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Recursive decision-making feedback extension (RDFE) for fuzzy scheduling scheme applied on electrical power control generation

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ABSTRACT

A new decision feedback extension (DFE) and an alternative application to schedule industrial processes are presented. The DFE is defined as a recursive decision feedback extension (RDFE), where the recursive part is developed to assign the probability of occurrence in the operation of a set of machines working together using an objective function of production. The fundaments of fuzzy factors and the principle of maximum membership function are used to develop the new extension. At last, RDFE is proposed to generate a fuzzy scheduler, which is used to apply an intelligent control scheme to a hydropower station.

1. Introduction

The industrial process of the 21st century is immersing into a global environment, where new technologies and competitors are continuously emerging and harvesting the market [1].

Therefore, new processing strategies should be designed to support global competitiveness, continuous innovation on new products and a fast response to the market. The next generation of the industrial processes must be strongly time-oriented, and mainly focused on cost and quality. The requirements of these systems should include enterprise integration, distributed organization, open and dynamic structure, integration of humans with software and hardware, agility and fault tolerance, among others.

Several recent contributions have considered the PLC as the typical solution to fulfill these close correlated requirements, and have already used them for several non-common techniques. One of them is Artificial Intelligence (AI), which has been used to improve the requirements in intelligent process control [2].

In the last ten years, developments in multi-agent systems in the domain of Distributed Artificial Intelligence (DAI) have brought new and interesting possibilities [3], which are mainly focused to improve the scheduling and control of production and resources [4,5].

A new proposition based in fuzzy decision-making environments to overcome the problem of scheduling using AI architectures has appeared over the last decades [6]. In terms of Scheduling and control for industrial processes, Dadone has proposed some schemes based on fuzzy strategies to increase the ability of scheduling [7]. As a result, new alternatives for industrial scheduling have been developed from the integration AI strategies in particular with fuzzy decision-making schemes [8,9]. Taking as a base the work of Garibaldi and Ozen [10], several contributions have evolutioned in the applications of human-aided decision for several types of control processes including power generation systems [11]. He et al. have developed a hybrid genetic algorithm approach for solving the economic dispatch problem with valve-point effect. The proposed method combines the GA algorithm with the differential evolution (DE) and sequential quadratic programming (SQP) technique to improve the performance of the algorithm. In this method GA is the main optimizer, while the DE and SQP are used to fine tune in the solution of the GA run [12].

This paper introduces an artificial intelligent agent (AIA) using fuzzy logic for decision-making, where the strategy of recursive decision-making feedback extension (RDFE) is introduced. The fundaments of this new strategy of decision are established in Section 3. To determine the benefits of the extension obtained, a scheduling problem for a hydroplant process is proposed. A novel scheme based on fuzzy agent scheduling (FAS) and its interconnection to classical digital control architecture is defined in Section 4. In Section 5, a comparison between the typical PLC solution and the proposed Agent-based scheme is made to demonstrate the

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improvements acquired for open and dynamic structure and fault tolerance requirements. Conclusions and future work are discussed in the last section.

2. Fundamental concepts

2.1. Agent definition

An agent can be defined as a resident program, which is capable of an autonomous action in order to meet the overall system objectives. An autonomous agent should have control over its own actions and internal state without the direct intervention of humans or other agents. Moreover, an "agent based system" is the one in which the key abstraction used is that of an agent [13].

In the particular case of intelligent control for industrial process, agents can be used to

(a) Encapsulate existing software systems and to solve legacy problems and integrate industrial process activities.
(b) Represent industrial process resources such as workers, cells, machines, tools, fixtures, and Auto-Guided Vehicles (AGVs). It can also be used to define products, parts, operations to facilitate industrial process resource planning, and scheduling and execution control.
(c) Incorporate a whole scheduler or planner into process planning and scheduling systems.

The artificial intelligent agent (AIA) can be used as an independent structure described by a fuzzy scheduling strategy, which is implemented in a field-gate programmable gate array (FPGA) [14].

Therefore, the AI agents are applied as a fuzzy coprocessor to improve the decision scheme of the programmable logic controller (PLC), developing a non-deterministic decision in the sequencing of activities of the industrial process environment.

