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APPLICATION OF REGULARIZATION TECHNIQUES TO IMPROVE FORECAST STABILITY IN NOISY DATA FOR INDUSTRIAL AUTOMATION

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Abstract. The article explores modern approaches to the application of regularization methods – Ridge and LASSO – in problems of forecasting technological process parameters under industrial automation conditions. Special attention is given to addressing challenges associated with the high-dimensional feature spaces and the presence of noise in input data, which are typical in industrial environments. The theoretical foundations of these methods are presented, along with their specific characteristics and mechanisms that reduce model overfitting and enhance robustness under varying input data. An experimental evaluation of the effectiveness of regularized regression models is conducted using real industrial datasets, including time series with missing and distorted values. The results demonstrate improved forecasting accuracy, model stability, and, consequently, the reliability of automated monitoring and control systems. These methods help cope with data noise, avoid retraining, and highlight key parameters, which is especially important in conditions of limited computational resources and complex production systems.

Keywords: regularization, industrial automation, ridge regularization method, LASSO, industrial control systems, regression models

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ИСПОЛЬЗОВАНИЕ МЕТОДИК РЕГУЛЯРИЗАЦИИ ДЛЯ ПОВЫШЕНИЯ СТАБИЛЬНОСТИ ПРОГНОЗОВ В УСЛОВИЯХ ШУМНЫХ ДАННЫХ В ПРОМЫШЛЕННОЙ АВТОМАТИЗАЦИИ

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Аннотация. В статье рассматриваются современные подходы к применению методов регуляризации – гребневого (Ridge) и лассо (LASSO) – в задачах прогнозирования параметров технологических процессов в условиях промышленной автоматизации. Особое внимание уделяется решению проблем, связанных с высокой размерностью признакового пространства и наличием шумов в исходных данных, характерных для производственной среды. Представлены теоретические основы указанных методов, их особенности и механизмы, позволяющие снижать переобучение моделей и обеспечивать их устойчивость при варьирующихся входных данных. Проведено экспериментальное сравнение эффективности регрессионных моделей с регуляризацией на основе реальных производственных выборок, включая временные ряды с пропущенными и искаженными значениями. Полученные результаты демонстрируют повышение точности прогнозов, устойчивости моделей и, как следствие, надежности работы автоматизированных систем мониторинга и управления. Эти методы помогают справляться с шумом в данных, избегать переобучения и выделять ключевые параметры, что особенно важно в условиях ограниченных вычислительных ресурсов и сложных производственных систем.

Ключевые слова: регуляризация, промышленная автоматизация, гребневый метод регуляризации, LASSO, алгоритмы оптимизации, регрессионные модели

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Introduction

Gas turbine plants (GTPs) play a key role in ensuring reliable and efficient electricity generation, particularly in the context of growing demands for power system stability and the reduction of operational costs. Under these conditions, methods for diagnosing and analyzing the performance of gas turbine equipment are of paramount importance, as they enable high operational reliability while reducing maintenance costs. Modern diagnostic approaches involve the use of advanced data processing techniques, which allow for addressing various malfunctions that occur during GTP operation [1].

One of the most critical tasks in GTP diagnostics is the processing and analysis of large volumes of data acquired from multiple sensors installed on various components of the power unit. Due to their nature, these data often contain gaps caused by failures in measurement equipment, instability of communication channels, or other technical issues. To ensure the accuracy of forecasting and diagnostics, it is necessary to develop and apply effective methods for imputing missing data [2]. Such methods restore the integrity of time series, ensuring the correct functioning of analytical algorithms and machine learning, which form the basis of modern approaches to forecasting and anomaly detection.

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Thus, the development and implementation of methods for data imputation, signal filtering, measurement recovery, and the application of regularization represent an important direction in the field of diagnostics and performance analysis of gas turbine power units. These approaches lay the foundation for building high-precision predictive and diagnostic models, which, in turn, contributes to enhancing the reliability and efficiency of power unit operation, minimizing downtime and reducing operational expenditures [1, 3].

