Application of fuzzy control to residential cogeneration with renewable energy sources

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Abstract— A fuzzy PI controller and a conventional PI controller were adopted to develop control for a residential cogeneration system made by a biomass-fired and solar-powered fluidized bed prototype. Its mathematical model is characterized by nonlinearities and, more important, by uncertainty and variability in parameters. The paper describes in detail the PI fuzzy controller, the development of which was based on the knowledge of the continuity diagrams of the process model. Then, the paper reports a comparison in simulation between the PI fuzzy controller and the conventional PI one. The PI fuzzy controller exhibits a superior performance, as far as both robustness and rate of response. As a result, the adoption of a PI fuzzy controller turns out the best choice for this residential cogeneration system and a favorable option for nonlinear processes with uncertain or time-varying parameters.

Keywords — *Fuzzy control, PI (proportional integrative) controller, mathematical model, simulation, continuity diagram, FBC (fluidized bed combustor).*

I. Introduction

Recently, in the framework of renewable energy exploitation, a new cogeneration concept system driven by two renewable energy sources, i.e., direct solar (thermodynamic solar) and biomass combustion (indirect solar energy) has been proposed by Angrisani et al. [1] and a small-scale fluidized bed prototype has been put into operation [2], [3].

Load regulation and automatic control of such systems is still a great challenge. The difficult task of modeling and controlling complex and nonlinear systems is well known. If a relatively accurate model of a dynamic system can be developed, it is often too complex to use it directly in controller development. Many conventional control design techniques in fact require restrictive assumptions (e.g., linearity), not only for the plant model, but also for control design. Traditional controllers are not able to perform very effectively when the systems to be controlled are characterized by high nonlinearity and parameter uncertainty. It is true that a PID (Proportional-Integral-Derivative) controller may be tuned to be effective at certain conditions, but a change in the value of some system parameters may also destabilize the whole control system, making ineffective the PID controller action.

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Many nonlinear systems are in fact characterized by dynamics that can be one strongly dependent on or more parameters and their operating conditions turn out stable or acceptable only if the values of these parameters remain in a limited range [4], [5]. In some cases, if the system parameters move out of this range, the equilibrium point becomes unstable. To handle these undesirable events it is necessary to switch to more robust controllers such as fuzzy logic controllers. Because of their underlying fuzzyness, these controllers are characterized by a high degree of clarity and robustness both in design and operation.

Fuzzy logic controllers (FLCs) have been reported to be successfully used for a number of complex and nonlinear processes, which are difficult to model analytically [6], [7] and are usually built up using fuzzy sets and fuzzy logic [8] - [14]. The list of applications includes cases from process industry like cement kilns [15], multi-level of a large scale industrial process [16], penicillin fermentation process [17] and non-process cases like subway trains [18]. More recently, an online adaptive fuzzy switching controller was designed, developed and implemented for real-time tracking control of an industrial SCARA robot by Marwan et al. [19]; Wang et al. [20] proposed a fuzzy control technique of auxiliary ventilation in heading laneway; an evolutionary optimization of interval mathematics-based design of a TSK fuzzy controller for anti-sway crane control was instead proposed by Smoczek [21].

It is well known that obtaining an optimal set of fuzzy sets and rules is not always an easy task because the tedious fuzzy tuning exercise requires time, experience and skills of the operator. Recently, some intelligent techniques were considered for the task of fuzzy set tuning [22], [23]. This paper presents the control of the conceptual dual-source fluidized bed cogeneration system, for which the underlying dynamic model, although very simple, is characterized by nonlinearity and parameters variability with time.

II. System Description

A. FBC

The system considered is a bubbling fluidized bed prototype (FBC) that uses two renewable energy sources: biomass firing (indirect solar energy) and direct solar heating (thermodynamic solar) [24], [25]. The fluidized bed acts as a solar receiver, through the direct irradiation of bed solids by means of a concentrated solar radiation.

A Stirling engine, integrated into the fluidized bed, converts part of thermal energy into electricity. The large and unconditioned availability of the solar energy, especially in tropical and subtropical regions and the possibility to reduce the consumption of biomass, supports the integration of the Concentrated Solar Power (CSP).

This source of energy allows to obtain fuel flexibility, low emissions and optimal operating conditions for the Stirling engine (SE) unit as well. A representation of the whole system is schematized in Fig.1. It consists of a solar collector (a mirror for the capture and concentration of the solar radiation); a FBC (used as: concentrated solar energy receiver, heat exchanger with the head of the SE and biomass combustor); a SE (to convert the heat collected in the FBC into mechanical and then electrical power); and a heat exchanger (to recover the unused low enthalpy heat).

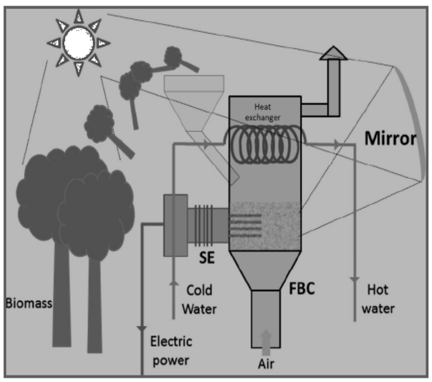

Fig.1 Schematic of the prototype.

In Fig. 2 a flow diagram of the principal energy fluxes is shown. The fluidization is obtained, as usual, by air flow blowing from the bottom of a vessel where a certain amount of granular material, like sand, is loaded over an air distributor. This allows all particles and the gas phase to carry out efficient mass and heat transfer in the bed.

