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Energy Efficient Policies, Scheduling, and Design for Sustainable Manufacturing Systems

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Ciclo XXXIV

Preface

The present thesis is the summary of the work performed during my Ph.D. program in "Engineering for Innovation and Sustainable Development" carried out at the School of Engineering of the University of Basilicata. The dissertation is based on the following publications:

- Renna, P., & Materi, S. (2021b). A Literature Review of Energy Efficiency and Sustainability in Manufacturing Systems. *Applied Sciences*, *11*(16), 7366. https://doi.org/10.3390/app11167366 (Chapter 1)
- Materi, S., D'Angola, A., & Renna, P. (2020). A dynamic decision model for energy-efficient scheduling of manufacturing system with renewable energy supply. *Journal of Cleaner Production*, *270*, 122028. https://doi.org/10.1016/j.jclepro.2020.122028 (Chapter 2)
- Materi, S., D'Angola, A., Enescu, D., & Renna, P. (2021). Reducing energy costs and CO_2 emissions by production system energy flexibility through the integration of renewable energy. *Production Engineering, 15,* 667-681. https://doi.org/10.1007/s11740-021-01051-5 (Chapter 2)
- Renna, P., & Materi, S. (2021a). Switch off policies in job-shop manufacturing systems including workload evaluation. *International Journal of Management Science and Engineering Management*. https://doi.org/10.1080/17509653.2021.1941369 (Chapter 3)
- Carlucci, D., Renna, P., Materi, S. (2021). A job-shop scheduling decision making model for sustainable production planning with power constraint. *IEEE Transactions on Engineering Management*. In Press. https://doi.org/10.1109/TEM.2021.3103108 (Chapter 4)
- Renna, P., & Materi, S. (2020). Design model of flow lines to include switch-off policies reducing energy consumption. *Applied Sciences*, *10*(4), 1475. https://doi.org/10.3390/app10041475 (Chapter 5)

The following article is not included in this thesis:

- Carlucci, D., Renna, P., Materi, S., & Schiuma, G. (2020). Intelligent decision-making model based on minority game for resource allocation in cloud manufacturing. *Management Decision*, *58*(11), 2305–2325. https://doi.org/10.1108/MD-09-2019-1303

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Abstract

Climate mitigation, more stringent regulations, rising energy costs, and sustainable manufacturing are pushing researchers to focus on energy efficiency, energy flexibility, and implementation of renewable energy sources in manufacturing systems. This thesis aims to analyze the main works proposed regarding these hot topics, and to fill the gaps in the literature. First, a detailed literature review is proposed. Works regarding energy efficiency in different manufacturing levels, in the assembly line, energy saving policies, and the implementation of renewable energy sources are analyzed. Then, trying to fill the gaps in the literature, different topics are analyzed more in depth. In the single machine context, a mathematical model aiming to align the manufacturing power required to a renewable energy supply in order to obtain the maximum profit is developed. The model is applied to a single work center powered by the electric grid and by a photovoltaic system; afterwards, energy storage is also added to the power system.

Analyzing the job shop context, switch off policies implementing workload approach and scheduling considering variable speed of the machines and power constraints are proposed. The direct and indirect workloads of the machines are considered to support the switch on/off decisions. A simulation model is developed to test the proposed policies compared to others presented in the literature. Regarding the job shop scheduling, a fixed and variable power constraints are considered, assuming the minimization of the makespan as the objective function.

Studying the factory level, a mathematical model to design a flow line considering the possibility of using switch-off policies is developed. The design model for production lines includes a targeted imbalance among the workstations to allow for defined idle time.

Finally, the main findings, results, and the future directions and challenges are presented.

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Introduction

The Paris Agreement is an international treaty on climate change and has been adopted by 196 Parties in the twenty-first session of the Conference of the Parties (UNFCCC, 2015). It has defined a limit to the increment in the global average temperature of 2°C compared to pre-industrial levels and the Parties makes efforts to contain the temperature increase to 1.5°C respect the same benchmark. In the last five years, as reported in (IRENA, 2019b), energy-related CO_2 emissions have risen by 1.3% per year. Fossil fuels impact around two-thirds of global greenhouse gas emissions and the increment of their use in emerging economies is affecting air quality, and then human health, together with climate changes (IEA, 2020). It's important that all economic sectors meet zero CO_2 emissions at the beginning of the second half of this century in order to limit the increase of the global average temperature to 1.5°C (IRENA, 2020). Climate change has several effects on environmental, human, and economic aspects; it impacts sea level rise, agriculture, human health, ecosystems, drought and flooding, weather conditions and so on (Watkiss et al., 2005). Europe, following the path of sustainability and climate change mitigation through the "20-20-20" targets, defined the goals for 2030 (Tsemekidi Tzeiranaki et al., 2020): reduction of 40% of greenhouse gas emissions with respect to 1990 values; minimum 32% of renewable energy consumption; increment of energy saving at least of 32.5%. About 24% and 5% of the global greenhouse gas emissions are related respectively to industrial energy consumption and to industrial processes (Ritchie & Roser, 2020), as in Figure I.1.

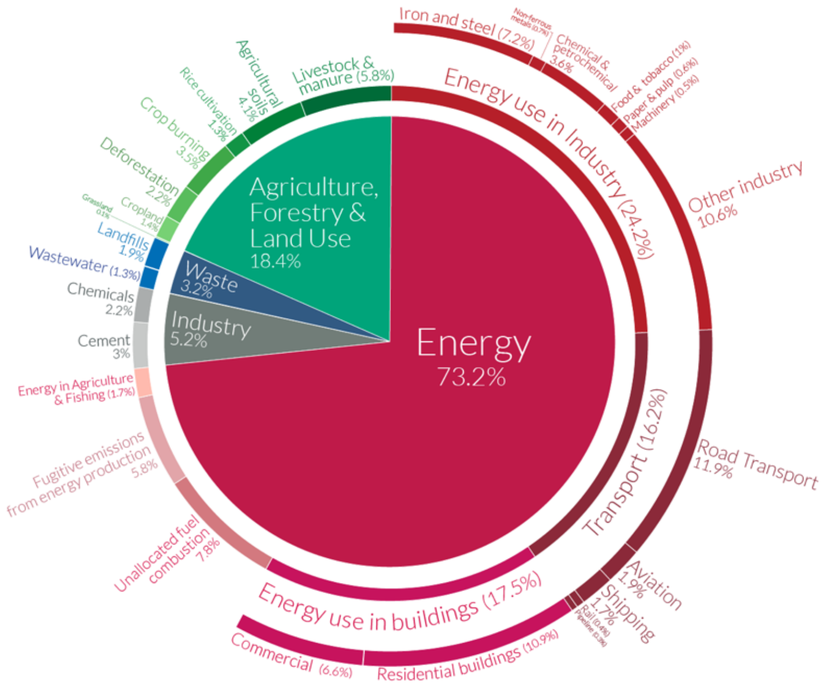

Figure I.1 Global greenhouse gas emissions by sector (Ritchie & Roser, 2020)

Energy efficiency and renewable energy sources could provide more than 80% of the emission savings required (IRENA, 2020). Improving energy efficiency and the implementation of renewable energy supplies could give also economic benefits. Indeed, the electricity price without taxes for non-household consumers varied similarly to the inflation trend till 2012, and after presented a decrement (Eurostat, 2020a). However, as discussed, the persistent increment in taxes has led to a growth in the electricity total price (evaluated in the second half of 2020) of 29.5% compared to the inflation-adjusted price of the first semester of 2008. The transition to a decarbonized global energy system will involve huge investments in energy efficiency, renewable energy sources and enabling infrastructure (IRENA, 2019b).

As reported in (Eurostat, 2020b) the renewable energy sharing has been more than doubled between 2004 and 2019, and this growth is expected to continue.

Indeed, only in 2020, the increment of renewable power generation capacity, defined as the maximum net generating capacity of power obtained with renewable energy sources to generate electricity, has been of about 10.3% respect the previous year (IRENA, 2021a). Solar and wind energy are driving the growth of renewable energy sources, covering about 91% of all net renewable additions. The power capacity trend of the main renewable energy sources from 2011 till 2020 has been reported in the following figure (Figure I.2) and it can be noticed the high increment of solar and wind sources.

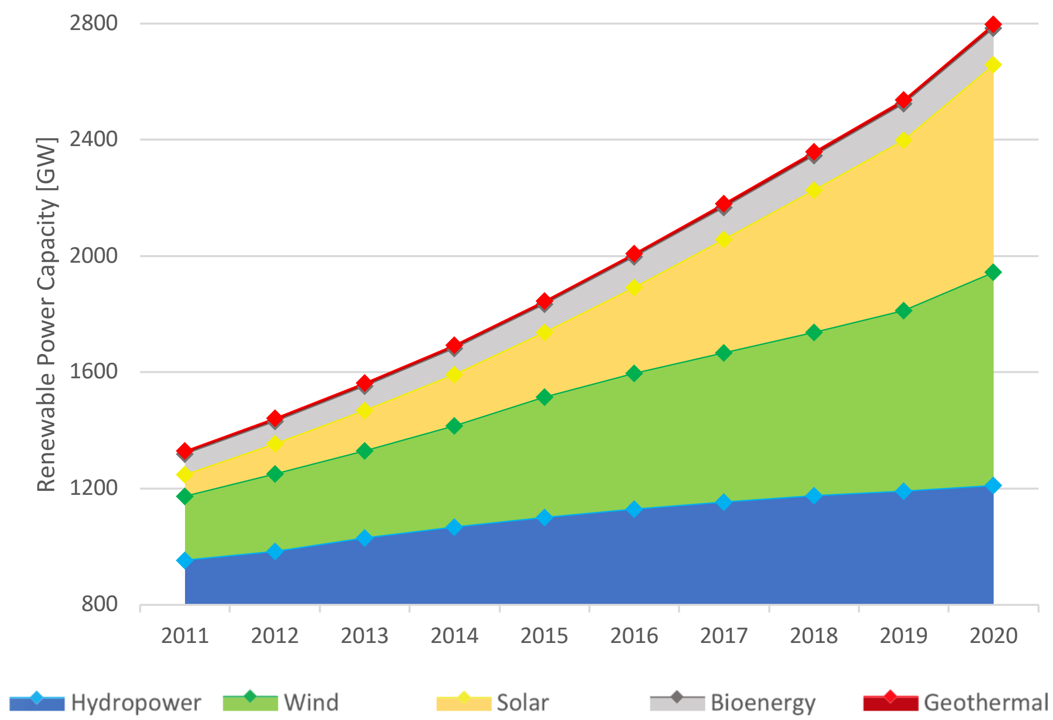

Figure I.2 Capacity power of the main renewable energy sources from 2011 till 2020 (data taken from (IRENA, 2021b))

The continuous expansion of renewable sources is also due to their lowing costs. For example, the total photovoltaic installed cost decreased between 66% and 84% during 2010-2018 (IRENA, 2019a). Furthermore, the energy transition impacts the socio-economic system. IRENA (2019b) called REmap case the scenario in which the temperature increase limit defined in the Paris Agreement is respected through renewable energy sources and energy efficiency. As argued, the REmap case could improve Gross Domestic Product and whole-economy employment, respectively they will be incremented relatively about of 2.5% and 0.2% by 2050.

Energy efficiency is defined as "the ratio of output of performance, service, goods or energy, to input of energy" (Directive 2012/27/EU, 2012). Energy flexibility is indicated as "[…] the ability of a production system to adapt itself fast and without remarkable costs to changes in energy markets." (Graßl et al., 2014). Energy flexibility is very important in order to implement renewable energy sources in manufacturing. Indeed, many renewable power systems are time-variable sources unlike traditional ones. As reported in (IRENA, 2018), a power system is defined as flexible if can in an economic and reliable way meet the peak load, avoid the load losses, balance supply and demand, have adequate storage, adjust the demand following needs, mitigate destabilizing events and operate with market efficiency. The flexibility enables optimal implementation of variable renewable energy supplies by enhancing their use. Synergies between energy flexibility and renewable energy sources have been discussed in (IRENA, 2017). The higher energy efficiency, the lower the overall energy demand, and then the higher sharing of renewable in the energy mix. Manufacturing firms could achieve sustainable production with energy efficiency, energy flexibility and renewable energy sources gaining also benefit in terms of costs and green reputation.

Manufacturing is defined as “The entirety of interrelated economic, technological, and organizational measures directly connected with the processing/machining of materials, i.e., all functions and activities directly contributing to the making of goods.” (Segreto & Teti, 2019). As argued by Segreto and Teti, in manufacturing physical and chemical processes are used to change shape, size, properties and characteristics in order to realize a part or several parts, that will be assembled, of a final product. Machines, robots, material-handling equipment, energy, workers and several tools are necessary to complete the manufacturing process. Manufacturing plays a role key in the global economy. As reported in (Eurostat, 2021b), about the 8.8% of non-financial business economy in the EU-27 are classified to manufacturing. The importance of manufacturing is demonstrated by its contribution to employment (Figure I.3), about 22.8%, and to non-financial business economy value added, about 29.3%, compared to the other NACE (European Classification of Economic Activities) sections in EU-27’s non-financial business economy (Eurostat, 2021b).

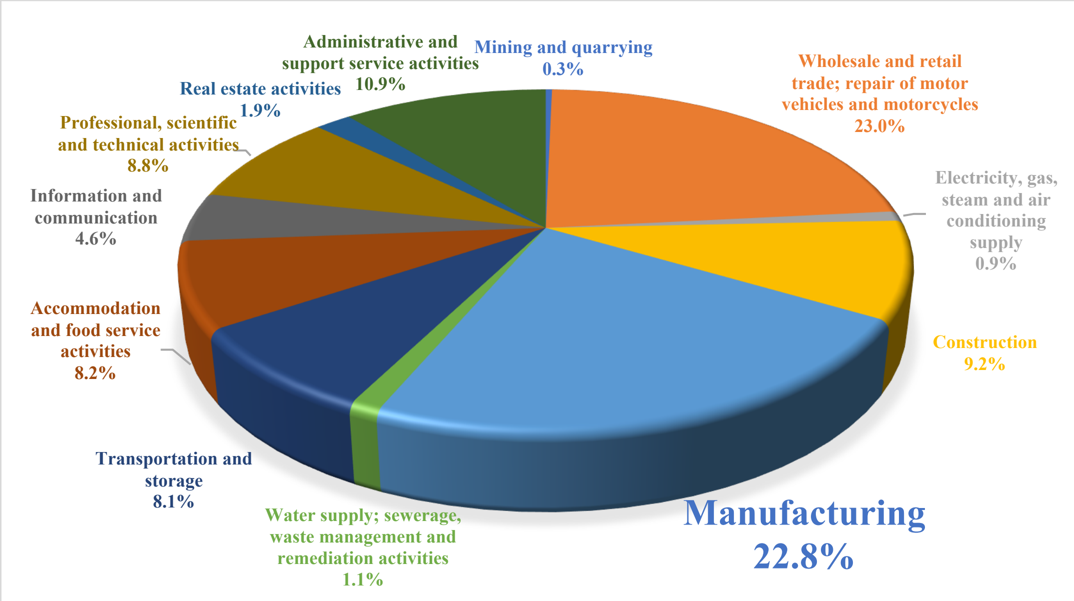

Figure I.3 Persons employed in EU-27 grouped by NACE sections in 2017 (data taken from (Eurostat, 2021a)

The importance of the manufacturing activities and the actual challenges to pursue green production have attracted the focus of researchers. Nowadays, indeed, energy efficiency and sustainability in manufacturing is a hot topic; scholars have provided several studies and have explored the wide ranges of manufacturing system typologies. This thesis aims to investigate the main works proposed in literature regarding energy efficiency, flexibility and the use of renewable energy sources in manufacturing systems and to cover the topics that have been insufficiently investigated. The dissertation is organized as follows.

Chapter 1 presents the literature review and extends the motivations of this study presenting the proposed research questions.

Chapter 2 analyzes the implementation of a renewable energy source in a single machine context.

New switch-off policies based on workload are provided and compared to others present in the literature in Chapter 3.

A scheduling model of a job shop system with power constraint is studied and developed in Chapter 4.

Chapter 5 provides a design model of a flow line that takes into account the switch-off policies.

Finally, the conclusions and future works are presented and discussed.

Chapter 1: Research background and motivations

1.1 Literature review

The number of articles regarding energy efficiency and sustainability in manufacturing systems analyzed in each year from 2007 until August 2021 has been reported in the following figure (Figure 1.1). The literature analysis has been conducted considering "Web of Sciences", "ScienceDirect" and "Google Scholar" databases; the main keywords used are "energy consumption", "energy-efficient", "energy-saving", "energy efficiency", "energy cost", "energy optimization", "sustainable", "renewable" in combination with "manufacturing", "manufacturing system". To deepen the state of the art, the previous keywords were used along with others related to the characteristics of the manufacturing system, for example "job-shop", "flow-shop", "single-machine", etc... It can be noticed that the number of papers has grown considerably in recent years.

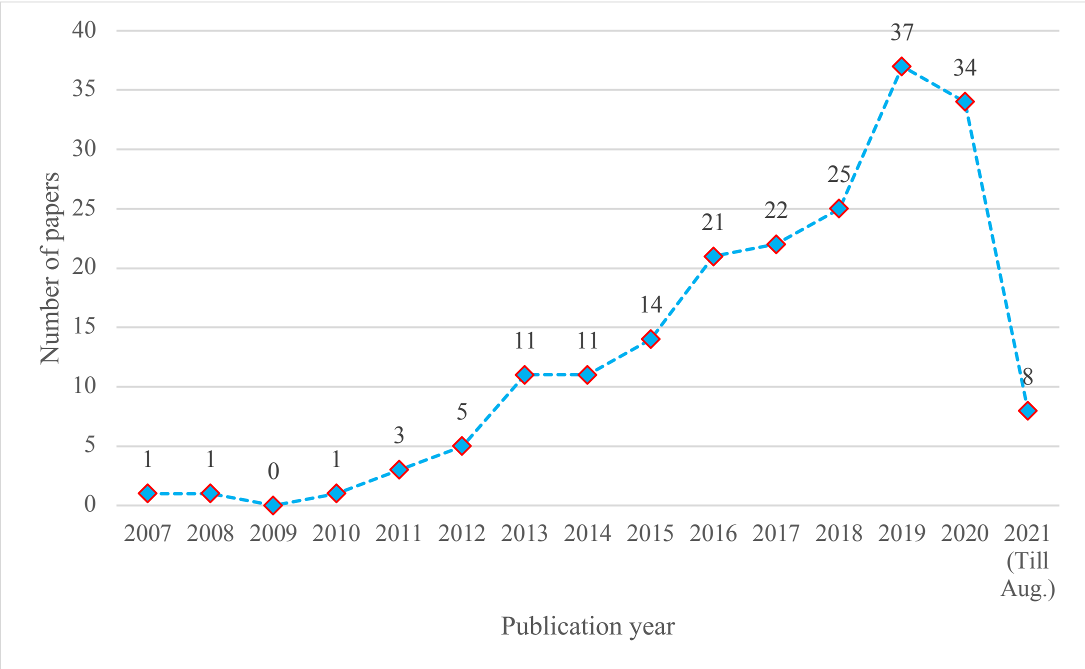

Figure 1.1 Publication year/number of articles graph

Figure 1.2 reports the eight journals in which are published the greatest number of papers analyzed. In "CASE" are grouped the articles presented in several years of the "International Conference on Automation Science and Engineering (CASE)". The other journals or proceedings present less than six articles for each of them.

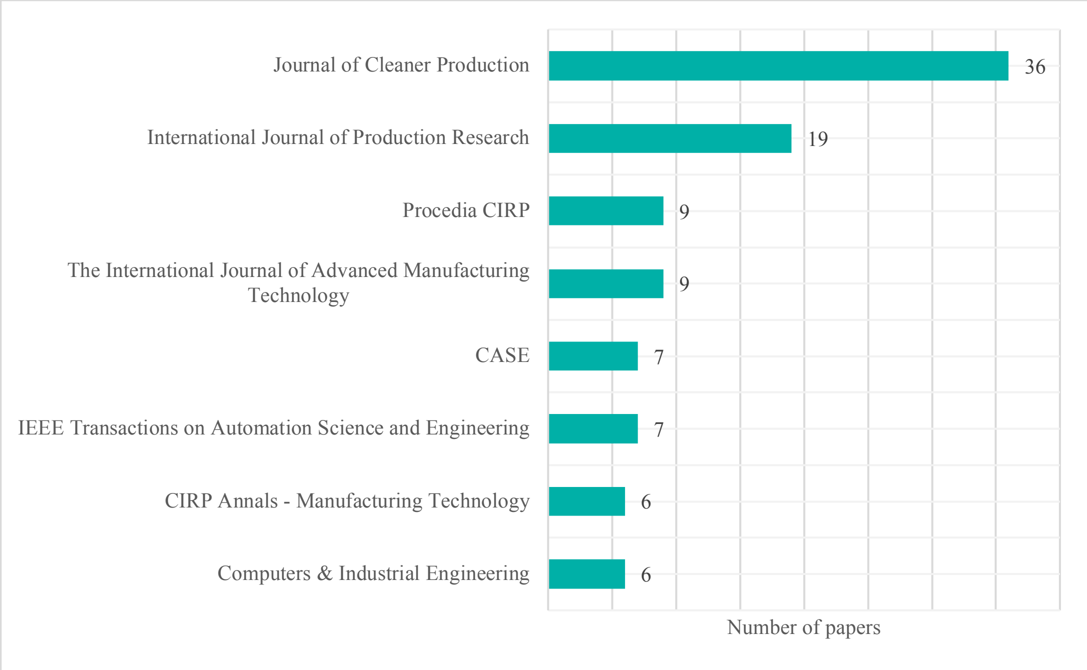

Figure 1.2 Journal/number of articles graph

The percentage of papers for each publisher has been reported in Figure 1.3; in the graph "other" groups the publishers with one article each.

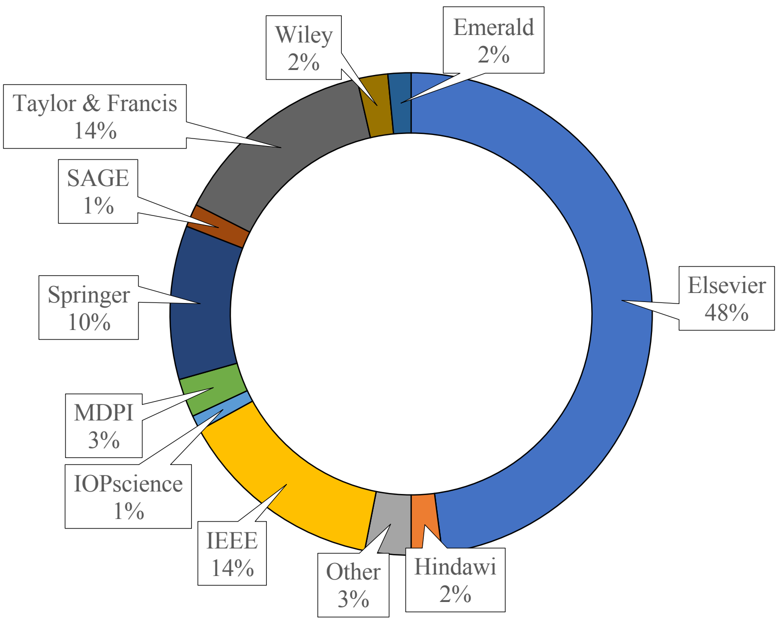

Figure 1.3 Percentage of papers in each publisher

A general overview of the different sections of the literature review has been reported in Figure 1.4.

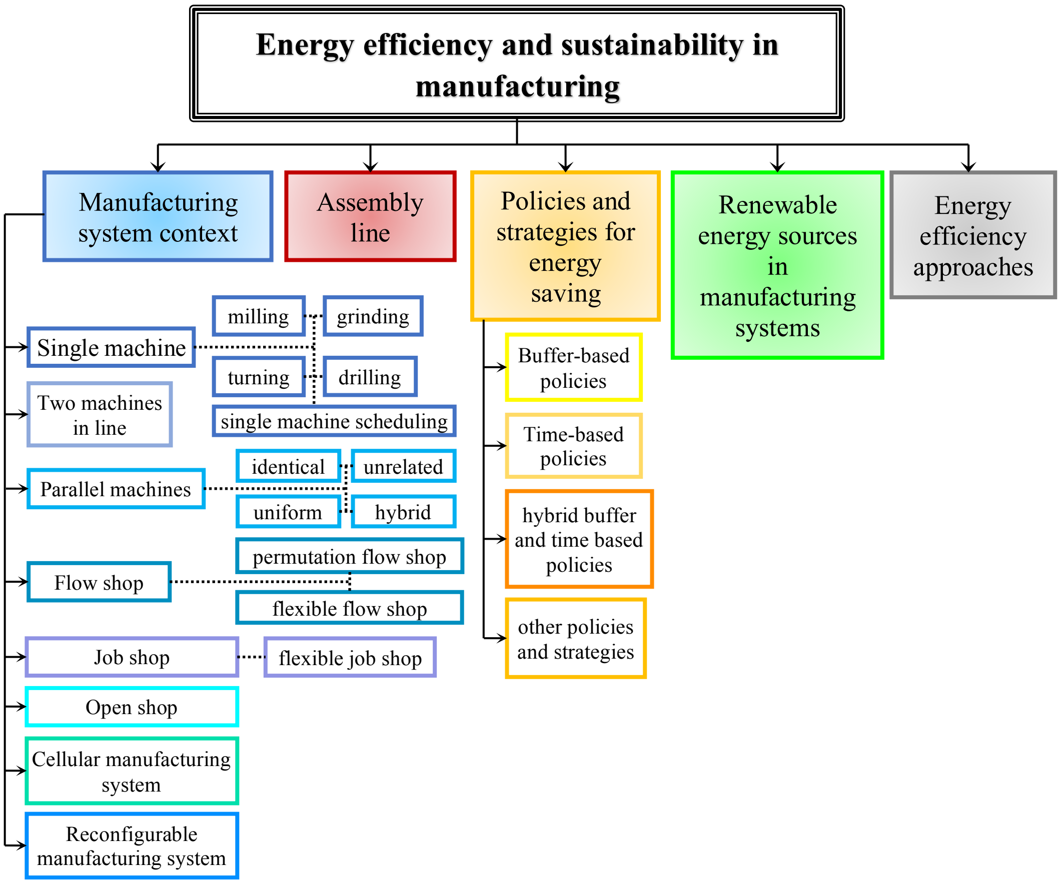

Figure 1.4 Literature analysis overview

The papers analyzed have been classified into four main groups, each of them can be split into other classes and subclasses.

The four main groups are:

- Manufacturing system context;
- Assembly line;
- Policies and strategies for energy saving;
- Renewable energy sources in manufacturing systems.

The first and the second group collect the papers regarding energy efficiency respectively in the manufacturing system and assembly line context. The first of them is also divided into subclasses considering the type of manufacturing system analyzed. The policies and strategies for energy saving group is considered apart from the previous ones as the results achieved concern several typologies of manufacturing system and could be extended to different contexts. For the same reason, the application of renewable energy sources in manufacturing is considered as a separate section. A separate paragraph (1.1.5) tries to sort the approaches used in the previous groups into different classes and discussed the several techniques, how they are widespread, and their use in the literature.

Figure 1.5 shows the number of articles included in each main class and subclasses analyzed.

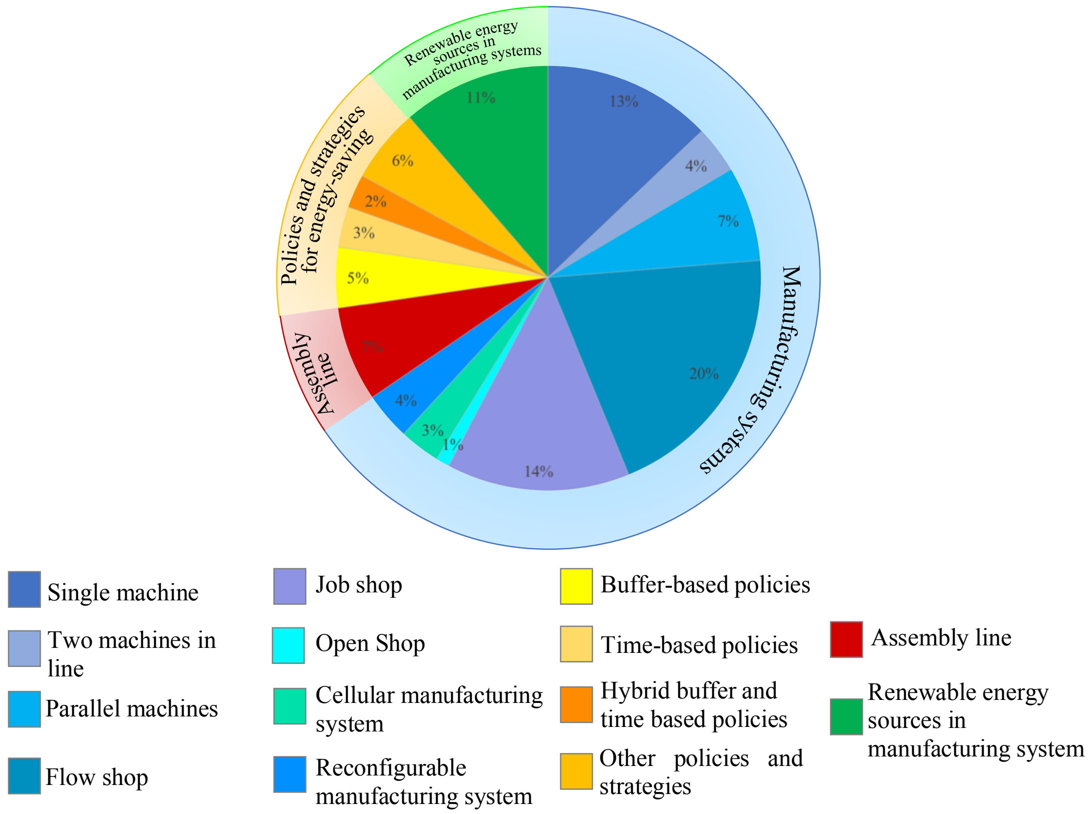

Figure 1.5 Percentage of papers in each class

1.1.1 Manufacturing system context

In the following section, the main studies focusing on energy efficiency and on the reduction of energy consumption in manufacturing systems are analyzed.

The section is composed of the following subsections based on the manufacturing level in which the energy-saving actions have been applied or on the characteristic of the manufacturing system:

1.1.1.1 Single machine
1.1.1.2 Two machines in line
1.1.1.3 Parallel machines
1.1.1.4 Flow shop
1.1.1.5 Job shop
1.1.1.6 Open shop
1.1.1.7 Cellular manufacturing system
1.1.1.8 Reconfigurable manufacturing system

A brief presentation of other process types is discussed in subsection 1.1.1.9.

1.1.1.1 Single machine

The single machine level is the first grade where energy-saving strategies can be implemented. One of the principal approaches proposed in the literature for energy-efficient machining is the optimization of the process parameters. Papers in the single machine context concern material removal processes and single-machine scheduling; conventional machining processes, i.e. milling, turning, and drilling, and the grinding operations (a typical abrasive process) have been selected among the several typologies of the material removal processes.

In the following, the studies concerning the cutting parameters have been grouped according to the type of machining process in subsection 1.1.1.1.1 to 1.1.1.1.4. Subsection 1.1.1.1.5 presents the works regarding the single machine scheduling with energy aspects.

1.1.1.1.1 Milling

Calvanese et al. (2013) found the optimal cutting condition in terms of cutting speed and feed rate in order to minimize the energy consumption of a machine tool. In their work, an analytical model for the energy characterization of a computer numerical control milling center has been discussed.

In the same context, Albertelli et al. (2016) provided an energy consumption model of a machine tool required during a face milling operation. In the evaluation of the energy consumption, several components needed for the milling, the cutting energy, and the passive phase energy have been considered. The objective function is the minimization of the energy consumption and the cutting speed, the feed rate, and the radial depth of cut have been considered as the parameters of the optimization. Other works concerning energy consumption, which is defined as one of the multiple objectives of the optimization in milling achievable through the proper selection of the cutting parameters, can be found in (C. Li et al., 2017; Jian-guang Li et al., 2014). Approaching the energy consumption, J. Yan and Li (2013) considered material removal rate, surface roughness, and cutting energy as the optimization objectives and addressed the investigation of the best parameters (spindle feed, feed rate, depth of cut, and width of cut) using the weighted grey relational analysis and the response surface methodology. Moreover, a Cuckoo search algorithm has been applied to a multi-objective optimization model considering the minimization of the energy footprint and of the production time (X. Chen et al., 2019). Another metaheuristic algorithm has been used for energy optimization in the milling context (W. Wang et al., 2020). In their work, W. Wang et al. developed a dual-objective optimization model, i.e. the minimization of the power consumption and of the processing time, and used an artificial bee colony algorithm to solve the mathematical problem to find the best parameters. T. Zhang et al. (2020) developed a mechanical milling power model with the aim of analyzing the main milling parameter effects on the specific milling energy, specific removing energy and energy efficiency. The main result of the study is that the lower the rotational speed, the feed rate per tooth, the axial cutting depth, and the cutting width, the higher the specific removing energy. This outcome is due to the increment of idle energy. The authors argued that an increment of the milling parameters leads to a higher value of energy efficiency.

Abdul Hadi et al. (2021) focused on the machining process of two aluminium pieces. The spindle power input is changed considering the high frequency data of the machine provided by an edge device. The optimization of the spindle power input achieves peak power smoothing and lower total energy consumption with negligible effect on costs and production time.

1.1.1.1.2 Turning

Hanafi et al. (2012) applied a grey relational theory and Taguchi optimization for the minimization of the power consumption and of the surface roughness during a turning process. The authors showed by using Pareto analysis that the depth of cut, followed by cutting speed and feed rate, is the parameter that most impacts the optimization objectives. Rajemi et al. (2010) proposed a machining energy model with the aim of finding the cutting speed that allows minimizing the energy consumption. They argued that the best energy conditions don't always are the same for the minimum cost criterion. Another work concerning the energy saving in turning can be found in (Q. Wang et al., 2014). In the paper, the effect of the cutting depth, feed rate, and cutting speed has been studied and the optimization model, considering as objectives the energy, the cost, and the quality, has been developed and solved using non-dominated sorting genetic algorithm II (NSGA-II).

1.1.1.1.3 Drilling

Mori et al. (2011) showed that the power consumption reduction can be achieved by the selection of cutting conditions also in drilling in addition to the face/end milling. Moreover, they argued that an appropriate pecking cycle and the synchronization of the spindle with the feeding system lead to a reduction of the power consumption.

Analyzing the energy efficiency in drilling, Zhongwei Zhang et al. (2020) proposed a mathematical model in order to minimize energy consumption and processing time. In their study, a deep-hole drilling process with two drills has been considered and a particle swarm optimization-based algorithm has been applied to find the best parameters setting. The energy prediction models in drilling (S. Jia et al., 2018, 2019) are really useful tools to obtain energy savings.

1.1.1.1.4 Grinding

Regarding the grinding process, Heinzel and Kolkwitz (2019) analyzed the effect of fluid supply on energy efficiency. The results showed that the modular nozzle has higher energy efficiency than the tangential flat nozzle despite the higher power consumption. Either the flow rate has an impact on the specific energy; therefore, the higher the flow rate, the higher the energy efficiency.

The eco-efficiency can be achieved by an optimal selection of the main influencing grinding parameters and considering surface roughness, costs, and carbon footprint as the objectives of the optimization process (Winter et al., 2014). Other works regarding the eco-efficiency and the energy consumption in grinding can be found in (P. Jiang et al., 2017; W. Li et al., 2012)

1.1.1.1.5 Single machine scheduling

In the single machine scheduling context, Mouzon and Yildirim (2008) developed a framework in order to minimize the total energy consumption and the total tardiness. In their work, an approximate Pareto front has been obtained using a greedy randomized multi-objective adaptive search metaheuristic method and the solutions have been compared by using an analytical hierarchy process. The minimization of the total completion time and of the total energy has been selected as the optimization objective in (Yildirim & Mouzon, 2012) and a genetic algorithm has been implemented to address the problem. Appropriate single machine production scheduling has been used to reduce the energy cost (Shrouf et al., 2014). The authors considered the variable energy cost; the job starting time, the idle and inactive time, and the energy cost have been obtained by using the proposed scheduling model.

Shijin Wang et al. (2016) addressed bi-objective single-machine batch scheduling with different job sizes, the time of use electricity tariffs, and various machine energy consumption to minimize both the total energy cost and the makespan. Two decomposition-based heuristic methods and an ε-constraint method have been applied to find respectively the approximate and the exact Pareto front.

Based on the work of Shijin Wang et al. (2016), S. Zhang et al. (2018) proposed two improved heuristic methods to solve the problem.

1.1.1.2 Two machines in line

The simplest multi-machine configuration is a manufacturing system composed of two machines in line. This setup is defined also as a flow shop with two machines. Regarding the context of the two-machine sequence-dependent permutation flow shop, the compromise between the minimization of the energy consumption and of the makespan has been studied in (Mansouri et al., 2016). Addressing this aim and finding the Pareto frontier, they proposed a mixed integer linear multi-objective optimization model and developed a constructive heuristic method to solve it. In subsequent work, this study is further analyzed and a new constructive heuristic method has been implemented with the purpose of outperforming the previous one (Mansouri & Aktas, 2016). The single job two machines scheduling problem has been studied in (Fang et al., 2020). In their work, the authors considered the possibility of divide the job into several sub-lots each of them characterized by different processing speeds. With these considerations, the aim of the paper is to obtain the optimal schedule (the size of the sub-lots and the processing speeds) that allows minimizing the total energy consumption. Assia et al. (2020) analyzed the energy-saving through scheduling in a flow shop composed of two machines. In the paper a mixed integer linear programming with two objectives is proposed; the mathematical model has been solved with an exact method in order to minimize the makespan and the total energy consumption. The optimization process provides the production and preventive maintenance planning that results in a minimization of the considered targets. Considering the electricity cost could be an alternative way to address the energy efficiency; usually, the energy costs are higher during the power peak period, so avoiding high power consumption when the electricity prices are high leads to less electric line saturation. Shijin Wang, Zhu, et al. (2018) provided a two-machine permutation flow shop scheduling model in order to minimize the total electricity cost, considering variable the electrical cost during the time. The authors used two heuristic algorithms to obtain the optimal schedule and in addition they proposed an iterated local search method. In another approach discussed in (Ho et al., 2020), the minimization of the total electricity cost has been achieved considering fixed the minimum makespan and under time-of-use electricity tariffs; six heuristic algorithms, three based on Johnson’s rule and three based on Hadda’s algorithm, have been proposed and tested. C.-B. Yan (2019) studied the energy consumption optimization problem in a two machines serial line considering the Bernoulli reliability model.

1.1.1.3 Parallel machines

In this subsection, the papers regarding the energy efficiency in parallel machine context have been grouped. A parallel machine system can be distinguished as identical, uniform, and unrelated (Graham et al., 1979). Paragraph 1.1.1.3.4 reports the works regarding a combination of the previous classes.

1.1.1.3.1 Identical parallel machines

In this case, the parallel machines of the manufacturing system are identical and work at the same speed.

The simultaneous minimization of the makespan and of the total electricity cost in identical parallel batch-processing machines has been studied in (Zhao-hong Jia et al., 2017). The scheduling problem has been solved using a Pareto-based ant colony algorithm. Together with the electricity cost under time-of-use tariffs, the total weighted tardiness has been considered as one of the targets of the optimization process, that is addressed with the ε-constraint method and with three heuristic methods based on grouping genetic algorithms (Rocholl et al., 2020). The ε-constraint method is suitable for the small-scale instances, and it has been applied for the identical parallel machine scheduling problem considering the total energy consumption and the makespan as the objectives of the optimization (Shijin Wang, Wang, et al., 2018); instead for the medium and large scale instances a developed constructive heuristic model with local search strategy and a non-dominated sorting genetic algorithm II have been used. C.-H. Liu et al. (2018) studied the concomitant minimization of the total weighted tardiness for one job and of the total completion time for another one considering a constraint on the peak power consumption. The set of solutions has been obtained using a domination number-based genetic algorithm.

