SURVEY AND STATE OF THE ART

A review of energy-efficient scheduling in intelligent production systems

Kaizhou Gao[1,2] · Yun Huang[1] · Ali Sadollah[3] · Ling Wang[4]

Abstract

Recently, many manufacturing enterprises pay closer attention to energy efficiency due to increasing energy cost and environmental awareness. Energy-efficient scheduling of production systems is an effective way to improve energy efficiency and to reduce energy cost. During the past 10 years, a large amount of literature has been published about energy-efficient scheduling, in which more than 50% employed swarm intelligence and evolutionary algorithms to solve the complex scheduling problems. This paper aims to provide a comprehensive literature review of production scheduling for intelligent manufacturing systems with the energy-related constraints and objectives. The main goals are to summarize, analyze, discuss, and synthesize the existing achievements, current research status, and ongoing studies, and to give useful insight into future research, especially intelligent strategies for solving the energy-efficient scheduling problems. The scope of this review is focused on the journal publications of the Web of Science database. The energy efficiency-related publications are classified and analyzed according to five criteria. Then, the research trends of energy efficiency are discussed. Finally, some directions are pointed out for future studies.

Keywords Production scheduling · Energy efficiency · Swarm intelligence · Evolutionary algorithm

Introduction

Energy consumption is an important issue in current society. In last 40 years, the energy demand of the world has doubled and will double again in next 10 years [1]. In general, the industry is one of the primary consumers of energy. In 2018, industry accounted for approximately 25% of energy consumption by end use in the European Union [2]. The energy consumption of industrial fields is about 26.3% of estimated U.S. energy consumption of 2018 [3]. As energy-intensive fields, manufacturing industries consumed nearly a third of the global energy consumption of the world [4, 5]. In China, more than 56% of the total energy consumption is occupied in manufacturing sector attributed [6].

It is essential to reduce the manufacturing industry's energy consumption and demand. The manufacturing industries play a key role to satisfy continuously growing of various goods as living standards increasing. It is unrealistic to reduce the energy supply for manufacturing industries directly, since energy is a non-substitutable production factor. In other words, it is limited to a certain extent to reduce energy consumption and to subject to the desired output simultaneously. Hence, how to improve energy efficiency or to reduce energy demands for the same output becomes a critical approach to achieve the purpose of reducing energy consumption and developing sustainably. It is a consensus in academic and business that "energy-efficiency gap" is a strong barrier which hinders energy-efficient manufacturing.

✉ Ling Wang
wangling@tsinghua.edu.cn

Kaizhou Gao
kzgao@must.edu.mo

Yun Huang
yuhuang@must.edu.mo

Ali Sadollah
ali_sadollah@yahoo.com

[1] Macau Institute of Systems Engineering, School of Business, Macau University of Science and Technology, Macau, China

[2] School of Computer, Liaocheng University, Liaocheng, China

[3] Department of Mechanical Engineering, University of Science and Culture, Tehran, Iran

[4] Department of Automation, Tsinghua University, Beijing, China

In manufacturing shops, the energy consumption is noticeable. In actual machining processes, machine tools stay in an idle state for the most of the time and consume about 80% energy with the idle state [7]. Machine tools have huge potential space for energy saving [8]. In general, scheduling is an effective approach to solve the issues about machine status and is an important decision-making process to decide which tasks to execute, when to execute them, and where to process them in which sequence. It is rarely considered as a suitable instrument to improve energy efficiency. In recent years, many researchers use scheduling approaches to improve energy efficiency in manufacturing industries and energy-efficient scheduling has been proved to be an effective way of reducing the energy consumption with none or little capital investment [9, 10]. Energy efficiency or energy consumption is considered as constraints or scheduling objectives, like makespan, machine workload, and due-date objectives.

Production scheduling has been proven as an NP-hard problem; hence, energy-efficiency scheduling is no exception. Traditional optimization approaches cannot solve large-scale scheduling problems with high efficiency, especially for some large-scale instances with real-time constraints. Therefore, swarm intelligence and evolutionary algorithms are employed for solving such problems as reported in many publications, since low computational time and high efficiency are the most important criteria [4, 5]. For large-scale cases with real-time constraints, swarm intelligence and evolutionary algorithms can obtain high-quality feasible solutions in very short computational time. Swarm intelligence and evolutionary algorithms are becoming more and more popular for solving large-scale scheduling and optimization problems with time constraints, including energy-efficiency scheduling in complex production.

