ARTICLE IN PRESS

Applied Energy xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

An adaptive Fuzzy logic-based approach to PID control of steam turbines in solar applications☆

S. Dettori[a,*], V. Iannino[a], V. Colla[a], A. Signorini[b]

[a] Scuola Superiore Sant'Anna TeCIP Institute PERCRO Laboratory, Via Alamanni 13D, Ghezzano, 56124, Italy
[b] General Electric Oil & Gas, Via F. Matteucci 2, Firenze 50127, Italy

HIGHLIGHTS

- An adaptive Fuzzy Logic PID approach is proposed to control steam turbines.
- A CSPP has been modeled focusing on power loop with variable steam conditions.
- Design of FPID controller through the knowledge acquired during simulation phase.
- FL allows to control steam turbines in off-design points with optimal performance.
- Control algorithm with reduced design and implementation time on PLC platforms.

ARTICLE INFO

Keywords:
Concentrated Solar Power Plant
Steam turbine control
PID
Tuning
Fuzzy logic
PLC

ABSTRACT

In Concentrated Solar Power Plants, steam turbines controlled with standard Proportional Integrative Derivative (PID) methods may suffer from performance downgrading in power generation when the steam conditions deviate from nominal ones. An enhancement of standard steam turbine controller can be the key to achieve optimal performance also in non-nominal steam conditions. This paper presents the improvement of the PID control concept by exploiting Fuzzy Logic, an artificial intelligence technique that allows taking into account the human experience and knowledge on the system behavior. A real Concentrated Solar Power Plant has been modeled focusing on generated power control loop, its stability and performance analysis, knowledge useful to design a Fuzzy Inference System. A fuzzy logic controller is proposed to continuously adapt the PID parameters, to improve the steam turbine governor action. Its performance is compared to the classical PID tuned according to three different approaches. The fuzzy logic PID controller extends the simplicity of PID and adapts the control action to actual operating condition by providing the system with a sort of "decision-making skill". The possibility to design implementable algorithms on a Programmable Logic Controller, which have stringent computational speed and memory requirements, has been explicitly taken into account in the developed work, through the minimization of the controller complexity with a reduced number of fuzzy sets and fuzzy rules within the fuzzy inference system.

1. Introduction

In the last decade, Concentrated Solar Power Plants (CSPP) showed an increasing diffusion worldwide [1], due, on one hand, to their increased efficiency and capacity of energy production [2], on the other hand, to the pressure toward an efficient exploitation of renewable energy sources in order to improve sustainable development of human activities [3]. In particular in the European Union, the CSPP power capacity installed is about 2312 MWe in the 2014, with more than 1 billion euros worth of projects expected in Italy, currently in the commissioning phase, for a total of 361.3 MWe to be installed [4].

A CSPP generates electrical power by using different kind of technologies [5] (e.g. parabolic trough, solar towers, etc.) and uses solar thermal energy to generate steam, normally exploited by steam turbines in a Rankine cycle, or integrated with other fossils combined cycles in cogeneration power plants, such as in [6], with the possibility to reduce the cost of solar electricity by 35–40% as pointed out in [7]. The available solar energy changes during the day, due to the daily cycle of irradiation and to the weather conditions. This implies a daily start-up and shut down cycle in the power generation unit and quite sensitive

☆ The short version of the paper was presented at ICAE2016 on Oct 8–11, Beijing, China. This paper is a substantial extension of the short version of the conference paper.

* Corresponding author.
E-mail address: s.dettori@santannapisa.it (S. Dettori).

http://dx.doi.org/10.1016/j.apenergy.2017.08.145
Received 14 January 2017; Received in revised form 20 April 2017; Accepted 12 August 2017
0306-2619/

Nomenclature

Abbreviations

AI	Artificial Intelligence
COA	Center of Area
CSPP	Concentrated Solar Power Plant
EG	Electric Generator
FIS	Fuzzy Inference System
FL	Fuzzy Logic
GB	Gearbox
HP	High Pressure
IAE	Integral Absolute Error
LP	Low Pressure
MF	Membership Function
MPC	Model Predictive Control
PI	Proportional Integrative
PID	Proportional Integrative Derivative
PLC	Programmable Logic Controller
PM	Power Measure
SP	Set Point
ST	Steam Turbine

Parameters and variables

K_{steam}	steam gain
P_{rated}	rated power
f_{rated}	maximum steam mass flow
K_{actual}	actual power of the steam
f_{inlet}	inlet steam mass flow
P_{out}	useful power output
P_m	turbine mechanical power
P_{Tfric}	turbine friction power losses
J	moment of inertia
P_{RatedF}	power losses at synchronism speed
ω_s	synchronism rotational speed
τ	torque
τ_{bw}	bearing and windage friction torque
P_{GBLoss}	gearbox power losses
P_{EGLoss}	electric generator mechanical losses
τ_{load}	gearbox full load power losses
P_{Rbw}	bearing and windage rated power losses
P_{Rl}	power losses at rated shaft load
e	error
Δe	derivative error
$\bar{e}$	conditioned error
$\overline{\Delta e}$	conditioned derivative error
K_p	correction of proportional gain
K_i	correction of integral gain

Subscript

i	i-th time step

variations in the steam production, with the possibility to continuously operate by incorporating thermal energy storage or backup system in the plant, such as discussed by Zhang et al. in [8]. The continuity of energy production of a CSPP is also one of the main factors that may result effective in the thermal conversion of solar energy with respect to the photovoltaic, as highlighted by Desideri et al. in [9]. This approach can be coupled to non-standard control techniques, which allow to face the complexity of CSPP systems, by exploiting, for instance, a Model Predictive Control (MPC) approach, such as proposed by Vassallo and Bravo in [10], or adaptive control approaches and Artificial Intelligence (AI) techniques, such as highlighted by Camacho et al. in [11].

The Steam Turbine (ST) has been originally designed for energy production from fossil fuels, thus both their mechanics and their control systems have been designed to face a quite stable steam production and very rare start-up and shut down cycles. As a consequence, in the context of CSPP, the standard PID control techniques currently applied to turbo-machinery are often not effective in the automatic adaptation to changing operating conditions of the machine [12]. Control system parameters are determined on the brand-new machine during the commissioning phase, with time consuming and effort-intensive procedures. In addition, these parameters are only occasionally re-adjusted on the basis of semi-heuristic procedures. This forces the machine to work in non-optimal efficiency conditions during its lifetime.

On the other hand, the control procedures need to allow correct and efficient machine operation in transient conditions without compromising its integrity, in particular focusing on variable operating conditions where steam turbines are subjected to continuous thermal stresses, premature aging and consequent lowering of efficiency. The turbine control problem with variable steam conditions can be addressed by looking for applicability of innovative control strategy. Adaptive Control approaches, which allow to adapt gains in different loading conditions and uncertainties are known. An example of this kind of strategy is described in [13], where the turbine speed control is adapted as a function of the load, as well as Model Based Control schemes, such as the Feedback Linearization and linear quadratic regulator described in [14], or Feedback Linearization combined with a PI controller designed by means of a H_∞ loop-shaping robust method as in [15], or internal model control techniques for the design of a robust Proportional Integrative Derivative (PID) controller in a speed control application as in [16]. Predictive control approaches have been investigated in [17], where the General Predictive Control and Constrained Receding-Horizon Predictive Control have been exploited for the control of large steam turbines during load variations and in [18], where an Exponential Auto-Regressive eXogenous (ARX) model-based multistep predictive control algorithm is applied to control a thermal power plant. An interesting MPC application for the design of fault tolerant control systems is presented by Salahshoor et al. in [19], where a Generalized Predictive Control, combined with support vector machine and adaptive neuro-fuzzy inference system, allows to recover the normal operation also in different fault scenarios. A complex control scheme, presented in [20], exploits a combined action of a feedforward controller based on nonlinear programming and a feedback controller designed with robust methods involving turbine governor valve and others control inputs, in order to control a fossil power plant in different load conditions.

