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IMPROVEMENT OF CONTROL MODELS OF CLOSED SYSTEMS USING NEURAL NETWORKS

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Abstract. *It is known that the importance of the modeling method in the research of technological systems is increasing. One of the main reasons for this can be attributed to the possibility of simplifying a complex system, as well as the priority aspects of logical consistency and mathematical laws. At the same time, the development of information technology, computing and artificial intelligence has strengthened the practice of using modeling methods. In other words, the modeling apparatus has a good integration feature with these concepts. In this article, the importance and relevance of the development of optimal control models based on a neural network is presented as the main scientific idea on the example of a closed-loop control system. When the control system is formed as an intelligent system, or when the system description is based on the concepts of an intelligent system, the main parameters of modeling are differentiated. It is theoretically and practically based that the results of modeling gain significance depending on these parameters. The effectiveness of the use of neural network models in the optimal control of the activity of the intelligent system is explained against the background of the possibility of minimizing the control error. It has been scientifically proven that modeling closed systems using neural networks has several advantages. Quantitative parameters that need to be paid attention to in the formation of an intelligent system are researched. Conclusions and proposals are presented on the effectiveness of using neural networks in modeling complex technological systems.*

Key words: *intelligent system, fuzzy logic, fuzzy regulator, system error, modeling, neural network, optimization, model control*

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BERK TIZIMDA BOSHQARUV MODELLARINI NEYRON TARMOQ YORDAMIDA TAKOMILLASHTIRISH

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Annotatsiya. *Ma'lumki, texnologik tizimlarni tadqiq etishda modellashtirish usulining ahamiyati ortib bormoqda. Bunga asosiy sabablardan biri sifatida, murakkab tizimni soddalashtirish imkoniyati, hamda mantiqiy izchil va matematik qonuniyatlarning ustuvor jihatlari bilan bogʻlash mumkin. Shu bilan birgalikda axborot texnologiyalari, hisoblash texnikasi hamda sun'iy intellektning rivoji modellashtirish ususllaridan foydalanish amaliyotini kuchaytirib yubordi. Boshqacha aytganda modellashtirish apparatining mazkur tushunchalar bilan yaxshi integratsiyalashuv xususiyati mavjud. Ushbu maqolada berk boshqaruv tizimi misolida neyron tarmoq asosida optimal boshqarish modellarini ishlab chiqish ahamiyati, dolzarbligi asosiy ilmiy* *g‘oya sifatida keltirilgan. Boshqaruv tizimi intellektual tizim sifatida shakllantirilganda, yoki tizim tavsifi intellektual tizim tushunchalari asosida keltirilganda modellashtirishning asosiy parametrlari farqlab berilgan. Modellashtirish natijalari aynan shu parametrlarga bog‘liq holda ahamiyat kasb etishi nazariy-amaliy jihatdan asoslangan. Intellektual tizim faoliyatini optimal boshqarishda neyron tarmoq modellaridan foydalanish samaradorligi boshqaruv xatoligini minimallashtirish imkoniyati fonida yoritib berilgan. Neyron tarmoqlardan foydalangan holda yopiq tizimlarni modellashtirish bir qancha afzalliklarga ega ekanligi ilmiy izohlangan. Intellektual tizimni shakllantirishda e’tibor qaratilishi zarur bo‘lgan miqdoriy parametrlar tadqiq etilgan. Murakkab, texnologik tizimlarni modellashtirishda neyron tarmoqlardan foydalanishning samaradorligi bo‘yicha xulosa va takliflar keltirilgan.*

Kalit so‘zlar: *intellektual tizim, noaniq mantiq, noaniq rostlagich, tizim xatoligi, modellashtirish, neyron tarmoq, optimallashtirish, modelli boshqaruv.*

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УСОВЕРШЕНСТВОВАНИЕ МОДЕЛЕЙ УПРАВЛЕНИЯ ЗАМКНУТЫМИ СИСТЕМАМИ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННЫХ СЕТЕЙ

