Enhancing Hardness Characterization in Austempered Ductile Iron with Jellyfish Swarm-Adaptive Hybrid Adaboost Approach

Anupam Kumar Gautam[1], Dr. Shweta Loonkar[2], Putane Sadashivrao Raghvendra rao[3], Manali Gupta[4]

[1]*Maharishi University of Information Technology, Uttar Pradesh, India, Email Id- anupamkumargautam12@gmail.com*
[2]*ATLAS SkillTech University, Mumbai, Maharashtra, India, Email Id- , shweta.loonkar@atlasuniversity.edu.in.*
[3]*JAIN (Deemed-to-be University), Ramanagara District, Karnataka, India, Email Id- , ps.raghavendra@jainuniversity.ac.in*
[4]*Noida Institute of Engineering and Technology, Greater Noida, Uttar Pradesh, India, Email Id- manaligupta@niet.co.in*

Hardness is an essential mechanical characteristic of austempered ductile iron (ADI) that affects its ability to perform in a variety of applications. To increase hardness characterization, dedicated testing methods that take into consideration the unique properties of ADI must be developed and used. The generalisation of hardness prediction algorithms could be complicated by the variations in composition of materials and processing circumstances. In this study, we proposed a jellyfish swarm adaptive hybrid AdaBoost approach to improve hardness characterization in austempered ductile iron. The complex relationship between the microstructure of ADI is influenced by chemical-based compositions, duration and austempering temperatures that determine the material's hardness and flexibility. A typical method for determining a material's hardness is to utilize its Hardness Number (HN). Five specimens that completed the process of austempering at different temperatures (240, 260 and 280 degrees celsius) and times (20, 40, 60 and 80 mins) are examined in this investigation. Examining seven chemical compositions, large-scale modelling demonstrated that the JSO-AdaBoost-based approach is capable of predicting the HN with the highest mean absolute error (MAPE) of 0.27%. Due to its desirable qualities, including its high tensile strength and exceptional flexibility, ADI is utilized in the automotive industry.

Keywords: F Austempered ductile iron (ADI) Hardness Number (HN), Jellyfish swarm optimization (JSO) AdaBoost, Chemical compositions.

1. Introduction

“Austempered Ductile Iron (ADI)” provides a unique combination of durability, toughness and corrosion resistance is a significant development in metallurgy. Austempering is a specific heat treatment method that separates this specialized category of ductile iron from other materials [1]. Austempering produces a microstructure with exceptional mechanical qualities by quenching the iron in a particular temperature range and applying an isothermal heating process.

The main component of ADI's microstructure, acicular ferrite, adds to its exceptional flexibility and strength [2]. This unique combination derives from the austempering process, which turns high-carbon austenite into acicular ferrite. Because of its outstanding tensile strength, resistance to impacts and fatigue strength, the final product is suitable for applications requiring extraordinary performance under changing circumstances. This makes ADI an excellent choice [3]. Due to its enhanced mechanical qualities, ADI has become prevalent in many engineering applications, such as industrial equipment, drives, shafts and automotive parts. Because of its increased durability and wear resistance, it is especially well-suited for demanding environments where conventional materials would perform poorly [4].

ADI is an innovative material that is highly performative and adaptable in the metallurgical field. Its exceptional durability, toughness and resistance to wear are made possible by its distinct microstructure, which was attained through careful heat treatment, giving engineers and manufacturers a beneficial option for a variety of challenging applications [5]. Engineers and metallurgists trying to customize ADI characteristics to meet particular application need demand to know that accurate and comprehensive hardness characterisation performs. Nuanced differences in durability across the acicular ferrite structure can be detected by conventional hardness testing techniques like Brinell or Rockwell [6]. Therefore, sophisticated methods such as micro-hardness testing at various material regions are utilized to offer an improved understanding of ADI's hardness distributions [7].

