β_0 = −0,0622	β_0 = −0,0639	β_0 = −0,0639	β_0 = 1,0657
	β_1 = 1,4089	β_1 = 1,4673	β_1 = 1,4673	β_1 = 1,5299
Corn Silage	β_0 = −0,0675	β_0 = −0,0693	β_0 = −0,0693	β_0 = 1,0710
	β_1 = 0,2326	β_1 = 0,2472	β_1 = 0,2472	β_1 = 0,2632
Clover	β_0 = −0,0510	β_0 = −0,0520	β_0 = −0,0520	β_0 = 1,0531
	β_1 = 1,064	β_1 = 1,1021	β_1 = 1,1021	β_1 = 1,1424
Wheat Hay	β_0 = −0,0663	β_0 = −0,0683	β_0 = −0,0683	β_0 = 1,0704
	β_1 = 0,4631	β_1 = 0,4864	β_1 = 0,4864	β_1 = 0,5080
Rye	β_0 = −0,0386	β_0 = −0,0391	β_0 = −0,0391	β_0 = 1,0395
	β_1 = 2,128	β_1 = 2,1841	β_1 = 2,1841	β_1 = 2,2424
Triticale	β_0 = −0,0112	β_0 = −0,0419	β_0 = −0,0419	β_0 = 1,0426
	β_1 = 1,9292	β_1 = 1,9799	β_1 = 1,9799	β_1 = 2,0327
Oats	β_0 = −0,0399	β_0 = −0,0406	β_0 = −0,0406	β_0 = 1,0413

Feed Raw Materials	ODGM(1,1)	EGM(1,1)	EDGM(1,1)	DGM(1,1)
	β_1 = 1,8715	β_1 = 1,9172	β_1 = 1,9172	β_1 = 1,9648
Wet Beet Pulp	β_0 = −0,01827	β_0 = −0,0091	β_0 = −0,0091	β_0 = 0,9997
	β_1 = 0,733	β_1 =0,8767	β_1 =0,8767	β_1 = 1,0147
Soy	β_0 = −0,0362	β_0 = −0,0368	β_0 = −0,0368	β_0 = 1,0373
	β_1 = 5,4395	β_1 = 5,56	β_1 = 5,56	β_1 = 5,6846
Beetroot	β_0 = −0,0362	β_0 = −0,0368	β_0 = −0,0368	β_0 = 1,0373
	β_1 = 5,4395	β_1 = 5,56	β_1 = 5,56	β_1 = 5,6846
Canola	β_0 = −0,0419	β_0 = −0,0424	β_0 = −0,0424	β_0 = 1,0430
	β_1 = 0,7982	β_1 = 3,9077	β_1 = 3,9077	β_1 = 4,0275
Carrot	β_0 = −0,0747	β_0 = −0,0745	β_0 = −0,0745	β_0 = 1,0737
	β_1 = 0,9952	β_1 = 1,1797	β_1 = 1,1797	β_1 = 1,3863
Barley Imported	β_0 = −0,0496	β_0 = −0,0503	β_0 = −0,0503	β_0 = 1,0509
	β_1 = 1,4691	β_1 = 1,5292	β_1 = 1,5292	β_1 = 1,5927
Corn on the Cob	β_0 = −0,0548	β_0 = −0,0552	β_0 = −0,0552	β_0 = 1,0554
	β_1 = 0,7331	β_1 = 0,7739	β_1 = 0,7739	β_1 = 0,8173
Wheat Imported	β_0 = −0,0440	β_0 = −0,0447	β_0 = −0,0447	β_0 = 1,0455
	β_1 = 2,1627	β_1 = 0,2239	β_1 = 0,2239	β_1 = 2,2879
Vetch	β_0 = −0,0551	β_0 = −0,0546	β_0 = −0,0546	β_0 = 1,0538
	β_1 = 2,4714	β_1 = 2,7195	β_1 = 2,7195	β_1 = 2,9859
Soft Wheat	β_0 = −0,04293	β_0 = −0,0437	β_0 = −0,0437	β_0 = 1,0444
	β_1 = 2,142798	β_1 = 2,2	β_1 = 2,2	β_1 = 2,2608
Clover Hay	β_0 = −0,0559	β_0 = −0,0567	β_0 = −0,0567	β_0 = 1,0575
	β_1 = 0,6655	β_1 = 0,7	β_1 = 0,7	β_1 = 0,7360
Oat Meal	β_0 = −0,0469	β_0 = −0,0479	β_0 = −0,0479	β_0 = 1,0489
	β_1 = 4,81729	β_1 = 4,9511	β_1 = 4,9511	β_1 = 5,0917
Wheat Flake	β_0 = −0,0416	β_0 = −0,0467	β_0 = −0,0467	β_0 = 1,0476
	β_1 = 3,7751	β_1 = 3,8822	β_1 = 3,8822	β_1 = 3,9944
Black. Chick.	β_0 = 0,0405	β_0 = −0,0405	β_0 = −0,0405	β_0 = 1,0404
	β_1 = 3,189	β_1 = 3,3176	β_1 = 3,3176	β_1 = 3,4513
Full Fat Soy	β_0 = −0,0368	β_0 = −0,0374	β_0 = −0,0374	β_0 = 1,0379
	β_1 = 5,2296	β_1 = 5,343	β_1 = 5,343	β_1 = 5,4606
Corn Grits	β_0 = −0,0161	β_0 = −0,0161	β_0 = −0,0161	β_0 = 1,0162
	β_1 = 3,9921	β_1 = 4,0308	β_1 = 4,0308	β_1 = 4,0700
Corn Bran	β_0 = −0,0375	β_0 = −0,0381	β_0 = −0,0381	β_0 = 1,0387
	β_1 = 2,3371	β_1 = 2,3877	β_1 = 2,3877	β_1 = 2,4401
Cottonseed Meal	β_0 = −0,0260	β_0 = −0,0261	β_0 = −0,0261	β_0 = 1,0262
	β_1 = 2,9144	β_1 = 2,9675	β_1 = 2,9675	β_1 = 3,0217
Molasses	β_0 = −0,0455	β_0 = −0,0459	β_0 = −0,0459	β_0 = 1,0464
	β_1 = 1,8208	β_1 = 1,8885	β_1 = 1,8885	β_1 = 1,9594
DDGS	β_0 = −0,0390	β_0 = −0,0396	β_0 = −0,0396	β_0 = 1,0402
	β_1 = 2,9827	β_1 = 3,0543	β_1 = 3,0543	β_1 = 3,1290

