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Comparing Alternative Power Control Policies in a Manufacturing Line Using Simulation

Athanasios Biblias[1] and Alexandros Xanthopoulos[2]

[1]Graduate Engineer, Department of Production & Management Engineering, Democritus University of Thrace, 12 V. Sofias, 67100, Xanthi, Greece, E-mail: thanasis.biblias@gmail.com

[2]Assistant Professor, Department of Production & Management Engineering, Democritus University of Thrace, 12 V. Sofias, 67100, Xanthi, Greece, E-mail: axanthop@pme.duth.gr (corresponding author).

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Abstract: As the public becomes more aware of environmental issues, there is a growing trend amongst manufacturers in adopting eco-friendly production practices. Consumers are increasingly favoring green manufacturers, and firms are realizing that the implementation of sustainable production processes tends to become a prerequisite for success. Reducing pollution through energy conservation is a key aspect of green manufacturing. Energy – efficient production processes improve the environmental impact of manufacturing while at the same time reducing production costs. In this paper we use discrete event simulation to evaluate and compare alternative power control policies in a manufacturing line. We examine a serial line that consists of several machines in tandem that are separated by buffers. The manufacturing line produces a single part type and completed products are stored in the finished goods at the end of the line. Stochastic demand patterns are considered, and if there is available inventory at the time of a demand arrival then the demand is satisfied immediately. If there is no available inventory at that time, then the demand is backordered and served at a later time. The system operates under a kanban production control policy that coordinates the manufacturing process according to actual demand realizations. We examine four existing power control policies, namely the "always on", "upstream", "downstream", "upstream and downstream" heuristics and we propose a new power control policy. The alternative power control schemes are evaluated in a series of simulation experiments under several performance metrics and conclusions regarding their effectiveness in various settings are drawn.

Keywords: green manufacturing, production line, kanban, power control policy, simulation.

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1. Introduction

Green manufacturing is probably one of the most notable buzzwords in the field of industrial engineering and operations management nowadays. In broad terms, green manufacturing refers to the assemblage of policies, operational practices and technologies that facilitate production processes that are eco-friendly and have limited impact on natural environment. Many leading manufacturers around the globe such as Dell, HP and Honda (Stevens, 2021) are putting substantial effort into committing to sustainable production processes (Lopes et al., 2022).

The first step to "go green" is to analyze the current environmental impact of the business and to cut down on waste wherever this is possible. This is why green and lean manufacturing are often considered to be two sides of the same coin (Rathi et al., 2022; Shokri et al., 2022). Manufacturing plants typically consume enormous amounts of energy in their various production processes. That makes the adoption of renewable energy, i.e. energy originating from solar panels, wind farms, and so forth (Bhaskar et al., 2022) a straightforward way to practice green manufacturing.

However, a business can practice green manufacturing not only by selecting the energy sources accordingly but also by promoting energy efficient operations. Reducing the amount of energy that it is required to manufacture products by means of re-designing and fine-tuning the associated processes is of paramount importance (Zhou et al., 2022). Manufacturers can also strengthen their environmental profile by limiting the amount of generated pollution by means of recycling and introducing pollution reduction technologies (Hu et al., 2022; Incekara, 2022; Santoso et al., 2022). Finally, sizeable factories are frequently associated with a big environmental footprint and the former can be ameliorated by company engagement in the protection of natural areas and the conservation of natural resources.

There are several significant benefits for a business that come with the commitment to sustainability. The most obvious is public relations; as the public becomes more aware of environmental issues, consumers are increasingly favoring green manufacturers. It has also been argued that a green profile might be advantageous in the quest of a firm to recruit new and talented employees. The human capital is often considered to be a company's largest asset and the feeling that your employer gives back to society boosts morale and increases motivation.

Besides the aforementioned, and perhaps intangible advantages, green manufacturing also offers substantial and measurable benefits. The most notable is probably the reduction in production costs; e.g. installing power-efficient equipment can cut the long-term energy cost of a manufacturer. Finally, national governments typically offer significant tax benefits to businesses willing to make the green transition.