The hardness profiles of intricate ADI components are better understood because of developments in non-destructive testing techniques like magnetic and ultrasonic hardness testing [8]. By using these techniques, one can assess local hardness differences more precisely and adjust the austempering procedure to get the necessary hardness levels in particular areas [9]. Through this effort, the mechanical qualities of ADI can be optimized to meet the demanding needs of a wider range of applications in different industries [10].

Study [11] assessed the impact of austempering duration and temperature on the microstructural features and rigidity of ductile iron, confirming it with a statistical approach to hardness predicting. As the duration of austempering increased, acicular ferrite needles were observed to thicken. It contributed to the observation of an inversely correlated behaviour for the hardness values, which was confirmed by data analysis, statistical techniques and a regression model that used hardness as the resulting variable along with time and temperature of austempering as the input parameters. The study [12] investigated on the impact of partitioned treatment on the mechanical properties and microstructure of austempered ductility iron (ADI). The carbon atoms moved from the α phase to the γ phase during the separation process, causing the α phase to become coarser and the γ phase to become increasingly concentrated in carbon. These changes in microstructure contributed to a roughly 50% increase in flexibility without compromising strength. The study [13] examined the transformation-induced plasticity (TRIP) and mechanical characteristics were affected by short-term austenitization in austempered ductile iron. Dilatometers, visualization programs, tensile as well as hardness tests, XRD examination, optic along with electronic scanning microscopies and other tools were used in the microscopy investigations. The smallest (15 min) austenitized sample yielded the largest TRIP effect and the best mixture of ductility coupled with hardness.

Research [14] utilized several machine learning-based intelligent classification approaches to determine the hardness of a less prevalent compact graphite iron cast and a conventional spheroidal iron cast. Accurately predicting the mechanical characteristics of casting alloys was a challenging attempt since significant differences in metallurgical conditions could occur during casting. Neural networks were trained using microstructures as inputs and the output of the training process was hardness. The effect of austempering temperature on the Mechanical capabilities and nanostructures of “austempered ductile iron casting (ADI)” was examined in the study [15]. The main focus of their investigation was to examine the austempering temperatures that affected the ADI altered by particular Ni, Cu and Mo concentrations to promote the development of microstructure, expansion, durability and fatigue endurance. 330 °C was the ideal temperature for ADI, according to the results of stress-controlled mechanical fatigue testing. The study [16] focused on the fact that heat treatment affected the tribological behaviours, rigidity and toughness of the materials. Case-hardening steel could be exchanged with austempered ductile iron (ADI) in numerous applications. They can adjust the chemical structure and heat treatment parameters of ADI to alter its mechanical qualities. Cryogenic treatment has been found to enhance wear resistance (20%) and enable some austenite to martensite conversions.

Study [17] examined that niobium addition affects the parameters of toughness and durability in graphite, bainite and the process of bainite conversion under specific heat-treatment configurations. An investigation of the niobium precipitate behaviour could be used to understand the impact of niobium inclusion on the graphite microstructure in the liquid state. That was discovered that adding niobium in a level of 0.2–0.5 weight percent enables the best possible balance of scratch resistance, impact durability and toughness. The study [18] provided a highly efficient enhanced multilayer perceptron (eMLP)-based method using available experimental data that models the ADI's austempering process for VHN predictions. Under the use of the correct technique, ADI's hardness and ductility could be customized for a certain purpose. They have demonstrated that the suggested model offers comparable efficiency but with less computing complexity by evaluating the eMLP model's performance with an MLP-based strategy.

Study [19] processed Carbamic austempered ductile iron (CADI), an innovative heat treatment method that included an austempering treatment and super-high temperatures pre-treatment. A significant quantity of Fe_3C nanoparticles was maintained inside the earlier austenite as grains after the ductile iron, including superfine pearlite, was reheated. The CADI that was developed through the treatment offers outstanding durability under high wear pressure and an impact toughness that was 120% stronger than the regular CADI without compromising hardness. The study [20] determined that shot-peening affects the as-cast and austempered ductile irons' dry-sliding wear characteristics. The materials under test were examined using optical, scanning electron and X-ray scattering microscopy to assess their microstructure. During shot-peening, the austempered specimens demonstrated a rise in surface hardness due to the pressure produced by martensite, but a decrease in resistivity to wear results to an increase in surface roughness. This paper presents a novel strategy, termed the jellyfish swarm adaptive hybrid AdaBoost method, which aims to enhance hardness characterisation in austempered ductile iron.

