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Review on Application of Machine Learning in Predicting Mechanical Properties of Metals

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Abstract: It is known that there are several types of metals present in real world in which we are supposed to choose the metal according to our need. Also, they possess several types of mechanical properties and according to these properties we can further proceed. In this work we use machine learning for calculating the mechanical properties. Also, in this work we use to increase the hardness of the steel. We need a metal piece and try to find the mechanical properties using machine learning algorithm. This metal piece is required to cut into many pieces of different grades and then find out the microstructures of those different grades of metals. For this work we require a microscope by which we find out the images of the microstructures and then apply the machine learning algorithm.
Keywords: Microstructures; Quenching; Quenching Medium; Machine Learning

I. INTRODUCTION

With the vast development of technologies different techniques are used to get the mechanical properties of the materials. To get the hardness of the material or to get another property of material different approach are there. Many researchers in the past does various work to get the mechanical properties. In this work we use quenching mediums to get the mechanical properties also use the microstructures of different grades of steel and with the use of machine learning algorithm we identify the properties of check the relationship between the microstructures and mechanical properties. Some characteristics of steel and Microstructures are given below.

II. STEEL

Steel is an alloy made up of iron with typically a few tenths of a percent of carbon to improve its strength and fracture resistance compared to other forms of iron. Carbon Steel contain trace amount of beside iron and Carbon. This group is the most popular group and mostly used. Most of the industries made carbon steel in large amount Because it is easy to make and demand in the market is high. Carbon steel is divided into three categories Low carbon steel/mild steel (0.3%) Medium carbon steel (0.3-0.6%) High carbon steel (.6) %. Stainless steel is used for outside construction work because of its good corrosion resistance quality and capability to withstand in the rough weather. These are also used in electrical equipment's. 304 stainless steel is extremely popular and most of the industries use this grade for the sanitary properties and used in medical fields and pipes, cutting tool etc. TOOL STEEL is used as a tool like for cutting drilling. The main component of this steel is tungsten, molybdenum, cobalt, vanadium which increase its heat resistance and its durability. And, tool made of this material do not loss its shape that is why also it is widely used. Alloy Steel is made by adding different alloying elements in it. The alloying material which are used in it are nickel, copper, chromium, and aluminum. This steel is used for their enhanced strength, ductility, corrosion, resistance, machinability by adding different elements in it.

III. MICROSTRUCTURE OF METALS

The microstructure of a material is composed of distinct phases of variable form, size, and distribution (grains, precipitates, dendrites, spherulites, lamellae, pores, etc.). The phases are distinguished from each other by their various crystalline, semi-crystalline or amorphous structures when observed with an optical or electron microscope. The engineer can obtain a wide range of properties by controlled microstructural modifications produced during processing. To have a clear understanding of the material behavior, it is needed to establish relationships between the macroscopic properties and phenomena occurring on the microstructural scale.

The microstructures formed in materials depend on the chemical composition and structure and the atomic mobility and on the presence of concentration gradients during processing. Microstructure formation is also strongly influenced by the amount of energy required to create new interfaces.

The microstructure of a material can influences its physical properties including corrosion resistance, strength, toughness, ductility, and hardness. These properties help determine how the material will perform in each application. Microstructures are always generated when a material undergoes a phase transformation brought about by changing temperature and/or pressure (e.g., a melt crystallizing to a solid on cooling). Microstructures can be created through deformation or processing of the material (e.g., rolling, pressing, and welding). The microstructure of a material (such as metals, polymers, ceramics, or composites) can strongly influence physical properties such as strength, toughness, ductility, hardness, corrosion resistance, high/low temperature behavior or wear resistance.

IV. AUSTENITE AND MARTENSITE MICROSTRUCTURE

Martensitic microstructures that are of various carbon contents and tempered at various temperatures not only compose the microstructure of through-hardened steel parts, but also are major components, in some form or another, of other heat-treated steel systems. Austenite has a cubic-close packed crystal structure, also referred to as a face-centered cubic structure with an atom at each corner and at the center of each face of the unit cell. Ferrite has a body-centered cubic crystal structure and cementite has an orthorhombic unit cell containing four formula units of Fe3C.

