

Contextualización educativa del control predictivo basado en redes neuronales artificiales en la formación en Automatización

Educational contextualization of predictive control based on artificial neural networks in automation training

Carlos Gabriel Mackencie Tobar¹**Deivis Rodrigo Parrales Chancay¹**¹Quevedo State Technical University. Ecuador**ORCID:** <https://orcid.org/0009-0006-3494-1839><https://orcid.org/0009-0006-5651-4899>**Email(s):**

cmackencie@uteq.edu.ec

dparralesc2@uteq.edu.ec

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RESUMEN: El artículo tiene como objetivo proponer pautas pedagógicas centrales para la integración del control predictivo basado en redes neuronales artificiales en la formación universitaria en automatización. La metodología se sustentó en una revisión sistemática de literatura especializada publicada entre 2013 y 2024. El análisis permitió identificar elementos técnicos con mayor potencial educativo para la enseñanza del control avanzado. Como resultado, se sistematizan cuatro pautas centrales. Se concluye que la implementación didáctica del control predictivo neuronal requiere un enfoque intencional que transforme la complejidad matemática en experiencias de aprendizaje significativas y orientadas al desarrollo de competencias profesionales.

Palabras clave: Didáctica de la ingeniería; Control predictivo neuronal; Sistemas no lineales; Educación en automatización; Laboratorio virtual; Competencias en ingeniería

ABSTRACT: This article aims to propose core pedagogical guidelines for integrating predictive control based on artificial neural networks into university-level automation education. The methodology was based on a systematic review of specialized literature published between 2013 and 2024. The analysis identified technical elements with the greatest educational potential for teaching advanced control. As a result, four core guidelines have been systematized. It is concluded that the didactic implementation of predictive neural control requires a deliberate approach that transforms mathematical complexity into meaningful learning experiences geared toward developing professional competencies.

Keywords: Engineering didactics; Neural predictive control; Nonlinear systems; Automation education; Virtual laboratory; Engineering competencies

Introduction

Education in control and automation engineering is at a turning point. On the one hand, advances in artificial intelligence and machine learning have revolutionized strategies for controlling complex systems, giving rise to approaches such as neural predictive control (ANN-MPC) that combine the predictive capability of traditional MPC with the learning flexibility of neural

networks. On the other hand, university classrooms face the constant challenge of making these advanced concepts accessible to students who have yet to master the fundamentals of classical control theory (Mosso *et al.*, 2021).

This disconnect between technical advances and their pedagogical assimilation constitutes a significant gap. There is abundant technical literature demonstrating the effectiveness of ANN-MPC in industrial applications (Montes, 2021; Rajasekhar *et al.*, 2024), but few studies go beyond reporting technical performance to propose systematic frameworks for curricular integration.

How can the mathematical complexity of nonlinear predictive control (NMPC) be transformed into meaningful learning experiences? Which elements of ANN-MPC design hold the greatest educational value? How can simulation environments be used not only as verification tools but also as spaces for developing engineering reasoning?

This article addresses precisely this gap by proposing a set of guidelines for the educational contextualization of neural predictive control. As a pedagogical scenario, it revisits the system of interconnected tanks—a classic in control theory education due to its intrinsically nonlinear dynamics, multivariable nature, and the non-minimum phase phenomena it exhibits.

This system offers a crucial didactic advantage: its behavior is physically intuitive (the flow between tanks, the liquid level), which allows students to focus on control concepts without losing touch with physical reality.

Education in automation and control faces the challenge of preparing students to understand and manage increasingly complex dynamic systems, characterized by nonlinear behavior, multivariable couplings, and uncertainties that are difficult to represent using traditional mathematical models. In this context, the integration of artificial intelligence techniques—particularly artificial neural networks (ANNs) and deep neural networks (DNNs)—has taken on a significant role in both scientific and educational settings by enabling new approaches to modeling, predicting, and analyzing complex dynamic systems (Castaneda *et al.*, 2023; Alzubaidi *et al.* (2021).

Model-based predictive control (MPC) has established itself as a widely used advanced strategy in industrial applications; however, its incorporation into educational contexts faces limitations associated with the high mathematical complexity of nonlinear models and the high computational cost of nonlinear predictive control (NMPC) (Alzubaidi *et al.*, 2021).

In response to these challenges, various studies have proposed the use of artificial neural networks as internal models for the predictive controller, giving rise to the approach known as neural network-based predictive control (ANN-MPC), which allows complex dynamics to be approximated based on data, thereby reducing the computational load and facilitating understanding from an educational perspective (Montes, 2021).

