Materials Science Forum
ISSN: 1662-9752, Vol. 1188, pp 85-94

Submitted: 2026-01-20
Revised: 2026-02-21
Accepted: 2026-02-22
Online: 2026-04-20

Exploiting Artificial Neural Networks for Digital Twins in Sand Casting

Evangelos Pischinas[1,a], Emmanouil Stathatos[1,b]
and George-Christopher Vosniakos[1,c*]

[1]National Technical University of Athens, School of Mechanical Engineering, Manufacturing Technology Laboratory, Heroon Polytehniou 9, 15773 Athens, Greece

[a]vaggelispischinas@mail.ntua.gr, [b]mstatha@mail.ntua.gr [c]vosniak@central.ntua.gr

Keywords: metal casting; neural networks; process simulation; digital twins.

Abstract. Dedicated simulation software is used to create a dataset which for a particular sand-cast part and various casting parameter values provide casting quality metrics based on temperature and solidification evolution. Based on simulation data, ANNs are trained to predict the successful or failed filling of the mold (a classification problem), as well as the quality of the part through solidification time, maximum microporosity, maximum von Mises residual stress, maximum displacement of any point in the casting and total volumetric shrinkage (a regression problem). Such ANNs can provide augmented information much faster than the simulation model to the process planner. A third category of ANNs (of the regression type, too) determine the temperature evolution with time at an inaccessible point, where no thermocouple can be placed, from the measurement history at two other thermocouples close to it. This data comes from real-time monitoring during casting. Such ANNs can aid the process supervisor in a 'digital shadow' context. The issues associated with generalizing these predictors to become independent of specific part geometry are also discussed.

Introduction

Selection of appropriate process parameters in metal casting remains a demanding task, owing to the strong interdependence between molten metal flow, heat transfer, solidification, and defect formation. Numerical simulation of casting processes has been widely adopted as a "virtual casting" tool, enabling the prediction of filling behaviour, temperature evolution, shrinkage, porosity, and residual stresses prior to production. Nevertheless, credible simulation results are contingent upon careful problem formulation, accurate input parameters, validation against experimental results and extensive computational effort [1].

In recent years, the concepts of Digital Twin (DT) [2] and Digital Shadow (DS) [3] have been introduced as an evolution of simulation-based approaches, aiming at the continuous replication of the physical process through the integration of process data, sensor measurements, and computational models. In metal casting, as in most manufacturing processes, DTs promise enhanced process planning, monitoring, and decision support. However, their deployment is hindered by limitations in data availability, uncertainties in model validation, and the computational burden associated with high-fidelity simulations, which restrict their use in real-time or iterative planning contexts [4].

An alternative is offered by Artificial Neural Networks (ANNs). When trained on simulation or experimental datasets, ANNs can provide rapid predictions of critical process outcomes, effectively acting as surrogate models [5]. Such models are particularly attractive in a DS framework, where fast, augmented information is required to support the process planner or supervisor without replacing the underlying physical process.

The present work investigates the use of ANNs for the creation of DTs and DSs in sand casting. Emphasis is placed on predicting mold filling completion, key quality indicators, and internal temperature evolution, with the objective of complementing conventional simulation tools and enabling faster, data-driven support for casting process planning and monitoring.

Literature Review

ANNs become central in DT/DS when they serve as fast surrogates for physics-based simulation or as soft sensors that infer unmeasured states. Recent casting-focused work demonstrates deep-learning surrogates for thermal fields. Kang et al. [6] propose deep learning to emulate heat-transfer simulation for casting, while Zhao et al. [7] predict spatiotemporal temperature fields during solidification using a physics-augmented learning approach. In continuous casting, Lu et al. [8] report real-time prediction of 3D temperature fields, enabling adaptive adjustment at millisecond scales. These studies support a DT pattern in which the NN surrogate replaces the slow solver during planning (design-of-experiments, parameter sweeps) and during operations (real-time forecasting, what-if control actions), while periodic synchronization with the physical process corrects drift.

Planning and monitoring also rely on quality prediction and defect detection. For X-ray based inspection of aluminum castings, CNN approaches have been demonstrated for defect recognition and classification [9,10] and for improved defect detection using attention-guided augmentation [11]. Such models can be embedded into a DS layer to provide rapid, structured quality signals (defect likelihood, type, location), which then feed back into DT analytics for root-cause exploration (e.g., linking porosity to melt treatment, venting, or thermal gradients) and for planning mitigations (parameter constraints, design changes). Process-condition ML can also predict quality outcomes from sensor streams, as shown for defect prediction in casting-related contexts such as slag inclusion prediction using condition data [12]. A "smart" DT for stabilizing return sand temperature illustrates closed-loop recommendations in foundry sand systems [13]. At a production-system level, a data-driven DT for foundry operations integrates operational models with predictive components to evaluate best-practice scenarios [14].

In summary, several directions are traceable in the research literature so far: (a) standardization and structured exploitation of casting data and real-time process context within a DS / DT layer to enable downstream analytics and decision support [15,16] (b) training neural surrogates and soft sensors for important hidden states (e.g., thermal history, solidification-related metrics) and quality outcomes [17,18] (c) coupling these data-driven models with physics constraints and selective high-fidelity simulation to improve extrapolation beyond the training set and to enable computationally efficient parameter-space exploration [18] (d) and embedding the resulting DT capabilities into planning and monitoring, ranging from design and parameter optimization to monitoring and adaptive recommendations [19–21].

