



**HAL**  
open science

# Reactive control of overall power consumption in flexible manufacturing systems scheduling: A Potential Fields model

Cyrille Pach, Thierry Berger, Yves Sallez, Damien Trentesaux

## ► To cite this version:

Cyrille Pach, Thierry Berger, Yves Sallez, Damien Trentesaux. Reactive control of overall power consumption in flexible manufacturing systems scheduling: A Potential Fields model. *Control Engineering Practice*, 2015, 44, pp.193-208. 10.1016/j.conengprac.2015.08.003 . hal-03428162

**HAL Id: hal-03428162**

**<https://uphf.hal.science/hal-03428162v1>**

Submitted on 30 Sep 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Reactive control of overall power consumption in flexible manufacturing systems scheduling: A Potential Fields model

C. Pach, T. Berger\*, Y. Sallez, D. Trentesaux

LAMIH, UMR CNRS 8201, University of Valenciennes and Hainaut-Cambrésis, F-59313 Valenciennes, France

## Keywords:

Overall consumption  
Reactive control, scheduling, Potential Fields  
Flexible manufacturing systems

## a b s t r a c t

In recent years, designing “energy-aware manufacturing scheduling and control systems” has become more and more complex due to the increasing volatility and unpredictability of energy availability, supply and cost, and thus requires the integration of highly reactive behavior in control laws. The aim of this paper is to propose a Potential Fields-based flexible manufacturing control system that can dynamically allocate and route products to production resources to minimize the total production time. This control system simultaneously optimizes resource energy consumption by limiting energy wastage through the real-time control of resource states, and by dynamically controlling the overall power consumption taking the limited availability of energy into consideration. The Potential Fields-based control model was proposed in two stages. First, a mechanism was proposed to switch resources on/off reactively depending on the situation of the flexible manufacturing system (FMS) to reduce energy wastage. Second, while minimizing wastage, overall power consumption control was introduced in order to remain under a dynamically determined energy threshold. The effectiveness of the control model was studied in simulation with several scenarios for reducing energy wastage and controlling overall consumption. Experiments were then performed in a real FMS to prove the feasibility of the model. The superiority of the proposition is its high reactivity to manage production in real-time despite unexpected restrictions in the amount of energy available. After providing the limitations of the work, the conclusions and prospects are presented.

## 1. Introduction

It is estimated that industrial power consumption worldwide will increase by 40 percent between 2006 and 2030 (Energy Information Administration, 2009), while power supplies will decrease due to the decline in fossil fuel-based energy sources (Chefurka, 2008). The manufacturing sector, which accounts for the biggest share of power consumption (33%) and greenhouse gases (38%), will have to cope with growing energy costs, the uncertainty related to renewable energy, new legislation regarding energy efficiency, and customers looking for sustainable production (Jänicke, 2008; Taylor, d’Ortigue, Francoeur, & Trudeau, 2010). That is why one of the IMS2020 project roadmaps (IMS2020, 2013) focuses on energy as one of the main concerns in manufacturing, the key area of Energy Efficient Manufacturing being to reduce the carbon footprint of manufacturing in the future.

There are many ways to design Energy Efficient Manufacturing systems since energy, typically electrical energy, can be considered in different stages of a product’s life cycle, namely procurement,

production, distribution and afterlife (Sarkis & Rasheed, 1995). This paper focuses on the production stage in manufacturing systems that play a vital role in the global economy, but have a significant environmental burden (Dufflou et al., 2012). As outlined in (Pach, Berger, Sallez, Adam & Trentesaux, 2013a), during the production stage, different solutions can be studied to reach the desired sustainability: resources or processes can be substituted with less consuming ones; resource optimization can be enhanced; processes can be fine-tuned and external energy-saving devices can be added to the system.

The first possibility is to substitute processes or resources with less consuming ones. Regarding processes, (He, Liu, Zhang, Gao & Liu, 2012) show that using alternative process schemes for two jobs can greatly affect energy-optimizing scheduling. (Zein, 2013) presents current work on machine tools to make them more efficient. The problem with changing a process or resource is that first, it can imply other modifications in the manufacturing system and second, it requires heavy initial investment for the manufacturer (Bi & Wang, 2012). The second way to increase the sustainability of a manufacturing system is to adjust processes with regard to power consumption. Optimizing a process can greatly improve power consumption (Dietmair & Verl, 2009; Ochoa George, Gutiérrez, Cogollos

\* Corresponding author. Fax: +33 3 2751 1310.

E-mail address: [thierry.berger@univ-valenciennes.fr](mailto:thierry.berger@univ-valenciennes.fr) (T. Berger).

## Nomenclature

### FMS notations

$R$	is the set of resources $r$ .
$Q_r$	is the queue size of resource $r$ .
$SR_r$	is the set of services provided by resource $r$ .
$SR_{r,s}$	is the service $s$ provided by resource $r$ .
$P$	is the set of products $p$ to be manufactured.
$SP_p$	is the set of services required by a product $p$ .
$SP_{p,s}$	is the service $s$ required by a product $p$ .
$Co(t)$	is the consumption of all the resources at time $t$ .
$Co_{i,r}$	is the consumption in state $i$ of resource $r$ , $i \in [1, 4]$ .
$Co_r(t)$	is the consumption of resource $r$ at time $t$ .
$Th(t)$	is the energy threshold not to be exceeded at time $t$ .
$Cmax$	is the total production time for a set of products $P$ to be manufactured.

### PF notations

$\alpha_{r,s}(t)$	attractiveness of resource $r$ for a service $s$ .
-------------------	--

$S_{r,s}(t)$	is a binary value set to 1 if resource $r$ is available for service $s$ at time $t$ and set to 0 if the resource is unavailable.
$w_{i,j,r}(t)$	is a binary value set to 1 if product $j$ is waiting for its service number $i$ in the input queue of resource $r$ at time $t$ , 0 otherwise.
$z_{i,j,r}(t)$	is a binary value set to 1 if service number $i$ of product $j$ is currently in progress on resource $r$ at time $t$ , 0 otherwise.
$\phi_{r,d,s}(t)$	PF propagated from resource $r$ , for a service $s$ , sensed by any product at a decisional node $d$ .
$\mu_r$	denotes the magnitude that determines the range of the PFs emitted by the resource $r$ .
$M_{r,d}(t)$	denotes the mitigation of the PFs by the environment (between resource $r$ and node $d$ ).
$r^*$	the resource with the highest PF.
$\beta_{p,r,s}(t)$	intention from product $p$ for resource $r$ and service $s$ .
$Z_{i,p}(t)$	is a coefficient that depends on the current state of the product.

Martínez & Vandecasteele, 2010). However, tuning the process implies good knowledge of the resource and the possibility of changing its parameters (e.g., speed, temperature). This can also lead to new problems, such as lower product quality or shorter resource lifespan. A third way to improve the energy efficiency of a machine is to add external devices to monitor or control power consumption (DMG, 2010). However, with these three technical solutions, the full potential to increase energy efficiency is not exploited (Pechmann & Schöler, 2011). Significant energy savings are attainable, but these three methods imply heavy investments for the necessary upgrades, refits and overhauls (Newman, Nassehi, Imani-Asrai & Dhokia 2012). Therefore, before investing in new machines or processes, or fine-tuning processes and power consumption, manufacturers have to consider: “Is my current manufacturing system used in the best possible way with regard to energy savings and restrictions?” This leads to the last way of improving the energy efficiency of the system: optimizing the scheduling and the control of existing resources by taking power consumption into consideration with regard to a level of available energy. In this way, resources and processes stay the same, and changes are made to the manufacturing scheduling and control system. The gain in energy can be significant (Devoldere, Dewulf, Deprez, Willems & Duflou, 2007). This paper deals with designing such energy-aware manufacturing scheduling and control systems.

In recent years, designing such “energy-aware manufacturing scheduling and control systems” has become more and more complex due to the increasing volatility and unpredictability of energy availability, supply and cost, and thus requires the integration of highly reactive behavior in control laws (Ghadimi, Kara & Kornfeld, 2015). For example, the carbon footprint is bigger during periods of peak load (e.g. electricity peak load) due to the use of more expensive and less clean sources (Prabhu, 2012). This can result in dynamic (i.e., real-time) electricity pricing. It is also important to note that, with provider–user energy supply agreements, exceeding the consumption defined will result in significant penalties. Another factor that will result in more unpredictable costs and availability, as well as volatile energy supplies, is the increasing use of solar panels or wind turbines in the energy grid. The evolution in the energy available has to be predicted, but the price, the load and the consumption behavior implied may be difficult to predict (Fan & Borlase, 2009; Ipakchi & Albuyeh, 2009).

In this context, the paper considers a specific but widespread kind of manufacturing system: flexible manufacturing system (FMS), and proposes a FMS control system that can reactively optimize and control the

overall power consumption of the Flexible Manufacturing System, with a variable and limited energy supply that is hard to predict.

Section 2 thus presents some studies dealing with power consumption control in manufacturing systems and positions our contribution. Section 3 formalizes the problem and Section 4 presents a reactive Potential Fields model to control the FMS taking energy into consideration. The FMS case study is presented in Section 5. Section 6 reports the simulations performed for this case study. Section 7 provides clues for the implementation of concepts in this case and an experiment in real conditions. Section 8 presents the limitations of the approach proposed. Our conclusions and prospects are presented in Section 9.

## 2. State of the art in energy-aware manufacturing scheduling and control

Contributions found in the literature focusing on optimizing the use of existing manufacturing resources by taking power consumption into consideration with regard to a level of available energy are two-fold. The first and most common are mathematical programming oriented approaches. There are numerous studies using Integer Linear Programming (Zhang, Li, Gao, Zhang & Wen, 2012), Mixed Integer Linear Programming (Bruzzone, Anghinolfi, Paolucci & Tonelli, 2012; Fang, Uhan, Zhao & Sutherland, 2011a), Fractional Mixed Integer Programming (Wang, Ding, Qiu, & Dong, 2011) or Mixed Integer Non-Linear Programming (Vergnano et al., 2010). The first problem tackled in the literature is peak power consumption. Peak power consumption can cause huge peaks in the energy grid and generate additional costs (Pechmann & Schöler, 2011). (Babu & Ashok, 2008) tackled the problem using mixed integer non-linear programming that reschedules the load and minimizes the energy peak. The problem is also tackled in (Bruzzone et al., 2012) with a two-step approach where a schedule is created by an advanced planning and scheduling system without considering energy savings, and then refined using mixed integer linear programming to control peak power consumption. The second problem tackled is the reduction of the overall power consumption of the manufacturing system. In (Zhang et al., 2012), this is controlled with a linear programming-based scheduling function. In (Vergnano et al., 2010), the problem is solved using non-linear programming. (Fang, Uhan, Zhao & Sutherland, 2011b)

used multi-objective mixed integer programming to integrate both peak power consumption and carbon footprint reduction. The problem is that exact approaches like mathematical programming are highly time-consuming, focus mainly on the static peak power consumption. They do not consider the real-time control of overall power consumption, thus they do not match the reactivity required in a dynamic and uncertain context (Marík & McFarlane, 2005), as stated in the introduction. The problem is indeed that, in most manufacturing systems, the scheduling problem is NP-hard (Mati & Xiaolan, 2003). Adding energy considerations to this problem makes it even harder to solve and transforms the problem into a multi-objective problem. That is why (Fang et al., 2011b) for example, advise using an approximated approach.

