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Machine Learning Based Online Tuning Single Input Type-1 Fuzzy PID Controller Approch

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Anahtar Kelimeler

Makine Öğrenimi
Tip-1 Bulanık Kontrolör
SIT1-PID
PID
Doğrusal Olmayan Sistem
Sağlamlık

Graphical/Tabular Abstract (Grafik Özet)

In this study, a machine learning-based single-input type-1 fuzzy PID (ML-SIT1-FPID) controller design has been developed. In the designed system, a dynamic equation was obtained using linear regression from machine learning-controlled learning methods. The machine learning algorithm linear regression (LR) metrics were found to be R^2=0.933426628, Prediction Accuracy (%): 94.02587, MSE(Training) = 0.000423, MSE(Validation) = 0.000878. / Bu çalışmada, makine öğrenmesi tabanlı tek girişli tip-1 bulanık PID (MÖ-TGT1-BPID) denetleyici tasarımı geliştirilmiştir. Tasarlanan sistemde dinamik bir denklem makine öğrenmesi denetimli öğrenme yöntemlerinden doğrusal regresyon ile elde edilmiştir. Makine öğrenmesi algoritması olan lineer regresyon (LR) metrikleri R^2 (%) =0.933426628, Tahmin Doğruluğu (%):94.02587, MSE(Eğitim): 0.000423, MSE(Doğrulama) = 0.000878 olduğu tespit edilmiştir.

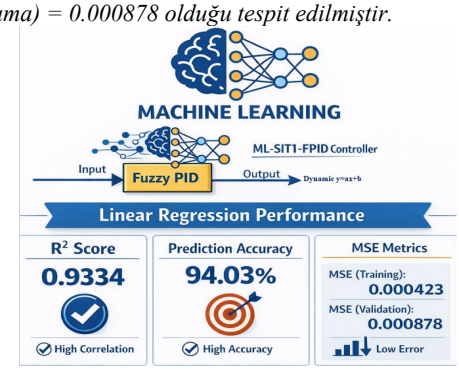


Figure A. *System Overview / **Şekil A**. Sistem Genel Bakışı*

Highlights (Önemli noktalar)

- *In this study, a machine learning-based single-input Type-1 fuzzy PID (ML-SIT1-FPID) controller design has been developed.*
- *The supervisory structure has become dynamic.*
- *The effect of internal and external disturbances on the system has been incorporated into the system using machine learning.*
- *Bu çalışmada, makine öğrenmesi tabanlı tek girişli tip-1 bulanık PID (MÖ-TGT1-BPID) denetleyici tasarımı geliştirilmiştir.*
- *Denetleyici yapısı dinamik hale gelmiştir.*
- *Sistemin iç ve dış bozuculardaki etkisi makine öğrenmesi ile sisteme eklenmiştir.*

Aim (Amaç): *In this study, a machine learning-based single-input type-1 fuzzy PID (ML-SIT1-FPID) controller design has been developed. / Bu çalışmada, makine öğrenmesi tabanlı tek girişli Tip-1 bulanık PID (MÖ-TGT1-BPID) denetleyici tasarımı geliştirilmiştir.*

Originality (Özgünlük): *Unlike controllers used today, a machine learning-based controller design has been implemented. / Günümüzde kullanılan denetleyicilerden farklı olarak makine öğrenmesine dayalı denetleyici tasarımı gerçeklenmiştir.*

Results (Bulgular): *The designed controller utilises a machine learning algorithm, linear regression (LR), with metrics R^2=0.933426628, Prediction Accuracy (%): 94.02587, MSE (Training) = 0.000423, MSE (Validation) = 0.000878. / Tasarlanan denetleyicide makine öğrenmesi algoritması olan lineer regresyon ile (LR) metrikleri R^2=0.933426628, Tahmin Doğruluğu (%): 94.02587, MSE (Eğitim) = 0.000423, MSE (Doğrulama) = 0.000878 olduğu tespit edilmiştir.*

Conclusion (Sonuç): *The LR equation model created has been found to be successful compared to the LSTM and NARX algorithms. / Oluşturulan LR denklem modelinin, LSTM ve NARX algoritmalarından başarılı olduğu görülmüştür.*

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Abstract

In this study, a machine learning-based single-input Type-1 fuzzy PID (ML-SIT1-FPID) controller design has been developed. The single-input Type-1 fuzzy PID controller (SIT1-FPID) consists of a single-input single-output Type-1 fuzzy controller (T1-FC) and a classical PID controller. The T1-FC behaves like the non-linear characteristic of the classical PID controller. In the SIT1-FPID controller design, five triangular Type-1 membership functions are used for the input variable, and five singular membership functions are used for the output variable. The structure of the ML-SIT1-FPID controller is the same as that of the SIT1-FPID controller, with the main difference being the output membership functions. Simulation studies were conducted under various conditions on a non-linear system using the SIT1-FPID controller, and data was collected accordingly. Based on the collected data, a dynamic equation was obtained using the machine learning supervised learning method of linear regression. The metrics of the machine learning algorithm linear regression (LR) were found to be R^2=0.933426628, Prediction Accuracy (%): 94.02587, MSE (Training) = 0.000423, MSE (Validation) = 0.000878. Using these metrics, the output membership functions of the ML-SIT1-FPID controller were adjusted online using dynamic equations. The performance of the proposed controller was compared with SIT1-FPID and classical PID controllers under different conditions on a non-linear system. The ML-SIT1-FPID controller demonstrated a more efficient performance compared to the other controllers.

Makine Öğrenmesi Tabanlı Çevrimiçi Ayarlı Tek Girişli Tip-1 Bulanık PID Denetleyici Yaklaşımı

Makale Bilgisi

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Öz

Bu çalışmada, makine öğrenmesi tabanlı tek girişli Tip-1 bulanık PID (MÖ-TGT1-BPID) denetleyici tasarımı geliştirilmiştir. Tek girişli Tip-1 bulanık PID denetleyici (TGT1-BPID), tek girişli tek çıkışlı Tip-1 bulanık kontrolcü (T1-BK) ile klasik PID denetleyiciden oluşmaktadır. T1-BK, klasik PID denetleyicinin doğrusal olmayan karakteristiği gibi davranmaktadır. TGT1-BPID denetleyici tasarımında, giriş değişkeni için beş adet üçgensel tip-1 üyelik fonksiyonu, çıkış değişkeni için ise beş adet tekil üyelik fonksiyonu kullanılmıştır. MÖ- TGT1-BPID denetleyici yapısı, TGT1-BPID denetleyiciyle aynı olup, aralarındaki temel fark çıkış üyelik fonksiyonlarından kaynaklanmaktadır. TGT1-BPID denetleyici kullanılarak doğrusal olmayan bir sistem üzerinde çeşitli koşullar altında benzetim çalışmaları gerçekleştirilmiş ve buna göre veri toplanmıştır. Toplanan verilere dayanarak, dinamik bir denklem makine öğrenmesi denetimli öğrenme yöntemlerinden doğrusal regresyon ile elde edilmiştir. Makine öğrenmesi algoritması olan lineer regresyon (LR) metrikleri R^2=0.933426628, Tahmin Doğruluğu (%): 94.02587, MSE (Eğitim) = 0.000423, MSE (Doğrulama) = 0.000878 olduğu tespit edilmiştir. Bu metrikler ile MÖ-TGT1-BPID denetleyicinin çıkış üyelik fonksiyonları dinamik denklem kullanılarak çevrimiçi ayarlanmıştır. Önerilen denetleyicinin performansı, doğrusal olmayan bir sistem üzerinde farklı koşullar altında TGT1-BPID ve klasik PID denetleyiciler ile karşılaştırılmıştır. MÖ-TGT1-BPID denetleyici, diğer denetleyicilere kıyasla daha performanslı bir durum sergilemiştir.