In the field of AI, Fuzzy Logic (FL) and Evolutionary Algorithms (EA) have sometimes been exploited to control steam turbines. For instance, in [21] FL is used in order to adjust the parameters of a PID controller during speed control, while PID controllers whose parameters are tuned through different EA methods are proposed in [22] and in [23]. However, none of the above-mentioned approaches definitely proved to overcome the other ones in any operating scenarios.

The main purpose of the work proposed here is to optimize the current control concept based on PID or Proportional Integral (PI) controllers by exploiting human knowledge and experience on the system behavior, with a focus on CSPP application and typical power loading profiles. The main goals have been achieved by using FL, an AI approach very close to human reasoning, which allows to formalize an effective control strategy that takes into account large operating point variations, large variations of steam features or other non-linear effects in a simpler way with respect to other approaches, such as MPC. Although FL in general allows to balance design and implementation time, and computational requirements, on the other hand, in some cases it is difficult to generalize an optimal methodology for the formalization of the rules within the Fuzzy Inference System (FIS) for control application. The novelty introduced in the proposed FL methodology is the simplification and optimization of the number of rules within FIS with respect to the standard Fuzzy PID described in literature. The FIS has been designed specifically for power control of steam turbines in CSPP applications. The restricted number of rules allows the field engineer to easily fine tune the performances achievable with the PID controller and to implement and upgrade an adaptive control algorithm on platforms such Programmable Logic Controller (PLC), which have stringent memory requirements and computational speed.

The paper is organized as follows: Section 2 describes the main elements of a CSPP power loop and the model used to characterize their dynamics; Section 3 focus on the FL approach and its fundamentals and describes the proposed FL-based PID gains adapter, which is named FPID; Section 4 presents the comparison between classical and fuzzy control approaches; In Section 5 the algorithm design and implementation problems for PLC platforms have been considered and described, while Section 6 provides some concluding remarks and hints for future work.

2. CSPP description and modeling

A real CSPP has been modeled focusing on the dynamic behaviors of the main component involved in the control loop of the generated electric power. In particular the CSPP is mainly composed by a steam generator and a steam re-heater, a non-condensing High Pressure (HP) ST, coupled with a gearbox to a condensing Low Pressure (LP) ST and an electric generator of rated power of 55 MW. The system is completed by two steam by-pass systems and a condensing system receiving the exhaust steam from the LP turbine outlet. An electro-hydraulic system controls the inlet valves of each turbine. The overall power control system is a cascaded PI control composed by an outer loop that follows a demand of power and gets a control signal demand from the inner loop. The inner loop controls the control oil pressure of the electro-hydraulic system and a demand of valve stroke. The demands of both HP and LP inlet valve stroke are coupled with a specific command ratio.

The non-condensing high pressure steam turbine, composed of an impulsive drum, 3 reaction drums and 1 bleeding, has an inlet rated steam pressure of about 106 bar, a temperature of 378 °C and an output power of about 18 MW. The condensing low pressure turbine, composed of 4 reaction drums, a condensing drum and 4 bleedings, has an inlet rated steam pressure of 18.3 bar, a temperature of 378 °C and an output power of about 40 MW.

In literature, different ST models have been exploited for control and monitoring purposes, which try to reproduce the real behavior of the machine, such as the non-linear relationships of the efficiency, the steam mass flow along the blades and the enthalpy drop between the ST drums. Some of the most important papers focus on the thermodynamic behavior of the machine, as described by Varbanov et al. in their work [24], where semi-empirical relationships and thermodynamic equations model the generated power, with minor attention to the dynamic behavior of the machine during transient operations. This aspect has been taken into account in two works, by Pourbeik et al. in [25] and by Chaibakhsh et al. [26]. In particular in the latter one, the ST models show good performance in the prediction of generated power through the use of thermodynamic principles and semi-empirical equations.

Starting from the literature examples, the adopted modeling methodology tries to represent and simulate the main issues that are typically faced by steam turbine control, in particular for the considered CSPP application: (see Fig. 1)

- the variability of Steam Pressure and Temperature in the steam header system and the relative static gain of the overall dynamic system;
- the non-linearity of the inlet valve behavior in function of the stroke, different for both HP and LP turbines.

The described system has been modeled through a quite complex model developed in the Matlab/Simulink environment shown in Fig. 4 and simplified in Fig. 2. In particular the modeling work has been

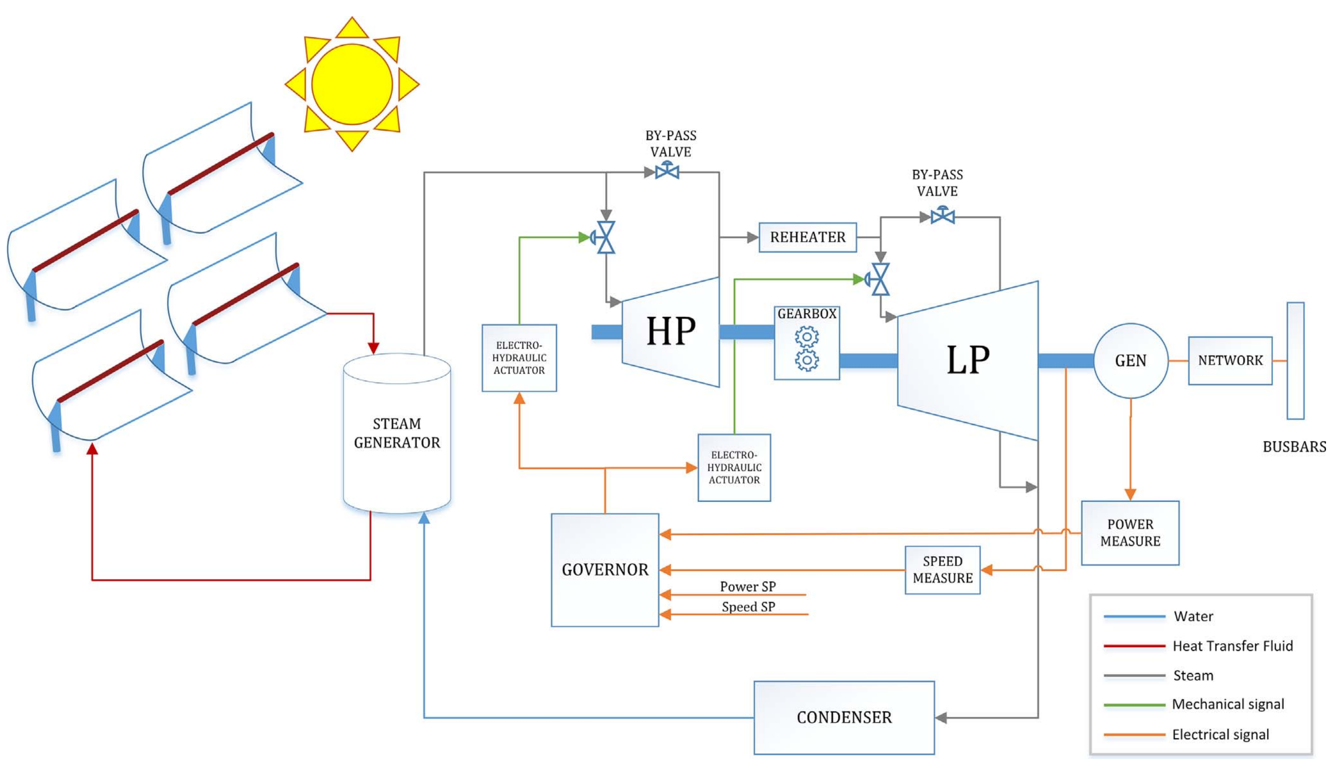

Fig. 1. CSPP schematic diagram of steam and turbine control systems.