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Аннотация. *Известно, что значение метода моделирования в исследовании технологических систем возрастает. К одной из основных причин этого можно отнести возможность упрощения сложной системы, а также приоритетные аспекты логической непротиворечивости и математических закономерностей. В то же время развитие информационных технологий, вычислительной техники и искусственного интеллекта усилило практику использования методов моделирования. Другими словами, аппарат моделирования имеет хорошую интеграцию с этими концепциями. В данной статье важность и актуальность разработки моделей оптимального управления на основе нейронной сети представлена как основная научная идея на примере замкнутой системы управления. При формировании системы управления как интеллектуальной системы или при описании системы на основе представлений об интеллектуальной системе различают основные параметры моделирования. Теоретически и практически обосновано, что результаты моделирования приобретают значимость в зависимости от этих параметров. Объясняется эффективность использования нейросетевых моделей при оптимальном управлении деятельностью интеллектуальной системы на фоне возможности минимизации ошибки управления. Научно доказано, что моделирование закрытых систем с помощью нейронных сетей имеет ряд преимуществ. Исследованы количественные параметры, на которые необходимо обратить внимание при формировании интеллектуальной системы. Представлены выводы и предложения по эффективности использования нейронных сетей при моделировании сложных технологических систем.*

Ключевые слова: *интеллектуальная система, нечеткая логика, нечеткий регулятор, системная ошибка, моделирование, нейронная сеть, оптимизация, управление моделью.*

Introduction

The application of intelligent control systems in the automatic control of complex chemical-technological processes or in general a wide class of dynamic systems determines the trend of today's development of the system. This is due to the application of intelligent control systems to control technical systems of a complex type, that is, deterministic and stochastic controllers cannot be used.

It is known that intelligent systems of automatic control are flexible systems that store and analyze the flow of information that describes the nature of the control object, information on the relationship between system elements, and analyze it [1, 3].

Typically, the application of a digital controller to continuous systems leads to a digital system, and the evaluation of the system behavior is carried out based on the digital control laws. Based on this analogy, the application of fuzzy regulator (FR) to systems allows us to talk about intelligent control systems. We explain the organization of the transition from a continuous system to a digital system and the reverse process with two concepts, that is, analog-to-digital converter (ADC) and digital-to-analog converter (DAC). In a similar intellectual system, the concepts of "Fuzzification" and "Defuzzification" establish a borderline correspondence. These concepts are characterized by "fuzzy" and "definite" input and output quantities, respectively.

Quality indicators of the system are determined by evaluating its errors. In this sense, this aspect is primary in improving the management system. In this case, any method or means of achieving system error reduction can be considered as an automatic control systems development apparatus. Instead, there are effective ways to achieve this in intelligent systems. This possibility is optimal adjustment based on broad-minded thinking [2].

Increasing the number of input errors received by the feedback system adjuster, increasing the comparison options, providing the optimal quality indicator of the classical control system is not studied as a significant aspect, because the transfer function of the stabilizing adjuster is more important than the above. In a closed system with an indeterminate adjuster, this factor has absolutely no meaning, that is, the concept of the transfer function of the adjuster does not exist. Then other factors related to the fuzzy setter may be the main influence on the quality of the system.

In modern science, the modeling method is widely used in the optimization of closed control systems. In turn, there are a number of methods of modeling, and one of the methods that has become popular in recent times is modeling with the help of neural networks.

Using neural networks in modeling optimal control of closed systems offers several important benefits:

Nonlinear Mapping: Neural networks are capable of capturing nonlinear relationships between the system inputs and outputs. Many closed systems exhibit complex, nonlinear dynamics, and traditional control methods may struggle to model and control such systems accurately. Neural networks can approximate these nonlinear mappings, enabling more effective control.

