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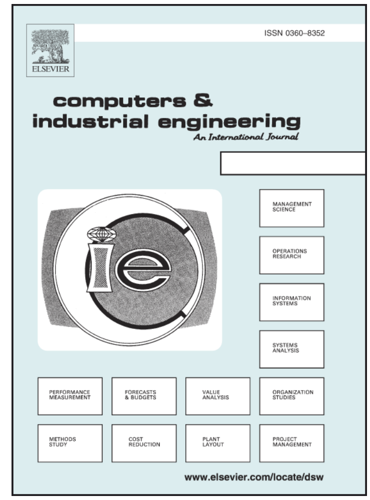

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Energy efficient production planning and scheduling problem with processing technology selection

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Abstract

Energy efficiency attains increasing attention in production systems due to growing energy costs and public perception of environmentally conscious operations. The paper features a capacitated production planning and scheduling problem (CPPS) with sequence-dependent setups for a continuous production line. Meanwhile, energy consumption costs associated with process techniques selection decisions are incorporated into the CPPS. A fix-and-optimize solution approach is proposed to solve the problem. Extensive computational experiments reveal an advantage of the proposed approach having a stable computational performance in solution quality. The optimal results also show the energy cutting benefits of the integrated decision considering operations and energy costs. Moreover, a case study of tea drink production line is presented to demonstrate the application of the model and the solution approach.

Keywords: energy efficient manufacturing; capacitated production planning and scheduling; mixed integer linear programming; fix-and-optimize

1. Introduction

With the increment in energy cost, government and companies have been promoting sustainable development policy to reduce energy consumption. Production systems are in great need of energy-saving and emission reduction because of their considerable energy consumption (such as electricity and fuel oil). Energy management is crucial, especially in energy-intensive industries such as chemicals, textiles, or food. Also, investments from environmental protection make operational costs of manufacturing industries increase significantly. Therefore, reducing energy consumption has become a vital factors when making production decisions such as production planning and scheduling (Gahm et al., 2015; Mejia-Maya et al., 2017).

We study the integrated production planning and scheduling problem with energy-saving consideration in continue production systems. The research is motivated from a real application in a tea production line in Digital

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Capability Centre Beijing (DCC), which produces tea drinks through a series of processes such as water purifying and heating, filtering, cooling, mixing, and high temperature sterilization (Refer to Section 6 for detailed introduction). The production line simulates real productions procedure of tea drinks. Although the production is in the laboratory, both the quality standards of products and the production processes are totally based on real-life industrial counterparts except of utilization of small-scale production equipment. The content of tea polyphenols in tea drinks is a key indicator of the quality of the drinks. It is impacted by temperature of hot purifying water and time length of tea extraction. Therefore, energy costs have to be considered when making production decisions due to that it is an energy-intensive procedure. Moreover, although energy contingency becomes increasingly serious and the benefit of integrated production decisions has been realized in academy and in industry, research that attempts to incorporate energy-saving considerations into integrated production decisions is relatively scarce. It also motives us to integrate the energy-saving considerations into the CPPS problem to optimize system-wide costs of production systems.

In this paper, we investigate a CPPS with sequence-dependent setups and energy-saving consideration. Aimed at quantifying energy costs, we consider energy expense incurred during the process of change-over and production. A mixed integer linear programming model (MILP) is proposed. The value of objective function varies as different process techniques are chosen, rendering the model a tool for cutting down energy consumption.

The major contributions of our work are as follows. First, a MILP model proposed for the CPPS problem is formulated with the consideration of a selection of process techniques with different energy consumptions and sequence-dependent setup time. Second, a fix-and-optimize (F&O) heuristic is proposed to tackle the problem. Computational experiments indicate that the F&O algorithm tends to have better performance and more stable feasibility with the growth of problem scale. Third, a case study of tea production line is presented to demonstrate the application of the model and the proposed algorithm.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature in the field of production planning and scheduling problems. In Section 3, the problem statement and assumptions are elucidated and the problem is formulated as a mixed-integer linear program. Section 4 proposes the F&O algorithm to solve the problem. The numerical experiments are reported in Section 5, followed by a case study which shed further light on the application of the model in Section 6. Finally, Section 7 concludes the paper and outlines further research directions.

2. Literature review

Integrated production planning and scheduling have been considered in past decades. And considerable efforts have been done in the related research. Several comprehensive literature reviews on production planning and scheduling problems have been proposed in the past decade. Zhu and Wilhelm (2006) presented a review on the problem with the consideration of sequence dependent setup cost. Most recently, Sel and Bilgen (2015) reviewed the literatures on continuous production planning. And, Gahm et al. (2015), Biel and Glock (2016) and Mejia-Maya et al. (2017) provided literature reviews on production planning and scheduling concerning energy efficiency.

In lot-sizing problem, especially in the continuous production line such as dairy industry, setup operations become more complicated with the consideration of sequence dependent setup cost (Sel and Bilgen, 2015). The discrete lot-sizing problem with sequence dependent setup costs was first studied by Haase (1996). Haase and Kimms (2000) further developed the model into a lot-sizing and scheduling problem with sequence-dependent setup costs and times (LSPSD), where decision variables were the inventory at the end of each period, production and sequence in each period. It resorted to enumeration of possible sequences and a Branch-and-bound algorithm. Almada-lobo et al. (2007) considered a single machine multiple-product capacitated lot-sizing problem (CLSP) with sequence-dependent setup costs and offered two MILP formulations for it. A heuristic was proposed that started from an initial solution which produced gross requirements in each period and reduced constraint violations and got improved afterwards. Several extensions have been made by considering CLSP with sequence dependent setup cost. Beraldi et al. (2008) formulated a similar problem and adopted a rolling-horizon and F&O algorithm to solve it. Kovcs et al. (2009) defined the problem as a capacitated LSPSD, using dynamic programming to sift the low-cost sequences first before optimization. Lang and Shen (2011) extended the model into capacitated lot-sizing problem with sequence-dependent setups and substitutions and resorted to a F&O algorithm to solve the model. Seeanner and Meyr (2013) put forward the general lot-sizing and scheduling problem for multiple production stages and adopted a relax-and-fix method to solve it. Xiao et al. (2013) considered sequence dependent setup costs in parallel machine production planning and scheduling problem and proposed a F&O and Tabu search algorithm in solution. Yang et al. (2017) discussed a stochastic multi-item capacitated lot sizing problem under two different types of setup cost motivated by a real-world steel enterprise, a k-degree connection decomposition-based F&O algorithm and a combination of the F&O and variable neighbourhood search were proposed to improve the solution efficiency and proved effective. Ceschia et al. (2017) considered the discrete single-machine, multi-item lot-sizing and scheduling problem and proposed a simulated annealing approach together with a statistically pricinpled tuning procedure to solve it. To deal with demand uncertainty, a multi-stage stochastic programming model is compared with the two-stage stochastic programming model and proved to improve the quality of solution by 10-13% (Hu and Hu, 2018). According to the existing literature, considering setup costs and designing efficiency improved algorithms are two heated topics. However, the researches that consider energy issue is scarce. In our research, based on a continuous flow production line, we not only consider the two topics also concern energy issue during modelling and discussion.

