

Article

An Intelligent System for Hardness-Oriented Embodiment Design in Casting Processes Using Fuzzy Neural Networks

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Abstract

In casting processes, mechanical properties such as hardness are highly sensitive to both chemical composition and process parameters, making parameter design a complex and uncertain task during the embodiment stage of engineering design. Conventional trial-and-error-based approaches are often costly, time-consuming, and impractical in industrial environments. To address these challenges, this study proposes an optimized fuzzy artificial neural network (FANN)-based decision-support approach for hardness-oriented parameter design in a casting process. The developed model uses chemical composition variables, including carbon, silicon, manganese, phosphorus, sulfur, chromium, copper, and tin, together with process parameters such as casting temperature and casting time as inputs, while Brinell hardness is considered as the output. A dataset consisting of 170 experimental casting samples was employed; 128 samples were used for model development and hyperparameter selection, and 42 samples were reserved as an independent final test set. The proposed model was implemented as a scaled direct FANN weighted ensemble, in which fuzzified input variables were used to predict standardized continuous hardness values. A total of 300 FANN configurations were evaluated using five-fold cross-validation, and the five best-performing configurations were combined through RMSE-based weighted ensemble averaging. The final model was compared with Random Forest, Linear Regression, Ridge Regression, and SVR-RBF models using MSE, RMSE, MAE, R^2 , MAPE, normalized RMSE, and $\pm 5\%$ prediction success rate. The results showed that the optimized FANN ensemble achieved the lowest mean RMSE in the full-data five-fold cross-validation analysis, slightly outperforming the Random Forest benchmark. In the independent final test set, Random Forest produced the lowest prediction error, whereas the proposed FANN ensemble remained competitive and achieved the same $\pm 5\%$ prediction success rate as Random Forest, Linear Regression, and Ridge Regression. Furthermore, a target-hardness case study demonstrated that the proposed approach could identify candidate casting conditions very close to a desired hardness level, with the nearest prediction reaching 202.985 HB for a target value of 203 HB. These findings indicate that the proposed FANN-based framework can serve not only as a hardness prediction model but also as a practical fuzzy decision-support tool for target-hardness-oriented parameter design in casting processes.



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conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.**Keywords:** fuzzy artificial neural network; casting process; hardness prediction; parameter design; target hardness; decision support; engineering design

1. Introduction

Engineering design involves the systematic transformation of functional requirements into manufacturable products through conceptual, embodiment, and detailed design stages [1]. Among these stages, the embodiment design phase is particularly critical because conceptual decisions are converted into numerical parameters that directly affect product performance, quality, and manufacturability. In manufacturing processes such as casting, this phase requires the selection of appropriate material and process parameters under uncertainty.

In casting processes, parametric design is challenging because the final mechanical properties are influenced by both chemical composition and process-related variables. Previous studies on casting process modelling and mechanical property prediction have commonly considered casting temperature, casting or filling time, mold-related variables, pressure, piston speed, and alloying elements as influential parameters in determining casting quality and mechanical performance [2–23]. In particular, studies on cast irons and casting alloys have used chemical composition variables such as C, Si, Mn, P, S, Cr, Cu, Sn, Ni, Mo, Mg, Al, V, and Ti to predict or optimize properties such as hardness, tensile strength, impact toughness, wear resistance, porosity, permeability, and other quality-related responses [14–23].

The input variables used in the present study were therefore not selected arbitrarily. Before model development, previous casting-related studies were reviewed in terms of the process and chemical composition variables used as model inputs. Based on this literature screening and the availability of experimental data, ten input variables were selected for the proposed model. These variables consisted of eight chemical composition parameters, namely C, Si, Mn, P, S, Cr, Cu, and Sn, and two process-related parameters, namely casting temperature and casting time. Carbon and silicon are directly related to matrix structure and graphite formation, while manganese, chromium, copper, and tin can influence hardenability, pearlite stabilization, and strength-related characteristics. Phosphorus and sulfur were also included because they are commonly monitored residual elements in casting practice and may affect microstructural quality and mechanical response.

Some parameters reported in previous studies, such as sand properties, mold temperature, piston speed, pressure, nickel, molybdenum, magnesium, aluminum, vanadium, scandium, titanium, casting modulus, and melting temperature, were not included in the present model because they were either not available in the experimental dataset, not measured consistently, or outside the controllable scope of the investigated casting process. Thus, the input space of the proposed model reflects a compromise between literature-supported metallurgical relevance and the practical availability of industrial casting data. Conventional parameter determination in casting and steel processing commonly relies on empirical knowledge, experimental trials, and hardness testing. Although such approaches provide useful process knowledge, they may become costly and time-consuming when multiple interacting variables must be evaluated. Recent materials-design studies emphasize that intelligent modelling approaches, particularly artificial neural network (ANN)-based and hybrid ANN-optimization frameworks, can reduce the number of experiments and support the selection of composition or process conditions required to achieve desired hardness levels [24,25]. Therefore, intelligent modelling approaches are needed to support hardness-oriented parameter selection and reduce dependence on extensive trial-and-error experimentation.

Traditional approaches to parameter design in casting largely rely on structured experimental and statistical methods such as Design of Experiments (DoE), Taguchi-based optimization, and regression-based modelling. These methods have been successfully applied to optimize casting quality characteristics such as permeability, dimensional accuracy, surface

quality, defect formation, and mechanical properties [2–13]. However, their effectiveness may decrease when the number of interacting variables increases and the process response becomes strongly nonlinear. In such cases, data-driven models provide an alternative by learning complex relationships directly from experimental or production data.

Data-driven modelling approaches, particularly machine learning and ANN-based methods, have therefore gained increasing attention in casting and materials processing. ANN, support vector regression, random forest, and other machine learning algorithms have been used to predict mechanical properties and process outcomes from chemical composition, heat treatment parameters, and manufacturing variables [7,10,14–23]. These studies demonstrate the potential of data-driven models for property prediction. However, many of them primarily focus on predictive accuracy and do not explicitly integrate the model into a practical design-support workflow for selecting process parameters according to a target property.

Despite their predictive capability, pure neural network models are often criticized for their limited interpretability and sensitivity to noisy, sparse, or uncertain data. To address these limitations, fuzzy artificial neural networks and adaptive neuro-fuzzy inference systems combine fuzzy reasoning with neural learning. Such models are particularly useful in engineering problems where process variables are uncertain and expert-like reasoning is required. Previous studies have shown that neuro-fuzzy and fuzzy inference models can be effectively used for hardness prediction, permeability optimization, casting alloy property estimation, and process parameter optimization [23,26,27]. Hybrid frameworks that combine neural networks, fuzzy logic, and meta-heuristic optimization algorithms have also been proposed to improve parameter selection and reduce manufacturing defects [24,25].

Recent studies in materials-by-design further indicate a shift from purely predictive modelling toward target-property-oriented decision support. Razavi et al. [24] used an ANN model to predict the hardness of 17-4PH stainless steel as a function of ageing time and temperature and subsequently combined the trained ANN with a genetic algorithm to determine ageing conditions for maximum hardness. Trzaska and Sitek [25] proposed a hybrid ANN–GA framework for calculating steel chemical compositions that satisfy a required hardness after cooling from the austenitizing temperature. Similarly, Tomašić et al. [28] developed an ANN-based inverse design approach for predicting the chemical composition of steels from a desired Jominy hardenability curve by considering both hardness and martensitic microstructure information. These studies show that machine learning models can be used not only for property prediction but also for target-property-driven material and process design.