2.2. Fuzzy decision-making for scheduling

2.2.1. Scheduling problem

Scheduling is an important aspect of automation in industrial process systems, because it helps in scheduling jobs and machines in the making and assembling process, picking, packaging, shipping, and purchase of components and subcomponents.

Furthermore, scheduling in material handling can occur at more than one level with varying degrees of detail and sophistication, e.g. a month-to-month schedule for orders and component purchase, a week-to-week schedule for components on the assembly line, and a day-to-day schedule for each machine in the shop.

Considering the work of Dadone [7], the industrial process scheduling is divided into three levels: long, mid and short term. In particular, for intelligent manufacturing process, scheduling is used to ensure smooth operation of mid and short term levels of the process.

2.2.2. Fuzzy decision-making theory

Bellman and Zadeh defined fuzzy decision-making as the process where the fundamental variables and relations for decision are described by fuzzy variables [15]. However, Li and Yen established fuzzy decision-making strategies, by applying factor and extension for alternative fuzzy structures [8].

Fuzzy decision-making is the study of both how decisions are actually made and how they can be better or more successful [16]. Applications of fuzzy sets within the field of decision making mostly consist of extensions or "fuzzifications" of the classical theories of decision making.

When classical decision theories are "fuzzified", they can be divided as [17]

- Individual decision making.
- Multiperson decision making.
- Multicriteria decision making.
- Multistage decision making.

Each one of these particular strategies can apply typical analysis techniques as

- Fuzzy classic probability (considering fuzzy entropy).
- Fuzzy-Bayes method.
- Feedback extension (DFE).
- Multi-factorial decisions.
- Linear programming methods.

Some fuzzy solutions have been implemented for scheduling in industrial process systems. One of the most recent works [5] proposes a fuzzy scheduler as an Evolutionary Programming Technique of sequences and times for a predetermined production goal.

Although for engineering applications linear and multi-factorial decisions technique has been the most common application for process control, in this work feedback extensions will be considered as the best alternative to deal with this issue. Feedback extensions showed to be the fastest scheme of decision for non-deterministic sequences, when historical values for one or more process parameters are obtained. Consequently, the computational time is lower than other approaches [18].

3. Recursive decision feedback extension

The next part is considered to define the new extension. The first approach was developed by Li and Yen [8]. In this section, the principle of the maximum membership is used to introduce the application of fuzzy extensions in the decision-making concept, where feedback scheme is used to define the new extension in terms of recursive algorithm.

3.1. Principles of the maximum membership

(a) The first principles of the maximum membership.
Let $(U,C,F]$ be a description frame and $A_1,A_2,\ldots,A_n \in F(U)$ be the extensions of concepts $\alpha_1,\alpha_2,\ldots,\alpha_n \in C$, respectively. For a given object $u_0 \in U$, if these exist an index $i \in \{1,2,\ldots,n\}$ such that A_1 satisfies:

$$A_i(u_0) = \max\{A_1(u_0), A_2(u_0), \ldots, A_n(u_0)\}, \ldots, (1) \tag{1}$$

Then u_0 is said to belong to A_i according to the first maximum membership principle.

(b) The second principle of the maximum membership.
Let $(U,C,F]$ be a description frame and $A \in C$ be the extension of $\alpha \in C$. For n objects $u_1,u_2,\ldots,u_n$, if these exist an index $i \in \{1,2,\ldots,n\}$ such that u_i satisfies:

$$A(u_i) = \max\{A(u_1), A(u_2), \ldots, A(u_n)\} \tag{2}$$

Then u_i is said to belong to A according to the second maximum membership principle.

3.2. DFE decisions and its types

Let us consider a more concrete setting under the description frame $(U,C,F]$ by defining a group of tactics U, called the tactics set, and C, a group of concepts upon tactics in U. For example, "good tactics", "fair tactics", and "bad tactics". F-the factor set with respect to these tactics.

If the extensions of concepts in C are known, then decision making will be simpler, because one can use the principles of the three highest memberships. However, decisions must be made when the extensions of concepts are unknown. An approach to decision making under such circumstances is to find the extensions of concepts in C.

These extensions could be found if we could obtain their feedback extensions (which, in turn, could be realized by G-envelopes). Then, the decision making through the process is based on feedback extensions (DFEs). There are three types of DFEs, which will be described as next.

