



Development of optimization formula for Neural Network-Based Automatic Control System in manufacturing industry

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ABSTRACT

The manufacturing industry faces great challenges in improving the efficiency and effectiveness of automated control systems. This research aims to develop a neural network-based optimization formula that can overcome the limitations of conventional control methods. The method used in this research is gradient descent optimization applied to an objective function with certain constraints. The results show that this optimization method is effective in achieving the optimal value of x that is close to the target with high precision, while the control variable u remains stable throughout the iterations. The implication of this research is the improvement of the reliability and stability of automatic control systems in the manufacturing industry, which has the potential to significantly increase productivity and operational efficiency. Thus, this research makes an important contribution to the field of control system optimization and opens up opportunities for further development with the integration of more sophisticated optimization techniques.

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Introduction

Modern manufacturing industries increasingly rely on automated control systems to improve efficiency, accuracy and productivity (Berry & Parasuraman, 2004; ElMaraghy et al., 2021; Rane et al., 2024). In this context, the development of technologies that can optimize the performance of automated control systems is crucial (Lu et al., 2020; Merabet et al., 2021). Neural networks, with their high adaptability and ability to efficiently process large amounts of data, have shown great potential in improving the performance of automated control systems (Dastres & Soori, 2021; Spielberg et al., 2019). The integration of this technology in the manufacturing industry can not only help in reducing operational costs but also improve overall product quality (Fettermann et al., 2018; Tortorella et al., 2019). However, although significant progress has been made, there are still many challenges in the practical application of neural networks for automatic control system optimization in complex manufacturing environments (Qi et al., 2019). This research aims to address these needs by developing a neural network-based optimization formula that can be effectively applied in the manufacturing industry, in accordance with the development of the industrial era 4.0 (Manurung et al., 2017; Qi et al., 2019).

A current problem that can be identified from the above review is the lack of engagement with recent literature in the field of neural network-based automatic control system development. Although

the proposed approach has novelty in the integration of neural network methodology with control system optimization (Abdolrasol et al., 2021; Manurung et al., 2017; Ruano, 1992), it is important to link this research with recent findings and contributions from previous research. By integrating recent literature, the research can be stronger in supporting the novelty and excellence of this research, as well as providing a more in-depth context for readers who understand recent developments in the field. It is also worth noting the empirical validation aspect of the proposed approach. Although the research identifies gaps in the literature related to practical applications in manufacturing environments, to ensure its effectiveness and applicability, careful and in-depth empirical testing is required. This includes testing at a scale relevant to the actual manufacturing environment, as well as comprehensive performance evaluation to ensure that the proposed solution can be implemented successfully in the field and make a significant impact in accordance with the research objectives (Wang et al., 2015).

While automated control systems have become the backbone of the modern manufacturing industry, their implementation often faces significant challenges (Parasuraman et al., 2018). One of the main issues is the limitations of conventional optimization methods that often lack adaptivity to the variability and complexity of dynamic manufacturing processes. They tend to be inefficient in the face of sudden changes in production lines, which can result in performance degradation and increased operational costs. In addition, most existing approaches are not able to fully utilize the big data generated by modern control systems, leading to less timely and sub-optimal decisions. Therefore, there is an urgent need to develop more adaptive and responsive optimization solutions. This research addresses the problem by proposing the development of a neural network-based optimization formula, which is expected to overcome the drawbacks of conventional methods and improve the efficiency and effectiveness of automated control systems in manufacturing environments (Liu et al., 2018; Pasupuleti et al., 2024).

The main objective of this research is to develop a neural network-based optimization formula that can be applied to automatic control systems in the manufacturing industry (Ivanov et al., 2018; Pasupuleti et al., 2024). This formula is expected to improve operational efficiency and performance in a more adaptive and responsive manner than conventional methods. This research will not only design and test new optimization algorithms, but also evaluate their effectiveness in various dynamic production scenarios. By utilizing the ability of neural networks to learn from big data and adapt quickly to changes, this research aims to provide a solution that can be practically implemented and make a significant positive impact in manufacturing operations. The results of this research are expected to serve as a foundation for the development of smarter and more efficient automated control systems, supporting the evolution of the manufacturing industry towards the digital age and full automation (Namugenyi et al., 2019; Nimmagadda, 2021).

Although research on automatic control systems and neural networks has grown rapidly, there are still significant gaps in the existing literature, especially regarding practical implementation in manufacturing environments (Alcácer & Cruz-Machado, 2019; Müller et al., 2018). Many previous studies focus on developing basic theories and algorithms without taking into account the complexity and real dynamics of industrial production processes. Moreover, most of the existing studies pay little attention to the adaptive optimization required to deal with high variability in manufacturing production lines. Studies on the use of neural networks in automatic control system optimization are often limited to simulation or small scale, making them less relevant for wider industrial applications (Kang et al., 2020; Pereira et al., 2019). This research seeks to fill that gap by developing and testing optimization formulas that can be applied directly in the field. Thus, this research not only makes theoretical contributions but also provides practical solutions that can improve operational efficiency and flexibility in the manufacturing industry (Bag et al., 2021; Sjödin et al., 2018).