Modern GTP diagnostic methods are based on the use of machine learning and AI techniques. Among these, clustering, classification, regression analysis, and neural network algorithms can be distinguished [4]. The application of such methods allows not only for the identification of equipment operation anomalies but also for predicting the development of faults based on historical data and current system performance indicators. The use of hybrid approaches, combining physical-mathematical modeling and machine learning, plays a significant role [5].

A promising direction is the implementation of digital twins – virtual copies of physical equipment – which enable real-time monitoring of the system state, simulation of potential event scenarios, and the making of optimal decisions [6]. These technologies not only improve diagnostic accuracy but also contribute to the optimization of power unit operating regimes.

Particular attention is also paid to the development of methods for estimating the residual life of GTP components [7]. This task requires accounting for multiple factors, such as temperature, pressure, vibrations, and the chemical composition of the environment. Predictive analytics methods are used to solve this problem, allowing for the determination of the remaining equipment service life and the planning of repair or replacement activities [8].

Furthermore, significant attention is given to the issues of energy efficiency and environmental safety of GTPs. Modern approaches include the use of fuel combustion technologies with low emissions of nitrogen and carbon oxides, as well as the application of renewable fuels [9]. This helps reduce the carbon footprint of the power system and comply with international environmental standards.

Thus, a comprehensive approach to the diagnosis and optimization of GTPs, based on the use of modern technologies and methods, enables the achievement of a high level of reliability, energy efficiency, and environmental safety of power units [10].

An important addition to these approaches is the use of regularization techniques to enhance the robustness of predictive models in the presence of noisy data. Within the framework of this work, the following main propositions are put forward:

1) The application of L1 and L2 regularization methods reduces the impact of noise and missing data, which are characteristic of industrial monitoring systems;

2) Regularization contributes to increased robustness and generalization capability of regression models when forecasting technical parameters of gas turbine units (GTUs);

3) Integration of regularized models into industrial automation loops creates a foundation for the implementation of predictive diagnostics.

Industrial automation is characterized by complexity and a large number of distortions arising from data noise or the instability of measurement systems. Under such conditions, regularization plays a key role, preventing the overfitting of machine learning algorithms and ensuring the stability of their operation.

The necessity of conducting this research is due to the fact that under real-world GTU operating conditions, measurement data are characterized by high noise levels, the presence of outliers, and missing values, which significantly reduces the accuracy of predictive models and the effectiveness of monitoring systems. The application of regularization methods enables robust predictive analysis aimed at the early detection of equipment degradation, failure forecasting, and optimization of gas turbine unit operating regimes.

The aim of this work is to evaluate and experimentally confirm the effectiveness of applying L1 and L2 regularization methods to improve the robustness and accuracy of forecasting gas turbine unit parameters under conditions of noisy, incomplete, and distorted data. The study intends to demonstrate that the use of regularization enhances the accuracy and robustness of predictive models, reduces the influence of noise and missing data in measurements, and improves the generalization capability of models when analyzing real operational data. To achieve this goal, the following research objectives are formulated:

- Analysis of modern methods for forecasting the technical condition of GTUs and identification of their limitations under noisy data conditions;
- Development and implementation of regression models for forecasting GTU parameters without regularization and with the application of Ridge and LASSO methods;
- Conducting an experimental study on archival data from a real gas turbine unit containing noisy data and missing values;
- Comparative evaluation of forecasting quality using metrics (MAE, RMSE, R^2);
- Comparison of the obtained results with those presented in the work of other authors, and formulation of conclusions regarding the feasibility of applying regularization for forecasting tasks in industrial automation.

The primary task is to develop solutions capable of effectively processing data, taking into account their characteristics and the specifics inherent in industrial conditions. Such solutions can significantly increase the operational stability of power units, minimizing the risks of unplanned shutdowns and optimizing operational costs.