V. MACHINE LEARNING

Machine learning is a branch of artificial intelligence and computer science. It focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. Machine learning is an important part of data science which is an ever-growing field. It uses statistical methods, algorithm to make classifications or prediction, and to uncover key insights in data mining projects. This subsequently drive decision making within applications and businesses and impacting key growth metrics. The market demand for data scientist is constantly growing as big data continues to expand and grow. Based on the way of learning machine learning is divided into four main parts which are as follows-

1) Supervised Machine Learning
2) Unsupervised Machine Learning
3) Semi supervised Machine Learning
4) Reinforcement Learning

The task of imparting intelligence to machine is a challenging task, so it is divided into 7 parts, which include- Collecting data, preparing the data, choosing a model, training the model, evaluating the model, parameter tuning and making predictions. These steps are briefly explained under: -

A. Collecting Data

The only way for machines to initially learn something is through the data that we input through them. It is an important part of machine learning to collect reliable data so that the machine learning model can find the correct patterns. The accuracy of the model depends upon the quality of data fed to it.

B. Preparing the Data

To prepare the data, we must first put together the data we have. This makes sure that the data is evenly distributed and the ordering does not affect the learning process so we can randomize data without any problems. Then we need to clean the data by removing unwanted data and empty columns, rows, and duplicate values. The last step of preparation separates the data into 2 sets, one called the training set and one testing set.

C. Choosing a Model

The machine learning model determines the output we get from running a machine learning algorithm on the collected data. It is important to choose a model which is relevant to the worker’s certain project. It is also made sure which model is suited for numerical or categorical data and chosen accordingly.

D. Training the Model

Training is the most crucial step in machine learning as it passes the prepared data to your machine learning model to find patterns and make predictions. This is the step that ensures that model keeps learning over time to find patterns and make predictions.

E. *Evaluating the Model*

After training, it is checked how the model is performing. This is done with the help of testing the performance on previously unseen data. It is the same data that we split earlier and we already know falls under which category, so it is easy to trouble shoot if we get the desired results from our model or not.

F. *Parameter Tuning*

Once the model is created and evaluated, it is seen if its accuracy can be improved in any way. This is done by tuning the parameters present in the model as they are the variables in the model that the programmer decides.

G. *Making Predictions*

In the end, the model is used on unseen data to make predictions accordingly and accurately.

VI. QUENCHING AND MECHANICAL PROPERTIES

Khorrami and Mostafaei [1] examine the microstructure and mechanical properties of plain carbon steel and AISI (American Iron and Steel Institute) 430 ferritic stainless steel dissimilar welds are carried out and welding is conducted using ER309. Weld metal in the specimen welded with filler metal consists of duplex ferritic–martensitic microstructure while the microstructure of autogenous weld metal is fully ferritic. Volume fraction of martensite and precipitates in HAZ of AISI. Harriott and D. Spea in 2020 [2] investigate the performance of data-driven modeling for mechanical property prediction of a simulated microstructural dataset. This work also investigates the ability of machine-learning (ML) and deep-learning (DL) models to predict microstructure-sensitive mechanical properties in metal additive manufacturing (MAM) using results from high-fidelity, multi-physics simulations as training data. H. Assadi and Ghani in 2009 [3] found that pure aluminum was subjected to friction stir processing (FSP) to study the microstructures developed and its effects on the mechanical properties. In this technique, a specially designed non consumable cylindrical tool, rotating at high speed is traversed into the material along a particular length at a desired traverse speed. Purohi in 2015 [4] work on the mechanical properties and were improved by addition of ceramic particle like SiC etc. In this study, AA 5083 alloy-SiC composites have been fabricated by ultrasonic assisted Stir casting. Different weight % of Sic (3, 5, 8 and 10 wt %) were used for synthesis of composites. Saeid and Zadeh in 25 November 2008 was determine that the effect of the welding speed on the microstructure properties of friction stir-welded SAF 2205 duplex stainless steel was investigated. Sound joints were produced at welding speeds of 50, 100, 150, and 200 mm (about 7.87 in)/min and a groove-like defect caused by insufficient heat input obtained at the speed of 250 mm (about 9.84 in)/min. The microstructures of the stir zones consisted of fine equiaxed grains of α and γ phases and their grain sizes decreased with increasing welding speed. I this work, the effect of arc welding on microstructures and mechanical properties of industrial low carbon steel (0.19 wt. % C) was studied. This work represents a contribution to the study of the effect of shielded metal arc welding on industrial low carbon steel (0.19 wt. % C).

Ilham et al. [2] Aluminum-based composites, also known as aluminum matrix composites (AMC), can be heat treated to improve their mechanical properties. Quenching process parameters such as cooling rate, coolant, and cooling temperature are predicted to affect the mechanical properties of AMC. In this work, we present the results of a series of laboratory experiments to observe the hardening ability of his Al6061-Al2O3 composites subjected to quenching and particle surface treatments. There are 3 types of quenching agents and 2 types of strengthening particle treatments. Water, oil, brine, and 0% and 10% of his Al2O3 reinforcement are used for quenching. Hardness testing is performed on the Rockwell B scale according to ASTM (American Society for Testing Materials) E-18 specifications. The results obtained showed that the largest distortion was because of brine extinguishing agents on each variation. 10E (electroless plating) is harder than 10N (electroless plating). Based on this result, it can be concluded that the quenching and electroless plating treatments clearly affected the hardness of Al6061-Al2O3 composites.

