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Scheduling Optimization For Energy-Efficient Flexible Flow Shops With Due Date Constraints

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ABSTRACT
Energy efficiency has become an essential component of manufacturing systems in light of the escalating costs of energy and the growing environmental concerns. This problem of scheduling optimization in flexible flow factories is addressed with a focus on minimizing energy consumption while adhering to due date constraints. Various processing routes are possible in a flexible flow shop, which is composed of multiple production phases, each with parallel machines. In addition to conventional scheduling objectives, such as tardiness and makespan, the proposed model includes energy consumption as a critical performance indicator. The traditional production scheduling problem takes cost, quality, and processing time into account to maximize manufacturing systems. However, it ignores the effects on the environment and energy usage. Consequently, this study presents an energy-efficient approach for the flexible flow-shop scheduling problem (FFSP). To manage multi-objective optimization, an FFSP model is presented. The basis of this model is a process that consumes less energy. An enhanced genetic-simulated annealing method is utilized to accomplish a feasible schedule because FFS is recognized as an NP-hard task. This approach implements a major trade-off between the total energy usage and the makespan. The results of the experiment indicate that there seems to be an inconsistency in the relationship between the makespan and energy consumption. Furthermore, a reasonable schedule is used to implement an energy-saving decision. The decision-making approach may be able to maintain the contradictory connection and drastically cut energy use at the same time.
Keywords: flexible flow shop (FFS), energy consumption, makespan

1. INTRODUCTION

Energy-efficient manufacturing has garnered increasing attention from manufacturers worldwide in recent years, as a result of the scarcity of energy resources and the severe effects of global warming [1]–[4]. It is a simple method to create energy-efficient apparatus in order to decrease energy consumption. Nevertheless, it necessitates substantial capital investment and has a lengthy life cycle. According to statistics, the idle condition of a machine tool in real production consumes 80% of the energy. Consequently, scheduling is an effective method for minimizing inactive time. Additionally, energy-efficient scheduling does not necessitate any additional investment or study cycle. Until now, energy-efficient scheduling has been a successful method for reducing energy consumption, and it is garnering increasing attention from studies[5]–[8].
One scheduling issue with broad applicability is the Flexible Job Shop Scheduling Problem. In addition, the problem has been shown to be NP-hard. The evolving nature of cooperative manufacturing has led to a rising interest in distributed scheduling from manufacturers and academic studies. Decreased manufacturing costs and increased production efficiency are two further benefits of dispersed scheduling [9,10]. A manufacturing system made up of several factories, each of which is a FJSP environment, is the subject of the distributed flexible job

shop scheduling issue. Due to its emphasis on industrial flexibility, DFJSP is consequently more difficult to resolve than FJSP. For the DFJSP, it is necessary to identify three sub-problems: factory selection, machine selection, and functions sequencing.

Until now, most DFJSP investigations have focused on makespan minimization, despite the many challenges it has raised [11]. Thus, no published research on FJSP that considers energy use in the setting of many factories exists. Closing this gap is the goal of this studies, which lowers overall energy usage by solving the energy-efficient DFJSP. In order to solve small-scale case optimalities, they first introduce a novel mixed integer linear programming paradigm [12–16]. Our approach, a hybrid shuffled frog-leaping method, is deemed beneficial for locating near optimal solutions for EE-DFJSP due to the NP issues that are inherent in the problem. This method is particularly useful in large-scale applications. In comparison to earlier studies, the contributions of this study can be summed up as follows:

- In terms of lowering energy usage in a multi-factory production system, this study is the first to take DFJSP into account.
- To tackle small-scale situations and arrive at optimal solutions, a novel MILP model is devised. It is recognized as the benchmark for comparison when assessing meta-heuristic algorithms.
- A highly effective hybrid randomized frog-leaping algorithm is developed to produce almost perfect answers for complex issues. Specifically, VNS and SFLA are integrated to form HSFLA. It is crucial to remember that the DFJSP has never been solved using the SFLA.
- An energy-efficient active decoding system has been specifically designed for the EE-DFJSP. Strategies for turning on and off as well as delaying are specifically made to lower the amount of energy used inactively during the decoding process.