The motivation of this review work is the green manufacturing and energy-saving awareness in production scheduling area. The design of intelligent scheduling strategies should consider energy efficiency and reducing energy consumption which is an important scheduling objective in current production scheduling area. The purpose of this study is to perform a literature review about production/shop scheduling with considering energy-efficiency objectives. It can be considered as a comprehensive reference for readers from both academia and industry. We will summarize existing achievements, analyze and discuss the current and ongoing research, and indicate some future directions, especially the

swarm intelligence and evolutionary algorithms for tackling such NP-hard problems. The remainder of this paper is organized as follows. "Scope" section describes the scope of this review work. Afterwards, existing achievement is summarized and analyzed in "Classification" section. Next, detail discussion and analyzing up to date and ongoing research in the field of production/shop scheduling with energy efficiency/consumption and constraints/objectives are given in "Research trends" section. Furthermore, some future research directions are also indicated in this section. Finally, this review paper is concluded in the last section.

Scope

An indispensable part of a literature review work is the review scope and purpose. The topic of this review is production/shop scheduling with energy efficiency, consumption, or cost as constraints or objectives, given in the following: (1) the category of the shop floor, (2) model of the scheduling problems, (3) objectives (e.g., energy, completion time, machine workload, due date, and so forth), (4) research approaches (strategies) or algorithms, especially swarm intelligence and evolutionary algorithms, and (5) the aspects of energy consumption.
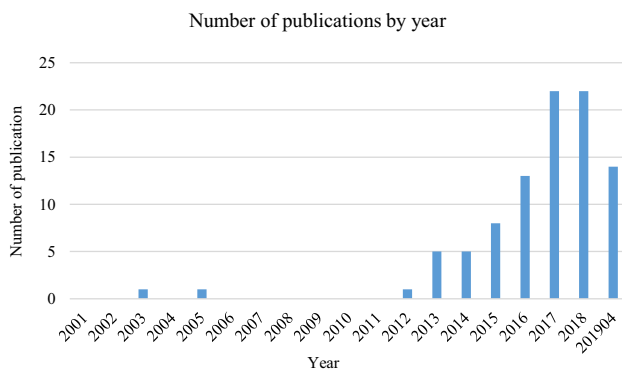
In some publications, energy efficiency or consumption is considered as constraints. Based on the topic and special review contents, we define the words "energy efficiency", "energy consumption", "energy cost", "production scheduling", "shop scheduling", "energy scheduling", "swarm intelligence", "evolutionary algorithm", and "meta-heuristics" as index keywords in the Web of Science database. As shown in Table 1, the energy keywords and the scheduling keywords work together to delimit the index results. In this section, we only indexed the journal articles and excluded books, theses, reports, and conference papers. The index results are shown in Table 2, including the names of journals and the number of relevant published papers in each journal is not less than 2. Hence, we only focus to analyze, discuss, and synthesize the academic journal publications, and do not consider publications with other publishing forms, since the most high-quality studies are published in the form of academic journals. In addition, we include some newest publications about the reviewed topic, which are not yet included in the Web of Science database at this moment. In total, to review the literature related to the "production/shop scheduling with energy

Table 1 Keywords for database index	Energy-related keywords	Scheduling-related keywords	Intelligent strategies
	Energy efficiency	Production scheduling	Swarm intelligence
	Energy consumption	Shop scheduling	Evolutionary algorithm
	Energy cost	Energy scheduling	Meta-heuristics

Table 2 Reviewed journals and number of relevant papers	Journals' names	Number of publications
	Journal of Cleaner Production	16
	International Journal of Production Research	8
	CIRP Annals-Manufacturing Technology	5
	IEEE Access	4
	Sustainability	4
	Computers & Chemical Engineering	3
	International Journal of Advanced Manufacturing Technology	3
	Journal of Engineering Manufacture	3
	Computers in Industry	2
	IEEE Transactions on Automation Science and Engineering	2
	IEEE Transactions on Industrial Informatics	2
	Mathematical Problems in Engineering	2
	Sensors	2

Fig. 1 Year-wise publication number addressing production scheduling with energy efficiency

efficiency or consumption as constraints or objectives" topic, 90 publications are analyzed, discussed, and synthesized till present. About 58% of articles are published in 13 journals (i.e., one journal published at least two papers). Among these journals, the Journal of Cleaner Production published the largest number of articles (13 papers), while the International Journal of Production Research journal is placed in the second rank having 8 articles.

Classification, analysis, and synthesis of existing achievements

As shown in Fig. 1, the number of publications addressing production scheduling with energy-efficiency constraints or objectives increases rapidly since 2013. Especially, in the first 4 months of 2019, the number of published articles is larger than half of 2018 throughout the year. These publications are classified by five criteria: shop floor category,

problem model, scheduling objectives, solving approach (algorithms), and aspects of energy consumption (see Table 3).

Shop floor category

For production scheduling, shop floor category is an important issue to distinguish problem model and solving strategies. Among the articles in Table 3, job shop (including flexible job shop)-related publication accounts 41% (see Fig. 2), the ratio of flow shop related articles is about 23%, and 4% publications are for single machine scheduling. Some publications do not illustrate the special shop floor category clearly and about 6% of articles addressed on a special product. Job shop scheduling and flow shop scheduling are considered as the most studied subjects, while the scheduling for a special product is rarely investigated. In fact, the energy-efficiency scheduling for a special product has more contributions and effects to the practice of scheduling theory and approaches.

