Pseudo-fuzzy discrete-event simulation for on-line production control

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Abstract

In this paper we propose an alternative use of commercial object-oriented discrete-event simulators. We attempt to bridge the intrinsic inaccuracy of simulators in modelling real systems affected by fuzziness. The strategy adopted, called pseudo-fuzzy discrete event simulation, models fuzziness through a set of several classic simulation runs to trace an output fuzzy performance function. The idea behind the approach proposed is to use the simulator as a fuzzy operator, which embeds some stochastic functions.

A benchmark industrial setting has been used to build a reference simulation model and perform evaluations of the simulation strategy proposed for a specific working case.

Keywords: Pseudo-fuzzy; Discrete event simulation; Production control

1. Introduction

Production planning and control of manufacturing systems in the present operating scenario is a decision-making activity involving effort. A number of sometimes conflicting features must be considered: on-line response, strong flexibility to adapt to changing situations, low cost, ease implementation and effective search capabilities amongst several alternative solutions.

These decision-making tasks are also constantly affected by uncertainties, arising from various sources, which contribute to the complexity of the task.

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These can be subdivided into two major classes:

- **randomness**, tied to objective sources of uncertainty (e.g. failures, unexpected shortage in supply, etc.), that can be treated using the established probability theory;
- **fuzziness**, deriving from subjective sources of uncertainty, such lack of knowledge (or imprecision) and ambiguity (e.g. the intrinsic limits of humans in forecasting and/or representing very complex and fast-changing production conditions) that can be treated using the possibility theory (e.g. see Zimmermann, 1987);

The need for effective tools to support the production planning and control task is perceived as a must, as also witnessed by the huge number of scientific papers devoted to the subject (e.g. see Brandimarte & Villa, 1999).

Discrete-event simulation has been used as a decision support tool for almost two decades in an off-line fashion and addressing only objective forms of uncertainty (Fortuin & Zijlstra, 2000).

The level of complexity and uncertainty in the operation of real manufacturing systems stresses the role that discrete-event (DE) simulation might play in driving appropriate decisions, also for production settings with a low level of flexibility.

Only recently have some real-time applications been studied and developed, mainly for FMS-like settings (e.g. see Wu, 1989 or ElMaraghy, Abdallah, & ElMaraghy, 1998), thus highlighting the enormous potential of the on-line use of this tool.

This recent trend towards the use of on-line discrete event simulation is widening the applications of DE simulators to those activities in manufacturing which traditionally relied upon human judgment based on personal experience and rules of thumb.

This kind of different perspective on the use of DE simulation, which is almost inherently non-stationary, is now challenging the scientific community with emerging problems related to development of new simulation tools, as well as control strategies and output analysis strategies (see Banks, 1998).

The term ‘on-line’ is almost commonly interpreted as the use of a generic tool in real-time fashion for different purposes (control, data acquisition, etc.). Very some interesting on-line applications of DE simulation into production planning and control have been under study in recent years (Banks, 1998). The on-line use of DE simulation requires different perspectives of both design and use of models. Modelling strategies have to take account of the data driven features of the applications, and of the need for continuously updating of data to make the model adherent to the evolution of the real system modelled.

On the other hand, another critical aspect of DE simulation that remains virtually unexplored, independently of its off-line or on-line use is accounting for subjective sources of uncertainties, which might be the stronger components in the variability of operating conditions. This topic is now becoming one of the most important in the field of operation management, as witnessed by the recent interest of the scientific community in new approaches, such as the fuzzy simulation concepts (see Chan et al. 1997; Perrone, Noto La Diega, & Zinno, 1998). Despite the efforts devoted to these applications, as yet few advances have been made which provide appropriate and reliable tools for the on-site use. A few testimonials of this use are available (Pugh, 1997).

This paper presents a hybrid approach (here defined as ‘pseudo-fuzzy’) for the use of a classic discrete-event simulation for on-line production planning and control (thus in clearly transient conditions) to take into account several sources of uncertainty. An appropriate simulation strategy set up
to exploit the potential of DE the simulator as an operator to obtain performances of a fuzzy simulator: this justifies the term ‘pseudo-fuzzy’. A real production setting was taken as a benchmark to test the feasibility of the on-site use of this approach to support decision making.

The arrangement of this paper is as follows. The pseudo-fuzzy approach is described in Section 2 and elaborated upon in further detail. An extensive discussion of the on-line simulation modelling strategies is presented in Section 3. Simulation results and discussion of results derived from the benchmarking case are presented in Section 4. Conclusions are drawn in Section 5.

2. ‘Pseudo-fuzzy’ simulation approach for production control

Discrete event simulation has been widely adopted for a variety of purposes in manufacturing, for representation of random events (arrival time; service time; failures; etc.). Fuzziness and/or vagueness, which are common aspects of almost every real operating situation, are seldom represented in this powerful approach. The idea of using discrete-event simulation for treating fuzziness is not new (see, e.g. Perrone et al., 1998; Pugh, 1997; Rogers & Badiru, 1993; Perrone & Noto La Diega, 1998). Recently an emerging field of fuzzy simulators has been attracting the interest of the scientific community. Despite this new approach being very attractive and promising, fuzzy simulators are still not so well established nor are their stability significant enough for practical purposes. The pseudo-fuzzy approach proposed in this paper represents an alternative to the above-mentioned fuzzy simulators. It consists of the use of a classical DE simulator to perform fuzzy simulations; hence the use of the term ‘pseudo-fuzzy’.

In this paragraph the theoretical basis of the approach proposed is discussed, consisting of two different aspects: namely the on-line correlated approach and the on-line uncorrelated approach. The on-line term indicates the feature of the approach that permits the use of outcomes of simulation in real-time, i.e. allowing decisions during ordinary operations. Detailed explanations of the terms correlated and uncorrelated can be found in below.