1.1.1.3.2 Uniform parallel machines

The uniform parallel machines can work at different processing speeds.

A scheduling model, solved by a differential evolution algorithm and considering the makespan and the total electricity cost minimization, in the context of uniform parallel batch processing machines can be found in (S. Zhou et al., 2018). Zandi et al. (2020) proposed a heuristic algorithm addressing the scheduling problem. The proposed method returns an exact Pareto frontier of the total energy consumption and of the total completion time.

1.1.1.3.3 Unrelated parallel machines

Parallel machines are defined unrelated if the processing time depends on the machine speed and the speed is specific per each machine and job matching.

The scheduling problem concerning the unrelated parallel machine environment has been analyzed by Kurniawan et al. (2017). In their work, a genetic algorithm has been developed in order to minimize the total cost composed of the makespan cost and the electricity cost, which is considered variable during the periods. Considering the time of use electricity tariffs, two different approaches based on genetic algorithm have been used to minimize the total cost composed of the makespan cost and the electricity cost (Kurniawan et al., 2017; Moon et al., 2013). Saberi-Aliabad et al. (2020) developed a mixed integer linear programming model with the objective of the minimization of the consuming energy cost, considering also different electricity tariffs. In addition, a fix and relax heuristic algorithm has been proposed to address a large-size instances problem. In the same manufacturing context, a memetic differential algorithm has been applied to minimize both the makespan and the total energy consumption (Xueqi Wu & Che, 2019).

To minimize the total tardiness, including also the total energy consumption as a non-key objective, an imperialist competitive algorithm has been proposed (Pan et al., 2018). The simulation results show the feasibility of using the algorithm proposed in the low carbon parallel unrelated machine scheduling context. Meng, Zhang, Shao, Ren et al. (2019) developed a five mixed integer linear programming model for the unrelated parallel machine scheduling of a hybrid flow shop. In this study, the energy saving is obtained by machines turning off/on, reducing in this manner the energy consumption in idle state. An improved genetic algorithm for addressing the minimization of the total energy consumption has been proposed and compared with other optimization algorithms. Cota et al. (2021) provided a mixed integer linear programming model in order to minimize the makespan and the total electricity consumption. By using a developed heuristic algorithm, called multi-objective smart pool search metaheuristic, the solution of the problem returns the allocation and the order of the jobs, and the processing speed.

1.1.1.3.4 Hybrid parallel machines

In (Hongliang Zhang et al., 2021) a scheduling problem with the objective of total electricity cost minimization considering the electrical prices variable during the time has been studied in two-stage parallel machine context. The manufacturing system consists of identical parallel machines and unrelated parallel machines respectively at stage 1 and at stage 2. A tabu search-greedy insertion hybrid algorithm has been developed to solve the new continuous-time mixed-integer linear programming model.

1.1.1.4 Flow Shop

In the flow shop context, scheduling is still a good strategy for energy saving and efficiency. Flow shop with specific characteristic have been grouped in subsection 1.1.1.4.1 and 1.1.1.4.2.

Hao Zhang et al. (2014) provided a time-indexed integer programming with the aim of minimizing the electricity cost and the CO_2 emissions without reducing productivity. The authors argued that shifting the greatest energy demands during off and mid peak hours leads to a reduction in electricity costs. However, CO_2 reduction does not always meet electricity cost reduction; the CO_2 emissions per kWh depend on the mix of power resources used and how they are combined during peak hours. The peak power consumption has been evaluated as an important issue of the flow shop scheduling in (Nagasawa et al., 2015). The approach proposed considered the uncertain processing time of the operations and consists of obtaining for first the initial schedule that allows minimizing the peak power consumption and the inventory cost. In a second phase, a rescheduling is provided to prevent the peak power due to the uncertainty of the processing time including idle times. Differing from the other works on the scheduling problem, G.-S. Liu, Yang, et al. (2017) considered the minimization of the energy consumption with the evaluation of the product quality. The machine speed influences the production time, energy consumption, and product quality. Quality control has been considered at the end of the line and, if the product quality doesn't satisfy the requirement, it's necessary to rework the piece with additional energy consumption and time. The authors developed a novel three-stage decomposition approach to address the scheduling problem. The minimization of the total energy cost as the objective function in flow shop energy-efficient scheduling has been addressed using a memetic algorithm in (Marichelvam & Geetha, 2021). In this paper, the workers' absenteeism, cancelled, and rush orders have been included. In (G.-S. Liu, Zhou, et al., 2017) the sum of the energy consumption and tardiness has been considered as the target of the optimization process. Fuzzy numbers have been formulated to consider the uncertainty in the scheduling problem and a genetic algorithm has been applied to solve it. Even in (B. Zhou & Liu, 2019), the fuzzy numbers have been used to take into account the uncertainty of processing time; in this paper, the minimization of the total weighted delivery penalty and of the total energy consumption has been defined as objective function and a multi-objective differential evolution algorithm has been provided. The flow line has been considered as a Bernoulli serial line with the aim of improving energy efficiency by scheduling machine shutdowns (G. Chen et al., 2013). The problem of single item capacitated lot-sizing in flow shop considering energy aspects has been studied in (Masmoudi et al., 2015). In this paper, two mixed integer programming models have been developed in order to minimize the total production cost consisting of electrical, holding, setup and power demand costs. Extending this work to address the lot-sizing problem in the case of the medium and large scale, Masmoudi et al. (2017a) proposed two heuristic methods based on movement techniques and Masmoudi et al (2017b) developed a fix-and-relax heuristic and a genetic algorithm. The multi-item capacitated sizing problem considering energy aspects has been investigated in (Masmoudi et al., 2016).

The blocking is typical in a flow shop system without buffers between machines or with limited and full intermediate buffers (Pinedo, 2008). This blocking condition imposes the impossibility of leaving the upstream machine until the job on the next machine is completed. In the blocking flow shop context, a scheduling problem considering also energy saving has been proposed (Han et al., 2020). The authors considered the minimization of the makespan and of the energy consumption during job blocks and machine idle time. A discrete multi-objective evolutionary optimization algorithm has been used to address the problem.

1.1.1.4.1 Permutation Flow Shop

The permutation flow shops are characterized by a fixed order of the jobs through the machines (Potts et al., 1991).

Controlling power peak is a very important issue in energy efficiency. A scheduling model that considering peak power as a constraint and makespan as the objective function has been discussed in (Fang et al., 2013). E. Jiang and Wang (2019) considered as objectives of the scheduling problem the maximum completion time and the total energy consumption and addressed the optimization using an evolutionary algorithm based on decomposition. The flow shop analyzed is characterized by the setup time of each job depending on the sequence. C. Lu et al. (2017) extended the permutation flow shop scheduling problem considering in their model also transportation time, sequence-dependent setup time, and the energy consumption in the setup stage, in the transportation phase, and in the public period with the classical time and energy features. A hybrid multi-objective backtracking search algorithm has been provided to solve the scheduling model.

A mixed integer linear programming model has been developed in (Öztop et al., 2020) considering as objective function the minimization of the total flow time and of the total energy consumption and assuming a machine variable processing speed. To address the problem for small instances an ε-constraint approach has been proposed, whereas for the large instance problems an ε-constraint approach and two iterated greedy algorithms, a variable block insertion heuristic algorithm, and construction heuristic procedure have been provided. Utama et al. (2020) developed a hybrid whale optimization algorithm in order to minimize the energy consumption in a permutation flow shop scheduling with a dependent sequence setup. Xueqi Wu and Che (2020) considered the simultaneous minimization of the makespan and the total energy consumption in the no-wait permutation flow shop scheduling problem. In their study machine processing speeds have been adapted respecting the objective functions and an adaptive multi-objective variable neighborhood search algorithm has been used to achieve the Pareto front. In the same manufacturing context, the total energy consumption and the total tardiness have been considered as objective functions and three metaheuristic algorithms (an ant colony algorithm, a genetic algorithm, and a genetic algorithm with local search) have been provided in (Yüksel et al., 2020).

The distributed permutation flow shop is a general case of a permutational flow shop characterized by several identical factories, each of them consisting of the same machines arranged in series (Naderi & Ruiz, 2010). J. Chen et al. (2019) proposed a scheduling model for the distributed no-idle permutation flow shop context with the aim of minimizing the total energy consumption and the makespan using a collaborative optimization algorithm. The same targets have been considered in (J.-J. Wang & Wang, 2020) regarding distributed permutation flow shop. In this work, the problem is solved using a knowledge-based cooperative algorithm.

1.1.1.4.2 Flexible Flow Shop

The flexible flow shop can be defined as “a generalization of the flow shop and the parallel machine environments” (Pinedo, 2008).

Regarding the flexible flow shop, Bruzzone et al. (2012) proposed an approach based on two phases to consider peak power in the scheduling problem. In the first phase using mixed integer programming, a production schedule is obtained in order to minimize the weighted sum of the total tardiness and the makespan, without considering a power constraint. The machine assignments and job sequences have been defined solving the mathematical model and considering fixed these values, defining a power constraint, the mathematical model is resolved. The new schedule respects the limits on the power consumption but could have a worsening of the objective function compared to the previous planning. Dai et al. (2013) used a genetic-simulated annealing algorithm to obtain the minimization of the maximum completion time and the total energy consumption in flexible flow shop scheduling problem. An ant colony optimization algorithm has been applied in the multi-objective hybrid flow shop scheduling (H. Luo et al., 2013); the minimization targets are the makespan, and the electrical power cost and time-of-use tariff is considered. Unlike other works, Gong et al. (2020) considered also worker flexibility to achieve energy efficiency. The authors developed a mathematical model in which the objective functions to be minimized are the makespan, the total worker cost, and the green production indicator. The last one is composed of the energy consumption, the noise, the recycling rate of tool chips, and the safety coefficient. The mathematical model has been solved using a hybrid evolutionary algorithm. The minimization of the energy consumption costs considering three possible machine states (standby, shut-down, operation) has been studied and solved with a hybrid genetic algorithm in (R.-H. Huang et al., 2017). Hasani and Hosseini (2020) considered in the bi-objective scheduling problem the production cost and the energy consumption as the two targets to be minimized and implemented a makespan constraint. The investigated flexible flow shop consists of unrelated parallel machines in the first stage and a single machine in the next stages; a Non-dominated Sorting Genetic Algorithm II has been used to address the problem. A dynamic scheduling model with the aim of minimizing the weighted aggregation of the makespan and the total tardiness, considering a bound on the power peak, has been analyzed in (J. Luo et al., 2019). The dynamic features of scheduling have been also studied in (Tang et al., 2016). The authors considered the makespan and the energy consumption as the objective functions and solved the scheduling problem with an improved particle swarm optimization method. A non-dominated sorting genetic algorithm II and a non-dominated ranked genetic algorithm have been used and tested in scheduling problem with two objective functions, i.e. the total weighted tardiness and the energy consumption, in (Nasiri et al., 2018). J. Yan et al. (2016) proposed an energy-efficient method based on multi-level optimization. The proposed approach aims to combine energy saving at the machine level and at the line level. The cutting energy and the cutting time have been considered as objectives in the machine tool level, whereas in the shop floor level the makespan and the total energy consumption have been defined as the targets; the optimization has been achieved using grey relational analysis and a genetic algorithm respectively at the machine and at the line grade. The flexible flow shop scheduling problem, considering the time of use electricity tariffs and makespan and electricity cost as the objective functions, has been addressed using an improved strength Pareto evolutionary algorithm in (M. Zhang, Yan, Zhang, et al., 2019). In addition to two typical objective functions in energy-efficient scheduling, i.e. the makespan and the electricity consumption, Zeng et al. (2018) considered also material wastage as one of the multi-targets of the optimization process. The mathematical model has been solved with a hybrid non-dominated sorting genetic algorithm II. New teachers' teaching-learning-based optimization has been proposed in the context of the hybrid flow shop scheduling problem (Lei et al., 2018). The total tardiness and the total energy consumption have been considered respectively as the key objective and the non-key objective. T.-L. Chen et al. (2020) provided a mixed integer programming with two objective functions, i.e. the minimization of the makespan and electric power consumption. The approximate Pareto solutions have been obtained using a non-dominated sorting genetic algorithm II. The simultaneous minimization of the total weighted tardiness and total price of the non-processing energy has been investigated and addressed using an evolutionary algorithm based on decomposition in (S. Jiang & Zhang, 2019). Jun-qing Li et al. (2018) studied the hybrid flow shop scheduling problem considering as objectives the minimization of the total energy consumption and of the makespan. The authors developed an algorithm characterized by exploitation search, deep-exploitation phases, exploration and deep-exploration phases to achieve optimization targets. The minimization of the total tardiness and energy cost considering variable discrete production speeds has been analyzed in (S. Schulz et al., 2020). S. Schulz et al. (2019) considered three objectives, i.e. makespan, total energy cost, and peak load, and provided an iterated local search algorithm to address the optimization scheduling problem.

1.1.1.5 Job Shop

Works regarding the energy efficiency in job shop have been discussed in the following. Subsection 1.1.1.5.1 grouped the paper related to the flexible job shop configuration.

Kemmoe et al. (2017) designed a mathematical model considering different power requirements in the initial phase and processing phase and selected the makespan as the objective function. The aim of the paper is to define a feasible production schedule that allows respecting the variable power threshold; the authors provided a Randomised Adaptive Search Procedure hybridized with an Evolutionary Local Search to solve the problem. Tang and Dai (2015) proposed to achieve energy saving starting from a defined schedule. The first phase consists of obtaining a production planning in order to minimize the makespan. Then, considering fixed the machine assignments and the job sequences, the approach aims to minimize the energy consumption by modifying the cutting speeds. The authors provided a genetic-simulated annealing algorithm to solve the problem. The minimization of the makespan and of the total energy consumption considering different speed rates has been selected as the objective function in (Escamilla et al., 2016; Salido et al., 2016); the job shop scheduling problem has been solved using a genetic algorithm. Together with the previously optimization targets, Yin et al. (2017) assumed that noise is affected by the machining spindle speed and provided a genetic algorithm based on simplex lattice design to solve the mixed integer programming model. Masmoudi et al. (2019) proposed two integer linear programming models to minimize the energy production costs under power peak constraints and used a heuristic method to solve the mathematical problem. One of the widely used heuristic models is the genetic algorithm. R. Zhang and Chiong (2016) studied the scheduling problem in a job shop system including the minimization of energy consumption. The developed genetic algorithm optimizes the scheduling problem by integrating the two sub-problems derived from the original model to reduce the computational complexity. A genetic algorithm has been implemented in the job shop scheduling model to obtain Pareto front solutions with the energy consumption and makespan as objectives in (May et al., 2015). Nie et al. (2019) modeled the job shop scheduling using the Game Theory and solved the problem using a genetic algorithm. H. Wang, Jiang, et al. (2018) proposed an approach that applies Modified Genetic Algorithm (MGA) at the first stage and a hybrid method, that integrates Genetic Algorithm (GA) with Particle Swarm Optimization (PSO), at the second stage. The model was tested for a flexible job shop scheduling problem. Lei et al. (2019) developed a two-phase meta-heuristic based on the imperialist competitive algorithm and variable neighborhood search in order to achieve a solution for the flexible job shop scheduling problem; the proposed algorithm allows obtain the minimization of the total tardiness and of the makespan considering the total energy consumption as a constraint. Renna (2020a) used a Gale-Shapley algorithm to share power among the machines of a manufacturing system under a peak power constraint. Ebrahimi et al. (2020) analyzed the application and the performance of four metaheuristic algorithms in the flexible job shop context. In their work, the minimization of a single objective function obtained as the sum of the energy cost and the tardiness penalty has been considered. The algorithms tested are two variants of the particle swarm optimization and two variants of the ant colony optimization. The best results considering both objective function and CPU (central processing unit) time have been obtained with the hybrid ant colony optimization and simulated annealing algorithm. Abedi et al. (2020) considered the variable speed of the machines and the productivity deterioration; the minimization of the total weighted tardiness and the total energy consumption can be achieved by properly selecting the operation sequences and the machine speeds. A multi-population and multi-objective memetic algorithm with periodic local search has been provided to address the optimization goal. L. Zhang, Li, Królczyk, et al. (2019) introduced an effective gene expression programming-based rule mining algorithm to define dispatching rules. In their work, the objective function is the minimization of the total energy consumption composed of direct and indirect energy consumption. The energy-efficient scheduling solved using respectively an improved whale and a grey wolf optimization algorithms can be found in (T. Jiang, Zhang, Zhu, Gu, et al., 2018) and in (T. Jiang, Zhang, Zhu, & Deng, 2018). The scheduling problem is designed in order to obtain in the first paper the minimization of the sum of the energy consumption cost and the completion-time cost and in the second one the minimization of the total cost of energy consumption and tardiness. In the distributed job shop scheduling context, i.e. an extension of the job shop that considers several factories, a multi-objective evolutionary algorithm with decomposition has been used to solve the mathematical model considering the minimization of the makespan and the total energy consumption (E. Jiang et al., 2020).

1.1.1.5.1 Flexible Job Shop

The Flexible Job Shop has been defined as "a generalization of the job shop and the parallel machine environments" (Pinedo, 2008).

Regarding the flexible job shop scheduling problem, Moon and Park (2014) developed mixed-integer programming and constraint programming approaches with the goal of obtaining the minimization of the total production cost. The total production cost is defined as the sum of the cost linked to the makespan and the electricity cost. Furthermore, the model is improved taking into account the cost related to energy storage and distributed energy resources. Meng, Zhang, Shao and Ren (2019) provided several mixed integer linear programming models selecting as objective function the minimization of total energy consumption. Lei et al. (2017) selected the workload balance, instead of time-related targets, together with the total energy consumption as one of the minimization objectives. The mathematical model has been solved using a shuffled frog-leaping algorithm. The simultaneous minimization of the total energy consumption and the makespan in a flexible job shop with variable processing speed context has been obtained using a multi-objective grey wolf optimization algorithm (S. Luo et al., 2019). The same targets of the optimization process have been considered in (Dai et al., 2019). In addition, in the paper, a transportation constraint has been implemented due to its high energy impact. The mathematical problem has been solved using a genetic algorithm. Mokhtari and Hasani (2017) provided a mathematical model with three objective functions, i.e. the total completion time, the total availability of the system, and the total energy cost, and addressed it using an

enhanced evolutionary algorithm. The number of machine turning on/offs has been considered as a minimization objective with the total energy consumption and the makespan in (Xiuli Wu & Sun, 2018). The non-dominated sorted genetic algorithm II and a green scheduling heuristic method have been implemented to deal with the mathematical model. In the context of a distributed and flexible job shop, Jin Wang et al. (2021) applied edge computing and the industrial internet of things in real-time scheduling. The real-time scheduling method proposed allows considering real-time data for the operations assignment and the real-time operations allocation has been done using an evolutionary game-based method.
The minimization of the tax cost on surplus energy consumption and the minimization total cost of jobs lateness based on soft time-windows have been considered as objective functions in (Ayyoubzadeh et al., 2021). In their study two types of uncertainties have been included; the first regards the pre-know probability distributions, the second, instead, the no well-known probability distributions. These two types of uncertainties have been addressed respectively with stochastic scheduling and reactive scheduling. The problem has been solved using a NSGA-II algorithm.

1.1.1.6 Open Shop

The literature is lacking in papers regarding the energy efficiency in the open shop systems. The researchers focused mainly in this context to the classical optimization objectives like the minimization of the makespan (Lawler et al., 1982; Sevastianov & Woeginger, 1998), of the maximum lateness (Lawler et al., 1981), of the number of late jobs (Kravchenko, 2000), of the weighted number of late jobs (Galambos & Woeginger, 1995), and of total completion time (Achugbue & Chin, 1982; Tautenhahn & Woeginger, 1997). Hosseinabadi et al. (2019) considered the open-shop scheduling problem with the objective to minimize the makespan. The genetic algorithm developed can find more optimal solutions for all kinds of problems and could find them in shorter computational times compared to the other algorithms. Works regarding the open shop considering energy issues have been developed in speed-scaling processor studies. Bampis et al. (2014) investigated the scheduling problem of an open shop with a speed-scaling setting considering as the objective function the minimization of the makespan with a constrain on the energy budget. The scheduling problem in speed scaling setting has been formulated as a convex flow problem in (Bampis et al., 2015). The proposed approach has been applied to the preemptive open-shop speed-scaling problem in order to minimize energy consumption.

1.1.1.7 Cellular Manufacturing System

Referring to the design of cellular facility layout, a mathematical model with minimization of the total cost and the total energy loss as objective has been proposed and solved using a Non-Dominated Sorting Genetic Algorithm II in (Niakan et al., 2014). Niakan et al. (2016) extended the studying of sustainable dynamic cellular manufacturing system and included in the second objective function not only energy loss but also other waste such as chemical, raw material waste, and greenhouse gas emission. Imran et al. (2017) focused on cell formation with the aim of minimizing the value-added work in process considering the electricity cost of the machine and of the material handling system. A simulation integrated hybrid genetic algorithm, i.e. the integration of genetic algorithm and discrete event simulation, addressed the layout design. Iqbal and Al-Ghamdi (2018) investigated the energy saving obtainable by properly assigning the manufacturing process to the machine and selecting the machines in each cell. The problem has been solved using a simulated annealing algorithm. Saddikuti and Pesaru (2019) aimed to minimize makespan, flowtime, and energy consumption and proposed a Non-dominated sorting genetic algorithm II to solve the model. Lamba et al. (2020) developed a mixed integer non-linear model and a simulated annealing meta-heuristic approach has been used to address the optimization problem. The objective function is the minimization of the sum of the material handling cost, the rearrangement cost (both considering inter and intra cell movement), and the total electrical cost.

1.1.1.8 Reconfigurable Manufacturing System

Choi and Xirouchakis (2015) proposed an approach based on holistic production planning to address the energy consumption problem in the reconfigurable manufacturing system. A linear programming model has been developed considering also part handling systems in energy consumption; the maximization of the throughput and the minimization of the energy consumption have been selected as objective functions. Jiafeng Zhang et al. (2015) investigated the energy saving obtainable by a dynamic local reconfiguration, i.e. the switch from the working to energy-efficient mode, of the system. Energy has been considered in the total cost in (M. Liu et al., 2019). The authors investigated the reconfigurable manufacturing system considering both the design and the manufacturing phase; a mixed integer programming model has been proposed with the objectives of the minimization of the total cost and the cycle time. The mathematical model has been addressed with an ε-constraint method and with a multi-objective simulated annealing algorithm respectively for small and practical problem sizes. Touzout and Benyoucef (2019) studied the process plan generation problem. In this paper a mathematical model has been proposed with the aim of minimizing the total production cost, the completion time, and the greenhouse gas emissions, the latter evaluated considering the total energy consumption. An iterative multi-objective integer linear programming approach, an archived multi-objective simulated annealing, and the non-dominated sorting genetic algorithm have been used and investigated. Regarding sustainable process plan, three objectives, i.e. the minimizations of the total production cost, of the total production time, and of an environmental criterion, have been identified and considered in (Khezri et al., 2020a, 2020b, 2019). Energy consumption has been defined as the environmental objective in (Khezri et al., 2020a), whereas Khezri et al. (2020b, 2019) considered that the energy consumption impacts on the amount of the greenhouse gas emissions included in the environmental criterion, which is, respectively in the two papers, the sustainability-metric value and environmental hazardous wastes. In (Khezri et al., 2020b) a posteriori approach, a non-dominated sorting genetic algorithm II, and a strength Pareto evolutionary algorithm II have been used to solve the mathematical model, whereas in (Khezri et al., 2019) an adapted version of weighted goal programming has been implemented. Khezri et al. (2020a) addressed the problem using an augmented ε-constraint based approach.

1.1.1.9 Other processes and technologies

Energy saving has been also studied in other processes. Some examples have been briefly discussed in the following, but they have not been considered in the literature analysis and in the comparison of the number of papers in the different sections. The minimization of the energy consumption has been considered in the multi-objective optimization in the sheet metal forming and in arc welding processes respectively in (Gao et al., 2019) and in (W. Yan et al., 2017); referring to the laser cutting, Xu et al. (2014) defined the minimization of the total energy consumption on the whole cutting path. Ma et al. (2021) proposed an energy prediction model for different additive manufacturing technologies and conducted an optimization of the energy consumption and surface quality. Always in the additive manufacturing context, Yang et al. (2017) developed a method to find the optimal parameters in order to minimize the energy consumption in stereolithography-based processes. Therefore, the reduction of energy consumption is very important issue in industry and in all production processes.

1.1.2 Assembly Line

Abdullah et al. (2019) developed an assembly sequence planning model in order to achieve energy efficiency. The objective function considered is the weighted sum of the number of tool changes, of the number of assembly direction changes, and of energy consumption in idle mode. The problem has been solved using a moth flame optimization algorithm.

In robotic and automatic assembly lines the energy saving is a very important issue and several papers in literature focused on this topic. Michalos et al. (2015) proposed an approach based on two stages to design and configure the assembly line considering multiple criteria, one of which is resource energy consumption. Nilakantan et al. (2016) and Nilakantan, Ponnambalam, et al. (2015) used particle swarm optimization and differential evolutionary algorithm to minimize the energy consumption in a U-shaped robotic assembly line. The particle swarm optimization algorithm has been also implemented to address the straight robotic assembly line considering the simultaneous minimization of the total energy consumption and the cycle time (Nilakantan, Huang, et al., 2015). B. Sun et al. (2020) aimed to minimize the previously cited objective functions using a bound-guided hybrid estimation of distribution algorithm. In the same robotic assembly line context, i.e. straight line, Nilakantan et al. (2017) proposed a multi-objective co-operative co-evolutionary algorithm to address the problem of minimizing the total carbon footprint and maximizing the line efficiency. Several studies focused on the U-shaped robotic assembly line and different approaches have been proposed to address the complexity of the problem. Zikai Zhang, Tang, Li, et al. (2019) provided a mathematical model for the assembly line balancing problem in order to minimize both the energy consumption and the cycle time and developed a Pareto artificial bee colony algorithm. Using a hybrid Pareto grey wolf optimization, Zikai Zhang, Tang and Zhang (2019) solved the balancing problem with the aim of minimizing the carbon emission, the noise emission, and the cycle time. The robot energy consumption has been evaluated in order to find the related carbon emissions. B. Zhang and Xu (2020) proposed a flower pollination-based algorithm to minimize both the smoothness index and the energy consumption. A cellular strategy-based genetic algorithm has been used to solve the problem of minimizing the energy consumption and of maximizing the system efficiency in the mixed-model assembly line (B. Zhang et al., 2020a), whereas an improved whale optimization algorithm has been proposed to minimize concurrently the energy consumption, the smoothness index, and the total cost in the semi-automated assembly line designing problem (B. Zhang et al., 2020b). Three objectives, i.e. the minimization of the cycle time, the minimization of the sum of energy consumption, and the minimization of the total cost, have been considered in the balancing problem of a multi-robot cooperative assembly line (B. Zhou & Kang, 2019). The authors developed and used a multi-objective hybrid imperialist competitive algorithm with a nondominated sorting strategy. The energy consumption of a two-sided robotic assembly line has been investigated in (Z. Li et al., 2016). In this work, a mixed-integer programming model has been proposed with the aim of minimizing the energy consumption and the cycle time and a restarted simulated annealing algorithm has been developed to address it.

1.1.3 Policies and Strategies for Energy-Saving

As shown in the previous section, energy efficiency can be achieved by properly selecting process parameters and with energy-oriented scheduling.

Moreover, policies and strategies for energy-saving can be useful tools for incrementing energy efficiency, reducing energy consumption and costs, and decrementing the carbon footprint. As argued by Frigerio et al. (2021) the energy-efficient control policies can be ranked in buffer-based policies and time-based policies; the class depends on the information used by the policy.

1.1.3.1 Buffer-based policies

G. Chen et al. (2011) applied energy-efficient policies based on buffer threshold in a Bernoulli serial line characterized by buffer stripping. In (Su et al., 2016), Upstream, Downstream, Upstream & Downstream policies have been investigated in a production line in order to evaluate the energy saving. These policies for changing machine states take into account information respectively from upstream, downstream, and simultaneously both upstream and downstream buffers. Zhiyang Jia et al. (2016, 2015) applied the buffer-based policy to switch on/off machines in Bernoulli serial production line. A fuzzy Petri net has been used to reduce the idle period by switching off/on the machines (Fei et al., 2018). The state commutation is defined by a fuzzy controller evaluating the real-time buffer occupancy and machine status. The results show that the approach proposed reduces energy consumption with a limited throughput loss. A fuzzy decision method to control the machine switch on/off taking into account the information regarding the pieces in the buffer and the machine states has been studied in (Junfeng Wang et al., 2017; Junfeng Wang, Fei, Chang, Fu, et al., 2019; Junfeng Wang, Fei, Chang, Li, et al., 2019). Junfeng Wang, Fei, Chang and Li (2019) proposed a dynamic adaptive fuzzy reasoning Petri net to establish the machine state. The fuzzy rules have been defined considering the upstream and downstream buffer levels and the certainty factor of the rules dynamically changes depending on the production rate.

1.1.3.2 Time-based policies

Mouzon et al. (2007) showed the possibility of energy saving by turning off underutilized machines and proposed a machine controller that aims to reduce energy consumption using dispatching rules. Furthermore, supporting the energy savings obtained with the controller, the authors developed a mathematical scheduling model to minimize the energy consumption and total completion time. Frigerio and Matta (2014) proposed a switch-off policy based on the time threshold, i.e. the machine shut down after an interval since the last departure. In (Frigerio & Matta, 2015a), the authors extended the energy-efficient control strategy defining the switching policy that establishes the commutation between machine states (from on to off and vice versa) according to specific time interval; special cases of the switching policy have been presented. An approach based on online arrival evaluation has been studied in order to provide optimal time thresholds of the time-based control policy (Marzano et al., 2019). Squeo et al. (2019) presented the Multi-Sleep policy, i.e. an extension of the switching policy, that uses time thresholds to change the state of the machine components.

1.1.3.3 Hybrid buffer and time based policies

Frigerio and Matta (2016) presented a control policy, based simultaneously on buffer and time information, that is called TNT policy; this new strategy turns off the machine when the buffer is empty and after a defined time interval from the last departure. The machine switches on, instead, when the threshold of the queue or of the time is reached. Other special cases of the policy have been also analyzed. In (Frigerio & Matta, 2015b) the TNT policy has been applied in a production line with finite buffer capacities. In the context of the pull production line, Renna (2018) developed a switch-off policy that uses the downstream buffer level and the customer satisfaction to commute the machine state. Stochastic factor and buffer utilization have been considered to evaluate the energy saving opportunity with machine shut down (Z. Sun & Li, 2013). A fuzzy controller has been used to switch the machine on and off in a one buffer one machine manufacturing system (Duque et al., 2018). The required production rate, the buffer level, and the state of the machine have been considered as input of the fuzzy logic module.

1.1.3.4 Other policies and strategies

In (Fernandez et al., 2013; Z. Sun et al., 2014), a "Just-for-Peak" buffer inventory policy has been developed in order to reduce the energy demand during peak periods. The proposed policy introduced additional buffers, coupled with the standard ones, which are filled during the non-peak period. The "Just-for-Peak" buffers allow switching off the upstream machines during the peak electricity demand without compromising the throughput. Evaluating the energy efficiency of the machine tool is a very important issue for production sustainability. Hu et al. (2012) proposed an online monitoring approach to measure energy efficiency. The method proposed by the authors doesn't require any sensor and, for this reason, the implementation cost is very low. The real-time information enables energy efficiency improvement through corrective and immediate actions. Diaz et al. (2019) developed a control strategy to reduce energy consumption in a manufacturing system. The authors studied the use of the receding horizon approach to switching on/off early the peripheral devices considering their dynamic with the aim of reducing the global energy consumption. Chang et al. (2013) focused on the energy saving opportunity in a serial production line; the authors defined the opportunity window as the maximum possible inactive time of a station that doesn't involve a reduction of productivity at the end-of-line station. Energy opportunity windows and energy profit bottleneck, i.e. the machine that results in the greatest profit loss on the line, have been investigated in (Brundage et al., 2016, 2014). Zou et al. (2016) provided an approach for evaluating the opportunity windows to reduce energy saving and to perform preventive maintenance in stochastic production systems. The reduction of the energy consumption using energy saving opportunity in multistage manufacturing system has been investigated in (Y. Li et al., 2018). In (Y. Huang et al., 2018), a max-plus algebra method has been used to evaluate the energy saving window in order to switch off the machines in a serial production line. Mashaei and Lennartson (2013) defined suitable conditions for switching off machines and included them in a mathematical model with the objective of minimization of the energy consumption in the context of a pallet-constrained flow shop.

1.1.4 Renewable energy sources in manufacturing systems

The integration of renewable energy sources in manufacturing allows reducing carbon footprint, and together with energy efficiency leads to sustainable manufacturing. However, the main issue regarding the variable renewable energy sources (such as solar and wind) is the dependence on the weather; thus, the energy supplied is intermittent and variable. For these reasons, the main challenge is the adoption of energy flexibility to align the energy demand with renewable sources. On the other hand, the alignment of the machine parameters to the renewable supply could affect the production and the product quality. Another strategy to overcome the power fluctuation is the installation of electricity storage systems.

Abikarram and McConky (2017) investigated the possibility of smoothing load profile to improve the use of the photovoltaic system. The authors claimed that the smoothing strategies allow reducing the effects of introducing the renewable energy source on the net demand variability and supporting the installation of the photovoltaic plant in the manufacturing system. Beier et al (2016) suggested using the batteries of the electric vehicle to improve the integration of the variable renewable energy sources in manufacturing. The results show that, whereas stationary batteries are characterized by continuous availability, the vehicle batteries are independent from the integration of the renewable energy source due to their traction uses. In the paper, it is also showed that energy flexibility further improves the variable renewable energy sources integration. An energy flexibility approach based on real-time control to align the energy demand to on-site renewable energy supply has been proposed in (Beier et al., 2017) without negative influence on the throughput. The method proposed leads to a more efficient integration of renewable sources in the context of a manufacturing system with several processes and intermediate buffers.

Schulze, Blume, Siemon et al. (2019) focused on the introduction of battery storage with the aims of improve the use of variable renewable energy sources. Energy storage systems and the energy management lead to an optimal energy self-sufficiency and at the same time a high productivity. A procedure to integrate renewable energy sources applying energy-flexibility has been studied in (J. Schulz et al., 2020). Popp et al. (2017) presented a real-time control approach that takes into account the renewable energy supply to plan the use of machine tool components characterized by energy-flexibility. The approach has been implemented in a manufacturing system composed of thirty machines and with on-site renewable sources in order to evaluate the economic gain. Biel et al. (2018) investigated the scheduling problem of a flow shop with an onsite wind power supply. The approach consists of the generation of several power wind scenarios which are considered after in a two-stage stochastic optimization. The first stage allows obtain the optimal production schedule in order to minimize simultaneous the total weighted flow time and the expected energy cost, whereas the second stage fixes the energy supply decision according to the wind power data. Santana-Viera et al. (2015) suggested using wind turbine and photovoltaic units to support facilities in interruptible/curtailable demand response programmes and proposed a stochastic programming model to define the optimal capacity of the renewable energy sources in order to maximize the annual utility saving.

A single machine scheduling model has been developed in (X. Wang et al., 2011) to minimize the total carbon emissions considering renewable energy. The single machine scheduling with renewable energy sources problem has been also studied in (C.-H. Liu, 2016a). In this work, C.-H. Liu developed two models; in the first, the objective is the simultaneous minimization of the total weighted flow time and the carbon emissions, whereas in the second case the objective function is the minimization of the total flow time while the CO_2 emissions are a constraint. C.-H. Liu (2016b) focused on the discrete lot-sizing and scheduling problem with renewable energy and provided two models: the first considers the simultaneous minimization of the earliness tardiness and CO_2 emissions, the second assumes earliness tardiness as optimization function and CO_2 emissions as a constraint.

Karimi and Kwon (2021) provided a mathematical optimization to study energy cost and makespan in the context of unrelated parallel machines with on-site solar power generation and a battery. Eight configurations have been analyzed, each of these is characterized by the presence of the solar power plant, the battery, and the energy-aware objective. In the first four configurations, the single objective is the minimization of the makespan; then the energy cost has been evaluated. In the last four configurations, the scheduling has been obtained in order to minimize simultaneously makespan and energy cost. Results demonstrate that energy-aware scheduling could lead to better use of the energy provided by the solar power plant and the battery.

Fattahi et al. (2018) focused on the mining supply chain and proposed a multi-stage stochastic program including strategic and tactical planning with wind and solar energy supplies. A mixed integer linear programming model considering a wind turbine integrated with the electrical grid has been provided in (Zhai et al., 2017). The manufacturing system is a flow line and the objective function is the minimization of the expected total energy cost. Still focused on the flow shop scheduling problem, Shasha Wang et al. (2020) proposed a two-stage multi-objective program taking into account energy provided by the electrical grid, on-site renewable energy sources, and energy storage. In the first step, the production schedule is defined in order to minimize the total weighted completion time, whereas the second phase consists of the energy supply decisions with the objective of minimizing the energy costs. Fazli Khalaf and Wang (2018) focused on the energy costs in the flow shop scheduling problem with intermittent renewable, energy storage, and real-time electrical price. The authors addressed the problem in two phases. The first phase results in the production schedule and the optimal electricity demand curve in order to minimize the purchased electricity considering the day-ahead electrical tariff and the forecasted renewable energy supply. The second stage concerns aligning the forecasted and the real energy supplied by the renewable energy sources and minimizing the real-time energy cost. A mathematical model with the objective of minimizing the levelized cost of energy by properly sizing wind turbine, photovoltaic, and battery storage in the context of a multi-stage flow shop in island mode has been proposed in (Jin et al., 2020). Subramanyam et al. (2020) focused simultaneously on defining the size capacity of renewable energy sources and on production schedule with the aim of minimizing the levelized cost of energy in a flow shop manufacturing system. Xiuli Wu et al. (2018) investigated the multi-objective scheduling problem in the context of a flexible flow shop with renewable energy sources. The minimization of the electricity cost, under the time of use electrical tariff, has been considered as the objective function in the scheduling problem of a hybrid flow shop connected to the electrical grid and with an onsite photovoltaic system (Hao Zhang et al., 2017). A dynamic load scheduling algorithm for the demand side management aiming to minimize the total electricity cost with controlled order delay has been investigated in the context of a job shop equipped with an onsite windmill (Nayak et al., 2019). Cui et al. (2019) developed a scheduling model in a manufacturing system with an onsite microgrid system with the target of minimizing the total energy cost by cutting the peak power load and reducing the energy bought from the electrical grid. In this paper, the manufacturing system has been defined as a Bernoulli serial line.

1.1.5 Energy Efficiency Approaches

The literature is rich in work regarding energy efficiency in manufacturing systems. The following figure (Figure 1.6) presents an overview of the main approaches used. The list in the figure of the mathematical method and the used approach is not exhaustive but limited to the papers investigated. The approaches analyzed are grouped in classes even if they are not original and are used only to evaluate a new method. For these reasons, an article can be classified into more than one class. Two colorbars have been used to show the number of papers respectively in each approach and in each subclass. It can be seen that the most of work approaches are heuristic and metaheuristic. In literature, there are several papers that focused on energy-efficient scheduling, and the scholars developed and extended different models that can be applied to real-life problems. Mathematical programming models can generate optimal solutions for small-scale multi-objective scheduling problems, but it is difficult to apply to large-scale problems because of their high complexity. Therefore, heuristics and meta-heuristics are proposed to solve large instances and multi-objective scheduling problems. The most common metaheuristic algorithms adopted are the evolutionary and the computational swarm intelligence algorithms. Regarding the evolutionary algorithm, the genetic algorithm, and its subclass NSGA-II, find wide applications in the literature. Algorithms based on evolution, and natural, animal, and human behavior are widely reported in the literature, so the development of hybrid algorithms is common in order to provide a new method with the strength of the native ones.

