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Comparative Forecasting of Some Key Economic Indicators Using Artificial Neural Networks and Ordinary Differential Equations: A Case Study of the Turkish Economy

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Abstract − This study explores the relationships between the USD opening exchange rate, the annual change rate of the Consumer Price Index (CPI), the housing loan interest rate in Turkish lira, and the residential construction cost index from January 2015 to May 2024 using data from the Turkish Statistical Institute (TUIK). Artificial Neural Networks (ANN) and Ordinary Differential Equations (ODE) methods were employed to model the interactions among these four variables. In the ANN approach, each variable was modeled as the dependent variable in turn, with the remaining three serving as independent variables, resulting in four distinct analyses. The ODE model, on the other hand, provided a holistic analysis by capturing the time-dependent relationships among all four variables simultaneously. The ANN model predictions achieved accuracy rates of 87.2% for the USD opening exchange rate, 91.4% for the CPI annual change rate, 85.9% for the housing loan interest rate, and 93.1% for the construction cost index. Meanwhile, the ODE model demonstrated its strength by offering a more comprehensive framework with an overall accuracy of 94.6%, effectively capturing the complex interdependencies among the variables. These findings highlight the strengths of both approaches: while the ANN model excels in analyzing individual variables, the ODE model offers a broader perspective by integrating all variables into a unified framework. This study contributes to developing economic forecasting models and provides valuable insights for decision-makers, particularly in times of economic uncertainty.

Keywords − *Turkish economy, artificial neural networks, ordinary differential equations, comparative forecasting*

1. Introduction

Economic indicators are critical in understanding a country's economic performance and predicting future trends [1]. In developing countries like Türkiye, variables like exchange, inflation, interest, and construction costs are crucial to economic growth and sustainability. Correctly modeling the relationships between these indicators enables economists and policymakers to make the right decisions [2].

The Turkish economy has faced significant challenges, especially between 2015 and 2024, due to fluctuations in global markets, volatility in exchange rates, and structural changes in domestic markets. The country's economic stability is affected by key financial indicators such as the USD opening rate, Consumer Price Index (CPI), mortgage interest rates, and construction cost index. These indicators are affected by both local and global market dynamics and have a complex relationship with each other. The exchange rate, especially the USD/TL rate, has become an important determinant of economic activity in Turkey [3]. The exchange rate,

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which has a major impact on foreign trade, borrowing, and investment decisions, is also closely related to inflation and interest rates. Inflation (CPI), in particular, affects consumer spending and investment decisions, putting pressure on interest rates and construction costs. Mortgage interest rates serve as an indicator of financial conditions for both individual and institutional investors. On the other hand, the construction cost index determines investment costs and growth potential in the sector, especially in countries like Turkey, where the construction sector has a significant share in growth.

Recent advancements in artificial intelligence (AI) and blockchain technologies have significantly impacted various fields, including healthcare and smart community applications. For instance, smart contract-enabled systems have demonstrated secure data-sharing capabilities in mobile cloud-based healthcare environments, ensuring data integrity and confidentiality [4]. Additionally, deep learning techniques, such as facial emotion recognition using principal component analysis (PCA) and neural networks (ANNs), have shown the robustness of AI in handling complex, data-intensive tasks [5]. Moreover, AI and machine learning have been integrated into smart community frameworks to enhance scalability, security, and accessibility in managing critical information systems [6]. These advancements underline the essential role of AI, particularly ANNs, in addressing challenges across dynamic and sensitive domains. Building on these innovations, our study applies ANN-based methodologies to the comparative forecasting of key economic indicators, aiming to leverage their data-driven precision for improved predictive accuracy.

In this study, Artificial Neural Networks (ANN) [7] and Ordinary Differential Equations (ODE) [8] models were applied to estimate the relationships between the USD opening exchange rate, CPI, housing loan interest rates, and construction cost index using Turkish Statistical Institute (TUIK) data. ANN was run as four separate estimation models with different data set combinations; each variable was treated as a dependent variable, respectively. The ODE model provided a holistic approach that evaluated the interactions of all variables in a single model [9].

This study seeks to evaluate the performance of two distinct modeling approaches and identify the scenarios in which each model proves more effective. The findings reveal that both ANN and ODE models successfully estimate economic indicators for Turkey, yet the nature of the relationships between variables varies based on the chosen modeling approach. This research enhances economic forecasting methodologies for the Turkish economy and offers valuable insights to policymakers, aiding them in making informed economic decisions in the future.

2. Related Works

Using methods such as ANN and ODE to model complex economic systems has become an increasingly popular area of research today. The accuracy and reliability of economic indicators play a major role in shaping public policies and making financial decisions. Alshawarbeh et al. [10] have estimated volatile stock market indices using the hybrid ARIMA-ANN model in this context. Their research shows that when combined with time series models, ANN significantly increases forecast accuracy, especially in complex and chaotic financial data. This hybrid approach is critical for forecasting highly volatile economic data, especially inflation and exchange rates. In a similar study, Mohamed et al. [11] discussed how ANN can be used in estimating macroeconomic performance indicators. Their analysis showed that ANN outperformed linear regression models and revealed important results encouraging using neural networks in economic forecasting. In this direction, the effectiveness of ANN-based forecasting models was emphasized to increase the accuracy of economic indicators such as inflation and exchange rate fluctuations. However, Wijesinghe et al. [12] also compared ARIMA and ANN models and showed that ANN performs better in stock prices and better captures the stock market's volatility. It was demonstrated that ARIMA handles linear trends well in short-term forecasts, but ANN is superior in adapting to complex and dynamic data models. The findings of this study show how effective ANN can be for long-term forecasts in economic forecasts.

There is a wide range of use of AI-based forecasting models, and significant successes have been achieved in adapting these methods to economic indicators. The systematic literature review conducted by Ramírez et al. [13] highlights the widespread use of AI methods such as artificial neural networks (ANN), fuzzy logic systems (ANFIS), genetic programming (GP), and support vector regression (SVR). This review revealed that these methods can predict economic indicators such as CPI, interest rates, and GDP. The studies show the potential of AI-based methods to increase the accuracy of economic forecasts. The study by Fani et al. [14] focused on using ANN in forecasting gasoline demand in the Tehran metropolis. The study analyzed seven social and economic indicators affecting gasoline demand using a multilayer perceptron artificial neural network (MLP) model. The findings of this study show how successful ANN can be in modeling economic data sets and its sensitivity to different social and economic variables.