(a) *Orderable:* In this case, $c = \{\alpha\}$ is a singleton, for instance, α = "good tactics". If we can find the G-envelope, $A[G]$, then $A[G] : U \to [0,1]$, which will order tactics of U in $[0,1]$. Therefore, if the set of tactics obtained by the strategy contains one element in the list which is maximum, then that element is taken as the best tactic.
(b) *Competitive:* In this case, $U = \{u\}$ is a singleton and C contains at least two concepts. Let $C = \{\alpha_1, \alpha_2, \ldots, \alpha_k\}$ and A be the extension of α_1 $1 \leqslant i \leqslant k$. If we can get $A_i[G]$ for each i, $1 \leqslant i \leqslant k$(or $\pi-$ closures $A_i[\pi]$), then we will be able to determine the concept (or A_i) to which u belongs.
(c) *Competitive/Orderable:* In this case, both U and C are not singletons. Let $U = \{u_1, u_2, \ldots, u_n\}$ and $C = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ .First we classify U by competition. For example, if $u_{i1}, u_{i2}, \ldots, u_{ip}, p \leqslant n$ belongs to α_q, some $q(\leqslant k)$, we can order $u_{i1}, u_{i2}, \ldots, u_{ip}$ via $A_q[G]$(or $A_q[\pi]$); the first on the list which takes a maximum value is considered the best tactic. Likewise, we can obtain the best tactic for each $\alpha_j, 1 \leqslant j \leqslant k$. We can adopt one or more of these best tactics if the condition dictates to do so.

3.3. Recursive procedure for DFE (RDFE)

Considering the outline of the DFE implementation procedure obtained by Li and Yen [8] in the following steps, the illustration is tailored to the type 1 DFE previously defined.

Step 1. Define a tactics set $U = \{u_1, u_2, \ldots, u_n\}$, which is a group of tactics or strategies.
Step 2. Determine the concept α in $C = \{\alpha\}$ and name that concept, e.g., "good tactic". U is the universe of the concept α.
Step 3. Determine the set of atomic factors $\pi = \{f_1, f_2, \ldots, f_m\}$ of U and is factor spaces $\{X(f_j)\}_{(1 \leqslant j \leqslant m)}$.
Step 4. Set $F = P(\pi)$, $\vee = U, \wedge = \cap, - = /, 1 = \pi$ and $0 = \Phi$. Then $(F, \vee, \wedge, c, 1, 0)$ is a Boolean algebra, and therefore, $(U, C, F]$ is a description frame.
Step 5. Construct $B(f_i), 1 \leqslant i \leqslant m$, the representation extensions of α, on the representation universe, $1 \leqslant j \leqslant m$, using the methods discussed later.
Step 6. Take an appropriate m-dimensional triangular norm and form the representation extension $B(1)$ in $X(1)$ from T_m and $B(f_i)$ as in

$$B(1)(x_1, x_2, \ldots, x_m) = T_m(B(f_1)(x_1), B(f_2)(x_2), \ldots, B(f_m)(x_m)) \tag{3}$$

Step 7. Determine $f_i\,(u_a)$, the state of the tactic on the atomic factor j, where $i = 1,2,\ldots,n$ and $j = 1,2,\ldots,m$. Then, we can obtain the state of the complete factor 1 on each tactic as in

$$1(u_i) = (f_1(u_1), f_2(u_2), \ldots, f_m(u_i)) \quad i = 1, 2, \ldots, n \tag{4}$$

Step 8. Construct 1^{-1}, the feedback extension of α, which is regarded as the approximation of A. For any $u_i \in U$, then

$$\begin{aligned} A(u_i) &\approx (1^{-1})(B(1))(u_i) = B(1)(1(u_i)) \\ &= B(1)(f_1(u_i), f_2(u_i), \ldots, f_m(u_i)) \\ &= T_m(B(f_1))(f_1(u_i), B(f_2)(f_2(u_i))), \ldots, B(f_m)(f_m(u_i)) \end{aligned} \tag{5}$$

Now we can proceed to pick the best tactic u_i by the principles of the maximum membership.

Step 9: Evaluate Eq. (5) for each change in any of the f_j fuzzified parameters under measurement.