Adaptability: Neural networks can adapt and learn from data, making them suitable for modeling dynamic systems. Closed systems often have time-varying dynamics or uncertainties that traditional control models may not capture adequately. Neural networks can adapt to changes in system behavior and adjust the control policy accordingly.

Function Approximation: Optimal control typically involves solving an optimization problem to determine the control inputs that optimize a given objective function. Neural networks can approximate the unknown objective function or the system dynamics, allowing for efficient and accurate optimization. This approximation capability is especially valuable when closed-form solutions are not readily available.

Generalization: Once trained, neural network models can generalize to unseen scenarios or system configurations. This is particularly useful when closed systems exhibit variations or parameter uncertainties. The neural network can learn patterns and generalize the optimal control policy to similar situations, improving the overall system performance.

Online Learning and Real-Time Control: Neural networks can facilitate online learning, where the model can continuously update and improve as new data becomes available. This is particularly advantageous for closed systems that require real-time control adjustments. Neural networks can quickly adapt to changing conditions and provide updated control policies, enhancing system performance and stability.

Reduced Modeling Effort: Neural networks can learn system dynamics and control policies directly from data, eliminating the need for explicit mathematical models. This reduces the modeling effort and can be advantageous when accurate mathematical models are difficult to obtain or involve complex equations [4, 5, 6].

Overall, neural networks provide a powerful framework for modeling optimal control of closed systems, offering the ability to capture nonlinear dynamics, adapt to changing conditions, approximate unknown functions, generalize to unseen scenarios, enable real-time control, and reduce modeling effort. These benefits make neural networks a valuable tool in optimizing the control of closed systems.

Materials and Methods

In scientific studies, it is very common to compare the concepts of classical management and intellectual management of technological systems. In this, the method of comparative analysis is mainly used. In this research, methods such as comparative analysis, mathematical modeling, modeling based on neural networks were used [7, 8, 9].

In the above case, the main research direction will be to construct two types of adjusters in one particular system and analyze the results obtained from their optimization. The main goal of these studies is to improve the conventional tuning system, which can be achieved by applying a fuzzy tuning system to create an intelligent control system. In conclusion, it is recognized that the system is an intellectual management system when further improvement (increase) of the quality indicator is carried out. If this claim is accepted as a valid assertion, another aspect of the above purpose is revealed. This is not a stage of transition to an intelligent control system, but an aspect of system quality assurance at this stage. This creates several problems. In particular, FR is a matter of determining the factors of increasing the quality indicator of the applied system. In this article, uncertain system parameters were studied using the method of modeling importance aspects [10, 20].

Results

We consider a closed technological system with an uncertain adjuster as an object of research. The fuzzy controller of the fuzzy logic controlled system has the following functional scheme (Fig. 1).

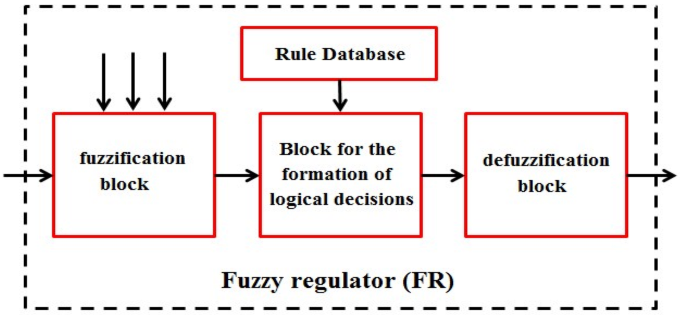

Figure 1. Functional block diagram of fuzzy regulator[1]

Now let's briefly clarify the parameters, input and output parameters of the fuzzy setter.

Fuzzification block. Converting the current value of the input variables of a fuzzy matcher to a linguistic quantity of validity is called the fuzzification operation [11, 17, 23].