The part and mold

The part studied is a pulley of outer diameter 96 mm, hole diameter 25 mm, thickness 14 mm and hub length 30 mm, see Fig. 1(a). The part is made of aluminum alloy EN AC-44000, containing 10-11.8% Si, with liquidus temperature 590 ºC solidus temperature 560 ºC and recommended casting temperature for gravity cating 640 – 740 ºC [21].

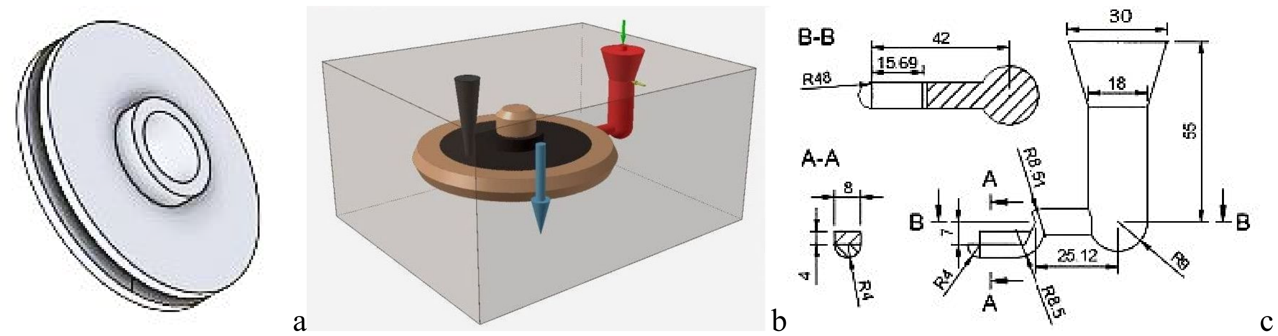

Fig. 1 (a) The part (b) The mold showing cavity and open riser (green), cores (beige), feeding system (red) (c) Feeding system detail.

The mold is made of green sand consisting of 85% silica sand, 4% water and 11% clay and bentonite. It mold includes two sand cores, corresponding to the pulley rim slot and the central hole, an open riser and the feeding system, see Fig. 1(b). The feeding system consists of the pouring basin, the sprue and the ingate, see Fig. 1(c). The open riser is of conical shape with bottom/top diameter 10/18 mm respectively and height 50 mm. All feeding and risering system calculations were made according to [22].

Simulation-based ANNs

Casting simulation. Casting simulation was performed using Altair Inspire Cast™. Following a mesh sensitivity analysis, the mesh size was set to 2.377 mm achieving both accuracy and speed. All three casting phases were modelled, i.e. filling, solidification and demolding. The interfacial heat transfer coefficient between the mold and the aluminum melt was set to the default recommended value of the simulation software used, i.e. 1500 W/m²·K. Thermomechanical simulation was enabled.

Three process parameters were investigated, namely: melt temperature, mold/core temperature (i.e. investigating also preheating as implemented through immersion of the mold in a furnace), inlet melt speed, see Table 1. These values were compatible with the recommendations of the simulation software. In addition, the gate area was varied as a key parameter pertaining to the mold design and determining volumetric flow rate when multiplied by ingate speed, see Table 1.

Table 1. Process parameters and values investigated.

Process parameter	Value 1	Value 2	Value 3	Value 4	Value 5	Value 6
Melt temperature (°C)	670	690	720	740		
Mold/core temperature (°C)	20	30	100	200	300	400
Inlet melt speed (m/sec)	0.63	0.79	0.99			
Gate area (mm^2)	12.57	28.27	50.27	78.54		

Simulation outputs included temperature evolution at indicated points, solidification time for the whole part, microporosity (% volume), maximum displacement (for any point compared to its initial position), shrinkage (% volume comprising both internal microporosity and surface or 'pipe' shrinkage) and minimum and maximum normal and shear stresses (12 values altogether) as well as the maximum von Mises stress at demolding at room temperature. Fig.2 presents indicative results.