Energy efficient scheduling (EES) has drawn more attention by adding energy eciency factors into the scheduling objective. Energy costs are traditionally viewed as fixed costs in this field, but in recent years a number of researchers have directed their efforts to including energy-saving in the scheduling problems from various perspectives. As the energy efficiency factor has a vital impact on manufacturing companies that focus on the sustainable development, extensive researchers and enterprises are paying increasing attention on energy efficient improvement. Although the adoption of new and improved production equipment is a broadly acknowledged method of achieving more efficient production processes, researches on EES provide us with great (additional) potential to increase energy eciency using the current equipment setting saving a large amount of investment cost (Gahm et al., 2015). Mouzon et al. (2007) observed that shutting down idle machines when bottleneck occurs can cut down energy remarkably, and hence introduced new scheduling rules for unutilized machines. Dong (2013) considered energy consumption in machine standbys and restart setup costs, deciding whether to let the machine stand by or be shut down while there is no production. Rager et al. (2014) presented an energy-oriented scheduling approach for a parallel machine, where the object was to minimize final energy sources and genetic and memetic algorithms were applied. Tang et al. (2015) studied an ingot heating process in the iron industry. Temperature of incoming material was considered, and the rule of thumb was to divide incoming materials into batches to reduce energy consumption. Although the scheduling rule was related to energy-saving, the model itself did not involve energy costs and correlated designs, but introduced a penalty cost for parts that violate the rule instead. Patterson et al. (2017) studied the energy efficient scheduling in mining, contributing a MILP formulation. They scheduled haulage activity with discrete time slots and applied Tabu search methods to solving the problem. The total energy consumption cost was the summation of the working and idling time of the modelled equipment activities. Koken et al. (2018) applied genetic based algorithm to solve a hybrid system with manufacturing and remanufacturing concerning energy efficency and proved better than simulated annealing, variable neighborhood search and neighborhood list algorithm. Shao et al. (2018) modeled a energy-aware fair based scheduling problem as multi-dimensional knapsack problem and proposed the energy-aware greedy algorithm to meet the computing requirements but also achieve the goal of energy savings.

Table 1 presents a summary of the related literature. In the existing literature, several researchers investigated a similar problem without the consideration of energy cost. In the contrast, we pay much attention on the energy efficiency. In addition, a customized fix and optimize heuristic is applied to large size instances with sequence dependent setup cost. Meanwhile, the energy-orient research abovementioned focused mainly on production scheduling, but not extended into the field of integrated production planning and scheduling models. Two objectives are thus promoted for this paper. On one hand, we build a model that includes both operation and energy costs for continuous production lines. On the other hand, production planning, scheduling, and energy-saving are integrated in the same model, and the results of the model balances the three factors, providing us with a centralized optimal solution that apparently dominates any other decentralized solution considering only one or two of them.

[Table 1 is inserted here.]

3. Problem Statement

We consider an integrated multi-period and multi-product capacitated production planning and scheduling problem with energy-related considerations and sequence dependent setup cost in a single-machine environment. The demand (d_{jt}) in period t for product j is deterministic and time-varying. At the end of each period, if the amount of the products exceeds the demand, an inventory cost (h_j) for product j occurs. Otherwise, the backlog for product j (b_j) is allowed for the unsatisfied demand. In a certain period, the processing time (p_o) is related to the different processing techniques o selected which have different energy cost (e_o). To minimize the total cost that consists of inventory and backlog costs, setup cost and energy-related cost, we determine the production quantities of the products and the corresponding processing technologies. The problem structure is illustrated in Figure 1 Before modelling, parameters and decision variables used throughout the paper are summarized as follow:

[Figure 1 is inserted here.]

Sets

T The set of time periods indexed by $t \in T = \{1, 2, \ldots, |T|\}$.

J The set of product types indexed by $j \in J = \{1, 2, \ldots, |J|\}$.

O The set of time periods indexed by $o \in O = \{1, 2, \ldots, |O|\}$.

Parameters

h_j Inventory holding cost per unit of product j per period.

b_j Backlog cost per unit of product j per period.

p_o Processing time per unit of product using technique o.

$s_{jj'}$ Setup time to convert the machine from producing j to $j'(j \neq j')$

d_{jt} The demand for product j at the end of period t.

c_t Production capacity of period t.

e_o Energy cost of using technique o per unit of product.

$sc_{jj'}$ Setup cost of converting the machine from producing j to $j'(j \neq j')$.

γ_{jo} 1 if product j can be produced using technique o and 0 otherwise.

M A sufficiently large and positive number.

Decision variables

I_{jt} The inventory of product j at the end of period t.

L_{jt} The backlog of product j at period t.

Q_{jot} The quantity of product j produced in period t with technique o.

X_{jot} 1 if product j is produced in period t with technique o and 0 otherwise.

$Y_{jj't}$ 1 if change-over from product j to j' happens in period t and 0 otherwise.

Z_{jt} 1 if the machine is set up for product j both at the end of period t and the beginning of period $t+1$, and 0 otherwise.

S_{jt} Indicates the sequence of product j produced in period t.

3.1. Basic assumptions

The following basic assumptions are made without causing harm to the practical meaning of the model.

- For every product, there must be one processing technique applicable at least.

- The same technique may be used to process multiple products.

- During the same time period, a type of product can only be processing using one technique in the same batch, i.e., once the production of a product stops and the machine is changed over to another product, it cannot be changed back to producing this product again within the same time period.

- Setups must be completed within a period.
- While setups cannot be located at the conjunction of two consecutive periods, production is capable of being so. In other words, if the machine is ready for, or already producing a product, it is allowed to continue in producing this same product at the beginning of the next period.
- Setup time satisfies the triangle inequality, That is, $s_{jj'} \leq s_{jk} + s_{kj'}, \forall j, j', k(j \neq j' \neq k)$.
- Setup time is dependent on the predecessor and successor products, not techniques used.
- The production quantity takes continuous values.
- For the same technique, the processing time and energy cost per unit product is insensitive to the product type. They stay constant as long as the same technique is used.
- The fixed costs of producing the required products are not included in the model. Only three types of variable costs are considered: inventory/backlog, change-over and energy costs.

It is necessary to clarify the meaning of process techniques here. This parameter may carry rich meaning in practice. Different technique can denote difference in design of process flow, but more often, they are used to indicate different sets of processing parameters, for instance, physical and chemical inputs like temperature, liquid flow speed and pressure. The major trend is that the production rate can be improved at the cost of more energy consumption. Therefore, the solution shows a trade-off between high production rate and high energy cost. With increment in the price of energy, process technique design and parameter settings may become a crucial measure to cut down energy costs.