ODE-based models are also of great importance in economic analysis. Guerrini et al. [15] studied the economic growth model with a time-lagged investment function. Their work transformed the lagged differential equations into ordinary differential equations (ODE) systems and analyzed the economic growth and investment dynamics over three- and four-dimensional systems. Such studies emphasize the power of ODE models in understanding the long-term dynamics of economic systems and how investments change over time. Similarly, Wu et al. [16] developed a model for parameter estimation and variable selection of linear ODEs. They presented an approach based on similarity transformation and separable least squares (SLS) methods to improve the performance of ODE models in ultra-high dimensional economic systems. This method allows linear ODE systems to provide more accurate and successful results on large data sets. These findings increase the importance of ODE-based approaches in modeling economic systems. Finally, the study of Georgiev et al. [17] on asset price estimation in financial markets using ODE-based methods provides a solution to increase the accuracy of financial models. The ODE-based model developed using polynomials and periodic functions successfully handles the complexity of financial data sets and provides a workable method for investors that can work with a wide set of parameters.

These studies clearly show how powerful the tools ANN and ODE are in estimating economic indicators. In the following sections, the methods used in these studies will be analyzed in depth, and how the current study applies these methods and what innovations it offers in economic estimations will be detailed.

3. Materials and Methods

This section first mentions the used data set and presents the ANN and ODE methods.

3.1. Dataset

The dataset used in this study includes economic indicators for different years related to the Turkish economy. The dataset covers a period starting from Jan 2015 to May 2024. Each observation presents important economic indicators, such as monthly Opening (USD), CPI (Annual % Change), Bank Housing Loan TL Interest Rate, and Construction Cost Index. The dataset reflects Turkey's exchange rate changes, inflation rates, housing loan interest rate fluctuations, and how costs change in the construction sector. It allows the application of time series analysis and econometric models. Within the scope of the research, the relationships between economic indicators were examined, and forecasting models were created using methods, such as ANN and ODE. The long-term coverage of the dataset allows for better training of the model, to increase the accuracy of economic forecasts. The data obtained from TUİK is presented in Table 1.

The observation in Table 1 details the changes that have occurred among the economic indicators over time, and these data provide an essential basis for the economic forecast models that form the main focus of the study. The data in Table 1 were normalized with the Euclidean norm and denormalization was done during the simulation phase. Data normalization is used in machine learning to make model training less sensitive to the scale of the features. This allows our model to converge to better weights, which leads to a more accurate model. Normalization makes the features more consistent, allowing the model to predict the output more accurately. In mathematics, normalizing a vector means dividing each element by a value V, so that the resulting vector has a length/norm 1. It turns out that the required V is equal to the length (length of the vector). The Euclidean norm is obtained as $\|\text{month}\| = 20667.3656$, $\|\text{USD}\| = 131.765362$, $\|\text{CPI}\| = 373.149781$, $\|\text{interest rate}\| = 211.818758$, and $\|\text{Construction cost index}\| = 5455.99528$ using the formula $\|x\|_2 = (\sum_{i=1}^{n}|x_i|^2)^{\frac{1}{2}} = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$. Then, each variable was divided into its norms, and normalization was achieved.

Table 1. Dataset

Order Number	Date	Month	USD	CPI	Real TL Interest rate	Construction cost index total for residential purposes
1	1.01.2015	0	2,3367	7,24	10,97	97,68
2	1.02.2015	30	2,4434	7,55	10,85	97,71
3	1.03.2015	60	2,5117	7,61	10,76	98,12
4	1.04.2015	90	2,598	7,91	10,96	98,91
5	1.05.2015	120	2,6718	8,09	11,18	99,63
6	1.06.2015	150	2,6606	7,2	11,63	99,48
7	1.07.2015	180	2,6817	6,81	12,18	100,61
8	1.08.2015	210	2,7689	7,14	12,42	101,45
9	1.09.2015	240	2,9144	7,95	13,3	102,23
10	1.10.2015	270	3,0254	7,58	14,08	101,57
11	1.11.2015	300	2,9154	8,1	14,29	101,4
12	1.12.2015	330	2,9136	8,81	13,98	101,23
13	1.01.2016	360	2,9177	9,58	14,08	109,67
14	1.02.2016	390	2,9561	8,78	14,47	109,67
15	1.03.2016	420	2,964	7,46	14,46	110,87
16	1.04.2016	450	2,8165	6,57	14,44	111,68
17	1.05.2016	480	2,7954	6,58	14,04	113,15
18	1.06.2016	510	2,9489	7,64	13,93	112,39
19	1.07.2016	540	2,8766	8,79	13,74	112,21
⋮	⋮	⋮	⋮	⋮	⋮	⋮
113	1.05.2024	3360	32,4178	75,45	44,02	1499,99

3.2. Artificial Neural Networks (ANN)

This study used Artificial Neural Networks (ANN) to predict economic indicators. ANN creates a multi-layered model by imitating the information processing structure of the human brain and is particularly successful in modeling complex and non-linear data relationships. The layers used in the model include input, hidden, and output layers. Neural network nodes represent each layer and process data by connecting with nodes in other layers. The training of the ANN is carried out by updating the weights in each iteration, and in this process, the error function is minimized, and the accuracy of the model is increased. In the ANN used in this study, one of the economic indicators is selected as the output (dependent variable). In contrast, the other three indicators are used as model inputs. The model was run four times, and each economic indicator was determined as the output in order. The model's success in predicting future economic indicators was measured by minimizing the error rate during training. The model's accuracy was evaluated with the average error rates in the training and test data sets. The structure of the ANN model used in this study is presented in Figure 1.

