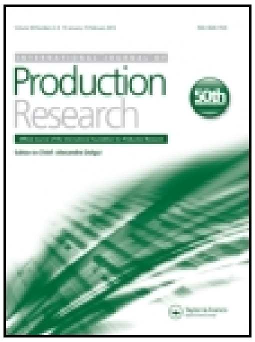

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Energy-aware manufacturing operations

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This editorial introduces the special issue on energy-aware manufacturing operations in the International Journal of Production Research. The 12 papers in this special issue were selected because of their high quality and also because they deal with topics related to energy-aware manufacturing operations. Three broad challenges are collectively addressed by the papers in this special issue: energy-efficiency vs. manufacturing-system effectiveness in optimisation; the volatility in energy availability, supply and cost; modelling energy consumption in varying scales and across different sub-systems. Previous global discussions about the state of the art in energy-aware manufacturing operations are provided, as well as exploratory guidelines for future research in this area.

Keywords: energy; manufacturing operations; scheduling; control; optimisation; simulation; sustainability

1. Introduction

Today, the industrial sector consumes a significant portion of the energy in the global economy; consequently, it has a significant impact on the environment and sustainability of our societies through resource consumption. This is driven by the fact that in the 2010s, the industrial sector has accounted for about 50% of the world's total energy consumption, while the sector's energy consumption has almost doubled over the last 60 years (Fang et al. 2011). Even though this energy consumption is concentrated primary metals and process industries (Waldemarsson 2012), manufacturing processes are also energy intensive, making this stage a primary source of energy consumption and carbon footprint generation (since manufacturing is responsible of more than 33% of global energy consumption, and 38% of direct and indirect CO_2 emissions worldwide (Garetti and Taisch 2012)); while the remainder is attributed to the transport sector, households and services. Furthermore, the energy efficiency of machine tools is generally less than 30% (Hu et al. 2012), which when combined with dynamic pricing and significant limitations on peak energy, will make detailed manufacturing scheduling and control systems considerably influent on the energy consumption and all associated costs.

Consequently, despite the fact that machinery represents a small fraction of a whole product's life cycle, reducing the energy consumed during production was recently identified as one of the most important strategies to improve sustainability in manufacturing (Pusavec, Krajnik, and Kopac 2010; He et al. 2012). Presently, and in the foreseeable future, there are significant opportunities to improve energy productivity in manufacturing, by reducing energy waste, using better technologies and techniques for designing and operating factories. Energy productivity will become an important competitive dimension for manufacturing enterprises, which can be viewed as a natural evolution towards leaner, cleaner and greener systems. Moreover, customers will increase the demand for green products manufactured in green manufacturing systems. Therefore, energy productivity needs to be characterised over a wide range of timescales ranging from sub-seconds to multiple years, through various metrics, physical measurements, empirical studies, analytical and computational techniques.

However, over the past five decades, energy productivity in manufacturing has not kept up with the remarkable strides that have been made in improving labour and material productivity. Therefore, it is critical for researchers in academia, government and industry to make all aspects of manufacturing much more energy efficient, and some efforts are nowadays being paid in that direction (Garetti and Taisch 2012), fostered by international funding organisms. To illustrate this, let us mention two representative applied research-oriented projects. First, the FP7 EU iProSPER project whose objective is to stimulate knowledge generation and sharing, the exchange of best practices, the results from

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research and case studies and the creation of new opportunities in the thematic area of sustainable energy-efficient manufacturing.[1] Second, the FP7 EU CASES project (Customised Advisory Sustainable manufacturing Services) that aims to provide manufacturing enterprises with new business and technical models to estimate, simulate and optimise manufacturing energy consumption in a predictive, cost-effective, efficient and networked means, calibrated by industrial cases in global chains.[2] Even if international funding organisms and industrialists are convinced by this necessity, scientific/academic research on reducing environmental impacts by controlling and scheduling manufacturing operations, including energy, has been relatively limited until 2012 (Fang et al. 2011; Bruzzone et al. 2012), whereas early efforts in this area have been applied in the chemical industry (Grau, Espuña, and Puigjaner 1995). Meanwhile, since few years, the research activity has been significantly increasing in the fields of sustainable manufacturing and energy-aware scheduling. As an illustration of this trend, let us mention three recent and complementary surveys (Gahm et al. 2015; Giret, Trentesaux, and Prabhu 2015; Schulze et al. 2015).

Hence, this special issue intends to contribute to the development of energy-aware manufacturing operations systems. Focus is set on manufacturing operations which are activities led at an operational level. Manufacturing operations include activities such as inventory, tooling, machining, task scheduling, process monitoring, supervision, quality control, maintenance and product routing for a given manufacturing system (Trentesaux and Prabhu 2013). In the light of the previous discussion, energy-aware manufacturing operations are an emerging and highly challenging concept. From our point of view, an energy-aware manufacturing operations management system (in short, *energy-aware manufacturing operations*) can be defined as *a manufacturing operations management system that considers in a predictive or a reactive way, and in addition to usual production decision variables, objectives and constraints (e.g. time based or time/quantity based), the energy as a decision variable, an objective or as a constraint*. This broad definition encompasses a large set of existing and potential research activities that pay attention to the interaction of one or several of the introduced manufacturing operations with the different dimensions of energy in manufacturing, typically:

(1) Real-time or forecasted manufacturing energy supply or needs;
(2) green manufacturing energy and energy co-generation in the grid;
(3) peak power during manufacturing;
(4) energy prices and energy costs for manufacturing;
(5) real-time measurement or forecasted manufacturing energy consumption;
(6) energy efficiency measures and related performance indicators;
(7) products, resources and process design for energy-aware manufacturing;
(8) recycled manufacturing energy wastes;
(9) opportunistic manufacturing energy savings, etc.