Despite extensive research on neural, fuzzy, and hybrid optimization methods in casting and materials engineering, several gaps remain. First, many studies focus mainly on prediction accuracy and do not explicitly position the model within the engineering design workflow, particularly the embodiment design phase. Second, limited attention has been given to using fuzzy neural models as practical decision-support tools for selecting casting parameters close to a desired hardness level. Third, comparative validation against conventional machine learning baselines and cross-validation-based robustness assessment are often insufficiently emphasized in small industrial datasets.

Figure 1 is structured into three categorical dimensions: Material Type, Main Modelling/Optimization Method, and Optimized Target Property. The numeric values in brackets correspond to the reference numbers in the bibliography of this paper. This visualization highlights the prevalence of hybrid approaches (such as fuzzy-neural and evolutionary methods) and identifies the research gap addressed by the present study, particularly in hardness-oriented embodiment design under uncertainty.

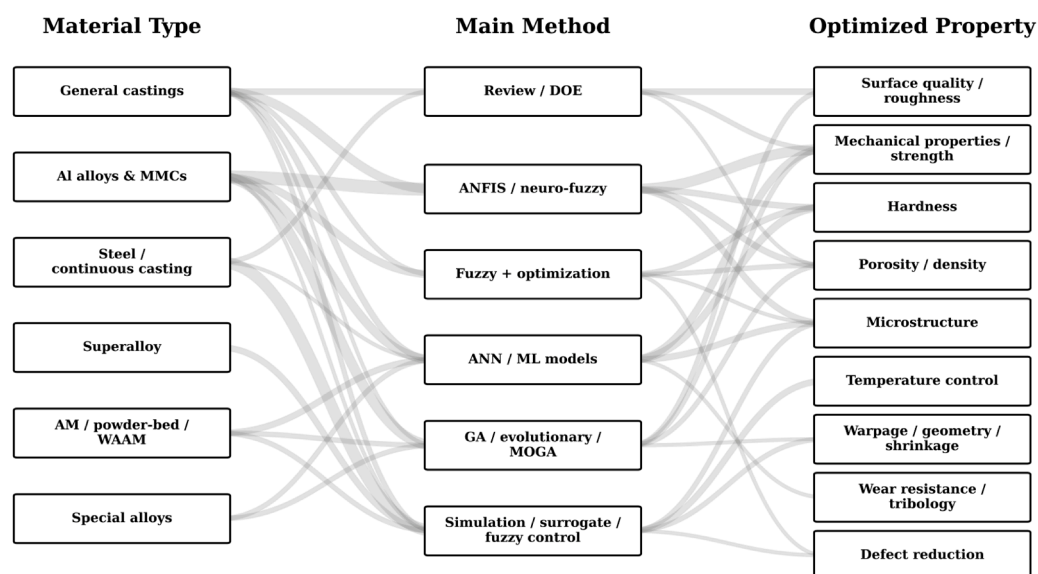


Figure 1. Alluvial diagram showing the relationship among material type, main modelling/optimization method, and optimized property in the reviewed casting and materials-processing literature, data from [29–57].

Figure 1 summarizes the literature distribution according to three main dimensions: material type, modelling or optimization method, and optimized target property. The left side of the diagram shows the material systems investigated in previous studies, including general casting applications, aluminium alloys and metal matrix composites, steels and continuous casting systems, superalloys, additive manufacturing materials, and special alloys. The middle section represents the main methodological approaches, such as review / DOE-based studies, ANFIS and neuro-fuzzy models, fuzzy optimization approaches, ANN/ML models, GA-based evolutionary optimization methods, and simulation- or surrogate-based fuzzy control strategies. The right side presents the optimized or predicted properties, including surface quality, mechanical properties, hardness, porosity or density, microstructure, temperature control, dimensional accuracy, wear resistance, and defect reduction.

The diagram indicates that aluminium alloys and metal matrix composites constitute the most frequently investigated material group in the reviewed literature [30,31,34,36,37,39,45,47,49,51,53,56]. These studies are mainly associated with ANFIS/neuro-fuzzy approaches, GA-based optimization, and ANN/ML-based models. In terms of target properties, mechanical properties, surface quality, porosity/density, and microstructure appear as the most common optimization objectives. This distribution shows that previous studies have largely focused on improving casting quality and mechanical performance through data-driven and hybrid optimization methods.

The reviewed literature also demonstrates that fuzzy and neuro-fuzzy approaches are frequently preferred when uncertainty, nonlinear process behaviour, and limited experimental data are involved [30,31,34,36,52,57]. Similarly, GA-based and evolutionary optimization methods are commonly used to search for optimal process parameter combinations in casting and related manufacturing processes [29,33,35,37,39,49,51,56]. Simulation- and surrogate-assisted approaches are particularly visible in steel continuous casting, superalloy casting, and special alloy applications, where direct experimentation is costly or difficult [32,38,41,54].

Data-driven and hybrid modeling approaches have attracted increasing interest for predicting mechanical properties and parameter design in casting processes. In this context, Yu et al. [57] proposed a convexity-guaranteed neural network (GCYN) trained on data from crystal plasticity simulations and demonstrated that the model can predict yield surfaces

with high accuracy across different material textures. Chen et al. [58] employed interpretable machine learning methods such as SHAP and PDP to predict fracture toughness in Nb-Si alloys, emphasizing the importance of feature engineering and model interpretability in alloy design. In the field of electrical automation, Liu et al. [59] developed a control algorithm that combines fuzzy neural networks (FANN) with reinforcement learning, revealing that this hybrid approach provides superior performance in nonlinear systems. Similarly, Wang [60] proposed a two-dimensional fuzzy semantic-based algorithm for target tracking in sports competitions, significantly reducing computational load through feature reduction and adaptive model reduction strategies. These studies demonstrate that the integration of fuzzy logic, neural networks, and optimization methods enables the development of effective decision support systems for engineering problems under uncertainty. Inspired by these approaches, the present study proposes an optimized FANN-based decision-support framework for hardness-oriented parameter design in casting processes.

Overall, the alluvial diagram shows that intelligent modelling approaches have been widely used for casting parameter optimization and property prediction. However, most existing studies focus on either prediction accuracy or optimization of a single response. Relatively fewer studies explicitly position the model as a hardness-oriented decision-support tool within the embodiment design stage. Therefore, the present study differs from the reviewed literature by integrating fuzzy input representation, neural regression, cross-validation-based model selection, benchmark comparison, and target-hardness candidate ranking in a unified decision-support framework.

To address these gaps, the present study develops an optimized fuzzy artificial neural network-based decision-support framework for hardness-oriented parameter design in a casting process. Chemical composition variables and process parameters are used as inputs, while Brinell hardness is considered as the output. The proposed model is optimized through cross-validation and compared with benchmark models, including Random Forest, Linear Regression, Ridge Regression, and SVR-RBF. In addition to prediction performance, a target-hardness case study is conducted to demonstrate how the model can support the selection of candidate casting conditions close to a desired hardness level. In this way, the study positions the proposed FANN model not merely as a prediction tool, but as a fuzzy decision-support mechanism for target-hardness-oriented embodiment design in casting processes.

