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MIXED ENERGY AND PRODUCTION SCHEDULING IN AN ECO-INDUSTRIAL PARK

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ABSTRACT

In recent times, eco-industrial parks (EIP) have taken on a significant role in addressing environmental challenges and supporting sustainable practices. To enhance the efficient utilization of energy within the park and ensure the achievement of production targets among its members, the implementation of energy and production scheduling is imperative. This paper addresses this optimization challenge by formulating it into a constraint programming (CP) model. The optimized scheduling solutions generated by the CP model will be directly used to guide the operations within the simulation environment of the EIP. The paper compares the CP results with the results of another method which we developed in our previous research stage. The outcomes of CP solver demonstrate its effectiveness in optimizing energy utilization and meeting production targets. This research contributes to developing a practical decision support system for resolving real-life scheduling problems in industry parks.

1 INTRODUCTION

With the growing environmental concern, in recent years, the reduction of energy consumption has become a global necessity. Industrial symbiosis (IS) has emerged as one of the mechanisms to achieve sustainable industrial ecology. IS is a collaborative approach where different industries and businesses work together to optimize resource utilization, reduce waste generation, and create mutual economic and environmental benefits (Chertow 2000). Eco-industrial Parks (EIP) are concrete realizations of the IS concept. Plenty of EIPs are designed and developed to facilitate the implementation of IS. They provide a physical space where companies from diverse sectors can locate their operations near one another and foster resource sharing, waste exchanges, and collaborative initiatives (Chertow and Ehrenfeld 2012).

The concept of EIPs has recently captured significant interest from both industry and academic research communities. Various aspects of EIPs have been widely studied over the past several decades. The majority of efforts are focused on the early planning and design phases of an EIP, which are often in the conceptual stage and not yet operational. For example, Afshari et al. (2017) introduced a framework to investigate uncertainties in EIP design, proposing a multi-objective model to decide the optimal network of symbiotic exchanges among firms while minimizing costs of multiple product exchanges and environmental impacts of flow exchanges. Similarly, Al-Quradaghi et al. (2020) proposed a generalized framework for designing EIPs, using the end-of-life vehicle (ELV) problem as an illustration to guide decision-makers during the initial stages of EIP development. Kuznetsova et al. (2016), Leong et al. (2017), and Nuhu et al. (2022) have all contributed to understanding the planning and design stages of EIPs. Boix et al. (2015) provided a comprehensive literature review on optimization methods applied to EIP design, consolidating various approaches to improving the planning process.

Research on operational parks, however, has been limited, often targeting specific environmental issues rather than providing comprehensive analyses for the whole industrial park for optimization opportunities. For instance, Long et al. (2019) utilized a Monte Carlo model to simulate wastewater treatment at various stages, aiming to reduce wastewater pollution. Their model was verified and applied to an industrial park in the Tianjin Economic-Technological Development Area in China. In 2011, Sakr et al. (2011) reported that there were over 20,000 operational industrial parks globally. Studying the operations of these industrial parks and identifying opportunities to optimize resource and energy utilization is crucial for sustainable and efficient industrial development. To address this gap, our previous work developed a simulation model using AnyLogic software to comprehensively analyze an operational industrial park. Each factory was modeled as a reusable modular component, capturing material and energy flows within and between factories.

Operational research has demonstrated success in various applications within the field of energy and the environment. Bloemhof-Ruwaard et al. (1995) aimed to inform operational researchers about the possibilities of incorporating environmental issues when analyzing industrial supply chains. Saharidis (2017) highlighted the effectiveness of OR in energy and environmental applications. Masmoudi et al. (2019) addressed job-shop scheduling problems with energy aspects, aiming to minimize production costs while adhering to power peak limitations and traditional production constraints. Salido et al. (2016) utilized a genetic algorithm to solve an extended version of the job-shop scheduling problem, considering machines with varying energy consumption rates (speed scaling). Yazıcı et al. (2022) explored studies using OR techniques in the context of industrial symbiosis, further demonstrating the value of these methods in environmental and industrial applications.