The last step (RFDE) refers to covert the fuzzy method into a recursive procedure. It includes the discrete operations Z-transform for each one of the parameters defined for each machine, which are being considered for the decision-making of the process.

Considering RFDE scheme, now a fuzzy scheduling strategy can be developed to obtain "good performance" in the use of the definition of fuzzy scheduler (FSch) using P_{ij} vector of parameters for each ith element under evaluation. The obtained RDFE algorithm is presented in Table 1.

If an industrial process is required in terms of one goal of production, FSch can obtain the best sequence of function for the set of machines involved in the process, considering several set of P_{ij}, which can be evaluated for any event time of digital supervisor and with this information calculate the candidature of one machine or machines to develop the task for the process.

4. Process decision scheduling – the case of a hydroplant

4.1. Model plant description

Dinorwig power station is a large pumped storage hydroelectric scheme located in North Wales. The station feeds power into the national grid from six 300 MW rated turbines, driving synchronous generators. Water flows from an upper reservoir (lake Marchlyn) through the main tunnel. Each turbine receives the water flow from a penstock, using a guide vane to regulate the flow; all the penstocks are connected to the main tunnel by a manifold. Individual classic controllers in each unit control the electrical power generated. The water is pumped back into the upper reservoir, during off-peak periods, using the turbo/generators as a motorised pump, Fig. 1.

The hydroelectric plant model can be separated into three subsystems: guide vane, hydraulics and turbine/generator (Fig. 2). In this work, a linearised model [19] of the hydraulic subsystem was used (Fig. 4). The transfer function of the guide vanes used to control the water flow is given in

$$G = \frac{1}{(0.19S + 1)(0.4S + 1)}(\text{set\_position}) \tag{6}$$

Fig. 3 shows the hydraulic subsystem. In this model G is the per unit (p.u.) gate opening, G_o is the operating point, P_{mech} is the mechanical power produced by a single turbine, T_{mt} is the water starting time of the main tunnel, T_w is the water starting time of any single penstock and T_{wt} is the water starting time of the main tunnel and a single penstock ($T_{wt} = T_{mt} + T_w$). The values of T_{mt}, T_w and T_{wt} depend directly on the constructional dimensions of the

Table 1
Algorithm for RFDE.

1.	Get [$P_1(t)$, $P_2(t)$, $P_3(t)$, $P_4(t)$] for each machine (i)
2.	Repeat
(a)	Z [$P_1(t)$, $P_2(t)$ $P_3(t)$, $P_4(t)$] = [$P_1(k)$, $P_2(k)$, $P_3(k)$, $P_4(k)$]
(b)	Fuzzyfing [$P_1(k)$, $P_2(k)$, $P_3(k)$, $P_4(k)$]
(c)	$A(u_{ij}) = B[1]$ [$f_{1j}(u)$, $f_{2j}(u)$, $f_{3j}(u)$, $f_{4j}(u)$]

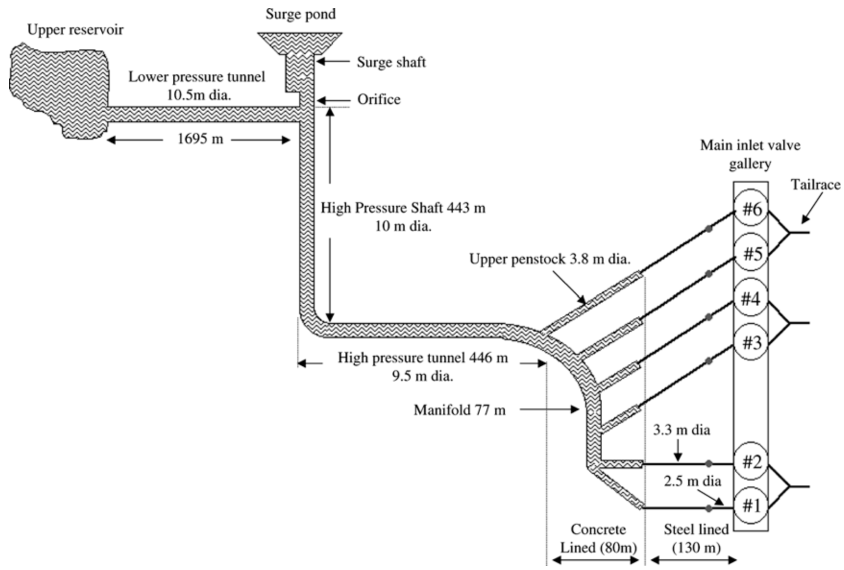

Fig. 1. Dinorwig hydraulic subsystem (not a scale).