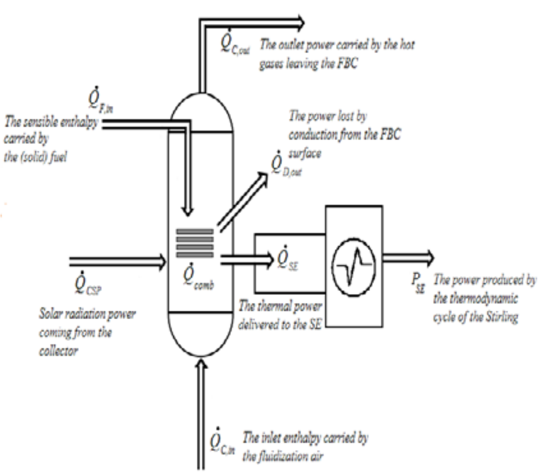

Fig.2. Flow diagram of the system with the indication of the control volume for the energy balance with the accounted energy fluxes.

B. Model of FBC

For simplicity, the model developed by Angrisani and coworkers [1], [3] is adopted here. It considers the direct coupling of a solar energy source and a SE hot heat exchanger in the bed of a FBC. Several models are proposed in the literature for a FBC. The approach by Galgano et al. [26] and Hatzantonis [27] is here adopted by the authors to determine the performance of the system. The various flux contributions to the energy balance are shown schematically in Fig. 2. The energy balance is written assuming the FBC working as a pseudo-homogeneous, perfectly stirred reactor including both solid-phase and gas-phase with bed and freeboard lumped together. Inside the FBC the temperature can be assumed uniform in space. With this assumption it is possible to assume only a single temperature for both solid- and gas-phase. The dynamic energy balance is: fluxes are:

$$\frac{dT}{dt} = \frac{1}{m_s c_s}\cdot\left[\dot{Q}_{C,in} + \dot{Q}_{F,in} + \dot{Q}_{CSP} + \dot{Q}_{SE} + \dot{Q}_{C,out} + \dot{Q}_{D,out} + \dot{Q}_{comb}\right] \tag{1}$$

The main energy fluxes, per (1) unit time, in (eq.1) are the following: the inlet enthalpy carried by the fluidization air, assumed as an ideal gas:

$$\dot{Q}_{C,in} = \dot{m}_{C,in} \cdot c_p\,(T_{in}) \cdot T_{in} \tag{2}$$

the sensible enthalpy carried by the (solid) fuel entering the fluidized bed:

$$\dot{Q}_{F,in} = \dot{m}_F \cdot c_{pF}\,(T_{Fin}) \cdot T_{Fin} \tag{3}$$

the solar radiation power coming from the collector:

$$\dot{Q}_{CSP} = \eta_{CSP} \cdot I_S \cdot A_S \tag{4}$$

where η_{CSP} is the global efficiency achieved in the process of collection and transmission to the fluidized bed of the solar power at irradiance I_S, adopting a mirror corresponding to a capture surface with area A_S.

The outlet power carried by the hot gases leaving the fluidized bed combustor, including both fluidization air and combustion gases:

$$\dot{Q}_{C,out} = -\dot{m}_{out} \cdot c_p(T) \cdot T \tag{5}$$

where $\dot{m}_{out} = \dot{m}_{C,in} + \dot{m}_F$;

the power lost by dispersion to the outside environment through the FBC walls:

$$\dot{Q}_{D,out} = -\alpha \cdot Q_{comb} \tag{6}$$

where α is a parameter expressing a proportionality factor; the thermal power released by biomass combustion:

$$\dot{Q}_{comb} = \eta_c \cdot \dot{m}_F \cdot \Delta H_F \tag{7}$$

where η_c is the in bed combustion efficiency, $\dot{m}_F$ the mass feeding rate of fuel and ΔH_F the lower heating value of the fuel.

The thermal power delivered to the Sterling engine: $\dot{Q}_{SE}$ is considered a disturbance from the viewpoint of the control system, because it is highly dependent on weather conditions (it reaches its maximum value during a sunny day, but it may decrease during a cloudy day, down to a limiting value of zero). Variables and parameters are listed in Table 1 and 2, respectively.

Table 1. Operating variables of the FBC

Air excess [-]	0.3
T_{in} Inlet gas temperature [K]	300
T_{Fin} biomass inlet temperature [K]	300
Biomass feed rate [kg/h]	1 - 4
Lower heating value of biomass [J/kg]	18.24 E+06
Air/Fuel stoichiometric ratio[kg/kg]	5.5814
m_s Total mass of bed particles [kg]	30 - 40
$\dot{Q}_{C,out} = -\dot{m}_{out} \cdot c_p(T) \cdot T$ The outlet power carried by the hot gases leaving the FB, including both fluidization air and combustion gas [W]	5000 - 10000

Table 2. Parameter values of the FBC

η_c biomass combustion efficiency	0.95
η_{CSP} global collector efficiency	0.75 – 0.85
I_S solar irradiance at the latitude of Naples [W/m^2]	500 - 1000
$\boldsymbol{\alpha}$ parameter of thermal dispersion to the environment	0.05 – 0.15
C_p Specific heat of air / flue gas at constant pressure [J/(kg K)]	9.460168275862069e+02 + 0.213095448275862·T +3.099045517241379e-05·T^2
C_{ps} Specific heat of solids forming the fluidized bed [J/(kg K)]	800
ρ_s Density of bed solid particles [kg/m^3]	2600
C_{pf} specific heat of biomass [J/(kg K)]	1000 - 1500

In the model (eq. 1), the heating of the bed due to heat released in the freeboard region is not considered. Further, the in-bed combustion efficiency is taken as η_c= 0.95, this value being reasonable on account of the amount of heat released in the bed as a function of the actual FBC conditions [28].

III. Fuzzy control scheme

A. PID control

It is well known that traditional controllers such as PI or PID lend themselves to the construction of feedback linearization control. PID control is presently more used than fuzzy control. It is quite intuitive, its actions depend on the current controller error (proportional term), the time history of the error (the integral term) and a time variation of the value of the error (the derivative term). The applicability of PID controllers is wide (they work well for a large class of processes) also in those cases where a process model is not always available and, in addition, there are many effective tuning rules. However, there are many cases where the process is highly nonlinear and is necessary to consider a control characterized by nonlinearity as well [4]. The controller nonlinearity in fact can be designed so as to compensate for process nonlinearities. The main advantage of fuzzy PID or fuzzy PI control is that of combining the advantages of ordinary linear PID or PI control with the possibility to introduce nonlinearities in the control law.