Aligned with these different aspects and dimensions, and as a guideline that will be used to position the papers composing this special issue, the next part details provides more details on three of the key challenges that can be faced when addressing energy-aware manufacturing operations. In the prospective part, we will reveal some complementary challenges that can be considered as a step beyond these three challenges.

2. Three of the key challenges in energy-aware manufacturing operations

2.1 *Challenge #1: energy efficiency vs. manufacturing-system effectiveness in optimisation*

Considering energy in manufacturing operations management significantly increases the complexity of classical problems (e.g. scheduling of job shops, already known as NP-hard problem). This indeed leads us to consider efficiency in addition to classical effectiveness when deciding manufacturing operations. In a general sense, seeking for the best use of means refers to efficiency while seeking for the best results, effectiveness (Roghanian, Rasli, and Gheysari 2012). Thus, efficiency is often defined as ‘doing things right’, while effectiveness is defined as ‘doing the right things’. But effectiveness and efficiency are conflicting objectives; for example, reducing energy consumption may imply a loss of performance in the time scheduling of operations (typically, the makespan). There are a lot of different ways to simultaneously manage energy-efficiency and manufacturing-system effectiveness (Pach et al. 2014): energy efficiency can be optimised considering manufacturing-system effectiveness as a constraint (e.g. opportunistic energy savings), or, manufacturing-system effectiveness can be optimised for a given profile, using the total available power as a constraint (e.g. peak load), or a simultaneous optimisation of both can be defined to get a balanced solution.

Even if mono-criterion optimisation function (e.g. weighted sum) is still used in this context (and especially for high-level studies at factory or supply chains levels), solving this challenge may logically push researchers to model the problem as a multi-criterion one, if a fine modelling of the optimisation mechanism is required. Indeed, beyond their natural antagonism, efficiency and effectiveness are expressed in different terms, ranges and units, which makes it rather sensitive to define a consistent mono-criterion optimisation function. Pareto analysis is then an interesting approach in such a context, even in the optimisation process itself. Moreover, since efficiency and effectiveness can be expressed either as a constraint or an objective depending on the context, multi-objective aggregation is also recommended in the optimisation stage, including lexicographical methods, constraint satisfaction problems, ε-constraints approaches or relaxation mechanisms. The use of learning mechanisms and joint simulation/optimisation techniques may also be interesting (in conjunction with challenges #2 and #3 below).

2.2 *Challenge #2: the volatility in energy availability, supply and cost*

In recent years, the increasing volatility and unpredictability of energy availability, supply and cost, require that management systems be more reactive (Ghadimi, Kara, and 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 a dynamic (i.e. real time) pricing of electricity. It is also important to note that, with provider–user energy supply agreements, exceeding the defined consumption 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 energy grids. The evolution in the energy available has to be predicted, but the price, the load and the consumption behaviour implied may be difficult to predict (Fan and Borlase 2009; Ipakchi and Albuyeh 2009), thus making it difficult to define accurate manufacturing operation strategies in this hardly predictable context (Kuhlmann and Bauernhansl 2015).

Solving this challenge will involve considering stochastics/probabilistic models, data analysis tools (including the design of experiments, statistical studies and data mining), risk management tools, simulation tools (e.g. to test ‘what if?’ scenarios) or highly reactive algorithms (including high-speed heuristics, rule-based behaviours or multi-agent techniques), in addition to long-term optimisation algorithms, with regards to the previous challenge. It may also require acquiring behavioural models of the energy grid, since this modelling is difficult to obtain, due to the increase in the energy supply from hardly predictable renewable energy systems (wind, water, sun, etc.).

2.3 *Challenge #3: modelling energy consumption in varying scales and across different sub-systems*

This third challenge is perhaps the more challenging one. It deals with the need for energy profiles of all energy-consuming/producing systems such as machines, robots, AGV and conveying systems, local wind turbine, heat gathering system, which must be finely modelled at a microscopic level (Kurp, Gao, and Sah 2012; Trentesaux and Prabhu 2014). Using these micro-models, several opportunities emerge since these models may be used in optimisation mechanisms or in simulation tools (see challenge #1), to evaluate different energy-saving strategies, or to evaluate different technologies. For example, a typical opportunity concerns the possibility of identifying which proportion of energy spent is used to add value to products so that mechanisms dealing with the reduction of the non-added value during machining (idle times, ramp-up, etc.) can be defined (cf. wastes reduction in lean manufacturing). Thus, it would help to evaluate the energy impacts on the manufacturing-system footprint (emission, pollutant), and losses (including scrap). Along with these micro-models, macro-models (at the enterprise level) can also be defined to identify global energy profiles and to estimate its evolution using for example history and past events.

The main reason why this challenge is hard to solve is due to the difficulty in accessing energy data when operating if nothing has been done during the design of the corresponding resource to facilitate this access in the first place, which is often the case in current industrial assets (Zein et al. 2011). As a result, researchers must either develop complex reverse engineering techniques and models to estimate energy profiles, or use external energy sensors. The first solution leads to side effect research efforts (such as handling multi-physics phenomena), while the second, despite the fact that the current technological offer in sensors allows the monitoring of energy in real time, leads to partial and often high-level measures.