Strobel et al. [3] High-strength 6000 series alloys use dispersoids formed during heating to homogenization temperatures to improve fracture toughness and suppress grain growth during the extrusion process. However, these dispersoids may serve as heterogeneous nucleation sites for unhardened Mg-Si precipitates upon delayed post-extrusion quenching. This reduces the content of Mg and Si in solid solution, lowering the achievable strength and hardness. This phenomenon is called extinction sensitivity. In this study, the hardening response of several 6000 series aluminum alloys is related to microstructural features, particularly dispersoid density. Therefore, after extrusion, the alloys were quenched at various rates and age hardened to peak strength. Quench sensitivity is related to the enthalpy associated with precipitation of the Mg-Si phase measured by DSC and to the dispersoid density. The results suggest that in alloys containing dispersoids, the quenching sensitivity is determined by the number density of the dispersoids. However, the influence of solute elements cannot be ruled out.

TEM (Transmission Electron Microscopy) investigations show that not only the general depletion of Mg and Si is responsible for the deterioration of mechanical properties, but the heterogeneous distribution of precipitates may be another determinant.

Nishibata and Kojima [4] studied the effect of cooling rate on hardness and microstructure of hot-worked boron steel containing 0.2% carbon by mass was investigated. Sheets with thicknesses of 1.6 mm (about 0.06 in) and 1.2 mm (about 0.05 in) were heated at 900 °C for 4 min. They were then pressed and simultaneously quenched in a mold or water. A simulated hot stamping test was also performed with different cooling rates. We measured the Vickers hardness of the quenched samples and observed their cross-sections with an optical microscope and a transmission electron microscope. The hot stamped samples have a self-tempered martensite microstructure and are softer than the water quenched samples which are lath martensite. Tempered martensite was distinguished from bainite by observing the precipitation of cementite. Below the Ms temperature, decreasing the cooling rate leads to a significant decrease in hardness, even if the cooling rate is higher than the upper critical cooling rate.

Hafeez and Farooq [5] investigated the effect of the quench bath on the microstructure and hardness of AISI 1035 steel. Two categories of quench baths were selected, including water-based and oil-based baths. Water-based baths include tap water, distilled water, brine solution, salt water, sodium hydroxide solution, and oil-based quench baths include fish oil, coconut oil, olive oil, used motor oil, and 310 Quench. Contains oil. Microstructure and Vicker hardness were characterized by optical microscope and micro-Vicker hardness tester. The results show that water-based quenching baths produced higher hardness values due to the formation of a greater proportion of martensite with low levels of retained austenite, whereas oil-based baths produced moderate hardness values due to the formation of bainite, pearlite, and it retains an austenitic structure which has shown to produce hardness values of about.

Zhu et al. [6] studied **t**he microstructure and hardness of high-carbon martensitic stainless steel (HMSS) were studied using thermal expansion spectroscopy, Thermo-Calc, scanning electron microscopy, X-ray diffraction, and ultra-high temperature confocal microscopy. The results show that the test steel should be austenitized in the temperature range of 1025-1075 °C. This results in a maximum hardness of 62 HRc with a microstructure consisting of martensite, retained austenite and some undissolved carbides. As the austenitizing temperature increases, the amount of retained austenite increases, while the carbide volume fraction first increases and then decreases. The onset and end temperatures of martensite formation decrease as the cooling rate increases. The air-quenched samples have less retained austenite, a more compact microstructure and higher hardness compared to the oil-quenched samples. In HMSS, martensitic transformation occurs in a few isolated regions with slow nucleation rates.

VII. MICROSTRUCTURE OF METALS

The International Welding Institute (IIW) microstructural classification scheme for ferrous weld metals was studied as a basis for quantifying the complex microstructure of steels. The aim was to cover the full range of microstructures observed in heat-affected zones of mild and low-alloy steel products, as well as ferritic weld metals and base plates. We briefly described the formation mechanism of the main structures and characteristic ferrite morphologies generated in the reconstruction and dislocation transformation regions of iron-based materials. The classifications and terminology used for intragranular and austenitic grain boundary microstructural components are considered, as are the ways in which transformation products are oriented in space. Issues arising in the relationship between microstructural components and main structures are discussed in detail and solutions are proposed. The microstructural classifications and terminology used in the IIW scheme were created, and new terminology was incorporated into tables containing descriptions of major structural and subcategory components. A new classification scheme was defined as a flow chart with guidelines for identifying the main structures. Evaluation exercises were performed using the new scheme. They demonstrate that they can achieve a reasonable degree of agreement between operators in identifying transformation products that form primary ferrite, pearlite, martensite, and ferrite cladding and acicular ferrite structures, particularly Widmannstatten ferrite and bainite. is showing. Thus, means are provided for obtaining database information for developing microstructure-property relationships or for generating data for calibrating physical models with dominant structures as an output.

