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Microstructure Image Analysis for Estimating Mechanical Properties of Ductile Cast Iron

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ABSTRACT

The digital image processing and computer vision technologies have key role to play in the field of material manufacturing and quality control. The microstructure images of materials provide vital information about materials properties. The microstructure visual and mechanical properties are strongly related. The mechanical properties, namely, yield strength, tensile strength and elongation, of ductile iron are directly dependent on ferrite composition and nodularity value of the material. Castings with poor nodularity will exhibit lower tensile elongation and often do not meet minimum tensile strength and finally impact strength requirements. Hence, it is established by experimental results that the composition and nodularity value of the material have paramount importance in material manufacturing.

In this paper, a novel automatic method of digital image analysis for estimating important mechanical properties with the help of microstructure visual properties has been proposed. Microstructure image analysis is performed for deriving microstructure properties, namely, nodularity value and percentage of ferrite phase present in material sample. A fuzzy rule based inference system is built using known authentic relationship data published in the research literature [3] to estimate important mechanical properties of the sample material using nodularity value and percentage of ferrite phase. With the inputs, namely, percentage of ferrite phase and nodularity values, to fuzzy inference system, the mechanical properties, namely, yield strength, tensile strength and elongation are predicted. The nodularity of the samples were determined by using image analysis techniques based on ASTM A 247-67(1968) standard. The automatic image analysis minimized the variability of the measurement due to operator bias. The results of the proposed method are compared with results obtained by manual method. The results of proposed method are accurate and close to practical limits. The proposed method is easily repeatable, fast and economical and is expected to be useful in manufacturing of ductile cast iron and quality control practices.

Keywords

Fuzzy inference system, ductile iron, nodularity, image analysis, microstructure

1. INTRODUCTION

It is not imperative that the digital image processing (DIP) and computer vision (CV) technologies are highly supportive in material manufacturing and quality control disciplines. Many visual based methods provide key inputs for material manufacturing and quality control, which are automated with the help of DIP and CV technologies [1,2,4,8,10,12]. The microstructure images of materials (Fig.1) are processed using digital image processing techniques and the microstructure properties are assessed. The microstructure properties of the material and the mechanical properties are closely related [3,5,6,7,9,11,13]. The ductile cast iron is produced to have a wide range of properties through control of the microstructure.

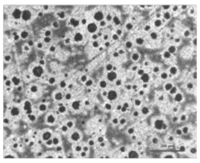

Fig.1: Microstructure image of ductile cast iron

Therefore, careful study of microstructure properties is very important in material manufacturing. The common defining characteristic of this group of materials is the shape of the graphite. The shape of the graphite is commonly defined as nodular, flake and irregular. The mechanical properties of ductile iron are dependent on nodularity value. The material sample with higher nodularity value is called nodular cast iron. Castings with poor nodularity will exhibit lower tensile elongation and often do not meet minimum tensile strength and finally impact strength requirements. Degenerate graphite particles are stress risers and can also reduce the fatigue strength of ductile iron. Consequently, industrial specifications usually establish the minimum acceptable percent nodularity allowed in a part. Hence, the accuracy in estimation of nodularity value of material is important. The prevailing visual based manual technique often produces biased results due to human natural fatigue and visual limitations [2,6,7,9,13]. Manual based results are highly dependent on expert's visual judgment and not repeatable.

The estimation of ferrite quantity and nodularity value by individuals has been shown to be quite subjective; particularly as nodularity decreases (it is easier to recognize 95 to 100% nodularity). Several investigators have shown a correlation between nodularity and mechanical properties but, again, the correlations are based on visual estimates of nodularity and ferrite quantity [1,4,8,11,2,13]. With the advent of modern computational facilities and analytical tools, it seems appropriate to reconsider this analytical issue. To improve the precision of the nodularity measurement, nodularity was determined based on ASTM A 247-67(1968) [3,6] standard. The shape factor used for distinguishing nodules from other graphite inclusions is "compactness". The measurement of 'compactness' of an object is determined using Eq. 1 and it is defined as,

$$Compactness = \frac{Perimeter^2}{4*\pi*Area} \quad (1)$$

where, $Perimeter$ is the length of border of the graphite particle and $Area$ is the area of graphite particle. Then the nodularity value is determined using the Eq.2 and it is defined as,

$$Nodularity = \frac{No.of\ particles\ meting\ compactness \geq 0.70}{Total\ No.of\ particles\ in\ sample}\ x100 \quad (2)$$