To solve this third challenge, there are two mainstreams in the literature. The first one aims to obtain ‘internal micro-models’. To generate such models, multi-physics knowledge and modelling capabilities in energetics, mechanics and electrical engineering are required to obtain the mechanical behaviour of tools and parts, of friction and heat generation, of the ageing of machines and tools, of torques, speeds, accelerations and their effects on energy generation or consumption. The second aims to obtain ‘external micro-models’. To generate such models, control theory knowledge is required to model ‘black boxes’, as precisely as possible and possibly hierarchically organised, in order to model these behaviours by transforming informational signal inputs into informational signal outputs. One advantage of the latter approach is that no attention is to be paid to the underlying multi-physics phenomena. If on the other hand, macro-models are sought, then knowledge in information processing (data mining, clustering, etc.) as well as in probabilistic/statistical studies (design of experiments, correlation analysis, Bayesian networks, etc.) are required. In addition to all these approaches, learning capabilities can be used to improve/adapt the models with time, using, for example, neural networks, case-based reasoning, adaptive mechanisms or reinforcement learning. One clear risk relevant to these micro-models is clearly related to the complexity they induce in calculations, which thus makes it harder to solve the challenges #1 and #2 or to support the design of integrated macro-models.

3. The contributions

In this special issue, 12 papers were selected after a robust peer-review process. They clearly illustrate the variety of approaches and contributions, and their relative complementarity which helps to design energy-aware manufacturing operations management systems. These papers are briefly introduced below and are positioned according to the particular challenge they address among the three stated, see Table 1. In this special issue, the challenge #3 is the most addressed. In this table, the modelling/solving tools are also introduced, pointing out the diversity of the research fields that are considered when designing energy-aware manufacturing operation management systems.

3.1 *Contributions relevant to challenge #1*

In Meneghetti, Dal Borgo, and Monti (2015), the authors considered automated storage and retrieval systems. In this context, they propose a classification of racks based on system height to select the proper crane specifications needed to compute the torque to be overcome by motors to serve a given location within a rack. An overall optimisation model based on constraint programming combined with large neighbourhood search is developed, allowing the joint

Table 1. Positioning of the 12 contributions in this special issue.

	Addressed challenge			
Contributions	Challenge #1: energy efficiency vs. manufacturing-system effectiveness in optimisation	Challenge #2: the volatility in energy availability, supply and cost	Challenge #3: modelling energy consumption in varying scales and across different sub-systems	Modelling/solving tools
May et al. (2015)	Yes			Multi-objective genetic algorithm
Meneghetti, Dal Borgo, and Monti (2015)	Yes			Constraint programming; large neighbourhood search
Lee and Prabhu (2015)	Yes			Continuous feedback controller, arrival time control
Mikhaylidi, Naseraldin, and Yedidsion (2015)	Yes	Partially		Dynamic programming
Tan and Yavuz (2015)		Yes		Stochastic modelling, probabilities
Jeon, Taisch, and Prabhu (2014)		Yes		Simulation, regression models
Santana-Viera et al. (2014)		Partially	Yes	Stochastic programming, Monte Carlo simulation, design of experiments, regression models
Xu et al. (2014)			Yes	Process simulation
Hu et al. (2014)			Yes	Feature technology, binary trees
Johansson et al. (2014)			Yes	Production flow analysis, data mining, discrete event simulation
Dhavale and Sarkis (2015)			Yes	Bayesian analysis, simulation
Mustafaraj et al. (2015)			Yes	Statistical analysis

application of the best control policies for storage assignment and sequencing both for time and energy-based optimisation, as well as the introduction of multiple weight unit loads and energy recovery. Based on a fine-tuned model of crane energy profile depending on its characteristics and its possible workload, they developed a balanced energy efficiency and effectiveness (time), based on specific tuning parameters which favour either the one or the other.

In May et al. (2015), the authors investigate the effects of production-scheduling policies, aimed at improving energy efficiency on the performances of a job shop manufacturing system. Hence, a new green genetic algorithm, which is able to consider objectives related to productivity and energy consumption is developed. To avoid a 'simple' mono-criterion aggregation, their approach involved integrating a measure of the domination degree (in the sense of Pareto) for chromosomes in their fitness value. They assumed that power consumption for the different machines are constant (challenge #3) on a static problem (challenge #2).

In Mikhaylidi, Naseraldin, and Yedidsion (2015), the authors address challenge #1, but also paid some attention to challenge #2. The authors considered a manufacturing operations control problem with known time-varying electricity prices in a finite planning horizon. Each operation is unique and has its own concave electricity consumption function. There is a fixed start-up cost incurred for switching on the machine, as well as a fixed reservation cost incurred for keeping the machine switched 'On'. The system also includes a rechargeable battery. The customer has to determine when to process each operation within the time frame so as to minimise total electricity consumption and penalty costs from postponing operations. The optimum amount of time required to both charge and discharge the rechargeable battery were sought.

In Lee and Prabhu (2015), the authors propose an energy-aware feedback control model for production scheduling and capacity control. They consider the costs of energy consumption, machine maintenance, production capacity and the penalty cost imposed by just-in-time production requirements. Continuous control variables are used to adjust the system.

3.2 *Contributions relevant to challenge #2*

In Tan and Yavuz (2015), the authors developed an original approach based on a detailed analytical model for the operation of energy-saving companies in a way which captures improvement in energy efficiencies and costs of technologies with time, variation in energy consumption, uncertainty in energy unit price and useful technology life and revenue from carbon offsets simultaneously. For that purpose, they developed a stochastic setting to analyse a business plan to offer energy-saving technologies as a service, by identifying for each candidate technology, its replacement cost, cost of energy usage, CO_2 emission and revenue from carbon offsets. Using a probabilistic approach, they address risk management by testing different effects and scenario in the context of uncertainties (e.g. energy pricing). Since they mainly work at a high business level, challenge #1 is addressed using a mono-criterion additive aggregation, while challenge #3 is addressed using a global linear regression of the day's temperature.