The main contributions of this study can be summarized as follows:

1. A literature-supported input-variable selection strategy is presented for hardness-oriented casting parameter design.
2. An optimized scaled direct FANN weighted ensemble model is developed for Brinell hardness prediction.
3. The proposed FANN model is compared with Random Forest, Linear Regression, Ridge Regression, and SVR-RBF models using independent final testing and full-data five-fold cross-validation.
4. Multiple performance metrics, including MSE, RMSE, MAE, R^2 , MAPE, normalized RMSE, and $\pm 5\%$ prediction success rate, are reported.
5. A target-hardness case study is conducted to demonstrate the decision-support capability of the proposed model for selecting casting conditions close to a desired hardness level.

2. Materials and Methods

2.1. Experimental Dataset and Material System

The experimental dataset used in this study was obtained from a casting company operating in Türkiye. The dataset consisted of production records collected over a two-year

period from similar grey cast iron parts manufactured under industrial casting conditions. Since the data were obtained from real production records rather than laboratory-scale experiments, they reflect the variability, uncertainty, and practical constraints of an industrial foundry environment.

The original production database contained a larger number of records. However, before model development, detailed data cleaning and screening process was carried out. During this process, records with missing values, incomplete chemical composition information, incorrect or inconsistent process entries, unrealistic measurement values, and possible data-entry errors were removed. Such inconsistencies may occur in industrial databases due to manual recording, operator-dependent data entry, incomplete production forms, repeated entries, measurement transfer errors, or missing hardness test results. Therefore, only complete and technically consistent records were retained for analysis.

After data cleaning, 170 valid casting samples remained in the final dataset. Each sample included chemical composition variables, process-related parameters, and the corresponding Brinell hardness value. The chemical composition variables were carbon (C), silicon (Si), manganese (Mn), phosphorus (P), sulfur (S), chromium (Cr), copper (Cu), and tin (Sn). In addition to these chemical variables, casting temperature and casting time were included as process-related input parameters. Brinell hardness (HB) was used as the output variable.

The chemical composition values were expressed in weight percent, whereas casting temperature and casting time represented the process conditions recorded during casting. The use of two-year industrial production data provides a realistic basis for evaluating the applicability of the proposed fuzzy artificial neural network model in practical casting environments. The descriptive statistics of the cleaned dataset are presented in Section 3.1.

The industrial production data used in this study were obtained from ÇEMAŞ Döküm Sanayi A.Ş. (Kırşehir, Türkiye), a grey cast iron foundry operating under industrial production conditions. The dataset consisted of archived routine production and quality-control records collected over a two-year period from grey cast iron casting operations. Only chemical composition data and Brinell hardness values were used in the present study. Accordingly, the input variables comprised eight chemical composition parameters (C, Si, Mn, P, S, Cr, Cu, and Sn) together with casting temperature and casting time, while Brinell hardness was considered as the output variable.

The chemical composition and Brinell hardness values analyzed in this study were not generated through laboratory experiments conducted specifically for the present research; rather, they were extracted from the company's archived industrial quality-control records. Therefore, the study is based on historical industrial production measurements routinely used in process monitoring and quality assurance. Since the present study relied on archived industrial records, detailed manufacturer information for the hardness testing and chemical analysis devices used during the original quality-control measurements was not available in the retrieved dataset and therefore could not be reported retrospectively.

All data preprocessing, fuzzy artificial neural network modelling, cross-validation, ensemble analysis, and comparative machine-learning analyses were carried out in Python using NumPy (v1.21.6), pandas (v1.3.5), scikit-learn (v1.1.3), SciPy (v1.7.3), matplotlib (v3.8.4), and openpyxl (v3.1.5). Preliminary data inspection, manual screening, and tabulation were additionally performed in Microsoft Excel (Microsoft Corporation, Redmond, WA, USA).

2.2. Selection of Input Variables

The input variables used in this study were not selected arbitrarily. Before model development, previous studies on casting process modelling, parameter optimization,

and mechanical property prediction were reviewed in terms of the material, process, and chemical composition variables used as model inputs. Previous studies have shown that casting temperature, casting or filling time, mold-related variables, piston speed, pressure, and alloying elements are frequently considered influential parameters in casting-related modelling and optimization studies [2–13]. In addition, studies focusing on cast irons, steels, and casting alloys have commonly used chemical composition variables to predict or optimize mechanical properties such as hardness, tensile strength, impact toughness, wear resistance, porosity, permeability, and other quality-related responses [14–23].

Based on this literature review and the availability of industrial production data, ten input variables were selected for the proposed model. These variables consisted of eight chemical composition parameters, namely C, Si, Mn, P, S, Cr, Cu, and Sn, and two process-related parameters, namely casting temperature and casting time. Carbon and silicon were included because of their direct influence on matrix structure and graphite formation in cast irons. Manganese, chromium, copper, and tin were included because they can affect hardenability, pearlite stabilization, and strength-related characteristics. Phosphorus and sulfur were included because they are commonly monitored residual elements in casting practice and may influence microstructural quality and mechanical response [14,20–23].

Recent materials-design studies also support the use of chemical composition and process parameters for target-property-oriented modelling. Razavi et al. used ageing time and temperature as input parameters for ANN-based hardness prediction and optimization of 17-4PH stainless steel [24]. Trzaska and Sitek developed a hybrid ANN–GA method to calculate steel chemical compositions satisfying a required hardness after cooling [25]. Similarly, Tomašić et al. proposed an ANN-based inverse design approach to determine steel chemical composition from a desired Jominy hardenability curve [26]. These studies indicate that chemical composition and process-related parameters can be effectively used not only for property prediction but also for target-property-oriented material and process design.

Some parameters reported in previous casting studies, such as sand properties, mold temperature, piston speed, pressure, nickel, molybdenum, magnesium, aluminum, vanadium, scandium, titanium, casting modulus, and melting temperature, were not included in the present model. These variables were excluded because they were either not available in the industrial dataset, not measured consistently in the company records, or outside the controllable scope of the investigated grey cast iron casting process. Thus, the final input set represents a compromise between literature-supported metallurgical relevance and the practical availability of two-year industrial production data.

2.3. Fuzzy Artificial Neural Network Model

The hybrid fuzzy artificial neural network (FANN) approach was developed by combining the ability of fuzzy logic to process linguistic knowledge and represent expert information with the learning capability and near-optimal solution performance of artificial neural networks. Systems in which artificial neural networks are guided by fuzzy logic are referred to as fuzzy neural networks [26,27].

As system complexity increases and the availability of data becomes limited, fuzzy approaches become more effective. In the exploration of solution spaces of complex systems, the use of fuzzy logic applied to fuzzified input and output information enables the derivation of meaningful and useful solution inferences. Fuller [26] defined a fuzzy neural network as a neural network that incorporates fuzzy signals and/or fuzzy weights, employs a sigmoidal transfer function, and performs all operations in accordance with Zadeh's extension principle.

Artificial neural networks and fuzzy logic systems exhibit different but complementary computational characteristics. While artificial neural networks are effective in learning from examples, they are limited in explaining how decisions are reached. In contrast, fuzzy logic systems are capable of explaining decision processes but cannot automatically acquire the rules required to make these decisions. These limitations have led to the hybrid utilization of the two approaches [26].