A review on various aspects of green manufacturing is given in the work of Paul et al. (2014). In the contemporary survey paper of Renna and Materi (2021), current developments in the fields of energy efficient and sustainable manufacturing systems are studied.

This paper focuses on advancing research on energy efficient production control methods. We study a transfer line that is controlled by a kanban production policy. The kanban control policy belongs to the family of pull type control mechanisms; several such control methods are examined in the context of mixed-model assembly lines and flexible flow shops in the works of Xanthopoulos and Koulouriotis (2021), Paraschos et al. (2022), and Katsios et al. (2018), respectively.

A relatively recent line of research studies on adaptive pull control policies, i.e. control schemes that adapt in response to changes in the demand pattern, production lead times, and so forth. Xanthopoulos et al. (2018) compute the optimal adaptive kanban control policy in a parallel machine system by means of Dynamic Programming. Recently, motivated by the advent of Smart Manufacturing (Xanthopoulos and Koulouriotis, 2018) and AI, Reinforcement Learning algorithms have been used to derive adaptive pull type control policies (Xanthopoulos et al., 2019).

We study the application of the Kanban production control policy together with switch-off policies for reducing energy consumption. Several relative works are cited hereafter. Pei et al., (2022) address a power control problem in a Bernouli serial line with two machines, setup and idle times. Frigerio and Matta (2016) examine the energy efficient control of a machine tool in the presence of stochastic demand and buffer information. Materi et al., (2020) propose a decision model for energy-efficient production scheduling with renewable energy supply considerations. Renna (2018) and Renna and Materi (2020) investigate switch-off policies in manufacturing flow lines using simulation.

This research primarily extends the works of Katsios et al., (2018) and Xanthopoulos and Koulouriotis (2021) by studying the synergy of pull type production control and energy-reducing control policies. We propose and evaluate a new power control heuristic.

The proposed heuristic is compared to several existing power control policies, namely the "always on", "upstream", "downstream", "upstream and downstream" approaches (Renna, 2018; Renna and Materi, 2020; Materi et al., 2020). The alternative power control schemes are evaluated in a series of simulation experiments under several performance metrics and conclusions regarding their effectiveness in various settings are drawn.

2. Methods

The system examined in this paper is a serial production line. The production line consists of a number of machines in tandem, with Work-In-Process buffers in between and a finished goods buffer at the end of the line (refer to Fig. 1).

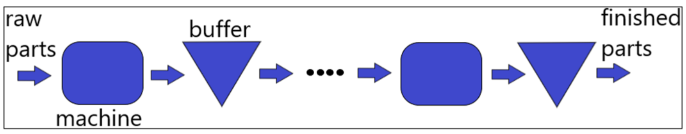

Fig. 1. Schematic representation of a serial manufacturing line with work-in-process and finished goods buffers

The system produces one type of finished products. In order to complete a product, raw parts must be processed by all machines sequentially, i.e. the production operations sequence is the same for all finished products.

Demands for finished goods arrive at the system at random time intervals and each demand requests for a single completed product. A demand is satisfied at the time of its arrival if there is available stock, otherwise the fulfillment of the demand is pending until a completed product is made available; it follows that no demand is eventually lost in the production system.

The machines have the ability to process only one part at a time and once a part starts being processed, the process cannot be stopped. Once the machine has finished processing a workpiece, it sends it to the downstream buffer and, subsequently, to the next machine. The processing times of all machines are considered to be random variables. The parts move along the production line by means of conveyors and the transit times of all conveyors are assumed deterministic and known.

The supply of raw parts is considered to have the ability to provide infinite workpieces and the times between raw material deliveries are thought to be random. If a machine finishes processing a part, but the downstream buffer is full, then the machine is blocked. A machine starves if it is authorized to produce but does not have parts to work on.