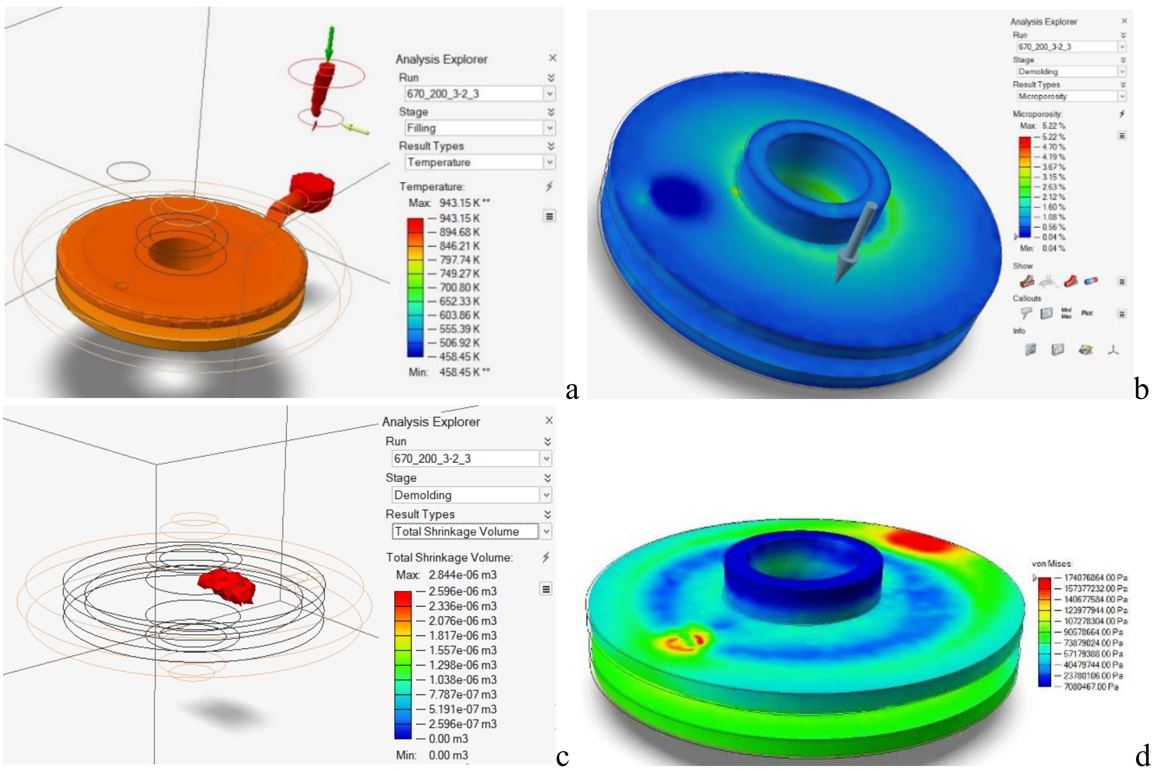

Fig. 2 Indicative simulation results for melt temperature: 670 °C, mold temperature: 200 °C, inlet melt speed: 0.79 m/sec, gate area: 28.27 mm^2 :(a) Temperature (b) Microporosity (c) Shrinkage (d) Von Mises stress.

All possible combinations of the parameter values of Table 1 amount to (4 X 6 X 3 X 4 =) 288, but only 234 were successful, the rest corresponding to combinations that did not achieve complete filling of the mold. This was due mainly to early solidification of the melt at particular points owing e.g. to low flow rate in combination with low melt temperature etc. Yet, even unsuccessful cases were retained and added to the dataset.

ANN predicting filling completion. This binary classification ANN is a shallow one following the feedforward-backpropagation paradigm. The inputs of this model are exactly those of the simulation, i.e. melt temperature, mold temperature, ingate speed and gate area. The output is completeness of mold filling including the open riser, thus prediction of one of two possible states: successful or incomplete filling.

The activation function was selected to be 'softmax'. Given an initial output vector of the ANN $\mathrm{z} = (z_1, z_2)$, the softmax function produces a new output vector $\sigma(\mathrm{z}) = (\sigma_1, \sigma_2)$ where each component is defined as: $\sigma_i(\mathrm{z}) = e^{z_i} / \sum_{j=1}^{2} e^{z_j}, i = 1,2$. This function is suitable for classification problems transforming linear outputs to probabilities, the sum of which is equal to 1, exponentiation emphasizing differences. The 'cross entropy' function was used to quantify training performance, expressing how well the probability distribution predicted by softmax matches the target distribution.

One hidden layer was explored in the architecture of this ANN, varying the number of its neurons from 1 to 10 and selecting the case giving the best results. To do so, 70% of the dataset was used for training, whilst 15% was used for validation and another 15% for testing of its generalization ability. Maximum number of training epochs was set to 10000. Training was performed on Matlab™.

The best architecture used 8 neurons in the hidden layer. Its training took only 100 epochs, see Fig. 3(a) achieving 100% prediction accuracy for all training, validation and testing cases, see Fig. 3(b).

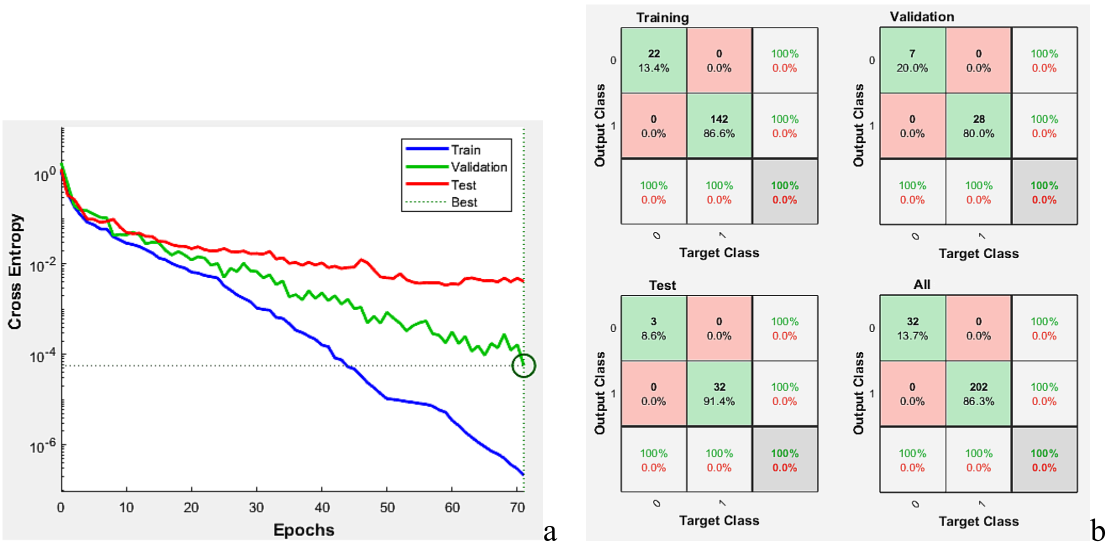

Fig. 3 Mold filling predictor ANN (a) evolution of training (b) confusion matrix results