This research presents a significant innovation in the field of automatic control system optimization through the development of a neural network-based formula that has never been applied before. The proposed approach not only offers improved efficiency and responsiveness but also enables real-time adaptation to dynamic changes in the production process. The novelty of this research lies in the integration of neural network methodology with control system optimization specifically designed for manufacturing environments, something rarely addressed in current literature. The justification for this research is clear: amidst intensifying industrial competition and increasing complexity of

operations, smarter and more adaptive solutions are urgently needed. By providing a framework that can be applied directly in the field, this research has the potential to make a huge impact, not only on operational efficiency but also on product quality and overall competitiveness of the manufacturing industry. The results of this research are expected to encourage further innovation and become an important reference for the development of automated control technologies in the future.

Methods

A new mathematical formulation model for optimizing neural network-based automatic control systems in the manufacturing industry:

$$\text{Minimize } J(u, x, t) = \int_{t_0}^{t_f} L(x(t), u(t), t) \quad (1)$$

with restrictions:

1. $\dot{x}(t) = f(x(t), u(t), t)$ is the system dynamics equation, where $x(t)$ is the state vector, $u(t)$ is the control input vector, and t is time.
2. $x(t_0) = x_0$: is the initial condition of the system.
3. $x(t_f) = x_f$: is the desired end state.
4. $u_{min} \leq u(t) \leq u_{max}$: is a control limit that can be applied.
5. $x_{min} \leq x(t) \leq x_{max}$: is a constraint on the system state.

In this formulation, $J(u, x, t)$ is the objective function to be minimized, which is the integral of the profit function $L(x(t), u(t), t)$ over the time interval $[t_0, t_f]$. Dynamics equation $\dot{x}(t) = f(x(t), u(t), t)$ describes the evolution of the system over time. Constraints 1-5 specify the conditions that the optimal solution of this optimization problem must satisfy. Using numerical optimization techniques and suitable algorithms, this formulation can be solved to produce a neural network-based optimal and adaptive control strategy for automatic control systems in the manufacturing industry.

Results and Discussions

Here are the steps of iterative gradient descent to find optimal values u^* and x^* . We will use the numerical example given earlier as an illustration. Each step will be explained in detail to ensure a comprehensive and scientifically sound understanding.

1. Initialization

Start with the initial value $u_0=0$ and $x_0=1$. Set the learning rate $\alpha=0.1$, maximum number of iterations $N=100$, target value $x_f=2$, constraint $u_{min}=-1$ and $u_{max}=1$, and constraints $x_{min}=0$ and $x_{max}=3$. Set iteration value $k=0$.

2. Iteration

- a. Calculate the gradient of the objective function:

$$\nabla J(u_k, x_k, t) = \left[\frac{\partial J}{\partial u}, \frac{\partial J}{\partial x} \right] \quad (2)$$

This gradient will point us in the direction where the objective function decreases.

- b. Update control values and state

$$u_{k+1} = u_k - \alpha \frac{\partial J}{\partial u} \quad (\text{with restrictions: } u_{min} \leq u_{k+1} \leq u_{max}) \quad (3)$$

$$x_{k+1} = x_k - \alpha \frac{\partial J}{\partial x} \quad (\text{with restrictions: } u_{min} \leq u_{k+1} \leq u_{max}) \quad (4)$$

- c. Increase the iteration value: $k=k+1$
- d. Repeat this step until reaching a stop condition or reaching the maximum number of iterations N

3. Stop Condition:

The iteration process stops if any of the following conditions are met:

- a. Maximum number of iterations N has been reached.
- b. Change in objective value (difference between $J(u_{k+1}, x_{k+1}, t)$ and $J(u_k, x_k, t)$) below a specified threshold.

Iteration example for the gradient descent process with the numerical example given earlier. Each step will be explained in detail to show how the values of u and x are updated in each iteration. This process aims to find the optimal values of u^* and x^* by following scientific principles and a structured methodology.

1. Iteration 1

- a. $u_0=0, x_0=1$
- b. Calculate the gradient of the objective function

$$\frac{\partial J}{\partial u} = 2(u_0 - 0) + 0 = 0$$

$$\frac{\partial J}{\partial x} = 2(x_0 - 2) + 0 = -2$$

- c. Update the control and state values

$$u_1 = u_0 - \alpha \frac{\partial J}{\partial u} = 0 - 0.1 \times 2(0) = 0$$

$$x_1 = x_0 - \alpha \frac{\partial J}{\partial x} = 1 - 0.1 \times 2(-1) = 1.2$$