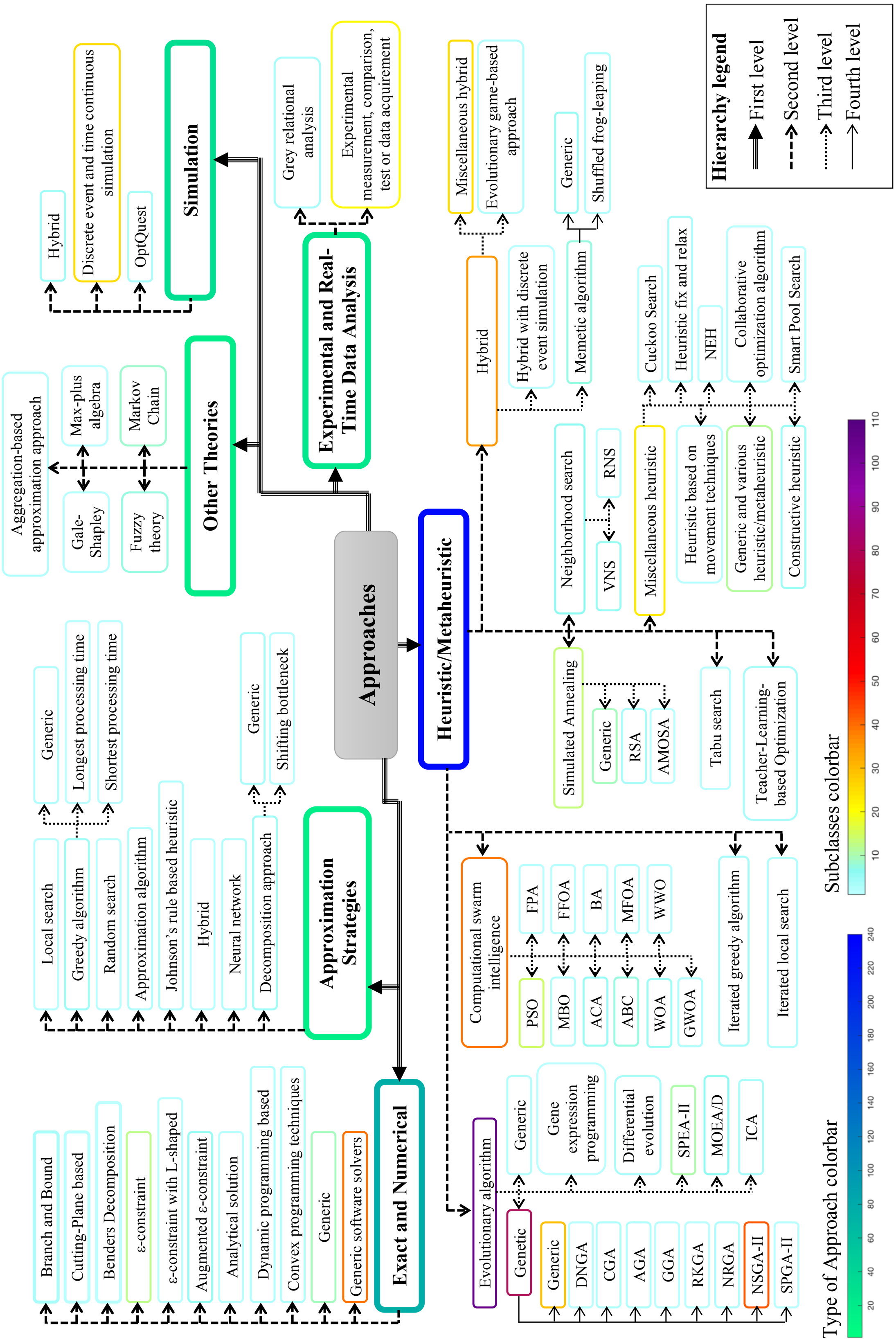

Figure 1.6 Energy Efficiency Approaches

In the following table (Table 1.1) the abbreviated name of the algorithms presented in Figure 1.6 has been reported

ABC	Artificial Bee Colony	MFOA	Moth Flame Optimization Algorithm
ACA	Ant Colony Algorithm	MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition
AGA	Adaptive Genetic Algorithm		
AMOSA	Archived Multi-objective Simulated Annealing	NEH	Nawaz-Enscore-Ham heuristic
		NRGA	Non-dominated Ranked Genetic Algorithm
BA	Bat Algorithm	NSGA-II	Non-dominated Sorting Genetic Algorithm II
CGA	Cellular Genetic Algorithm	PSO	Particle Swarm Optimization
DNGA	Domination Number-based Genetic Algorithm	RKGA	Random Key Genetic Algorithm
		RNS	Randomised Neighborhood Search
FFOA	Fruit Fly Optimization Algorithm	RSA	Restarted Simulated Annealing
FPA	Flower Pollination Algorithm	SPEA-II	Strength Pareto Evolutionary Algorithm II
GGA	Grouping Genetic Algorithm	SPGA-II	Sub Population Genetic Algorithm II
GWOA	Grey Wolf Optimization Algorithm	VNS	Variable Neighborhood Search
ICA	Imperialist Competitive Algorithm	WOA	Whale Optimization Algorithm
MBO	Migrating Bird Optimization	WWO	Water Wave Optimization

Table 1.1 Algorithm abbreviations

Several studies used the exact and numerical approach. In particular, a significant number of works uses the mathematical solvers offered by different software due to the high quality of solutions obtained. As previously stated, the exact and numerical approaches however require high computational complexity and solution time; for these reasons, the application is restricted to the small scale instances problems. Also, simulations, real-time data acquirement, and experimental tests have been used to develop, implement and evaluate energy-efficient strategies. Discrete event simulations have been used mainly compared to the time continuous simulations; discrete event and time continuous simulations have been grouped due to the fact that in many cases, simulative approaches used both of them or a hybridized approach. Other theories have been limitedly studied, but among these, a larger number of works concerns Markov chain and Fuzzy Theory. Few papers regarding approximation strategies have been presented in the energy-efficient context.

1.1.6 Literature limitations and implications for future research

The energy efficiency in manufacturing system has been widely analyzed, indeed about 66% of the papers considered in the literature analysis concerns this topic. The higher number of articles in this context examines the flow shop configuration. Respecting the other works in the manufacturing system group a significant number of articles analyses job shops and single machines. Energy efficiency in open shops has been limited analyzed covering only the 1% of the total papers. Moreover, these studies considered the open shop layout in processor environments and not in a typical manufacturing system.

In the single machine context, the main limit of the state of art regards the alignment of the process parameters such as cutting speed, feed rate and so on to renewable power supply. The investment analysis of the adoption of renewable energy supply has been poorly investigated. Analyzing the switch-off policies, the works proposed in the literature focused mainly on a single machine or on a production line disregarding their implementation in production systems with the unfixed flow of pieces, such as job shops. Moreover, the performance reduction due to the adoption of energy saving policies has also been poorly studied.

Deeping the job shop context, there is a lack of papers that investigated the production scheduling, considering both the power constraint and the variable speed of machine tools. Finally, at the factory level, few works take into account the opportunity of implementing the switch-off policy from the design step of the manufacturing system.

The actual state of the art is rich in works that implement and develop heuristic and metaheuristic approaches, especially evolutionary algorithms. The main reason is the great number of articles regarding scheduling problem that requires heuristic techniques to be applied in real life and large instance cases. A limited number of articles proposed the application of other theories, for example fuzzy theory. Furthermore, only about 11% of the analyzed articles focused on the implementation of renewable energy sources in manufacturing. Renewable energy sources in manufacturing systems could be a hot topic for the next years. The decreasing cost of adopting renewable resources is pushing their use in complex manufacturing systems; particularly photovoltaic and wind power systems are driving the increment adoption of renewables. The main limitation of using renewable energy sources is the intermittent power provided; for these reasons, researchers are studying new energy efficient strategies and energy flexibility. One of the main challenges is mainly the development of renewable energy-oriented policies and strategies in order to obtain not only energy saving but also an efficient use of renewable energy; another way to save and use when needed the variable energy is the adoption of batteries. However, the introduction of energy storage requires attention to its sizing, both to have enough energy when needed and not exceed in battery size with a consequent increase in costs. A lack of works has been found regarding the development of energy-saving policies that consider renewable energy sources. For these reasons, future directions and challenges for researchers could be the implementation of energy-saving policies considering the availability of renewable energy supply, in-depth analysis of other and noncommon theory applied in different contexts, considering renewables and energy efficiency as one target for sustainability and not as separate issues.

1.2 Motivation and Research Questions

This thesis, motivated by the importance of sustainable production as demonstrated in the analysis of the literature, focused and deepened several aspects of energy efficiency and sustainability in manufacturing systems trying to cover the lack in the state of art. The main topics analyzed, each of them is extensive discussed in a separate chapter, are the implementation of the renewable energy sources in the single machine context, the development of new switch-off policies, the scheduling problem in job shop context and the design of flow line in order to apply switch-off policies.

For each topic, this thesis aims to answer to several research questions indicated as follows.

Chapter 2 analyzes the implementation of renewable energy supply (in particular a photovoltaic plant) in the single machine context and the effects of the addition of energy storage. The research questions addressed are:

> RQ1: *what is the impact of the renewable energy source on the time evolution of the parameter settings of machine under different conditions over a planning horizon*?
>
> RQ2: *what is the economic gain that can be obtained by the method proposed*?
>
> RQ3: *what is the impact of the introduction of battery storage on a manufacturing production system?*

Chapter 3 focuses on switch off policies in job-shop for energy-efficiency and aims to respond to the following RQs:

RQ4: *what is the impact of the most used switch-off policy in flow lines in the case of job shop manufacturing systems?*

RQ5: *can a switch-off policy based on the evaluation of the workload be applied efficiently in job shop systems?*

Deeping the job shop context, Chapter 4 investigates the job shop scheduling problem with the introduction of power constraint dealing with the following issues:

RQ6: *can a scheduling model provide production planning considering the minimization of makespan as the objective function and the power as a constraint?*

RQ7: *can the developed scheduling model find a solution considering a variable available power in order to meet the decision maker's requirements based on sustainability and consumption criteria?*

The last topic investigated is discussed in Chapter 5 and regards the design of flow line with the purpose of responding to the following questions:

RQ8: *what is the impact of the design model proposed on the performance of the production line in terms of energy saving maximizing the production rate?*

RQ9: *can the constraint of a limited reduction loss improve significantly the energy saving of the production line obtaining an adequate trade off?*

As Duflou et al. (2012) argued, the manufacturing system can be decomposed into five levels:

- Unit process;
- Multi-machine;
- Factory;
- Multi-factory system;
- Supply chain.

For this reason, this thesis deepened different topics aiming to extend the studies regarding the energy efficiency in manufacturing at each level. The topics analyzed are related to the first three grades (Chapter 2 regards the unit process, Chapter 3 and 4 concern multi-machine and finally Chapter 5 is linked to the line design of a flow factory). Firstly, the single machine context has been investigated considering the implementation of a photovoltaic plant and a battery. Subsequently, deepening the multi-machine level, two different strategies of energy saving have been studied, i.e. switch-off policies and scheduling. Finally, at the upper grade of multi-machine, the energy-saving strategy analyzed regards the design of a flow line. The combination of the methodologies proposed at different grades could provide further benefits. In the following figure (Figure 1.7) has been reported the planning horizon required for the application of the energy saving strategies at different grades.

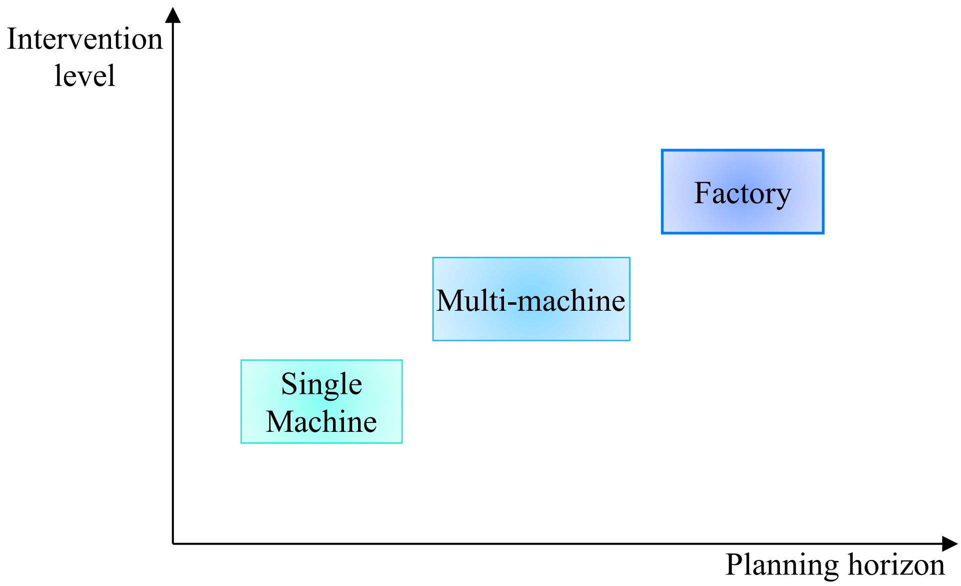

Figure 1.7 Planning horizon of the possible level intervention

Chapter 2: Renewable energy sources in single machine

The climate mitigation and the reduction of energy cost in manufacturing processes drive to expand the electricity generation from renewable sources. Nonetheless, the intermittency of renewable energies, especially solar and wind energy, represents one of the main challenges, typically overcome by the installation of electricity storage systems. This issue can be addressed by a new and original approach, consisting in the energy-flexibility of the production, in which manufacturing parameters are selected to optimize and to align production planning to renewable energy availability. This chapter deals with a time dependent theoretical and numerical model developed to calculate the time evolution of the electric power required by a manufacturing system, self-consistently coupled with a renewable plant.

The aim of the model is to align the power required by the manufacturing system with the renewable energy supply in order to obtain the maximum monthly profit. The model has been applied to a single work center powered by the electric grid and by a photo-voltaic system, performing the machining process over one year of production. The model includes the tool cost, the stocked units, the energy cost and the penalty for the unsatisfied demand. The maximum profit has been calculated with an hourly adaption of manufacturing parameters, i.e. the cutting speed, to the renewable time dependent power profile. The model presents general features and can be applied when production processes are fully characterized. In order to find the maximum profit, the model, inherently nonlinear, has been solved by recurring to the Trust-Region Method. Different scenarios characterized by fluctuations of product demand are considered in order to investigate the sensitivity of the manufacturing system to the uncertainty of the forecast demand. The influence of the photo-voltaic supply has been investigated, comparing results obtained in the case of manufacturing systems powered only by the electric grid. The main limitation of the overall literature concerns the alignment of the manufacturing process parameters (as the cutting speed, feed rate, etc.) to the intermittent renewable energy source. In fact, in the theoretical models analyzed in this context, cutting parameters have been adjusted to minimize the energy consumption without considering the alignment with the power supplied by the renewable energy source. Another limit related to the research activity is the investment analysis of renewable energy sources. The major part of the works focused on the design of the renewable source to supply the manufacturing system. These investigations don't consider how an existing energy source can impact the manufacturing system when process parameters change. The addition of electric storage allows storing the excess of the energy supplied by the PV (Photovoltaic) plant in order to use it, for example, during the dark hours of the day. Subsequently, the model has been tested considering the addition of energy storage to evaluate its effect to the manufacturing system. A basic storage model has been developed and implemented to pursue this issue. Therefore, as previously mentioned, this Chapter aims to respond to the following research questions.

RQ1: *what is the impact of the renewable energy source on the time evolution of the parameter settings of machine under different conditions over a planning horizon*?

RQ2: *what is the economic gain that can be obtained by the method proposed*?

RQ3: *what is the impact of the introduction of battery storage on a manufacturing production system?*

Nomenclature			
α	Taylor coefficient	HSS	High Speed Steel
η	solar plant efficiency	K	Taylor constant [m min^{-1}]
$\eta_g^{(s)}$	specific emissions of the greenhouse gas g emitted by the energy source s to generate electricity	K_{cs}	specific cutting pressure [N mm^{-1}]
		L	working length [mm]
		m_{CO_2eq}	CO2-equivalent mass emitted
γ	maximum power coefficient [%°C^{-1}]	n_{ct}	number of tools
a	Feed [mm rev^{-1}]	n_r	number of rapid movements
a_z	feed per tooth [mm tooth^{-1}]	$NOCT$	Nominal Operating Cell Temperature [°C]
C_d	daily cost [€]		
C_E	energy cost	P_{ax}	axes power during machining [W]
C_h	hourly cost [€ h^{-1}]	P_c	cutting power [W]
C_m	machining cost [€ h^{-1}]	P_d	daily profit [€]
C_{st}	storage unit cost [€ unit^{-1}]	P_m	monthly profit [€]
C_t	tool cost [€ tool^{-1}]	P_{PV}	Photovoltaic system power [W]
C_u	unit cost [€ unit^{-1}]	P_s	unit selling price [€ unit^{-1}]
CNC	Computer Numerical Control	P_{supp}	auxiliary units power [W]
D	mill diameter [mm]	P_{STC}	Power of photovoltaic system in Standard Test Conditions [W]
d_c	depth of cut [mm]		
d_m	days of the month	Pen	Penalty [€]
De	daily demand	Pen_s	penalty cost for unit [€ unit^{-1}]
Dem	effective daily demand	$prodh$	hourly productivity [unit h^{-1}]
E_{ac}	hourly energy in the battery	$PVGIS$	Photovoltaic Geographical Information System
E_b	hourly energy bought from the grid		
E_{bu}	energy bought from the grid for a single piece	R_d	daily proceeds [€]
		S_E	Selling price of energy
E_{ct}	energy for a tool change [J tool^{-1}]	St	stocked unit [€ unit^{-1}]
E_{fix}	fixed energy consumption [J]	T_a	ambient temperature [°C]
E_r	Energy for a single rapid movement [J]	T_c	cell temperature [°C]
E_{sc}	Self-consumed energy	t_{ct}	time to change a tool [s]
$E_{kt}^{(s)}$	electrical energy of the production process k supplied by the energy source s at time interval t	t_{fix}	fixed time [s]
		t_m	unit manufacturing time [min]
		t_p	unit production time [s]
Ep	energy for the production of a single unit [J unit^{-1}]	t_r	rapid movement time [s]
		T_{tool}	tool life [min]
Epv	PV energy for a single unit [J unit^{-1}]	U_{av}	available unit
F_c	cutting force [N]	U_p	daily produced unit
G	Irradiance [W m^{-2}]	v_c	cutting speed [m min^{-1}]
GHG	Greenhouse Gas	v_f	feed speed [m min^{-1}]
$GHGES$	Greenhouse Gas Emission Savings	z_e	number of engaged teeth
GWP_g	Global warming potential of greenhouse gas g		

Table 2.1 Nomenclature of Chapter 2

2.1 The implementation of PV plant in a single machine manufacturing system

2.1.1 Reference context basic assumptions of the model

In this paragraph, the basic assumptions of the model are introduced and discussed. The model under investigation is represented by the time dependent simulation of a single work center (a computer numerical control machine) of a manufacturing system that performs the machining process over one year of production, 24 hours per day. The model includes the tool cost, the storage, the energy cost and the penalty for the unsatisfied demand.

The model is developed in order to find the best compromise between the market demand and the power required with the aim of obtaining the maximum profit. The model is inherently nonlinear and a proper numerical model has been developed.

The model is simplified considering one work center supplied by the electric grid and by a PV (Photovoltaic) plant. The characterization of the energy consumption and power of the machine is evaluated according to Calvanese et al. (2013) and to Albertelli et al. (2016) and the process considered is the face milling of prismatic workpieces. For these reasons, the model has a general feature and basic assumptions considered do not limit the results that could be extended to a more realistic plant composed of several work centers supplied by an high-power PV plant. Finally, the model is able to catch the fundamental behavior of manufacturing systems with variable renewable energy supply and can be generalized when production processes are fully characterized.

More specifically, the demand for items is daily and the possibility of storing any excess production and a penalty for unsatisfied demand is considered. According to the sketch reported in Figure 2.1, the items stocked can be used the day after to satisfy the demand, reducing, consequently, the production.

The model includes a photovoltaic (PV) plant designed to provide energy to a single work center of the manufacturing system. During the dark hours, the machine works using the grid electricity and during the light hours, the photovoltaic can be used to supply the energy request for machining. The plant does not have energy storage so that an excess of power produced by the photovoltaic plant must be sold. The proposed approach aims to calculate the variable time profile, on an hourly base, of the optimal cutting speed to maximize the monthly profit, considering the following main parameters: the cost of the tools, the work center, the energy cost, the availability of energy supplied by the photovoltaic plant, the cost of storage and any penalties for failure to deliver the product. More in detail, regarding the PV system, hourly irradiance and ambient temperature have been taken from the PVGIS database (PVGIS, 2018) for a site located in Potenza, in the south of Italy. The photovoltaic system has been considered with a maximum power of 10 kW in Standard Test Conditions. The tilt and the azimuth are respectively 30° and -45° (SUD-EAST).

Figure 2.1 shows the reference context described for the daily production, divided into three main coupled areas: the market, the manufacturing system and the electric power system.

The aim is to suggest a methodology to increase efficiencies in the use of energy by implementing cleaner production and technical processes. More specifically, the model calculates the hourly profile of an operating parameter, i.e. the cutting speed, which maximizes the monthly profit recurring to the hourly time evolution of the PV power. In the model, the demand, daily generated from a discrete uniform distribution, and the buffer, due to the production of the day before, are the input of the manufacturing system. The work center (manufacturing) manufactures the parts by recurring to the grid and, whenever possible, to the PV system to maximize the profit changing hourly the cutting speed. The feed is not modified because it can affect the roughing of the items. In the next paragraphs, the mathematical model is described in detail and numerical results have been presented.

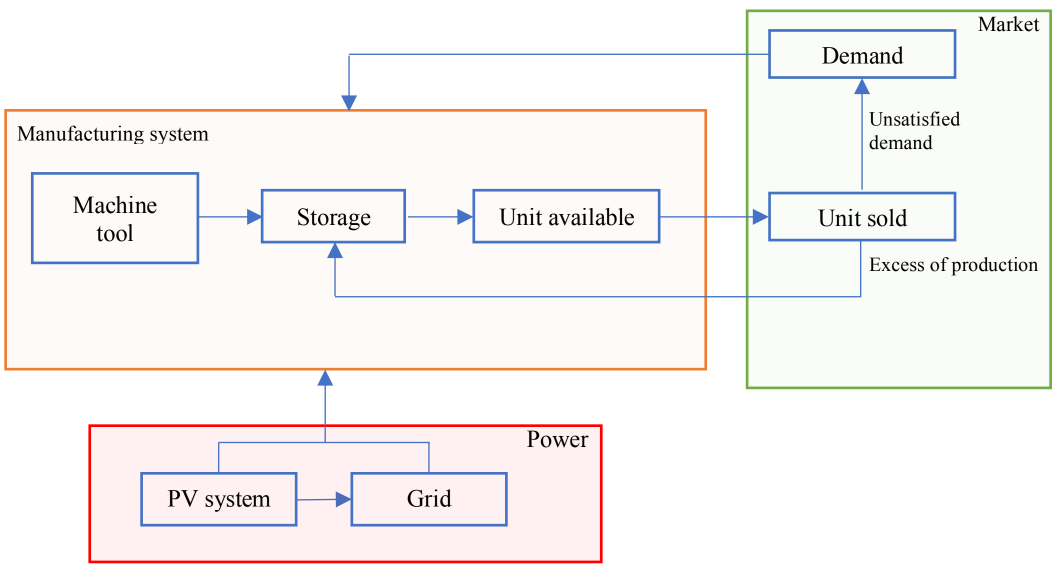

Figure 2.1 Schematization of the reference context

2.1.2 Mathematical and numerical model

2.1.2.1 Formulation of monthly profit

The objective function is the maximization of the monthly profit (P_m) (Eq. 2.1) calculated as the sum of daily profit:

$$MAX\ P_m = \sum_{j=1}^{d_m} P_{d,j}\left(v_c(t)\right) \tag{2.1}$$

where $P_{d,j}$ is the daily profit of the j-th day of the month, d_m is the number of days of the month and $v_c(t)$ is the time-dependent machining parameter (i.e., the cutting speed). In the following, the dependence of the daily profit from the cutting speed will be described and the hourly profile of the cutting speed that maximizes the monthly profit will be calculated by a numerical algorithm. The maximization of the objective function (the profit) has been carried out by recurring to the trust region method, a numerical method based on the interior point technique (Byrd et al., 2000).

The daily profit can be calculated as shown in Eq.2.2:

$$P_{d,j} = R_{d,j} - C_{d,j} - C_{st} \cdot St_{j-1} \tag{2.2}$$

where $R_{d,j}$ is the daily income of the j-th day of the month, $C_{d,j}$ is the daily cost of the j-th day of the month, C_{st} is the cost of a unit in storage, St_{j-1} is the number of units in storage from the production of the day before.

More, in particular, the daily incomes, i.e. the number of units sold times the selling price, are obtained as follows:

$$R_{d,j} = P_s \cdot \min\left(Un_{av,j}\ ;\ Dem_j\right) \tag{2.3}$$

where P_s is the unit selling price, $Un_{av,j}$ are the available units on the j-th day, and Dem_j is the effective demand on the j-th day. In turn, the available units can be calculated as the sum of the produced units on the j-th day, $Un_{p,j}$, and the units stocked the day before, St_{j-1}, as follows:

$$Un_{av,j} = Un_{p,j} + St_{j-1} \tag{2.4}$$

while the effective demand (Eq. 2.5) is calculated as the sum of the daily demand (De_j) and the unsatisfied demand of the day before, i.e.:

$$Dem_j = \begin{cases} De_j & if\ Dem_{j-1} \leq Un_{av,j-1} \\ De_j + Dem_{j-1} - Un_{av,j-1} & if\ \ Dem_{j-1} > Un_{av,j-1} \end{cases} \quad (2.5)$$

Finally, stocked units of the j-th day depend on the available units and on the effective demand of the (j-1)-th day as follows:

$$St_j = \begin{cases} 0 & if\ Dem_{j-1} \geq Un_{av,j-1} \\ Un_{av,j-1} - Dem_{j-1} & if\ \ Dem_{j-1} < Un_{av,j-1} \end{cases} \quad (2.6)$$

The following non-linear system can express double formulations given by Eq. 2.5 and Eq. 2.6 in the unknown's Dem_j and St_j.

$$\begin{cases} Dem_{j+1} = De_{j+1} + \left(Dem_j - St_j\right) \cdot \max\left\{0, 1 - \frac{Un_{p,j}}{(Dem_j - St_j)}\right\}; \\ St_{j+1} = \left(Dem_j - St_j\right) \cdot \max\left\{0, \frac{Un_{p,j}}{\left(Dem_j - St_j\right)} - 1\right\}; \end{cases} \quad (2.7)$$

A matrix formulation of Eq. 2.5 and Eq. 2.6 is given in the Appendix A, where a nonlinear system of equations must be solved to obtain the effective demand and the stocked units as functions of the demand and of the produced units. Nonlinearity arise due to the double formulations of equations 2.5 and 2.6.

By introducing the penalty for unit cost, Pen_s, the daily penalty for unsatisfied demand is expressed as

$$Pen = \begin{cases} 0 & if\ Un_{av} \geq Dem. \\ Pen_s \cdot (Dem - Un_{av}) & if\ Un_{av} < Dem \end{cases} \quad (2.8)$$

and the daily cost is defined as

$$C_d = \sum_{i=1}^{24} C_{h,i} + Pen \quad (2.9)$$

where $C_{h,i}$ is the hourly cost, which is strictly related to the hourly productivity, *prodh*, using the following equation:

$$C_h = C_u \cdot prodh \quad (2.10)$$

where C_u is the unit cost and the hourly productivity, i.e. the inverse of the unit production time t_p, depends on the cutting speed.

The unit cost, considering that the production system is equipped with a photovoltaic system without battery and is linked to the electrical grid, can be calculated by the following equation:

$$C_u = \begin{cases} \dfrac{C_m \cdot t_p}{3600} + C_t \cdot n_{ct} + C_E \cdot (Ep - Epv) & if\ Ep \geq Epv \\ \dfrac{C_m \cdot t_p}{3600} + C_t \cdot n_{ct} - S_E \cdot (Epv - Ep) & if\ Ep < Epv \end{cases} \tag{2.11}$$

where C_m is the hourly machining cost, C_t is the tool cost, n_{ct} is the number of tools for single piece, C_E is the energy cost, S_E is the selling price of energy to the grid, Epv and Ep are the energy given by the photovoltaic plant and the energy needed for the production of a single unit, respectively.

2.1.2.2 Formulation of unit energy and unit production time

The energy required to produce a single unit (Eq. 2.12) is written as (Albertelli et al., 2016):

$$Ep = E_{fix} + E_{ct}n_{ct} + E_r n_r + \left(P_c + P_{ax} + P_{supp}\right) 60 t_m \tag{2.12}$$

where E_{fix} is the energy used when the machine is on, E_{ct} is the energy used for a single tool change, n_{ct} is the number of tools changed, E_r is the energy used for a single rapid movement, n_r is the number of rapid movements, P_{supp} is the power request by the machine auxiliary units P_c is the cutting power, P_{ax} is the power request by the axes during machining and t_m is the manufacturing time. The energy needed for a single rapid movement is calculated by using Eq. 2.13 (Calvanese et al., 2013):

$$E_r = \sum_{k=x,y,z} \int_{t_0}^{t_1} P_{ar,k} \cdot dt + \int_{t_1}^{t_2} P_{r,k} \cdot dt - \eta_d \int_{t_2}^{t_3} P_{dr,k} \cdot dt \tag{2.13}$$

where $P_{ar,k}$, is the power absorbed during the acceleration of the axis k; $P_{r,k}$ is the power when the axis k is moving at the maximum speed and $P_{dr,k}$ is the power during the deceleration of the axis k and η_d is the fraction of energy recovered during the braking phase.

The time for a rapid movement (Eq. 2.14) it's given by (Albertelli et al., 2016):

$$t_r = (t_1 - t_0) + (t_2 - t_1) + (t_3 - t_2) \tag{2.14}$$

The cutting power P_c and the power request by the axes during machining P_{ax} can be calculated as follows (Eqs. 2.15):

$$P_c = \frac{F_c v_c}{60}, \qquad P_{ax} = \frac{1}{3}\frac{F_c v_f}{60} \tag{2.15}$$

where F_c is the cutting force, v_c is the cutting speed and v_f is the feed speed.
The cutting force (Eq. 2.16) is computed as follows:

$$F_c = K_{cs} \cdot d_c \cdot a_z \cdot z_e \tag{2.16}$$

where K_{cs} is the specific cutting pressure, d_c is the depth of cut, a_z is the feed per tooth and z_e are the number of engaged teeth.
The unit production time is given considering all the contributions involved in the production by the following expression (Eq. 2.17):

$$t_p = t_{fix} + t_r n_r + t_{ct} n_{ct} + 60 t_m \tag{2.17}$$

where t_{fix} is the fixed time for a single process, t_r is the time linked to a single rapid movement, t_{ct} is the tool change time e t_m is the unit manufacturing time.
The tool life is given by Taylor tool life equation (Eq. 2.18) as follows:

$$v_c {T_{tool}}^{\alpha} = K \tag{2.18}$$

where T_{tool} is the tool life, and K and α are Taylor parameter.
The unit manufacturing time (Eq. 2.19), the number of tools (Eq. 2.20) and the number of rapid movements (Eq. 2.21) are given by the following equations:

$$t_m = \frac{\pi\, L\, D}{1000\, a\, v_c} \tag{2.19}$$

$$n_{ct} = \frac{t_m}{\left(\frac{K}{v_c}\right)^{1/\alpha}} = \frac{\pi\, L\, D}{1000\, a} K^{-1/\alpha}\, v_c^{\,1/\alpha-1} \tag{2.20}$$

$$n_r = 2n_{ct} + 2 \tag{2.21}$$

where *L* is the length of manufacturing and *D* is the mill diameter.

By using Eqs. 2.1-2.6 and 2.8-2.21, the monthly profit can be expressed as a function of the time-dependent profile of the cutting speed. In the Appendix A, the complete dependence of the monthly profit on the cutting speed is described, in particular in Figure A.1, where all the quantities are expressed as a function of the cutting speed except for the time evolution of the PV power and for the demand, considered as input quantities of the model. The model calculates the time profile of the cutting speed on an hourly base which maximizes the monthly profit.

2.1.2.3 Formulation of PV power

In order to evaluate the hourly time evolution of the PV power, empirical correlations based on the International standard for electrical performances of PV systems have been used (ASTM Standard E1036, 1998; Skoplaki & Palyvos, 2009). The electric power is strongly affected by the cell temperature, *Tc*, and by the irradiance, *G*, and can be calculated by recurring to a formula which involves a certification parameter, called the NOCT (Nominal Operating Cell Temperature) (IEC 61215, 2005). The NOCT is reported by the PV module manufacturer and is obtained from outdoor measurements by a thermal probe placed on the rear side of the PV module which is located on an open structure. It represents the temperature reached by the back sheet of the module in open circuit when the solar irradiance is 800 W m^{-2}, the ambient temperature Ta (20 °C), and the wind speed (1 m s^{-1}). The cell temperature can be calculated for different values of solar irradiance and ambient temperature (D'Angola et al., 2020; Skoplaki & Palyvos, 2009; Spertino et al., 2016), using a linear expression as follows (Eq. 2.22):

$$T_c = T_a + \frac{NOCT - 20}{800} G \tag{2.22}$$

and the electric power, P_{PV}, can be calculated starting from the Standard Test Conditions by using the following expression (Eq. 2.23)

$$P_{PV} = \eta \frac{P_{stc}}{1000} G(1 + \frac{\gamma}{100}(T_c - 25)) \tag{2.23}$$

where P_{stc} is the power in standard test conditions, η represents the system efficiency (0.85) and γ the temperature coefficient given by the manufacturer (-0.45 %/°C, while NOCT=45 °C).

Finally, the energy produced by the PV system for a single unit in the time interval [t_0, $t_0 + t_p$] is given by Eq. (2.24):

$$Epv = \int_{t_0}^{t_0+t_p} P_{PV}(t) \cdot dt \tag{2.24}$$

where the time evolution of the electric power is related to the time evolution of irradiance and ambient temperature and, as a consequence, of the cell temperature. The values of *G(t)* are based on calculations from satellite images performed by CM-SAF and the database represents a total of 12 years of data (Huld et al., 2012; Šúri et al., 2005) and are reported in Figure 2.2.

As previously discussed, the average profile of the irradiance, given by PVGIS database, does not match a real day profile, but results can be considered satisfactory being obtained over a year. In order to optimize the performances, a real-time system made by a set of sensors for measuring both meteorological and electrical parameters and a data control system can allow to obtain the maximum performance in different ambient conditions. Moreover, also forecasting model, able to calculate irradiance profile and climate conditions with short horizons, can be implemented in the model (Reikard & Hansen, 2019).

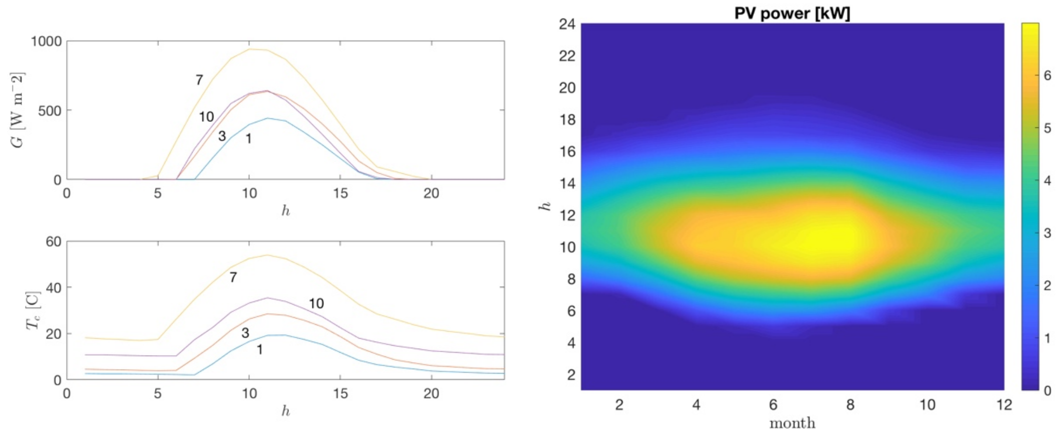

Figure 2.2 Irradiance and cell temperature during the average day of January (1), March (3), July (7) and October (10). Electric power produced during the average day of the year.

2.1.3 Test case and numerical results

The numerical method developed to calculate the maximum monthly profit as a function of the cutting speed, has been extensively described in the previous paragraph and more in detail in the Appendix, in which the iterative procedure adopted to solve the nonlinear model has been illustrated (Figure A.2). By using the model, a strategy to increase efficiencies in cleaner production and technical processes can be designed implementing renewable energy. In the following section, some numerical results have been presented.

In particular, the proposed method has been used in a test case whose details are reported in Table 2.2. Cutting and machine tool parameters are taken from Albertelli et al. (2016) and Calvanese et al. (2013), while the tool used is in high speed steel (HSS) and Taylor's parameters are taken from Groover (2012).

Cutting parameter, tool properties and material properties		Selling data, production cost and solar plant data	
feed per tooth a_z	0.3 [mm tooth^{-1}]	unit selling price	6.5 [€ unit^{-1}]
depth of cut d_c	2 [mm]	unit storage cost	0.13 [€ unit^{-1}]
Taylor's constant K	120 [m min^{-1}]	penalty	0.65 [€ unit^{-1}]
Taylor's coefficient α	0.125	machining cost	25 [€ hr^{-1}]
mill diameter D number of teeth	40 [mm] 6	energy cost Selling price of energy	from 20:00 to 07:00 0.18 [€ kWh^{-1}] from 07:00 to 20:00 0.22 [€ kWh^{-1}] 0.04 [€ kWh^{-1}]
tool cost	2 [€ tool^{-1}]	peak power	10 [kW]
specific cutting pressure	2300 [N mm^{-2}]	solar plant efficiency	0.85
workpiece length	400 [mm]	PV plant size	80 [m^2] (Lasnier & Ang, 1990)
workpiece width	500 [mm]	Temperature power coefficient	-0.45 [%/°C]
		Tilt angle	30°
		Azimuth angle	-45° (-45° SUD, -90° EAST)
Machine tool parameter			
Fixed power	1200 [W]		
Auxiliary units power	1200 [W]		
tool change time	10 [s]		
Tool changer power	80 [W]		
fixed time	120 [s]		

Table 2.2 Data and simulation parameters of the test case

The unit selling price (Eq. 2.25), the penalty (Eq. 2.26) and a cost of unit stocked (Eq. 2.27) are defined as follows:

$$P_s = 1.2\frac{C_{u,vC} + C_{u,vP}}{2} \tag{2.25}$$

$$Pen_s = 0.1\, P_s \tag{2.26}$$

$$C_{st} = 0.02\, P_s \tag{2.27}$$

where $C_{u,vC}$ and $C_{u,vP}$ are respectively the units cost at the speed that minimizes the cost at the speed that maximizes the production. The assumptions of the simulation tests are the following:

- the cutting speed can change hourly.
- the demand of products is daily and is already known at the first day of the month under investigation.
- the storage capacity is infinite. This assumption allows evaluating if the proposed model increases the fixed assets due to the higher work in process.
- solar radiation and temperature data are considered as monthly averages of daily profiles on a hourly time scale.

To define the different demand scenarios, the number of pieces obtainable at the minimum production cost and the number of pieces obtainable at maximum production capacity were calculated (CIRP, 2019). By using the parameters given in Table 2.2, the daily productivity at the minimum production cost is 186 units, the maximum daily production is 220 units. In the test cases, daily demand is generated sampling from a discrete uniform distribution. The lower bounds of the three intervals are one-third, half of the daily productivity and the daily productivity that can be achieved when the cutting speed is the one that minimizes the production cost, respectively 62, 98 and 186 units a day. The upper bound is the maximum production capacity.