In this paper, our objective is to comprehensively explore the operational dynamics of industrial parks and devise strategies to enhance their efficiency and environmental sustainability through the lens of operation research. Specifically, we aim to integrate energy scheduling and production scheduling to meet production requirements while optimizing energy utilization. To achieve this, we have developed a constraint programming (CP) model tailored for optimizing energy utilization and job scheduling within an EIP. Central to our approach is the integration of this CP model into the simulation framework of the EIP, which we previously constructed in our research using AnyLogic software. The simulation model serves as a dynamic environment where CP-generated schedules are executed. The process unfolds as follows: The CP model generates optimized schedules for energy utilization and job assignments based on predefined objectives and constraints. These schedules are then input into the simulation model, which simulates real-world operations of the EIP, executing tasks as per the schedules provided. The simulation model provides critical feedback on schedule performance.

The structure of the paper is organized as follows: The second section provides an overview of EIP and details the specific research problem, laying the foundation for our study on mixed energy and production scheduling. The third section outlines the formulation of our research problem into a mathematical model. In the fourth section, we delve into the solution approach for our mathematical model. Finally, the last two sections cover the experiment conducted and the conclusions drawn from our study.

2 PROBLEM STATEMENT

In this study, our primary focus is on optimizing energy consumption and production scheduling within an industrial park. Illustrated in Figure 1, an industrial park serves as a complex ecosystem where multiple factories coexist, engaging in diverse goods production. Each factory, a pivotal element within the park, has been modeled as a modular component within an input-output framework in our prior research. This model intricately captures production processes, including specific input ratios defining raw material requirements per unit of primary product, and mathematically represents outputs, including by-products and waste streams. Beyond conventional models, this industrial park integrates sustainable practices, particularly in resource utilization and waste management. Diverging from traditional practices, the park not only relies on external suppliers for raw materials but also fosters resource synergy among its internal factories. This includes the exchange of by-products among factories, promoting a circular economy and reducing external dependencies. Moreover, the park adopts Waste-to-Energy (WTE) technology (Cucchiella et al. 2017), converting waste into valuable forms of energy such as heat, electricity, or transport fuels. A dedicated power plant within the park efficiently converts waste produced by members into energy, minimizing environmental impact and establishing the park as a self-sufficient energy entity. WTE plants in many cases serve as combined heat and power (CHP) producers (Touš et al. 2015), further enhancing energy efficiency. CHP plants simultaneously generate electricity and useful heat from a single fuel source, utilizing waste heat for heating and cooling applications. This holistic approach optimizes energy utilization, aligning with the industrial park's sustainability goals.

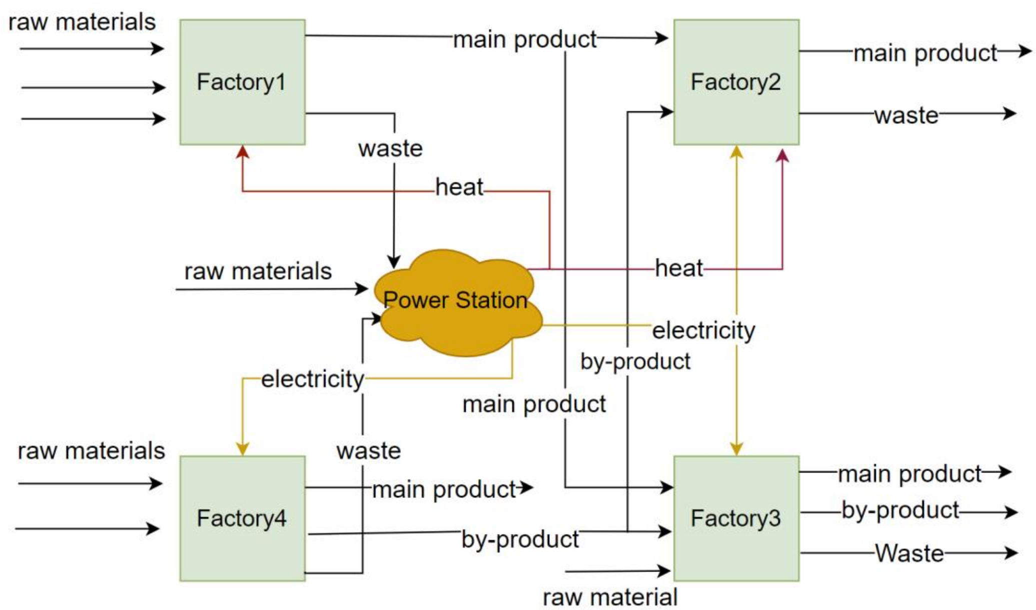

Figure 1: Eco-industrial park.

