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Process Planning Optimization With Energy Consumption Reduction From a Novel Perspective: Mathematical Modeling and a Dynamic Programming-Like Heuristic Algorithm

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ABSTRACT Process planning can be deemed as an important component in manufacturing systems. It bridges the gap between designing and manufacturing by specifying the manufacturing requirements and details to convert a part from raw materials to the finished form. For the purpose of low carbon emission, this paper pays attention to both technical performance measures and environmental impact criteria. In this problem, a part may have more than one process plans and only one process plan can finally be adopted. Due to the non-deterministic polynomial-hardness, it is rather difficult to conduct operation selection, machine determination, operation sequencing, and energy consumption reduction simultaneously with various constraints from technical requirements or the shop floor status. A novel position-based mixed integer linear programming model is developed to reduce total production time and the total energy consumption. The energy consumption coefficient matrix is proposed to evaluate the energy consumption in process planning. Because of the complexity in solving the model, this research proposes dynamic programming-like heuristic algorithm to tackle this problem. The weighted sum method is applied in multi-objective optimization and three typical instances with operation flexibility, sequencing flexibility, and processing flexibility are used to test the proposed algorithm. According to the results, both the total production time and the energy consumption criteria are optimized; in the best case, the energy consumption after optimization takes only 21.2% of the one before optimization. On average, about 40.9% of the total energy consumption can be reduced after optimization. Computational results also show that the proposed algorithm is generally better than the genetic algorithm. This research gives a novel perspective to reduce energy consumption in the process planning stage.

INDEX TERMS Energy consumption reduction, dynamic programming, green process planning, heuristic algorithms, operations selection & sequencing, production time minimization.

I. INTRODUCTION

Process planning is an important component in a manufacturing system because it bridges the gap between designing and manufacturing to convert a part from raw material to the finished form [1]. The technical requirements for manufacturing procedures on the basis of the corresponding design schemes or blueprints will be specified in process planning stage. Usually, a part is formed by some features and each feature corresponds to at least one operation. A part will not be finished unless all the features(operations) have been processed. In this research, process planning determines the necessary operations with a feasible operation sequence, and it also assigns each operation to an available machine to finish the part, such that corresponding criteria, e.g. the machining cost and the machining time, can be optimized and more importantly the decision making as well as knowledge management in manufacturing processes can be improved [2]. The process planning problem have been paid more research attentions for decades because it is quite a challenging problem in determining the most suitable machining resources, e.g. machines, tools and operation permutations, among all the alternative ones. Such flexibilities in machining resources as well as the organization of machining procedures increase the difficulty of the problem at both manufacturing systems level and operations level [3]. Therefore, lots of investigations on process planning optimizations have been performed and some fruitful results are observed. For instance, Hu *et al.* [4] suggested an ant colony algorithm in process planning to ensure feasible operation permutations. In general, existing publications regarding process planning optimization put more emphasis on obtaining an optimal process plan of a part with the minimum machining cost or the shortest machining time [5].

Admittedly, the machining cost and the machining time are two crucial criteria in process planning optimization; nevertheless, environment friendliness is assuming ever greater prominence with industry and government entities; sustainability is becoming a big concern in manufacturing sectors [6]. The shortcomings of existing research stem from the lack of concerns of environmental friendliness [7]–[9], e.g. carbon emission reduction, and relative research regarding low carbon emission or energy saving in process planning is rather limited. In fact, environmental problems grow grimmer by the day in industrial sectors: the massive consumption of coal-fired electricity in manufacturing sectors indirectly contributes the carbon emission, and hence this causes global warming and has raised worldwide concerns [10], [11]. Since manufacturing processes have already become a major source of energy consumption, energy consumption (carbon emission) reduction has received high publicity. Many countries issued critical environmental regulations to enforce enterprises to take carbon emission reduction as a mandatory action. Achieving low carbon emission and decoupling the manufacturing sector from high emissions is highly desired [12]. Therefore, only the economical criteria, e.g. total production time or machining cost minimization, in process planning optimization can no longer meet the actual low carbon emission requirements in manufacturing sectors today. Duflou *et al.* [13] have pointed out that both product manufacturing and design decisions control intensity of the energy and resource consumed. The desire of energy saving in manufacturing is the driving force of this research: to produce more and fast with less energy consumption. Since process planning relates closely with actual manufacturing activities [14], different with existing research papers, in this research we take a step of exploration to realize energy consumption reduction (and also carbon emission reduction) in process planning stage from a novel perspective .