Interconnected tank systems are a classic reference in the teaching of automatic control, due to their nonlinear, multivariable nature and the presence of phenomena such as the non-minimum phase. Previous research has shown that these systems effectively illustrate fundamental concepts of modeling, parameter identification, controller tuning, and stability analysis, making them an ideal teaching resource for the educational contextualization of advanced predictive control (Roa *et al.*, 2017).

In this regard, recent literature shows that the integration of artificial and deep neural networks into predictive control schemes improves the technical performance of systems and, at the same time, offers high educational value by promoting data-driven learning and the use of computational simulation as a virtual laboratory (Bamimore *et al.*, 2019); (Yankai & Bhushan, 2020). Comparative studies have shown that the ANN-MPC and RNN-MPC approaches achieve accuracy levels similar to those of traditional NMPC, but with shorter computation times, which is particularly advantageous for their implementation in educational environments and real-time simulation platforms (Rajasekhar *et al.*, 2024; Jian *et al.*, 2024).

From this perspective, it is necessary to systematize guidelines for the educational contextualization of neural networks integrated into predictive control, addressing not only their technical efficiency but also their educational potential in teaching automation, intelligent control, and applied artificial intelligence. Consequently, this article seeks to answer the question: How can we design learning activities that enable engineering students not only to understand but also to design, implement, and evaluate neural network-based predictive control strategies, using resources and timeframes compatible with a university course?

The research is grounded in a qualitative approach, employing the documentary analysis method, aimed at the pedagogical interpretation of scientific advances in the field of neural network-based predictive control. The analysis–synthesis method was used to examine the fundamentals of artificial and deep neural networks and their integration into predictive control strategies, and to

synthesize guidelines for their educational application; the induction–deduction method was employed to identify patterns in the analyzed studies and derive didactic principles applicable to the teaching of nonlinear control.

The methodology was structured in four stages, explicitly geared toward the educational contextualization of the content, in accordance with the stated objective.

Stage 1. Identification and selection of relevant sources.

A targeted search was conducted of scientific literature published between 2019 and 2024 related to: artificial and deep neural networks, nonlinear predictive control (MPC, NMPC, ANN-MPC, RNN-MPC), interconnected tank systems, and simulation and modeling applications for educational purposes.

Priority was given to studies with clear methodological contributions, reproducible results, and potential for educational use.

Stage 2. Technical–pedagogical analysis of the models

The selected sources were analyzed based on: types of neural architectures (MLP, NARX, RNN, DNN), training and optimization algorithms, predictive controller tuning parameters (NP, NC, Ts, Q, R), and the level of complexity and comprehensibility for students. This analysis made it possible to identify which models are best suited for use as teaching resources in the instruction of advanced control.

Stage 3. Systematization of Guidelines for Educational Contextualization

Based on the analysis, guidelines were systematized focused on the use of computer simulation as a virtual laboratory, learning based on data generated by dynamic systems, understanding nonlinearity and multivariable coupling, and the development of competencies in modeling, prediction, and decision-making. The interconnected tank system was considered the ideal pedagogical scenario for introducing concepts of neural predictive control.

Stage 4. Integration of the Theoretical-Referential Framework

An integrated theoretical framework was constructed that synthesizes the contributions of various authors, highlighting its value for university teaching, educational research, and the teaching of artificial intelligence applied to process control.

Development

Deep neural networks (DNNs) are an extension of traditional neural networks that use multiple hidden layers to process complex information. These architectures are designed to learn hierarchical representations of data, enabling them to capture high-level features and complex patterns. They are considered part of deep learning and can handle millions of parameters, depending on the complexity of the problem they address (Alzubaidi *et al.*, 2021).

DNNs consist of multiple hidden layers located between the input layer and the output layer. Each hidden layer performs nonlinear computations and transforms the input so that the next layer can extract more abstract features. These layers can be fully connected or partially connected, depending on the model's design. Additionally, some architectures include recurrent structures to enable feedback and the learning of temporal dependencies (Alzubaidi *et al.*, 2021).

In DNNs, data propagates forward through the layers (feed-forward), passing through nonlinear activation functions that allow the model to learn complex relationships. During training, the model modifies its weights using an optimization algorithm that seeks to minimize an error function, employing the backpropagation method. This iterative process gradually adjusts the weights to improve the model's accuracy (Alzubaidi *et al.*, 2021).

The model proposed by Roa *et al.* (2017) allows for the simulation of complex nonlinear dynamics in three-tank systems using differential equations based on mass conservation principles.