2. MATERIALS USED

Selected test bars were chosen for metallographic evaluation. The samples were polished using standard mechanical techniques using silicon carbide abrasives in accordance with ASTM standard E3-01. The mounted specimens were final-polished using colloidal silica media with a 0.05 µm particle size. The microstructure images of polished specimens were acquired by exposing the polished surface under light optical microscope. For each sample, 25 microstructure images from 25 distinct places (fields) on surface of the sample are acquired.Analysis of more number of microstructure images from more number of fields provides more accurate average rating in quantification results.

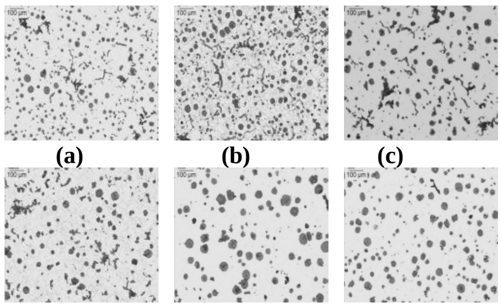
(a) (b) (c) (d) (e) (f)

Fig. 2: (a)-(f). Microstructure images of cast iron

3. PROPOSED METHOD

The proposed method consists of three stages, namely, (i) microstructure image processing, (ii) determining nodularity value of graphite and the quantity of ferrite phase and (iii) building the fuzzy rule based inference system for estimating mechanical properties. Each of these stages is presented in the following sections.

3 1 .Microstructure image pre-processing

De-nosing microstructure image: Generally, microstructure images suffer from impulse noise. In the proposed method, all the microstructure images are pre-processed to remove impulse noise by applying 'selective median switching filter' [14].

Segmentation: The de-noised image is segmented using Otsu's segmentation method for segmentation of various regions present in the microstructure images. Each region is potentially a graphite particle. The background region is the ferrite (Fe) region. Then each particle is subjected to determination of its nodularity value. The Fig. 3 (a) – (c) shows sample results of de-noising and segmentation of the microstructure images shown in Fig. 2(a)-(c), respectively.

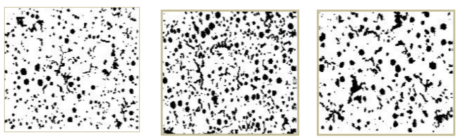
(a) (b) (c)

Fig. 3: (a)-(c) Results of de-noising and segmentation of microstructure images shown in Fig. 2(a)-(c).

3.2 Determining the nodularity value and quantity of ferrite phase

Nodularity of the sample microstructure image is determined by automatic digital image analysis. In automatic digital image analysis method, twenty five random fields of microstructure image at 100x magnification were analyzed. ASTM A 247-67(1998) standard proposed by American Standards for materials manufacturing is used as the basis for determining nodularity. The shape factor used for distinguishing nodules from other graphite inclusions is "compactness". As per the said standards, a particle is considered as nodular only when it's 'compactness' value is more than or equal to 0.70 and the size of particle is more than 10 µm.

The ferrite phase is determined using pixel count method. If a pixel value is above 238 (heuristic value) [2], then it is considered as belonging to ferrite phase and hence, considered in determining the quantity of ferrite phase. The ferrite phase is determined using Eq. 3.

$$Ferrite\ phase\ \% = \frac{No.of\ pixels\ belonging\ to\ Fe\ phase}{Total\ No.of\ pixels\ in\ the\ image} \times 100 \quad (3)$$

Algorithm 1:

Step 1: Input the RGB microstructure image of a sample specimen and convert it into grayscale image.

Step 2: Apply 'selective median switching filter' method for de-noising the image.

Step 3: Segment the image using Otsu's segmentation method and obtain granular region and background region.

Step 4: Eliminate the border touching grains and the grains having the size less than 10 µm from the segmented binary image, and then label the image.

Step 5: Each labeled region is a graphite particle and measure it's 'compactness' using Eq. 1.

Step 6: Count only the particles having compactness shape value more than 0.70.

Step 7: Determine the nodularity value using Eq.2.