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1. INTRODUCTION (GİRİŞ)

Fuzzy logic is an artificial intelligence technique introduced by Lotfi A Zadeh [1-2]. Mimicking human reasoning and decision-making abilities, fuzzy logic reaches conclusions through IF-THEN rules. In the literature, fuzzy logic has been combined with classical PID to design intelligent control systems. This controller provides a more robust response to noise, disturbances, and parameter changes compared to classical controllers. In chase-and-escape games, a fuzzy PD (FPD) controller was designed to define the pursuer agent's pursuit strategy [3]. A fuzzy PID (FPID) controller was developed for the position and altitude control of an unmanned aerial vehicle (UAV) [4-5]. Liquid level control in a two-tank system was achieved using a FPID controller [6]. In a magnetic balance system, a FPID controller design was implemented for the position control of a metal ball [7]. In their work, García-Martínez and colleagues examine the design of fuzzy controllers, their rule bases, and how fuzzy PID-type controllers are tuned using methods such as particle swarm optimization (PSO). They provided information about the design and optimization processes of the PID-type FLC (Fuzzy Logic Controller) part of the controller in your study [8]. Another similar study by Ahmed, M. T. Details the steps of fuzzy controller design, how linguistic variables and membership functions are defined, and provides guidance on adjusting parameters such as membership functions and output scaling factors mentioned in your machine [9]. The importance of the number of parameters in these applications is understood. The study by Chao, C.-T. And colleagues examines the equivalence between Fuzzy Logic Controllers (FLCs) and traditional PID controllers. It demonstrates how Genetic Algorithms (GA) can be used to optimize the design of Fuzzy PID controllers with fewer parameters and a more concise structure. It is understood that the SIT1-FPID structure in your article is an important resource for gaining a deeper understanding of parameter reduction and systematic optimization [10].

In research conducted for industrial application of this optimization, Reznik, L. and colleagues examine the design paths for effective combinations of classical PID controllers with intelligent technologies (fuzzy controllers) and the evolution of fuzzy controller design methodology. They have been found to provide information about the role of fuzzy controllers in controlling the online adjustment of PID parameters [11]. In another industrial application area, the work by Nguyen, V.-K., and colleagues explains how PID controller parameters are finely tuned using a self-tuning mechanism based on a fuzzy-PD controller. This bears strong similarities to the online tuning and machine learning (data-driven) part of your controller. They have demonstrated how the fuzzy PD controller uses its rule set to adjust the coefficients of the target PID controller [12]. A single-input fuzzy PID controller has been proposed to improve the performance of these controls. In this context, the single-input fuzzy PID controller consists of a fuzzy controller and a classical PID controller [13-15]. In this controller structure, the fuzzy controller behaves like a non-linear gain and enhances the performance of the classical PID controller. The main advantage of this controller is that it reduces the number of inputs, gains, rules, and membership functions. The single-input type-1 fuzzy PID (SIT1-FPID) controller consists of a type-1 fuzzy controller (T1-FC) and a PID controller. In the SIT1-FPID controller, the system error is taken as the input, and the control signal is obtained as the output of the proposed controller.

Artificial intelligence technologies have begun to take their place in many scientific fields. Artificial intelligence is a software system that represents human intelligence and enables machines to think and make decisions like humans. In its knowledge base on machine learning, a sub-field of artificial intelligence, Siskon explains what machine learning is as a structural function, the construction of algorithms, and its overlapping aspects with data mining [16]. Data and data analysis are the most important elements in the studies conducted in this context. A review of the literature reveals that curve fitting methods are commonly used. The study by Akson and Karakuş shows that models created with these methods should focus on model success evaluation types to determine whether a model is useful and address the importance of the comparison label (label, dependent variable) through Supervised Learning [17,18]. In this context, in a literature study, Qıngjıan Liu and colleagues developed an elliptic arc-based curve fitting algorithm that provides high accuracy with fewer parts in situations where traditional curve fitting methods are insufficient. This method, developed using elliptic arcs, has been successfully applied to different types of functions such as parabolic, sinusoidal, spiral, butterfly, and NURBS curves, achieving the same or higher accuracy than other methods by reducing the number of segments [19]. In another study conducted by Jin Yaohua, a Bezier curve-based segmentation algorithm was developed as a solution to the shadow effect and crowd (neighboring cyclists) separation problems

encountered in video-based lane detection systems. The proposed method offers an automatic, fast solution with low hardware requirements and has been successfully tested on video data [20]. In another study on electric machines, Zhiwei Chen and colleagues propose a new least-loss control (LMC) strategy to improve the efficiency of surface-magnetized synchronous motors (SPMSM). In this study, a curve fitting method was developed to accurately determine the current reference on the d-axis. Analyses show that the proposed method reduces total losses and increases efficiency [21]. A review of this literature reveals that curve fitting methods provide improvements in terms of accuracy and gain, and that studies have focused on this point.

Within the scope of this study, a machine learning-based online tuning single-input type-1 fuzzy PID controller (ML-SIT1-FPID) approach has been designed. In the SIT1-FPID controller design, five triangular type-1 membership functions were selected for the input variable and five singleton membership functions for the output variable. Following the design of the SIT1-FPID controller, simulation studies were conducted under five conditions: internal disturbance, external disturbance, parameter change, nominal state, and noise. Data obtained from the system were collected. Based on the information gathered from the collected output data, machine learning model training was planned for the input data. In this context, based on the information obtained from the literature review, the linear curve fitting method was used to create the set of equations required for model training. In this curve fitting method, the activation function was not used; instead, the data was normalized and constrained between −1 and 1. The learning process was performed using the equation, and the coefficients were estimated. The R^2 accuracy ratio and error calculations were performed considering the maximum gain. Improvements in the model equation were made based on the gain. The original part of this study is defined as follows. Fundamentally, the structure of the ML-SIT1-FPID controller is determined to be the same as the SIT1-FPID controller, with the main difference being in the output membership function. The result membership function of the ML-SIT1-FPID controller is adjusted online via the dynamic equation obtained through the machine learning algorithm. The performance of the ML-SIT1-FPID controller has been compared with the SIT1-FPID and classical PID controllers under various conditions, such as nominal conditions and disturbing effects, on a non-linear system. The simulation results have shown in detail that the ML-SIT1-FPID controller exhibits better and more robust performance compared to the other controllers.

The article is organized as follows: Section 2, Methodology, provides a schematic diagram of the system to be designed and details the structure of the machine learning module, the training process, parameter selection, validation stages, the algorithm used, the data set size, and the training/validation ratios. In addition, the proposed structure of the ML-SIT1-FPID controller is designed and explained. Section 3 presents the state responses of the classical PID, SIT1-FPID, and ML-SIT1-FPID controllers in simulation studies, explained graphically and in tables. Furthermore, comparisons between them are provided using error metrics for evaluation. Section 4, the results section, provides a general commentary, explaining the performance by interpreting the error metric graphs, indicating that the linear regression (LR) algorithm is suitable for the ML-SIT1-FPID controller. Section 5, the discussion section, discusses the future applications of this work in relation to the states of the algorithms and controllers.

2. MATERIALS AND METHODS (MATERYAL VE METOD)

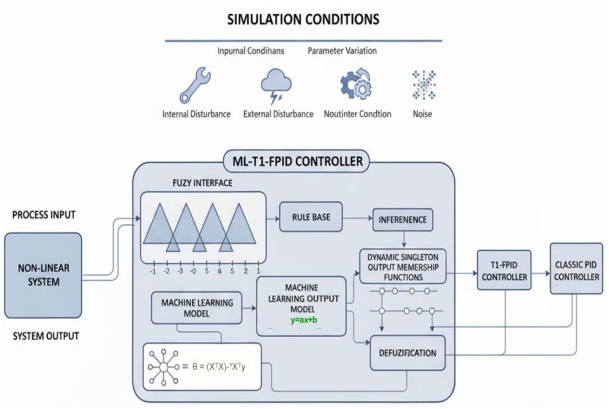


Figure 1. System design (Sistem tasarımı)

As shown in Figure 1, a machine learning-based online tuning single-input type-1 fuzzy PID controller (ML-SIT1-FPID) approach has been designed. In the design, five triangular type-1 membership functions were selected for the input variable of the SIT1-FPID controller, and five singleton membership functions were selected for the output variable. Following the design of the SIT1-FPID controller, simulation studies were conducted for the system design under five conditions: internal disturbance, external disturbance, parameter change, nominal state, and noise. Data obtained from the system were collected. Based on the information gathered from

the collected output data, machine learning model training was planned for the input data. In this context, based on the information obtained from the literature review, the linear curve fitting method was proposed and used to create the equation set required for model training. These technical details are described in detail under the main headings below.

2.1. Machine Learning (Makine Öğrenmesi)

Machine learning, a subfield of artificial intelligence, lies at the heart of today's high-capacity computers, machines, and devices. Machine learning enables the creation of systems that make decisions based on data and can improve themselves. It is one of the practical and effective methods of artificial intelligence. It can be applied in many fields such as healthcare, industry, education, and transportation [22, 23].