2.1. On-line correlated approach

The idea of the so-called correlated approach in the use of DE simulation is fundamentally based on the following statements. Given two independent variables of the simulation model (e.g. two service times) \( x \) and \( y \); if these variables are also subject to sources of subjective uncertainty, an appropriate fuzzy representation of them can be made by introducing two fuzzy sets, say \( X \) and \( Y \) as below. Given the non fuzzy sets \( E \) and \( F \), in general terms,

\[
X = \{ x, \mu_x | x \in E \} \quad \text{and} \quad Y = \{ y, \mu_y | y \in F \}
\]

where

\[
\mu_x : E \rightarrow [0, 1] \quad \text{and} \quad \mu_y : F \rightarrow [0, 1]
\]

represents the membership function (Cox, 1999). If, for instance, \( X \) and \( Y \) are triangular fuzzy numbers \( (x_a, x_b, x_c) \) and \( (y_a, y_b, y_c) \) then \( \mu_{x_a} = 0; \mu_{x_b} = 1; \mu_{x_c} = 0; \mu_{y_a} = 0; \mu_{y_b} = 1; \mu_{y_c} = 0 \).

According to (Perrone et al., 1998), the correlated approach assumes that

(i) the settings of a level at the beginning of the simulation run must be taken as constant throughout all the simulation horizon for each variable;
(ii) during the generic simulation run, both the fuzzy independent variables $x$ and $y$ should be set in an identical manner; that is, if $x$ takes the value $x_b$ then $y$ also has to take the same value, i.e. that corresponding to the maximum value of the degree of membership $y_b$. Formally this can be stated as the existence of an equal correspondence ($e \leftrightarrow e$): $X \leftrightarrow Y$.

As a result of these assumptions, the output function at a generic time $t$, $z(t)$, may also be represented through a fuzzy number $z(t) = f_{\text{sim}}(x(t), y(t))$

Assumptions (i) and (ii) above might be too restrictive and thus too far from reality to be accepted for the aims of a simulation study in practice.

In the present study, we removed both the assumptions in order to represent the subjective form of uncertainty, while maintaining the use of classical DE simulators, which are stable and well experienced enough to give confidence in the effectiveness of results as well as, most importantly, on the possibility of logically interpreting the outputs.

In the present paragraph we remove assumption (i), namely the invariance of the values settings for independent variables: the resulting simulation approach is thus called on-line correlated simulation. This statement is extremely important for the correct representation of state dependent systems, because of the influence of the variables changing with time on the performance of the production system modelled. As already stated above, on-line modelling requires continuous updating of the state of the system simulated. Setting the appropriate updating frequency with respect to the simulation horizon adopted is therefore critical.

In a more formal way, the above reasoning can be stated as follows, considering again only two independent variables ($x(t)$ and $y(t)$) and the generic output variable $z(t)$, representing the performance metric considered. Given the non-fuzzy sets $E$ and $F$, in very general terms, considering the transient nature of the simulation application considered (on-line features) the $x$ and $y$ variables can be modelled through the following fuzzy sets

$$X(t) = \{x(t), \mu_x|x(t) \in E\} \quad \text{and} \quad Y(t) = \{y(t), \mu_y|y(t) \in F\}$$

where values taken may change over the time $t$ of the simulation run, while the membership functions always maintain the same value taken at the beginning of the simulation. Values of $x$ can vary either continuously or discretely in a predetermined way, change values at a fixed instant in time (time dependent, as in the present study) or change upon occurrence of specific events (e.g. state dependent).

As a consequence of this, the generic output fuzzy variable will be now dependent on the evolution of $X(t)$ and $Y(t)$ with time as follows, where $n$ discrete values are considered for the time dependent case:

$$z(t_n) = f_{\text{sim}}(x(t_n), y(t_n)) \mid f_{\text{sim}}(x(t_i), y(t_i)), \quad i \in \{1, 2, \ldots, n - 1\}$$

where the symbolism ‘$|$’ represents the dependency from, as in probability calculus. The equal correspondence constraint still holds: $X(t_i) \leftrightarrow Y(t_i), \ i = 1, \ldots, n$.

Removing the first assumption (i) can by itself avoid the correct criticism made by (Perrone et al., 1998) of inconsistency with real situations: as long as an appropriate updating strategy is adopted while running the simulation (e.g. correct updating frequency), the group of parts which have to be processed during the interval between one updating and the other does indeed experience homogeneous working
conditions, to a greater extent. Thus the on-line correlated approach might give good results worthy for real production scenarios where subjective uncertainty has to be taken into account.

2.2. On-line uncorrelated approach

Despite the on-line correlated approach being closer to the real operating conditions, it is still undermined by assumption (ii) stated in paragraph 3.1, namely the correspondence between the two fuzzy membership levels. This can prove to be a stronger limitation, which can be explained easily by adopting the concept of system state

\[
\begin{align*}
\mu_{xa} &= 0(1\text{st min}); \\
\mu_{xb} &= 1(1\text{st MAX}); \\
\mu_{xc} &= 1(2\text{nd MAX}); \\
\mu_{xd} &= 0(2\text{nd min}); \\
\end{align*}
\]

and

\[
\begin{align*}
\mu_{ya} &= 0(1\text{st min}); \\
\mu_{yb} &= 1(1\text{st MAX}); \\
\mu_{yc} &= 1(2\text{nd MAX}); \\
\mu_{yd} &= 0(2\text{nd min}). \\
\end{align*}
\]

Let us firstly refer to the case where values of variables \(x\) and \(y\) do not change with simulated time. If statement (ii) in the preceding paragraph is removed, the input states to the simulation can be applied as in Table 1.

