

Artificial Intelligence Applications In Engineering: Bridging Computational Models And Real-World Systems

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Abstract

The application of artificial intelligence as a supplement to classical mathematical models is becoming more common in the engineering field, but the high-level connection between formulations based on a set of differential equations and neural approximations has not been fully exploited. This study investigates how a simple neural network can approximate a canonical heat-conduction model and what this implies for bridging computational and AI-based representations. A one-dimensional steady-state heat-conduction problem with fixed boundary conditions is modelled using a linear second-order differential equation. The exact solution is derived in closed form and evaluated at discrete points on the spatial domain. A single-hidden-layer ReLU neural network with three neurons is then constructed to approximate the same temperature profile. Functional behaviour, pointwise approximation error, and computational structure are analyzed. The neural surrogate closely reproduces the classical linear temperature distribution, with absolute errors remaining below 2 °C at all evaluation points. The approximation is most accurate in the central region of the domain, while small deviations appear near the boundaries due to activation transitions. Despite its simplicity, the network provides a flexible piecewise-linear representation with modest computational overhead. The findings demonstrate that compact neural networks can act as effective surrogates for classical engineering models, supporting an integrated view in which AI complements, rather than replaces, traditional mathematical formulations.

Keywords: Artificial intelligence, Engineering applications, Heat conduction, Neural networks, Surrogate modelling.

1. Introduction

With the rapidly growing development of computational mathematics, data-driven modelling, and decision-support technologies, artificial intelligence (AI) has become a prominent part of the current engineering practice. Initial advances of the mathematical foundations of AI took the focus on systemic thinking and formal computational structures, which are still present in modern engineering systems [1]. Simultaneously,

studies in cognitive and behavioural modelling expanded the knowledge of intelligent systems and the importance of the interaction between an algorithmic design and adaptive reasoning [2]. This intersection has made AI a disruptive technology that can be used to handle the increasing complexity of engineered systems.

The growing complexity of engineering applications has heightened the demand for modelling strategies that blend computational intelligence with an already existing mathematical knowledge. The attempt to enhance complex adaptive systems by means of modelling, simulation, and AI represents how these procedures can augment the system-level perception and sensitivity [3]. New research also highlights the importance of AI in decision intelligence and highlights the advantages of more predictive and adaptive computing systems in engineered systems [4]. These advancements put AI at the crossroads of engineering innovation, where they provide new forms of mentally representing and streamlining engineered processes [5]. Meanwhile, researchers have investigated wider socio-technical aspects of computational modelling, especially in areas where engineering systems are subject to social, political, or environmental limits. Modelling based on scenarios has demonstrated the ability of computational and mathematical models to be connected to broader system transitions to give insights into the long-term viability and policy effects [6]. To supplement these initiatives, engineering mathematics has advanced to reinforce the theoretical framework necessary to combine AI with conventional tools of analysis [7]. These theoretical instruments justify AI to be applied to real-world engineering challenges, where the uncertainty, complexity, and nonlinear dynamics are predominant [8].

AI has rapidly adopted methods in several subfields of engineering. Structural engineering has shown significant performance prediction and monitoring enhancements through the combination of learning algorithms with standard mechanics [9]. Neural and fuzzy intelligent systems have also been implemented in a variety of engineering issues and show how mathematical modelling can be incorporated with adaptive computation to improve the accuracy of systems at the system level [10]. A more general overview of the use of AI in engineering and manufacturing highlights the significant productivity and reliability improvements and fault detection obtained through automated learning methods [11]. In addition to classical engineering, computational modelling has been found to play a critical role in the discrimination between theoretical complexities and practical implementation. Functional analysis models have shown how computational models can be used to convert complex system dynamics to actionable information especially in multidisciplinary contexts [12]. Essential work in mathematics remains a source of such progress, which provides opportunities to keep developing and perfecting AI models [13]. But with AI becoming more integrated with the physical world, the issue of system robustness and security has surfaced as well, particularly in systems that use large-scale language models or systems with safety-critical applications [14].

The uses of AI are now well beyond the scope of traditional engineering applications, and have been applied in biotechnology, materials science and new processes in industry. To illustrate, AI-driven microbial engineering presents the concept of how computational modelling fosters innovation in unconventional engineering areas [15]. Embodied, situated agents as a study further presents the contribution made by artificial life methodologies in developing autonomous systems that have the ability to interact with the real-world environments [16]. These various points of view collectively evidence the wide and changing contribution of AI to the engineering sciences.