In casting applications, experimental studies are associated with high costs due to production interruptions, material scrap, and the frequent need for destructive testing. Therefore, achieving reliable analysis results with the minimum possible number of experiments is of critical importance, particularly during the embodiment design stage of the engineering design process. In this study, a fuzzy neural network-based modeling approach is adopted to support parameter design under uncertainty in casting processes.

Artificial neural networks are derived from a fundamental artificial neuron known as the perceptron. Their learning capability is achieved through the adjustment of network weights during the training process, which is historically inspired by early neural learning concepts such as Hebbian learning [61].

In an artificial neuron, the weighted sum of input variables is calculated and combined with a bias term. This basic operation represents the fundamental working principle of artificial neural networks. Within the scope of this study, the core mathematical representation of this process is given in a condensed form as follows:

$$v_j = \sum_{i=1}^n w_{ij}x_i + \theta_j \quad (1)$$

$$y_j = f(v_j) \quad (2)$$

where x_i denotes the input variables, w_{ij} represents the connection weights, θ_j is the bias term, f denotes the activation function, and y_j denotes the neuron output. This formulation provides a compact representation of the neural network structure and corresponds to the detailed mathematical expressions presented in the doctoral thesis.

In this study, the fuzzy neural network was not used as a classical rule-based ANFIS model. Instead, fuzzified input variables were used as the transformed input space of a neural regression model. This design was preferred because the present problem includes ten input variables, and a conventional rule-based fuzzy inference system would lead to a large number of fuzzy rules. Therefore, the adopted FANN structure provides a more compact and computationally efficient modelling framework while preserving the ability of fuzzy logic to represent uncertainty in casting parameters.

In fuzzy neural networks, the classical neural network structure is enhanced with fuzzy information processing capability. In the approach developed by Yamakawa et al. [27], each input variable is associated with a set of fuzzy weights rather than a single crisp weight. This structure enables a more effective representation of uncertainty and variability in input data.

Although fuzzy neural networks are often associated with classical Adaptive Neuro-Fuzzy Inference System (ANFIS) structures, the fuzzy neural network architecture adopted in this study follows the approach proposed by Yamakawa et al. [27]. Unlike rule-based ANFIS models, which rely on explicit fuzzy if-then rules and a predefined inference mechanism, the Yamakawa-type fuzzy neural network incorporates fuzziness directly into the neuron structure through fuzzy-weighted connections. This structure results in a more compact model architecture and avoids rule explosion, particularly in problems involving a relatively high number of input variables, such as the present casting application. Consequently, the adopted fuzzy neural network structure is well suited for modeling nonlinear relationships under uncertainty while maintaining computational efficiency and scalability.

The objective of the model is not parameter ranking, but to support feasible parameter combination selection during the embodiment design stage.

The fuzzy neural network model employed in this study consists of fuzzification of input variables, propagation through one or more hidden layers via fuzzy-weighted connections, and direct continuous hardness prediction. The overall workflow and structural components of the proposed model are schematically illustrated in Figure 2, which presents a simplified representation of the detailed network structures described in the study.

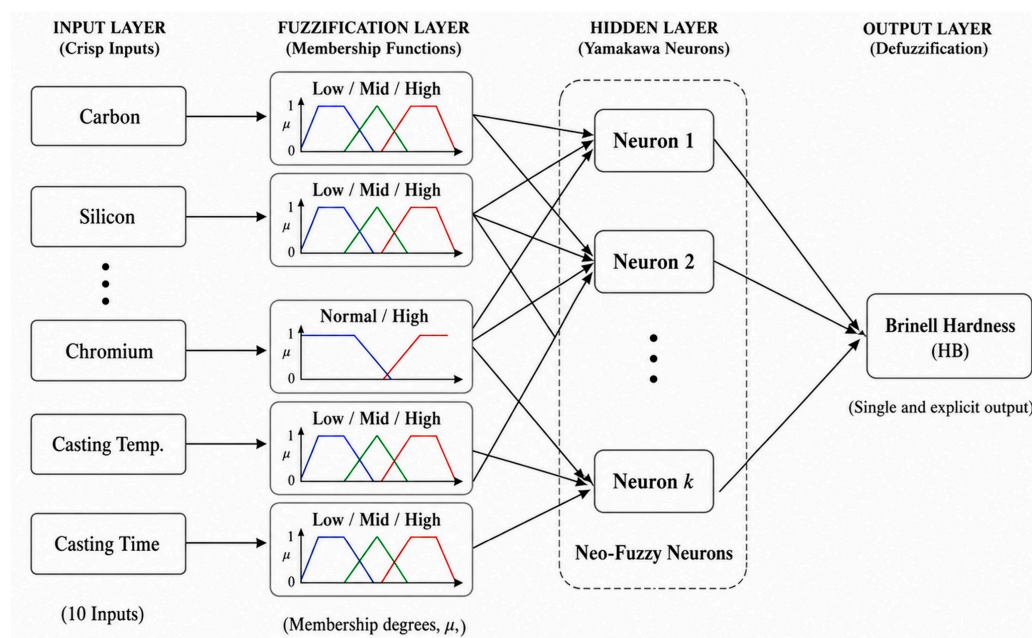


Figure 2. Architecture of the proposed fuzzy artificial neural network model. The input variables used in the model are listed in Table 1.

Table 1. Fuzzy sets used in the thesis-like input representation.

Attribute	Description	Number of Fuzzy Sets	Linguistic Fuzzy Sets
% C	Carbon content (%)	3	{Low}, {Medium}, {High}
% Si	Silicon content (%)	3	{Low}, {Medium}, {High}
% Mn	Manganese content (%)	3	{Low}, {Medium}, {High}
% P	Phosphorus content (%)	2	{Normal}, {High}
% S	Sulfur content (%)	3	{Low}, {Medium}, {High}
% Cr	Chromium content (%)	2	{Normal}, {High}
% Cu	Copper content (%)	2	{Normal}, {High}
% Sn	Tin content (%)	3	{Low}, {Medium}, {High}
T	Casting temperature (°C)	3	{Cold}, {Normal}, {Hot}
t	Casting time (s)	3	{Short}, {Normal}, {Long}

The role of the FANN model in this study is therefore twofold. First, it learns the nonlinear relationship between chemical composition, casting parameters, and Brinell hardness. Second, it provides a fuzzy decision-support basis for identifying candidate casting conditions close to a desired hardness value. Thus, the model is positioned not merely as a prediction tool but as a hardness-oriented parameter design support mechanism for the embodiment design stage.

2.4. Fuzzification and Membership Functions

In the proposed FANN model, the numerical input variables were first transformed into fuzzy representations through a fuzzification process. The purpose of fuzzification was to handle uncertainty and gradual transitions inherent in casting processes by mapping

crisp numerical values into linguistic membership degrees. In this way, each input variable was not represented by a single rigid category, but by membership degrees corresponding to different linguistic regions.

Different fuzzy membership structures were evaluated during model development. In the thesis-like structure, selected variables were represented using three fuzzy sets and the remaining variables using two fuzzy sets. The variables C, Si, Mn, S, Sn, casting temperature, and casting time were represented by three fuzzy sets. For these variables, Low, Medium, and High fuzzy regions were used. For casting temperature, the fuzzy regions were expressed as Cold, Normal, and Hot; for casting time, they were expressed as Short, Normal, and Long. The variables P, Cr, and Cu were represented by two fuzzy sets, namely Normal and High.