2. LITERATURE REVIEW

Zhao et. al. (2022) [17] conducted those two significant national measures for sustainable development, carbon peaking and carbon neutrality, have been the subject of meticulous attention by production firms. The distributed obstructed flow shop scheduling problem in this study encompasses energy consumption. A hyperheuristic that is based on Q-learning is recommended for the energy-efficient DBFSP.The low-level heuristic provides historical data among a preset collection of LLHs, which is used in conjunction with Q-learning to determine the ideal LLH.The first population must be created using an initialization approach that takes into account the entire amount of energy utilized as well as the total amount of tardiness. Utilizing the acquired knowledge, the ε-greedy strategy is presented to maintain a certain level of exploration in the LLH selection process. The key route acceleration strategy for this investigation aims to maximize TTD. Raising TEC is the aim of the task's noncritical path delay operation. An extended benchmark study's statistical and computational analyses reveal that the HHQL solves EEDBFSP more effectively and considerably than the other equivalent technique.

Ding et. al. (2021) [18] examined that the study integrates energy consciousness with the flexible flow shop scheduling system, which concurrently minimizes two goals: total lateness and electricity expenses. Practical considerations include time-of-use electricity cost and processing speed fluctuations. They create a brand-new hybrid particle swarm optimization method with a number of unique characteristics. The discrete domain rapidly modifies the particle representation according to work activity and machine assignment. More importantly, they introduce a position-based crossover operator and a multi-objective tabu search technique that reconciles global exploration with local exploitation. To compare the effectiveness of the proposed HPSO algorithm with the widely used techniques in the literature, experiments are carried out. The results show how important HPSO is for computing efficiency as well as the quantity and caliber of non-dominated solutions.

Zanjani et. al. (2021) [19] analyzed that the goal of scheduling, a crucial decision-making process, is to distribute scarce resources across the tasks in a manufacturing process. Hybrid Flow Shop (HFS) scheduling, when it comes to scheduling problems, is quite flexible and can be applied to most real-world scenarios, including many situations where there are uncertainties about parameters that could affect how tasks are processed while the schedule is being executed. Consequently, it is imperative to consider the uncertainty of the parameters in a scheduling model that is appropriate for the situation. A multi-objective resilient mixed-integer linear programming model is proposed in the study to address the issue of unknown processing deadlines and durations in real-world scenarios. The current model may be compelled to distribute a batch of work among the available computers in an effort to optimize the trade-off between total tardiness and makespan due to unforeseen circumstances. In order to resolve this multiobjective issue, fuzzy goal programming (FGP) is implemented. In order to evaluate and verify the efficacy of the proposed RMILP model, a diverse array of scenarios with varying degrees of uncertainty are generated and resolved using the CPLEX solver in the GAMS program. The results of the experiment show that the created model can offer a solution that minimizes the amount of change needed in an HFS situation to account for deadline and processing time uncertainty.

Gong et. al. (2020) [20] investigated that only machine flexibility is taken into account in the traditional flexible flow shop scheduling problem. The relevant literature has not examined worker flexibility in FFSPs, a trait common to real-world industrial systems. Employee flexibility has the potential to have a big impact on productivity and production efficiency. In addition, with energy consumption on the rise and environmental damage increasing, manufacturers must find new ways to increase energy efficiency. Based on processing time, energy consumption, worker flexibility, and worker cost-related characteristics, the study recommends an energy-efficient FFSP with worker flexibility. The subsequent step involves the implementation of a hybrid evolutionary approach to resolve the proposed EFFSPW. This approach integrates a novel variable neighborhood search methodology with a number of efficient operators. According to the experimental results, the proposed HEA outperforms two other well-known methods in terms of computing efficiency and solution quality, and it can produce superior solutions for the majority of these benchmark scenarios.