The buffers located in between the machines contribute in smoothing the flow of materials across the production line and synchronizing the various production operations. Each time a part exits a machine after its processing has been completed, it is stored in the downstream buffer until the next machine becomes available to receive the part for processing. The last buffer is the finished goods stock since it holds completed products.

The machines and the material handling equipment in the production line consume energy when they are operational, i.e. when they are working on some part or when they are idling.

2.1. Kanban Production Control Policy

Currently, one of the most powerful tools for achieving lean production is the pull type control paradigm and the kanban type control policies that implement it (Xanthopoulos and Koulouriotis, 2021). According to pull type control, production and order decisions are based on actual demand occurrences, i.e. the items that have actually left the stock. Nowadays, pull control is powered by IT solutions such as real-time inventory tracking with RFID and web-based logistics software.

The manufacturing line examined in this research operates under a kanban production control policy (refer to Fig. 2). The material flow in the production system is coordinated with the use of kanban cards. A kanban card can either be a physical one or a digital entity in an information system. Each step in the production process, i.e. some machine coupled with the adjacent downstream buffer, will be called stage hereafter. Each stage has a number of kanban cards. The number of cards is the target inventory level for that production stage. Each product that flows within stage *i* has a stage-*i* card associated to it.

At the arrival of a demand for a stage–*i* product, an item is released from the corresponding buffer (if it is not empty) and the associated stage–*i* kanban card is sent upstream to authorize the production of a new stage–*i* product (provided that the inventory level in the aforementioned buffer is less than some pre-defined reorder point).

Demand arrival information is propagated accurately along the production line with the flow of kanban cards. Inventory levels in each stage can never exceed the predefined targets because each item is associated to a kanban card. No production orders are issued if the inventory has not been consumed first and this prevents bottlenecks. The coordination of production operations is simplified because relevant decisions are local.

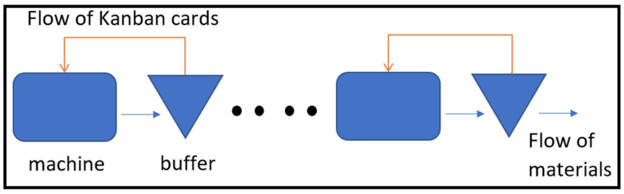

Fig. 2. Schematic representation of a serial manufacturing line with Kanban production control

2.2. Power Control Policies

Limiting the power consumption during the machine idle periods can provide energy savings (Renna, 2018). Several heuristic strategies for switching-off machines according to the current Work-In-Process inventories have been proposed in the literature. In this paper we examine the “always on”, “upstream”, “downstream”, and “upstream and downstream” heuristics.

According to the “always on” strategy, as it is implied by its name, the machines are constantly up and running and they are never switched-off. Clearly, this strategy is useful as a benchmark in order to compare the alternative power control policies.

Fig. 3 shows the logic of the “upstream” power control policy (Frigerio and Matta, 2016; Renna, 2018). Decisions to switch on or off machines are made locally for each production stage. For each stage there is a control parameter T pertaining to the current level of the upstream buffer. The idea here is that there is no point keeping the machine up and running if no parts are available to work on. The machine is switched on again at the time when the inventory level of the upstream buffer exceeds the threshold T.

Fig. 4 shows the logic of the “downstream” power control policy (Frigerio and Matta, 2016; Renna, 2018). Again, decisions to switch on or off machines are made locally for each production stage. Each stage has two control parameters L and U that are related to the current level of the downstream buffer. The rationale of this strategy is to switch off the machine (in order to preserve energy) if there is enough inventory (i.e. more than U parts) in the downstream buffer to serve the next production process. The machine is switched on again at the time when the inventory level of the downstream buffer drops below the threshold L.

The “upstream and downstream” strategy is a combination of the “upstream” and “downstream” control policies. As such, decisions to switch on or off some machine are based on its current state as well as on the state of the downstream and upstream buffers. This heuristic is of increased complexity, compared to the two previously described, because it entails three control parameters per production stage. The reader is referred to Renna (2018) for additional details on this switch-off policy.