Fernandez et al. [7] studied the microstructure and high-temperature mechanical properties of siliconized silicon carbide ceramics (reaction-bonded, reaction-formed, and biomorphic SiC) have been studied. We analyzed the microstructural differences between these materials. Reaction-formed biomorphic SiC exhibits superior creep resistance and high-temperature strength to reaction-bonded SiC. Moreover, both materials show a continuous decrease in creep rate. This is more pronounced at higher temperatures and higher silicon content. This behavior is explained in detail using a model of creep driven by a viscous grain boundary phase. Biomorphic SiC exhibited the greatest strength when axially compressed. The strength of the reaction-formed SiC is about the average of the axially and radially compressed biomorphic SiC. The dependence of hot compressive strength on microstructure and SiC volume fraction is discussed in relation to the minimum solid area approach.

Peel et al. [8] studied the friction welding processes, friction stir welding (FSW) involves precise control of many welding parameters (e.g., tool design, rotational speed, travel speed), thus allowing control of the energy input to the system. However, the effect of different welding speeds on welding properties remains an area of uncertainty. In this article, the microstructures, mechanical properties, and residual welds of four AA5083 aluminum friction stir welds produced under different conditions are investigated. We report the results of a stress study, showing that weld properties are governed by heat input rather than mechanical deformation by the tool.

Bhadeshia and Svensson [9] studied the physical models for developing microstructures have the potential to reveal new phenomena and properties. It also helps identify the driving variables. The ability to model the microstructure of weld metal derives from a deep understanding of the phase transformation theory that governs the changes that occur as the weld solidifies and cools to ambient temperature. Significant advances have been made using thermodynamics and dynamics theory, considering various alloying additions, non-equilibrium cooling conditions, and many other variables necessary to fully characterize the weld components. increase.

These aspects are reviewed to provide a detailed description of the methods involved and some important unresolved issues. It is now well known that trace concentrations of certain elements can have a significant effect on the transformation behavior of weld metals. Some of these elements are the same as those used in the production of micro alloyed forged steel, while others enter the fusion zone as an inevitable consequence of the welding process. The theory available for dealing with such effects is still insufficient. Learn how to include the effects of trace elements, such as oxygen, aluminum, boron, nitrogen, titanium, and rare earth elements, into your microstructure prediction scheme. The extremely high sensitivity of advanced micro alloy steel to carbon concentration is also evaluated. We discuss some basic ideas on how to incorporate the approximate relationship between weld microstructure and mechanical properties into a computer model.

Monzen and Watanabe [10] studied the correlation between microstructure and mechanical properties of 0.1 weight% Magnesium-added and Magnesium-free Copper-2.0 wt% Ni-0.5 wt% Si alloys were tested at 400°C aging. The addition of Mg promotes the formation of disc-shaped Ni2Si precipitates. Cu-Ni-Si-Mg alloys have higher strength and stress relaxation resistance than Cu-Ni-Si alloys. The improvement in strength and stress relaxation resistance is considered due to the reduction of the distance between precipitates due to the addition of Mg and the drag effect of Mg atoms on dislocation movement. The Cu-Ni-Si alloy with large grain size of 150 μm exhibits higher stress relaxation resistance than the alloy with small grain size of 10 μm due to the lower density of mobile dislocations in the former alloy.

Lutjering [11] studied that when we attempt to summarize the relationships between processing, microstructure, and mechanical properties of two-phase (α+β) titanium alloys. Most structural applications of titanium alloys require optimization or balancing of a variety of key mechanical properties (yield strength, ductility, HCF, LCF, da/dN for micro- and macro-cracks, $K^{I}C$ and creep). There are many variables in fine structure, but of the many possible correlations, only a few basic principles can be shown to be really important. One of these is the relationship between cooling rate, colony size, and hatch length. This translates directly to the advantages of bimodal (duplex) microstructures, including reproducible and robust processing pathways that can be used for most applications.