Gao et. al. (2020) [21] analyzed that these days, a lot of manufacturing companies focus more on energy efficiency because of rising energy costs and environmental consciousness. Energy-efficient scheduling can be implemented in production systems to increase energy efficiency and save energy expenditures. A significant amount of study on energy-efficient scheduling has been published in the last ten years. In almost half of this study, the difficult scheduling problems have been resolved using swarm intelligence and evolutionary algorithms. The goal of this study is to conduct a thorough literature analysis on production scheduling for intelligent manufacturing systems that considers the limits and goals linked to energy. The primary goals are to give relevant insights into future studies, particularly creative solutions to energy-efficient scheduling issues, and to summarize, assess, discuss, and incorporate the most recent, cutting-edge findings from ongoing investigations. Five criteria are used to categorize and analyze the study pertaining to energy efficiency. Next, trends in energy efficiency are discussed.

Jiang et. al. (2019) [22] conducted that Effective scheduling boosts customer satisfaction, cost savings, and productivity. Energy-oriented scheduling will be a critical concern for sustainable manufacturing in the coming years, as there is an increasing concern regarding the environmental impact and energy prices. An analysis is conducted on an energy-focused scheduling issue with restricted buffers that originates from the hybrid flow shop. The scheduling problem is initially formulated using a mixed integer linear programming model. It includes the weighted total delay and the elimination of non-processing energy. In order to address the NP-hard problem in the literal sense within the framework of the multi-objective objective evolutionary algorithm based on decomposition, they develop a successful multi-objective optimization techniques. In order to incorporate the search space of the scheduling solution, they generate a job-permutation vector. They offer a two-pass decoding technique that integrates a greedy post-shift operation with a discrete-event system simulation approach, as NPE is a non-regular function. In addition, they establish a local search mechanism and an external archive population to enhance the diversity of the population and direct the algorithm toward convergence on a Pareto frontier. Ultimately, they conduct extensive computer simulations to verify the effectiveness of the proposed energy-oriented multi-objective optimization approach. The study's findings may be advantageous for future studies on scheduling issues associated with energy in actual production systems.

Lei et. al. (2017) [23] analyzed that the primary goals of the hybrid flow shop scheduling problem, which has received a lot of attention, are completion time. In the era of green production, HFSP should give careful consideration to reducing energy use. The study focuses on energy-efficient biobjective HFSP. Three subproblems make up this problem: speed selection, machine assignment, and scheduling. Three subproblem answers are indicated by three-string coding. Modern teaching-learning-based optimization techniques should be used by educators to reduce tardiness and overall energy consumption. The primary goal is to decrease total tardiness, and lexicographical analysis is employed to assess possible remedies.TTLBO combines interactive learning, self-study, and instructor-led education into a single optimization process that generates new solutions. The algorithm removes the learning process of the students. A global search that is based on crossover is chosen to replicate the behaviors of other educators, while a number of local searches are implemented to assist instructors in their individual learning. In order to evaluate the efficacy of TTLBO in comparison to other algorithms from the literature and assess the impact of the novel optimization method, numerous experiments are conducted. The computational results indicate that TTLBO is a competitive approach for the HFSP under consideration.

Yan et. al. (2016) [24] investigated that the environment could benefit from the combination of energy savings at the shop floor and machine tool levels. A novel energy-efficient multi-level optimization strategy for flexible flow shop scheduling is focused on the reduction of energy consumption in shop floor operations. This technique combines the optimization of a single machine's cutting parameters and power models with energy-efficient scheduling challenges.Multi-level optimization is used to achieve the operation scheme; in particular, machine tool cutting parameter optimization and shop floor schedule optimization are accomplished at the same level. Grey relational analysis is implemented at the machine tool level to optimize the cutting parameters of each machine, thereby reducing cutting energy and cutting time. The current flexible flow shop energy consumption model employs a genetic algorithm to optimize the overall energy consumption and the makespan at the shop floor level. To illustrate the application of the multi-level optimization method, a case study of a flexible flow shop is presented. The multi-level optimization approach is a helpful tool for assisting in the selection of methods that reduce the manufacturing process's makespan and overall energy consumption, as indicated by the scheduling results. Moreover, the utilization of multi-level optimization may result in synergistic energy savings.