Overview of regularization and its significance in forecasting tasks

Regularization is a technique in machine learning aimed at improving the generalization capability of models. The primary goal of regularization is to prevent overfitting, which occurs when a model adapts too closely to the training data, including noise and outliers, thereby losing its ability to accurately predict new, unseen data. Overfitting is particularly critical in tasks related to industrial automation, where data quality can vary significantly due to interference, technical failures, and other factors. Regularization helps balance the model, reducing the risk of overfitting and improving its stability in forecasting.

The problem of overfitting is often associated with excessive model complexity. The more parameters a model has, the higher the probability that it will begin to “memorize” random noise in the data. This leads to a decrease in prediction accuracy on new data and reduces the model’s practical utility. Regularization addresses this problem by adding penalty terms to the error function, which constrain the values of the model coefficients or their number. This makes the model more robust to data variability and enhances its ability to identify general patterns.

There are two main types of regularization: L1 and L2. L1 regularization, known as Least Absolute Shrinkage and Selection Operator (LASSO), adds a penalty to the error function in the form of the sum of the absolute values of the model coefficients. This causes some coefficients to become exactly zero, effectively discarding insignificant features. This approach is useful for feature selection, which is particularly relevant when working with high-dimensional data. The main advantages of L1 regularization include model simplification and improved interpretability. However, it may be less effective when dealing with highly correlated features.

L2 regularization, also referred to as Ridge regression, adds a penalty to the error function in the form of the sum of the squares of the coefficients. Unlike L1, L2 does not zero out coefficients but only reduces their values, thereby mitigating the influence of noise and stabilizing the model. L2 regularization is particularly effective in tasks where all features are important and a balanced distribution of weight among them is required. However, this approach does not aid in explicit feature selection, which can be a limitation when working with data where only a small subset of parameters is meaningful.

A comparison of L1 and L2 regularization shows that both approaches have their advantages and limitations. L1 is well-suited for feature selection and creating simpler models but can yield unstable results in the presence of correlated variables. L2 provides a smoother distribution of weights and stability but does not simplify the model, as it does not zero out coefficients. These methods can be combined to leverage their joint benefits, as implemented in ElasticNet, which uses a linear combination of L1 and L2 penalties.

The LASSO method is actively used for selecting key parameters in complex systems, such as sensor data analysis in GTPs, where it is necessary to identify the most important characteristics from a multitude of available data. Ridge regression finds application in tasks requiring accurate prediction that accounts for the influence of all parameters, for example, in forecasting system energy consumption.

ElasticNet, combining the properties of LASSO and Ridge, represents a versatile approach well-suited for working with data where features may be both correlated and redundant. This method is actively used in industrial automation for creating predictive models robust to noise and outliers, thereby improving both prediction accuracy and model interpretability [11, 12].

Theoretical foundations of the methods

L2 regularization adds a penalty to the error function proportional to the square of the model coefficient values. This leads to the minimization of the following function:

$$J(\theta)=\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2+\lambda\sum_{j=1}^{p}\theta_j^2, \tag{1}$$

where y_i is the real values, $\hat{y}_i$ is the predicted values, θ_j is the model coefficients, p is the number of features, λ is the regularization hyperparameter determining the degree of penalty.

The main idea of L2 regularization is to constrain the values of the coefficients, preventing their excessive growth, which can be caused by noise or multicollinearity in the data.

Ridge regression reduces the influence of features that contribute disproportionately to the model, especially if these features are associated with data noise. By smoothing the coefficients, the model becomes more stable and capable of identifying general patterns. This is particularly important in tasks related to forecasting in automation systems, where data can be highly noisy. In GTPs, Ridge can be used for predicting temperature, pressure, or vibration, providing stable results even in the presence of imperfections in the measurement data.

