MEASURING SYSTEMS

THEORETICAL FOUNDATIONS OF THE DUAL CONTROL ALGORITHM FOR MULTI-AGENT INFORMATION-MEASURING SYSTEMS

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Abstract. This article examines the theoretical foundations of the dual control algorithm in the context of machine learning, focusing on its application for intelligent agents in multi-agent information-measuring systems. A proposed algorithm combines anomaly detection in data with telemetry-based sensor calibration, opening new possibilities for improving the accuracy and reliability of data in complex and dynamic environments. The advantages of the algorithm are analysed concerning adaptability, forecasting, and data integration, comparing it with other machine learning algorithms. A scheme of the software algorithm for the sensor data acquisition module is presented. A machine learning model of the dual control algorithm is developed and compared with the isolation forest model, highlighting the advantages of applying the dual control algorithm for building multi-agent information-measuring systems.

Keywords: Multi-agent systems (MAS), Machine Learning (ML), dual control algorithm, nonlinear calibration, adaptability, double-check algorithm model, Kohonen maps (SOM), uncertainty; anomaly detection; measurement; metrology; data processing; machine learning algorithms; sensors

1. Introduction

Multi-agent systems (MAS) are being integrated into the concept of Industry 4.0 across various sectors of the economy, including for the creation of adaptive and self-learning production systems. In smart factories (Smart Factories), agents automatically adjust production processes based on data from sensors and production history, adapting them to optimize productivity. Multi-agent systems are used for coordinating different stages of the production process, optimizing resource usage, managing flows of goods and materials within production and warehouse facilities, automating logistics, and managing quality control systems. For instance, [1] proposes the creation of a multi-agent system for a smart factory (SF-MAS) with a partially decentralized control architecture that can effectively plan production and quickly respond to disruptions. In [2], a multi-agent approach to planning for automated guided vehicles and machines in a manufacturing system is proposed. The suggested multi-agent approach operates in real-time and generates possible schedules through negotiation and bidding mechanisms among agents.

Multi-agent systems (MAS) are gaining increasing popularity in information-measurement technologies due to their unique characteristics, which allow them to effectively solve complex tasks under dynamic conditions. Multi-agent information-measurement systems are complex systems consisting of several autonomous agents that interact to collect, process, analyse, and transmit information about research objects in real time. These systems combine information system technologies, metrology, and the principles of multi-agent systems (MAS). Key aspects of their relevance include:

Adaptability: Multi-agent systems (MAS) can quickly respond to environmental changes, which is especially important for systems operating under variable conditions, such as environmental monitoring or production.

Load distribution: By distributing tasks among agents, the system can optimize resource usage, increasing efficiency and reducing costs.

Self-organization: Agents can independently organize their activities to achieve common goals, increasing system resilience to failures.

Anomaly detection: Multi-agent systems (MAS) can use machine learning algorithms to detect data anomalies, enabling rapid responses to potential issues.

Multi-agent systems (MAS) consist of several autonomous agents that interact to achieve common goals. They can self-organize and adapt to environmental changes, making them ideal for application in various technological fields, including information-measurement technologies. In this field, multi-agent systems (MAS) are used for monitoring, managing, and analyzing data in real time, enhancing the accuracy, reliability, and speed of information processing. The key metrological characteristics of multi-agent systems (MAS) include:

Accuracy: The ability to provide measurements close to true values (0.05–0.1 %).

Reliability: Resistance to failures and errors.

Sensitivity: The ability to detect small environmental changes.

Data processing speed: The time required for data processing and analysis.

Adaptability: The ability to change behaviour in response to environmental changes.

At the same time, modern multi-agent systems (MAS) face increasing demands for high adaptability and accuracy under complex and dynamic conditions.

Despite their advantages, multi-agent systems (MAS) have some disadvantages:

Coordination complexity: Inter-agent interactions can lead to conflicts and errors.

High computational cost: Significant resources are required for processing large volumes of data.