ANN predicting casting quality. Five ANNs were developed independently in this case. The inputs of all of them are exactly those of the previous one, whilst the outputs are solidification time, maximum microporosity, maximum displacement, maximum von Mises stress, and total shrinkage, respectively. Inputs and outputs are normalized in the [0,1] interval.

The activation function was selected to be 'logsig' $f(x) = 1/(1+e^{-x})$ outputting values in the range [0,1], whilst for the output layer the 'purelin' function f(x)=x was used to maintain the normalization range which is necessary for a regression problem.

For each predictor ANN one hidden layer was used for which 1 to 20 neurons were tried, and the best case was selected, see Table 2.

Table 2. Architecture and performance details of the casting quality predictor ANNs (HLN: hidden layer neurons, MSE: Means Squared Error, MAE: Mean Absolute Error, MRA: Mean Relative Error, R-train / R-valid / R-test: correlation coefficient of the training / validation / testing data subset.

Output	HLN	Epochs	MSE	MAE	MRE(%)	R-train	R-valid	R-test
Solidification time (sec)	6	7	299	8.9	4.4	0.9977	0.9957	0.9977
Max displace-ment (mm)	16	11	0.007	0.054	6.88	0.9803	0.9103	0.9077
Max von Mises stress (MPa)	15	7	189.4	10.2	5.2	0.9547	0.9288	0.8811
Total shrinkage (mm^3)	17	12	22211	72.3	3.3	0.9935	0.8573	0.9965
Max micro-porosity (%)	0	3	0.112	0.228	4.7	0.3549	0.5927	0.5372

The correlation coefficients shown in Table 2, broken down into training, validation and testing, are generally acceptable except for those of the max microporosity which are clearly problematic. Therefore, the corresponding ANN is not trustworthy. The training curves are shown in Fig. 4.

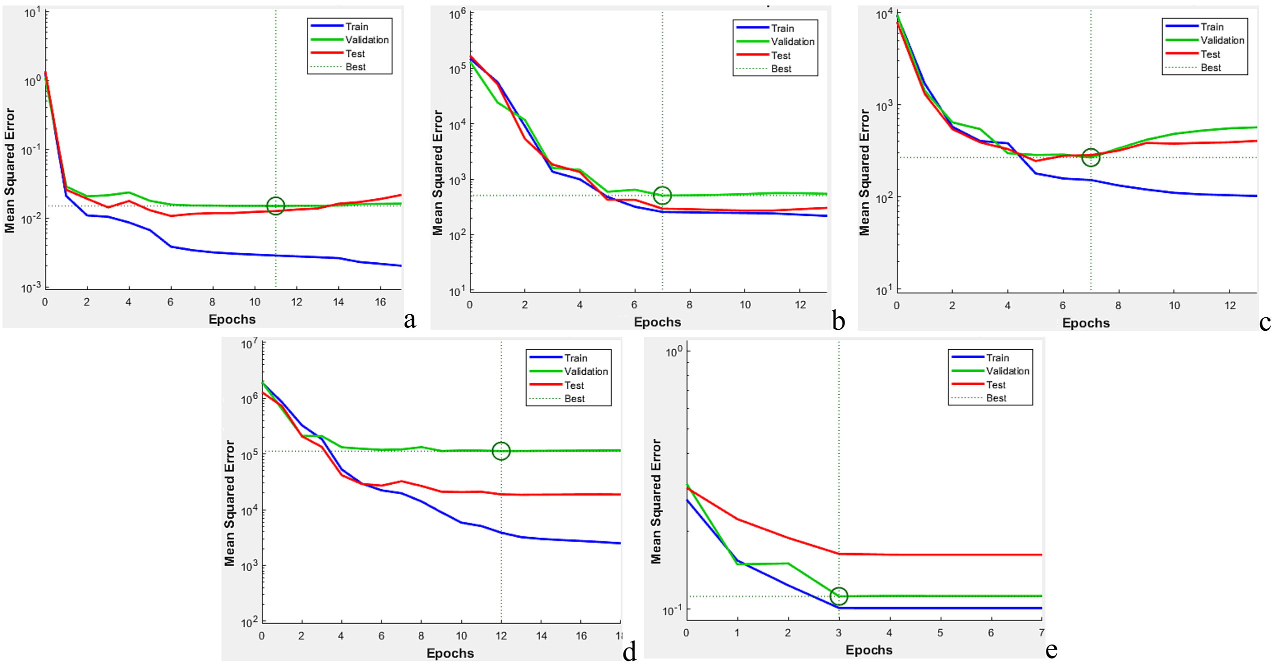

Fig. 4 Training curves of predictor ANNs for (a) Solidification time (b) Max displacement(c) Max von Mises stress (d) Total shrinkage (e) Max microporosity

Experiment-based ANNs

Casting Experiment. The model including the part cavity, cores and feeding system, was 3D printed on PLA and was used to create the mold with manual action by an experienced technician, see Fig. 5(a). A physical experiment was conducted under analogous conditions as in the simulations: melt temperature: 720 °C, mold temperature: 30 °C, ingate melt speed: 0.89 m/sec and gate area: 50.27 mm^2. Pouring lasted 4.87 sec.