To optimize energy utilization, the implementation of energy scheduling is a key strategy. This encompasses determining the quantity of energy to be generated, and strategically coordinating how individuals or organizations utilize this energy. Operating within a defined time frame, such as a week or a month, the factories situated within the industrial park systematically devise their production plans including all the planned jobs which need to be completed within this period. Concurrently, they formulate power usage plans aligned with these production schedules. Subsequently, these power usage plans are transmitted to the central controller for coordination, the central planning and control system serves as a platform for collaboration and communication among stakeholders within the park. Simultaneously, the central controller receives crucial information from the power plant, encompassing details such as available power generators and the raw materials at hand for power production. Energy scheduling ensures that the power scheduling strategy is not only responsive to the production needs of the factories but also takes into account the capabilities and constraints of the power plant. By aligning the production plans of the factories with the power usage plans and the operational status of the power plant, the central controller can optimize the overall energy utilization within the industrial park. This synchronization allows for a more efficient and balanced distribution of power, contributing to the overarching goal of sustainable and optimized energy management.

Our initial strategy for managing energy, shown in Figure 2, involves several steps. In each planning period, the center controller starts by gathering energy requests from customers and information from the CHP, such as material and capacity details. With this data, the center controller decides how many power generators to activate. Next, we select users in a way that minimizes unused power, similar to solving a knapsack problem with a limit on planned power. Following factory selection, we proceed to schedule jobs, determining the start time for each. This decision can be made by either evenly distributing the starting times or assigning them randomly throughout the planned period. The final step in this energy scheduling plan focuses on improving the schedule derived from earlier steps, a rehearsing technique is used here. A virtual power station is set up to check and improve the existing schedule. In this phase, jobs that are already scheduled request power according to the initial schedule. If there is not enough power available to meet a job's power requirements, that specific job is excluded from the pre-determined scheduling.

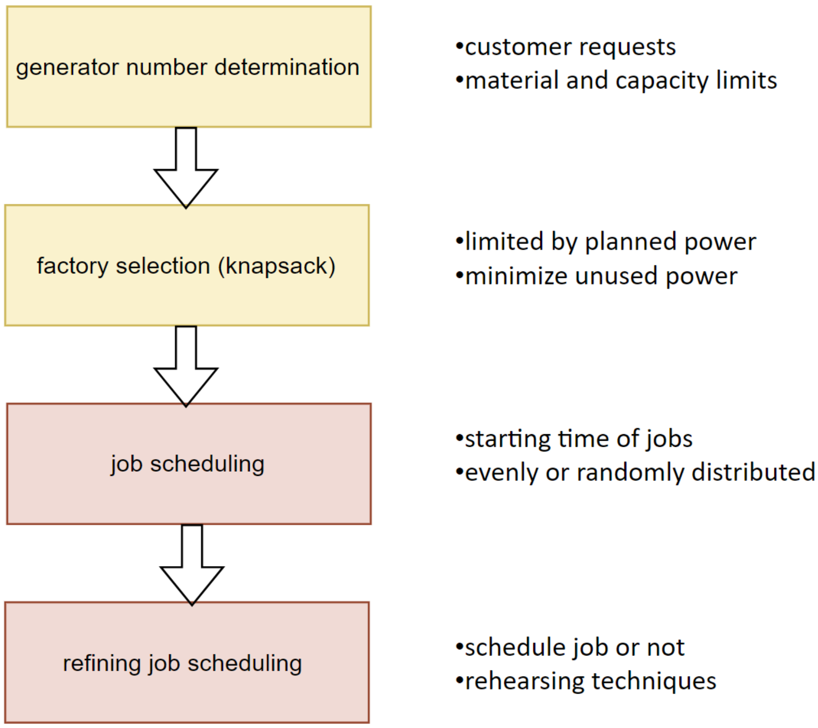

Figure 2: Initial strategy.

In this study, our goal is to improve this energy scheduling strategy. Instead of handling energy and production scheduling separately, we want to consider them together. That's why we call it mixed energy and production scheduling. We have turned this into a constraint programming problem. Solving it will give us both energy and production schedules. By integrating energy and production scheduling, we can achieve a more harmonized utilization of resources. This ensures that energy generation aligns precisely with the requirements of production processes, minimizing both underutilization and overuse of energy resources.

3 MODEL FORMULATION AND SOLUTION

In this section, the constraint programming (CP) model is designed to address the interconnected objectives of job scheduling and energy utilization within the intricate dynamics of the industrial park. The decision variables, parameters, and constraints are seamlessly integrated into a comprehensive framework.