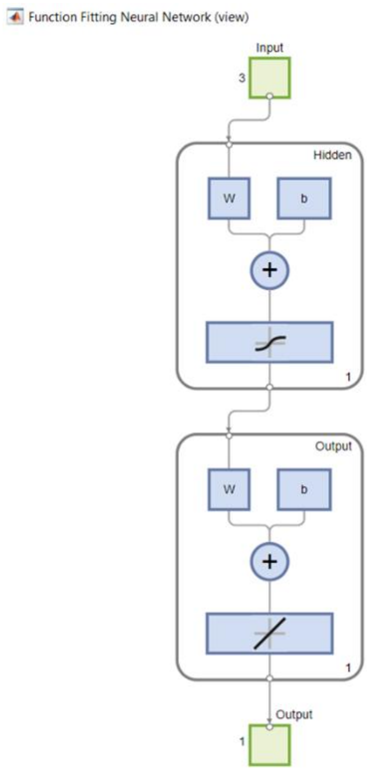

Figure 1. Structure of the used ANN model

The ANN model in Figure 1 consists of 3 input layers, a hidden layer, and an output layer. In the input layer, three economic indicators the model will predict are taken as inputs. These inputs are processed with a specific weight and activation function and transferred to the hidden layer. The hidden layers have nodes that increase the learning capacity of the model and enable the neural network to model non-linear relationships. Activation functions are usually non-linear ReLU (Rectified Linear Unit) or sigmoid functions so that the model can obtain more accurate results in complex data. The output layer contains the economic indicator the model will predict (e.g., exchange rate, CPI, or interest rate). The ANN model is trained with the backpropagation algorithm, and the error function is minimized in each iteration. This process increases the model's performance, and the trained network can predict future data.

3.3. Ordinary Differential Equations (ODE)

This study used the Ordinary Differential Equations (ODE) approach to model the relationships between economic indicators. ODE is a mathematical modeling method used to analyze the dynamic behavior of systems that change over time. This method defines the rates of change of dependent variables over time and their relationships. Therefore, differential equations and their mathematical models are widely used in many fields of science, such as biomathematics [18,19], physics [20,21], medicine [22,23], chemistry [24-26], engineering [26-28], economics [29,30], etc.

The linear ODE model examined four economic indicators simultaneously and modeled their interactions and how they evolved. ODE models are especially effective in long-term predictions of complex economic processes because these models can capture transitions and dynamic processes in time series. The ODE approach aims to increase the model's accuracy by optimizing the system's parameters and initial conditions. In this study, the model parameters were estimated using numerical methods and used to accurately predict the long-term trends of economic indicators. The linear ODE model presented within the scope of this study was designed to model the dynamic relationships between economic indicators. ODE models are based on differential equations to understand how variables in the system change over time. In such models, the interactions between economic indicators are considered a process that develops over time.

4. Results and Discussion

This section delves into a comprehensive analysis of the estimation processes conducted using ANN and ODE models. The study focuses on the predictability of four critical economic variables: the USD Opening Exchange Rate, the Consumer Price Index Annual Percentage Change, the Bank Housing Loan TL Interest Rate, and the Residential Construction Cost Index. These variables, chosen for their significance in understanding economic dynamics, were derived from the dataset summarized in Table 1.

To ensure the reliability and validity of the modeling process, the dataset was meticulously partitioned into three subsets: 70% for training to build the models, 15% for validation to fine-tune and prevent overfitting, and 15% for testing to evaluate the models' predictive performance. This structured approach enhances the robustness of the analysis. It provides a solid foundation for comparing the estimation capabilities of ANN and ODE in capturing the intricate relationships between the selected variables.

By integrating these models with a carefully prepared dataset, this section aims to provide valuable insights into their practical applicability and effectiveness in modeling complex economic interactions.

4.1. Metrics and Equations

Experimental evaluations were evaluated using MAD, MSE, RMSE, MAPE, and R^2 metrics [31-34]. As shown in Equation 4.1, MAD calculates the average of the absolute differences between the estimated and actual values. On the other hand, MSE is used to measure the model's error rate and gives the average of the square of the errors. A high MSE indicates that the model makes large errors in its predictions. RMSE is calculated by taking the square root of MSE and expressing the magnitude of the prediction errors more clearly. MAPE expresses the error rate as a percentage and allows the model's performance to be evaluated on a percentage basis. R^2 is a coefficient that measures how well the model makes a prediction. An R^2 value of 1 indicates that the model makes a high-accuracy prediction, as shown in (4.1).

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.1}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

In Eqs. (4.1), y_i is real data, $\hat{y}_i$ is predicted data, and $\bar{y}_i$ is the mean value.

The resulting model with ANN's activation function (tanh) has been written as in (4.2).

$$y = b_2 + LW\tanh(b_1 + IWx) \tag{4.2}$$

The general linear ODE mathematical model is shown in (4.3), as t is the time parameter and the independent variable.

$$\begin{aligned} \frac{dx}{dt} &= \theta_1 x + \theta_2 k + \theta_3 z + \theta_4 h + \theta_5 \\ \frac{dk}{dt} &= \theta_6 x + \theta_7 k + \theta_8 z + \theta_9 h + \theta_{10} \\ \frac{dz}{dt} &= \theta_{11} x + \theta_{12} k + \theta_{13} z + \theta_{14} h + \theta_{15} \\ \frac{dh}{dt} &= \theta_{16} x + \theta_{17} k + \theta_{18} z + \theta_{19} h + \theta_{20} \end{aligned} \tag{4.3}$$

where variables $x, k, z,$ and h represent the USD opening exchange rate, CPI annual change rate, housing loan interest rate in Turkish lira, and residential construction cost index values at time t, respectively.

4.2. Analysis of ANN and ODE Models

The ANN model was employed to predict four different variables individually, with the other three as inputs in each case. Specifically, the variables are USD, CPI, Real TL Interest rate, and Construction cost index total for residential purposes. A separate ANN model was trained for each output, and each model's best validation performance was recorded at different epochs. The results for the four trainings are shown in Figures 2-5.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	10000	10000
Elapsed Time	-	00:00:09	-
Performance	0.979	3.32e-05	1e-10
Gradient	2.48	4.61e-08	0
Mu	0.001	1e-16	1e+10
Validation Checks	0	9.88e+03	1.11e+04

Figure 2. Best validation performance is 2.2541e-05 at epoch 116 (USD)

As shown in Figure 2, the model achieved its best validation performance with a minimal error of 2.2541e-05 at epoch 116. This exceptionally low error indicates that the model performs well in predicting USD opening values. The relatively large number of epochs required to reach this performance suggests that the model required extensive training to minimize the error effectively.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	111	10000
Elapsed Time	-	00:00:02	-
Performance	0.0756	0.000352	1e-16
Gradient	0.564	6.29e-12	0
Mu	0.001	1e+10	1e+10
Validation Checks	0	107	1.11e+06