Problem models

With respect to the problem model, 34% of publications developed standard mathematical program model, including integer programming (IP), integer linear programming (ILP), mixed integer linear programming (MILP), mixed integer non-linear programming (MINLP), mixed integer programming (MIP), and non-linear programming (see Fig. 3). Except standard mathematical models, some different models are used to describe energy-efficiency scheduling problems, including feedback control, neural network, decision support system, monitoring system, and time-series model. There are quite a number of articles (53%) developed mathematical models; however, these models are not

**Table 3** Literature classification [4–6, 8–94]

| Articles	Shop floor category	Model	Objectives	Approach (algorithm)	Energy consumption aspect
Lora et al., 2003	Unknown	NLMIP	Energy	GA	Start-up and shut-down
He et al., 2005	Job shop	Others	Energy and makespan,	TS	Unknown
Bruzzone et al., 2012	Flexible flow shop	MIP	Energy	Heuristics	Unknown
Cao et al., 2013	Unknown	Neural network model	Energy	FSM	On/off, warm up, idle, and processing
Chen et al., 2013	Unknown	Others	Energy	Greedy algorithm	Machine start-up/shut-down
Dai et al., 2013	Flexible flow shop	Others	Energy and makespan	Genetic SA	Setup and idle
Moon et al., 2013	Unknown	MILP	Energy and makespan	Improved GA	Unknown
Jiang et al., 2014	Flexible job shop	Others	Energy and others	NSGAII	Processing
Moon and Park, 2014	Flexible job shop	MIP	Energy and others	CPLEX	Peak load, mid-load and off-peak load
Pach et al., 2014	FMS	Unknown	Energy and others	Unknown	Unknown
Shrouf et al., 2014	Single machine	Others	Energy	GA and analytical solution	Processing and Idle
Zhang et al., 2014	Flow shop	IP	Energy	Unknown	peak hour, mid-peak, and off peak
Dai et al., 2015	Job shop	MIP	Energy and makespan	Modified GA	Loading/unloading, processing
Duerden et al., 2015	Unknown	Others	Energy	Modified GA	Unknown
Garcia-Santiago et al., 2015	Job shop	Unknown	Energy	HS	Unknown
Lee and Prabhu, 2015	Unknown	Feedback control	Energy and others	Integral controller approach	Processing
May et al., 2015	Job shop	Others	Energy and makespan	Green GA	Processing, idle, setup, standby, and ramp
Tang and Dai, 2015	Job shop	MIP	Energy and makespan	Genetic SA	Setup, processing and idle
Tong et al., 2015	Unknown	MINLP	Energy	DICOPT	Unknown
Zhang et al., 2015	Multi-factories	Others	Energy	Distributed optimization	Unknown
Escamilla et al., 2016	Job shop	Others	Energy and makespan	GA and CPLEX	Unknown
Li et al., 2016	Specific product	MIP	Energy	CPLEX	Unknown
Oddi and Rasconi, 2016	Flexible job shop	Others	Energy and makespan	NLS	Unknown
Salido et al., 2016a	Job shop	Others	Energy and others	CPLEX	Unknown
Salido et al., 2016b	Job shop	Others	Energy and makespan	GA and CPLEX	Unknown
Su et al., 2016	Cracking production	MINLP	Energy and others	DICOPT	Unknown
Tang et al., 2016	Flexible flow shop	Others	Energy and makespan	Improved PSO	Setup, idle and operation
Tonelli et al., 2016	Unknown	MIP	Energy and tardiness	Multi-agent	Unknown
Tong et al., 2016	Unknown	Others	Energy	Improved GA	Unknown
Yan et al., 2016	Flexible flow shop	Others	Energy and makespan	GA	Unknown
Yang et al., 2016	Flexible job shop	Others	Energy and makespan	NSGA-II	Start-up, shut-down, idle and processing
Zhang and Chiong, 2016	Job shop	MILP	Energy and tardiness	MOGA	Processing and Idle energy
Giglio et al., 2017	Job shop scheduling	MIP	Energy	Relax-and-fix heuristic	Setup and processing
Gong et al., 2017	Specific product	Others	Energy and labor-aware	GA with heuristic	Unknown

Table 3 (continued)

