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# Optimizing the SG Iron Properties by Designing an Automated Microstrucure Image Analysis System

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***Abstract—In this work an attempt has been made to optimize the SG iron properties by designing an automated microstructure image analysis system. Samples of different diameters were used, to cover a wide range of solidification cooling rate. The microstructures were observed and we have generated the correlations between mechanical properties, nodularity and diameter (cooling rate). This knowledge based data is used for designing the network. We have designed an algorithm using artificial neural network [4]. The microstructural images are segmented using Otsu's threshold segmentation technique. By training and testing the network, the system can identify the optimized mechanical properties and cooling rate for a given nodularity of SG iron sample and vice versa. Also it can predict the expected chemical composition of the sample material. Also microstructure observation reveals that, as the sample diameter increase the graphite nodule diameter increases and the nodule count decreases [1]. As the Sample diameter increases, hardness value, yield strength and ultimate tensile strength decrease. All these properties vary as the sample diameter (cooling rates) varies.***

***Keywords—Artificial Neural Network, SG iron, Nodularity, Solidification Cooling rate.***

## I. INTRODUCTION

In the manufacturing of materials, the morphology of the graphite grains and its distribution is regarded as the key factor. When the carbon is diluted in iron at molten state with amount of more than 2.1% up to 6.67%, it precipitates to form graphite grains (particles) [21]. The shape of these particles can vary widely depending up on the presence of other impurities (particularly nodularizing elements such as Mg) and on the cooling rate. A way of controlling the microstructure (shape of graphite grains) of cast iron is done by varying the chemical composition and by controlling the cooling rates during solidification. By controlling the cooling rate we can obtain optimum nodularity [17]. This optimum nodularity helps to get the optimum mechanical properties, a component should posses. Controlling the cooling rate by manual methods is very difficult task, as it requires knowledge based expert metallurgist, who can analyze the various parameters that affects the cooling rate. It is time consuming, non repetitive, costly and may leads to subjective errors.

With the advent of modern analytical tools it seems appropriate to make automation in the system, which can give precise, accurate and consistent results. Automated image analysis allows the operator to evaluate many more fields to better obtain an average rating of the microstructure. Image analysis will also minimize the variability of the measurement due to operator bias. As we are studying SG iron material, its properties depends on the microstructure, and microstructure can be more precisely analyzed by using digital image analysis systems [10]. Hence in this project an attempt has been made, to develop an algorithm by using artificial neural network system, which correlates nodularity, mechanical properties and the cooling rate. Further this trained system automatically identifies the best possible or optimized results for a given nodularity. Hence we can obtain the optimized mechanical properties. The important applications of SG Iron in the manufacturing of critical components like crank shaft in of Engine, Brake caliper, Rolling mill rolls, Piston for impact drills and molding boxes and mould box clamps etc[11]. The graphite nodularity is a critical attribute for materials selections in the above applications and its effect on the mechanical properties.

## II. MATERIAL USED

We have used the microstructure images of SG iron material with varying compositions, magnifications and diameters to cover wide range of cooling rates. The microstructure images are used for experimentation and for training neural network.

## III. PROPOSED METHOD

The proposed method is based on neural network approach and has two phases: training and testing. Each phase consists of preprocessing of microstructure images as described below.

### A. Preprocessing

Generally, the microstructure images suffer from noise and artifacts developed at the time of specimen preparation. This stage is of high importance in achieving good results in segmentation and further process [9]. We have used circular averaging filter with radius 2, followed by the morphological closing with fixed structuring element, „disk" of radius 2, in order to de-noise the image. We have used threshold segmentation method for segmenting the graphite grains from the background ferrite matrix. The segmented image is labeled.

**B. Algorithm**

The training phase of neural network is given in the following algorithm.