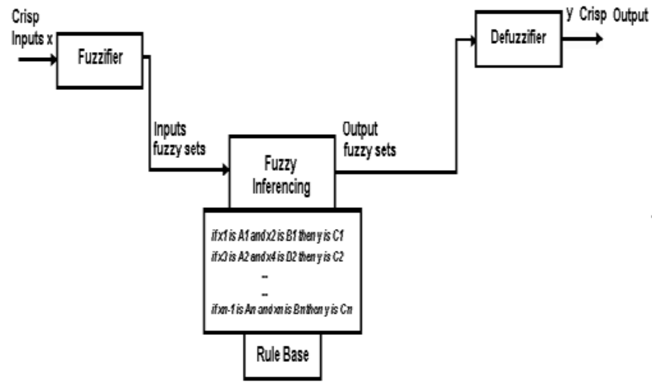

Fig. 3. Fuzzy logic system.

B. Fuzzy logic system

Four main components characterize the fuzzy controller [7], as shown in Fig. 3; they are: a) the fuzzification (fuzzifier block), necessary to modify the inputs to be interpreted in the rule base, by fuzzifying the crisp inputs (through membership functions that derive the membership grades of the crisp inputs); b) the inference mechanism (fuzzy inferencing block), to evaluate which controls at the current time are relevant and then to decide consecutively what input (output of the fuzzy logic system) must be sent to the plant; c) the rule base (expressed in the form *if-then*) where all the knowledge of the control process is contained; d) the defuzzification (defuzzifier block), to convert the conclusions of the inference mechanism into the inputs (as crisp value) to the plant. The last block is a fundamental one because the resulting fuzzy set must be converted to a single number in order to form a control signal to the plant.

The input measurements are evaluated according to the premise of the rules. Each premise produces a membership grade expressing just the degree of membership of that premise. Generally, the rule base is constructed so as to represent a human expert in the loop. Each rule has this form: *if* the behavior of the plant output is this *and* the reference input (set point) of the plant is this, *then* the plant input (the manipulation variable) should be this value. The rule base formalism is intuitive and easy to understand, in each rule there is a local process knowledge and it is described how the control signal should be selected for certain inputs.

It is necessary to load a whole set of *if-then* rules in the rule-base and, once the inference strategy has been chosen, the system is ready to be tested. Fuzzy systems allow a flexible categorization of a domain of interest. Membership functions and rules are therefore the heart of fuzzy logic and the right choice of them influences the whole system behavior.

C. FBC control

Control of FBC systems is a widespread issue. As an example, Vamvuka et al. [29] proposed control methods for mitigating biomass ash-related problems in fluidized beds; an innovative, bed temperature-oriented modeling and a robust control of a circulating fluidized bed combustor were proposed by Hadavand et al. [30]; a control system for an oxy-fuel combustion fluidized bed with flue gas recirculation was developed by Guedea et al. [31]; the control of NO_x and N_2O in pressurized fluidized-bed combustion was proposed by Lu et al [32]; the emission control devices to fit environmental regulations for a biomass fluidized bed combustor were proposed by Grass et al. [33].

In this paper the proposed control scheme is that of a simple feedback (Fig.4).

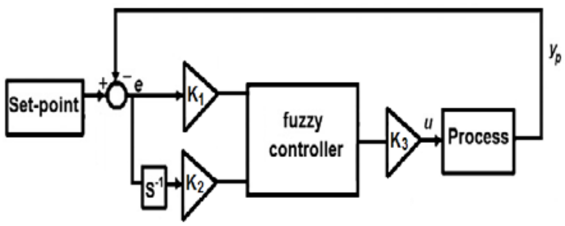

Fig. 4. Diagram block for the PI fuzzy control system.

The controlled variable is the bed temperature and the manipulated variable is the fuel feed rate (Fuel_in). The inputs of the fuzzy logic controller are given by the error and the integral of the error.

The scale factors at the entrance of fuzzy controller adjust the error and the integral of the error values to the range of the input fuzzy sets. Before designing the controller, the dynamics of the open loop system was explored and the system solution diagrams were obtained [5]. This step is very important to understand and master the dependence of the system behavior from input variables and parameter values.

The software used was Matlab®, integrated with Simulink toolbox and Matcont, this latter for the numerical study of a continuation or bifurcation on the continuous and discrete parameterized dynamical systems [5].

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IV. Results and discussions

A. Dynamics and solution diagrams at open loop

The dependence of the system bed temperature from Fuel_in (i.e., the manipulation variable in the control system) has been analyzed first. In Fig. 5A the time trajectory from the steady state a) to the new one b) and in Fig. 5B the solution diagram of the system bed temperature are shown, respectively, for Fuel_in step change from a) 0.00028 to b) 0.000417 kg/s at fixed values of csp_irradiance = 750 W/m^2 and Q_{SE} = -9000 W.

The contributions of the various terms in the energy balance in correspondence of the new steady state b) are shown in Table3.

Table 3 - Contributions of the various terms in the energy balance (Fuel_in = 0.000417 kg/s, csp_irradiance = 750 W/m^2 e Q_{SE} = -9000 W).

Qcin [W]	Qcsp [W]	Qcomb [W]	Q_{SE} [W]	Qcout [W]	Qrout [W]	QFin [W]
914.20	7312.5	7225.8	-9000	-5525	-1083.9	156.38

It is easy to note that in input the incoming solar heat and the chemical energy released from the fuel prevail, whereas in output the heat transferred to the Stirling engine prevails. It should be noted that under the conditions of Table 3, the values of solar irradiance and power transferred to the Stirling engine have been fixed in the calculation. Obviously, being a steady state, the energy balance, which contributes to the terms listed in Table 3, closes to zero. The above trend is confirmed by Fig. 6 that shows the temperature of the bed as a result of the step change in Fuel_in from 0.00028 to 0.000417 kg/s at 10000 s, at fixed csp_irradiance = 750 W/m^2, for three different values of the load to the Stirling engine Q_{SE} = -10000, -9000 and -8000 W, respectively.