A potential shortcoming of the existing switch-off policies is that they require considerable fine-tuning regarding the selection of their control parameters. Moreover, the fixed thresholds T, L, U do not take into consideration possible perturbations in the demand arrival and the production process. In this paper we propose a new power control heuristic differing from the ones presented above in two major points.

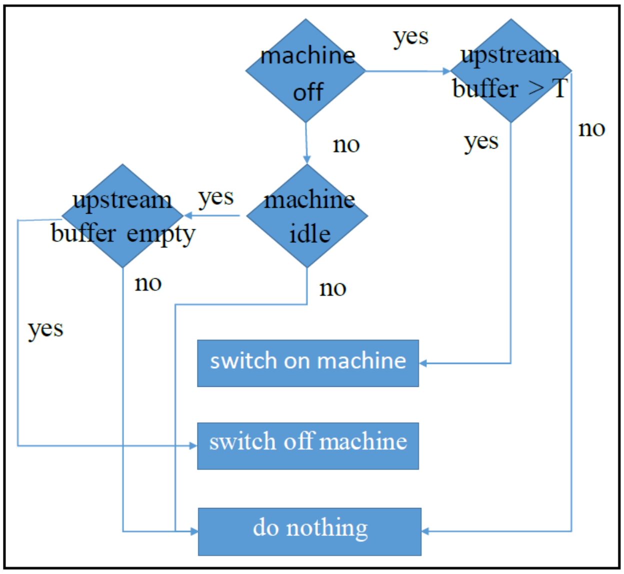

Fig. 3. Control logic of the "upstream" power control policy

The first one is that it switches off and on the entire production line as a whole and the second one is that it takes into account advance demand information (ADI) in the form of forecasts or estimates of the demand for end items. Clearly, this has the potential for successful application in settings where the demand pattern is stationary, or seasonal or predictable in general. For example, using historical data, we can obtain predictions for the aggregate demand over a period of time. The production line can produce continuously in order to cover the demand (in a single batch). After covering the required demand, it continues producing parts until the end of the day and then it switches off in order to preserve energy. It remains switched off while the condition that the number of produced parts is equal to or greater than the given demand is not satisfied. Once the condition is satisfied, it switches on again for another production run.

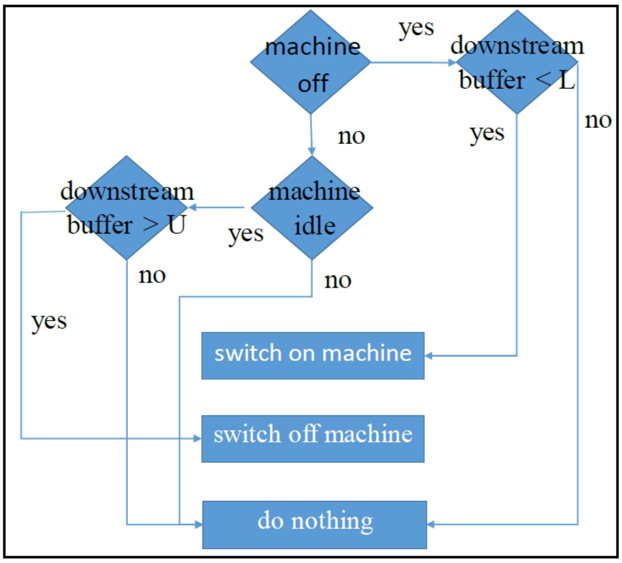

Fig. 4. Control logic of the "downstream" power control policy

2.3. Discrete Event Simulation

Discrete-event simulation (DES) was used to model and evaluate the various control schemes described in section 2. The simulators were implemented in the Plant Simulation software and utilized the provided library of basic objects as well as the programming language SimTalk (refer to Fig. 5). All simulation experiments were executed on a personal computer with 64-bit operating system, 4 GB RAM and 3.4 GHz CPU.

