# A Process Knowledge-based Controller for Maneuverability Improvement of a Nonlinear Industrial Process

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**Abstract.** This paper is concerned with the formulation of a process knowledge based controller (PKBC) for maneuverability improvement of nonlinear processes operation. The capacity for empirical knowledge acquisition from artificial intelligence systems was utilized in the development of the strategy. The PKBC is a neuro-fuzzy system obtained from process data. The GT 5001 type is the selected nonlinear process, for speed control during startup operation, where the GT has to follow a specific speed path that imposes tight regulation requirements for the control system, including fast response and precision. The proposed control strategy is a feedforward-feedback one. In the feedback path a PID controller is used. In the feedforward path a PKBC provides most of the control signal for wide-range operation, diminishing the control effort on the PID controller. Simulation tests were carried on a dynamic mathematical model of the GT, and demonstrate the maneuverability improvement concerning the startup speed response.

## 1 Introduction

Industrial processes are dominated by nonlinear and time-varying behavior presented during changes in operating conditions and operation modes. Throughout the process

behavior, startup, normal operation and shutdown, the conventional controllers have to lead the process to the desired target. These controllers belong to the PID class and have been widely used in various industrial control applications. Their almost universal use is mainly attributed to their simple structure and robust performance in a wide range of operating conditions. However, real industrial processes may have characteristics such as high-order, dead-time, nonlinearity, etc. which make the PID controller inaccurate because they are designed only to regulate the process for an operating point. Additionally, these processes may also be affected by parameter variations, noise and load disturbances.

Although operators are able to control complicated nonlinear and time varying systems after a long acquired experience, PID controllers are not good at coping with non-linearity, operational constraints and interaction between process variables [1]. In these cases the operator, based on his experience on the process, has to tune-up the controller parameters to reject the disturbances. This can lead to a good controller for disturbances rejection, but a malfunctioning controller for regulation purposes. To overcome the regulation problem, a reference feedforward control is proposed to free the PID controller of set-point tracking chores to almost exclusively deal with these events, in a more effective way.

Successful implementation of the fuzzy logic technology has become an even greater interest in the field and currently new applications, as reported in this paper, are emerging every day [9, 10]. Benefits in using fuzzy logic for control in place or besides of conventional methods in that they are easy to design, easy to implement, and generally more robust than conventional controllers [11].

The feedforward fuzzy controller is a wide range nonlinear static mapping of the reference signal and the control signal, which approximates a process steady state inverse model. The mathematical formulation of the process model is a complex and difficult task, so we take advantage of the fuzzy systems universal approximation property, to obtain a good process representation. The feedforward fuzzy controller is designed off-line from input-output data measurements using a neural network learning method, resulting in a neurofuzzy feedforward controller

Previous approaches on real applications for power control [2], considered a constant feedforward action, which is only valuable for an operating point. In this paper a wide-range feedforward controller implemented as a fuzzy system. Thus, main difference with previous approaches is the variable reference feedforward action, providing a variable gain based on the operating point throughout the unit operating range.

This paper is organized in four sections; Section 2 describes the PKBC formulation, which is based on input-output process data along the whole operating range of the process, Section 3 presents the knowledge acquisition process for the PKBC design, Section 4 shows a case study based on the gas turbine operation. Simulation tests were carried out with a dynamic mathematical model of a GE-5001 Turbogas unit. Speed control over the whole operating range shows a better performance overcoming the change on the operating point during startup. Finally, Section 5 summarizes and concludes this work.

## 2 PKBC Formulation

The PKBC is a fuzzy controller with a TSK (Takagi-Sugeno-Kan) inference fuzzy system where the consequents of the inference rules are a linear combination of the system inputs. The design problem is based on the constant consequent values determination and the membership functions parameters in the antecedent part of each rule. This problem is resolved by using a neural supervised learning procedure from a collection of process input-output data. The convenience of this design procedure resides on the obtained fuzzy inference systems that can be directly implanted, without additional adjustment and may be utilized as a base design to improve the process performance.

Several methods may be used to design the PKBC from input-output data. The combination of neural networks and fuzzy systems in a homogenous structure, synthesizes both techniques advantages in a complementary way. Neural network learning characteristics make easy the fuzzy system tuning. We can find several methods to synthesize fuzzy systems, including GARIC, NEFCON, FuNe, ANFIS, etc [3]. The method known as adaptive neuro-fuzzy inference system (ANFIS) was used here [4], [5]. This technique allows the implementation of multi-input single output first order TSK-type model with weighted average defuzzification.