Feed Raw Materials	ODGM(1,1)	EGM(1,1)	EDGM(1,1)	DGM(1,1)
Corn Imported	β_0 = −0,0320	β_0 = −0,0322	β_0 = −0,0322	β_0 = 1,0325
	β_1 = 2,5253	β_1 = 2,5802	β_1 = 2,5802	β_1 = 2,6367
Moist Corn	β_0 = −0,0365	β_0 = −0,0370	β_0 = −0,0370	β_0 = 1,0373
	β_1 = 1,8423	β_1 = 1,8884	β_1 = 2,5802	β_1 = 1,9361
Rough Wheat Bran	β_0 = −0,0413	β_0 = −0,0420	β_0 = −0,0420	β_0 = 1,0426
	β_1 = 1,8989	β_1 = 0,9486	β_1 = 0,9486	β_1 = 2
Thin Wheat Bran	β_0 = −0,0369	β_0 = −0,0375	β_0 = −0,0375	β_0 = 1,0381
	β_1 = 1,7201	β_1 = 1,756	β_1 = 1,756	β_1 = 1,7926

The application of 11 distinct forecasting methodologies, with their respective parameters outlined above, enabled the projection of prices for 43 distinct feed types over the period spanning September 2022 to June 2023. Subsequently, the performance criteria of the forecasting models were calculated following the generation of the price forecasts. A comparison was conducted between the forecasted values and the actual market values between September 2022 and June 2023. In calculating the performance measures, The mean squared error (MSE), the median absolute deviation (MAD) and the mean absolute percentage error (MAPE) were employed for this purpose. The performance criteria calculated for each of the 43 feeds and 11 forecasting methods were averaged. The values of MAPE, MSE and MAD obtained are presented in Table 7 and Figure 4 in full detail. Upon analysis of the calculated mean measurement errors, it becomes evident that the DGM(1,1) method exhibits the lowest mean error across all three criteria.

