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ORIGINAL ARTICLE

Intelligent modeling using fuzzy rule-based technique for evaluating wood carbonization process parameters

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Abstract The structural changes of the porosity in three wood species in a pyrolysis system at several temperature ranging and time periods were investigated to study the wood carbonization characteristics. Rectangular cuboid wood samples were dried and then carbonized in an inert atmosphere furnace and their mass and dimensional changes were recorded before and after process. SEM observation indicated that anatomical feature of final porous carbon remains unchanged with respect to the initial wood precursor. This research also intends to develop an intelligence model based on fuzzy logic theory. The model considers the final density as the end result of the process and establishes relations with carbonization process parameter (carbonization temperature, carbonization time period, initial density of wood) on the basis of fuzzy linguistic rules. Besides, a regression equation was established between above parameters and afterward, considering the constant of the derived model, significance of each one was identified. The results of the fuzzy model were found to be very close to the experimental data and show the possibility of improving rule-based modeling for such engineering challenges.

Keywords Carbonization process · Density · Solid carbon · Fuzzy logic model

1 Introduction

In the last decades, investigators have shown so many interests in determining innovative natural resource of materials for substitution of artificial synthesized products. Deficiency of materials and outlay of conventional fabrication procedures enhance the support for this new materials utilization and application.

The use of carbonized wood as a matrix for the production of cellulose-derived composites (CDC), including carbon/polymer, carbon/carbon, carbon/ceramics, and carbon/metal composites, is being considered in recent researches [1–3]. This type of composites have several thermal, mechanical, and also tribological applications such as using in templates, chops, and husks form.

The chemical composition of a typical dried wood sample is approximately: 50 wt.% carbon, 44 wt.% oxygen, and 6 wt.% hydrogen. While carbonization, the anatomical features of wood stay unchanged while a complete dissimilar composition reached [4]. Wood includes with several natural polymers, which form a complex body of different interconnected long cells which are parallel with central horizontal axis of the plant trunk. Cellulose, hemicellulose, and lignin are the three main polymers of wood material. The most momentous is cellulose, hemicelluloses, and lignin, depending on the sample place selection in the tree trunk, are present in the net shape body of cellulose with the different ratio. At heating rate of 5 °C min^{-1}, hemicelluloses is decomposed at temperatures ranging from 170 °C to 240 °C, cellulose 240–310 °C, and lignin 320–400 °C [5]. Aggregation of crystalline cellulose into larger aligned parts in the cell wall of wood shapes elementary fibrils known as microfibrils [6].

Porous carbon has numerous desired properties such as stable coefficient of friction (μ), self-lubricity, relative high strength, good electromagnetic shielding, high capacity of damping, and low coefficient of thermal expansion (α) [2, 3].

Different studies have been done on thermophysical and microstructural aspects of wood carbonizations .Microstructural change of disordered carbon after carbonization [7] and cell-wall evolution during heating process [8] were

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investigated using X-ray diffraction and Raman spectroscopy. In the literature, considerable studies were carried out on the effect of parameters like furnace flow rate [9], heating rate [10], and also physical properties of net shape carbon such as thermal conductivity and diffusivity on the final density of the product [11]. Besides, the extent to which the carbon stable isotopes of carbon during wood carbonization for different wood species was reported [12].

However, there are just only a few researches which have worked on numerical view of the process utilizing artificial intelligence techniques [13, 14]. Rule-based fuzzy logic is a very useful and outstanding computational tool in different complex and nonlinear engineering problem [15]. Since any logical system can be fuzzified [16] and a general logical relationship exists between solid carbon density and above carbonization factors, a fuzzy logic (FL) approach would be very proficient and effectual for this problem. This study also implements a useful fuzzy logic model for evaluating the effects of process parameters namely, heat treatment temperature, carbonization time, and initial density of wood on the bulk density variation of porous carbon during heating.