3.2. Model construction

$$min \quad \sum_{t=1}^{|T|}\sum_{j=1}^{|J|}(h_j I_{jt} + b_j L_{jt}) + \sum_{t=1}^{|T|}\sum_{j=1}^{|J|}\sum_{j'=1}^{|J|} Y_{jj't} sc_{jj'} + \sum_{t=1}^{|T|}\sum_{j=1}^{|J|}\sum_{o=1}^{|O|} e_o Q_{jot}, \tag{1}$$

$$s.t. \quad I_{j,t-1} + \sum_{o=1}^{|O|} Q_{jot} - I_{jt} + L_{jt} = d_{jt}, \ldots \forall j \in J, \forall t \in T, \tag{2}$$

$$Q_{jot} \leq MX_{jot}, \forall j \in J, \forall o \in O, \forall t \in T, \tag{3}$$

$$\sum_{j=1}^{|J|}\sum_{o=1}^{|O|} p_o Q_{jot} + \sum_{j=1}^{|I|}\sum_{j'=1}^{|J|} Y_{jj't} s_{jj'} \leq c_t, \forall t \in T, \tag{4}$$

$$X_{jot} \leq \gamma_{jo}, \forall j \in J, \forall o \in O, \forall t \in T, \tag{5}$$

$$\sum_{o=1}^{|O|} X_{jot} \leq 1, \forall j \in J, \forall t \in T, \tag{6}$$

$$\sum_{j=1}^{|J|} Z_{jt} = 1, \forall t \in T, \tag{7}$$

$$\sum_{j'=1}^{|J|} Y_{j'jt} + Z_{j,t-1} = \sum_{j'=1}^{|J|} Y_{jj't} + Z_{j,t} = \sum_{o=1}^{|O|} X_{jot}, \forall j \in J, \forall t \in T, \tag{8}$$

$$Y_{jjt} = 0, , \forall j \in J, \forall t \in T, \tag{9}$$

$$S_{j't} - S_{jt} + (1 - Y_{jj't})M - 1 \geq 0, \forall j \in J, \forall j' \in J, \forall t \in T, \tag{10}$$

$$I_{j0} = 0, I_{jT} = 0, L_{j0} = 0, L_{jT} = 0, \forall j \in J, \tag{11}$$

$$I_{jt}, L_{jt}, Q_{jot}, S_{jt} \geq 0, \forall j \in J, \forall j' \in J, \forall o \in O, \forall t \in T, \tag{12}$$

$$X_{jot}, Y_{jj't}, Z_{jt} \in \{0, 1\}, \forall j \in J, \forall j' \in J, \forall o \in O, \forall t \in T. \tag{13}$$

The objective function (1) aims to minimize the total costs, which include inventory/backlog, change-over costs, and energy costs in production. Energy costs are determined by the selection of different processing techniques. In detail, the first expression is the inventory and backlog costs, generally for every single period except periods 0 and $|T|$, at most one part of them is not zero. The second part refers to the sequence dependent setup cost. And the third part is the energy cost where different processing techniques charge different processing cost delivering different levels of processing time.

Constraint (2) is inventory balance constraint. Constraint (3) indicates that X_{jot} is one if product j is processed using technique o in period t and zero otherwise. Constraint (4) illustrates that the summation of production and setup times does not exceed the maximum of time available in any period. Constraints (5) and (6) are eligibility constraints that indicate in any period, a product can only be produced with no more than one technique which is capable of being adopted to produce this product. Constraint (7) indicates that there must be a product which is produced the last in a period and will be the first to be produced next. Constraint (8) denotes the balance of production status that must be maintained. In any period t, if product j is being produced, then either it was the last product in the last period, or the machine has experienced a change-over from another product j' to product j in the current period. The other side of this deduction is stated as follows. If product j is being produced in period t, then either it is the last and will continue to be produced in $t + 1$, or the machine is changed over to produce another product j'. Only the first product to be produced in the first planning period does not fit into Constraint (8) since there is no change-over from other product to it. Since change-over can never happen from one product to itself, decision variable Y_{jjt} is always 0 and all the relevant cost parameters are also set to 0, which is restricted in Constraint (9). Since change-over can never happen from one product to itself, decision variable Y_{jjt} is always 0 and all the relevant cost parameters are also set to 0, which is restricted in Constraint (9). Constraint (10) is introduced to break the loops by affiliating each product in every period with a sequence variable S. Constraint (8) alone may produce production loops instead of a chain, where the production returns to the same product after producing other products. Constraint (11) gives the values of inventory and backlog in periods 0 and $|T|$. Note that period 0 is a dummy period, so the inventory/backlog at the end of period 0 is the actual input into the model, while those at the end of period $|T|$ must equal zero to indicate there is no inventory or backlog at the end of the last period. Constraints (12) and (13) are non-negative constraint and standard binary constraint, respectively.

4. The fix-and-optimize heuristic

For general CLSP with sequence dependent setup cost, fix-and-optimize heuristics have been proved effective (Furlan and Santos, 2017; Goren and Tunal, 2018; Li et al., 2017). The fix-and-optimize heuristic decomposes a large-scale MILP into a series of relaxed sub-problems that contain much fewer integer variables. Optimization methods are then applied to these subproblems, resulting in a heuristic solution but shorter time and higher efficiency. Basically, the mainstream decomposition includes time, product and order decomposition. The feasibility of sub-model in F&O algorithm is guaranteed by the backlog assumption. In this study, the MILP is decomposed using time periods (Figure 2). A straight-forward way to understand time-decomposed MILP is that we plan the variables in a few periods first regarding the integer variables in the remaining periods as continuous on $[0, 1]$ and solve a small-scale MILP. The variables in the current planning periods are then fixed and will never be altered. Then, we move on to the next periods, and treat them in the same way. The iteration continues until a stop criterion is attained.

[Figure 2 is inserted here.]

There are three types of integer variables: optimized, waiting to be optimized and fixed. In each iteration, the integer variables solved in previous iterations are fixed. Integer variables of two periods are solved as integers, while integer variables of other periods are relaxed to continuous variables, waiting to be optimized. Apart from integer variables X, Y and Z, the value of continuous variables I, L, Q and S in solution also need to be fixed in each iteration. In implementation, decision variables are fixed by adding new constraints into the model. Table 2 shows the classification and notations.

[Table 2 is inserted here.]

We used t to denote the beginning period of each iteration and w is the length of the iteration window ($w < T$). At the beginning of the heuristic, we initialize the whole sets and parameters. In each iteration, we push w decision variables into the fix set: the integer decision variables are put into V_I^t; and the continuous decision variables are put into V_C^t. After that, we update the set of variables waiting to be optimized V_w^U and the sets of decision variables optimized V_{opt}^U and V_{opt-c}^U. As a result, the sub-problem considering decision variables in V_{opt}^U and V_{opt-c}^U is constructed. In turn, the sub-problem is solved by an off-the-shelf solver such as CPLEX. The decision variables in V_{opt}^U and V_{opt-c}^U are then added into sets of fixed decision variables V_{fix}^U and V_{fix-c}^U accordingly. The iteration process is terminated once the set of variables waiting to be optimized V_w^U is empty. And the decision variables in V_{fix}^U and V_{fix-c}^U are the final solution for this problem. Pseudocode for this process is as below:

Algorithm 1 Fix and optimize Heuristic

Require: $t = 0, U = 0, V_w^U = \cup V_I^t (w \le t \le T), V_{opt}^U = \cup V_I^t (0 \le t \le w-1),$
$V_{opt-c}^U = \cup V_C^t (0 \le t \le w-1), V_{fix}^U = \emptyset, V_{fix-c}^U = \emptyset$