Taking position UC1 (uncorrelated no. 1) as an example, this corresponds to an input state where the variable \(x\) takes value \(x_a\) during the simulation (with \(\mu_{xa}\) degree of membership) and the variable \(y\) takes the value \(y_b\) (with \(\mu_{yb}\) degree of membership). Independently of the degree of membership, the simulation will return the generic performance as an output of that specific input state

\[
z_{UC1}(t) = f_{sim}(x_a, y_b)
\]

This means limiting the ‘state space’ of input variables only to correlated states as in paragraph 3.1; given the nature of fuzziness, in fact, it makes absolutely no sense to limit the correspondences only to the equal correspondence (\(\leftrightarrow\)), corresponding to the cells laying on the diagonal of the correspondence matrix in Table 1 (correlated approach).

In more general terms, the values taken by \(x\) and \(y\) might also be allowed to change over time. The above reasoning can be thus extended by representing the two variables \(x\) and \(y\) by means of the following fuzzy sets:

\[
\begin{align*}
X(t, y(t)) &= \{x(t), \mu_x(t)|x(t) \in E \text{ and } \leftrightarrow \mu_y(t)\} \quad \text{and} \quad Y(t, x(t)) = \{y(t), \mu_y(t)|y(t) \in F \text{ and } \leftrightarrow \mu_x(t)\}
\end{align*}
\]

where

\[
\begin{align*}
\mu_x(t) : E &\leftrightarrow [0, 1] \quad \text{and} \quad \mu_y(t) : E &\leftrightarrow [0, 1]
\end{align*}
\]

Table 1
Input-state identification matrix: states in cells correspond to pairs of independent variables \(X\) and \(Y\)

<table>
<thead>
<tr>
<th>(X)</th>
<th>(Y)</th>
<th>1st min</th>
<th>1st MAX</th>
<th>2nd MAX</th>
<th>2nd min</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st min</td>
<td>C1</td>
<td>UC1</td>
<td>UC2</td>
<td>UC3</td>
<td></td>
</tr>
<tr>
<td>1st MAX</td>
<td>UC4</td>
<td>C2</td>
<td>UC5</td>
<td>UC6</td>
<td></td>
</tr>
<tr>
<td>2nd MAX</td>
<td>UC7</td>
<td>UC8</td>
<td>C3</td>
<td>UC9</td>
<td></td>
</tr>
<tr>
<td>2nd min</td>
<td>UC10</td>
<td>UC11</td>
<td>UC12</td>
<td>C4</td>
<td></td>
</tr>
</tbody>
</table>
and $\leftrightarrow$ represents the type of correspondence between levels imposed on the two membership functions, as stated in Table 1. Generally speaking, this correspondence may also vary over time or, as is the case in the present paper, this can be taken as fixed during each simulation run. This reasoning is similar to exploring all the possible states of the input variables and close to the enumerative technique in probability calculus.

The problem then arises as how to determine the degree of membership of these output values. A simple approach is proposed here.

Let us first pose the problem as follows, referring to Table 1: the $i$th row in the matrix represents a particular set of $j$ possible input states $(x_j, y_j)$ for the simulator, where one membership is fixed ($\mu_i$) while allowing the other memberships ($\mu_j$) to vary (the same reasoning as for columns). That is, for instance, the first row of Table 1 represents the variable $x$ taking the value corresponding to the 1st min value of the membership function ($\mu_x = 0$) while leaving the other variable $y$ taking the values corresponding to all the possible values of its membership function ($\mu_y = 0; 1; 1; 0$). Cells of the first row thus represent simulation outputs corresponding to all the possible states $(x_1, y_j)$, i.e. sets of input values in the simulated system, which are mutually exclusive. The same reasoning applies to the columns.

At the end of this process, $i$ pairs $(z_i, \mu_{xi})$ will form a trapezoidal fuzzy set of $z_i$ corresponding to the $x$ values (formed by all the pairs in the rows), and $j$ pairs $(z_j, \mu_{yj})$ will lead to a trapezoidal fuzzy set of $z_j$ corresponding to the $y$ values (formed by all the pairs in the columns).

In order to derive a unique fuzzy set for comparison purposes of the output, it is then necessary to join these two fuzzy sets using the logical AND ($\land$) operator, since both variables $x$ and $y$ are used as input variables for the same simulation run.

A defuzzification criterion then needs to be applied to find unique value of the output $z_i$ for each row corresponding to the membership $\mu_i$, and $z_j$ for each column corresponding to $\mu_j$.

Fig. 1 gives a graphical example of the above reasoning for the first row of Table 1, where $z(t)$ is here the production volume.

The only problem that remains is the correct choice of the defuzzification criterion, which belongs to the ongoing debate on classes of fuzzy operators or to the choice of ranking methods to compare different outputs (Novak,Perfilieva, & Mockor, 1999). Later on, in the presentation of results, standard techniques are used, without attempting to give a finite answer to this unresolved problem.

3. The benchmarked industrial case

For explanation purposes, one industrial setting is referred to throughout the paper as our benchmark. This consists of a production channel (ATG22) of the whole manufacturing system of the Getrag S.p.A. plant in Bari-Italy-, where 20 mechanical transmission variants are produced over 4 shifts (6 h each). The ATG22 channel is dedicated to the manufacturing of the ‘output transmission shaft’, produced in 9 different variants depending on the type of mechanical transmission. Cycle times for each shaft variant are all slightly different (only a few seconds of treatments on dedicated machines).