Fuzzy sets and membership is the key approach in decision making when faced with uncertainty [17]. Fuzzy set can be defined as a set of crisp values that can be group together with an associated fuzzy term and contains objects that satisfy imprecise properties of membership. So, a fuzzy set is totally characterized by a membership function. In a formal definition, a fuzzy set A in X is expressed as a set of ordered pairs according to Eq. 1.

$$A = \{(x, \mu_A(x)) | x \in X\} \tag{1}$$

Where A is the fuzzy set, x and $\mu_A(x)$ are the member of the universe and its related membership function, respectively, and X is the universe of discourse [18]. There are basically two types of fuzzy sets: normal and subnormal. A normal fuzzy set is one whose membership function has at least one element x in the universe whose membership is unity, and on the other hand, a subnormal fuzzy set is one whose membership function does not have an element x in the universe whose membership is unity. All information contained in a fuzzy set is described by its membership function. For crisp sets an element x in the universe X is either a member of some crisp set, say A on the universe or it is not that means A is not in the universe (binary membership); but in a fuzzy membership, the notion of binary membership has been extended to accommodate various "degrees of membership" on the real continuous interval between zero and one, where the endpoints conform to no membership and full membership, respectively. The sets on the universe X that can accommodate "degrees of membership" are referred as "fuzzy sets" [19].

2 Materials and experimental methods

2.1 Materials selection and preparation

Samples from oak (scientific name: *Quercus*), maple (scientific name: *Acer*), and basswood (scientific name: *Tilia*) trees, which have different bulk densities, were prepared in similar shape using a particular cutting tool of wood. They have length and width of 20 and 10 mm in height. Before carbonization, in order to avoid fungus and spoiling during the test in laboratory atmosphere, two steps of drying were carried out for taking structural water of wood out; first, air drying for 1 week in a warm location, and secondly, drying for 48 h at 103 °C in an electric oven with air circulation.

2.2 Carbonization of wood samples

In various time sets, wood samples were heated to different temperatures in order to produce a porous carbon. Among the selected tree samples, maple has the denser structure with bulk density of 0.75 g/cm^3, oak posses the second rank with density of 0.7 g/cm^3, and at last, basswood has the lowest density of all with about 0.5 g/cm^3. By using an argon atmosphere control electrical furnace, cubic wood samples were carbonized at different temperatures (i.e., 400 °C, 450 °C, and 500 °C) and three different durations: 1.5, 2, and 2.5 h. Table 1 designates the design of performed experiments and the final measured density of each run. Since the density change of product is the desired output of the work, exact values of wood mass and dimensions were measured before and after the test by precise balance tools. Figure 1 indicates wood samples as starting materials for this study.

2.3 Fuzzy logic (FL) model

The use and application of numerical methods in new fields of manufacturing and engineering subjects are getting raised day to day. Soft computation methodology based on the knowledge of artificial intelligence has recently found its place in advanced materials challenges and applications. Artificial neural network (ANN) is the most well-known tool in prediction and classification of complex and multidimensional material characterization with its stupendous ability of learning from sets of examples and generalizing the knowledge to new circumstances [20]. However, the above method has many drawbacks, which may get the simulation process into difficulty, very slow convergence, entrapment in the local minimum, and of course, requirement of a large number of data sets are some of occurring problems. Therefore, fuzzy logic can be used as a superior modeling approach [21]. Fuzzy logic theory was first introduced by L. A. Zadeh in 1965 [17]. Fuzzy logic is a