In addition to the thesis-like structure, two alternative membership structures were evaluated. In the first alternative, all input variables were represented using two fuzzy sets. In the second alternative, all input variables were represented using three fuzzy sets. This strategy allowed the effect of different fuzzy input representations on model performance to be examined systematically. Therefore, the fuzzy structure was not fixed manually, but evaluated as part of the model optimization process.

Different membership function types were also considered during model optimization. Triangular, trapezoidal, and Gaussian membership functions were evaluated for variables represented by three fuzzy sets, while sigmoid and shoulder-type membership functions were evaluated for variables represented by two fuzzy sets. The sigmoid slope factor and Gaussian sigma factor were also included in the hyperparameter search. Thus, both the fuzzy set structure and the shape of the membership functions were optimized through cross-validation rather than being selected only by subjective judgement.

In the earlier fuzzy-output formulation, the output variable, Brinell hardness, was represented using three linguistic terms, namely Soft, Normal, and Hard. In the final optimized model, however, a scaled direct output strategy was adopted. In this strategy, the input variables were fuzzified, but the output hardness value was predicted directly as a continuous numerical value. The HB values were standardized before neural network training and inverse-transformed after prediction. This scaling step improved numerical stability and allowed the model to perform direct hardness regression while preserving the uncertainty-handling advantage of fuzzy input representation.

The fuzzy sets defined for each input variable in the thesis-like fuzzy representation are summarized in Table 1.

The proposed FANN model is structured as an integrated decision-support framework that maps multi-dimensional input spaces to target mechanical properties as shown in Figure 3. Unlike black-box neural models, the schematic flow of the proposed architecture incorporates a fuzzification layer that translates precise industrial measurements into linguistic variables, which are then processed through fuzzy-weighted neural connections. This structural design enables the system to handle the inherent stochastic nature of the casting process. In practical application, a design engineer can compare candidate casting conditions according to their predicted closeness to a desired hardness value. Thus, the model supports the selection of promising parameter combinations from available or candidate production records. This transformation of the model from a simple predictive tool into a prescriptive decision-support mechanism allows for rapid prototyping and reduces the need for physical pilot heats in a foundry environment.

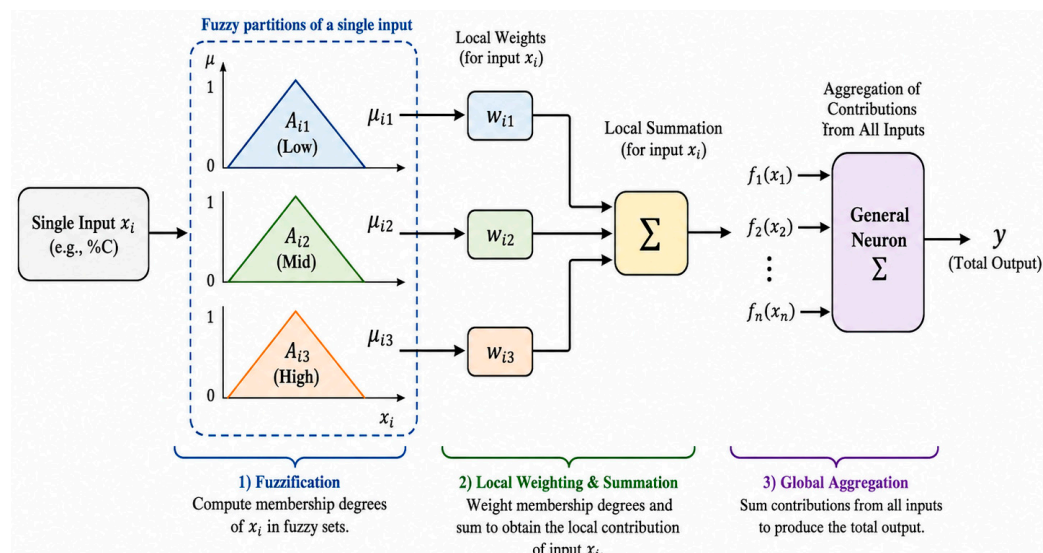


Figure 3. Schematic architecture of the FANN-based decision-support system for hardness-oriented parameter design.

2.5. Data Splitting and Validation Strategy

The dataset was divided into a training-validation subset and an independent final test subset. A total of 128 samples were used for model development, hyperparameter selection, and cross-validation, while 42 samples were reserved as an independent final test set. The final test set was not used during model selection or hyperparameter optimization.

The training-validation subset was used to optimize the proposed FANN model. During this stage, five-fold cross-validation was applied. In each fold, the training-validation data were divided into training and validation partitions, and model performance was calculated on the validation fold. This procedure allowed different FANN configurations to be compared under the same internal validation framework.

After selecting the best-performing FANN configurations based on cross-validation results, the final FANN ensemble was retrained using the entire 128-sample training-validation subset. The trained model was then evaluated on the independent 42-sample final test set. In addition to this independent final test evaluation, a full-data five-fold cross-validation analysis was conducted using all 170 samples to compare the proposed FANN ensemble with benchmark models under a common cross-validation framework.

2.6. Training, Hyperparameter Optimization, and Weighted FANN Ensemble

During model development, different fuzzy input structures, membership function types, neural network architectures, activation functions, regularization coefficients, and learning rates were systematically evaluated. Unlike the earlier model version, in which the architecture was selected mainly according to the mean squared error criterion, the revised model used a broader cross-validation-based optimization strategy.

A total of 300 different FANN configurations were evaluated. Each candidate configuration was assessed using five-fold cross-validation on the 128-sample training-validation subset. The hyperparameter search space included the membership structure, membership function type, sigmoid slope factor, Gaussian sigma factor, hidden-layer architecture, activation function, regularization coefficient, and learning rate. The candidate activation functions were tanh, ReLU, and logistic sigmoid. Thus, the activation function was treated as a tunable hyperparameter rather than being fixed a priori.

The selection of the best FANN configurations was based on a cross-validation selection score. This score considered the mean RMSE, the variability of RMSE across folds, and a small model-complexity penalty. In this way, the model selection process favored

configurations that provided low prediction error, stable cross-validation performance, and reasonable architectural complexity.

After the 300-trial optimization process, the five best FANN configurations satisfying the predefined cross-validation RMSE threshold were selected. Candidate models with a mean cross-validation RMSE greater than 8 were excluded from the ensemble. The remaining top five models were combined using an RMSE-based weighted averaging strategy. The weight of each model was calculated as the inverse square of its cross-validation RMSE:

$$w_k = \frac{1/RMSE_k^2}{\sum_{j=1}^K 1/RMSE_j^2} \quad (3)$$

where w_k denotes the ensemble weight of the k th FANN model, $RMSE_k$ denotes the mean cross-validation RMSE of the k th model, and K denotes the total number of selected models in the ensemble.

The final weighted ensemble prediction was calculated as follows:

$$\hat{y} = \sum_{k=1}^K w_k \hat{y}_k \quad (4)$$

where $\hat{y}_k$ denotes the prediction of the k th FANN model and $\hat{y}$ denotes the final weighted ensemble prediction.

The final optimized model was therefore implemented as a scaled direct FANN weighted ensemble. This approach preserved the fuzzy representation of the input variables while improving the stability and generalization ability of direct hardness prediction.