Thus, some researchers use heuristics (Vallada, Ruiz & Minella, 2008) and meta-heuristics (Voß, 2001) to solve the scheduling problem instead. These methods focus on rapidly providing a good solution instead of looking for the optimal solution. This greatly reduces the resolution time and so makes these approaches more reactive than exact ones, rendering them more suitable in the context introduced where energy availability and costs will become more and more unpredictable and highly variable. Genetic algorithms are typical meta-heuristics that can be used in such a context. For example, they have been used to optimize both energy costs and production rates (Santos & Dourado, 1999) or power consumption and  $C_{max}$  (Dai, Tang, Giret & Salido, 2013). Other methods are designed to dynamically integrate constraints and perturbations, as well as to provide negligible resolution times in comparison, for example, with average operating times. A typical representative contribution looking at energy integration is proposed by (Küster, Lützenberger, Freund & Albayrak 2012). In this work, production optimization is based on an evolution strategy that takes energy price predictions into consideration. In (Artigues, Lopez & Hait, 2010), a two-step approach is proposed that uses constraint programming first and then mixed integer linear programming. However, despite the fact that the algorithms proposed offer lower computational times because of the use of approximated approaches, experiments performed by these authors led us to estimate that the problem is still difficult to solve in real time for realistically sized problems with regard to the context presented. Consequently, reactive approaches seem promising for the integration of power consumption and overall power limitation in scheduling in the highly dynamic context described in the introduction (Trentesaux & Prabhu, 2014). These approaches are specific heuristics that only consider the present and do not involve predictions of the future. For example, (Prabhu & Taisch, 2012) used a powerful heuristic, called “distributed arrival time control”, to control the power consumption of a single machine. More recently in (Pach et al., 2013a; Pach, Berger, Sallez & Trentesaux, 2013b), the overall power consumption of a whole manufacturing system was reduced reactively using a Potential Fields (PF) model. The entities in a PF model do not need prior knowledge of the system; they sense online the necessary information propagated by the PFs. Allocation and routing are only controlled according to the PF, and there is no need for a priori scheduling or complex closed-loop feedback. This work highlighted the interest of reactive approaches and provided promising results. However, the problem is that this work only concerned energy wastage and there was no control of the overall power consumption in relation to the energy supply.

The work proposed in this paper aims to supplement the studies presented previously. Indeed, due to the uncertain context of current FMS and the dynamic pricing of electricity as well as the risk of unpredictable power restrictions, reactive handling of electricity in scheduling seems very promising. This paper proposes an extended PF model integrating a dynamic threshold to be respected in order to adapt the scheduling to the energy price or maximum availability in real time. This will be useful for the next

generation of manufacturing systems that must be designed and controlled taking the context of high volatility of availability and pricing of electrical energy into account. Before presenting our approach, the next section presents the problem statement in detail, including the assumptions on which our model relies.

### 3. Problem statement

As stated in the introduction, the manufacturing system studied is a flexible manufacturing system. A FMS is defined (El-Maraghy & Caggiano, 2014) as “an integrated group of processing CNC machines and material handling equipment under computer control for the automatic processing of palletized parts. It is implemented for the mid-volume, mid-variety production and represents a compromise between the high flexibility of versatile job shops and the high production rate of a dedicated mass production system (e.g., transfer lines). It is capable of producing limited number of preplanned part families and utilizes similarities between members of a parts family using group technology”.

In this paper, the assumptions relevant to the kind of FMS studied, including energy consumption and restrictions, are the following (see the nomenclature for a complete list of the notations used in this paper):

1. The FMS is modeled as a set of resources  $R$  where each resource  $r$  can perform at least one service  $s$  belonging to a set of services  $SR_r$ .  $SR_{r,s}$  denotes the service  $s$  provided by resource  $r$ . Services are non preemptive. They are required iteratively to produce a set of products  $P$  requested by customers whose orders arrive randomly in terms of type and quantity.
2. It is assumed that these resources are linked via a one-way transportation system composed of convergent and divergent nodes. Redundant (i.e., alternative) paths to reach resources may exist.
3. Products are conveyed by conveying systems (e.g., self-propelled shuttles) using this one-way transportation system. For each of these products  $p$ , a set of services  $SP_p$  must be iteratively provided by the resources.  $SP_{p,s}$  denotes the service  $s$  requested by a product  $p$ .
4. Each resource has a waiting queue  $Q_r$  for the products to be processed. The length of this queue is assumed to be limited.
5. Each resource has different states (e.g., standby, working...).  $Co_{i,r}$  is a known constant that denotes the consumption (in watts) of resource  $r$  in state  $i$ .  $Co_r(t)$  denotes the consumption of a resource  $r$  at time  $t$ . The total consumption of the whole set of FMS resources at time  $t$  is denoted  $Co(t)$ .
6. A global power consumption limit  $Th(t)$ , modeling a variable amount of total available energy, set by the market or managers, is defined. It can vary dynamically (in real-time) and unpredictably.

The aim of the work can be stated as follows: to design an energy-aware FMS scheduling and control system dynamically allocating and routing products to production resources to obtain services to minimize the total production time (completion time, denoted  $C_{max}$ ). This control system must simultaneously optimize resource energy consumption by limiting energy wastage through the real-time control of resource states, and by dynamically controlling overall power consumption taking, for example, limited availability of energy into consideration.

In the remainder of this paper, a Potential Fields-based modeling approach is proposed. Section 4 is organized as follows:

1. Section 4.1 presents the concept of Potential Fields and provides justifications,
1. In Section 4.2, the original Potential Fields model (not taking

- energy into account) for dynamic FMS manufacturing scheduling and control is presented briefly,
- Section 4.3 contains the first adaptation of the initial model to reduce energy wastage,
  - Section 4.4 contains the second adaptation of the model with the integration of the dynamic control of overall power consumption.

#### 4. A Potential Fields model to dynamically control overall power consumption

##### 4.1. Concept of Potential Fields

The proposed control approach is based on the concept of Potential Fields. The concept of PF is traditionally used to influence the reactive behavior of mobile entities, seen as particles, in a changing environment subjected to uncertainties (Kim, Wang & Shin, 2006). The first applications were related to the navigation of mobile robots (Khatib, 1986), where attractive PFs attract the robots to the desired destinations. In previous studies, our team used PFs and implemented attractive fields in a real FMS to simultaneously and dynamically allocate resources and route products towards these resources (Pach, Bekrar, Zbib, Sallez & Trentesaux, 2012). These studies concluded that it is worth studying PFs because of their simplicity, reactivity and adaptability for controlling the allocation and routing in FMS while maintaining a global level of scheduling performance for time-based criteria such as completion time. Assuming a highly dynamic environment, the following elements differentiate the PF model from other interaction mechanisms (e.g., Contract Net Protocol, stigmergy):

- By essence, it can simultaneously solve the dynamic allocation of resources and product routing.
- It automatically takes into account the spatial dimension of the FMS by altering the fields' value according to the distance.
- It does not require any exploration stage or knowledge about other entities in the system.

In this paper, the idea was to extend our previous work by integrating energy-based mechanisms in PF models to dynamically control the overall power consumption. Before presenting these mechanisms, the next section describes the notations and basics of PF-based FMS dynamic scheduling control systems. These basics were first introduced in (Pach et al., 2012).

##### 4.2. Potential Fields for dynamic FMS scheduling and control

In the proposed approach, products make decisions reactively for the allocation of resources (i.e. find a resource for a service) and routing process (i.e. move to the resource found). The products considered match the concept of "intelligent products" proposed in (McFarlane, Sarma, Chim, Wong & Ashton, 2002) or (Meyer, Främling & Holmström, 2009), and so play an "active" role in the manufacturing process (Sallez, Berger, Deneux & Trentesaux, 2010). Resources emit attractive PFs depending on the services provided. The products then sense these PFs locally when a decision has to be made. To attract products, each resource emits an attractiveness value, which is amplified, propagated and altered by the environment (e.g. transportation time) between the product and the emitting resource.

Fig. 1 illustrates the Potential Fields model that controls allocation and scheduling in FMS.

In the Fig. 1, the FMS is composed of three resources ( $r_1$ ,  $r_2$  and  $r_3$ ) and one product  $p_1$  looking for the service  $SP_{1,1}$ . Both  $r_1$  and  $r_3$  can provide this service (i.e.,  $SR_{1,1}$  and  $SR_{3,1}$ ). Each of them emits Potential Fields to attract product  $p_1$  (blue Potential Fields).

Assuming that the potential field emitted by  $r_1$  is the highest,  $p_1$  chooses  $r_1$  and tries to reach this resource to obtain the service.

Fig. 2 describes the entities (products, resources) and decision making in this model.

The attractiveness  $\alpha_{r,s}(t)$  of the resource was established according to the following Eq. (1). This formula, inspired by (Pach et al., 2012), has been updated and harmonized with the extended models proposed in this paper.

$$\alpha_{r,s}(t) = \frac{S_{r,s}(t)}{1 + \sum_i \sum_j (W_{i,j,r}(t) + Z_{i,j,r}(t))} \quad (1)$$

Where

$S_{r,s}(t)$  is a binary value set to 1 if resource  $r$  is available for service  $s$  at time  $t$  and set to 0 if the resource is unavailable.

$W_{i,j,r}(t)$  is a binary value set to 1 if product  $j$  is waiting for its service number  $i$  in the input queue of resource  $r$  at time  $t$ , 0 otherwise.

$Z_{i,j,r}(t)$  is a binary value set to 1 if the service number  $i$  of product  $j$  is currently in progress on resource  $r$  at time  $t$ , 0 otherwise.

This attractiveness is then modulated to form a PF that is propagated through the system environment. This PF, noted  $\Phi_{r,d,s}(t)$ , propagated from resource  $r$  for a service  $s$  is sensed at a decisional node  $d$  (where products have to make decisions) according to the Eq. (2)

$$\Phi_{r,d,s}(t) = \max(\alpha_{r,s}(t) * \mu_r - M_{r,d}(t), 0) \quad (2)$$

where

$\mu_r$  denotes the magnitude that determines the range of the emitted PFs,

$M_{r,d}(t)$  denotes the mitigation of the PFs through the environment,

$\max()$  is the function that ensures the PFs are never negative since in this paper a linear function  $M_{r,d}(t)$  is considered to alter the PFs according to the distance.

The decision to be made by the product based on the PF propagated is reduced to selecting the resource with the maximum PF value

$$r^* = \underset{r}{\operatorname{argmax}}(\Phi_{r,d,s}(t)) \quad (3)$$

This model has been extended in this paper to permit the control of the overall power consumption. The goal is to dynamically control the scheduling to limit energy wastage first, then to control the scheduling to produce with overall power restrictions. To reach this goal, a two-step process is proposed. First, a model to limit energy wastage in the FMS scheduling using PF must be designed. Then, the handling of the overall power consumption will be integrated.