Table 7. Details of Mean Errors of Forecasting Methods According to Performance Criteria

Forecasting Methods	MAPE	MAD	MSE
HW- Multiplicative Exponential Smoothing Method	16828571	1222651	11616342
Holt (Double) Exponential Smoothing Method	19397469	1163298	10722768
Simple Exponential Smoothing Method	8758527	576713	2591925
HW- Additive Exponential Smoothing Method	15784375	1129122	10440476
Regression Analysis Method	1461,66	103,97	1370,62
ODGM (1,1) Method	8935612	419794	911332
EGM(1,1) Method	6587323	390813	817686
EDGM(1,1) Method	6464101	412606	1023152
DGM(1,1) Method	6118226	385458	80238
Minimum Average Error	6118226	385458	802388

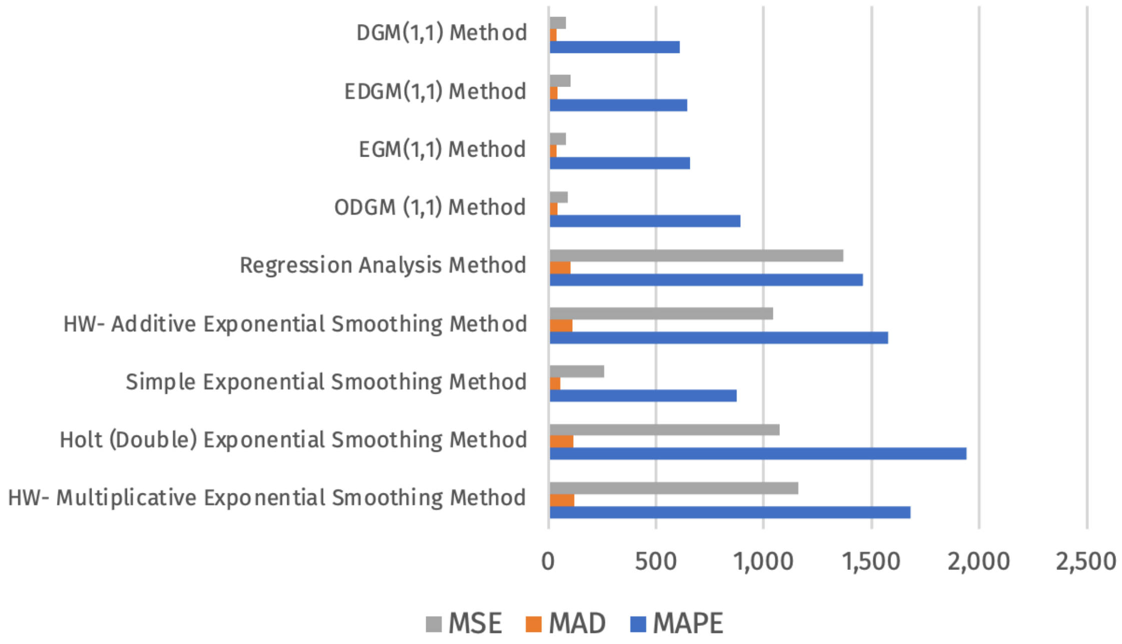

Figure 4. Average Errors of Forecasting Methods According to Performance Criteria

The best forecasting models according to MSE, MAD and MAPE performance measures for each feed material are presented in Table 8.

Table 8. Best Forecasting Models for Feed Raw Material Prices According to Forecast Values

Feed Raw Material	MAPE	MAD	MSE
Wheat	DGM (1,1)=4.49	DGM (1,1)=0.34	DGM (1,1)=0.25
Fractured Wheat	Simple E.S.M..=10.93	Simple E.S.M..=0.52	Simple E.S.M..=0.58
Barley	HW-Additive E.S.M.=1.82	HW-Additive E.S.M.=0.10	HW-Additive E.S.M.=0.02
Corn	Simple E.S.M.=5.19	Simple E.S.M.=0.29	Simple E.S.M.=0.16
Barley Flour	HW-Additive E.S.M.=8.55	HW-Additive E.S.M.=0.79	HW-Additive E.S.M.=0.92
Bonkalite	Holt (Double) E.S.M.=10.77	Holt (Double) E.S.M.=0.68	Holt (Double) E.S.M.=0.57
Bran	DGM (1,1)=13.54	DGM (1,1)=1.18	DGM (1,1)=7.62
Rasmol	DGM (1,1)=2.96	DGM (1,1)=0.15	DGM (1,1)=0.03
Sunflower Meal	EDGM (1,1)=4.38	HW-Additive E.S.M.=0.68	HW-Additive E.S.M.=0.56
Soy Meal	Simple E.S.M.=11.25	Simple E.S.M.=1.03	Simple E.S.M.=2.58
Hazelnut Meal	DGM (1,1)=15.32	DGM (1,1)=0.48	DGM (1,1)=0.42
Beetroot Meal	DGM (1,1)=21.94	DGM (1,1)=1.25	DGM (1,19=2.00
Potato	Regression Analysis=9.38	Regression Analysis =0.66	Regression Analysis=0.59
Corn Silage	ODGM (1,1)=14.42	ODGM (1,1)=0.27	DGM (1,1)=0.18
Clover	ODGM (1,1)=10.42	ODGM (1,1)=0.45	ODGM (1,1)=0.32
Wheat Hay	Regression Analysis =5.48	ODGM (1,1)=0.42	DGM (1,1)=0.21
Rye	HW-Additive E.S.M.=6.06	HW-Additive E.S.M.=0.36	HW-Additive E.S.M.=0.25
Triticale	Simple E.S.M.=4.26	Simple E.S.M.=0.23	Simple E.S.M.=0.08
Oats	Holt (Double) E.S.M.=11.60	Holt (Double) E.S.M.=0.63	Holt (Double) E.S.M.=0.48
Wet Beet Pulp	DGM (1,1)=26.46	EDGM (1,1)= 0.35	EDGM (1,1)=0.19