According to Montes (2021), one of the main challenges in the design of nonlinear model predictive controllers (MPC) is the appropriate selection of the prediction model, as well as tuning parameters such as the prediction horizon (NP), the control horizon (NC), and the weighting matrices Q and R for the cost function. Furthermore, the author highlights the importance of considering input and output constraints to ensure the system's stability and operational safety.

A review of the literature revealed that technical studies on ANN-MPC, although not written for pedagogical purposes, hold valuable educational potential when examined through an educational lens.

1. The interconnected tank system: a microcosm for integrated learning

More than just a simple example, the tank system constitutes a pedagogical “microcosm.” Its dynamics, described by nonlinear differential equations based on mass conservation principles, are

complex enough to exceed the capabilities of conventional linear control techniques, yet transparent enough for students to develop a physical intuition, Roa *et al.* (2017).

The educational value of this scenario lies in its ability to illustrate multiple advanced control concepts in an interconnected manner: multivariable coupling (the level in one tank affects the other), non-minimum phase behavior (an initial response in the opposite direction of the desired one), and the need to manage physical constraints (maximum levels, limited flow rates). By keeping this scenario constant throughout a course, students can observe how different control strategies (PID, linear MPC, ANN-MPC) address the same fundamental challenges, facilitating in-depth comparison.

2. *Data-Driven Modeling as a Democratizer of Advanced Control*

One of the historical obstacles to teaching NMPC has been the need for a precise analytical model of the system, whose derivation and linearization are time-consuming and focus on mathematical rather than engineering skills. This is where ANN-MPC introduces a paradigm shift with profound pedagogical value.

Research such as that by Saldaña *et al.* (2023) and Bamimore *et al.* (2019) show how a neural network (for example, an NARX or an LSTM) can learn the dynamics of the tank system directly from operational data, obtained either from a physical test bench or—more accessible for a classroom setting—from a detailed simulation in MATLAB/Simulink or Python. This approach focuses students' efforts on the engineering process: designing experiments for data collection, preprocessing, and training and validating the neural network model.

Data-driven learning lowers the mathematical barrier to entry and aligns teaching with current industry practices, where data-driven models are increasingly prevalent. Furthermore, it allows for the discussion of crucial concepts such as overfitting, generalization, and the importance of validation datasets, thereby connecting control theory with fundamental topics in data science (Zhang *et al.*, 2021).

3. *The Tank System as an Integrative Teaching Platform*

Interconnected tank systems have been widely used in the literature as case studies for teaching automatic control, due to their nonlinear behavior, multivariable coupling, and the presence of non-minimal phase dynamics (Roa *et al.*, 2017). These systems allow students to visualize and analyze

how small variations in inputs can produce significant effects on outputs—a phenomenon that, from an educational perspective, facilitates the understanding of concepts such as stability, response time, and dynamic coupling.

Furthermore, studies by Bamimore *et al.* (2019) show that neural networks trained on simulation data can effectively model this type of multivariable system. This evidence suggests that the introduction of interconnected tanks as a teaching platform promotes the integration of theory and practice, allowing students to work with real or simulated data and observe firsthand how neural-predictive models respond to various conditions.

4. Pedagogical Advantages of the ANN-MPC Approach Over Classical NMPC

A comparative analysis of recent studies reveals that the ANN-MPC approach offers significant pedagogical advantages over classical nonlinear predictive control (NMPC). On the one hand, Rajasekhar *et al.* (2024) and Jian *et al.* (2024) demonstrate that neural network-based schemes reduce the computation time required to obtain control actions, while maintaining accuracy levels similar to those of traditional NMPC. From a pedagogical perspective, this reduction in execution time allows students to conduct iterative experiments in near real time, which increases opportunities for learning through experimentation and trial and error.

Furthermore, Saldaña *et al.* (2023) note that ANNs allow for the abstraction of complex dynamics without the need to explicitly formulate sophisticated differential equations. This abstraction enables students to focus on understanding the system's behavior and the logic of predictive control, rather than getting bogged down in extensive mathematical derivations, thereby reinforcing deeper conceptual learning.

5. Computational Simulation as an Essential Virtual Laboratory

The use of computer simulation has emerged as a key component in teaching neural predictive control. The work of Bamimore *et al.* (2019) and Yankai and Bhushan (2020) shows that generating synthetic data through simulations provides a safe and controlled environment where students can explore, modify parameters, and observe system responses without the risks and costs associated with physical experiments.

This strategy aligns with constructivist pedagogical approaches, in which learning is built upon experience and reflection on the results obtained (Yankai and Bhushan, 2020). Furthermore,

computer simulation environments allow for the incorporation of visualization tools and immediate feedback, aspects that enhance student motivation and self-assessment.

