energies

Review

A Systematic Review on Predicting and Forecasting the Electrical Energy Consumption in the Manufacturing Industry

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Abstract: In the context of the European Green Deal, the manufacturing industry faces environmental challenges due to its high demand for electrical energy. Thus, measures for improving the energy efficiency or flexibility are applied to address this problem in the manufacturing industry. In order to quantify energy efficiency or flexibility potentials, it is often necessary to predict or forecast the energy consumption. This paper presents a systematic review of state-of-the-art of existing approaches to predict or forecast the energy consumption in the manufacturing industry. Seventy-two articles are classified according to the defined categories System Boundary, Modelling Technique, Modelling Focus, Modelling Horizon, Modelling Perspective, Modelling Purpose and Model Output. Based on the reviewed articles future research activities are derived.

Keywords: energy; manufacturing; prediction; forecasting; modelling

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1. Introduction

In the European Green Deal [1], the European Commission has set the goal of making Europe climate-neutral by 2050. To achieve this objective, a severe reduction in greenhouse gas emissions is necessary. Energy use has an essential part in achieving this goal, as almost three-quarters of the global emissions (measured in Carbon Dioxide Equivalents (CO_2-eq)) were caused by energy use in 2016. The industry sector accounts for about 30% of emissions, with 24.2% attributable to energy use, making it the top emission source [2]. Focusing on energy consumption, the industrial sector is the largest electricity consumer worldwide, accounting for 42% in 2018 [3]. The manufacturing sector is a subset of the industrial sector, which converts raw materials into products utilising energy while simultaneously generating waste and emissions. This sector accounts for 77% of the global end-use of energy of the industrial sector in 2018 [3]. These high levels of consumed energy during manufacturing are a great opportunity to reduce the Carbon Dioxide Equivalents (CO_2-eq) emissions, while also leading to an economic motivation for companies to increasing their energy efficiency [4].

Additionally, the utilisation of renewable energy sources are increasing. In 2019 renewable electricity generation rose 6% to a total of almost 27% share of renewable energies in global electricity generation [5]. Renewable energy sources are characterised through a volatile power generation. This volatility, and thus reduced predictability compared to conventional power generation, leads to new opportunities for savings through electricity procurement or demand response applications in the industry [6].

Thus, manifold measures to improve the energy efficiency and flexibility on different levels within a factory have gained in importance and are still increasing in the manufacturing industry. Those measures can be supported by an accurate energy prediction or forecasting model (A distinction between predicting and forecasting is made in Section 4.4) of the respective system under consideration.

On that account, a systematic literature research and classification on predicting and forecasting the energy consumption in the manufacturing industry was conducted. In the following, the related work is summarised, the methodology for the systematic literature review is presented, a classification scheme is developed and finally an analysis of the examined articles according to the developed classification scheme is performed. Eventually, a conclusion is drawn and future research fields are derived.

2. Related Work

For over 25 years models for predicting the electrical energy consumption in the manufacturing industry have been a subject of research interest. However, it is due to the increasing importance of sustainability, resource and energy efficiency that the field has gained in relevant within the last decade.

There are not only different system levels for which an energy model is created, but also different areas of application, purposes and objectives. All these factors influence the model to be developed. An overview of the different dimensions that impact the development of an energy model is only partially covered in studies so far.

Zhao et al. classify different approaches in the field of energy modelling in machining processes in the three areas cutting energy, machining process energy, and machining system energy. The category cutting energy is distinguished in the dimensions net cutting specific energy, spindle specific energy, and machine tool energy consumption during cutting. Different process stages and machine tool components are considered in the machining process energy category. In the area of machining system energy different approaches to model the energy flow at machining system level are presented. In some areas, different modelling methods are discussed in more detail. Where possible, the authors have provided the basic formulas for calculating the energy consumption of the various studies [7].

Reinhardt et al. understand the energy consumption prediction as a modelling problem and therefore derive their classification scheme from the model development input-processing-output cycle. The distinguished categories are system (consisting of the dimensions factory, multiple machines, single machine, and machine part), input (consisting of the dimensions energy, environment, process, and product) and processing (consisting of the dimensions artificial neural network, fuzzy logic, empirical expression, simulation, and theoretical expression) [8].

In this study a morphology for classifying different approaches in the field of energy prediction and forecasting is developed based on identified influencing factors. Selected articles, which are based on a systematic literature search, are then classified according to the developed scheme.

3. Methodology for Systematic Literature Review

A multi-step approach to identify articles of high scientific value was conducted as summarised in Figure 1 based on the procedures of Glock and Hochrein [9] and Reynolds et al. [10]. The process consists of eight steps. First, the search strategy was determined by conceptualising the topic. The result was a list of keywords on the subject, on which the search string is based on. Next, the data bases to be searched and the respective publication titles listed in Table 1 were selected. The meta data (title, keywords, abstract) were searched in regards to combinations of the keywords in the search string. 969 articles meet the search criteria. To identify the articles of relevance, first the title and subsequently the abstract was screened. For the resulting selection, a thorough full text analysis was performed. Additionally, the references of the analysed articles were screened to identify further articles of relevance. These articles were added to the abstract screening point in the review process. Finally, the essential characteristics in regards to the developed classification scheme were recorded and summarised for the selected articles. 72 articles were identified as relevant in this process.

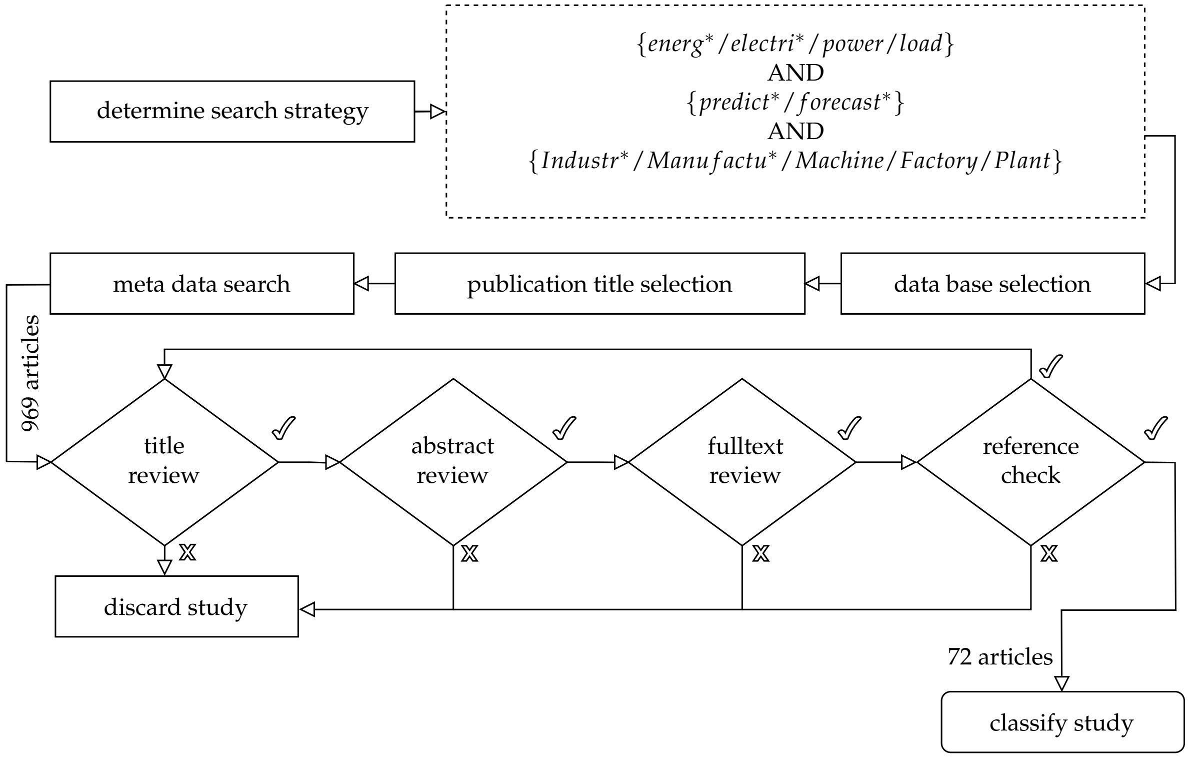

Figure 1. Methodology for systematic literature search.

Table 1. Searched data bases with respective publication titles.

Data Base	Publication Titles
Science Direct	Procedia CIRP Applied Energy Energy International Journal of Machine Tools and Manufacture International Journal of Mechanical Science
IEEE Xplore	IEEE Access IEEE Transactions on Sustainable Energy IEEE Transactions on Industry Applications IET Renewable Power Generation IEEE Transactions on Components, Packaging and Manufacturing Technology IEEE Transactions on Industrial Informatics
OCLC Worldcat	No journal restriction possible

4. Classification Scheme

Work in the field of energy modelling in the manufacturing industry can be classified into the categories and dimensions listed in Figure 2 based on the influencing factors of an energy model on an abstract level.