To optimize the control system, it is necessary to delineate the different stability regions in the system and to study the effect of some relevant operating parameters on the dynamics. The Fig.7a shows the time trajectory of the system bed temperature (K), for csp_irradiance step change from c) 750 W/m^2 to a) 0 W/m^2 (cloudy day); b) 300 W/m^2; d) 1000 W/m^2 (sunny day) at fixed Qse = -8000 W and Fuel_in = 0.0006 kg/s.

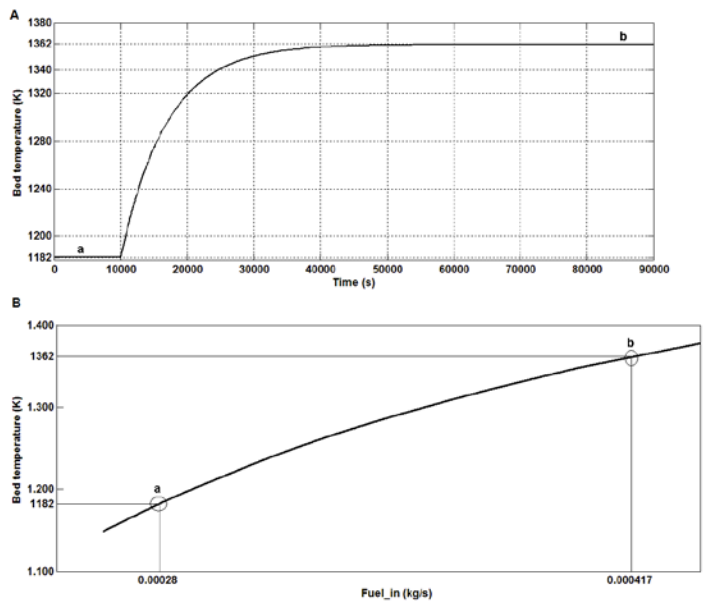

Fig. 5 – A) Time trajectory of the system bed temperature (K), for Fuel_in value step change from a) 0.00028 to b) 0.000417 kg/s at fixed values of csp_irradiance = 750 W/m^2 and Q_{SE} = -9000 W.
- B) Solution diagram Bed temperature (K) vs Fuel_in (kg/s). The diagram shows the equilibrium point in correspondence of a) Fuel_in = 0.00028 kg/s and Bed temperature T =1182 K and b) Fuel_in = 0.000417 kg/s and Bed temperature T =1362 K (b), at fixed values of csp_irradiance = 750 W/m^2 and Q_{SE} = -9000 W.

Obviously, the characteristics of the dynamic response of the system do not change. The settling time is in fact always of the order of 20000 s. The Fig. 7B shows the corresponding solution diagram of the bed temperature. It shows the locus of equilibrium points as a function of biomass feed rate (Fuel_in) for a variation of csp_irradiance parameter.

It is easy to note that a decrease in the value of csp irradiance has negative consequences on system bed temperature. This can lead to the shutdown of the FBC. Therefore, an effective control action is necessary to handle these contingencies.

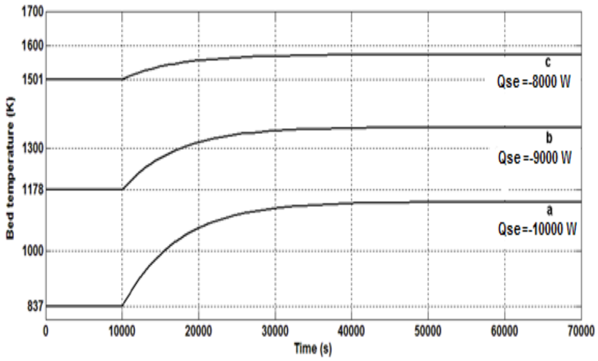

Fig. 6 Time trajectory of the system bed temperature (K), for Fuel_in step change from 0.00028 to 0.000417 kg/s at 10000 s, at fixed csp_irradiance = 750 W/m^2, for different Q_{SE} values: a) Q_{SE} = -10000 W; b) Q_{SE} = -9000 W; c) Q_{SE}= -8000 W.

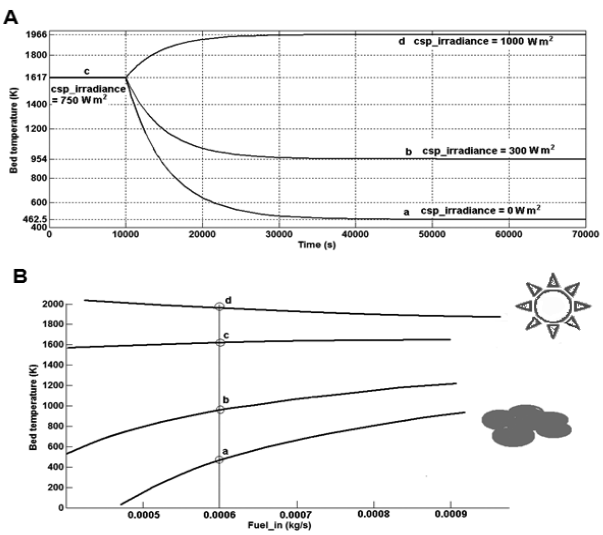

Fig. 7 – A) Time trajectory of the system bed temperature (K), for csp_irradiance step change from c) 750 W/m^2 to a) 0 W/m^2; b) 300 W/m^2; d) 1000 W/m^2 at fixed Qse = -8000 W and Fuel_in = 0.0006 kg/s.

- B) Solution diagram of Bed temperature (K) vs Fuel_in (kg/s). The diagram shows the equilibrium point in correspondence of Fuel_in = 0.0006kg/s for different values of the csp_irradiance (disturbance): a) 0 W/m^2; b) 300 W/m^2; c) 750 W/m^2; d) 1000 W/m^2, at the fixed value Qse= -8000 W.