Existing literature [6] reveals that the arrangement of features to be processed in a part will affect the total energy consumption during manufacturing, and there is no systematic research or approaches proposed to realize energy saving in process planning stage. Besides the traditional process planning optimization, this research therefore tries to develop a quantification method to evaluate the energy consumption in different feature (operation) permutations for the optimization of both the total production time and the energy consumption. In this research, the proposed energy consumption coefficient matrix (ECCM) enables the quantification of the energy consumption of features in different operation permutations; The outstanding feature of this research is that we construct a general optimization framework to facilitate energy consumption reduction in process planning optimization based on the energy consumption coefficient matrix. In addition, a novel position based mixed integer linear programming (MILP) model of process planning problems with energy consumption reduction is proposed; due to the characteristics of the problem, we develop a dynamic programming-like heuristic algorithm to addressed the problem, and both the total production time as well as the energy consumption are optimized in a weighted sum manner. Besides the promising results, the novelty of this research consists of the following points:

- This research presents a novel perspective to realize carbon emission reduction in process planning. Especially, the ECCM is established to model the influence on energy consumption induced by different feature (operation) permutations. This method has not been considered by other researchers.
- A novel position based MILP modeling method is developed to accommodate tabular based process planning problems for energy consumption reduction.
- A DP-like heuristic algorithm is proposed. Process planning problems (instances) that once were solved by meta-heuristics can now be optimized by the proposed method with more promising results.

II. RELATED WORKS

A considerable amount of attempts have been paid in both academia and engineering practice to determine the optimal process plan from all the alternative ones of a part; nevertheless, since meta-heuristics are the effective approaches to address NP-hard problems in engineering [15], [16], close attentions have been paid mainly to evolutional and meta-heuristic based approaches in process planning optimization. For instance, Lian *et al.* [17] proposed an imperialist competitive algorithm (ICA) in process planning optimization to minimize total weighted sum of manufacturing costs including machine cost, tool cost, machine change cost, set-up change cost and tool change cost. Shin *et al.* [18] presented a multi-objective symbiotic evolutionary algorithm for the process planning problem, where flexible process plans are presented using network graphs. Manupati *et al.* [19] suggested a near optimal process plan selection method in the context of network based manufacturing system, and a territory defining evolutionary algorithm based multi-objective optimization technique is developed. Liu *et al.* [20] gives an ant colony optimization (ACO) algorithm to reduce the total cost in machining process. In recent years, novel evolutionary or meta-heuristic algorithms have received wide applications. Hu *et al.* [4] developed a hybrid ant colony algorithm to facilitate a feasible operation sequencing in process planning optimization with the objective of total weighted production cost reduction. More meta-heuristic algorithm based process planning optimization methods can be found in other existing publications. Due to limited space, interested readers can refer to Li *et al.*'s work [21] and Kumar's research [22] for more information.

Apart from the literature reviewed above, other solution approaches, such as integer programming approaches, have also been investigated although such methods are seldom been applied in the discussed problem. An integer programming model is established recently in [23] to reduce the total production time and detailed optimal machining parameters can be obtained. Nevertheless, massive 0-1 variables are significant barriers in solving integer programming models. Since the process planning optimization stems from multistage manufacturing processes, interactions between sequentially performed operations should be considered during the optimization process [3]; therefore, the dynamic programming (DP) based approach is another method to address process planning problems. Dynamic programming is a sequential interrelated decision and optimization method; it usually cuts a large unwieldy problem into a series of small and tractable problems in a recursive manner. Park and Khoshnevis [5] introduced a computer aided process planning (CAPP) system for product design. In their approach, operation (feature) sequencing is achieved using a heuristic algorithm while machine determination is performed using a dynamic programming technique, and these two procedures are performed in two sequential levels. Since the two procedures are performed separately, the critical deficiency is that optimal operation (feature) sequence cannot ensure optimal or near optimal machines that are determined for certain operations in the dynamic programming stage. Besides, the machine change cost induced by machine tool change in two sequential operations (features) was not considered in their research. Nevertheless, such cost is quite important in real-life shop floor environment because frequent machine changes between operations will affect raw material storages as well as increase machine workload burden.