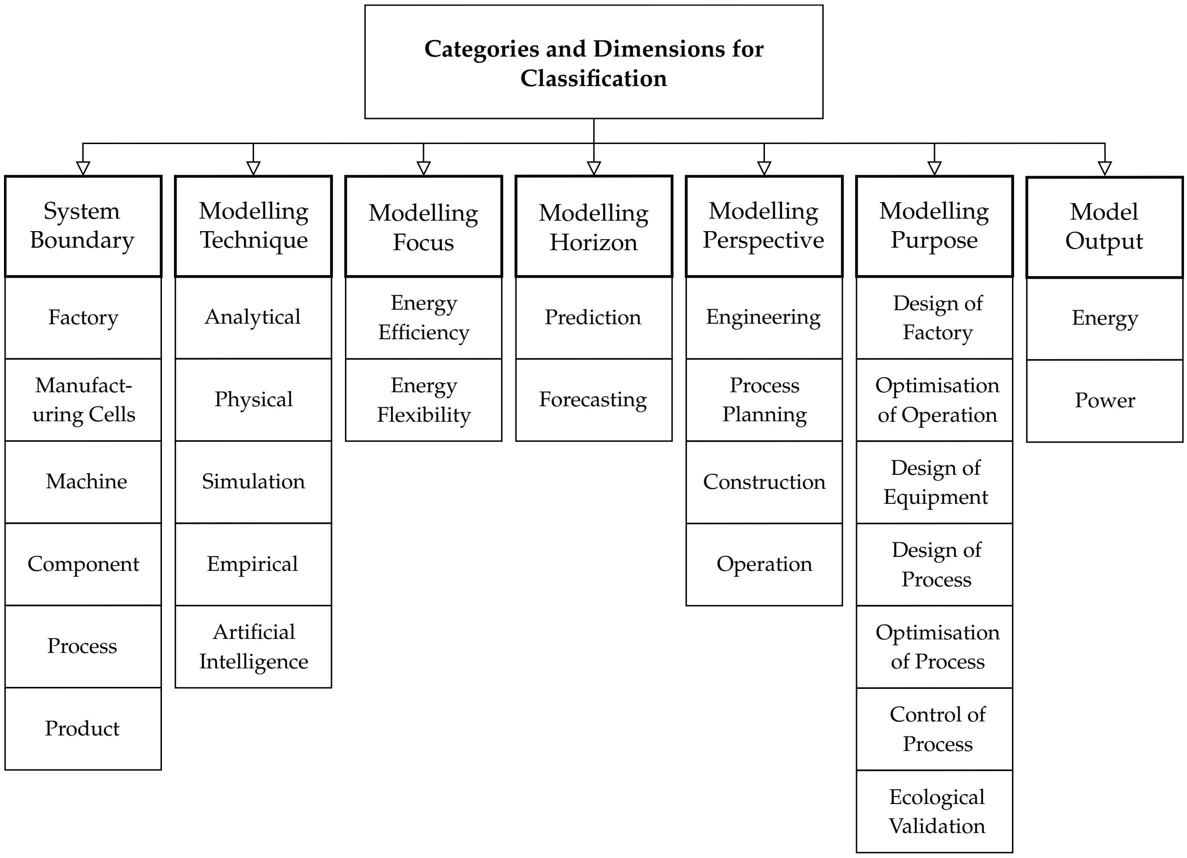

Figure 2. Dimensions for classifying work in the field of energy modelling.

4.1. System Boundary

In the context of industrial energy prediction or forecasting six dimensions can be distinguished regarding the system boundary [11].

- Factory: An energy model for factory-level demand is being developed.
- Manufacturing cell: An energy model is developed for a manufacturing cell containing several production machines.
- Machine: A machine-level energy model is developed.
- Component: An energy model of individual components of a production machine is developed.
- Process: An energy model for a specific process is developed.
- Product: An energy model is developed for the energy embedded in a product.

4.2. Modelling Technique

Generally, energy prediction or forecasting can be conducted with model-driven or data-driven approaches. Model-driven approaches include analytical, physical, simulation and empirical models, whereas Artificial Intelligence (AI) approaches are data-driven approaches.

- Analytical modelling: Theoretical analysis of the research question is conducted. In terms of energy models, the analytical procedure refers to the decomposition of the energy consumption. Different functions and areas are defined, which are usually represented by an average energy demand.
- Physical modelling: Fundamental physical relationships are described by mathematical equations.
- Simulation approaches: Physical models are solved numerically with simulation tools.

- Empirical modelling: Empirical research is performed via the systematic evaluation of experiences. Empirical models often use statistical methods, which require an explicit mathematical representation for the problem under consideration.
- Artificial Intelligence (AI) approaches: Many different approaches are summarised under the term Artificial Intelligence (AI). In general the term Artificial Intelligence (AI) encompasses three related concepts, which are illustrated in Figure 3. The broadest concept Artificial Intelligence (AI) encompasses the two sub-fields Machine Learning (ML) and Deep Learning (DL), while Deep Learning (DL) is again a sub-field of Machine Learning (ML). Artificial Intelligence (AI) is the study of "intelligent agents", which refers to any device that perceives its environment and, acting on that basis, carries out actions that maximise the chances of success for a given objective. Machine Learning (ML) is a collection of data-driven algorithms that can learn form data without being explicitly programmed. Deep Learning (DL) refers to the study of Artifical Neural Networks and related machine learning algorithms that contain more than one hidden layer, also known as deep neural networks [12].

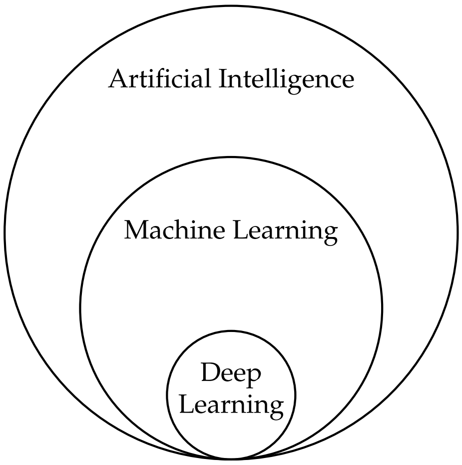

Figure 3. The relationship between Artificial Intelligence, Machine Learning, and Deep Learning [13].

4.3. Modelling Focus

Two categories can be distinguished, on which the studies in the field of energy modelling are focused.

- Energy efficiency: The "relationship between the results achieved and the resources used, where resources are limited to energy" [14]
- Energy flexibility: The "ability of a production system to adapt quickly and in a process-efficient way to changes in the energy market" [15]

4.4. Modelling Horizon

Two temporal dimensions can be distinguished regarding the modelling horizon.

- Prediction: Is the process to predict an unknown value from known inputs. In the case of energy modelling, this means that the available observations at time t of a time series are used to predict the output (energy or load) at time t.
- Forecasting: Is a procedure for making statements about the future. For energy modelling, this means that future values t + x of a time series are estimated based on current and/or past information at time t [16].

4.5. Modelling Perspective

There are different phases in the Factory Life Cycle (FLC) and Product Life Cycle (PLC) [11] in which an energy model is useful.

- Engineering (within the Factory Life Cycle (FLC)): Energy models are applied to plan the electrical energy grid of a new factory.
- Process Planning (within the Factory Life Cycle (FLC)): Designing and optimising manufacturing processes in regards to energy consumption is the objective to use energy models in this phase.
- Construction (within the Product Life Cycle (PLC)): Energy models are used to design products that are energy efficient in their production.
- Operation (within the Factory Life Cycle (FLC) and Product Life Cycle (PLC)): The operation phase is where the actual production takes place. Energy models are deployed to optimise the operation in regards to one of the two above mentioned focuses (Energy Efficiency or Flexibility). The optimisation of the operation phase can be distinguished in the operation on factory, machine and process level.

4.6. Modelling Purpose

Several reasons can be distinguished for developing an energy model.

- Design of Factory: The objective is to design the electrical grid of a new factory.
- Optimisation of operation: The operation phase is optimised with respect to different objectives.
- Design of Equipment: The objective is to configure production machines in an energy efficient way.
- Design of Process: Energy models are utilised to design energy efficient production processes.
- Optimisation of Process: The process is optimised in regards to the the most energy efficient process parameters.
- Control of Process: The objective is to control the process in regards to predictive maintenance (tool wear), anomaly detection or energy consumption allowance.
- Ecological Validation: Energy models are used for a life cycle assessment.

4.7. Model Output

Two main dimensions can be distinguished regarding the output of the energy model.

- Load: In technical usage, load is the power taken up by a plant or machine, where the power is the quotient of the work performed in a period of time and the period of time [17].
- Energy consumption or Specific Energy (SEC): "Energy consumption is the quantity of particular forms of energy consumed in order to cover energy demand under real conditions" [17] (p. 14). For the Specific Energy (SEC) the energy consumption is related to a suitable functional unit, where the functional unit may be cm^3 or kg for instance [17].

5. Analysis and Synthesis

Tables 2 and 3 provide an overview of the 72 examined articles according to the developed classification scheme. Please note that many of the articles can be assigned to more than one dimension within a category. Therefore, more than 72 articles are listed in the total column for the individual categories. Additionally, an evaluation of the time dependencies for the different categories was conducted. Figure 4 displays the total number of articles over time from 2009, as approx. 95% of the articles are in the time span from 2009. The total number of articles fluctuates around the value of five articles per year with a maximum value of 13 in 2011. Since 2017, the number of articles per year has been steadily increasing, with nine articles in 2019. For 2020, three articles have already been recorded by the time the literature search was conducted in April. The results for the different categories are displayed in the Figures 5–9 and are discussed in the following.

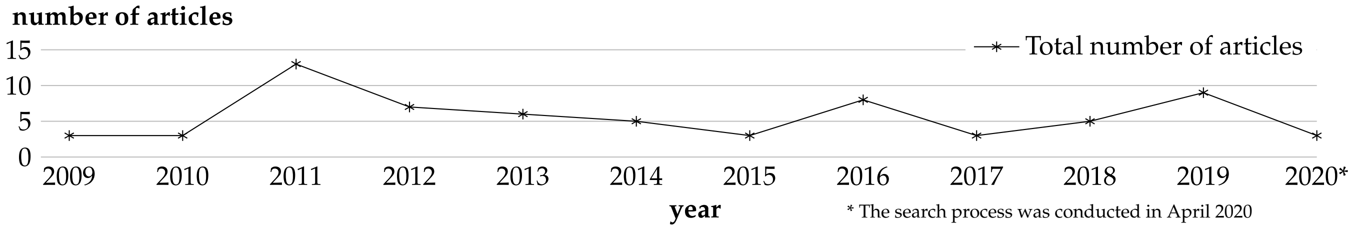

Figure 4. Total number of articles over time.