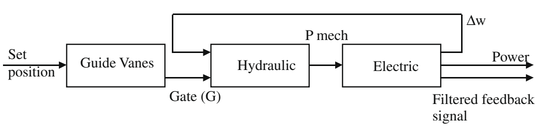

Fig. 2. The three subsystems of the hydroelectric plant.

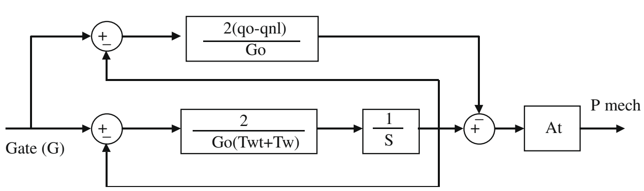

Fig. 3. Linear model of the hydraulic subsystem.

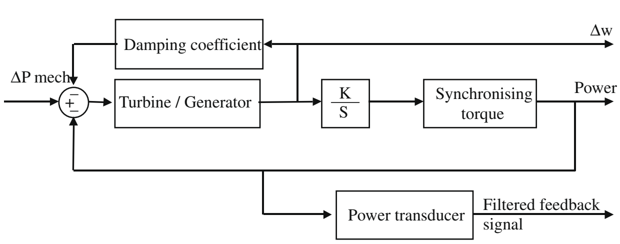

Fig. 4. Electric subsystem of the hydroelectric plant.

main tunnel and the penstocks. A_t is the turbine gain, whose value depends directly on the turbine MW rating and inversely on the Generator MVA rating. The electrical subsystem (Fig. 4) is based on the 'swing' equations [20], and includes the effect of synchronizing torque. The first-order filter is included in the feedback loop for noise reduction. The models are expressed in the per-unit system, normalized to 300 MW and 50 Hz.

The water starting time varies depending on the number of active units [21,22]. Fig. 5 presents a MIMO model of the hydraulic subsystem, considering two penstocks only, showing the hydraulic coupling of the plant. Because the units have the same manifold, a change in the position of either guide vane affects the output of both machines. A MIMO model representing all six machines is used in later simulations. If the operating point is fixed to 0.95 p.u., the parameters of the hydraulic model are

$$G_o = 0.95 \quad q_{nl} = 0 \quad T_w = 0.31$$
$$T_{wt} = 0.67 \quad A_t = 1.12$$

This model was implemented in Simulink. It was designed to be scalable, allowing different behaviours to be selected according to the objective of the study. For the purposes of this work, a multivariable linear model was chosen.

4.2. Process decision scheduling of the power plant

The process proposed to show the benefits of the novel decision-making scheme is a typical hydroplant, where the hydromechanical power is applied to four independent electrical generators. The plant is controlled by 1 PLC configured in close loop and supported by a digital event recorder for four digital channels and four analogue variables.

The performance of the power generation is evaluated in terms of four parameters defined for each generator. The fuzzy scheduler controls the connection between each machine and the electrical net. For the engineering applications of this novel fuzzy strategy, a model proposed by Gracios-Marin et al. was used to simulate a Neural PID for a typical hydroplant [23].

The scanning cycle of the event recorder was 40 ms for all the registered values. The simulated process is presented schematically in Fig. 6.

Let us consider the problem of how to select the best scheduling pattern among four Power Generators: PG_1, PG_2, PG_3 and PG_4 (Fig. 7). Following the procedure proposed just described, we have

Step 1: Let $u_1 = PG_1$, $u_2 = PG_2$, $u_3 = PG_3$ and $u_4 = PG_4$, so:$U = \{u_1, u_2, u_3, u_4\}$;
Step 2: Define α = "good performance"; then $C = \{\alpha\}$ = {good performance};
Step 3: Let f_1 = parameter 1, f_2 = parameter 2, f_3 = parameter 3, and f_4 = parameter 4. Set $\pi = \{f_1, f_2, f_3, f_4\}$ and $X(f_j) = [0,1]$, $j = 1,2,3,4$;
Step 4: Let $F = P(\pi)$ .Then $(U,C,F]$ is a description frame.