Table 1.1: Comparison of reviews

Study	**Focus**	**Findings**
Zhao et al. (2022)	Distributed Blocking Flow Shop Scheduling (DBFSP)	HHQL outperforms other algorithms in efficiency and significance for solving EEDBFSP.
Ding et al. (2021)	Flexible Flow Shop Scheduling System	HPSO shows high quality and quantity of non-dominated solutions and computational efficiency.
Zanjani et al. (2021)	Hybrid Flow Shop (HFS) Scheduling	RMILP model effectively handles uncertain parameters in due dates and processing times
Gong et al. (2020)	Flexible Flow Shop Scheduling with Worker Flexibility (FFSP)	HEA provides superior solutions in terms of solution quality and computational efficiency.
Gao et al. (2020)	Energy-Efficient Scheduling in Manufacturing Systems	Summarizes insights and trends in energy-efficient scheduling study.
Jiang et al. (2019)	Hybrid Flow Shop with Restricted Buffers	EOMO algorithm efficiently solves energy-oriented scheduling problems.
Lei et al. (2017)	Hybrid Flow Shop Scheduling (HFSP)	TTLBO shows competitive performance for HFSP considering energy efficiency.
Yan et al. (2016)	Flexible Flow Shop Scheduling	Multi-level optimization effectively reduces energy consumption and makespan, demonstrating synergistic energy savings.

3. RESEARCH METHODOLOGY

Optimizing scheduling in flexible flow shops to enhance energy efficiency while adhering to due date constraints involves a multi-faceted approach:

Define the problem formally, identifying key elements:

- **Jobs**: A set of jobs $J=\{J_1, J_2, \ldots, Jn\}$
- **Machines**: A set of machines $M=\{M_1, M_2, \ldots, M_m\}$
- **Stages**: Each job passes through several stages, with each stage having one or more machines.
- **Due Dates**: Each job J_i has a due date D_i
- **Processing Times**: Processing time P_{ij} for job Ji on machine M_j
- **Energy Consumption**: Energy consumption E_{ij} for job J_i on machine M_j

3.1 Objective Functions

- **Minimize Total Energy Consumption**: $E_{total} = \sum^{n}_{i=1} \sum^{m}_{j=1} E_{ij} \times T_{ij}$ where Tij is the processing time of job Ji on machine Mj

- **Minimize Total Tardiness**: $T_{total} = \sum^{n}_{i=1} \max(0, C_i - D_i)$ where C_i is the completion time of job J_i.

3.2 Constraints

- **Job Precedence**: Each job must follow the prescribed order of stages.
- **Machine Availability**: Each machine can process only one job at a time.
- **Due Dates**: Ensure jobs are completed by their due dates, if possible.

a. Scheduling Algorithm

Develop an algorithm that balances energy efficiency and due date constraints. Common approaches include:

- **Mixed-Integer Linear Programming (MILP)**

Formulate the problem as a MILP, incorporating both energy and due date constraints. Use solvers like CPLEX or Gurobi.

- **Heuristic Methods**

Develop heuristic methods such as Genetic Algorithms (GA), Simulated Annealing (SA), or Particle Swarm Optimization (PSO).

- **Hybrid Approaches**

Combine MILP with heuristic methods to improve solution quality and computational efficiency.

3.4 Energy-Aware Scheduling Policies

Integrate energy-saving policies such as:

- **Idle Time Reduction**: Minimize machine idle times to reduce energy consumption.
- **Energy-Efficient Sequencing**: Sequence jobs in a way that machines operate in their most energy-efficient states.
- **Batch Processing**: Group jobs with similar processing requirements to reduce machine start-up/shutdown energy.

4. RESULT AND DISCUSSION

The efficacy of proposed algorithms is frequently compared to that of existing methods using benchmark datasets such as FFSP and Carlier, Taillard, and Reeves. This investigation was designed to assess the efficacy of the JAYA in addressing these issues. An investigation is conducted using a bus system that includes forty-one transmission lines, six generators, four tap-changing transformers, and two shunt compensators. This is done to demonstrate the efficacy of the approach that was previously presented.