Iteration

for $0 \le U \le \left\lfloor \frac{T+1}{w} \right\rfloor$ **do**
  if $U \ge 0$ **then**
    $V_w^U = V_w^{U-1} \backslash (\cup V_I^t \cup V_C^t), (wU \le t \le minwU + w - 1, T)$
    $V_{opt}^U = \cup V_I^t, (wU \le t \le min\{wU + w - 1, T\})$
    $V_{opt-c}^U = \cup V_C^t, (wU \le t \le min\{wU + w - 1, T\})$
  end if
  Solve the sub-problem with decision variables $V_{opt}^U \cup V_{opt-c}^U$
  If feasible, return the variable values
  If infeasible, exit the loop and end the heuristic
  if $U \ge \left\lfloor \frac{T+1}{w} \right\rfloor$ **then**
    $V_{fix}^{U+1} = V_{opt}^U \cup V_{fix}^U$
    $V_{fix-c}^{U+1} = V_{opt-c}^U \cup V_{fix-c}^U$
  end if
end for
End the iteration and return the solution

For each sub-problem, the main structure of the model resembles that in Section 3 . However, Constraint (13) is removed in iteration U, while the following constraints are added.

$$X_{jot} = FX_{jot}, Y_{jj't} = FY_{jj't}, Z_{jt} = FZ_{jt}, \text{for } 0 \le t \le 2U - 1, \text{when } U \ge 1, \tag{14}$$

$$X_{jot}, Y_{jj't}, Z_{jt} \in \{0, 1\}, 2U \le t \le min\{2U + 1, T\}, \tag{15}$$

$$X_{jot}, Y_{jj't}, Z_{jt} \in [0, 1], t \geq 2U + 1. \tag{16}$$

Where the sets FX, FY and FZ denote the values of fixed integer variables, respectively.

5. Numerical experiments

The proposed F&O algorithm is coded in C++. All the experiments were conducted in a HP 380 G7 server with 2.80 GHz Intel Xeon X5660 CPU and 16G RAM running the CentOS 7.0 operating system. The sub-problems in the F&O algorithm are solved using CPLEX12.6 with the default settings, and the final solution is compared to the solution obtained by directly adopting CPLEX 12.6 to solve the original model. In CPLEX, the memory space limit is set to 2G. The calculation time limit remains constant across different problem volumes, the time limits are set to 1800 seconds in performance evaluation and 5400 seconds in sensitivity analysis, respectively. As the F&O algorithm requires multiple calls of CPLEX to solve subproblems, only the calculation time in CPLEX is counted. We do not take the execution time of other program statements into account.

An additional remark is made regarding the complementation of this program. Constraint (10) is indispensable for the validity of the model. However, this constraint can very easily render the original problem infeasible in CPLEX when the volume of the MILP is large. In order to improve the feasibility of the original model, it can be substituted with the following constraint:

$$S_{j't} - S_{jt} + (1 - Y_{jj't})\bar{M} - 1 \geq 0. \tag{17}$$

$\bar{M}$ is set to be an integer larger than the maximum product types possible. Constraint (17) can work just as well as the previous one since it is unnecessary to guarantee that the S value of products on the product line is an arithmetic progression with a difference of 1. The numerical experience has shown that Constraint (17) extends the span of the S value and make the model easier to be solved with the built-in algorithms in CPLEX.

5.1. Performance evaluation

In this section we compare the performance of the F&O algorithm and CPLEX. For both J and T there are three types of scale (small, medium and big) while for O there is two types of scale (small and big). Find the product of the scale types and we have $3 \times 2 \times 3 = 18$ types of problem scales. On each scale, 5 experiments are run and the results of the F&O algorithm are compared to those of the original MILP solved in CPLEX. The different scales are set to be 25, 30 and 35 for J; 10 and 15 for O; and 25, 30 and 35 for T.

Most of the parameters in the model are assigned random values within a range. The calculation time limits of both CPLEX and the F&O algorithm are set to 1800 seconds. The ranges and values are given in Table 3. The value ranges are based on real-life scenarios of production and defined so as to make the randomization and calculation easier to conduct. Moreover, we assume that the processing time p_o and e_o are inverse.

[Table 3 is inserted here.]

The results are reported in Table 4 and Table 5. The meaning of the notations used in Table 4 and Table 5 are listed as below. $\overline{Gap_{CPLEX}}$ and $\overline{Gap_{F\&O}}$ represent the mean gap of CPLEX and the F&O respectively compared with the lower bound in CPLEX ($\overline{Gap_{CPLEX}} = \frac{result - LB_{CPLEX}}{LB_{CPLEX}}$, result refers to the value of objective function of CPLEX or F&O) for both CPLEX and F&O. ΔGap is the difference between the gap of F&O and that of CPLEX results. Note that we exclude the instances that CPLEX cannot find any feasible solution. And, $r_{CPLEX\_feasible}$ and $r_{F\&O\_feasible}$ are introduced to count the rate of feasibility for CPLEX and F&O respectively ($r_{CPLEX\_feasible} = \frac{\text{number of experiments with feasible solution}}{\text{number of experiments}}$) for both CPLEX and F&O. $r_{optimal}$ is the rate of optimality of CPLEX (only when all five examples are CPLEX feasible). $r_{outperform}$ is the rate of F&O algorithm outperforms CPLEX, feasible or not. The outperform here refers to a better running time performance. $\overline{t_{CPLEX}}$ is the mean solution time using CPLEX, while $\overline{t_{F\&O}}$ is the mean solution time of F&O when all five examples are CPLEX feasible.

[Table 4 is inserted here.]

[Table 5 is inserted here.]

Normally, CPLEX solve fails to find a feasible solution when it violates either time limit or memory space limit. Separating infeasible examples from feasible ones makes it easier to analyse the indicators related to performance. For example, when CPLEX cannot find feasible solutions, the gap of both algorithms cannot be determined either.

Combining the results in Table 4 and Table 5, we discuss the impact of problem scale on performance of both algorithms and the comparison between them. The performance is graded with both calculation time and quality of the solution.

5.1.1. Impact of problem scale on computational performance

It is self-explanatory that $\overline{t_{CPLEX}}$ grows with problem scale. However, the number of variables in the MILP model is $|J| \times |O| \times |T|$. Since the calculation time cannot exceed 1800 s, which is the time limit, we only compare smaller scales where the time limit has not been reached, starting from $25 \times 10 \times 25$. Notice that the average calculation time actually grows faster than the total number of variables, which justifies our motives to propose a heuristic for the MILP, since minor increment of problem scale could result in greater reduction of algorithm efficiency.

The average gap of CPLEX is not such an accurate indicator of solution quality as the rate of optimality, since gap has no meaning when the example is infeasible within the given time and memory space allocated. In addition, in large-scale problems, gap is usually fluctuating violently even when it exists. Therefore, it is not appropriate to analyse the effects of problem scale on gap. As can been seen from Table 4 and Table 5, the loss of effectiveness of CPLEX is manifested more by the rate of optimal solutions and feasible solutions found in such conditions. Both experience dramatic decline when problem scale becomes great enough, putting strain on the algorithm, and drop close to zero when the scale reaches its maximum.