Although AI and computational modelling have made major progress, there is still a noticeable methodological gap between the mathematical engineering models and AI-based functional approximators, considering how the two are connected to each other. Most studies are aimed at empirical performance or application-specific outcomes, but a

small number of them offer a formal analytical comparison to demonstrate their structural, functional, and computational properties. Minimal literature focuses on explicitly analyzing the way neural approximations can be used to model classical engineering systems and how such representations can be used to supplement known mathematical equations.

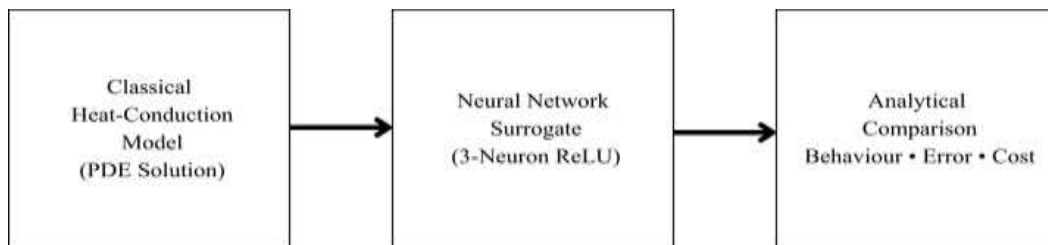
The paper aims to fill the gap between classical engineering formulations and AI-based modelling by comparing their correspondence to each other in terms of mathematics and functions. It initially examines the behaviour of a model representative of steady-state heat-conduction in the form of a differential equation to provide a clear physical base point. A neural network approximation is subsequently simplified and assessed to establish in what manner the classical solution can be replicated by the simplified neural network. The two modelling frameworks are systematically compared with regard to their functional features, approximation patterns, and structure of their computations. This comparative analysis reveals that neural networks can serve as useful surrogate models to the classic engineering equations, and so serves to support the connection between computational models and the physical engineering system.

2. Methodology

2.1 Research Design

The study makes two complementary modelling formulations to facilitate a systematic comparison between the classical approach and the AI-based approach. The former is a classical model of engineering characterized by a second-order linear differential equation, which has a linear answer in a closed form. The second is the neural network approximation that is built with a one-layer feedforward architecture of a small number of neurons to represent the underlying functionality trend. The two formulations are compared concurrently with references to their functional behaviour, approximation properties, and computational structure to comprehend how much the neural surrogate can replicate the features of the classical model. The general study workflow, which connects the classical form of the PDE model, the neural surrogate, and the analytic comparison, is represented in Figure 1. The framework demonstrates the sequence of operations that were used in this study: the classical heat-conduction model will be taken as the analytical reference, and will be approximated by a three-neuron ReLU neural network. The two formulations are compared on the basis of functional behaviour, error in approximation, and computational structure.

Figure 1. Conceptual framework of the modelling approach.



2.2 Classical Engineering System

A one-dimensional steady-state heat conduction model is used to represent the classical formulation. The governing equation is:

$$\frac{d^2T}{dx^2} = 0, \quad (1)$$

defined on the domain $[0,10]$. To obtain a concrete temperature profile, the following boundary conditions are imposed:

$$T(0) = 40^{\circ}\text{C}, T(10) = 80^{\circ}\text{C}. \quad (2)$$

Substituting the conditions in equation (2) into the general solution of (1):

$$T(x) = ax + b, \quad (3)$$

Yields:

$$T(x) = 4x + 40. \quad (4)$$

Equation (4) represents the exact linear temperature distribution along the rod and serves as the benchmark for comparison.

2.3 Analytical Properties of the Classical Model

In equation (4) the classical solution is of a purely linear nature over the whole domain and is continuously differentiable with a constant gradient of 4. It meets the given boundary conditions precisely, as formulated in equation (2) and shows predictable and stable behaviour that is in line with the steady-state heat conduction. Collectively, these properties create a definite and trustworthy structural reference in comparison with which the neural network approximation may be evaluated.

2.4 Neural Network Approximation Model

The artificial intelligence model is developed based on a single-hidden-layer neural network, having three neurons, which are chosen in order to demonstrate the basic approximation behaviour. The model is defined as:

$$\hat{T}(x) = \sum_{i=1}^3 w_i \sigma(v_i x + c_i) + d, \quad (5)$$

where

- $\sigma(\cdot)$ denotes the ReLU activation,
- w_i , v_i , c_i , and d are scalar parameters.