Feed Raw Material	MAPE	MAD	MSE
Soy	Simple E.S.M.=4.91	Simple E.S.M.=0.64	Simple E.S.M.=0.58
Beetroot	Holt (Double) E.S.M.=24.57	ODGM (1,1)=1.61	ODGM (1,1)=4.57
Canola	Simple E.S.M.=6.60	Simple E.S.M.=0.80	Simple E.S.M.=0.72
Carrot	HW-Additive E.S.M.=27.45	ODGM (1,1)=2.11	ODGM (1,1)=8.04
Barley Imported	DGM (1,1)=16.43	DGM (1,1)=0.90	DGM (1,1)=1.27
Corn on the Cob	HW-Additive E.S.M.=10.77	EDGM (1,)=0.71	DGM (1,1)=0.93
Wheat Imported	DGM (1,1)=9.39	DGM (1,1)=0.62	DGM (1,1)=0.43
Vetch	DGM (1,1)=0.25	DGM (1,1)=3.55	DGM (1,1)=15.92
Soft Wheat	Simple E.S.M.=6.32	Simple E.S.M.=0.40	Simple E.S.M.=0.21
Clover Hay	DGM (1,1)=28.21	DGM (1,1)=0.83	DGM (1,1)=0.83
Oat Meal	Simple E.S.M.=7.41	Simple E.S.M.=1.26	Simple E.S.M.=1.74
Wheat Flake	DGM (1,1)=4.35	DGM (1,1)=0.54	DGM (1,1)=0.40
Black. Chick.	Holt (Double) E.S.M.=29.90	Regression Analysis =2.04	HW-Additive E.S.M.=6.73
Full-Fat Soy	ODGM (1,1)=1.13	Simple E.S.M.=0.44	Simple E.S.M.=0.36
Corn Grits	DGM (1,1)=3.60	DGM (1,1)=0.22	DGM (1,1)=0.08
Corn Bran	DGM (1,1)=4.86	DGM (1,1)=0.29	DGM (1,1)=0.13
Cottonseed Meal	ODGM (1,1)=4.46	ODGM (1,1)=0.26	ODGM (1,1)=0.09
Molasses	DGM (1,1)=19.20	DGM (1,1)=0.87	DGM (1,1)=1.49
DDGS	DGM (1,1)=4.99	DGM (1,1)=0.39	DGM (1,1)=0.25
Corn Imported	DGM (1,1)=11.80	DGM (1,1)=0.64	DGM (1,1)=0.58
Moist Corn	Holt (Double) E.S.M.=9.46	Holt (Double) E.S.M.=0.40	Holt (Double) E.S.M.=0.23
Rough Wheat Bran	DGM (1,1)=15.34	DGM (1,1)=0.75	DGM (1,1)=0.88
Thin Wheat Bran	HW Multiplicative ESM=3.44	Simple E.S.M.=0.63	DGM (1,1)=0.04
Summary	DGM (1,1) = 17	DGM (1,1) = 16	DGM (1,1) = 20
	Simple E.S.M.= 8	Simple E.S.M.= 10	Simple E.S.M.= 9
	HW-Additive E.S.M.= 5	HW-Additive E.S.M.= 4	HW-Additive E.S.M.= 5
	Holt (Double) E.S.M.= 5	Holt (Double) E.S.M.= 3	Holt (Double) E.S.M.= 3
	EDGM (1,1)= 1	EDGM (1,1)= 2	EDGM (1,1)= 1
	Regression Analysis = 2	Regression Analysis = 2	Regression Analysis = 1
	ODGM (1,1)= 4	ODGM (1,1)= 6	ODGM (1,1)=4
	HW-Multiplicative E.S.M =1	HW-Multiplicative E.S.M = 0	HW-Multiplicative E.S.M = 0

