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OPTIMIZATION OF CYBER-PHYSICAL SYSTEM PARAMETERS BASED ON INTELLIGENT IOT SENSORS DATA

The optimization of parameters of cyber-physical systems (CPS) is studied taking into account various calculations, physical processes, Internet of Things (IoT).

The use of intelligent IoT sensors is crucial for collecting real-time data, which is necessary for enhancing the efficiency, reliability, and performance of CPS.

Various methods of CPS parameters optimization are analyzed and categorized into model-based approaches, data-driven approaches, and hybrid approaches. The model-based approaches rely on mathematical models to describe CPS behavior and use optimization algorithms like linear programming and evolutionary algorithms to predict system responses and optimize parameters. But, the limitations of model-based approaches are related to complex systems with uncertain or dynamic behavior. The data-driven approaches are more suitable for complex cyber-physical systems. These approaches utilize machine learning and data analytics techniques to extract patterns from sensor data, which are then used to adjust system parameters. The hybrid approaches combine elements of both model-based and data-driven methods.

The method of cyber-physical system parameters optimization based on intelligent IoT sensors data processing is developed with using of distributed neural network. The optimization problem is formulated with constraints for the system parameters. The neural network mathematical model and learning algorithm are proposed.

The performed research shows the importance of developing optimization methods for CPS parameters based on intelligent IoT sensor data, considering the evolving nature of IoT technology. The integrating intelligent sensors into CPS offers new opportunities for optimizing system performance but also presents challenges in data management and security that should be addressed in future.

Keywords: optimization, artificial intelligence, cyberphysical systems, internet of things, sensors.

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ОПТИМІЗАЦІЯ ПАРАМЕТРІВ КІБЕРФІЗИЧНОЇ СИСТЕМИ НА ОСНОВІ ДАНИХ ІНТЕЛЕКТУАЛЬНИХ СЕНСОРІВ IoT

Оптимізація параметрів кіберфізичних систем (КФС) виконується з інтеграцією обчислень, мереж та фізичних процесів у структурах Інтернету речей (IoT). Використання інтелектуальних сенсорів IoT має вирішальне значення для збору даних у реальному часі, що необхідно для підвищення ефективності, надійності та продуктивності КФС.

Проаналізовано різні методи оптимізації параметрів КФС, які розподілено на підходи на основі моделі, підходи на основі даних та гібридні підходи. Підходи на основі моделей, функціонують згідно з математичними моделями для опису поведінки КФС і використовують алгоритми оптимізації, такі як лінійне програмування та еволюційні алгоритми, щоб передбачити реакцію системи та оптимізувати параметри. Проте, обмеження підходів на основі моделей пов'язані зі складними системами з невизначеною або динамічною поведінкою. Підходи, керовані даними, більш ефективні для складних кіберфізичних систем. У цих підходах використовуються методи машинного навчання та аналізу даних для визначення шаблонів із даних сенсорів, які потім використовуються для налаштування параметрів системи. Гібридні підходи поєднують елементи методів, заснованих на моделях, і методів, керованих даними.

За результатами проведених досліджень розроблено метод оптимізації параметрів кіберфізичної системи на основі обробки даних інтелектуальних сенсорів IoT з використанням розподіленої нейронної мережі. Поставлено задачу оптимізації з обмеженнями для параметрів системи. Запропоновано математичну модель нейронної мережі та алгоритм навчання.

Проведене дослідження показує важливість розробки методів оптимізації для параметрів КФС на основі даних інтелектуальних сенсорів, враховуючи еволюцію сучасних технологій IoT. Інтеграція інтелектуальних датчиків у КФС пропонує нові можливості для оптимізації продуктивності системи, але також може призводити до проблем в управлінні даними та безпеці, які слід вирішити в майбутньому.

Ключові слова: оптимізація, штучний інтелект, кіберфізичні системи, Інтернет речей, сенсори.

Introduction

The optimization of cyber-physical systems (CPS) parameters is crucial for enhancing their efficiency, reliability, and performance [1–3]. The emergence of the Internet of Things (IoT) has made the deployment of smart sensors crucial for gathering data for cyber-physical systems [4–6]. Let's explore various methods of CPS parameters optimization based on data from intelligent IoT sensors, focusing on model-based approaches, data-driven approaches, and hybrid approaches.