Uncertainty: Agents may operate under incomplete or inaccurate information, complicating decision-making.

Lack of standards and regulations: The diversity of architectures and protocols can hinder system integration.

Absence of metrological research results for multi-agent systems (MAS) in information sources.

These aspects underscore the need for research to optimize and improve multi-agent systems (MAS) to ensure their effective application in information-measurement technologies.

The relevance of the double control algorithm in multi-agent systems (MAS) lies in its ability to integrate data from multiple sensors, performing two main functions: periodic calibration of "field" sensors by correlating data obtained telemetrically from reference sensors, and detecting anomalies and measurement errors. The algorithm provides continuous adjustment of sensor readings in real time, enhancing the accuracy and stability of measurements, which is particularly important for information-measurement systems.

In previous studies [3], the authors proposed the dual control method as a mechanism for improving information-measuring technologies in multi-agent systems. This article examines the main mechanism of the method–the double control algorithm–which the authors consider an innovative and promising approach to organizing multi-agent systems.

However, ensuring the effective operation of MAS requires solving several issues related to data quality and the unpredictability of agent behavior. In this context, the role of machine learning (ML) becomes critically important, as these algorithms allow agents to learn from data, adapt their strategies, and improve decision-making processes. Machine learning enables the identification of complex patterns in data and the development of models that can enhance system accuracy and reliability.

Machine learning (ML) plays a key role in the development of multi-agent systems (MAS), providing agents with the ability to adapt to changing environmental conditions, improve their behavior, and make more informed decisions. The application of machine learning algorithms in MAS allows for optimizing data collection, processing, and analysis processes, as well as improving system efficiency. Researchers in machine learning for MAS, such as Przemyslaw Spychalski and Ryszard Arendt [4], argue that systems equipped with machine learning algorithms begin to exhibit creativity and even predict human decisions. The ability to learn is critically important for intelligent agents, especially when facing a multi-agent environment [5].

There are three main types of machine learning (which also apply to multi-agent systems): supervised, unsupervised, and reinforcement learning.

Supervised learning involves generalizing a problem and constructing a more general hypothesis based on labeled training data. Unsupervised learning involves detecting structures and patterns in data without predefined labels or annotated training data [6]. In this approach, agents independently analyse data, attempting to classify it based on internal mechanisms, allowing them to identify similarities and differences between various samples. The results of learning are then analyzed further to identify potential groups or clusters that may be useful for understanding the data structure and decision-making. Recent applications of supervised learning in multi-agent systems relate to the generation of adaptation strategies for service-oriented architecture under changing conditions [7]. The difference between supervised learning and reinforcement learning lies in the assumption that the dual control algorithm evaluates agent behavior based on detected anomalies, allowing for the adaptation of response strategies in real time (supervised learning differentiates the evaluation of system output rather than agent behavior).

Key Areas of Machine Learning Application in MAS:

Adaptive Agent Learning: Agents use machine learning methods to learn from their experiences and interactions with the environment. This allows them to make decisions based on historical data and the behavior of other agents.

Process Optimization: Machine learning algorithms can be used to optimize resource allocation in MAS, reducing costs and increasing productivity.

Anomaly Detection: Using machine learning technologies, agents can detect anomalies in data, enabling quick responses to potential issues or system failures.

Decision-Making: Machine learning helps agents form decision-making strategies based on analyzing large data volumes, ensuring more precise and well-founded management.

Agent Collaboration: Research in machine learning fosters the development of cooperation and coordination algorithms among agents, which is essential for achieving common goals.

Thus, machine learning is an integral part of multi-agent systems, contributing to increased efficiency, adaptability, and reliability. Integrating ML into MAS opens up new opportunities for process automation and data-driven decision-making, making these systems more powerful and capable of self-improvement.

The relevance of the dual control algorithm in MAS lies in its ability to integrate data from multiple sensors, performing two main functions: periodic calibration of field sensors through data correlation obtained telemetry from reference sensors and anomaly detection and error correction in measurements. The algorithm provides continuous real-time sensor data adjustment, enhancing measurement accuracy and stability, which is especially crucial for information-measuring systems.