When analysing the methods that give the most accurate price prediction for each feed raw material through Table 8, it can be seen that DGM (1,1) is the method that predicts the price of 17 feed raw materials according to the MAPE criterion, 16 feed raw materials according to the MAD criterion and 20 feed raw materials according to the MSE criterion with the least error. This method is followed by the Simple E.S.M. method. The corresponding visualisation can be seen in Figure 5.

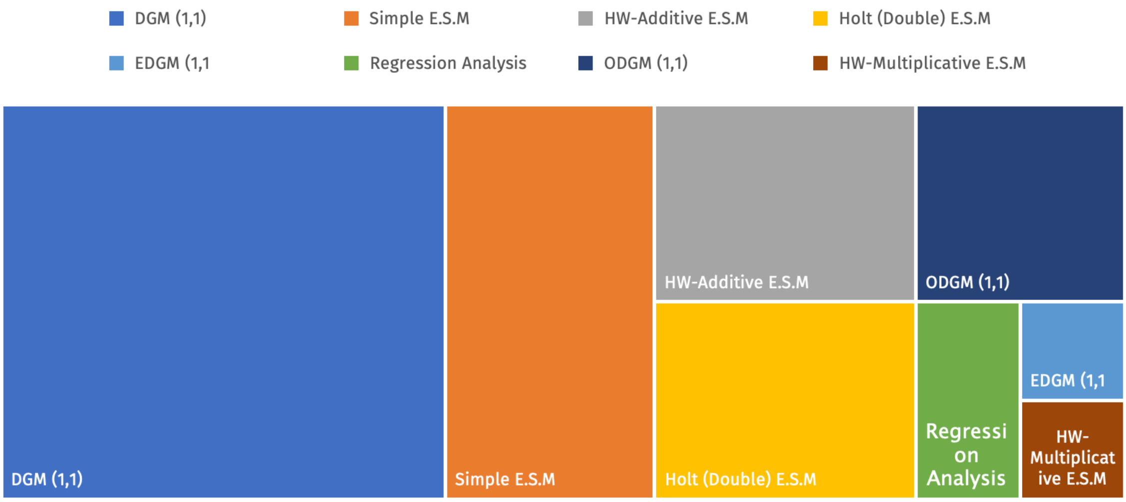

Figure 5. Best Predictor for each Feed Material

The GM (1,1) forecasting method, a particular type of grey forecasting model, offers several advantages compared to traditional regression analysis and exponential smoothing models. Each of these methods has its strengths and weaknesses, but the unique characteristics of GM (1,1) make it particularly suitable for certain forecasting scenarios, especially those involving limited data or non-linear trends. One of the main advantages of the GM(1,1) method is that it can perform well with small sample sizes. Unlike regression analysis, which typically requires a larger data set to establish reliable relationships between variables, GM(1,1) can produce forecasts using as few as four data points. This is particularly useful in areas where data collection is difficult or expensive, such as health or environmental studies (Dang et al., 2016). For example, in the context of predicting malaria incidence, the GM (1,1) model has shown superior accuracy compared to both regression and exponential smoothing methods, especially when data are limited (Zhao et al., 2021). In contrast, regression analysis usually assumes a linear relationship between the dependent and independent variables, which may not always be the case in real-world scenarios. However, since the GM (1,1) model is based on grey system theory, it can capture non-linear trends more effectively. This flexibility allows GM (1,1) to adapt to various data models without the need for extensive transformations or assumptions about the underlying distribution of the data (Şahin, 2018). For example, in the estimation of electricity consumption in Turkey, the GM (1,1) model provided more accurate predictions than traditional regression models, which struggle to account for the complexity of the data (Şahin, 2018). Exponential smoothing models, while effective in many time series forecasting applications, tend to rely heavily on past data trends and may not perform well when faced with sudden changes or outliers in the data. The GM (1,1) method, on the other hand, includes a smoothing factor that allows it to adapt to changes in the data in a more dynamic way. This feature is particularly advantageous in volatile environments, such as forecasting economic indicators or energy demands, where sudden changes can significantly affect forecasts (Iqelan, 2017).