The production rate for the mechanical transmissions is almost constant every month (roughly 2400 parts per day in the observed period). Production is nearly always driven by customer demand, which pulls the production of the assembly channel (GPS4). This situation allows the whole work-in-process to be kept to the minimum (about one shift) while making the system very sensitive to fluctuations in demand, as well as to reductions in machine performance. The production schedule is fixed at the
beginning of each month. Based on the bill of material, the weekly production schedule is detailed for each production channel (e.g. the ATG22), under the responsibility of the team leaders. The weekly production schedule contains information on the number of parts per code to be produced per day. This information then pushes the production of the entire line. Production control is at the present performed by line coordinators, based on personal experience and rule-of-thumb reasoning. Despite the almost inherent stability of the production, even significant variations to the schedule might even occur weekly or daily due to reactions by team leaders to internal uncertainties (e.g. machine failure, interaction between channels, etc.) and external uncertainties (e.g. shift of priorities; customer’s requirements; etc.). This situation requires the efficient and reliable control of production by the same team leader, given the low profitability of the product itself. A quick response to variations is thus needed, by taking appropriate short-term decisions, sometime within a shift.

### 3.1. The discrete event model

The processing sequence for the output shaft also defines the physical layout of the ATG22 channel: (1) centring (EBA); (2) turning (DRA); (3) hobbing (FRW); (4) deburring (EGW); (5) splining (WAW); (6) drilling (FZA); (7) cleaning (ORE); (8) heat treatment; (9) shot-penning (KG); (10) straightening

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Fig. 1. Graphical representation of the on-line uncorrelated approach: calculations for the first row of Table 1 ($z(t)$ = production volume).
(RIA); (11) grinding (SLA); (12) power honing (HNW); (13) super finishing (HNA). The line consists of 22 stations, one dedicated heat-treatment oven, consisting of 6 parallel cells, 16 on-board buffers and 10 interoperation buffers. The line is interfaced with the raw-part warehouse and with the assembly channel (GPS4) through another warehouse. The production pace of ATG22 is set by the assembly channel (‘internal customer’). For more details on the manufacturing system refer to (Dassisti, Galantucci, & Cicirelli, 2000).

The simulation model was constructed using the EM-PLANT simulation environment, as shown in Fig. 2 (Aesop, 1999). The model was subdivided into modules (group of machines, buffers, operator, control point and/or transport system) corresponding to a set of resources controlled by one human operator. This configuration was chosen to appropriately incorporate into model the human resources and their subjective uncertainty influence on the channel performance into the model, as explained below in Section 3.3.

In order to test the feasibility of the approach proposed, several blank tests were run using a single pallet (racks containing 72 shafts each), also considering occurrence of scraps, for a single product variant (referred to here as part code, or simply code), to validate the whole model and its logic. Parts are not allowed to move independently between stations. The grouping rule is to put semi-finished parts into the pallet until it is full and this logic was also embedded into the simulation model. A single pallet takes an average of 27,182 s—with a standard deviation of 1385 s—to flow throughout the channel (according to the processing features reported in Table 1), almost independently of the variants (part

![Fig. 2. Discrete-event simulation model built using EM-PLANT simulation environment.](image-url)
code) considered, as above indicated. Stochastic variability in processing times were only considered for some machines, the effect of the other machines being insignificant over the whole processing time.

Table 2 reports the operating characteristics of the channel considered (resources; times and inventories) for the benchmarking case presented in the paper (standard conditions derived from a set of observations over one year).

3.2. Modelling assumptions for on-line use

It is extremely important to define the scope of the on-line simulation study performed as well as the data, information and knowledge structure underlying the functioning of the real system. These are in fact the most critical aspects of the modeling task for the success of the simulation study, as it is pointed out in the present paragraph.

As previously stated, the application of discrete-event simulation for on-line production control requires different assumptions from a traditional steady-state DE simulation analysis. Some of these are general, i.e. independent of the specific application, while others are application-dependent, i.e. specific to the setting modelled, as well as to the scope of the analysis.

Concerning this latter point, for instance, in the industrial setting benchmarked no automatic recording facilities were available for production data; it was thus necessary to set up an appropriate internal procedure for data collection for the simulation purposes here presented. The updating strategy is generally a critical aspect to be considered for on-line applications, given their features of state-dependency, where states evolve during the same simulation horizon. A constant initialisation to the most updated system state before each simulation trial has proved to be, in our initial experience, the most appropriate strategy and was also adopted here.

The DE simulation approach proposed is a clear application of transient analysis, i.e. on-line application (Banks, 1998). The general modelling hypotheses adopted in the model for production control are summarised in Table 3. They are based on the assumption that the discrete-event simulation

<table>
<thead>
<tr>
<th>RESOURCE</th>
<th>Number of machines</th>
<th>CYCLE TIME per part (sec.)</th>
<th>Scraps - $N(\mu,\sigma)$</th>
<th>BUFFERS state</th>
<th>PART CODE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centering</td>
<td>1</td>
<td>30 (S)</td>
<td>0.0085</td>
<td>10</td>
<td>735</td>
</tr>
<tr>
<td>turning</td>
<td>3</td>
<td>80 (S)</td>
<td>0.0085</td>
<td>5</td>
<td>735</td>
</tr>
<tr>
<td>hobbing</td>
<td>2</td>
<td>53 (S)</td>
<td>0.0085</td>
<td>4</td>
<td>735</td>
</tr>
<tr>
<td>deburring</td>
<td>1</td>
<td>22</td>
<td></td>
<td>2</td>
<td>735</td>
</tr>
<tr>
<td>spining</td>
<td>1</td>
<td>24</td>
<td></td>
<td>2</td>
<td>735</td>
</tr>
<tr>
<td>drilling</td>
<td>4</td>
<td>96</td>
<td></td>
<td>2</td>
<td>735</td>
</tr>
<tr>
<td>cleaning</td>
<td>8</td>
<td>42</td>
<td></td>
<td>0</td>
<td>735</td>
</tr>
<tr>
<td>Heat treatment</td>
<td>6cells +2 +10</td>
<td><strong>40.28 +8.33 +10.25</strong></td>
<td>-</td>
<td>10</td>
<td>735</td>
</tr>
<tr>
<td>Shot-peening</td>
<td>1</td>
<td>8</td>
<td>-</td>
<td>4</td>
<td>457</td>
</tr>
<tr>
<td>Straightening</td>
<td>1</td>
<td>20</td>
<td>-</td>
<td>2</td>
<td>457</td>
</tr>
<tr>
<td>grinding</td>
<td>2</td>
<td>50</td>
<td>-</td>
<td>2</td>
<td>457</td>
</tr>
<tr>
<td>Power honing(HNW)</td>
<td>3</td>
<td>84</td>
<td>-</td>
<td>2</td>
<td>457</td>
</tr>
<tr>
<td>Superfinishing (HNA)</td>
<td>1</td>
<td>23</td>
<td>-</td>
<td>2</td>
<td>457</td>
</tr>
</tbody>
</table>
models have been built to be suitable for interfacing with the line (both automatic data collection and human responsibility) for downloading data.