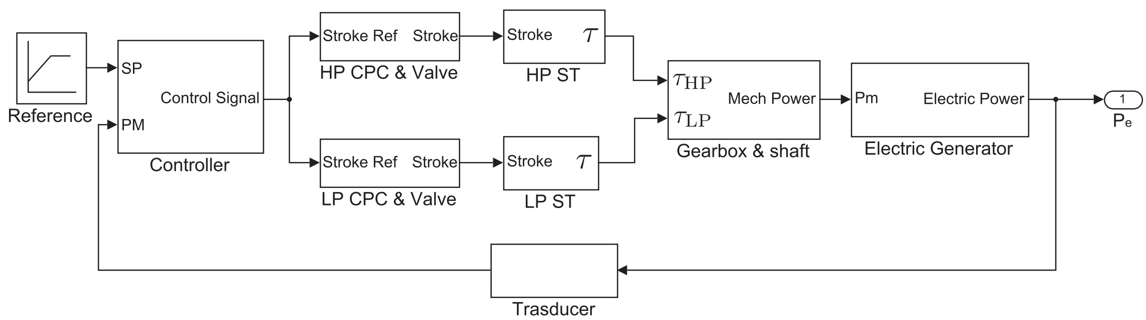

Fig. 2. Simplified CSPP Simulink model.

focused on the turbines, the electro-hydraulic system and electric generator.

Both the STs models (shown on Fig. 3) are mainly composed by:

- a *Mass Flow block*, which computes the inlet steam mass flow as a function of control valve stroke;
- a *Steam Gain*, which takes into account the characteristics of flow rate and power of steam;
- a model of the turbine pressurization dynamics;
- a Friction Model.

More in detail, the *Mass Flow block* takes into account the non-linearity of the inlet valve behavior as a function of the stroke, due to the iteration of the steam with the valve geometry for variable values of the stroke as well as of the effect of the steam partialization in the nozzle governing. In particular, the block computes the inlet steam mass flow f_{inlet} by means a lookup table calibrated with a steam at rated conditions.

The *Steam Gain* K_{steam} takes into account both steam enthalpy and mass flow as a function of the inlet pressure and temperature. The gain is computed as function of a corrective factor that takes into account the actual power of the steam K_{actual}, the rated power P_{rated} and the maximum steam mass flow f_{rated}. For a given header steam pressure and temperature, K_{actual} is computed externally by means of a Neural Networks technique described in [27].

The turbine pressurization has been simplified through a dynamic model characterized by a transfer function of first order, that takes into account the pressure transients along the turbine box.

The turbine mechanical drive power is computed as follows:

$$P_m = \left(\frac{P_{\text{rated}}}{f_{\text{rated}}} K_{\text{actual}}\right) f_{\text{inlet}} \tag{1}$$

The useful power output P_{out} is computed as:

$$P_{\text{out}} = P_m - P_{\text{Tfric}} \tag{2}$$

where the friction power losses P_{Tfric} are computed as a function of P_{RatedF} the Power losses at rated synchronism speed ω_s and the rotational speed ω as follows:

$$P_{\text{Tfric}} = \frac{P_{\text{RatedF}}}{\omega_s^2}\omega^2 \tag{3}$$

The gearbox model computes the balance of the torques acting on the LP turbine shaft. Both torques and angular velocities are reduced to the same LP shaft. The angular speed is computed through the balance of both LP and HP turbine torques, electric generator torque and gearbox friction torque τ_{GB}, then integrated and divided by the total moment of inertia acting on the LP turbine shaft, as follow:

$$(J_{\text{GB}} + J_{\text{HP}} + J_{\text{LP}} + J_{\text{EG}})\dot{\omega} = \tau_{\text{GB}} + \tau_{\text{HP}} + \tau_{\text{LP}} + \tau_{\text{EG}} \tag{4}$$

The gearbox friction torque τ_{GB} is equal to the sum of two contributions, one due to bearing and windage friction τ_{bw} and the other due to full load power losses, computed as follows:

$$\tau_{\text{GB}} = \tau_{bw} + \tau_{\text{load}} = \frac{P_{Rbw}}{\omega_s^2}\omega + \frac{P_{Rl}}{\max\tau_{\text{HP}}\,\omega}\tau_{\text{HP}} \tag{5}$$

where P_{Rbw} are the Rated power losses due to bearing friction and windage and P_{Rl} are the power losses at rated shaft load.

The electric generator model computes the generated electric power P_e as the useful mechanical power at generator shafts minus the gearbox power losses P_{GBLoss} and electrical and mechanical losses on the electric generator P_{EGLoss}, namely as:

$$P_e = P_{\text{HP}} + P_{\text{LP}} - P_{\text{GBLoss}} - P_{\text{EGLoss}} \tag{6}$$

The complex hydraulic parts of the electro-hydraulic actuator system and relative PI controller have been modeled by means of Simscape library of Matlab Simulink. For the purpose of this study, the nonlinear model has been linearized and introduced as transfer function in the CSPP model. The outer loop controller is a non-standard PI controller with the task to follow a demand of power and to request a control signal demand to the actuators. The non-standard PI controller software, property of General Electric Oil & Gas, has three main features: (I) an anti-windup action, obtained by differential formulation of integral component, (II) a limiter in the output, (III) a proportional gain involved as well in the integral component calculation.

3. The FPID gains adapter

In the field of industrial systems control, FL is increasingly used,

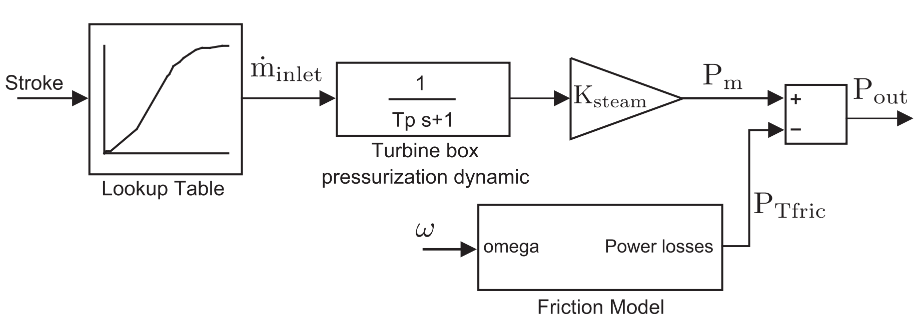

Fig. 3. Simplified Simulink model of a steam turbine.