The dimension System Boundary, Modelling Technique, Focus, and Horizon (Time) are displayed in Table 2. With 50 articles in total, Machines predominate the considered System Boundary (see Figure 5). Fewer than ten articles are found in each of the remaining dimensions of the System Boundary. From the analysed articles only four develop hierarchical models (Hierarchical models decompose complex problems into simpler parts or primitives. For example 3d objects can naturally be decomposed into object parts, these parts into geometric primitives [18]. In regards to the industrial application of energy models, factories can be decomposed into manufacturing cells, which in turn into production machines, which can be be decomposed into components. A hierarchical model of a manufacturing cell for example could consists of several models of production machines.), where one model constitutes as a part of the other. In the analysed literature hierarchical models are either used at machine level, where models at component level are incorporated into the machine model or at manufacturing cell or factory level, where individual machine models are incorporated into the higher level.

Regarding the Modelling Technique, there is a more even distribution of the used methods within the examined literature. However, Analytical and Empirical models are being used most frequently with 19 and 22 articles in total. Analytical models are primarily used at Machine level. Here, the energy demand of the different operating modes—off, standby, ready for processing, and processing—and different processing steps such as handling, tool exchange or welding are usually analysed. For each operating mode and processing step an average energy consumption is calculated. The energy consumption is then predicting by combining the average consumption for the respective operating mode and process step in the form of a step function. Therefore, these models are highly simplified. The application of Analytical approaches is almost constant over time with around two articles per year (see Figure 6).

Physics-based models are mainly developed for predicting the energy consumption at Machine level. Nonetheless, Physical models are also applied at the Process or Component level. However, Physical models are often difficult to implement, because they are not lean and require a large number of parameters that are difficult to obtain. Furthermore, the incorporation of the stochastic nature of a manufacturing process is challenging [19–21] and, in addition, highly complex processes such as machining processes do not permit purely Physical modelling [21]. The development of Physical models is consistently low at between zero and two articles per year (see Figure 6).

Empirical models use experimental data and often utilise statistical methods to fit the parameters of a previously defined functional form to the problem under consideration. Empirical models are applied in all defined system boundaries. The most common statistical technique in the analysed literature to develop energy models is the Multiple Linear Regression. Empirical models prove to be very applicable and accurate in certain cases. However, formulating the right model, which requires a deep understanding of the phenomenon in question and the need for heavy experimentation are limitation factors [21,22]. Empirical models were used very frequently between 2011 and 2016 with up to six articles per year. Since 2017, the use of Empirical models has decreased sharply with a value of zero as of 2019 (see Figure 6).

As a result of the advances in machine automation and sensing, which start to overcome these limitations by allowing continuous measurements, data-driven models are gaining importance. Several energy models based on Artificial Intelligence (AI) methods have been developed recently, as they provide insights to problems that could not be addressed with a purely theoretical analysis based on physical principals [23]. Artificial Intelligence (AI) modelling techniques do not require to model the underlying physical system explicitly, as they map the input upon the output [24]. The most common Artificial Intelligence (AI) technique is the Artifical Neural Network (ANN) with 13 articles in total. Further modelling techniques are Support Vector Regression, Gaussian Process Regression, and Random Forest. When using Artifical Neural Network (ANN), ten articles used a simple Multilayer Perceptron. Only one articles applied a modelling technique from the filed of Deep Learning (DL) with the development of a Convolutional Neural Network [25]. Three of the analysed articles compared several Artificial Intelligence (AI) techniques [25–27]. Considering the time trend, Artificial Intelligence (AI) methods show a strong increase since the year 2019 with a maximum value of seven. The three articles recorded for the year 2020 are all assigned to the Artificial Intelligence (AI) modelling technique (see Figure 6).

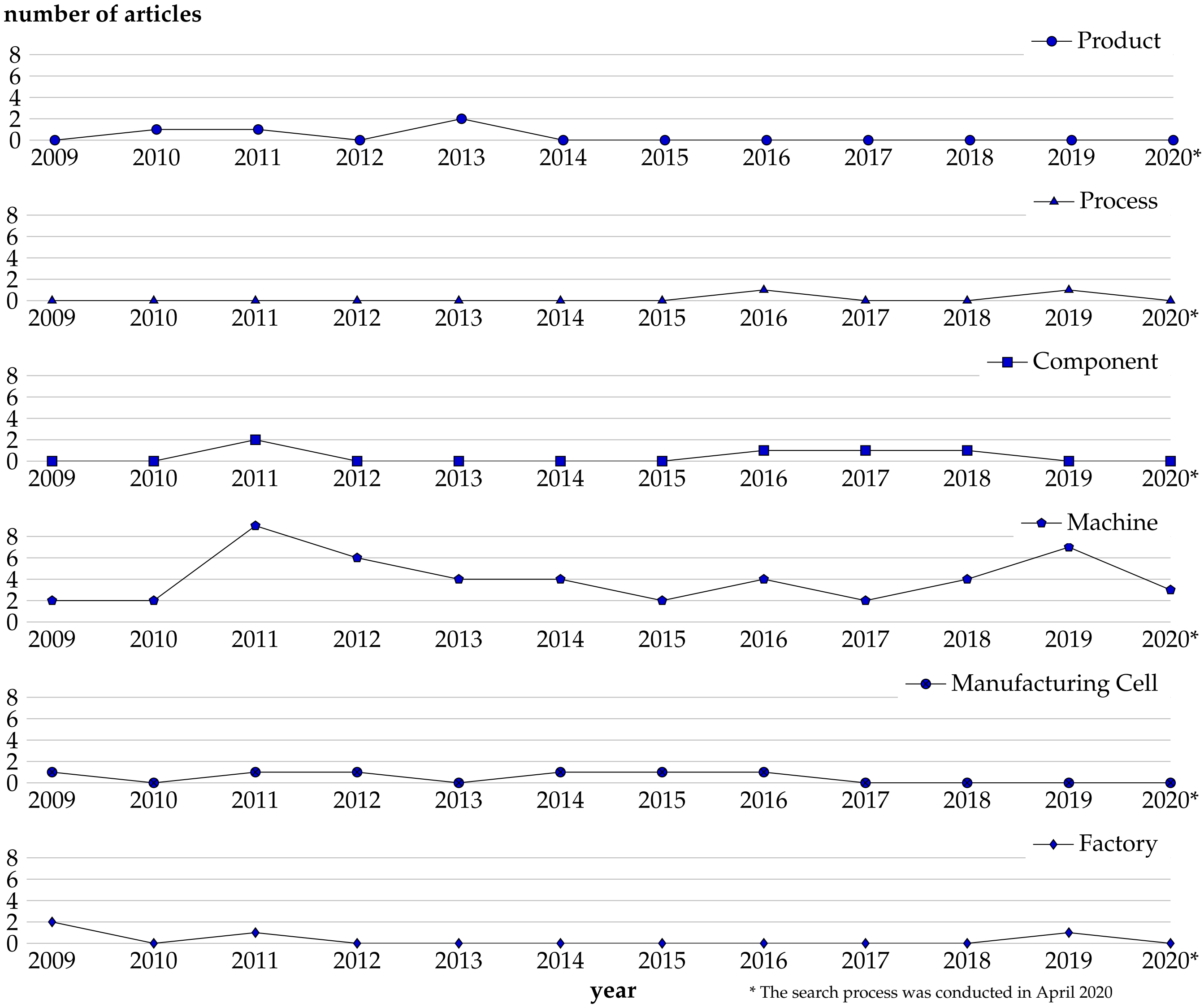

Figure 5. Number of articles over time for the category System Boundary.