In the present paper given the on-line feature we adopted 1–2 horizon shifts, namely 6 and 12 h, and therefore the updating frequency of time dependent variables was set to 1/h, based also on the characteristics of the variables considered (human performance).

3.2.1. Stochastic modelling assumptions

A wide on-site analysis, based on six months observation, was carried out of the manufacturing system considered in order to recognize sources of uncertainty in the production control. A set of records of critical events was analysed, recognizing the relationships between sources of uncertainty and their effect. The objective forms of uncertainty are thus reported in Table 4, indicating the sources and factors which influence performance that can be considered while designing a DE model. This form of uncertainty is well treated using classical statistics theory by representing the main effects of uncertainty as random variables, based upon appropriate assumptions or data analysis.

According to the above classification, the following hypotheses were adopted concerning stochastic events:

Table 4
Analysis of the objective uncertainty for the industrial case considered

<table>
<thead>
<tr>
<th>uncertainty forms</th>
<th>source of uncertainty</th>
<th>effects on performance</th>
<th>Higher effect</th>
<th>Lower effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>OBJECTIVE</td>
<td>a) machine breakdown;</td>
<td>number of scraps</td>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td></td>
<td>b) unexpected code-production shift (unexpected variation of production order)</td>
<td>maintenance time (down time)</td>
<td>a; b</td>
<td></td>
</tr>
<tr>
<td></td>
<td>c) intersection with other processes (first part control)</td>
<td>WIP</td>
<td>a; b</td>
<td>C</td>
</tr>
<tr>
<td></td>
<td></td>
<td>material shortage</td>
<td>c</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>total process time</td>
<td>a;b;c</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>set-up time</td>
<td>b</td>
<td>C</td>
</tr>
</tbody>
</table>
(1) scraps were generated according to a truncated normal distribution (see Table 1), given that an appropriate SPC system was running in the line, with standard control limits. Therefore, scraps were generated when the actual critical size variable fell outside the control limits. Scraps depend essentially on the quality of input material rather than on the specific processes themselves. This explains the similarity with features in modelling scraps reported in Table 1.

(2) No failure was modelled because a very intensive preventive maintenance program was ongoing in the production setting. In fact, a number of minutes of each shift were devoted to preventive maintenance.

Given the above point 2 and the fact that the decision horizon for the application considered is very short for the production control (6–12 h), the probability of occurrence of unexpected severe failures (i.e. that class of failure which might occur independently of the ordinary preventive maintenance programs) was assumed to be negligible.

3.3. Sources of uncertainty in process control

Treating and representing the subjective forms of uncertainty is a task of formidable importance from the process control point of view. As already stated in Section 3.2.1, Table 5 was built after an observation period of 6 months on-site to give a list of sources of subjective uncertainties in the test case analysed and their effect. From the analysis of information structure and human performance at the industrial setting studied, it was realized that the most critical aspects were information flows and the influence of the human operator on the performance of this section of the line, which results in a stronger effect on the operation of the whole line. Both of them are under the influence of human operators indeed: this explains the subjective nature of the sources included in Table 5 with respect to sources in Table 4. The two sources of subjective uncertainty modelled in the simulation model were, in fact, the operator and the information flow.

Table 5
Sources of subjective uncertainty in process control at Getrag S.p.A

<table>
<thead>
<tr>
<th>uncertainty forms</th>
<th>source of uncertainty</th>
<th>effects on performance</th>
<th>Higher effect</th>
<th>Lower effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>SUBJECTIVE</td>
<td>o) Operators:</td>
<td>number of scraps</td>
<td>o1, o2, o3</td>
<td>i, t, o4</td>
</tr>
<tr>
<td></td>
<td>1. number of machine controlled;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. tiredness;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. personal attitude;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4. skill</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>i) Information flow:</td>
<td>Processing time increase</td>
<td>o3, o4</td>
<td>o1, o2, i</td>
</tr>
<tr>
<td></td>
<td>1. pertinence;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. completeness</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>t) Timeliness</td>
<td>Throughput time reduction</td>
<td>o2, o4, i,t</td>
<td>o2, o3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downtime</td>
<td>i2, o1</td>
<td>o2, o3, o4</td>
</tr>
</tbody>
</table>
Fuzzy set theory was adopted both to represent the main causes of subjective uncertainty, as a fuzzy set with an appropriate membership function, fuzzy rules and inference operations (Zimmermann, 1987), and for simulation output analysis.