B. Conventional PI controller

The transfer function of the PID controller is:

$$G_{PID} = K_c \cdot \left(1 + \tau_D s + \frac{1}{\tau_I s}\right)$$

where K_c is the controller gain, τ_D is the *derivative time* e τ_I is the integral time or *reset time*. In this case, only a PI controller is considered because the derivative action would give a negligible contribution due to the slow system response characteristics.

Tuning of the controller, i.e., the final adjustment of its parameters, is a topic extensively discussed in the literature. Nevertheless, the controller tuning is done, in most cases, manually "on the field" (e.g., by trial and error). In the present case the authors used a method based on the minimization of an objective function, i.e., the closed loop IAE index as obtained by simulation of the controlled system response over a suitable time. This method led to the determination of the theoretically optimal values for the parameters of the PI controller, as follows:

K_c = 12 (control gain)

τ_I = 0.008 s (integral time)

These values allowed reaching a good compromise on the response of the controlled system so as to eliminate the offset in a reasonable time and reduce the overshoot as much as possible.

C. Nonlinear PI fuzzy controller

Regarding the non-linear fuzzy controller, the values of fuzzy set parameters, the rule base developed by the authors and its characteristics are reported in Tables 4, 5 and 6, respectively. The performance of the first fuzzy controller built following the method of Jantzen (2007) is very similar to that of the PI controller; for this reason, it has not been reported in the following simulations. Such a controller is actually linear, as seen from the surface of the rules shown in Fig. 8A.

Table 4. Fuzzy sets for the error and the integral of the error.

Error	Gaussian membership functions
Negative	[42.46 -100]
Zero	[42.46 0]
Positive	[42.46 100]
Integral of the error	Triangular membership function
Negative’	[-200 -100 -20]
Zero’	[-100 0 100]
Positive	[20 100 200]
Output (crisp values)	[-200 -100 0 100 200]

Table 5. Rule base of nonlinear fuzzy controller

Error / Int Error	Negative	Zero	Positive
Negative’	-200	-100	0
Zero’	-100	0	100
Positive’	0	100	200

Table 6. Fuzzy Controller characteristics

NumInputs	2
NumOutputs	1
NumRules	9
AndMethod	Prod
OrMethod	Probor
ImpMethod	Prod
AggMethod	Sum
DefuzzMethod	Wtaver

By suitably modifying the fuzzy sets of the first and second input, it was possible to obtain a non-linear PI fuzzy controller (Nonlinear FLC) characterized by high-performance (Fig. 8B).

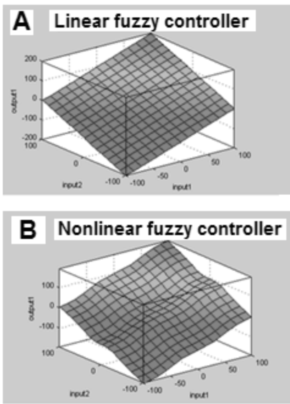

Fig. 8. Rule surface for linear fuzzy controller (A) and nonlinear fuzzy controller (B).

The following Fig. 9 graphically shows the input, output and Sugeno fuzzy inference system that has been implemented into the adopted nonlinear fuzzy controller.

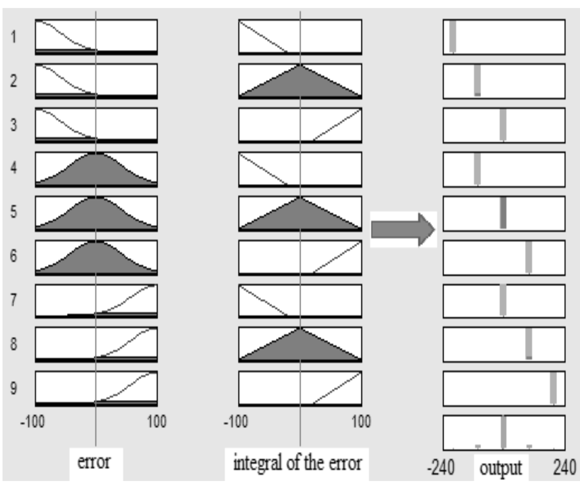

Fig. 9. Input, output and Sugeno fuzzy inference system for nonlinear fuzzy controller.

D. Simulation at closed loop

The qualification of the control system and the performance of the controller, either the conventional PI or the nonlinear fuzzy controller, have been investigated in simulation.

First, the "servo" problem has been analyzed in detail, then the "regulator" problem has been investigated and, finally, the two above cases have been taken into account simultaneously.

Servo control

The "servo" problem has been tackled by taking into account a reasonable change in set point, e.g., a step down in bed temperature from a steady-state value of 1177 K to 1160 K.

The time trajectory of the system temperature (K) following the set point step at t = 1000 s, for fixed values of Qse = −8000 W and csp_irradiance = 750 W/m^2, is shown in Fig. 10A.

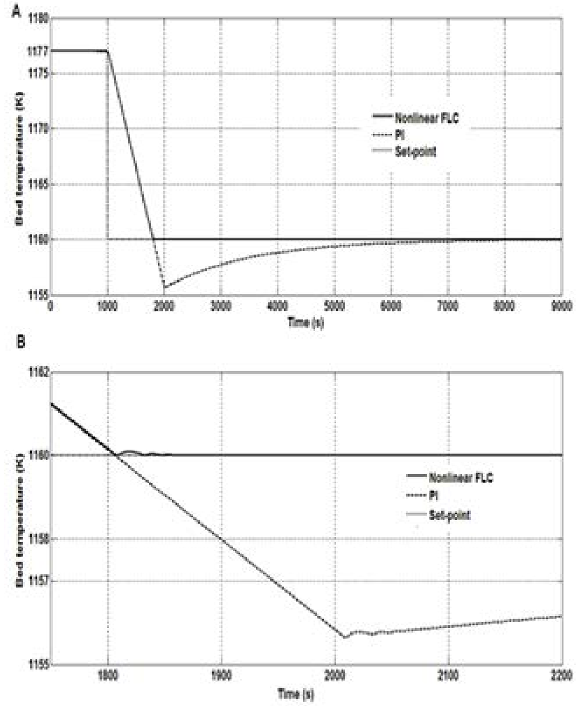

Fig. 10. A) Time trajectory of the system bed temperature (K), for set point value step change from 1177 a 1160 K at t = 1000 s, at fixed values of Qse = -8000 W and csp_irradiance = 750 W/m^2 - B) Zoom of Fig. 10A.