In the fuzzification block, the system error ε, the rate of change of the error $\dot{\varepsilon}$, the acceleration of the error $\ddot{\varepsilon}$, the expression of the input linguistic variables is qualitatively described by the term – sets. Suppose the input of the system is $u(t)$ and the output is $x(t)$. Then the continuous error of the system is represented by the equation $\varepsilon(t) = u(t) - x(t)$. The continuous error of the system is quantized by the ADC device with a h step and outputs the $\varepsilon[k]$ quantization error. The first- and second-order error formulas are as follows.

$$\dot{\varepsilon}[k] = (\varepsilon[k] - \varepsilon[k-1]) / h; \ddot{\varepsilon}[k] = (\varepsilon[k] - 2\varepsilon[k-1] + \varepsilon[k-2]) / h^2 \quad (1)$$

Initial separation: as factors of influence on the results of the uncertain adjuster (initial effect), we specify input quantities - discrete error and its subsequent orders. Logical solution formation block. In this case, working rules are written based on the knowledge matrix

[1] Source: Compiled by the authors

IF <initial state> THEN <response function>

linguistic rules in the form are understood. It represents the knowledge about the interaction of the NR with the control object (CO). The interaction between the inputs and outputs of the if-then type defined relevance function (RF) is related to the concept of implication (activation), which represents the act of finding the degree of validity of each of the logical rules of this type (Fig. 2).

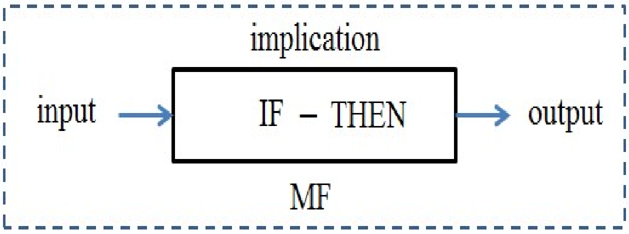

Figure 2. Activation rule for relevance function [2]

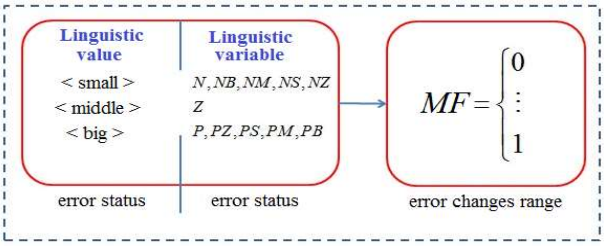

Figure 3. A state of continuous association with the basic concepts of a fuzzy set

The range of variation of variable $NB, NM, NS, NZ, Z, PZ, PS, PM, PB$ is divided into subsets, each with a TF relative to this variable. The state of continuous connection with the basic concepts of the fuzzy set can be seen in the following diagram (Fig. 3). Suppose that the number of values that the fuzzy setter output variables can take is m , and we write them as m terms as.

$$A = \left(A_0 = 0, A_1 = 1, \ldots, A_{m-1} = m-1\right).$$

Uncertain term - we determine the number of sets by the number of relevance functions, conditionally set it to s and look at its relevance to m . The importance of (s, m) pairs of quantities in the formulation of control rules is that they specify the number of all possible combinations of fuzzy reasoning. However, another aspect remains open, that is, the existence of the law of interdependence of these pairs [12, 13, 15, 24]. Indeed, we have the following table (Table 1).

Table 1.

Resultant connection of neural rules

ε	$\dot{\varepsilon}$	T_1	T_2	$\cdots$	T_s
P	PB	A_2	A_3		A
	PS	A_2	A_2		A
	Z	A_0	A_{m-1}		A
	NS	A_1	A_1		A
	NB	A_{m-1}	A_1		A
Z	PB	A_2	A_3	$\cdots$	A
	PS	A_2	A_3		A
	Z	A_{m-1}	A_0		A
	NS	A_{m-1}	A_0		A
	NB	A_{m-n}	A_1		A
N	PB	A_3	A_4		A
	PS	A_4	A_4		A

[2] Source: Compiled by the authors

	Z	A_{m-1}	A_{m-1}		A
	NS	A_5	A_5		A
	NB	A_5	A_{m-n}		A

Here we assume that the table is filled, for example, based on the following rule:

$$IF < \varepsilon = P > AND < \dot{\varepsilon} = PB > AND < \ddot{\varepsilon} = T_1 > THEN, IN\ IT < A = A_2 >$$

Further classification: the factor of structuring linguistic rules, the structuring factor of membership functions, the vague term - the factor of whether or not the number of sets depends on the number of membership functions.