According to the literature reviewed above, most of the research papers focus on traditional process planning problems; nevertheless, with the awareness of the importance of environmental friendliness, researchers are showing their interests on carbon emission reduction or energy saving in manufacturing activities [24]–[30]. For instance, Ding *et al.* [30] suggested an effective multi-objective NEH algorithm as well as a modified multi-objective iterated greedy algorithm to achieve low carbon emission and makespan minimization in a permutation flow shop; their methods enriched and developed the well-known NEH algorithm. Apart from heuristic based approaches, meta-heuristic based algorithms are more popular in solving such problems. Liu *et al.* [31] adopted an NSGA-II algorithm for carbon emission reduction; their experimental results show that the cutting speed is more important than the feed rate in carbon emission reduction. Bhanot *et al.* [32] developed an integrated sustainability assessment framework for the turning process; two machining scenarios, e.g. dry and wet turning, have been investigated from both economic and environmental perspectives; it shows that dry turning may perform better at specific conditions. In order to determine energy-efficient flow shop scheduling schemes, Fang *et al.* [33] presents a mathematical model for the flow shop scheduling problem to optimize peak power load, energy consumption and associated carbon footprint; however, the computation is quite time consuming. Meanwhile, single machine scheduling problems with both total earliness/tardiness and energy consumption reduction have bee considered by Yin *et al.* [26], they use local multi-objective evolutionary algorithm to tackle this problem. Meng *et al.* [34] investigated an energy-conscious hybrid flow shop scheduling problem with unrelated parallel machines and an improved genetic algorithm is developed.

Most of the aforementioned publications, nevertheless, mainly concentrate on either energy-efficient scheduling problems or energy saving methods for a specific machining procedure instead of paying attentions to carbon reduction or energy-awareness at the process planning stage. In fact, carbon emission awareness can also be considered at the process planning stage although such research is limited. For example, Tao *et al.* [35] hybridizes the artificial bee colony (ABC) algorithm and Tabu search (TS) algorithm; they applied the hybrid algorithm for both energy consumption and processing time reduction in process planning optimization. In Zhang *et al.*'s work [36], the authors developed an ant colony optimization based algorithm to reduce energy consumption in a flexible manufacturing system by introducing energy consumption evaluation criteria and three energy efficiency indicators. Yi *et al.* [37] pointed out that determinations of processing methods, machines, cutting tools, sequence of process stages, etc. in process planning have significant impact on carbon emission in manufacture procedures; therefore, they used a coefficient multiplied evaluation method as well as a non-dominated sorting genetic algorithm to seek an acceptable solution.

Based on our observations, the process planning optimization with carbon emission reduction or energy consumption awareness can be divided into two levels: the micro level and the macro level. In the micro level, detailed methods for carbon emission or energy consumption evaluation for a general process (a stage or a feature) will be developed based on the mechanical or electrical theory; after that, the carbon emission or energy consumption can thus be quantified. The other level, however, concentrates mainly on the optimization method, e.g. optimal operation(feature) sequence, to achieve a reasonable solution that can strike a balance between the economical criterion and the energy-conscious criterion. Yin *et al.* [6] in 2014 introduced a novel method to evaluate the energy consumption for each feature in process planning, and they found that different feasible feature (or operation) sequences can induce significant impact on carbon emission (energy consumption); therefore, Yin *et al.* developed a carbon emission function at first and in the second level the genetic algorithm based solution method was proposed to obtain a comparatively "green" and economical process plan. In their research, the proposed carbon emission function gives the clue to evaluate carbon emission in process planning; however, there lacks a more general framework to reduce both the total production time as well as energy consumption in process planning based on the carbon emission value obtained in the first level.

In this research, we consider both the economical and the energy-awareness related criteria in multi-objective process planning optimization. Since different feature sequences will induce discrepant energy consumption situations, inspired by Yin *et al.*'s energy consumption evaluation method [6], we propose a more general method to reduce energy consumption in process planning stage using an energy consumption coefficient matrix. A novel mixed integer linear programming model is first established for the considered problem with the criteria of total production time and the sum of energy consumption coefficients (total energy consumption). Different with the problem where only the optimal sequencing is considered [38], the machine determination and the operation sequencing are performed simultaneously in the developed model as well as the proposed search mechanism. Instead of the abused meta-heuristics, this paper presents a novel way for process planning optimization by using a dynamic programming-like search procedure to obtain near optimal solutions. This paper therefore proceeds as follows. The problem description, energy consumption representation, and the mixed integer linear programming model will be presented in the next section. Section IV gives the dynamic programming like solution approach and the corresponding experiments will be reported in Section V. Conclusions will be presented in the last section to finalize the paper.