2.7. Benchmark Models

To evaluate the predictive performance of the proposed FANN ensemble, four benchmark models were used: Random Forest, Linear Regression, Ridge Regression, and Support Vector Regression with a radial basis function kernel (SVR-RBF). These models were selected because they represent different modelling assumptions and are commonly used for regression-based prediction tasks.

Linear Regression was included as a simple baseline model representing a linear input-output relationship. Ridge Regression was included as a regularized linear model to account for possible multicollinearity among input variables. SVR-RBF was included because it can model nonlinear relationships through kernel-based regression. Random Forest was included as a tree-based ensemble method capable of modelling nonlinear interactions and variable effects.

The benchmark models were trained using the same training-validation and final test split as the proposed FANN model. In the independent final test evaluation, each benchmark model was trained on the 128-sample training-validation subset and tested on the same 42-sample final test set. In the full-data cross-validation comparison, the benchmark models were evaluated using the same five-fold cross-validation framework applied to the proposed FANN ensemble.

2.8. Performance Metrics

Model performance was evaluated using multiple regression metrics to provide a comprehensive assessment of prediction accuracy. The metrics included mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), mean absolute percentage error (MAPE), normalized RMSE, and the $\pm 5\%$ prediction success rate.

MSE and RMSE were used to measure the magnitude of prediction errors, with RMSE providing error values in the same unit as hardness. MAE was used to represent the average

absolute prediction deviation. R^2 was used to assess the proportion of variance explained by the model. MAPE was calculated to evaluate the relative prediction error as a percentage. Normalized RMSE was reported to allow scale-independent interpretation of model error. In addition, the $\pm 5\%$ prediction success rate was calculated as the percentage of samples for which the predicted hardness was within $\pm 5\%$ of the experimental hardness value.

These metrics were reported for both the independent final test set and the full-data five-fold cross-validation analysis. This dual evaluation strategy allowed both final unseen-test performance and cross-validation robustness to be examined.

2.9. Target-Hardness Decision-Support Procedure

In addition to conventional prediction performance evaluation, a target-hardness case study was conducted to demonstrate the decision-support capability of the proposed model. The purpose of this case study was to show how the optimized FANN ensemble could be used to identify candidate casting conditions close to a desired hardness level.

For this purpose, the trained FANN ensemble was used to predict the hardness values of the available casting samples. The predicted hardness values were then compared with a predefined target hardness value. The candidate samples were ranked according to the absolute distance between the predicted hardness and the target hardness. The samples with the smallest distance to the target value were considered the most suitable candidate casting conditions.

In the present study, a target value of 203 HB was used to demonstrate this procedure. This analysis was not intended to replace experimental validation but to illustrate how the proposed FANN-based decision-support framework can assist parameter selection by ranking existing casting conditions according to their closeness to a desired hardness level.

2.10. Controlled Foundry Process Parameters and Metallurgical Context

To improve the metallurgical interpretation of the proposed model, it should be noted that the investigated dataset was obtained from a long-term industrial grey cast iron production line operating under relatively stable manufacturing conditions. Several process variables known to influence hardness, including inoculation practice, mold characteristics, section geometry, and pouring conditions, were maintained within standard production ranges throughout the data collection period. Inoculation was consistently performed using a FeSi-based inoculant according to the foundry's standard production procedure. Likewise, green sand molds prepared under controlled production conditions were employed for all castings included in the dataset. The investigated cast components belonged to a similar product family with comparable section geometries and dimensions, thereby reducing variations associated with cooling behavior. Although cooling rate, mold thermal properties, and detailed flow characteristics were not directly recorded in the production database, their variation was limited by the stable manufacturing environment and standardized operating procedures. Consequently, the proposed model should be interpreted as a decision-support tool applicable to castings produced under similar metallurgical and processing conditions rather than as a universally applicable hardness prediction framework. Future studies should incorporate directly measured cooling rate data, microstructural descriptors, inoculation parameters, and section geometry variables to further improve the physical interpretability and generalizability of the model.

3. Results

This section presents the results obtained from the optimized fuzzy artificial neural network (FANN) weighted ensemble model developed for hardness-oriented parameter design in grey cast iron casting processes. The results are evaluated in terms of the descriptive

statistics of the cleaned industrial dataset, the optimization outcomes of the FANN configurations, the independent final test performance, the full-data five-fold cross-validation comparison, and the target-hardness case study. In addition, the statistical consistency between the experimental and predicted hardness values is examined.

3.1. Descriptive Statistics of the Cleaned Industrial Dataset

The dataset used in this study consisted of 170 valid grey cast iron production records obtained after the cleaning of a two-year industrial production database. A total of 128 samples were used for model development and cross-validation-based optimization, while 42 samples were reserved as an independent final test set. This separation enabled the evaluation of the model's generalization capability using production records that were not used during model selection.

The descriptive statistics of the input parameters and the output variable are presented in Table 2. The input variables consisted of eight chemical composition parameters, namely C, Si, Mn, P, S, Cr, Cu, and Sn, and two process parameters, namely casting temperature and casting time. The output variable was Brinell hardness.

Table 2. Summary statistics of the input and output variables.

Input Parameters	Symbol	Min	Max	Mean	S.D.
Carbon content (%)	C	3.49	3.72	3.597176	0.048896
Silicon content (%)	Si	1.81	2.23	1.983706	0.066799
Manganese content (%)	Mn	0.40	0.72	0.549353	0.068840
Phosphorus content (%)	P	0.005	0.19	0.049976	0.049357
Sulfur content (%)	S	0.0103	0.27	0.122296	0.025205
Chromium content (%)	Cr	0.011	0.23	0.095476	0.029689
Copper content (%)	Cu	0.01	0.90	0.142094	0.086446
Tin content (%)	Sn	0.011	0.066	0.031853	0.008978
Casting temperature (°C)	T	1378	1405	1394.935	5.817968
Casting time (sec.)	Sec	7	11	10.07647	1.163175
Output Parameter	Symbol	Min	Max	Mean	S.D.
Hardness (HB)	HB	179	229	203.1118	7.008766

The descriptive statistics show that the dataset covers a practical industrial range in terms of both chemical composition and process parameters. The mean hardness value was approximately 203 HB, with values ranging from 179 HB to 229 HB. This variation indicates that the cleaned dataset contains sufficient variability for modelling the relationship between casting parameters and hardness.

3.2. Optimization Results of the FANN Configurations

During model development, 300 different FANN configurations were evaluated using five-fold cross-validation on the 128-sample training-validation subset. The optimization process included different fuzzy membership structures, membership function types, hidden-layer architectures, activation functions, learning rates, and regularization settings. The final model was constructed as a weighted ensemble of the five best-performing FANN configurations.

The selected FANN configurations are presented in Table 3. The ensemble included thesis-like, all-two, and all-three fuzzy input structures. The cross-validation RMSE values of the selected configurations were very close to each other, indicating that the final ensemble was formed from consistently performing models. The ensemble weights were calculated according to the inverse square of the cross-validation RMSE values.

The results in Table 3 indicate that no single fuzzy membership structure dominated the ensemble. Instead, the final weighted model benefited from combining different

fuzzy representations and neural architectures. This supports the use of an ensemble strategy rather than relying on a single manually selected FANN configuration. The thesis-like fuzzy structure appeared in the two highest-ranked configurations, suggesting that the original fuzzy representation derived from domain knowledge remained useful. However, the inclusion of all-two and all-three structures also shows that alternative fuzzy representations contributed to model robustness.