Three different fluctuations of the demand have been considered:

- Test case 1 with high fluctuation: [62-220], mean daily demand: 141 units;
- Test case 2 with medium fluctuation: [98-220], mean daily demand: 159 units;
- Test case 3 with low fluctuation: [186-220], mean daily demand 203 units;

Each test was also repeated considering the work center powered only by the electricity grid in order to obtain the performance evaluation.

To compare results obtained in the test cases, the following performance parameters have been considered:

- Profit gained over the year; it is the total profit derived from the production of the items.
- Energy cost; it is the total energy cost due to the electricity grid.
- Unit stocked; it is the total unit of items stored between two days that is a fixed asset.
- Penalty over the year; it is the total cost due to the items delivered in delay.

For each experimental class, simulations are repeated and averaged to guarantee a statistical validity of the results, considering that the daily demand is extracted by a statistical distribution. For each test case, 150 replications have been conducted to assure a 10% confidence interval and a 95% confidence level for each performance. The confidence interval describes a range of likely values of a statistic and typically, 95% or 90% confidence intervals are calculated (for more details (Currie, 2019)). The performance with the largest confidence interval is the annual penalty, which however is below 10% with the number of replications considered. Regarding the statistical average and confidence intervals, Figure 2.3, as an example, shows the trend of the average of the yearly profit and of the yearly penalty with the number of replications for the test case 1. In the figure, the confidence intervals have been also reported showing a decreasing behavior with the number of replications.

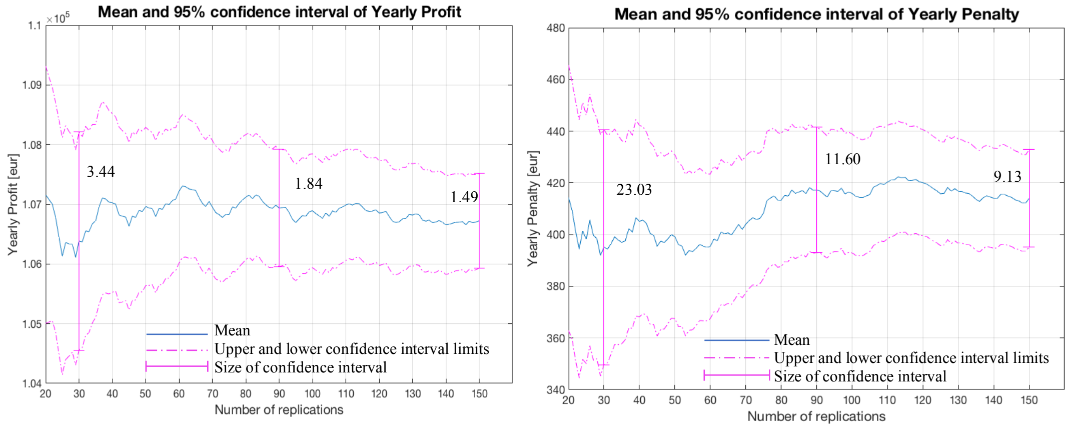

Figure 2.3 Mean and 95% confidence interval for yearly profit and yearly penalty for test case 1

Results obtained in the three different cases have been reported in Table 2.3, where mean values of the performances are shown.

	Case 1			Case 2			Case 3		
	Photovoltaic +Grid	**Grid**		**Photovoltaic +Grid**	**Grid**		**Photovoltaic +Grid**	**Grid**	
Yearly profit [€]	106724.70	103803.72	+2.81%	144763.40	141767.52	+2.11%	186922.14	183836.11	+1.68%
Energy bought [kWh]	30680.59	44091.26	-30.42%	34559.43	48299.75	-28.45%	44152.22	58375.44	-24.37%
Energy cost [€]	5913.23	8812.14	-32.90%	6681.51	9658.27	-30.82%	8590.58	11675.02	-26.42%
Units stocked [units]	9176.63	9131.93	+0.49%	9128.31	9114.15	+0.16%	2107.37	2106.83	+0.03%
Yearly penalty [€]	414.07	411.25	+0.69%	570.38	572.11	-0.30%	1700.13	1701.09	-0.06%
yearly self-consumed energy [kWh]	13411.36			13740.45			14223.43		
Energy sold [kWh]	851.45			522.37			39.38		

Table 2.3 Simulation results obtained for the three different test cases.

In the table, results obtained when the work center is self-consistently coupled to the PV plant and when it is powered only by the electric grid are compared. Results show the effectiveness of the energy-flexibility approach, aligning production planning and manufacturing parameters to the renewable energy supply. In all cases the energy bought decreases of about 30%. In test case 3, characterized by a greater demand, the yearly profit is higher due to the higher units provided. It can be noticed that the stocked units are lower than in other cases, and the yearly penalty increases. Indeed, increasing production to satisfy demand leads to an increase in tool and energy costs, and in this case, it is more suitable to pay the penalty rather than increasing the cutting speed with the linked costs.

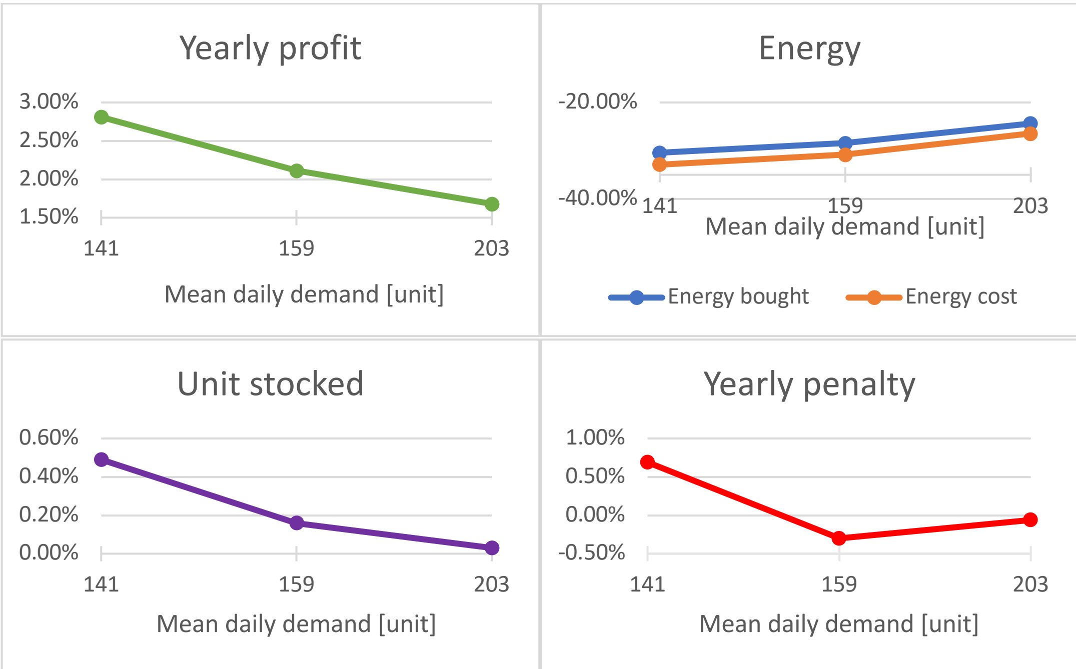

Figure 2.4 Percentage variation of the parameters in the three test cases from the benchmark (work center powered by the grid without PV plant)

Figure 2.4 shows the percentage variations from the benchmark (energy is given only from electricity grid) of the considered performances in the three test cases reported in Table 2.3.

Higher demand fluctuation (case 1) leads to a higher increase of the profit (2.81%), while the reduction of the fluctuations reduces profit gained. The other relevant result is the reduction of about 30% of the energy bought from the grid, that leads to reduce considerably the CO_2 emission. Lower fluctuations of the demand lead to reduce the benefits in terms of profit. Figures 2.5-2.8 show an example of time evolution of the parameters (cutting speed, energy bought, daily productivity, energy sold, energy self-consumed, PV energy produced) in the full model, where the PV plant has been self-consistently coupled to the manufacturing process in order to maximize the profit.

Results obtained in two selected months (January and July) have been reported for a single replication, in order to show how the model works on the time control of the cutting speed and the energy bought and sold. These figures show how the proposed model controls the cutting speed of the CNC (Computer Numerical Control) machine. A constant cutting speed profile is obtained when the PV plant is off and when the energy cost is always the same during the day. A slight dependence characterizes the time depended profile when different energy costs between day and night have been considered.

Analyzing the result for July in Figure 2.5, it can be observed that there is an increase in cutting speed during the light hours, especially in test cases 1 and 2. The increase of the production, linked to the cutting speed, is due to less cost of energy, when it is produced by the photovoltaic system. The increase in the speed in July in test case 3 is not relevant, because, in this case, a further increment of production implicates higher cost of tool and energy. In winter months, like January, there is no increment in cutting speed during the light hours, due to a lower value of irradiance and, thus, to a lower value of energy produced by the photovoltaic system. However, a few decreases in cutting speed during the light hour can be observed, due to a higher cost of energy bought from the grid during the central hours of the day.

Figure 2.6(a) shows the cutting speed profile in July when a single replication of the daily demand is generated. In Figure 2.6(b) the difference between the cutting speed at the Zenith and at midnight is reported being strictly related to daily production; in fact, the higher the production, the smaller the gap between the two speeds and the quantities are in phase opposition. However, it can be noticed that the gap is small in the day 13, despite the low daily production. This is because the cutting speed is close to its lower limit during the night, and due to the small number of units to be produced, it is not necessary to increase the speed during the day to meet the demand.

Figure 2.7 shows the energy bought and sold from and to the grid during the hours of the days of July and January for test case 1. In all simulations, the time dependent irradiance profile for each month is the average one as given by PVGIS database and are reported in Figure 2.2. It can be seen that in July, due to the greater values of irradiance, it is not necessary to buy energy from the grid, while in January the energy given by the photovoltaic system is not sufficient to guarantee the production. For this reason, the purchase of energy from the grid must be increased. Furthermore, there is no surplus of energy in January, while in July the excess energy is sold to the grid. In the other two cases, the same hourly behavior has been obtained, but with a lower daily variation of the energy bought and sold during the same month, due to the narrower range of daily demand.

Finally, Figure 2.8 shows the time evolution during one day of July of the energy bought, sold, self-consumed from PV system, produced by PV system and requested by the machine when a single replication of the demand is generated.

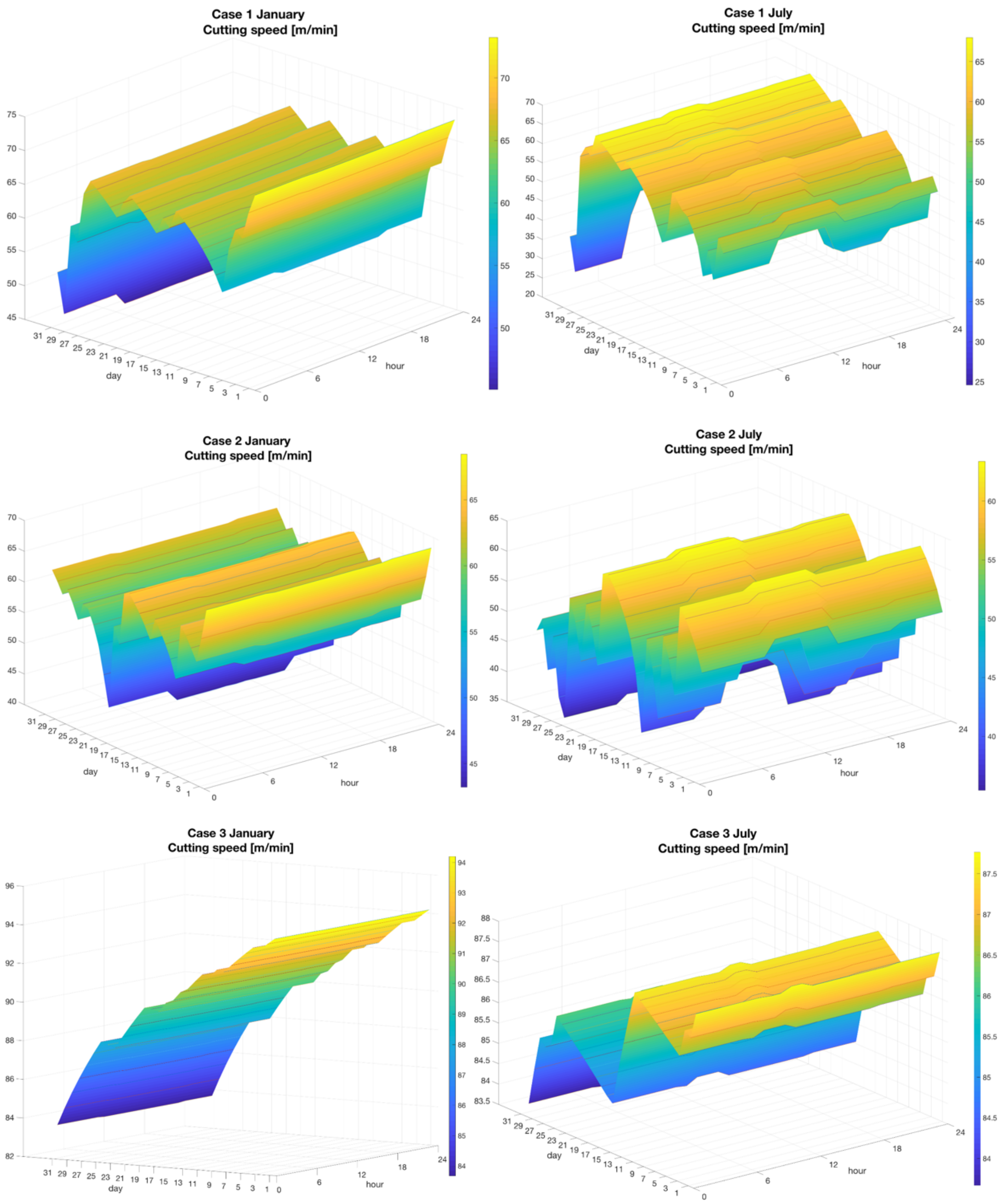

Figure 2.5 Cutting speed profiles for three test cases in January and July. The single replication of the daily demand is generated sampling from a discrete uniform distribution

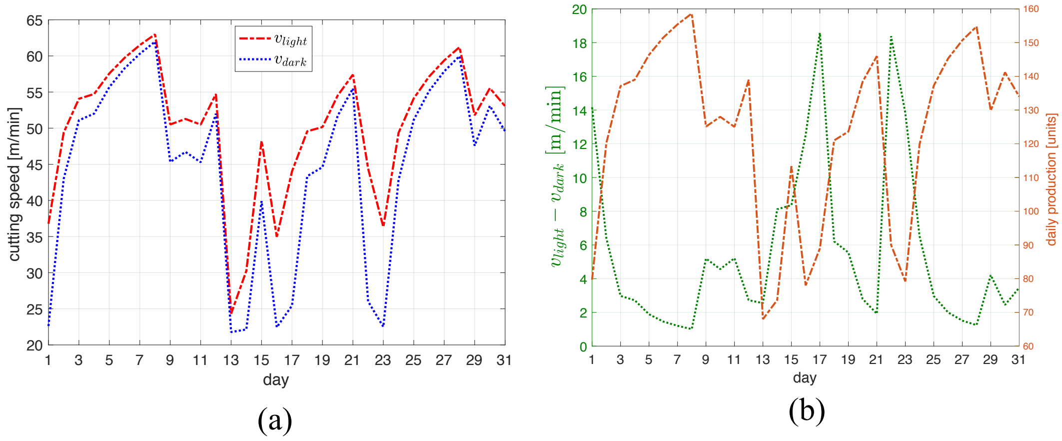

Figure 2.6 Cutting speed profile at the Zenith (v_{light}) and at midnight (v_{night}) (a) and differences of the two cutting speed profiles and daily productions (b) in July. The single replication of the daily demand is generated sampling from a discrete uniform distribution

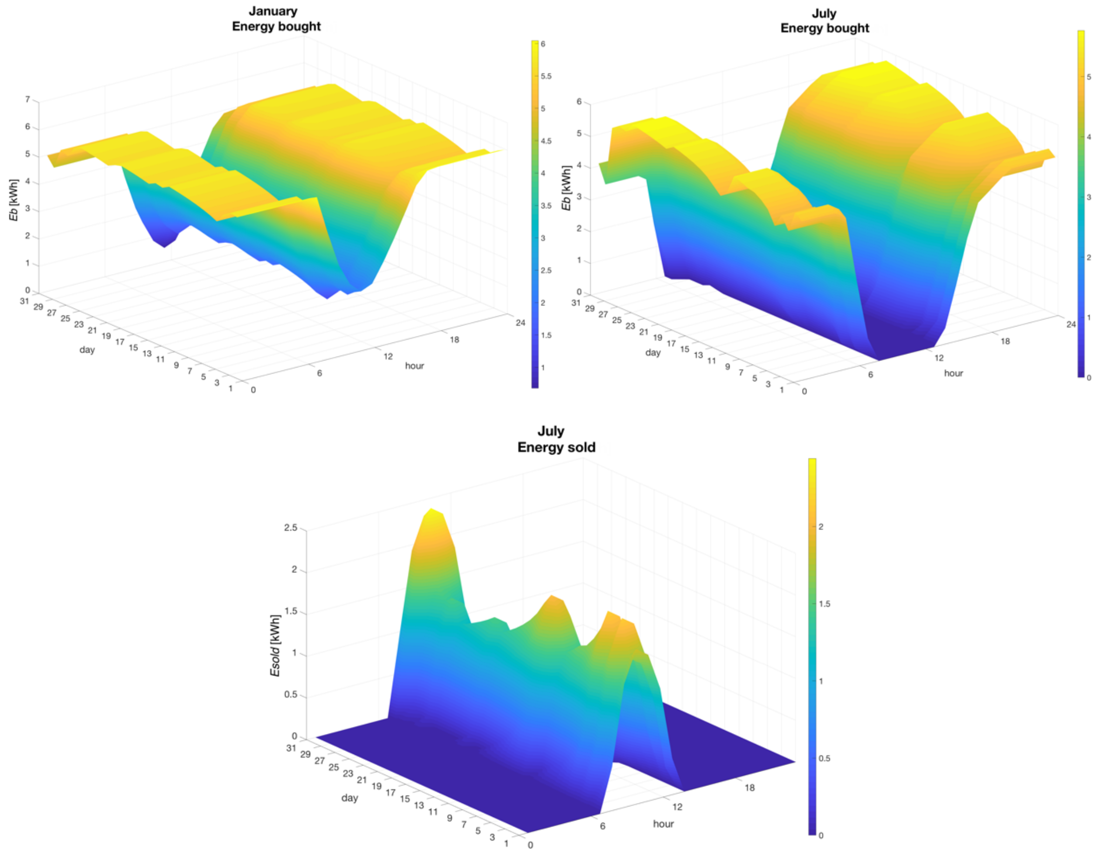

Figure 2.7 Energy bought (*Eb*) from the grid and sold (*Esold*) in January and July. The single replication of the daily demand is generated sampling from a discrete uniform distribution

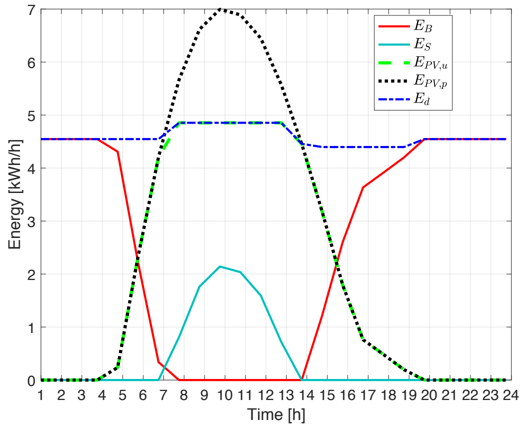

Figure 2.8 Daily profile of Energy bought (E_B), Energy sold (E_S), Energy self-consumed from PV system ($E_{PV,u}$), Energy produced by PV system ($E_{PV,p}$), Energy demand (E_d). The single replication of the daily demand (July) is generated sampling from a discrete uniform distribution

The main outcome of the model is represented by a strong reduction of the energy cost, obtained by finding the maximum monthly profit in a manufacturing system where the production and the required electric power is self-consistently aligned with the renewable energy source. Compared to the case where only the connection to the electricity is available, in the three test cases, the mean of energy cost is reduced by 32.9%, 30.8% and 26.4%, respectively.

To define the economic feasibility of the investment the well known Net Present Value formula has been used (Eq. 2.28):

$$NPV = -I_0 + \sum_{t=0}^{n} \frac{CF_t}{(1+i)^t} \tag{2.28}$$

The price of the solar system in the last 8 years decreased of 85% and the benchmark cost of the plant is about 1300 € kWp^{-1} (Jäger-Waldau, 2018). Thus, the investment for a 10 kW PV plant is 13000 €. Considering that the average saving on energy demand compared to the absence of the photovoltaic plant of the test cases analyzed is about 2986.67 € $year^{-1}$ and considering a cost of capital *"i"* of 3% (Bortolini et al., 2013), the payback period is 5 years.

2.2 The battery addition

The addition of electric storage allows storing the excess of the energy supplied by the PV plant in order to use it, for example, during the dark hours of the day. The aim is to find the cutting speed profile that achieves the maximum profit, including the possibility of storing energy. By using battery storage, the cutting speed profile has a lower fluctuation during a single day compared to the system composed only of the PV plant and connected to the electrical grid.

Figure 2.9 represents the reference context, i.e. the manufacturing system linked to the power system, composed of photovoltaic system (photovoltaic plant and battery) and of electrical grid, affected by the market demand.

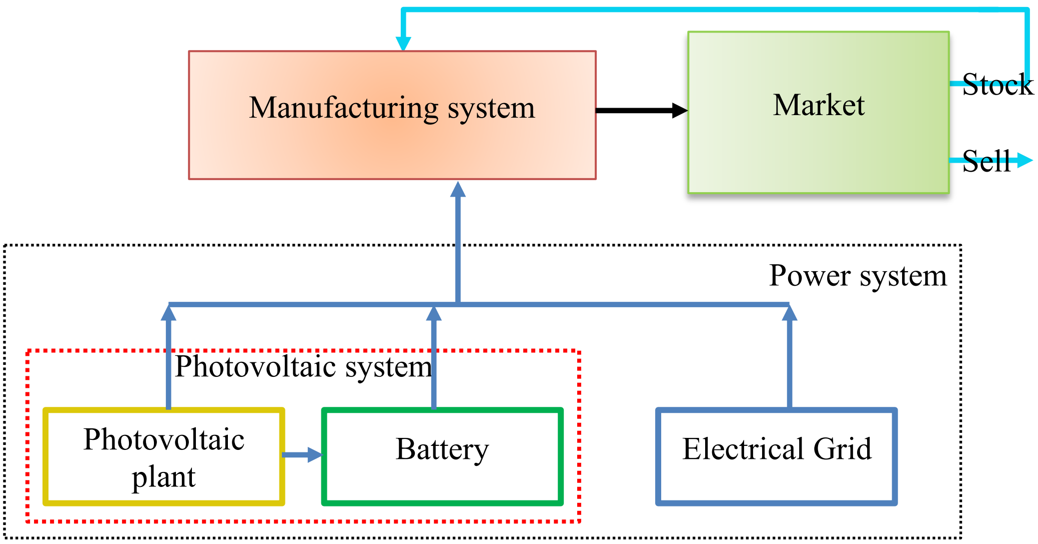

Figure 2.9 The addition of the battery to the power system

The battery charge level is also calculated on an hourly basis, as follows (Eq. 2.29):

$$Eac_{i,j} = \begin{cases} Eac_{i-1,j} + \left(Epv_{i,j} - Ep_{i,j}\right) \cdot prodh_{i,j} & if\ Ep_{i,j} \cdot prodh_{i,j} < Eac_{i-1,j} + Epv_{i,j} \cdot prodh_{i,j} \\ 0 & if\ Ep_{i,j} \cdot prodh_{i,j} \geq Eac_{i-1,j} + Epv_{i,j} \cdot prodh_{i,j} \end{cases} \quad (2.29)$$

where $Eac_{i,j}$ is the energy in the battery in the i-th hour of the j-th day, $Epv_{i,j}$ is the energy supplied by PV plant during the production of a piece in the i-th hour of the j-th day, $Ep_{i,j}$ is the energy required for the production of a piece during the i-th hour of the j-th day, and $prodh_{i,j}$ is the hourly productivity during the i-th hour of the j-th day.

Using Eq. 2.29, the battery is charged when the energy given by the PV plant is higher than the energy required for the production.

The battery can be in one of the following states:

- charge state, when $Epv_{i,j} > Ep_{i,j}$
- discharge state, when $Epv_{i,j} < Ep_{i,j}$
- neutral state, when $Epv_{i,j} = Ep_{i,j}$

For the first hour of a day, the stored energy must include the battery charge level of the previous day as follows (Eq. 2.30):

$$Eac_{1,j} = \begin{cases} Eac_{24,j-1} + \left(Epv_{1,j} - Ep_{1,j}\right) \cdot prodh_{1,j} & if\ Ep_{1,j} \cdot prodh_{1,j} < Eac_{24,j-1} + Epv_{1,j} \cdot prodh_{1,j} \\ 0 & if\ Ep_{1,j} \cdot prodh_{1,j} \geq Eac_{24,j-1} + Epv_{1,j} \cdot prodh_{1,j} \end{cases} \tag{2.30}$$

Similarly, the battery charge level at the beginning of a generic month must take into account the energy stored in the battery at the end of the previous months, as follows (Eq. 2.31):

$$Eac_{1,1} = \begin{cases} Eac_{24,l} + \left(Epv_{1,1} - Ep_{1,1}\right) \cdot prodh_{1,1} & if\ Ep_{1,1} \cdot prodh_{1,1} < Eac_{24,l} + Epv_{1,1} \cdot prodh_{1,1} \\ 0 & if\ Ep_{1,1} \cdot prodh_{1,1} \geq Eac_{24,l} + Epv_{1,1} \cdot prodh_{1,1} \end{cases} \tag{2.31}$$

where the subscript "*l*" denotes the last day of the previous month.

By using Eqs. 2.29-2.31, the level of the charge of the battery is initialized only the first day of the year.

Considering the presence of the battery, the energy bought by the grid is given by the following equation:

$$Eb_{i,j} = \begin{cases} Ep_{i,j} \cdot prodh_{i,j} - Eac_{i-1,j} - Epv_{i,j} \cdot prodh_{i,j} & if\ Ep_{i,j} \cdot prodh_{i,j} > Eac_{i-1,j} + Epv_{i,j} \cdot prodh_{i,j} \\ 0 & if\ Ep_{i,j} \cdot prodh_{i,j} \leq Eac_{i-1,j} + Epv_{i,j} \cdot prodh_{i,j} \end{cases} \tag{2.32}$$

where $Eb_{i,j}$ is the energy bought from the electrical grid during the *i*-th hour of the *j*-th day. When the energy required is higher than the energy given by the PV plant and by the energy storage, it is necessary to buy energy from the electrical grid for the production. The energy for the production of a single piece, is calculated as follows:

$$Ebu = \frac{Eb}{prodh} \tag{2.33}$$

where *Ebu* is the energy bought from the grid for a single piece. Then the unit cost in the case of addition of the battery, is calculated as:

$$C_u = \frac{C_m}{3600} t_p + C_t n_{ct} + C_E Ebu \quad (2.34)$$

where C_u is the unit cost, C_m is the hourly manufacturing cost, t_p is the production time, C_t is the tool cost, n_{ct} is the number of tools needed for the production of a single unit and C_E is the energy cost.

2.2.1 Simulation experiments and results

In the model, the energy can be bought from the grid, supplied directly by the PV plant and by the battery storage, which is sized in order to minimize the energy sold to the grid. In fact, if the PV production is greater than the energy demand for production, the excess energy is used to charge the battery. The energy costs during the day are reported in Table 2.4.

Hour	Energy cost
from 8:00 to 19:59	0.22 [€ kWh^{-1}]
from 20:00 to 07:59	0.18 [€ kWh^{-1}]

Table 2.4 Energy costs during the day

Regarding the daily demand of products, the same scenarios of the system composed of only PV plant have been considered. The scenarios analyzed are the same of the case of the system composed of only photovoltaic plant and connected to the grid and of the case of system only linked to the grid and have been presented in paragraph 2.1.3. Therefore, the fluctuation ranges are high, medium and low (case 1, case 2 case 3). The three test cases have been applied both to the production system assisted by the PV plant with energy storage and linked to the grid and to the production system equipped only with the PV plant and connected to the electrical grid (no battery storage). In the second case, the excess energy is sold to the electrical provider.
The percentage of variations has been obtained referring to the system assisted by the PV plant and linked to the grid (no battery storage). In the last case, energy costs are mainly reduced by the PV plant up to about 33%, 31%, and 26% respectively in the high, medium and low fluctuation of the demand, as evaluated in the previous paragraph.

To evaluate the effect of the battery storage, the following performances were considered:

- Yearly profit;
- Energy cost;
- Energy bought;
- Self-consumed energy.

In the following figures, the hourly profiles of the cutting speed are reported. Figure 2.10 shows the cutting speed (v_c) profile in January obtained finding the maximum of the monthly profit in the case of high demand fluctuation. The hourly profile of the cutting speed is characterized by a slow variation, due to the different value of the energy costs during the day. In January, for the lower energy supplied by the PV system, the behaviour of the system with and without the battery storage is the same, due to the low energy produced by the PV system.

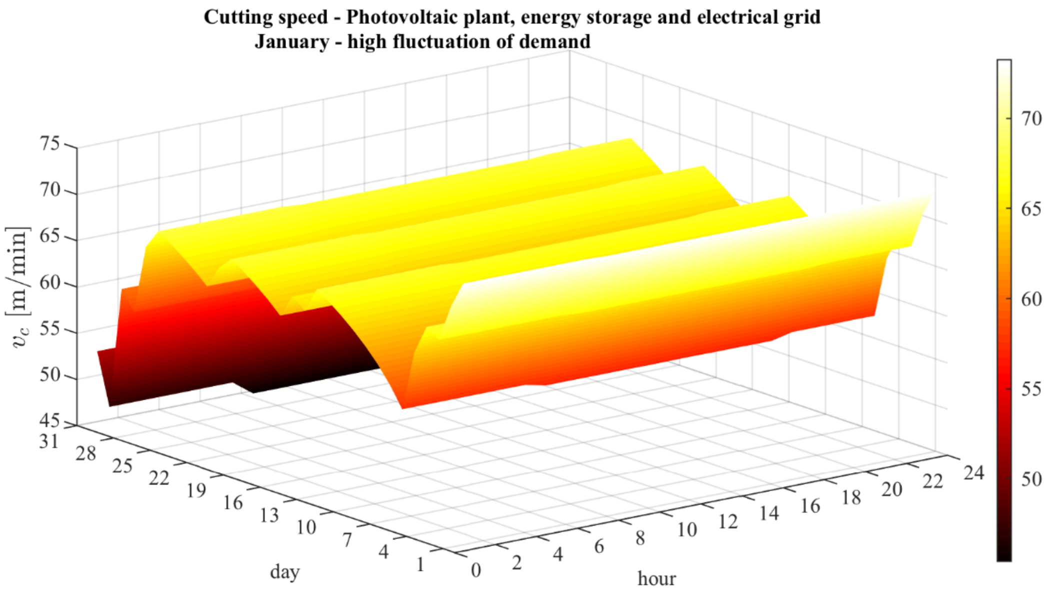

Figure 2.10 Cutting speed (v_c) profile for the case of high demand fluctuation in January in the system equipped with a PV plant, energy storage, and connected to the electrical grid

During the summer, when the energy supplied by the PV plant is higher, the cutting speed profile for the two production systems (with and without battery storage) is different. Figure 2.11 shows the two cutting speed profiles in August in the case of high demand fluctuation. It can be noticed that, in contrast to the system without energy storage, the presence of the battery storage reduces the fluctuations considerably during the day by finding a different cutting speed due to an increased self-consumed energy at a more favorable fare. The different values of the cutting speed in different days depending on the daily demand. The higher the daily demand, the higher the cutting speed. Higher increases in cutting speed during the light hour in the case without the battery storage occur when demand is low. To obtain profit it's required to meet the demand, for this reason when the market requires few pieces in a day to satisfy the requirements it's not necessary to produce at high cutting speed during the day. Incrementing the production during the light hours allows to reduce energy costs compensating the tool costs. Indeed, the lower the cutting speed, the lower the tool cost, but the higher the machining costs.

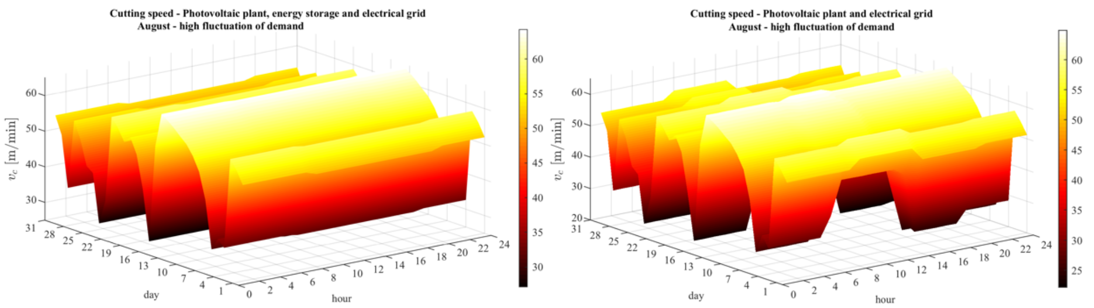

Figure 2.11 Cutting speed (v_c) profile in August for the high fluctuation demand in the system with and without battery storage

In the second test case, i.e. medium fluctuation demand, the cutting speed profiles for the two systems analyzed have the same behaviour of the case with high fluctuation demand. In the case of low fluctuation demand, the cutting speed profiles present low variations during the days, due to the lower variations of pieces to be produced and to the higher daily demand.

Figure 2.12 shows the energy bought from the electrical grid during January and August in the case of a system with battery storage and high fluctuation of demand. During January the battery storage never charges and energy must be taken from the grid even during the light hours. On the other side, during the summer months, the battery storage system increases the self-consumed energy, so it is not necessary to buy energy from the grid.

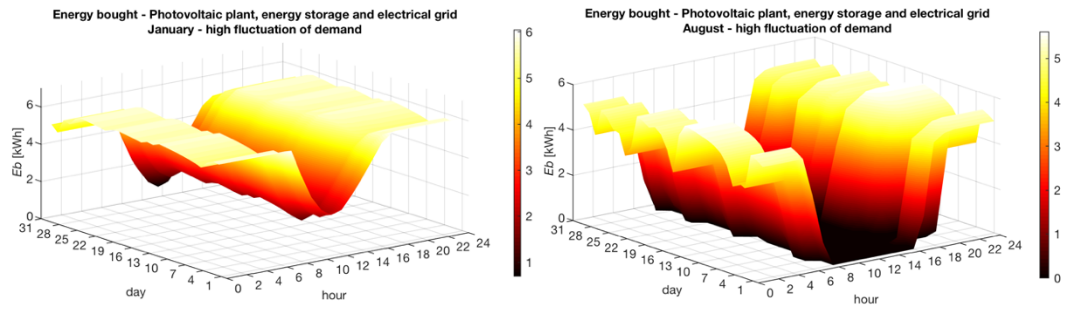

Figure 2.12 Energy bought (*Eb*) for the case of high demand fluctuation in January and in August in the system equipped with a PV plant, energy storage, and connected to the electrical grid

Figure 2.13 shows the energy stored during April and August. The peaks of stored energy occur during the summer months. The level of charging depends on daily demand: the lower the demand, the higher the energy stored during the same day.

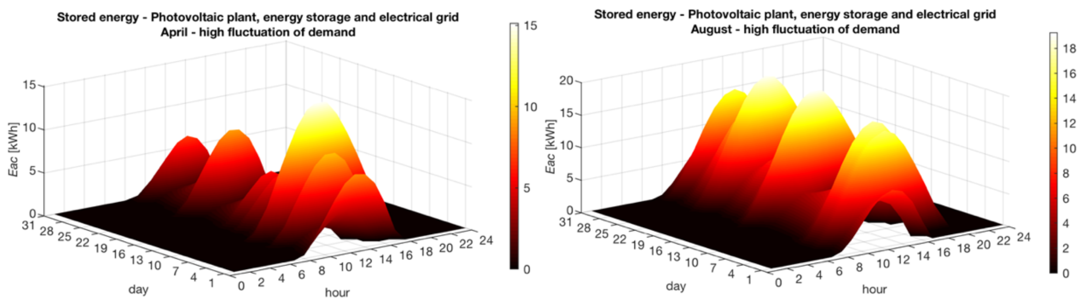

Figure 2.13 Stored energy (*Eac*) during April and August for the case of high demand fluctuation in the system equipped with a PV plant, energy storage, and connected to the electrical grid

Figure 2.14 represents the self-consumed energy in the system in the presence of battery storage and high fluctuation of demand. The figure shows that the presence of the battery allows to increase self-consumed energy over a long period of time, so that even when there is no photovoltaic energy available. The addition of the energy storage extended the time of using the self-consumed energy instead of selling it to the electrical provider at a non-affordable tariff. It can be noticed that the system can use the energy produced by the PV plant or stored in the battery, reducing considerably the energy bought from the electrical grid. When the energy supplied by the PV system and by energy storage is not enough for the production, the system is powered by the grid.

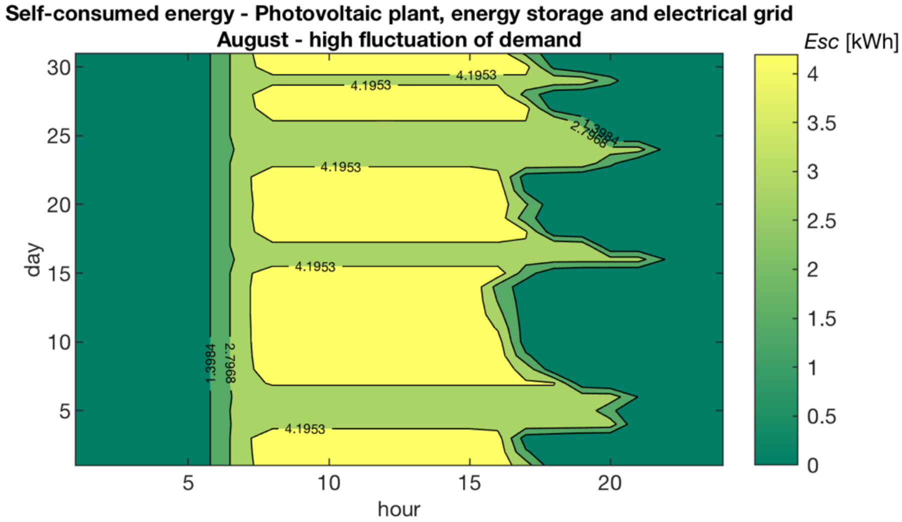

Figure 2.14 Self-consumed energy (*Esc*) in the system equipped with a PV plant, energy storage, and connected to the electrical grid with high fluctuation of demand

Figure 2.15 shows the charge level of the battery during the year. It can be noticed that energy is mainly stored between hours 2000 and 6500 and, for this reason, the addition of the battery storage has influence mainly during the spring and the summer. The level of charge is also influenced by the daily demand. In particular, the peaks of charge occur when the demand is low. For about 88% of the total time the energy stored, for this single work center model, ranges between 0 to 2 kWh.