Final separation: an optimization factor for the fuzzy adjuster synthesis algorithm.

Let's consider the system error minimization model against the background of allocations. We believe that it is possible to rely on the results of modeling with the help of neural networks. In this sense, we use reasoning analysis and modeling methods based on neural networks to solve the problem.

We accept isolated factors as input factors. We make the conditional designations as follows:

X_1 – system error is determined by formula $\varepsilon[k] = u[k] - x[k]$;

X_2 - the first-order error is determined from the formula (1);

X_3 - the second-order error is determined from the formula (1);

Y – output size (response function).

In accordance with the designations, the exemplar values are given in the following table (Table 2).

Table 2.

Indicators of feedback monitoring and reaction of an uncertain technological system

№	X_1	X_2	X_3	Y
1	0,20000	0,04000	0,59460	0,60000
2	0,12000	0,00800	0,51532	0,52000
3	0,10400	0,01120	0,40433	0,40800
4	0,08160	0,00800	0,33000	0,32800
5	0,06560	0,00659	0,25972	0,26208
6	0,05242	0,00524	0,20784	0,20973
7	0,04195	0,00400	0,17000	0,16777
8	0,03355	0,03355	0,13297	0,13418
9	0,02684	0,02684	0,10600	0,10737

The neural network modeling information table is given below (Table 3).

Table 3.

Information about the neural network

Input layer	**Factors**	**1**	**X1**
		2	**X2**
		3	**X3**
	Number of neurons		**17**
Hidden layer	**Number of neurons**		**8**
	Activation function		**Softmax**
Output layer	**Dependent variables**	**1**	**Y**
	Number of neurons		**1**
	Scale Change Method for Scale-Dependent Items		**Standardized**
	Activation function		**Identity**
	Error function		**Sum of squares**

The information table of modeling using a neural network contains information such as factors, their number, number of neurons, dependent variable and its number, modeling method, active function, type of error.

The constructed neural network structure is shown in Figure 4. In the conclusion of the model constructed according to it, the value of the sum of squares is $1{,}031 \cdot 10^{-30}$, and the relative error is represented by $4{,}123 \cdot 10^{-31}$.

The normalized level of significance of independent variables is 100% for variable 1, 94,9 % for variable 2, and 100% for variable 3.

The above aspects justify the use of the model. The results of modeling based on the neural network are presented below (Table 4).

Table 4.