##### 4.3. First step: reducing energy wastage

The extension of the initial PF model presented in (Pach et al., 2013a) integrates here power consumption to reduce energy wastage based on a switching mechanism between different resource states. The role of this switching mechanism is to save energy on the resource itself whenever possible using the following principle: resources are not always working, so why not shut down the power supply opportunistically when they are idle. If a product selects a resource and comes near it, the resource should turn the power supply on. However, to make this behavior consistent,



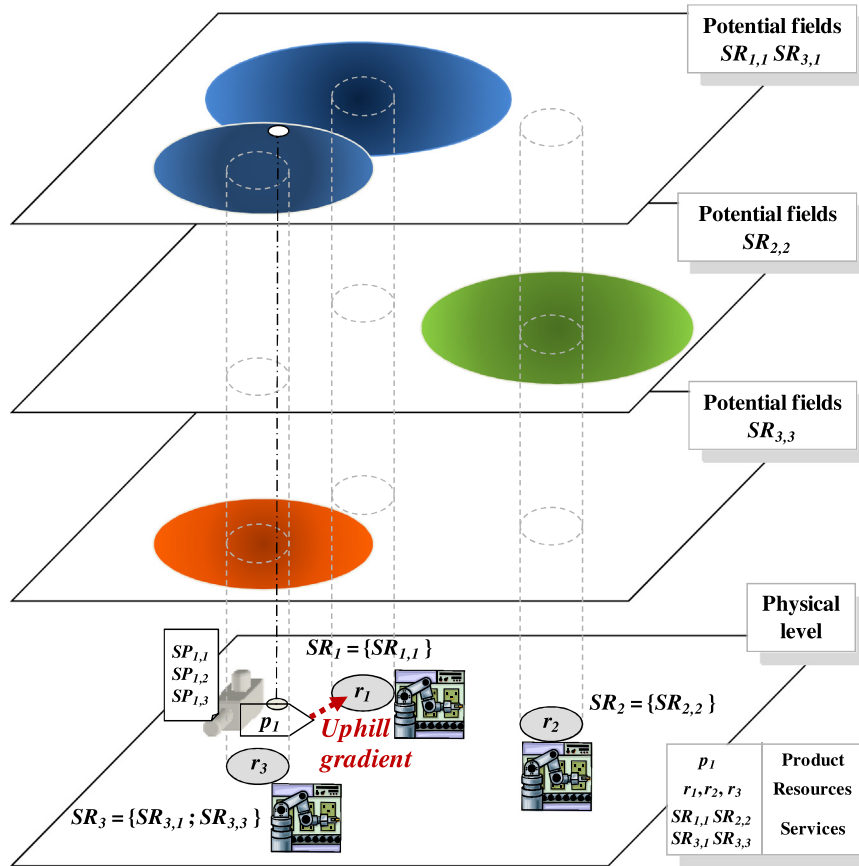


Fig. 1. Potential Fields model in FMS.

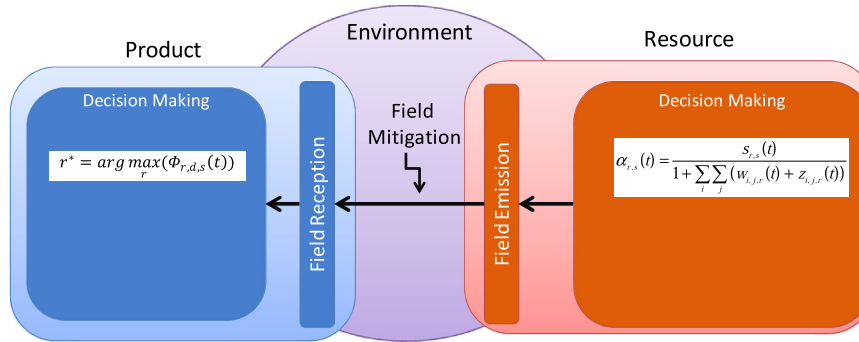


Fig. 2. Potential Fields Model. Entities and decisions (Pach et al., 2012).

resources need information about the products surrounding them. This information is provided by the product emitting a new type of PF (intention field) when it has chosen a resource. A resource can sense all the PFs emitted by the products that have chosen it and can then control its power supply dynamically. Fig. 3 provides a global view of the model, including the PFs emitted and sensed by the products and resources.

As depicted on the left in Fig. 3, three stages are considered in product information processing: field reception, decision making and field emission. This process is periodically triggered by an event (e.g. every ten seconds) or aperiodically (e.g. when there is a change in the received fields).

First, the PFs emitted by resource  $r$  for the service  $s$ ,  $\Phi_{r,d,s}(t)$ , are sensed and filtered according to the current service  $s$  required by product  $p$ . The product status can then evolve according to the Petri net detailed in Fig. 4.

Four possible states are defined

*Out of system*: this state characterizes a finished or rubbished product (quality issue) or not yet launched.

*Standby*: this state is reached if the product cannot sense any attractive PF for its current service. This situation occurs for example in the case of a resource breakdown or maintenance. It stays in this mode until a PF is detected.

*Active*: this state is reached when at least one PF is sensed for the current service. In this state, the product controls its allocation and routing in real time, and moves towards the chosen resource able to provide the service.

*Being processed*: This state characterizes the arrival of the product on the chosen resource, its processing and its departure. After completion, the product returns to active state until the remaining list of services is empty, and then it leaves the production system.

Second, when several resources emit a set of PFs for the required service  $\Phi_{r,d,s}(t)$ , the product in active state senses PFs emitted by the resources and chooses the resource  $r^*$  with the

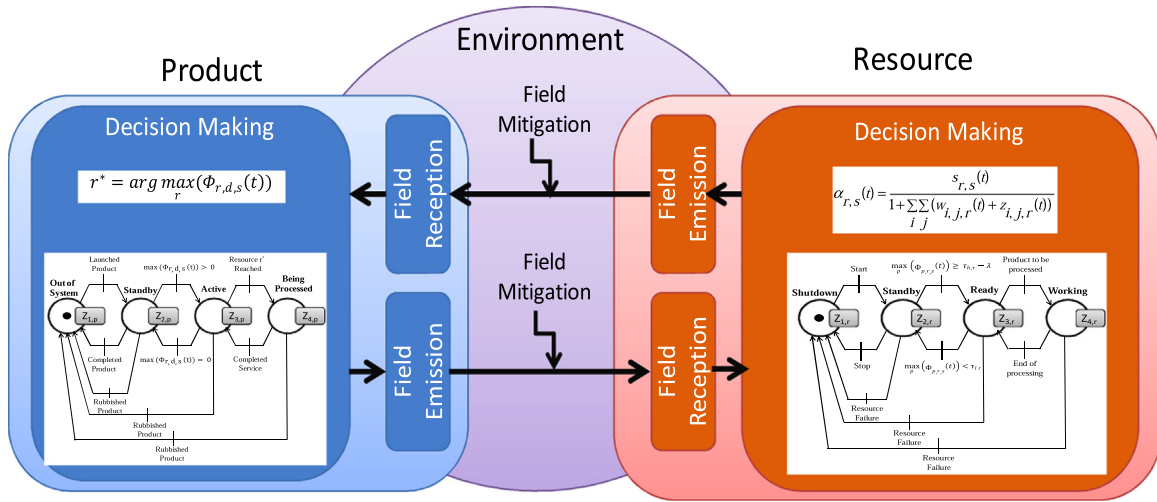


Fig. 3. Potential Fields Model extended to reduce energy wastage.

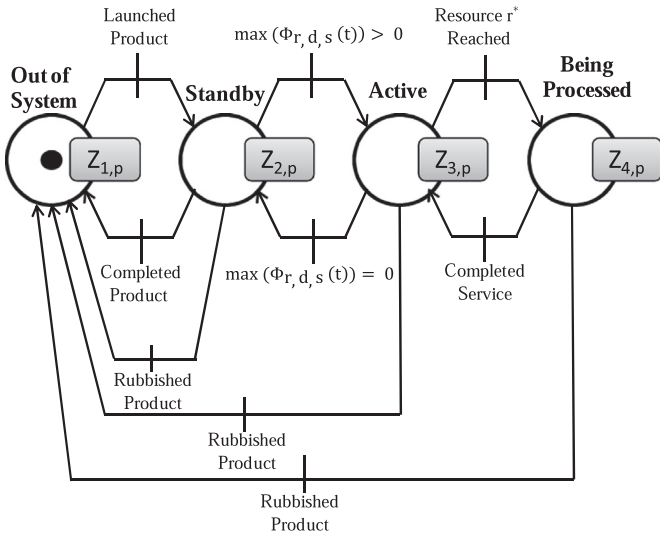


Fig. 4. Petri Net for product status.

highest PF (i.e. the most attractive), Fig. 3. Once a resource is chosen, the product elaborates an intention for this resource.

$$\beta_{p,r,s}(t) = Z_{i,p}(t) * C_{p,r,s}(t) \quad (4)$$

where

$Z_{i,p}(t)$  is a coefficient that depends on the current state of the product (Fig. 4)

$C_{p,r,s}(t)$  equals 1 if resource  $r$  is chosen by product  $p$  for the service  $s$  at time  $t$ , 0 otherwise.

Third, the product then emits a field corresponding to the intention. At this stage, the intention established previously is amplified, propagated and mitigated in relation to the environment according to the following formula:

$$\Phi_{p,r,s}(t) = \max(\beta_{p,r,s}(t) * \mu_p - M_{p,r}(t), 0) \quad (5)$$

where

$\mu_p$  denotes the magnitude that determines the range of the emitted PFs,

$M_{p,r}(t)$  denotes the mitigation of the PFs by the environment,  $\max()$  function that ensures the PFs are never negative since in this paper a linear function  $M_{p,r}(t)$  is considered to alter the PFs

according to the distance.

Resource information processing is similar to that of the product (Fig. 3). Likewise, it is divided into three stages: field reception, decision making and field emission. It is also triggered by an event.

First, the resource senses the PFs ( $\Phi_{p,r,s}(t)$ ) emitted by products  $p$  intending to reach this resource  $r$  for the service  $s$ .

Second, depending on these PFs, the resource states are decided according to the Petri net in Fig. 5.

In this Petri net, four possible resource states are defined *Shutdown (state 1)*: the resource is not available (e.g., under maintenance, failure, or not started).

*Standby (state 2)*: the resource is available and idle, and its power supply is off.

*Ready (state 3)*: the resource is available and idle, and its power supply is on.

*Working (state 4)*: the resource is currently manufacturing a product.

Resources can switch between these states. In ready state, the resource is ready to manufacture but consumes energy; in standby state, the energy consumed by the resource is assumed to be negligible. Having resources in ready state can imply variations in power consumption, so the model has been designed to take this aspect into consideration. A resource will only switch to ready state if it detects at least one PF from a product coming to it. This switch from standby to ready state is triggered when the product's PF exceeds a pre-determined high threshold denoted  $\tau_{h,r}$ . This high threshold allows the sensitivity of the switching mechanism to be finely tuned. A set-up time with an offset value  $\lambda$  has been integrated in case the resource  $r$  must be prepared (set up) to provide the service  $s$  requested by product  $p$ . The switching condition is given by the following formula:

$$\max_p(\Phi_{p,r,s}(t)) \geq \tau_{h,r} - \lambda \quad (6)$$

Conversely, a resource switches to standby if it does not sense any PF emitted by products that are above a low threshold  $\tau_{l,r}$ , as described below:

$$\max_p(\Phi_{p,r,s}(t)) < \tau_{l,r} \quad (7)$$

Third, depending on its state, the resource establishes an attractiveness, which models the ability of a resource  $r$  to perform a service  $s$ . Then, this attractiveness is amplified, and then propagated and mitigated through this environment. The attractiveness of the resource  $r$  for a service  $s$  in this model is now:

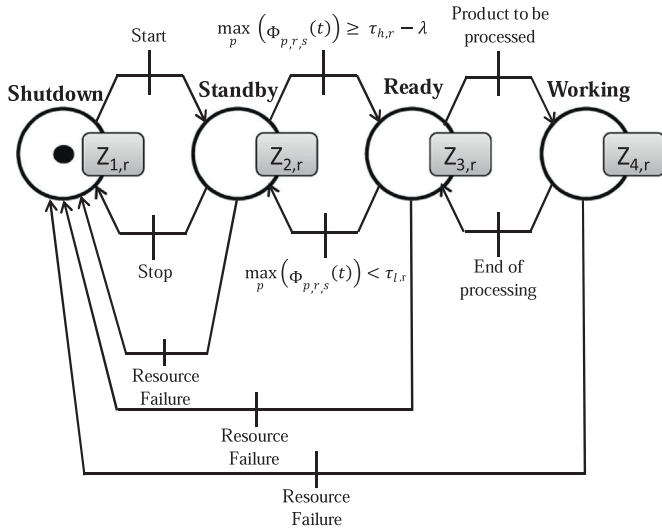


Fig. 5. Petri Net for resource status.

$$A_{r,s}(t) = Z_{i,r}(t) * \alpha_{r,s}(t) \quad (8)$$

where

$\alpha_{r,s}(t)$  corresponds to the formula presented in the model in Section 4.2

$Z_{i,r}(t)$  is a coefficient that enables the attractiveness to be modulated according to the current state  $i \in [1,4]$  of the resource  $r$  (Fig. 5)

This first mechanism defined, it is now possible to dynamically control the scheduling to maintain the overall power consumption of the system below a variable threshold, which is described in the next section.