The PKBC is based on the TSK [6] model that is the best suited for implementation purposes, since it significantly reduces complexity at the output defuzzyfication layer, using input-related output hyper planes instead of output membership functions. The ANFIS method allows first order TSK controller design with the following IF-THEN rules:

$$\begin{aligned} &IF\ u_1 \text{ is } \mathrm{A}_1^{\mathrm{j}} \text{ and} \cdots \text{and } \mathrm{u}_{\mathrm{n}} \text{ is } \mathrm{A}_{\mathrm{n}}^{\mathrm{j}} \text{ THEN } \mathrm{b}_{\mathrm{i}} = \mathrm{g}_{\mathrm{i}}(.) \\ &\mathrm{b}_{\mathrm{i}} = g_i(.) = a_{i,0} + a_{i,1}(u_1)^2 + \cdots + a_{i,n}(u_n)^2 \end{aligned} \tag{1}$$

where *An* represent the input fuzzy sets, $a_{i,n}$ are the constants and $j=1,2,\ldots n$ is the rule number in the fuzzy processor. For the functional fuzzy system the crisp output is obtained by the discrete center-of-mass defuzzyfier:

$$y = \frac{\sum_{i=1}^{R} b_i m_i}{\sum_{i=1}^{R} m_i} \tag{2}$$

where $m_i$ represent the membership values of the inputs.

Given an arbitrary set of inference rules, the ANFIS method adjust the membership functions *An*, and the $a_{i,n}$ constants of the consequent part by a neural learning standard process until the desired input-output pattern set is reproduced. To accomplish this, the TSK fuzzy system is represented as a feedforward neural network with *n* inputs, *N* rules,

with five layers with $N$ neural processing units in layers $L_1$ to $L_4$, and a single neural unit in layer five, $L_5$. Layer 0 with $n$ distribution units is not considered as a neural processing layer (Figure 1).

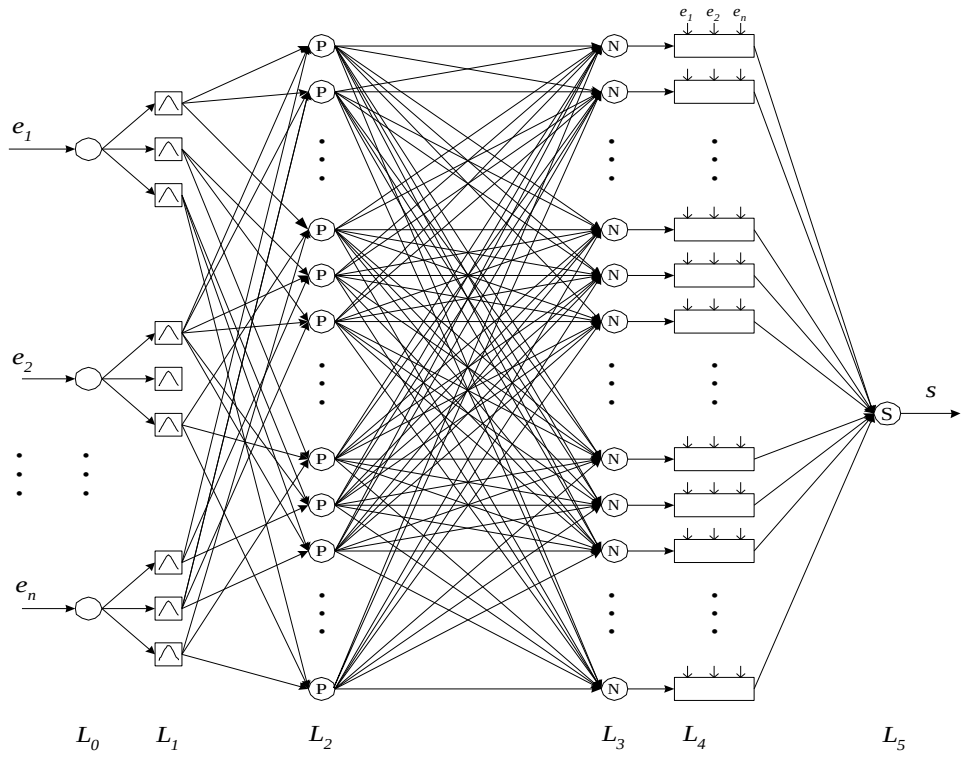


**Fig. 1**. TSK fuzzy-system structure as a feedforward neural-network

The implementation of the controller is based on the structure depicted in figure 2, which consists of a feedforward and feedback control processors. The feedback control processor is a PID based controller that provides the control signal $u_{fb}$, and it is designed for disturbances rejection. The feedforward control processor provides the control signal $u_{ff}$, and it is designed to provide the maneuverability needed during the startup operation.