III. MATHEMATICAL MODELING

A. PROBLEM DESCRIPTION

As shown in Table 1, the process planning problem can be expressed in a tabular form [21], where machining details with requirements are specified. Usually, a part has several features and each feature contains one or more operations. A feature sometimes may contain two or more alternative operation sets and only one set of operations is required to complete the feature. Each feature (operation) can be performed by one of the available machines with corresponding processing times. Moreover, different feature permutations are allowed as long as the features follow a feasible precedence relationship specified in the table. The complexity involved in process planning stems from three kinds of flexibilities: operation flexibility (OF), sequencing flexibility (SF) and processing flexibility (PF). For the case in Table 1, it can be found that feature 2 can be completed either by performing operation set O_2 and O_3 or operation set O_4 and O_5; this represents the processing flexibility in process planning; in the first operation set of feature F_2, operation O_2 can be processed by machine M_5, M_6 or M_8 with processing times 16, 12 and 13 respectively, and this reflects the operation flexibility. Moreover, the sequencing flexibility allows feature F_2 to be arranged at any position in a feature processing sequence provided it is processed before feature F_3. Sometimes, a certain feature may include a fine machining procedure to meet the technological requirements; in such a case, additional features(operations) can be added to facilitate such requirements. The optimization of this problem should treat the following issues properly:

- The feature(operation) sequence in each plan should follow a feasible precedence relationship such that a part can be processed accurately.
- Each operation should be assigned a proper machine tool such that total transmission time between machines can be minimized.
- Since different feature sequences have significant impact on carbon emission (energy consumption), the feature(operation) sequence in an optimal process

TABLE 1. Flexible process planning representation of a part.

Feature	Operations	Alternative machines	Processing time	Feature precedence
F_1	O_1	M_3, M_8	$8, 13$	BeforeF_2, F_3
F_2	$O_2 - O_3$	$M_5, M_6, M_8/M_2$	$16, 12, 13/21$	BeforeF_3
	$O_4 - O_5$	$M_1, M_5, M_{10}/M_9$	$13, 16, 18/17$	
F_3	O_6	M_5, M_8	$46, 47$	
F_4	O_7	M_3, M_7, M_{13}	$44, 48, 49$	BeforeF_5, F_6, F_7
F_5	O_8	M_5, M_6, M_{13}	$17, 14, 10$	BeforeF_6, F_7
	O_9	M_5, M_{15}	$16, 13$	
F_6	O_{10}	M_3, M_{11}, M_{15}	$28, 27, 30$	BeforeF_7
F_7	O_{11}	M_{10}, M_{13}	$48, 50$	
F_8	O_{12}	M_5, M_{13}, M_{15}	$31, 32, 36$	BeforeF_9, F_{10}, F_{11}
F_9	O_{13}	M_3, M_6, M_9	$30, 28, 26$	BeforeF_{10}, F_{11}
	$O_{14} - O_{15}$	$M_2/M_1, M_{14}$	$11/16, 18$	
F_{10}	O_{16}	M_4, M_{15}	$18, 19$	BeforeF_{11}
F_{11}	O_{17}	M_3, M_{10}, M_{14}	$36, 32, 35$	

TABLE 2. Energy consumption and carbon emission of two process plans [6].

Alternative process plans	Energy consumption (J)	Carbon emission (kg CO_2e)
Drilling → Milling	4250	9.4E-4
Milling → Drilling	2810	6.2E-4

plan should also achieve optimal or near optimal carbon emission or energy consumption.