#### 4.4. Second step: integration of dynamic overall power consumption control

This section presents the dynamic control of the overall power consumption of the Potential Fields model presented above. In this model, it is assumed the products are aware of the instantaneous system consumption. Depending on this consumption and on the dynamically determined maximum threshold  $Th(t)$  not to be exceeded (established by the production manager or energy supplier), they can choose to be produced or not. They will leave a resource or stay in standby mode if the activation of the resource chosen implies an instant consumption above the maximum level determined. The goal of this mechanism is to avoid consumption that exceeds the threshold, which is assumed to be a priori unknown and may evolve in real time. However, in some cases, even if it means exceeding the maximum threshold, resources have to produce whatever the energy costs. For example, the product could be produced anyway if it is considered as urgent because delaying this product would be more costly than exceeding the energy threshold. To handle this possible situation, products have two modes: "Energy" and "Production". In "Energy" mode, they take into account the maximum energy threshold and production can be delayed. In "Production" mode, they choose the best resource, in terms of effectiveness, and ignore the maximum energy threshold. The choice of the next resource, for a product in "Production" mode, is defined according to the model formula:

$$r^* = \underset{r}{\operatorname{argmax}}(\Phi_{r,d,s}(t)) \quad (9)$$

However, for a product in "Energy" mode, the choice of the

next resource depends on the power consumption:

$$r^* = \underset{r}{\operatorname{argmax}}(\Phi_{r,d,s}(t) * C(t)) \quad (10)$$

where

$C(t)$  is a binary value set to 1 if  $Co(t) + Co_{4,r} - Co_r(t) \leq Th(t)$ , 0 otherwise.

This ensures that a resource is not used if the threshold has already been exceeded, and that a machine is not woken up if it results in the consumption exceeding the threshold, and finally, that an already ready resource is not to be used if it results in the consumption exceeding the threshold. The choice of "Energy" mode or "Production" mode for each product is at the discretion of the production manager.

Fig. 6 illustrates the entire Potential Fields model, including overall power consumption.

## 5. Case study

The model introduced was applied to a case study in simulation and in a real situation. This case study corresponds to an existing FMS (AIP PRIMECA VALENCIENNES, 2013) illustrated in Fig. 7 and described briefly in the following paragraphs.

This FMS is built around a central conveyor belt with transfer gates to reach the resources or to move from one loop to another. Before each transfer gate, a "divergent node" (seen as a decisional node by each product where a decision has to be made) allows the product to make routing decisions and to position the gate. Auto-propelled shuttles that transport products through the cell use the conveyor.

This FMS can manufacture several products by mounting raw components on a plate to form letters such as "A", "I", "P". A client's order is a combination of these products (e.g., AIP, IPA and IAPIAP). The product manufacturing sequence  $SP_p$ , (i.e. services wanted by a product  $p$ ) is organized as follows: plate loading, mounting a series of components, final inspection and plate unloading. A shuttle is attached to a product at loading and detached at unloading.

The resources  $r$  are all located on different "service nodes" (Fig. 7). The ones used in this paper are the loading/unloading unit (the resource is denoted  $r_1$ ), the three assembly workstations (denoted  $r_2, r_3$  and  $r_4$ ), and the automatic inspection unit (denoted  $r_5$ ). The workstations on the left loop were not used (Fig. 7). The queue size limit for all the resources is set to 2 ( $Q_r=2, r \in [1, 5]$ , including the product being processed). Loading and unloading are performed by  $r_1$ . The components are assembled by  $r_2, r_3$ , and  $r_4$ , and the inspection is carried out by  $r_5$ . Resources  $r_2, r_3$ , and  $r_4$  are partially redundant (flexibility) so there are possibilities for improving the control of these resources regarding power consumption. Conversely, resources  $r_1$  (loading / unloading) and  $r_5$  (automatic inspection) are mandatory for each product, which is why only the consumption of  $r_2, r_3$ , and  $r_4$  were considered in the study. The electrical consumption  $Co_{i,r}$  of these resources  $r$  in state  $i$  (in Watts) is summarized in Table 1. These values have been established from tests done on the real FMS.

Interested readers can read the benchmark proposed in (Trentesaux et al., 2013) for details about the FMS. The parameters and simulations chosen in this paper are compliant with this benchmark.

## 6. Simulation

This section presents the principal FMS data used for the simulations to validate our proposal. The objective of the simulations was



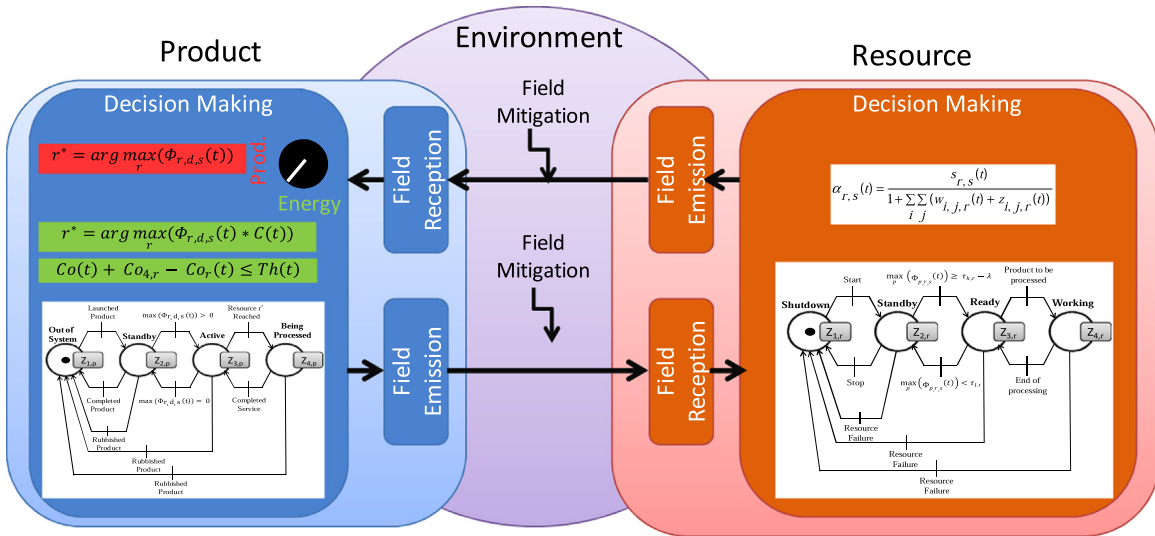


Fig. 6. Potential Fields Model integrating overall power consumption.

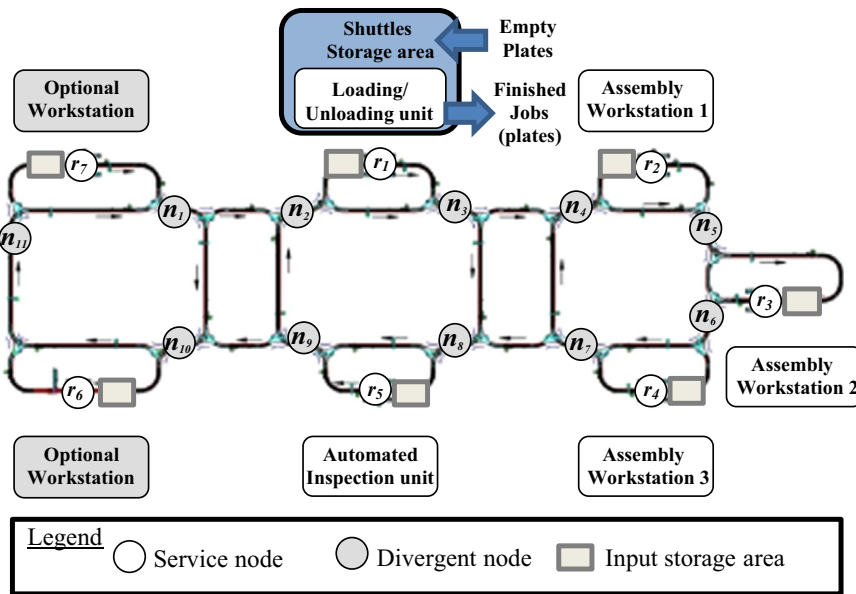


Fig. 7. FMS case study.

to evaluate how the PF model can effectively control the FMS with a dynamic power supply, including large scale studies. Simulations were also led to validate the global behaviors of products and resources before applications on a real cell. In these simulations, the client order used was “AIP”. The simulation was divided in two parts: the first scenarios studied the reduction in energy wastage, and the second, the control of the overall power consumption. It is important to note that the same model was used for both parts so the wastage and the overall consumption could be controlled simultaneously. However, for clarity, the presentation of the simulations is divided into two Sections (6.2 and 6.3). The next subsection briefly presents the simulator used for the simulation study.

### 6.1. Simulation environment

NetLogo (Wilensky, 1999) was chosen for the simulation studies. It is an agent-based parallel modeling and simulation environment. It directly provides functions for indirect communication (i.e. via the environment), which matches the PF model. NetLogo is known to be a rapid prototyping proof-of-concept

simulator and allows elegant graphical interfaces to be developed rapidly.

Fig. 8 shows the NetLogo interface developed to simulate the PF model. The FMS is represented graphically on the right and the input and output data can be controlled on the left.

All the simulations were launched on the same computer (Intel Core i3, 2.13 GHz, 4 GB RAM). The results of the simulations presented in Table 2 took no more than 1 s to obtain, the “10 × PIA” case in Table 3 no more than 4 s, the “50 × PIA” case in Table 3 no more than 17 s, and each of the simulations presented in Table 4 no more than 2 s (Sections 6.2 and 6.3).

### 6.2. Simulations for the reduction of energy wastage

To evaluate the reduction in energy wastage in a dynamic context with the products being introduced randomly, simulations were performed for all six combinations (i.e., IAP, PIA...) for the products in the client’s order (i.e., A, I and P). Four sets of threshold values were chosen for the model presented in Section 4.3. As a reminder, for the resource  $r$ , the high threshold  $\tau_{hr}$  is responsible for the switch from

standby to ready mode, and the low threshold  $\tau_{l,r}$  is responsible for the switch from ready to standby mode. The sets of threshold values are:

$\tau_{h,2}=\tau_{h,3}=\tau_{h,4}=\tau_{l,2}=\tau_{l,3}=\tau_{l,4}=0$ : this set matches the model with no energy control. The resources are always ready.