Table 1 Carbonization test's experimental design and corresponding density

Test run	Carbonization temperature (°C)	Time period (h)	Initial density (g/cm^3)	Carbon density (g/cm^3)
2	600	1.5	0.7	0.257
3	600	1.5	0.75	0.271
1	600	1.5	0.5	0.186
4	600	2	0.5	0.255
5	600	2	0.7	0.313
6	600	2	0.75	0.351
7	600	2.5	0.5	0.279
8	600	2.5	0.7	0.372
9	600	2.5	0.75	0.355
10	650	1.5	0.5	0.219
11	650	1.5	0.7	0.303
12	650	1.5	0.75	0.344
13	650	2	0.5	0.311
14	650	2	0.7	0.351
15	650	2	0.75	0.372
16	650	2.5	0.5	0.403
17	650	2.5	0.7	0.425
18	650	2.5	0.75	0.447
19	700	1.5	0.5	0.383
20	700	1.5	0.7	0.391
21	700	1.5	0.75	0.392
22	700	2	0.5	0.382
23	700	2	0.7	0.396
24	700	2	0.75	0.478
25	700	2.5	0.5	0.513
26	700	2.5	0.7	0.553
27	700	2.5	0.75	0.639

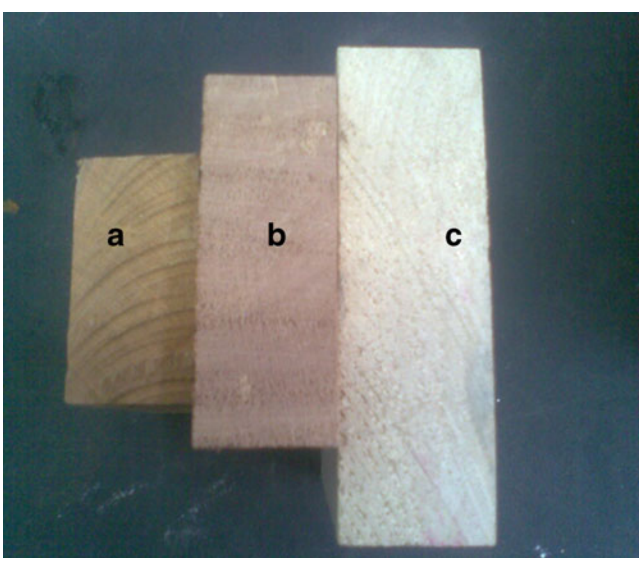

Fig. 1 Selected wood samples of *a* oak, *b* *Tilia*, and *c* maple

powerful problem-solving methodology with a lot of applications in embedded control and materials processing such as prediction of roughness [22] and hardness [23] of components, mechanical properties of FGM [24], and composite materials [25, 26]. Fuzzy concepts provide a remarkably simple way to draw definite conclusions from vague, ambiguous, or imprecise information. In a sense, fuzzy logic resembles human decision-making with its ability to work from approximate data and find precise solutions. Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numeric values, fuzzy logic incorporates an alternative way of thinking, using a higher level of abstraction compromised from our past experiences so it simplifies design complexity and solution implementation. In fuzzy logic, numbers replaced by linguistic variables whose values are words and specific rules. The conventional coding of a classical set (crisp set) has only two values: one uses when a member is in the set; and zero, when it is out of it but in fuzzy logic theory, everything is a matter of degree. Membership function is used for clarifying the value of each element in fuzziness. Considering the above concepts, deterministic uncertainty in fuzziness may be confused with nondeterministic probability. Fuzziness describes event ambiguity but probability describes event occurrence. Whether an event occurs is random, the degree to which it occurs is fuzzy.

The fuzzy logic-based modeling is much more in-line with the human's interpretation system, which implements an "if–then" code. In the fuzzy theory texts, "if" is usually named the premise and "then" is the subsequence. Basically, fuzzy logic has three steps: fuzzification, rule evaluation, and defuzzification process. Fuzzification is a process that switches decimal values into fuzzy sets. The rule evaluation step includes "if…then" phrases that form the linguistic formation of rules. Finally, a defuzzification procedure transforms the fuzzy outputs to crisp ones that can be interpreted for later applications.

3 Results and discussion

3.1 Microstructure study of carbonized wood

Scanning electron microscope (SEM) images of dry wood and carbonized wood are illustrated in Fig. 2. It can be seen from the micrographs that the wood anatomical feature remains without any substantial transform and the shape of porosities in initial wood templates is similar to heated wood in the form of the carbon and this leads to the different separated pores in carbon surface. In wood-based carbon matrix composites, by using a vacuum infiltration method, metals, ceramics, or even polymers can play the role of reinforcement component and fill these cylindrical porosities.