The parameter values are chosen in a way that they are used to approximate the temperature distribution in equation (4) with a piecewise-linear structure that is compatible with the use of ReLU activation. The model would then be tested at discrete points on the domain using the selected numerical parameters.

2.5 Numerical Points for Evaluation

To compare the two models, evaluations are carried out at the following uniformly spaced points:

$$x = \{0, 2, 4, 6, 8, 10\}. \quad (6)$$

For each point, the value of the classical solution given in equation (4) and the neural approximation from equation (5) are computed and tabulated in the results section.

2.6 Evaluation Criteria

Three dimensions of analysis are used to conduct the comparison of the classical model with the neural network approximation. First, their functional properties are investigated by evaluating the linearity, smoothness, continuity, piecewise structure, the behaviour of the overall domain, and how they treat the boundary conditions. Second, approximation accuracy is evaluated by measuring deviations between $T(x)$ and $\hat{T}(x)$, analysing the error

profile across the domain, and considering how the activation functions influence local approximation behaviour. Third, the computational form of each model is discussed, where the simplicity of the classical closed-form expression and the computational cost of the neural model, which grows with the number of neurons but provides more representational flexibility, are discussed. Every comparison is based on conventional postulates of the differential equations and the function approximation, and the specified boundary conditions, and a three-neuron architecture guarantees transparency and enables direct evaluation of the relationship between the two modelling approaches to each other.

3. Results

3.1 Classical Solution Values

The classical solution derived in equation (4) is expressed as:

$$T(x) = 4x + 40. \quad (7)$$

Evaluating equation (7) at the designated points

$$x = \{0, 2, 4, 6, 8, 10\} \quad (8)$$

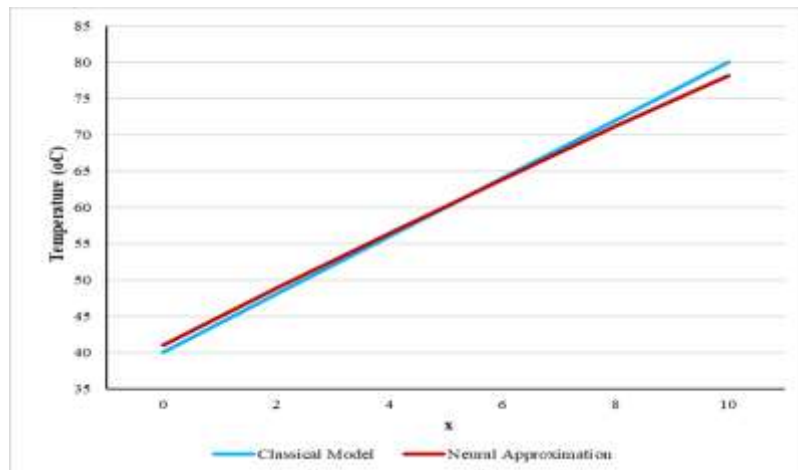
yields the values listed in Table 1.

Table 1. Classical Temperature Values Computed from Equation (7)

x	$T(x)(^{\circ}\text{C})$
0	40
2	48
4	56
6	64
8	72
10	80

Table 1, displaying the classical model, gives rise to a steady increment in temperature with an equal gradient, which is characteristic of steady-state conduction. The linear behaviour is well observed in Figure 2, whereby the classical profile looks like a straight line across the domain.

Figure 2. Comparison of Classical Model with Neural Approximation



3.2 Neural Network Approximation Values

The neural approximation from equation (5) is evaluated using the following parameter set:

$$w = [6, -4, 3], v = [0.4, 0.5, 0.2], c = [-1, 0, -0.5], d = 41. \quad (9)$$

The ReLU activation function is defined as:

$$\sigma(z) = \max(0, z). \quad (10)$$

Substituting the parameters from equation (9) into the neural model expression produces the approximate temperature values given in Table 2.

Table 2. Neural Network Approximated Temperature Values

x	$\hat{T}(x)(^{\circ}\text{C})$
0	41.0
2	48.8
4	56.4
6	63.8
8	71.2
10	78.2

Table 2 shows that the neural approximation preserves the overall rising pattern of the classical temperature distribution with minor variations of the linear profile. Figure 2 displays this behaviour by showing that the neural curve is very close to the classical line in a majority of the domain.