Articles	Shop floor category	Model	Objectives	Approach (algorithm)	Energy consumption aspect
Kim et al., 2017	Unknown	Unknown	Energy	Additive regression algorithm	Unknown
Lee et al., 2017	Single machine	MINLP	Energy and E/T	DIATC Heuristic	Unknown
Lei et al., 2017	Flexible job shop	Others	Energy and workload balance	SFLA	Unknown
Liu et al., 2017	Fuzzy flow shop	Others	Energy and tardiness	IGA with heuristics	Idle, setup and processing
Lu et al., 2017	Permutation flow shop	Others	Energy and makespan	HBSA	Setup, transportation, and idle
Misra et al., 2017	Specific product	MILP	Energy	FXOS	Unknown
Modos et al., 2017	Single machine	Others	Energy constraint	Branch-and-Bound and TS	Unknown
Mokhtari and Hasani, 2017	Flexible job shop	Unknown	Energy and makespan	Enhanced GA	Unknown
Otis and Hampson, 2017	Unknown	Unknown	Energy	Advanced scheduling and ERP	Changeover and start-up
Plitsos et al., 2017	Flexible job shop	DSS	Energy constraint	ILS	Processing, idle, subsidiary equipment
Rahimi and Ziaee, 2017	Permutation flow shop	Others	Energy and makespan	GA and SA	Setup and processing
Raileanu et al., 2017	Job shop	Others	Energy and makespan	CPLEX	Unknown
Ramos and Leal, 2017	Unknown	ILP	Energy	CPLEX	Unknown
Sundstrom et al., 2017	Unknown	MINLP	Energy and others	Systematic method	Unknown
Wang et al., 2017	Unknown	MINLP	Energy	DICOPT	Production
Xu and Wang, 2017	Job shop	Others	Energy and makespan	feedback control method	Unknown
Yin et al., 2017	Job shop	MIP	Energy and others	GA with simplex lattice design	Loading, idle, and processing
Zhai et al., 2017	Unknown	Time-series model	Energy	Dynamic scheduling	Unknown
Zhang et al., 2017a	Flow shop	IP	Energy	Unknown	Unknown
Zhang et al., 2017b	Flexible job shop	Others	Energy and makespan	BBO + VNS	Unknown
Aghelinejad et al., 2018	Single machine	Others	Energy	GA and CPLEX	Processing and idle energy
Escamilla and Salido, 2018	Job shop	Unknown	Energy and makespan	GA + LS	Unknown
Feng et al., 2018	Job shop	Monitoring system	Energy	Modified GA	Processing and idle
Jiang and Deng 2018	Flexible job shop	Others	Energy and E/T	DCSO	Processing and idle
Jiang et al., 2018a	Job shop	Others	Energy and tardiness	GWO	Idle cost and tardiness
Jiang et al., 2018b	Job Shop	Others	Energy and completion time	Improved WOA	Machine speed, processing, and idle
Khalaf and Wang, 2018	Flow shop	MILP	Energy	General Algebraic Modeling System	Unknown
Lei et al., 2018	Hybrid flow shop	Others	Energy and tardiness	TLBO	Unknown
Leo and Engell, 2018	Unknown	MILP	Energy	CPLEX	Unknown
Li et al., 2018a	Hybrid flow shop	Others	Energy and makespan	MOA	Processing, standby, and setup
Li et al., 2018b	Flow shop	Others	Energy and makespan	ABC	Unknown
Liu et al., 2018a	Permutation flow shop	Others	Energy	NEH heuristic	Idle
Liu et al., 2018b	Flexible flow shop	Others	Energy and makespan	Improved NSGAII	Unknown
Lu et al., 2018	Flow shop	Others	Energy and others	GWA + LS Grey wolf + LS	Unknown
Meziane et al., 2018	Flexible job shop	Others	Energy	NSGAII	Unknown

Table 3 (continued)