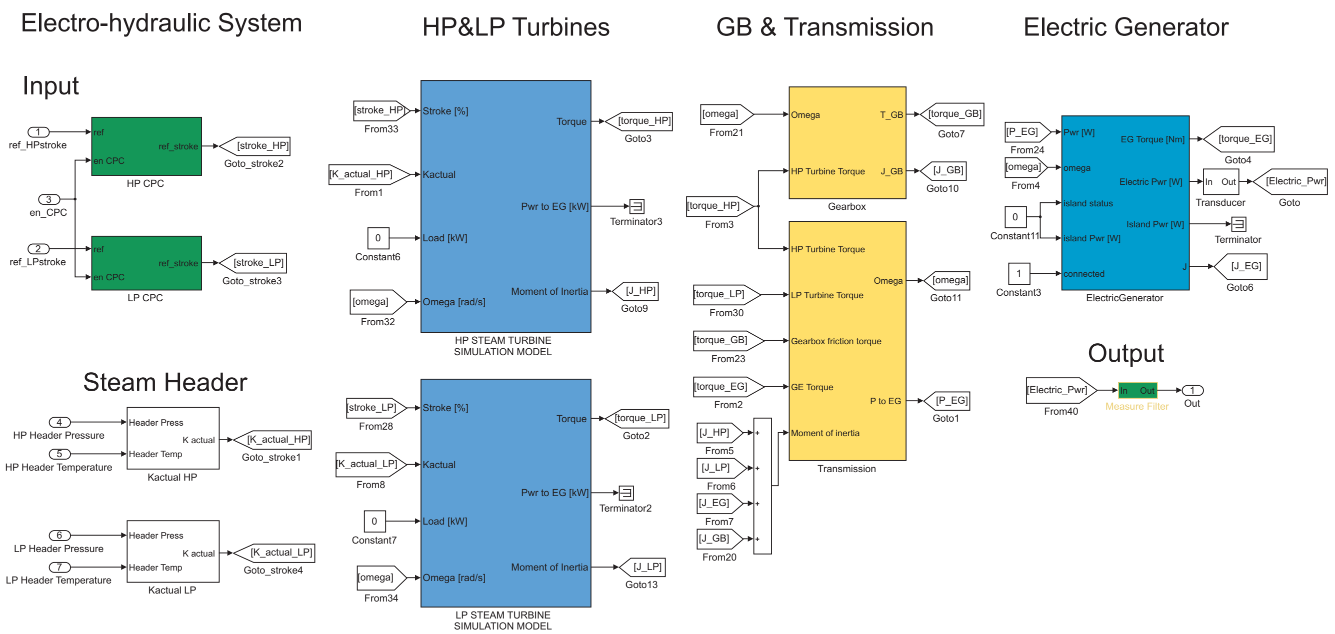

Fig. 4. CSPP Simulink model.

particularly in the case of complex nonlinear systems, starting from the studies described in [28,29], the foundations for the FL and the use of FL in the field of automatic controls. The term ”fuzzy” can lead to a misconception, but actually the FL is a structured framework allowing to formalise and represent imprecision and approximate reasoning, as pointed out in the article by Zadeh [30]. The main idea within FL is the possibility to describe complex systems with linguistic variables, that allow to make decision in a field similar to human reasoning and to convert a linguistic control strategy into an automatic controller, based on the knowledge acquired on the system, for example on its dynamic behavior. An example of the flexibility of FL is described in [31], where the author proposes a Fuzzy multi-criteria method (TOPSIS fuzzy) with the aim of investigating the use of a molten salt as heat transfer fluid in CSPP. One of the first turbo-machinery control approaches through the exploitation of FL is described in [32], where the pressure and speed error, the heat change and throttle change are described with linguistic qualitative variables and then used to control a steam engine and a boiler combination. The FL has been often juxtaposed with classical PID controllers, especially with the aim of achieving a trade-off between flexibility and simplicity, such as in [33], where the PID controller is obtained by means of a set of rules based on the error and its derivative. In [34] a fuzzy-based PID is designed by means of genetic algorithms which allow to optimally tune the FIS, whereas in [35] different fuzzy-based PID architectures are self-tuned by means of a set of rules within the FIS. In [36] a direct drive electro-hydraulic position servo system is presented, where a FL PID achieves automatic adjustment of PID

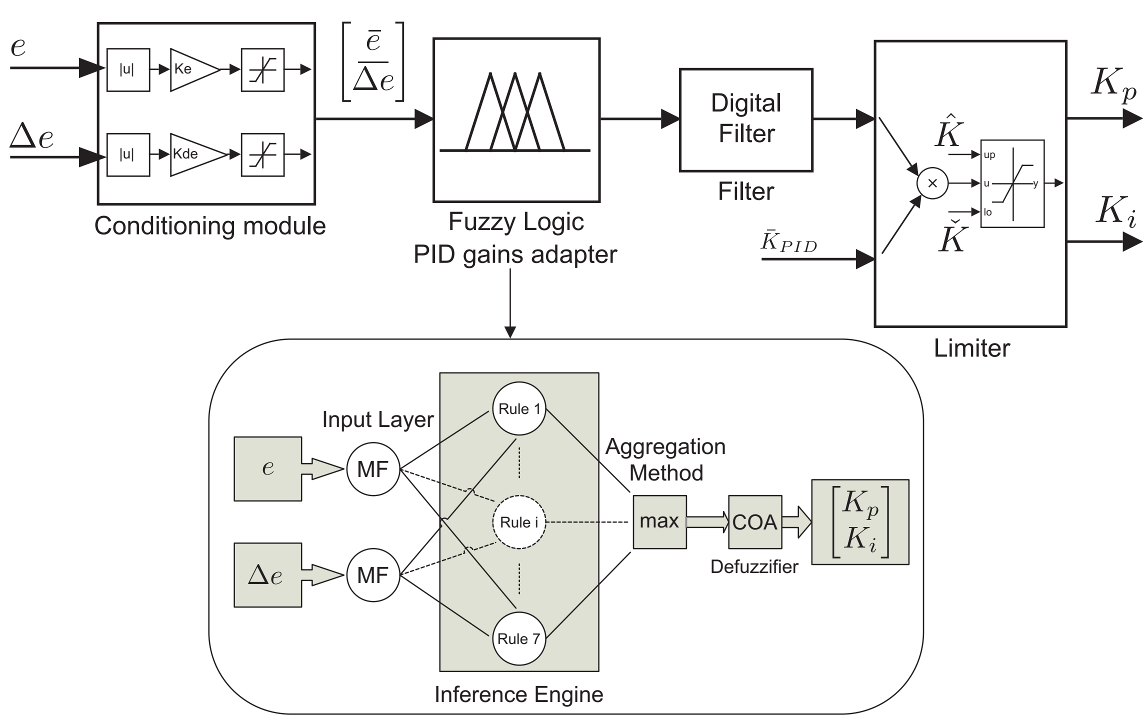

Fig. 5. Schematic of the FPID gains adapter.

parameters, improving different performance compared to classic PID approach. In [37] a FL controller, similar to aforementioned works, is presented with the aim to control a distributed collector field of a solar power plant.

When summarizing the main issues which are identified in the wide literature on the application of Fuzzy PID in real world contexts, it is clear that the complexity of the FIS to be designed mainly depends on the number of inputs and fuzzy sets used to partition the input variables. In a FIS, the rules represent a description of the system behavior in the classical "if-then" formulation. In general, the maximum number of rules n_r within a consistent rule basis of a FIS is computed as follows:

$$n_r = \prod_{j=1}^{n} N_j \tag{7}$$

where n are the number of inputs, and N_j the number of fuzzy sets for the j-th input. For a typical Fuzzy PID application, where the FIS has 2 inputs (typically the error and derivative error) and 7 fuzzy sets for each input, $n_r = 49$. The approach of establishing a complete set of rules covering all the possible combinations of fuzzy sets is usually adopted for a precise tuning of the Fuzzy controller in all the possible operating conditions. However, in a real application, 49 rules results to be impractical, as the fine tuning operations of the final controller to be performed on the field is overcomplex and not viable. For practical reasons, fuzzy rules or sets must be included only where it is justified by the need to increase accuracy or to obtain a desired behavior in some particular conditions. The proposed control approach essentially aims at adapting the proportional and integrative gains of the original PID through weighting factors which are computed through a FIS and to finally minimize the complexity of the FL controller in terms of number of rules and sets. Despite the fact that the actual power controller is a PID without derivative component (and here results are shown referring to a PI controller, namely a PI), the study and the development of the FIS have been based on a more general PID configuration.