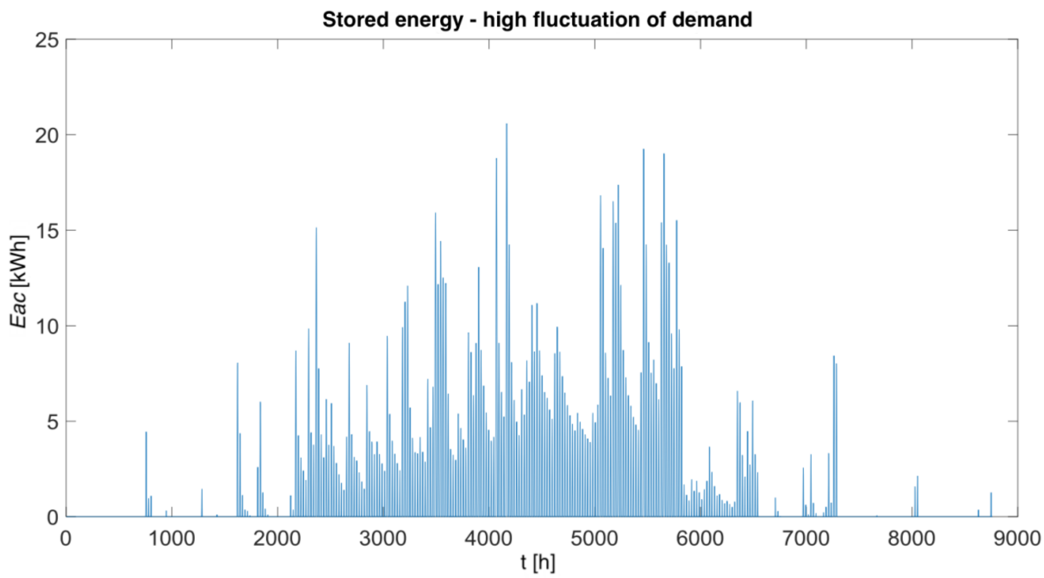

Figure 2.15 Stored energy (*Eac*) during the years. Simulations have been performed in the case of high fluctuation of the demand

The cutting speed profile requires further investigation and discussion, as reported in the following.

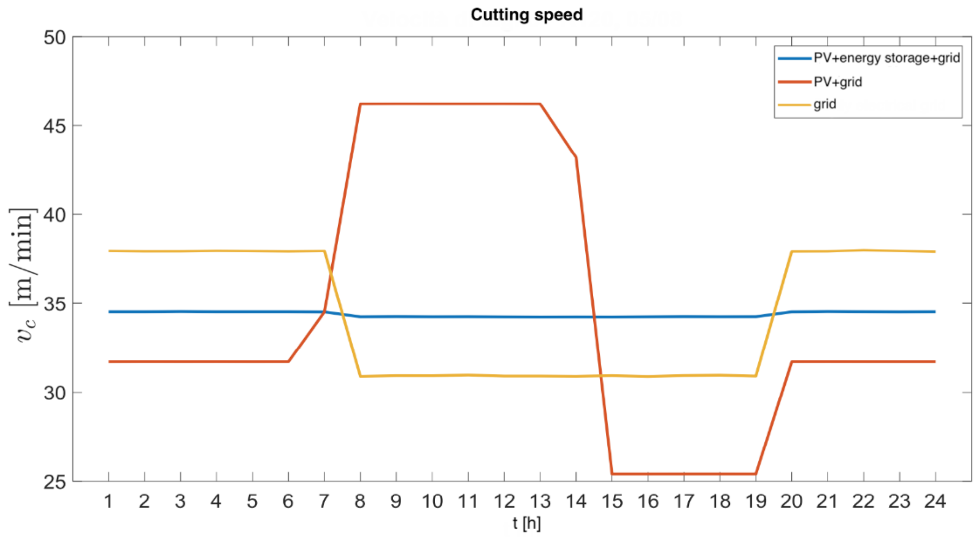

Figure 2.16 Cutting speed (v_c) during the 5th of August in the three power systems (grid, PV and grid, PV with energy storage and grid)

Figure 2.16 shows the cutting speed during the hours of one day simulated in the three cases: electrical grid (grid), PV plant and grid (PV+grid) and PV plant with battery storage and electrical grid (PV+energy storage+grid). In the case of only connection to the electrical grid, the cutting speed profile presents a decrement in the central hour of the day due to the higher electricity tariff. Considering the power system composed of the photovoltaic plant and linked to the electrical grid, the cutting speed raises during the light hour reducing the energy cost optimizing energy self-use. The introduction of the battery implies a constant cutting speed to optimize the profit. As described above, this circumstance allows to reduce the stress of the cutting tools and to improve the cutting life derived from the fatigue effect. The constant cutting speed reduces the percentage of life used for the manufacturing operation compared to the other two cases.

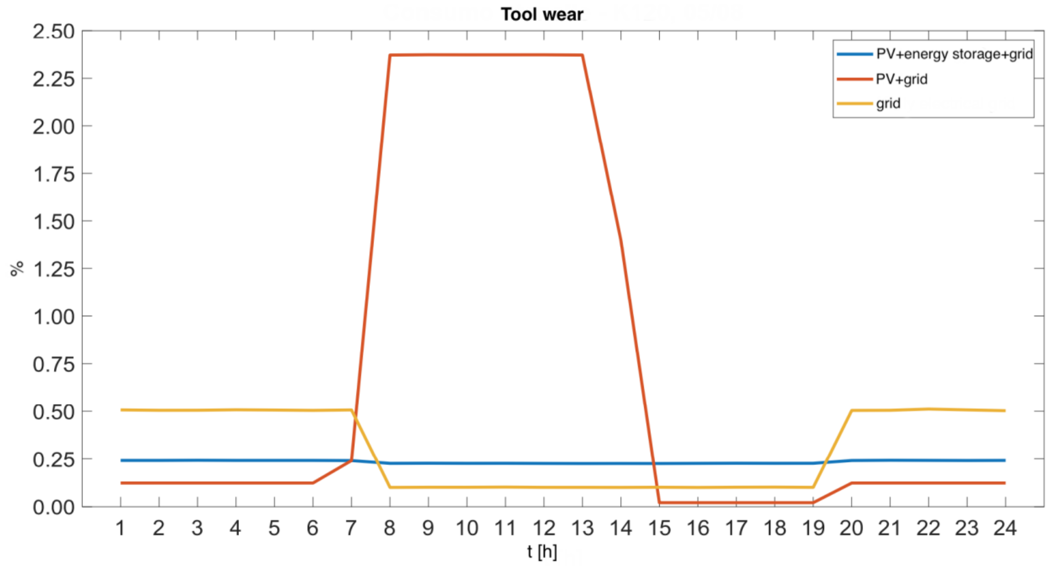

Figure 2.17 Percentage of tool wear during the 05th August in the three power systems (grid, PV and grid, PV with energy storage and grid)

Figure 2.17 shows the percentage consumed of the cutting tools for the three cases studied. Integrating the curve of the cutting speed, the total life consumed for the day can be obtained. It can be noticed that the percentage of the tool wear follows the cutting speed profile; analyzing the case of photovoltaic plant and electrical grid, the reduction of energy cost during the light hour allows increment the stress of the tools, and then their cost, in order to maximize the profit.

As shown in Table 2.5, the introduction of the battery reduces the life consumed at the same level as the network supplier. The benefit of this condition is the reduction of the tools used, and the management of the tool's inventory is simpler. The forecast for the tools is stable, and this allows us to improve the performance of inventory management.

	grid	PV+grid	PV+energy storage+grid
tool consumed % of total life	6.75%	18.75%	6%

Table 2.5 Percentage of tool wear

Table 2.6 reports the percentage variations of the performances analyzed with respect to the chosen benchmark. Energy costs are reduced by the PV plant up to 30% and the addition of battery storage leads to an additional reduction in energy cost, especially in the case of high fluctuation of demand.

	Per cent variations		
	High fluctuation	Medium fluctuation	Low fluctuation
Yearly profit [€ $year^{-1}$]	+0.16%	+0.068%	+0.004 %
Energy cost [€ $year^{-1}$]	-3.26%	-1.73%	-0.10%
Energy bought [kWh $year^{-1}$]	-2.79%	-1.51%	-0.09%
Self-consumed energy [kWh $year^{-1}$]	+6.37%	+3.79%	+0.28%

Table 2.6 Percentage variations of yearly profit, energy cost, energy bought and self-consumed energy of the system equipped with the PV plant, battery storage and linked to the grid respect to the system with only the PV plant and connected to the grid

In fact, it can be seen, in particular in the case of high fluctuation in demand, a reduction of about 3% the energy cost and an increase of more than 6% in self-consumed energy, producing for the system composed by PV plant and energy storage savings up to 35%. On the other side, in the case of medium fluctuation of the demand, the benefits obtained adding the battery storage are reduced and, in the low fluctuation demand, the performance variations from the benchmark are negligible. In fact, in this case, the system absorbs almost all the energy supplied by the PV system due to the higher production required and does not charge the storage system, behaving as if it were practically absent. As previously discussed, the addition of the battery results in a cutting speed profile with lower fluctuation during the day and this circumstance allows to reduce the stress of the cutting tools and to improve the cutting life derived from the fatigue effect.

Therefore, analyzing the results in both cases, i.e. with and without energy storage, the main findings of the numerical experiments are:

- energy flexibility approach allows to increase the profit;
- the hourly adaption of the cutting speed leads to a reduction of the energy bought from the electrical grid;
- the implementation of PV pant and energy flexibility approach allows reducing the CO_2 emissions, especially with high demand fluctuations;
- the introduction of a battery reduces the cutting speed fluctuations and limits tools fatigue stress.

2.3 CO_2 reduction through the integration of renewable electrical power

The simultaneous growth of the use of photovoltaic technology and the reduction in its cost has favoured the diffusion of solar power on a large scale, leading the solar power contribution to more than 20% of the world's electricity by 2050, as reported by the International Energy Agency (IEA, 2020), of which 16% is covered by photovoltaic systems (IEA, 2014). Moreover, in (IEA, 2020) solar energy, used for power generation and heating in buildings and industry, is considered to become by 2070 the largest primary energy resource, serving more than 20% of the global primary energy demand. The direct consequence is the reduction of a significant fraction of the growing global CO_2 emissions from fossil generation. Renewable sources typically produce emissions during manufacture but reduce carbon emissions considerably by replacing carbon-intensive sources. In order to calculate the emissions reduction, the energy that is replaced and its carbon intensity must be evaluated. Moreover, the energy consumed in manufacturing processes by installing the renewable system must be computed and added.

In PV energy conversion, solar radiation is directly converted into electric current self-consumed, dispatched to the grid or stored. The crystalline or multi-crystalline silicon (c-Si) devices convert sunlight to electricity with efficiency in the range 15-25% and cover around the 90% of the market due to the consolidated experience in manufacture and processing from the microelectronics industry. The cost of silicon PV modules has felt down from 15 €/Wp to lower than 1 €/Wp encouraging its growth (Jäger-Waldau, 2018; Marigo & Candelise, 2013). Alternative technologies are represented by thin films, characterized by lower cost (0.6 €/Wp) and efficiency, and multiple layers of different semiconductors with efficiency over 30%, but, due to the expensive manufacturing production, lower diffusion (Louwen et al., 2016).

Carbon intensity is strictly related to the characteristics of different PV technologies and ranges between 15 gCO_2/kWh and 38 gCO_2/kWh in the case of CdTe systems or c-Si, respectively, considerably lower than the intensity of fossil fuel (500 gCO_2/kWh), according to de Wild Schotten (2013).

The reduction of anthropogenic CO_2 (and, more generally, greenhouse gas GHG) emissions is seen as a mandatory objective for the next years to avoid harmful global warming problems (UNFCCC, 2015). However, the CO_2 emissions related to the energy sector continued to increase in the last five years, at an annual rate of 1.3% (IRENA, 2019b). According to IRENA (IRENA, 2019b), "*Renewable electricity paired with deep electrification could reduce CO_2 emissions by 60%, representing the largest share of the reductions necessary in the energy sector*". In addition, the combined effect of electrification and increased RES (renewable energy sources) deployment, together with a better energy efficiency of the energy components and systems, reduces the total energy demand from power plants based on fossil fuels. The corresponding environmental impact leads to a substantial reduction of CO_2 emissions. Besides the energy consumption aspects of energy flexibility, the assessment of the environmental impact of the products is crucial to enable the decision-makers reaching their strategic decisions. In this respect, the study carried out in Pfeilsticker et al. (2019) for the manufacturing industry considers the overall production cost (composed of energy cost, inventory cost, and processing costs defined with hourly rates per machine), as well as the emissions costs due to the use of energy during the production process.

The greenhouse gas emissions are considered by determining the CO_2-equivalent mass (Chicco & Mancarella, 2008), by using the emission factor (i.e., the specific emissions in g/kWh of a greenhouse gas produced by an energy source in the production process) multiplied by the global warming potential (GWP_g) to obtain the CO_2-equivalent mass. The emission factors depend on the production process, as different equipment and energy sources are used in each process. The emission factor referring to the electricity taken from the grid depends on the energy mix for electricity production in the country. An updated emission factor database can be found in IPCC (2020). For energy flexibility analyses, in which the variations of the operational schedules with respect to a baseline scenario are of interest, the relevant emission factors can be the marginal emission factors instead of the average emission factors (Harmsen & Graus, 2013). In fact, considering the average emission factors would imply that all the equipment undergo some changes, while flexibility is assessed by considering only the changes occurring for some equipment that form the operational energy and emission profiles. The application of energy flexibility strategies results in changing the energy used at different time intervals, with the consequent variation of the equivalent CO_2 emissions. Alternative expressions based on similar concepts are provided as the Carbon

Emission Signature (Jeswiet & Kara, 2008), in which the primary energy sources replace the production processes.

In the realm of sustainable manufacturing, an established method for CO_2 emission assessment is the carbon emission accounting (CEA), which considers energy, raw materials, and waste disposal. Recent advances include the extension of the CEA method to consider also capital factors and labour, leading to the Extended Carbon-Emission Accounting (ECEA) (Zhao-hui et al., 2020).

Some solutions that provide significant energy and CO_2 emissions savings in industrial plants include:

1. Enhancing self-sufficiency through flexible energy production in the manufacturing processes, also using demand response and energy storage to shape the energy demand profiles (J. Schulz et al., 2020). However, self-sufficiency cannot guarantee CO_2-neutrality (i.e., the absence of anthropogenic CO_2 production), because the type of equipment used in the energy systems could not be CO_2-free.
2. Enhancing energy flexibility from the combination of RES and carbon capture and utilization (CCU) solutions (Mikulčić et al., 2019). The CO_2 "wasted" from a manufacturing process can be used in other energy and chemical processes, also at relatively low scale. Since the actions needed to make CO_2 available for other processes may require energy, the CCU solution is viable only when this energy is produced from RES. Moreover, CCU could be more expensive than other solutions (e.g., energy storage (Schulze, Blume, Herrmann, et al., 2019)), then a specific analysis of convenience has to be carried out for the case under consideration.
3. Including recovering solutions and recycling strategies in the manufacturing processes (S. Lu et al., 2019), provided that the related costs are reasonable, and the corresponding energy requested comes from RES.

The solutions indicated above have the common advantage to require energy inputs from RES. This fact can be positive when the manufacturing system is located in an area in which a large extent of RES is available, or even the existing RES would be curtailed in the absence of further energy demand.

The emission factor model is used to assess the CO_2 equivalent emissions. The emissions considered are the ones due to the use of electrical energy taken from different sources. The emission factor $\mu_g^{(s)}$ represents the specific emissions of the greenhouse gas g emitted by the energy source s to generate electricity. The global warming potential GWP_g of greenhouse gas g is introduced to obtain the CO_2 equivalent emissions. The electrical energy $E_{kt}^{(s)}$ refers to the production process k supplied by the energy source s at time interval t.

Let us denote with **G** the set of greenhouse gases, with **S** the set of energy sources, and with **K** the set of production processes. The CO_2-equivalent mass emitted during the production process in the time period composed of successive time intervals $t = 1,\ldots, T$, is calculated as follows:

$$m_{CO_2eq} = \sum_{t=1}^{T} \sum_{k\in\mathbf{K}} \sum_{s\in\mathbf{S}} \mu_{CO_2eq}^{(s)} E_{kt}^{(s)} \tag{2.35}$$

where the CO_2-equivalent emission factor is expressed as:

$$\mu_{CO_2eq}^{(s)} = \sum_{g\in\mathbf{G}} \mu_g^{(s)} GWP_g \tag{2.36}$$

Eq. 2.35 can be used with regular or non-regular time intervals, provided that the actual energy values are used in each time interval.

The usage of different energy sources s to supply the electrical energy $E_{kt}^{(s)}$ changes the emissions because of the different emission factors involved. Hence, different ways to supply the same demand through the electrical grid or with local sources (photovoltaic systems and batteries) correspond to different emissions.

The combined effect of reducing the energy needed to carry out the process and using electricity taken from the local sources leads to reducing the CO_2-equivalent emissions. To quantify the emission savings, a baseline scenario is considered, in which no actions are done to enhance the effectiveness of the production process and the electricity is taken from the grid. In this case, the emission factor referring to the electricity taken from the grid depends on the energy mix for electricity production in the country (Nieuwlaar et al., 1997). For example, in Italy the GHG emission factor for electricity production from the national energy mix has decreased from 575.9 g/kWh in 1990 to 477.7 g/kWh in 2005, and to 307.7 g/kWh in 2017 (Caputo, 2019). For photovoltaic systems, the emission factor is the GHG emission rate of per unit electrical energy generated by the photovoltaic system (Peng et al., 2013); the CO_2-equivalent emission factors reported in the literature vary from 14 to 73 g/kWh (Tawalbeh et al., 2021). The GHG emission factor 40 g/kWh has been used in applications of photovoltaic systems with batteries (Jurasz et al., 2020).

For battery systems to be used together with photovoltaic systems, the GHG emission factor represents the pre-operation phase and is expressed in g/kWh with respect to the maximum energy capacity (in kWh) of the batteries; the value 200 kg/kWh has been considered in (Jurasz et al., 2020) for a battery lifetime of 10 years and has to be multiplied by the energy capacity of the battery storage system to get the overall mass of CO_2 emitted during the construction phase. This information is not directly translated into a GHG emission factor to be used during the battery operation, for example depending on the energy discharged by the battery.

The CO_2-equivalent mass $m_{CO_2eq}^{\text{base}}$ is then calculated from Eq. 2.35. Furthermore, the CO_2-equivalent mass m_{CO_2eq} is calculated after applying changes in the production process and/or changing the electricity supply sources. The GHG Emission Savings (*GHGES*) indicator is then introduced as:

$$GHGES = \frac{m_{CO_2eq}^{\text{base}} - m_{CO_2eq}}{m_{CO_2eq}^{\text{base}}} \tag{2.37}$$

Positive values of the *GHGES* indicator represent satisfactory cases in which the CO_2-equivalent emissions are reduced. The maximum value that can be obtained is $GHGES_{\max} = 1$, when the local electricity is totally produced from sources that do not produce GHGs. On the other side, negative values indicate that the new situation is worse than the baseline scenario, and the minimum value is not limited.

The energy balance due to the supply of the useful electrical energy E_{kt}^{demand} from the grid ($E_{kt}^{\text{gen,grid}}$) and from the local sources (photovoltaic $E_{kt}^{\text{gen,PV}}$, and battery discharge $E_{kt}^{\text{discharge,battery}}$) is:

$$E_{kt}^{\text{gen,grid}} + E_{kt}^{\text{gen,PV}} + E_{kt}^{\text{discharge,battery}} = E_{kt}^{\text{demand}} \tag{2.38}$$

In the situation analyzed here, in which the presence of a photovoltaic system with batteries is expected to reduce the GHG emissions, the battery is connected in such a way that can be charged only by the photovoltaic system and is never charged by the grid, to avoid increasing the GHG emissions.

The use of renewable energy sources in the manufacturing system allows reducing the energy bought from the electrical grid. The integration of the battery permits a further reduction of purchased energy. Electrical consumption involves CO_2 emissions due to the different technologies used in power plants. For this reason, the reduction of energy bought from the electrical grid by the integration of in-situ renewable and clean energy sources decreases proportionally the CO_2 emissions.

The assessment of the GHG emission savings is carried out by using Eq. 2.37. The GHG emission factors considered are:

- for the electricity taken from the grid: $\mu_{CO_2eq}^{(\text{gen,grid})}$ = 307.7 g/kWh for Italy (Caputo, 2019);
- for the electricity taken from the photovoltaic system: $\mu_{CO_2eq}^{(\text{gen,PV})}$ = 40 g/kWh (Jurasz et al., 2020);
- for the electricity taken from the battery: $\mu_{CO_2eq}^{(\text{discharge,battery})}$ = 0, neglecting in the operational phase the GHG emissions referring to the battery construction (Jurasz et al., 2020).

The GHG Emission Savings (*GHGES*) indicator for high, medium and low fluctuation case is respectively 0.28, 0.26, and 0.21.

In the following figure (Figure 2.18) has been reported the prevented CO_2 for each month in one replication of the high fluctuation case with the integration of the photovoltaic plant and energy storage.

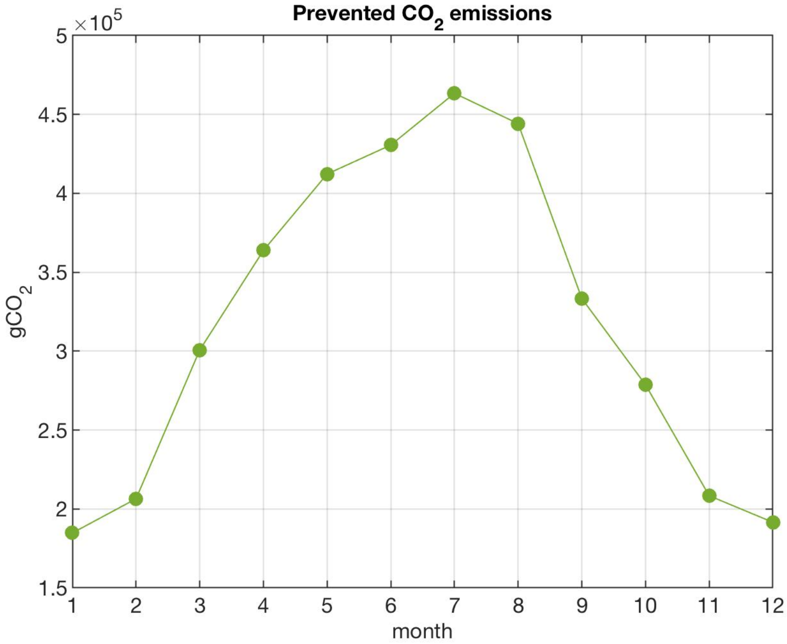

Figure 2.18 Prevented CO_2 emissions

The annual value of the prevented CO_2 emissions in the case of high, medium and low fluctuation is the same, as the presence of the battery allows storing excess energy without selling it to the electrical grid and enables maximizing self-consumed energy. The yearly mass of saved CO_2 emissions is about $3.82 \cdot 10^6$ gCO_2.

Chapter 3: Job shop policies

One of the main methods that can be used to reduce energy consumption in manufacturing systems is the adoption of policies and strategies that consider the energy issues. Energy saving can be achieved without investment in new equipment or changing the manufacturing process through the reduction of the standby periods (W. Li et al., 2011), e.g. using the switch-off approach (Frigerio & Matta, 2015a). The main potential application field is the machining operations where the CNC (Computer Numerical Control) machines can switch off (Su et al., 2016). This field concerns several manufacturing operations as milling, lathe, drilling, etc. This chapter concerns two main issues: the evaluation of the switch-off policy proposed in the literature for production line in a job shop without preferential routing of the jobs and the development of policies derived from the workload control approaches to support the switch-off of the machines.

The workload control is used to take into account the interaction among the machines in a job shop context. The WorkLoad Control (WLC) is a production planning control used for the small and medium enterprises that work in make to order way (Fernandes & Carmo-Silva, 2011; Stevenson et al., 2005). The main problems addressed by the WLC methods are the following (Renna, 2015): order release level, priority dispatching level and workload computation. The proposed method uses the workload computation to evaluate the interconnection among the machines of the job shop and decide the switch off/on. A simulation model tests the developed methods compared to the approach proposed in the literature to set the parameters of the policy and evaluate the benefits in terms of energy-saving and impact on the manufacturing system performance.

The works proposed in the literature have the following limits:

- The switch-off policies proposed works on a single machine or production line, the application in the job shop manufacturing system with no determined flow of the items was not investigated.
- Few works evaluate the reduction of the performance level, due to the introduction of the switch-off policy, in addition to the energy consumption;

In response, this chapter proposes switch-off policies in job shop systems by first asking:

RQ4: *what is the impact of the most used switch-off policy in flow lines in the case of job shop manufacturing systems?*

The policy proposed in the literature cannot take into account the interconnection among the machines of a flexible manufacturing system, then the second research question of this chapter asks:

RQ5: *can a switch-off policy based on the evaluation of the workload be applied efficiently in job shop systems?*

Nomenclature	
α, β	switching variable weights
Mc_{f1}	Classic aggregate workload formulation 1 policy
Mc_{f2}	Classic aggregate workload formulation 2 policy
Mwd_{f1}	Corrected aggregate dynamic workload formulation 1 policy
Mwd_{f2}	Corrected aggregate dynamic workload formulation 2 policy
Mws_{f1}	Corrected aggregate static workload formulation 1 policy
Mws_{f2}	Corrected aggregate static workload formulation 2 policy
N	N-policy
n_j	number of pieces in the buffer of the j-th workstation
np	product type number
nw	number of work centers
$po_{i,j}$	position of the j-th work center in the routing of the i-th job type
PR_j	binary working variable of the j-th work center
$re_{i,j}$	position of the j-th work center in the remaining routing of the i-th job type
SWc_j^{f1}	j-th work center switching variable of the formulation 1 in the classic aggregate workload
SWc_j^{f2}	j-th work center switching variable of the formulation 2 in the classic aggregate workload
$SWwd_j^{f1}$	j-th work center switching variable of the formulation 1 in the corrected aggregate dynamic workload model
$SWwd_j^{f2}$	j-th work center switching variable of the formulation 2 in the corrected aggregate dynamic workload model
$SWws_j^{f1}$	j-th work center switching variable of the formulation 1 in the corrected aggregate static workload model
$SWws_j^{f2}$	j-th work center switching variable of the formulation 2 in the corrected aggregate static workload model
WC_j	j-th work center
WLc_j	classic aggregate workload of the j-th work center
$WLwd_j$	corrected aggregate dynamic workload of the j-th work center
$WLws_j$	corrected aggregate static workload of the j-th work center
$x_{i,j}$	Binary routing variable
$xu_{i,k}$	Element of the updated routing matrix
XU	Updated routing matrix

Table 3.1 Nomenclature of Chapter 3

3.1 Reference context

The switch-off policies considered have been applied in a job shop manufacturing system. The job shop consists of three work centers each with a single machine. For this reason, the terms workstation and work center have been used in the text with the same meaning.

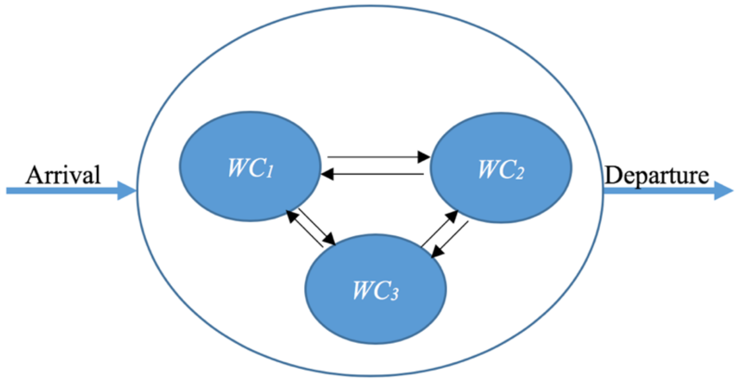

Figure 3.1 Three work center job shop manufacturing system

The number of job types that enter the manufacturing system is 15 with the same probability to arrive. Each job type is characterized by the number and order of the work centers visited. Table 3.2 reports the routing of the jobs considered. Each job can be processed at most once by each machining center and the flow is completely random, without a preferential flow.

Job type	Routing	Job type	Routing	Job type	Routing
1	WC_1	6	WC_1; WC_3	11	WC_1; WC_3; WC_2
2	WC_2	7	WC_3; WC_1	12	WC_2; WC_1; WC_3
3	WC_3	8	WC_2; WC_3	13	WC_2; WC_3; WC_1
4	WC_1; WC_2	9	WC_3; WC_2	14	WC_3; WC_1; WC_2
5	WC_2; WC_1	10	WC_1; WC_2; WC_3	15	WC_3; WC_2; WC_1

Table 3.2 Routing of jobs

The assumption of three machining centers with one machine each has been done to limit computational complexity and make the model easier to develop. Furthermore, the limited set of work-centers enables defining an acceptable number of job routings that represent all possible flows between the machines; increasing the number of work centers results in very numerous typologies of job. However, the choice to consider different types of jobs has allowed realizing a fluctuation in the arrival of the pieces; the same possibility of entry and into the system and the type of routing of all the pieces allows to obtain the same use of the machines. The job shop manufacturing system is tested considering different switch-off policies in order to evaluate the performance of each policy.

3.2 Switch-off policies

As described in Frigerio and Matta (2015a) there are four machine states: the out-of-service state (or off state), the idle state (or on-service state), the warm-up state, and the working state. The reduction of energy during the unproductive states (idle, off, and warm-up states) is a very important issue, in particular, switching off the machine in the idle state. However, turning on the machine while in out-of-service state as soon as a new job arrives at the buffer increases the energy consumption during the warm-up phase, due to the higher number of warmups. Moreover, having machines in off state and pieces in buffer results in an increment of the lead time. One of the policies used in the manufacturing system for energy saving is the *N-policy* (Frigerio & Matta, 2016). The *N-policy* uses the buffer information to switch the machine off or on. In particular, the machine goes in the out-of-service state when no pieces are in the buffer, and it switches on when the level of the buffer reaches *N*. This policy only considers the information of each workstation buffer to switch off/on. The *N-policy* achieves a reduction of warmups by storing more than one job in the buffer. On the other hand, waiting for several jobs to reactivate the machine results in a higher lead time. For these reasons switching policies that also consider the other jobs that will arrive at the machine could be useful tools to achieve energy saving. These policies could achieve a reduction of the mean lead time and a reduction of energy consumption during the warm-up phase compared to the classic *N-policy*. Nevertheless, the energy consumption in the idle state, caused by starvation while waiting for jobs to arrive at the machine, increases. In the following, the workload is evaluated by taking into account the number of workpieces, and not considering the processing time as it is the same for all jobs; this choice allows to evaluate the switch-off models without the processing time influence. The proposed policies differ mainly for the workload calculation, therefore we distinguish three types of policies according to the workload evaluation proposed in the literature, as follows:

- Classic aggregate workload (*WLc*) (Hendry, 1989; Tatsiopoulos, 1983);
- Corrected aggregate static workload (*WLws*) (Land & Gaalman, 1996; Oosterman et al., 2000);

– Corrected aggregate dynamic workload (*WLwd*) (Renna, 2020b).

In the classic aggregate workload, the direct load and the indirect load are considered without any distinction, while in the corrected aggregated workload the position of the work center in the routing is relevant. When the *i*-th job type enters in the manufacturing system, the workload of each work center is updated respectively as follows (Eqs. 3.1-3.3):

$$WLc_j = WLc_j + x_{i,j} \quad \forall \text{j} \tag{3.1}$$

$$WLws_j = WLws_j + \frac{x_{i,j}}{po_{i,j}} \quad \forall \text{j} \tag{3.2}$$

$$WLwd_j = WLwd_j + \frac{x_{i,j}}{re_{i,j}} \quad \forall \text{j} \tag{3.3}$$

Where $x_{i,j}$ is a binary routing variable equal to 1 if the *i*-th job type need to be worked at the *j*-th workstation, equal to 0 otherwise, $po_{i,j}$ is the position of the *j*-th work center in the routing of the *i*-th job and $re_{i,j}$ is the position of the *j*-th work center in the remaining routing of the *i*-th job type. Indeed, the main difference between the corrected aggregate static workload (*WLws*) and the corrected aggregate dynamic workload (*WLwd*) is that $po_{i,j}$ is fixed when the *i*-th job type enters in the system, while $re_{i,j}$ is updated every time a job exits a work center. When the *i*-th part type has been processed by the *j*-th machine and is ready to leave for the next work center, the *j*-th workload is updated in the classic aggregate workload (*WLc*) and in the corrected aggregate static workload (*WLws*) respectively as follows (Eqs. 3.4-3.5):

$$WLc_j = WLc_j - 1 \tag{3.4}$$

$$WLws_j = WLws_j - \frac{1}{po_{i,j}} \tag{3.5}$$

Instead, in the corrected aggregate dynamic workload (*WLwd*), when a part type leaves a work center, the workload of each workstation is updated as follows (Eq. 3.6):

$$WLwd_j = WLwd_j - \frac{xu_{i,nw(is-1)+j}}{re_{i,j}} \quad \forall \text{j} \tag{3.6}$$

Where *is* is the current step in the sequence of the *i*-th piece, *nw* is the number of workstations in the manufacturing system, and *xu* is the element of the updated routing matrix *XU*. The binary matrix *XU* is a binary matrix of dimension *np* x *nw(nw+1)*, in which *np* is the product type number. The element $xu_{i,nw\cdot k+j}$ is set equal to 1 if the *i*-th job type needs to be worked after the *k-1* job step by the j-th machine, 0 otherwise. Then the position in the i-th job remaining routing of the work centers that still have to process the part is updated as follows (Eq. 3.7) (Renna, 2020b):

$$re_{i,j} = re_{i,j} - 1 \tag{3.7}$$

The corrected aggregate dynamic workload of each machine is recalculated as follows (Eq. 3.8):

$$WLwd_j = WLwd_j + \frac{xu_{i,nw \cdot is + j}}{re_{i,j}} \quad \forall \mathrm{j} \tag{3.8}$$

To control the work center state, the switching variable has been defined in two different ways. In the first case, the switching variable is evaluated as the sum of direct and indirect load, properly multiplied by α and β coefficients. In the second case instead, the switching variable is obtained as the sum of the pieces in the buffer and the indirect load, and as previously done each term is multiplied by α and β. Nonetheless, when the aggregate static workload method is used, the second term of the sum does not represent the indirect workload, but the total workload. Indeed, in the $WLws$ the workload computation is static, and then considering the indirect workload (the difference between the total workload and direct workload) instead of the total workload may result in a negative value.

The different formulations of the switching variable allow defining two types of control mechanisms. The first formulation supposes that the signal for switching off the machine can start only when the machine has finished working, while in the second formulation, the switch-off signal starts in real-time, i.e. when the buffer level and the indirect workload are equal to zero. Having defined two formulations of the switching variables and applying this to the three workload calculation methods considered, six policies have been defined. Each model differs for the workload calculation and for the switching variable formulation. The switching variables of the j-th work center are defined in the six models considered as follows (Eqs. 3.9-3.14):

$$SWc_j^{f1} = \alpha\,(n_j + PR_j) + \beta(WLc_j - n_j - PR_j) \tag{3.9}$$

$$SWc_j^{f2} = \alpha\, n_j + \beta(WLc_j - n_j - PR_j) \tag{3.10}$$

$$SWws_j^{f1} = \alpha \left(n_j + PR_j\right) + \beta\, WLws_j \quad (3.11)$$

$$SWws_j^{f2} = \alpha\, n_j + \beta\, WLws_j \quad (3.12)$$

$$SWwd_j^{f1} = \alpha\, (n_j + PR_j) + \beta(WLwd_j - n_j - PR_j) \quad (3.13)$$

$$SWwd_j^{f2} = \alpha\, n_j + \beta(WLwd_j - n_j - PR_j) \quad (3.14)$$

Where n_j is the number of pieces in the j-th workstation buffer, PR_j is a binary variable equal to 1 if the j-th machine is processing a piece, and 0 otherwise, and α and β are two parameters that regulate in the two formulations respectively the contribution of the direct and indirect workloads and of the buffer level and indirect workload. The parameters α and β are between 0 and 1 and such that $\alpha + \beta = 1$. By choosing α equal to 1 and β equal to zero, the models with formulation 2 degrade in the *N-policy*.
A signal to switch off the machine starts when the switching variable is equal to zero. The machine switches on and is ready to work after the warmup phase when the switching variable reaches a defined value. The main problem of the *N-policy* and of the policies that only consider the buffer information to switch the machine state is that they do not consider the jobs that will arrive at the machine, but are still in another manufacturing center. The proposed policies also consider the entire workload of each machine in the variable for changing the state, and can achieve in a reduction of the switching-off and warming-up. For these reasons, the energy loss during the warm-up can be reduced.

switching policy name	type of workload calculation	switching variable formulation
Mc_{f1}	Classic aggregate workload	formulation 1
Mc_{f2}	Classic aggregate workload	formulation 2
Mws_{f1}	Corrected aggregate static workload	formulation 1
Mws_{f2}	Corrected aggregate static workload	formulation 2
Mwd_{f1}	Corrected aggregate dynamic workload	formulation 1
Mwd_{f2}	Corrected aggregate dynamic workload	formulation 2

Table 3.3 Simulated models

3.3 Simulation experiments and results

To evaluate the proposed policies, different simulation scenarios have been tested. These scenarios are also tested considering the Always On (AO) policy, where the machine is never switched off, and considering the *N-policy*. The simulation cases have been conducted following the terminating analysis approach. For each simulation case, several replications have been conducted to assure a 5% confidence interval and a 95% confidence level for each performance. The simulation scenarios and the statistical analysis are supported by the Rockwell simulation platform (Arena). The performances analyzed are: mean lead time, unproductive states energy consumption and total energy consumption. The performances have been evaluated as a percentage variation from the always on case, which is set as the benchmark. The assumptions are: the time to transfer a product between the work centers is zero; no energy is required to hold pieces in buffers; the job types have the same probability of entering the system; the processing time of each job at each work center is the same and follows a discrete distribution [100s-95%; 280s-5%] (Su et al., 2016). The power required in each state has been considered the same for all machines, as follows (Su et al., 2016): 5.35 kW in on-service (idle) state; 0.52 kW in out-of-service (off) state; 6 kW in warmup state; 12 kW in working state. Considering that the processing time of a piece at each work center is in mean about 110s, the warmup time is defined as equal to 66s (about 60% of process time). According to Su et al. (2016), the simulation length is 10^7s and the initial transient is $5 \cdot 10^5$s.

To evaluate the behavior of the different switching policies in the two formulations and different values of the parameters α and β, the models are tested considering that the jobs inter-arrival time follows an exponential distribution with an expected value of 110 seconds (Expo110). The models are simulated considering that the machines switch off when the switching variable is equal to zero and they reactivate when the switching variable reaches two different limits, respectively 1 and 2. Figure 3.2 shows the percentage variation of mean lead time and energy consumption in unproductive states considering the case in which that the machine never goes in the out of service state (Always On) as the benchmark. The results are reported as a percentage variation compared to the benchmark case.

One of the effects of the switch-off policies is the increment in the lead lime with respect to the always on case, due to the waiting time of the jobs in queue during the out of service state, and to the time required for the warm-up.
The best performances are obtained with a higher value of α. Indeed, the higher α, the lower the increment of the mean lead time, and the higher reduction of energy consumption in unproductive states compared to the always on case (Figure 3.2). Giving more weight to direct workload or to the number of pieces in the queue (respectively in formulations 1 and 2) than to the indirect workload leads to better performance. It can be noticed that in the corrected aggregate static models (Mws_{f1} and Mws_{f2}), the influence of the coefficients α and β is limited compared to the other cases. In the corrected aggregate static workload model, the two proposed formulations achieve the same results. This is because in the analyzed case the value of the switching variable to switch off the machine is equal to zero, i.e. when the total workload is null. When the machine is in out-of-service states, the binary working variable PR is zero, and for this reason, the machine warms up in the same condition.
The second formulation in the classic aggregate workload model and in the corrected aggregate dynamic model achieves a higher number of switch-offs, and then the machine stays in the out-of-service state for a longer time, as shown in Figure 3.2. Indeed, the second formulation does not exhibit the variable PR_j in the first term of the switching variable, which indicates the working state of the machine. For this reason, the signal to switch off the machine starts in real-time, differently from the first formulation where the switching signal starts only when the machine is not occupied with a job. Therefore, the second formulation gives a higher reduction in energy consumption, but a higher increment of mean lead time.