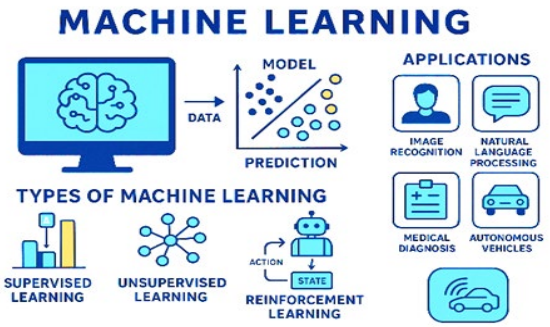


Figure 2. Types of Machine learning and application areas (Makine öğreniminin türleri ve uygulama alanları)

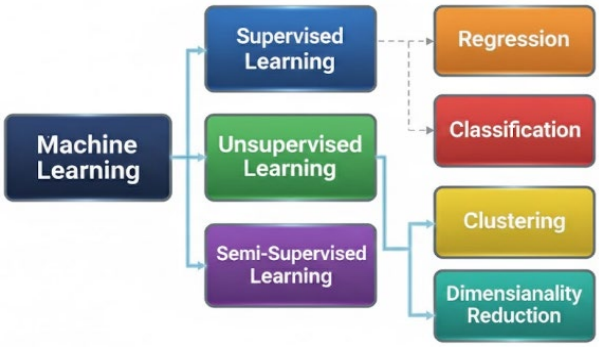


Figure 3. Types of machine learning (Makine öğrenme türleri)

Machine learning is divided into three types. These types are called supervised learning, unsupervised learning, and semi-supervised learning. Each of these types have different algorithms. The supervised learning type performs classification and regression operations using input and output data. In classification, the output is categorical, while in regression, the output is a real number value. Unsupervised learning attempts to make predictions using only input data. It aims to make predictions by examining the relationship between data. Semi-supervised learning, on the other hand, uses both supervised and unsupervised learning to learn through an agent [23]. When examining the algorithm hierarchy presented in Figure 3, it is evident that learning types are more suitable for making model predictions based on data. Upon examining machine learning algorithms, it is understood that they are fundamentally designed to classify events, find patterns, predict outcomes, and make meaningful decisions. With today's advancing technology and the presence of complex and unpredictable data, it is clear that algorithms can create models to achieve the best accuracy. The machine learning process to be created basically consists of 8 stages. These are:

1. Data Collection: Collection of high-quality and meaningful data
2. Data Cleaning: Correcting missing and outlier values
3. Feature Selection: Identifying meaningful features
4. Model Selection: Choosing the appropriate algorithm for the objective
5. Model Training: Creating the model using training data
6. Model Testing: Evaluating performance with test data
7. Model Optimization: Hyperparameter optimization and cross-validation
8. Application: Implementation in a real-world environment.

As can be understood from literature research, machine learning enables us to increase our efficiency by creating models with the data obtained and producing future-oriented results in our work and processes.

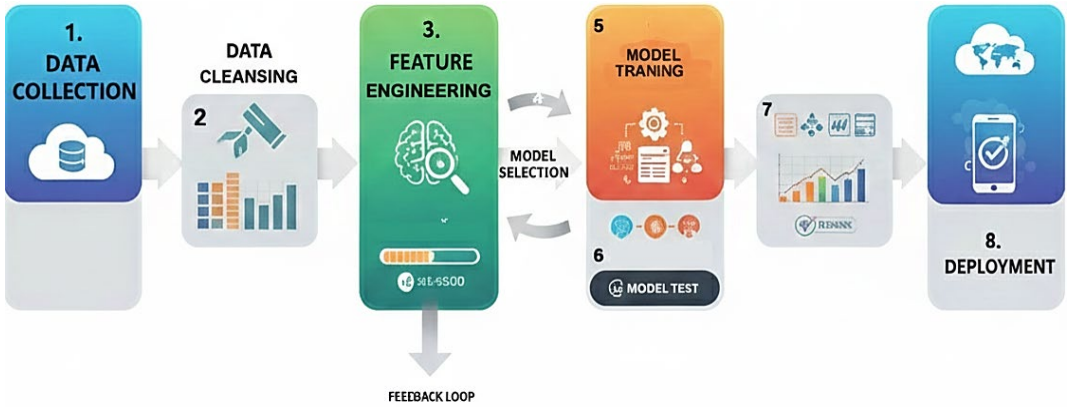


Figure 4. Machine learning processe. (Makine öğrenme süreçleri)

As shown in Figure 4, it is planned to design the SIT1-FPID controller approach, which can perform online tuning by progressing according to machine learning processes. Within this scope, a study was conducted to create a model from the input and output data in our system, based on the information obtained from the literature review. The aim is to develop a model that will optimize the fuzzy output using machine learning in order to maximize the profit in the system to be created within the scope of the study. In this context, based on the information and data obtained from our system, it has been understood that a linear regression algorithm of the supervised learning type would be appropriate. Accordingly, a study has been conducted to create a model decomposition. The linear regression equation model planned to be created in this direction is given in Equation 1.

$$y = ax + b \quad (1)$$

As shown in Equation 1, in the given regression model equation, y is the output, x is the input, and the input and output constant terms are defined as a and b. In line with machine learning processes, it was planned that these constants could be estimated using regression. Accordingly, it was decided that all inputs and outputs in our system would be analyzed and taken as data. The data collection process was developed as follows. During the data collection process, our system was analyzed, and all inputs and outputs were determined. The external disturbance, internal disturbance, noise, nominal state, and parameter change data, which are the five input values affecting the output of our system, are presented as a five-row data table as an example. Considering the data in general, the entire data set consists of 13,100 input and 13,100 output data points.

As this data contains all the information, it was cleaned and used on the system. Table 1: Nominal state examples, Table 2: Internal disturbance state examples, Table 3: Parameter change state examples, Table 4: External disturbance state examples, and Table 5: Noise state examples are provided to facilitate the examination of the data.

Table 1. Examples of nominal situations
(Nominal durum örnekleri)

Table no	Nominal Case		
	Time	İnput	Target
1	0.650000000000000	0.756685161804025	0.994884186330220
2	0.700000000000000	0.720749096276150	0.959368004963170
3	0.750000000000000	0.683125542848139	0.922874163601940
4	0.800000000000000	0.644037003601406	0.885829326168510
5	0.850000000000000	0.603719657691903	0.848667957303365

Table 2. Examples of internal disruptive situations (İç bozucu durum örnekleri)

Table no	Internal Corrosive		
	Time	İnput	Target
1	0.650000000000000	0.756685161804025	0.959368004963170
2	0.700000000000000	0.720749096276150	0.922874163601940
3	0.750000000000000	0.683125542848139	0.885829326168510
4	0.800000000000000	0.644037003601406	0.848667957303365
5	0.850000000000000	0.603719657691903	0.811824690007683

Table 3. Examples of parameter change conditions
(Parametre değişiklik koşul örnekleri)

Table no	Parameter Change		
	Time	İnput	Target
1	0.600000000000000	0.789734901247376	0.988218298322634
2	0.650000000000000	0.755239969337139	0.950215044271504
3	0.700000000000000	0.718709000243034	0.910658005372787
4	0.750000000000000	0.680324624550500	0.869925609129442
5	0.800000000000000	0.640285067481284	0.828416252204133

Table 4. Examples of external disruptive situations
(Dış bozucu durum örnekleri)

Table no	External Disruptor		
	Time	İnput	Target
1	0.950000000000000	0.520398579305526	0.740784348634283
2	1	0.477914875968441	0.707386353301784
3	1.05000000000000	0.435236686502341	0.675889777416447
4	1.10000000000000	0.392630781281606	0.646615074442147
5	1.15000000000000	0.350360897420190	0.619840423705202

Table 5. Examples of noise conditions (Gürültü koşul örnekleri)

Table no	Noise Change		
	Time	İnput	Target
1	0.950000000000000	0.501453643348427	0.944089186297707
2	1	0.517995790405235	1.69841824581100
3	1.05000000000000	0.397033341049486	-0.621982176165278
4	1.10000000000000	0.365531377744842	0.790376699377344
5	1.15000000000000	0.360453616793968	1.22429703208598

During the data cleaning process, the data obtained from the system was examined and optimised to ensure that our data fell within the range of -1 to 1. All data that could disrupt this range was removed. Care was taken to ensure that the data was meaningful. During this process, the entire dataset was reviewed again and a total of 13,100 data points were separated into training, validation and test data. Of this data, 10,480 items (80%) were used for training, 1,310 items (10%) for validation, and 1,310 items (10%) for testing. Accordingly, the validation data was evaluated and used for the K=5 cross-validation technique.

During the feature selection process, the data distribution was analyzed, and it was observed that the data progressed from 1 to 0 and then towards -1. At this point, time was set as a reference, and data within each time interval was considered. Data selection was performed in this manner, and details are provided in the data collection section. The most fundamental aspect of the model selection process is understanding the characteristics of the data. In this context, examining the distribution of the data and observing the clustering points is the most appropriate approach for the model to be created.