A great advantage of the F&O algorithm is that it is able to find feasible solutions in all numerical examples. Greater problem scale still produces longer calculation time, however, the growth is not as great as that of CPLEX. Referring to Table 4 and Table 5, we notice that the $35 \times 15 \times 35$ is overloading CPLEX, but the time limit is far from constraining the F&O algorithm even in this case. The gap of F&O algorithm can be used to grade the quality of solution. Although a value of gap can only be found when CPLEX finds a lower bound, the F&O gaps have much smaller variation than those of CPLEX, over 80% of which fall on the range [3%, 5%]. Astonishingly, the average gap does not seem to grow with increment of problem scale, or at least the growth is minor, which further underlines the stability of the F&O algorithm, for it guarantees a feasible and ideal solution.

The numerical results have testified the hypothesis that the F&O algorithm should gradually eclipse the algorithm in CPLEX as the MILP gains on its scale. In smaller scale problems, CPLEX provides an optimal solution, while the F&O algorithm provides a fast and efficient solution. Its calculation time grows slower, lending it to large-scale MILP problems. Apart from efficiency, the F&Os greatest advantage over CPLEX is its stability. Moreover, the F&O algorithm is able to provide a stable gap with smaller variance, which guarantees the quality of solution. The calculation time of the F&O algorithm also has smaller variation in the same problem scale.

5.1.2. Sensitivity analysis

Further experiments were designed to conduct sensitivity analysis on the effects of J, O and T sets on the algorithms performance. We put forward a factorial design with three factors, and each has three level: low, medium and high. Three levels are needed to show the potentially remarkable growth in difficulty of solving the model when problem scale is large. They are 5, 20 and 35 for J; 5, 10 and 15 for O, 12, 24 and 36 for T. At each design corner, the time limit is maintained at 5400s.

The parameter settings are the same with those in the previous section, apart from different capacity levels. The volume of capacity will have great impact on the operational costs in our model. If the capacity is not bounding, the industry has enough process time so that it can always pick the most time-consuming but energy-saving technique for each product. In order to study the balance between saved energy consumption and the increment in time needed to process the products, the capacity is set to be proportional to the number of products.

At each design corner, we run five replicates of numerical examples to observe how the efficiency of solution reacts to different levels of each parameter. For each numerical instance, we run the model with the objective function with and without energy costs. Thus there are nine design corners and 540 runs in total. We analyse first how the performance of both solution methods change when size of products, techniques and periods change, respectively. For the F&O algorithm, we trace how the solution time and gap compared to the lower bound change. However, for CPLEX it is difficult to compare the gap, because there are cases where no feasible solution is found yet within the given time limit.

An ANOVA is conducted respectively on the solution time of CPLEX and the F&O algorithm. The results are reported in Table 6.

[Table 6 is inserted here.]

The R-sq values for CPLEX and the F&O algorithm are 62.12% and 96.10%, respectively. It is clear that all three factors affect solution times, whether in CPLEX or the F&O algorithm. However, the number of product types is the most powerful and can greatly burden the solution process when it grows big. The number of time periods is the next, while the number of techniques is the least dominant.

In CPLEX, 2-way interactions of factors are not considered significant. In contrast, they passed the P-value test in F&O, hinting of a possibility that F&O time might grow faster when both factors are elevated to a higher level. However, generally the F&O solution time changes in a more linear and regular way than CPLEX, having a greater R-sq value.

The ANOVA analysis on the gap between the F&O results and the lower bound indicates no significant effect of the three factors. In other words, the gap of the F&O does not depend on the volume of either product, or techniques, or periods.

5.2. Managerial insights

In this part, we analyse how the factors levels influence the extent of energy savings. The results might be enlightening for managerial efforts to cut down energy costs.

(1) Cost reduction

Based on the experiment results, cost reduction is noticed. With an objective function which contains both operations and energy costs, the model has the trend of incurring operation costs (about 1.88% higher on average). However, it significantly cuts down the energy costs. The extent of energy saving is sufficient to make up for the increment in operation costs and make the total costs of the new model favourable. The reduction of total cost averaged to be about 34.74%, while energy costs reduce by 55.52% on average, a rather attractive percentage. The result is shown in the Table 7.

[Table 7 is inserted here.]

(2) Sensitivity of cost reduction to factor levels

The analysis on both the total savings and energy savings of CPLEX in different problem scales shows that the number of techniques can have positive effects on reducing costs. This conclusion is in accordance with intuition, for a greater number of techniques may provide more alternatives for producing the same product, so that the product plan is able to make proper use of the capacity in each time period.

The type of products may have negative effects on total cost savings, indicating that it might be more difficult to reduce energy costs with greater number of products. However, the same effect is not significant with a 95% confidence interval in the energy cost saving ANOVA. The effect of time periods is not considered significant in either analysis.

Based on these results, managers are able to take some measures to further reduce energy consumption. More techniques of producing the same product should be taken into consideration. Moreover, it is not advisable to put a great number of products into the model.as the CPU time of CPLEX dramatically rises with the increase of the number of product types, the proposed F&O algorithm can reduce a large amount of CPU time by choosing effective iteration window and guarantee a stable gap (about 4%) in the optimizing process. Increasing the length of time in the planning itself, for instance from half a year to one year, will not affect energy saving aversely.

6. Case study: tea drink production line

The case demonstrates the application of the model and the proposed F&O algorithm in the tea drink production line in DCC Beijing. DCC Beijing is a plant-like laboratory, which have two production lines, one is a discrete production line and another is the continue tea drink production line. Both of the production lines are designed and built based on real-life industrial counterparts and real products instead of fake products such as toys are processed in the production lines based on the industrial standards.

6.1. Factory profile

The tea drink production line is composed of 9 systems in total, respectively named pure water manufacturing, hot water, tea extraction, filtering, buffering and water adding, concoction, bacteria-killing, can storage (Figure 3), and CIP cleaning system. The main raw materials in the line are tea leaves, water and flavourings. Although there is moderate discrepancy between this production line and real-life industrial production, it is nonetheless a good representative of continuous production lines.

[Figure 3 is inserted here.]

6.2. Energy consumption

The tea drink production line has been a subject of energy-saving related research. Basically, over-production and over-processing factors are one of the major contributors to the energy problems of the production line. The former means that the device or technique used exceeds the demand, while the latter means that the processing standards is set over the level expected. For instance, waste is incurred when the tea soup sterilization temperature is set at 100°C instead of 80°C, which would suffice, or when only 10L of tea drinks is produced out of an extraction can with a volume of 50L. Both behaviour will lower energy utilization. The above-mentioned facts taken into consideration, the model in this paper can be applied to address the selection of techniques and processing parameters.

6.3. Model application

6.3.1. Choosing subject of the model

The tea drink production line is a completed, closed system of which the core processing technology is extraction (handled in equipment D&E in Figure 3). This step is also the most susceptible to different processing parameter settings. Temperature and time are two parameters that defines the quality of tea extraction. Extraction time will be shortened as the temperature climbs, which suits the assumption that production rate is increased at the cost of more energy consumption. The water heating and tea extraction can be viewed as single-machine continuous production. We choose extraction as the subject to which we apply the model. Since the current main raw material is green-tea tealeaves, the products are green tea and derived drinks.