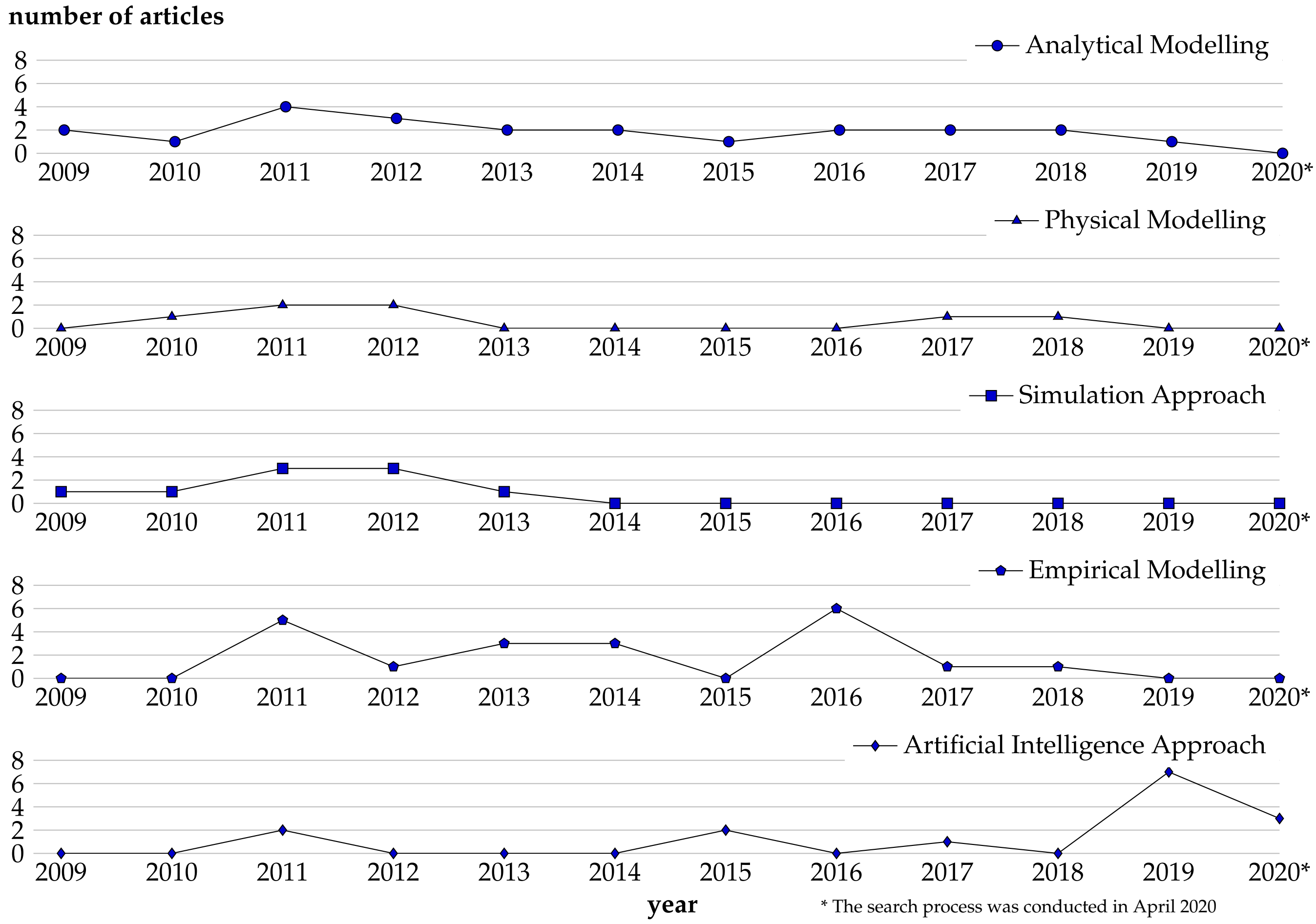

Figure 6. Number of articles over time for the category Modelling Technique.

In regards to the Focus of the studies, the field of Energy Efficiency predominates Energy Flexibility. Only three articles can be assigned to the field of Energy Flexibility. Additionally, only those three articles address the field of Forecasting in the category Horizon. The other articles are part of the field Prediction. As can be seen in Figure 7, the fields of Energy Flexibility and Forecasting are rather young research areas with zero articles before the year 2019.

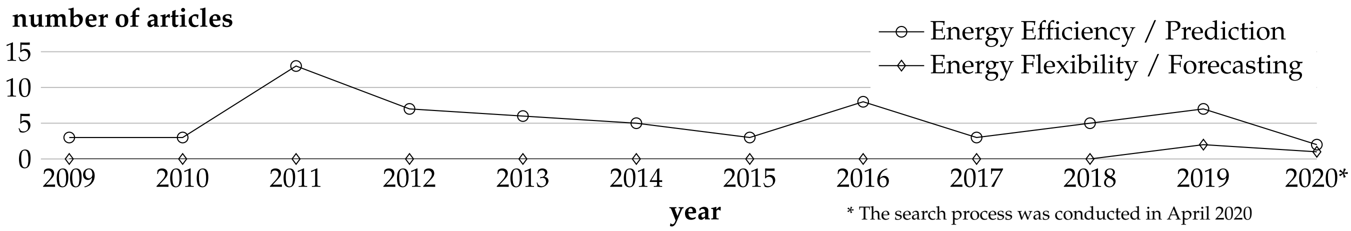

Figure 7. Number of articles over time for the categories Focus and Horizon.

Table 3 displays the categories Perspective, Modelling Purpose and Output. In regards to the Perspective, the majority of the analysed approaches focus on the Process Planning or Construction phase (see Figure 8) with 57 and 20 articles in total, of which 12 articles address both perspectives simultaneously. A predictive model within the framework of the Engineering phase in the Factory Life Cycle (FLC) has only been developed in one study. Models for usage in the Operational phase have been developed by 10 studies.

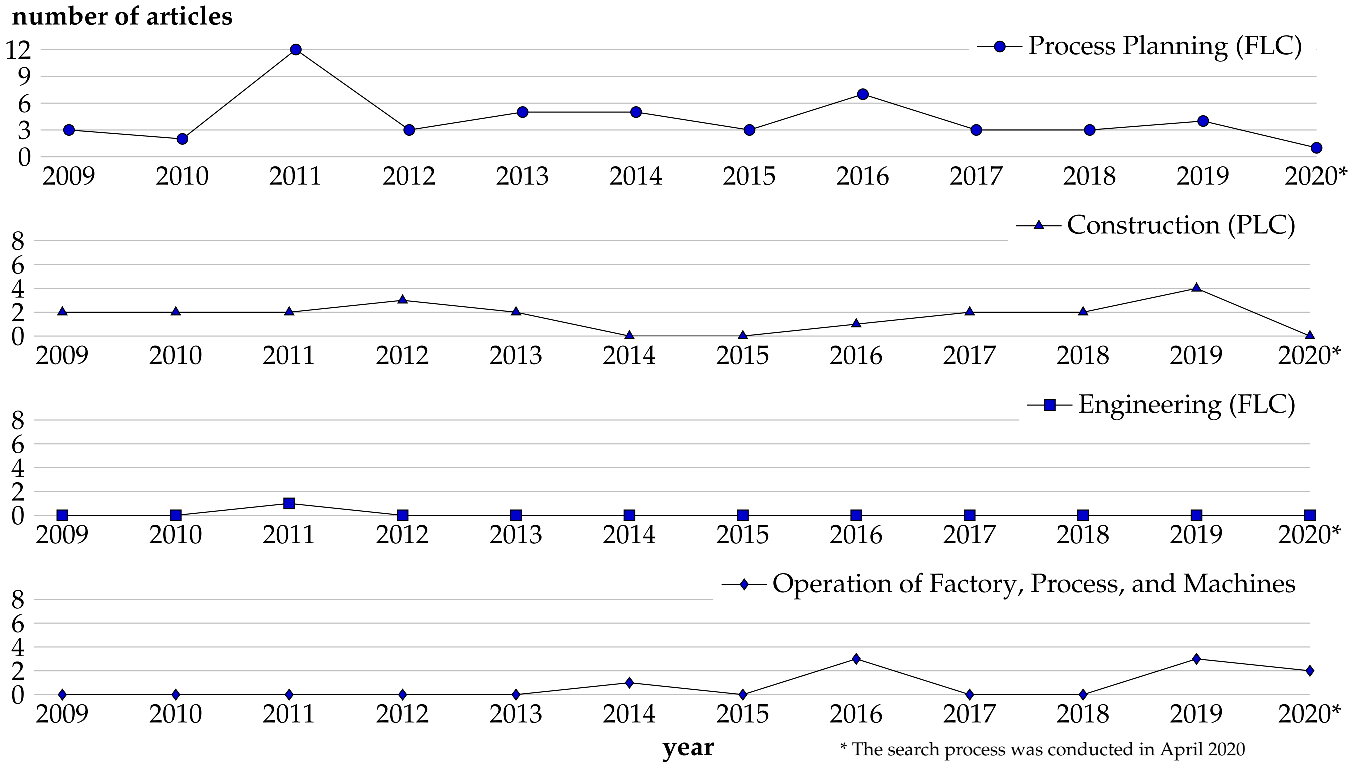

Figure 8. Number of articles over time for the category Perspective.

With 40 articles in total the Optimisation of Processes predominates as a Modelling Purpose followed by the Design of Processes with a total of 15 articles (see Figure 9). None of these studies addresses both purposes simultaneously. Of the eight studies dealing with the Control of the Process, only three focus on it. The rest of the studies additionally address the Optimisation of the Process purpose. Furthermore, the use of models to Design Equipment seems to be a co-product in most of the approaches, as only two articles focus on this perspective. Only two of the analysed articles deal with the Design of the Factory purpose, where one addresses the Engineering phase of the Factory Life Cycle (FLC) and the other develops the model for application in Process Planning and Design phase. Of the 19 articles that undertake Ecological Validation, only 5 studies develop an energy model solely for this purpose. For the remaining studies, this is an additional purpose.

Regarding the Output of the model, 19 studies analyse the Power and thus the power curve. From the ten articles, which address the Optimisation of Operation phase, six consider the power consumption of the respective system as the Output of the model. The remaining articles develop models with the Energy or Specific Energy (SEC) as the Output with 42 and 11 articles in total.