Neural network training (or Network 1)

**Step 1:** Read input image.

**Step 2:** Segment the image using Otsu's threshold segmentation method.

**Step 3:** Label the regions.

**Step 4:** Compute the nodularity by area value of each of the labeled region, which is a graphite grain using eqn (2).

**Step 5:** Compute the nodularity by count using eqn (3).

**Step 6:** Compute average nodule size.

**Step 7:** Input mould diameter.

**Step 8:** Input diameter of mould, average nodule size, nodule count, nodularity value to ANN (Radial basis function) and train the network.

**Building more neural networks:**

**Network 2:** By changing the input sets in the Step 7 to, {Carbon, silicon, manganese, phosphorous, sulphur, magnesium, aluminium and iron} a new network for determining microstructure properties and mechanical properties of the material can be built.

**Network 3:** By changing the input sets in the step 7 to, {tensile strength, yield strength, % elongation and hardness} a new network for determining microstructure properties and chemical composition of the material can be built.

**Network 4:** By changing the input sets in the step 7 to, {Carbon, silicon, manganese, phosphorous, sulphur, magnesium, aluminium and iron} a new network for determining mechanical properties of the material can be built.

## IV. EXPERIMENTAL RESULT AND DISCUSSION

For the experimentation, the artificial neural network system is used. The cylindrical bars (samples) of SG iron were cast in sand mould. The microstructures were observed in as polished condition [Annexure II] using the microscope of 100x magnification. The microscope is connected to CCTV Camera, which grabs the images. These images are captured with the help of image card reader, and it is saved in Jpeg format. By analyzing the variation in microstructures and mechanical properties with the variation of sample diameter, we have developed a correlation between microstructure mechanical properties and sample diameter (cooling rate).

With this knowledge base data obtained from the experimentation is used for training the system. By training and testing the artificial neural network system, the system can identify the best possible (optimized) mechanical properties for a given nodularity of the sample and vice versa. It can also identify the diameter for which these mechanical properties can be obtained. Also this automated system can predict the expected chemical composition of the sample material. The below tables 1, 2 & 3 show the chemical analysis of the sample materials, mechanical properties and microstructural properties.