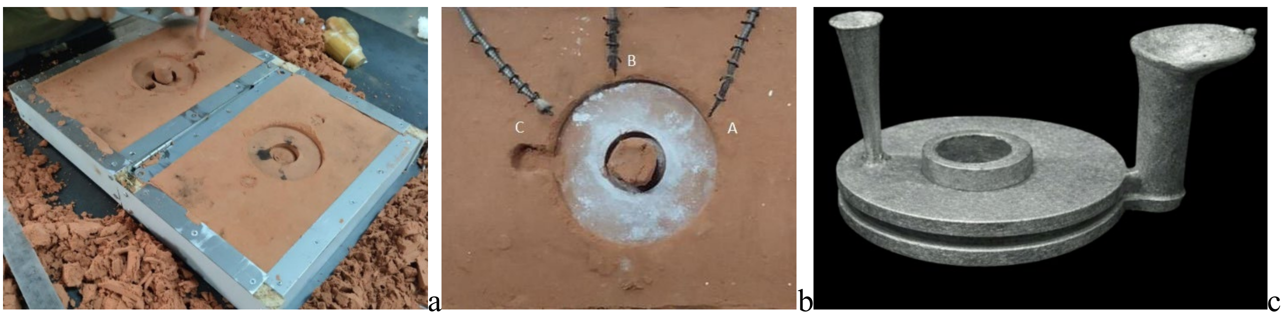

Fig. 5 (a) Mold preparation (b) Thermocouple positions (c) Casting.

Real-time temperature data was acquired using three K-type thermocouples with a range -180 to 1350 ^{o}C embedded in the mold, at distances 2, 5, and 10 mm respectively from the wall of the cavity, see Fig. 5(b). There is inherent difficulty in measuring these distances with accuracy, which renders validation of the simulation challenging, especially in view of the sharp decrease of temperature of the sand mold with the distance from the cavity wall [23]. Thermocouples were connected to a Advantech^{TM} USB 4761 A/D converter feeding signals to LABVIEW^{TM} software on a laptop. The casting obtained is shown in Fig. 5(c). The thermocouple measurements are shown in Fig. 6.

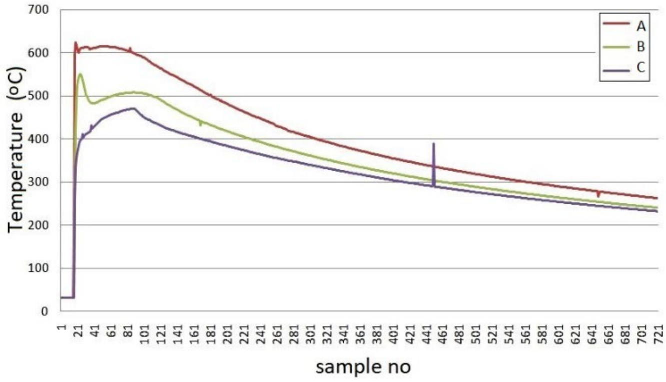

Fig. 6 Thermocouple measurements (sampling rate: 1/sec).

ANN predicting temperature evolution. This ANN predicts temperature at one of the three thermocouple points using the other two thermocouple measurements. This is a preamble to the capability to estimate the temperature of a point which is inaccessible, just based on the temperature of accessible points. Equally importantly, this is achieved in real time. All three combinations were tested, i.e. estimating temperature at A / B / C based on measurements of B,C / A,C / A,B respectively. The input to this ANN is the temperature curve corresponding to the last 10 measurements of both known thermocouples (20 input neurons altogether) and the output is the current reading of the third thermocouple (one output neuron). Therefore, the prediction is based not on the current temperature of the other two thermocouples but on their recent history.

This is clearly a regression problem for which normalization in the interval [0,1] applies. Activation function ‘logsig’ was used for the hidden layer and ‘purelin’ for the output layer, exactly as in the previous group of ANNs of regression nature.

For each predictor ANN one hidden layer was used for which 1 to 30 neurons were tried, and the best case was selected, see Table 3. All metrics indicate an excellent prediction ability of all three ANNs. The results for thermocouple B were particularly accurate, surpassing those of thermocouples A and C. This is attributed to the fact that thermocouple B is placed between thermocouples A and C, hence its measurements are naturally ‘interpolated’ between those of those of the surrounding thermocouples.

Table 3. Architecture / performance of temperature evolution predictor ANNs (legend as in Table 2).

Thermocouple	HLN	Epochs	MSE	MAE	MRE (%)	R-train	R-valid	R-test
C	26	20	15.97	1.04	0.326	0.9981	0.9998	0.9997
A	22	7	40.93	1.63	0.861	0.9985	0.9978	0.9997
B	22	40	0.67	0.18	0.048	0.9999	0.9999	0.9999

The training curves are shown in Fig. 7.