4.1 Voltage with bus number

Through adjustments to the devices' control parameters, the bus voltage, line power flows, and system losses can all be measured. Figure 4.1 shows the maximum values of the bus voltage as they change over time visually. Bus-2 experiences a significant voltage shift because it is attached to the receiving end. The link between the receiving end and bus-2 is the cause of this.

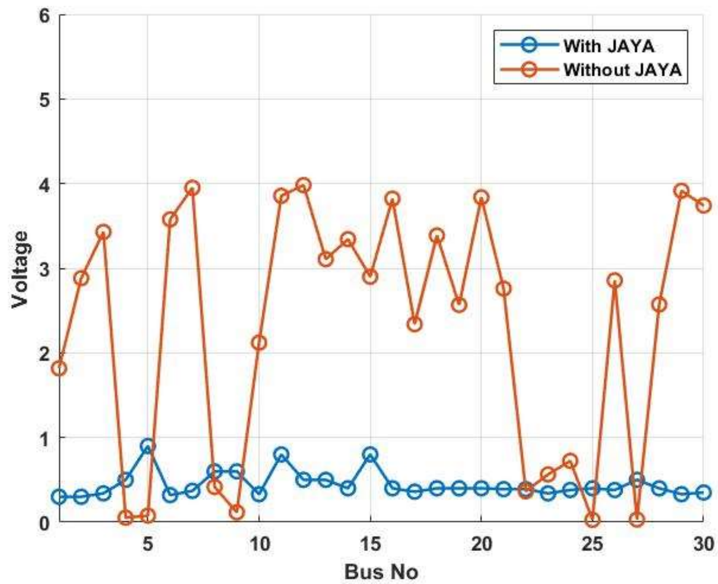

Figure 4.1: Voltage with bus number during Jaya

4.2 Power Loss with Line number

Figure 4.2 illustrates the potential variation in transmission line power loss that may be observed both within and outside of Jaya. This figure demonstrates that the simultaneous failure of both the lines and the generator has a greater impact on the quantity of power lost than any other potential scenario. When there is a line outage, the majority of transmission lines operate at or near their maximum rated voltage and amperage (MVA).

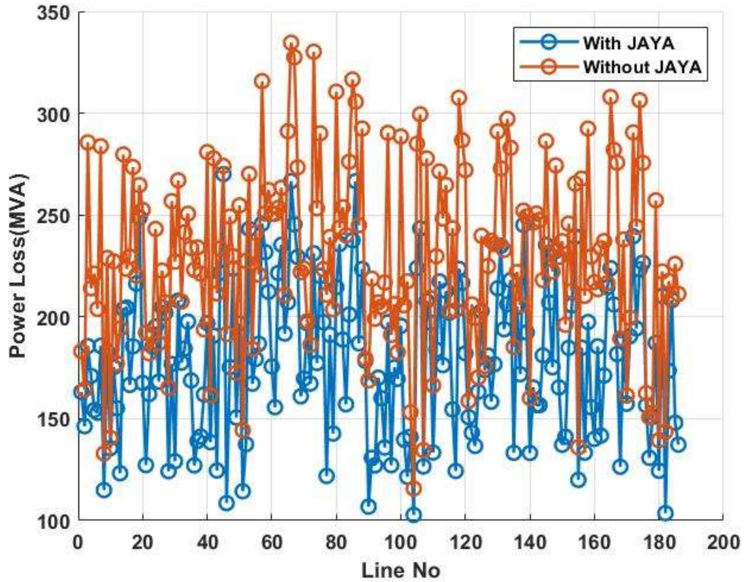

Figure 4.2: Power Loss with Line number during Jaya

Table 4.1: Results of flexible flow shop scheduling under normal and contingency conditions