6.3.2. Methods used to determine input parameter

Basically, the parameters in the model are determined according to the real processing of heating and extraction. The currently missing parameters, demands for example, are simulated. Other undetermined parameters are measured with experiments.

In order to determine the number of processing techniques, the so-called tea-making experiments were carried out. Extraction temperature and time are a pair of undetermined parameters, the combination of the two variables makes different processing techniques. The original parameter used in the production line is (70°C, 10 min). The experiments were designed with the guide of research in factors affecting the quality of extraction.

Step 1: Put water into the Extraction Preheating Can (Equipment D).

Step 2: Wait until the water in the can reaches the extraction temperature. It automatically keeps the water temperature.

Step 3: Open the sluice and let the water into the Extract Can (Equipment E).

Step 4: Start the device and the beater begins to stir the liquid.

Step 5: Repeat steps (1) and (2) until the extract time runs out.

Step 6: The beater stops. Fetch out the tea drink.

Step 7: Repeat step (3) to (6).

Tea leaves are soaked in water with different temperature and time. We measure the concentration of tea polyphenols, the amount of which is an indicator of the tea drink quality. Only the parameter sets whose extract contains abundant tea-polyphenol are deemed eligible in the model.

6.3.3. Model parameter settings

From the abovementioned analysis and experiments, the input parameters of the model are determined or simulated. Table 8 demonstrates the three techniques, i.e., processing parameter sets, eligible in the model and their corresponding energy consumption.

[Table 8 is inserted here.]

Since we study the extraction of tea drinks and the products are green tea and derived products, each one of the techniques should be eligible for all products, i.e., $\Gamma_{jo} = 1$ stands for all the $j's$ and $o's$.

The production setup time is mainly incurred by the CIP cleaning of devices. The minimum cleaning time is 4 hours and the time could be increased according to demand. There are complicated factors affecting the cleaning time. To simplify the model, the setup time is randomized. A week is considered as a time period. Intuitively, capacity should be a deterministic value. However, due to device maintenance and potential rests, the capacity is also randomized. Table 9 gives the value settings for model parameters.

[Table 9 is inserted here.]

6.3.4. Results of the model

For all the randomized MILPs, both CPLEX and the F&O algorithm are applied. From the results in Section 5, it is safe to conclude that the problem scale is not large enough to justify the use of F&O algorithm in this case, although the latter is capable of giving a rather small and stable gap at about 4.2% on average. In addition, from the application of F&O algorithm, we can solve larger size instances and then dramatically reduce the total cost and the energy cost. Meanwhile, two conclusions are pointed out that the total cost reduces with the increase of number of alternative techniques and the decrease of types of product to be manufactured. In order to study the models improvement on energy and total costs, the same numerical experiments are calculated again adopting integrated production planning and scheduling model without energy considerations. The model shares the same constraints while dropping the energy costs in the objective function.

Despite the fact that energy consumption is not considered in this model, the energy costs associated with the obtained solutions can be calculated using the technique and quantity of each product in the periods. The results of case study are reported in Table 10. ΔEC_{CPLEX}, ΔTC_{CPLEX}, $\Delta EC_{F\&O}$, and $\Delta TC_{F\&O}$ represent the difference between energy costs of CPLEX, total costs of CPLEX, energy costs of F&O and total costs of F&O based on the two different models, one with the consideration of energy consumptions and one without, respectively.For example, ΔEC_{CPLEX} means the difference on energy cost between the model with the consideration of energy cost and one without both solved by CPLEX.

[Table 10 is inserted here.]

The comparison shows that the slash in energy costs more than covered the increment in operation costs. Both CPLEX and the F&O algorithm are able to bring the energy costs and total costs down. The maximum reduction rate of total cost is 9.4% in the table, which is impressive for industries seeking to cut down production costs. It is thus shown that taking energy costs into consideration while doing production planning and scheduling is promising in cutting down energy and total costs. In general, the proposed model and the F&O algorithm can dramatically reduce total cost. Based on the numerical experiments, the reductions of total cost and energy cost are dramatic. Meanwhile, increasing the number of techniques and reducing the number of product types would have positive effect on total cost reduction in the aspects of industry applications.

Note that although the DDC is a lab-environment, the problem size is close to the scale of an industrial application (Sel and Bilgen, 2014). In addition, product types in those scenarios are much more variegated. For instance, a combination of green tea, black tea, oolong tea and jasmine tea might be produced instead of green tea alone, in which case the F&O algorithm may have even better performance.

7. Conclusions and future research

In this paper, we extend the research to production planning and scheduling integrated with energy consideration. Adding to this, the processing techniques, especially the parameters, are chosen in the energy-saving scheduling, which is based on fixed production flow and variegated processing parameters. The problem is formulated as a MILP model and a F&O algorithm is proposed to solve it. Constraints such as sequence-dependent setup time and capacity constraints are put into the model to adapt to the characteristics of continuous production lines. Extensive numerical experiments are carried out to evaluate the performance of the model and the proposed F&O algorithm. In our research, the proposed F&O algorithm provides an effective way to solve the larger-size problem with relatively stable gaps within an acceptable time. Generally, in larger-scale problems the proposed F&O algorithm performs better, and the number of product types is the most dominant factor. For general cases, the proposed model and the F&O algorithm can dramatically reduce the total cost. Based on the numerical experiments, large reductions of total cost and energy cost are made, about 34.74% and 55.52% on average, respectively. Meanwhile, with the increase of the number of techniques and decrease of the number of product types, positive effect on total cost reduction in the aspects of industry applications would grow bigger. Finally, a case study on the tea drink production line is presented. The solution shows a strong application of the model in continuous production lines with a strong optimization effect.

Admittedly, the consumption of energy in continuous production lines are wide-ranging. It may be complicated to convey comprehensive management over production. However, there are many directions in this field awaiting further research. The single-machine continuous production can be extended towards multi-stage production lines. An important problem would be to solve the production planning and scheduling in a complicated production line, which covers the line balance and temporary inventory of work-in-process. In addition, the research can be extended to a production line concerning uncertain factors such as uncertain operations time (Sel and Bilgen, 2014). It is also interesting to relax the assumption of backlog and further broaden the range of applications. In the respect of algorithms, further improvements of the F&O algorithms will be made further. A hybrid heuristic can be designed to better accommodate the model for combining other heuristics like Tabu Searching. Comparative researches between the F&O and the hybrid heuristics are needed. Another way to improve the results of F&O algorithm is to design a second-stage algorithm to further optimize the solution.