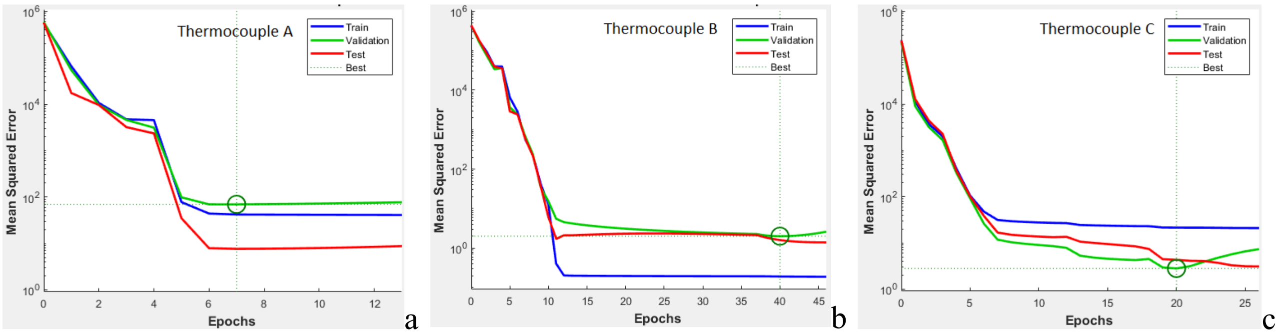

Fig. 7 Training curves of predictor ANNs for temperature evolution at thermocouples (a) A based on B and C (b) B based on A and C and (c) C based on A and B.

The predicted temperature evolution curves are also presented in comparison to the corresponding actual recorded curves from the experiment, see Fig. 8. Any differences are restricted to the very first points where the transient nature of heat transfer is more pronounced. Some differences are also spotted at sample No 450, where thermocouple C exhibits a sudden jump that is possibly due to hardware inconsistency, local collapse of the cavity wall or other anomaly, see Fig. 6. In fact, this jump is filtered out in Fig. 8(c) since the input based on which this is computed do not exhibit such a jump; this is a desired behavior of the ANN, given that only smooth temperature evolution curves are naturally expected in sand casting. However, when predicting temperature evolution at point B, for which thermocouple C provides an input, a spike is predicted, without being present in reality. Yet, this is not the case when predicting temperature evolution at point A despite thermocouple C providing input there, too.

Each diagram in Fig. 8 also depicts the corresponding temperature evolution curves resulting from the simulation, using input data identical to the experiment for comparison purposes. Although the simulation curves follow the general shape of the experimental data, they underestimate the latter by a significant offset of 100 to 150 ºC. This is expected to some extent, as no attempt was made to calibrate the simulation by adjusting the heat transfer coefficient. This is commonly done given (a) its strong dependency on various casting parameters, of which predominant is the geometry of the casting [24], and (b) its variation during solidification following alternative functions reported in research literature, rather than being fixed as in the simulation software's recommended default. However, the primary source of deviation is the inability to determine the exact location of thermocouples once the drag and cope have been assembled. This likely results in comparing simulation curves with experimental curves corresponding to displaced locations, i.e. not the true counterparts in the mold.

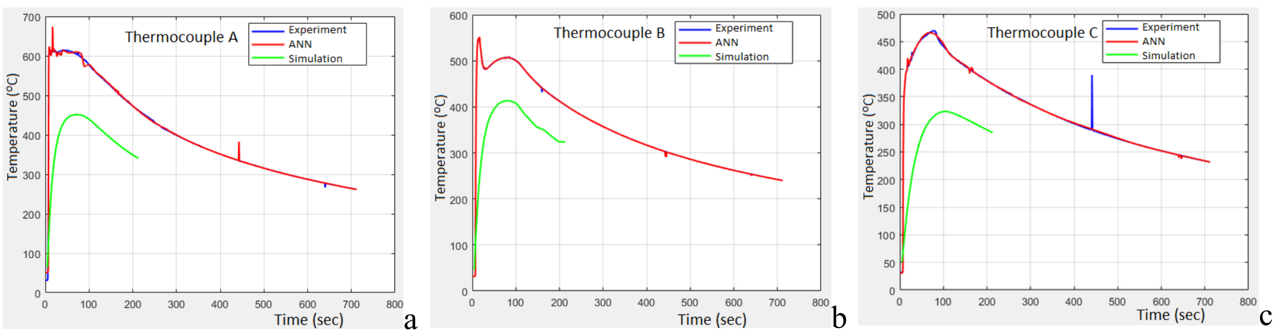

Fig. 8 Predicted vs measured temperature evolution at thermocouple positions (a) A, (b) B (c) C.

Discussion

Using simulation-trained neural networks without direct experimental validation. Training neural networks on simulation data, even in the absence of direct experimental validation, can be justified by several practical and methodological considerations. High-fidelity casting simulations embed decades of validated physical modelling, including heat transfer, phase change, and fluid flow, and are already trusted for process design and optimization. Neural networks trained on such simulations can therefore be viewed as surrogate models that inherit this embedded physics indirectly. Simulation-trained models can therefore serve as decision-support tools rather than absolute predictors, guiding process adjustments and narrowing the experimental search space even before direct validation is feasible.