There are several important reasons why the DGM (1,1) method can make more accurate forecasts than the EDGM (1,1), ODGM (1,1) and EGM (1,1) methods. These reasons are due to the advantages of the DGM (1,1) model in terms of data processing, flexibility and forecast accuracy. Firstly, the DGM (1,1) model can optimise the data collection and processing processes. The DGM (1,1) model is an improved version of the classical GM (1,1) model and allows for more efficient processing of the data set. This model provides better data accumulation while increasing the accuracy of forecasts (Tulkinov, 2023). For example, the DGM(1,1) model has achieved higher accuracy rates in electricity generation forecasts compared to traditional methods (Tulkinov, 2023). Secondly, the DGM(1,1) model can better reflect the dynamics of the data set. The fact that the DGM(1,1) model better analyses changes over time increases the accuracy of forecasts. This model can make more accurate forecasts by better-capturing fluctuations and trends in the data set (Singh et al., 2022). For example, the DGM (1,1) model gave better results in energy demand forecasts than other grey forecasting methods (Singh et al., 2022). In addition, the DGM (1,1) model also offers advantages in terms of parameter optimisation. The approach of optimising the background values and initial elements of the DGM (1,1) model significantly improves the prediction accuracy (Hu & Jiang, 2017). Such improvements are one of the main reasons why the DGM (1,1,1,1) model can make more accurate predictions than other grey prediction methods. For example, the DGM(1,1,1) model achieved lower error rates than traditional methods when estimating the effects of COVID-19 (Hu & Jiang, 2017). Finally, the DGM(1,1) model can adapt to different data sets thanks to its flexible structure. This flexibility increases the applicability of the model in various sectors and different decision-making scenarios (Arsy, 2021). For example, the DGM(1,1) model has achieved higher accuracy rates in agricultural yield forecasts than other grey forecast methods (Arsy, 2021).

5. Forecasting 6-Month Price Data with DGM (1,1) Method

As a result of the predictions, the performance measures of the 11 models were compared using MAPE, MSE and MAD error calculation tools. As a result of the comparison, the DGM (1,1) model was selected as the best forecaster according to all the performance measures used. After the selection of the method, the number of forecasting models was reduced from 11 to 1. All 30 months of data between January 2021 and June 2023 were used to forecast year-end prices for 2023. The 6-month price data forecasted by the DGM (1,1) method are presented in Table 9.

Table 9. 6-Month Feed Raw Material Prices Forecasted Using DGM (1,1) Method

Feed Raw Material	2023					
	July	August	September	October	November	December
Wheat	7.35	9.82	10.29	10.78	11.3	11.84
Fractured Wheat	6.13	7.07	7.33	7.61	7.9	8.2
Barley	7.31	7.85	8.2	8.56	8.93	9.33
Corn	6.79	7.64	7.94	8.25	8.57	8.91
Barley Flour	6.41	11.58	12.04	12.52	13.01	13.53
Bonkalite	6.07	7.61	7.92	8.23	8.57	8.91
Bran	5.57	7.09	7.4	7.73	8.07	8.43
Rasmol	3.72	6.67	6.95	7.23	7.53	7.83
Sunflower Meal	6.02	6.17	6.27	6.38	6.48	6.59
Soy Meal	10.27	15.14	15.73	16.34	16.97	17.63
Hazelnut Meal	2.18	3.8	3.89	3.97	4.06	4.15
Beetroot Meal	5.46	7.28	7.54	7.81	8.09	8.39
Potato	4.08	10.94	11.66	12.43	13.24	14.11
Corn Silage	2.09	2.33	2.5	2.67	2.86	3.07