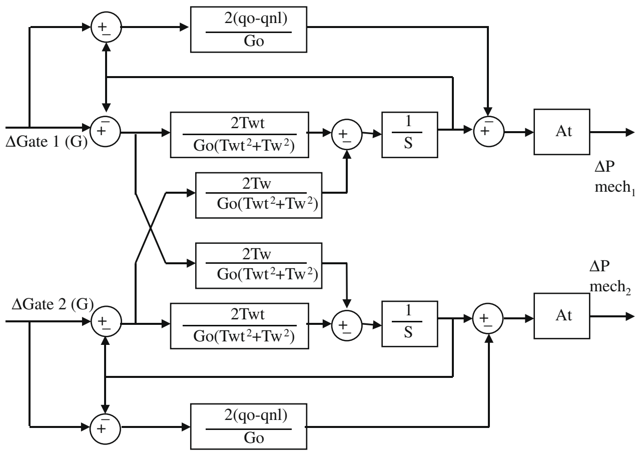

Fig. 5. MIMO linear model of the hydraulic subsystem.

Step 5: Define

$B(f_i), 1 \leqslant i \leqslant m \rightarrow$

$$B(f_j)(x) = \begin{cases} 1 & ,0.9 \leqslant x \leqslant 1.0 \\ \frac{x-0.8}{0.1} & ,0.8 \leqslant x < 0.9 \\ 0 & ,0.0 \leqslant x < 0.8 \end{cases} \tag{7}$$

This membership function was obtained by the experience operator in the plant of Dinorwig [23].

Step 6: Construct T_m T(4), a four-dimensional triangular norm, as

$$T_4 = (x_1, x_2, x_3, x_4) = \prod_{j=1}^{4} x_j = x_1 \cdot x_2 \cdot x_3 \cdot x_4 \tag{8}$$

Hence,

$$\begin{aligned} B(1)(x_1, x_2, x_3, x_4) &= T_4(B(f_1)(x_1), B(f_2)(x_2), \\ &\quad \times B(f_3)(x_3), B(f_4)(x_4)) = B(f_1)(x_1) \\ &\quad \cdot B(f_2)(x_2) \cdot B(f_3)(x_3) \cdot B(f_4)(x_4) \end{aligned} \tag{9}$$

Step 7: The values of each performance parameter (f_j) by each machine (u_i) are given in Table 2. Its corresponding membership function values B (f_i) ($f(u_i)$) are given as follows in Table 3.

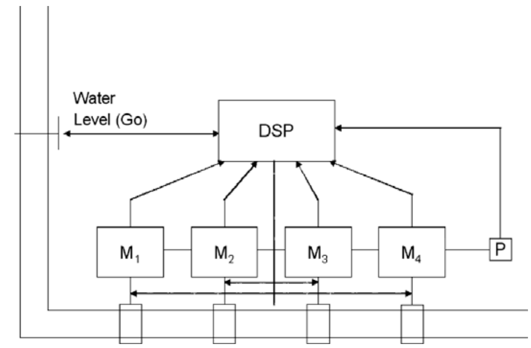

Fig. 7. Schematic for the hydroplant with four turbines.

Step 8: Calculate A (ui)) for $i = 1$, 2, 3, 4.

$$\begin{aligned} A(u_1) \approx B(1)(1(u_1)) &= B(1)(f_1(u_1), f_2(u_1), f_3(u_1), \\ &\quad \times f_4(u_1))T_4(B(f_1)(f_1(u_1)), B(f_2)(f_2(u_1)), \\ &\quad \times B(f_3)(f_3(u_1)), B(f_4)(f_4(u_1))) \\ &= B(f_1)(f_1(u_1)) \cdot B(f_2)(f_2(u_1)) \\ &\quad \cdot B(f_3)(f_3(u_1)) \cdot B(f_4)(f_4(u_1)) \\ &= 0.6x1x1x1 = 0.6 \end{aligned} \tag{10}$$

Similarly, we get $A\,(u_2)$ 0.9, $A\,(u_3)$ 0.5 and $A\,(u_4)$ 0.3. So, for this particular case PG_2 has the best performance of the four machines, where in the actual condition, it can be considered to have a good functioning condition.