B. ENERGY CONSUMPTION EVALUATION

Carbon emission in manufacturing can usually be divided into three categories [39]: fossil fuel emission (Scope 1), the carbon emission from indirect energy consumption (Scope 2), and the indirect carbon emission from supply chain (Scope 3). Following Yin *et al.*'s work [6], we mainly consider electrical energy consumption as the major source of carbon emission in this paper. Yin *et al.* have pointed out that the carbon emission or energy consumption will change with the machining sequence of features (operations) in a process plan. For the part shown in Fig. 1, it contains two features: a hole and some planes, and therefore it has two exchangeable operations: drilling and milling. Beyond one's expectation, the carbon emission values differ greatly in two process plans when the processing order of drilling and milling is changed according to table 2. If drilling is scheduled before milling, the total energy consumption is 4250J; however the value drops to 2810J when the two operations are exchanged. In other words, the latter process planning scheme can save about 1/3 of the energy consumed in former scheme. Clearly, a proper feature processing sequence can bring benefits to the total carbon emission.

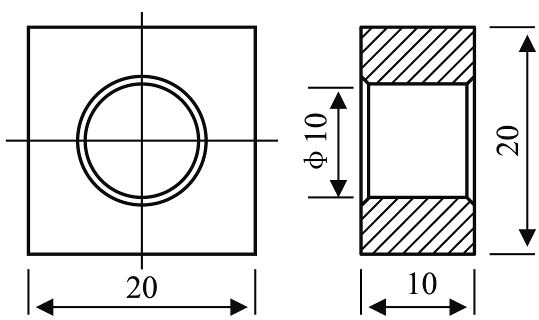

FIGURE 1. An example part [6].

Obviously, if any two features have no precedence relationships, we can determine a more "green" precedence relationship for the two features. Therefore, after evaluating the energy consumption of any two features that have no precedence relationship as the case in Table 2 based on the Yin *et al.*'s energy consumption evaluation method, a normalized matrix called the energy consumption coefficient matrix (ECCM) can be introduced to calculate total energy consumption. For instance, the corresponding ECCM of the part in Fig. 1 can be expressed as $\lambda = \begin{bmatrix} 0 & 1 \\ 0.66 & 0 \end{bmatrix}$ and this means that if process plan "Drilling → Milling" consumes "1" unit energy, the process plan "Milling → Drilling" consumes only "0.66" unit energy. More generally, a nonzero element λ_{ij} in an ECCM λ stands for the normalized energy consumption degree if feature j is processed immediately after feature i. With the ECCM, the total energy consumption can be evaluated easily.

C. MODELING THE PROBLEM

In this section, a novel MILP model is developed with the purpose of total production time reduction and total energy consumption reduction. According to existing publications, the proposed position based MILP model for process planning optimization, where corresponding data are described in a tabular form (Table 1, for example), has not been considered before. In the established MILP model, a position based modeling strategy is developed to accommodate operation permutations and hence the total transmission time between machines can be calculated. By introducing proper constraints, proper operation selection, manufacturing resource determination and operation sequencing in process planning can be achieved simultaneously. In the following, some sets, subscriptions are first introduced.

SUBSCRIPTS & NOTATIONS

i, i'	features, $1 \leq i, i' \leq \lvert F \rvert$,
j, j'	operation sets, $1 \leq j, j' \leq \lvert S_i \rvert$,
k, k'	operations,
l, l'	machines,
r	positions,
h	places, where a feature can be assigned, $1 \leq h \leq \lvert F \rvert$

SETS & PARAMETERS

F	the set of total features,
R	the set of positions,
OP	the set of all the operations,
M_k	the set of available machine tools of operation O_k,
S_i	the operation set that contained in the ith feature (for example, feature F_2 in Table 1 has two operation sets: '$O_2 - O_3$' and '$O_4 - O_5$' and Features F_5 and F_9 also have two two operation sets each; sometimes, there is only one operation set for a feature),
OS_{ij}	the set of operations in the jth operation set of feature i,
$P_{k,k'}$	=1, if operation O_k is processed directly before $O_{k'}$ according to the table (e.g. Table 1); =0, otherwise,

$Q_{k,k'}$ =1, if operation O_k is processed directly or indirectly before $O_{k'}$ based on the data in the table (for example, we have $Q_{1,6} = 1$ and $Q_{2,3} = 1$ according to Table 1); =0, otherwise,

t_{kl} the machining time of operation k on machine l,

$MT_{l,l'}$ the machine transmission time from machine l to machine l',

$\lambda_{i,i'}$ the normalized energy consumption degree if feature i' is processed immediately after feature i.