In Jeon, Taisch, and Prabhu (2014), the authors proposed a method that starts by extracting parameters at the product level, and links the parameters to machine-level power and plant-level energy footprints, thereby enabling a comparison of manufacturing energy footprints at the industry level. A case study shows in detail how parameterised information at each level is systemically used as input data for the next level. Simulating the energy consumption of a hypothetical plant with five managerial factors, the case study presents the total energy consumption and the energy consumption per unit product in closed-form equations. By using the equations, the manufacturing energy can be estimated with the factors at different levels, and ways to reduce manufacturing energy consumption can be analysed in regards to a higher order interaction.

3.3 *Contributions relevant to challenge #3*

In Xu et al. (2014), the authors present a method to build an energy consumption model for the printing stage of a binder-jetting process in the promising context of additive manufacturing. For that purpose, they developed mathematical analyses to determine the correlation between the energy consumption and geometry of the manufactured part. Based on the analyses, total energy consumption is calculated as a function of part geometry and printing parameters. Test printings were performed to check the accuracy of the model. This process model was then designed to provide a tool for optimising part geometry design with regards to energy consumption.

In Hu et al. (2014), the authors estimate, from the design phase, the energy consumption of a part using the features approach. They propose that an energy profile can be associated to each product feature. The proposed method can well achieve a comprehensive and very efficient estimation of energy consumption of parts at the design phase. According to the estimation result, product designers and energy managers can judge whether the design scheme is energy efficient or not. This kind of research work is thus a necessary prerequisite for every research development in the field of energy-aware manufacturing operations management since, for example, planning alternative manufacturing operations in reconfigurable manufacturing systems should have, as an input, the energy profile for each of the machines able to perform these alternative operations of each required product feature.

In Santana-Viera et al. (2014), the authors proposed using onsite wind and solar energy resources to assist large manufacturing facilities in meeting the load curtailment goal in interruptible/curtailable demand response programmes. For that purpose, stochastic programming models were developed to perform a central composite design to determine the optimal capacity of wind turbines and solar photovoltaic units that maximise the annual utility savings subject to uncertain contingency calls. A stochastic programming model considers installation and operation costs, utility discounts as a result of demand response participation, carbon credits/government subsidies and production losses during contingent events. They mainly addressed challenge #3 but they also addressed challenge #2. The proposed model is intended for use by manufacturing firms to assess the cost benefits as result of discount utility prices and the carbon savings from renewable integration.

In Johansson et al. (2014), the authors starting point was that additional input parameters, such as electrical power consumed by machines, are needed in energy-aware manufacturing operations. Using discrete event simulation, they investigated how NC machine power consumption should be represented in simulation models for factories, and how they can be used to optimise production flows as well as to reduce non-value-added activities. To limit the complexity of modelling in the context of challenge #2, their approach tries to determine whether a representation of the energy consumption as a deterministic variable for each machine’s busy state (i.e. the different operations it can perform) is sufficient or not. If not, statistical distribution for example may be used in the simulations. For that purpose, they studied data from three factories. They concluded that it is important to choose a good representation of the machines’ energy consumption in a discrete event simulation model, to assure valid and qualitative results.

In Dhavale and Sarkis (2015), the authors chose a unique method to consider the link between energy savings and carbon credit market. The idea is that the reduction in energy usage due to efficient and sustainable manufacturing systems creates credits for the firm in a carbon trading market. The firm is then able to sell these carbon credits on the market or use the credits elsewhere in its operation thus avoiding the need to purchase them. For that purpose, they develop a Bayesian net present value framework. Their approach allows decision-makers to integrate their knowledge, past experience, and uncertain and volatile cash flows from carbon emissions credits into decisions dealing with energy efficient, sustainable manufacturing equipment.

In Mustafaraj et al. (2015), the authors described an interesting technique aiming at differentiating, from the consumption of electricity in manufacturing operations, the part relevant to value-added operations (value-added electricity), from that relevant to auxiliary operations (non-added value). For that purpose, historical production and electricity-consumption data were collected over a period of three months, from four different machines in a value stream at a manufacturing facility. The data were examined using a methodology based on the statistical analysis of the historical data collected and were verified using heuristic machines profiles.

4. Prospective

In this special issue, three of the key challenges that can be faced when addressing energy-aware manufacturing operations are addressed. By going one step beyond these three challenges, we can identify some urgent prospects to address in the near future. The following parts introduce some of these prospects according to different points of view, namely informational, organisational, and product and resource life cycle points of view.

4.1 *Informational point of view*

Information and communication systems must be adapted to enable the handling of energy in manufacturing operations. Typically, a first prospect concerns *the integrated design of energy-aware manufacturing information systems*, from the lower levels (e.g. SCADA) to management levels (e.g. ERP) (Bonino et al. 2014). Indeed, the complete energy-related decision loop from the long-term strategic and tactical term systems to the short-term physical systems and back again to these long-term systems still does not exist in an integrated and generic way.

A second prospect concerns *the use of emerging information and communication paradigms* such as cyber-physical systems, smart/intelligent products, ambient manufacturing, industrial internet, internet of things, and more globally, intelligent manufacturing systems would easily complete the use of classical modelling techniques to enable more bottom-up, reactive and adaptive behaviour in combination with top-down approaches, that find it difficult to handle the growing introduced unpredictability in the availability of natural and technological resources (Thomas and Trentesaux

2014), especially in the context of the smart energy grid (Strasser et al. 2015). Multi-agent or Holonic principles are highly consistent within such a context (Trentesaux and Giret 2015).

4.2 *Organisational point of view*

The manufacturing organisations themselves must be revised to define more energy-friendly manufacturing systems. This may have major impacts on research developments, implying, for example, the adaptation of scheduling models to support this evolution.

A first prospect concerns the need to consider *energy wastes as a possible input in the system*. Indeed, despite the fact that this is a widespread approach in specific industries, such as chemical/process industry, few works consider the possibility of re-injecting energy waste into the system (e.g. waste generated from heat losses during machining) (Fu et al. 2015), even in manufacturing. Research activities that aim at translating in manufacturing systems ideas and developments from these experiences should be dealt with in the near future.