3.3 Pointwise Approximation Error

To quantify the difference between the two models, the absolute error is defined as:

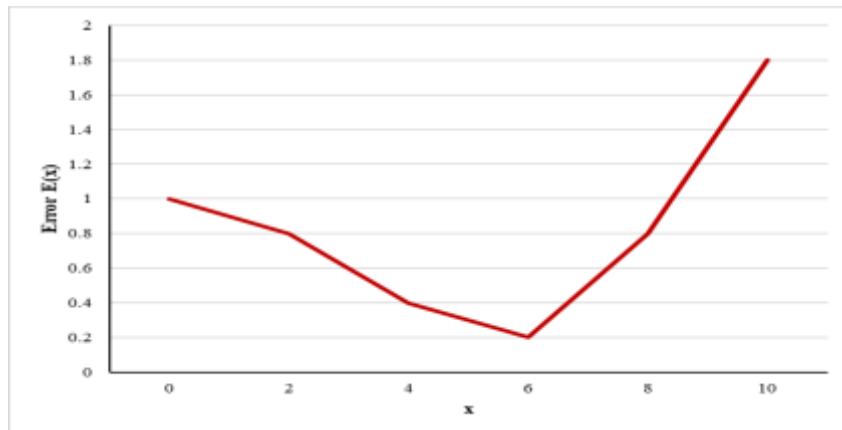
$$E(x) = |T(x) - \hat{T}(x)|. \quad (11)$$

Evaluating equation (11) at the specified points leads to the error values summarised in Table 3.

Table 3. Absolute Error Between Classical and Neural Predictions

x	Classical $T(x)$	Neural $\hat{T}(x)$	Error $E(x)$
0	40	41.0	1.0
2	48	48.8	0.8
4	56	56.4	0.4
6	64	63.8	0.2
8	72	71.2	0.8
10	80	78.2	1.8

As shown in Table 3, the error remains below 2°C across the domain. The error distribution in Figure 3 represents a smooth central value and slightly growing deviations along the edges as seen with ReLU-based approximations of a linear function.

Figure 3. Absolute Error Plot

3.4 Functional Comparison

The mathematical findings indicate that the neural model resembles the classical linear trend, particularly at the midpoint of the area (e.g., $x = 4$ and $x = 6$). The fact that there are minor deviations at the edges is due to the transition of some neurons that are neither active nor inactive, but the deviations are not very large and do not change the overall direction. This behaviour is well depicted in Figure 2, in which the neural and classical curves coincide in the centre but slightly separate towards $x = 0$ and $x = 10$.

3.5 Structural and Computational Interpretation

The structural behaviour of the two models records their underlying formulations. The classical solution still takes a perfectly linear expression as expressed in equation (7), and the neural approximation gives segmented linear regions defined by the activation behaviour in equation (10). This provides the network with the added flexibility of being able to be slightly curved, but boundary alignment is available with the right choice of parameters. The neural model has small errors throughout the domain, as shown in Table 3, and the error distribution follows equation (11) along with typical approximations by ReLU of functions; more neurons would further decrease these deviations. In terms of computation, it means that, with the classical model, there is only one linear evaluation, and the neural network involves calculating three terms of activation and one term of summation, yet it is still lightweight. The structure has more expressive power, and the increase in computer cost is a small fraction.

The findings indicate that the neural approximation is similar to the classical temperature profile with a low absolute error throughout the domain. It can have adaptable, piecewise-linear behaviour, and it does so with efficiency in computational requirements. The similarity between the curves in Figure 2, along with the balanced and decent error profile in Figure 3, further substantiates the fact that the neural model is a viable substitute for the classical formulation of heat-conduction.

4. Discussion

The analytical comparison that has been performed in this research proves the ability of a small neural network to be close to the behaviour of an ordinary heat-conduction model with a small error and predictable structure. The results of these findings are consistent with the general discourse in the engineering and AI literature, where authors acknowledge the significance of combining computational intelligence and known

mathematical formulations to advance the intelligibility of modelling and the comprehension of the system.

