Bofy-fuzzy logic control for the basic oxygen furnace (BOF)

Cemalettin Kubat a,⁎, Harun Taşkin a, Recep Artir b, Ayten Yılmaz c

a Department of Industrial Engineering, Sakarya University, Turkey
b Department of Materials and Metallurgical Engineering, Sakarya University, Turkey
c Data Processing Department, Sakarya University, Turkey

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Abstract

In this paper, fuzzy modeling for the control of basic oxygen furnace (BOF) processes is proposed. BOF is a widely preferred and effective steel making method due to its higher productivity and considerably low production cost. Therefore, today almost 65% of the total crude steel production in the world is met by using the BOF method. Higher steel output at lower cost is one of the main objectives of modern steel making methods. In order to accomplish this objective, fuzzy modeling was employed in this study in order to control some variables related to the BOF process. Fuzzy modeling and control in BOF promise a solution to the strongly non-linear problems associated with the process, which have so far proven extremely difficult to be solved by conventional control methods. Data set was selected as inputs from the real empirical BOF data in an integrated steel plant based in Turkey. Although there were negligible deviations from the target values, most of the fuzzy results obtained using MATLAB-Fuzzy Logic Toolbox version 5.0 were found to be acceptable. As a result of the application of the proposed modeling, acceptable levels of compatibility were achieved compared to the empirical BOF data and targeted steel composition. The paper indicates how fuzzy logic would be effectively used for improved process control of BOF furnace in steel making industry.

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Keywords: Steel making; Basic oxygen furnace (BOF); Fuzzy process modeling; Fuzzy process control

1. Introduction

The International Iron and Steel Institute (IISI), Brussels, in 1992, carried out a survey among its members, asking which technology has to be developed in order to enable the steel industry to meet the market and social requirements at the beginning of the 21st century. According to this study, two major demands have to be satisfied:

1. The steel market will ask seemingly contradictory things of the steel industry, i.e., to deliver higher quality products at lower cost, to offer small lots in
a variety of sizes and grades, and to observe short delivery times.

2. Steel makers must expect to face increasing constraints over environmental issues such as the mini-
mization of emissions and effluents, the recovering and recycling of spent products, and effective uti-
lization of resources, by-products, and wastes.

In a global competition, the earnings of the steel indus-
try tend to decrease rapidly under these constraints and new processes are needed to keep this industry profitable, while allowing it at the same time to satisfy the customer demands and to ensure the protection of the environment. Short- and medium-term objectives must be distinguished:

1. For the short-term, it is important that the best presently available technologies are implemented rapidly and used efficiently.

2. For the medium-term, i.e., for the years 2000–2010, it appears that a certain number of new, alternative technologies have to be developed [9].

1.1. Steel making process

There are various steps in steel making process from raw materials up to the final products. These steps can be summarized as follows.

First step is charging of raw materials into the fur-
nace as being either iron ore or scrap iron, depending
on the process. These are converted into molten steel.
The ore-based process uses a blast furnace + basic oxy-
gen furnace (BOF) and the scrap-based process uses an
electric arc furnace only.

Next step for both routes is pouring the molten steel
from the furnace and it is eventually solidified in a con-
tinuous caster.

Finally, these semi-finished products are trans-
formed, or “rolled” into finished products. Some of
these undergo a heat treatment, known as “hot rolling”.

More than half of the hot-rolled sheet is subsequently
rolled again at ambient temperatures (known as “cold
rolling”). It can then be coated with an anti-corrosion
protective material [1].

Steel in general is an alloy of iron and carbon, often
with an admixture of other elements such as silicon,
manganese, and nickel. Some alloys that are commer-
cially called irons contain more carbon than commer-
cial steels. Open-hearth iron and wrought iron contain
only a few hundredths of 1% of carbon. Steels of vari-
ous types contain from 0.04% to 2.25% of carbon [2].

In this investigation, fuzzy modeling for the control
of basic oxygen furnace processes is studied.