The FIS, which is shown in the top of Fig. 5, takes as input the error at time i and its derivative error defined as: (see Fig. 6)

$$e(i) = \frac{\mathrm{SP}(i) - \mathrm{PM}(i)}{\max(\mathrm{PM}) - \min(\mathrm{PM})} \tag{8}$$

$$\Delta e = e(i) - e(i-1) \tag{9}$$

where SP(i) and PM(i) are, respectively, the Power Set Point and the Power Measure at time i. The outputs of FIS are the PID gains correction parameters.

Table 1
Input and output membership function parameters.

Input	Range	Fuzzy Set	Type of MF	Parameters
Error	[0,1]	S	TRAPMF	[0 0 0.0001 0.001]
		M	TRIMF	[0.0009 0.2 0.4]
		B	TRAPMF	[0.303 0.803 0.999 1.32]
Derivative Error	[0,1]	S	TRAPMF	[−0.0927 −0.0103 0.02513 0.0516]
		M	TRIMF	[0.04101 0.2 0.4]
		B	TRAPMF	[0.3 0.8 1 1]
Output	**Range**	**Fuzzy Set**	**Type of MF**	**Parameters**
K_p	[0,2]	S	TRAPMF	[−0.1855 −0.0206 0.4 1]
		M	TRIMF	[0.9 1 1.1]
		B	TRAPMF	[1 1.6 2 2]
K_i	[0,4]	S	TRAPMF	[−0.371 −0.0412 0.8 1]
		M	TRIMF	[0.9 1 1.1]
		B	TRAPMF	[1 3.2 4 4]

The FIS is composed of 4 modules (see Table 1):

1. a conditioning module, rescaling the inputs in the range [0, 1];
2. the FPID, the main component of the FIS, which modulates the default PID gains according to a set of rules and functions, based on conditioned $\bar{e}$ and $\overline{\Delta e}$;
3. a filter, a second order Butterworth digital filter which smooths the PID parameters variation in order to avoid the possibility of instability effects;
4. a threshold operator, limiting the PID parameters value in a fixed range.

The main components of the FPID, shown in the bottom of Fig. 5, are:

1. An input layer (*Fuzzifier*) that essentially converts the inputs $\bar{e}$ and $\overline{\Delta e}$ into fuzzy variables, determining their degree of membership to the fuzzy sets (Small S, Medium M, Big B) that are defined on the universe where they are defined by means of Membership Functions (MF). Both input and output MF are trapezoidal for the sets S and B,

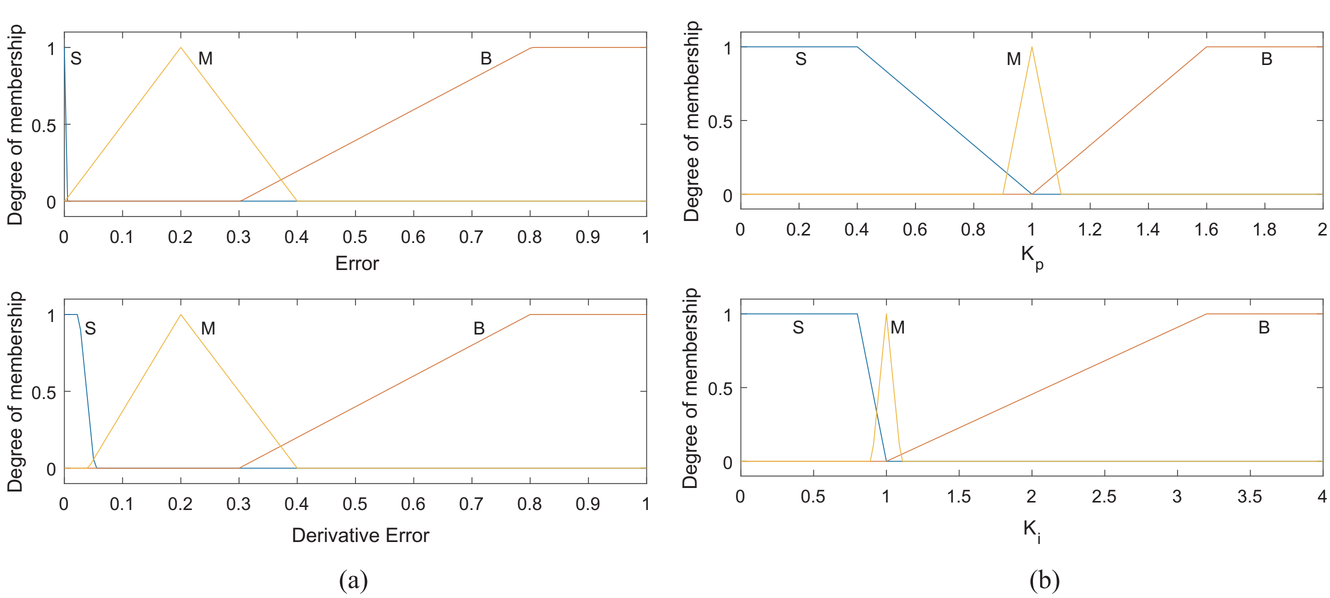

Fig. 6. Input (a) and output (b) membership functions.

and triangular for M. The function parameters, the vertices of geometric shapes, are listed in the table shown on Fig. 5;
2. The *inference engine*, which enables making decision by means of a series of rules shown in Table 2;
3. The *aggregation method* that combines all the results of rules into a single fuzzy set, one for each output variable (K_p and K_i). In particular, in this implementation of the algorithm, the aggregation is computed as the maximum of all rules result;
4. The *defuzzification layer*, where the final crisp values of the output variables are computed by means of Center of Area (COA) algorithm which has been already applied in [38].

The rules have been designed according to the behavior of the system during the simulations. Such rules improve the operation of the PID for the analyzed load ramp, which is often used in the power plant, but are not meant to be general and to give optimal results for similar systems or for different set point profiles. The number of rules and sets have been minimized in order to facilitate the implementation on a PLC. In particular, the final FIS includes a set of 3 linguistic fuzzy sets for each input and 7 rules, with respect to the typical 49 rules of a Fuzzy PID described in literature.

4. Numerical results

In order to assess the validity of the proposed approach, the performances of the FL-based approach have been evaluated on the tuning of a standard PI controller, whose parameters are heuristically set and then compared with the same PI controller after a tuning with the well-known Relay auto-tuning method [39]. Among the different literature methods which were applied in a preliminary phase of the study (e.g. Ziegler-Nicholson [40] and minimum error criteria of Integral Absolute Error), the Relay method provides the best results and is very similar to the practical method that can also be applied at site, therefore it is taken hereafter as reference for the optimal pre-tuning of the PI controller.