Table 3. Selected Top-5 optimized FANN configurations.

Rank	Architecture	Fuzzy Structure	Activation Function	CV RMSE	Ensemble Weight
1	$27 \times 12 \times 23 \times 8 \times 1$	thesis_like	logistic	6.4494	0.2046
2	$27 \times 20 \times 23 \times 32 \times 1$	thesis_like	logistic	6.5241	0.2000
3	$30 \times 8 \times 32 \times 23 \times 1$	all_three	ReLU	6.5373	0.1992
4	$20 \times 23 \times 23 \times 8 \times 1$	all_two	logistic	6.5508	0.1983
5	$30 \times 16 \times 8 \times 20 \times 1$	all_three	logistic	6.5579	0.1979

3.3. Independent Final Test Performance

After the optimization process, the selected FANN ensemble was retrained using the full 128-sample training-validation subset and evaluated on the independent 42-sample final test set. The same train-test split was also used for the benchmark models. Table 4 presents the independent final test performance of the proposed FANN ensemble and the benchmark models.

Table 4. Independent final test performance comparison.

Rank	Model	MSE	RMSE	MAE	R ²	MAPE (%)	±5% Success (%)
1	Random Forest	42.7244	6.5364	4.6352	0.3167	2.2434	88.0952
2	Linear Regression	48.6671	6.9762	5.0586	0.2217	2.4561	88.0952
3	Ridge Regression	48.6777	6.9769	5.0606	0.2215	2.4571	88.0952
4	Optimized Scaled Direct FANN Weighted Top-5	57.7089	7.5966	5.3656	0.0771	2.6033	88.0952
5	SVR-RBF	66.2231	8.1378	5.0687	−0.0591	2.4308	85.7143

According to the independent final test results, Random Forest achieved the lowest error values, with an RMSE of 6.5364 and an MAE of 4.6352. Linear Regression and Ridge Regression also produced competitive final test results. The proposed optimized FANN weighted ensemble achieved an RMSE of 7.5966, an MAE of 5.3656, and a MAPE of 2.6033%. Although the FANN ensemble did not produce the lowest final test error, it achieved the same ±5% prediction success rate as Random Forest, Linear Regression, and Ridge Regression. Specifically, 37 out of 42 final test samples were predicted within the ±5% error margin.

These findings indicate that the proposed FANN ensemble remained competitive on unseen industrial data. The Random Forest model performed better in terms of final test error, whereas the FANN ensemble provided a fuzzy decision-support structure that is useful for target-hardness-oriented parameter design.

3.4. Full-Data Five-Fold Cross-Validation Comparison

In addition to the independent final test evaluation, a full-data five-fold cross-validation analysis was conducted using all 170 samples. This analysis was performed to compare the robustness of the proposed FANN ensemble and the benchmark models under a common cross-validation framework. The results are presented in Table 5.

Table 5. Cross-validation performance metrics of the FANN ensemble and benchmark models.

Rank	Model	MSE_mean	RMSE_mean	MAE_mean	R ² _mean	MAPE (%)	±5% Success (%)
1	Optimized Scaled Direct FANN Weighted Top-5	43.7485	6.5945	5.1268	0.0685	2.5324	87.6471
2	Random Forest	43.7254	6.6046	5.0223	0.0575	2.4722	92.3529
3	Ridge Regression	46.5354	6.8092	5.2851	−0.0062	2.6018	88.2353
4	Linear Regression	46.6303	6.8163	5.2900	−0.0088	2.6042	88.2353
5	SVR-RBF	50.3422	7.0610	5.3367	−0.0850	2.6245	87.0588

The full-data cross-validation results show that the optimized FANN weighted ensemble achieved the lowest mean RMSE value among the compared models. Its mean RMSE was 6.5945, slightly lower than the Random Forest value of 6.6046. The Random Forest model achieved a marginally lower mean MSE and the highest ±5% success rate, whereas the proposed FANN ensemble provided the best mean RMSE performance. These results suggest that the FANN ensemble has a robust cross-validation performance despite the limited size and industrial variability of the dataset.

The difference between the independent final test and the full-data cross-validation results also indicates that model performance should not be interpreted using a single metric or a single validation strategy. While Random Forest was the strongest model on the independent final test set, the proposed FANN ensemble showed strong and stable performance in the cross-validation analysis. Therefore, the FANN model should be interpreted not as a universally superior prediction model, but as a competitive fuzzy decision-support model that combines acceptable predictive accuracy with target-hardness-oriented parameter selection capability.

3.5. Target-Hardness Case Study

To demonstrate the decision-support capability of the proposed FANN ensemble, a target-hardness case study was conducted. The purpose of this analysis was to identify candidate casting conditions close to a desired hardness level. A target hardness value of 203 HB was selected because it is close to the mean hardness value of the cleaned industrial dataset and represents a realistic hardness target for the investigated grey cast iron parts.

The trained FANN ensemble was used to predict the hardness values of candidate casting records. The candidates were then ranked according to the absolute difference between the predicted hardness and the target hardness value. The closest candidate is presented in Table 6.

Table 6. Target-hardness case study for 203 HB.

Target HB	Actual HB	Predicted HB	Distance to Target	C	Si	Mn	P	S	Cr	Cu	Sn	T	Sec
203	207	202.985150	0.014850	3.56	1.97	0.55	0.090	0.132	0.12	0.11	0.028	1400	11

The case study shows that the proposed FANN ensemble was able to identify a candidate casting condition with a predicted hardness value of 202.985150 HB, which is extremely close to the target value of 203 HB. The absolute distance between the predicted hardness and the target was only 0.014850 HB. This result demonstrates the practical use of the model as a target-hardness-oriented decision-support tool.

It should be noted that this case study does not represent a fully inverse optimization procedure. Instead, the model ranks existing or candidate production conditions according to their closeness to a desired hardness value. Therefore, the proposed approach can sup-

port engineers by narrowing the parameter search space and identifying promising casting conditions before conducting additional production trials or experimental validation.

3.6. Statistical Consistency of FANN Predictions

To examine the statistical consistency between the experimental and predicted hardness values, a paired *t*-test was applied to the independent final test predictions of the optimized FANN ensemble. The null hypothesis was that there was no statistically significant difference between the mean experimental hardness values and the mean predicted hardness values.

The paired *t*-test produced a *p*-value of 0.5435. Since this value is greater than the conventional significance level of 0.05, the null hypothesis could not be rejected. This result indicates that there was no statistically significant mean difference between the experimental and predicted hardness values in the independent final test set.

Although the paired *t*-test does not alone prove prediction superiority, it supports the statistical consistency of the FANN predictions with the experimental hardness measurements. Together with the $\pm 5\%$ prediction success rate and the cross-validation results, this finding suggests that the proposed FANN ensemble can provide practically acceptable hardness predictions for the investigated grey cast iron casting process.

4. Discussion

The results of this study demonstrate that the proposed optimized FANN weighted ensemble can be used as a practical decision-support model for hardness-oriented parameter design in grey cast iron casting processes. The model was developed using cleaned two-year industrial production data obtained from similar grey cast iron parts, which makes the modelling task more representative of real foundry conditions than laboratory-scale datasets. Industrial production data naturally include variability caused by raw material differences, operator-dependent recording practices, process fluctuations, and measurement uncertainty. Therefore, the ability of the proposed model to provide competitive prediction performance under such conditions is an important outcome of the study.