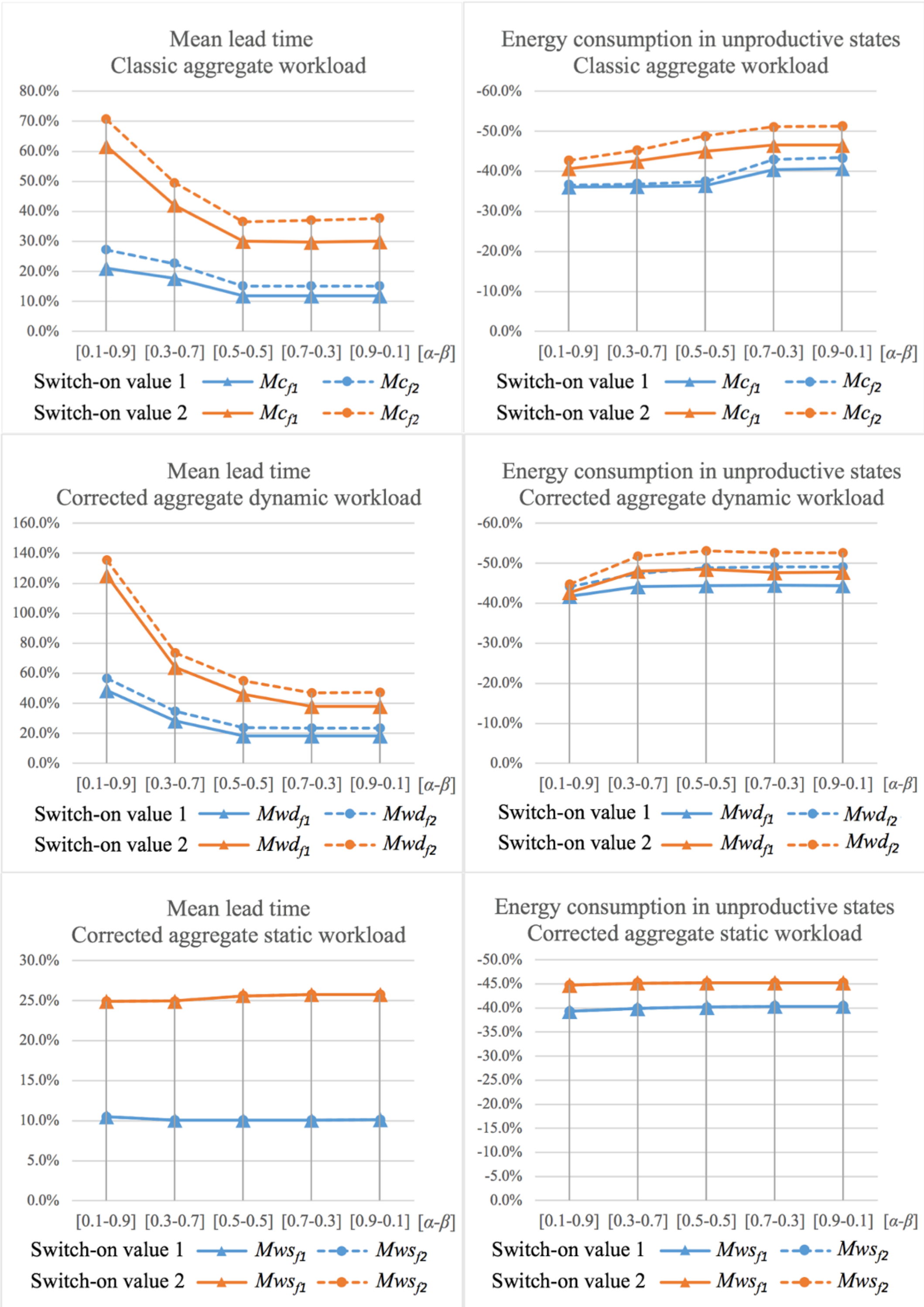

Figure 3.2 Mean lead time and energy consumption in unproductive states with different value of coefficient α and β

To evaluate the results of the proposed switching policies, the same model is repeated considering the classic *N-policy* proposed in the literature.

Figure 3.3 compares the performances (Mean lead time, energy consumption in unproductive states, total energy consumption) obtained with the *N-policy* and the proposed policies considering 1 and 2 as the limit to reach to reactivate the machine. The coefficients α and β have been chosen respectively equal to 0.9 and 0.1. Figure 3.3 also reports the results obtained with the two proposed formulations. Considering the case where the machines warm up in the proposed policies and in the *N-policy* respectively when the switching variable and the buffer level reach 2, the results show that the corrected aggregate static model achieves a lower increment of the mean lead time from the benchmark. The *N-policy* as shown in the figure leads to the highest reduction in energy consumption but also to higher lead time.

Setting the switch-on value from 1 to 2 achieves a reduction of energy consumption, but at the same time an increment of the mean lead time. This effect can be mitigated with the proposed policies, which not only consider the information of each work center to change the state of the machine, but also the jobs that are currently in the entire production system.

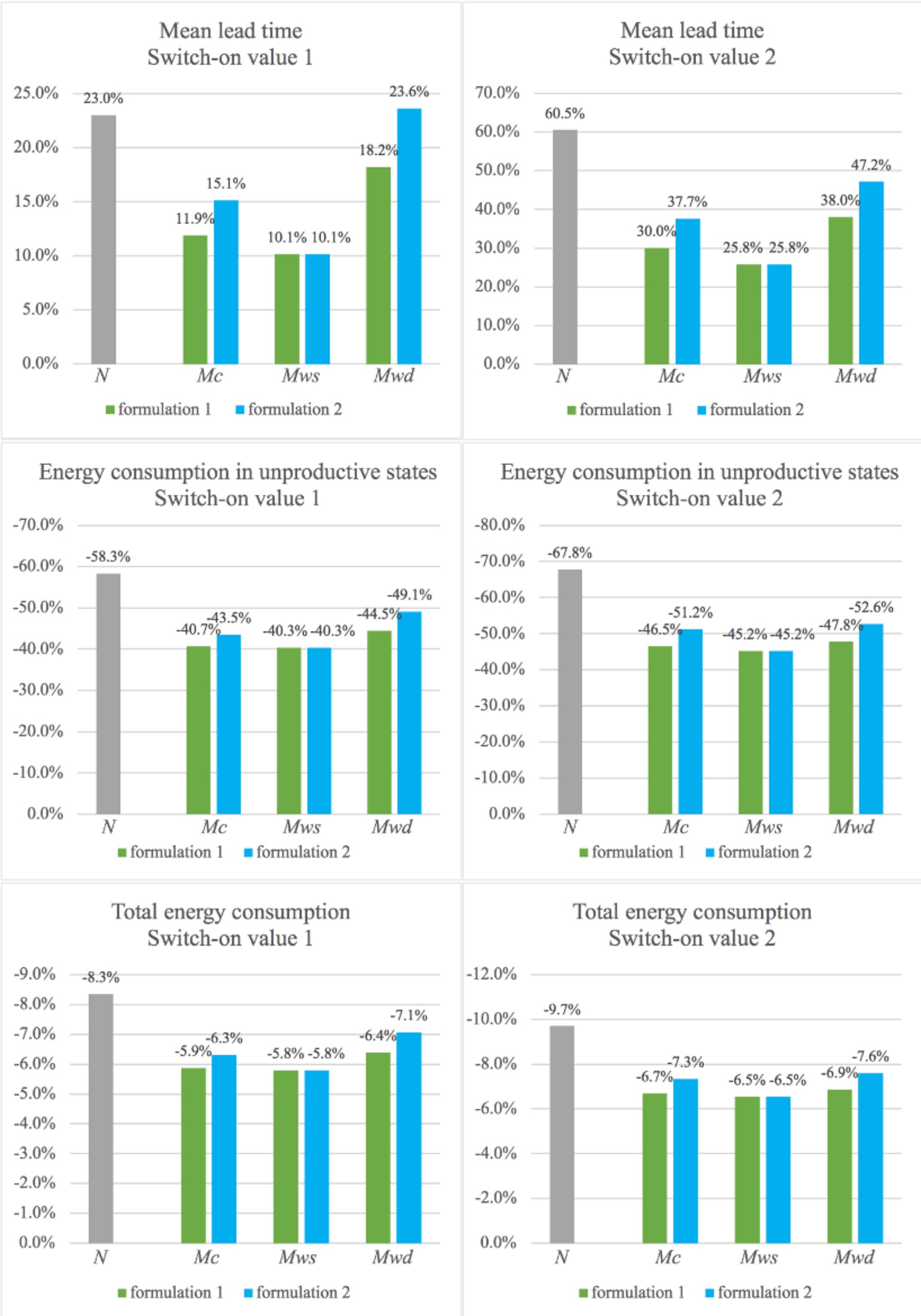

Figure 3.3 Performances of *N-policy* and *Mc*, *Mws*, *Mwd* considering switch-on value of 1 and 2

The proposed policies are tested with other exponential distributions for the inter-arrival time of jobs, with an expected value of 100 and 90 seconds (respectively Expo100 and Expo90).

Figure 3.4 reports the performances with different values of the expected value of the inter-arrival time of jobs. The machine utilization in the three test cases is respectively about 73%, 80% and 89%. In these test cases, the machines switch on when the switching variable reaches 2, the performances are evaluated considering the AO (Always On) as a benchmark, and compared to the *N-policy* with the same condition of inter-arrival of jobs. Higher congestion of the production system leads to a reduction of the total energy saving, since each machine needs to be in a working state for more time to satisfy the production. Regarding lead time, it can be noticed that its increment in all switching policies with respect to the Always on is reduced. This is due to the higher utilization of the machine, indeed the switching-off policies in this case act for a lower time. The proposed policies compared to the *N-policy* with different values of machine utilization result in the same behavior, i.e. in a reduction of the mean lead time increment but in a reduction of energy saving with respect to the Always-on case.

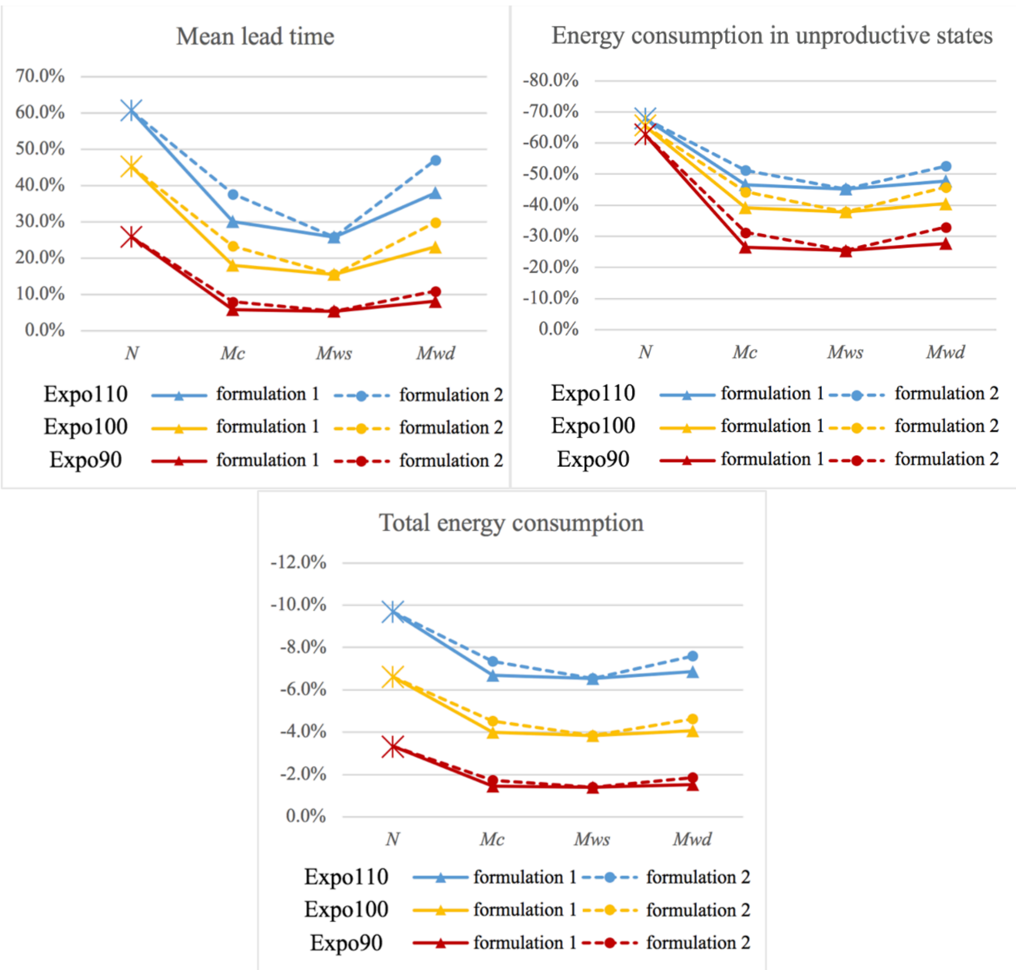

Figure 3.4 Performances of *N-policy* and *Mc*, *Mws*, *Mwd* with different value of inter-arrival time and switch-on value equal to 2

To evaluate the effect of different power requests by machines during the warm-up phase, two other values of power absorbed during this state have been considered. Figure 3.5 shows the percentage variation of the energy consumption in unproductive states and the total energy consumption (considering that the power requested during the warm-up phase is 12 and 15 kW) with respect to the Always On model. The simulations have been proposed considering 1 and 2 as switch-on values. An increment of warmup power reduced the energy saving benefits of *N-policy* compared to the proposed policies. The energy saving with respect to the Always-on case is smaller in all the switch-off policies, but the proposed policies achieve better performances compared to the *N-policy* in some test cases. Indeed, having a machine with a high-power request during warm-up suggests that switching-off machines several times leads to very high energy consumption during startup. For this reason, the proposed policies that limit the switch-off by considering the jobs in the entire system, could in some case work better also in energy saving compared to *N-policy*, for example when considering a warmup power of 15 kW. As previously, a higher value of the switch-on limit leads to higher energy savings, but at the same time, to an increment of the mean lead time.

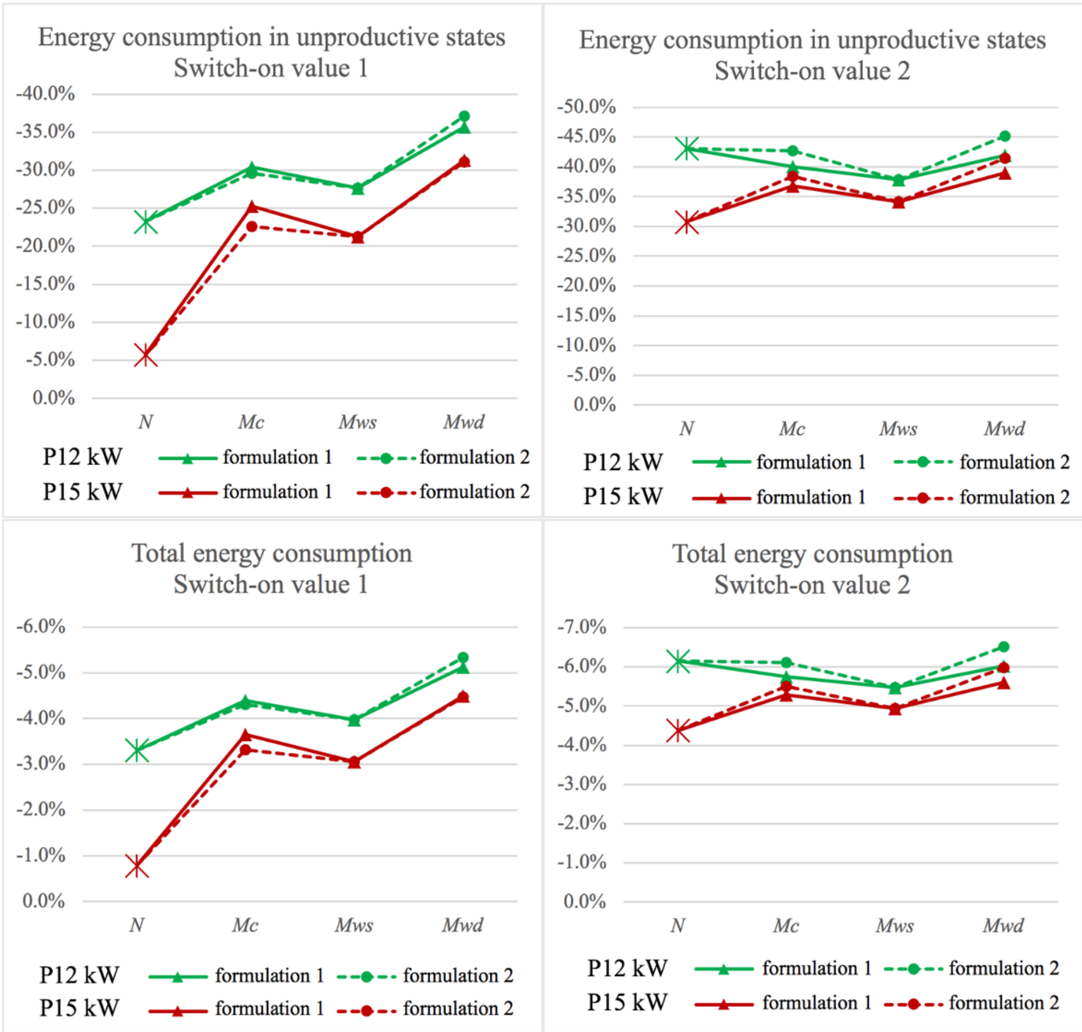

Figure 3.5 Energy consumption in unproductive states and total energy consumption of the *N-policy* and of the *Mc*, *Mws*, *Mwd* considering two different values of warmup power

The simulations results lead to these main findings:

- the *N-policy* works better for the reduction of energy consumption in unproductive states compared to the proposed policies;
- the *N-policy* and the proposed switch-off policies achieve in an increment of mean lead time considering as benchmark the case in which the machines never turn off;

- the developed switch-off policies allow to reduce the increment of the mean lead time compared to the *N-policy*;
- the proposed policies have the same behavior with different values of jobs inter-arrival compared to the performance of the *N-policy*;
- in the case of high warmup power, the proposed policies limiting the number of switch-on achieve higher energy savings compared to the *N-policy*;

Chapter 4: Job shop scheduling

Scheduling and production planning are additional methods to obtain energy efficiency at different manufacturing levels. It can be useful planning the order of operations of one-machine, coordinating the tasks of multi-machine and the factory procedures. Scheduling models in job shop systems (multi-machine level) can be adopted to obtain energy efficiency and saving. The literature review analysis shows the high number of papers regarding the energy-efficient scheduling in job-shop and in flexible job-shop systems. However, in literature, there is a lack of studies about the scheduling considering both the power constraint and the variable speed of machine tools in the job-shop context. Yet, a scheduling which conceives the power as a constraint is useful in those contexts where the power supply is limited, for example when renewable energy sources are employed. In fact, as above mentioned, the fluctuating energy supply of renewable energy systems requires to adapt production processes to the power constraint. On the other hand, taking into account the speed of machine tools in the job-shop context in order to adapt the process times and the needed power consumption, is equally important. Dealing with the power constraint and the variable speed of machine tools in the job-shop context to achieve energy efficiency optimisation, is not a simple matter. Operational processing times and power consumption of the machines are variables and, on the other hand, their values depend on the available power. Addressing the production planning with the impossibility of exceeding a certain threshold of power absorption and the minimization of the makespan as an objective function, this chapter has attempted to answer the following research question:

> RQ6: *can a scheduling model provide production planning considering the minimization of makespan as the objective function and the power as a constraint?*

In order to answer the research question, a first scheduling model was developed. It was applied in a case study where the maximum possible power consumption of the system is fixed. Then, since in many planning scenarios the available and usable power is variable during the planning horizon, the study has explored another research question:

RQ7: *can the developed scheduling model find a solution considering a variable available power in order to meet the decision maker's requirements based on sustainability and consumption criteria?*

To address this question, a further case study has been developed in which energy is supplied by a photovoltaic system. In this context, the decision-maker considered the variability of available power in the scheduling program. The results show how the proposed mathematical model allows to provide a production schedule respecting the power constraint in both the analyzed cases. Therefore, production planners can utilize the model to define production schedule in all the different contexts where there is a power limit, such as in the case of use of variable energy sources, included variable renewable sources. The proposed scheduling model represents a useful tool that manufacturing organizations can adopt to deal with the tradeoff between production targets, energy-saving, the use of renewables and the rethinking of their production objectives and practices. The mathematical model is solved using the Global Solver provided by LINGO software of LINDO Systems Inc. The Global Solver merges several range bounding and range reduction techniques in a branch and bound framework to obtain global solutions (LINGO, 2020).

$a_{i,l,j}$	binary precedence variable
$C_{0,j}$	specific coefficient of the j-th machine
$C_{1,j}$	specific coefficients of the j-th machine
C_i	completion time of the i-th job
C_{max}	makespan
I	set of the jobs
M	large value variable
$MRR_{i,j}$	material removal rate of the j-th machine when is working the i-th job
$P_{i,j}$	Power required by the j-th machine processing the i-th job
$P_{i,j,k}$	power absorbed by the j-th machine processing the i-th job during the k-th time period
P_{lim}	imposed power limit
P_{M1}	power requirement of machine 1
P_{M2}	power requirement of machine 2
P_{M3}	power requirement of machine 3
P_{M4}	power requirement of machine 4
P_{TOT}	the total system power consumption
PL_k	maximum power available during the k-th time period
PT_k	total power requested by the system during the k-th time period
$Q_{i,j}$	removing volume during the operation (i,j)
SEC	specific energy consumption
t_k	start time of the k-th time period
$tl_{i,j}$	processing time of the i-th job on the j-th machine
$U_{i,j,k}$	binary variable
$V_{i,j,k}$	binary variable
W	set of the machines
WS	workstation
$y_{i,j}$	starting time of the i-th job on the j-th machine
$Z_{i,j,k}$	binary variable

Table 4.1 Nomenclature of Chapter 4

4.1 The job shop scheduling problem

The job shop scheduling problem concerns the assignment of jobs to the machine in order to optimize a defined objective function. The key features of the job shops are that each job has a specific and fixed routing and that each machine can work only one job at a time.

In literature, several works proposed the minimization of the makespan as the objective function of the job shop scheduling problem. There are further objective functions that can be considered for the minimization, e.g. the total weighted tardiness, the maximum lateness, the total weighted completion time, the discounted total weighted completion time and the weighted number of tardy jobs (Pinedo, 2016).

As Abdorlazzagh-Nezhad and Abdullah (2017) argued in their work, the main constraints considered in the literature are the precedence, the capacity, the release date and due date.

The first mathematical formulations for scheduling problems were provided by Bowman (1959), Wagner (1959) and Manne (1960). Bowman proposed a formulation based on the discretization of the time. The decision variables are binary and define if a job is processed on a machine during a time period. Wagner proposed an integer linear programming model where binary decision variables have been defined considering the position of the machine in the sequence of the job. Manne's approach is based on the disjunctive constraints for defining the precedence of the jobs on the same machine and for guarantees the not simultaneous processing. The decision variables in this formulation are the start time of the jobs on the machines and the binary variables that define the order of the jobs on the same machine.
Due to the importance of the scheduling problem and the computational complexity, several studies focused on the optimization algorithm. A number of studies used branch and bounds techniques in job shop scheduling problem for minimizing the makespan, e.g. (Barker & McMahon, 1985), (Carlier & Pinson, 1989) and (Brucker et al., 1994). As remarked by Jian Zhang, Ding, Zou et al. (2019), many researchers focused also on approximation methods for the job shop scheduling problem. Jian Zhang, Ding, Zou et al. proposed a review of the main methods applied in the job shop scheduling and grouped the approximate approaches in constructive methods, artificial intelligence methods, local search methods and meta-heuristic methods.

4.2 Mathematical model

The mathematical model has been developed starting from the disjunctive formulation proposed by Manne (1960). The objective function is the minimization of makespan C_{max} as follows:

$$min\ (C_{max}) \tag{4.1}$$

The decision variables of the mathematical model are:

- $y_{i,j}$ is the starting time of the i-th job on the j-th machine;
- $tl_{i,j}$ is the processing time of the i-th job on the j-th machine (linked to the material removal rate (*MRR*)).

The finite set of the jobs, of the machines and of the time periods are respectively *I, W* and *T*. The time periods have been obtained by dividing the planning horizon (i.e. *[0-*

$t_{max}]$) in N_T interval each with the same length equal to the time step. Each operation is defined by a couple of indexes (i,j). The operation (i,j) is the task of the i-th job on the j-th machine.

The variable $y_{i,j}$ must be equal to one of the start times of the time periods. The makespan is evaluated as the maximum completion time of the jobs, i.e. the completion time of the last job that leaves the system (Pinedo, 2016), as follows:

$$C_{max} = max_i(C_i) \tag{4.2}$$

where C_i is the completion time of the i-th job that is calculated as follows:

$$C_i = y_{i,e} + tl_{i,e} \quad \forall i \in I \tag{4.3}$$

where $y_{i,e}$ and $tl_{i,e}$ are respectively the starting time and the processing time of the i-th job on the last machine *"e"* of the i-th job routing.

The precedence relations are defined by the following (Eq. 4.4). This constraint assures that the operation (i,j) starts after the completion of the task (i,v).

$$y_{i,j} - y_{i,v} \geq tl_{i,v} \quad \forall (i,v) \rightarrow (i,j) \tag{4.4}$$

The following constraint assures that the makespan is greater than or equal to the completion time of all operations.

$$C_{max} - y_{i,j} \geq tl_{i,j} \quad \forall\ i \in I, j \in W \tag{4.5}$$

The disjunctive constraints ensure that different jobs can't be processed on the same machine at the same time, as follows (Ku & Beck, 2016) (Eqs. 4.6-4.7):

$$y_{i,j} \geq y_{l,j} + tl_{l,j} - M\ a_{i,l,j} \quad \forall\ i,l \in I, i < l, j \in W \tag{4.6}$$

$$y_{l,j} \geq y_{i,j} + tl_{i,j} - M\left(1 - a_{i,l,j}\right) \quad \forall\ i,l \in I, i < l, j \in W \tag{4.7}$$

where M is a large value variable, and $a_{i,l,j}$ is a binary variable defined as follows (Eq. 4.8):

$$a_{i,l,j} = \begin{cases} 1 & if\ the\ i\text{–}th\ job\ \ precedes\ the\ l\text{–}th\ job\ on\ j\text{–}th\ machine \\ 0 & otherwise \end{cases} \tag{4.8}$$

The processing time of the i-th job on the j-th machine is defined in Eq.4.9:

$$tl_{i,j} = \frac{Q_{i,j}}{MRR_{i,j}} \quad \forall\, i \in I, j \in W \tag{4.9}$$

where $Q_{i,j}$ is the volume that needs to be removed during the operation (i,j), i.e. the volume that needs to be removed when the i-th job is on the j-th machine, and $MRR_{i,j}$ is the material removal rate of the j-th machine when is working the i-th job. According to (Ku & Beck, 2016), the large variable M is defined equal to $\Sigma_i \Sigma_j tl_{i,j}$ and in the case proposed, having different possible values of the MRR, M is defined equal to the sum of all processing times at the minimum possible material removal rate.

The specific energy consumption (SEC) of the j-th machine during the processing of the i-th job is linked to the power absorbed by the j-th machine that is working the i-th job as shown in Z. Jiang et al. (2019) (Eq. 4.10):

$$SEC_{i,j} = \frac{P_{i,j}}{MRR_{i,j}} \quad \forall\, i \in I, j \in W \tag{4.10}$$

The specific energy consumption (SEC) is calculated as shown in Kara and Li (2011), as follows (Eq. 4.11):

$$SEC_{i,j} = C_{0,j} + \frac{C_{1,j}}{MRR_{i,j}} \quad \forall\, i \in I, j \in W \tag{4.11}$$

Where $C_{0,j}$ and $C_{1,j}$ are the specific coefficients of the j-th machine.

The power absorbed by the j-th machine processing the i-th job during the k-th time period is called $P_{i,j,k}$ and is defined as follows (Eq. 4.12):

$$P_{i,j,k} = \begin{cases} P_{i,j} & if\ t_k \geq y_{i,j}\ and\ t_k < y_{i,j} + tl_{i,j} \\ 0 & otherwise \end{cases} \tag{4.12}$$

where t_k is the start time of the k-th time period.

Equation 4.12 can be replaced with the following equations (Eqs. 4.13-4.18)

$$t_k \geq y_{i,j} - M\left(1 - Z_{i,j,k}\right) - 0.01 \quad \forall\, i \in I, j \in W, k \in T \tag{4.13}$$

$$t_k \leq y_{i,j} + M\, Z_{i,j,k} - 0.01 \quad \forall\, i \in I, j \in W, k \in T \tag{4.14}$$

$$t_k \leq y_{i,j} + tl_{i,j} + M\left(1 - U_{i,j,k}\right) - 0.01 \quad \forall\, i \in I, j \in W, k \in T \tag{4.15}$$

$$t_k \geq y_{i,j} + tl_{i,j} - M\, U_{i,j,k} - 0.01 \quad \forall\, i \in I, j \in W, k \in T \tag{4.16}$$

$$V_{i,j,k} = Z_{i,j,k}\, U_{i,j,k} \qquad \forall\, i \in I, j \in W, k \in T \tag{4.17}$$

$$P_{i,j,k} = P_{i,j}\, V_{i,j,k} \qquad \forall\, i \in I, j \in W, k \in T \tag{4.18}$$

where $Z_{i,j,k}$ and $U_{i,j,k}$ are two binary variable respectively equal to 1 if $t_k \geq y_{i,j}$ and if $t_k < y_{i,j}+tl_{i,j}$. Then $V_{i,j,k}$ is equal to 1 if $y_{i,j} \leq t_k < y_{i,j}+tl_{i,j}$.

The total power requested by the system during the k-th time period (PT_k) is calculated as follows (Eq. 4.19)

$$PT_k = \sum_i \sum_j P_{i,j,k} \;\; \forall k \in T \tag{4.19}$$

The following constraint assures that the power requested by the system is lower or equal to the imposed limit value (Eq. 4.20):

$$PT_k \leq PL_k \;\forall k \in T \tag{4.20}$$

where PL_k is the maximum power available during the k-th time period.

4.3 Reference context and simulation results

The reference context is a job shop composed of four workstations and three job types that are processed in the system. Each workstation consists of a single machine. The words "workstation" and "machine" have been considered with the same meaning. Each operation is characterized by a couple of one job and one machine, i.e. the operation (*i,j*) is the operation of the *i*-th job on the *j*-th machine. The choice of a simple job shop system is due to the high computational complexity of the mathematical model that could lead to a very long simulation time. The routing of the jobs, i.e. the order of workstations "WS" that need to be visited to complete the piece, has been defined as follows (Table 4.2):

	Routing
Job1	WS1→WS2→WS3→WS4
Job2	WS3→WS1→WS4→WS2
Job3	WS4→WS3→WS1→WS2

Table 4.2 Jobs routing

The specific energy consumption (*SEC*) formulation of the four machines has been taken from Kara and Li (Kara & Li, 2011), as shown in Table 4.3.

Machine 1	$SEC = 1.494 + 2.191/MRR$
Machine 2	$SEC = 3.600 + 2.445/MRR$
Machine 3	$SEC = 2.830 + 1.344/MRR$
Machine 4	$SEC = 2.411 + 5.863/MRR$

Table 4.3 Machines specific energy consumption (*SEC*)

The processing time of each operation to simplify the problem has been rounded to the integer value, and the material removal rates can be chosen between 0.1 and 2 cm^3/s with step of 0.1. The unit time considered is the minute ([min]).
The cutting volume ($Q_{i,j}$) in cm^3 of each operation has been reported in the following table (Table 4.4):

	Machine 1	Machine 2	Machine 3	Machine 4
Job1	40000	14000	16000	20000
Job2	15000	24000	10000	18000
Job3	16000	8000	12000	26000

Table 4.4 Cutting volume [cm^3] of each operation

The following table (Table 4.5) shows the machining time in minutes of each operation with the maximum admissible material removal rate (2 cm^3/s), for the sake of simplicity the values have been rounded to the nearest integer number.

	Machine 1	Machine 2	Machine 3	Machine 4
Job1	333	117	133	167
Job2	125	200	83	150
Job3	133	67	100	217

Table 4.5 Operation processing times [min] at the maximum admissible material removal rate

Limits to the makespan have been defined as follows:

- The upper bound of the makespan has been set equal to the sum of all the processing time with the minimum material removal rate, i.e. 0.1 cm^3/s;
- The lower bound of the makespan has been defined equal to the minimum makespan of the same scheduling problem, considering the material removal

rates fixed to the maximum value (2 cm^3/s), with the precedence constraints and without power limit.

The upper limit on the makespan has been defined considering that the worst production planning condition is that operations can be performed one at a time in the entire system and at the lowest admissible material removal rate. The mathematical model for the lower limit, since it does not need the evaluation of the power, uses only Eqs. 4.1-4.9 setting the material removal rates to the maximum value. Moreover, since the computational complexity is reduced, it is not necessary to divide the programming horizon into N_T intervals and the starting time of each operation ($y_{i,j}$) is set greater or equal to zero.

The makespan obtainable from the scheduling must be into the interval defined by the lower and upper bound. The production planning obtainable at the lower bound is the best scheduling of the production system because it considers the minimum processing times (or equivalently the maximum material removal rates); maximum material removal rates can be imposed for several reasons such as technological motivation or for the product quality.

In Figure 4.1 is reported the production schedule corresponding to the lower bound of the makespan. In each bar is shown the couple of indexes (i,j) that indicates the operation. In the figures reporting the power consumption, P_{TOT}, P_{M1}, P_{M2}, P_{M3}, P_{M4} and P_{lim} represent respectively the total system power consumption, the power requirement of machine 1,2,3 and 4 and the power limit imposed.

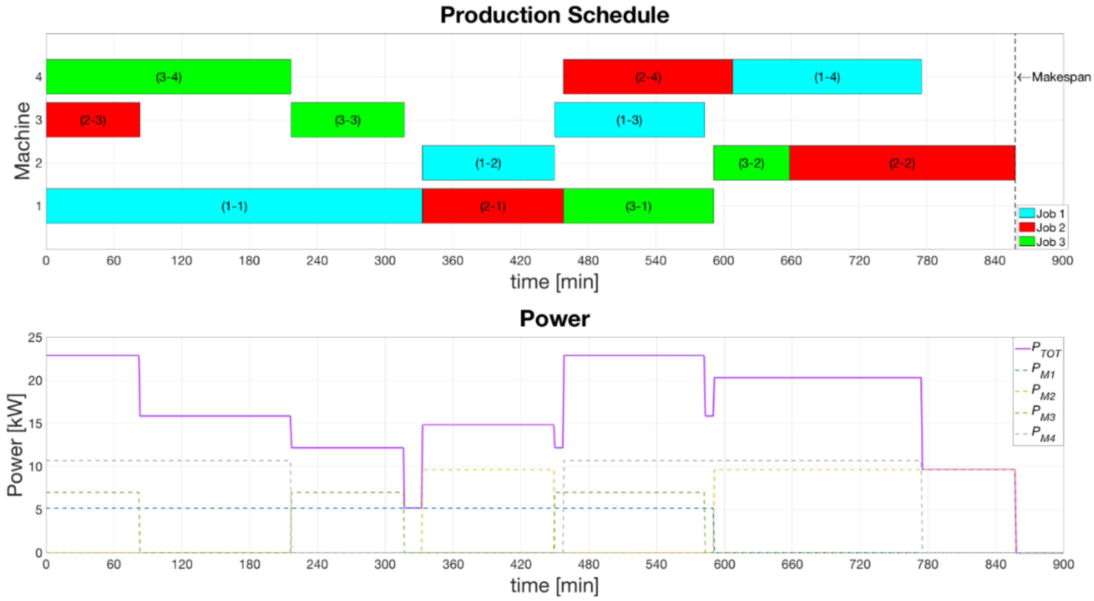

Figure 4.1 Schedule of the jobs and power consumption considering the maximum material removal rate and without power constraint

To evaluate the developed mathematical model, the same scheduling problem has been analyzed considering also power constraint.

Two different power limits have been considered:

- fixed available power profile for all the programming horizon;
- variable available power profile during the programming horizon.

In the first case there is set a fixed power limit of 10 kW and a time step of 30 minutes. The mathematical model results in the production schedule showed in Figure 4.2. Each bar shows the value of the material removal rate as well as the identification of the operation. It can be noted that the mathematical model provides the production planning and adjusts the *MRR* to the available power to achieve the minimization of makespan. As a result, the total power absorbed by the system never exceeds the limit value respecting the optimization of the objective function. However, the value of the makespan increases compared to the case in which the power constraint is absent because the machines during some operations do not work at the maximum value of the material removal rate.

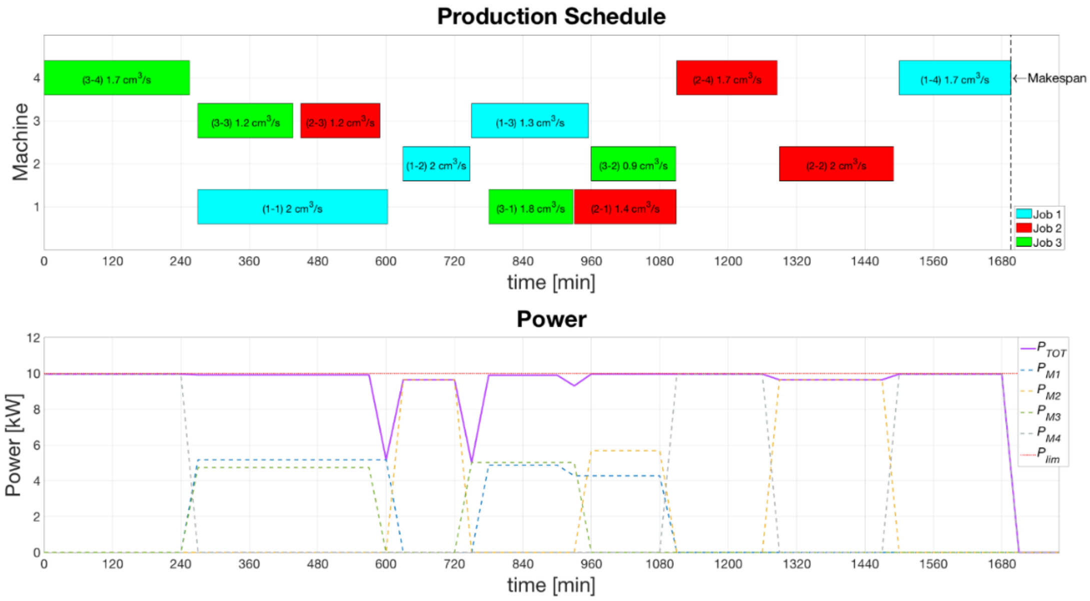

Figure 4.2 Schedule of the jobs and power consumption considering a fixed power limit and time step of 30 minutes

In the second case, a power profile has been modeled considering the possibility of using the power supplied by a photovoltaic system, thus variable during the time. The power given by the photovoltaic system is calculated on an hourly basis using empirical correlations (ASTM Standard E1036, 1998; Skoplaki & Palyvos, 2009). The influence of irradiance and cell temperature has been considered according to (D'Angola et al., 2016) and (Spertino et al., 2016). The photovoltaic plant has been considered with a maximum power of 20 kW in Standard Test Conditions and the tilt and the azimuth angles are respectively 30° and −45°. The plant has been designed to be located in the city of Potenza (Italy) and the data have been taken from the PVGIS database (PVGIS, 2020) for the month of July. A guaranteed minimum power of 4 kW has been considered to allow the system working during the night or when the power of the photovoltaic system is not sufficient. Considering the available power profile above discussed and a time step of 60 minutes, the mathematical model results in the production schedule depicted in Figure 4.3. The production planning defines the operation start times and the material removal rates in such a way that most of the operations are performed during the daylight hours, i.e. when the photovoltaic system supplies more power; during the dark hours, on the other hand, operations are performed at a low *MRR* value, considering the minimum guaranteed power of 4 kW as a constraint.