The developed tests are related to the loading ramp power control, with generator synchronized and connected with the grid, when the bypass valves are ramping to closure and the Governor must follow a demand of power ramp. The adopted performance indexes are:

- the *settling time*, in this work defined as the time elapsed from the ramp command start to the actual power within $\pm$ 5% of target value;
- the *rise time*, in this work defined as the time elapsed from the ramp command start to 90 % of target value;
- the *overshoot*, defined as the difference between the maximum power reference and the power peak during the transient;
- the *integral absolute error* (IAE), evaluated along the entire ramp until time T is reached, between set point SP and actual value PM:

$$\mathrm{IAE} = \int_0^T |\mathrm{SP}(t)-\mathrm{PM}(t)dt \tag{10}$$

In order to analyze the performance of the proposed approach, the power control loop has been simulated in three different scenarios. In the first one, the power reference is a nominal loading ramp with maximum power set to 30 MW, a nominal condition of steam at the inlet of turbines is assumed. In the second experiment, a reduced pressure steam on the inlet turbines is simulated, causing the reduction of 30% of the system static gain. In such case, the PI tuned in nominal condition has low gains for the actual steam condition and a slower control action. In the last experiment, a typical condition during the start-up operation is simulated, with a system static gain reduced to 12% of rated power.

Table 3 depicts the achieved results: in the first trial (shown in Fig. 7), the Fuzzy procedure for the PI gains adaptation provides a very limited benefit starting from optimal parameters, with small improvement on settling and rise time of about 0.1 s. On the other hand, the improvements are more evident when the FPID adapts the field parameters, with a reduction of both rise and settling time of about 5 s. In the second trial (shown in Fig. 8), the Fuzzy approach substantially improves both the Relay PI and the Field PI, by achieving a good match between the Fuzzy PI response and the Set Point. The third trial (shown in Fig. 9) highlights the fuzzy approach action during the adaptation of PI Parameters, evident in both relay and field PI, with improvement respectively of about 3.6 and 134 s.

Comparing the Relay PI and the FPID, a little improvement is obtained as the original PI was already optimally tuned in a way that allows to have a quite fast control action. The benefits are more evident in scenarios characterized by steam conditions far from the nominal ones or starting from the PI with field gains, where the overall performances of the control loop are recovered and comparable to the nominal steam pressure case.

Compared to other complex control approaches, the FL-based method allows to design an optimal controller starting from the classic PID, the typical speed/power controller in CSPP and in general in thermal power plants, with a reduced implementation time and the possibility of upgrading the control scheme and its performance through the use of the knowledge acquired during both design and simulation phases, or even the experience of field engineers. In particular, the simulation phase has allowed to implement a reduced number of rules (7), with respect to other Fuzzy PID and FL-based implementations presented in the literature, thus allowing much more simple procedures for the fine-tuning on site.

5. PLC implementation

In this section some considerations about the PLC implementation of the FPID algorithm are reported. In particular, regarding the implementation difficulties typically faced during the translation of an algorithm validated on a Simulink environment, where several toolboxes offers ready-to-use functions implementing complex calculations into a target which is typically a controller based on PLC architecture. Matlab/Simulink it is a powerful simulation environment which allows to pre-validate the algorithm but also to export the same code using the PLC Coder Toolbox as structured text, or compiling a C version, which many PLC platforms accept. Despite latest generations of PLCs are using powerful CPU with expanded memory, their proprietary project software development environment is often offering a traditional functional block library which can be considered limited when exploring adaptive control strategies. Still, this useful exporting code feature of Simulink is not enough to produce a PLC library with the typical features useful to integrate the desired algorithm into the entire Governor program. In addition it is often necessary to have the possibility to carry out some modification during site activity.

Regarding to the case study described in this article, the original code produced through the Fuzzy toolbox has been re-written as Matlab code to extract from the body of the code some coefficients that need to

Table 2
Rule base for the update of PID gains.

ID	Rule
1	IF **error** is *Small* AND **derivative error** is *Small* → K_p is *Medium* AND K_i is *Medium*
2	IF **error** is *Big* AND **derivative error** is *Small* → K_p is *Big* AND K_i is *Small*
3	IF **error** is *Big* AND **derivative error** is *Big* → K_p is *Medium* AND K_i is *Small*
4	IF **error** is *Medium* AND **derivative error** is *Small* → K_p is *Big* AND K_i is *Small*
5	IF **error** is *Big* AND **derivative error** is *Medium* → K_p is *Big* AND K_i is *Big*
6	IF **error** is *Small* AND **derivative error** is *Big* → K_p is *Big* AND K_i is *Small*
7	IF **error** is *Medium* AND **derivative error** is *Big* → K_p is *Medium* AND K_i is *Small*

Table 3
Performances of Relay PI, field PI and FPID applied in the trials.

Trials	Indexes	Relay	Fuzzy	Field PI	Fuzzy
1	Overshoot (%)	0.11	0.16	0	0
	Settling Time [s]	139.64	139.53	146.16	141.34
	Rise Time [s]	129.97	129.86	136.41	131.39
	IAE	2.62e+4	2.18e+4	4.70e+5	1.62e+5
2	Overshoot (%)	0.04	0.13	0	0
	Settling Time [s]	139.91	139.72	154.90	143.11
	Rise Time [s]	130.20	129.98	139.22	132.84
	IAE	3.41e+4	3.02e+4	6.63e+5	2.28e+5
3	Overshoot (%)	0	0.43	0	0
	Settling Time [s]	8.01	4.41	197.5	63.39
	Rise Time [s]	6.14	3.77	145.2	45.98
	IAE	1.58e+5	1.01e+5	3.12e+06	9.67e+5

become adjustable parameters, and also to simplify some calculations with the aim of optimizing the computational time requested by the algorithm. The design phase of the control algorithm has been carried out in order to ensure that a site engineer could tune a set of parameters:

- the definition of the region where the control error and its derivative are small is actually the definition of a dead-band where the fuzzy corrections are not applied;
- two weight parameters for the error and its derivative value are introduced to easily amplify or attenuate the effect of the set of rules without changing the complete structure of the algorithm;
- the filter behavior applied on output corrections;
- the membership functions generated by the fuzzy toolbox were defined as arrays of hundreds of points, these have been simplified through 4 point definition and a linear interpolator (once fixed the choice of trapezoidal or triangular membership functions).

The final library block, shall also include some feature for a safe deployment of the algorithm itself. The computation can be monitored while the final correction values are “disabled”, fixed to 1, so that the effect of the enabling can be analyzed in a sort of silent way and some setting can be adjusted before enabling the actual usage of the correction parameters.

6. Conclusions

The paper proposes an adaptive fuzzy approach to PID parameters tuning as an alternative to standard approaches. The various methods are applied on a modeled CSPP composed by a generator, two turbines and a gearbox, in particular focusing on power loop control. The results show that the fuzzy approach applied to an optimally tuned PID only slightly improves the system performance. On the other hand, when applied to the field tuned PID, which is result of standard site