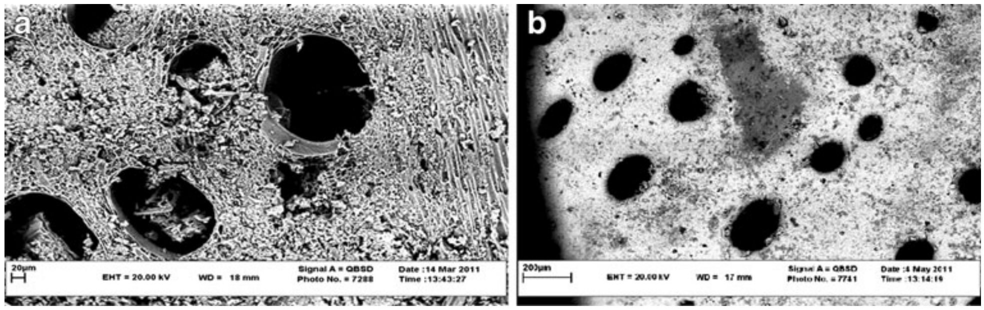

Fig. 2 Micrographs of **a** oak wood and **b** carbon derived from initial precursor

Basically, density change in wood structure with temperature increasing during carbonization in an inert gas atmosphere condition depends upon two thermophysical factors, which act just in an opposite way with each other: (a) weight loss due to degradation of some wood component while heating and also evaporation of volatile chemicals in wood. This phenomenon causes a decrease in the density of solid carbon. (b) Wood cell-wall expansion and shrinkage of wood samples leads to reduce the pore diameter and increase density in fabricated product [27]. In the temperature range of 400 °C to 1,000 °C, the second effect is the leading mechanism of density variation and the first effect is more active in upper temperatures. In the current study, selected temperatures were between 600 °C and 700 °C in which density increases as temperature increases. At a constant temperature, higher carbonization time gets more opportunities to organic wood components to rearrange during heating. This longer time period leads to more complete reshape of survived organic chain. Consequently, cell wall expansion process improvement takes place in a better mode. In addition, it was proven that the density of fabricated solid carbon and dry wood has a linear relation, and many in use conditions affect the linear equation slope and this slope is a function of parameters like pressure and atmosphere of heating media [4].

3.2 Regression analysis for input parameters of wood carbonization

In this research, a number of experiments are carried out for calculation and quantification the final product density in carbonization of wood considering the related parameters including temperature and time of heating and also initial wood strain. In order to obtain this purpose, carbon density expresses as a linear function of its process parameters like the following Eq. 2.

$$\mathrm{CD} = \mathrm{F0} + (\mathrm{F1} \times \mathrm{WD}) + (\mathrm{F2} \times \mathrm{TP}) + (\mathrm{F3} \times \mathrm{HTT}) \qquad (2)$$

Where CD is the final carbon density in g/cm^3 and F1 to F4 are equation constants. HTT is the heat treatment temperature (°C), TP is the time period of heating (h), and WD is the approximate wood initial density (g/cm^3). Neglecting the interaction between above parameters, the constants are identified using an appropriate regression analysis with a correlation coefficient (R^2) of 0.872.

$$\mathrm{CD} = -1.1 + (0.257 \times \mathrm{WD}) + (0.136 \times \mathrm{TP}) + (0.00157 \times \mathrm{HTT}) \qquad (3)$$

3.3 Prediction of solid carbon density using fuzzy logic approach

Implementation of the Mamdani-type fuzzy model applied to density prediction followed the steps listed below:

Fuzzification: choosing the most appropriate membership functions for the three input variables. Fuzzification is the process of making a crisp quantity fuzzy and converts definite data in the input of controller to the format of linguistic variables. This is achieved by simply evaluating all the input membership function with respect to the current set of input values in order to establish the degree of participation of each membership function.