The initial idea of the control structure comes from the two degrees of freedom linear control system [7]. For the feedforward path the PKBC proposed is based on the inverse steady state behavior is approximated, as a fuzzy system, using input-output process data along the whole operating range of the nonlinear industrial process. This configuration permits to maneuver the process to follow the reference, while the feedback controller reduces disturbances.

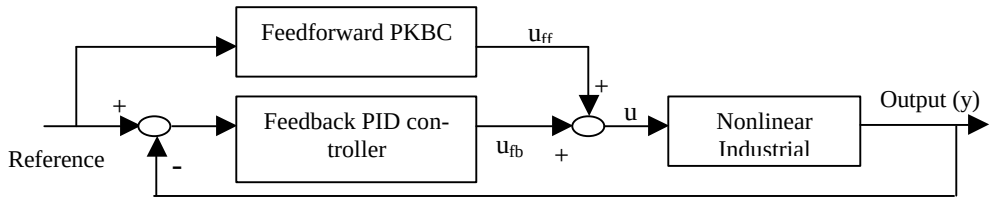


**Fig. 2.** Feedforward/feedback control configuration.

## 3 Knowledge acquisition

Fuzzy systems theory proposes a systematic method for mapping human knowledge into an input-output nonlinear relation. The operator's process knowledge can be represented by a PKBC integrated to the existing control strategy. The implementation of the PKBC is based on the steady-state data along the operation range of the nonlinear process.

The inverse model is obtained by measuring the steady state process behavior. The input to the PKBC is given by the current output of the nonlinear process, and the output of the PKBC is given by the current demand to the process (control valve). Once the PKBC is designed, and included in the control system, its input is supplied by the reference (setpoint) to obtain the feedforward contribution to the final control element demand (control valve).

A classical feedback control loop, one input one output, is shown in figure 3, where $r$, $u$, and $y$ are the reference, the control and the output signals respectively. $w$ is the disturbance effect on the control loop, $G(s)$ and $G_c(s)$ are the process and controller transfer functions, and $s$ is the Laplace operator. The closed loop transfer function is:

$$Y(s) = [1 + G(s)G_c(s)]^{-1}[G(s)G_c(s)R(s) + W(s)] \tag{1}$$

where $R(s)$, $W(s)$, and $Y(s)$ are the Laplace transfer functions of $r$, $w$, and $y$, respectively.

Clearly, only by $G_c(s)$ design is difficult to achieve a precise reference pursuit (speed regulation), $Y(s)=R(s)$. In order to accomplish this, a feed forward control path may extend the control loop from the reference, as shown in figure 4. The closed loop function would be:

$$Y = \left[1 + GG_c\right]^{-1}\left[\left(GG_r + GG_c\right)R + \left(GG_c\right)W\right] \tag{2}$$

where, $G_r$ is the feed forward control transfer function, omitting for brevity the Laplace operator dependency.

In theory, $G_r$ can be designed as:

$$G_r = G^{-1} \tag{3}$$

to accomplish a perfect following for reference changes, and $G_c$ can be designed to compensate for disturbances effects.

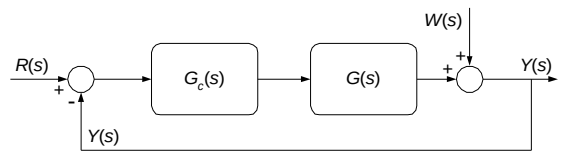


**Fig. 3**. Typical closed control loop.

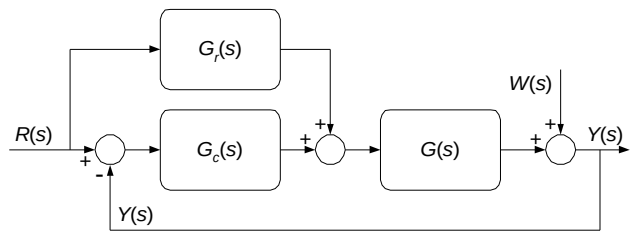


**Fig. 4**. Loop with feedforward control trajectory.

Feedforward and feedback controllers can be complementary. Feedforward control actions allows fast following on reference signal changes. Feedback control actions give a corrective action over a lower time scale to compensate for model inaccuracies presented by the feedforward control, measurements errors and non-measured disturbances.