2. Basic oxygen process and BOF

The BOF comprises a vertical solid-bottom crucible
with a vertical water-cooled oxygen lance entering the
vessel from above. The vessel is tiltable for charg-
ing and tapping. The charge is normally made up of
molten pig iron (“hot metal”), plus scrap and fluxes.
Small quantities of cold pig iron and iron ore may also
be charged. The distinguishing feature is that the heat
produced by reaction of the various constituents of the
charge is used without other sources of energy to bring
the metal to the desired final conditions of compositions
and temperature. Typical tonnage of BOF is between
100 tonnes/heat and 400 tonnes/heat. General view of
BOF is given in Fig. 1.

Basic oxygen furnace can produce steel with wide
range of carbon, alloy, and special alloy steels. Aver-
age molten steel capacity of BOF is normally between
100 tonnes and 400 tonnes of steel. When the molten
iron arrives at the BOF via rail, it is processed through a
desulfurization facility before being poured into a ladle

![General view of basic oxygen furnace (BOF)](image)
in preparation for charging. In basic-oxygen steel making, hot metal and scrap are charged into a converter, along with lime and other fluxing materials. Oxygen is blown, and carbon, silicon, phosphorus, manganese, and some iron are oxidized.

The objective is to produce a desired amount of steel, of specified chemical composition, at the proper tapping temperature. Control is difficult because the entire refining period takes only half an hour and there are no opportunities for sampling and analysis during this time [13]. The BOF generally operates on a charge of 75% hot metal and 25% scrap. The scrap is loaded into a vessel via crane, and then the molten iron is poured into the vessel. A water-cooled oxygen lance is lowered into the vessel and high-purity oxygen is blown into the top of the metal at a speed of 16,000 cubic feet a minute. The oxygen combines with carbon and other elements to reduce impurities in the molten metal and convert it into clean, high-quality liquid steel. The steel is poured into a ladle and sent to the ladle metallurgy facility [3].

3. Control of basic oxygen process and its behavior

Prior to the development of control models, it is important to decide on proper associated control factors. Such factors should be selected after careful technical analysis as whether computer control is possible or not. In the design and control of BOF, there are a lot of factors such as charging, oxygen blowing, bath slag activity, furnace design, lance design, liquid steel, slag control, hot metal composition, and targeted steel composition.

3.1. Analysis of the basic oxygen process

The analysis of how the process will work begins with a definitive mathematical model of the metallurgical reactions involved in the steel making process. The amenability of the basic oxygen process to this type of thermo-chemical analysis is that thermo-chemistry in the form of mass and energy balances could predict the performance of the basic oxygen converter, particularly in regard to scrap melting capability. Control of the process is provided by variations in certain input variables, i.e., scrap or hot metal weight, flux weight, and possibly rate of oxygen delivery or blowing practice [11].

High level of steel production and lower cost are the main goals and desirable features of modern steel making methods such as BOF processes with top, bottom, and combined top–bottom blowing with oxygen. The sequence of calculations with the models and of the technological operations during the converter process is as follows:

- first calculation of input materials;
- calculation of the heat and then prediction of the composition of the metal being tapped;
- calculation of alloying elements;
- checking calculation and adaptation of model.

Control of the (BOF) process with the aid of models for calculating the input materials and dynamic models for determining the time of completing blowing provides following advantages: a high accuracy of the steel tapping temperature and carbon content, small proportion of heats with additional blowing, shortening of the heat cycle, high output, reduction of the temperature of the metal at tapping, decrease of the consumption of refractoriness, lines, ferroalloys, and deoxidizes, and increase of the yield of steel and proportion of scrap in the metallic charge [15].

4. Intelligent control of chemical process

It is a common understanding that intelligence describes the level of autonomy of the control systems. Intelligent control system can be described as a device to control with the ultimate degree of autonomy in terms of self-learning, self-reconfigurability, reasoning, planning and decision making, and the ability to extract most valuable information from unstructured and noisy data from any dynamically complex systems and/or environment.

Complex industrial processes such as batch chemical reactors, blast furnaces, cement kilns, and basic oxygen steel making are difficult to control automatically. This difficulty is due to their non-linear, time varying behavior, and the poor quality of available measurements.

In such cases, automatic control is applied to those subsidiary variables, which can be measured and controlled, for example, temperatures, pressures, and
The overall process controls objectives, such as the quality and quantity of product produced, have been left in the hands of the human operator in the past [5].