L1 regularization introduces a penalty proportional to the sum of the absolute values of the model coefficients. The objective function for LASSO is as follows:

$$J(\theta)=\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2+\lambda\sum_{j=1}^{p}\left|\theta_j\right|. \tag{2}$$

Unlike L2 regularization, L1 leads to the zeroing of coefficients for some features, making it particularly useful for feature selection in tasks with high-dimensional data. Lasso automatically selects the most significant features, reducing the others to zero. This not only improves model interpretability but also allows for data dimensionality reduction, which is critical in systems where a large number of parameters are analyzed. In GTP condition monitoring systems, LASSO helps identify key parameters, such as vibration or rotational speed, while ignoring less significant data. This simplifies the interpretation of results and reduces the computational load.

ElasticNet combines the advantages of L1 and L2 regularization by adding a penalty to the error function that includes both the sum of squared coefficients (L2) and the sum of their absolute values (L1):

$$J(\theta) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \alpha\lambda \sum_{j=1}^{p} \theta_j^2 + (1-\alpha)\lambda \sum_{j=1}^{p} |\theta_j|, \quad (3)$$

where α regulates the balance between the L1 and L2 components.

ElasticNet is particularly effective in situations where features are correlated with each other or when the data contain both relevant and irrelevant variables. Unlike LASSO, which tends to select one feature from a group of correlated ones, ElasticNet can retain several such features [13].

In forecasting tasks for equipment parameters, ElasticNet enables:

- Accounting for correlated parameters, such as pressure and temperature in power equipment systems;
- Selecting key features while maintaining model robustness to noise;
- Providing a better balance between accuracy and interpretability, especially when working with high-dimensional and noisy data.

For example, in GTP control systems, ElasticNet can be used for predicting component wear, where data is collected from dozens of sensors, many of which have interrelated measurements.

Application of regularization in PLC-based systems

Programmable Logic Controllers (PLCs) play a key role in industrial automation systems. Modern data analysis approaches, such as machine learning and predictive analytics, are increasingly being applied at the PLC level. However, the implementation of such technologies faces a number of unique constraints, including limited computational resources, strict processing time requirements, and the necessity of integration with existing systems. Regularization methods, such as L1 and L2, can be adapted for these conditions, ensuring algorithm robustness to noise and improving prediction accuracy [14].

Modern PLCs, such as Siemens SIMATIC or Allen-Bradley CompactLogix, support analytics and machine learning algorithms, including linear regression, time series forecasting, and anomaly recognition. However, most complex computations, such as neural network training, are performed on external devices, for instance, in the cloud or on local servers. PLCs are then integrated with these systems to perform real-time predictions [15].

To apply L1 and L2 regularization methods under constrained computational resources, it is necessary to adapt the algorithms. This may include:

- Model compression: Using pre-trained models where regularization was applied during the training phase, with a simplified version deployed on the PLC.
- Data dimensionality reduction: L1 regularization (e.g., via LASSO regression) allows for the exclusion of irrelevant features, minimizing the volume of data processed by the controller.
- Data preprocessing: Regularization can be used to stabilize predictive models on an external server, after which the optimized model is loaded into the PLC for executing predictions.

Regarding integration possibilities with existing automation systems, the integration of regularization methods with PLC systems can be achieved through the use of existing communication protocols (Modbus, OPC UA) and specialized libraries. For example:

- Using data from the PLC for preliminary processing on an external device and returning optimized parameters;
- Embedding regularized models (e.g., Ridge regression equations) directly into the PLC code written in IEC 61131-3 languages (ST or SCL).

Such integration minimizes modifications to the existing infrastructure and maximizes the use of analytics capabilities in real-time conditions.