## 4 Case Study: Gas Turbine Operation.

### 4.1 Combustion Turbine System Description.

Figure 5 shows the main components of the GT system: a starting device, the air compressor, the gas turbine and the generator. All are on a common shaft. The starting device is an induction motor which accelerates the turbine from initial start, through fuel ignition and light off, and continue to aid acceleration to about 25% of rated speed; at this point the fuel combustion process maintains acceleration and the starting motor is turned off. The compressor accepts filtered inlet air from the environment and passes it through 17 stages to produce a compression ratio, which yields a discharge pressure of combustion airflow.

Three bleed valves bypass portion of the compressor air during startup to produce stabilizing turbine acceleration and avoid the *surge* phenomenon. An Inlet Guide Vane (IGV) at the front of the compressor is modulated to improve GT performance.

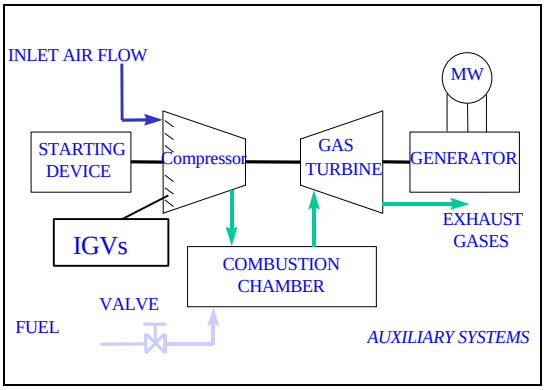


**Fig. 5.** Combustion Turbine System

The combustion chamber burns natural gas in the proper air mixture to provide hot gases for the two-stage power turbine. The fuel throttle valve is controlled to develop speed turbine following the speed profile first, and megawatt generation later, within appropriate turbine exhaust gasses temperature limits.

As driving force of the electric generator, safety, availability, and efficiency are important factors to be searched with an effective control system to:

- Restore stability of turbine operation after a disturbance and to obtain precision response in normal operation
- Follow the acceleration startup curve to minimize fuel consumption before synchronization and minimize the high vibration periods
- Keep the main variables of the unit, temperature and pressure, close to the operating limits without exceeding them to preserve the unit

The operation procedures of the GT generate important process disturbances, figure 6:

Starting motor outage: when the speed path follows the desired acceleration pattern and reaches the 25% of rated speed, the starting motor goes out. Then the GT experiences a speed disturbance that the control system has to overcome. This is shown by an exhaust temperature variation that may cause thermal shock in the gas turbine mechanical parts

Bleed valves closing and IGVs opening: When the GT reaches the 95% of rated speed the bleed valves close and the IGVs open. The combined effect increases the combustion chamber's pressure, decreases the exhaust gases temperature and consequently the GT experiences another speed disturbance, over-speed transient, which needs to be corrected by the control system.

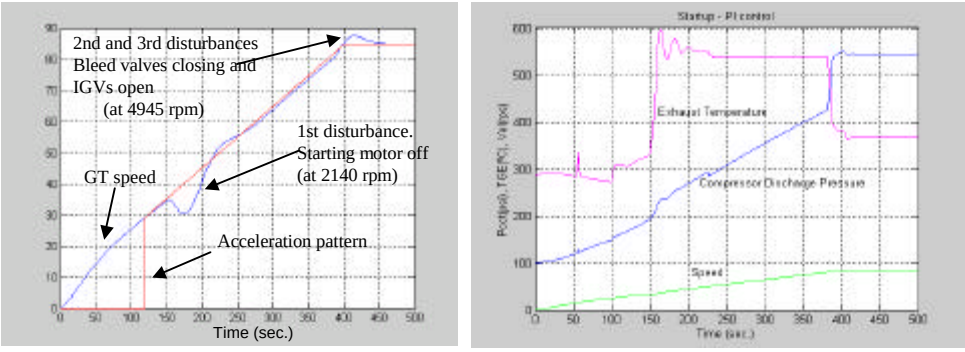


**Fig. 6.** Process disturbances.

### 4.2 Simulation Results

The simulation platform was the Matlab/Simulink programming environment, where the GT dynamic mathematical model was developed [8]. The design data was obtained by GT simulation under feedback control. This PID feedback controller was tuned to get the best process response. Once the tuning process was finished, the simulation established the training data.