$FP_{i,i'}$ =1, if feature i is processed before feature i'; =0, otherwise,

H an integer in the range $[1, |F|]$,

A a very large positive integer,

VARIABLES

X_{ij} =1, if the jth operation set of the ith feature is selected; =0, otherwise,

O_k =1, if operation k is selected; =0, otherwise,

Y_{kl} =1, if operation k is processed on machine l; =0, otherwise,

$u_{k,k'}$ =1, if operation k is processed before operation k', where operations k and k' has no precedence relationship (that is, $Q_{k,k'} = Q_{k',k} = 0$); =0, otherwise,

MTT_r the transmission time between two machines of two operations in positions r and $r+1$ respectively, $1 \leq r \leq (|R| - 1)$,

T_{rk} =1, if operation k is located at the rth position; =0, otherwise,

V_{ih} =1, if feature i is arranged in h-th place; =0, otherwise,

W_h the energy consumption coefficient of two features that are assigned in the h-th and $(h+1)$-th place,

Z_1 total production time,

Z_2 total energy consumption (the sum of energy consumption coefficients of the features),

OBJECTIVES

The first objective is to minimize total production time, and it contains the sum of machining time of operations and the total transmission time between operations.

$$\min \quad Z_1 = \sum_{k \in OP} \sum_{l \in M_k} Y_{kl} t_{kl} + \sum_{r=1}^{|R|-1} MTT_r \tag{1}$$

In the second objective, the sum of the energy consumption coefficients is calculated and minimized.

$$\min \quad Z_2 = \sum_{h=1}^{|F|-1} W_h \tag{2}$$

CONSTRAINTS

For each feature, exactly one operation set should selected.

$$\sum_{j \in S_i} X_{ij} = 1, \quad \forall\, i \in F \tag{3}$$

Since for some features that have more than one operation sets, only one operation set is selected; some operations are bound to be redundant. Then, constraint sets 4 are introduced to identify the selected operations.

$$O_k = X_{ij}, \quad \forall k \in OS_{ij}, \ \forall i \in F, \forall j \in S_i \tag{4}$$

Naturally, each selected operation should determine exactly one machine such that the machining process can be completed.

$$\sum_{l \in M_k} Y_{kl} = O_k, \quad \forall k \in OP \tag{5}$$

Due to the processing flexibility, some operations are not selected; thus, it is quite difficult to sequence the selected operations and this makes it impossible to calculate the total transmission time between machines. In this paper, a position based modeling strategy is developed; in such modeling strategy, the selected operations together with corresponding machines are sequenced in a series of stationary positions (locations). A variable T_{rk} is introduced to decide toward which position an operation can be located. First, a position r can hold only one operation at most, and we have constraint set 6 as follows

$$\sum_{k \in OP} T_{rk} \leq 1, \quad \forall r \in R \tag{6}$$

Second, if two selected operations has a certain precedence relationship, e.g. $Q_{k,k'} = 1$, their positions should be determined: the position that holds operation O_k should appear before the one hold $O_{k'}$. In constraint set 7, the constraint is relaxed unless $Q_{k,k'} = 1$ and both of the two operations $(O_k, O_{k'})$ is selected. Before this, however, the parameter $Q_{k,k'}$ needs to be determined. As discussed above, the parameter $P_{k,k'}$ specifies the direct precedence relationship between operations. Nevertheless, there are other direct precedence relationships; for instance, $P_{2,3} = 1$ for operations O_2 and O_3 in the first operation set of feature 2 in Table 1. The parameter $Q_{k,k'}$ is thus introduced to specify the precedence relationship between any two operations: if $Q_{k,k'} = 1$ or $Q_{k',k} = 1$, then $O_k(O_{k'})$ will be processed before $O_{k'}(O_k)$; further, $O_{k,k'} = O_{k',k} = 0$ denotes there is no precedence relationship between two operations and additional constraints will be introduced. The parameter $Q_{k,k'}$ can be obtained by Algorithm 1.