6. *Summary of Guidelines for Educational Contextualization*

A synthesis of the reviewed findings identifies a set of methodological guidelines for the educational contextualization of neural network-based predictive control, taking into account the logical progression of content and students' learning needs:

1. **Progressive sequencing of models:** Initially introduce simple neural networks (e.g., MLP) before moving on to more complex models (NARX, RNN, DNN), thereby facilitating the gradual development of cognitive skills.
2. **Use of interconnected tank systems:** Employ this type of system as an integrative teaching scenario that allows for the observation of nonlinear phenomena and multivariable responses in real time or in simulation.
3. **Computational simulation as a laboratory:** Encourage the use of simulation environments to generate and manipulate data, allowing students to experiment with neural models and predictive controllers without practical risks.
4. **Comparison of control approaches:** Design activities that allow students to compare linear MPC, NMPC, and ANN-MPC approaches, so that they understand the advantages, limitations, and applications of each.
5. **Interpretation of results and critical analysis:** Emphasize the interpretation of system responses, error analysis, and evaluation of controller performance in terms of formative concepts.
6. **Development of cross-disciplinary competencies:** Promote activities that integrate modeling, programming, data analysis, and responsible decision-making, thereby reinforcing skills applicable in real-world contexts.

Analysis of the reviewed literature identified a set of findings relevant to the **educational contextualization of predictive control based on artificial and deep neural networks**, particularly in educational settings related to automation and process control.

First, it was found that artificial neural networks—especially architectures such as MLP, NARX, and RNN—constitute suitable models for representing nonlinear dynamic systems from an

educational perspective, as they allow for approximating system behavior without resorting to complex mathematical formulations (Bamimore *et al.*, 2019; Saldaña *et al.*, 2023). This characteristic facilitates their gradual introduction into advanced control courses, promoting conceptual understanding of prediction and decision-making in dynamic systems.

Second, the studies analyzed show that the integration of ANNs and DNNs into predictive control schemes (ANN-MPC and RNN-MPC) significantly reduces the computational load compared to traditional NMPC, while maintaining acceptable levels of accuracy (Rajasekhar *et al.*, 2024; Jian Yi *et al.*, 2024). From an educational standpoint, this finding enables the implementation of these strategies in academic simulation environments and on platforms with limited resources, thereby broadening their accessibility for teaching and learning processes.

Another relevant finding is the identification of **interconnected tank systems** as an effective teaching resource for contextualizing the use of neural predictive controllers. The literature demonstrates that these systems allow for the illustration of complex phenomena such as non-linearity, multivariable coupling, and non-minimum phase, thereby promoting meaningful learning through virtual experimentation and the analysis of simulated data (Roa *et al.*, 2017).

Furthermore, it was shown that the use of data generated by computer simulation constitutes a valid pedagogical strategy for training neural models in educational contexts, promoting data-driven learning and the development of competencies in system modeling, analysis, and validation (Bamimore *et al.*, 2019; Yankai and Bhushan, 2020).

The analysis made it possible to systematize a set of **methodological guidelines** aimed at guiding the progressive incorporation of neural predictive control into academic training, taking into account students' cognitive complexity, the gradual progression of content, and the integration of theory and practice.

The results confirm that predictive control based on artificial and deep neural networks not only represents a technical advance in the field of nonlinear system control but also holds significant educational potential when used in a contextualized and didactically structured manner.

The possibility of using neural networks as internal models of the predictive controller allows the educational emphasis to shift from the analytical solution of complex equations toward an understanding of the system's dynamic behavior and the interpretation of results, which aligns with pedagogical approaches centered on active and problem-based learning. In this regard, the

contributions of Saldaña *et al.* (2023) reinforce the idea that ANNs facilitate the transition from abstract theoretical models to functional representations that are understandable to students.

It is also noted that the reduction in computation time achieved by the ANN-MPC and RNN-MPC schemes, as reported by Rajasekhar *et al.* (2024) and Jian *et al.* (2024), has significant educational implications, as it enables near-real-time interaction during simulation activities, thereby increasing motivation and experiential learning.

Furthermore, the use of interconnected tank systems as a learning scenario reinforces the contextualization of the content, as these systems are widely recognized in the literature and in the teaching of automatic control. This promotes knowledge transfer and the integration of concepts from artificial intelligence, predictive control, and nonlinear modeling within a single educational environment.

Consequently, the discussion reaffirms that the incorporation of neural networks into predictive control should be viewed not only as a strategy for optimizing system performance but also as a pedagogical resource that contributes to the development of professional competencies in automation, systems analysis, and data-driven decision-making.