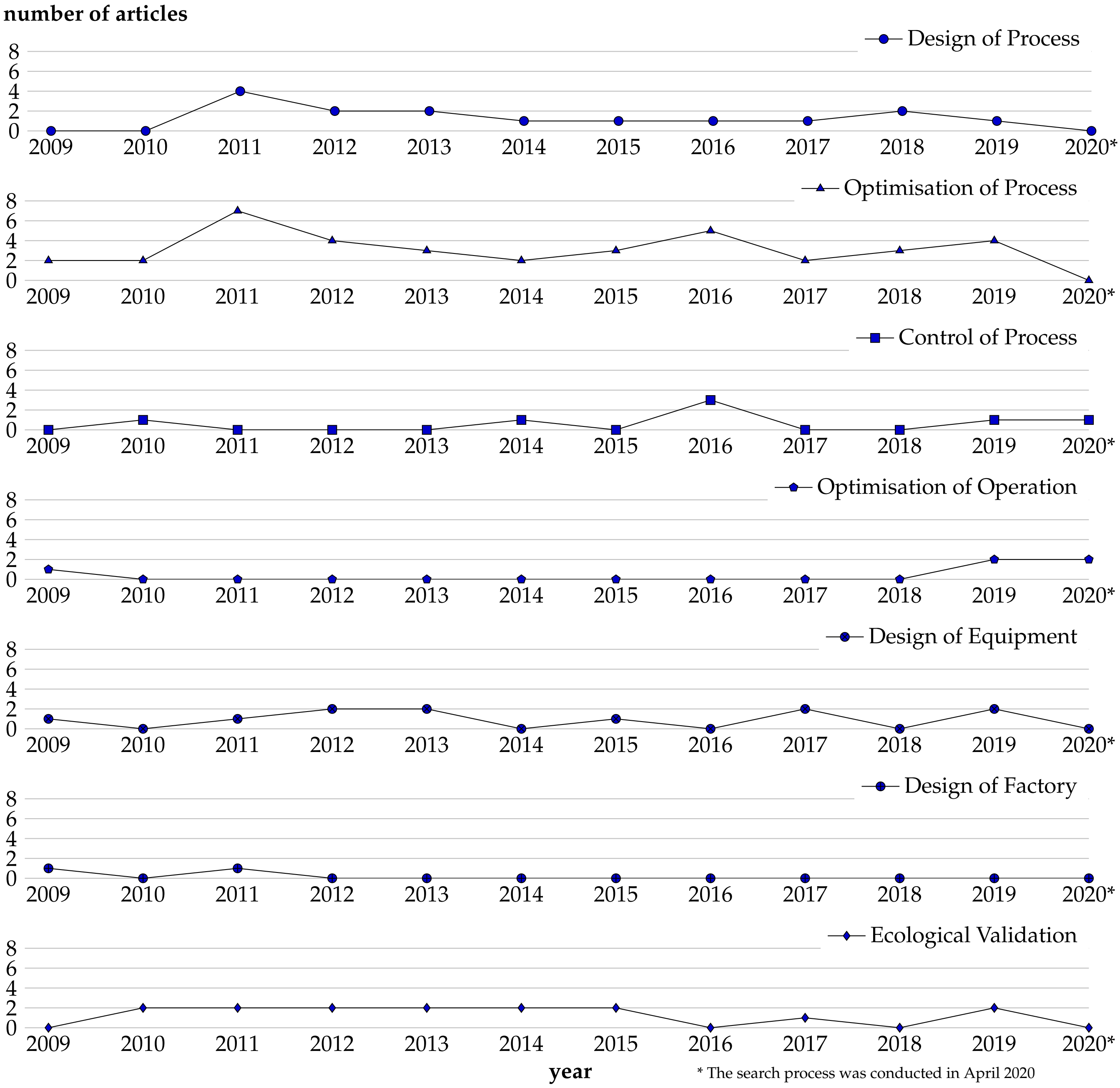

Figure 9. Number of articles over time for the category Purpose of Modelling.

Table 2. Classification for Dimensions Modelling Technique, System Boundary, Focus, and Horizon (Time).

Dimension / **Approach from**	**System Boundary**						**Technique**					**Focus**		**Time**	
	Product	**Process**	**Component**	**Machine**	**Manufacturing Cells**	**Factory**	**Analytical**	**Physical Modelling**	**Simulation**	**Empirical**	**Artificial Intelligence**	**Energy Efficiency**	**Energy Flexibility**	**Prediction**	**Forecast**
Number of Articles	4	5	6	50	8	4	19	9	9	22	15	69	3	69	3
Abele et al. [28]				•					•			•		•	
Abeykoon et al. [29]				•						•		•		•	
Aramcharoen and Mativenga [30]				•			•					•		•	
Avram and Xirouchakis [31]				•					•			•		•	
Balogun and Mativenga [32]				•			•					•		•	
Bhinge et al. [19]				•							•	•		•	
Bi and Wang [33]				•				•				•		•	
Bi and Wang [34]				•				•				•		•	
Bornschlegl et al. [35]					•		•					•		•	
Braun and Heisel [36]				•					•			•		•	
Budinoff et al. [37]				•						•		•		•	
Diaz et al. [38]				•			•					•		•	
Diaz et al. [39]			•							•		•		•	
Dietmair and Verl [20]				•			•					•		•	
Dietmair and Verl [40]				•	•	•	•					•		•	
Dietrich et al. [41]				•							•		•		•
Doreth [26]				•							•	•		•	
Doreth et al. [42]				•						•		•		•	
Draganescu et al. [43]			•							•		•		•	
Feng et al. [44]				•							•	•		•	

Table 2. *Cont.*

Dimension / Approach from	System Boundary						Technique					Focus		Time	
	Product	**Process**	**Component**	**Machine**	**Manufacturing Cells**	**Factory**	**Analytical**	**Physical Modelling**	**Simulation**	**Empirical**	**Artificial Intelligence**	**Energy Efficiency**	**Energy Flexibility**	**Prediction**	**Forecast**
Number of Articles	**4**	**5**	**6**	**50**	**8**	**4**	**19**	**9**	**9**	**22**	**15**	**69**	**3**	**69**	**3**
Goldhahn et al. [45]				•			•					•		•	
Gutowski et al. [46]				•				•				•		•	
Al-Hazza et al. [47]				•							•	•		•	
He et al. [48]					•				•			•		•	
He et al. [49]				•			•					•		•	
He et al. [25]				•							•	•		•	
Herrmann and Thiede [50]						•			•			•		•	
Huang et al. [51]			•							•		•		•	
Imani Asrai et al. [52]				•						•		•		•	
Jia et al. [53]		•								•		•		•	
Kant and Sangwan [27]				•	•						•	•		•	
Kant and Sangwan [54]				•	•						•	•		•	
Kara and Li [55]				•						•		•		•	
Kong et al. [56]				•			•					•		•	
Larek et al. [57]				•					•			•		•	
Li et al. [58]				•						•		•		•	
Li and Kara [59]				•						•		•		•	
Li et al. [60]					•		•					•		•	
Li et al. [61]					•		•					•		•	
Li et al. [62]				•						•		•		•	

Table 2. *Cont.*

Dimension / Approach from	System Boundary						Technique					Focus		Time	
	Product	Process	Component	Machine	Manufacturing Cells	Factory	Analytical	Physical Modelling	Simulation	Empirical	Artificial Intelligence	Energy Efficiency	Energy Flexibility	Prediction	Forecast
Number of Articles	**4**	**5**	**6**	**50**	**8**	**4**	**19**	**9**	**9**	**22**	**15**	**69**	**3**	**69**	**3**
Li et al. [63]				•						•		•		•	
Li et al. [64]			•					•				•		•	
Mori et al. [65]				•			•					•		•	
Mose and Weinert [66]	•						•					•		•	
Munoz and Sheng [67]		•						•				•		•	
Peng and Xu [68]				•			•			•		•		•	
Quintana et al. [69]			•	•							•	•		•	
Rahimifard et al. [70]	•								•			•		•	
Rajemi et al. [71]				•				•				•		•	
Rief [72]				•						•		•		•	
Sato et al. [73]			•					•				•		•	
Sealy et al. [74]		•								•		•		•	
Seow and Rahimifard [75]	•						•			•		•		•	
Seow et al. [76]	•								•			•		•	
Shang et al. [77]				•			•					•		•	
Shao et al. [78]		•								•		•		•	
Shin et al. [79]				•							•	•		•	
Sossenheimer et al. [80]				•							•	•		•	
Sossenheimer et al. [81]				•							•	•		•	
Su [82]						•				•		•		•	

Table 2. *Cont.*

Dimension / Approach from	System Boundary						Technique					Focus		Time	
	Product	**Process**	**Component**	**Machine**	**Manufacturing Cells**	**Factory**	**Analytical**	**Physical Modelling**	**Simulation**	**Empirical**	**Artificial Intelligence**	**Energy Efficiency**	**Energy Flexibility**	**Prediction**	**Forecast**
Number of Articles	**4**	**5**	**6**	**50**	**8**	**4**	**19**	**9**	**9**	**22**	**15**	**69**	**3**	**69**	**3**
Teiwes et al. [83]				•			•					•		•	
Verl et al. [84]				•					•			•		•	
Walther et al. [85]						•					•		•		•
Walther et al. [86]				•							•		•		•
Wang et al. [87]		•						•				•		•	
Weinert et al. [88]					•		•					•		•	
Wu et al. [89]				•						•		•		•	
Yi et al. [90]				•				•				•		•	
Yi et al. [91]				•							•	•		•	
Yoon et al. [92]				•						•		•		•	
Yoon et al. [93]				•						•		•		•	
Zhou et al. [94]				•			•					•		•	

Table 3. Classification for Dimensions Perspective, Purpose of Modelling, and Output.

Dimension / Approach from	Perspective						Modelling Purpose							Output	
	Process Planning (FLC)	**Construction (PLC)**	**Engineering (FLC)**	**Operation of Factory**	**Operation of Machines**	**Operation of Process**	**Design of Processes**	**Optimisation of Processes**	**Control of Processes**	**Optimisation of Operation**	**Design of Equipment**	**Design of Factory**	**Ecological Validation**	**Energy/SEC**	**Power**
Number of Articles	**57**	**20**	**1**	**1**	**5**	**4**	**15**	**40**	**8**	**5**	**11**	**2**	**19**	**53**	**19**
Abele et al. [28]		•									•			•	
Abeykoon et al. [29]	•							•					•	•	
Aramcharoen and Mativenga [30]	•					•		•	•					•	
Avram and Xirouchakis [31]	•	•					•							•	
Balogun and Mativenga [32]	•	•					•				•		•	•	
Bhinge et al. [19]	•							•						•	
Bi and Wang [33]	•							•					•	•	
Bi and Wang [34]	•							•					•	•	
Bornschlegl et al. [35]	•	•											•	•	
Braun and Heisel [36]	•	•						•			•				•
Budinoff et al. [37]	•							•					•	•	
Diaz et al. [38]	•	•						•					•	•	
Diaz et al. [39]	•						•							•	
Dietmair and Verl [20]	•	•						•			•			•	
Dietmair and Verl [40]	•	•						•				•		•	
Dietrich et al. [41]					•					•					•
Doreth [26]		•									•		•	•	
Doreth et al. [42]		•									•			•	
Draganescu et al. [43]	•							•						•	