Figure 3. Best validation performance is 0.00011765 at epoch 4 (CPI)

As shown in Figure 3, the best validation performance for the CPI variable was achieved early, with an error of 0.00011765 at epoch 4. The model's ability to converge to an optimal solution in such a short number of epochs indicates that predicting this variable required less complexity, and the model quickly adapted to the underlying patterns within the data.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	2877	10000
Elapsed Time	-	00:00:04	-
Performance	0.421	0.00034	1e-16
Gradient	1.43	2.95e-09	0
Mu	0.001	1e+10	1e+10
Validation Checks	0	2.81e+03	1.11e+06

Figure 4. Best validation performance is 0.00011765 at epoch 4 (Real TL interest rate)

As shown in Figure 4, the model's best validation performance for the real TL Interest rate was recorded at epoch 67, with an error of 0.0003889. Although this error is slightly higher than the other variables, the model still demonstrated reasonable predictive capability. The comparatively higher error suggests that this variable might exhibit more complexity or variability, making it somewhat more challenging to predict accurately.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	32	10000
Elapsed Time	-	00:00:01	-
Performance	0.0867	4e-05	1e-16
Gradient	0.234	1.25e-13	0
Mu	0.001	1e+10	1e+10
Validation Checks	0	2	1.11e+06

Figure 5. Best validation performance is 4.1379e-05 at epoch 30 (Construction cost index total for residential purposes)

As shown in Figure 5, The model achieved its best validation performance at epoch 30, with a low error of 4.1379e-05. This result reflects a strong performance in predicting the construction cost index. The moderate number of required epochs indicates that the model efficiently learned the relationships within the data without extensive training. In this context, the activation functions in (4.2) obtained in the estimation process ($y = b_2 + LW\tanh(b_1 + IWx)$) are given in Table 2.

Table 2. Parameters of ANN

	For the USD opening exchange rate (x)	**For the Consumer Price Index (CPI) annual change rate (k)**	**For housing loan interest rates in Turkish lira (z)**	**For residential construction cost index (h)**
b1	$-0{,}8464$	$-2{,}1941$	$2{,}9691$	$0{,}8936$
b2	$-1{,}0069$	$0{,}0940$	$0{,}7691$	$0{,}1714$
IW	$\begin{pmatrix} -0{,}0846 \\ -0{,}0916 \\ -1{,}5066 \end{pmatrix}^T$	$\begin{pmatrix} 16{,}6979 \\ 8{,}8024 \\ 0{,}6858 \end{pmatrix}^T$	$\begin{pmatrix} -12{,}4050 \\ 0{,}1422 \\ 4{,}0140 \end{pmatrix}^T$	$\begin{pmatrix} -5{,}6276 \\ 0{,}1945 \\ 0{,}2734 \end{pmatrix}^T$
LW	$-1{,}4558$	$0{,}0839$	$-0{,}7070$	$-0{,}2306$

The ANN model's performance across the four variables highlights differences in the complexity and predictability of each target. USD and Real TL Interest rates exhibited low error rates, indicating that the model captured the relationships between the input features and these outputs well. On the other hand, CPI reached optimal performance quickly, suggesting less complexity in the data structure for this variable. In contrast, the

Real TL Interest rate prediction was comparatively more challenging, as evidenced by the higher error and the greater number of epochs required to achieve the best performance. These results demonstrate that the ANN model can handle varying complexity across economic variables. Early stopping ensured that each model's training was halted once the optimal performance was reached, thus preventing overfitting and ensuring robust generalization. Therefore, the activation equations obtained with the coefficients given in Table 2 for each variable are in the form of

$$x = (-1{,}0069)_{1\mathrm{x}1} + (-1{,}4558)_{1\mathrm{x}1} \tanh\left((-0{,}8464)_{1\mathrm{x}1} + \begin{pmatrix} -0{,}0846 \\ -0{,}0916 \\ -1{,}5066 \end{pmatrix}^T \begin{pmatrix} k \\ z \\ h \end{pmatrix} \right)$$

$$k = (0{,}0940)_{1\mathrm{x}1} + (0{,}0839)_{1\mathrm{x}1} \tanh\left((-2{,}1941)_{1\mathrm{x}1} + \begin{pmatrix} 16{,}6979 \\ 8{,}8024 \\ 0{,}6858 \end{pmatrix}^T \begin{pmatrix} x \\ z \\ h \end{pmatrix} \right)$$

$$z = (0{,}7691)_{1\mathrm{x}1} + (-0{,}7070)_{1\mathrm{x}1} \tanh\left((2{,}9691)_{1\mathrm{x}1} + \begin{pmatrix} -12{,}4050 \\ 0{,}1422 \\ 4{,}0140 \end{pmatrix}^T \begin{pmatrix} x \\ k \\ h \end{pmatrix} \right)$$

$$h = (0{,}1714)_{1\mathrm{x}1} + (-0{,}2306)_{1\mathrm{x}1} \tanh\left((0{,}8936)_{1\mathrm{x}1} + \begin{pmatrix} -5{,}6276 \\ 0{,}1945 \\ 0{,}2734 \end{pmatrix}^T \begin{pmatrix} x \\ k \\ z \end{pmatrix} \right)$$

This study uses the linear ODE model to predict the values of key economic indicators, namely USD, CPI, Real TL Interest rate, and Construction Cost Index (Residential). The aim is to evaluate the ability of the model to predict these economic time series based on historical data. Therefore, the parameters θ_i for $i \in \{1,2,\dots,n\}$ used in (4.3) are calculated by the least squares method. For this, the approach used in [35] is considered. In this sense, these parameters obtained with the lsqcurvefit function (options.MaxFunctionEvaluations = 2.700000e+03) by solving with the Matlab R2023b program RungeKutta45 are given as $\theta_1 = -0{,}43409$, $\theta_2 = 25{,}35903$, $\theta_3 = 2{,}88139$, $\theta_4 = -0{,}22453$, $\theta_5 = 0{,}13318$, $\theta_6 = 0{,}00496$, $\theta_7 = 53{,}26714$, $\theta_8 = 46{,}52477$, $\theta_9 = -0{,}23567$, $\theta_{10} = -89{,}32466$, $\theta_{11} = 1{,}84924$, $\theta_{12} = -14{,}07299$, $\theta_{13} = -21{,}62068$, $\theta_{14} = -39{,}76487$, $\theta_{15} = 74{,}41487$, $\theta_{16} = 0{,}58824$, $\theta_{17} = -17{,}67795$, $\theta_{18} = 42{,}26980$, $\theta_{19} = -25{,}89622$ and $\theta_{20} = 19{,}47007$. A comprehensive discussion of the performance of the linear ODE model for each variable is visualized in Figures 6-9.