Within this framework, the following decision variables guide the optimization process:

- $x_{i,j}$, the binary decision of whether a job j in factory i should be scheduled or not.
- $\tau_{i,j}$, if a job is scheduled, determine the precise starting time for this job within the corresponding factory.
- y, the optimal number of CHP generators that should be activated.
- z, the ratio of power to heat.

The additional parameters in this model are represented as follows:

- $E_{i,j}$ and $H_{i,j}$ represent the electricity power requirement and the heat power requirement for job j in factory i respectively.
- $T_{i,j}$ represent the processing time of job j in factory i.
- P_e and P_s are the end time and start time of the corresponding plan period.
- C is the capacity of the CHP generator.
- B_i is the set of shifts starting times for Factory i.
- W is the predefined constant which signifies the duration of a small period, during which it is crucial to guarantee that the aggregate energy consumption by the jobs located in this period does not surpass the total energy production.
- M represents the total amount of waste produced by all factory members within the park during each planning period.
- Q denotes the energy production rate associated with the utilization of one unit of material.

The decision framework encompasses two key objectives: firstly, to maximize energy utilization, operationalized as the ratio of consumed energy to the total energy output from the CHP system, displayed in equation (1) and secondly, to efficiently schedule as many jobs as possible within the industrial park, ensuring the fulfillment of the production plan, expressed as the ratio of scheduled job number to the total job number, as in Equation (2).

$$Max \quad [\sum_{i\in I}\sum_{j\in J_i} T_{i,j}(E_{i,j}+H_{i,j})x_{i,j}]/\left[(P_e-P_s)Cy\right] \tag{1}$$

$$Max \quad \sum_{i\in I}\sum_{j\in J_i} x_{i,j}/\left|J\right| \tag{2}$$

In the pursuit of these objectives, the model is governed by the following constraints:

$$\tau_{i,j} \ge P_s \quad \forall i,j, \quad x_{i,j}=1 \tag{3}$$

$$\tau_{i,j}+T_{i,j} \le P_e \quad \forall i,j, \quad x_{i,j}=1 \tag{4}$$

$$\begin{gathered}\tau_{i,j'}+T_{i,j'} \le \tau_{i,j''} \quad \vee \quad \tau_{i,j''}+T_{i,j''} \le \tau_{i,j'} \quad \forall j',j'', \\ j' \ne j'', \quad j',j'' \in J_i, \quad x_{i,j'}=x_{i,j''}=1, \quad i\in I\end{gathered} \tag{5}$$

$$\tau_{i,j} \in B_i \quad \forall i,j, \quad x_{i,j}=1 \tag{6}$$

$$(P_e-P_s)Cy \le M/Q \tag{7}$$

$$N=\{1,2,\cdots,(P_e-P_s)/W\} \tag{8}$$

$$\begin{gathered}J_n=\{(i,j) \quad \forall i,j, \quad S_n \le \tau_{i,j} \le S_{n+1} \quad \vee \quad S_n \le \tau_{i,j}+T_{i,j} \le S_{n+1} \\ \vee \quad (\tau_{i,j} \le S_n \wedge \tau_{i,j}+T_{i,j} \ge S_{n+1}), x_{i,j}=1\}, i\in I, j\in J_i, n\in N\end{gathered} \tag{9}$$

$$\sum_{(i,j)\in J_n} E_{i,j} \le Cyz \quad \forall n, \quad n \in N \tag{10}$$

$$\sum_{(i,j)\in J_n} H_{i,j} \le Cy(1-z)\ \forall n,\ n \in N \tag{11}$$

$$x_{i,j} \in \{0,1\} \quad \mathrm{y} \in \{1,2,3,...,\mathrm{Y}\} \quad 0.0 \le \mathrm{z} \le 1.0 \tag{12}$$

Constraints (3) and (4) ensure that if one job is scheduled, then the starting time of this job is after or equal to the start time of the plan period and the end time of this job is before or equal to the end time of the plan period. Constraint (5) is the disjunction constraint and prevents overlap between scheduled jobs within one factory. Constraint (6) makes sure the starting time of the scheduled job should satisfy the constraint of its factory; for example, this constraint can be shift constraint which means that the starting time of the scheduled job aligns with the factory shift. Constraint (7) ensures that the total energy produced cannot exceed the energy production capacity determined by the available material. Constraint (8) mathematically defines the subdivision of the plan period into small periods based on the predefined unit length W.