A second prospect concerns the *automatic reconfiguration of manufacturing systems according to the cost and availability of energy*. This includes, for example, the dynamic plugging and unplugging of resources in the production network aligned with an adaptive layout redefinition, or the automatic adaptation of operations to meet some dynamic and unpredictable energy requirements. This reconfiguration process should consider resources that consume energy and others that produce energy (even locally, within a company). Reconfigurable manufacturing systems may then gain new interest within the context of energy-aware manufacturing systems (Leitão, Barbosa, and Trentesaux 2012; Azab et al. 2013) but the link with energy is still not made despite this potential benefit.

A third prospect is relevant to *the broadening of the manufacturing activities* that researchers consider when designing energy-aware manufacturing operations. Indeed, to the best of our knowledge, and as illustrated by the papers composing this special issue, most of the works in the domain of energy-aware manufacturing operations management focus on a single specific activity or function at the manufacturing operations level, typically, monitoring, control or scheduling. It is obvious that broadening the scope of the study will help to improve the global management of energy at the manufacturing operation level. For example, coupling energy-aware maintenance with energy-aware scheduling may lead to limit the misuse of machining tools to limit possible over consumptions of energy or energy wastage. Meanwhile, despite its immediate appeal for energy savings, this kind of studies has been seldom proposed (Senechal et al. 2015).

4.3 *Product and resources life cycle point of view*

As a kind of generalisation of the previously introduced prospect (broadening of the manufacturing activities), considering the whole life cycle of systems, being products and resources, when designing energy-aware manufacturing operations management systems seems to be promising. To illustrate this, let us mention three innovative prospects.

A first prospect concerns *the development of applications based on the concept of product-service systems* (PSS) to design energy-aware manufacturing operations. PSS is known to be by essence more sustainable than classical not service-oriented approaches, reducing the total product and material use and improving the life cycle of products, including the global footprints, and especially energy consumptions (Chou, Chen, and Conley 2015). The concept of PSS can then be applied to the manufacturing resource themselves, which leads us to define here a new innovative concept: *resource-service system*. Typically, instead of owning production resources, manufacturers may buy for the services (manufacturing operations) thus for the dynamic capacity these resources are able to provide to manufacture a product. This would lead to indirect energy savings through the definition of innovative mechanisms. For example, it would lead to the globalisation and the optimisation of the manufacturing resources assets done transversally to a group of manufacturers using the same production technologies. The global optimisation of the maintenance of these assets will be eased. The balance of the workload vs. capacity will also be eased since handled globally. Such an approach forces thus the globalisation and the federation of the management of a whole set of production resources beyond a single company.

A second prospect concerns the *globalisation of the design of energy-aware manufacturing operations management systems* alongside the design of products and processes. The idea is to make jointly product and manufacturing system design choices that will limit the use of energy during the future manufacturing of the product. The *monozukuri* principle is a famous industrial flagship approach aligned with this idea (Aoki, Staeblein, and Tomino 2014) that is not sufficiently considered in the research world. From our point of view, defining energy-aware *monozukuri* mechanisms would help to handle this prospect.

Aligned with the previous prospect, a third prospect deals with *the design for energy-aware*, that is, the design of manufacturing machines ready for energy-aware management. Since production resources, like any product, must also be designed, identifying and considering the potential need to get simple but high-quality energy profile information when they will be used, from the early stage of their design, will ease in consequence the definition of energy-aware manufacturing operations management systems both from a predictive and a reactive point of view. This logically leads to the energy-efficient products and resources development process itself since the energy profile of manufacturing operations (estimated or sensed) would be possible thanks to this anticipated easy-access measurement. Typically, in the near future, each production resource should be accompanied with an integrated module enabling the easy management of its energy profile (including monitoring of energy consumption/production, energy-state management, energy-losses or energy-savings management, easy switch off/on, etc.). Axiomatic or feature-based design may be useful in this context (Zein et al. 2011; Hu et al. 2014), as well as function block-oriented approaches (Peng, Xu, and Wang 2014).

5. Conclusion

This editorial aims to introduce the special issue on energy-aware manufacturing operations in the International Journal of Production Research. In this special issue, 12 high-quality papers are presented. Three broad challenges are collectively addressed by these papers: energy efficiency vs. manufacturing-system effectiveness in optimisation; the volatility in energy availability, supply and cost; and modelling energy consumption in varying scales and across different sub-systems.

Despite the huge societal and environmental stakes, research in this field is still nascent. It is, for example, noticeable that, even in some papers, two among the three challenges were addressed; none of the papers composing this special issue have addressed all of them in a balanced way, which should normally be the case when seeking real applications or mature research. This shows that the journey to real industrial applications of energy-aware manufacturing management systems is still quite long, despite local success stories.

Meanwhile, a growing number of researchers address energy-aware manufacturing operations. It is worth mentioning that energy is the most studied subject in sustainable manufacturing (from our point of view, its growing cost explains this situation). Other subjects relevant to the societal and environmental aspects of sustainability remain unaddressed. Thus, the guest editors think that we are only at the early stages of a new era, where manufacturing operations management systems must evolve several steps beyond classical manufacturing operations modelling approaches to seek a controlled limitation of environmental footprints and resource usage beyond energy (limitation of biological and technical 'nutrients' or use of supplies, reduction of pollutant emissions, etc.), and to the societal responsibilities of manufacturing companies (such as the welfare of operators during manufacturing, mental and physical workload management).

To conclude this editorial, let us mention two important notes.