Recent research has also emphasized the necessity to develop AI-thinking in STEM and engineering instruction, where learners should be taught to think in a coherent way not only about analytical equations but also about computational models [17]. The parallel analysis herein offered helps to contribute to this educational viewpoint by demonstrating, in a transparent way, how a neural approximation can be specified with regard to a physically derived mathematical model. This form of conceptual correlating gives the power to the development of analytical literacy demanded by contemporary engineering practice. On a systems level, researchers posit that AI and machine learning can offer additional ways of dealing with complexity in engineered processes, especially in situations where the conventional analytical models can be inadequate to encompass interactions or adaptivity [18]. Even though the current example is intentionally simplistic, it represents the crucial concept behind most AI-based engineering models: a trained model can be used to provide a surrogate that is flexible, yet retains important structural characteristics of the physical system. This theoretical construct continues to gain relevance as the engineered systems get more interconnected and dynamic.

The wider modelling community has long been keen on the importance of methods that relate mathematical structure, data, and intelligent approximation. In computational neuroscience, AI plays a role in mediating between theory and experimental results, and supports the possibility of hybrid computational schemes [19]. The same relationship can be observed in the engineering field, where machine learning has been extensively used in prediction, monitoring, and decision-support activities [20]. Most of such applications are, however, focused on performance and not structural comparability. The gap in the current study is that it provides explicit analysis of the behaviour of a neural surrogate in comparison to a well-defined differential equation, where it can be seen that there are similarities in functional behaviour and deviations. The mathematical modelling itself can be frequently referred to as an intermediate between the theoretical reasoning and the behaviour of the world, which offers a systematic means of interpreting the engineered systems [21]. The present findings build on this idea by demonstrating that neural networks, which are generally considered data-driven methods, may also be involved in this bridging action based on a mathematical perspective. In this spirit, the neural model is seen as a supplementary model that does not substitute the physical solution, but as an analogous one. Other hybrid approaches are also used with growing popularity in communication systems and signal-processing applications, where simulations and approximate models have been used to augment analytical expressions to aid in design and analysis [22].

Another example is civil engineering, where AI technologies are regularly used with structural analysis, materials evaluation, and infrastructure management [23]. However, most of these applications do not investigate the degree to which the learned model is consistent with the underlying mechanics. The current work presents a methodological basis of such comparisons: beginning with a known physical equation, building a neural surrogate, and performing their correspondence by comparing errors and applying a functional comparison. Such a form of system evaluation is capable of elucidating the scenarios in which AI-based forecasts can be trusted within the confines of the existing engineering theory.

There are also practical implications of the results. The near consistency between the classical and neural solutions hints that a small neural network can be used as a lightweight surrogate in engineering processes, especially when it is necessary to perform fast assessments. The latter surrogates can be applicable to initial design, sensitivity analysis, or an iterative maximization problem, in which classical models are accessible

but the computational cost or operational constraints mean that quicker approximations are required. This is consistent with general attempts to implement AI tools in the analysis and decision-making process of engineering [18], [20].

It has its obvious shortcomings, however. The issue here is of one-dimensional, linear, and steady-state type; actual engineering systems can be nonlinear, transient, or multi-physics in nature. To continue this analytical comparison with more complicated models, it will be necessary to pay close attention to adapting it to maintain interpretability. Also, the parameter settings of the neural network in this case were chosen so as to demonstrate approximation behaviour instead of being obtained by optimisation. The training may be introduced in future work while maintaining the analytical transparency, which would allow seeing how the learned parameters interact with the classical model structure better.

The research supports the fact that AI, when analyzed in terms of a mathematical model, can be used as an interpretive interface between computational modelling and engineering machinery. The functional similarity here shows that neural surrogates can supplement (not replace) classical engineering models, and explains why neural surrogates should be part of a more holistic approach to modelling, analysis, and understanding the system.

5. Conclusion

The paper has investigated how a simple artificial neural network can be used to predict a classical steady-state one-dimensional heat-conduction model and thus demonstrates a tangible point of contact between mathematical engineering expression and AI-based function approximators. The neural surrogate was applied to recreate the overall temperature profile, with a low absolute error and predictable structural behaviour, which shows that a small three-neuron architecture can be an effective surrogate model. In the comparison, it was indicated that each framework has its distinct roles, namely, the classical model has physical interpretability, strict boundary satisfaction, and analytical transparency, and the neural model has a flexible representation with a low computational overhead. They all show that AI can be used to supplement instead of substitute conventional modelling in engineering analysis. It is restricted to a linear, steady-state problem, with manually chosen parameters, although a more complex, nonlinear, or transient problem can be approached using the methodology. Research in the future can also involve trained networks, higher-dimensional architecture, and physics-informed architecture in order to enhance greater integration of AI with standard engineering mathematics and to further emphasize the connection between computational models and real-world systems.

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