Step 8: Determine the percentage of ferrite phase area (background region) using pixel count method (Eq. 3).

Step 9: Repeat Step 1 to Step 8 for all the microstructure images of the sample specimen and compute the average nodularity vale and ferrite phase (%) of the sample, which will be used as inputs to fuzzy inference system.

3.3 Fuzzy rule based classifier for estimating the mechanical properties

A fuzzy rule based inference system is proposed for deriving the mechanical properties of the material using only two microstructure properties, namely, nodularity value of graphite and percentage of ferrite phase. The main reason for using the fuzzy rule based inference system is that fuzzy logic can be built based on the experience of experts. Also, fuzzy logic is conceptually easy to understand and is an intuitive approach. It is tolerant of imprecise data and can model nonlinear functions of arbitrary complexity. Fuzzy logic is built on the structures of qualitative description represented by linguistic variables in a natural language [13,15,16].

Fuzzy inference systems can be categorized into two families: 'Mamdani' and 'Sugeno'. Mamdani-type inference system expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. Sugeno-type system can be used to model any inference system in which the output membership functions are either linear or constant.

In the present work, the Mamdani model of fuzzy inference system is employed due to the fact that the outputs that represent a set of mechanical properties are fuzzy sets and not single output value. The Gaussian membership functions are used for each input and output represented by linguistic variables.

The input fuzzy quantities, namely, FE and NOD, represent percentage of ferrous phase and nodularity value of graphite respectively. The linguistic variables for FE are the fuzzy sets Fe1,Fe2 and Fe3. For NOD, linguistic variables are N1 thru N8. These fuzzy sets have Gaussian membership functions that are defined using the knowledge base [3] of metallurgical experts given in Table 1.

The output fuzzy quantities, namely, YS, TS and EL represent, yield strength, tensile strength and elongation, respectively. The linguistic variables for YS are YS1 thru YS4, for TS are TS1 thru TS4 and for EL are ELl thru EL4. The Table 1 shows knowledge-base [3] used in defining Gaussian membership functions for input and output linguistic variables of the proposed fuzzy inference system. Thus there are 24 if-then rules used in the fuzzy inference system. Some of them are given below:

IF ((FE) is Fe1 AND (NOD)) is N1 THEN (YS1,TS1,EL1),
IF ((FE) is Fe2 AND (NOD)) is N2 THEN (YS2,TS2,EL2),
IF ((FE) is Fe2 AND (NOD)) is N3 THEN (YS3,TS3,EL3),
. . . , . . . , . . . ,
IF ((FE) is Fe8 AND (NOD)) is N8 THEN (YS8,TS8,EL8)
ELSE Unknown.

The Fig. 4 and Fig.5 show screenshots of stepwise design of the proposed fuzzy inference system based on Mamdani model, using MATLAB.

The algorithm for estimation of mechanical properties, namely, YS,TS and EL, using fuzzy inference system is given in the Algorithm 2.

Algorithm 2: Determining mechanical properties using fuzzy inference system

Step 1: Input RGB microstructure image (test image) of a test sample and convert it into grayscale image.

Step 2: Perform preprocessing and apply Otsu's segmentation method on grayscale image and obtain segmented binary image, which is then labeled.

Step 3: Compute the nodularity value and quantify ferrite phase using pixel count method as in Algorithm 1.

Step 4: Repeat Steps 2 and 3 for all the microstructure images of the test sample.

Step 5: Compute the average nodularity value and ferrite phase quantity in the test sample.

Step 6: Input the nodularity and ferrite phase quantity values computed in Step 5 to the fuzzy inference system (Mamdani model).

Step 7: The output of fuzzy inference system is the fuzzy membership function, which is defuzzified using centroid formula, to indicate the corresponding set of mechanical properties of the test sample.