Rule evaluation and inference system: design of the related rule which link up the three input variables to the single output variable and also assigning membership functions to them. Inference unit is a unit that performs fuzzy inference on fuzzy rules. This unit performs the operation resembling the way that people think.

Defuzzification: after computing the fuzzy rules and evaluating the fuzzy variables, we will need to translate these results back to the real world and make a fuzzy quantity crisp with the goal of obtaining a real number for next numerical interpretation. In the most conventional method, the so-called center of area, the weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the sum of the weighted member function strengths and the result is taken as the crisp output.

The first phase in the fuzzy system design is assigning a membership function to each variable. Depending on the problem conditions and user's experience, different shapes

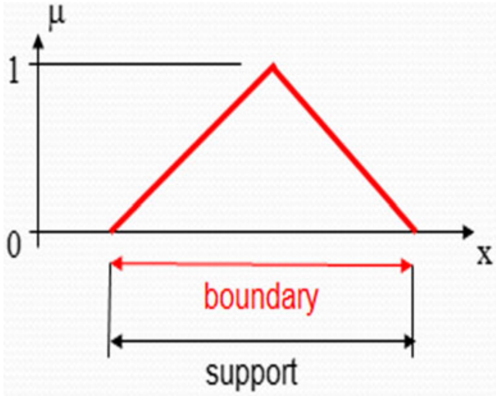

Fig. 3 Different parts of a triangular membership function

of membership functions can be used. Membership function can have a symmetrical or asymmetrical shape. In the present work, fuzzy triangular membership function was chosen sets because they are commonly applied because of their simplicity and ability for coding non-linearity. Fuzzy membership converts the notion of binary membership to various degrees of membership value on a two-dimensional diagram. Figure 3 introduces different parts of a typical triangular membership function and Fig. 4 illustrates fuzzy diagram for carbon density analysis

Fuzzy membership extends the concept of binary membership to accommodate a range of "degrees of membership" on the real continuous interval between zero and one, where the endpoints conform to no and full membership, in that order. The sets on the universe *X* that can accommodate "degrees of membership" are referred as "fuzzy sets." Any kind of membership functions had different parts in its graphs which assign membership values to the corresponding variable considering function's configuration like type, number, shape, etc.

The core of a membership function is defined as the region (a single point in triangular membership factions) that is identified by complete and full membership in the set. The core consists of elements with unit membership value ($\mu(x)=1$). Boundary is called to the region that is characterized by positive membership in the set. The combination of all boundary regions is called support zone ($0\leq\mu(x)\leq1$) which supposed to be the same in triangular