To ensure that the power consumed by the scheduled jobs always remains within the maximum power output of the power station, we have partitioned the entire planning period into the smallest possible intervals. Our objective is to guarantee that, within each of these shorter intervals, all scheduled jobs adhere to the specified constraint, thereby preventing any exceedance of the power station's maximum capacity. Constraint (9) expresses three conditions to judge if one scheduled job belongs to one given small period or not. The three conditions are starting time of the job is within the starting and end time of the small period; Ending time of the job is within the starting and end time of the small period; Starting time of the job is earlier than the starting time of the small period, and the ending time of the job is later than the end time of the small period. Only one condition is satisfied, then this small period set J_n contain this scheduled job. The last two constraints (10) and (11) ensure that, within each small period, the total electricity and heat power usage from the scheduled jobs that belong to this small period does not surpass the total produced power. Constraint (12) defines the binary nature of variable.

In the model formulation, we address two objectives: first, to maximize energy utilization, and second, to schedule as many jobs as possible. In multi-objective optimization, a common method to handle multiple objectives is to combine them into a single composite objective function. This is typically done by assigning weights to each objective, reflecting their relative importance. The general form of a weighted objective function can be represented as $Z = w_1 * f_1(x) + w_2 * f_2(x)$,where: Z is the composite objective function. $f_1(x)$ is the first objective function, in this case, the energy utilization ratio, $f_2(x)$ is the second objective function, the job scheduling ratio. w_1 and w_2 are the weights assigned to each objective function, respectively. By introducing these weights, we effectively convert the two-objective problem into a single-objective problem, allowing for a balanced consideration of both energy utilization and scheduling efficiency. The choice of weights becomes an important factor, reflecting the significance assigned to each objective in the overall optimization strategy.

The CP optimization model presented previously contains numerous constraints, posing a significant challenge in finding a solution. Based on the many experiments performed using the CP model, IBM ILOG CPLEX Optimization Studio proved to be a useful tool for constraint programming. It is available freely for academic use (Menesi et al. 2013). ILOG CPLEX Optimization Studio provides a user-friendly programming language that allows problem description in terms of variables, objective functions, constraints, and internal computations. According to the IBM documentation for the CP optimizer, this tool utilizes two key techniques to find a solution: constructive search and constraint propagation, both initially and during the search process. During the initial constraint propagation, unnecessary variable values are eliminated, reducing the search space. Constraint propagation during the search phase eliminates values that violate constraints. The CP optimizer employs a constructive search strategy to navigate the remaining search space and find a solution. This process continues iteratively until a solution is successfully found. In this study, the previously formulated model has been implemented within IBM ILOG CPLEX Optimization Studio.

4 EXPERIMENT

Our experiment is conducted on an industrial park example, which consists of six factories and one CHP factory. The simulation model is built in AnyLogic which is a simulation software tool that is wildly used for modeling complex systems and conducting simulation-based analysis. The experiment unfolds over a series of planning periods, where the simulation model initiates each phase by dispatching job assignments to the scheduler. Once the scheduler completes the scheduling process, it transmits the resulting schedule back to the simulation model. The simulation model then executes tasks based on this schedule, as outlined in Figure 4.