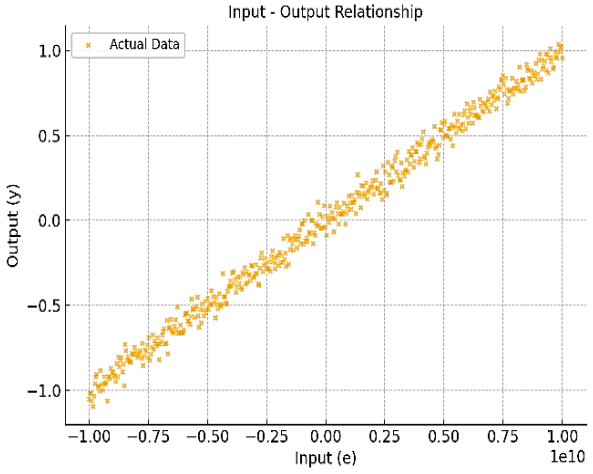


Figure 5. Output relationship of the models (Modellerin çıktı ilişkisi)

Upon examining the data provided in Figure 5, it is understood that the data is close to the linear regression model. In this context, the code required for model estimation has been developed by referring to the regression model equation shown in Equation 1. In these developments, the importance of linear regression model hyperparameters and their comparison with other models are presented in Table 6.

Tablo 6. Linear regression hyperparameters (Doğrusal regresyon hiperparametreleri)

Hyperparameter	Description	Used Value	Recommended Range	Effect
fit_intercept	Whether to estimate the intercept term	True	True / False	Shifts regression line
normalize *(deprecated)*	Normalize input features	False	—	Handled by scaler
copy_X	Copy input matrix	True	True / False	Memory vs safety
positive	Force coefficients to be positive	False	True / False	Physical constraints
solver *(implicit)*	Numerical solver (SVD)	SVD	SVD	Stable solution
loss function	Error minimization criterion	MSE	MSE	Least squares optimality

The code developed taking these hyperparameters into account was trained to estimate the a and b parameters on the incoming data. During the model training process, 80% of the 13,100 data points were allocated for training. To prevent data loss during training, the data was normalized again between −1 and 1, and as a result of the training;

The original model equation is shown as follows:

$$y = 0.5680 * e + 0.0217 \qquad (2)$$

As shown in Equation 2, the parameters in the given equation were reduced to 12,011 data points by removing the normalized outliers. The equation was revised using the reduced data to achieve sufficient accuracy. In the revision process, a new estimation was made using all the data. As a result of this estimation, the results shown in Equation 3 were obtained.

$$y = 0.0354 * e + 0.9786 \qquad (3)$$

As shown in Equation 3, the parameters in the given equation were estimated using 12,011 data points. The model's success rate was determined to be 93% based on the R^2 coefficient, indicating the equation's accuracy. This result demonstrates that our model has a high accuracy rate. Other learning and prediction metrics are presented in Table 7.

Table 7. Regression model learning metrics and rates (Regresyon modeli öğrenme metrikleri ve oranları)

Metric	Value
RMSE	541155064.7
MAE	87096073.82
R^2	0.933426628
NRMSE	0.029654626
Prediction Accuracy	94%

As shown in Table 7, when the learning metrics and ratios of the given regression model are evaluated, R^2=0.933426628 indicates that the model correctly forms its significant linear components. When examining the RMSE > MAE situation, it shows that this is due to the absolute magnitude of the output variables being very high and that the model generally works stably. NRMSE = 0.0297 indicates that the error is normalized and the system dynamics are high. Despite being a linear model, it shows that the prediction accuracy is effective at 94%. These values are presented as shown in Figure 6.

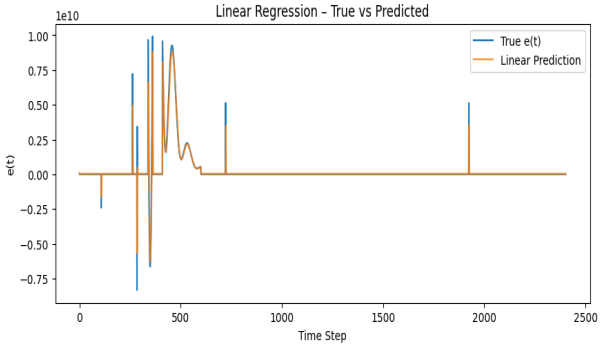


Figure 6. Output equation value curve estimation graph (Çıkış denklemi değer eğrisi tahmin grafiği)

As shown in Figure 6, the graph indicates that an efficient approach is followed in predicting the curves. In this context, for the purpose of generalizing the system, different algorithms were investigated, and models capable of processing control and time series, namely Nonlinear Autoregressive with Exogenous Inputs (NARX) vs Long Short-Term Memory (LSTM), were evaluated. The most important factor in evaluating these algorithms is their proximity to curve fitting. Other PSO, ANN, and genetic algorithms were not included in the evaluation because these metrics were not available and their performance in curve fitting was very low. Considering the hyperparameters of the NARX and LSTM algorithms, it is understood that there are differences. This situation is presented comparatively in Table 8.

Table 8. Comparison of NARX and LSTM algorithms (NARX ve LSTM algoritmalarının karşılaştırılması)

Criterion	LSTM	NARX
Memory representation	Internal gated cells	Explicit time delays
Interpretability	Medium	High
Data requirement	High	Medium
Control-system suitability	Medium	Very high
Hyperparameter tuning complexity	High	Low

As shown in Table 8, a software application was implemented by comparing the NARX and LSTM algorithms. The performance of the NARX and LSTM algorithms was revealed in the implemented software application. This information is presented in Table 9, where it is compared with LR performance metrics.

Table 9. Performance information for NARX, LSTM, and LR algorithms (NARX, LSTM ve LR algoritmaları için performans bilgileri)

Metric	LSTM	NARX	LR
RMSE	475872783.9	538051811.6	541155064.7
MAE	69706989.95	86402648.0	87096073.82
R^2	0.863623252	0.825445940	0.933426628
NRMSE	0.026077238	0.029484571	0.029654626
Prediction Accuracy (%)	92.39227623	93.05154287	94.02587

Table 9. As shown in the table, when examining the performance information of the given NARX, LSTM, and LR algorithms, it is seen that LR R^2 is 0.933426628 and the prediction accuracy is 94%. Although the metrics of the NARX and LSTM algorithms are close in value, it is seen that the LR metric values are better. The most obvious reason for this is that it captures the system dynamics more accurately with less data. With this comparison, it can be generalized that the model we created has been modelled with the best accuracy rate. After this stage, the validation process was performed using the K=5 cross-validation technique in the Model Improvement process. The results obtained from this show that the performances are very close to each other. Due to this validation, the values obtained were applied to the real system in equation 3, and a high gain was observed. In this context, the parameters applied to the real system were subjected to hyperparameter optimization using K-NN (K-Nearest Neighbors) logic and added to the output of the fuzzy system. During the application process, the model data and training results were stored to form the basis for future work. In real-world applications, this situation is defined as commissioning. This situation is explained in detail under the heading Machine Learning-Based Single-Input Type-1 Fuzzy PID Controller Design.

2.2. Design of a Machine Learning-Based Single-Input Type-1 Fuzzy PID Controller (Makine Öğrenimi Tabanlı Tek Girişli Tip 1 Bulanık PID Kontrolör Tasarımı)

This section first explains the design of the SIT1-FPID controller, followed by the ML-SIT1-FPID controller design. The TGT1-FPID controller consists of a single-input single-output Type-1 fuzzy controller (T1-FC) and a classical PID controller. The T1-FC acts as a non-linear gain of the classical PID controller. The structure of the SIT1-FPID controller is presented in Figure 7.

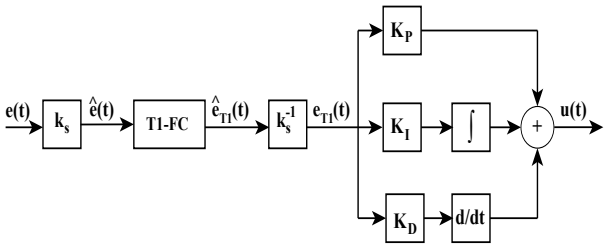


Figure 7. Single-input type-1 fuzzy PID control structure (Tek girişli tip 1 bulanık PID kontrol yapısı)

In Figure 7, e(t) represents the system error, while k_s, the input gain of T1-FC, is defined as follows:

$$k_s = \frac{1}{e_{max}} \tag{4}$$

Here, e_{max} denotes the maximum error value in the system. ê(t) represents the input applied to T1-FC, while $\hat{e}_{T1}$ represents the output of the type-1 fuzzy controller. In the T1-FC structure, the antecedent membership functions are type-1 triangular membership functions, while the output membership functions consist of discrete numbers, as shown in Figure 8. In the rule table, NB stands for 'Negative Large', N for 'Negative', Z for 'Zero', P for "Positive", and PB for 'Positive Large'.