***Table 1:*** **Chemical Composition SG Iron sample**

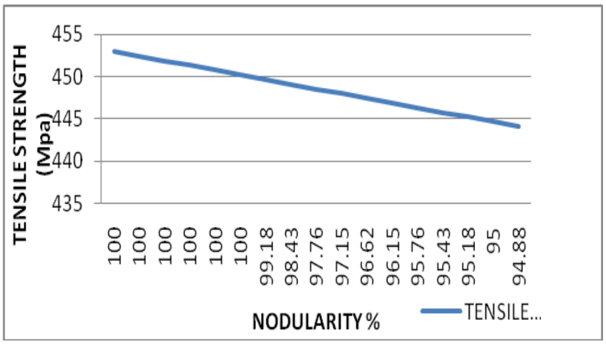
| DIAMETER (mm) | Fe% | C% | Si% | Mn% | P% | S% | Mg% | Al% |
|---|---|---|---|---|---|---|---|---|
| 15 | 91.35 | 3.655 | 1.3875 | 0.47525 | 0.036 | 0.0357 | 0.00125 | 0.055 |
| 17 | 93.24 | 3.6744 | 1.4376 | 0.4724 | 0.03732 | 0.0344 | 0.00144 | 0.054 |
| 19 | 94.22 | 3.6906 | 1.4839 | 0.46941 | 0.03848 | 0.0332 | 0.00161 | 0.053 |
| 21 | 93.16 | 3.7036 | 1.5264 | 0.46616 | 0.03948 | 0.0321 | 0.0176 | 0.052 |
| 23 | 92.13 | 3.7134 | 1.5651 | 0.4626 | 0.04032 | 0.0310 | 0.00189 | 0.051 |
| 25 | 90.14 | 3.720 | 1.600 | 0.459 | 0.041 | 0.030 | 0.002 | 0.005 |
| 27 | 94.06 | 3.7234 | 1.6311 | 0.45509 | 0.04152 | 0.0290 | 0.00209 | 0.049 |
| 29 | 92.04 | 3.7236 | 1.6584 | 0.45096 | 0.04188 | 0.028 | 0.00216 | 0.048 |
| 31 | 91.03 | 3.7206 | 1.6819 | 0.44661 | 0.04208 | 0.0272 | 0.00221 | 0.047 |
| 33 | 93.02 | 3.7144 | 1.7016 | 0.44204 | 0.04212 | 0.0264 | 0.00224 | 0.046 |
| 35 | 94.02 | 3.705 | 1.7175 | 0.43725 | 0.042 | 0.0257 | 0.00225 | 0.045 |
| 37 | 92.03 | 3.6924 | 1.7296 | 0.43224 | 0.04172 | 0.0250 | 0.00224 | 0.044 |
| 39 | 94.04 | 3.6766 | 1.7379 | 0.42701 | 0.04128 | 0.0244 | 0.00221 | 0.043 |
| 41 | 91.07 | 3.6576 | 1.7424 | 0.42156 | 0.04068 | 0.0239 | 0.00216 | 0.042 |
| 43 | 90.10 | 3.6354 | 1.7431 | 0.41589 | 0.03992 | 0.0234 | 0.00209 | 0.041 |
| 45 | 92.13 | 3.610 | 1.740 | 0.410 | 0.039 | 0.023 | 0.002 | 0.040 |
| 47 | 91.17 | 3.5704 | 1.7521 | 0.4038 | 0.03872 | 0.022 | 0.00199 | 0.039 |
| 49 | 93.18 | 3.5576 | 1.7604 | 0.39756 | 0.03828 | 0.0217 | 0.00196 | 0.038 |
| 51 | 94.2 | 3.5416 | 1.7649 | 0.39101 | 0.03768 | 0.0211 | 0.00191 | 0.037 |
| 53 | 93.23 | 3.5224 | 1.7656 | 0.38424 | 0.03692 | 0.0206 | 0.00184 | 0.036 |
| 55 | 92.26 | 3.5 | 1.7625 | 0.37725 | 0.036 | 0.0202 | 0.00175 | 0.035 |
| 57 | 93.30 | 3.4744 | 1.7556 | 0.37004 | 0.03492 | 0.0198 | 0.00164 | 0.034 |
| 59 | 91.36 | 3.4456 | 1.7449 | 0.36261 | 0.03368 | 0.0195 | 0.00151 | 0.033 |
| 61 | 94.46 | 3.4136 | 1.7304 | 0.35496 | 0.03228 | 0.0193 | 0.00136 | 0.032 |
| 63 | 93.48 | 3.3784 | 1.7121 | 0.34709 | 0.03072 | 0.0191 | 0.0019 | 0.031 |
| 65 | 94.56 | 3.340 | 1.690 | 0.350 | 0.029 | 0.019 | 0.001 | 0.003 |