Feed Raw Material	2023					
	July	August	September	October	November	December
Clover	5.04	5.75	6.06	6.38	6.72	7.08
Wheat Hay	3.63	4.37	4.68	5.01	5.36	5.74
Rye	7.01	7.37	7.66	7.97	8.28	8.61
Triticale	6.98	7.34	7.65	7.98	8.32	8.67
Oats	6.64	6.9	7.19	7.48	7.79	8.11
Wet Beet Pulp	0.89	1.01	1.01	1.01	1.01	1
Soy	11.89	17.62	18.27	18.96	19.66	20.39
Beetroot	7.04	9.09	9.57	10.06	10.59	11.14
Canola	14	15.12	15.77	16.45	17.15	17.89
Carrot	8.65	12.76	13.71	14.72	15.8	16.97
Barley Imported	5.24	7.4	7.78	8.17	8.59	9.03
Corn on the Cob	3.25	4.22	4.46	4.7	4.96	5.24
Wheat Imported	3.87	9.04	9.45	9.88	10.33	10.8
Vetch	11.55	16.06	16.93	17.84	18.8	19.81
Soft Wheat	6.07	8.62	9	9.4	9.82	10.26
Clover Hay	4.17	4.09	4.32	4.57	4.84	5.11
Oat Meal	16.62	22.6	23.71	24.87	26.09	27.37
Wheat Flake	16.59	16.84	17.64	18.48	19.36	20.28
Black. Chick.	7.58	11.62	12.09	12.58	13.09	13.62
Full-Fat Soy	16.53	17.26	17.91	18.59	19.3	20.03
Corn Grits	6.52	6.7	6.81	6.92	7.03	7.14
Corn Bran	7.17	7.88	8.18	8.5	8.83	9.17
Cottonseed Meal	6.81	6.7	6.88	7.06	7.24	7.43
Molasses	5.78	7.87	8.23	8.61	9.01	9.43
DDGS	6.99	10.58	11.01	11.45	11.91	12.39
Corn Imported	5.49	7.03	7.26	7.49	7.74	7.99
Moist Corn	4.53	6	6.22	6.45	6.69	6.94
Rough Wheat Bran	6.94	7.28	7.59	7.92	8.26	8.61
Thin Wheat Bran	4.79	5.7	5.92	6.15	6.38	6.62

6. Conclusion and Discussion

In this study, the prices of feed raw materials commonly used in the dairy cattle sector were forecasted. Time series, statistical and grey system theory-based methods were used in the forecasting process. Simple exponential smoothing, double exponential smoothing, Holt-Winters additive exponential smoothing and Holt-Winters multiplicative exponential smoothing methods were preferred for time series. As statistical methods, linear regression, polynomial regression, dummy variable regression and DMG (1,1), ODGM (1,1), EGM (1,1) and EDGM (1,1) methods within the category of grey system theory were used. The performance criteria of the forecasting models were compared and the model with the least error was selected.

When the performance ratios calculated by MSE, MAD and MAPE methods are analyzed, it is observed that the grey system theory-based DGM (1,1) model produces forecasts with the lowest error. It is also observed that the DGM (1,1) model, which is called the discrete form of the GM (1,1) model, forecasts more correctly than the grey system theory-based methods and other methods and can be adaptive to instantaneous price changes. In the literature, most of the studies on price forecasting of agricultural products are based on econometrics and time series: ARIMA, SARIMA, LSTM, CNN, VAR and ARMA. Artificial intelligence-based methods such as ANN are also among the models used in recent years.

The DGM (1,1) method, one of the grey system-based forecasting methods, is a useful alternative model for price forecasting of agricultural products as it can adapt to unexpected price changes and work with small data sets. This is because the predicted prices obtained are consistent with Turkey's 2023 inflation rate (64.77%). To examine the correlations between the input costs used in the production of agricultural products and the prices of agricultural products, it is foreseen that multivariate grey forecasting methods can also achieve similarly effective results.

Forecasting feed prices offer significant benefits to dairy farmers in an inflationary environment such as Turkey. However, the fact that the dataset of the present study is limited to only 30 months may affect the reliability and generalisability of the estimates. To extend the data set, future studies can use data sets on feed prices covering a longer period. In this way, seasonal and annual variations can be better analysed. In addition to the DGM (1,1) method, comparative analyses can be carried out using different and integrated variations of grey forecasting methods. This helps to determine the best forecasting method and to identify the strengths and weaknesses of different methods. Panel data analysis methods can be used to better understand the factors influencing feed prices in the dairy sector. This type of analysis makes it possible to examine price fluctuations in different regions and their impact on the sector. Including macro-economic indicators (e.g. inflation rate, exchange rates, agricultural production) that may have an impact on feed prices in forecasting models provides a more comprehensive analysis. This can provide a more robust basis for forecasting feed prices. The results of the studies can contribute to the development of sectoral policies. In particular, recommendations can be made on government support and incentives to control feed prices.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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