The research and development of math-model-based modern control techniques have been significantly progressing in both theoretical and practical aspects in past two decades. However, it is still difficult to design and implement a real-time optimization control for some complex industrial processes, if they are highly non-linear, highly complex, seriously coupled, and significantly uncertain. It has been an attractive area in the control industry to explore the novel control strategies, which can be designed and implemented with limited deep (process principle and mathematical) knowledge of the controlled environment. With the rapid progresses of the studies on fuzzy logic, neural networks, genetic algorithms, and rule-based expert systems, the intelligent system techniques with remarkable capabilities of dealing with system’s imprecise and/or incomplete information and knowledge have been recognized as one of the most important measures in solving complex industrial control problems. As noted by Kosko, adaptive math-model free estimation is an intelligent system that adaptively estimates continuous function from data without specifying mathematically how outputs depend on inputs [7].

In conventional hard controllers, the knowledge, which is pertinent to the process being controlled, and the methods for using this knowledge are interrelated and can be expressed in analytical form. To apply such techniques, explicit knowledge of the microscopic behavior of the process is essential. In contrast, in intelligent or soft control, there is a clear demarcation between the knowledge and the information about the process dynamics, i.e., the macroscopic behavior of our process is not essential [8].

Modern control techniques, e.g., parameter estimation, stochastic control, and optimal control, are used in either model identification or design of matchable control law. However, some industrial processes are too complicated to be modeled and/or controlled by math-algorithms, because they are highly non-linear and significantly uncertain with unknown structure and imprecise information [6].

Intelligent control is therefore particularly attractive when the expertise to control a process is available in the form of linguistic rules acquired from normal operational experience. A fundamental attribute of intelligent control is its ability to work with symbolic, inexact, and vague data that human operators comprehend best. Indeed, its ability to deal with incomplete and ill-defined information, an inherent characteristic of wastewater treatment plants, permits implementation of human-like control strategies which have hitherto defined solution by any of the conventional hard control techniques. Certainly for processes, which are known microscopically, hard control is clearly the methodology to be preferred. Modern technology techniques have, however, in general failed to solve industrial problems and the thousands of industrial plants worldwide that rely on three-term (PID) controllers attest to the limitations of these techniques. Fuzzy logic and artificial neural networks are two examples of soft computing, which have migrated into the realm of industrial control over the last two decades. Chronologically, fuzzy control was the first and its application in the process industry has led to significant improvements in product quality, productivity, and energy consumption. Fuzzy control is now firmly established as one of the leading advanced control techniques in use in industry [8].

### 4.1. Fuzzy control

With rapid progresses of the studies on fuzzy logic, neural networks, genetic algorithms, and rule-based expert systems, the intelligent system techniques with remarkable capabilities of dealing with system’s imprecise and/or incomplete information and knowledge have been recognized as one of the most important measures in solving complex industrial control problems. Five main steps are involved in modeling fuzzy expert system:

1. Define the input variables for the system and their corresponding ranges of values.
2. Define the output variables for the system and their corresponding ranges of values.
3. Develop fuzzy membership functions for every input and output.
4. Develop a rule base based upon the potential outcomes of the system.
5. Determine how each action establishing the rule strengths and defuzzification will carry out (see in Fig. 2).
MATLAB Fuzzy Logic Toolbox has been used for the control of BOF process. Fuzzy Logic Toolbox is a collection of functions built on the MATLAB numeric computing environment. It provides tools for user to create and edit fuzzy inference systems within the framework of MATLAB, or if preferred, it can integrate the fuzzy systems into simulations with Simulink; it can even build stand-alone C programs that call on fuzzy systems user build with MATLAB. This toolbox relies heavily on graphical user interface (GUI) tools to help users accomplish their work [4].

Modeling of industrial processes, in particular, modeling of continuous processes, is very difficult if a control model is established. It is far beyond to reflect the behavior of the real process system. However, the establishment of mathematical model is much harder if industrial process has non-linear structure. This particular problem has been solved mostly by development of artificial intelligent and its algorithms, especially by the application of fuzzy logic in fuzzy control. Fuzzy control system is based on the expression and development of expert system in which the system is designed to reduce the input values for each interval, and then relationship and the effect of variables on each other are carried out by the development of expert system and by expressing the rules.