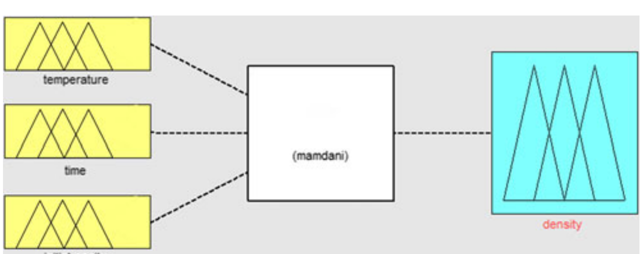

Fig. 4 Fuzzy diagram for carbon density analysis

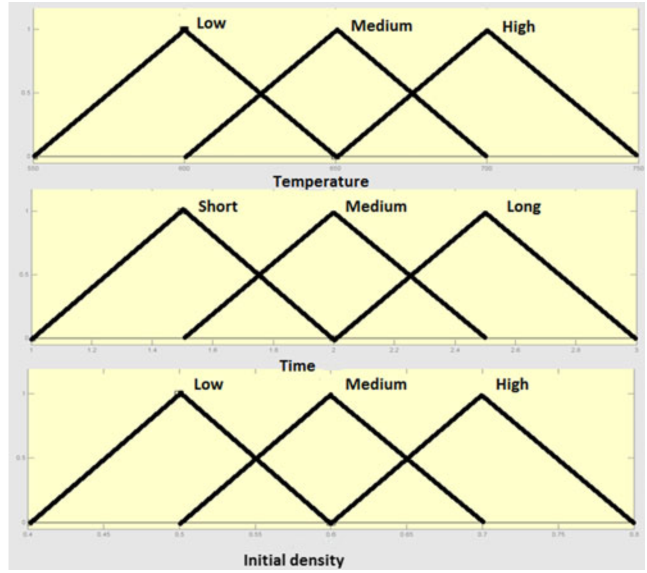

Fig. 5 Membership functions for three inputs

membership function. Figures 5 and 6 illustrate the shape and range of each membership function for inputs and output variables, respectively.

The heat treatment temperature is input 1and has three member functions i.e. low, medium and high. It is ranged from 550 °C to 750 °C. Carbonization time period is input 2, has three membership functions, i.e., short, medium, and long. It ranged from 1 to 3 h and finally initial wood density as third input has three membership functions, that is to say low, medium, and high. It ranged from 0.4 to 0.8 g/cm^3. The only output, net shape carbon density, has ten fuzzy terms. It ranged from 0.1 to 0.7 g/cm^3 and includes extreme low (EL), very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH), extreme high (EH), and super high (SH). Rule evaluation is the second step in constructing a fuzzy system. The goal is to establish a connection among multiple inputs and final density of carbon. Table 2 shows 17 accomplishing "if–then" rules. Deffuzification is the ending process in the fuzzy logic analysis. Many defuzzification methods can be utilized including centre-of-area, weighted average, max-

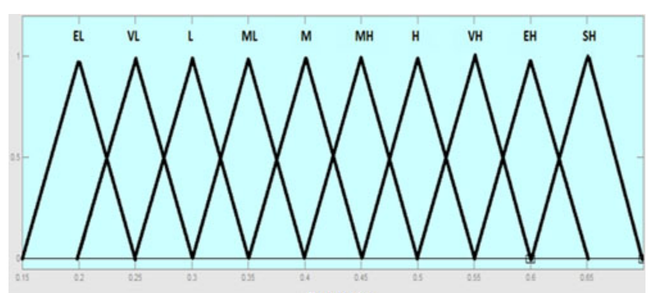

Fig. 6 Membership function for single output

Table 2 Rules for the fuzzy inference system

Rule definition	No.
If (temperature is low) and (time is short) and (initial density is low) then (final density is EL)	1
If (temperature is low) and (time is medium) and (initial density is low) then (final density is VL)	2
If (temperature is low) and (time is medium) and (initial density is high) then (final density is ML)	3
If (temperature is low) and (time is medium) and (initial density is medium) then (final density is L)	4
If (temperature is medium) and (time is short) and (initial density is medium) then (final density is L)	5
If (temperature is medium) and (time is long) and (initial density is low) then (final density is M)	6
If (temperature is medium) and (time is medium) and (initial density is medium) then (final density is ML)	7
If (temperature is medium) and (time is long) and (initial density is high) then (final density is MH)	8
If (temperature is medium) and (time is long) and (initial density is medium) then (final density is MH)	9
If (temperature is high) and (time is medium) and (initial density is low) then (final density is M)	10
If (temperature is high) and (time is short) and (initial density is high) then (final density is ML)	11
If (temperature is high) and (time is long) and (initial density is high) then (final density is SH)	12
If (temperature is high) and (time is short) and (initial density is medium) then (final density is M)	13
If (temperature is high) and (time is medium) and (initial density is high) then (final density is H)	14
If (temperature is high) and (time is long) and (initial density is high) then (final density is SH)	15
If (temperature is high) and (time is long) and (initial density is medium) then (final density is EH)	16
If (temperature is high) and (time is long) and (initial density is low) then (final density is VH)	17

membership or height method, and center of sums. We choose the first one of the above as one of the most common defuzzification method named center-of-area or centroid. Fuzzy model results and real carbon density values obtained from experimental tests were compared in Fig. 7 for verifying the accuracy of the model in prediction of density changes. The comparison of the actual and fuzzy model value with R^2=0.9781 shows the trustable ability of proposed approach for evaluating the porous structure of carbon product. Figure 7 presents a regression graph which shows the fuzzy and actual results compression and Fig. 8 shows the fuzzy surfaces and rule viewer. Since all 27 possible combination of affecting parameters had been used in fuzzy model, interaction between inputs seems to be taken into account in analysis and improves prediction