Suppose a time series describing equipment temperature is being analyzed, where the data contains noise and outliers due to sensor malfunctions. Using Ridge regularization, probable deviations from

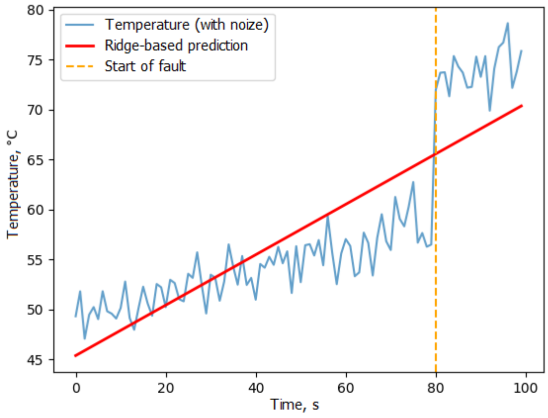

Fig. 1. Prediction of the best model

the norm can be forecast. Suppose a time series describing equipment temperature is being analyzed, where the data contains noise and outliers due to sensor malfunctions (Fig. 1). Using Ridge regularization, probable deviations from the norm can be forecast.

In a GTU diagnostic system, parameters must be adjusted under unstable data conditions using LASSO to identify the most significant parameters for optimization. LASSO effectively identifies key parameters by zeroing out insignificant ones. This helps focus on important features, minimizing model complexity and improving result interpretability.

The performance of the methods is analyzed using real data from a gas turbine engine within the framework of the research problem of reconstructing the time series of oil temperature at the GTU bearing outlet. It is assumed that the corresponding sensor has failed, and its readings need to be reconstructed based on measurements from other standard engine parameters. Time series of the following parameters are used as input features:

- Oil temperature readings in various GTU components;
- Fuel gas consumption;
- Power turbine rotational speed;
- Compressor turbine rotational speed;
- Vibration displacement;
- Oil pressure;
- Exhaust gas temperature;
- Air inlet pressure.

Some of these parameters are physically related to oil temperature. However, to complicate the task, features possessing weak or no correlation with the target variable are additionally introduced into the model. This creates a redundant feature space that includes irrelevant data. Furthermore, the experimental data contain noise due to measurement errors and outliers.

This problem formulation allows for demonstrating the impact of regularization under conditions of:

- Multicollinearity;
- Presence of irrelevant features;
- Noisy and unstable measurements;
- Risk of model overfitting.

The test set is formed from the last 20–30% of the time-series measurements, which corresponds to a real-world scenario of forecasting future values based on historical data.

To ensure experimental reproducibility, the pseudo-random number generators for Python, NumPy, and TensorFlow were fixed, and random shuffling of the training set was disabled.

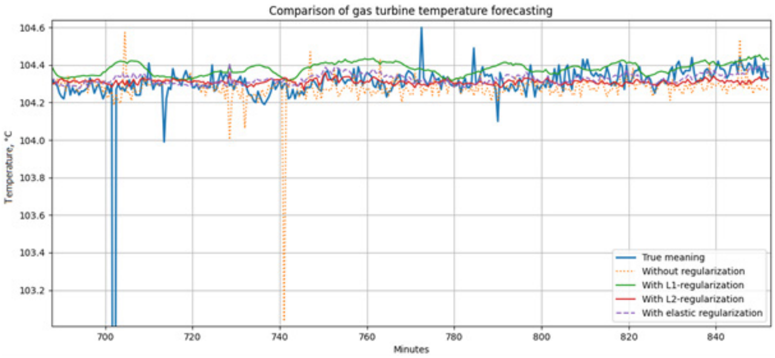

Fig. 2. Model prediction

To solve the problem, a regression-type neural network model with regularization is used: LASSO (L1), Ridge (L2), and ElasticNet (combination of L1 and L2). The obtained models are depicted in Fig. 2.

In the scikit-learn library implementation, the regularization parameter is denoted as α, which corresponds to the coefficient λ in the mathematical notation of formulas 1 and 2.

The parameter λ (α) determines the trade-off between approximation accuracy and model complexity. For small values of λ, the model seeks to minimize the error on the training set, which can lead to overfitting. For excessively large values of λ, the model becomes overly smoothed and loses its ability to adequately describe the data (underfitting).