Standard trapezoidal fuzzy sets were adopted in their simpler form (Lootsma, 1997) as follows, with \( x \) being the fuzzy variable modelled:

\[
(x_a, x_b, x_c, x_d)
\]

where membership functions are (see Fig. 3 for a clear representation)

\[
\mu_{xa} = 0(1st \ min); \quad \mu_{xb} = 1(1st \ MAX); \quad \mu_{xc} = 1(2nd \ MAX); \quad \mu_{xd} = 0(2nd \ min).
\]

This choice was related to their simplicity in specification, ease of visualization, and, more important, stability, in the sense of ease of understanding by experts. The trapezoidal form is not as simple as triangular fuzzy sets, however it allows a higher flexibility of representation and is as powerful as the sigmoid in representing the semantics of most of the variables encountered, without requiring complex representations. Furthermore, the output function remains almost trapezoidal shaped, thus allowing for easy comparisons between competing solutions.

All the sources of fuzzy variability were modelled using appropriate membership functions shaped, according to the atomic evaluating syntagms (sequence of words in a particular syntactic relationship to one another) and the linguistic edges (Novak et al., 1999) of opinions collected from three experts: one team leader and two line coordinators.

Concerning the operator source, two aspects were considered as causative of subjective uncertainty for the present application: the tiredness of and the number of machines controlled by the operator.

The tiredness of the operator is seldom represented using stochastic variables given the difficulty in measuring it. In literature a few attempts have been made to model human operator behavior based on the stochastic approach (Crawford and Gallwey, 1999). As for the number of machines, uncertainty derives from the fact that the number of machines controlled by a single operator is not necessarily fixed a priori; it might depend on the specific situation. For instance, due to the unforeseen breakdown of a machine (stochastic event) in the channel the same operator might be requested to use additional machines, based on his/her personal judgment of the state of urgency. This source of variability was modelled using appropriate trapezoidal membership functions (refer to Dassisti et al., 2000 for details).
Both the sources referred to above are then composed to give a unique fuzzy representation of the operator source of uncertainty, using the fuzzy system approach (Zadeh, 1965) as described in Fig. 4, where (f.r.) is the $i$th fuzzy rule. Nine rules were used to derive the operator efficiency as summarized in Table 6. The correlation-minimum encoding activation method was adopted to derive the operator efficiency, using Mamdani’s inference method (Jang & Gulley, 1996). Tiredness varies with time and thus also operator efficiency. In the present paper operator efficiency has been modelled to vary with each hour of the simulated time.

Similarly, the second source of uncertainty (information flow) was modelled. The first aspect considered was completeness, which presents an intrinsic uncertainty due to the fact that there is never a clear way of defining and/or measuring it, due to the huge amount of information which flows through the system daily for control purposes. This aspect was modelled again using appropriate membership functions (refer to Dassisti et al. (2000) for details).

The second aspect was information pertinence, which embedded clearness and timeliness, representing the relevance to the use of information flows, which is the result of complex interactions between different actors. Membership functions are detailed in (Dassisti et al., 2000).

Again, as for the first source of subjective uncertainty, a fuzzy system was used to define ‘information efficiency’; see Table 7. The correlation-minimum encoding activation method was adopted to derive the information efficiency using Mamdani’s inference method, as shown in Fig. 5 (Jang & Gulley, 1996).

Note that for the information efficiency, the linguistic hedge ‘quite’ was also adopted in the consequence part of the rule to dilute the membership curve due to, say, interaction of both aspects of information flow.

Starting from the two sources of uncertainty previously modelled, namely operator efficiency and information efficiency, it was possible to represent the overall subjective uncertainty deriving from human resources in the discrete-event model adopted. This was done by introducing a fuzzy corrective factor (named the machine efficiency factor-MEF) to those resources indicated by the experts and by performance data considered to be the most critical after a brainstorming session (see Ledolter et al. (1999)). MEFs thus serve to modify the processing time of the corresponding machines controlled by the ‘critical’ human resources.

![Fig. 4. Operator efficiency.](image)

### Table 6
Set of 9 fuzzy rules adopted for the man efficiency (IF (Machine) ∧ IF (Hrs) THEN consequence statements in frame)

<table>
<thead>
<tr>
<th>(If No Machin. →) ∧ (If No. hrs ↓)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>
The MEF was calculated according to the fuzzy system shown in Fig. 6 with the set of 15 different rules from Table 8. The correlation-minimum encoding activation method has been adopted to derive the information efficiency using Mamdani’s inference method (Jang & Gulley, 1996).

After a defuzzification operation was performed using the centroid criteria (Jang & Gulley, 1996), the modification of the processing time (PT) of the critical group of machines was carried out according to the following equation:

\[
(PT_i^t) = (PT_i)/\text{MEF}_i(t)
\]

where the ME factor is a function of time, as is operator efficiency, thus changing during the simulation run.

4. Output analysis of the test case

A defined production situation, for the industrial setting considered, was analysed in order to test the approaches proposed, as reported in Table 1. Only two groups of machines were considered to be subjected to subjective uncertainty, namely those for honing (HNW, 3 machines) and super-finishing (HNA, 1 machine) which were recognized over a six months observation period as the most critical in the line, as stated above in Section 3.3. According to the approach explained in Section 2, service times of HNW will represent a variable (Y) subject to the two sources of uncertainty recalled in Section 3, while HNA will represent another variable (X).

The simulation horizons selected were 6 and 12 h (1 and 2 shifts) because of the type of decisional problem addressed. The line operator was asked to decide whether to put another operator on the group of machine-honing and super-finishing- for the next one or two shifts in order to get an appropriate output rate (here referred to as solution ‘A’) or to leave a single operator (solution ‘B’). The updating strategy adopted was to input the channel state by giving information on existing pallets and all the technological information (Table 1). Runs were made without other orders allowed onto the line, as fixed in the production plan for the week considered because it was not a useful disturbance effect on output

![Fig. 5. Information efficiency.](image-url)
Several system performance metrics were collected at the end of the horizon of analysis: total number of good finished products or total production volume; total work in progress; number of scraps; average life span of products. For the sake of brevity, also given the kind of test case considered, only the total production volume is reported here: it is thus evident that, for comparison purposes, the higher the total production volume, the better the solution is.