4. EXPERIMENTAL RESULTS AND DISCUSSION

For the purpose of experimentation, 100 digital microstructure images containing graphite inclusions of class flake, nodular, and irregular were considered. The microstructure images are acquired in the metallurgy lab by experts. The implementation of the proposed method was done on a Pentium Dual Core computer system @ 2.6 GHz using MATLAB R2009b. The fuzzy inference system is built using the knowledge of known microstructure and mechanical properties of materials. Various classes of mechanical properties are defined for each set of microstructure properties as discussed in [3]. Microstructure properties are used to build Gaussian membership functions of the linguistic variables of the fuzzy quantities, namely, nodularity and percentage of ferrite phase, for the proposed fuzzy inference system (Mamdani model). The Table 2F shows the results obtained by the proposed system and its comparison with results obtained by manual methods on the same samples used in the proposed system. The sample microstructure images M1 thru M10 (Table 2) are given in the Fig. 7. It can inferred from the Table 2 that the estimated mechanical properties on the basis of microstructure image analysis are in agreement with results obtained manually by experts using the same sample materials.

During the experimentation, the microstructure images of known mechanical properties are used, which form the ground truth for our experimental study. The manual methods are error prone due to physiological limitations of human beings, non repeatable and time consuming. The proposed method is simple to implement and fast, because the only effort required is in sample preparation for extracting only two microstructure properties. The proposed method is economical because time, effort and cost of determining mechanical properties is saved to a considerable extent. Therefore, the proposed method has practical importance in material manufacturing industries and quality control activities.

5. CONCLUSION

A novel, efficient, automatic microstructure image analysis for estimating mechanical properties of ductile cast iron is proposed. The method is robust and computationally inexpensive. Any changes to the fuzzy inference system can be made very easily, and the learning process of the fuzzy system is fast. The fuzzy logic addresses such applications more realistically as it resembles human decision making with an ability to generate precise solutions from certain or approximate information. The experimental results show that the proposed method, which uses only two microstructure properties and fuzzy rule based classifier, estimates accurate mechanical properties. These results confirm that the proposed system is efficient and robust. The proposed method has potential for considerable industrial applications in the field of material manufacturing industry.

Future Scope of the work:

This work can be extended to estimate more complex mechanical properties with proper knowledge-base acquired from experts as the proposed work provides a perfect frame work using fuzzy inference system.

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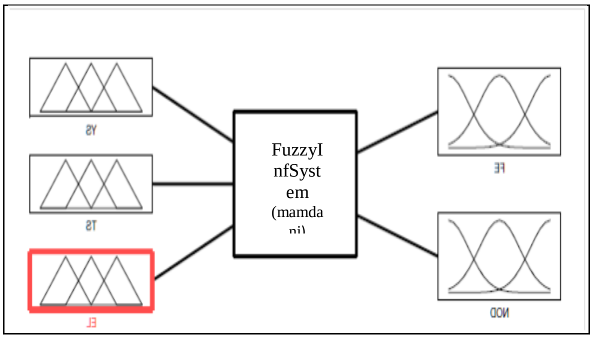
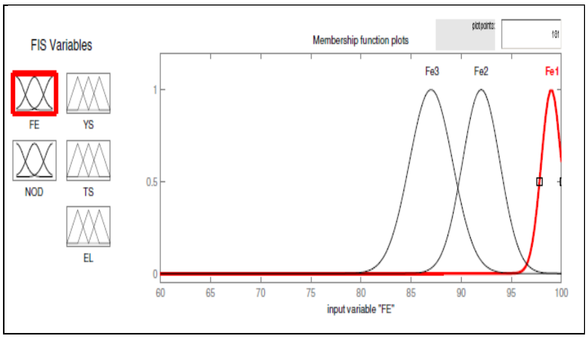
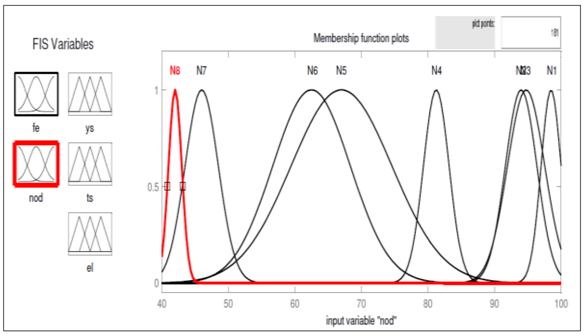


(a)



(b)



(c)

Fig. 4: Screen shots of design of proposed fuzzy inference system: (a) Overview of fuzzy inference system (Mamdani type) with two input (FE and NOD) and three output (YS,TS and EL) linguistic variables, (b) Gaussian membership functions for fuzzy input variables Fe1 thru Fe3 of FE, (c) Gaussian membership functions for fuzzy input variables N1 thru N8 of NOD.