Model-based approaches rely on mathematical models that describe the behavior of the CPS [7,8]. These models are used to predict the system's response to different inputs and to optimize its parameters accordingly. Optimization algorithms such as linear programming, nonlinear programming, and evolutionary algorithms are commonly used in model-based approaches. For example, in a smart grid system, a model-based approach can be used to optimize the flow of electricity based on demand forecasts and generation capacity, ensuring efficient and reliable power distribution [9]. However, model-based approaches have limitations, especially when dealing with complex systems with uncertain or dynamic behavior [10]. In such cases, data-driven approaches are more suitable.

These approaches use machine learning and data analytics techniques to extract patterns and insights from sensor data, which are then used to adjust the system parameters [2,11–16]. Techniques such as regression analysis, neural networks, and reinforcement learning are commonly employed in data-driven approaches. For instance, in a manufacturing CPS, sensor data from the production line can be analyzed using machine learning algorithms to predict equipment failures and to optimize maintenance schedules, thereby reducing downtime and improving productivity [17,18]. Hybrid approaches combine elements of both model-based and data-driven methods. They use models to provide a structured understanding of the system, while incorporating data-driven techniques to adapt to changes and uncertainties in the environment. Hybrid approaches aim to leverage the strengths of both methods to achieve more robust and adaptive optimization [19–21]. For example, in an autonomous vehicle system, a hybrid approach can be used to combine a physics-based model of the vehicle's dynamics with data-driven algorithms that learn from sensor data to optimize the vehicle's control strategies in real-time [22,23].

The choice of optimization method depends on several factors, including the complexity of the CPS, the availability and quality of sensor data, and the specific optimization objectives. Model-based approaches are well-suited for systems with well-understood dynamics and clear mathematical formulations. Data-driven approaches are more appropriate for systems with complex or uncertain behavior, where traditional modeling techniques may not be feasible. Hybrid approaches offer a balance between the two, providing a flexible framework for optimizing CPS parameters in dynamic and uncertain environments. There are practical considerations in the optimization of CPS parameters based on IoT sensor data. These include ensuring reliability and security of sensor data, agreement, integration of optimization algorithms into the existing CPS infrastructure. In addition, the optimization process must constantly monitor and update the environment.

Usually, the optimization of cyber-physical system parameters based on intelligent IoT sensors data is a complex problem that requires a combination of model-based, data-driven, and hybrid approaches. When choosing a method, it is necessary to take into account certain characteristics of the CFS and optimization goals. As IoT technology continues to evolve, the integration of intelligent sensors into CPS will provide new opportunities for optimizing system performance and achieving greater efficiency and reliability. However, this also brings challenges in terms of data management, security, and integration of IoT-enabled CPS optimization.

Therefore, the development of methods for optimizing the parameters of cyber-physical systems based on the data of intelligent IoT sensors is relevant today.

The purpose is to develop a method of cyber-physical system parameters optimization with processing of intelligent IoT sensors data by a distributed neural network.

The Optimization Method Based on Distributed Neural Network Architecture

Optimizing a cyber-physical system action described by the function $y = F(x, a_1, a_2, \ldots, a_N)$, where x is the input signal, y is the output signal, and $a_1, a_2, \ldots, a_N$ are the parameters of the system, can be achieved using an artificial neural network (ANN) trained with the gradient descent backpropagation method. The goal is to minimize the loss function described by the expression (1):

$$L = | y - y_0 |, \tag{1}$$

where y_0 is the desired output signal. This process involves training the ANN to adjust its weights and biases so that the predicted output y closely matches the desired output y_0 for a given input signal x.

The optimization task is as follows:

$$\min_{a_1, a_2, \ldots, a_N} | F(x, a_1, a_2, \ldots, a_N) - y_0 | \quad such\ that \quad \begin{cases} B_1 \le a_1 \le C_1, \\ B_2 \le a_2 \le C_2, \\ \ldots \\ B_N \le a_N \le C_N, \end{cases} \tag{2}$$

where $B_1, B_2, \ldots, B_N$ are the lower bounds and $C_1, C_2, \ldots, C_N$ are the upper bounds of the corresponding system parameters with the numbers $1, 2, \ldots, N$.

The distributed neural network that performs the minimization of the loss function $L = | F(x, a_1, a_2, \ldots, a_N) - y_0 |$ is structured as a connection of artificial neurons which are situated in different intelligent IoT devices. The network aims to approximate the nonlinear function $F(x, a_1, a_2, \ldots, a_N)$ and minimize the absolute difference between its output and the desired output y_0 for a given input x. The mathematical model of the distributed neural network involves the formulation of its architecture, the activation functions, the forward propagation process, and the optimization of its parameters through backpropagation and gradient descent [24,25].