Generalization beyond the specific part geometry. The ANNs developed in this work are clearly part-specific. To make such networks useful for predicting properties of entirely different cast parts, new inputs must be added. Geometry-dependent descriptors—such as local section thickness, distance from feeders, surface-to-volume ratio, or local cooling conditions—would need to be incorporated. Alternatively, mesh- or field-based learning approaches [25] could be employed that predict spatially and temporally distributed physical fields, such as temperature or stress, rather than global scalar quantities, thereby enabling geometry-aware generalization and soft sensing. For instance, Convolutional Neural Networks, Graph Neural Networks, Neural operators (Fourier, DeepONet, etc.) and Physics-informed neural networks (PINNs) are pertinent examples. Another promising direction is transfer learning, where an ANN trained on one part serves as a starting point and is subsequently fine-tuned using a limited number of simulations or experiments for a new geometry, e.g. [26]. The present study therefore represents a foundational step toward more general digital twin architectures rather than a fully geometry-agnostic solution.

Number of thermocouples required for temperature field inference. The experiment-based ANN results provide insight into the minimum sensing requirements for inferring temperature evolution at unmeasured locations. Thus, thermocouples should be placed strategically to capture the dominant thermal gradients and time constants within the mold. In practice, a small number of sensors, on the order of two to three per critical region, may suffice to enable soft-sensor functionality, provided that their locations are chosen based on simulation-guided sensitivity analysis. The implication for industrial practice is significant: reliable temperature field estimation may be achievable without excessive instrumentation, which is impractical in sand casting production environments.

Integration of simulation-trained neural networks into a digital twin. ANNs trained on simulation data can play a central role in a casting digital twin, acting as fast predictive engines embedded within a real-time monitoring framework. In such a system, sensor data from the actual process (e.g., thermocouples, flow sensors, infrared measurements) continuously update the state of the digital twin. The ANN can be used to:

- Predict unmeasured variables (e.g. internal temperature fields or solidification progress),
- Forecast downstream quality indicators (e.g. hot tearing risk or porosity formation),
- Perform rapid "what-if" analyses in response to detected deviations.

Mitigation actions when a digital twin predicts an out-of-spec part. If a digital twin predicts that a cast part is likely to be out-of-spec, several corrective actions may be possible, depending on the process stage and defect type. During casting or early solidification, active process interventions may include adjusting cooling intensity, modifying mold insulation, or altering secondary cooling conditions. If the issue is detected later, downstream mitigation strategies such as controlled heat treatment, localized rework, or selective machining allowances may still salvage the part. In some cases, the prediction may inform process learning rather than immediate correction, allowing future cycles to be adjusted while accepting the current part as scrap. Very importantly, early and reliable prediction shifts quality control from a reactive to a preventive paradigm, reducing waste and enabling data-driven continuous improvement.

Conclusions and Future Work

The mold-filling classification ANN achieved perfect prediction accuracy. Thus, it can provide immediate feedback during process planning, identifying infeasible casting process parameter combinations.

The regression-based ANNs predicting casting quality metrics showed mixed results. Solidification time and total shrinkage were predicted with high correlation and low relative errors. Predictions of maximum displacement and von Mises stress were also acceptable, though mild overfitting was observed. In contrast, the ANN trained to predict maximum microporosity performed poorly, indicating that additional inputs related to feeding or thermal gradients may be necessary.

The experiment-based ANN predicting temperature evolution represents an interesting contribution toward real-time digital shadow functionality. Using only recent temperature histories from two thermocouples, the models accurately reconstructed the temperature at a third location with very high accuracy.

Notably, temperature evolution curves obtained from the experiment and used for ANN training were substantially offset from their simulation counterparts, due to uncertainties in thermocouple placement as well as uncalibrated heat transfer coefficients used in the simulation.

The work performed confirmed that ANNs should not be viewed as replacements for physics-based models or experiments, but as complementary tools. Their true value lies in accelerating prediction, enhancing observability, and enabling proactive control in complex, data-scarce manufacturing environments. ANNs can complement casting simulation tools in the context of digital twins and digital shadows for sand casting, provided that their scope and limitations are clearly understood. However, their validity remains tightly coupled to the part geometry, parameter ranges, and data sources used for training.

Future work should focus on improving model generalization beyond the specific part and mold geometry investigated, enabling ANN predictors to be transferable across different casting designs and alloys. This may be achieved through larger, more diverse training datasets, the integration of physics-informed or hybrid models that embed fundamental heat transfer and solidification constraints or, alternatively, transfer learning. An additional interesting direction would be the merging of simulation and experimental data in datasets.

References

[1] Z. Chen, Y. Li, F. Zhao, S. Li, J. Zhang. Progress in numerical simulation of casting process. Measurement and Control, 55/5-6 (2022) 257-264.

[2] I. Onaji, D. Tiwari, P. Soulatiantork, B. Song, A. Tiwari. Digital twin in manufacturing: Conceptual framework and case studies. International Journal of Computer Integrated Manufacturing, 35/8 (2022) 831–858.

[3] C. Brecher, M. Dalibor, B. Rumpe, K. Schilling, A. Wortmann, A. An ecosystem for digital shadows in manufacturing. Procedia CIRP, 104 (2021) 833–838.