It is easy to note that only with the nonlinear fuzzy controller it is possible to reach the new set point and remain on it, without falling below this value and approaching it only after a long time. In particular, with the zoom shown in Fig. 10B, it is possible to note on one side just a negligible overshooting for the fuzzy controlled system, on the other side an evident downward peak for the PI controlled system.

The same analysis has been repeated in simulation by taking into account a reduced-size change in set point under the same conditions. Fig. 11 presents the time trajectory of the bed temperature following a set point step down of –7K, i.e., from 1177 to 1170K. This simulation confirms the previous finding, with the fuzzy controller showing a better performance than the conventional PI. Moreover, a similar analysis has been repeated in simulation by taking into account a step up in set point under the same conditions. In Fig. 12 the time trajectory of the bed temperature (K) is shown for a positive set point change from 1177 K to 1220 K, at t = 1000 s, for fixed values of Qse = -8000 W and csp_irradiance = 750 W/m^2.

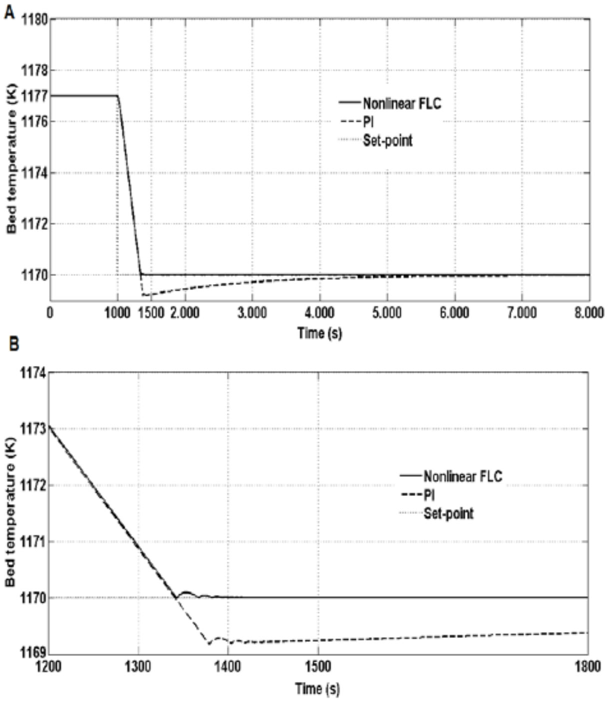

Fig. 11. A) Time trajectory of the system bed temperature (K), for set point step down from 1177 to 1170 K at t= 1000 s, at fixed values of Qse = -8000 W and csp_irradiance = 750 W/m^2 - B) Zoom of Fig. 11A.

The system response shows an overshoot of about the same size for both the conventional PI and the nonlinear fuzzy controller. However, past the overshoot, the system controlled by PI controller crosses the new set point line and drops below it, whereas the system controlled by fuzzy controller reaches the new set point value and remains on it just at its second crossing point, thus demonstrating to be more efficient and faster.

On the basis of results in Figs.10 through 12, it is easy to conclude that the superiority of the fuzzy controller does not depend on either step amplitude or step change sign.

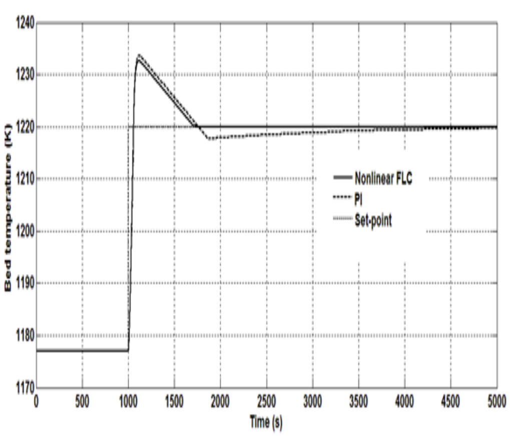

Fig. 12. Time trajectory of the system bed temperature (K), for set point value step change from 1177 to 1220 K at t = 1000 s, at fixed values of Qse = -8000 W and csp_irradiance = 750 W/m^2.

In Fig 13 the time trajectory of the system bed temperature (K) is reported for a further simulation in which the set point undergoes a number of random step variations, at fixed values of Qse = -8000 W and csp_irradiance = 750 W/m^2.

Also in this case the results confirm the better performance of the fuzzy control, for both positive and negative step changes.

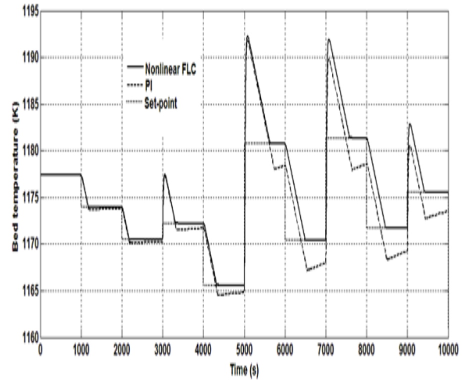

Fig. 13 - A) Time trajectory of the system bed temperature (K), for set point value random variation at fixed value of Qse = -8000 W and csp_irradiance = 750 W/m^2.

Only with fuzzy control the system can reach and settle to the new set point value before the set point changes again its value randomly.

Regulatory control

In a further simulation (Fig. 14) the closed loop performances of nonlinear fuzzy control and traditional PI control are compared following a step down change in disturbance (i.e., csp_irradiance), from 750 down to 0 W/m^2 at t = 100 s, for a fixed value of Qse = -8000 W. It is as if during the operation of the system, at some point, the solar energy collector became unable to capture energy anymore (e.g., clouds obscure the sun).