The implemented simulators follow the process-oriented approach of DES. Typically, a process-oriented simulator includes elements such as entities, arrival processes, resources, delays, queues and so forth. In our case, the entities clearly represent Work-In-Process and completed products as well as demands.

Resources are seized by entities as they flow into the model and provide some form of service to them. For example, in our production line models, a resource may be a conveyor. The conveyor belt is seized by the materials (entities) that are loaded on it and provides the task of transporting the materials from one point to another. The entities seize the necessary resources in every step of their "route" within the system and in this way they advance from one stage of their processing to the next until they are completed.

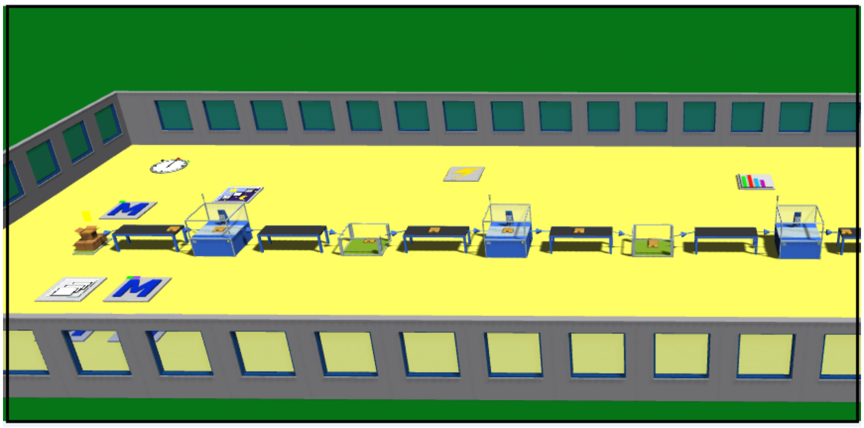

Fig. 5. An indicative view of the production line simulation model

The times required for resources to be seized in order to complete the work provided to the entities are called delays. It is important not to confuse delays with the total flow times of entities within the system. More specifically, when we refer to a delay we do not include in it the queue waiting times.

In a simulation model following the process-oriented approach there can be many types of entities as well as many types of queues. Similar entities enter specific queues that correspond to them, e.g. pending order queues, customer waiting queues and so on. Queues are created because system resources are finite.

Queue discipline describes the order in which the "customers" included in it are served. In the implemented simulators all queues follow the First-Come-First-Served rule.

The simulation of the examined system is achieved through the creation of a series of arrivals of entities and the realization of the associated procedures or equivalently through the implementation of the "flow" of each entity through the system.

3. Results

The parameters of the simulation models are summarized in Table 1. The times between demand arrivals and raw material deliveries, as well as the processing times are assumed to be exponentially distributed.

Table 1. Nomenclature

Parameter	Symbol
Mean time between demand arrivals	a
Mean time between raw material deliveries	r
Mean processing time of machine i	p_i
Speed of conveyor j	t_j
Capacity of conveyor j	c_j
Max inventory (capacity) of buffer k	$b_{k,max}$
Min inventory (reorder point) of buffer k	$b_{k,min}$
Power consumption (in operational state) of machine i	$e_{i,mach}$
Power consumption (in operational state) of conveyor j	$e_{j,con}$
Total throughput	T_t
Throughput per day	T_d
Total energy consumption	E_t
Energy consumption per finished product	E_p

The capacity of a conveyor is the maximum number of parts that can travel on that conveyor at the same time. The speed of some conveyor gives the time needed by a part to traverse it. The maximum inventory of a buffer equals the number of kanban cards for that production stage. The minimum inventory of some buffer refers to the reorder point for that stage. The machines and the conveyors in the system consume power when they are operational, i.e. when they are processing parts or when they are idling. The total throughput and the total energy consumption refer to the duration of the entire simulation. The blocking time of some machine refers to the interval where it could not process additional parts because the downstream buffer was full.