For a clearer understanding of these conditions, the numerical values of the rule table are given as shown in Figure 8.

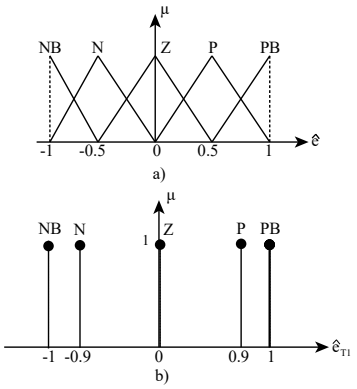


Figure 8. The antecedent and consequent membership functions of T1-FC (T1-FC'nin öncül ve sonuç üyelik fonksiyonları)

The rule table for the T1-FC controller is defined as follows:

Table 10. T1-FC rule table

$\hat{e}$	NB	N	Z	P	PB
$\hat{e}_{T1}$	NB	N	Z	P	PB

k_s^{-1}, T1-FC is the output gain and is defined by the following equation:

$$k_s^{-1} = \frac{1}{k_s} \tag{5}$$

$e_{T1}(t)$, It represents the output of T1-FC and the input of the classic PID controller. The control signal $u(t)$ is defined as follows:

$$u(t) = K_p e_{T1}(t) + K_I \int e_{T1}(t)\,dt + K_D \frac{de_{T1}(t)}{dt} \tag{6}$$

where, K_P is the proportional gain, K_I is the integral gain and K_D is the derivative gain.

The proposed ML-SIT1-FPID controller structure is identical to the SIT1-FPID controller structure. The difference lies in the result (which stems from the membership function). In the result membership function, the N and P values are adjusted using the dynamic function defined below via the online tuning method [24]:

$$c = a * abs(e(t)) + b \tag{7}$$

Here, a and b are adjusted using machine learning algorithms. P is equal to c, and N represents the value of c.

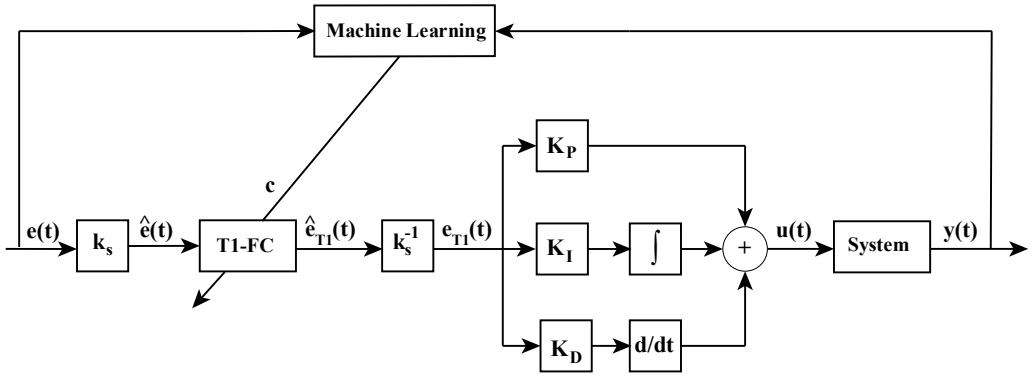


Figure 9. Structure of the ML-SIT1-FPID controller (MÖ-TGT1-BPID kontrolörünün yapısı)

3. SIMULATION STUDIES (SİMÜLASYON ÇALIŞMASI)

In this section, the performance of classical PID, SIT1-FPID and ML-SIT1-FPID controllers applied to non-linear systems has been tested with the system presented below [24]:

$$\ddot{y} + 0.8\dot{y}y + y^2 = u \qquad (8)$$

The gains of the classic PID controller are found in [24]. The gains of the TGT1-FPID and ML-SIT1-FPID controllers are the same as those of the classic PID controllers. In the result membership function of the ML-SIT1-FPID controller, the N and P values are equal as follows:

$$c = 0.1 * abs(e(t)) + 0.9 \qquad (9)$$

All control curves for the controllers are shown in Figure 10.

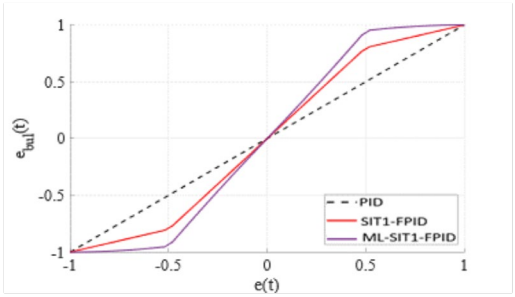


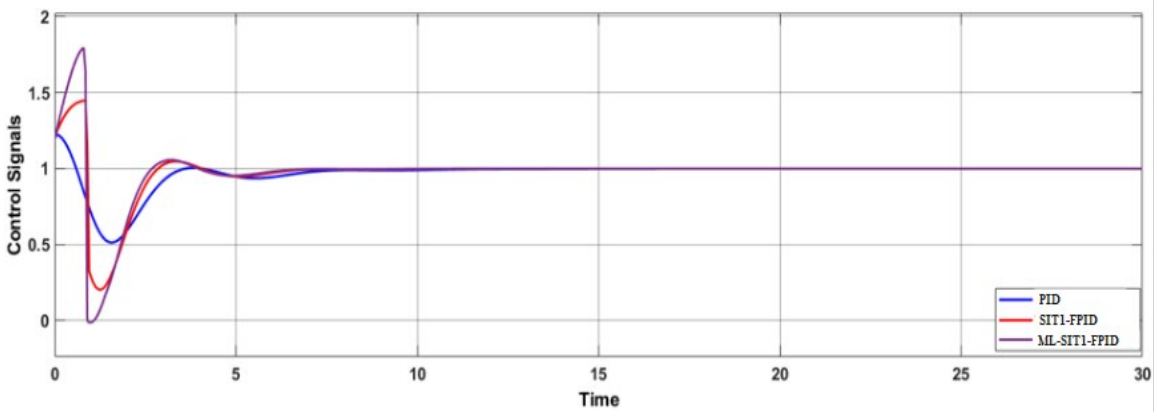
Figure 10. Control curves (Kontrol eğrileri)

Simulation studies were conducted in the MATLAB/SIMULINK environment with the sampling time set to 0.05 s.

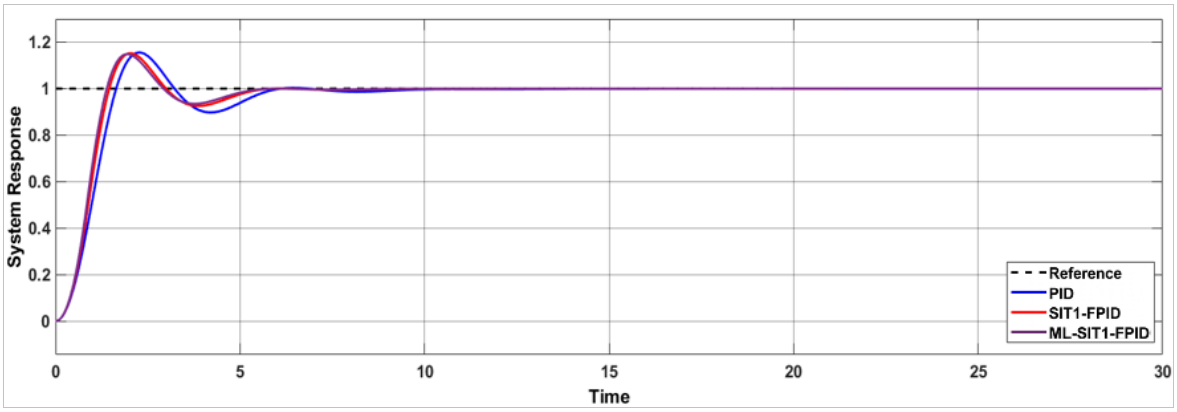
ntegral Absolute Error was selected as the performance indicator.