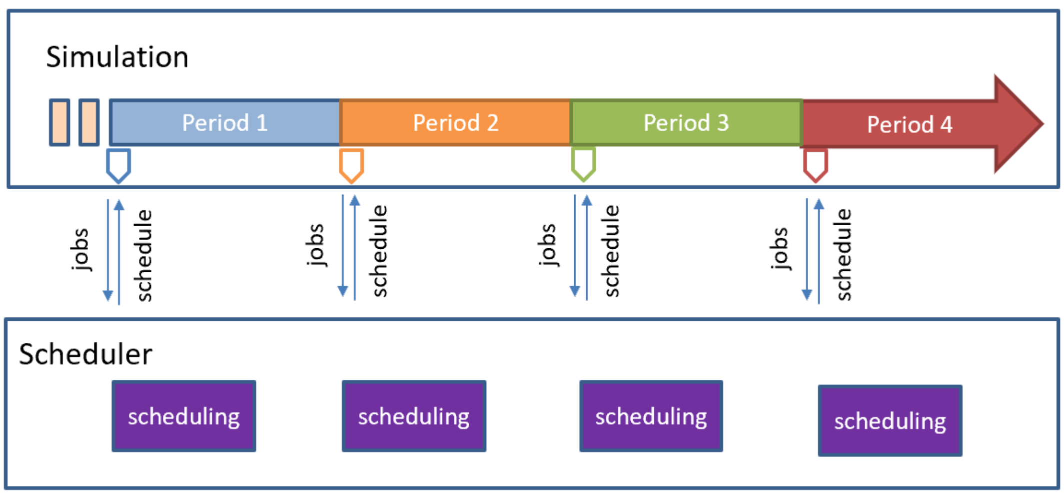

Figure 4: Simulation model workflow in the industrial park experiment.

In our experiment, the simulation duration spans 10 weeks, with each planning period structured as a one-week timeframe, totaling 10 planning periods. The objective was to maximize the scheduling of all the planned jobs from six factories while optimizing energy utilization in each planning period. Both objectives carried equal weight in our experiment. Detailed experimental data is provided in Table 1, which includes the start and end times of each period, the capacity of each power generator in the CHP, the total number of generators in the CHP, the planned job numbers from all factories within each plan period, and the total requested energy for all jobs in each planning period.

The complexity of this scenario in each plan period involved around 8000 variables and 9000 constraints, rendering the scheduling problem intricate. The CP optimizer required a considerable amount of time to find feasible solutions. To manage this, we imposed a time limit of 10 hours for the optimizer, allocating 10 hours for optimization in each plan period and totaling 100 hours for the entire experiment.

Leveraging the computational power of our computer with 128 kernels, the CPLEX CP optimizer utilized 128 multiple workers to collaboratively address the optimization challenge. This was contrasted with a laptop having only 6 kernels and 6 multiple workers, showcasing a notable 75% time-saving advantage. Additionally, we use the automatic search method within the optimizer. To enhance the optimization model, we introduced criteria for minimal energy utilization (0.5) and a minimal job schedule ratio (0.7) to prevent the generation of impractical results, which means the objective of the CP model should be greater than 1.2.

Table 1: Experiment data.

Period	Start	End	Gen Capacity	Total Gen Num	Planned Job Num	Requested Energy (J)
1	0	7	5000	6	109	4127782.55
2	7	14	5000	6	91	3106900.61
3	14	21	5000	6	105	3933048.11
4	21	28	5000	6	103	3751989.67
5	28	35	5000	6	103	3850050.25
6	35	42	5000	6	93	3299827.42
7	42	49	5000	6	97	3408009.81
8	49	56	5000	6	116	4656246.15
9	56	63	5000	6	115	4436306.32
10	63	70	5000	6	116	4565504.29

Under these constraints, the best schedule plan obtained from the CP model is presented in Table 2. "Gen Num" refers to the number of generators planned to start in each period to achieve an optimal objective. Currently, the result of the electricity and heat ratio is 1, as the heat requirement for each job has not been considered in this experiment, meaning that the energy request for each job is solely for electricity. The produced energy is calculated by multiplying the number of generators by the capacity of each generator and the duration of period. The used energy is calculated based on the energy request of all scheduled jobs. The scheduled job ratio is derived from the number of scheduled jobs divided by the total number of jobs in each planning period. The planned objective of the CP model is the sum of the energy utilization ratio, and the job scheduled ratio.

As illustrated in Table 2, except for the fourth period, not all jobs will be scheduled in the other periods. The possible reasons why some jobs cannot be scheduled could be insufficient energy production or constraints in factory capacity. During this experiment, our primary focus was on scheduling the planned jobs obtained from the planning system in order to maximize the internal energy utilization in the park. We did not directly address the issue of unscheduled jobs. If there were unscheduled jobs, we provided feedback to the planning system, which is responsible for managing them in operational environments. Typically, unscheduled jobs undergo reassessment by the planning system. Depending on their urgency and due dates, the planning system decides whether to reschedule these jobs for future periods or discard them altogether.

Table 2: Results from CP model.