5. Fuzzy process control of BOF

The process operator’s control strategy can be expressed linguistically as a set of imprecise conditional statements which form a set of decision rules. First, we must determine input–output variables. Input–output variables of the BOF as a system are in general shown in Fig. 3. Note that the process is modeled by fuzzying the control variables. The description of this is given below.

Standard steel composition “7112 K” was used for this study. Chemical composition for 7112 K is C% 0.02–0.04, P% 0.015, S% 0.015, Mn% 0.10–0.20, and Si% 0.030. The rest is iron. Hot metal composition is C% 4.443, Mn% 0.644, Si% 0.506, S% 0.076, and P% 0.096. Each input variable and its corresponding data used in this study were taken from a database containing 288 data obtained from an integrated steel plant covering 30 working days. The input variables are given in Table 1.

Input descriptions are given below:

- hot metal temperature (°C): the liquid iron’s temperature to satisfy the heat balance requirement in the BOF;
- scrap + hot metal weight—total charge (tonnes): scrap is necessary to adjust excessive heat after blowing period and hot metal weight is directly linked to the steel output;
- end point blowing oxygen (ppm): the quantity of oxygen blown before tapping;
- end point blowing temperature (°C): measured temperature after oxygen blown;
- hot metal C% (carbon content), hot metal Mn% (manganese content), hot metal P% (phosphorous content), hot metal S% (sulfur content), hot metal
Table 1: Inputs, crisp variables, intervals, and linguistic variables of BOF

<table>
<thead>
<tr>
<th>Inputs of BOF process</th>
<th>Crisp variables</th>
<th>Intervals and linguistic variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Hot metal temperature (°C)</td>
<td>HotMtTemp</td>
<td>130–1345</td>
</tr>
<tr>
<td>Scrap + hot metal weight—total charge (tonnes)</td>
<td>ScplHotM</td>
<td>116–126</td>
</tr>
<tr>
<td>End point blowing oxygen (ppm)</td>
<td>EndPBOxy</td>
<td>411–567</td>
</tr>
<tr>
<td>End point blowing temperature (°C)</td>
<td>EndPTemp</td>
<td>1588–1666</td>
</tr>
<tr>
<td>Hot metal C% (carbon content)</td>
<td>HotMtC%</td>
<td>1.675–3.948</td>
</tr>
<tr>
<td>Hot metal Mn% (manganese content)</td>
<td>HotMtMn%</td>
<td>0.337–0.629</td>
</tr>
<tr>
<td>Hot metal P% (phosphorous content)</td>
<td>HotMtP%</td>
<td>0.0364–0.0893</td>
</tr>
<tr>
<td>Hot metal S% (sulfur content)</td>
<td>HotMtS%</td>
<td>0.0036–0.0135*</td>
</tr>
<tr>
<td>Hot metal Si% (silica content)</td>
<td>HotMtSi%</td>
<td>0.085–0.2608</td>
</tr>
<tr>
<td>Bath height (cm)</td>
<td>BathHght</td>
<td>197–215</td>
</tr>
</tbody>
</table>

* Optimal interval.
### Outputs, crisp variables, and linguistic variables of BOF

<table>
<thead>
<tr>
<th>Outputs of BOF process</th>
<th>Crisp variables</th>
<th>Intervals and linguistic variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low (103.800–114.700)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium (111.600–124.100)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High (122.900–126.500)</td>
</tr>
<tr>
<td>Casting weight</td>
<td>CastWght</td>
<td>103.800–114.700</td>
</tr>
<tr>
<td>Final oxygen level in steel (ppm)</td>
<td>FnlOxySt</td>
<td>111.600–124.100</td>
</tr>
<tr>
<td>Final temperature of steel (°C)</td>
<td>FnlOxySt</td>
<td>122.900–126.500</td>
</tr>
<tr>
<td>TSOC% (end of blowing, the last sample’s carbon content, %)</td>
<td>TSOC%</td>
<td>0.0166–0.0412*</td>
</tr>
<tr>
<td>TSOMn% (end of blowing, the last sample’s manganese content, %)</td>
<td>TSOMn%</td>
<td>0.061–0.1022</td>
</tr>
<tr>
<td>TSOP% (end of blowing, the last sample’s phosphorus content, %)</td>
<td>TSOP%</td>
<td>0.0939–0.22*</td>
</tr>
<tr>
<td>TSOS% (end of blowing, the last sample’s sulfur content, %)</td>
<td>TSOS%</td>
<td>0.0045–0.0093*</td>
</tr>
<tr>
<td>TSOsi% (end of blowing, the last sample’s silicon content, %)</td>
<td>TSOsi%</td>
<td>0.0003–0.0103*</td>
</tr>
</tbody>
</table>

* Optimal interval.