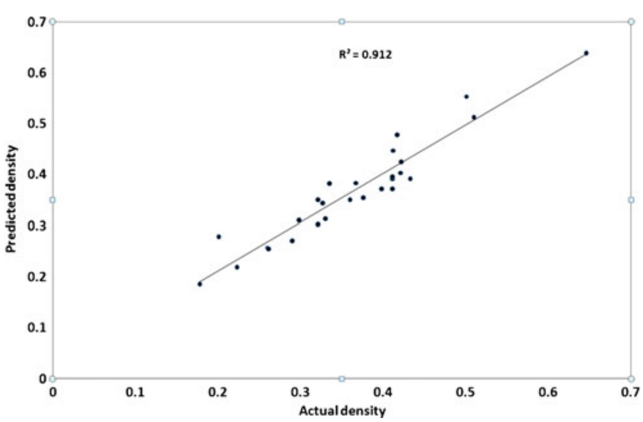

Fig. 7 Regression plot of fuzzy system prediction

accuracy. There is no considerable difference between the predicted and the actual data. However, for having an effective and efficient modeling with fuzzy logic, it would be more acceptable to use the least number of rules which can get a good results instead of using all possible rules that can be implemented. (All rules that can be written for three inputs with three memberships for each). In conclusion, the fuzzy model showed better performance and accuracy rather than the regression model with the higher R^2.

As real word evaluation, the final density of some carbonized wood from same species was measured with the same instruments, and of course, the same conditions and achieved information with corresponding data were implemented to fuzzy inference model. Table 3 presents a comparison between the experimental values and the FIS predicted results for the final density of net-shape porous carbon body.

The percentage errors associated in each test run with respect to the experimental results are also given in the table. It is observed that the error in FIS prediction lies approximately in the range of 0–11 % which establishes the validity of the fuzzy rule-based prediction.

4 Conclusions

In this study, an attempt is made to apply the fuzzy logic approach in predicting of variation in porous carbon density in an atmosphere control carbonization. Manipulating of fuzzy rule-based technique, a real reduction in mathematics and graphs happens in modeling through fuzzy subsets of