The independent final test results showed that the Random Forest model achieved the lowest prediction error among the compared models. This result is reasonable because tree-based ensemble methods are often effective in modelling nonlinear relationships and interactions in relatively small tabular datasets. The proposed optimized scaled direct FANN weighted ensemble did not outperform Random Forest in terms of final test error. However, it achieved the same $\pm 5\%$ prediction success rate as Random Forest, Linear Regression, and Ridge Regression, with 37 out of 42 test samples predicted within the $\pm 5\%$ error margin. This indicates that the FANN ensemble produced practically acceptable predictions on unseen industrial data, even though its numerical error values were slightly higher than those of the best-performing benchmark model.

The full-data five-fold cross-validation results provide a complementary perspective. In this analysis, the optimized FANN weighted ensemble achieved the lowest mean RMSE among all compared models, slightly outperforming Random Forest in terms of average RMSE. Random Forest, on the other hand, achieved a slightly lower mean MSE and the highest $\pm 5\%$ success rate. These findings show that model performance depends on the evaluation criterion and validation strategy used. Therefore, the proposed FANN model should not be interpreted as universally superior to all benchmark models. Instead, it should be considered a competitive fuzzy decision-support model that combines acceptable prediction accuracy with a structure suitable for handling uncertainty in casting parameter design.

One important contribution of the proposed approach is the use of fuzzy input representations. Casting processes involve gradual transitions rather than strict boundaries between operating regions. For example, changes in chemical composition or casting temperature do not usually produce abrupt changes in hardness; instead, their effects are continuous, uncertain, and sometimes nonlinear. The fuzzification stage allows such gradual transitions to be represented through membership degrees. In this sense, the FANN model provides a more flexible representation of process uncertainty than purely crisp input-output models.

Another important point is that the fuzzy structure was not fixed only according to subjective judgement. In the revised modelling strategy, different fuzzy membership structures and membership function types were evaluated through cross-validation. The selected Top-5 FANN ensemble included thesis-like, all-two, and all-three fuzzy input structures. This shows that different fuzzy representations contributed to the final model. The presence of the thesis-like structure among the best-performing configurations also indicates that the original domain-informed fuzzy representation remained useful. However, the inclusion of alternative fuzzy structures improved the robustness of the final ensemble and reduced dependence on a single manually selected architecture.

The target-hardness case study demonstrates the practical value of the proposed model beyond conventional prediction accuracy. For a target value of 203 HB, the optimized FANN ensemble identified a candidate casting condition with a predicted hardness of 202.985150 HB, corresponding to an absolute distance of only 0.014850 HB from the target value. This result illustrates how the model can support engineers in selecting candidate parameter combinations close to a desired hardness level. In this respect, the model is not limited to predicting hardness after production; it can also assist the embodiment design stage by narrowing the search space before additional production trials are conducted.

However, the target-hardness analysis should be interpreted carefully. The current approach does not perform a fully inverse optimization in which entirely new chemical compositions or casting process parameters are generated automatically. Instead, it ranks available or candidate production records according to their predicted closeness to a target hardness value. Therefore, the proposed model should be considered a decision-support and candidate-selection tool rather than a complete inverse design optimizer. This interpretation is important for avoiding overstatement of the model's capability.

From a metallurgical perspective, the selected input variables are meaningful for grey cast iron hardness prediction. Carbon and silicon are directly related to matrix formation and graphite characteristics, while manganese, chromium, copper, and tin may influence hardenability, pearlite stabilization, and strength-related behaviour. Phosphorus and sulfur are also important residual elements monitored in industrial casting practice. In addition, casting temperature and casting time reflect process-related effects that may influence solidification behaviour and final hardness. Therefore, the model input space is consistent with both metallurgical reasoning and practical industrial data availability.

The relatively low R^2 values observed in both the independent final test and cross-validation results should also be discussed. Although the absolute error metrics and $\pm 5\%$ success rates indicate practically acceptable prediction performance, the R^2 values suggest that a substantial portion of hardness variability remains unexplained. This may be related to the limited number of available records, the narrow hardness range of the investigated parts, and the absence of some potentially influential variables, such as cooling rate, mold temperature, inoculation practice, section thickness, metallographic phase fractions, and detailed microstructural descriptors. Since the dataset was obtained from real industrial records, not all potentially relevant metallurgical and process variables were consistently available.

Despite these limitations, the proposed model provides a useful framework for integrating fuzzy reasoning and neural learning into hardness-oriented parameter design. The results show that the model can achieve competitive predictive performance and can be used to identify promising casting conditions for a desired hardness level. Therefore, the main value of the study lies not only in prediction accuracy but also in the positioning of the FANN model as a decision-support mechanism within the embodiment design stage of casting process planning.

Future studies should extend this framework by increasing the number of industrial production records and including additional metallurgical and process variables. In particular, cooling rate, mold properties, section thickness, microstructural information, and heat treatment-related variables could improve model performance and interpretability. Moreover, the current target-hardness candidate-ranking approach can be extended into a true inverse design framework by integrating the FANN model with metaheuristic optimization algorithms such as genetic algorithms, particle swarm optimization, or Bayesian optimization. Experimental validation of newly suggested parameter combinations would further strengthen the industrial applicability of the proposed approach.

5. Conclusions

This study developed an optimized fuzzy artificial neural network (FANN)-based decision-support framework for hardness-oriented parameter design in grey cast iron casting processes. The model was constructed using 170 cleaned industrial production records collected over a two-year period from a casting company in Türkiye. Eight chemical composition variables (C, Si, Mn, P, S, Cr, Cu, and Sn), together with casting temperature and casting time, were used as inputs, while Brinell hardness was selected as the output. To improve robustness, 300 FANN configurations were evaluated using five-fold cross-validation. The five best-performing models were combined through RMSE-based weighted ensemble averaging, allowing different fuzzy membership structures and neural architectures to contribute to the final prediction model.

The results showed that Random Forest achieved the lowest prediction error on the independent test set. However, the optimized FANN ensemble achieved the same $\pm 5\%$ prediction success rate, correctly predicting 37 of 42 test samples within the $\pm 5\%$ error margin. Furthermore, the FANN ensemble produced the lowest mean RMSE in the full-data five-fold cross-validation analysis, demonstrating competitive and stable predictive performance. A target-hardness case study further demonstrated the practical applicability of the proposed framework. For a target hardness of 203 HB, the model identified a candidate casting condition with a predicted hardness of 202.985 HB, corresponding to an absolute deviation of only 0.015 HB. This result indicates that the proposed approach can support engineers in selecting candidate process conditions close to desired hardness values while reducing reliance on repeated trial-and-error production.

The main contribution of this study is the integration of fuzzy input representation, cross-validation-based model selection, benchmark model comparison, and target-hardness candidate ranking within a hardness-oriented embodiment design framework.

Several limitations should be acknowledged. The dataset was limited to 170 production records obtained from similar grey cast iron components produced by a single company. In addition, potentially important variables such as cooling rate, mold characteristics, section thickness, inoculation practice, and microstructural descriptors were not available in the industrial records. Future studies should incorporate these variables, expand the dataset, and investigate inverse-design approaches integrated with optimization algorithms.

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