$\tau_{h,2}=\tau_{h,3}=\tau_{h,4}=\tau_{l,2}=\tau_{l,3}=\tau_{l,4}=200$ : this threshold is equivalent to the product's maximum field so resources are ready when a product is on them and switch to standby as soon as they are empty.

$\tau_{h,2}=\tau_{h,3}=\tau_{h,4}=200, \tau_{l,2}=\tau_{l,4}=195, \tau_{l,3}=189$ : resources are ready when a product is on them but do not switch to standby if a product is in their queue.

$\tau_{h,2}=\tau_{h,3}=\tau_{h,4}=200, \tau_{l,2}=195, \tau_{l,3}=189, \tau_{l,4}=0$ : same as before for resource  $r_2$  and  $r_3$ , but the low threshold is set to 0 for  $r_4$  to prevent it switching to standby. Since the products arrive distributed over time on  $r_4$ , this is a way of producing only 1 switch on each resource and thus match the original scenario, but with a lower power consumption.

The simulation results for this product order are summarized in Table 2. Since the resources' consumption in a state is considered fixed, by monitoring the time spent by resources in each of their states, the overall power consumption can be calculated. This consumption is given in Watts per hour and the times are given in seconds. A column has been added to represent the overall energy for a 12 h production period with the same orders. Indeed, the case study taken gives a  $C_{max}$  of over 300 s, which results in a very low consumption (only a few tens of Watts per hour). With the equivalent for a 12 h production period, the consumption values are more realistic. The bottom lines are the averages of all the simulations.

In a previous study, the optimal solution was obtained using Integer Linear Programming (ILP) with a  $C_{max}$  of 219 s and an I-A-P launching sequence (interested readers can refer to (Pach, Berger, Bonte & Trentesaux, 2014)). In this paper, the reference scenario ( $\tau_{h,r}=\tau_{l,r}=0$ ) with only 1 switch from standby to ready at

the start, resulted in an average consumption of 65.6 W h and a  $C_{max}$  of 255 s. If both thresholds were set to 200, the resources switched to standby as soon as possible, resulting in an average consumption of 33.3 W h (51.1% of reference scenario). This was the lowest power consumption but involved several switches (5.7 on average, almost twice the initial number).  $C_{max}$  is a little higher than the initial one (around 262 s) because the allocation priority was given to resources already ready. The third scenario, where the resources did not switch to standby between queuing products resulted in the same  $C_{max}$  as scenario 2 and consumed a little more (+0.2%), but the number of switches was reduced (3.7 on average instead of 5.7). Finally, the last scenario minimized the number of switches (3, meaning 1 for each resource at the start), with a  $C_{max}$  of 258.3 s and a consumption of 37.9 W h (58% of the reference scenario). The average score was quite similar for each of the simulations and the behavior of the model was the same for each order of introduction. This model is efficient without knowing the clients' orders in advance and saves energy (on average 50% energy saving with these scenarios).

Other scenarios have been performed: for example, in large scale simulations provided in Table 3, the gain in energy (compared to the model not taking energy into consideration) differed according to the system load and the number of products, but remained between 20% and 40%. The first three scenarios in Table 3 used the same product orders but with different intervals between each order to highlight the importance of the system load. The last scenario increased the number of products to provide results for a saturated system over a long period.

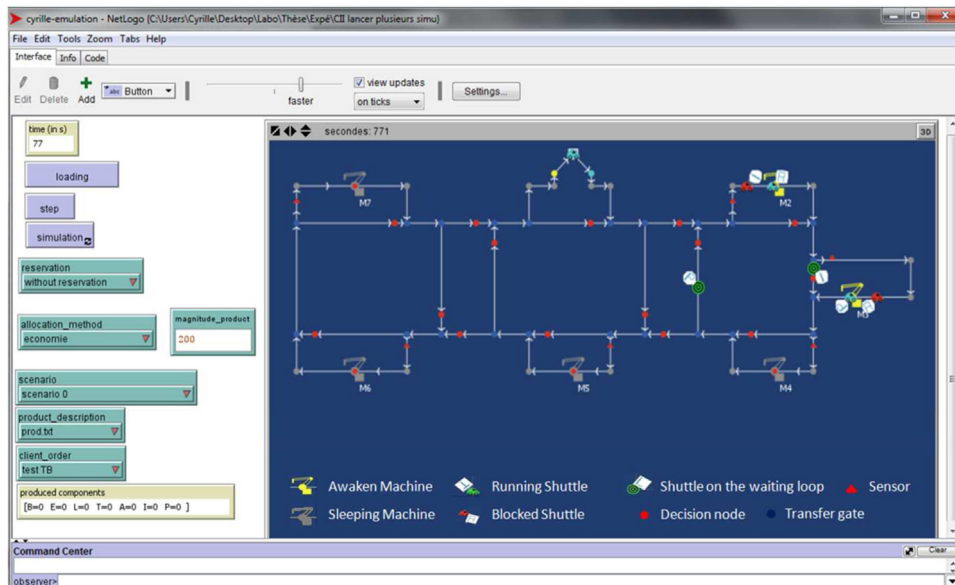
When the system was saturated, the model could not save much energy because all the resources were working and could not be turned off. However, these scenarios confirm the ability of the proposed control system to reduce energy wastage in more complex cases without significantly increasing  $C_{max}$ . The next sub-section presents the simulations relating to the dynamic control of the overall consumption.

**Table 1**  
Electrical consumption of resources Table 1

Resource	Electrical consumption (W)		
	Standby ( $Co_2, r$ )	Ready ( $Co_3, r$ )	Working ( $Co_4, r$ )
$r_2$	0	250	400
$r_3$	0	250	400
$r_4$	0	250	400

### 6.3. Simulations for the dynamic control of the overall consumption

Three simulation sets are presented in this section. The goal of these simulation sets was to study, in three stages, the impact of dynamic scheduling control integrating power consumption. First,



**Fig. 8.** NetLogo simulator's GUI.

**Table 2**  
Simulation resultsTable 2

Simulation	$r_{h,2}$	$r_{h,3}$	$r_{h,4}$	$r_{l,2}$	$r_{l,3}$	$r_{l,4}$	$C_{max}$ (s)	Overall energy (W h)	Energy for 12 h (kW h)	Overall energy (%)	Overall switches
AIP #1	0	0	0	0	0	0	248	64.2	11.2	–	3
AIP #2	200	200	200	200	200	200	255	33.3	5.8	51.9	6
AIP #3	200	200	200	195	189	195	255	33.5	5.8	52.3	3
AIP #4	200	200	200	195	189	0	255	36.3	6.3	56.5	3
API #1	0	0	0	0	0	0	251	64.8	11.0	–	3
API #2	200	200	200	200	200	200	248	33.3	5.7	51.4	5
API #3	200	200	200	195	189	195	248	33.5	5.8	51.7	3
API #4	200	200	200	195	189	0	248	36.5	6.3	56.4	3
PAI #1	0	0	0	0	0	0	265	67.7	11.0	–	3
PAI #2	200	200	200	200	200	200	291	33.3	5.4	49.2	5
PAI #3	200	200	200	195	189	195	291	33.4	5.4	49.3	4
PAI #4	200	200	200	195	189	0	291	41.5	6.8	61.2	3
IAP #1	0	0	0	0	0	0	224	59.2	11.4	–	3
IAP #2	200	200	200	200	200	200	251	33.3	6.4	56.3	6
IAP #3	200	200	200	195	189	195	251	33.4	6.4	56.5	5
IAP #4	200	200	200	195	189	0	251	39.0	7.5	65.8	3
PIA #1	0	0	0	0	0	0	291	73.1	10.9	–	3
PIA #2	200	200	200	200	200	200	272	33.3	4.9	46.1	6
PIA #3	200	200	200	195	189	195	272	33.7	5.0	46.1	3
PIA #4	200	200	200	195	189	0	272	36.3	5.4	49.7	3
IPA #1	0	0	0	0	0	0	251	64.8	11.2	–	3
IPA #2	200	200	200	200	200	200	254	33.3	5.7	51.4	6
IPA #3	200	200	200	195	189	195	254	33.6	5.8	51.9	4
IPA #4	200	200	200	195	189	0	233	37.7	6.5	58.2	3
Average #1 s	0	0	0	0	0	0	255	65.6	11.1	–	3
Average #2 s	200	200	200	200	200	200	261.8	33.3	5.7	51.1	5.7
Average #3 s	200	200	200	195	189	195	261.8	33.5	5.7	51.3	3.7
Average #4 s	200	200	200	195	189	0	258.3	37.9	6.5	58.0	3

**Table 3**  
Large-scale resultsTable 3

Scenario	$r_{h,2}$	$r_{h,3}$	$r_{h,4}$	$r_{l,2}$	$r_{l,3}$	$r_{l,4}$	$C_{max}$ (s)	Overall energy (W h)	Overall energy (%)	Overall switches
10 × PIA	0	0	0	0	0	0	1369	410.2	–	3
10 × PIA	200	200	200	200	200	200	1398	333.3	81.3	55
10 × PIA	200	200	200	195	189	195	1398	336.9	82.1	8
10 × PIA (space by 150 s)	0	0	0	0	0	0	1626	463.8	–	3
10 × PIA (space by 150 s)	200	200	200	200	200	200	1622	334.0	72.0	60
10 × PIA (space by 150 s)	200	200	200	195	189	195	1622	338.0	72.9	27
10 × PIA (space by 200 s)	0	0	0	0	0	0	2091	560.6	–	3
10 × PIA (space by 200 s)	200	200	200	200	200	200	2072	333.3	59.5	60
10 × PIA (space by 200 s)	200	200	200	195	189	195	2072	336.9	60.1	30
50 × PIA	0	0	0	0	0	0	6192	1915.0	–	3
50 × PIA	200	200	200	200	200	200	6241	1668.8	87.1	290
50 × PIA	200	200	200	195	189	195	6241	1685.7	88.0	35

the same simulation was repeated with a different percentage of products concerned by the energy threshold to study the variations in system behavior. Second, the same simulation was repeated with different energy thresholds to study the impact of the threshold value on production. Finally, the last simulation set presents the behavior of the system with a dynamic energy threshold.

The first simulation set studied the impact of introducing energy-concerned products into the system. The results are provided in Table 4. In this simulation set, the energy threshold was set to  $Th(t)=800$  W for all the simulations. The scenario chosen was the production of  $2 \times$  AIP, which corresponds to 6 products. The reference scenario was performed with 6 products in production mode (not considering the energy threshold). The focus was set on effectiveness, so the  $C_{max}$  was the lowest for the simulations (358 s). For a lower bound, the  $C_{max}$  provided by the introduced ILP was 309 s for this scenario (Pach et al., 2014). Conversely, a maximum Time Over Threshold of 116 s was reached (around 1/3 of the  $C_{max}$ ). Then simulations were performed with 2 products in energy mode. As there were 2 out of 6 products in energy mode, simulations were performed for the 15 possible combinations. The combination is detailed in the last column in Table 4. The  $C_{max}$  of

these simulations was higher than the reference one, from 379 (+6%) to 434 s (+21%). As there were three different products, the choice of the two products in energy mode led to different results. For the Time Over Threshold, there was a significant decrease in the value compared with the reference scenario. The maximum Time Over Threshold for 2 products in energy mode was 60 s (58% of the reference) and the minimum was 15 (13% of the reference). So, even with only 2 products in energy mode, the gain was very significant with a gain of at least 42% for the time over threshold. With four products in energy mode, the time over threshold was reduced even more with a maximum of 23 s over the threshold and a minimum of 0 s. However, the augmentation in  $C_{max}$  was higher, from +13% to +25%. However, the choice of  $C_{max}$  or Energy is not within the scope of this paper. Only the system user can make a choice depending on the situation. Finally, when all the products were in energy mode, the energy threshold was never exceeded. This avoids any additional costs due to energy provision, but extends the  $C_{max}$  by 23% to reach 441 s.