***Table 2:*** **Mechanical properties**

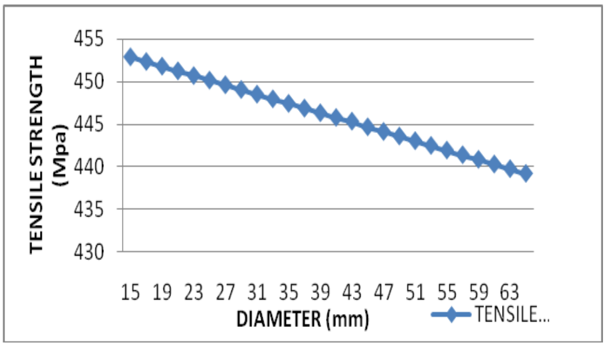
| **Sample dia (mm)** | **Ultimate tensile strength (Mpa)** | **% Elongation** | **Hardness (BHN)** | **Yield strength (Mpa)** |
|---|---|---|---|---|
| 15 | 452.91 | 17.92 | 166.5 | 294.48 |
| 17 | 452.36 | 18.0 | 165.6 | 294.25 |
| 19 | 451.81 | 18.08 | 164.7 | 294.01 |
| 21 | 451.26 | 18.16 | 163.8 | 293.74 |
| 23 | 450.71 | 18.24 | 162.9 | 293.46 |
| 25 | 450.17 | 18.32 | 162.0 | 293.16 |
| 27 | 449.62 | 18.40 | 161.10 | 292.84 |
| 29 | 449.07 | 18.48 | 160.20 | 292.51 |
| 31 | 448.52 | 18.56 | 159.3 | 292.16 |
| 33 | 447.97 | 18.64 | 158.4 | 291.79 |
| 35 | 447.43 | 18.72 | 157.5 | 291.40 |
| 37 | 446.88 | 18.80 | 156.6 | 291.0 |
| 39 | 446.33 | 18.89 | 155.7 | 290.58 |
| 41 | 445.78 | 18.97 | 154.8 | 290.14 |
| 43 | 445.34 | 19.05 | 153.9 | 289.69 |
| 45 | 444.68 | 19.14 | 153.0 | 289.22 |
| 47 | 444.13 | 19.21 | 152.10 | 288.73 |
| 49 | 443.59 | 19.30 | 151.20 | 288.22 |
| 51 | 443.04 | 19.38 | 150.30 | 287.70 |
| 53 | 442.49 | 19.46 | 149.40 | 287.16 |
| 55 | 441.94 | 19.54 | 148.50 | 286.60 |
| 57 | 441.39 | 19.62 | 147.60 | 286.03 |
| 59 | 44.085 | 19.71 | 146.70 | 285.44 |
| 61 | 440.30 | 19.79 | 145.80 | 284.83 |
| 63 | 439.75 | 19.87 | 144.90 | 284.20 |
| 65 | 439.20 | 19.96 | 144.0 | 283.56 |

***Table 3.*** **Microstructural properties**

| Sample materials (dia) | Nodule Size (µm) | Nodule count/ ($mm^2$) | Nodularity percentage |
|---|---|---|---|
| 15 | 9 | 1120 | 100 |
| 17 | 9.2 | 1110 | 100 |
| 19 | 9.4 | 1100 | 100 |
| 21 | 9.6 | 1090 | 100 |
| 23 | 9.8 | 1080 | 100 |
| 25 | 10.0 | 1070 | 100 |
| 27 | 10.2 | 1060 | 99.18 |
| 29 | 10.4 | 1050 | 98.43 |
| 31 | 10.6 | 1040 | 97.76 |
| 33 | 10.8 | 1030 | 97.15 |
| 35 | 11.0 | 1020 | 96.62 |
| 37 | 11.2 | 1010 | 96.15 |
| 39 | 11.4 | 1000 | 95.76 |
| 41 | 11.6 | 990 | 95.43 |
| 43 | 11.8 | 980 | 95.18 |
| 45 | 12 | 970 | 95 |
| 47 | 12.2 | 960 | 94.88 |
| 49 | 12.4 | 950 | 94.83 |
| 51 | 12.6 | 940 | 94.86 |
| 53 | 12.8 | 930 | 94.95 |
| 55 | 13 | 920 | 95.12 |
| 57 | 13.2 | 910 | 95.35 |
| 59 | 13.4 | 900 | 95.66 |
| 61 | 13.6 | 890 | 96.03 |
| 63 | 13.8 | 880 | 96.48 |
| 65 | 14 | 870 | 97 |