As already mentioned there are three parameters to set for the switch off policies. The first control parameter T relates to the current level of the upstream buffer and its value is set to 1 as a threshold. The other two control parameters L and U

relate to the current level of the downstream buffer. In order to avoid machine deadlock the following condition has to be verified:

$$L > U \geq 0 \tag{1}$$

otherwise the switch-on control will never be issued (Frigerio and Matta, 2016; Renna, 2018).

For the purposes of this research we examined four simulation cases with 3 machines where the simulation duration for each case was set to 116 working days and the assumption was made that the plant works seven days per week and each day has one 8-hour shift. For each case and alternative control policy we executed five independent replications. The parameters for the four simulation cases are given in Table 2.

Table 2. Parameters of simulation cases

Parameters	Case 1	Case 2	Case 3	Case 4
a	1 min	1 min	30 sec	1 min 30 sec
r	1 min	1 min	1 min	1 min
p_i	1 min, for all i	1 min, for all i	1 min, for all i	1 min, for all i
t_j	0.12 m/s, for all j	0.12 m/s, for all j	0.12 m/s, for all j	0.12 m/s, for all j
c_j	1 part, for all j	10 parts, for all j	1 part, for all j	1 part, for all j
$b_{k,max}$	5,10,15, for k=1,2,3	5,10,15, for k=1,2,3	5,10,15, for k=1,2,3	5,10,15, for k=1,2,3
$b_{k,min}$	3,5,8, for k=1,2,3	3,5,8, for k=1,2,3	3,5,8, for k=1,2,3	3,5,8, for k=1,2,3
$e_{i,mach}$	12 kW, for all i	12 kW, for all i	12 kW, for all i	12 kW, for all i
$e_{j,con}$	1 kW, for all j	1 kW, for all j	1 kW, for all j	1 kW, for all j

Case 1 is the base case and case 2 pertains to a situation where the capacity of all conveyors is increased and all other system parameters are kept fixed. In the third case all parameters are kept fixed (in relation to the first case) with the exception of the mean time between arrivals (in this case we consider increased frequency of demand arrivals). Finally, the fourth case examines a situation with lower demand arrival rate (a = 1 min and 30 sec).

4. Discussion

Fig. 6 and Fig. 7 show the total system throughput and the throughput per day for every control policy and simulation case. For the first, third and fourth scenario the proposed heuristic results in the lowest throughput levels (12560, 12773 and 12552 parts in total, respectively) and the remaining policies are tied.

In the second simulation case the "downstream" and the "upstream & downstream" policies achieve the best performance in terms of throughput (12837 and 12829 parts in total, respectively).

Fig. 8 and Fig. 9 present the total energy consumption and the energy consumption per produced part, respectively, for all control policies and simulation cases. As expected, the "always on" control scheme exhibits the worst performance in terms of minimizing energy expenditure.

