Abstract—The optimal control of parameters in a system assumes an important role in industrial processes. Models based on boiler-turbine plant are proposed in various applications. The target of this paper is to apply intelligent techniques on a boiler simulator to improve the speed and precision of control. In order to release such task, genetic-fuzzy controllers able of tuning the time duration of specific boiler drum signals, are designed. The results show good precision and relevant speed of control system improving the control performances of classical control structures.

Keywords—Drum boiler, fuzzy controller, control algorithms, Genetic Algorithms.

I. INTRODUCTION

The control of pressure and level on boilers is a delicate issue in situations requiring good robustness of system. This is the case where an object must remain to the target value when environmental changes happen. The automatic control of pressure and level is very important in drum boilers where the load demand of electric power and pressure and level tolerance are joined. In order to solve such kinds of problems, suitable models are applied [24], [25]. Un-Chul Moon et. al. [30] presented a comparative study of dynamic matrix control to a drum-type boiler-turbine system in a fossil power plant. Another challenge is to ensure the safe operation of the drum through optimal water level controllers. In [9] the level simulation results show that the cascade control based on immune feedback mechanism can improve the system dynamic performance. Recent studies [8] have developed models able to control the water level in boiler drum using Proportional Integral Derivative (PID) control tuning methods. On the other hand, the control mechanism of pressure and level can be improved with the application of Artificial Intelligence techniques [28], [6], [31], [17]. Because conventional controllers do not work accurately in nonlinear systems, a suitable fuzzy controller is proposed in [28]. Moreover, some researches have compared the performance of traditional PID controllers with fuzzy logic controllers [2]. In order to improve the control features of fuzzy logic controllers, optimal control theory can be applied [11].

A significant approach is presented in [29] where an application of online self-organizing fuzzy logic controller to a boiler-turbine system in a fossil power plant is designed. The novelty of such approach is that the fuzzy rules are updated each time using a self-organizing procedure.

Genetic Algorithms are matched with fuzzy techniques to solve the nonlinear model predictive control problem [31]. Further improvements are achieved using artificial Neural Network able to reduce the frequency of deviations and the degree of deviation of the water level in the drum [17]. Neural identification models are proposed by Hendookolaei et. al. [12] to control the outlet steam pressure of boilers.

In this paper, a fuzzy simulator designed to control pressure and level of drum boiler in [26] is proposed. The aim is to introduce intelligent approaches rather than classical solution with feedback and feedforward strategies [26]. Such strategies was inspired on the 160 MW-Sweden P16-G16 power plant [7]. The built simulator mainly includes two parts: (i) drum boiler dynamic natural circulation [3] and (ii) its valve actuators in [15].

The goal of this work is to improve the precision and speed performances of drum boiler classical control model [26]. Because fuzzy logic is good for decisional models and Genetic Algorithms are efficient search algorithms, genetic-fuzzy controllers are designed. In order to realize such task, Matlab-Simulink tools are used.

II. DESIGN OF INTELLIGENT CONTROLLER

Simulink model in Figure 1 includes a non linear drum boiler dynamics, valve actuators dynamics, and linear dynamics for sensor-transmitters. Drum boiler control requires two valves: one to control feedwater mass flow flowing to the drum and another to control fuel oil mass flow to burners. Figure 2 shows control linear structure system design applied to the drum boiler. On it, steam mass flow rate measuring is necessary to perform a feedforward control. Nomenclature can be found in the Appendix.

Our task is to design suitable intelligent controllers able to achieve the output values closer to the reference value in slow time. Each controller has two inputs: the error $e$ and the change in error $de$ at time $t$ of level $l$ and pressure $p$. Formally:

$$e_l(t) = l(t) - l_0$$

(1)

$$e_p(t) = p(t) - p_0$$

(2)

and
\[ de(t) = e(t) - e(t-1) \]  
\[ dp(t) = p(t) - p(t-1) \]