2. Drawbacks

An important aspect of the effective operation of a multi-agent information and measurement system is solving the problem of processing multidimensional data. The complexity associated with processing such data can significantly reduce the capabilities of the algorithm, especially when the data is characterized by a high level of complexity and variability. This can complicate the analysis and lead to less accurate results.

The lack of a single standard for implementing algorithms in different multi-agent systems can be a serious obstacle. Since there are many types of MAS, the lack of common protocols can make it difficult to apply the algorithm in different contexts and lead to incompatibility between systems. This emphasizes the importance of developing universal solutions that can adapt to different requirements and operating conditions.

3. Goal

The goal of this article is to develop and explore the theoretical foundations of the dual control algorithm in information-measuring systems based on multi-agent systems (MAS).

4. Dual Control Algorithm for MAS

The dual control algorithm operates based on the integration of data from reference sensors and field measurements to ensure accuracy and reliability in information-measuring systems. It performs sensor calibration through continuous adjustment of their readings using real-time data.

Another important principle of the algorithm is anomaly detection in data, which is carried out using self-organizing Kohonen maps (SOM – self-organizing maps). These maps classify data by distributing them into different clusters, allowing the identification of anomalous objects. Anomalies that significantly deviate from normal indicators tend to cluster separately, simplifying their detection.

The dual control algorithm provides measurement correction based on detected anomalies. Since anomalous data require special attention, the algorithm can quickly respond to environmental changes by adapting sensor calibration to new conditions. This reduces the risk of errors and increases measurement accuracy.

The detection of anomalies in data is a critical issue for industries such as the fuel and energy sector, healthcare, and cybersecurity. Numerous approaches to the detection of anomalies have been proposed [8, 9]. However, almost all these methods and approaches depend on supervised machine learning models, which, in turn, require large labeled datasets. The process of data labeling (normal or anomalous) in fields such as healthcare can be time-consuming and require specific knowledge and experts, thus limiting the use of supervised models. Moreover, some previous approaches to the detection of anomalies do not account for the sequential nature of data, assuming that data points are independent and identically distributed over time. When dealing with time-series data, it is important to consider temporal dependencies. Therefore, interest in unsupervised learning has recently been renewed, as it is expected to play a key role in future machine learning models capable of classifying data and anomalies [10].

The dual control algorithm is closely related to several existing approaches and algorithms in machine learning and data analysis. Here are some of the most similar algorithms that may share common features or concepts. The Anomaly Detection Algorithm is used to identify unusual or anomalous patterns in data. Algorithms such as LOF (Local Outlier Factor), Isolation Forest, and Autoencoders can be used for this purpose. Change Detection Algorithms analyze data to detect changes over time that may indicate significant events or system alterations. Examples include CUSUM (Cumulative Sum Control Chart) and changes in time series. Classification Algorithms, such as Random Forest, SVM (Support Vector Machines), and neural networks, are used to classify data based on different characteristics. Forecasting Algorithms, such as ARIMA, Exponential Smoothing, or LSTM, are used to predict future values based on historical data. Early Warning Systems monitor data and identify potential threats to provide timely alerts about possible risks (e.g., natural disasters). Time Series Analysis Methods are used to analyze data collected over time to identify trends, seasonality, and cyclicality.

The advantages of the dual control algorithm lie in its ability not only to perform calibration but also to detect anomalies, making it a powerful tool for ensuring data reliability. It can make predictions based on historical data, allowing users to make informed decisions and ensure system stability. Thus, the dual control algorithm is an essential tool in the development of intelligent agents in multi-agent systems that work with large volumes of data.

The dual control algorithm for information-measuring systems based on unsupervised machine learning algorithms performs several key functions:

1. *Anomaly Detection*: Identification of anomalies, gaps, and erroneous data, as well as extraordinary events or patterns in environmental monitoring system data.