The second simulation set studied the impact of the threshold  $Th(t)$  on production. Three simulations were performed with products  $2 \times$  AIP. First, all the products were in “Production” mode,

so the energy threshold  $Th(t)$  could be considered as infinite (Fig. 9). Then, the threshold  $Th(t)$  was set to 800 W. This allowed two resources to be turned on simultaneously (Fig. 10). Finally, the threshold was set to 400 W. Only one resource could be turned on at each moment during the simulation (Fig. 11). The evolution in the instant consumption of each simulation is associated with the Gantt diagram corresponding to the simulation.

Fig. 12 summarizes these simulations and presents the three curves on one graph.

As seen in Fig. 12, our model was able to control the production systems without exceeding a predetermined threshold to the detriment of effectiveness, and could smooth or speed up production according to this threshold. Thus, our model is configurable to control the compromise between overall energy threshold and  $Cmax$ .

**Table 4**  
Variations in the number of products in "Energy" mode. Table 4

Number of products in "Energy" mode	Threshold (W)	$Cmax$ (s)	Time over the threshold (s)	products in "Energy" mode
0	800	358	116	-
2	800	398	49	$p_1p_2$
2	800	394	58	$p_1p_3$
2	800	393	39	$p_1p_4$
2	800	394	38	$p_1p_5$
2	800	394	31	$p_1p_6$
2	800	398	68	$p_2p_3$
2	800	410	60	$p_2p_4$
2	800	395	51	$p_2p_5$
2	800	398	24	$p_2p_6$
2	800	414	59	$p_3p_4$
2	800	394	59	$p_3p_5$
2	800	395	31	$p_3p_6$
2	800	434	15	$p_4p_5$
2	800	379	47	$p_4p_6$
2	800	379	48	$p_5p_6$
4	800	439	0	$p_1p_2p_3p_4$
4	800	418	15	$p_1p_2p_3p_5$
4	800	439	9	$p_1p_2p_3p_6$
4	800	449	19	$p_1p_2p_4p_5$
4	800	424	23	$p_1p_2p_4p_6$
4	800	424	23	$p_1p_2p_5p_6$
4	800	394	18	$p_1p_3p_4p_5$
4	800	404	11	$p_1p_3p_4p_6$
4	800	434	15	$p_1p_4p_5p_6$
6	800	441	0	$p_1p_2p_3p_4p_5p_6$

Typically, in the above example, the  $Cmax$  was 358 s without a threshold and was extended to 441 s with the threshold set to 800 W and 680 s with the threshold set to 400 W. However, if the additional cost for exceeding the threshold is high, this type of measure is mandatory.

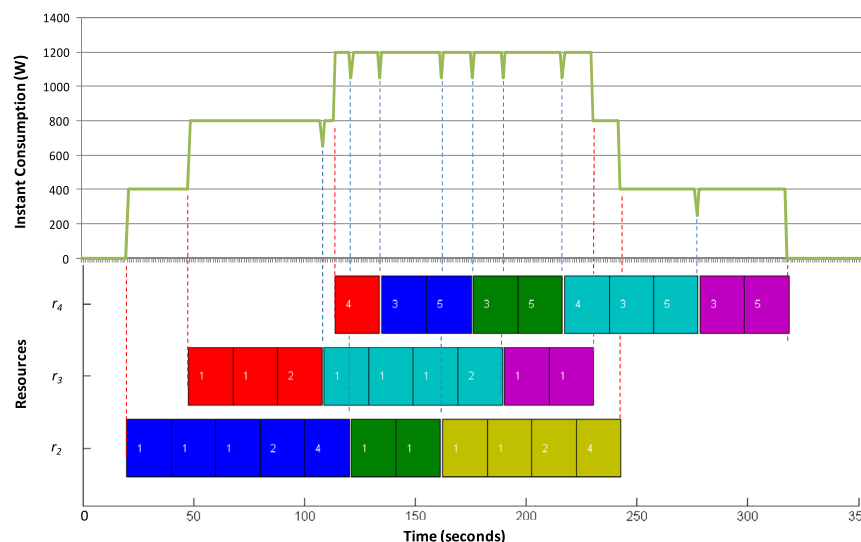
The third simulation presented the system's behavior with a dynamic energy threshold, which was as expected and consistent with the context introduced in this paper. This shows the ability to cope with perturbations that lower or increase the energy available, and with the dynamic pricing of electricity. In this simulation, the normal threshold value was set to 800 W. In order to study the system with different thresholds, the number of products was  $6 \times AIP$ . The evolution of the system's instant power consumption and the Gantt diagram for the three resources are given in Fig. 13. At  $t=200$  s, a perturbation occurred and forced the system to reduce its consumption. After completion of the operations in progress on the resources (no-preemptive resources), the threshold was lowered to 400 W. Thus, resource 2 was no longer being used and only resource 3 was working. At  $t=300$  s, the energy available greatly increased. So, after completion of the operations in progress, the threshold was set to 1200. The products were then dispatched to the three resources. Finally, the energy threshold was reset to normal at the end of the operations at  $t=600$  s.

Fig. 14 provides the results of a  $6 \times AIP$  production without taking overall power into consideration (i.e. all the products were in "Production" mode). In this reference case, the three redundant resources were always working so the power consumption was around 1200 W for most of the production.

This last simulation set clearly shows that the model was able to cope with a dynamic energy threshold. In a highly dynamic context with a variable power supply, the Potential Fields model was still able to control production while taking into account the overall power consumption. Section 6 showed that this model was able to control effectiveness as well as overall power consumption.

## 7. Implementation in real conditions

This section presents elements concerning the implementation of the proposed model in real conditions. The aim of the real implementation was to prove the feasibility of the model on a real system. Our model can be implemented in different ways, from



**Fig. 9.** Power consumption and Gantt diagram without threshold.

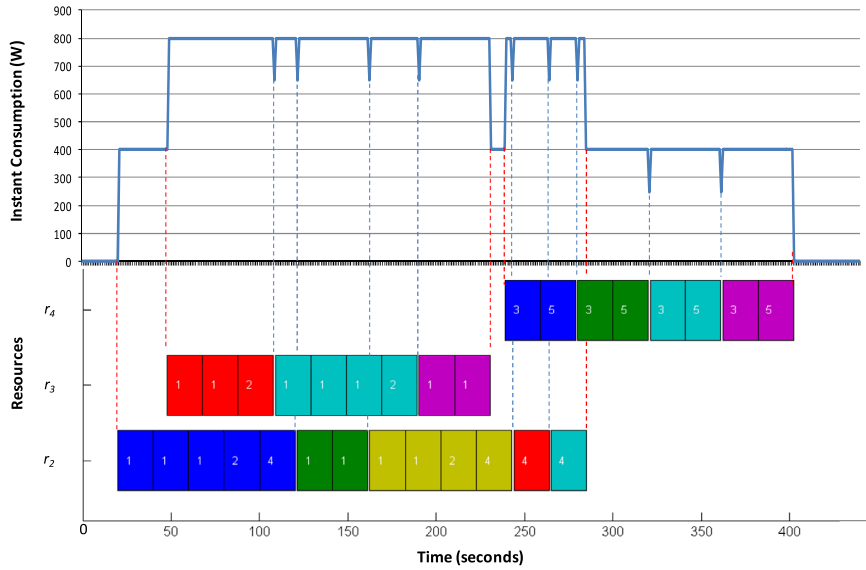


Fig. 10. Power consumption and Gantt diagram with threshold=800.

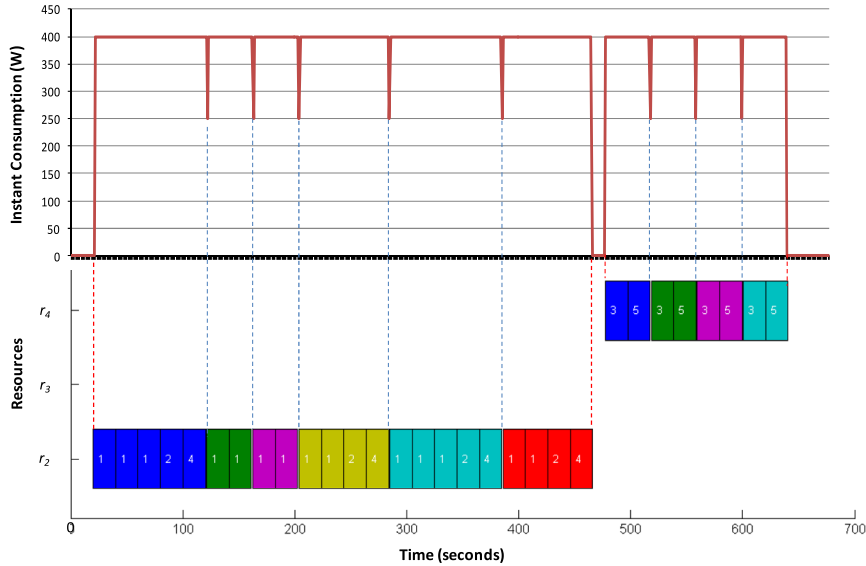


Fig. 11. Power consumption and Gantt diagram with threshold=400.

centralized to fully distributed. Since the PFs are naturally distributed, the chosen implementation was distributed. The requirements for the implementation were: (1) provide products and resources with a processing capability to sense and establish PFs; (2) provide them with a communication capability to emit fields through the environment. One usable concept already tested by our team is the Intelligent (or Active) Product concept (Sallez et al., 2010). Here, this concept was extended to the resources to enable them to sense the product PF and to control the switch between states. A proof-of-concept version of Intelligent Products and Resources is illustrated in Fig. 15. In our validations, an Intelligent Product was composed of a “passive” product (i.e. part to be manufactured), an Eeepc providing the processing capability, and a shuttle for mobility. An Intelligent Resource was composed of a robot, its stock, its queue and a Programmable Logical Controller (PLC) providing communication and processing capabilities. Industrial versions of Intelligent Products and Resources will obviously be embedded in the Shuttle/Robot.

These proof-of-concept versions have been tested to validate two real experiments for an “AIPAIP” order. The first one, presented in Table 5, corresponds to energy wastage reduction and

presents two scenarios performed in simulation and in real conditions. In the scenario that does not consider energy (all thresholds set to 0), all the machines wake up at time 0 and stop after completion of the last products. In the second scenario, each resource decides to wake up only when a product is approaching it and to switch to standby after it has dealt with the last product. So, with the same amount of wake-ups (i.e. 1 for each resource), energy savings are easily achieved. Similar results were observed in simulation and in real conditions. The gain in energy was 32% and 26%, respectively compared with the scenario that does not consider energy. At the same time,  $C_{max}$  values only increased by 6% and 7%, respectively.