Conclusions

The analysis conducted revealed that the integration of artificial and deep neural networks into nonlinear predictive control schemes constitutes a relevant pedagogical alternative for education in automation and control, as it facilitates the understanding of complex dynamic systems through a data-driven and computational simulation-based approach.

It was found that neural predictive control facilitates the educational contextualization of advanced concepts such as nonlinearity, multivariable coupling, and non-minimum phase, reducing reliance on highly complex mathematical models and promoting more meaningful and applied learning.

Interconnected tank systems have established themselves as an effective teaching resource for instruction in neural network-based predictive control, as they allow for the coherent integration of content related to modeling, identification, prediction, and decision-making within a single educational environment.

The proposed methodological guidelines offer a structured framework for the gradual incorporation of neural network-based predictive control into teaching and learning processes, taking into account

students' cognitive complexity and the development of competencies in modeling, systems analysis, and the use of applied artificial intelligence tools.

The educational approach to neural network-based predictive control helps strengthen the comprehensive training of future automation professionals by integrating theory and practice through innovative, contextualized teaching strategies aligned with current demands in engineering and higher education.

This framework has been derived from a review of the technical literature; therefore, its empirical validation in real classrooms is the natural next step. Future research should measure the impact of these guidelines on the development of specific competencies and on student motivation. In addition, there is a need for the collaborative development of open educational resources (datasets, simulation models, activity guides) that will enable more instructors to adopt this approach without having to start from scratch.

Bibliographic references

- Bamimore, K. M., Kehinde, L. O., & Abajo, O. A. (2019). Artificial neural network model-based predictive real-time control of a cascaded two tank system. *European Journal of Engineering Research and Science*, 4(5), 1-7. <https://ijt.oauife.edu.ng/index.php/ijt/article/view/141>
- Castaneda, W. A., Benjamín, P. E., y Vega, F. (2023). Redes neuronales artificiales: una medición de aprendizajes de pronósticos como demanda potencial. *Revista de Ingeniería y Automatización*, 27(18), 45-58 http://ve.scielo.org/scielo.php?script=sci_arttext&pid=S1316-48212023000100051
- Montes, D. A. (2021). *Implementación de un controlador predictivo no lineal y una estrategia de optimización en tiempo real a una planta piloto híbrida* (Trabajo de fin de Máster) Universidad de Valladolid
- Mosso, A., Hernández-Pérez, J. A., Nagarajan, G., & Juárez-Romero, D. (2021). Una incursión al aprendizaje profundo para la regulación de procesos. *Programación Matemática y Software*, 13(2). <https://doi.org/10.30973/progmat/2021.13.2/4>

- Roa, B., Contreras, O. L., Medina, G. A., Vega, L. V. (2017). Modelado matemático, simulación, análisis y control de un sistema hidráulico interactivo-tres tanques. *Revista de Tecnología*, 16(1), 77-98 <https://revistas.unbosque.edu.co/index.php/RevTec/article/view/2318>
- Jian, Y., Xialai, W., Ling, L., Jiabin, Q., y Junghui, C. (2024). Data-driven model predictive control for vehicle trajectory tracking using recurrent neural networks. *IFAC PapersOnLine*, 58(29), 367-372. www.sciencedirect.com
- Yankai, R. y Bhushan, R. (2020). Deep Neural Network Approximation of Nonlinear Model Predictive Control. *IFAC PapersOnLine*, 53(2), 11319-11324 <http://creativecommons.org/licenses/by-nc-nd/4.0>
- Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J BigData*, 8(1), 53. <https://pubmed.ncbi.nlm.nih.gov/33816053/>
- Saldaña, C. A., Tumbaco, A. R., Kuonquí, F. I., Pasmay, P. I., & Malave, C. A. (2023). Simulación y comparación de controladores PID, Liapunov y redes neuronales artificiales: Abordando el rechazo de perturbaciones en sistemas no lineales a través de modelado computacional. *Ciencia Latina Revista Científica Multidisciplinar*, 7(4), 3849-3865. https://doi.org/10.37811/cl_rcm.v7i4.7234
- Rajasekhar, N., Nagappan, K. K., Radhakrishnan, T. K., y Samsudeen, N. (2024). Effective MPC strategies using deep learning methods for control of nonlinear system. *International Journal of Dynamics and Control*, (10), 3694-3707 https://www.researchgate.net/publication/380820118_Effective_MPC_strategies_using_deep_learning_methods_for_control_of_nonlinear_system
- Zhang, A., Zhiyun, B., Wangand, H. (2021). Differential evolution optimized RNN-based NMPC for flexible joint robots. *Electronics*, 10(19), 2426. <https://doi.org/10.3390/electronics10192426>