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Tables

Table 1: Summary of related studies in literature

Study	Item	Demand	Setup Cost	Period	Energy affair	Methodology
Goren and Tunal (2018)	M	S	SD	S	N	Fix and optimize
Xiao et al. (2013)	M	D	SD	S	N	Fix and optimize
Lang and Shen (2011)	M	S	SD	M	N	Fix and optimize
Yang et al. (2017)	M	D	SD	M	N	Fix and optimize
Ramezanian et al. (2017)	M	D	SD	M	N	Fix and relax
Seeanner and Meyr (2013)	M	S	SD	M	N	Fix and relax
Beraldi et al. (2008)	S	S	SD	M	N	Rolling Horizon and Fix and relax
Haase (1996)	S	D	SD	M	N	Backward Oriented Heuristic
Almada-lobo et al. (2007)	M	D	SD	M	N	Five step Heuristic
Kovcs et al. (2009)	M	D	SD	M	N	LP relaxation-based Heuristic
Haase and Kimms (2000)	M	D	SD	M	N	Branch and bound
Rager et al. (2014)	M	D	SI	S	C	Evolutionary algorithms
Tang et al. (2015)	M	D	SI	M	C	Scatter Search
Li et al. (2007)	S	S	SI	S	C	Dispatching rule
Dong (2013)	S	D	SI	M	C	Column generation
Rahmani et al. (2013)	M	S	SI	M	N	Robust optimization
Ceschia et al. (2017)	M	D	SI	M	N	Simulated annealing
Hu and Hu (2018)	M	S	SD	M	N	Stochastic programming
Koken et al. (2018)	S	D	SI	M	C	Genetic algorithm
Patterson et al. (2017)	M	D	SI	M	C	Constructive Tabu Search
Our research	M	D	SD	M	C	Fix and optimize

Item	S for Single-item	M for Multi-item
Demand	S for Stochastic demand	D for Deterministic demand
Setup cost	SI for Sequence independent	SD for Sequence dependent
Period	S for Single-period	M for Multi-period
Energy affair	C for Energy affair concerned	N for Energy affair not concerned

Table 2: Variable sets and decision variables

V_w^U	Set of variables waiting to be optimized after iteration U
V_{opt}^U	Set of integer variables optimized in iteration U
V_{fix}^U	Set of fixed integer variables in iteration U
V_{opt-c}^U	Set of continuous variables optimized in iteration U
V_{fic-c}^U	Set of fixed continuous variables in iteration U
V_C^t	Set of continuous variables in period t
V_I^t	Integer decision variables in period t, including X, Y, Z

Table 3: Ranges and values of parameters

Parameter Input	Value of Range
h_j	$U(1,5)$
b_j	$U(40,50)$
p_o	$U(0.1,0.2)$
$s_{jj'}(j \neq j')$	$U(3,4)$
d_{jt}	$U(0,50)$
c_t	$U(3100,3200)$
e_o	$U(2,10)$
γ_{jo}	$\{0,1\}$, $\sum_{o=1}^{\lvert O \rvert} \gamma_{jo} \geq 1$
M	100
$sc_{jj'}$	$U(60,70)$

Table 4: Results of numerical experiments totally CPLEX feasible)

For problem scales where all numerical examples are CPLEX-feasible							
$\|J\| \times \|O\| \times \|T\|$	$\overline{Gap_{CPLEX}}$	$\overline{t_{CPLEX}}$(s)	$r_{optimal}$	$\overline{Gap_{F\&O}}$	$\overline{t_{F\&O}}$(s)	ΔGap	$r_{outperform}$
$25 \times 10 \times 25$	0%	460.21	100%	4.72%	425.85	4.72%	0%
$25 \times 10 \times 30$	0%	565.62	100%	4.07%	536.75	4.07%	0%
$25 \times 15 \times 25$	1.44%	1003.34	80%	4.35%	602.63	2.91%	20%
$25 \times 15 \times 30$	1.96%	913.75	80%	4.42%	533.59	2.46%	20%
$30 \times 10 \times 25$	0%	822.62	100%	4.20%	443.11	4.20%	0%
$30 \times 15 \times 25$	0%	842.76	100%	4.61%	521.65	4.61%	0%
$35 \times 10 \times 25$	0%	943.9	100%	4.22%	585.6	4.41%	0%
$35 \times 10 \times 30$	3.70%	1151.53	60%	3.73%	714.35	0.03%	40%
$35 \times 15 \times 25$	0%	969.95	100%	4.44%	587.5	4.44%	0%

Table 5: Results of numerical experiments partly CPLEX feasible

For problem scales where numerical examples are partly CPLEX-feasible								
$\|J\| \times \|O\| \times \|T\|$	$r_{CPLEX\_feasible}$	$\overline{Gap_{CPLEX}}$	$\overline{t_{CPLEX}}$(s)	$r_{optimal}$	$r_{CPLEX\_feasible}$	$\overline{Gap_{F\&O}}$	$\overline{t_{F\&O}}$(s)	$r_{outperform}$
$25 \times 10 \times 35$	80%	2.69%	927.44	60%	100%	4.47%	785.97	40%
$25 \times 15 \times 35$	80%	1.88%	1044.81	60%	100%	3.85%	787.32	40%
$30 \times 10 \times 30$	60%	0%	946.82	60%	100%	4.15%	1044.55	40%
$30 \times 10 \times 35$	80%	0%	1462.47	60%	100%	4.24%	1285.76	20%
$30 \times 15 \times 30$	80%	0%	1203.74	80%	100%	4.52%	707.73	20%
$30 \times 15 \times 35$	40%	0.18%	1426.27	20%	100%	4.69%	1091.4	60%
$35 \times 10 \times 35$	20%	0%	1518.82	20%	100%	5.03%	1154.88	80%
$35 \times 15 \times 30$	60%	4.16%	1586.34	20%	100%	4.09%	956.73	60%
$35 \times 15 \times 35$	20%	4.10%	1815.81	0%	100%	4.35%	1191.08	80%

Table 6: Results of ANOVA on CPLEX and the F&O algorithm solution time

Factor	Products	Techniques	Periods	Linear	2-way Interaction
CPLEX					
F-Value	41.3	8.87	16.44	20.6	1.5
P-Value	0.00	0.00	0.00	0.00	0.14
F&O					
F-Value	628.69	33.28	282.02	314.67	61.6
P-Value	0.00	0.00	0.00	0.00	0.00

Table 7: Results of numerical experiments focusing on the cost

Result	Model A with $F\&O$		Model B with CPLEX		Ratio	
$\lvert J\rvert \times \lvert O\rvert \times \lvert T\rvert$	Total cost	Energy cost	Total cost	Energy cost	Total cost	Energy cost
$25 \times 10 \times 25$	57609	27184	89883	63175	35.91%	56.97%
$25 \times 10 \times 30$	70375	32554	105370	72869	33.21%	55.33%
$25 \times 10 \times 35$	82784	39884	121582	83427	31.91%	52.19%
$25 \times 15 \times 25$	59105	28038	86340	58999	31.54%	52.48%
$25 \times 15 \times 30$	71510	33524	110646	77892	35.37%	56.96%
$25 \times 15 \times 35$	84228	41008	126979	88508	33.67%	53.67%
$30 \times 10 \times 25$	71925	34324	106358	72794	32.37%	52.85%
$30 \times 10 \times 30$	86709	40228	127743	87437	32.12%	53.99%
$30 \times 10 \times 35$	102314	46640	149578	102143	31.60%	54.34%
$30 \times 15 \times 25$	73954	34848	111643	76645	33.76%	54.53%
$30 \times 15 \times 30$	89595	40920	141444	99046	36.66%	58.69%
$30 \times 15 \times 35$	104425	49982	163916	114429	36.29%	56.32%
$35 \times 10 \times 25$	84706	40384	126936	87741	33.27%	53.97%
$35 \times 10 \times 30$	102231	47812	163136	115822	37.33%	58.72%
$35 \times 10 \times 35$	120317	58504	204075	136331	41.04%	57.09%
$35 \times 15 \times 25$	83946	40654	131949	94503	36.38%	56.98%
$35 \times 15 \times 30$	101064	47828	155778	110368	35.12%	56.66%
$35 \times 15 \times 35$	117538	57664	188926	136260	37.79%	57.68%