$$IMH = \int_0^{\infty} |e(t)|dt \qquad (10)$$

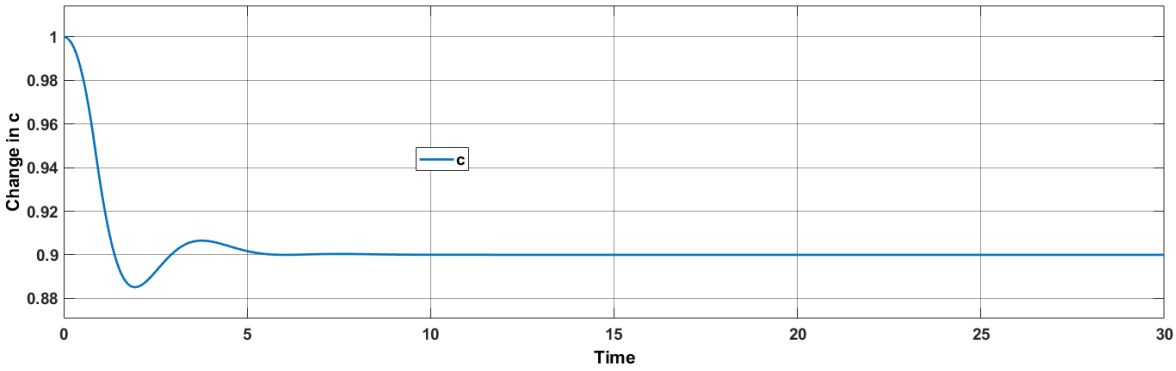
The perforance of the PID, TGT1-FPID, and ML-TGT1-FPID ontrollers has been compared under nominal conditions and varying disturbances. Under normal conditions, the nominal state responses are shown in Figure 10. The performance index values are given in Table 11. The simulation results revealed that the ML-SIT1-FPID controller performed better than the SIT1-FPID and classical PID controllers.



a



b



c

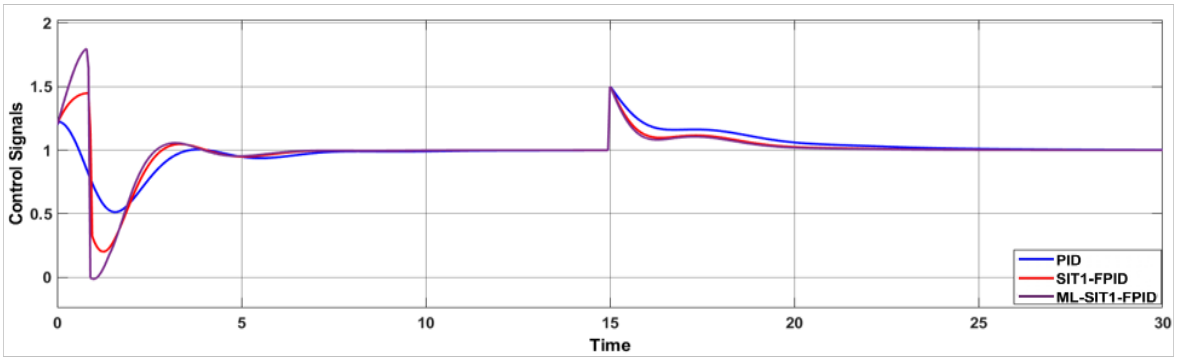
Figure 11. Nominal condition (a) (Control Signals), (b) (System Response) ,(c) Change in c responses.
(Nominal koşul (a) (Kontrol Sinyalleri), (b) (Sistem Tepkisi) , (c) c tepkilerindeki değişiklik)

As shown in Figure 11, when examining the nominal conditions given (a) Control Signals, (b) System Response, and (c) C's change responses, it can be seen that the controller we designed works efficiently. The metrics obtained from this study are given in Table 11.

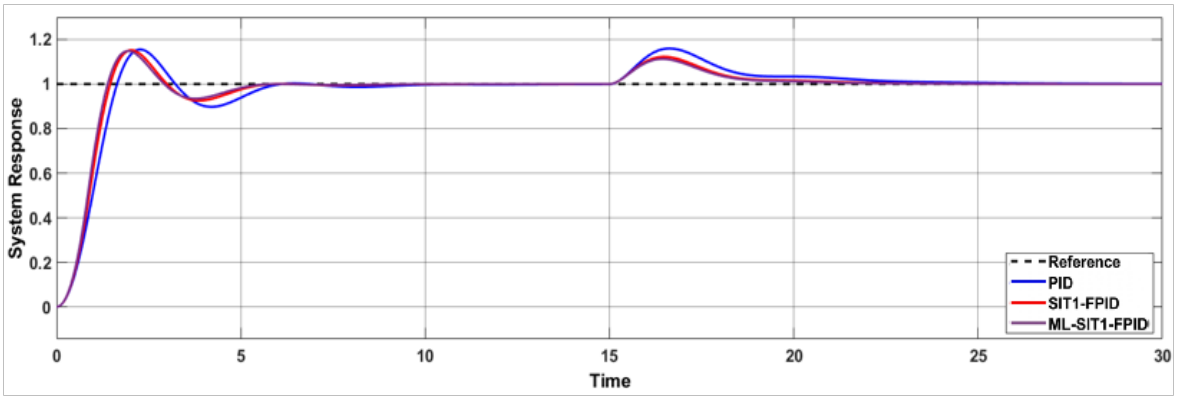
Table 11. Performance comparison of controllers under nominal conditions (Nominal koşullar altında kontrolörlerin performans karşılaştırması)

Controllers	Nominal Case		
	IAE	ITAE	ISE
PID	1.312	1.985	0.7634
SIT1-FPID	1.138	1.319	0.6987
ML-SIT1-FPID	1.076	1.156	0.6697

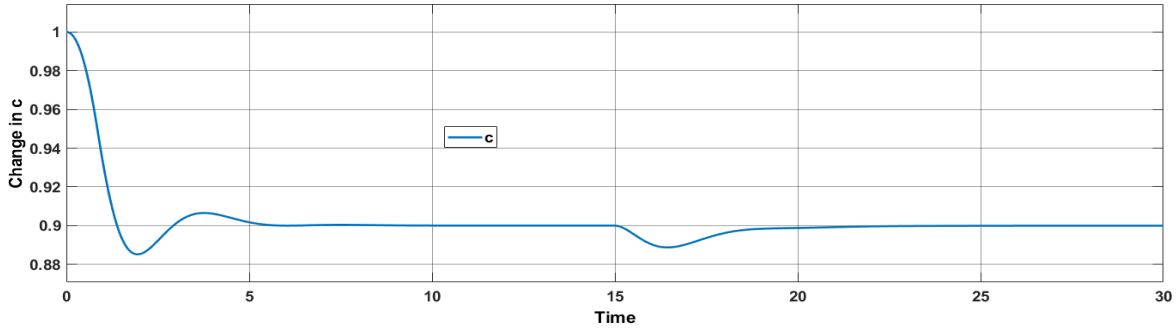
In the disturbance scenario, a disturbance of magnitude 0.5 was applied to the non-linear system at 15 seconds. The system responses under disturbance conditions are shown in Figure 12, while the performance index values are presented in Table 12. The simulation results reveal that the ML-SIT1-FPID controller exhibits more robust performance compared to the SIT1-FPID and classical PID controllers.



a



b



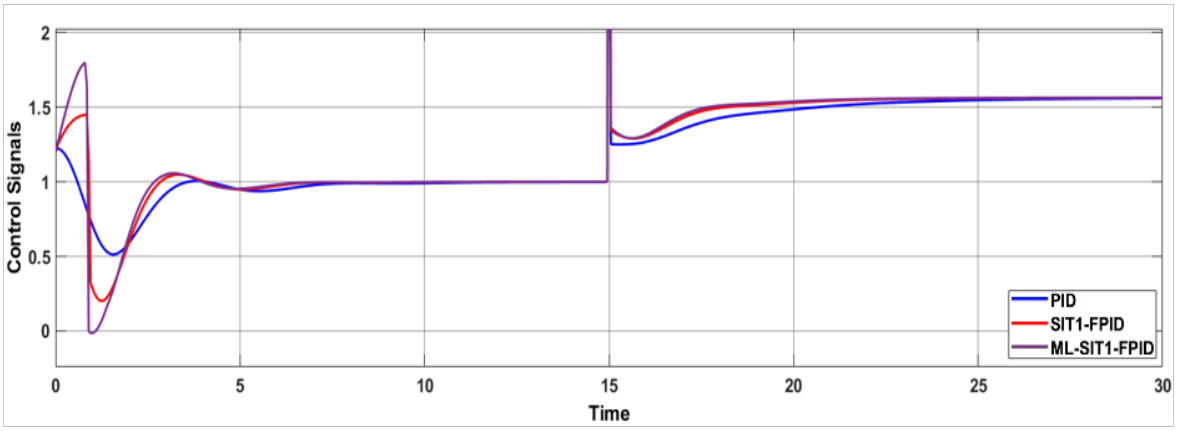
c

Figure 12. Internal disturbances (a) Control Signals, (b) System Response (c), Change in c state response (İçsel bozukluklar (a) Kontrol Sinyalleri, (b) Sistem Tepkisi, (c) c durum tepkisindeki değişiklik)