2. *Data Calibration and Event Classification*: Automatic calibration based on reference sensors and classification of events into categories such as critical states, technological accidents, and parameter changes.

3. *Prediction of Possible States*: Formation of forecasts based on detected patterns that indicate potential risks for automated control systems.

4. *Adaptive Model Learning*: Algorithm adaptation to new data to improve detection and classification accuracy.

5. *Data Visualization*: Tools for graphical representation of data and detected events to facilitate situation understanding for operators.

In our view the relevance of the dual control algorithm in multi-agent systems (MAS) lies in its ability to integrate data from multiple sensors. It performs two primary functions: periodic calibration of "field" sensors through correlation of data obtained via telemetry from reference sensors and detection of anomalies and measurement errors. Adjusting sensor readings in real-time significantly improves measurement accuracy and stability, which is especially important when information-measuring systems operate in complex dynamic environments.

Additionally, its application in existing monitoring systems significantly enhances environmental monitoring efficiency, allowing timely responses to potential threats and emergencies.

The algorithm also optimizes resources, reducing the need for manual data analysis and allowing focus on more complex tasks. It improves risk management, as risk forecasting enables proactive measures to minimize them.

The architecture of the dual control algorithm is illustrated in Fig. 1.

The dual control algorithm is a complex system that ensures the integration of data from various sources, such as sensors, control modules, communication devices, and other MAS intelligent agent components. It begins by receiving diverse periodic raw data, which may include numerical values, command strings, and other data types and categories. The data then passes through a preprocessing module, where it is filtered and normalized. At this stage, random and anomalous values are removed, and inaccuracies are corrected. Next, in the anomaly detection module, self-organizing Kohonen maps are used to identify unusual patterns in the data. Once anomalies are detected, the data is classified in the classification module, where machine learning algorithms determine the type of events or anomalies. This module is also responsible for comparing and correcting data obtained from "field" sensors relative to data from reference sensors. The next stage is the decision-making module, which uses adaptive thresholds and dynamic rules to respond to real-time data changes. Finally, the output module generates anomaly alerts, reports for further analysis, and visualizations for better situation understanding. This architecture enables efficient real-time monitoring and management.

The dual control algorithm consists of several main components, each performing specific functions:

1. Data Input. This module receives data via communication channels from various sources, such as sensors, control modules, relay devices, and other terminal devices, as well as other systems. The data may include numerical values, command strings or numbers, categorical data, or time series.

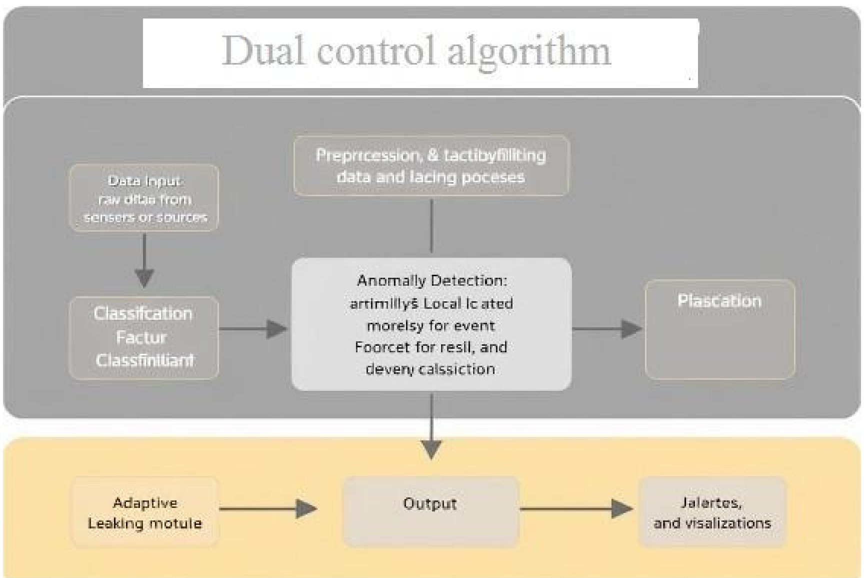

Fig. 1. Architecture of the dual control algorithm

2. Preprocessing Module. In this module, data is filtered and normalized. The main stages include:

– noise filtering (removal of random and anomalous values to improve data quality);

– normalization (adjusting data to a common scale for further analysis);

– data cleaning (correction or removal of inaccuracies in the data).