Articles	Shop floor category	Model	Objectives	Approach (algorithm)	Energy consumption aspect
Wang et al., 2018a	Blocking flow shop	Others	Energy and makespan	PVNS + LS + NEH	Blocking and idle energy
Wang et al., 2018b	Flexible job shop	NLP	Energy and cost	GA + PSO	Unknown
Wu et al., 2018	Flexible flow shop	Others	Energy and makespan	Hybrid NSGA-II with local search	Processing and Idle
Wu and Sun, 2018	Flexible job shop	Others	Energy and others	NGSA_II with heuristics	Unknown
Zhang et al., 2018a	Flexible job shop	Others	Energy and others	IMHGA	Processing, idle and transportation
Zhang et al., 2018b	Flexible job shop	Unknown	Energy and makespan	Modified SFLP	Unknown
Zhao et al., 2018	Unknown	MILP	Energy	CPLEX.	Unknown
Cui et al., 2019	Unknown	NLMP	Energy	Sub-gradient descent	On-peak and off-peak
Faria et al., 2019	Unknown	Others	Energy	GA	Unknown
Gong et al., 2019	Flexible job shop	Others	Energy and others	NSGA-III	Processing, setup, idling
Gong et al., 2019	Specific product	Others	Energy and labor	MA and NSGA-II	Processing, setup, idling
Hassani et al., 2019	Job shop	MILP	Energy	CPLEX	Setup, processing, and inventory
Jiang and Wang 2019	permutation flow shop	Others	Energy and makespan	MOEA	Setup, processing, and transportation
Jiang and Zhang, 2019	Hybrid flow shop	MILP	Energy and tardiness	EOMO algorithm	Non-processing
Lei et al., 2019	Flexible job shop	Others	Energy constraint	ICA	Unknown
Liu et al., 2019	Flexible job shop	MIP	Energy and makespan	GA + GSO	Processing and transportation
Meng et al., 2019a	Flexible job shop	MILP	Energy	CPLEX	Idle and common consumption
Meng et al., 2019b	Hybrid flow shop	MILP	Energy	IGA	Processing, idle, and common
Shen et al., 2019	Unknown	Others	Energy	Improved GA	Processing and failure
Wu et al., 2019	Unknown	MILP	Energy	Score ranking algorithm	Unknown
Zhang et al., 2019	Flexible job shop	Others	Energy and makespan	NSGA-II	Processing, idle, and setup
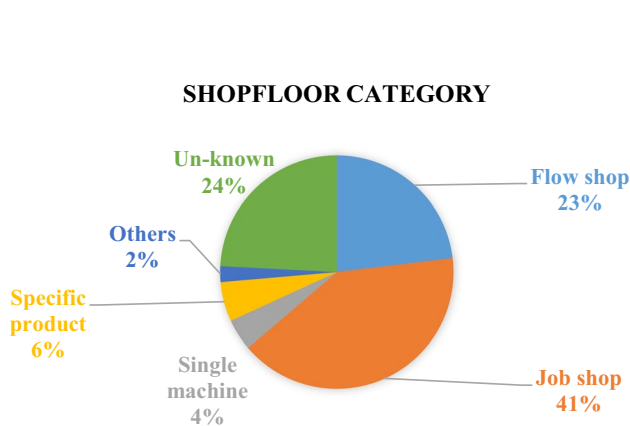
Fig. 2 Distribution of shop floor category
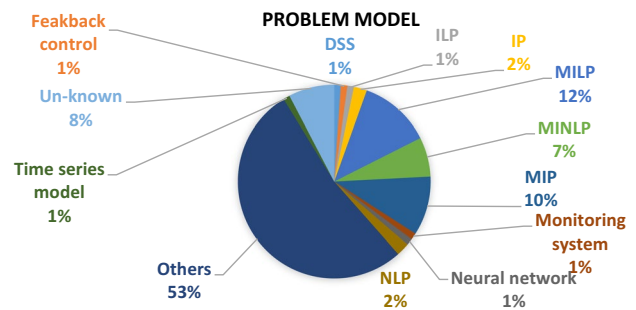
Fig. 3 Model systems

converted to standard mathematical program models or the authors did not state the model type clearly, it is categorized

as "Others" class. We will discuss this situation in detail in the first part of next section.

Swarm intelligence and evolutionary algorithms

To solve energy-efficiency scheduling problems, many articles employed or improved swarm intelligence and evolutionary algorithms, e.g., genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), shuffled frog-leaping algorithm (SFLA), grey wolf optimizer (GWO), and so forth. The detail analysis of these algorithms for energy-efficiency scheduling will be shown in part one of "Research Trend" Section. To solve energy-efficiency scheduling problem, swarm intelligence and evolutionary algorithms do not need standard mathematical models; indeed, they need mathematical formulations to compute objective functions. Among all approaches, the ratio of swarm intelligence and evolutionary algorithms is 59%, which almost matches to the ratio of unstandard models (i.e., "Others" class), as shown in Fig. 3. It means that swarm intelligence and evolutionary algorithms are mainstream approaches for energy-efficiency scheduling, which has affected the problem modeling. The main procedures of swarm intelligence and evolutionary algorithms are shown as follows:

1. Initializing algorithm's parameters and the population.
2. Evaluate initializing solutions in population and objectives values.
3. Generating new solutions based on the current solutions in population.
4. Evaluate new solutions and replace the current ones.
5. If the stop criterion is not satisfied, go to Step (3); else, go to Step (6).
6. Stop and report the best solution and corresponding objective values.

For different algorithms, the strategies to generate new solutions are different, and the stop criterion is different. For different scheduling problems in intelligent production systems, there are different initializing rules and different local search operators.

To improve the convergence performance of swarm intelligence and evolutionary algorithms, some intelligent strategies are proposed in some reviewed articles. Here, we introduce several representative ones. Wu et al. [79] proposed idle time and machine turn on/off strategies for operation assignment and energy-saving purposes. Elapsed time for time turning off the idle machines is dependent on the length of idle time slots. May et al. [25] proposed an intelligent strategy to remove the overlapping solutions in the population initialization and new solutions generating phases. It can improve the diversity of population and avoid repeat solutions with the same function values. Zhang et al.

[6] developed an intelligent strategy to reduce energy consumption and improved energy efficiency in a production sequence fixed solution, by controlling the additional tardiness allowed for each job in the solution. These intelligent strategies improve the convergence performance of swarm intelligence and evolutionary algorithms, and their details can be found in the corresponding articles.