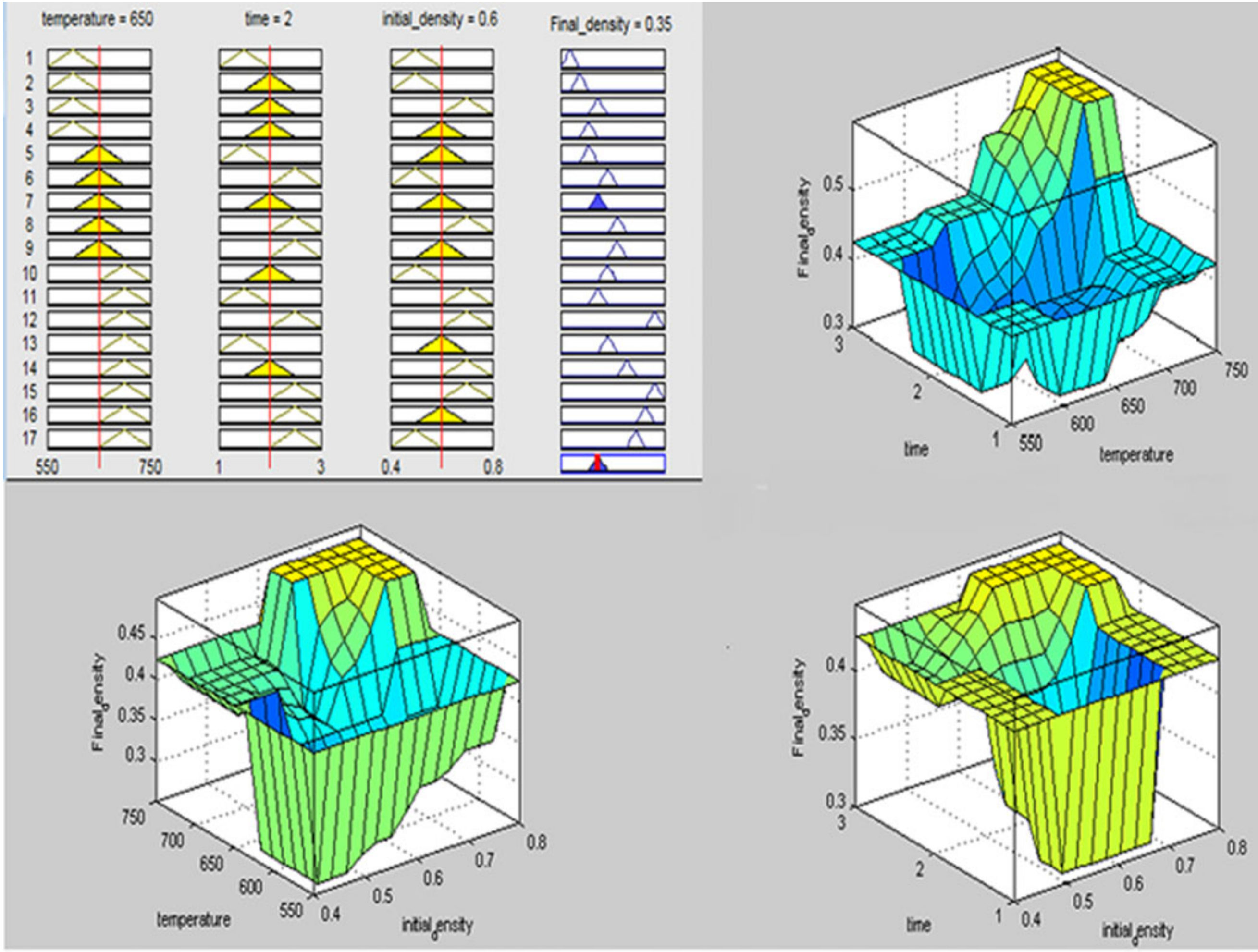

Fig. 8 Fuzzy surfaces for three inputs parameters and rule viewer of carbonization system model

linguistic pyrolysis parameters. The effects of heat treatment temperature, carbonization time and initial density of wood, as three input parameters, have been modeled by implementing both regression and fuzzy inference system. The results show that the fuzzy logic is a useful tool for prediction the microstructure change in porous carbon and indicates acceptable agreement with tests data. In addition, linguistic concepts in the form of fuzzy logic are proven to be simpler, more efficient, and effective in modeling multi-dimensional complex problems without using lengthy formulations which needs a large number of experiments. Regression model shows that, the initial density of selected

Table 3 Comparison of experimental results and FIS results

Test	Carbonization temperature (°C)	Time period (h:min)	Initial density (g/cm^3)	Carbon density (g/cm^3)—experiment	Carbon density (g/cm^3)—FIS	Error (%)
1	630	1:15	0.5	0.228	0.254	−10.23
2	630	1:15	0.7	0.266	0.255	4.31
3	630	1:15	0.75	0.321	0.311	6.43
4	660	1:45	0.5	0.303	0.295	2.71
5	660	1:45	0.7	0.336	0.354	−7.90
6	660	1:45	0.75	0.369	0.385	−4.15
7	690	2:15	0.5	0.385	0.364	5.76
8	690	2:15	0.7	0.402	0.416	−8.17
9	690	2:15	0.75	0.464	0.466	3.86

wood is the most significant factor among carbonization parameters. This model could simply be employed to arrange carbonization stage and for testing the correctness of influence of heating process.

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