The optimal value of λ cannot be determined analytically and depends on:

- Sample size;
- Level of noise in the data;
- Degree of feature correlation;
- Model complexity.

Increasing the data volume generally allows for a smaller λ, whereas a high noise level or the presence of numerous irrelevant features necessitates stronger regularization.

In this work, the optimal value of λ is selected through a grid search over a logarithmic scale (e.g., 10^{-6}–10^{-1}) using a validation set. The selection criterion is the minimum error on the validation data. The final quality assessment is conducted on the test set, which was not involved in hyperparameter tuning.

This approach ensures a correct assessment of the model's generalization capability and eliminates bias in the results.

For the investigated problem, the optimal λ value was selected through a grid search over a logarithmic scale from 10^{-6} to 10. The coefficient selection plots for the Ridge and LASSO methods are shown in Fig. 3. Based on this method, the following regularization coefficients were obtained: L1 – 0.0025, L2 – 0.04. Additionally, a heatmap was generated to find the optimal coefficients for the ElasticNet method (Fig. 4), yielding the following regularization coefficients: L1 – 10^{-5}, L2 – 0.023.

For this problem, the following model quality metrics were obtained (Table 1). Based on the presented results, a significant influence of regularization on the generalization capability of the neural network model can be concluded.

Analysis of the mean squared error (MSE) values shows that the model without regularization demonstrates the worst result. This indicates pronounced overfitting: the model approximates the training set too precisely but generalizes poorly to the test interval data.

The addition of regularization leads to a sharp decrease in error:

- with L1 regularization, the MSE value reduces to 0.021;

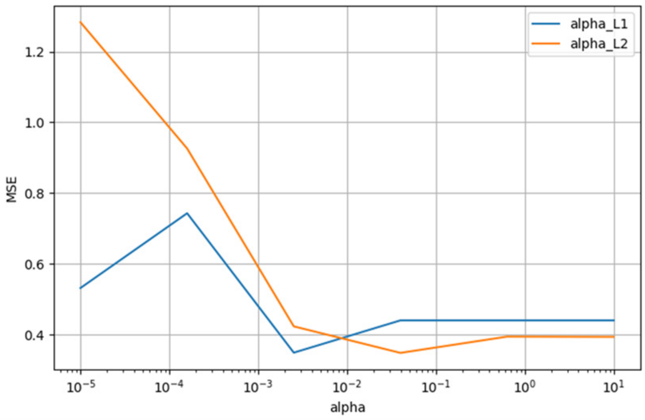

Fig. 3. Finding optimal L1 and L2 regularization coefficients for Ridge and LASSO methods

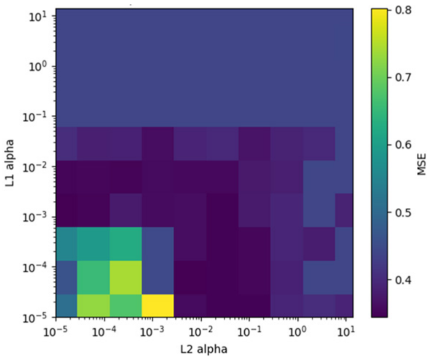

Fig. 4. Finding optimal L1 and L2 regularization coefficients for the ElasticNet method

Table 1

Training results

Model		**MSE**	**MAE**	**R^2**
Without regularization	train	0.015	0.059	0.734
	test	0.072	0.097	–2.752
L1 regularization	train	0.05	0.056	0.118
	test	0.021	0.054	–0.119
L2 regularization	train	0.051	0.057	0.1016
	test	0.019	0.045	–0.0079
ElasticNet	train	0.051	0.058	0.099
	test	0.02	0.045	–0.022

- with L2 regularization, the best result is achieved – 0.019;
- the ElasticNet (L1+L2) model shows a comparable value – 0.020.