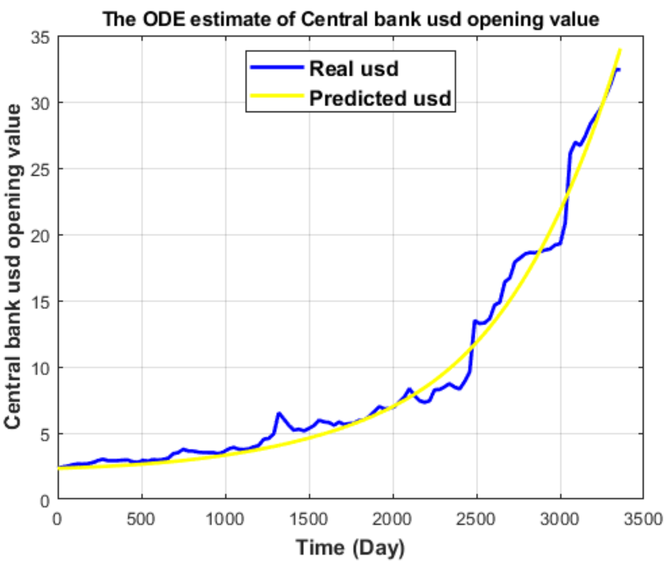

Figure 6. ODE estimate for USD

As shown in Figure 6, USD values exhibit a consistent upward trajectory with intermittent spikes, especially in the later stages. The predicted USD values follow this upward trend closely, with a smooth curve that largely tracks the real data but overlooks the smaller fluctuations. The results highlight the model's robustness in handling the long-term dynamics of the USD exchange rate. Nevertheless, more responsive models, such as those incorporating stochastic components, might be required for short-term financial planning or hedging purposes.

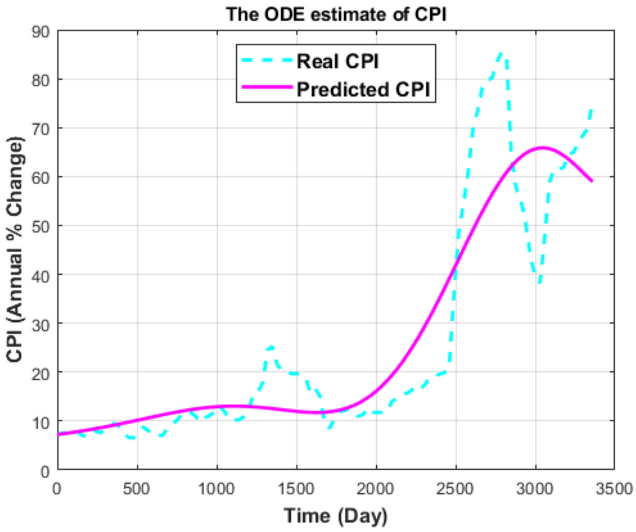

Figure 7. ODE estimate for CPI

As shown in Figure 7, CPI exhibits significant volatility throughout the period, with sharp rises and falls in certain intervals. In contrast, the predicted CPI (solid magenta line) shows a much smoother trajectory, capturing the long-term upward trend while attenuating short-term fluctuations. The smoothing effect observed in the predicted CPI is typical in ODE models, which focus on continuous, gradual changes. The model's limitation in capturing volatility may indicate the need for additional components to account for external shocks or seasonal patterns affecting inflation.

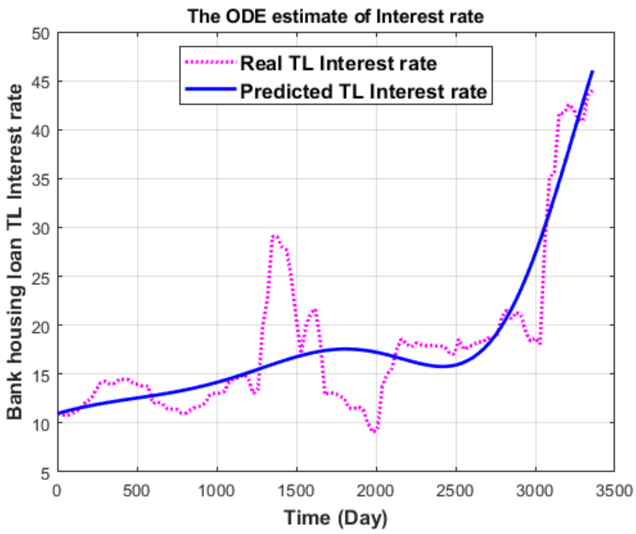

Figure 8. ODE estimate for interest rate

As shown in Figure 8, Real interest rates exhibit high volatility, with significant swings throughout the time series, especially in the mid-period (between day 1000 and 2000). In contrast, the predicted interest rates present a much smoother, steadily increasing curve. The divergence between predicted and real values, particularly in periods of volatility, suggests that the ODE model may require adjustments, such as introducing exogenous factors or coupling with stochastic models, to better capture market reactions to economic or political events.