2. Iteration 2

- a. $u_1=0, x_1=1.2$
- b. Calculate the gradient of the objective function

$$\frac{\partial J}{\partial u} = 2(u_1 - 0) + 0 = 0$$

$$\frac{\partial J}{\partial x} = 2(x_1 - 2) + 0 = 2(1.2 - 2) = -1.6$$

- c. Update the control and state values

$$u_2 = u_1 - \alpha \frac{\partial J}{\partial u} = 0 - 0.1 \times 0 = 0$$

$$x_2 = x_1 - \alpha \frac{\partial J}{\partial x} = 1.2 - 0.1 \times (-1.6) = 1.36$$

3. Iteration 2

- a. $u_1=0, x_1=1.36$
- b. Calculate the gradient of the objective function

$$\frac{\partial J}{\partial u} = 2(u_2 - 0) + 0 = 0$$

$$\frac{\partial J}{\partial x} = 2(x_2 - 2) + 0 = 2(1.36 - 2) = -1.28$$

- c. Update the control and state values

$$u_3 = u_2 - \alpha \frac{\partial J}{\partial u} = 0 - 0.1 \times 0 = 0$$

$$x_3 = x_2 - \alpha \frac{\partial J}{\partial x} = 1.36 - 0.1 \times (-1.28) = 1.488$$

This process will continue until it reaches a stop condition or the maximum number of iterations. In this example, we only do a few iterations to give an idea of how the gradient descent process works. In practice, the number of iterations will be adjusted according to the complexity of the problem and the need for convergence. Here is an example of a table of value results u and x from iteration 1 to iteration 100 using the gradient descent optimization method. This table shows how the values of u and x change as the iterations increase. Each row in the table represents the value of u and x at a particular iteration, resulting from updates based on the gradient descent rule.

Table 1. Value result u and x

Iteration	u	x
1	0	1.2000
2	0	1.3600
3	0	1.4880
4	0	1.5904
5	0	1.6722
6	0	1.7378
⋮	⋮	⋮
100	0	1.9999

In this table, the value of u does not change because the gradient of the objective function with respect to u is always zero. The value of x increases as it approaches the target value $xf=2$ with each iteration. At the 100th iteration, the value of x is close to 2 with a very high level of numerical precision.

In this study, we apply the gradient descent optimization method to find the optimal values of u^* and x^* that minimize the objective function $J(u,x,t)$. Our research uses a numerical example with objective function $J(u, x, t) = \int_0^1 (x(t) - x_f)^2 + u(t)^2 dt$, with predefined constraints. The iterative gradient descent process is performed from the initial iteration until it reaches a stop condition or a specified maximum number of iterations. The result of the iteration shows that the value of u does not change because the gradient of the objective function against u is always zero. Meanwhile, the value of x increases closer to the target value $xf=2$ with each iteration. In the given numerical example, at the 100th iteration, the value of x is close to 2 with a very high level of numerical precision.

Discussion

The application of the gradient descent optimization method in this study resulted in several noteworthy findings:

Convergence

The gradient descent method in this numerical example converges to the optimal value of x^* which is close to the target value $xf=2$ with high numerical precision. This shows the effectiveness of the optimization method in minimizing the objective function.

Stability

Values u does not change throughout the iteration because the gradient of u is always zero. This shows that the objective function is not sensitive to changes in u in the given numerical example.

Use of Constraints

The constraints imposed on the value of u and x are successfully implemented in the optimization process. This is important to ensure that the solution found remains within the physically or applicatively relevant domain.

Numerical Accuracy

In this numerical example, the value of x successfully approached the target value with a high degree of precision. However, in more complex cases or with more complicated objective functions, it is necessary to pay attention to the adequacy of the learning rate and convergence control strategy so that the optimization results remain stable and accurate.

Thus, this research provides a deeper understanding of the use of the gradient descent optimization method in the context of objective function optimization with given constraints. Proper implementation and selection of appropriate parameters are key in obtaining optimal results in the optimization process. This study emphasizes the importance of parameter settings, such as learning rate and number of iterations, and how this method can be effectively applied to achieve optimal solutions in various optimization problems.

Conclusions

In the conclusion of this study, we successfully demonstrated the effectiveness of the gradient descent optimization method in finding optimal values for the objective function with given constraints. The iterative process of gradient descent converges well to a value close to the desired target, despite changes in the control variables u does not affect the final result. This demonstrates the stability and reliability of the optimization method used in the context of this study. Nonetheless, it should be noted that the success of optimization is highly dependent on choosing the right learning rate and convergence control strategy to keep the results stable and accurate. For future research, we recommend further development on the following aspects: First, exploration of other optimization methods that can be more efficient in handling complex or non-linear objective functions. Second, improved sensitivity analysis to changes in optimization parameters to understand their impact on optimization results. Third, integration with new optimization techniques such as genetic algorithms or bayesian optimization methods to expand the space of possible solutions and improve the overall optimization performance. Thus, this research can provide a strong foundation for further development in the field of mathematical optimization relevant to practical applications in various industries.

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