where \( l_0 \) and \( p_0 \) are the steady state conditions for drum boiler level and pressure respectively. The outputs of fuzzy controllers are the time duration of feedwater mass flow rate \( q_f \) and fuel oil mass flow rate \( q_o \) (see Appendix). The Membership Functions (MF) and fuzzy rules definition follows the findings of [22], [20], [21], [19]. The choice of MF shape depends on specific problem [10], [13], [27], [18]. There are situation where triangular membership functions give better results than gaussian MF in AC voltage controller [18] and in power system stabilizer [10]. Zhao et. al. [32] evaluated the speed-controlled induction motor drive using different membership functions. The results show that triangular MF give the best drive performances and the trapezoidal MF response is very close to that of triangular MF. However, recent studies show that in hand-printed recognition systems, the best recognition results are obtained using gaussian MF rather than triangular or trapezoidal MF [13]. Analogue result appears in software development effort estimation [27]. Finally, taking into account the specific applications of [32], [18], [10] and their findings, triangular/trapezoidal MF are chosen. The triangular/trapezoidal membership functions are: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positive Small), PM (Positive Medium), PB (Positive Big). The Table I shows the fuzzy rules for the two controllers. The target is to design fuzzy logic controllers with less number of rules avoiding huge computational time [5].

The working of control system shown in Fig. 3 is the following. The difference between the references values \( l_0 \) and \( p_0 \) and drum boiler outputs \( l(t) \) and \( p(t) \) (see equation (1) and (2)) are passed with the change in error (equation (3) and (4)) to the inputs of fuzzy logic controller. The outputs of fuzzy controller serves as inputs to tune the time duration of feedwater mass flow rate \( q_f \) and the fuel oil mass flow rate \( q_o \) of drum boiler (see Figure 1). The outputs of drum boiler are compared with the reference values and thus the process restarts.

In order to obtain the optimal membership functions, our procedure makes use of genetic techniques. Genetic Algorithms are based on the survival principle of the fittest. We define a fitness function which provides a performance measure of tuning parameters. In fact, the fitness function should reflect the individual performance in the current problem. In our case, such function can be expressed as

\[ f(x) = \frac{1}{\sum_{i=1}^{n} 1 + x_i} \]

where \( x = \sum_{i=1}^{n} (e_l(i) + e_p(i))^2 \) and \( n \) is the number of iterations during simulation. Similar equation to (5) is used by Ling et. al. [16] to tune the node-to-node relationship in Neural Networks hidden layers. Analog choice has been made to perform the fuzzy grammatical inference using Genetic Algorithms [4]. A typical equation which gives a higher fitness with lower overshoot, control effort and steady state error is proposed in [1]. To identify the least important fuzzy rules, fitness functions of form (5) are proposed [14]. Finally, our goal is to maximize the fitness value of (5) using genetic procedures. In this way, the errors \( e_l(i) \) and \( e_p(i) \) are reduced at minimum.

The working of designed controllers is based on the following algorithm.

**Step 1.** Initialize the MF scaling parameters. The number of parameters is 69, because each trapezoidal membership function is characterized by 4 parameters, whereas each triangular membership function by 3 parameters. The population number is 100 and the number of generations is 20. A population of problem solutions is expressed in the form of chromosomes, i.e. strings encoding problem solutions.

**Step 2.** Define the range of each MF scaling parameter. This is a delicate phase because there could be undesirable overlapping. Subsequently, compute randomly the scaling parameters and establish the termination criteria.

**Step 3.** When it is achieved the termination criteria, the intelligent procedure is stopped and go to Step 9.

**Step 4.** Compute the fitness function defined in (5) to select good strings. The task is to achieve the maximum of \( f(x) \).

**Step 5.** Implement the selection. The selection process copies parent chromosomes into a tentative new population. The number of copies reproduced for the next generation by an individual is expected to be directly proportional to its fitness value.

**Step 6.** Compute the crossover. Such genetic procedure recombines genetic material of parent chromosomes to produce offspring on the basis of crossover probability. Let \( y, z \) be two chromosomes of length 5. As an example, considering \( y = 01001 \) and \( z = 11010 \) and one-point crossover at the fourth point, two new chromosomes \( y' = 01010 \) and \( z' = 11001 \) are produced.

**Step 7.** Implement the mutation. The mutation selects a random position of a random string and complements the bit value. For example, if mutation is applied to the third bit of string \( y' \), the transformed string becomes 01110.