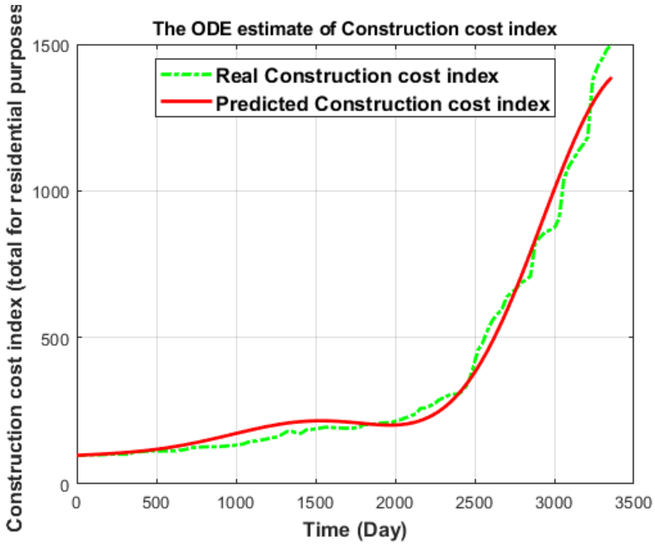

Figure 9. ODE estimate for the construction cost index

As shown in Figure 9, the construction cost index (dashed green line) follows an exponential growth pattern with moderate fluctuations. The predicted cost index (solid red line) closely follows the actual data, with only minor deviations throughout the time series. The model's success in predicting the construction cost index suggests that the index's relatively stable growth is well-suited for ODE modeling. This makes the ODE model a reliable tool for forecasting construction-related costs over time, where market conditions are less prone to abrupt changes than other economic variables.

The ODE model's performance across the four economic indicators reveals its strengths and limitations. The model excels in predicting long-term trends, such as the general upward trajectories of USD opening values, construction cost indices, and, to a lesser extent, the CPI and interest rates. However, it struggles with capturing the real CPI and interest rate data volatility, where rapid changes and external shocks significantly influence the time series. This indicates that while ODE models are useful for trend analysis and forecasting stable, long-term economic behaviors, they may require augmentation with other techniques—such as stochastic differential equations or machine learning models—when attempting to model highly volatile or shock-prone variables.

4.3.Analysis of ANN and ODE Models

To comprehensively evaluate the predictive capabilities of the ANN and ODE models, several performance metrics were calculated for each model about the four target variables: USD, CPI, Interest Rate, and Construction Cost Index. The metrics used include MAD, MSE, RMSE, MAPE, and R^2, as presented in Table 3.

Table 3. Result of ANN and ODE models

Metric	ANN prediction results for USD	ANN prediction results for CPI	ANN prediction results for Interest Rate	ANN prediction results for Cost Index	ODE prediction results for USD	ODE prediction results for CPI	ODE prediction results for Interest Rate	ODE prediction results for Cost Index
MAD	0,51	5,14	2,71	22,49	0,68	6,99	2,83	262,32
MSE	0,53	69,65	15,05	1275,94	0,92	105,25	15,710	145722,6
RMSE	0,73	8,35	3,88	35,72	0,96	10,25	3,96	381,73
MAPE	7,08	19,21	16,00	5,88	12,95	17,15	10,92	69,64
R^2	0,99	0,88	0,78	0,998	0,98	0,81	0,77	0,99

The ANN model performs well regarding MAD, with particularly low values for USD (0,51) and Interest Rate (2,71). However, it shows higher deviations in CPI (5,14) and Construction Cost Index (22,49), suggesting that the model struggles more with predicting these two variables. On the other hand, The ODE model exhibits slightly higher MAD values for USD (0,68) and CPI (6,99) but remains comparable to the ANN model for these variables. However, the ODE model's MAD for Construction Cost Index (262,32) is significantly higher than the ANN model's, indicating substantial deviation in predicting this variable.

The ANN model achieves very low MSE for USD (0,53), indicating strong predictive performance. Conversely, CPI (69,66) and Interest Rate (15,05) show much higher MSE, indicating larger squared errors and potential issues predicting these variables. Moreover, The ODE model shows higher MSE values across most variables, particularly for CPI (105,25) and Construction Cost Index (145722,65), suggesting that the ODE model struggles to minimize the squared differences between predicted and actual values, especially for variables with higher volatility or complexity.

Similar to MSE, RMSE values for USD (0,73) and Interest Rate (3,88) are relatively low for the ANN model, while higher errors are observed for CPI (8,35) and Construction Cost Index (35,72). The RMSE metric highlights the difficulties the model encounters in capturing the variability of these latter variables. On the other hand, The ODE model exhibits slightly higher RMSE for USD (0,9604) and substantially higher for Construction Cost Index (381,73), again highlighting the challenge of accurately predicting the construction index using this model.

The ANN model delivers competitive MAPE values for USD (7,08) and Construction Cost Index (5,88), suggesting it performs well in predicting these variables regarding relative error. However, the model has higher MAPE for CPI (19,21) and Interest Rate (16,00), indicating that it struggles to effectively capture these variables' dynamics. Moreover, The ODE model shows a generally higher MAPE for most variables, particularly for USD (12,96), CPI (17,16), and Construction Cost Index (69,64), indicating that its predictions deviate significantly in percentage terms, especially for the Construction Cost Index, where large relative errors occur.

The R^2 values for the ANN model demonstrate strong performance for USD (0,9921) and Construction Cost Index (0,9907), indicating that the model explains over 99% of the variance in these variables. However, R^2 values are lower for CPI (0,8774) and Interest Rate (0,7816), suggesting a reduced ability to explain the variance in these more complex and volatile variables. On the other hand, The ODE model also demonstrates high R^2 values for USD (0,9866) and Construction Cost Index (0,9930) but performs less effectively for CPI (0,8121) and Interest Rate (0,7723), which indicates a somewhat reduced predictive capability in capturing the full variability of these economic indicators.

The results suggest that while the ANN model generally provides superior predictive performance across the board, the ODE model remains a competitive alternative for variables with more stable, long-term trends, such as the USD opening value and Construction Cost Index. However, for highly volatile economic indicators, such as CPI and Interest Rate, the ANN model is better equipped to handle the complexities and non-linear relationships present in the data.

ANN analysis showed better performance for USD and cost index. However, with the ANN model, the output variable can be calculated with the current value of the input variables. On the other hand, the system is an initial value problem throughout the ODE model. In this context, forward-looking estimates can be made with the ODE model. Thus, the scenario envisaged for the USD exchange rate and cost index in the long term is shown in Figure 10.