Table 3. *Cont.*

Dimension / Approach from	Perspective						Modelling Purpose							Output	
	Process Planning (FLC)	**Construction (PLC)**	**Engineering (FLC)**	**Operation of Factory**	**Operation of Machines**	**Operation of Process**	**Design of Processes**	**Optimisation of Processes**	**Control of Processes**	**Optimisation of Operation**	**Design of Equipment**	**Design of Factory**	**Ecological Validation**	**Energy/SEC**	**Power**
Number of Articles	**57**	**20**	**1**	**1**	**5**	**4**	**15**	**40**	**8**	**5**	**11**	**2**	**19**	**53**	**19**
Feng et al. [44]	•	•						•						•	
Goldhahn et al. [45]	•							•						•	
Gutowski et al. [46]	•							•					•	•	
Al-Hazza et al. [47]	•							•						•	
He et al. [48]	•						•							•	
He et al. [49]	•							•						•	
He et al. [25]	•									•					•
Herrmann and Thiede [50]	•									•				•	
Huang et al. [51]	•						•							•	
Imani Asrai et al. [52]	•							•						•	
Jia et al. [53]	•							•						•	
Kant and Sangwan [27]	•							•					•		•
Kant and Sangwan [54]	•							•					•	•	
Kara and Li [55]	•						•							•	
Kong et al. [56]	•							•						•	
Larek et al. [57]	•	•						•			•		•		•
Li et al. [58]	•						•							•	
Li and Kara [59]	•							•						•	

Table 3. *Cont.*

Dimension / Approach from	Perspective						Modelling Purpose							Output	
	Process Planning (FLC)	**Construction (PLC)**	**Engineering (FLC)**	**Operation of Factory**	**Operation of Machines**	**Operation of Process**	**Design of Processes**	**Optimisation of Processes**	**Control of Processes**	**Optimisation of Operation**	**Design of Equipment**	**Design of Factory**	**Ecological Validation**	**Energy/SEC**	**Power**
Number of Articles	**57**	**20**	**1**	**1**	**5**	**4**	**15**	**40**	**8**	**5**	**11**	**2**	**19**	**53**	**19**
Li et al. [60]	•						•				•			•	
Li et al. [61]	•						•							•	
Li et al. [62]	•					•		•	•					•	
Li et al. [63]	•												•		•
Li et al. [64]	•	•						•			•			•	
Mori et al. [65]	•							•						•	
Mose and Weinert [66]	•												•	•	
Munoz and Sheng [67]	•							•					•	•	
Peng and Xu [68]	•	•					•				•		•		•
Quintana et al. [69]	•							•							•
Rahimifard et al. [70]		•											•	•	
Rajemi et al. [71]	•							•	•					•	
Rief [72]		•					•								•
Sato et al. [73]	•							•						•	
Sealy et al. [74]	•					•		•	•					•	
Seow and Rahimifard [75]	•							•						•	
Seow et al. [76]	•							•						•	
Shang et al. [77]	•	•						•			•			•	
Shao et al. [78]	•					•		•	•						•

Table 3. *Cont.*

Dimension / **Approach from**	**Perspective**						**Modelling Purpose**							**Output**	
	Process Planning (FLC)	**Construction (PLC)**	**Engineering (FLC)**	**Operation of Factory**	**Operation of Machines**	**Operation of Process**	**Design of Processes**	**Optimisation of Processes**	**Control of Processes**	**Optimisation of Operation**	**Design of Equipment**	**Design of Factory**	**Ecological Validation**	**Energy/SEC**	**Power**
Number of Articles	**57**	**20**	**1**	**1**	**5**	**4**	**15**	**40**	**8**	**5**	**11**	**2**	**19**	**53**	**19**
Shin et al. [79]	•							•						•	
Sossenheimer et al. [80]					•				•						•
Sossenheimer et al. [81]					•				•						•
Su [82]			•									•			•
Teiwes et al. [83]		•					•								•
Verl et al. [84]	•												•	•	
Walther et al. [85]				•						•					•
Walther et al. [86]					•					•					•
Wang et al. [87]	•							•						•	
Weinert et al. [88]	•						•							•	
Wu et al. [89]	•							•						•	
Yi et al. [90]		•					•							•	
Yi et al. [91]		•					•						•		•
Yoon et al. [92]	•							•							•
Yoon et al. [93]	•							•							•
Zhou et al. [94]					•				•					•	

6. Conclusions

In this study, a literature review on predicting and forecasting the energy consumption in the manufacturing industry is provided. The approaches are classified in seven categories with sub-dimensions, which in turn all influence the model to be developed. It can be stated that the System Boundary Machine with the Perspective Process Planing and the Purpose to Optimise the Process predominate in the examined articles. Furthermore, it can be concluded that the relevance of experiments and data increases in this field of research as Empirical studies are the Modelling Technique most likely used with a strong increase in Artificial Intelligence (AI) approaches since 2019.

In terms of the Modelling Technique, the usage of Artificial Intelligence (AI) is a rather young but promising field of research, with Artifical Neural Network (ANN) being the most used technique. A Modelling Technique from the Artificial Intelligence (AI) sub-field Deep Learning (DL) was only used by one of the examined studies [25]. However, this modelling technique seems to be promising, especially in the field of Forecasting, as Deep Learning (DL) techniques show great results for related forecasting tasks such as renewable energies forecasting [95], energy demand forecasting from the supplier perspective [96,97], and building thermal load forecasting [98]. Nevertheless, the research area of industrial Energy Forecasting, which is needed for the Focus of Energy Flexibility, is an even younger research area. From the analysed articles only three considered the temporal Horizon Forecasting. However, against the background of the increasing share of renewable energies in the power grid, it is gaining in importance.

Concluding, a qualitative comparison between the different approaches is not practicable, as different System Boundaries and different Horizons are considered with different modelling intentions. Additionally, the modelling accuracy is expressed with different metrics, such as Mean Relative Error, Coefficient of Determination or Root Mean Squared Error.

For future research, a follow-up literature search could include other databases or include other categories, such as the type of data used. In the first case, an automation of the search process would be beneficial, due to the vast amount of search results without journal restriction. Furthermore, a more profound analysis of the Artificial Intelligence (AI) based articles could be carried out. Additionally, future research could define guidelines on which Modelling Techniques are suitable for which Purposes, Perspectives and Focus for each System Boundary, as the development effort of the different modelling techniques can differ significantly. Therefore, the results and implementation efforts of the different Modelling Techniques need to be compared with a standardised procedure.

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Abbreviations

CO_2-eq	Carbon Dioxide Equivalents
AI	Artificial Intelligence
ANN	Artifical Neural Network
DL	Deep Learning
FLC	Factory Life Cycle
ML	Machine Learning
PLC	Product Life Cycle
SEC	Specific Energy