Neural network based modeling results

№	1-Exogenous	2-Exogenous	3-Exogenous	Model Value	System Output	Model Error
1	0,10507266	0,196689587	0,064160797	0,107217	0,107249988	0,0000330
2	0,104909	0,196383225	0,064060861	0,10705	0,107082972	0,0000330
3	0,10473554	0,196058519	0,063954941	0,106873	0,106905901	0,0000329
4	0,104557474	0,19572519	0,063846208	0,1066913	0,106724013	0,0000327
5	0,104369608	0,195373516	0,063731491	0,1064996	0,106531923	0,0000323
6	0,104148422	0,19495947	0,063596427	0,1062739	0,106305537	0,0000316
7	0,103994562	0,194671453	0,063502475	0,1061169	0,106147468	0,0000306
8	0,103840702	0,194383437	0,063408523	0,1059599	0,105988962	0,0000291
9	0,103686842	0,19409542	0,063314571	0,1058029	0,105830019	0,0000271
10	0,103532982	0,193807404	0,063220619	0,1056459	0,105670706	0,0000248
11	0,103379122	0,193519387	0,063126668	0,1054889	0,105511145	0,0000222
12	0,103225262	0,193231371	0,063032716	0,1053319	0,105351489	0,0000196
13	0,103071402	0,192943354	0,062938764	0,1051749	0,105191885	0,0000170
14	0,102917542	0,192655338	0,062844812	0,1050179	0,10503245	0,0000145
15	0,102763682	0,192367321	0,06275086	0,1048609	0,104873255	0,0000124
16	0,102609822	0,192079305	0,062656908	0,1047039	0,104714333	0,0000104
17	0,102455962	0,191791288	0,062562956	0,1045469	0,104555685	0,0000088
18	0,102302102	0,191503272	0,062469004	0,1043899	0,104397292	0,0000074
19	0,102148242	0,191215255	0,062375052	0,1042329	0,104239125	0,0000062
20	0,101994382	0,190927239	0,0622811	0,1040759	0,104081155	0,0000053
21	0,101840522	0,190639222	0,062187148	0,1039189	0,103923349	0,0000044
22	0,101686662	0,190351206	0,062093196	0,1037619	0,10376568	0,0000038
23	0,101532802	0,190063189	0,061999244	0,1036049	0,103608124	0,0000032
24	0,101378942	0,189775173	0,061905292	0,1034479	0,103450662	0,0000028
25	0,101225082	0,189487156	0,06181134	0,1032909	0,103293276	0,0000024
26	0,101071222	0,18919914	0,061717388	0,1031339	0,103135952	0,0000021
27	0,100917362	0,188911123	0,061623436	0,1029769	0,10297868	0,0000018
28	0,100763502	0,188623107	0,061529485	0,1028199	0,10282145	0,0000016
29	0,100609642	0,18833509	0,061435533	0,1026629	0,102664256	0,0000014
30	0,100455782	0,188047074	0,061341581	0,1025059	0,10250709	0,0000012

Discussion

According to the modeling results, the optimality of the calculation algorithm can be explained by the decrease of the model error. In fact, in the 1st control cycle, the error is represented by a value of 0.0000330, while in the 30th control cycle, this indicator is equal to 0.0000012, and these indicators have a monotonous decrease during the process. Thus, we have an adequate model of a closed system. This creates the following possibilities.

System Identification: Adequate models can help identify the dynamics and characteristics of a closed control system. By analyzing input-output data, such as step responses or frequency responses, mathematical models can be developed that accurately represent the behavior of the system [13, 21].

Controller Design: Adequate models are essential for designing controllers that can achieve optimal system performance. By understanding the system dynamics, control engineers can use model-based techniques to design controllers that stabilize the system, improve response time, reject disturbances, and meet other performance requirements.

Simulation and Analysis: Adequate models allow for the simulation and analysis of closed control systems before implementing them in real-world scenarios. By simulating the system behavior using the model, engineers can evaluate the system's response under different operating conditions, test different control strategies, and identify potential issues or limitations.

Performance Optimization: Adequate models can be used to optimize the performance of closed control systems. By formulating mathematical optimization problems based on the model, engineers can determine the optimal setpoints, control parameters, or control strategies that maximize certain performance criteria such as energy efficiency, stability, robustness, or throughput.

Fault Detection and Diagnosis: Adequate models can be employed for fault detection and diagnosis in closed control systems. By comparing the predicted behavior of the model with the actual behavior of the system, deviations can be detected and analyzed to identify faults or anomalies in the system components. This information can help facilitate timely maintenance and prevent system failures.

Control System Tuning and Adaptation: Adequate models can assist in the tuning and adaptation of control systems. By using the model to estimate the current system state, control algorithms can be adjusted or adapted to optimize the control performance based on real-time measurements and changing system conditions.

Overall, adequate models play a crucial role in the optimal management of closed control systems by providing insights, facilitating design and analysis, enabling optimization, supporting fault detection and diagnosis, and aiding in control system tuning and adaptation.