**Step 8.** Repeat the steps 3-7.

**Step 9.** Print the optimal values of MF scaling parameters.

The optimized MF of fuzzy controllers are shown in the Fig. 4, 5 and 6. We can note that the MF have different slopes. Thanks this algorithm, the measured values of level and pressure are very close to reference parameters values.

**III. SIMULATION RESULTS**

One of main problems of search algorithms is the convergence time required to obtain the optimal solution. Such time depends on individuals number in the initial population and number of generations. In order to avoid such problems, the individuals number has been set to 100 and the number of generation to 20.

The genetic optimization results show that the membership functions of fuzzy input error \( e \) are more narrow than fuzzy input \( de \) (see Fig. 4 and 5). This means that the change in
errors of level and pressure need of more precision. Moreover, MF of change in error shows a considerable zero positive shift. The optimal fuzzy output shows that all MF are narrow (see Fig. 6): this means that the fuzzy controllers give good precision.

Once the fuzzy controller has been optimized, the intelligent control system can begin to work. In Fig. 7 is shown the pressure and level trend of boiler overtime. In this figure, the pressure and level values are normalized. We can note that the pressure has trend characterized by constant slope equal to 0.4. The level curve is smooth and tends to have value $-0.3 m$. During the simulation, the threshold time (i.e. the time value beyond level and pressure change value) assumes different values. The Table II resumes the timing values $q_p$ and $q_l$ of drum boiler. Observing the Table II, we can note that the threshold value of time duration of feedwater mass flow rate $T_{q_p}$ is achieved before than time duration fuel oil mass flow rate $T_{q_l}$. The results of Fig. 7 and Table II show that the speed performance of our intelligent controllers are...
TABLE II
TIMING VALUES

<table>
<thead>
<tr>
<th>( t_p [s] )</th>
<th>( t_q [s] )</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.76</td>
<td>8.44</td>
</tr>
<tr>
<td>6.50</td>
<td>8.77</td>
</tr>
<tr>
<td>6.50</td>
<td>8.23</td>
</tr>
<tr>
<td>6.50</td>
<td>8.22</td>
</tr>
</tbody>
</table>

better than controllers in [17], [26].

The main sensitive parameters in drum boiler are level and pressure. Such parameters depend on the goodness of control system. The Fig. 8 and 9 show the trend of pressure and level over the number of iteration \( n \) to achieve the desired values. Observing such figures, we can note that the target values are achieved after 11 iterations. This result improves the convergence time using Neural Networks in [17]. Moreover, the slopes of shapes in Fig. 8 and 9 are greater than back propagation Neural Network results [17].

The good precision given by fuzzy controllers is confirmed by the difference between the parameters values from an iteration to another one (see Fig. 8 and 9). As an example, the difference between the pressure at seventh iteration and eighth one is 0.005 Bar. Such results improve the precision of control of drum boiler in [26].

IV. CONCLUSION

Classical solutions for the control systems use feedback and feedforward strategies. Some real drum boilers multi-loop linear control exemplify the computational thinking under simulated environment with amendable property. In order to improve the control strategies, intelligent techniques as fuzzy logic and Genetic Algorithms can be applied. Genetic-fuzzy controllers able of tuning the time duration of feedwater mass flow rate and fuel oil mass flow rate of drum boiler, are designed. The results show that the intelligent approach improves the precision and speed performances of drum boiler compared with [17], [26]. Future developments will focus on the optimization of fuzzy rules of controllers through genetic techniques.