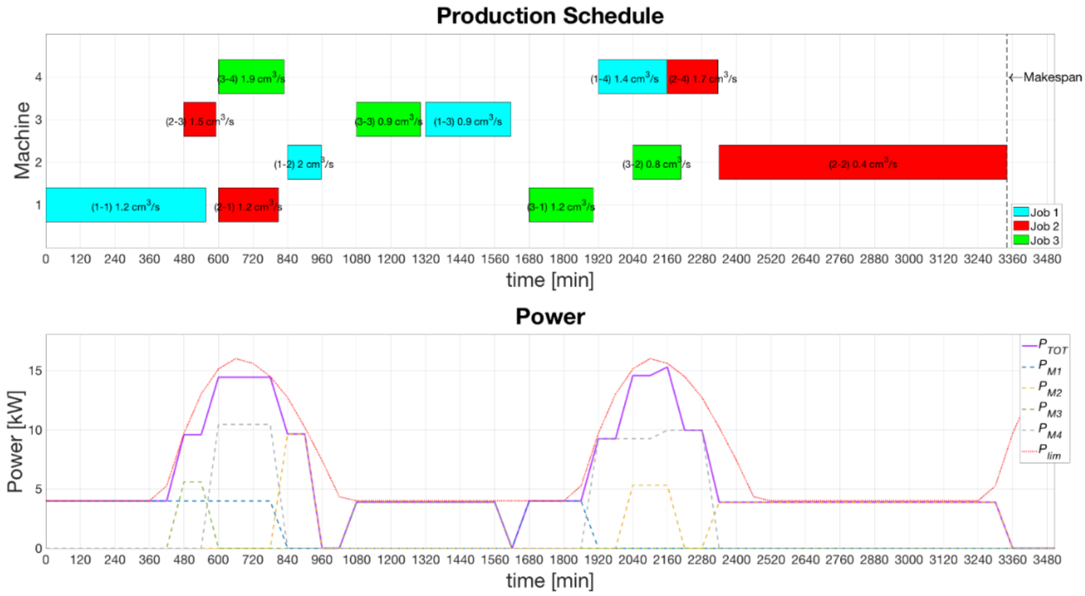

Figure 4.3 Schedule of the jobs and power consumption considering a variable power limit and time step of 60 minutes

In the following table (Table 4.6) are reported the makespan and the completion times of the jobs in minutes obtained with the mathematical model in the three cases analyzed. The completion times reported in Table 4.6 represent one of the different possible solutions that can be obtained with the mathematical model.

	maximum fixed material removal rate - no power constraint	variable material removal rate - fixed available power profile	variable material removal rate - variable available power profile
C_{max} [min]	858	1696	3340
C_1 [min]	775	1696	2158
C_2 [min]	858	1490	3340
C_3 [min]	658	1108	2207

Table 4.6 Makespan and completion times of the jobs in the three test cases

The experimental results achieve the main following outcomes:

- The scheduling model provides a feasible production planning achieving the minimum makespan and respecting both a fixed and variable power constraint;
- the scheduling model is applicable in the context of variable renewable energy sources providing their power profile;
- the mathematical model can be adapted in several cases with variable power profile, for example in the smart grid context, in order to avoid peak power periods.

Chapter 5: Flow line design

One of the most promising approaches to reduce the amount of energy consumed in manufacturing systems is the switch off policy. This policy reduces the energy consumed when the machines are in the idle state. The main weakness of this policy is the reduction in the production rate of the manufacturing systems. The works proposed in the literature do not consider the design of the production lines for the introduction of switch off policies. The main models proposed in the literature, for the design of manufacturing systems, focused primarily on the performance in regards to productivity, quality, and work in process, etc. Recently, the models proposed include the energy efficiency issue, but Gahm et al. (2016) emphasized how the scheduling models that include energy-saving may reduce the other goals of the manufacturing systems. Then, it is more important to propose a model that reduces energy consumption without reducing the productivity performance of manufacturing companies.

The literature analysis showed the following limits:

- Few works evaluate the reduction of the performance level due to the introduction of the switch-off policy, but only energy consumption;
- A limited number of works were proposed to consider the possibility of adoption of the switch-off policy from the design step of the production line.

Trying to cover the lacking of design model that implements this issues, the following research questions have been addressed.

> RQ8: *what is the impact of the design model proposed on the performance of the production line in terms of energy saving maximizing the production rate?*
>
> RQ9: *can the constraint of a limited reduction loss improve significantly the energy saving of the production line obtaining an adequate trade off?*

Nomenclature			
C	Cycle time	P_{off}	Power in out-of-service state
C_{max}	Maximum fixed cycle time	P_w	Power in working state
d_j	Distance between nearby stations	P_{wu}	Power in warm up state
$i = 1,..,N$	Operation index	s_j	State of the j-th station
$j = 1,..,M$	Station index	$T_{d,j}$	j-th station idle time
K_j	j-th buffer capacity	t_i	i-th operation processing time
n_j	Number of parts in j-th buffer	T_j	j-th station processing time
N^D_{off}	Downstream buffer level to switch off	t_{wu}	Time in warm-up state
		TT_d	Cycle idle time
N^D_{on}	Downstream buffer level to switch on	v_{ik}	Precedence constrains binary variable
N^U_{on}	Upstream buffer level to switch on	WS_j	j-th station
		x_{ij}	Operation assignment binary variable
P_i	Power in idle state		

Table 5.1 Nomenclature of Chapter 5

5.1 Flow Line Design Model

The problem deals with the designing of a flow line composed by M stations that manufactures one product type. The product consists of N operations to process; these operations should be assigned to the M workstations, following the precedence constrains. The variables of the model are the assignments of the operations to the workstations of the flow line. The operation assignment binary variable x_{ij} is defined as follows (Eq. 5.1):

$$x_{ij} = \begin{cases} 1 & if\ the\ i-th\ operation\ is\ assigned\ to\ the\ j-th\ station \\ 0 & Otherwise \end{cases} \tag{5.1}$$

The precedence constrains binary variable ensures that the i-th operation must be completed before the k-th operation, and it is computed as Eq. 5.2:

$$v_{ik} = \begin{cases} 1 & if\ the\ i-th\ operation\ preceds\ the\ k-th\ operation \\ 0 & Otherwise \end{cases} \tag{5.2}$$

The processing time T_j of the j-th station is the sum of the processing time of the operations assigned to j-th station, as follows (Eq. 5.3):

$$T_j = \sum_i^N t_i\, x_{ij} \tag{5.3}$$

The cycle time C of the production line is equal to the maximum of the stations' processing times, as shown in Eq. 5.4

$$C = MAX_j\{T_j\} \tag{5.4}$$

The j-th station idle time is defined as follows (Eq. 5.5):

$$T_{d,j} = C - T_j \tag{5.5}$$

The idle time for each cycle is given by Eq. 5.6:

$$TT_d = \sum_{j=1}^{M} (T_{d,j}) \tag{5.6}$$

The difference of processing time between nearby stations is called distance d_j and it is defined as follows (Eq. 5.7):

$$d_j = T_{j+1} - T_j \tag{5.7}$$

A positive value of the distance d_j forms a couple of workstations when the first has a higher velocity than the second workstation. Then, the first workstation can fill the downstream buffer and goes into the off state, reducing energy consumption. Therefore, the flow line consists of a couple of workstations to facilitate the off state of the first workstation of the couple. Figure 5.1 shows the concept of the distance of a couple of workstations. In the following figure, the term WS_j has been used to identify the j-th workstation; the distance between two stations has been obtained as the difference of the processing time of the second workstation (with higher working time) and the first workstation of the couple. In Figure 5.1, the processing time is linked to the stations with, respectively, lower and higher productivity per couple, as represented in blue and green.

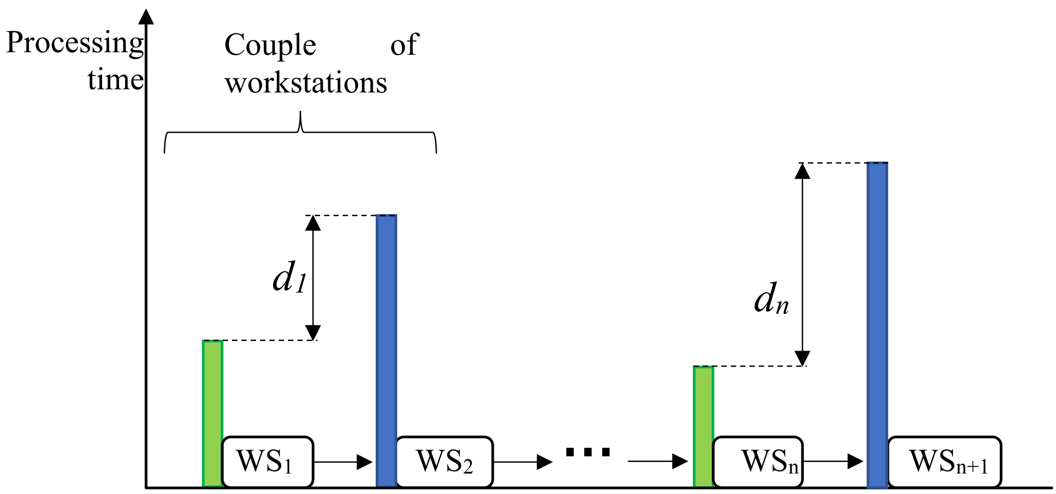

Figure 5.1 Distance between stations

To achieve an unbalanced flow line, the objective function is achieved by maximizing the sum of the distance between stations (Eq. 5.8):

$$MAX\left(\sum_{j} d_j\right) \quad with\, j = 1,3,5,\dots \tag{5.8}$$

This is subject to the following constrains (Eq.s 5.9–5.11))

$$\sum_{j=1}^{M} x_{ij} = 1 \qquad with\, i = 1,\dots,N \tag{5.9}$$

$$\sum_{j=1}^{M} j\, x_{ij} \leq \sum_{j=1}^{M} j\, x_{kj} \qquad \forall\, v_{ik} = 1 \tag{5.10}$$

$$\sum_{i=1}^{N} t_i\, x_{ij} \leq C_{max} \qquad with\, j = 1,\dots,M \tag{5.11}$$

Eq. 5.9 ensures that each operation is only assigned to one machine. Equation 5.10 ensures that the constraints on the precedence of operations are respected. Finally, Eq. 5.11 ensures that the station processing times are below the maximum fixed cycle time. By setting the cycle time, maximizing the objective function achieves an unbalanced line that respects the targeted productivity. Equation 5.8 results in an unbalanced flow line with high idle times between sequential stations. In order to achieve more downtime, and therefore higher energy saving, this research proposes a different objective function from past literature, where the focus instead is on obtaining the minimum cycle time (Baybars, 1986), the minimum number of stations, and the minimum idle time (Scholl, 1999).

Figure 5.2 shows the framework used for the design of unbalanced flow lines. First, using the mathematical model, the flow line with maximum productivity and minimum cycle time has been achieved. The obtained maximum productivity flow line and the minimum cycle time has been calculated as the bottleneck station processing time. The minimum cycle time has been used as a parameter to design unbalanced flow lines using the maximization of the sum of distances as the objective function according Eq. 5.8. Then, increasing and fixing the cycle time, the maximization of the sum of the distance results in several unbalanced flow lines (three unbalanced flow lines have been obtained). Then, the simulation will be studied if the increment of the cycle time can lead to important energy reduction.

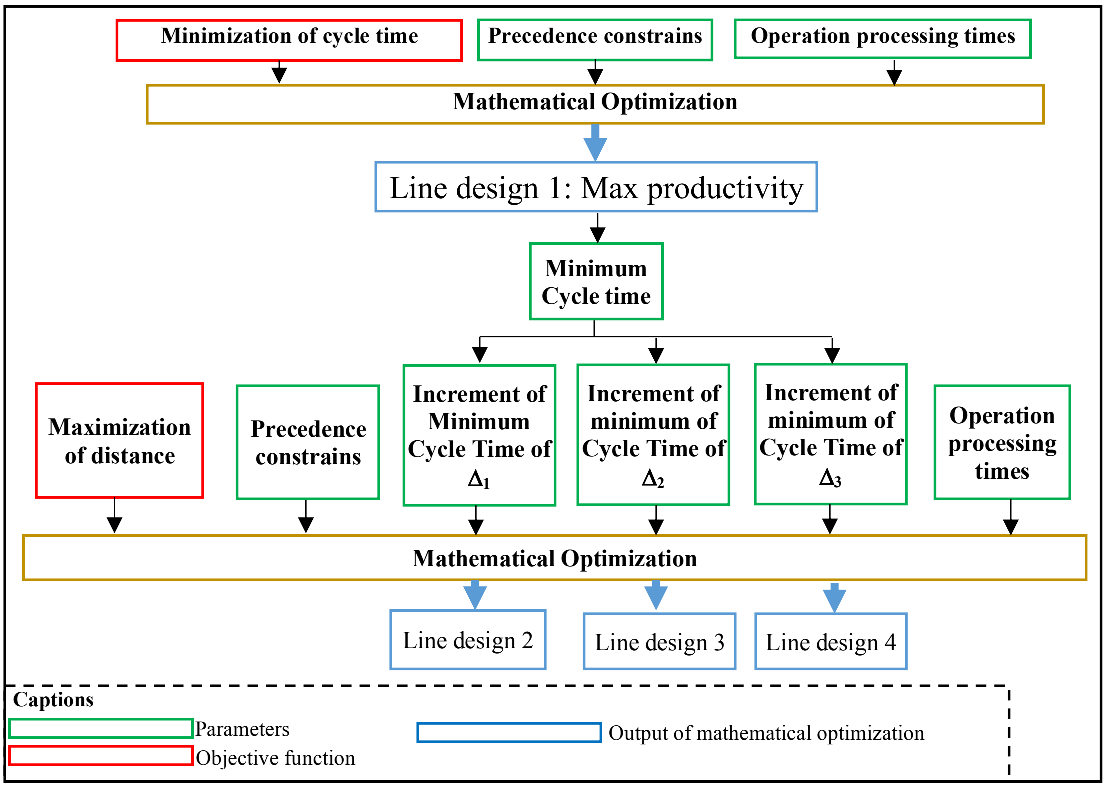

Figure 5.2 Framework for flow line designs

5.2 Switch off Policy

As described in the literature (Su et al., 2016), switching off policies based on buffer level information can lead to significant energy savings without reducing productivity. The proposed policies are upstream (UP), downstream (DP), and upstream and downstream (UDP). In the upstream policy, the machine switches off when the upstream buffer is empty and switches on when the upstream buffer level is $N^{U}{}_{on}$. The level of downstream buffer controls the state in the downstream policy. The machine switches off when the threshold $N^{D}{}_{off}$ is reached and turns on when the number of pieces in the buffer is equal to $N^{D}{}_{on}$. According to (Frigerio & Matta, 2015a), the state of machine s_j is defined as follows (Eq. 5.12):

$$s_j = \begin{cases} 1 & if\ out-of-service \\ 2 & if\ idle \\ 3 & if\ in\ start-up \\ 4 & if\ working \end{cases} \tag{5.12}$$

The states 1, 2 and 3 are unproductive, i.e., no pieces are being processed when a machine is in one of these states. The states 1 and 2 are called inactive states.

According to (Su et al., 2016), the upstream and downstream combines the UP and DP policies as follows (Eq. 5.13):

$$\begin{cases} Switch-Off & if\ s_j = 2\ AND\ (n_j = 0\ OR\ \ n_{j+1} \geq N_{off}^{D}) \\ Switch-On & if\ s_j = 1\ AND\ (n_j = N_{on}^{U}\ AND\ \ n_{j+1} \leq N_{on}^{D}) \end{cases} \quad (5.13)$$

Figure 5.3 summarizes the states of the generic machine and the transition from one state to another.

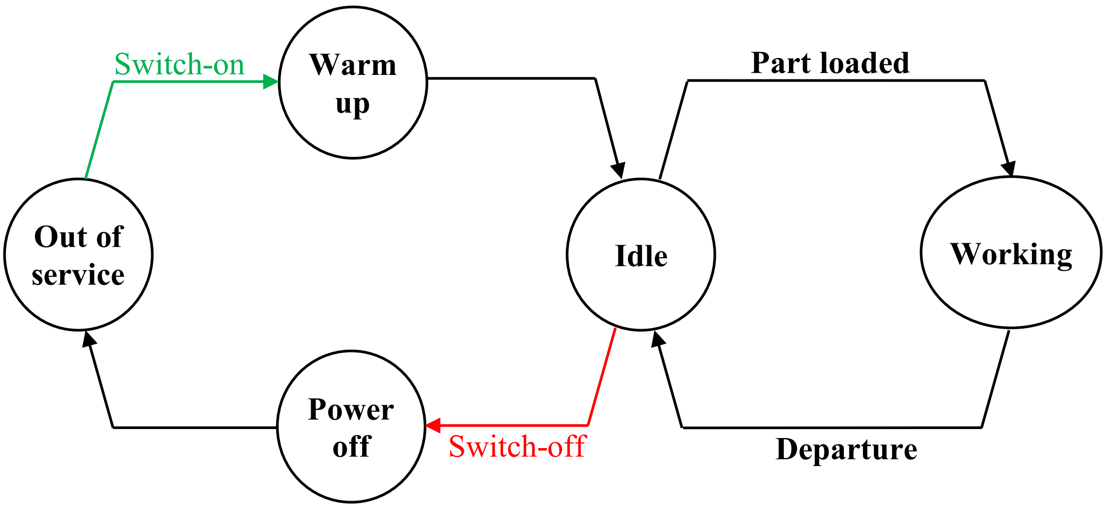

Figure 5.3 Machine states

5.3 Reference Context and Simulation Scenarios

Using the mathematical model described in Section 5.1, four production lines with 10 stations and 20 tasks to complete have been designed. The flow line only produces one product type.

The operation processing times and the precedence constraints are described in Table 5.2 and have been obtained from the simple assembly line balancing problem dataset (SALBP) according to (Otto et al., 2013).

Operations	Processing Time (s)	Precedence	Operations	Processing Time (s)	Precedence
1	142	-	11	97	7
2	34	-	12	132	8
3	140	-	13	107	10, 11
4	214	-	14	132	12
5	121	-	15	69	12
6	279	1	16	169	13
7	50	2	17	73	13
8	282	4	18	231	13
9	129	5	19	120	15
10	175	6	20	186	14

Table 5.2 Operation processing time [s]

The basic assumptions for the line design are the following:

- The stations can perform every possible operation assigned by the design model;
- The precedence constraints are fixed;
- No machine failure has been considered;
- The operations processing times are deterministic and are the same for each station.

Figure 5.4 shows the precedence graph. In the precedence graph, each task is represented as a node, and each direct precedence constraint is illustrated as an arrow that links node *i* and *k* if the *i*-th operation must precede the *k*-th operation. For example, in Figure 5.4, operation 6 must be executed before operation 10.

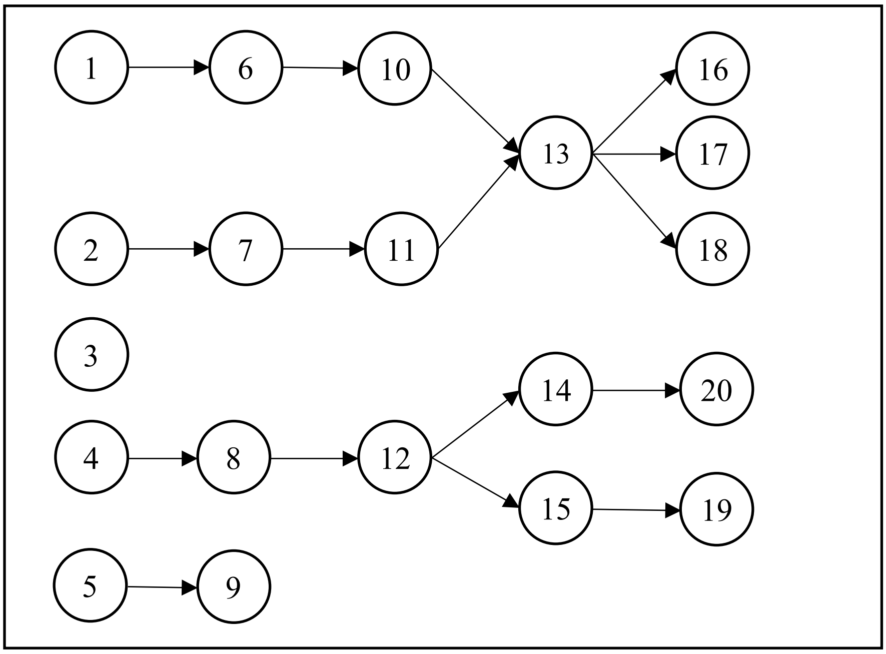

Figure 5.4 Precedence graph

Four flow lines are obtained in order to get respectively:

1. Minimization of total idle time for each cycle with minimum Cycle Time ($MinTT_d$);
2. Maximization of distance between stations with a 2.5% increment of minimum Cycle Time (2.5% loss production rate, MaxD_2.5%);
3. Maximization of distance between stations with a 5% increment of minimum Cycle Time (5% loss production rate, MaxD_5%);

4. Maximization of distance between stations with a 10% increment of minimum Cycle Time (10% loss production rate, MaxD_10%).

The solution of the mathematical model, considering the previous constrains, gives the following flow line designs (Table 5.3); moreover, the station processing times and the station idle times have been reported in Table 5.3.

	MinTT$_d$		MaxD_2.5%		MaxD_5%		MaxD_10%	
Station	**Station Processing Time [s]**	**Station Idle Time [s]**	**Station Processing Time [s]**	**Station Idle Time[s]**	**Station Processing Time [s]**	**Station Idle Time [s]**	**Station Processing Time [s]**	**Station Idle Time [s]**
1	298	6	248	63	248	70	214	119
2	282	22	311	0	313	5	282	51
3	272	32	282	29	282	36	263	70
4	274	30	298	13	298	20	333	0
5	279	25	274	37	279	39	279	54
6	287	17	306	5	315	3	329	4
7	304	0	279	32	236	82	269	64
8	293	11	304	7	304	14	333	0
9	304	0	276	35	289	29	276	57
10	289	15	304	7	318	0	304	29
TT_d		158		228		298		448

Table 5.3 Stations processing and idle times [s]

The first production line is considered to be the benchmark of the other production lines, because it gives a balanced production line with 10 stations and the minimum cycle time.

A discrete event simulation, implemented in Arena, has been used to evaluate the performances of the four flow line designs and to analyze the application of switch off policies in unbalanced production lines.

Each model has been simulated by considering machines in the “always on” (AO) state and the UDP switch off policy.

The basic assumptions of the AO model are:

- Each station has a buffer;
- The buffer capacity is fixed, and equal to *K*;
- The buffer of the first station is always full, that is the raw material is always available;
- The power absorbed in each state is equal for all machines.

In addition, for the models with switch off policies, the following conditions apply:

- Each station is controlled by a switch off policy;
- The control policy parameters ($N^U_{on}, N^D_{off}, N^D_{on}$) are the same for stations from 2 to 9;

- The first station has only DP policy;
- The last station has only UP policy.

As described by Frigerio and Matta (2015a), the production line machines can be in the following states:

- Working state: the machine is processing a piece and absorbs the power P_w;
- Idle state: the machine is ready to work a part, and absorbs the power P_i;
- Out-of-service (Inactive) state: the machine is not ready to process a part. In this state the machine absorbs the minimum amount of power P_{off};
- Warmup state: the machine changes its state from Out-of-service in idle or working state, consuming the power P_{wu} for the time to complete the warmup t_{wu}.

According to (Su et al., 2016), the power required by a generic machine in each state is:

- P_w = 12 kW;
- P_i = 5.35 kW;
- P_{off} = 0.52 kW;
- P_{wu} = 6 kW for t_{wu} = 20 s.

To determine the best switch off control parameters, a full factorial design has been developed. The factors considered are N^U_{on}, N^D_{off}, N^D_{on}, and three levels for each factor are evaluated as follows:

- N^U_{on} = [1, 2, 3];
- N^D_{on} = [4, 5, 6];
- N^D_{off} = [7, 8, 9];

According to (Su et al., 2016), the levels of buffer to switch off or switch on machines respect the following constraints (Eqs. 5.14-5.16):

$$N^D_{off,j} > N^D_{on,j} \tag{5.14}$$

$$N^D_{off,j} \geq N^U_{on,j+1} \tag{5.15}$$

$$N^D_{on,j} \geq N^U_{on,j+1} \tag{5.16}$$

Figure 5.5 reports on the experiment results for model 1. The design with the lowest inactive time has a value of 0, the design with the highest inactive time has a value of 1. These results are used to set these parameters for the simulation tests.

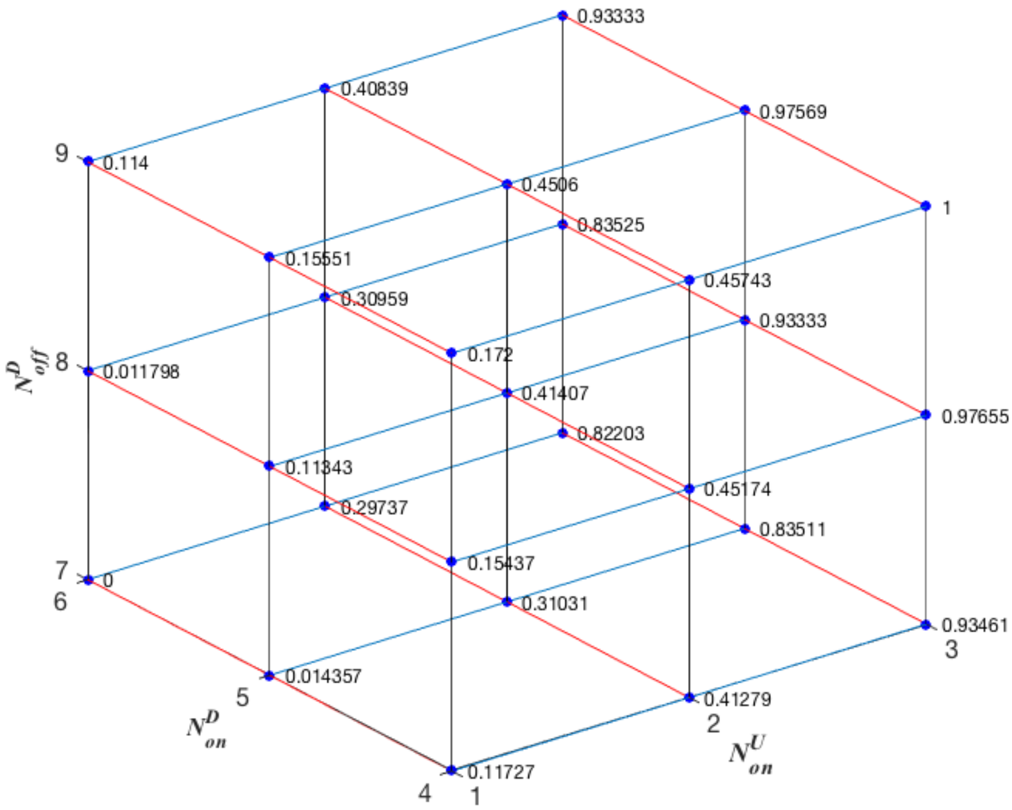

Figure 5.5 Experiments results for line design MinTT$_d$

The results of the other experiments for models MaxD_2.5%, MaxD_5%, and MaxD_10% are reported in Appendix B.

As shown in Figure 5.5, and in the figures (Figures B.1–B.3) in Appendix B, for all the four design models, the set $N^U{}_{on} = 3$, $N^D{}_{on} = 4$, $N^D{}_{off} = 9$, gives the maximum time spent in the idle and inactive state. Therefore, the simulation scenarios and the evaluation of the performances have been obtained by considering the best control parameters. According to (Su et al., 2016), the discrete event simulation length is 10^7 s, and the initial transient is $5{\cdot}10^5$ s.

Figure 5.6 shows the setting of simulation scenarios and performance evaluations. Using mathematical optimization, the flow line design and the operations assignment to the stations have been achieved. Using discrete event simulation, the best set of switch off-parameters have been obtained. Finally, by employing this set, the performances of the four lines have been evaluated and compared.

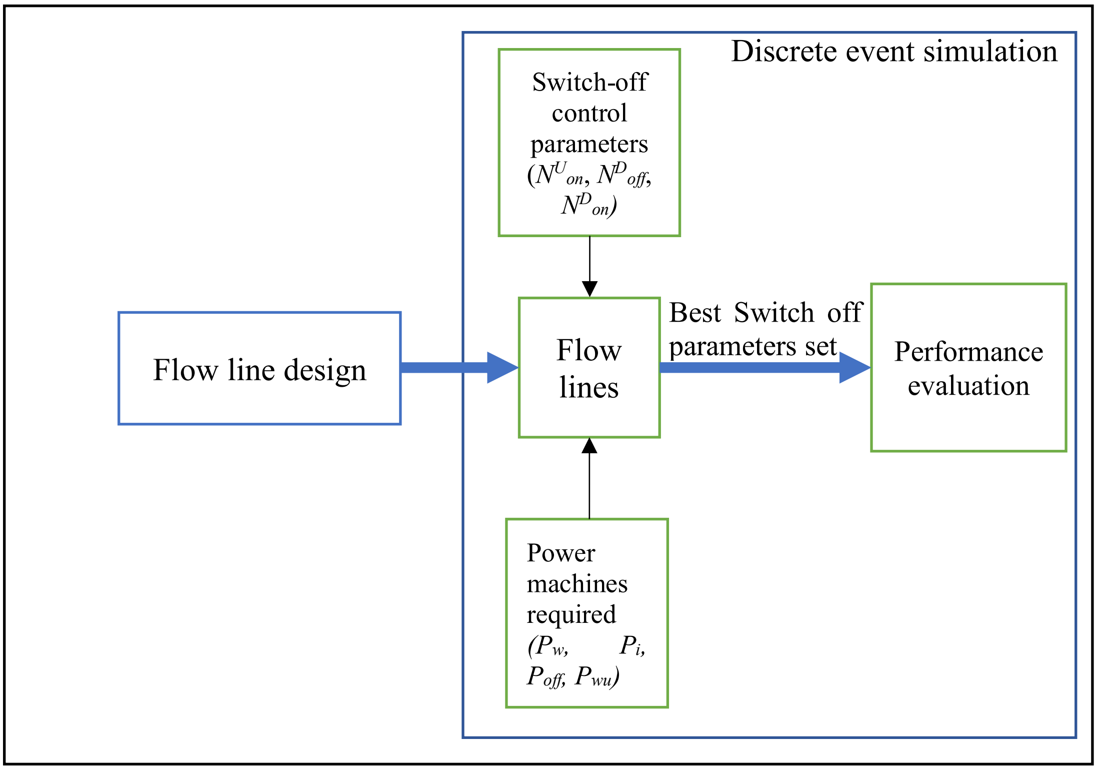

Figure 5.6 Simulation process and performances evaluation

5.4 Numerical Results

As shown in the following figure (Figure 5.7), an increment of the cycle idle time for each station has been achieved by choosing the maximization of the distance between stations as the objective function, instead of the minimization of idle time. The maximum increment of TT_d has been obtained in the case where the cycle time has been increased by 10%.

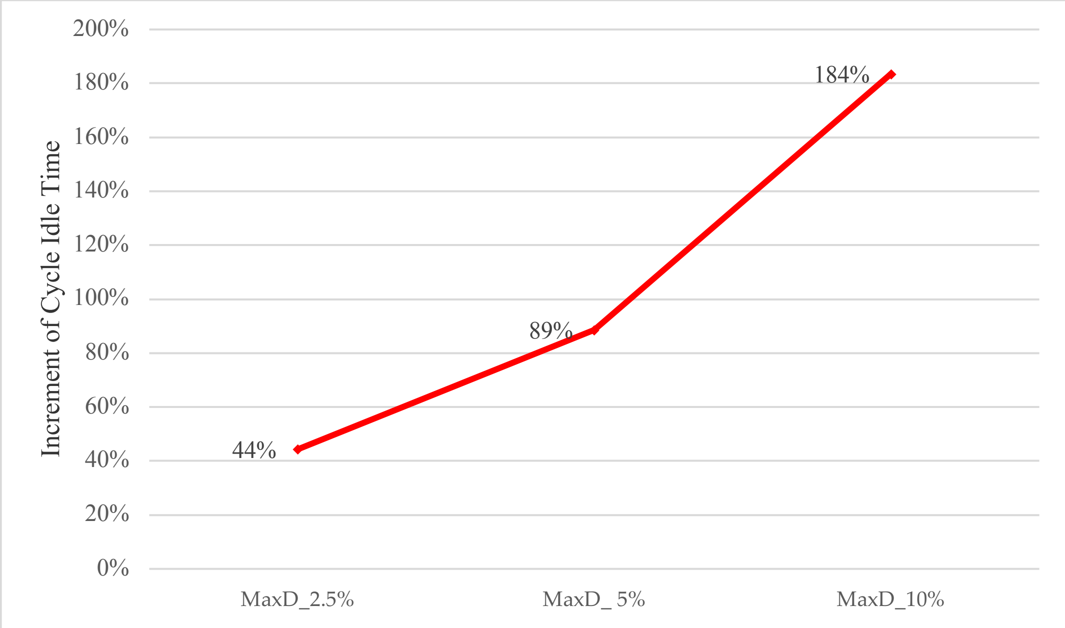

Figure 5.7 Increment of idle time for each cycle

The discrete event simulation results, as compared to the model MinTT$_d$, are shown in Figure 5.8. The results in the figure only consider the effects of the unbalanced line on the idle time, so the simulations have been made by considering machines with an always on control policy. It can be noticed that the higher the idle time, the lower the throughput. Indeed, by increasing the distance, stations are in the idle state for longer than in a balanced flow line. Increased cycle time allows for mathematical optimization, which aims to maximize the distance between station process times and to have greater freedom in assigning operations to the machines. The 10% increase in cycle time (MaxD_10%) results in a flow line where the idle time has grown by 159%, but productivity has decreased by only 9%.

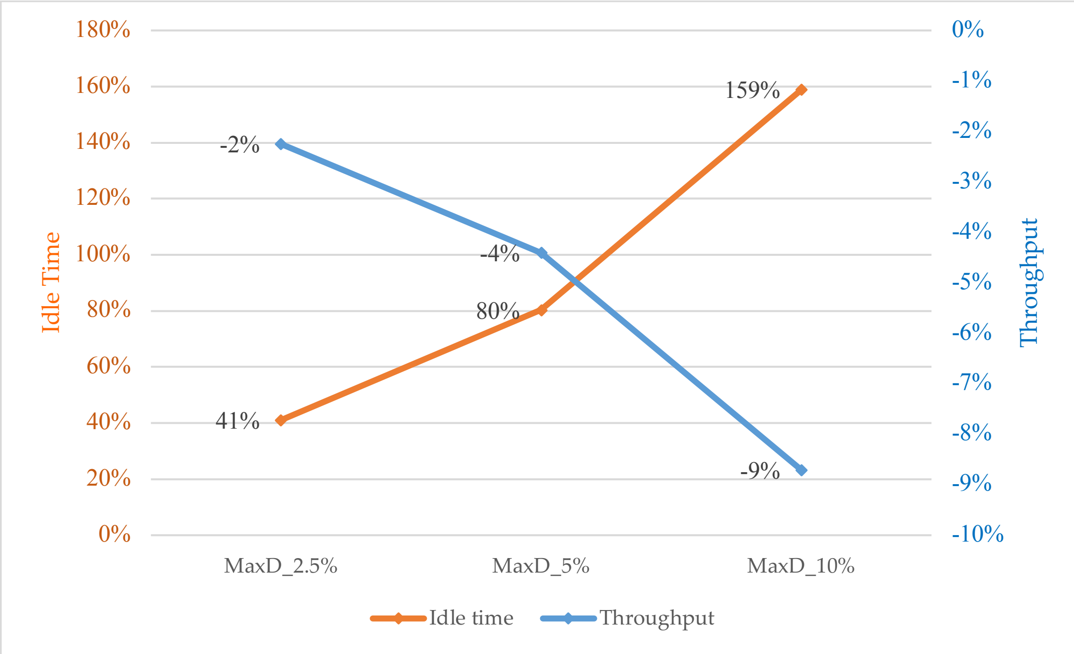

Figure 5.8 Results with always on policy

However, the increase in downtime leads to more energy consumption in a non-productive state. In order to reduce energy consumption, switch-off policies should be in place. The UDP policy achieves a significant reduction in energy consumption in non-productive states. In Figure 5.9, the energy consumption in unproductive states (Idle, Out-of-service, Warmup) of the four lines ($MinTT_d$, MaxD_2.5%, MaxD_5%, MaxD_10%) are compared to a case with machines that are always on and those applying switch off policies. In all the cases analyzed, adopting a shutdown policy allows for a significant reduction in energy consumption in non-productive states, ranging from 86% to 89%.

For these reasons, switch-off policies in unbalanced flow lines are necessary and achieve a reduction in unproductive state energy consumption. If the machines are in always on states, the unbalancing flow line leads to a reduction in throughput and energy consumption due to more time being spent in the idle state. Staying for a long time in the idle state is detrimental, since in this state, the machine is ready to work and then absorbs power without producing. The switch-off policies warrant energy saving due to the lower energy consumption during warmup.

Designing an unbalanced flow line and controlling the machines state with a switch-off policy can lead to a reduction in total energy consumption, not only in unproductive states. Figure 5.10 shows the increment of reduction of energy consumption for an unbalanced flow line design with switch-off policies, compared to an always on balanced flow line. For this reason, designing a flow line to achieve a high unbalance under cycle time constraints, and applying a machine shutdown policy, leads to a reduction in total energy consumption.