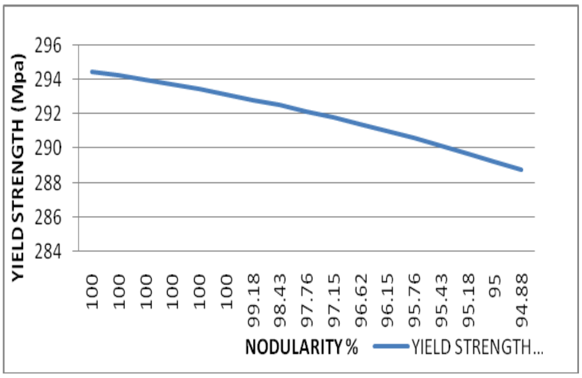



***Graph1.*** **Tensile strength v/s Nodularity**

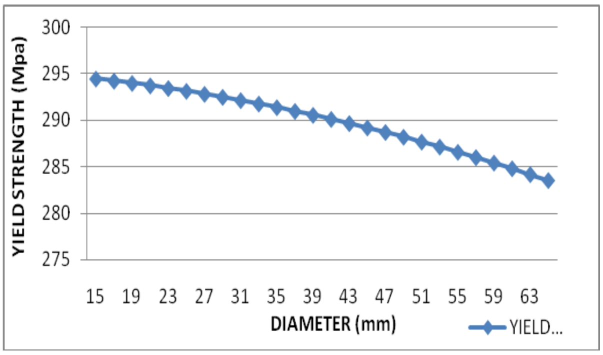



***Graph 2.*** **Tensile strength v/s Diameter**

Table 2 summarizes the tensile properties of the SG iron sample cast in sand mould. The above graph1shows that the tensile properties of the SG iron depend on nodularity, as the nodularity decreases the tensile properties also decreases [4]. From the graph 2 it is observed that there is decrease in the tensile strength with increase in the sample diameter [3]. The expected chemical composition of the sample materials is shown in table1

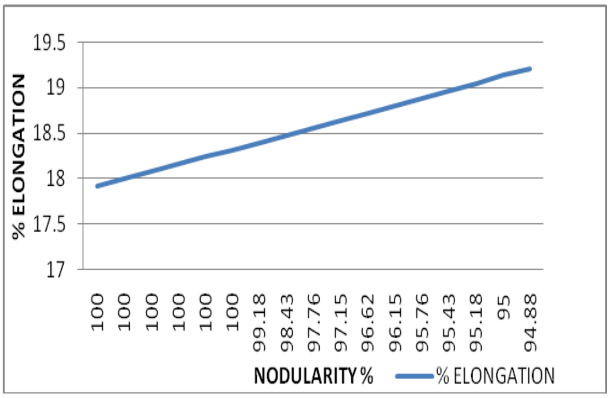



***Graph 3.*** **Yield strength v/s Nodularity**

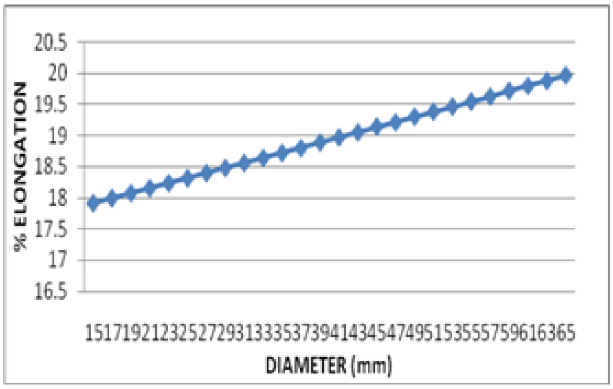



***Graph 4.*****Yield strength v/s Diameter**

Table 2 summarizes the Yield strength properties of the SG iron sample cast in sand mould. From the graph 3 it is observed that there is a decrease in the yield strength with decrease the nodularity [4]. From the graph 4 it is observed that there is a decrease in the yield strength with increase the sample diameter [3]. The expected chemical composition of the sample materials is shown in table1.