Period	Gen Num	Electric Heat Ratio	Produced Energy(J)	Used Energy(J)	Energy Utilization	scheduled Job Num	Scheduled Job Ratio	Objective
1	6	1	5040000	3875063.33	0.77	106	0.97	1.74
2	5	0.99	4200000	3090364.32	0.74	90	0.98	1.72
3	6	0.99	5040000	3842489.08	0.76	104	0.99	1.75
4	6	1	5040000	3751748.33	0.74	103	1	1.74
5	5	0.99	4200000	2716537.38	0.65	73	0.71	1.36
6	5	0.99	4200000	3109118.48	0.74	90	0.97	1.71
7	5	0.99	4200000	3369994.02	0.80	96	0.99	1.79
8	6	1	5040000	3806625	0.76	106	0.91	1.67
9	6	0.99	5040000	4121063.05	0.82	108	0.94	1.76
10	6	0.99	5040000	4003773.42	0.79	104	0.90	1.69

Each plan period in our experiment involves the execution of outputs from the CP model by our simulation framework. Table 3 comprehensively detail the simulation outcomes over the course of 10 periods. It records the released jobs, representing those initiated in each period as determined by the CP model, along with the total energy requested for all released jobs. Work in Progress (WIP) is calculated to reflect ongoing tasks, while Finished jobs denotes the number successfully completed by the end of each simulation period. The job scheduled ratio is computed by dividing the number of finished jobs by the total number of jobs that were initially planned to be scheduled at the beginning of each planning period. As shown in Table 3, the actual number of finished jobs may not always match the released job numbers due to uncertainties incorporated into our simulation model, such as potential capacity fluctuations. Despite the model's intention to adhere to the initial schedule, deviations can occur. These deviations often stem from changes in factory capacities, affecting job processing times differently than initially planned by the CP model. Consequently, a portion of jobs may not start as scheduled. If this situation occurs, feedback will be provided to the planning system. Additional simulation results detailing the energy utilization metrics are also included in Table 3. These metrics include the energy produced by the CHP factory, the total energy used by all completed jobs, and the internal energy utilization.

Table 3: Simulation results from Sv2.

Period	Released Jobs	Requested Energy(J)	WIP	Finished Jobs	Job Schedule Ratio	Produced Energy	Used Energy(J)	Internal Energy Utilization
1	106	3816525.56	5.05	103	0.94	5040000	3809526.75	0.76
2	90	3140732.76	4.95	90	0.99	4200000	3133000.24	0.75
3	104	3805954.05	4.69	102	0.97	5040000	3805813.37	0.76
4	103	3591800.31	5.23	100	0.97	5040000	3591798.23	0.71
5	73	2925720.19	4.48	73	0.71	4200000	2900193.56	0.69
6	90	3079984.88	3.98	86	0.92	4200000	3075254.53	0.73
7	96	3372051.39	3.66	96	0.98	4200000	3350892.99	0.79
8	106	3813344.96	3.99	106	0.91	5040000	3813344.96	0.76
9	108	3886872.32	9.34	101	0.88	5040000	3874746.62	0.77
10	104	4109295.69	11.08	103	0.89	5040000	4097254.55	0.81

Table 4: Comparison results.

Scheduler	Scheduled jobs ratio	Energy utilization (power station)	Objective
Sv1	0.89	0.69	1.58
Sv2	0.93	0.75	1.68

Table 4 presents a comparison of results between two scheduling strategies: "Sv1," our initial scheduling approach, and "Sv2," the current strategy integrating energy and production scheduling based on CP model outcomes. Average values across 10 simulation periods were calculated using final results. It is clear from the data that "Sv2," despite relying solely on feasible solutions, consistently outperforms the initial scheduling version "Sv1" in terms of both scheduled job ratios and energy utilization. These findings confirm that integrating production and energy scheduling in EIP effectively enhances overall performance and promotes environmental sustainability. By leveraging the CP model's outputs, "Sv2" demonstrates superior efficiency in job scheduling and resource utilization, highlighting its effectiveness in achieving optimal operational outcomes within the industrial park setting.

5 CONCLUSION

In the face of increasingly severe environmental challenges, numerous industrial parks are emerging and becoming operational. The efficient management in these parks to achieve energy efficiency and meet production targets is of great importance. This study begins by simulating a basic example of an industrial park, addressing optimization through a constraint programming model. The IBM ILOG CPLEX CP solver engine is employed for effective problem-solving. Due to the problem's complexity, the IBM CP solver couldn't find the optimal solution within a reasonable timeframe. However, the feasible outcomes still outperform our initial strategy from previous research stages. The comparison highlights the CP model's efficacy in optimizing energy utilization and ensuring successful production targets within the park. Essentially, this study provides a foundation for further exploration and application in the broader field of eco-industrial park management.