The study components could be classified: The approaches are discussed in section 2. The experimental setups are presented in section 3. Result & Discussion is presented in section 4. The last section of this paper, section 5, is the conclusion.

2. METHODOLOGY

2.1 Jellyfish swarm optimization hybrid

AdaBoost approach (JSO-AdaBoost)

To enhance the characterization of hardness in “austempered ductile iron”, the Jellyfish Swarm Optimization (JSO) hybrid Adaboost strategy integrates two innovative techniques. Motivated by jellyfish behaviour, JSO maximizes feature selection to increase the accuracy of the ensuing Adaboost predictive model. Adaboost is an ensemble learning technique that creates a robust model by combining weak classifiers.

Jellyfish swarm optimization

There are species of jellyfish anywhere in the earth, from shallow waters to deep oceans. Their soft bodies are bell-shaped, with long, stinging tentacles on the bottom they employ to disable and sting their victims, which are microscopic fish and plankton creatures. They are available in a broad range of colours, shapes and sizes. Each one of the several species displays distinct adaptations to the sea environment. Features on jellyfish enable them to regulate their mobility. To move themselves ahead, they flex their bodies like an umbrella forcing water out. They primarily depend on currents and tides to drift in the sea without their capacity. Jellyfish have the ability to create swarms when the conditions are right and a large number of jellyfish known as Jellyfish bloom. The formation of a swarm is controlled by a number of elements, such as temperatures, oxygen supply, accessible nutrients, predators and water currents.

Water currents are thought to be the most significant of these components in the formation of a swarm. The way jellyfish search and travel in the ocean became the model for the jellyfish search algorithm. Three probable courses of action during jellyfish movement are as follows:

- A “time control mechanism” controls jellyfish that alternate between moving as they are part of a swarm and tracking the current in the water.
- Jellyfish swim through the ocean in search of food. They are attracted to areas where there is a greater supply of food available.
- The location and its related purpose determine the quantity of food is found there.

The behaviour of jellyfish in the ocean.

A swarm is a big group of jellyfish that migrate in different directions, either in their passive (type A) or active (type B) positions.

Type “A” motion is the movement of jellyfish about their individual locations and each jellyfish's current location is provided by,

$$W_j(s+1) = W_j(s) + \gamma * \mathrm{rand}(0,1) * (U_b - L_b) \quad (1)$$

Where gamma is the motion coefficient related to the length of motion towards jellyfish establishes in citechou 2021 distinct γ=0.1 is determined, yet U_band L_b are the upper and lower bounds of the search space, respectively.

Then randomly select a jellyfish (i) that is not important to imitate the type B movement (Equation 2) and select an angle of the jellyfish in attention (j) to the specified jellyfish (i) to establish the direction of the movement (Equation 3). The latter moves toward the initial when the quantity of food at the chosen jellyfish's (i) position is greater than that at the interested jellyfish's (j) location. If the amount of food accessible for the chosen jellyfish (i) is lower than the position of the jellyfish of interest (j), it continues to travel straight away from that spot. Equation (4) indicates a jellyfish's updated location.