Control parameters		**Normal condition**	**Outage condition**		
			Lines	**Generator**	**Both lines & generator**
Real power generation (MW)	P_{G1}	74.8460	72.7799	163.5706	128.8717
	P_{G2}	75	49.9491	77.5815	-
	P_{G5}	52	52	0	0
	P_{G8}	37	37	31.7327	37
	P_{G11}	23.8406	32	18.7654	31
	P_{G13}	23.8407	21.3817	29.8113	29.2725
Generator voltages	v_{G1}	1.0369	1.08	1.0515	1.0337
	v_{G2}	1.0275	1.0601	1.0284	1.0425
	v_{G5}	1.0140	1.0287	1.0462	0.9869
	v_{G8}	1.0110	1.0318	0.9803	0.9520
	v_{G11}	1.012	1.0353	1.0138	0.9890
	v_{G13}	1.0180	1.0586	1.0280	1.0454
Generation fuel cost		924.4158	935.7120	846.8251	906.8277
Severity function value		0.3398	1.2227	1.1179	3.1236
Total power losses (MW)		4.1367	5.7611	10.4289	17.3259

Time (s)	14.5766	31.2839	23.7264	39.9485

Table 4.1 presents the system severity function results obtained using the suggested Jaya approach. The study's findings take into consideration both typical and unforeseen circumstances, such as situations in which generators or transmission lines encounter one or more disturbances. When the transmission line is interrupted compared to the typical situation, both the total generation and the total transmission power losses rise. Furthermore, there is an increase of 0.8829 and 11.298 $/h in the severity function value and the overall generation fuel cost, respectively. Not to mention, because of the increased active power generation during a generator outage, the total transmission power losses are larger than they would be under normal circumstances.

DISCUSSION

Flexible flow shops, a prevalent manufacturing environment, involve multiple stages with each stage having one or more parallel machines. Optimizing scheduling in these settings is critical for improving operational efficiency and reducing energy consumption. The challenge becomes more complex when due date constraints are imposed, necessitating a delicate balance between meeting production deadlines and minimizing energy usage. In this context, energy-efficient scheduling aims to reduce power consumption without compromising the completion times of jobs. One effective approach involves the integration of energy-aware algorithms that consider machine idle times, power states, and job sequencing to minimize energy usage. These algorithms often leverage techniques such as machine on/off switching and speed scaling, aligning operational periods with actual production needs to reduce unnecessary energy expenditure. Due date constraints add another layer of complexity, as jobs must be completed within specified time frames. This requirement can conflict with energy-saving strategies, necessitating sophisticated optimization methods to find a feasible solution that meets both objectives. Approaches such as mixed-integer linear programming (MILP), genetic algorithms, and dynamic programming have been employed to navigate these challenges. These methods strive to identify optimal or near-optimal schedules that align with due dates while minimizing total energy consumption.

CONCLUSION

In order to decrease the overall energy consumption and the required production time in a flexible flow shop, this study introduces a multi-level optimization technique. Through the application of this multi-level optimization technique, the cutting parameters of individual machines impact both the total processing time and the energy usage. The scheduling results demonstrate how the multilayer optimization technique can reduce production costs and save businesses both time and energy. Reduced energy consumption is one potential synergistic advantage of applying optimization at the machine tool and shop floor levels. The sequential approach used in multi-level optimization can yield a local optimal solution, it must be stressed. The multi-level optimization technique's results, however, unequivocally demonstrate that there is still room to improve energy efficiency. Integrating energy-related concerns on numerous fronts begins with the approach that was outlined. A multi-level optimization approach for flexible flow shop scheduling is proposed to investigate potential energy savings in shop floor activities. This method combines scheduling issues that are energy-efficient with machine-specific power models that optimize cutting parameters. However, optimizing parameters particular to an algorithm may be challenging and time-consuming when attempting to solve the flexible flow shop scheduling problem. In the study, a unique severity function that accounts for variations in the amount of transmission line loadings and bus voltage is presented. It simultaneously optimizes the total energy consumption, the makespan, and the overall agreement index. Throughout history, a plethora of meta-heuristics have been developed to obtain approximately optimal solutions in a reasonable computational time. They also look into the viability of flexible flow shop scheduling with shared deadlines in an effort to reduce overall wait times as well as tardiness/earliness issues. However, there haven't been many studies on FFSP with uncertainty and energy-related components.

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