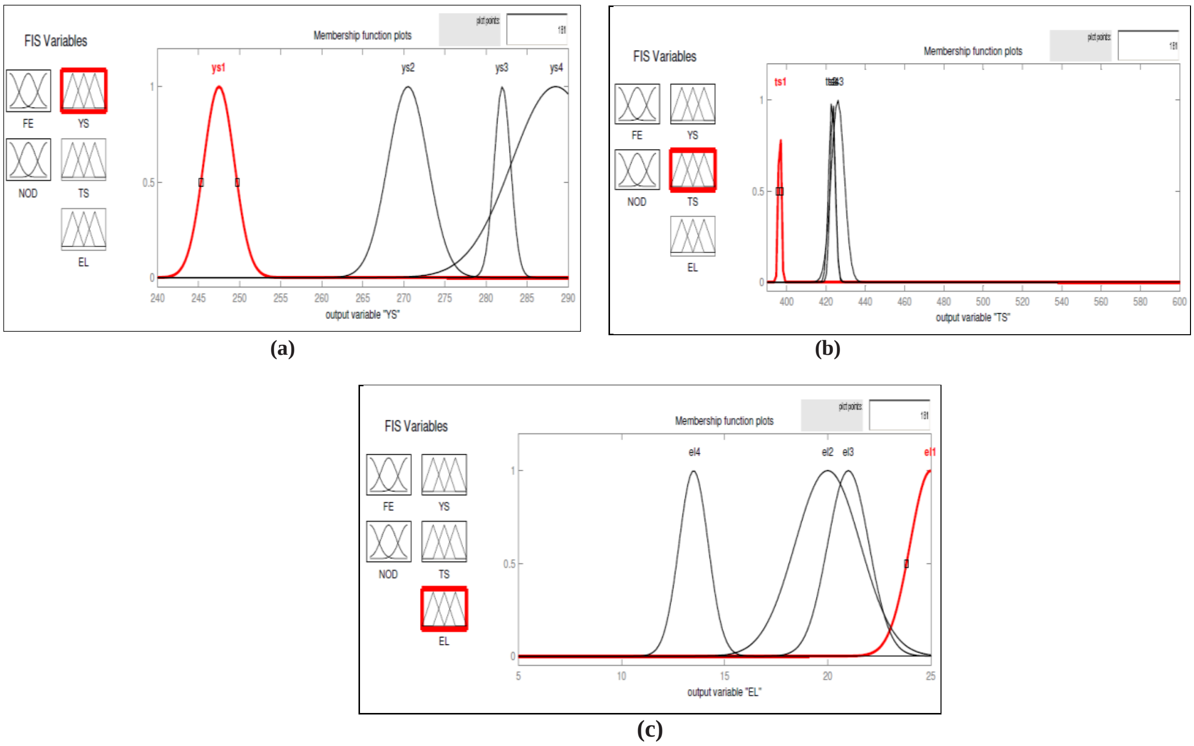


Fig. 5: Screen shots of design of proposed fuzzy inference system: (a) Gaussian membership functions for fuzzy output variables YS1 thru YS4 of YS, (b)Gaussian membership functions for fuzzy output variables TS1 thru TS4 of TS and (c) Gaussian membership functions for fuzzy output variables EL1 thru EL4 of EL.