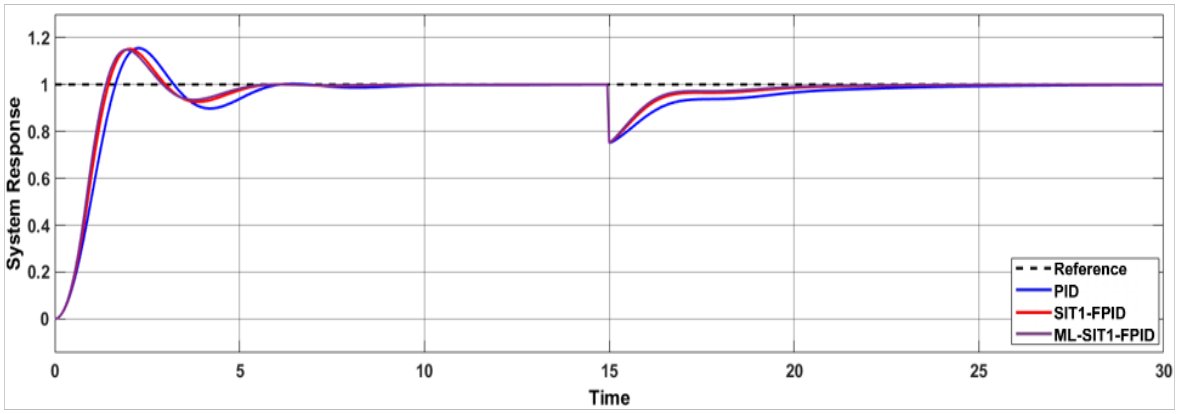
Table 12. Performance comparison of controllers in the internal disturbance condition (İçsel bozulma koşullarında kontrolörlerin performans karşılaştırması)

Controllers	Internal disruptive situation		
	İAE	İTAE	ISE
PID	1.806	10.98	*0.8089*
SIT1-FPID	1.45	6.776	0.7225
ML-SIT1-FPID	*1.351*	*5.929*	*0.6893*

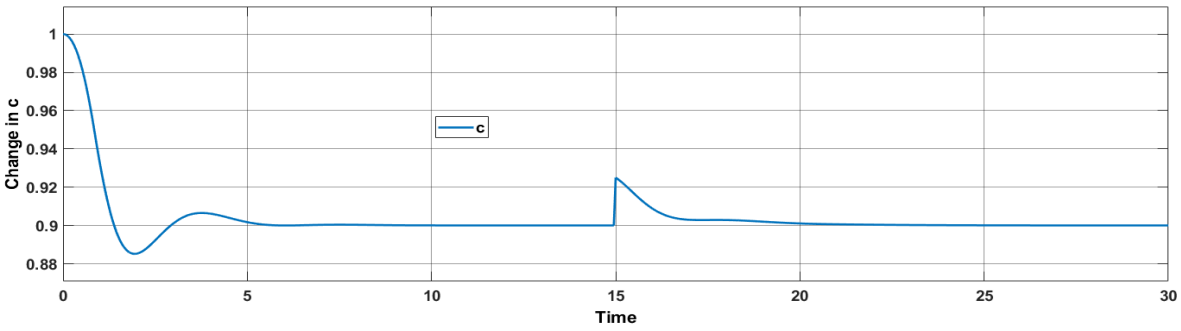
In the disturbance scenario, a disturbance of magnitude 0.5 was applied to the non-linear system at 15 seconds. The system responses under disturbance conditions are shown in Figure 13, and the performance index values are given in Table 13. The simulation results reveal that the ML-SIT1-FPID controller exhibits more robust performance compared to the SIT1-FPID and classical PID controllers.



a



b



c

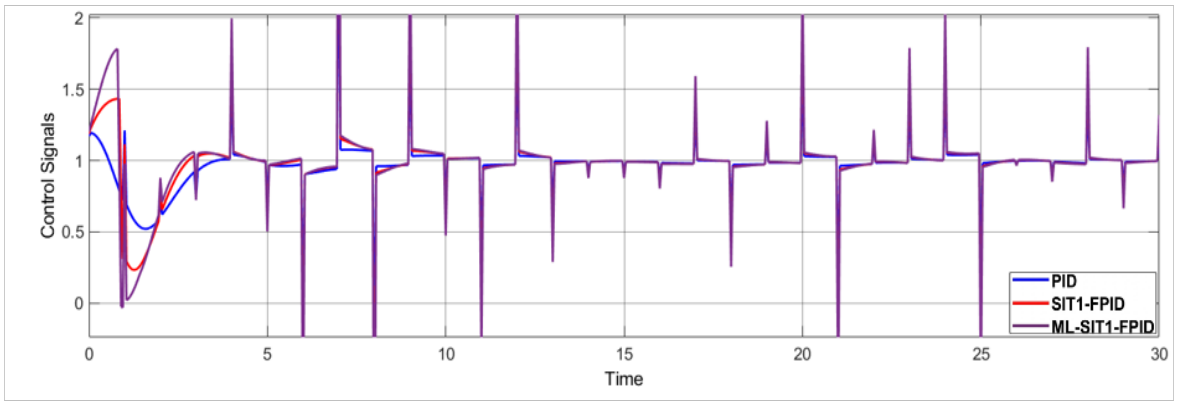
Figure 13. External disturbance (a) Control signals, (b) System response, (c) Change in c state responses
(Dış bozulma (a) Kontrol sinyalleri, (b) Sistem tepkisi, (c) c Durum tepkilerindeki değişim)

As shown in Figure 13, the external disturbance (a) Control Signals, (b) System Response (c) Change in c shows that the state responses are efficient. The performance under external disturbance is given in Table 13.

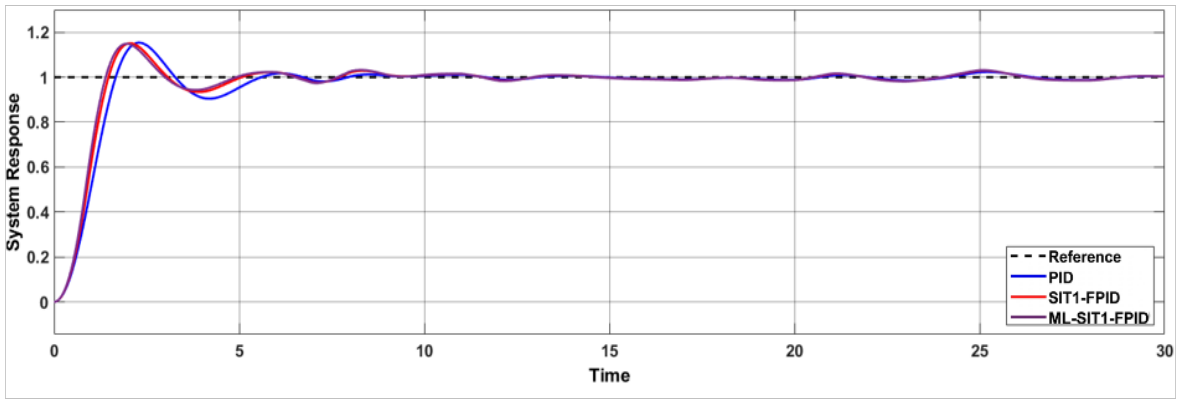
Table 13. Performance comparison of controllers under external disturbance conditions (Dışsal bozucu koşullar altında kontrolörlerin performans karşılaştırması)

Controllers	External disruptive situation		
	İAE	İTAE	ISE
PID	1.87	11.91	0.8239
SIT1-FPID	1.489	7.249	0.7382
ML-SIT1-FPID	1.384	6.294	0.7051

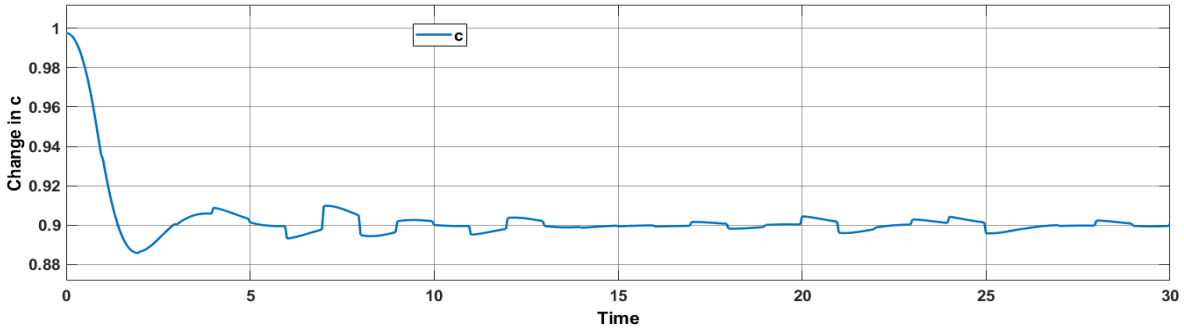
A noise of magnitude 0.5 was applied to the non-linear system at 15 seconds, outside the external disturbance scenario. The system responses to the noise are shown in Figure 14, and the performance index values are given in Table 14. The simulation results demonstrate that the ML-SIT1-FPID controller exhibits more robust performance compared to the SIT1-FPID and classical PID controllers.