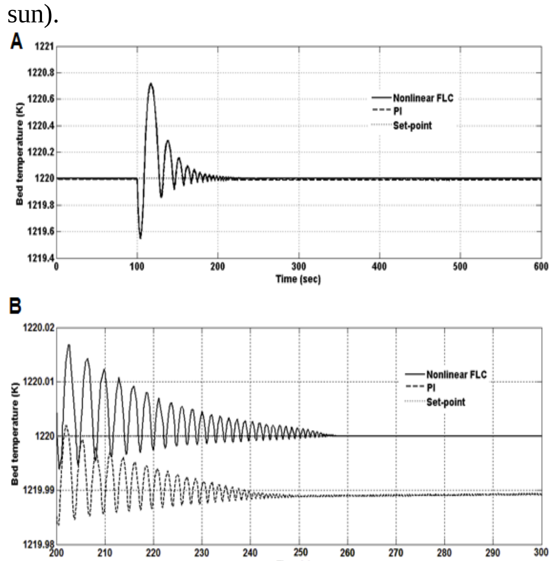

Fig. 14. - A) Time trajectory of the system bed temperature (K), for csp_irradiance (disturbance) value step change from 750 to 0 W/m^2 at t= 1000 s, at fixed value of Qse = -8000 W - B) Zoom of Fig. 14 A.

Although the dynamics are much faster and the oscillations less pronounced than in the “servo” problem, it is possible to note in the zoomed region (Fig. 14B) that the nonlinear controller FLC is a bit faster than the PI in rejecting the disturbance and precisely keeping the set-point value of 1220K.

Servo and regulatory control

In this analysis, the effects of set point change and disturbance variation are summed in simulation. This time a ramp change was considered for the disturbance (csp_irradiance) rather than a step starting at t=1000 s with a slope = -0.03. Following the previous discussion after Fig. 7, a linear change for csp_irradiance is more realistic than a step change; in a sunny day, in fact, the sun is likely to be obscured by clouds gradually and not abruptly. Vice versa, the bed temperature was changed by a down step from 1177 to 1150 K simultaneously at t = 1000 s. The overall system response in reported in Fig. 15.

The simulation results in Fig. 15 evidently confirm the preference for the non-linear fuzzy controller also in this case. Hence, the fuzzy controller proves to be a good choice for both servo and regulatory control.

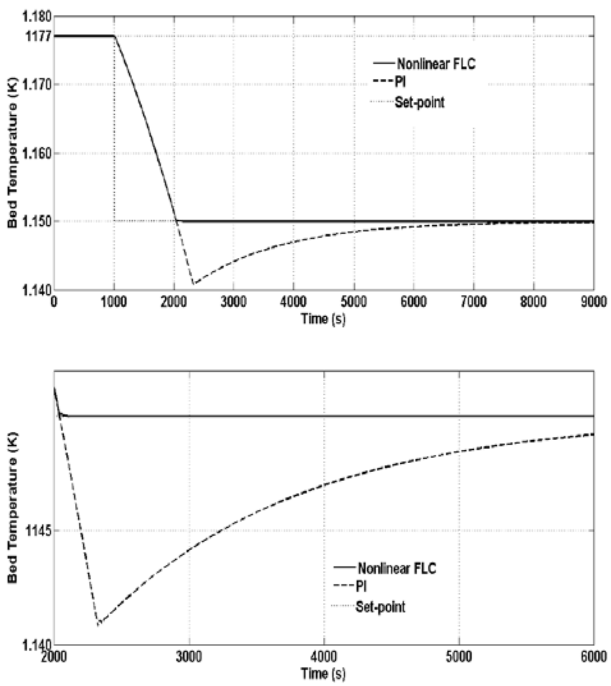

Fig. 15. - A) Time trajectory of the system bed temperature (controlled variable) following a ramp in csp_irradiance (disturbance) at t = 1000 s with initial value 750 W/m^2 and slope = -0.03, for a fixed value of Qse = -8000W
- B) Zoom of Fig. 15 A.

V. Conclusions

A feedback control system has been conceived, tuned and simulated for a cogeneration system driven by two renewable energy sources: direct solar and biomass combustion. In the simulations the system bed temperature was considered as the controlled variable, while the solar irradiance as a disturbance and the biomass feed rate as the control variable (manipulation variable).

Two different approaches were chosen for the choice and the development of controllers, the first conducted to a traditional PI controller, the second to a more advanced nonlinear fuzzy controller.

When compared to the conventional PI controller, the nonlinear FLC controller clearly and widely demonstrated to yield a better performance, in terms of response oscillation, set point following, velocity and rejection of disturbances.

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References

[1] G. Angrisani, K. Bizon, R. Chirone, G. Continillo, G. Fusco, S. Lombardi, F.S. Marra, F. Miccio, C. Roselli, M. Sasso, R. Solimene, F. Tariello, M. Urciuolo, “Development of a new concept solar-biomass cogeneration system,” *Energy Conversion and Management*, 75, pp. 552-560, 2013.

[2] G. Angrisani, K. Bizon, R. Chirone, G. Continillo, B. Cosenza, G. Fusco, S. Lombardi, F.S. Marra, F. Miccio, M. Miccio, C. Roselli, M. Sasso, R. Solimene, F. Tariello, M. Urciuolo, “Automatic control and load regulation of a solar-biomass powered prototype combining a fluidized bed and a stirling engine for household cogeneration”, Abstract Book of the Joint Meeting of FRENCH & ITALIAN IFRF and THE COMBUSTION INSTITUTE, Pisa, ISBN 978-88-88104-16-4, 2014; pp. 94.

[3] K. Bizon, F.S. Marra, G. Continillo, *Fast Predictive Model for Design and Optimization of a Low Emission Biomass Fueled CHP System.* In 23rd European Biomass Conference and Exhibition, Vienna, Austria. 2015, pp. 724-731.