The distributed neural network is organized as a connection of the input, hidden and output layers. In accordance with the IoT devices characteristics and settings, the neural network can be fully connected or partially connected. The input layer receives the input signal x, which can be a vector of features. The number of neurons in this layer corresponds to the dimensionality of the input. The hidden layers perform the bulk of the computations in the network. They are responsible for capturing the nonlinear relationships. The quantity of hidden layers and the number of neurons within each layer are adjustable hyperparameters, tailored according to the function's complexity $F(x, a_1, a_2, \ldots, a_N)$ behaviour. The output layer produces the final output, which is the network's approximation of $F(x, a_1, a_2, \ldots, a_N)$. For the loss function L minimization problem like, the output layer consists of a single neuron with multiple inputs. Neurons in the layers applies an activation function to its input. By introducing nonlinearity, the activation function allows the network to learn intricate relationships between inputs and outputs. The optimization problem (2) can be solved by neural network.

The sigmoid activation function, often referred to as the logistic function, is employed to activate artificial neurons [26,27]. It is defined by the following formula:

$$f(z) = \frac{1}{1+e^{-z}} \tag{3}$$

where $f(z)$ is the output of the sigmoid function, z is the input to the function, typically the weighted sum of the inputs to the neuron with a bias term, e is the base of the natural logarithm.

The sigmoid function transforms any real-valued input z into a value ranging from 0 to 1. This property renders it valuable for binary classification endeavors, as the output can be interpreted as the likelihood of membership in a particular class. The function is smooth and differentiable, which is important for gradient-based optimization. One of the key characteristics of the sigmoid function is that it introduces non-linearity into the neuron's output. This non-linearity is essential for learning of complex patterns in the data.

The process of forward propagation involves passing the input signal through the network to compute the output. Every neuron computes the weighted sum of its inputs, which includes the input x and the outputs of other neurons, multiplied by the corresponding weights with a bias term [13,28]. Next, the neuron applies its activation function to the weighted sum to produce its output.

$$a = f\left(\sum_{i=1}^{n} w_i u_i + b\right) \tag{4}$$

where a is the output of the neuron, f is the activation function, w_i are the weights, u_i are the inputs, and b is the bias.

To minimize the loss function, the network's parameters (weights and biases) need to be optimized. This is achieved through backpropagation and gradient descent [24,25]. The backpropagation algorithm is employed to determine the gradients of the loss function concerning the network's parameters. It involves propagating the error signal backward through the network, starting from the output layer and moving towards the input layer. The gradients are calculated through the chain rule of calculus. The gradient descent process modifies the parameters in a manner that minimizes the loss.

Gradient descent is an iterative method adjusting a model's parameters to diminish the loss function, quantifying the variance between predicted and observed outcomes.. The method is based on the principle that if the multi-variable function L is defined and possesses differentiability within a certain vicinity of a point a, then L decreases fastest in the direction of the negative gradient $-\nabla L(a)$ at that point.

The gradient of the loss function L is computed as a vector $\nabla L(\theta)$ that contains the partial derivatives of L concerning to each parameter in $\theta = \{\theta_1, \theta_2, ..., \theta_K\}$:

$$\nabla L(\theta) = \left(\frac{\partial L}{\partial \theta_1}, \frac{\partial L}{\partial \theta_2}, \ldots, \frac{\partial L}{\partial \theta_K}\right) \tag{5}$$

where K is the number of parameters.

The parameters are then updated iteratively. The update rule for the parameters is given by:

$$\theta_n = \theta_{n-1} - \alpha \nabla L(\theta_{n-1}) \tag{6}$$

where n is the iteration number and α is the learning rate, a positive scalar that controls the size of the step. This cycle of calculating the gradient and adjusting the parameters continues iteratively until a predefined condition is satisfied. This condition might be reaching a set number of iterations, a threshold for the change in the value of the loss function between iterations, or a threshold for the magnitude of the gradient.