First, in the near future, the researches in energy-aware manufacturing operations should be led logically by teams of specialists who come from diverse scientific domains (mechanical, electrical or control engineering, energetics, product design and development, product life cycle management, computer science, electronics, production control, etc.). If not, it may lead specialists from scientific domains that were initially not involved in the research to judge the derived models as inconsistent or too simple from their point of view. For example, a researcher in computer science may choose to simplify the energetic behaviour of systems, and to model energy profiles using as many high-level constant values as possible, estimated from long-term average studies (average energy consumption while moving, average energy waste when milling, etc.). In that case, a researcher in electrical or mechanical engineering may criticise these strong assumptions and consider the designed energy-aware manufacturing operations management systems to be highly unrealistic.

Second, future researches in the field of energy-aware manufacturing operations will have to comply with the new production technologies (e.g. additive manufacturing, micro factories, cobotic manufacturing, etc.), new industrial processes and markets (e.g. de-manufacture, re-manufacture, reverse and green logistics, recycling industry, etc.) and new manufacturing paradigms (e.g. the manufacturer as my neighbour, home-made manufacturing, manufacturing grid, industrial internet, circular production, etc.).

The guest editors hope that all these key issues will soon be addressed by a growing number of researchers and research communities.

Special note on IJPR's anniversary in 2016

In 2016 IJPR will celebrate its 55th anniversary. IJPR was created in 1961 and was a pioneer multidisciplinary journal publishing results of scientific research on manufacturing technologies, product/process design, production engineering, operations management and logistics (Dolgui, 2013). The scientific domain "Production Research" was indeed born with the journal. Since then, IJPR has become a flagship journal in production. As (Corlett, 2013) mentioned few years ago, the changes in industries over the last 50 years are enormous. In the last half century, the penetration of information and communication technologies, computers and electronics in many forms and other developments has changed the processes dramatically. IJPR has always been one of the best places to publish innovative ideas in these fields, accompanying the constant evolution of industries. As scientific researchers, the editors of this special issue appreciate this possibility. The publication of this special issue on a topic with huge societal and environmental stakes is a clear illustration of the will of the journal not only to keep pace with the constant evolution of production systems and society's need but also to stay at the cutting edge of the research in that field.

List of the twelve papers composing this special issue

Dileep Dhavale & Joseph Sarkis (2015): Integrating carbon market uncertainties into a sustainable manufacturing investment decision: a Bayesian NPV approach, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1018450

Luoke Hu, Renzhong Tang, Keyan He & Shun Jia (2014): Estimating machining-related energy consumption of parts at the design phase based on feature technology, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2014.944281

HyunWoo Jeon, Marco Taisch & Vittaldas V. Prabhu (2014): Modelling and analysis of energy footprint of manufacturing systems, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2014.961208

Björn Johansson, Anders Skoogh, Jon Andersson, Karin Ahlberg & Lars Hanson (2014): Power-level sampling of metal cutting machines for data representation in discrete event simulation, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2014.980456

Seokgi Lee & Vittal Prabhu (2015): Energy-aware feedback control for production scheduling and capacity control, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1082666

Gökan May, Bojan Stahl, Marco Taisch & Vittal Prabhu (2015): Multi-objective genetic algorithm for energy-efficient job shop scheduling, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1005248

Antonella Meneghetti, Eleonora Dal Borgo & Luca Monti (2015): Rack shape and energy efficient operations in automated storage and retrieval systems, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1008107

Yevgenia Mikhaylidi, Hussein Naseraldin, & Liron Yedidsion (2015): Operations scheduling under electricity time-varying prices, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1058981

Giorgio Mustafaraj, John Cosgrove, Maria J. Rivas-Duarte, Frances Hardiman & John Harrington (2015): A methodology for determining auxiliary and value-added electricity in manufacturing machines, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1026615

Victor Santana-Viera, Jesus Jimenez, Tongdan Jin & Jose Espiritu (2014): Implementing factory demand response via onsite renewable energy: a design-of-experiment approach, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2014.957877

Barış Tan & Yahya Yavuz (2015): Modelling and analysis of a business model to offer energy-saving technologies as a service, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2015.1055343

Xin Xu, Simon Meteyer, Nicolas Perry & Yaoyao Fiona Zhao (2014): Energy consumption model of Binder-jetting additive manufacturing processes, International Journal of Production Research, http://dx.doi.org/10.1080/00207543.2014.937013

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Notes

1. http://www.iprosper.eu/home/.
2. http://www.fp7cases.eu/.

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References

Aoki, K., T. Staeblein, and T. Tomino. 2014. “Monozukuri Capability to Address Product Variety: A Comparison between Japanese and German Automotive Makers.” *International Journal of Production Economics, Building Supply Chain System Capabilities in the Age of Global Complexity: Emerging Theories and Practices* 147 (Part B): 373–384. doi:10.1016/j.ijpe.2013.02.026.

Azab, A., H. ElMaraghy, P. Nyhuis, J. Pachow-Frauenhofer, and M. Schmidt. 2013. “Mechanics of Change: A Framework to Reconfigure Manufacturing Systems.” *CIRP Journal of Manufacturing Science and Technology* 6: 110–119. doi:10.1016/j.cirpj.2012.12.002.

Bonino, D., L. De Russis, F. Corno, and G. Ferrero. 2014. “JEERP: Energy-aware Enterprise Resource Planning.” *IT Professional* 16: 50–56.

Bruzzone, A. A. G., D. Anghinolfi, M. Paolucci, and F. Tonelli. 2012. “Energy-aware Scheduling for Improving Manufacturing Process Sustainability: A Mathematical Model for Flexible Flow Shops.” *CIRP Annals – Manufacturing Technology* 61: 459–462. doi:10.1016/j.cirp.2012.03.084.