[4] B. He, K.-J. Bai, J. Ren. Digital twin-based sustainable intelligent manufacturing: A review. Advances in Manufacturing, 9/1 (2021) 1–21.

[5] Á. Bárkányi, T. Chován, S.Németh, J. Abonyi. Modelling for digital twins—Potential role of surrogate models and uncertainty quantification. Processes, 9/3 (2021) 476.

[6] J. Kang, J. Wang, X. Han, Q. Zhao. Deep learning based heat transfer simulation of the casting process. Scientific Reports, 14 (2024) 29068.

[7] Q. Zhao, B. Wang, J. Kang. A PIKAN-based model for the prediction of the temperature fields of castings. Scientific Reports (2025) in-press.

[8] Z. Lu, N. Ren, X. Xu, J. Li, C. Panwisawas, M. Xia, H. Dong, E. Tsang, J. Li. Real-time prediction and adaptive adjustment of continuous casting based on deep learning. Communications Engineering, 2 (2023) 34.

[9] D. Mery. Aluminum casting inspection using deep learning: A method based on convolutional neural networks. Journal of Nondestructive Evaluation, 39/1 (2020) 12.

[10] İ. E. Parlak, E. Emel. Deep learning-based detection of aluminum casting defects and their types. Engineering Applications of Artificial Intelligence, 118 (2023) 105636.

[11] L. Jiang, Y. Wang, Z. Tang, Y. Miao, S. Chen. Casting defect detection in X-ray images using convolutional neural networks and attention-guided data augmentation. Measurement, 170 (2021) 108736.

[12] Y. Zhang, Z. Gao, J. Sun, L. Liu. Machine-Learning Algorithms for Process Condition Data-Based Inclusion Prediction in Continuous-Casting Process: A Case Study. Sensors, 23/15 (2023) 6719.

[13] J. Nieves, B. Bravo, D.-C. Sierra. A Smart Digital Twin to Stabilize Return Sand Temperature without Using Coolers. Metals, 12/5 (2022) 730.

[14] D. A. Howard, M. Værbak, Z. Ma, B. N. Jørgensen, Z. Ma. Data-driven digital twin for foundry production process: Facilitating best practice operations investigation and impact analysis. In: Energy Informatics: 4th Energy Informatics Academy Conference (EI.A 2024), Proceedings, Part I, Lecture Notes in Computer Science, 15271 (2025) 259–273.

[15] T. Bauernhansl, S. Hartleif, T. Felix. The digital shadow of production—A concept for the effective and efficient information supply in dynamic industrial environments. Procedia CIRP, 72 (2018) 69–74.

[16] D. Liu, Y. Du, W. Chai, C. Lu, M. Cong. Digital twin and data-driven quality prediction of complex die-casting manufacturing. IEEE Transactions on Industrial Informatics, 18/11 (2022) 8119–8128.

[17] A. Shafyei, S. H. M. Anijdan, A. Bahrami. Prediction of porosity percent in Al–Si casting alloys using ANN. Materials Science and Engineering: A, 431/1–2 (2006) 206–210.

[18] S. Shahane, N. Aluru, P. Ferreira, S. G. Kapoor, S. P. Vanka. Optimization of solidification in die casting using numerical simulations and machine learning. Journal of Manufacturing Processes, 51 (2020) 130–141.

[19] Z. Jiang, C. Xu, J. Liu, W. Luo, Z. Chen, W. Gui. A dual closed-loop digital twin construction method for optimizing the copper disc casting process. IEEE/CAA Journal of Automatica Sinica, 11/3 (2024) 581–594.

[20] A. Ktari, M. El Mansori. Digital twin of functional gating system in 3D printed molds for sand casting using a neural network. Journal of Intelligent Manufacturing, 33/3 (2022) 897–909.

[21] https://www.bayrammetal.com.tr/uploads/docs/en-ab-and-ac-44000.pdf

[22] J. Campbell. Complete Casting Handbook: Metal Casting Processes, Metallurgy, Techniques and Design, 2nd edition, Butterworth-Heinemann,2015.

[23] G. C. Vosniakos, A. Vassiliou, S. Tsekouras. Numerical simulation of sand casting of an aluminium part. In: B. Katalinic (ed), Annals of DAAAM for 2011 & Proceedings of the 22nd International DAAAM Symposium, Vol. 22, No. 1, November 2011, 445-446, Danube Adria Association for Automation and Manufacturing (DAAAM), Vienna, Austria.

[24] A. N. Vasileiou, G.-C. Vosniakos, D.I. Pantelis. Determination of local heat transfer coefficients in precision castings by genetic optimisation aided by numerical simulation. Proc. Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 229/4 (2015) 735-750.

[25] N. Kovachki, Z. Li, B. Liu, K. Azizzadenesheli, K. Bhattacharya, A. Stuart, A. Anandkumar. Neural Operator: Learning Maps Between Function Spaces, Journal of Machine Learning Research, 24/89 (2023) 1–97.

[26] G. Baruffa, A. Pieressa, M. Sorgato, G. Lucchetta. Transfer learning-based artificial neural network for predicting weld line occurrence through process simulations and molding trials. Journal of Manufacturing and Materials Processing, 8/3 (2024) 98.