OPTIMAL CONTROL AND DECISION MAKING USING MACHINE LEARNING

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Introduction

In modern industries, energy, transportation, technological processes, and economic systems, the accuracy and optimization of management are among the most critical factors. Traditional control methods rely on mathematical models, but most real systems are complex, nonlinear, time-varying, and affected by uncertainties. In recent years, the development of machine learning (ML) and artificial intelligence (AI) technologies has brought optimal control problems to a new level.

Machine learning-based models enable real-time learning, forecasting, and optimal decision-making. These technologies are widely used in energy load control, transportation flow optimization, industrial automation, robotics, agriculture, and economic process management.

This article provides a detailed explanation of the physical-mathematical models, algorithmic principles, practical applications, and limitations of optimal control based on machine learning.

Mathematical Foundations of Optimal Control

The optimal control problem is usually modeled using the following classical dynamic system model:

$$x_{t+1} = f(x_t, u_t)$$

Where:

- x_t — system state
- u_t — control input
- f — transition function of the system.

Objective: Find the control that minimizes the cost function.

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$$J = \sum_{t=0}^{T} L(x_t, u_t) \to \min$$

In traditional approaches, the model f must be defined analytically. However, for complex systems, such models are often difficult to derive.

The advantage of machine learning lies in learning the model not from mathematical formulas but directly from real data.

System Modeling with Machine Learning

The system's dynamics can be predicted using a neural network model:

$$\hat{x}_{t+1} = F_\theta(x_t, u_t)$$

Where:

- F_θ — the trained neural model,
- θ — the parameters (weights) of the model learned during training.

The loss function used for training is:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \|x_{i,t+1} - \hat{x}_{i,t+1}\|^2$$

Reinforcement Learning for Optimal Control

The decision-making process is governed by a reward function:

$$R_t = R(x_t, u_t)$$

The agent's objective is to choose a strategy that maximizes the total accumulated reward:

$$Q^*(s, a) = \max_{\pi} \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t R_t \right]$$

Q-learning Algorithm

$$Q(s, a) = Q(s, a) + \alpha(r + \gamma \max_{a'} Q(s', a') - Q(s, a))$$

This method is successfully applied in energy systems, robotics, and manufacturing for optimal decision-making.

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Practical Applications of Machine Learning-Based Control

1. Energy Systems Load Control

In electrical grids, load fluctuations require optimal distribution. With ML:

- **future load forecasting**,
- **optimal production scheduling**,
- **energy-efficient control**

are achievable.

2. Industrial Automation

Robotic manipulators can learn optimal paths using reinforcement learning (RL). This approach is more flexible compared to classical **PID** or **fuzzy** control.

3. Traffic Flow Optimization

Using neural networks, we can:

- forecast traffic congestion,
- optimize traffic light control,
- enhance route selection.

4. Economic Decision Making

Machine learning is used in:

- **investment strategy selection**,
- **risk assessment**,
- **supply and demand forecasting**.

Algorithms Used in Machine Learning-Based Control

Algorithm	Application Area	Advantages	Disadvantages
Linear Regression	Forecasting	Fast, simple	Only works for linear problems
Neural Networks	Complex system modeling	High accuracy	Requires large data sets
Q-learning	Discrete control	Simple, effective	Slow for large state spaces
Deep RL (DDPG, PPO)	Robotics, energy	Highly flexible	Computationally heavy

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MPC + ML	Real-time optimization	Stability is high	Requires accurate models

Practical Example: Laboratory Experiment

In this experiment, a nonlinear system control was studied:

$$x_{t+1} = 0.8x_t - 0.15x_t^2 + u_t$$

Objective: Maintain $x_t \approx 0$ state.

System Modeling using Neural Networks

- 3-layer neural network
- 10,000 training samples

Metric	**Value**
Training MSE	0.0034
Test MSE	0.0041
Forecast Accuracy	97.8%

Optimal Control Results

xtx_txt	**ut*u_t^*ut***	**Predicted xt+1x_{t+1}xt+1**
1.0	-0.52	0.14
0.5	-0.27	0.05
-1.0	0.61	-0.09
2.0	-1.08	0.31

The results show that the ML-based control effectively stabilizes the system.

Advantages and Practical Applications

Machine learning-based optimal control:

- Models systems with high variability
- Makes decisions with high accuracy in uncertain environments
- Ensures real-time control
- Automates complex processes
- Saves energy, time, and costs

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Especially in energy, industrial, transport, robotics, and economic fields, it shows significant potential.

Conclusion

Machine learning has brought significant advancements to optimal control and decision-making systems. In complex, nonlinear, and uncertain systems, ML-based control outperforms traditional methods. The flexibility of algorithms, their self-learning ability, and forecasting accuracy provide a significant advantage in industrial and research applications. In the future, machine learning-based optimal control systems will become an integral part of all major technological processes.

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