The training process involves iteratively performing forward propagation to compute the output and the loss, performing backpropagation to compute the gradients, and using gradient descent to update the parameters. This process is repeated for a specified number of epochs or until the loss converges to a minimum value. During forward propagation, the input signal x is passed through the network, and the output y is computed. The loss function $L = | y - y_0 |$ is then evaluated to quantify the error between the outputs. The gradients indicate how much each weight and bias contributes to the error. The weights and biases are computed by the expressions (7) and (8):

$$w_n = w_{n-1} - \alpha \frac{\partial L}{\partial w}, \quad (7)$$

$$b_n = b_{n-1} - \alpha \frac{\partial L}{\partial b}, \quad (8)$$

where w_n and b_n are the updated weights and biases, w_{n-1} and b_{n-1} are the current weights and biases, α is the learning rate, and $\frac{\partial L}{\partial w}$ and $\frac{\partial L}{\partial b}$ are the gradients of the loss function of weights and displacements, respectively, respectively. This process of forward propagation, loss evaluation, backpropagation, and weight and bias updates is iterated for multiple epochs or until the loss converges to a minimum value. The learning rate α is a critical hyperparameter that controls the step size of the updates and can affect the convergence and stability of the training process.

After training, the optimized weights and biases of the neural network represent the parameters $a_1, a_2, \ldots, a_N$ of the nonlinear system that minimize the loss function. A neural network can predict the result y for new input signals x, aiming to achieve outputs that closely match the desired values y_0.

The main advantage of the proposed optimization of cyber-physical system parameters is that the intelligent IoT sensors form the distributed neural network, which is flexible and reliable because the data analysis operation is performed by (7) and (8) mappings at all devices uniformly. Thus, each IoT device makes its proportional contribution to the overall cyber-physical operation with impact on all parameters $a_1, a_2, \ldots, a_N$. When a device is disconnected or failed, then the system operation continues without that device and does not change significantly. The computational burden is proportional to the overall number of neurons in the network and distributed between different IoT devices without excessive concentration at the server side.

Results & Discussion

The optimization of cyber-physical system (CPS) parameters using distributed neural networks is characterized by high efficiency, reliability, and performance. Advanced learning capabilities allow the network to accurately model complex patterns and relationships in data. Additionally, the scalability of distributed neural networks allows them to handle large-scale systems and vast amounts of data generated by IoT devices, making them suitable for extensive CPS. The distributed nature of these networks also provides fault tolerance, ensuring system reliability even if one node fails. Furthermore, they offer real-time processing capabilities, allowing for dynamic optimization of CPS parameters in response to changing conditions, and adaptability to new data and system changes over time.

However, there are several disadvantages to consider. The complexity of designing and implementing distributed neural networks can be challenging due to the need for coordination among multiple nodes. Communication overhead is another concern, as nodes in distributed networks need to communicate with each other, which can introduce latency and increase bandwidth demand. Security is also a critical issue, as distributing data across multiple nodes creates multiple potential points of attack. The performance of neural networks heavily relies on the quality of input data.

Thus, the further development of IoT technologies with cyber-physical system parameters optimization is required for increasing the security and computational performance in the cases of great network elements numbers.

Conclusions

In conclusion, the optimization of cyber-physical system (CPS) parameters based on intelligent Internet of Things (IoT) sensors data is a critical area of research with significant implications for enhancing the efficiency, reliability, and performance of these systems. The integration of intelligent sensors into CPS offers the ability to collect real-time data, which is crucial for accurate modeling and optimization.

Various methods of CPS parameters optimization, including model-based approaches, data-driven approaches, and hybrid approaches, each have their strengths and are suitable for different scenarios. Model-based approaches are effective for systems with well-understood dynamics, while data-driven approaches are more suitable for complex systems with uncertain behavior. Hybrid approaches provide a balance between the two, leveraging the strengths of both methods to achieve robust and adaptive optimization.

The proposed method of cyber-physical system parameters optimization allows to increase the flexibility and reliability of IoT technologies with performing the data analysis operations by the same mappings at all devices uniformly. The use of distributed neural networks for optimization presents several advantages, such as enhanced learning capabilities, scalability, fault tolerance, real-time processing, and adaptability. However, it also introduces challenges related to complexity, communication overhead, security, data quality, and resource requirements. These factors must be carefully considered when implementing distributed neural networks in CPS optimization.

As IoT technology continues to evolve, the integration of intelligent sensors into CPS will provide new opportunities for optimizing system performance. However, this also brings challenges in terms of data management, security, and integration. Overall, the development of effective optimization methods for CPS parameters based on intelligent IoT sensors data is essential for advancing the capabilities and applications of cyber-physical systems in various domains.

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