Other approaches

By observing Fig. 4, the ratio of mathematical optimization and control approach is 13%, and the ratio of software solvers, e.g., CPLEX, DICOPT, is also 13%. These two approaches need standardized mathematical models. The total ratio of these approaches (26%) is near to the ratio of standard mathematical programming models (34%) given in Fig. 3. In addition, 7% of articles employed heuristics to solve scheduling problems, which are also not strongly dependent on standard mathematical models of the scheduling problems. Furthermore, there are 4% articles use other approaches for solving energy-related scheduling and 4% articles do not state the applied approaches clearly.

Objectives or constraints

The objectives of energy-efficiency scheduling are distinguished as single objective and multi-objective strategies. Single objective represents only energy-related objective, including energy efficiency, energy consumption, energy cost, and so forth. Multi-objective approaches means that energy objective and traditional scheduling objectives, e.g., completion time-related objectives, machine workload-related objectives, due-date-related objectives and other objectives, are considered simultaneously. Based on the relationship among different objectives, multiple objectives are solved in three forms, weighted summation, non-domination, and others (normalization or as constraints). It can be seen from Fig. 5 that the total ratio of multi-objective is about 61%, which is much larger than that of a single objective (36%). It is mainstream to consider energy-related
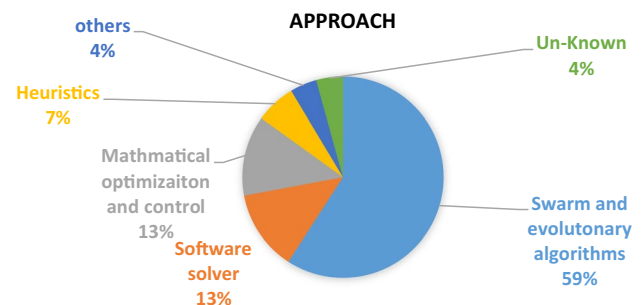

Fig. 4 Approaches and algorithms attempted
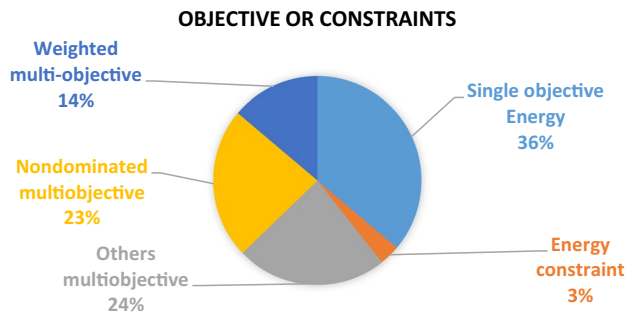
OBJECTIVE OR CONSTRAINTS

Fig. 5 Objectives systems

criteria as a single objective or one of the multiple objectives even reporting by a few articles (3%) assuming them as scheduling constraints. To improve energy efficiency and input–output ratio, the relationship among energy-related objectives and traditional objectives must be more investigated and analyzed.

Aspects of energy consumption

To reduce energy consumption or increase energy efficiency, it is a key issue to clear the aspects of energy consumption or energy demand. Processing product, machine idle, machine setup and on/off, and product or components transportation are the aspects of energy consumption considered the most. The energy consumption in processing and machine idle is considered in more than 30% reviewed articles, and the ratio of machine setup and on/off is larger than 20% (see Fig. 6). These three aspects of energy consumption are the mainstream of energy-efficiency scheduling. More than 50% of publications have assumed energy efficiency as scheduling objective; however, the aspects of energy consumption or energy demand are not described clearly in these articles. Since one article may consider more than one aspects of energy consumption, the total ratio of all aspects in Fig. 6 is much larger than one.
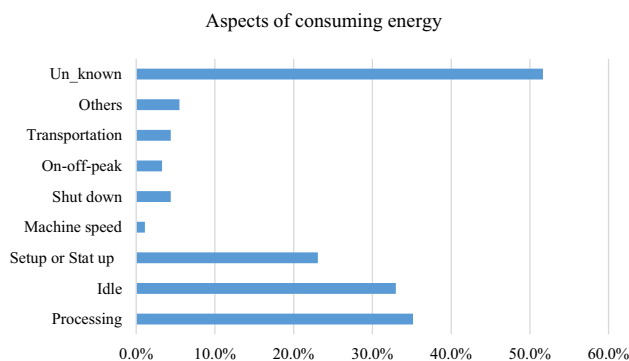
Research trends

The awareness of energy efficiency, sustainability, and green manufacturing, and production scheduling with energy objectives has becomes a hot topic in the past 5 years (see Fig. 1). From 2013, the number of published articles increases year by year. The number of published articles in 2017 and 2018 is more than 20. Till April 2019, more than ten production scheduling articles for energy-related objectives are published. Energy-related objectives become a new trend of production scheduling and will play vital and important role in production scheduling.