Chou, C.-J., C. -W. Chen, and C. Conley. 2015. “An Approach to Assessing Sustainable Product-service Systems.” *Journal of Cleaner Production* 86: 277–284. doi:10.1016/j.jclepro.2014.08.059.

Corlett, N. 2013. “The Last Fifty Years, and the Next.” *International Journal of Production Research* 51: 6739–6739. doi:10.1080/00207543.2013.852701.

Dhavale, D., and J. Sarkis. 2015. “Integrating Carbon Market Uncertainties into a Sustainable Manufacturing Investment Decision: A Bayesian NPV Approach.” *International Journal of Production Research* 1–14. doi:10.1080/00207543.2015.1018450.

Dolgui, A. 2013. “In 2012 IJPR Published its 50th Volume.” *International Journal of Production Research* 51: 6733–6738. doi:10.1080/00207543.2013.853434.

Fan, J., and S. Borlase. 2009. “The Evolution of Distribution.” *IEEE Power and Energy Magazine* 7: 63–68. doi:10.1109/MPE.2008.931392.

Fang, K., N. Uhan, F. Zhao, and J. W. Sutherland. 2011. “A New Approach to Scheduling in Manufacturing for Power Consumption and Carbon Footprint Reduction.” *Journal of Manufacturing Systems* 30: 234–240. doi:10.1016/j.jmsy.2011.08.004.

Fu, Q., C. Song, Y. Kansha, Y. Liu, M. Ishizuka, and A. Tsutsumi. 2015. “Energy Saving in a Biodiesel Production Process Based on Self-heat Recuperation Technology.” *Chemical Engineering Journal, Tailoring Sustainability through Chemical Reaction Engineering* 278: 556–562. doi:10.1016/j.cej.2014.11.027.

Gahm, C., F. Denz, M. Dirr, and A. Tuma. 2015. “Energy-efficient Scheduling in Manufacturing Companies: A Review and Research Framework.” *European Journal of Operational Research*. doi:10.1016/j.ejor.2015.07.017.

Garetti, M., and M. Taisch. 2012. “Sustainable Manufacturing: Trends and Research Challenges.” *Production Planning & Control* 23: 83–104. doi:10.1080/09537287.2011.591619.

Ghadimi, P., S. Kara, and B. Kornfeld. 2015. “Renewable Energy Integration into Factories: Real-time Control of On-site Energy Systems.” *CIRP Annals – Manufacturing Technology* 64: 443–446. doi:10.1016/j.cirp.2015.04.114.

Giret, A., D. Trentesaux, and V. Prabhu. 2015. “Sustainability in Manufacturing Operations Scheduling: A State of the Art Review.” *Journal of Manufacturing Systems*. doi:10.1016/j.jmsy.2015.08.002.

Grau, R., A. Espuña, and L. Puigjaner. 1995. “Environmental Considerations in Batch Production Scheduling.” *Computers & Chemical Engineering* 19 (Supplement 1): 651–656. doi:10.1016/0098-1354(95)87109-8.

He, Y., B. Liu, X. Zhang, H. Gao, and X. Liu. 2012. “A Modeling Method of Task-oriented Energy Consumption for Machining Manufacturing System.” *Journal of Cleaner Production* 23: 167–174. doi:10.1016/j.jclepro.2011.10.033.

Hu, S., F. Liu, Y. He, and T. Hu. 2012. “An On-line Approach for Energy Efficiency Monitoring of Machine Tools.” *Journal of Cleaner Production* 27: 133–140. doi:10.1016/j.jclepro.2012.01.013.

Hu, L., R. Tang, K. He, and S. Jia. 2014. “Estimating Machining-related Energy Consumption of Parts at the Design Phase based on Feature Technology.” *International Journal of Production Research* 1–18. doi:10.1080/00207543.2014.944281.

Ipakchi, A., and F. Albuyeh. 2009. “Grid of the Future.” *IEEE Power and Energy Magazine* 7: 52–62. doi:10.1109/MPE.2008.931384.

Jeon, H. W., M. Taisch, and V. V. Prabhu. 2014. “Modelling and Analysis of Energy Footprint of Manufacturing Systems.” *International Journal of Production Research* 1–11. doi:10.1080/00207543.2014.961208.

Johansson, B., A. Skoogh, J. Andersson, K. Ahlberg, and L. Hanson. 2014. “Power-level Sampling of Metal Cutting Machines for Data Representation in Discrete Event Simulation.” *International Journal of Production Research* 1–11. doi:10.1080/00207543.2014.980456.

Kuhlmann, T., T. Bauernhansl. 2015. “Method for Designing an Energy-agile Energy System for Industrial Manufacturing.” Procedia CIRP, The 22nd CIRP Conference on Life Cycle Engineering 29: 179–184. doi:10.1016/j.procir.2015.02.005.

Kurp, T., R. Gao, S. Sah. 2012. "Adaptive Sensing for Energy-efficient Manufacturing System and Process Monitoring." CIRP Journal of Manufacturing Science and Technology, Special issue from 44th CIRP Conference on Manufacturing Systems 5, 328–336. doi:10.1016/j.cirpj.2012.09.008.

Lee, S., and V. V. Prabhu. 2015. "Energy-aware Feedback Control for Production Scheduling and Capacity Control." *International Journal of Production Research* 1–13: doi:10.1080/00207543.2015.1082666.

Leitão, P., J. Barbosa, and D. Trentesaux. 2012. "Bio-inspired Multi-agent Systems for Reconfigurable Manufacturing Systems." *Engineering Applications of Artificial Intelligence* 25: 934–944. doi:10.1016/j.engappai.2011.09.025.

May, G., B. Stahl, M. Taisch, and V. Prabhu. 2015. "Multi-objective Genetic Algorithm for Energy-efficient Job Shop Scheduling." *International Journal of Production Research* 1–19. doi:10.1080/00207543.2015.1005248.