a



b



c

Figure 14. Noise condition (a) Control signals, (b) System response, (c) Change in c condition response
(Gürültü koşulu (a) Kontrol sinyalleri, (b) Sistem tepkisi, (c) c Koşulunda değişiklik cevabı)

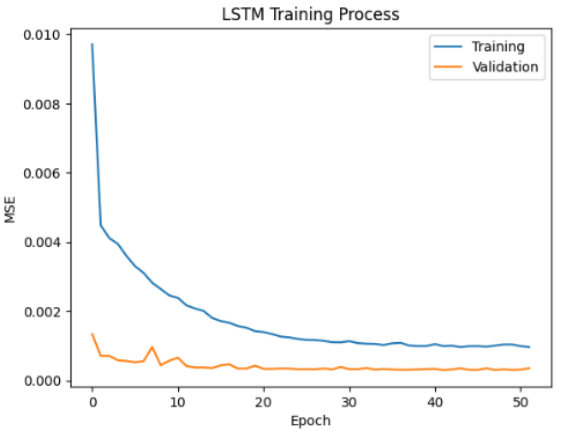
Table 14. Performance comparison of controllers under noisy conditions (Gürültülü koşullarda kontrolörlerin performans karşılaştırması)

Controllers	Noise situation		
	İAE	İTAE	ISE
PID	3.512	40.4	1.126
SIT1-FPID	3.419	40.18	1.072
ML-SIT1-FPID	3.384	40.11	1.052

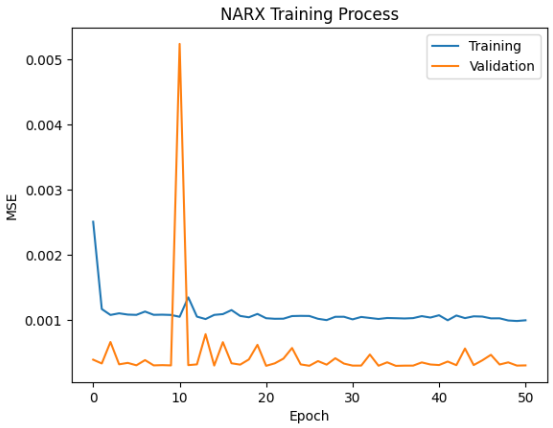
As shown in Table 14, an analysis of the values provided indicates that the machine learning method is more efficient. The overshoot and settling times of the controllers have not been included in the tables as they were kept constant. Overall, it is understood that the machine learning method is efficient.

4. RESULTS (SONUÇLAR)

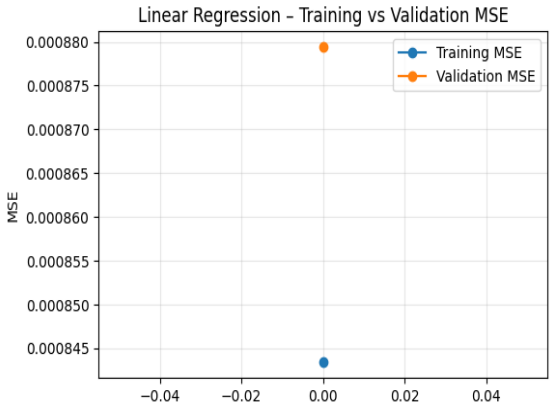
In this study, an LR model, a machine learning method, is proposed for the implementation of control design. In line with this proposal, the information obtained from the literature review was processed in detail to create the model definition. The model was defined as $y = ax + b$, and the control design was performed by obtaining the necessary input and output data for the ML-SIT1-FPID controller design. This equation, created as a dynamic equation, was obtained using a machine learning algorithm. First, 13,100 input (x) and output (y) data obtained from the system were analyzed, and the values of a and b were estimated from the data. The LR equation creation method was evaluated and used in this estimation. The obtained equation was applied to the control system and its performance was analyzed. As it was seen that sufficient performance could not be achieved, clustering was performed on the data and the data analysis was redone. As a result of the revision, the data count was given as 12,011, and the equation value $c = 0.1 * abs(e(t)) + 0.9$ was obtained through the LR machine learning algorithm. In this equation model, $R2$ was taken as the success criterion, and this value was determined to be 93%. Since the result of this system needed to be generalized, the SIT1-FPID and classic PID used in real systems were designed and compared with the responses in this system. Furthermore, in order to increase the generalization in machine learning algorithms, the performance of the model was compared with error metrics and R^2 using NARX and LSTM algorithms. These results are presented in the graphs provided in Figure 15 and the metrics in Table 15.



a



b



c

Figure 15. (a) NARX training and validation error graph, (b) LSTM training and validation error graph, (c) Linear graph and validation error graph
((a) NARX eğitim ve doğrulama hatası grafiği, (b) LSTM eğitim ve doğrulama hatası grafiği, (c) Doğrusal grafik ve doğrulama hatası grafiği)

As shown in Figure 15, the epoch values were kept constant in the MSE information of the given NARX, LSTM, and LR algorithms. When these values are examined, the most efficient algorithm with little data was obtained from the linear regression algorithm. However, evaluating this performance alone is not sufficient for generalization. Therefore, it would be more accurate to interpret the metrics in the Performance Information table for the NARX, LSTM, and LR algorithms, as shown in Table 15.

Table 15. Performance information for NARX, LSTM, and LR algorithms (NARX, LSTM ve LR algoritmalarına ilişkin performans bilgileri)

Metric	LSTM	NARX	LR
R^2:	0.863623252	0.825445940	0.933426628
Prediction Accuracy (%):	92.39227623	93.05154287	94.02587
MSE (Training)	0.001650	0.00103	0.000423
MSE(Validation)	0.000625	0.000345	0.000878

Table 15 As shown in Table 15, when examining the performance information of the given NARX, LSTM, and LR algorithms, it is evident that their R^2 and prediction accuracy performance is high at 80% and above. However, upon examining the data, it is observed that there are differences between the R^2 and Prediction Accuracy (%) of the LSTM and NARX algorithms. Another issue is that these algorithms cannot directly generate equations. It is understood that they are insufficient in determining the values in the equation set. For this reason, it was determined that the LR model has $R^2 = 0.933426628$, Prediction Accuracy (%): 94.02587, MSE (Training)=0.000423, MSE (Validation)= 0.000878. The values of a and b obtained from these values were used to form $c = 0.1 * abs(e(t)) + 0.9$. The output membership functions of the proposed controller were adjusted online based on this dynamic equation derived from the system error

5. DISCUSSION (TARTIŞMA)

The performance of the proposed controller in this study was compared with SIT1-FPID and classical PID controllers under nominal conditions and disturbance variations. Simulation results revealed that the ML-SIT1-FPID controller demonstrated superior and robust performance compared to other controllers. It clearly demonstrates that system performance increases when dynamic equations are derived using machine learning methods. The machine learning supervised learning type linear regression model controller we designed has a dynamic structure dependent on input and output data, which is the biggest factor in increasing performance. Since this ML-SIT1-FPID is a real system model, it has created an applicable infrastructure. It was understood that the model was more successful when compared to NARX and LSTM, exhibiting a performance of 93.34%.

However, the NARX and LSTM algorithms were not preferred because they could not form a model and lagged behind Linear Regression in terms of performance. This controller design has created an infrastructure for real-time applications due to its superior performance.

It is understood that this designed controller will reduce losses when used in future studies in the fields of motor control applications, anomaly detection, and general system controls used in unmanned systems, hybrid and electric vehicles. This reduction in losses and regular system control are expected to contribute to the formation of new structures for unmanned systems and hybrid and electric vehicles. When applied to these areas, these contributions are expected to return to the national economy as added value.

ACKNOWLEDGMENTS (TEŞEKKÜR)

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Bu çalışma herhangi bir kurum ya da kuruluş tasarından desteklenmedi

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

Mehmet DEMİR: He conceived the idea for the study, conducted the experiments, analysed the results, and wrote the paper.

Mehmet DEMİR: He conceived the idea for the study, conducted the experiments, analysed the results, and wrote the paper.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada çıkar ilişkisi yoktur.

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