From single objective to multi-objective

Compared to traditional scheduling objectives, energy-related objectives are novel, however, important to economic indicators. The relationship between energy-related objectives and traditional objectives are analyzed and discussed in many publications. Many publications have considered energy-related objectives with traditional objectives simultaneously. From 2013 to April 2019, the number of articles for energy-related multi-objective scheduling is much larger than those for single energy-related objectives (see Fig. 7). It means that energy-related scheduling objectives should be considered together with traditional objectives for obtaining better decision-making by different performance indicators.

Swarm intelligence and evolutionary algorithms

With respect to approaches for solving energy-related scheduling objectives, swarm intelligence and evolutionary algorithms account 59% among various different approaches (see Fig. 4), and all these articles are published after 2013. The GA as one of classical evolutionary algorithm and a multi-objective GA (NSGA-II) are the most employed optimizer for solving the production scheduling problems (see Fig. 8).
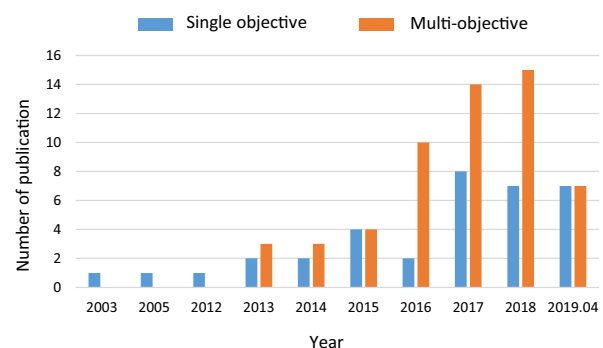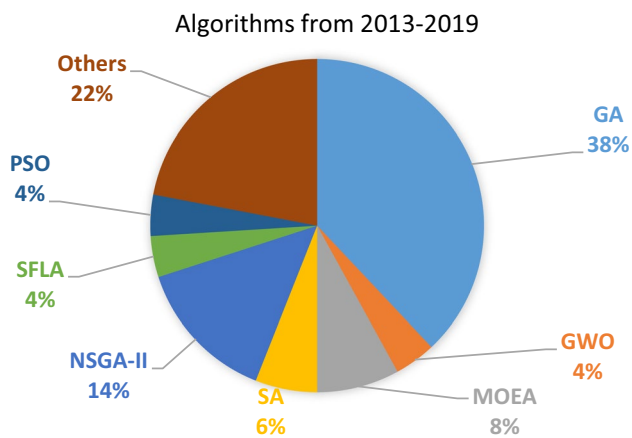

Fig. 6 Aspects of energy consumption

Fig. 7 Year-wise comparisons of single objective and multi-objective publications

Fig. 8 Swarm and evolutionary algorithms for solving energy-related scheduling

Fig. 9 Year-wise aspects of energy consumption

The total ratio of GA and NSGA-II is about 52% among all swarm intelligence and evolutionary algorithms. Beside the NSGA-II, multi-objective evolutionary algorithm (MOEA) is also used in about 8% articles. The ratios of SA, PSO, shuffled frog-leaping algorithm (SFLA), and Grey wolf optimizer (GWO) are equal to or larger than 4%. The algorithms with ratios less than 4% are recorded as "Others" class and the total ratio of them is 22%, which means that at least six swarm intelligence and evolutionary algorithms are included in the "Others" class. Totally, more than 13 algorithms are employed or improved for solving production scheduling problems with energy-related objectives in the past 5 years. In fact, swarm intelligence and evolutionary algorithms are effective and widely used for solving energy-efficiency scheduling problem.

Extending of energy consumption aspects

In the reviewed literature, the energy consumption in a production process mainly includes two parts, processing energy and non-processing energy. The non-processing energy mainly includes idle energy and setup time. From 2015, more publications focus on these three energy consumption aspects (i.e., processing energy, idle energy, and setup energy) and the total number of articles for processing energy (i.e., 25 articles) and idle energy (i.e., 25 articles) are larger than that for setup energy (i.e., 15 articles) (seen in Fig. 9). Since energy is a non-substitutable production factor, setup energy is a necessary step for manufacturing. It is a realistic way to improve machines' efficiency, reduce processing time, and reduce the machine idle time. In addition, the transportation energy among production is considered in some publications, it is also a potential way to reduce energy consumption (see Fig. 6).
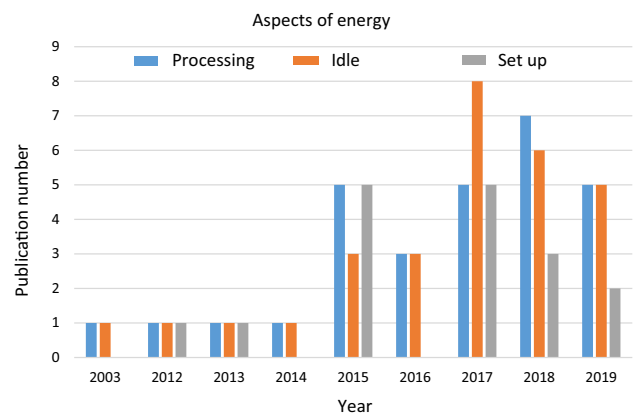
In summary, energy-related objectives are aware of production scheduling from 2012, especially in the past 5 years. In view of the high complexity of production scheduling, many swarm intelligence and evolutionary algorithms are employed and improved to solve this problem. Energy-related objectives are optimized with traditional scheduling objectives, simultaneously. The main aspects of energy consumption, e.g., processing energy, idle, and setup energy, in a production process are modeled and evaluated. Some researchers have started to consider other energy consumption in a production process, for instance, energy for component transportation [80, 88].