The simulation strategy adopted was to make 10 independent replication runs to get a statistically significant result for the output analysis (Banks, 1998), due to the presence of scraps. At the beginning of each run the stream generator was reset and the input seeds were changed so as to assure the independence of replications.

In order to get a statistically significant output analysis, even though a generally accepted procedure is not yet available, the method of \( k^* = 10 \) independent runs per simulation condition was adopted according to (Banks, 1998). It was calculated on the basis of the stopping rule proposed by Fishman, always starting from the same line state (taking a sample during current operating).

This method was carried out for each point in time (2, 4, 6, and 12 h) for the centroid simulation and at 6 and 12 h for the pseudo-fuzzy, in such a way that the time series of the output performance derived can be considered to be independent from the others.

The following performance measures were considered both for the single workstations as well as for the whole line: work-in-process, throughput.

The approximated \((1 - \alpha)\%\) confidence interval of the estimated mean of the generic output performance \( E(Y_k) \) can thus be evaluated as:

\[
[-t_{(k-1),(1-\alpha/2)} \cdot S_k(Y)/\sqrt{k}, \ t_{(k-1),(1-\alpha/2)} \cdot S_k(Y)/\sqrt{k}]
\]

with \( S_k(Y) \) being the sample variance (unbiased estimator of the sample variance)

### Table 8

<table>
<thead>
<tr>
<th>Set of 15 fuzzy rules adopted for the MEF (IF (Machine) &amp; IF (Hrs) THEN consequence statements in frame)</th>
</tr>
</thead>
<tbody>
<tr>
<td>((\text{If Inform. efficiency } \rightarrow) \land (\text{If Op effic. } \downarrow))</td>
</tr>
<tr>
<td>Low</td>
</tr>
<tr>
<td>Medium</td>
</tr>
<tr>
<td>High</td>
</tr>
</tbody>
</table>
\[ S_k^2(Y) = \frac{1}{(k - 1)} \cdot \sum_{i=1}^{k} [Y_i - E(Y_k)] \]

and

\[ Y_i = \frac{1}{n} \cdot \sum_{j=1}^{n} X_{ij} \quad i = 1, \ldots, k \]

where \( k \) stands for the number or independent replications and \( n \) the total number of output data

\[ E(Y_k) = \frac{1}{k} \cdot \sum_{i=1}^{k} Y_i. \]

The results derived for the three different approaches for the analysis of the decisional problem under investigation are presented in Section 4.1.

### 4.1. Centroid-based approach

The centroid method reproduces a crisp use of the DE simulation, which is very well experienced. It consists of a defuzzification of the fuzzy variables at the input of the simulation.

The paragraph presents the results of 60 simulation runs made by applying the criterion of modifying the machine performance using a crisp weight according to Fig. 8 (the centroid of the MEF represented in Fig. 7).

Table 9 below reports simulation outcomes evaluated at different levels of information efficiency for the two solutions considered: in reading the table, for instance, A-98.7 means solution A at 98.7% level of efficiency. The IDEAL condition corresponds to the condition of absence of subjective uncertainty.

### 4.2. On-line correlated and on-line uncorrelated approaches

In order to test the performance of the two on-line approaches presented, namely correlated vs non-correlated, based on the indication derived from Section 4.1, we only considered the worst condition
here as concerns the information flow (INFO 76.1), which gave the most problems in discriminating between solutions A and B. By coincidence, this was also the true condition experienced in the reference case adopted. Here we only report the results at the end of the 2nd shift, where differences were much more evident.

Results derived for the on-line correlated approach are reported in Table 10 together with the 99% confidence intervals for the two solutions. Fig. 9 compares the two fuzzy numbers, reported in Table 10, where it is now slightly more evident that solution A is the best, also taking into account the confidence intervals obtained.

Finally, Table 11 reports the output derived for the on-line uncorrelated approach for the solution A (diagonal cells correspond to the correlated approach for sol. A). The structure of Table 11 represents a special type of fuzzy relation (Novak et al., 1999) where the figures in the cells of the matrix are not membership functions, but crisp values.

Note that it was not possible to perform an uncorrelated simulation for solution B, given that there was only one operator for all the machines.

Table 9
Average values of total production volume at the different points in time

<table>
<thead>
<tr>
<th></th>
<th>IDEAL</th>
<th>A-98,7</th>
<th>A-90</th>
<th>A-76</th>
<th>B-98,7</th>
<th>B-90</th>
<th>B-76</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 h</td>
<td>144</td>
<td>144</td>
<td>144</td>
<td>144</td>
<td>144</td>
<td>144</td>
<td>144</td>
</tr>
<tr>
<td>4 h</td>
<td>216</td>
<td>216</td>
<td>216</td>
<td>216</td>
<td>216</td>
<td>216</td>
<td>216</td>
</tr>
<tr>
<td>6 h</td>
<td>431.8</td>
<td>360</td>
<td>288</td>
<td>288</td>
<td>360</td>
<td>288</td>
<td>288</td>
</tr>
<tr>
<td>12 h</td>
<td>1145.7</td>
<td>1028</td>
<td>858.7</td>
<td>858.7</td>
<td>1000.6</td>
<td>858</td>
<td>855.6</td>
</tr>
</tbody>
</table>
Accordingly, it is not easy to compare the two solutions at this point, because the two solutions have different output states. According to the method shown in Section 2.2, the defuzzification method adopted for rows and columns was the centroid method. In this way two trapezoidal fuzzy numbers were formed, one for HNW (honing machines) and one for HNA (superfinishing) as reported here:

HNA (858, 862, 885, 907) and HNW (745, 857, 891, 1018).

At the end of this operation, in order to get a unique fuzzy set, the logical AND (\(\land\)) operator was applied to both the fuzzy numbers. The class of AND operator adopted was the Zadeh min(\(\land\)) (Cox, 1999).