Si% (silica content): these are the essential and vital elements comprising steel composition; bath height (cm): height of liquid steel in the furnace [10].

#### 5.1. Membership functions

According to data, variables were designated as membership functions intervals and levels shown above (Tables 1 and 2). There are 10 input and 8 output variables.

Fig. 4 shows screens of Membership Function Editor giving the intervals of selected input variables used in this study.

Fig. 5 displays screens of Membership Function Editor giving the intervals of selected output variables used in this study.

Fig. 6 shows FIS Editor screen which enables to enter input and outputs variables. All variables can be seen on this screen.

After membership functions are determined, the inference is performed in accordance with 20 fuzzy linguistic rules:

1. If (HotMetalTemp is low) and (Scrap + HotMetal is high), then (EndTimeBlowOxy is high).
2. If (HotMetalTemp is low) and (Scrap + HotMetal is high), then (FinalTempSteel is low).
3. If (HotMetalTemp is medium) and (Scrap + HotMetal is medium), then (FinalTempSteel is high).
4. If (HotMetalTemp is high) and (Scrap + HotMetal is low), then (FinalOxySteel is high).
5. If (HotMetalTemp is medium) and (Scrap + HotMetal is high), then (CastingWeight is medium).
6. If (HotMetalTemp is medium), then (FinalTempSteel is medium).
7. If (Scrap + HotMetal is high), then (CastingWeight is medium).
8. If (HotMetalTemp is medium) and (Scrap + HotMetal is high), then (TSOC% is low), (TSOMn% is low), (TSOP% is low), (TSOS% is low).
9. If (EndPointBlowOxy is high) and (HotMetalC% is high), then (TsoC% is low).
10. If (HotMetalTemp is medium), then (FinalTempSteel is medium).
11. If (Scrap + HotMetal is high), then (CastingWeight is medium).
12. If (EndTimeBlowOxy is medium), then (TsoMn% is medium), (TsoP% is low), (TsoSi% is low).
13. If (Bath Height is high), then (FinalTempSteel is high).
14. If (Bath Height is medium), then (FinalTempSteel is medium).
15. If (HotMetalTemp is medium) and (Scrap + HotMetal is high), then (TsoC% is low), (TsoMn%
Fig. 4. Membership functions of inputs 1–10.
number of rules used as fuzzy rules were restricted such that only the rules affecting the BOF process were taken into account. Fig. 7 illustrates an example of Surface Viewer screen obtained from Fuzzy Toolbox.
Fig. 6. Fuzzy Inference System (FIS) Editor screen (inputs and outputs of BOF).

Fig. 7. A plot of the output surface of a fuzzy system using the second input-output rule.
or three-dimensional graphic results of variables can be plotted and compared.

Fig. 8 shows the results of applied rules and their corresponding outputs according to the mass center of variables.

Each application step was obtained using MATLAB-Fuzzy Logic Toolbox version 5.0.

Comparison of the fuzzy results with the optimal control range is shown in Table 3.

6. Results and discussions

There is no general solution for the control if the plant to be controlled is complex and non-linear. The modeling of the process and its solution becomes even more difficult if a sufficiently precise model is unknown or cannot be identified. It is well known, however, that in many cases, a human operator can master the performance of such plant using linguistic control algorithms that represent the operator knowledge and experience about the plant as If-Then-Rules. A decisive idea has been that the qualitative character of linguistic rules can be quantitatively realized by a computer using fuzzy logic and representing with real data of fuzzy modeling. In next stage, development and application of dynamic model based optimization and fuzzy control were performed. The idea behind this kind of fuzzy control has been to take the respective advantages in math-model based control.