3. Anomaly Detection Module. This module is responsible for detecting unusual patterns in the data. For this purpose, self-organizing Kohonen maps are used, which enable anomaly detection based on structural patterns in the data.

4. Classification Module. In this module, data is classified based on detected patterns. For this, machine learning models are used to identify types of events or anomalies.

5. Decision-Making Module. This module uses adaptive thresholds and dynamic rules to make decisions based on incoming data and classification results. This allows the system to respond to changes in data in real time.

6. *Output.* The output module generates results in various formats, including:

– alerts – notifications about detected anomalies or significant events;

– reports – documentation of analysis results for further use;

– visualizations – graphs and charts that facilitate better understanding of data and results.

To obtain "field" data, the dual control algorithm uses a sensor module, which operates according to a programmed algorithm in Fig. 2.

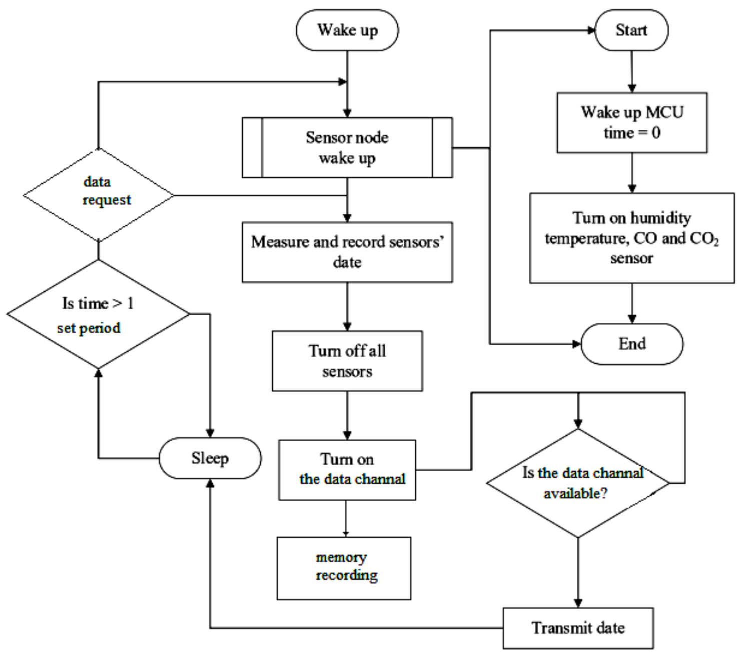

Fig. 2. Software algorithm of the sensor module of the MAS intelligent agent

The software algorithm of the MAS intelligent agent sensor module functions as follows: first, it wakes up the microcontroller (MCU) after a set time has elapsed, or when a data transmission command is received. Next, the sensors are activated, which measure and record environmental data, such as temperature, humidity, and CO_2, etc. Once the data is collected, all sensors are turned off to reduce power consumption. The system then checks if a data channel is available to transmit the collected information. If the channel is available, the data is transmitted to the appropriate receiver and/or recorded in the module's memory. The algorithm then goes into sleep mode, waiting for the next wake-up, which optimizes the use of system resources and ensures efficient real-time data collection and transmission.

After the data from the sensors is transmitted, a machine learning model is applied, which implements further work with the data using parallel computing and distributed programming [11].

5. Development of the Machine Learning Model for the Dual Control Algorithm

The double control algorithm proposed by the authors differs from traditional data processing methods in that it integrates information from different sources for continuous monitoring. Conventional data processing methods, such as least squares or maximum likelihood, analyze the mean and scatter of data to assess anomalies [12].