[4] A. Isidori, *Nonlinear Control System: An Introduction*. New York: Springer Verlag, 2nd edition, 1989.

[5] B.W. Bequette. Process dynamics: modeling, analysis and simulation, New Jersey: Prentice Hall, 1998.

[6] M. Sugeno, *Industrial applications of fuzzy control*. Elsevier Science Pub. Co. 1985.

[7] K. M. Passino, S. Yurkovich, *Fuzzy Control*, AddisonWesley Longman, Menlo Park, CA (later published by Prentice-Hall); 1998.

[8] L. A. Zadeh , “Fuzzy sets”. *Information and Control*, 8, pp. 338-353, 1965.

[9] L. A. Zadeh ,“Outline of a new approach to the analysis of complex systems and decision processes”, *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3, pp. 28–44.

[10] L. A. Zadeh, “Fuzzy sets as a basis for a theory of possibility”, *Fuzzy Sets Syst*, 1, 1, pp. 3-28, 1978.

[11] E. H. Mamdani, “Applications of fuzzy algorithms for simple dynamic plant”, *In Proceedings IEEE*, 121, pp. 1585–1588, 1974.

[12] E. H. Mamdani, "Applications of fuzzy logic to approximate reasoning using linguistic synthesis", IEEE Transactions on Computer, 26 (12), pp. 1182-1191, 1977.

[13] B. Kosko, "Fuzzy systems as universal approximators", IEEE Trans. Computers, 43, pp. 1329-1333, 1994.

[14] P. Andrzej, "What is not clear in fuzzy control systems" *International Journal of Applied Mathematics and Computer Science*, 16, 1, pp. 37-49. 2006,

[15] J. J. Ostergaard, L. P. Holmblad, "Control of Cement kiln by Fuzzy Logic. Fuzzy Information and Decision Processes", M.M. Gupta and E. Sanchez, eds, North-Holland, Amsterdam; 1982, p.389-399.

[16] R. E. King, F. C. Karonis, "Multi-Level Expert Control of a Large-Scale Industrial Process", in Fuzzy Computing Theory, Hardware and Applications, M.M. Gupta and T. Yamakawa, eds., Amsterdam: North-Holland; 1988, pp. 323-340.

[17] E. Xu , G. Xu, S. Zhang, "Application of expert fuzzy controller in the penicillin fermentation processes". Annual Review in Automatic Programming, 15, pp. 97-100, 1989.

[18] S. Yasunobu, S. Miyamoto, "Automatic Train Operation System by Predictive Fuzzy Control", Industrial Applications of Fuzzy Control, M.Sugeno, eds, North-Holland, Amsterdam, pp.1-18, 1985,.

[19] A. Marwan, N. Farrukh, S. Ksm, S. Hanim, I. Fadi, "On-line adaptive fuzzy switching controller for SCARA robot", *WSEAS Transactions on Systems and Control*, 6, pp. 404-416, 2011.

[20] S. Wang, D. Zhou, Z. Yang, "Fuzzy Control Technique of Auxiliary ventilation in Heading Laneway". *Research Journal of Applied Sciences, Engineering and Technology*, 5, pp. 914-921, 2013.

[21] J. Smoczek, "An evolutionary optimization of interval mathematics-based design of a TSK fuzzy controller for anti-sway crane control", *International Journal of Applied Mathematics and Computer Science*, 23, pp. 749-759, 2013.

[22] J. Jantzen, *Foundations of Fuzzy Control*. John Wiley and Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex, England; 2007.

[23] O. Castillo, H. Neyoy, J. Soria, P. Melin, F. Valdez, "A new approach for dynamic fuzzy logic parameter tuning in Ant Colony Optimization and its application in fuzzy control of a mobile robot", Applied Soft Computing, 28: pp.150-159, 2015.

[24] R. L. Bain, "Overend RP. Biomass for heat and power", *Forest Products Journal*, 52, pp. 12–9, 2002.

[25] J. Vos "Biomass energy for heating and hot water supply in Belaru". Contract Report (BYE/03/G31), BTG; 2006.

[26] A. Galgano, P. Salatino, S. Crescitelli, F. Scala, P. Maffettone, "A model of the dynamics of a fluidized bed combustor burning biomass". *Combust Flame*, 140, pp. 371–84, 2005.

[27] H. Hatzantonis, H. Yiannoulakis, A. Yiagopoulos, C. Kiparissides, "Recent developments in modeling gas-phase catalyzed olefin polymerization fluidized-bed reactors: the effect of bubble size variation on the reactor's performance", *Chem Eng Sci* 55, pp. 3237–59, 2000.

[28] F. Miccio, On the integration between fluidized bed and stirling engine for micro-generation", *Appl Therm Eng*, 52, pp. 46–53, 2013.

[29] D. Vamvuka, D. Zografos, G. Alevizos, "Control methods for mitigating biomass ash-related problems in fluidized beds". *Bioresource Technology*, 99, pp. 3534-3544, 2008.

[30] A. Hadavand, A. A. Jalali, P. Famouri, "An innovative bed temperature-oriented modeling and robust control of a circulating fluidized bed combustor". *Chemical Engineering Journal*, 140, pp. 497-508, 2008.

[31] I. Guedea, I. Bolea, C. Lupiáñez, N. Cortés, E. Teruel, J. Pallarés, L. I. Díez, L. M Romeo, "Control system for an oxy-fuel combustion fluidized bed with flue gas recirculation". *Energy Procedia*, 4, pp. 972-979, 2011.

[32] Y. Lu, I. Hippinen, A. Jahkola. "Control of NO_x and N_2O in pressurized fluidized-bed combustion. *Fuel*, 74, pp. 317-322, 1995, .

[33] S. W. Grass, B. M Jenkins, "Biomass fueled fluidized bed combustion: Atmospheric emissions, emission control devices and enviromental regulations. *Biomass and Bioenergy*, 6, pp. 243-260, 1994.