Zaefferer et al. [12] studied that SEM (Scanning Electron Microscopy) and TEM electron diffraction techniques were used to examine different heat treated samples of low-alloy TRIP steel. The aim was firstly to identify the structural components of austenite, ferrite, bainite and martensite, secondly to obtain information on the γ-α phase transformation mechanism, and thirdly to relate the mechanical properties and structure of the samples. did. Bainite always occurs in relation to the orientation gradient of the surrounding ferrite matrix. It consists of fine flakes of ferrite and austenite in sharp Kurdyumov-Sachs orientations with each other. This has been interpreted in terms of the substitutional bainite formation mechanism. The microstructure is formed by the growth of γ-grains during intercritical annealing and the subsequent shrinkage of these grains during cooling without the nucleation of new α-grains. The transformation occurs first reconstitutionally to ferrite and then transiently to bainite at low temperatures. The mechanical properties of samples with different heat treatments are most affected by the amount and distribution of carbon in retained austenite and the degree of recovery of bainite and austenite.

Wood et al. [13] studied the effects of austenitizing temperature on both the plane strain fracture toughness, KIC, and microstructure of AISI 4340 were investigated. Austenitizing temperatures of 870°C and 1200°C were used. All 1200 °C austenitized samples were furnace cooled from a higher austenitizing temperature and then oil quenched from 870 °C. Transmission electron microscopy showed a clear significant increase in the amount of retained austenite present in the samples austenitized at higher temperatures. Automatization at 870°C produced virtually no retained austenite. Only small amounts were found sparsely scattered over the examined area.

Significantly altered microstructures were observed for the samples austenitized at 1200 °C. A fairly continuous 100-200 Å thick film of retained austenite was observed between the martensitic ridges over most of the examined area. Furthermore, the sample austenitized at 870 °C contained twinned martensitic plates, whereas the sample austenitized at 1200 °C showed no twinning. Plane strain fracture toughness measurements showed an approximately 80% increase in toughness for specimens austenitized at 1200°C compared to those austenitized at 870°C. Yield strength was not affected by austenitizing temperature. The possible role of the removal of retained austenite and twinned martensite in improving the fracture toughness of samples austenitized at higher temperatures is discussed.

Youngblood and Raghavan [14] shows that 300M steel undergoes various quenching and tempering heat treatments. The areal elongation fracture toughness, tensile strength and yield strength were evaluated. Results show that for hardened and tempered steels, austenitizing above 1255 K (1800°F) can significantly improve toughness without loss of strength. The low fracture toughness of conventionally austenitized 300M steel (1144 K (1600°F)) is attributed to undissolved precipitates present on both the sub microstructure and fracture surface that promote quasi-cleavage fracture. It seems to be. These precipitates appeared to disappear in the range 1200-1255 K (1700-1800°F).

VIII. APPLICATION OF MACHINE LEARNING IN PREDICTING MECHANICAL PROPERTIES

Bulgarevich et al. [15] shows a novel and highly effective approach to pattern recognition in optical microscope images of steel is demonstrated for advanced material characterization. It is based on a fast random forest statistical machine learning algorithm for reliable automatic segmentation of typical steel microstructures. Their proportions and location ranges showed excellent agreement between machine learning and manual findings. Combining accurate microstructural pattern recognition/segmentation techniques with other appropriate image processing and analysis mathematical methods, large amounts of image data can be processed quickly for quality control and new steels with desirable properties. can find.

LeiWang and YoshitakaAdachi [16] studied that the designing the new materials with useful properties is becoming increasingly important. The Materials Genome Integration System Phase and Property Analysis (MIPHA) and rMIPHA (based on the R programming environment) machine learning tools were independently developed to accelerate the materials discovery process through a data-driven materials discovery approach. In current work, MIPHA and rMIPHA are applied to steels to perform machine learning-based 2D/3D microstructural analysis, direct property prediction analysis, and inverse property versus microstructural analysis. The results show that the predictive model works well. Microstructural inverse investigations related to desired target properties (stress-strain curves, tensile strength, total strain, etc.) were achieved. MIPHA and rMIPHA are still being improved. Inverse analysis from microstructure to processing will be realized in the future.

IX. CONCLUSION

Through this paper, we have studied the effects of quenching on mechanical properties of metal, and the difference in those mechanical properties from different quenching mediums and the speed at which workpiece is cooled. We also studied about microstructures and correlated them to the mechanical properties of metals, so that we can develop a machine learning algorithm, to find the mechanical properties of metal based on the microstructures. Different people have taken different approach towards microstructures and mechanical properties, such as the formation of martensite and austenite and how it affects the hardness of metal workpiece. At last, it is shown as how to apply machine learning after taking a large sample data for training and testing sets.

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