Future directions

Based on the previous analysis of research trends of production scheduling with energy-related objectives, we consider and indicate some future research directions for this topic.

Modeling of energy efficiency-related constraints and objectives

All aspects of energy consumption in production should be classified based on necessity and possibility of reducing the cost. The aspects of energy consumption with reduction possibility should be considered and modeled as scheduling constraints or objectives in production scheduling. The more aspects of energy consumption with reduction possibility are modeled, the higher possibility to reduce energy consumption and to improve energy efficiency.

Analysis of the relationship between energy-related objectives and the traditional objectives

Production scheduling is a multi-objective problem. Energy-related objectives are emerging targets compared

to traditional objectives, e.g., completion time, machine workload, due date, and so on, The relationship between energy-related objectives and the traditional objectives must be researched and analyzed. Does energy-related objective conflict to a certain extent with traditional objectives? It is a precondition to solve energy-efficiency scheduling and does not affect the optimization of other goals.

Developing swarm intelligence and evolutionary algorithms

Based on the synthesis and analysis in above two sections, swarm intelligence and evolutionary algorithms are efficient and effective to solve energy-efficiency scheduling problems, especially for the large-scale problems. How to design and develop more high-quality algorithms, especially non-dominated multi-objective algorithms, for solving energy-efficiency scheduling problem which is an important direction. Some local search operators based on the feature of energy-efficiency scheduling can conduce to improve the convergence speed of swarm intelligence and evolutionary algorithms. Algorithmic accuracy and time efficiency are the key performance indicators.

Energy efficiency-based multi-objective scheduling strategy

Energy-efficiency scheduling is an important objective in intelligent production system. There are some other objectives, e.g., completion time-related objectives, machine workload-related objectives, and the due date-related objectives and so forth. How to design energy efficiency-based multi-objective scheduling strategy is a novel and interesting direction. Especially, the non-dominate strategy for multi-objective scheduling is the key issue to improve algorithms' performance.

Develop energy-efficiency intelligent scheduling framework

Energy-efficiency scheduling is a novel topic in production scheduling. It would be a great contribution to this topic if a general framework, especially an intelligent scheduling framework, can be established, which can guide the research and development of this topic. For energy-efficiency scheduling, it would be a good way to be integrated into the overall framework of production scheduling and to be embedded into an intelligent scheduling framework with intelligent scheduling strategizes. Furthermore, the existing modeling strategies, solving approaches and algorithms (including swarm intelligence and evolutionary algorithms), and benchmark instances for general production scheduling can be directly applied to energy-efficiency scheduling or be used after appropriate adjustments.

Practice in some special fields and even special products

For production scheduling, manufacturing enterprises are more focused on the practicality of models and algorithms, especially for a special product. Till now, few published articles addressed on this matter because of since the complexity and multi-constraints in real-life situations. It is an important and practical work to model energy-efficiency scheduling for a special product and develop a high-quality meta-heuristic to solve it. This research direction can effectively promote Industry-University-Research Collaborations.

Conclusions

The growing awareness of energy efficiency and sustainable development has led to persistent attention to energy efficiency in production scheduling. The growing number of published articles, especially in the past 5 years, makes energy-efficiency scheduling a hot research topic. In the review process of this review work, there are several newest publications related to the scope of this review paper [95–99] which shows the importance and high relevancy of the studied subject. Intelligent strategies are used by many researchers in scientific community. This study presented the review of five indicators, including shop floor, models, approaches and algorithms, objectives, and aspects of energy consumption in the literature for solving energy-efficiency scheduling problems. Intelligent strategies, including swarm intelligence, evolutionary algorithms, and improvement strategies, are synthesized, discussed, and analyzed in detail. Furthermore, the current research trends, especially the intelligent strategies, are analyzed and summarized. For the continued study of this topic, five instructive directions, including modeling, objectives, intelligent strategies, intelligent scheduling framework, and practice, are given which provide an insight for future studies.

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