TABLE III
DRUM BOILER CONSTRUCTIVE PARAMETERS

<table>
<thead>
<tr>
<th>( A_{dc} ) ( [m^2] )</th>
<th>( V_t ) ( [m^3] )</th>
<th>( k )</th>
<th>( T_d ) ( [s] )</th>
<th>( V_{sd0} ) ( [m^3] )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.38</td>
<td>31</td>
<td>25</td>
<td>12</td>
<td>7.55</td>
</tr>
<tr>
<td>( V_t ) ( [m^3] )</td>
<td>( m_f ) ( [kg] )</td>
<td>( C_p ) ( [J/(kg \cdot C)] )</td>
<td>( m_a ) ( [kg] )</td>
<td>( m_d ) ( [kg] )</td>
</tr>
<tr>
<td>88</td>
<td>3( e^3 )</td>
<td>600</td>
<td>1( e^3 )</td>
<td>92432.43</td>
</tr>
<tr>
<td>( \rho )</td>
<td>( V_{dc} ) ( [m^3] )</td>
<td>( A_{d} ) ( [m^2] )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.3</td>
<td>11</td>
<td>20</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

V. APPENDIX

I. Sweden power plant [7]
- Active power: 160MW
- Steam mass flow rate: 138.9kg/s
- Drum pressure: 15MPa
- Drum water temperature: 342.1C
- Feed water temperature: 300C

II. Drum boiler dynamic [3]
- \([V_{wt}, P, A_r, V_{sd}]^T\): State variables
- \([q_f, q_p]^T\): Control input variables
- \([T_f, q_s]^T\): Disturbance input variables
- \([Y, P]\): Output variables.
- \([Y_r, \rho_r]\): Set-points variables.
- \(V_{wt} \) \( [m^3] \): total water volume.
- \( Y \) \( [m] \): drum water level
- \( P \) \( [Bar] \): Drum pressure.
- \( A_r \) \( [Non \ unit] \): the steam quality at the riser outlet
- \( q_f \) \( [kg/s] \): feedwater mass flow rate
- \( q_p \) \( [kg/s] \): Fuel oil mass flow rate.
- \( q_s \) \( [kg/s] \): Steam mass flow rate
- \( T_f \) \( [C]\): feedwater temperature.
- \( q_{cd} \) \( [kg/s] \): Condensation mass flow rate.

Notations of Table III:
TABLE IV  STEADY STATES VALUES

<table>
<thead>
<tr>
<th>State variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_0$</td>
<td>85Bar</td>
</tr>
<tr>
<td>$V_{drum}$</td>
<td>57.2m$^3$</td>
</tr>
<tr>
<td>$A_{drum}$</td>
<td>0.0351 m$^2$</td>
</tr>
<tr>
<td>$V_{down}$</td>
<td>4.9m$^3$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Operation values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{op}$</td>
<td>238.1C</td>
</tr>
<tr>
<td>$V_{o}$</td>
<td>1.205[29]m$^3$</td>
</tr>
<tr>
<td>$p_{o}$</td>
<td>85Bar</td>
</tr>
</tbody>
</table>

TABLE V  MAIN PARAMETERS IN ACTUATOR DYNAMIC

<table>
<thead>
<tr>
<th>Fuel flux</th>
<th>Water flux</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>y_{e}</td>
</tr>
<tr>
<td>$0 &lt; y_e &lt; 14Kg/s$</td>
<td>$0 &lt; y_e &lt; 140Kg/s$</td>
</tr>
</tbody>
</table>

### IV. Sensor transmisrors dynamic [26]

- **$A_{dc}$**: Area of the cross section of downcomer tubes
- **$V_{r}$**: riser volume.
- **$k$**: friction coefficient in downcomer-riser loop
- **$T_{dc}$**: residence time of steam in drum.
- **$V_{dc}$**: Total volume of the drum, downcomer, and risers.
- **$m_d$**: total metal mass
- **$C_P$**: specific heat of the metal
- **$m_r$**: total riser mass.
- **$m_d$**: Drum metal mass.
- **$\beta$**: Parameter in an empirical equation
- **$V_{dc}$**: downcomer volume.
- **$A_{dc}$**: wet surface, i.e., drum area at normal operating level.

### III. Actuator dynamic [15]

- See Table V

### IV. Sensor transmisrors dynamic [26]

- **$G_{STP}$**: Transfer function for pressure sensor-transmitter
- **$G_{STY}$**: Transfer function for level sensor-transmitter

### REFERENCES

12. A. Hendookolaei, N. Bahrami Ahmad, Neural Indirect adaptive control applied in thermal power plants, Canadian Journal on Electrical and Electronics Engineering, Vol. 3, No. 6, July 2012