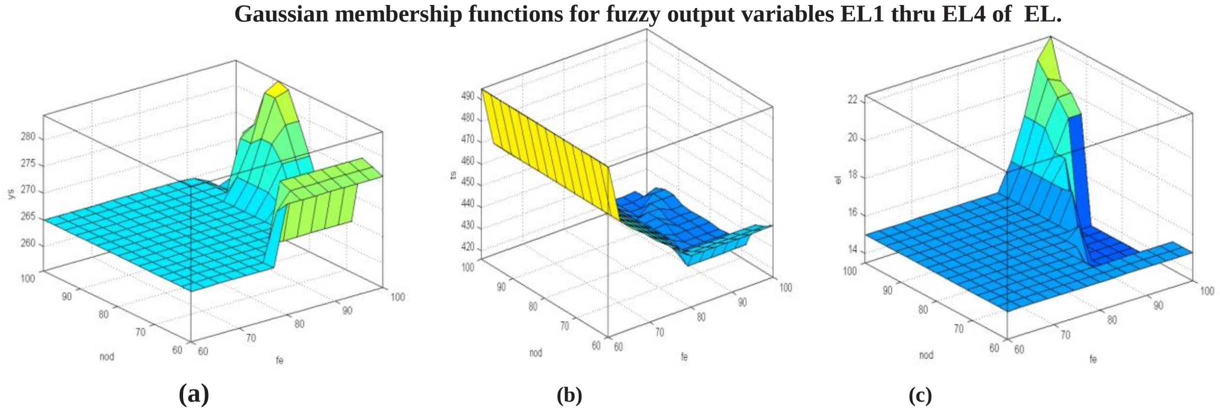


Fig. 6: Graphical representation of rules defined in proposed fuzzy inference system with respect to each output linguistic variable: (a) For Yield Strength(YS), (b) For Tensile Strength (TS) and (c) Elongation (EL).

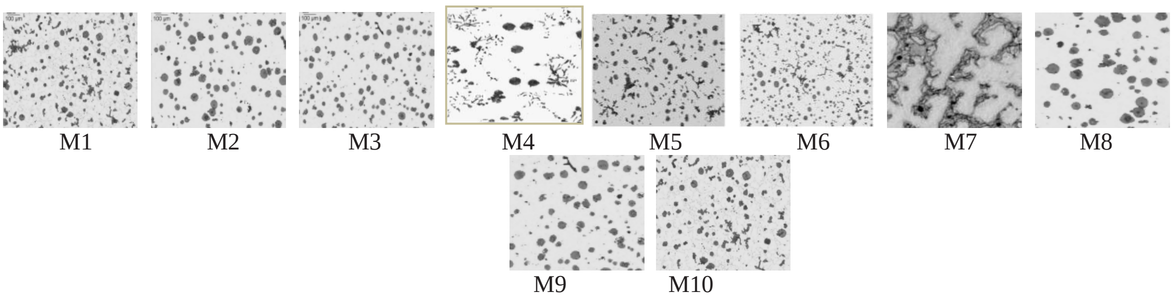


Fig. 7: Sample test microstructure images

Table 1. Knowledge-base for Ductile cast iron used in building the fuzzy inference system obtained by metallurgy experts [3].

Linguistic variable	Value defined
Fe1	80 to 84
Fe2	86 to 97
Fe3	95 to 100
N1	98 to 100
N2	94 to 98
N3	93 to 97
N4	80 to 83
N5	60 to 74
N6	72 to 45
N7	45 to 48
N8	40 to 45
YS1	246 to 249
YS2	267 to 273
YS3	281 to 283
YS4	283 to 293
TS1	395 to 397
TS2	421 to 423
TS3	423 to 429
TS4	420 to 424
El1	24 to 26
EL2	18 to 22
EL3	20 to 22
EL4	12 to 14

Table 2. Results obtained by proposed method and its comparison with results obtained by manual method.

Microstructure image	Method	Microstructure properties determined on test material microstructure images		Mechanical properties inferred by fuzzy inference system		
		% of ferrite phase	Nodularity value	Yield Strength (Mpa)	Tensile Strength (Mpa)	Elongation (%)
M1	Manual	97	92	220	380	20
	Proposed	98	95	245	396	24
M2	Manual	96	92	223	392	24
	Proposed	98.3	94	274	410	23
M3	Manual	96	94	279	413	22
	Proposed	97	95	267	409	23
M4	Manual	97	94	262	404	24
	Proposed	99	95	271	414	24
M5	Manual	96	95	245	396	24
	Proposed	99	95	245	396	24
M6	Manual	97	94	270	400	21
	Proposed	98	95	245	397	24
M7	Manual	40	32	U.C.	U.C.	U.C.
	Proposed	45	38	U.C.	U.C.	U.C.

M8	Manual	95	88	210	360	19
	Proposed	97.5	94	273	412	24
M9	Manual	93	90	211	373	18
	Proposed	94	95	256	413	23
M10	Manual	94	92	212	379	19
	Proposed	93	95	247	407	25

Legend: U.C - Unknown Class, Mpa –Mega-pascal (SI unit of pressure)