Our upcoming task will initially concentrate on enhancing the outcomes generated by the constraint programming model. We are actively exploring the possibility of incorporating alternative search strategies to optimize the overall performance of the model. Furthermore, a central emphasis will be placed on understanding the dynamic interplay between energy and material flows within the park. Our forthcoming tasks encompass a comprehensive examination of how energy and material flow mutually influence each other. Through this exploration, our aim is to formulate specific strategies that not only align with the economic objectives but also contribute to environmental sustainability within the industrial park.

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REFERENCES

Afshari, H., Farel, R. and Peng, Q. 2017. "Improving the resilience of energy flow exchanges in eco-industrial parks: optimization under uncertainty". *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering 3(2): 021002.*

Al-Quradaghi, S., Zheng, Q.P. and Elkamel, A. 2020. "Generalized framework for the design of eco-industrial parks: Case study of end-of-life vehicles". *Sustainability* 12(16): 6612.

Boix, M., Montastruc, L., Azzaro-Pantel, C. and Domenech, S. 2015. "Optimization methods applied to the design of eco-industrial parks: a literature review". *Journal of Cleaner Production* 87:303-317.

Bloemhof-Ruwaard, J.M., Van Beek, P., Hordijk, L. and Van Wassenhove, L.N. 1995. "Interactions between operational research and environmental management". *European Journal of Operational Research* 85(2): 229-243.

Chertow, M. and Ehrenfeld, J. 2012. "Organizing self-organizing systems: Toward a theory of industrial symbiosis". *Journal of Industrial Ecology* 16(1): 13-27.

Chertow, M.R. 2000. "Industrial symbiosis: literature and taxonomy". *Annual review of energy and the environment* 25(1): 313-337.

Cucchiella, F., D'Adamo, I. and Gastaldi, M. 2017. "Sustainable waste management: Waste to energy plant as an alternative to landfill". *Energy Conversion and Management* 131:18-31.

Kuznetsova, E., Zio, E. and Farel, R. 2016. "A methodological framework for Eco-Industrial Park design and optimization". *Journal of Cleaner Production* 126: 308-324.

Leong, Y.T., Lee, J.Y., Tan, R.R., Foo, J.J. and Chew, I.M.L. 2017. "Multi-objective optimization for resource network synthesis in eco-industrial parks using an integrated analytic hierarchy process". *Journal of Cleaner Production* 143: 1268-1283.

Long, S., Zhao, L., Liu, H., Li, J., Zhou, X., Liu, Y. *et al*. 2019. “A Monte Carlo-based integrated model to optimize the cost and pollution reduction in wastewater treatment processes in a typical comprehensive industrial park in China”. *Science of the total environment* 647: 1-10.

Masmoudi, O., Delorme, X., & Gianessi, P. 2019. “Job-shop scheduling problem with energy consideration”. *International Journal of Production Economics* 216: 12-22.

Menesi, W., Golzarpoor, B., & Hegazy, T. 2013. “Fast and near-optimum schedule optimization for large-scale projects”. *Journal of construction engineering and management* 139(9): 1117-1124.

Nuhu, S. K., Manan, Z. A., Alwi, S. R. W., & Reba, M. N. M. 2022. “Integrated modelling approach for an eco-industrial park site selection”. *Journal of Cleaner Production* 368: 133141.

Saharidis, G. K. 2017. “Operational research in energy and environment”. *Operational Research* 17: 693-696.

Sakr, D., Baas, L., El-Haggar, S., & Huisingh, D. 2011. “Critical success and limiting factors for eco-industrial parks: global trends and Egyptian context”. *Journal of Cleaner Production* 19(11): 1158-1169.

Salido, M. A., Escamilla, J., Giret, A., & Barber, F. 2016. “A genetic algorithm for energy-efficiency in job-shop scheduling”. *The International Journal of Advanced Manufacturing Technology* 85: 1303-1314.

Touš, M., Pavlas, M., Putna, O., Stehlík, P., & Crha, L. 2015. “Combined heat and power production planning in a waste-to-energy plant on a short-term basis”. *Energy* 90: 137-147.

Yazıcı, E., Alakaş, H. M., & Eren, T. 2022. “Analysis of operations research methods for decision problems in the industrial symbiosis: a literature review”. *Environmental Science and Pollution Research* 29(47): 70658-70673.

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