The final trapezoidal fuzzy set for solution A is the following general fuzzy number: solution A (858, 862, 885, 907). This then allowed comparison of the fuzzy number of the two solutions, showing that solution A almost outperforms solution B (see Table 10).

### 4.3. Discussion of the test case analysed

It is easy to see that at info efficiency 90 and 76.1 there is almost no difference between solution A and solution B, whereas at a very high level of information efficiency solution A outperforms solution B. Comparison seems quite logical, given the criterion adopted, based on the total production volume: solution A should be preferable to solution B. This fact allows better understanding of the behaviour of

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>716.4</td>
<td>± 2.18</td>
<td>716.4</td>
<td>± 2.18</td>
</tr>
<tr>
<td>1</td>
<td>857.1</td>
<td>± 2.92</td>
<td>840.4</td>
<td>± 28.06</td>
</tr>
<tr>
<td>1</td>
<td>903.1</td>
<td>± 30.56</td>
<td>858.7</td>
<td>± 2.83</td>
</tr>
<tr>
<td>0</td>
<td>1046.9</td>
<td>± 32.40</td>
<td>1000.6</td>
<td>± 2.23</td>
</tr>
</tbody>
</table>

Table 10
Total production volume on the 2nd shift; on-line correlated approach.

Fig. 9. Total production volume on the 2nd shift; on-line correlated approach.
different techniques, which are here compared in the most critical condition from a decision making point of view: INFO 76.

The use of the centroid is a typical crisp approach that allows on one hand the easy ranking of different solutions while, on the other hand, it might give less significant results. Fig. 10 shows this evidence at the INFO 76 level of information efficiency.

Concerning the on-line correlated and uncorrelated results, sound criteria need to be used for significant comparison of the two solutions A and B.

Firstly we compared the two solutions by using a simple defuzzification method of centroids (C), which is reported here:

\[ C(\text{correlated A}) = 881; \quad C(\text{uncorrelated A}) = 879 \quad \text{vs} \quad \text{Centroid(B)} = 855. \]

These results seem to say that solution A is performing the best, by considering the output parameters performance total production volume. This is, again, a crisp comparison which does not take into account the true shape of fuzzy numbers in Figs. 9 and 11, where one can see how difficult it is to derive a significant statement as regards the output of the correlated approach. The uncorrelated approach presented is slightly different, where a lower degree of fuzziness allows more confidence in the answers.

For this reason, the so-called ‘ratio of overlap and underlap’ was used (Lootsma, 1997), to provide numerical evidence for the degree of confidence compared to the outputs of the different approaches adopted, defined as follows for the two solutions A and B:

\[
\text{ROU} = \frac{\mu_{A \cap B}(x)}{\mu_{A \cup B}(x)}
\]

As a result we found that ROU(correlated) = 0.725 versus ROU(uncorrelated) = 0.214.

---

**Table 11**

<table>
<thead>
<tr>
<th>HNA</th>
<th>HNW</th>
<th>1st min</th>
<th>1st MAX</th>
<th>2nd MAX</th>
<th>2nd min</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st min</td>
<td>716.4</td>
<td>857.1</td>
<td>858.7</td>
<td>1000.2</td>
<td></td>
</tr>
<tr>
<td>1st MAX</td>
<td>716.7</td>
<td>857.1</td>
<td>875.1</td>
<td>1003</td>
<td></td>
</tr>
<tr>
<td>2nd MAX</td>
<td>758.7</td>
<td>857.4</td>
<td>903.1</td>
<td>1015.9</td>
<td></td>
</tr>
<tr>
<td>2nd min</td>
<td>787.5</td>
<td>857.4</td>
<td>927.1</td>
<td>1046.9</td>
<td></td>
</tr>
</tbody>
</table>

---

**Fig. 10. Solution A vs. solution B-centroid method at INFO 76.**
Despite the fact that this indicator might be subject to criticism, this last result stresses how only the uncorrelated approach allows to better discrimination between the two solutions, as it has a very low degree of fuzziness.

5. Conclusions

This paper presents a non-classical application of discrete-event simulation for on-line production control subject to different sources of uncertainty has been presented, both objective and subjective. The results derived from the benchmark case analysed are quite interesting, even if they do not represent an absolute proof of the quality of the approach.

Taking into account subjective sources of uncertainty within the DE simulation is similar to ‘fine tuning’, which refines the model output coming from the classical discrete-event simulation use (which represents a rough tuning). The classical stochastic approach essentially belongs to the realm of longer and more stable horizons, while the fuzzy representation belongs to that of shorter and transient ones. The non-traditional use of discrete-event simulation proposed here takes into account both these aspects, thus promising lower relative errors in forecasting system behaviour compared to the traditional DE simulation applications.

The use of a commercial code is another strength of the approach proposed, because of the debugging facilities as well as the amount of standard macros already available (Aesop, 1999); it represents a significant amount of know-how that should not be neglected in the name of computational efficiency. It also avoids incurring the difficulties-even paradoxes-faced when adopting fuzzy simulators, to produce very effective tool in supporting decision making in ordinary manufacturing situations.

One limitation of the proposed approach, particularly for the uncorrelated one, is the combinatorial explosion of simulation runs as far as the number of fuzzy factors to be taken into account increases. However, as shown in this case, by appropriately combining problem solving methodologies with the design of dedicated simulation routines it is possible to automate the process of the output fuzzy-set reconstructions as well as data comparisons to reduce the state space size.

Fig. 11. Comparison of on-line uncorrelated approach sol. A vs. solution B.
The application outcomes give confidence in the value of the strategies proposed for further practical applications of discrete event simulation as a valuable tool for supporting daily decision making tasks involving production control activities.

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