Now consider that a performance curve index is proposed to define the best schedule for the four machines in terms of the four parameters defined, then a novel algorithm can be developed for a recursive version for the DFE strategy (see Fig. 2).

In this case for each time analysis, the "best" candidate machine is selected in terms of index variation. The deterministic scheduling is obtained, when a 300 MW of average power generation is programmed. If the second feedback connection is established for each machine, then a soft function is obtained when the actual of next machine will be on, which was developed in a FPGA architecture using typical floating point for ARX scheme.

The parameters considered for each machine were P_1: electrical power efficiency, P_2: frequency, P_3: phase, and P_4: velocity.

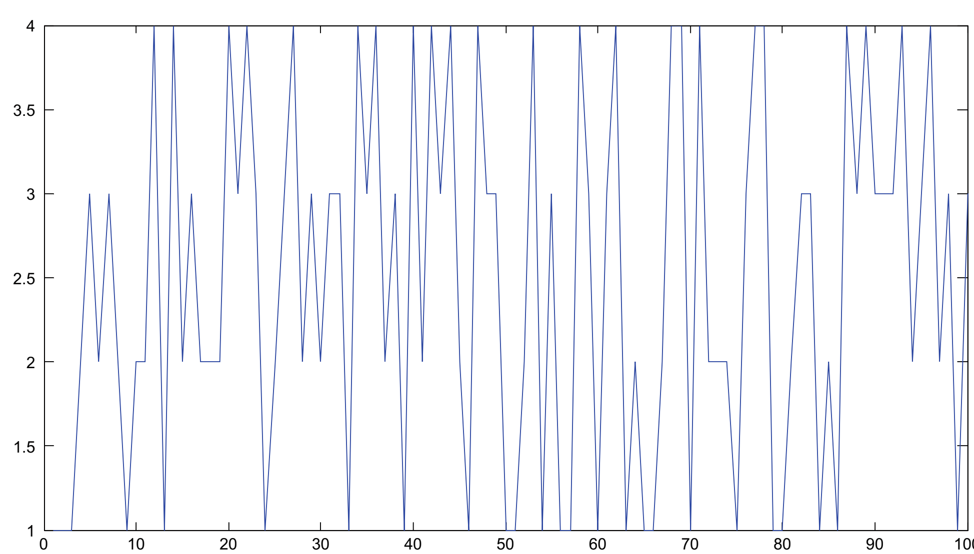

Fig. 6. Fuzzy scheduling for the four machines.

Table 2
Average performance indexes.

$u\backslash f$	P_1	P_2	P_3	P_4
M1	0.86	0.91	0.95	0.93
M2	0.98	0.89	0.93	0.90
M3	0.90	0.92	0.85	0.96
M4	0.91	0.83	0.91	0.87

Table 3
Fuzzy membership.

$u\backslash f$	f_1	f_2	f_3	f_4
u_1	0.6	1	1	1
u_2	1	0.9	1	1
u_3	1	1	0.5	1
u_4	1	0.3	1	0.7

5. Conclusions and future work

The possibility of non-deterministic activities on the industrial processes by using fuzzy scheduling has been demonstrated in the present paper. Fuzzy decision using feedback extensions was used to implement a novel fuzzy scheduling scheme, which was applied to achieve a pre-established performance that allows a production goal. This type of schedule represents a novel alternative to transform typical industrial process on "intelligent process" inserting AI agents in the regulation/control of activities for each resource. Consequently, the control now has a better capacity to take control decisions. RDFE also improves the requirements of agility and fault tolerance of processes, and because the computational requirements are low and the fuzzification process is simple, the agent can be developed using rapid prototyping architectures like FPGA.

The practical results compared using Matlab© showed the best performance in the function of the machines processes, validating the possibility to recursive a basic feedback extension definition.

The next step for the scheduling scheme is to obtain a soft behaviour in the decision, increasing the number of tactics that RDFE evaluates for the decision process and introducing the concept of multifunction/multivariable on the decision structure. The objective function could include other characteristics such as lifetime consumption. Furthermore, the information collected from RDFE could derivate into an expert system that may be able to tune the power plant governors.

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