The degree of compatibility between a response function and object values can vary depending on the specific context and requirements. However, here are some general considerations and requirements that can contribute to a higher degree of compatibility [23]:

Consistency: The response function should be consistent with the object values in terms of their meanings and interpretations. If the object values represent certain concepts or attributes, the response function should align with those concepts and attributes in a coherent and logical manner. Relevance: The response function should be relevant to the object values and provide information or actions that are useful and applicable in relation to those values. It should address the specific needs or objectives associated with the object values. Accuracy: The response function should accurately represent the object values and provide reliable information or perform actions that reflect the true nature of those values. It should minimize errors, inaccuracies, or inconsistencies that may lead to misunderstandings or incorrect outcomes. Completeness: The response function should encompass the full range of possibilities and variations inherent in the object values. It should account for different scenarios, options, or aspects related to the values and provide a comprehensive and thorough response. Flexibility: The response function should be adaptable and flexible to accommodate changes or updates in the object values. It should be able to handle dynamic situations and adjust its behavior or output accordingly. Efficiency: The response function should be efficient in terms of computational resources, response time, or any other relevant performance metrics. It should deliver its responses or actions in a timely manner and avoid unnecessary delays or inefficiencies.

User-Friendliness: The response function should be user-friendly and easy to understand and interact with. It should provide clear and intuitive responses that are easily interpretable by the users. Additionally, the function should facilitate a smooth and seamless user experience when working with the object values.

It can be noted that the fulfillment of the above requirements is based on the results of modeling.

Results

Modeling closed systems using neural networks can offer several advantages and remain relevant in various domains. Here are some conclusions that can be drawn:

Pattern recognition and non-linear relationships: Neural networks excel at capturing complex patterns and non-linear relationships within data. This makes them suitable for modeling closed systems where the underlying dynamics are intricate and may involve intricate interactions and dependencies.

Flexibility and adaptability: Neural networks can adapt to changing conditions and new data without requiring explicit reprogramming. This flexibility is beneficial for modeling closed systems that may evolve over time or encounter unforeseen scenarios.

Feature extraction and representation learning: Neural networks are capable of automatically learning meaningful features and representations from raw or high-dimensional data. This allows them to capture relevant information and reduce the dimensionality, which can be advantageous for modeling closed systems with large and complex datasets.

Generalization and predictive capabilities: Neural networks can generalize from observed data to make predictions or infer hidden patterns in closed systems. By learning from past data, they can potentially make accurate predictions about future behavior, which is valuable for decision-making and planning.

Integration of heterogeneous data: Neural networks can effectively handle and integrate various types of data, such as numerical, categorical, text, or image data. This ability is relevant for modeling closed systems that involve diverse sources of information, enabling a comprehensive understanding of the system.

Modeling complex dynamics: Closed systems often exhibit intricate dynamics with feedback loops, delays, and interdependencies. Neural networks, particularly recurrent neural networks (RNNs) and their variants like long short-term memory (LSTM) networks, are well-suited for capturing such complex temporal dynamics, making them suitable for modeling closed systems with time-dependent behavior.

Simulation and optimization: Neural networks can be trained to simulate closed systems, enabling virtual experimentation and optimization. This allows for the exploration of different scenarios, parameter tuning, and analysis of system behavior under various conditions, without the need for physical experimentation.

Insights and interpretability: Neural networks, especially those with attention mechanisms or explainability techniques, can provide insights into the internal workings of closed systems. By understanding the relationships and factors contributing to the model's predictions, stakeholders can gain valuable insights into the underlying mechanisms and drivers of the system.

Despite these advantages, it is essential to consider the limitations of neural network modeling, such as the need for large amounts of labeled data, potential biases, interpretability challenges in complex models, and the possibility of overfitting or underfitting. Additionally, the relevance of using neural networks for modeling closed systems depends on the specific problem domain, available data, and the expertise of domain specialists in interpreting and validating the results.

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