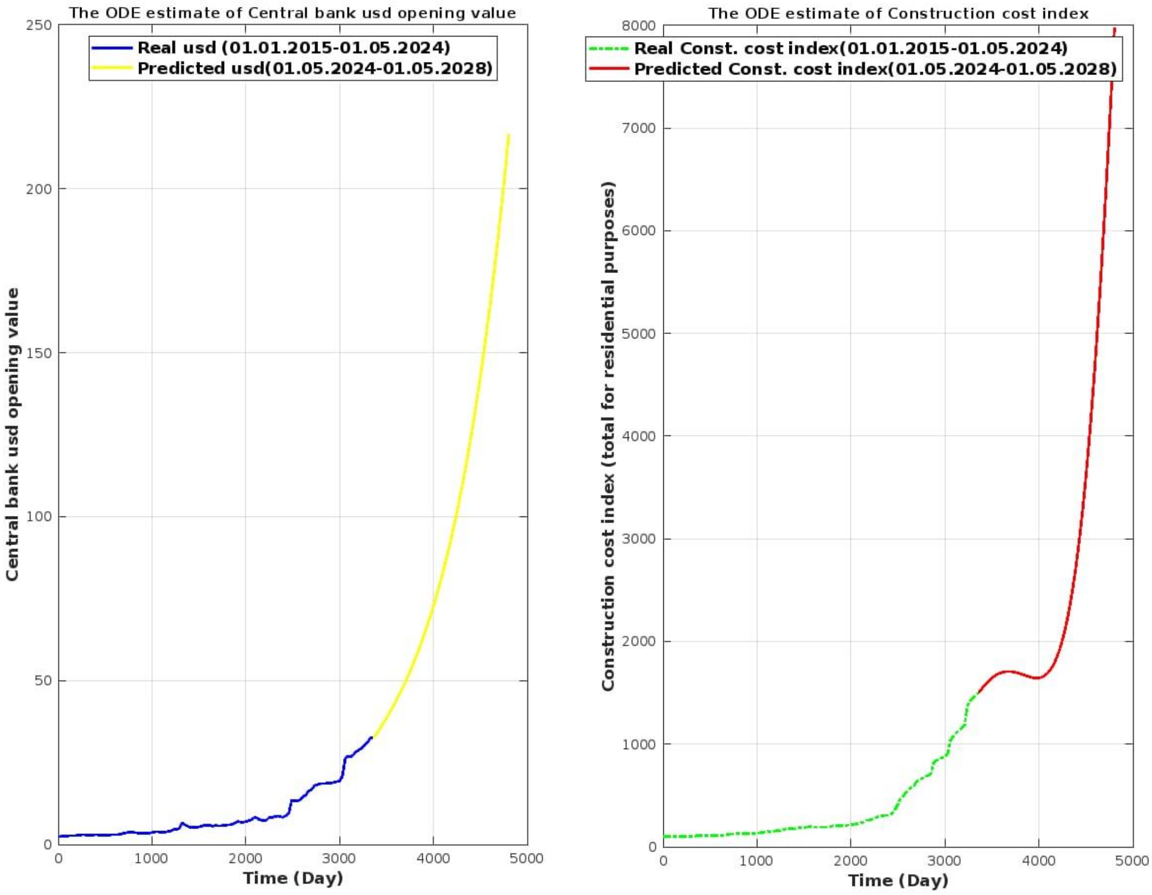

Figure 10. ODE estimate for the USD exchange rate and construction cost index (01.05.2024-01.05.2028)

5. Conclusion

In this study, we explored the predictive performance of ANN and ODE models for key economic indicators, including USD opening value, Consumer Price Index (CPI), TL housing loan interest rate, and residential construction cost index, using Turkish Statistical Institute (TUIK) data from 2015 to 2024. The aim was to evaluate and compare the accuracy of both models in forecasting economic trends and fluctuations in the Turkish economy.

The results indicate that both models have strong predictive capabilities, but their effectiveness varies depending on the complexity and volatility of the economic indicator. The ANN model demonstrated superior performance in handling variables with complex, non-linear relationships, such as the USD opening value and housing loan interest rates, as evidenced by lower error metrics and higher R-squared values. The ODE model, on the other hand, was particularly effective in capturing the long-term trends of more stable indicators, such as the construction cost index.

The comparison of the models revealed that the ANN model is better equipped to manage volatility and sudden market changes, particularly in variables like CPI and interest rates, which exhibit significant fluctuations. Meanwhile, the ODE model excels in long-term trend analysis, offering a more holistic understanding of the system's dynamic behavior over time.

These findings underscore the importance of selecting the appropriate model based on the specific economic indicator and the analysis context. ANN models are recommended for short- to medium-term forecasts where volatility is expected, while ODE models are more suitable for long-term trend predictions in stable markets. Policymakers and economists can leverage the strengths of both models to enhance the accuracy of economic forecasts, especially during periods of uncertainty or economic instability.

Ultimately, this study contributes to the growing body of literature on economic forecasting by demonstrating the complementary nature of ANN and ODE models. Future research could explore hybrid approaches that combine the strengths of both models to provide more robust predictions across a wider range of economic variables.

Author Contributions

All the authors equally contributed to this work.

Conflicts of Interest

All the authors declare no conflict of interest.

Ethical Review and Approval

No approval from the Board of Ethics is required.

References

[1] N. Frumkin, Guide to economic indicators, 4th Edition, New York, 2015.

[2] M. K. Heun, J. Santos, P. E. Brockway, R. Pruim, T. Domingos, M. Sakai, *From theory to econometrics to energy policy: Cautionary tales for policymaking using aggregate production functions*, Energies 10 (2) (2017) Article Number 203 44 pages.

[3] D. Güneş, İ. Özkan, L. Erden, *Economic sentiment and foreign portfolio flows: Evidence from Türkiye*, Central Bank Review 24 (1) (2024) 100147 9 pages.

[4] P. Chinnasamy, A. Albakri, M. Khan, A. A. Raja, A. Kiran, J. C. Babu, *Smart contract-enabled secure sharing of health data for a mobile cloud-based e-health system*, Applied Sciences 13 (6) (2023) 3970 19 pages.

[5] M. Khan, S. Hariharasitaraman, S. Joshi, V. Jain, M. Ramanan, A. SampathKumar, A. A. Elngar, *A deep learning approach for facial emotions recognition using principal component analysis and neural network techniques*, The Photogrammetric Record 37 (180) (2022) 435–452.