The inverse model of the GT was obtained by measuring the steady state process behavior. The input to the PKBC is given by the output speed of the GT, and the desired output of the PKBC is given by the current demand to the control valve.

After several essays with different membership partitions and forms, the resulting system is a one-input one-output fuzzy system, composed of seven rules, seven triangular membership functions and seven crisp values. Performance of the FF path to reproduce the inverse static behavior of the process was verified by reproducing the steady state data of figure 7. The universal approximation property of fuzzy systems is confirmed.

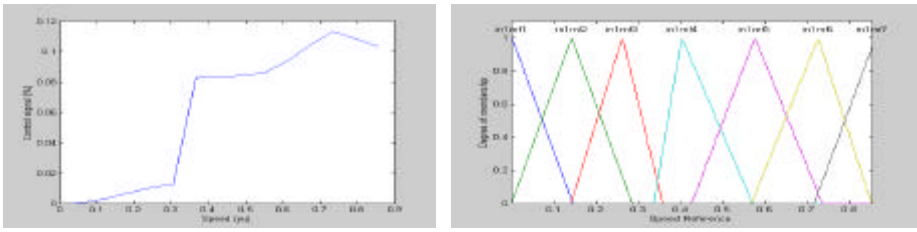

**Fig. 7.** Inference curve and membership functions.

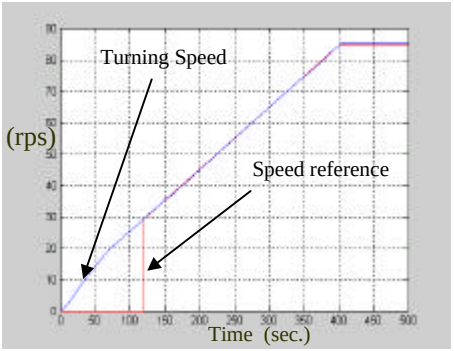


**Fig. 8.** GT startup operation.

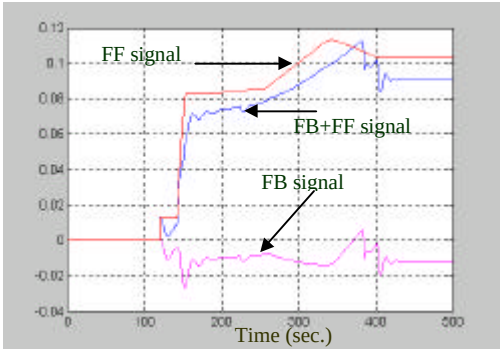


**Fig. 9.** Control signals behavior.

Once the PKBC is designed, and included in the control system, its input is supplied by the acceleration startup reference curve to obtain the feedforward contribution to the control valve. A typical startup operation is shown in figure 8, where the turning speed and the speed reference are shown.

The speed response with the PKBC follows the speed reference without disturbances effects over the operation. Almost all the control effort over the process is given by the PKBC, and the FB control signal (PID controller) realizes disturbance compensation, as shown in figure 9. The main component of the final control signal is the feedforward contribution, while the feedback controller contributes the regulation of the controlled variable about the commanded trajectory.

## 5 Summary and Conclusions

In this paper, a PKBC for maneuverability improvement of a non-linear industrial process, such as a gas turbine for power generation, was presented.

Training data for feedforward fuzzy controller design was obtained from the process controlled by a conventional PID, with no process model requirement at all. A neural network learning technique, available in Matlab, was used for controller's parameters tuning, resulting in a neurofuzzy feedforward controller.

The results show that the PKBC (feedforward control) signal successfully drives the process close to the desired state through wide-range operating maneuvers. On the other side, the feedback controller (FB) signal compensates for disturbances about the reference speed. This is due to the PKBC nature, which maps the steady-state behavior over the operating range.

After simulation tests have been realized the following phase of this work are: the extension of this strategy for load control, an analysis of performance robustness and, the

real-time platform tests. The real-time platform test will be composed of an industrial controller, an operator interface and a dynamical simulator, which will emulate the real process.

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