The second experiment illustrates energy control using the dynamic overall energy threshold in the real FMS. The threshold was first set to  $Th(t)=1200$  W (no limitation for the system), then progressively reduced to 800, 400 and then 0 to study product behavior. Finally, the threshold was set to 400 W to finish the experiment. Fig. 16 presents the Gantt diagram for the experiment.

When the threshold  $Th(t)$  was set to 800 W, resource  $r_3$  stopped to avoid exceeding the threshold. This was the same for  $r_4$  when



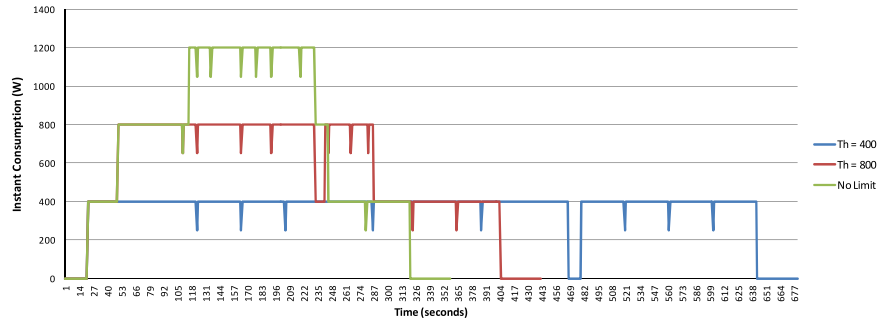


Fig. 12. Comparison of the evolution in consumption for the three previous simulations.

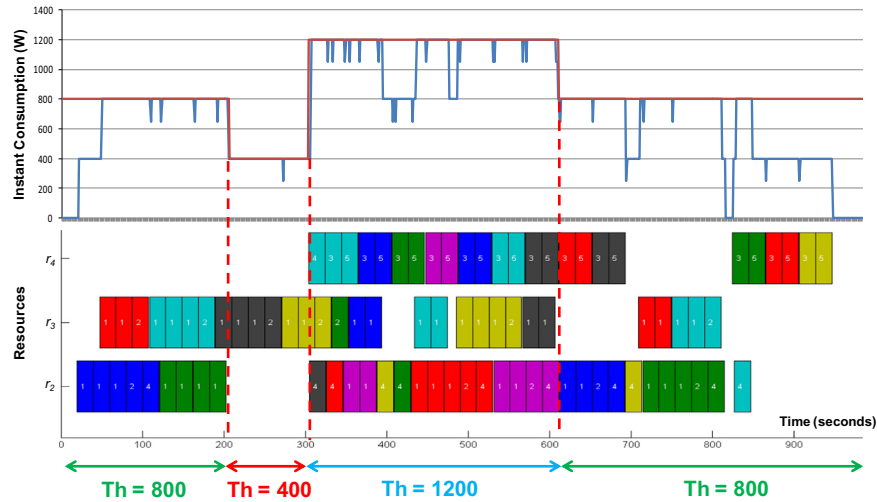


Fig. 13. Simulation results for  $6 \times$  AIP with a dynamic threshold.

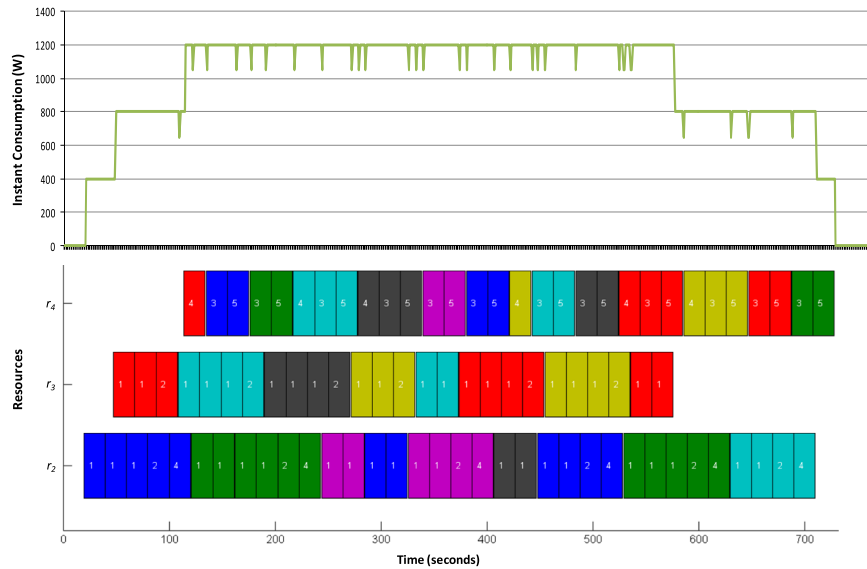


Fig. 14. Simulation results for  $6 \times$  AIP without threshold.

only one resource could produce at one time ( $Th(t)=400$  W). If there was no energy supply ( $Th(t)=0$ ) products waited in the main FMS loop and did not use any resources. There is no comparison with simulations due to some differences with the models. Especially, the loading of products was slightly slower in the experiments, so with a varying threshold, the situation is different. For example, in the case studied above, products on  $r_3$  reached the

resource sooner in simulation, resulting in products quitting  $r_2$  and using  $r_3$  and  $r_4$ . However, the goal of the experiment was to prove the feasibility of this kind of approach in a real FMS, which was achieved as the products adapted their behavior dynamically to match the threshold. These two real experiments clearly provide us with strong confidence in their potential use and interest in a real FMS.

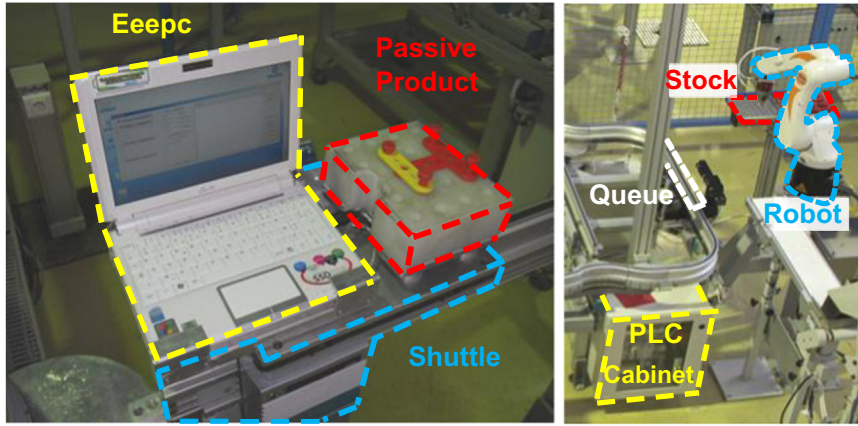


Fig. 15. Proof-of-concept Intelligent Product & Resource.

Table 5  
Results of Experiments and Simulations. Table 5

	$\tau_{h,2}$	$\tau_{h,3}$	$\tau_{h,4}$	$\tau_{l,2}$	$\tau_{l,3}$	$\tau_{l,4}$	$C_{max}$ (s)	$C_{max}$ (%)	Overall energy (J)	Energy for 12 h (KW h)	Overall energy (%)	Overall switches
Experiments	0				0		397	–	107.71	11.72	–	3
	200			195	189	190	421	106	73.47	7.99	68.2	3
Simulations	0				0		333	–	94.38	10.27	–	3
	200			195	189	190	357	107	69.93	7.61	74.1	3

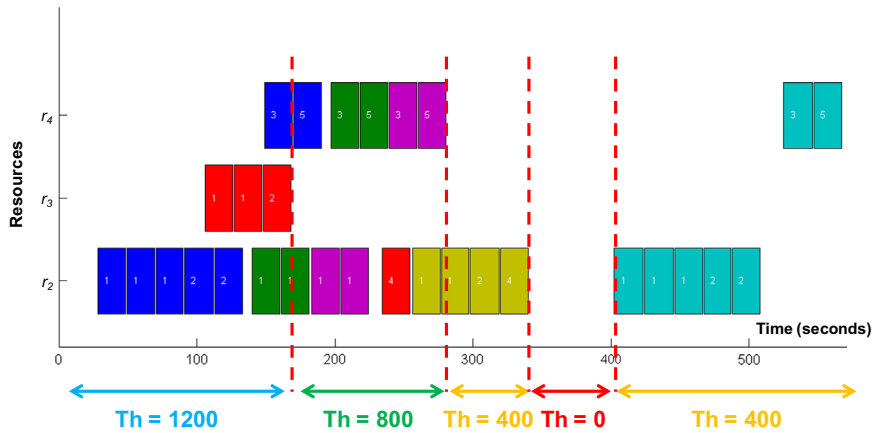


Fig. 16. Experimental results for  $2 \times$  AIP with a dynamic threshold.

## 8. Limitations of the work

From the experiments conducted and despite the promising results obtained, some limitations were identified. First, PF is a purely reactive approach by nature. Scheduling and control issues can be handled easily in real time but it is hard to extend PF to take events in the near future into consideration. In this paper, we considered the worst case where, for example, the threshold  $Th(t)$  is only known in real time. Using an estimated near future value of this threshold  $\hat{Th}(t + \Delta t)$  can however be considered, which opens up the way to using predictive models (e.g., from operation research or control theory) to complete our PF model. Second, from the real experiment conducted, we realized that the implementation of the PF approach requires skills beyond those usually required in automation. Indeed, cutting-edge technological skills in distributed control systems, microcontrollers, embedded systems, embedded networks (wired and wireless), real-time

programming, smart systems... are required to implement our models. Even if these skills are in total compliance with “smart factory”, “connected object” or “factory of the future” principles, they are still seldom deployed in industry, limiting for the moment the application of our models to academic platforms, even if they are composed of commercial and industrial components.

## 9. Conclusion and prospects

This paper proposed a Potential Fields model to dynamically control the overall consumption of a FMS to cope with the challenging near future context where the volatility of energy availability and costs will strongly increase because of the rise in new kinds of energy supplies from renewable but unpredictable energy sources such as wind or solar. This model takes the power consumption of the resource into consideration in the decision control in addition to typical indicators such as completion time. A state switching

mechanism based on the intention PF emitted by the products allowing resources to save energy was thus proposed first. Depending on this state, resources also emit PF to attract products. This reactive control method suits the dynamic context and has provided promising results (energy savings of 50% on average for simple cases, from 20% to 40% in large simulations and 32% in experiments) with a limited increase in  $C_{max}$  values (3% on average for simple cases, 2% in large simulations and 6% in experiments). Second, an extension of the PF model based on a dynamic threshold to be respected was proposed. Using this model, products adapt their decisions to respect an overall energy threshold in case of variable energy supply or energy costs. Simulations and real experiments point out the capability of our model to match the highly dynamic context of FMS energy control, which is implied by new energy supplies (e.g. wind turbines, solar panels, smart grid) and dynamic electricity pricing. The advantage here is that there is no need to predict behavior of the energy profiles, but the resulting scheduling is still effective in terms of classical time-based performance indicators such as  $C_{max}$ .