$\overrightarrow{\mathrm{step}}$ is simulates as $\mathrm{rand}\ (0,1)\ \overrightarrow{\mathrm{D\imath rect\imath on}}$ (2)

$$\overrightarrow{\mathrm{D\imath rect\imath on}} = \begin{cases} W_i(s) - W_j(s) \text{ if } f(W_j) \geq f(W_i) \\ W_j(s) - W_i(s) \text{ if } f(W_j) < f(W_i) \end{cases} \quad (3)$$

$$W_j(s+1) = -W_j(s) + \overrightarrow{\mathrm{step}} \quad (4)$$

Adaptive Boosting

Boosting is a popular method for turning a weak learner into a strong learner to acquire classifiers. By improving the prediction capabilities of the weak categorization algorithm, the boosting technique intends to create a very advantageous classifier by starting with a weak classifier. The yields of numerous weak classifiers are equalized to prepare this expectation. Adaptive Boosting, or AdaBoost, is a common boosting technique that targets classification issues by constructing a powerful classifier from a large number of weak classifiers. The process involves creating an initial version using the training set of data, followed by the construction of an additional model designed to address the shortcomings of the initial model. Until a training set is determined or the greatest number of entries is merged, models are added.

AdaBoost is a widely used technique for improving decision tree output on binary classification tasks. The AdaBoost algorithm was selected because it could be used to improve the efficiency of any machine learning technique. When it is done with weaker students, it is usually excellent. One-level decision trees are the traditional algorithm used with AdaBoost. The trees are called decision stump because they are small and store a single option for a class. Weak models are generated using weighted training data and combined one after the other. The process keeps going until either a certain number of poor learners are generated or the training dataset cannot be improved effectively. Every node in a decision tree reflects a search for a characteristic in the context of machine learning. Each branch provides an explanation of the test outcome and the leaf nodes provide an explanation of the class label that supports each branch's decisions. A categorization rule is provided by the paths from the starting point to the leaf. The purpose of this approach is to display the data while making the design less complex. JSO-AdaBoost is represented in Algorithm 1.

Algorithm 1: (JSO-AdaBoost)

```
initialize_swarm()
initialize_adaboost()
for iteration in range(max_iterations):
        evaluate_fitness()
    update_best_positions()
    update_jellyfish_positions()
    selected_features = feature_selection()
    adaboost_model = train_adaboost_model(selected_features)
    adaboost_accuracy = evaluate_adaboost_model(adaboost_model)
    update_jellyfish_weight(adaboost_accuracy)
    hardness_prediction = predict_hardness(adaboost_model, selected_features)
    update_best_hardness_characterization(hardness_prediction)
print ("Final hardness characterization:", best_hardness_characterization)
```

3. EXPERIMENTAL SETUP

The present investigation examines five specimens that have experienced the process of austempering at varying temperatures and times, their chemical compositions varies. Table 1 lists the five specimens' chemical compositions (in weight percentage). The samples were austenitized, quenched and submerged in a salt solution instantly for varying amounts of time 20, 40, 60, or 80 minutes at 240, 260, or 280 °C. Each specimen was divided into nine samples, producing a total of 86 samples. For every sample, the HN was determined as the sample was loaded with 8 kg. 75 percent of the 86 data sets (60 items) were used as a training set, while the final 25% (26 items) were used as the evaluation set. Figure 1 shows the modelling schemes.

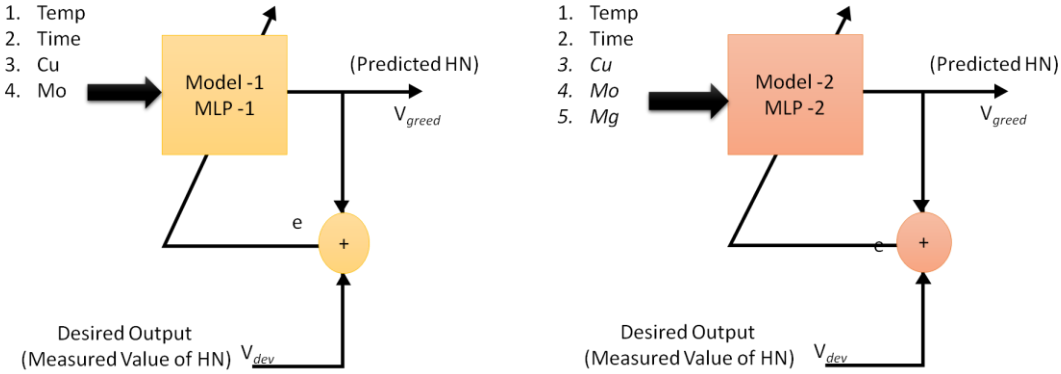

Fig. 1. The modelling schemes.