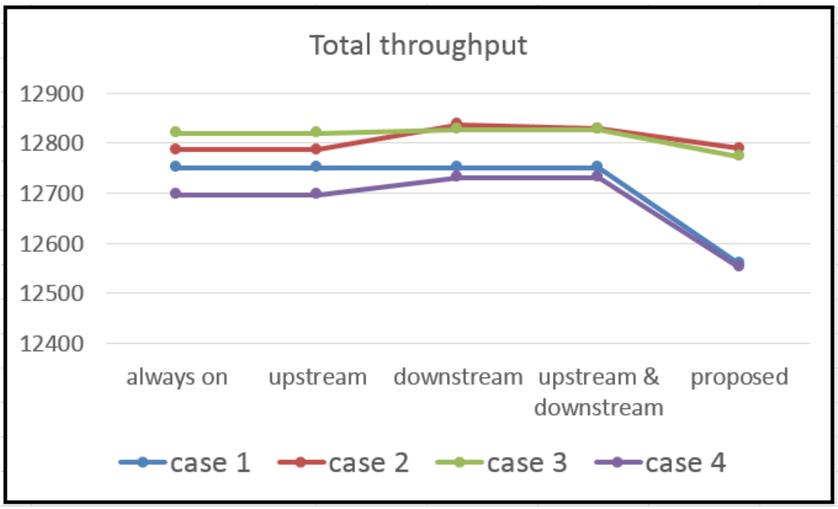

Fig. 6. Total throughput for all power control policies and all simulation cases

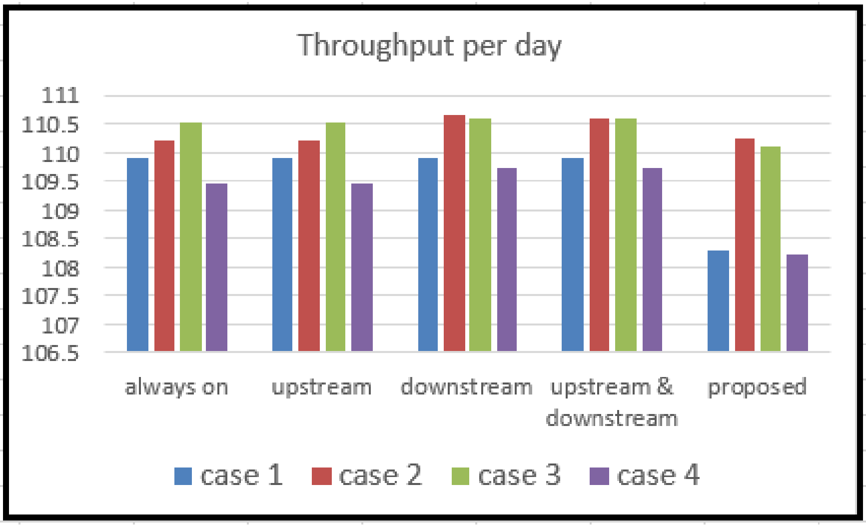

Fig. 7. Throughput per day for all power control policies and all simulation cases

Despite its intuitive approach the "upstream" heuristic is found to perform rather poorly regarding this metric. The proposed technique outperforms all other alternatives in terms of total power consumption (13765, 12347, 11556 and 14947 kWh in cases 1 to 4) and power consumption per finished good (1.09, 0.96, 0.9 and 1.19 kWh/part in cases 1-4). However, as previously seen, this often comes at the expense of a reduced system throughput.

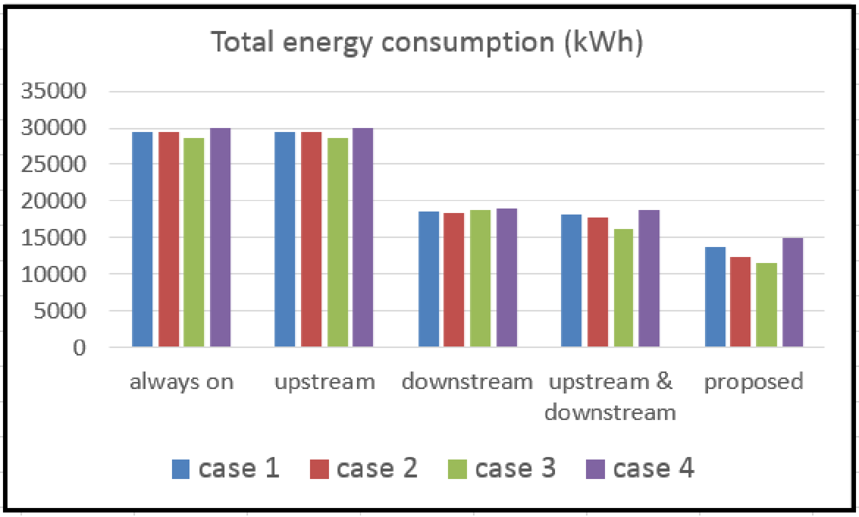

Fig. 8. Total energy consumption for all power control policies and all simulation cases

The "downstream" and the "upstream & downstream" approaches also perform well when the power consumption metrics are considered (see Figs. 8 and 9). Since these two heuristic policies also excel in respect to maximizing system throughput it can be argued that they are the most "well rounded" solutions in this series experiments.