There are three approaches to solving the problem of finding anomalies in data [13]. The “teacher-assisted anomaly detection” approach refers to the presence of an additional feature in the original data sets - class labels that indicate whether a particular data instance is normal or abnormal. Such tasks are usually solved by building and training classifiers – machine learning algorithms capable of learning from data with unbalanced classes.

In the case of “anomaly detection with partial teacher involvement”, the original dataset contains information only about normal objects and does not include anomalous ones. However, in the proposed algorithm, anomaly detection is performed without a teacher, which means that there is no labeled data, including anomaly labels. This allows the model to independently classify data as anomalous during training, as instances that are least consistent with the majority of the sample are considered anomalous.

To more accurately separate the data into normal and anomalous, the dual supervision algorithm first cleans and normalizes the data, and then detects unusual patterns using self-organized Kohonen maps. This approach allows the model to detect anomalies based on structural patterns in the data, without the need to know their distribution or mean.

Kohonen models, or self-organized maps (SOMs), are a type of neural network used for multivariate data analysis, classification, visualization, and dimensionality reduction. In a dual supervised algorithm, they provide reliable results compared to traditional data processing methods, as they are a powerful tool for analyzing multidimensional data, including sensor data, due to their ability to self-organize, classify, and visualize.

Their use in information and measurement technologies has great potential, as it allows for better understanding of data, quick response to changes in the environment, and support for analytics-based decision-making. The dual control algorithm is an effective tool for detecting anomalies in real time, which is critical for risk management and responding to potentially dangerous situations in various fields in Table 1.

The double control algorithm in the context of machine learning is based on the idea of anomaly detection and model adaptation. The main variables and mathematical formula may vary depending on the specific implementation, but the general structure is described as follows:

– *Data filtering and normalization*. Before the data gets to the self-organizing maps, it goes through the stages of cleaning and normalization. This helps to reduce noise and simplify the data structure, which facilitates further analysis.

– *Structural detection.* A neural network is used to detect structural patterns in the data. During training, agents adapt their weights to the input data, classifying it into clusters based on similarity. This means that anomalies can be detected as points that do not fit into any of the clusters defined by the model.

– *Creating a topological structure*. One of the key features of Kohonen maps is their ability to preserve topological distances between data. This means that similar data will be close to each other in the map, which allows you to detect not only anomalies but also patterns that may not be obvious with traditional analysis methods. For effective model training, we selected the variables listed in the implementation matrix in Table 2.

Table 1. Comparative characteristics of data analysis using the dual control algorithm model and traditional methods

Criterion	Dual Control Algorithm	Traditional Methods
Sensor Data Processing	Effectively processes multidimensional data, detects patterns and anomalies	Usually requires preliminary data processing and aggregation
Data Classification	Self-organizes and classifies states, grouping similar samples	Often requires class labels and may be less flexible
Data Visualization	Forms visual two-dimensional maps for multidimensional data visualization	Visualization is usually limited to simple graphs and charts
Adaptability	Adapts to changes in dynamic environments	May require retraining or adjustments when conditions change
Decision Support	Pattern detection helps make data-driven decisions	Usually requires additional data processing to reach conclusions
Integration with Other Methods	Easily integrates with other machine learning algorithms	Integration can be more complex and require significant effort

Table 2. Matrix of realizations of variables in the data of the double control algorithm

Variable	Description	Type	Dimension	Example
X	Input data vector	Vector	n	$[x_1, x_2, \ldots, x_n]$
D	Dataset	Matrix	$m \times n$	$\begin{bmatrix} d_{11} & d_{12} & \ldots & d_{1n} \\ d_{21} & d_{22} & \ldots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \ldots & d_{mn} \end{bmatrix}$
W	Weight vector	Vector	k	$[w_1, w_2, \ldots, w_k]$
Y	Output vector	Vector	m	$[y_1, y_2, \ldots, y_m]$
L	Loss function	Scalar	1	$L = \frac{1}{N}\sum_{i=1}^{N}(Y_i - Y_{\text{true},i})^2$
R	Reward or penalty	Scalar	1	$R = \begin{cases} r_{\text{success}} & \text{if action is successful} \\ r_{\text{failure}} & \text{otherwise} \end{cases}$

Each variable in the table has a specific role in the data processing process:

– *Input data vector (X).* It includes information received from sensors that serves as the basis for model training. This vector is the first step in passing data to the algorithm.