The short-term prospects are firstly to perform other more large-scale scenarios to confirm the validity of the simulations in other situations (e.g., resource breakdown) even if the Potential Fields model (without power consumption control) has already been largely tested. Methodological aspects, especially the way the two main parameters  $\tau_{h,r}$  and  $\tau_{l,r}$  can be fine-tuned in the energy wastage reduction model, must also be addressed. Indeed, their values during simulations and experiments were determined heuristically, according to our knowledge of the models and the flexible cell. In addition, the consumption values introduced were assumed constant for each of the different states for each resource, which is consistent with robotics systems in FMS for example, but not necessarily with other kinds of production systems. Thus, our models must be extended to encompass larger situations and other production systems. In addition, as introduced in the previous section, an interesting prospect concerns the hybridization of the PF model with short-term predictive methods to improve the performance of our energy-aware manufacturing scheduling and control system and to reduce "temporal myopia" (Zambrano Rey, Bonte, Prabhu & Trentesaux, 2014). In the long term, the transportation system consumption could also be taken into account, as well as the loading and inspection resources.

## Acknowledgments

The authors would like to thank Andreas Kugi, the Editor-in-Chief, the Associated Editor, and the anonymous referees for their comments, feedback, and suggestions.

## References

AIP PRIMECA VALENCIENNES (2013). (<http://www.univ-valenciennes.fr/aipnpdc/val/>) Accessed 16.01.13.

Artigues, C., Lopez, P., & Hait, A. (2010). The energy scheduling problem: Industrial case-study and constraint propagation techniques. *International Journal of Production Economics*, 143, 13–23.

Babu, C. A., & Ashok, S. (2008). Peak load management in electrolytic process industries. *IEEE Transactions on Power Systems*, 23, 399–405.

Bi, Z. M., & Wang, L. (2012). Optimization of machining processes from the perspective of energy consumption: A case study. *Journal of Manufacturing Systems*, 31, 420–428.

Bruzzone, A. A. G., Anghinolfi, D., Paolucci, M., & Tonelli, F. (2012). Energy-aware scheduling for improving manufacturing process sustainability: A mathematical model for flexible flow shops. *CIRP Annals – Manufacturing Technology*, 61, 459–462.

Chefurka, P., 2008. The looming energy shortfall (<http://paulchefurka.ca/EnergyGap.html>) Accessed 08.01.14.

Dai, M., Tang, D., Giret, A., Salido, M. A., & Li, W. D. (2013). Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm. *Robotics and Computer Integrated Manufacturing*, 29(2013), 418–429.

Devoldere, T., Dewulf, W., Deprez, W., Willems, B., & Dufloy, J. (2007). Improvement

potential for energy consumption in discrete part production machines In: S. Takata, & Y. Umeda (Eds.), *Advances life cycle engineering for sustainable manufacturing businesses* (pp. 311–316).

Dietmair, A., & Verl, A. (2009). Energy consumption forecasting and optimisation for tool machines. *Energy*, 62, 63.

DMG (2010). DMG EnergySave ([http://www.gildemeister.com/ino/journal\\_2010\\_01/uk/energysave.htm](http://www.gildemeister.com/ino/journal_2010_01/uk/energysave.htm)) Accessed 10.01.14.

Dufloy, J. R., Sutherland, J. W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., et al. (2012). Towards energy and resource efficient manufacturing: A processes and systems approach. *CIRP Annals – Manufacturing Technology*, 61, 587–609.

ElMaraghy, H., & Caggiano, A. (2014). *Flexible manufacturing system, CIRP encyclopedia of production engineering* (pp. 524–530).

Energy Information Administration (2009). International energy outlook 2009. (<http://www.eia.doe.gov/oiiaf/ieo/industrial.html>) Accessed 01.07.14.

Fan, J., & Borlase, S. (2009). The evolution of distribution. *IEEE Power and Energy Magazine*, 7, 63–68.

Fang, K., Uhan, N., Zhao, F., & Sutherland, J. W. (2011a). A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. *Journal Manufacturing Systems*, 30, 234–240.

Fang, K., Uhan, N., Zhao, F., & Sutherland, J. W. (2011b). A new shop scheduling approach in support of sustainable manufacturing In: J. Hesselbach, & C. Hermann (Eds.), *Glocalized solutions for sustainability in manufacturing* (pp. 305–310).

Ghadimi, P., Kara, S., & Kornfeld, S. (2015). Renewable energy integration into factories: Real-time control of on-site energy systems. *CIRP Annals – Manufacturing Technology*, 64, 443–446.

He, Y., Liu, B., Zhang, X., Gao, H., & Liu, X. (2012). A modeling method of task-oriented energy consumption for machining manufacturing system. *Journal of Cleaner Production*, 23, 167–174.

IMS2020 (2013). IMS2020 project. ([http://data.fir.de/projektseiten/ims2020/files/IMS2020\\_Brochure\\_KAT1-5.pdf](http://data.fir.de/projektseiten/ims2020/files/IMS2020_Brochure_KAT1-5.pdf)) (Accessed 01.16.13).

Ipakchi, A., & Albayeh, F. (2009). Grid of the future. *IEEE Power and Energy Magazine*, 7, 52–62.

Jänicke, M. (2008). Ecological modernisation: new perspectives. *Journal Cleaner Production*, 16, 557–565.

Khatib, O. (1986). Real-time obstacle avoidance for manipulators and mobile robots. *International Journal Robotics Research*, 5, 90–98.

Kim, D. H., Wang, H., & Shin, S. (2006). Decentralized control of autonomous swarm systems using artificial potential functions: analytical design guidelines. *Journal of Intelligent and Robotics System*, 45, 369–394.

Küster, T., Lützenberger, M., Freund, D., Albayrak, S. (2012). Distributed optimization of energy costs in manufacturing using multi-agent system technology. In *Proceedings of the Second International Conference on Smart Grids, Green Communications and IT Energy-Aware Technologies* (pp. 53–59).

Marik, V., & McFarlane, D. (2005). Industrial Adoption of Agent-Based Technologies. *IEEE Intelligent Systems*, 20, 27–35.

Mati, Y., Xiaoan, Xie (2003). A polynomial algorithm for a two-job shop scheduling problem with routing flexibility. Presented at the 2003 *IEEE International Conference on Robotics and Automation* (pp. 157–162).

McFarlane, D., Sarma, S., Chirn, J. L., Wong, C. Y., Ashton, K. (2002). The intelligent product in manufacturing control and management. In *Proceedings of the 15th Triennial World Congress*. Barcelona, Spain.

Meyer, G. G., Främling, K., & Holmström, J. (2009). Intelligent products: A survey. *Computers in Industry*, 60, 137–148.

Newman, S. T., Nassehi, A., Imani-Asrai, R., & Dhokia, V. (2012). Energy efficient process planning for CNC machining. *CIRP Journal of Manufacturing Science and Technology*, 5, 127–136.

Ochoa George, P. A., Gutiérrez, A. S., Cogollos Martínez, J. B., & Vandecasteele, C. (2010). Cleaner production in a small lime factory by means of process control. *Journal of Cleaner Production*, 18, 1171–1176.

Pach, C., Bekrar, A., Zbib, N., Sallez, Y., & Trentesaux, D. (2012). An effective potential field approach to FMS holonic heterarchical control. *Control Engineering Practice*, 20, 1293–1309.

Pach, C., Berger, T., Bonte, T., & Trentesaux, D. (2014). ORCA-FMS: A dynamic architecture for the optimized and reactive control of flexible manufacturing scheduling. *Computers in Industry*, 65, 706–720.

Pach, C., Berger, T., Sallez, Y., Adam, E., & Trentesaux, D., 2013a. Reactive and energy-aware scheduling of flexible manufacturing systems using potential Fields. *Computers in Industry* (Special Issue on ICT for Sustainability in Industry).

Pach, C., Berger, T., Sallez, Y., & Trentesaux, D. (2013b). Effective, energy-aware control of a production system: a potential fields approach. Presented at the Intelligent Manufacturing System 2013, Sao Paulo.

Pechmann, A., & Schöler, I. (2011). Optimizing energy costs by intelligent production scheduling In: J. Hesselbach, & C. Hermann (Eds.), *Glocalized solutions for sustainability in manufacturing* (pp. 293–298).

Prabhu, V., Taisch, M., (2012). Simulation modeling of energy dynamics in discrete manufacturing systems In *Proceedings of the information control problems in manufacturing* (pp. 740–745).

Prabhu, V. V. (2012). Services for competitive and sustainable manufacturing in the smart grid In: T. Borangiu, A. Thomas, & D. Trentesaux (Eds.), *Service orientation in holonic and multi-agent manufacturing control, studies in computational intelligence* (pp. 227–240). Berlin Heidelberg: Springer.

Sallez, Y., Berger, T., Deneux, D., & Trentesaux, D. (2010). The lifecycle of active and intelligent products: The augmentation concept. *International Journal on Computer Integrated Manufacturing*, 23, 905–924.

Santos, A., Dourado, A., (1999). Global optimization of energy and production in

- process industries: a genetic algorithm application.
- Sarkis, J., & Rasheed, A. (1995). Greening the manufacturing function. *Business Horizons*, 38, 17–27.
- Taylor, P. G., d' Ortigue, O. L., Francoeur, M., & Trudeau, N. (2010). Final energy use in IEA countries: The role of energy efficiency. *Energy Policy*, 38, 6463–6474.
- Trentesaux, D., Pach, C., Bekrar, A., Sallez, Y., Berger, T., Bonte, T., et al. (2013). Benchmarking flexible job-shop scheduling and control systems. *Control Engineering Practice*, 21, 1204–1225.
- Trentesaux, D., Prabhu, V. -V. (2014). Sustainability in manufacturing operations scheduling: stakes, approaches and trends. In Grabot, B., Vallespir, B., Gomes, S., Bouras, A., Dimitris, K. (Eds.), *Proceedings of the IFIP WG 5.7 international conference advances in production management systems, IFIP AICT* (Vol. 439, pp.106–113).
- Vallada, E., Ruiz, R., & Minella, G. (2008). Minimising total tardiness in the m-machine flowshop problem: A review and evaluation of heuristics and meta-heuristics. *Computers and Operations Research*, 35, 1350–1373.
- Vergnano, A., Thorstensson, C., Lennartson, B., Falkman, P., Pellicciari, M., Yuan, C., et al. (2010). Embedding detailed robot energy optimization into high-level scheduling. In: *Proceedings of the 2010 IEEE conference on automation science and engineering (CASE)* (pp. 386–392).
- Voß, S. (2001). Meta-heuristics: The state of the art In: A. Nareyek (Ed.), *Local Search for Planning and Scheduling, Lecture Notes in Computer Science*, Vol. 2148.
- Wang, X., Ding, H., Qiu, M., & Dong, J. (2011). A low-carbon production scheduling system considering renewable energy. In: *Proceedings of the 2011 IEEE international conference on service operations, logistics, and informatics (SOLI)* (pp. 101–106).
- Wilensky, U. (1999). Center for Connected Learning and Computer-Based Modeling. Evanston, IL: Northwestern University. (<http://ccl.northwestern.edu/netlogo/>) Accessed 01.16.13.
- Zambrano Rey, G., Bonte, T., Prabhu, V., & Trentesaux, D. (2014). Reducing myopic behavior in FMS control: A semi-heterarchical simulation–optimization approach. *Simulation Modelling Practice and Theory*, 46, 53–75.
- Zein, A. (2013). Transition towards energy efficient machine tools In: C. Hermann, & S. Kara (Eds.), *Sustainable Production, Life Cycle Engineering and Management*. Berlin: Springer Verlag.
- Zhang, L., Li, X., Gao, L., Zhang, G., & Wen, X. (2012). Dynamic scheduling model in FMS by considering energy consumption and schedule efficiency. In *Proceedings of the 2012 IEEE 16th International Conference on Computer Supported Co-operative Work in Design (CSCWD)* (pp. 719–724).