Model A stands for model with the consideration of energy cost

Model B stands for model without the consideration of energy cost

Table 8: Techniques and energy consumption

Technique	Temperature (°C)	Extraction Time (min)	Processing Time (h)	Energy Cost (RMB)
1	65	13	0.36	2.53
2	70	9	0.29	2.81
3	75	6	0.25	3.15

Table 9: Value settings for parameters

Parameter Input	Value of Range
J	5
O	3
T	12
d_{jt}	$U(0, 100)$
s_{jj}	$U(4, 6)$
h_j	$U(1, 5)$
b_j	$10h_j$
$sc_{jj'}$	$U(140, 160)$

Table 10: Results of case study

Number	ΔEC_{CPLEX}	ΔTC_{CPLEX}	$\Delta EC_{F\&O}$	$\Delta TC_{F\&O}$
1	12.86%	7.14%	14.71%	9.40%
2	7.53%	4.06%	7.98%	4.36%
2	9.16%	5.40%	11.83%	6.57%
4	9.32%	5.55%	10.24%	5.40%
5	11.78%	6.63%	9.98%	5.11%
Average	10.13%	5.76%	10.95%	6.17%

Figure Captions

Figure 1. Structure of the considered problem

Figure 2. Fix and optimize heuristic

Figure 3. The production process of tea production line

Figures

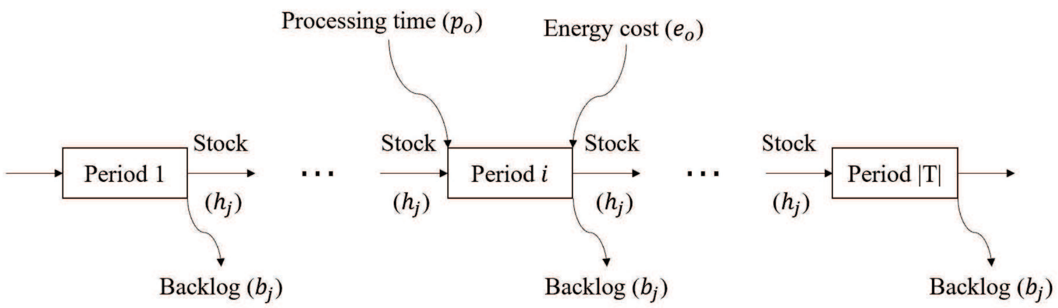

Figure 1: Structure of the considered problem

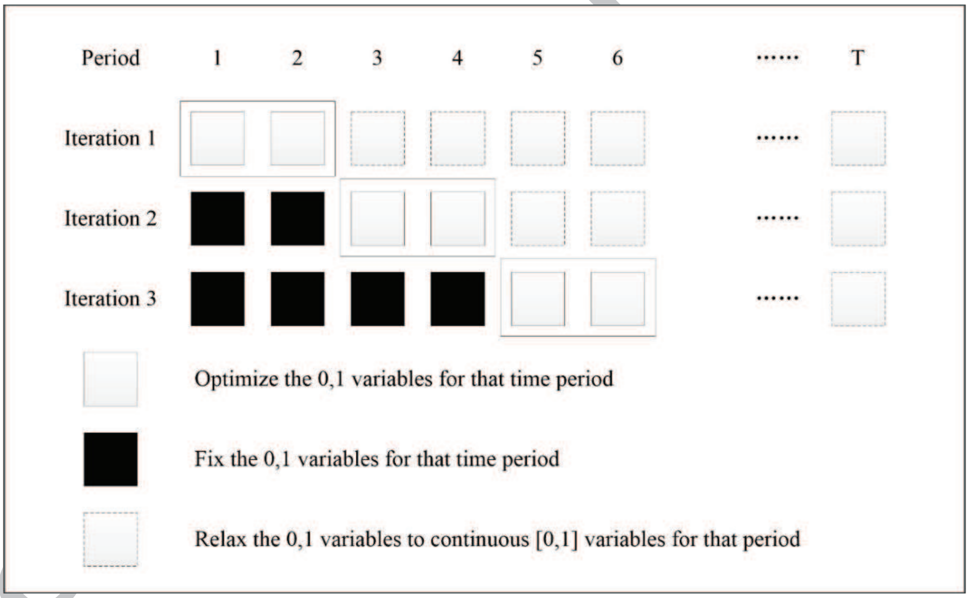

Figure 2: Fix and optimize heuristic

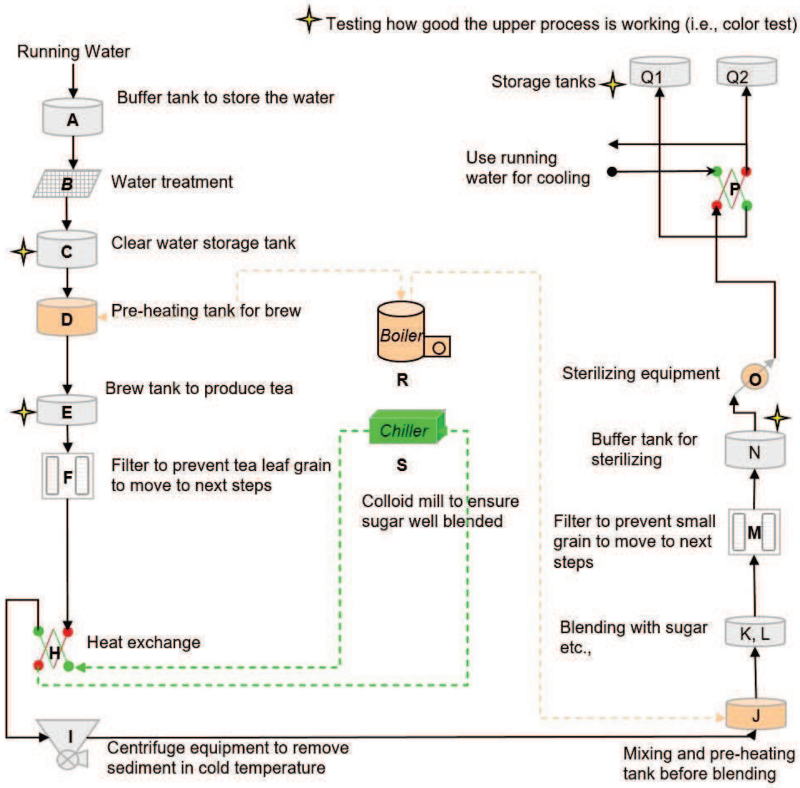

Figure 3: The production process of tea production line

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Highlight

- A capacitate production planning and scheduling problem with energy concerns is studied.
- An efficient fix and optimize heuristic algorithm is proposed.
- The numerical study illustrates that larger number of techniques contributes to cost reduction.
- The case study demonstrates that large declines of total and energy cost are made by applying the proposed algorithm.