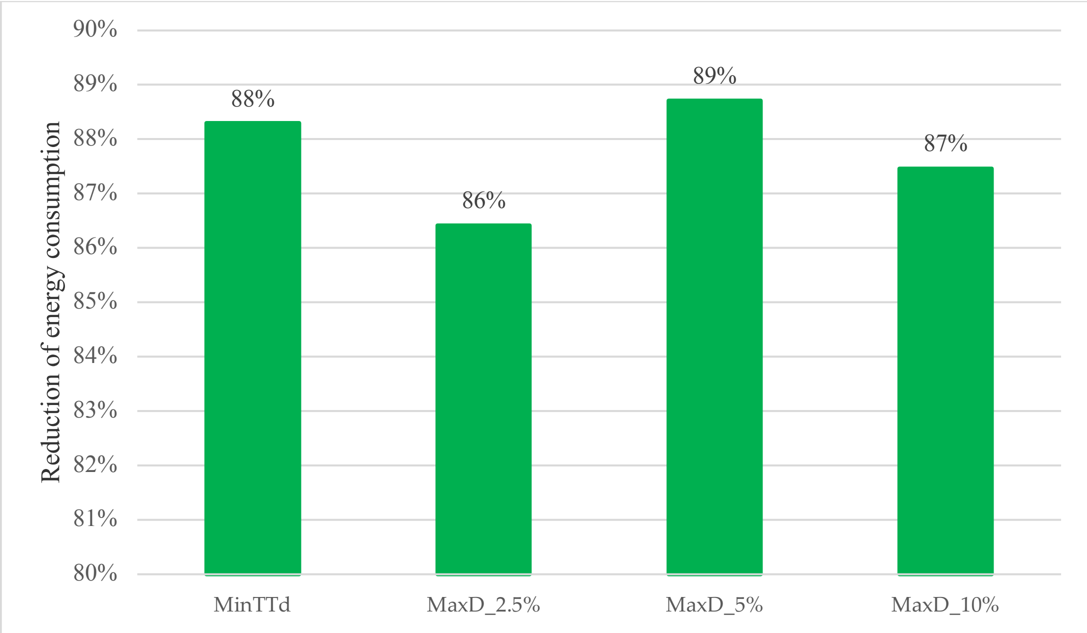

Figure 5.9 Reduction of energy consumption in unproductive states using switch-off policies

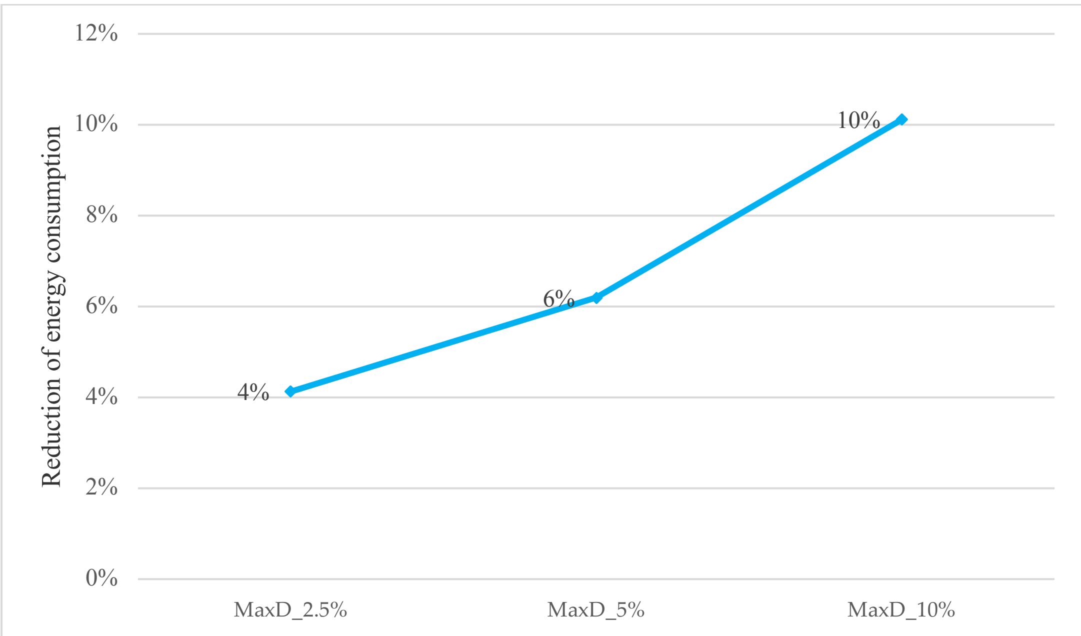

Figure 5.10 Total energy reduction

Figure 5.11 shows the total time that stations hold in the inactive state and the number of warmups.

Like the number of pieces in the buffer, the number of times that machines switch on depends on the position of the bottleneck. Machines turn on fewer times when using model MaxD_5% than model Max_2.5%, even if the total inactive time is longer, because the last station is the bottleneck. It can be seen that, if the bottleneck is among the first machines on the line, it can lead to a reduction of the work in process and storage costs. However, this leads to more switch-ons and higher energy consumption during warmup.

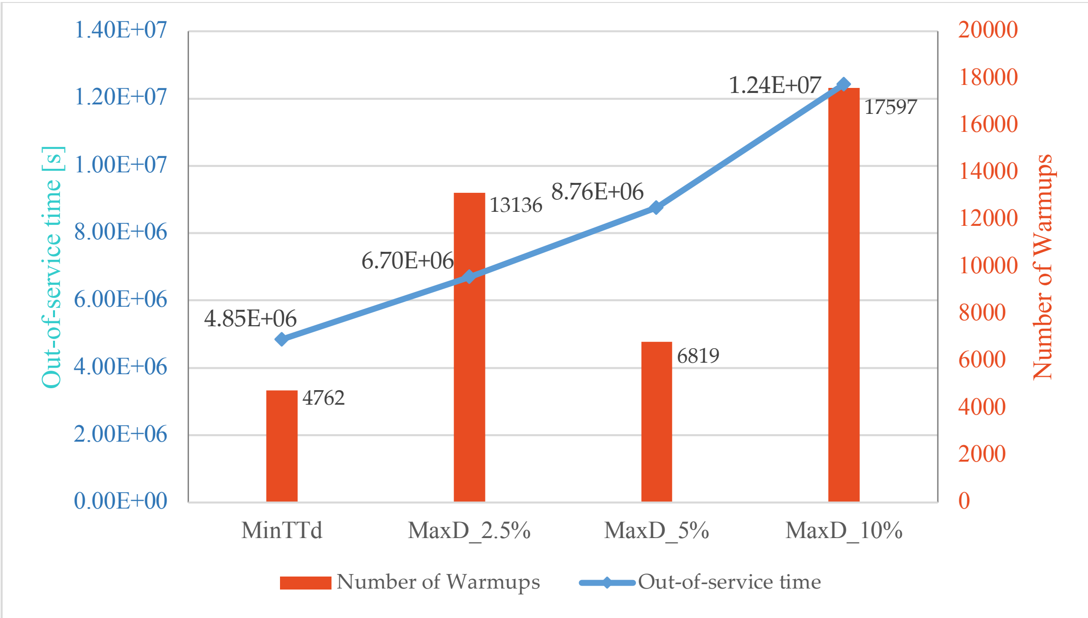

Figure 5.11 Warmup and out-of-service time

Figure 5.12 reports the switch-off mean times. It can be noticed that the model MaxD_5% gives the maximum value of the mean inactive time. Thus, this configuration leads to a high inactive time for each switch off. Instead, in the model MaxD_2.5%, the mean time in the inactive state is the lowest; the machines turn into off-state since there are only few pieces in the buffer. The UP policy achieves a reduction in the machine energy consumption removing resource starvation. Indeed, the machine turns off when the upstream buffer is empty and then does not wait in the idle state using a high quantity of energy.

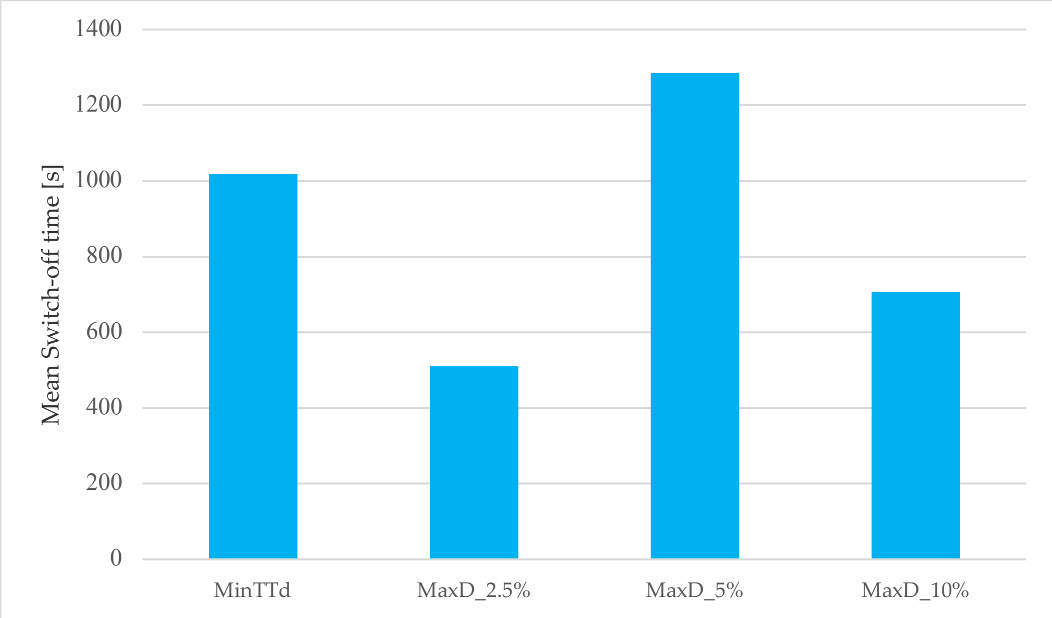

Figure 5.12 Mean switch off time for the four lines design with UDP policies

The following figure (Figure 5.13) shows the mean of the pieces in the buffers of the four models with the switch off policy. It can be noticed that the number of pieces in the buffers does not depend on the chosen objective function. Indeed, the number of elements in the buffers depends on the position of the bottleneck. In fact, in model MaxD_2.5%, as written in Table 5.2, the bottleneck is the second machine on the line. For these reasons, if the elements in the buffers are lower than $N^{U}{}_{on}$, then the UDP policy degrades for the machines below the bottleneck in the upstream policy.

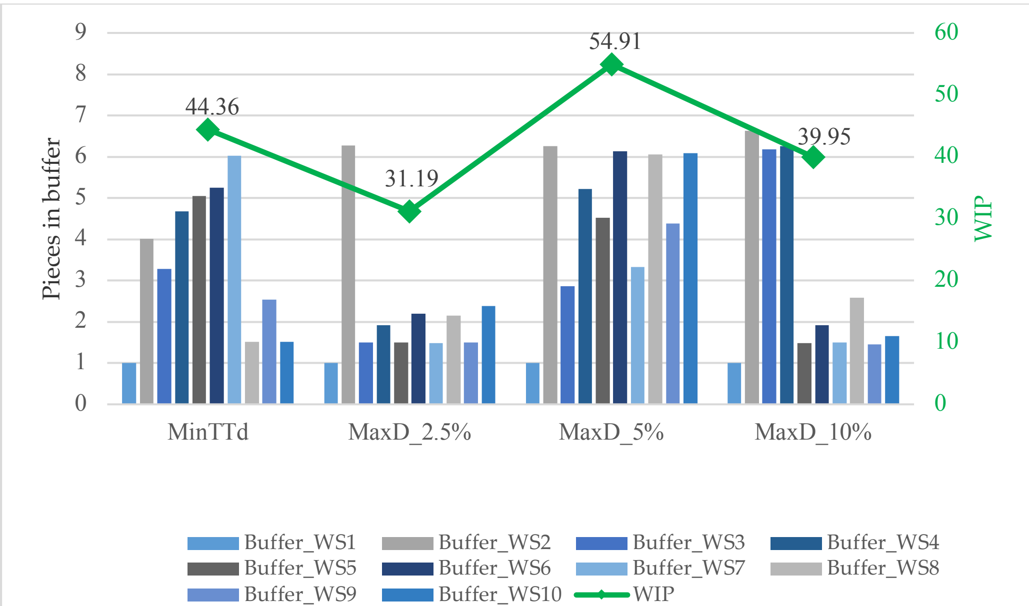

Figure 5.13 Pieces in buffer and mean of the work in progress.

Conclusions

Sustainability and energy efficiency have become hot topics in all human activities. Scholars have focused on energy efficiency, energy saving strategies and implementation of renewable energy sources in manufacturing systems. Indeed, industries are great energy consumers and taking green actions in this sector could achieve a reduction of CO_2 emissions in order to mitigate climate change.

The present thesis aimed to suggest and analyze the effect of several strategies and actions to achieve energy efficiency and implementation of renewable energy sources in manufacturing systems at different levels and with several actions.

In the single machine context, an approach based on energy flexibility has been proposed (Chapter 2). The alignment of renewable energy supply with the machining process requirement is a crucial issue to take advantage of renewable energy and to reduce energy consumption and CO_2 emission. The method proposed supports the hourly adaption of the machining process cutting speed to obtain the maximum profit aligning the power of the machine to a photovoltaic energy supply. A simulation model is used to evaluate the performance indicators in terms of profit, costs, and energy. The numerical results show how the energy flexibility approach allows to increase the profit and reduces drastically the energy bought from the grid with a relevant reduction of the CO_2 emission. The answer to the first research question (RQ1: *what is the impact of the renewable energy source on the time evolution of the parameter settings of machine under different conditions over a planning horizon*?) is: the numerical analysis demonstrated that the improvements in profit and reduction of CO_2 can be obtained especially when the fluctuations of the product demand are higher.

However, in response to RQ2 (*what is the economic gain that can be obtained by the method proposed*?), the economic gain can be obtained by the optimization of the use of electricity (grid and PV), reducing the energy sold in the framework of an energy-flexibility approach. The benefits of the proposed approach are directed to the manufacturing enterprises with several machining processes. It was motivated by an important issue encountered when an industrial plant installed a photovoltaic plant in order to optimize the energy supplied for the manufacturing system. The method proposed, supported by an infrastructure of sensors, can improve the use of the photovoltaic source for the machining processes. Moreover, the decision maker can evaluate the sizing of the photovoltaic plant evaluating both the manufacturing performance and the reduction of the costs. The method can be easily generalized, including different cutting tools typology and machine characteristics to evaluate the performance indicators. The model has been applied and limited to a specific machining process, but could be extended to a more complete plant composed of different and several work centers supplied by a high power PV plant when the energy demand profile of each machine is known. Then the effects of the introduction of an energy storage have been studied by answering to the third research question (RQ3: *what is the impact of the introduction of battery storage on a manufacturing production system?*). The fluctuation of the cutting speed leads to reduce the tool life due to the fatigue stress, and the forecast of the tools to order is more difficult, increasing the costs of inventory. The introduction of battery storage reduces these effects limiting the cutting speed fluctuations. The numerical results show that in the framework of the proposed model with constant rate production, the battery does not affect appreciably the profit with respect to the case of a system powered by a PV plant without storage, but reduces the fluctuation of the cutting speed drastically.

The development of switching-off policies has been discussed in Chapter 3.

These policies based on different workload approaches proposed in the literature have been studied in a job-shop system. To evaluate the behavior of proposed policies, the simulations have been repeated by also considering the application of the *N-policy* to switch off the machine.

In response to RQ4, the results show that the *N-policy* works better for the reduction of energy consumption in unproductive states. Higher energy saving can be achieved by setting a higher value of the queue limits for the warmup, thus reducing the number of switch-on. On the other hand, keeping more pieces in the buffer leads to a higher mean lean time. The main problem of the *N-policy* is that does not consider jobs that will arrive at the machine, but which are currently in another workstation, as information to switch on/off. Indeed, the switching-off policies proposed in the literature are applied in flow lines, where the routing of the jobs is fixed.

Addressing RQ5, several policies based on different approaches considering also two different formulations have been proposed. The simulations have compared the proposed switching policies based on workload evaluation with the *N-policy* and

Always-on case set as a benchmark. The results show that with respect to the Always-on case, the *N-policy* achieves a higher energy saving, but with a worst mean lead time compared to the performances obtained with the proposed policies based on workload. The classic aggregate, corrected static and corrected dynamic workload policies achieve a reduction of warm-ups, as they take into account the current jobs in the system. For this reason, the proposed policies allow having a compromise between a reduction of the energy consumption and an increment of lead time compared to the Always-on case. Comparing the two formulations, it can be seen that formulation 2 leads to a higher number of switches off/on, and therefore to a worsening of the mean lead time, but also to a higher energy saving compared to formulation 1. The policies have been repeated considering different values of the machine utilization. The tests demonstrate that the policies have the same behavior with different values of jobs inter-arrival. Different values of the power required by machines during the warmup phase have been studied. The results show how, as the warmup power is increased, the proposed policies limiting the number of switch-on achieve higher energy savings compared to the *N-policy*, keeping anyway a lower increment of mean lead time with respect to the benchmark. In this case, the higher energy saving of one formulation compared to the other depends on the chosen switch-on value.

The proposed policies support an energy-efficient control model for job-shop manufacturing system focusing on metal cutting processes. The proposed model has a relevant significance for processes such as grinding, turning, and milling that are primary value-added manufacturing operations to produce components and final products. In these environments, the results of the model suggest the choice of the more adapt model to reduce the energy consumption or to pursue the compromise between the energy consumption and lead time. The decision depends also on the power consumption of the machines in the different states: work, idle and warm-up.

Deeping the job-shop context, scheduling has been studied in Chapter 4. Proper scheduling and production planning can lead to energy saving and more environmentally sustainable production without reinvesting in new equipment or implementing re-engineering procedures. In the literature, most of the studies proposed a scheduling model where energy costs and energy consumption are one of the objectives of the optimization process. However, the optimization can also entail the accomplishment of multiple objectives. In this case, a compromise between energy consumption and traditional scheduling goals, such as makespan, total tardiness and so on, has to be reached. This Chapter proposes a job-shop scheduling model that considers as objective function the minimization of the makespan, i.e. the maximum completion time of the jobs, in presence of a power constraint. The model helps decision makers plan production taking into account power constraint and variable processing times. Considering different completion times for each job and different order of the jobs, the model provides several optimal solutions in compliance with the power constraint. Developing the model has allowed to answer the research questions RQ6 and RQ7. Especially, responding to the RQ6, the results have highlighted that the scheduling model provides a feasible production planning obtaining the minimum makespan and respecting a fixed power constraint. Answering the RQ7, the research has underlined that considering a variable available power, the model provides a feasible job scheduling. These theoretical findings show the usefulness of the model even when utilizable power is variable during the planning horizon. From a practical viewpoint, the proposed decision model can support the decision-maker (e.g. production planning manager, energy manager, etc.) in production planning taking into account the impossibility of exceeding a fixed threshold of power absorption and the minimization of the makespan as an objective function. Managers and production planners can utilize the scheduling model in all the different situations where there is a power limit. Some typical situations can be the use of a renewable energy source, the utilisation of smart grids, or even situation where exceeding a certain threshold of power required to the electrical grid involves the payment of a penalty. The model can help decision making about production planning in a manufacturing system that uses PV plants and other variable power sources. The proposed model, indeed, is a useful tool to support company’s managers in their decision making about the energy transition, i.e. the shift from fossil fuels to sustainable power and business model transformation towards sustainability. Using an optimal schedule, they can better deal with the tradeoff between production and energy efficient targets and look for a more efficient use of renewable energy. The scheduling model provides useful insights about the proper use of renewable energy sources in situ against power constraints and the variable speed of machine tools. However, it can also be used to plan production of several manufacturing facilities involved in energy community grid. In this case, proper production planning is crucial to avoid peak power periods due to the energy requirements of several factories. The proposed model can support the formulation of such planning. In such a prospect the model represents a tool that can drive managers and entrepreneurs towards the choice of new forms of energy use that include renewable energy sharing (e.g. through community grid) energy flexibility, and energy-oriented production planning.

Finally, the flow line design problem with energy issue has been investigated in Chapter 5 proposing the following RQs:

RQ8: *what is the impact of the design model proposed on the performance of the production line in terms of energy saving maximizing the production rate?*

RQ9: *can the constraint of a limited reduction loss improve significantly the energy saving of the production line obtaining an adequate trade off?*

Using the simulation has been demonstrated that the model proposed could improve the reduction of energy consumption of the flow line more than the design model that does not consider the possibility of introducing the switch-off policy. The results showed that the model can support the decision about the better trade-off between the production rate level and energy consumption reduction. Moreover, if the objective is also the reduction in the number of on/off activities that can affect the maintenance of the machines, the results highlighted the better choice. The simulation tests prove that the number of warmups can be reduced by properly choosing the bottleneck position, respecting the precedence constraints, in order to achieve further energy saving. Regarding the flow line design, it can be resumed: (i) the design model should be adapted to introduce the switch-off policy to obtain a higher benefit from the switch-off policies; (ii) it is possible to evaluate, with the use of the simulation, the effect of a targeted reduction of production rate (for example in a determined production planning period) to improve the energy consumption reduction; and (iii) the model proposed can be extended to different flow lines to support the decision making about the design and potential energy reduction.

The present thesis has deepened several production levels and strategies to achieve energy efficiency and energy saving in manufacturing system. The main limitation of the mathematical model presented in Chapter 2 regards the application to a specific machining process and the simplified energy price policy. Regarding job shop scheduling, the mathematical model has been applied in a simple case due to the high computational complexity. The flow line design model (Chapter 5) presents the weakness of not having considered machine failures and that processing times are deterministic.

The present thesis, investigating different manufacturing aspects and grades, could be a starting point for grouping several energy-saving strategies to reach higher energy efficiency. For these reasons future works aim to consider a more complex manufacturing system with several and different machining process, considering machine failures, implementing several renewable energy supplies and storage systems. Parameters optimization, energy-saving policies, scheduling and design can be coordinated with the goal of achieving energy-efficiency and of reduction of the energy consumption not at the level at which they are applied.

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Appendix A

In the following Appendix, details on the numerical model have been reported.

In particular, Figure A.1 illustrates the dependence of the monthly profit on the cutting speed. The model in non linear, so an iterative procedure has been implemented. The time evolution of the PV plant and the daily demand are considered as inputs and a maximization algorithm has been developed in order to calculate the time profile of the cutting speed which maximizes the monthly profit. More in detail, the maximization of the objective function has been carried out by recurring to the trust region method, a numerical method based on the interior point technique (Byrd, 2000).

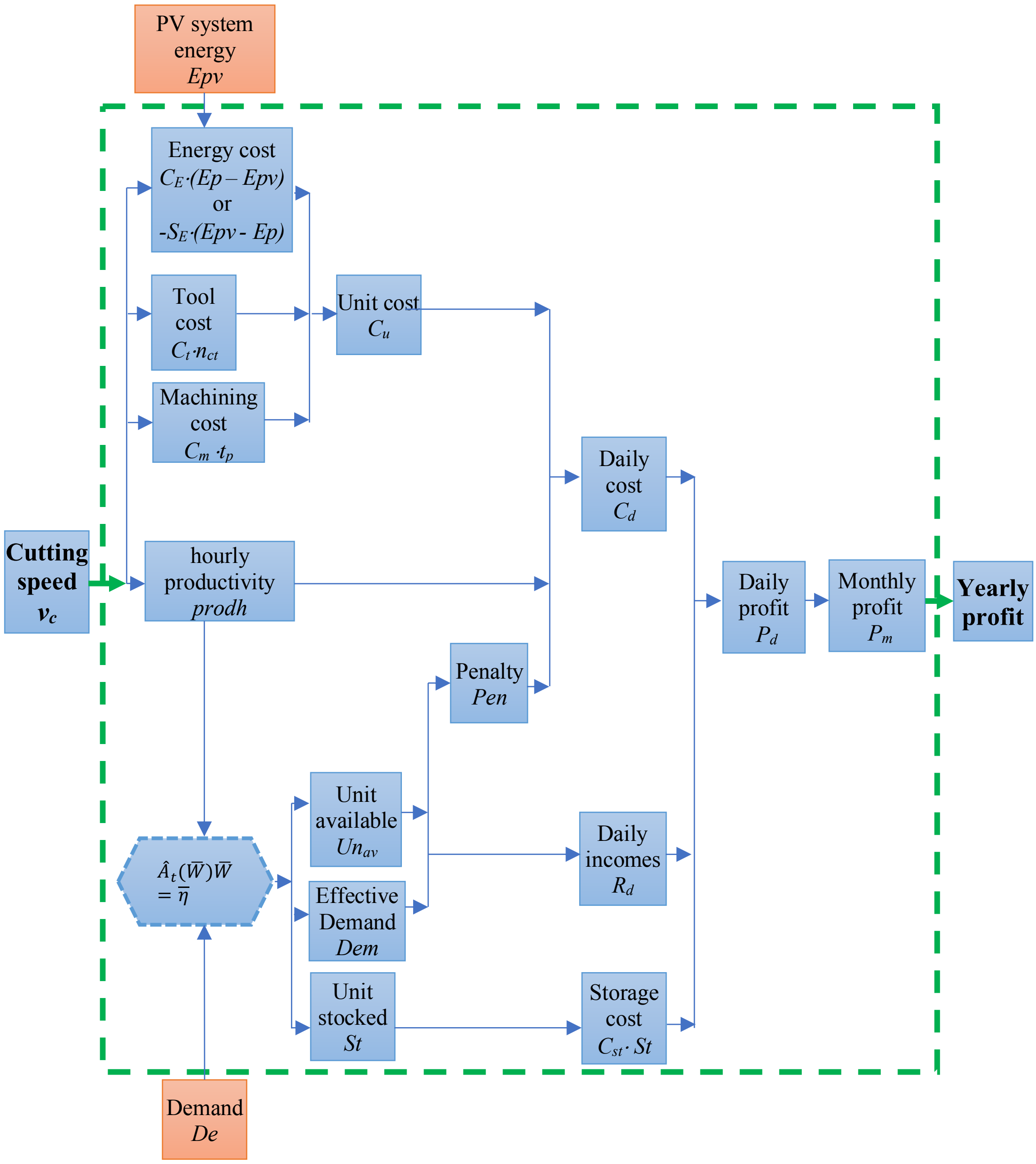

Figure A.1 Dependence of the monthly profit on the cutting speed

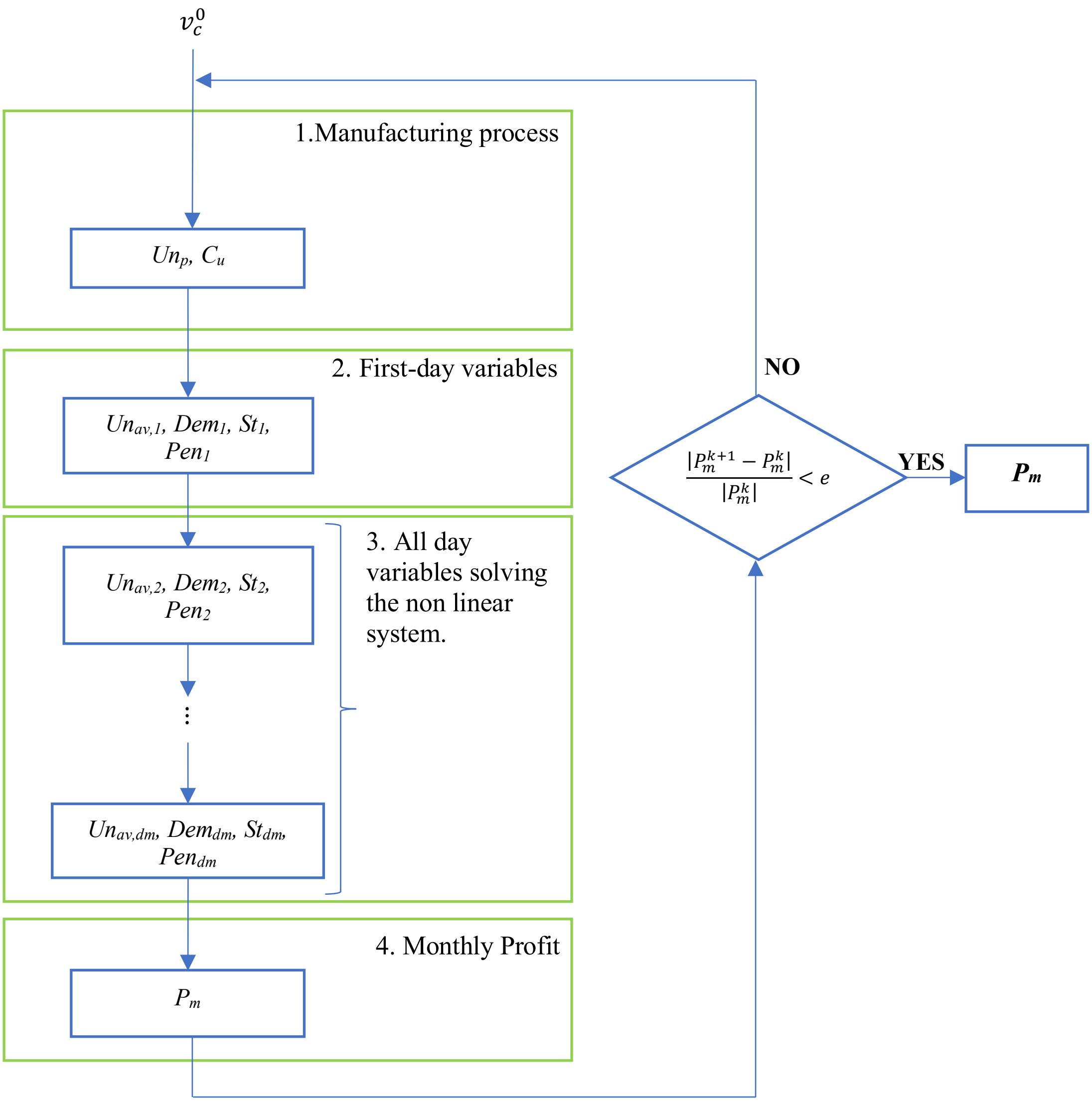

Figure A.2 numerical procedure to calculate the maximum monthly profit

As described in Figure A.2, the algorithm starts from a guess value of cutting speed, v_c^0, calculated as the mean value of the cutting speed with minimum cost and the cutting speed that achieves the maximum production rate. The daily demand and the PV power time evolution are considered as input quantities. The cutting speed is implemented as a N_d *x* 24 matrix with N_d rows corresponding to the *j*-th day of the month and 24 columns, corresponding to the hours of the day.

The procedure can be divided into four phases:

1. Manufacturing process. In this phase, the variables linked to the process are evaluated; using equations (2.11)-(2.24) the daily productivity and the unit cost can be calculated.

2. First-day parameters. The available units, the units stocked, the effective demand and the penalty for the first day of the month can be calculated by using equations (2.5), (2.6).
3. Available units, stocked units, effective demand and penalty for all the days of each month can be calculated. In order to calculate the stocked units and the effective demand a nonlinear system of equations must be solved (more details in the following).
4. Monthly Profit. The maximum monthly profit can be calculated by using the interior point technique with an assigned tolerance on the relative error. The procedure is repeated for all the months of the year.

The non linear system to calculate the stocked units and the effective demand is explained in the following, by recurring to a matrix formulation of Equations (2.5) ad (2.6).

If we define $x_j = Dem_j$; $y_j = st_j$; $b_j = Un_{d,j}$; $a_j = De_j$, Equations (2.5) and (2.6) reduce to

$$\begin{cases} x_{j+1} = a_{j+1} + \max\{0, x_j - b_j - y_j\} \\ y_{j+1} = \max\{0, y_j + b_j - x_j\} \end{cases}$$

Evaluate the first attempt system:

$$\begin{cases} x_{j+1} = a_{j+1} + x_j - b_j - y_j \\ y_{j+1} = y_j + b_j - x_j \end{cases} \rightarrow \begin{cases} x_{j+1} = a_{j+1} - y_{j+1} \\ y_{j+1} = y_j + b_j - x_j \end{cases}$$

$$\begin{cases} x_2 + y_2 = a_2 \\ y_2 = b_1 - x_1 \\ x_3 + y_3 = a_3 \\ y_3 - y_2 + x_2 = b_2 \\ x_4 + y_4 = a_4 \\ y_4 - y_3 + x_3 = b_3 \\ \vdots \\ x_{dm} + y_{dm} = a_{dm} \\ y_{dm} - y_d + x_{dm-1} = b_{dm-1} \end{cases}$$

We obtain the following system:

$$\hat{B}_t \overline{W}_0 = \bar{\eta}_0$$

$$\begin{vmatrix}
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & \dots & \dots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & \dots & \dots & 0 & 0 & 0 & 0 \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1
\end{vmatrix}
\begin{vmatrix} x_2 \\ y_2 \\ x_3 \\ y_3 \\ x_4 \\ y_4 \\ x_5 \\ y_5 \\ x_6 \\ y_6 \\ \dots \\ \dots \\ x_{dm-1} \\ y_{dm-1} \\ x_{dm} \\ y_{dm} \end{vmatrix}
=
\begin{vmatrix} a_2 \\ b_1\text{-}a_1 \\ a_3 \\ b_2 \\ a_4 \\ b_3 \\ a_5 \\ b_4 \\ a_6 \\ b_5 \\ \\ \\ a_{dm-1} \\ b_{dm-2} \\ a_{dm} \\ b_{dm-1} \end{vmatrix}$$

$$\begin{cases} x_{j+1} = a_{j+1} + (x_j - y_j) \cdot \max\left\{0, 1 - \dfrac{b_j}{(x_j - y_j)}\right\}; \\ y_{j+1} = (x_j - y_j) \cdot \max\left\{0, \dfrac{b_j}{(x_j - y_j)} - 1\right\}; \end{cases}$$

Defined the coefficient C_j and D_j

$$C_j = \max\left\{0, 1 - \frac{b_j}{(x_j - y_j)}\right\};$$

$$D_j = \max\left\{0, \frac{b_j}{(x_j - y_j)} - 1\right\};$$

The system can be rewritten as:

$$\begin{cases} x_{j+1} = a_{j+1} + C_j\left(x_j - y_j\right); \\ y_{j+1} = D_j\left(x_j - y_j\right); \end{cases}$$

$$\left|\begin{array}{cccccccccccccccc}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-C_2 & C_2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-D_2 & D_2 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -C_3 & C_3 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -D_3 & D_3 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & -C_4 & C_4 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & -D_4 & D_4 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & -C_5 & C_5 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & -D_5 & D_5 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \ldots & \ldots & -C_{29} & C_{29} & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \ldots & \ldots & -D_{29} & D_{29} & 0 & 1
\end{array}\right|
\left|\begin{array}{c}
x_2 \\ y_2 \\ x_3 \\ y_3 \\ x_4 \\ y_4 \\ x_5 \\ y_5 \\ x_6 \\ y_6 \\ \ldots \\ \ldots \\ x_{dm-1} \\ y_{dm-1} \\ x_{dm} \\ y_{dm}
\end{array}\right|
=
\left|\begin{array}{c}
a_2+c_1*x_1 \\ d_1*x_1 \\ a_3 \\ 0 \\ a_4 \\ 0 \\ a_5 \\ 0 \\ a_6 \\ 0 \\ \\ \\ a_{dm-1} \\ 0 \\ a_{dm} \\ 0
\end{array}\right|$$

$$\begin{cases}
x_2 = a_2 + C_1 x_1 \\
y_2 = D_1 x_1 \\
x_3 - C_2 x_2 + C_2 y_2 = a_3 \\
y_3 - D_2 x_2 + D_2 y_2 = 0 \\
x_4 - C_3 x_3 + C_3 y_3 = a_4 \\
y_4 - D_3 x_3 + D_3 y_3 = 0 \\
\vdots \\
x_{dm} - C_{dm-1} x_{dm-1} + C_{dm-1} y_{dm-1} = a_{dm} \\
y_{dm} - D_{dm-1} x_{dm-1} + D_{dm-1} y_{dm-1} = 0
\end{cases}$$

where C_1, D_1 are known and the following nonlinear system holds:

$$\hat{A}_t(\overline{W})\overline{W} = \overline{\eta}$$

Appendix B

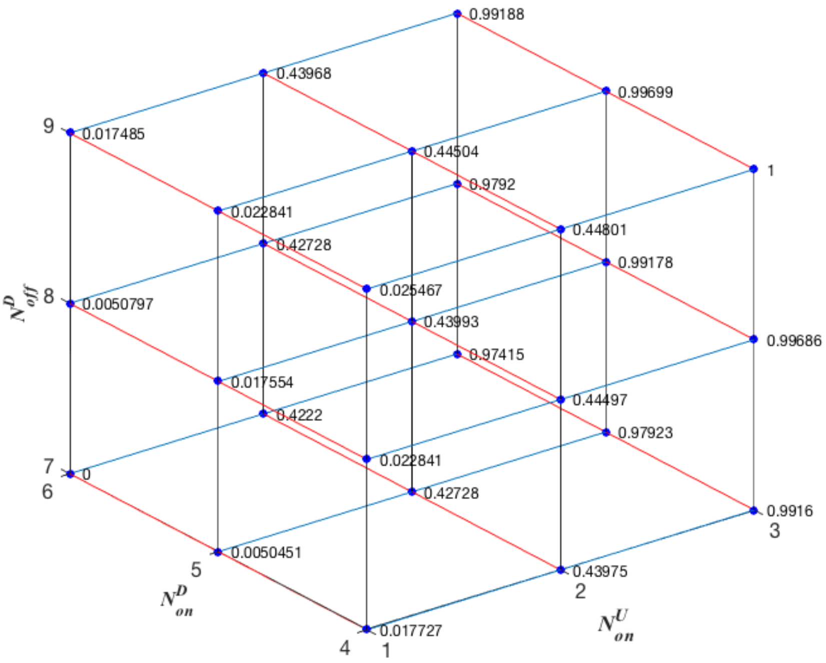

Figure B.1 Experiments results for line design MaxD_2.5%

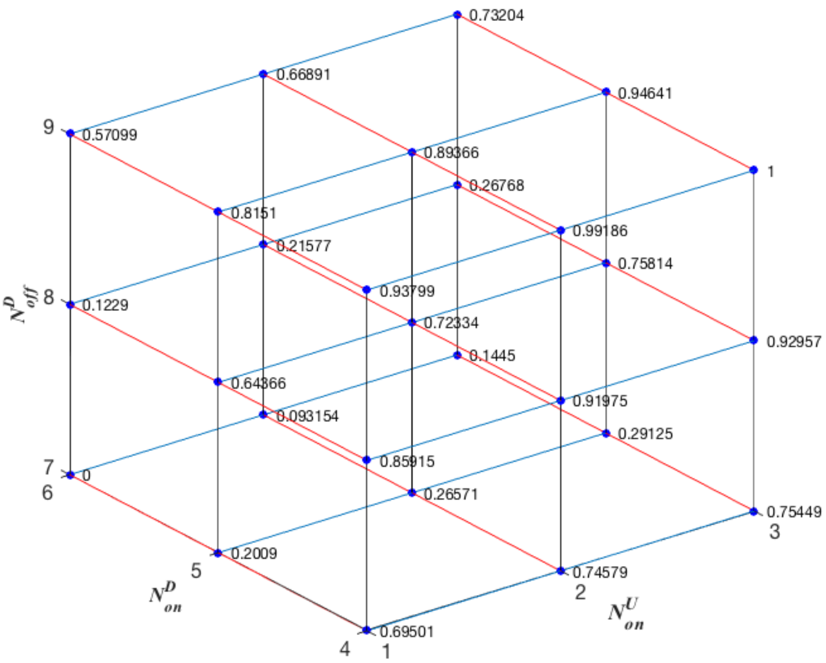

Figure B.2 Experiments results for line design MaxD_5%

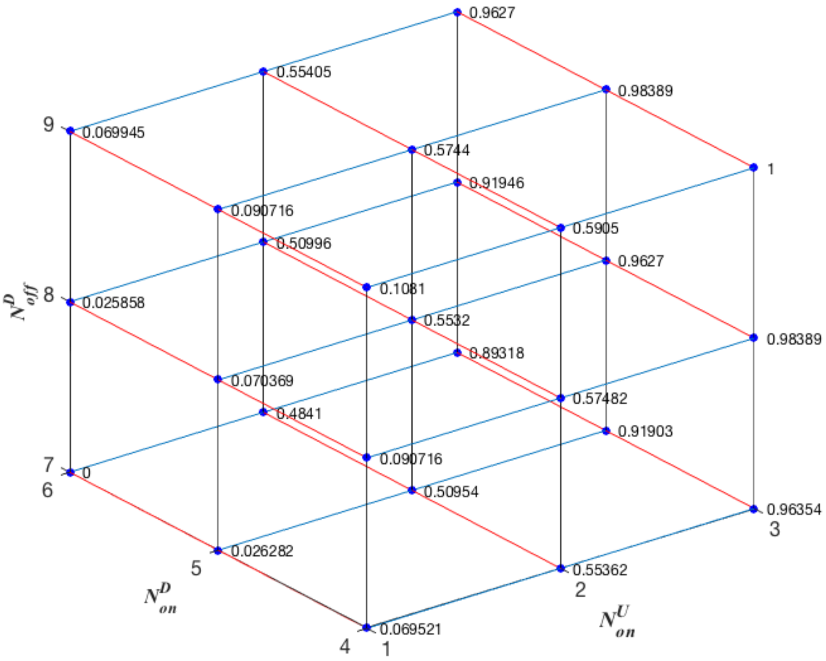

Figure B.3 Experiments results for line design MaxD_10%