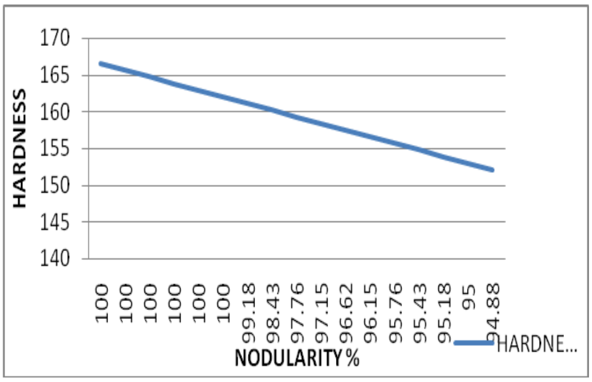



***Graph 5.*** **% Elongation v/s Nodularity**

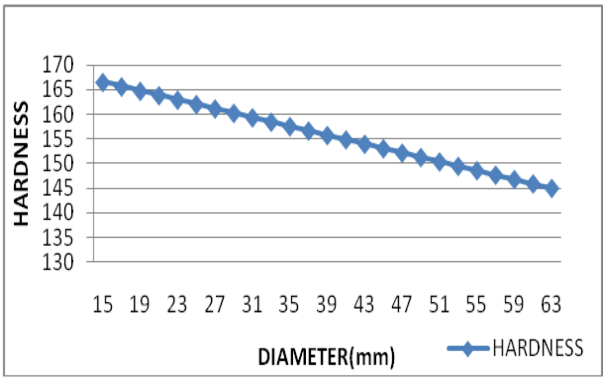



***Graph 6.*** **% Elongation v/s Diameter**

Table 2 summarizes the % elongation of the SG iron sample. From graph5, it is observed that there is an increase in the% elongation with the decrease in the nodularity % [4]. Graph6 shows an increase in the% elongation can be observed with the increase in the sample diameter [3]. The expected chemical composition of the sample materials is shown in table1.

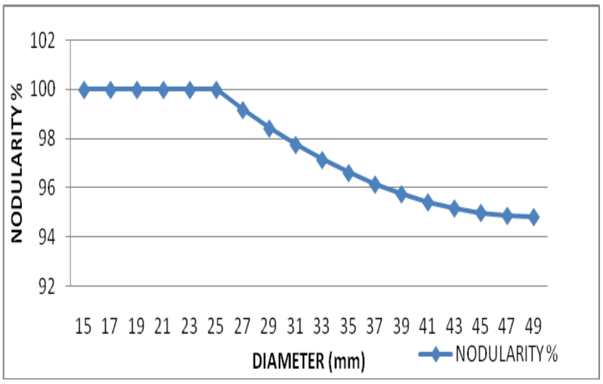



***Graph7.*** **Hardness v/s Nodularity**




***Graph 8.*** **Hardness v/s Diameter**

Table2 summarizes the variation of hardness valve with the nodularity and sample diameter. Graph 7, shows there is an increase in the hardness value with the increase in the nodularity% [4]. From the graph 8, it is observed that there is a decrease in the hardness valve with increase of sample diameter [3]. The expected chemical composition of the sample materials is shown in table1.




***Graph9.*** **Diameter v/s Nodularity**

From the graph1 to graph 8, it can be observed that, there is a correlation between the nodularity, mechanical properties and the sample diameter. This can be clearly observed in the graph 9. Graph 9 shows there is decrease in the nodularity with the increase in the sample diameter.

## V. CONCLUSION

We have developed an automated image analysis system. This system generates the best possible (optimized) results, which helps in optimizing the SG Iron properties. It is fast, economical and simple to operate.

The developed system uses artificial neural network approach, to predict the optimum nodularity of SG iron for a given set of mechanical properties and determines what should be the sample diameter, so as to obtain that nodularity and vice versa. Also the expected chemical composition of the material can be predicted by using this automated system.

The method is robust and invariant under geometry, lighting transforms, quality and variety of magnifications of microstructure images. The experimental results show that as the sample diameter increases the nodule size (µm) and graphite nodule diameter increases. And as the sample diameter increases the number of nodules/mm² and nodularity (%) of the sample decreases.

The results can be further improved by using suitable preprocessing methods and feature sets. The training samples images play an important role in artificial neural network approach. Hence the testing and judgment of properties can be expected with increase in samples and acquiring more microstructure images from more fields. Specimen preparation techniques can also improve results.

Also we have developed the correlation between microstructural properties with mechanical properties and cooling rate of known samples .The microstructural feature reveals that, as the sample diameter increases, the nodularity of the sample decreases and the ultimate tensile strength, yield strength and hardness also decrease and the Percentage elongation will increase.

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