References

1. European Commission. *The European Green Deal: Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Comittee and the Committeee of the Regions*; European Commission: Brussels, Belgium, 2019.
2. Ritchie, H.; Roser, M. Emissions by Sector. Our World in Data. 2020. Available online: https://ourworldindata.org/emissions-by-sector#sector-by-sector-where-do-global-greenhouse-gas-emissions-come-from (accessed on 29 December 2020).
3. International Energy Agency (IEA). Key World Energy Statistics 2020. Paris. 2020. Available online: https://www.iea.org/reports/key-world-energy-statistics-2020 (accessed on 29 December 2020),
4. Hesselbach, J.; Herrmann, C.; Detzer, R.; Martin, L.; Thiede, S.; Ludemann, B. Energy efficiency through optimised coordination of production and technical building services. In *LCE 2008: 15th CIRP International Conference on Life Cycle Engineering: Conference Proceedings*; The University of New South Wales: Sydney, Australia, 2008; p. 624.
5. International Energy Agency (IEA). Tracking Power. Paris. 2020. Available online: https://www.iea.org/reports/tracking-power-2020 (accessed on 29 December 2020),
6. Beier, J. *Simulation Approach towards Energy Flexible Manufacturing Systems*; Sustainable Production, Life Cycle Engineering and Management; Springer International Publishing: Cham, Switzerland, 2017. [CrossRef]
7. Zhao, G.Y.; Liu, Z.Y.; He, Y.; Cao, H.J.; Guo, Y.B. Energy consumption in machining: Classification, prediction, and reduction strategy. *Energy* **2017**, *133*, 142–157. [CrossRef]
8. Reinhardt, H.; Bergmann, J.P.; Münnich, M.; Rein, D.; Putz, M. A survey on modeling and forecasting the energy consumption in discrete manufacturing. *Procedia CIRP* **2020**, *90*, 443–448. [CrossRef]
9. Glock, C.H.; Hochrein, S. Purchasing Organization and Design: A literature review. *Bus. Res.* **2011**, *4*, 149–191. [CrossRef]
10. Reynolds, N.; Simintiras, A.; Vlachou, E. International business negotiations. *Int. Mark. Rev.* **2003**, *20*, 231–261. [CrossRef]
11. Westkämper, E. Digitales Engineering von Fabriken und Prozessen. In *Schriftliche Fassung der Vorträge zum Fertigungstechnischen Kolloquium am 10 und 11 September in Stuttgart*; [Tagungsband]; Ges. für Fertigungstechnik: Stuttgart, Germany, 2008; Volume 10, pp. 427–452.
12. Ongsulee, P. Artificial intelligence, machine learning and deep learning. In Proceedings of the 2017 Fifteenth International Conference on ICT and Knowledge Engineering (ICT&KE), Bangkok, Thailand, 22–24 November 2017; pp. 1–6. [CrossRef]
13. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; Adaptive Computation and Machine Learning, The MIT Press: Cambridge, MA, USA, 2016.
14. ISO—International Organization for Standardization. *ISO 14955-1—Machine tools—Environmental Evaluation of Machine Tools—Part 1: Design Methodology for Energy-Efficient Machine Tools*; ISO: Geneva, Switzerland, 2017.
15. VDI—Verein Deutscher Ingenieure e.V. *VDI 5207 Blatt 1—Energieflexible Fabrik: Grundlagen*; VDI: Düsseldorf, Germany, 2020.
16. Box, G.E.P.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. *Time Series Analysis: Forecasting and Control*; John Wiley & Sons: Hoboken, NJ, USA, 2015.
17. VDI—Verein Deutscher Ingenieure e.V. *VDI 4661—Energiekenngrößen: Definitionen-Begriffe-Methodik*; VDI: Düsseldorf, Germany, 2003.
18. Spehr, J. On Hierarchical Models for Visual Recognition and Learning of Objects, Scenes, and Activities. Ph.D. Thesis, Universitätsbibliothek Braunschweig, Braunschweig, Germany, 2013. [CrossRef]
19. Bhinge, R.; Park, J.; Law, K.H.; Dornfeld, D.A.; Helu, M.; Rachuri, S. Towards a generalized energy prediction model for machine tools. *J. Manuf. Sci. Eng.* **2017**, *139*. [CrossRef] [PubMed]
20. Dietmair, A.; Verl, A. Energy consumption forecasting and optimisation for tool machines. *Energy* **2009**, 62–67. [CrossRef]
21. van Luttervelt, C.A.; Childs, T.; Jawahir, I.S.; Klocke, F.; Venuvinod, P.K.; Altintas, Y.; Armarego, E.; Dornfeld, D.; Grabec, I.; Leopold, J.; et al. Present Situation and Future Trends in Modelling of Machining Operations Progress Report of the CIRP Working Group 'Modelling of Machining Operations'. *CIRP Ann.* **1998**, *47*, 587–626. [CrossRef]
22. Hahn, H.; Meyer-Nieberg, S.; Pickl, S. Electric load forecasting methods: Tools for decision making. *Eur. J. Oper. Res.* **2009**, *199*, 902–907. [CrossRef]
23. Walsh, T. Empirical methods in AI. *AI Mag.* **1998**, *19*, 121–121.
24. Hong, T.; Fan, S. Probabilistic electric load forecasting: A tutorial review. *Int. J. Forecast.* **2016**, *32*, 914–938. [CrossRef]
25. He, Y.; Wu, P.; Li, Y.; Wang, Y.; Tao, F.; Wang, Y. A generic energy prediction model of machine tools using deep learning algorithms. *Appl. Energy* **2020**, *275*. [CrossRef]
26. Doreth, K. *Einsatz Maschineller Lernverfahren zur Lebenszyklusbasierten Energieprognose für Werkzeugmaschinen*; TEWISS: Garbsen, Germany, 2019.
27. Kant, G.; Sangwan, K.S. Predictive Modeling for Power Consumption in Machining Using Artificial Intelligence Techniques. *Procedia CIRP* **2015**, *26*, 403–407. [CrossRef]
28. Abele, E.; Eisele, C.; Schrems, S. Simulation of the Energy Consumption of Machine Tools for a Specific Production Task. In *Leveraging Technology for a Sustainable World*; Dornfeld, D.A., Linke, B.S., Eds.; Springer: Berlin/Heidelberg, Germany, 2012; Volume 143, pp. 233–237. [CrossRef]
29. Abeykoon, C.; Kelly, A.L.; Brown, E.C.; Vera-Sorroche, J.; Coates, P.D.; Harkin-Jones, E.; Howell, K.B.; Deng, J.; Li, K.; Price, M. Investigation of the process energy demand in polymer extrusion: A brief review and an experimental study. *Appl. Energy* **2014**, *136*, 726–737. [CrossRef]

30. Aramcharoen, A.; Mativenga, P.T. Critical factors in energy demand modelling for CNC milling and impact of toolpath strategy. *J. Clean. Prod.* **2014**, *78*, 63–74. [CrossRef]
31. Avram, O.I.; Xirouchakis, P. Evaluating the use phase energy requirements of a machine tool system. *J. Clean. Prod.* **2011**, *19*, 699–711. [CrossRef]
32. Balogun, V.A.; Mativenga, P.T. Modelling of direct energy requirements in mechanical machining processes. *J. Clean. Prod.* **2013**, *41*, 179–186. [CrossRef]
33. Bi, Z.M.; Wang, L. Energy Modeling of Machine Tools for Optimization of Machine Setups. *IEEE Trans. Autom. Sci. Eng.* **2012**, *9*, 607–613. [CrossRef]
34. Bi, Z.M.; Wang, L. Optimization of machining processes from the perspective of energy consumption: A case study. *J. Manuf. Syst.* **2012**, *31*, 420–428. [CrossRef]
35. Bornschlegl, M.; Bregulla, M.; Franke, J. Methods-Energy Measurement—An approach for sustainable energy planning of manufacturing technologies. *J. Clean. Prod.* **2016**, *135*, 644–656. [CrossRef]
36. Braun, S.; Heisel, U. Simulation and prediction of process-oriented energy consumption of machine tools. In *Leveraging Technology for a Sustainable World*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 245–250.
37. Budinoff, H.; Bhinge, R.; Dornfeld, D. A material-general energy prediction model for milling machine tools. In Proceedings of the 2016 International Symposium on Flexible Automation (ISFA), Cleveland, OH, USA, 1–3 August 2016; pp. 161–164.
38. Diaz, N.; Choi, S.; Helu, M.; Chen, Y.; Jayanathan, S.; Yasui, Y.; Kong, D.; Pavanaskar, S.; Dornfeld, D. Machine tool design and operation strategies for green manufacturing. In Proceedings of 4th CIRP International Conference on High Performance Cutting, Gifu, Japan, 24–26 October 2010.
39. Diaz, N.; Redelsheimer, E.; Dornfeld, D. Energy Consumption Characterization and Reduction Strategies for Milling Machine Tool Use. In *Glocalized Solutions for Sustainability in Manufacturing*; Hesselbach, J.; Herrmann, C.S., Eds.; Springer: Berlin/Heidelberg, Germany; New York, NY, USA, 2011; Volume 53, pp. 263–267. [CrossRef]
40. Dietmair, A.; Verl, A. A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing. *Int. J. Sustain. Eng.* **2009**, *2*, 123–133. [CrossRef]
41. Dietrich, B.; Walther, J.; Weigold, M.; Abele, E. Machine learning based very short term load forecasting of machine tools. *Appl. Energy* **2020**, *276*, 115440. [CrossRef]
42. Doreth, K.; Henjes, J.; Kroening, S. Approach to Forecast Energy Consumption of Machine Tools within the Design Phase. *Adv. Mater. Res.* **2013**, *769*, 278–284. [CrossRef]
43. Draganescu, F.; Gheorghe, M.; Doicin, C.V. Models of machine tool efficiency and specific consumed energy. *J. Mater. Process. Technol.* **2003**, *141*, 9–15. [CrossRef]
44. Feng, M.; Hua, Z.; Hon, K.K.B. A Qualitative Model for Predicting Energy Consumption of Rapid Prototyping Processes—A Case of Fused Deposition Modeling Processe. *IEEE Access* **2019**, *7*, 184825–184831. [CrossRef]
45. Goldhahn, L.; Pietschmann, C.; Eckardt, R. Process for the machine specific analysis and modeling of the technology based energetical demand forecasts. *Procedia CIRP* **2018**, *77*, 405–408. [CrossRef]
46. Gutowski, T.; Dahmus, J.; Thiriez, A. Electrical energy requirements for manufacturing processes. In Proceedings of the 13th CIRP International Conference on Life Cycle Engineering, Leuven, Belgium, 31 May–2 June 2006; Volume 31, pp. 623–638.
47. Al-Hazza, M.H.F.; Adesta, E.Y.; Ali, A.M.; Agusman, D.; Supr, M.Y. Energy Cost Modeling for High Speed Hard Turning. *J. Appl. Sci.* **2011**, *11*, 2578–2584. [CrossRef]
48. He, Y.; Liu, B.; Zhang, X.; Gao, H.; Liu, X. A modeling method of task-oriented energy consumption for machining manufacturing system. *J. Clean. Prod.* **2012**, *23*, 167–174. [CrossRef]
49. He, Y.; Liu, F.; Wu, T.; Zhong, F.P.; Peng, B. Analysis and estimation of energy consumption for numerical control machining. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2012**, *226*, 255–266. [CrossRef]
50. Herrmann, C.; Thiede, S. Process chain simulation to foster energy efficiency in manufacturing. *CIRP J. Manuf. Sci. Technol.* **2009**, *1*, 221–229. [CrossRef]
51. Huang, J.; Liu, F.; Xie, J. A method for determining the energy consumption of machine tools in the spindle start-up process before machining. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2016**, *230*, 1639–1649. [CrossRef]
52. Imani Asrai, R.; Newman, S.T.; Nassehi, A. A mechanistic model of energy consumption in milling. *Int. J. Prod. Res.* **2018**, *56*, 642–659. [CrossRef]
53. Jia, S.; Tang, R.; Lv, J.; Zhang, Z.; Yuan, Q. Energy modeling for variable material removal rate machining process: An end face turning case. *Int. J. Adv. Manuf. Technol.* **2016**, *85*, 2805–2818. [CrossRef]
54. Kant, G.; Sangwan, K.S. Predictive Modelling for Energy Consumption in Machining Using Artificial Neural Network. *Procedia CIRP* **2015**, *37*, 205–210. [CrossRef]
55. Kara, S.; Li, W. Unit process energy consumption models for material removal processes. *CIRP Ann.* **2011**, *60*, 37–40. [CrossRef]
56. Kong, D.; Choi, S.; Yasui, Y.; Pavanaskar, S.; Dornfeld, D.; Wright, P. Software-based tool path evaluation for environmental sustainability. *J. Manuf. Syst.* **2011**, *30*, 241–247. [CrossRef]
57. Larek, R.; Brinksmeier, E.; Meyer, D.; Pawletta, T.; Hagendorf, O. A discrete-event simulation approach to predict power consumption in machining processes. *Prod. Eng.* **2011**, *5*, 575. [CrossRef]
58. Li, L.; Yan, J.; Xing, Z. Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modelling. *J. Clean. Prod.* **2013**, *52*, 113–121. [CrossRef]