– *Training data set (D).* This is a matrix containing all the training data required to train the model. This allows the algorithm to identify patterns and relationships between the input data.

– *Weights vector (W).* Includes parameters that determine the influence of each feature on the model results. Optimizing the weights is critical to improving the accuracy of the algorithm.

– *Output vector (Y).* Includes the results obtained during the algorithm's operation, which need to be compared with the true values to evaluate the efficiency.

– *Loss function (L).* Determines the quality of forecasts, which allows the algorithm to adjust its parameters to reduce errors. It is the basis for model training.

– *Reward or penalty (R).* Determines which actions are successful or unsuccessful, which is important for the adaptability of the system. This component influences the agent's learning, stimulating it to improve results.

The matrix of variable realizations is an important tool for understanding the data structure and mechanisms underlying the dual control algorithm, contributing to its effective implementation in multi-agent systems.

Thus, the dual control algorithm combines anomaly detection through model training and adaptation through feedback, which allows it to respond effectively to changes in the data and environment.

To compare the effectiveness of the dual control algorithm for detecting anomalies and errors in sensor data, we selected the isolation forest model described in [14].

Table 3. Comparative analysis of the dual control algorithm and isolation forest model

Criterion	Dual Control Algorithm Model	Isolation Forest Model
Operating Principle	Integration of data from reference sensors and field measurements	Decision tree construction for data partitioning
Anomaly Detection Method	Classification using Kohonen maps	Isolation of anomalies through shorter paths to the tree root
Application	In information-measuring systems to ensure accuracy	Primarily in financial analysis, fraud detection, and other tasks
Forecasting	Provides the ability to forecast based on historical data	Focuses on anomaly detection without a forecast emphasis
Adaptability	Adapts to environmental changes and timely response to anomalies	Quickly detects deviations from normal patterns
Implementation Complexity	May require significant resources for implementation	Less complex to implement, quickly applicable
Data Processing	Requires correction of measurements based on detected anomalies	Separates anomalies from normal data

Both algorithms have their strengths and weaknesses. The dual supervised algorithm is best suited for applications where calibration and prediction are important, while the isolated forest is effective in detecting anomalies in data with high variability.

6. Conclusions

The necessity of applying the double control algorithm for machine learning in multi-agent information measurement systems has been substantiated, representing a relevant solution to applied problems in the field of information measurement technologies related to the optimization and enhancement of data processing efficiency in multi-factor information measurement systems.

The directions for the application of machine learning in multi-agent systems, which are an integral part of improving such systems, have been examined. A double control algorithm for multi-agent systems has been developed, which implements real-time anomaly detection in measurement process data.

The essence of the developed architecture of the double control algorithm has been presented, taking into account a series of specific algorithms necessary for its functionality. The structure of the software algorithm for double control utilizing a sensor module has been outlined, ensuring the practical implementation of the double control algorithm for machine learning in multi-agent information measurement systems.

The essence of the developed machine learning model of the double control algorithm has been compared with traditional methods of analyzing data obtained from sensors. An example of an input data implementation matrix for training the double control algorithm model has been provided. A comparative analysis of the methodology for implementing the developed double control algorithm and the well-known isolated forest model has been conducted.

The goal of future research will be the practical implementation of the machine learning model of the double control algorithm for measuring environmental technological parameters (temperature, pressure, humidity, etc.) for a specific object of control, as well as the enhancement of the algorithm regarding the provision of telemetry calibration of “field” sensors using the obtained reference data.

Conflict of Interest

The authors state that there are no financial orother potential conflicts regarding this work.

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