Meneghetti, A., E. Dal Borgo, and L. Monti. 2015. "Rack Shape and Energy Efficient Operations in Automated Storage and Retrieval Systems." *International Journal of Production Research* 1–14. doi:10.1080/00207543.2015.1008107.

Mikhaylidi, Y., H. Naseraldin, and L. Yedidsion. 2015. "Operations Scheduling under Electricity Time-varying Prices." *International Journal of Production Research* 1–22. doi:10.1080/00207543.2015.1058981.

Mustafaraj, G., J. Cosgrove, M. J. Rivas-Duarte, F. Hardiman, and J. Harrington. 2015. "A Methodology for Determining Auxiliary and Value-added Electricity in Manufacturing Machines." *International Journal of Production Research* 53 (17): 5265–5277.

Pach, C., T. Berger, Y. Sallez, T. Bonte, E. Adam, and D. Trentesaux. 2014. "Reactive and Energy-aware Scheduling of Flexible Manufacturing Systems using Potential Fields." *Computers in Industry*. 65 (3), 434–448. doi:10.1016/j.compind.2013.11.008.

Peng, T., X. Xu, and L. Wang. 2014. "A Novel Energy Demand Modelling Approach for CNC Machining Based on Function Blocks." *Journal of Manufacturing Systems* 33: 196–208. doi:10.1016/j.jmsy.2013.12.004.

Prabhu, V. V. 2012. "Services for Competitive and Sustainable Manufacturing in the Smart Grid." In *Service Orientation in Holonic and Multi-agent Manufacturing Control*, edited by T. Borangiu, A. Thomas, and D. Trentesaux, 227–240. Berlin: Springer-Verlag.

Pusavec, F., P. Krajnik, and J. Kopac. 2010. "Transitioning to Sustainable Production – Part I: Application on Machining Technologies." *Journal of Cleaner Production* 18: 174–184. doi:10.1016/j.jclepro.2009.08.010.

Roghanian, P., A. Rasli, and H. Gheysari. 2012. "Productivity Through Effectiveness and Efficiency in the Banking Industry." *Procedia – Social and Behavioral Sciences* 40: 550–556. doi:10.1016/j.sbspro.2012.03.229.

Santana-Viera, V., J. Jimenez, T. Jin, and J. Espiritu. 2014. "Implementing Factory Demand Response via Onsite Renewable Energy: A Design-of-experiment Approach." *International Journal of Production Research* 1–15. doi:10.1080/00207543.2014.957877.

Schulze, M., H. Nehler, M. Ottosson, and P. Thollander. 2015. "Energy Management in Industry – A Systematic Review of Previous Findings and an Integrative Conceptual Framework." *Journal of Cleaner Production*. doi:10.1016/j.jclepro.2015.06.060.

Senechal, O., D. Trentesaux, S. Pires, E. Loures, E. Santos. 2015. "Sustainable Performance: A Paradigm Inducing New Needs of Interoperability between Maintenance and Scheduling Activities in Manufacturing." Presented at the 5th International Workshop Advances in Cleaner Production, Sao Paulo.

Strasser, T., F. Andren, J. Kathan, C. Cecati, C. Buccella, P. Siano, P. Leitao, et al. 2015. "A Review of Architectures and Concepts for Intelligence in Future Electric Energy Systems." *IEEE Transactions on Industrial Electronics* 62: 2424–2438. doi:10.1109/TIE.2014.2361486.

Tan, B., and Y. Yavuz. 2015. "Modelling and Analysis of a Business Model to Offer Energy-saving Technologies as a Service." *International Journal of Production Research* 1–18. doi:10.1080/00207543.2015.1055343.

Thomas, A., and D. Trentesaux. 2014. "Are Intelligent Manufacturing Systems Sustainable?" In *Service Orientation in Holonic and Multi-agent Manufacturing and Robotics, Studies in Computational Intelligence*, edited by T. Borangiu, D. Trentesaux, and A. Thomas, 3–14. Springer International Publishing.

Trentesaux, D., and A. Giret. 2015. "Go-green Manufacturing Holons: A step Towards Sustainable Manufacturing Operations Control." *Manufacturing Letters* 5: 29–33. doi:10.1016/j.mfglet.2015.07.003.

Trentesaux, D., V. V. Prabhu. 2013. "Introduction to Shop-floor Control." In *Wiley Encyclopedia of Operations Research and Management Science*. Wiley.

Trentesaux, D., V. Prabhu. 2014. "Sustainability in Manufacturing Operations Scheduling: Stakes, Approaches and Trends." In *Advances in Production Management Systems. Innovative and Knowledge-based Production Management in a Global-local World, IFIP Advances in Information and Communication Technology*, edited by B. Grabot, B. Vallespir, S. Gomes, A. Bouras, and D. Kiritsis, 106–113. Heidelberg: Springer.

Waldemarsson, M. 2012. "Energy and Production Planning for Process Industry Supply Chains." PhD Thesis No. 1555 LiU-TEK-LIC 2012:40, Linköping Studies in Science and Technology, Linköping.

Xu, X., S. Meteyer, N. Perry, and Y. F. Zhao. 2014. "Energy Consumption Model of Binder-jetting Additive Manufacturing Processes." *International Journal of Production Research* 1–11. doi:10.1080/00207543.2014.937013.

Zein, A., W. Li, C. Herrmann, and S. Kara. 2011. "Energy Efficiency Measures for the Design and Operation of Machine Tools: An Axiomatic Approach." In *Glocalized Solutions for Sustainability in Manufacturing*, edited by J. Hesselbach and C. Herrmann, 274–279. Berlin Heidelberg: Springer.