(Source: Author)

Table 1. Five specimens' chemical composition.

Chemical composition	Specimen #							
	1	2	3	4	5	Min	Max	Avg.	SD
C	3.43	3.46	3.41	3.41	3.45	3.41	3.46	3.432	0.0136
Si	2.31	2.34	2.31	2.32	2.41	2.31	2.41	2.338	0.0381
Mn	0.23	0.23	0.23	0.22	0.25	0.22	0.25	0.464	0.1039
Ni	1.01	1.01	1.01	1.03	1.01	1.01	1.03	1.014	0.0100
Cu	0.51	0.51	0.52	0.52	1.01	0.51	1.01	0.614	0.2292
Mo	0.11	0.14	0.20	0.24	0.24	0.11	0.24	0.816	0.0591
Mg	0.050	0.051	0.047	0.048	0.053	0.047	0.053	0.0498	0.0026

4. RESULT & DISCUSSION

The model's distribution and measurements' scatter plots generated HN values for the entire dataset (86 items) are displayed in Figure 2a. This figure displays the CC, MAPE and MSE values. Figure 2b displays scatter plots for Model-2. The entire set is stored in Model-2 and the evaluation set's CC values can be 0.9988 and 0.9995, proving the effectiveness of this modelling process. Low MAPE values indicated excellent HN estimation efficiency.

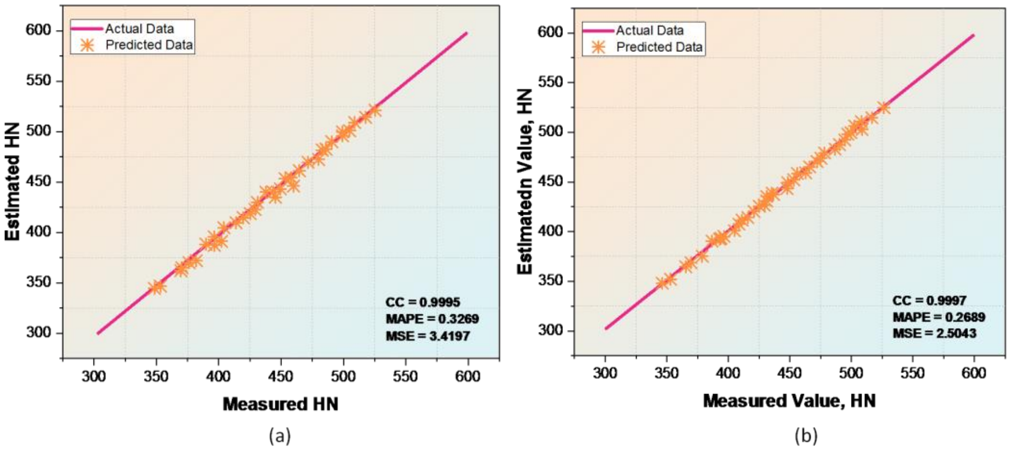

Fig.2. Scatter plots of the generated and evaluated HNs

(Source: Author)

The outcomes of Model-2's predictions for the five different specimens are displayed in Figure 3, these outcomes are for the temperature at a range of different values and austempering times of 20, 40, 60 and 80 minutes, respectively. The measured values are shown by the pink symbols, whereas the anticipated values for HN are represented by the orange symbols. It appears that the framework is able to provide accurate predictions of HN for a variety of values associated with the austempering temperature, which can range anywhere from 230 to 290 degrees Celsius. In Figure 4, for each of the five specimens, the prediction capabilities of Model-2 are displayed over a range of various quantities of austempering time duration at one of three distinct austempering temperatures, namely 240, 260, or 280 degrees Celsius. 10 to 90 minutes is the range of austempering time that the model can properly predict for HN.