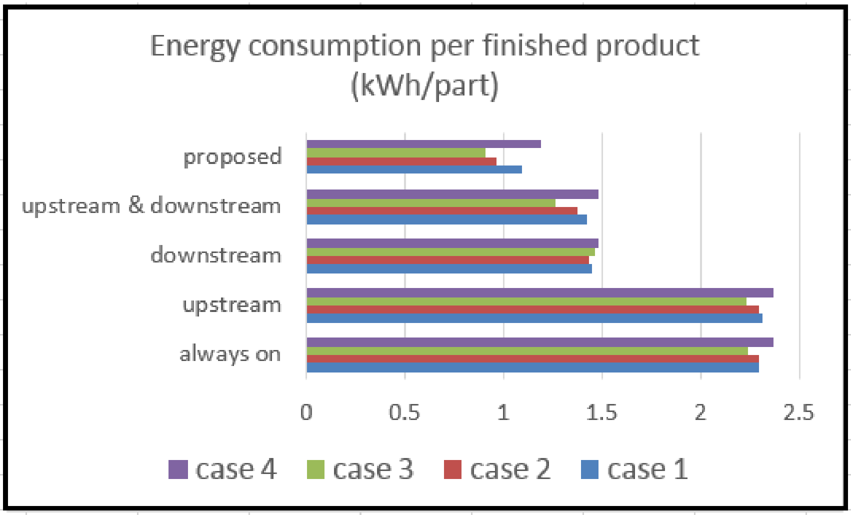

Fig. 9. Energy consumption per finished product for all power control policies and all simulation cases

5. Conclusions

The continuously rising electricity costs and the growing public awareness for sustainable operations call for the adoption of energy saving production practices. In a production line, energy can be preserved by switching off equipment when they are idling. Nonetheless, there is a trade-off between minimizing energy consumption and maximizing the throughput of a manufacturing plant. Efficient power control policies can be useful in balancing this trade-off effectively.

In this paper we examined the performance of several alternative power control policies in manufacturing lines using simulation. The "always on" and the "upstream" approaches performed poorly in terms of saving energy. The proposed policy exceled in conserving energy, nonetheless this was often at the expense of reduced throughput. The "downstream" and the "upstream & downstream" heuristics were shown to be the most balanced alternatives in this experimental trial.

Some possible directions for expanding this research are cited hereafter. It would be interesting to develop adaptive power control policies that take into account the dynamic pricing of energy. The implementation of a machine learning tool that could predict the variations of demand and pricing in the power grid would be also of interest.

Finally, the adoption of AI techniques for deriving intelligent power control mechanisms based on the current system state would be of great value. The various switch-off polices examined in this paper, including the proposed one, are heuristics and, as such, they might perform well but they do not come with optimality guarantees. By using learning algorithms, we can train intelligent agents to derive optimal power control policies, i.e. to switch off and on production equipment optimally for each possible system state.

Author Contributions

Biblias contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, and visualization. Alexandros Xanthopoulos contributes to conceptualization, methodology, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

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Athanasios Bimplias received the Master degree in Production & Management Engineering from the Democritus University of Thrace, Greece. His thesis focused on the comparative evaluation of energy saving policies in simulated production lines. He has work experience as Productivity Consultant with Bedor EXCEM, Greece. Currently, he is Construction Site Manager with Artemis GMBH, Germany.

Alexandros Xanthopoulos holds a PhD in Production and Management Engineering from the Democritus University of Thrace, Greece. He was a recipient of a two-year post-doctoral scholarship from the State Scholarships Foundation (IKY). Currently, he is Assistant Professor and Head of the Logistics Lab with the Production and Management Engineering Department of the Democritus University of Thrace. In addition, he is an Adjunct Lecturer at the postgraduate program Supply Chain Management of the Hellenic Open University. He has authored 2 books and over 30 journal papers, book chapters and conference papers. He has worked in several funded projects as principal investigator or team member.