In the real plant where the data and variables were taken, BOF control is carried out by a program (soft-
Table 3

<table>
<thead>
<tr>
<th>Output</th>
<th>Variation intervals of empirical data</th>
<th>Optimal range</th>
<th>Mode</th>
<th>Targeted steel data</th>
<th>Fuzzy result</th>
<th>Deviation (mode, fuzzy)</th>
<th>Deviation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Casting weight (tonnes)</td>
<td>103.8–126.5</td>
<td>111.6–124.1</td>
<td>120.00</td>
<td>119</td>
<td>1.2</td>
<td>0.0099</td>
<td></td>
</tr>
<tr>
<td>Final temperature (°C)</td>
<td>1535–1716</td>
<td>1633–1669</td>
<td>1673</td>
<td>1650</td>
<td>1670</td>
<td>3</td>
<td>0.0018</td>
</tr>
<tr>
<td>Final O₂ in steel (ppm)</td>
<td>411–1500</td>
<td>411–1500</td>
<td>707</td>
<td>650</td>
<td>960</td>
<td>–253</td>
<td>0.4166</td>
</tr>
<tr>
<td>TS0 C%</td>
<td>0.0166–0.1174</td>
<td>0.0166–0.0412</td>
<td>0.0251</td>
<td>0.02–0.04</td>
<td>0.05</td>
<td>–0.0249</td>
<td>0.9920</td>
</tr>
<tr>
<td>TS0 Mn%</td>
<td>0.061–0.2676</td>
<td>0.099–0.22</td>
<td>0.121</td>
<td>0.10–0.20</td>
<td>0.140</td>
<td>–0.019</td>
<td>0.1570</td>
</tr>
<tr>
<td>TS0 P%</td>
<td>0.0046–0.0141</td>
<td>0.0046–0.0065</td>
<td>0.0053</td>
<td>0.015</td>
<td>0.0010</td>
<td>0.0043</td>
<td>0.8131</td>
</tr>
<tr>
<td>TS0 Si%</td>
<td>0.0045–0.0229</td>
<td>0.0045–0.0093</td>
<td>0.0071</td>
<td>0.015</td>
<td>0.011</td>
<td>–0.0039</td>
<td>0.5493</td>
</tr>
</tbody>
</table>

ware) which is based on consultancy of the expert people or the experienced operators. However, this control system used in that plant is not fully integrated and manual intervention is required by the operator. Time and product losses are caused by this intervention during the steel making process. Fuzzy control software has been developed and is being used by some Japanese BOF based steel making plant and it is claimed that fuzzy control is more efficient than conventional methods.

The most repeated results were selected as data set from the empirical BOF data to appoint to use as rules that were obtained in one of the integrated steel plant based in Turkey.

Although some variables were deviated from the targeted values, most of the fuzzy results obtained from this study were found to be acceptable and reasonable level of compatibility was achieved compared to the empirical BOF data and targeted steel composition.

Deviated output results such as final oxygen level, C% and Si% contents could be rectified and optimized by further secondary metallurgical processes. However, casting weight, final temperature, P%, S%, Mn% results were acceptable and in good agreement with the targeted steel data.

In this work, the results obtained using fuzzy control are found to be very close to the real plant’s results. This study can be extended using different steel compositions because in this work, fuzzy control studies were based on just one special steel composition.

Optimization of the BOF outputs via fuzzy control was notably achieved to some extent. Results achieved in this study were not compared with other studies because almost no publications were available in the literature and directly involved in fuzzy logic control of BOF.

7. Conclusions

The following conclusions can be drawn from the application of fuzzy logic to the control of BOF as described in this paper:

- A fuzzy logic based model control system was developed to estimate the variables in a BOF steel making process. By careful selection of the input variables and designing the rules for the system and its statistical analysis, 99% of control accuracy can be obtained.

- The results were generally in compliance with the empirical BOF data. However, in most cases, even though limited number of rules and inputs were applied, the results obtained indicated a very high accuracy. This clearly shows that by increasing the number of inputs and by improving the rules used in the MATLAB package, more proper and accurate results could be expected.

- There could be a deviation between the results obtained in this study and the steel plant’s empirical values because of the assumptions and limited number of inputs.

- As a final remark, fuzzy logic is a promising control technique and would be effectively used for
improved process control of BOF furnace in steel making industry. The study will continue to increase the effectiveness of the proposed model by increasing the content of the rules and number of the variables.

References