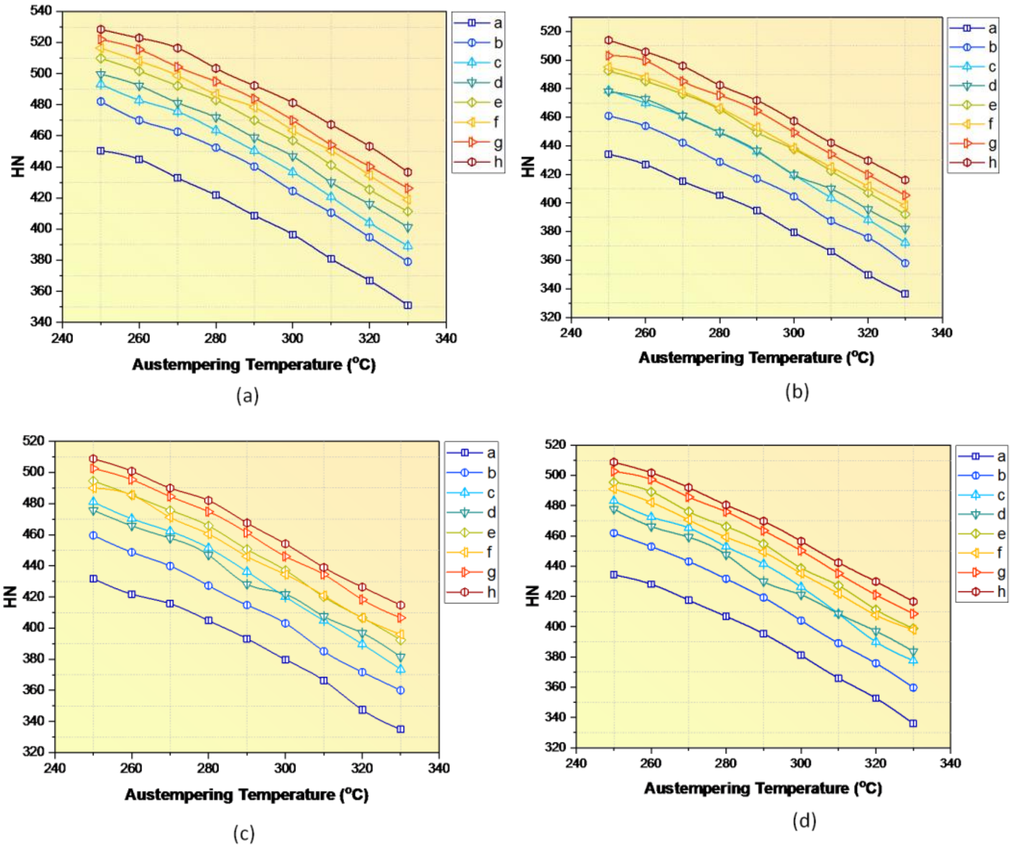

Fig. 3. Prediction of HN for durations of 20, 40, 60 and 80 minutes at various austempering temperatures.

(Source: Author)

5. CONCLUSION

Hardness characterization was the process of measuring and analyzing the susceptibility of a substance to stretching, piercing, or penetration. Austempered ductile iron (ADI)'s hardness was a crucial mechanical property that influences its performance in a range of applications. The development and application of specialized testing procedures that allow for the special characteristics of ADI were required to improve hardness characterization. In this study, we proposed Jellyfish swarm adaptive hybrid AdaBoost approach (JSO-AdaBoost) to improve hardness characterisation in austempered ductile iron. These models were capable of predicting HN at a certain temperature, period of time and weight proportion of the seven combinations of chemicals that were austempering. The correlation ratio between the predicted and observed HN values was near to 1, as demonstrated by the findings. The Model-2 outperforms the Model-1 in terms of performance. It was discovered that the mean absolute errors were as low as 0.27%. The generalisation of hardness prediction algorithms could be complicated by the variations in composition of materials and processing circumstances. Advanced machine learning techniques and optimization algorithms can be explored in future investigations for the purpose of improving the characterization of hardness in ADI.

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