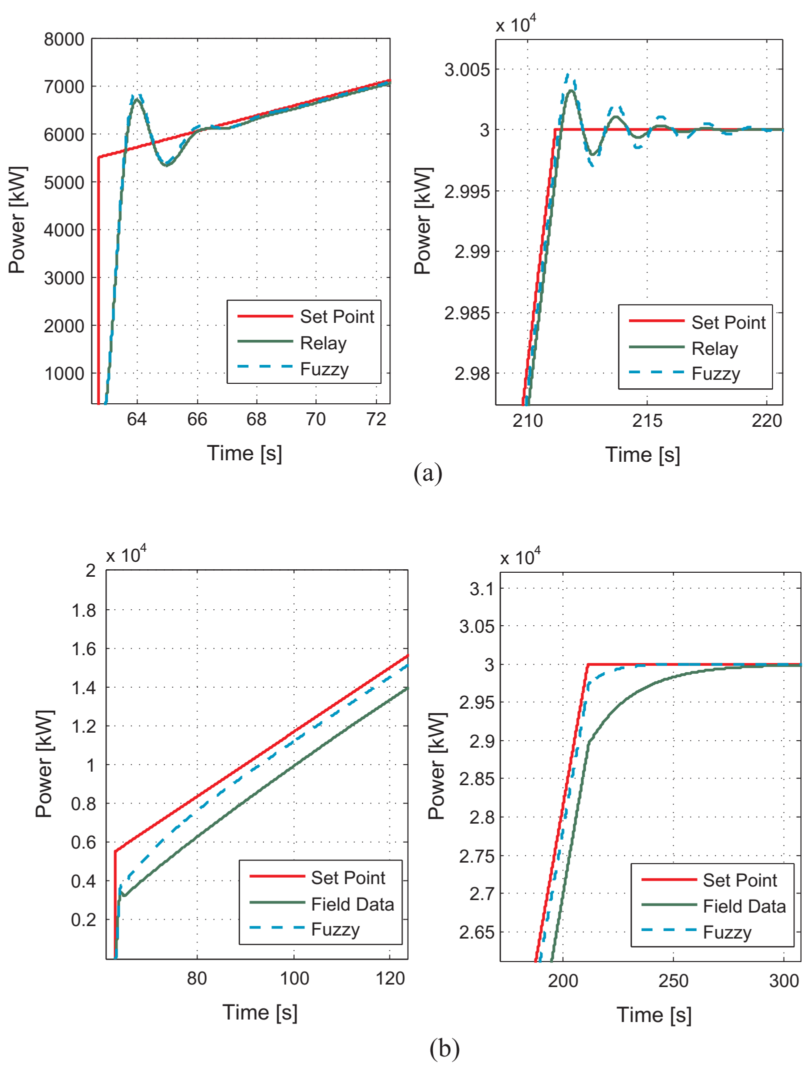

Fig. 7. Power Response in the first scenario, with steam at nominal conditions. Comparison between PI Controller tuned by Relay method and Fuzzy PI controller performances (a). Comparison between PI Controller tuned with Field settings and Fuzzy PI controller performances (b).

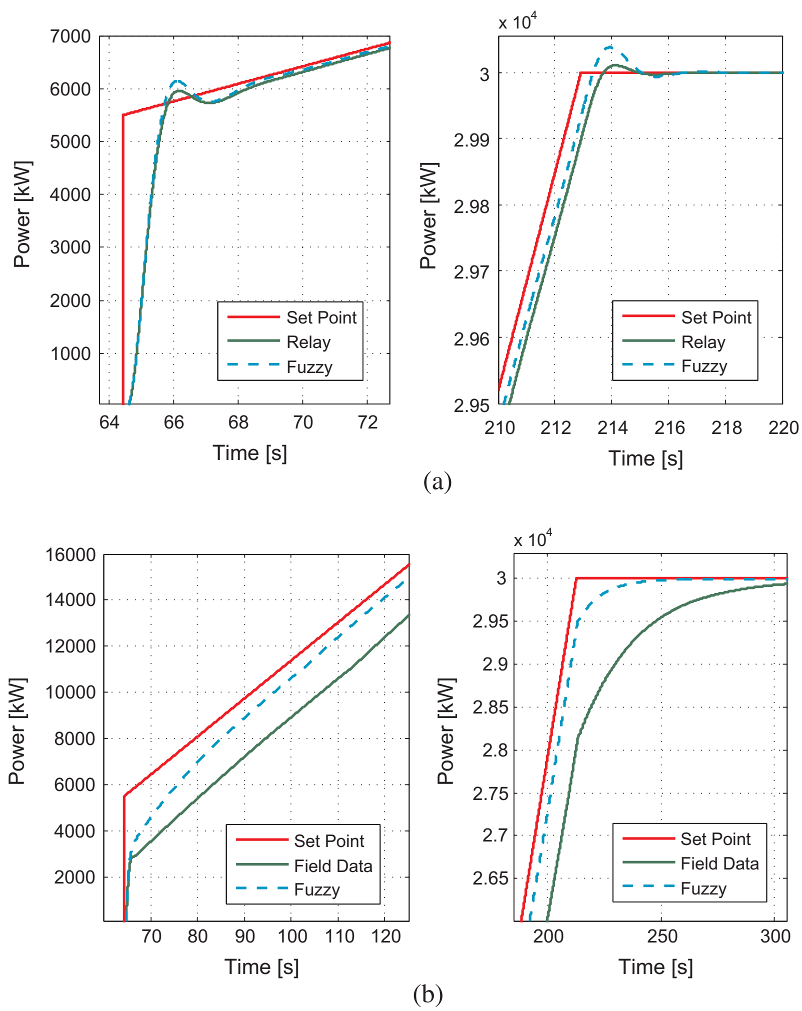

Fig. 8. Power Response in the second scenario, with steam at 70% of nominal conditions. Comparison between PI Controller tuned by Relay method and Fuzzy PI controller performances (a). Comparison between PI Controller tuned with Field settings and Fuzzy PI controller performances (b).

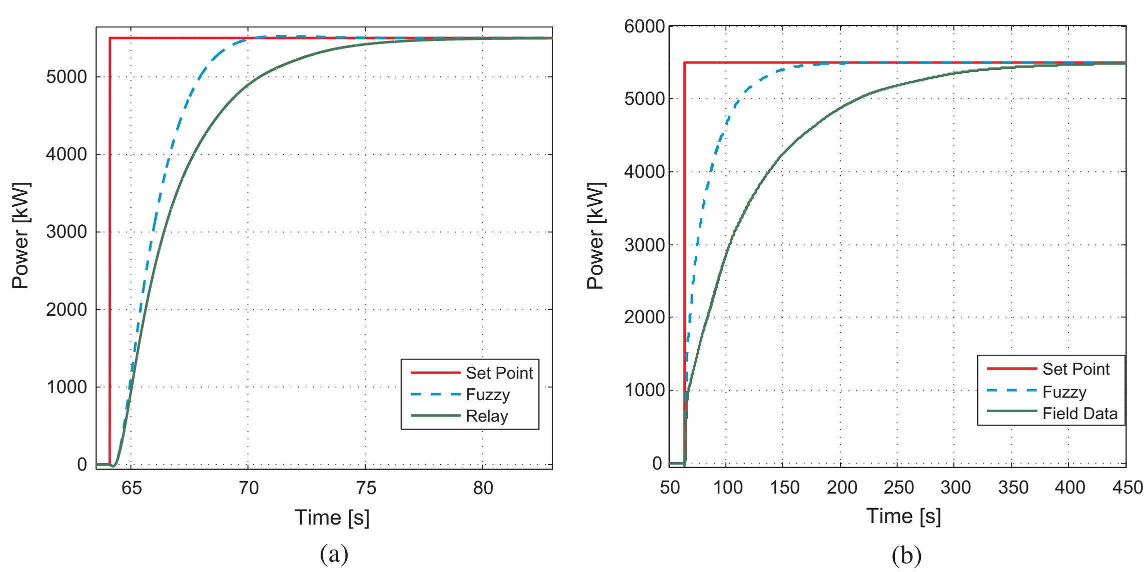

Fig. 9. Power Response with steam at 12% of nominal conditions. Comparison between PI Controller tuned by Relay method and Fuzzy PI controller performances (a). Comparison between PI Controller tuned with Field settings and Fuzzy PI controller performances (b).

commissioning procedure, the benefit is more evident. The application of the fuzzy approach to the PID parameters tuning allows achieving the same performances of the optimally tuned PID in an automatic way. In particular, when actual boundary conditions are changing, the controller gains are adjusted in real time in order to obtain a good control loop response as demonstrated even in case the steam pressure on turbine inlet is reduced of 30%. The performance improvements are more evident in the case study typically faced during the start-up operations, when the steam pressure and enthalpy are in the range of 10–15% of nominal conditions. In the present study, the fuzzy structure and the reduced rules set have been identified with the aim of optimizing the tracking of a loading power ramp and, in particular, the design approach of the FPID allowed to develop a FIS with a limited number of fuzzy sets defined for each input and a limited number of rules. Finally, it also allows to refine the controller in a short time, avoiding a re-implementation of the governor software based on PID algorithm, while other complex control paradigms, which allow to obtain good performance even in off-design conditions, need algorithms that often discourage the implementation in industry and also have the problem of being more computationally onerous for industrial platforms such as PLCs.