[6] T. V. Ramana, G. S. Ghantasala, R. Sathiyaraj, M. Khan, Artificial intelligence and machine learning for smart community; concepts and applications, CRC Press, Florida, 2024.

[7] J. Zou, Y. Han, S. S. So, *Overview of artificial neural networks*, Artificial Neural Networks: Methods and Applications 458 (2009) 14–22.

[8] P. Hartman, Ordinary differential equations, Society for Industrial and Applied Mathematics, Philadelphia, 2002.

[9] B. Zheng, *Ordinary Differential equation and its application*, Highlights in Science, Engineering and Technology 72 (2023) 645–651.

[10] E. Alshawarbeh, A. T. Abdulrahman, E. Hussam, *Statistical modeling of high frequency datasets using the ARIMA-ANN hybrid*, Mathematics 11 (22) (2023) 4594 17 pages.

[11] A. R. Mohamed, *Artificial neural network for modeling the economic performance: A new perspective*, Journal of Quantitative Economics 20 (3) (2022) 555–575.

[12] G. W. R. I. Wijesinghe, R. M. K. T. Rathnayaka, *Stock market price forecasting using ARIMA vs ANN: A case study from CSE*, In 2020 2nd International Conference on Advancements in Computing (ICAC), IEEE, 2020, Vol. 1, pp. 269–274.

[13] K. M. Ramírez, J. M. Hormaza, S. V. Soto, *Artificial intelligence and its impact on the prediction of economic indicators*, In Proceedings of the 6th International Conference on Engineering and MIS, 2020, pp. 1–8.

[14] M. Fani, N. Norouzi, *Using social and economic indicators for modeling, sensitivity analysis and forecasting the gasoline demand in the transportation sector: an ANN Approach in case study for Tehran metropolis*, Iranian Journal of Energy 23 (2) (2020) 71–91.

[15] L. Guerrini, A. Krawiec, M. Szydlowski, *Bifurcations in an economic growth model with a distributed time delay transformed to ODE*, Non-Linear Dynamics 101 (2) (2020) 1263–1279.

[16] L. Wu, X. Qiu, Y. X. Yuan, H. Wu, *Parameter estimation and variable selection for big systems of linear ordinary differential equations: A matrix-based approach*, Journal of the American Statistical Association 114 (526) (2019) 657–667.

[17] I. Georgiev, V. Centeno, V. Mihova, V. Pavlov, *A modified ordinary differential equation approach in price forecasting*, in AIP conference proceedings, AIP Publishing 2459 (1) (2022) 030008 7 pages.

[18] B. Daşbaşı, İ. Öztürk, *The dynamics between pathogen and host with Holling type 2 response of immune system*, Journal Of Graduate School of Natural and Applied Sciences 32 (1) (2016) 1–10.

[19] S. Paul, A. Mahata, S. Mukherjee, M. Das, P. C. Mali, B. Roy, P. Bharati, *Study of fractional order SIR model with MH type treatment rate and its stability analysis*, Bulletin of Biomathematics 2 (1) (2024) 85–113.

[20] R. B. Guenther, J. W. Lee, Partial differential equations of mathematical physics and integral equations, Courier Corporation, New Jersey, 1996.

[21] K. Sobczyk, Stochastic differential equations: with applications to physics and engineering, Springer Science and Business Media, Dordrecht, 2013.

[22] B. Daşbaşı, *Fractional order bacterial infection model with effects of anti-virulence drug and antibiotic*, Chaos, Solitons and Fractals 170 (2023) 113331 17 pages.

[23] H. Niu, Y. Zhou, X. Yan, J. Wu, Y. Shen, Z. Yi, J. Hu, *On the applications of neural ordinary differential equations in medical image analysis*, Artificial Intelligence Review 57 (9) (2024) 236 32 pages.

[24] B. Daşbaşi, T. Daşbaşi, *Mathematical analysis of Lengyel-Epstein chemical reaction model by fractional-order differential equations system with multi-orders*, International Journal of Science and Engineering Investigations 6 (11) (2017) 78–83.

[25] N. Manhas, *Mathematical model for IP33 dependent calcium oscillations and mitochondrial associate membranes in non-excitable cells*, Mathematical Modelling and Numerical Simulation with Applications 4 (3) (2024) 280–295.

[26] E. Sönmez, B. Daşbaşı, T. Daşbaşı, Some applications on stability analysis of incommensurate and commensurate fractional-order differential equation systems: Brusselator chemical reaction model and bacterial infection model, Academic Studies in Physics and Mathematics from Theory to Application II, Chapter 10, IKSAD Publishing House, 2022.

[27] B. Goodwine, Engineering differential equations: theory and applications, Springer Science and Business Media, 2010.

[28] K. S. Miller, Partial differential equations in engineering problems, Courier Dover Publications, New Jersey, 2020.

[29] B. Ersoy, B. Daşbaşı, E. Aslan, *Mathematical modelling of fiber optic cable with an electro-optical cladding by incommensurate fractional-order differential equations*, An International Journal of Optimization and Control: Theories and Applications 14 (1) (2024) 50–61.

[30] R. Boucekkine, G. Fabbri, P. Pintus, *On the optimal control of a linear neutral differential equation arising in economics*, Optimal Control Applications and Methods 33 (5) (2012) 511–530.

[31] M. D. Johansyah, A. K. Supriatna, E. Rusyaman, J. Saputra, *Application of fractional differential equation in economic growth model: A systematic review approach*, AIMS Mathematics 6 (9) (2021) 10266–10280.

[32] Z. Hosseini-Nodeh, R. Khanjani-Shiraz, P. M. Pardalos, *Portfolio optimization using robust mean absolute deviation model: Wasserstein metric approach*, Finance Research Letters 54 (2023) 103735 13 pages.

[33] Z. Wang, A. C. Bovik, *Mean squared error: Love it or leave it? A new look at signal fidelity measures*, IEEE Signal Processing Magazine 26 (1) (2009) 98–117.

[34] T. O. Hodson, *Root means square error (RMSE) or mean absolute error (MAE): When to use them or not*, Geoscientific Model Development Discussions, 15 (2022) 5481–5487.

[35] E. Işık, B. Daşbaşı, *A compartmental fractional-order mobbing model and the determination of its parameters*, Bulletin of Biomathematics 1 (2) (2023) 153–176.