A similar trend is observed for the MAE metric: a decrease from 0.097 (without regularization) to 0.045–0.054 when using penalty terms. The minimum MAE value (0.045) is achieved with L2 regularization and ElasticNet.

The coefficient of determination R^2 remains negative in all cases, indicating that the models are still inferior to a naive mean prediction. However, the addition of regularization significantly brings the model closer to an adequate description of the data: the R^2 value improves from −2.752 (without regularization) to −0.0079 with L2 regularization. This signifies the virtual elimination of the overfitting effect and a substantial increase in model robustness.

In a similar study [17], comparable results were obtained. The authors note that the application of L1 regularization allowed for a reduction in the number of initial features by 60–90%, which is consistent with the results obtained in the present work, where a significant decrease in the effective dimensionality of the input space is also observed.

Furthermore, study [17] showed that L2 regularization helps reduce the impact of multicollinearity among features and provides a 12–18% increase in prediction accuracy. In the present study, the application of L2 regularization also led to a significant improvement in model quality compared to the version without regularization, confirming its effectiveness for the considered time series reconstruction task.

Thus, the results confirm that for the task of reconstructing a sensor time series from indirect measurements, the application of regularization is a necessary condition for obtaining a robust model. In this experiment, L2 regularization proved to be the most effective, providing the minimum MSE and MAE values, as well as the best coefficient of determination.

The LASSO method demonstrates the ability for automatic feature selection. As the parameter α increases, some coefficients are zeroed out, leading to the exclusion of irrelevant parameters from the model. This is particularly effective under conditions of introduced redundant and weakly correlated features.

At small values of α, LASSO's behavior is close to that of ordinary linear regression. As α increases, a sequential zeroing of weights occurs, which reduces the influence of noise and enhances model interpretability. However, excessive regularization can lead to the removal of informative features and an increase in error.

The Ridge method smoothly reduces the values of coefficients, without bringing them to zero. This ensures smoothing of weights and model stability in the presence of multicollinearity among GTU parameters.

Ridge is better suited for tasks where most features contain useful information, but their influence needs to be constrained to prevent overfitting. Model predictions are characterized by greater stability on the test set.

ElasticNet combines the properties of L1 and L2 regularization and is an effective tool in the presence of correlated features and redundant data. Under the conditions of this experiment, this method simultaneously allows for reducing model dimensionality and smoothing coefficients, ensuring robustness to noise.

Advantages and limitations of regularization methods

Regularization methods, such as LASSO and Ridge, are powerful tools in machine learning and statistics. They find application in forecasting and data analysis tasks due to their ability to improve model generalization capability and combat the problem of overfitting. The advantages of these methods include the reduction of overfitting, increased model robustness to noise, and the ability to work with high-dimensional data. Various limitations arise. When working with high-dimensional data, finding a suitable α can be challenging due to the difficulty of assessing model generalization capability. This leads to specific requirements for hyperparameter tuning. ElasticNet, combining L1 and L2 regularization, is often used to overcome the shortcomings of LASSO and Ridge. However, the interpretation of coefficients becomes more complex, as the model includes components from two different methods. There is also a dependency on the quality of the initial data and sensitivity to the scale of the data (requiring feature normalization).

Conclusion

The conducted experiment on reconstructing the oil temperature time series under sensor failure demonstrated that regularization methods significantly enhance model robustness under conditions of noise, redundant, and weakly correlated features. Methods for finding regularization coefficients (α) for industrial systems were also addressed, and recommendations for finding optimal model regularization hyperparameters were proposed.

L1 regularization is effective when automatic selection of significant parameters is necessary, whereas L2 regularization ensures more stable model behavior in the presence of multicollinearity. The optimal value of the parameter α is determined experimentally through validation and depends on the data structure and noise level.

The practical application of L1 and L2 regularization methods in diagnostic and parameter reconstruction tasks for gas turbine units confirms their feasibility for industrial automation, where data are characterized by noise, correlation, and the potential redundancy of measured parameters.

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