59. Li, W.; Kara, S. An empirical model for predicting energy consumption of manufacturing processes: A case of turning process. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2011**, *225*, 1636–1646. [CrossRef]
60. Li, Y.; He, Y.; Wang, Y.; Wang, Y.; Yan, P.; Lin, S. A modeling method for hybrid energy behaviors in flexible machining systems. *Energy* **2015**, *86*, 164–174. [CrossRef]
61. Li, Y.; He, Y.; Wang, Y.; Yan, P.; Liu, X. A framework for characterising energy consumption of machining manufacturing systems. *Int. J. Prod. Res.* **2014**, *52*, 314–325. [CrossRef]
62. Liu, Z.Y.; Guo, Y.B.; Sealy, M.P.; Liu, Z.Q. Energy consumption and process sustainability of hard milling with tool wear progression. *J. Mater. Process. Technol.* **2016**, *229*, 305–312. [CrossRef]
63. Lv, J.; Tang, R.; Jia, S. Therblig-based energy supply modeling of computer numerical control machine tools. *J. Clean. Prod.* **2014**, *65*, 168–177. [CrossRef]
64. Lv, J.; Tang, R.; Tang, W.; Liu, Y.; Zhang, Y.; Jia, S. An investigation into reducing the spindle acceleration energy consumption of machine tools. *J. Clean. Prod.* **2017**, *143*, 794–803. [CrossRef]
65. Mori, M.; Fujishima, M.; Inamasu, Y.; Oda, Y. A study on energy efficiency improvement for machine tools. *CIRP Ann.* **2011**, *60*, 145–148. [CrossRef]
66. Mose, C.; Weinert, N. Evaluation of Process Chains for an Overall Optimization of Manufacturing Energy Efficiency. In *Advances in Sustainable and Competitive Manufacturing Systems*; Azevedo, A., Ed.; Lecture Notes in Mechanical Engineering; Springer: Cham, Switzerland, 2013; pp. 1639–1651.
67. Munoz, A.A.; Sheng, P. An analytical approach for determining the environmental impact of machining processes. *J. Mater. Process. Technol.* **1995**, *53*, 736–758. [CrossRef]
68. Peng, T.; Xu, X. An interoperable energy consumption analysis system for CNC machining. *J. Clean. Prod.* **2017**, *140*, 1828–1841. [CrossRef]
69. Quintana, G.; Ciurana, J.; Ribatallada, J. Modelling Power Consumption in Ball-End Milling Operations. *Mater. Manuf. Process.* **2011**, *26*, 746–756. [CrossRef]
70. Rahimifard, S.; Seow, Y.; Childs, T. Minimising Embodied Product Energy to support energy efficient manufacturing. *CIRP Ann.* **2010**, *59*, 25–28. [CrossRef]
71. Rajemi, M.F.; Mativenga, P.T.; Aramcharoen, A. Sustainable machining: Selection of optimum turning conditions based on minimum energy considerations. *J. Clean. Prod.* **2010**, *18*, 1059–1065. [CrossRef]
72. Rief, M. *Vorhersagemodell für den Energiebedarf bei der Spanenden Bearbeitung für eine Energieeffiziente Prozessgestaltung*; Shaker: Magdeburg, Germany, 2012.
73. Sato, R.; Shirase, K.; Hayashi, A. Energy Consumption of Feed Drive Systems Based on Workpiece Setting Position in Five-Axis Machining Center. *J. Manuf. Sci. Eng.* **2018**, *140*, 25. [CrossRef]
74. Sealy, M.P.; Liu, Z.Y.; Zhang, D.; Guo, Y.B.; Liu, Z.Q. Energy consumption and modeling in precision hard milling. *J. Clean. Prod.* **2016**, *135*, 1591–1601. [CrossRef]
75. Seow, Y.; Rahimifard, S. A framework for modelling energy consumption within manufacturing systems. *CIRP J. Manuf. Sci. Technol.* **2011**, *4*, 258–264. [CrossRef]
76. Seow, Y.; Rahimifard, S.; Woolley, E. Simulation of energy consumption in the manufacture of a product. *Int. J. Comput. Integr. Manuf.* **2013**, *26*, 663–680. [CrossRef]
77. Shang, Z.; Gao, D.; Jiang, Z.; Lu, Y. Towards less energy intensive heavy-duty machine tools: Power consumption characteristics and energy-saving strategies. *Energy* **2019**, *178*, 263–276. [CrossRef]
78. Shao, H.; Wang, H.L.; Zhao, X.M. A cutting power model for tool wear monitoring in milling. *Int. J. Mach. Tools Manuf.* **2004**, *44*, 1503–1509. [CrossRef]
79. Shin, S.J.; Kim, Y.M.; Meilanitasari, P. A Holonic-Based Self-Learning Mechanism for Energy-Predictive Planning in Machining Processes. *Processes* **2019**, *7*, 739–766. [CrossRef]
80. Sossenheimer, J.; Walther, J.; Fleddermann, J.; Abele, E. A Sensor Reduced Machine Learning Approach for Condition-based Energy Monitoring for Machine Tools. *Procedia CIRP* **2019**, *81*, 570–575. [CrossRef]
81. Sossenheimer, J.; Vetter, O.; Abele, E.; Weigold, M. Hybrid virtual energy metering points—A low-cost energy monitoring approach for production systems based on offline trained prediction models. *Procedia CIRP* **2020**, *93*, 1269–1274. [CrossRef]
82. Su, C.L. Load Estimation in Industrial Power Systems for Expansion Planning. *IEEE Trans. Ind. Appl.* **2011**, *47*, 2311–2323. [CrossRef]
83. Teiwes, H.; Blume, S.; Herrmann, C.; Rössinger, M.; Thiede, S. Energy load profile analysis on machine level. *Procedia CIRP* **2018**, *69*, 271–276. [CrossRef]
84. Verl, A.; Abele, E.; Heisel, U.; Dietmair, A.; Eberspächer, P.; Rahäuser, R.; Schrems, S.; Braun, S. Modular Modeling of Energy Consumption for Monitoring and Control. In *Glocalized Solutions for Sustainability in Manufacturing*; Hesselbach, J., Herrmann, C.S., Eds.; Springer: Berlin/Heidelberg, Germany; New York, NY, USA, 2011; Volume 28, pp. 341–346. [CrossRef]
85. Walther, J.; Spanier, D.; Panten, N.; Abele, E. Very short-term load forecasting on factory level—A machine learning approach. *Procedia CIRP* **2019**, *80*, 705–710. [CrossRef]
86. Walther, J.; Dietrich, B.; Abele, E. Generic Machine Learning Approach for very short term load forecasting of production machines. In Proceedings of the International Conference on Applied Energy 2019, Västerås, Sweden, 12–15 August 2019.

87. Wang, L.; He, Y.; Li, Y.; Wang, Y.; Liu, C.; Liu, X.; Wang, Y. Modeling and analysis of specific cutting energy of whirling milling process based on cutting parameters. *Procedia CIRP* **2019**, *80*, 56–61. [CrossRef]
88. Weinert, N.; Chiotellis, S.; Seliger, G. Methodology for planning and operating energy-efficient production systems. *CIRP Ann.* **2011**, *60*, 41–44. [CrossRef]
89. Wu, Z.; Hobgood, M.; Wolf, M. Energy Mapping and Optimization in Rough Machining of Impellers. In *International Manufacturing Science and Engineering Conference*; The American Society of Mechanical Engineers: New York, NY, USA, 2016. [CrossRef]
90. Yi, L.; Krenkel, N.; Aurich, J.C. An energy model of machine tools for selective laser melting. *Procedia CIRP* **2018**, *78*, 67–72. [CrossRef]
91. Yi, L.; Gläßner, C.; Krenkel, N.; Aurich, J.C. Energy simulation of the fused deposition modeling process using machine learning approach. *Procedia CIRP* **2019**, *86*, 216–221. [CrossRef]
92. Yoon, H.S.; Lee, J.Y.; Kim, M.S.; Ahn, S.H. Empirical power-consumption model for material removal in three-axis milling. *J. Clean. Prod.* **2014**, *78*, 54–62. [CrossRef]
93. Yoon, H.S.; Moon, J.S.; Pham, M.Q.; Lee, G.B.; Ahn, S.H. Control of machining parameters for energy and cost savings in micro-scale drilling of PCBs. *J. Clean. Prod.* **2013**, *54*, 41–48. [CrossRef]
94. Zhou, X.; Liu, F.; Cai, W. An energy-consumption model for establishing energy-consumption allowance of a workpiece in a machining system. *J. Clean. Prod.* **2016**, *135*, 1580–1590. [CrossRef]
95. Wang, H.; Lei, Z.; Zhang, X.; Zhou, B.; Peng, J. A review of deep learning for renewable energy forecasting. *Energy Convers. Manag.* **2019**, *198*, 111799. [CrossRef]
96. Chen, C.; Liu, Y.; Kumar, M.; Qin, J. Energy Consumption Modelling Using Deep Learning Technique—A Case Study of EAF. *Procedia CIRP* **2018**, *72*, 1063–1068. [CrossRef]
97. Bianchi, F.M.; Maiorino, E.; Kampffmeyer, M.C.; Rizzi, A.; Jenssen, R. *Recurrent Neural Networks for Short-Term Load Forecasting: An Overview and Comparative Analysis*; Springer: Cham, Switzerland, 2017.
98. Cheng Fan.; Fu Xiao.; Yang Zhao. A short-term building cooling load prediction method using deep learning algorithms. *Appl. Energy* **2017**, *195*, 222–233. [CrossRef]