Future work will deal with the identification of a set of rules that are more generally applicable to any PID control loop: for instance, additional rules can be included in order to consider gains scheduling, based on the range of delivered power or the header steam pressure and temperatures instead of limiting the observation to the control error and its derivative.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2017.08.145.

References

[1] Camacho EF, Samad T, Garcia-Sanz M, Hiskens I. Control for renewable energy and smart grids. The impact of control technology control systems society 2011; 2011. p. 69–88.
[2] Viebahn P, Lechon Y, Trieb F. The potential role of concentrated solar power (csp) in africa and europe-a dynamic assessment of technology development, cost development and life cycle inventories until 2050. Energy Policy 2011;39(8):4420–30.
[3] Commission E-E, et al. Energy, transport and environment indicators; 2016.
[4] EurObserv E. Concentrated solar power and solar thermal barometer, EurObserv'ER May; 2015.
[5] Barlev D, Vidu R, Stroeve P. Innovation in concentrated solar power. Sol Energy Mater Sol Cells 2011;95(10):2703–25.
[6] Mokheimer EM, Dabwan YN, Habib MA. Optimal integration of solar energy with fossil fuel gas turbine cogeneration plants using three different csp technologies in Saudi Arabia. Appl Energy 2017;185:1268–80.
[7] Alqahtani BJ, Patiño-Echeverri D. Integrated solar combined cycle power plants: paving the way for thermal solar. Appl Energy 2016;169:927–36.
[8] Zhang H, Baeyens J, Degrève J, Cacères G. Concentrated solar power plants: review and design methodology. Renew Sustain Energy Rev 2013;22:466–81.
[9] Desideri U, Campana PE. Analysis and comparison between a concentrating solar and a photovoltaic power plant. Appl Energy 2014;113:422–33.
[10] Vasallo MJ, Bravo JM. A mpc approach for optimal generation scheduling in csp plants. Appl Energy 2016;165:357–70.
[11] Camacho E, Rubio F, Berenguel M, Valenzuela L. A survey on control schemes for distributed solar collector fields. Part II: Advanced control approaches. Sol Energy 2007;81(10):1252–72.
[12] Ang KH, Chong G, Li Y. Pid control system analysis, design, and technology. IEEE Trans Control Syst Technol 2005;13(4):559–76.
[13] Morris E, Abaza B. Adaptive digital control of a steam turbine. Proc Inst Electric Eng 1976;123(6):549–53.
[14] Bolek W, Sasiadek J, Wisniewski T. Two-valve control of a large steam turbine. Control Eng Pract 2002;10(4):365–77.
[15] Fang F, Liu J, Tan W. Nonlinear inversion-based output tracking control of a boiler-turbine unit. J Control Theory Appl 2005;3(4):415–21.
[16] Subramanyam M, Prasad KS, Rao PGK. Robust control of steam turbine system speed using improved imc tuned pid controller. Procedia Eng 2012;38:1450–6.
[17] Kordestani M, Khoshro MS, Mirzaee A. Predictive control of large steam turbines. 2013 9th Asian Control Conference (ASCC). IEEE; 2013. p. 1–6.
[18] Peng H, Ozaki T, Haggan-Ozaki V, Toyoda Y. A nonlinear exponential arx model-based multivariable generalized predictive control strategy for thermal power plants. IEEE Trans Control Syst Technol 2002;10(2):256–62.
[19] Salahshoor K, Kordestani M. Design of an active fault tolerant control system for a simulated industrial steam turbine. Appl Math Model 2014;38(5):1753–74.
[20] Weng C-K, Ray A. Robust wide-range control of steam-electric power plants. IEEE Trans Control Syst Technol 1996;5(1):74–88.
[21] Han G, Chen L, Shao J, Sun Z. Study of fuzzy pid controller for industrial steam turbine governing system. IEEE International Symposium on Communications and Information Technology, 2005. ISCIT 2005, vol. 2. IEEE; 2005. p. 1275–9.
[22] Ismail MM. Adaptation of pid controller using ai technique for speed control of isolated steam turbine. 2012 Japan-Egypt Conference on Electronics, Communications and Computers (JEC-ECC). IEEE; 2012. p. 85–90.
[23] Na L, Lige L. Parameter optimization for turbine deh control system based on improved genetic algorithm. Electric Power Sci Eng 2010;4:013.
[24] Varbanov P, Doyle S, Smith R. Modelling and optimization of utility systems. Chem Eng Res Des 2004;82(5):561–78.
[25] Pourbeik P, et al. Dynamic models for turbine-governors in power system studies, IEEE Task Force on Turbine-Governor Modeling; 2013.
[26] Chaibakhsh A, Ghaffari A. Steam turbine model. Simul Model Pract Theory 2008;16(9):1145–62.
[27] Dettori S, Colla V, Salerno G, Signorini A. Steam turbine models for monitoring purposes. Energy Procedia 2017;105:524–9.
[28] Zadeh LA. Fuzzy sets. Inf Control 1965;8(3):338–53.
[29] Lee C-C. Fuzzy logic in control systems: fuzzy logic controller. ii. IEEE Trans Syst Man Cybernet 1990;20(2):419–35.
[30] Zadeh LA. Is there a need for fuzzy logic? Inf sci 2008;178(13):2751–79.
[31] Cavallaro F. Fuzzy topsis approach for assessing thermal-energy storage in concentrated solar power (csp) systems. Appl Energy 2010;87(2):496–503.
[32] Mamdani EH, Assilian S. An experiment in linguistic synthesis with a fuzzy logic controller. Int J Man-Mach Stud 1975;7(1):1–13.
[33] Li H-X, Gatland H. Conventional fuzzy control and its enhancement. IEEE Trans Syst Man Cybernet Part B (Cybernet) 1996;26(5):791–7.
[34] Hu B, Mann GK, Gosine RG. New methodology for analytical and optimal design of fuzzy pid controllers. IEEE Trans Fuzzy Syst 1999;7(5):521–39.
[35] Mudi RK, Pal NR. A robust self-tuning scheme for pi-and pd-type fuzzy controllers. IEEE Trans Fuzzy Syst 1999;7(1):2–16.
[36] Lin-ke Y, Jian-ming Z, Qi-long Y, Ji-ming X, Yan L. Fuzzy pid control for direct drive electro-hydraulic position servo system. 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet). IEEE; 2011. p. 370–3.
[37] Rubio FR, Berenguel M, Camacho EF. Fuzzy logic control of a solar power plant. IEEE Trans Fuzzy Syst 1995;3(4):459–68.
[38] Hellendoorn H, Thomas C. Defuzzification in fuzzy controllers. J Intell Fuzzy Syst 1993;1(2):109–23.
[39] Åström KJ, Hägglund T. Automatic tuning of simple regulators with specifications on phase and amplitude margins. Automatica 1984;20(5):645–51.
[40] Ziegler JG, Nichols NB. Optimum settings for automatic controllers. Trans ASME 1942;64(11).