For the operations that have no precedence relationships, constraint set 7 is powerless to deal such issue. In such a case, only the operations that satisfy $Q_{k,k'} = Q_{k',k} = 0$ will be considered; constraint sets 8 and 9 are thus introduced to force one of the 0-1 variables $u_{k,k'}$ and $u_{k',k}$ to take value 1. Two terms $A(Q_{k,k'} + Q_{k',k})$ and $A(2 - O_k - O_{k'})$ are added in the constraints to hedge against the operations that already has a precedence relationship between each other and the unselected operations (if $Q_{k,k'} = 1$ or $Q_{k',k} = 1$ the

Algorithm 1 Determine Parameters $Q_{k,k'}$

```
for k := 1 to |OP| do
  for k' := 1 to |OP| do
    if (k ≠ k')and(P_{k,k'} = 1) then
      Q_{k,k'} :=1
    end if
  end for
end for
for k := 1 to |OP| do
  for k' := 1 to |OP| do
    for k'' := 1 to |OP| do
      if (k ≠ k')and(k' ≠ k'')and(k ≠ k'')and(Q_{k,k'} =
      1)and(Q_{k',k''} = 1) then
        Q_{k,k''} :=1
      end if
    end for
  end for
end for
```

constraint is relaxed).

$$T_{rk} \geq T_{rk'} - A\left(1 - Q_{kk'}\right) - A\left(2 - O_k - O_{k'}\right), \quad \forall r \in R, \quad \forall k, k' \in OP \tag{7}$$

$$u_{k,k'} + u_{k',k} \geq 1 - A\left(Q_{k,k'} + Q_{k',k}\right) - A\left(2 - O_k - O_{k'}\right), \quad \forall k, k' \in OP, \quad k \neq k' \tag{8}$$

$$u_{k,k'} + u_{k',k} \leq 1 + A\left(Q_{k,k'} + Q_{k',k}\right) + A\left(2 - O_k - O_{k'}\right), \quad \forall k, k' \in OP, \quad k \neq k' \tag{9}$$

Similar to the case in constraint set 7, we have the following constraints:

$$T_{rk} \geq T_{rk'} - A\left(1 - u_{k,k'}\right) - A\left(Q_{k,k'} + Q_{k',k}\right) - A\left(2 - O_k - O_{k'}\right), \quad \forall r \in R, \ \forall k, k' \in OP \tag{10}$$

For a selected operation O_k, it is bound to be assigned to a position:

$$\sum_{r \in R} T_{rk} = O_k, \quad \forall k \in OP \tag{11}$$

After selected operations are all assigned to positions, the transmission time between machines is still unable to be calculated because there may have one or more vacant position(s) and it is quite difficult to evaluate transmission time between machines in this case. The following constraint set is developed to facilitate the transmission time calculation by edging out the vacant position(s) between two occupied positions.

$$\sum_{k \in OP} T_{rk} \geq \sum_{k \in OP} T_{r+1,k}, \quad \forall r \in R \tag{12}$$

The principle of inequality set 12 is easy: suppose there is a vacant position r between two occupied positions $r-1$ and $r+1$, it then follows that $\sum_{k \in OP} T_{rk} = 0$ (a given position r will not be occupied by any operation) and $\sum_{k \in OP} T_{r+1,k} = 1$; therefore, the inequality $\sum_{k \in OP} T_{rk} < \sum_{k \in OP} T_{r+1,k}$ holds. Constraint set 12 is introduced to edge out vacant position(s).

Finally, the transmission time between machines in positions r and $r+1$ can be determined as follows.

$$MTT_r \leq MT_{l,l'} + A\left(2 - T_{rk} - T_{r+1,k'}\right) + A\left(2 - O_k - O_{k'}\right) + A\left(2 - Y_{kl} - Y_{k'l'}\right), \quad \forall l, l' \in M_k, \quad \forall r \in R, r < |R|, \ \forall k, k' \in OP, k \neq k' \tag{13}$$

$$MTT_r \geq MT_{l,l'} - A\left(2 - T_{rk} - T_{r+1,k'}\right) - A\left(2 - O_k - O_{k'}\right) - A\left(2 - Y_{kl} - Y_{k'l'}\right), \quad \forall l, l' \in M_k, \quad \forall r \in R, r < |R|, \ \forall k, k' \in OP, k \neq k' \tag{14}$$

After applying constraint set 12, vacant positions are all arranged at the bottom of positions. The transmission time between two machines can be calculated for two adjacent positions where operations with corresponding machines have been assigned; the two constraint sets will be relaxed if either one position (position r or $r+1$) is a vacant position (T_{rk} or $T_{r+1,k'}$ equals 0), and corresponding transmission time is 0.

For each feature, it should be assigned to a proper place, and more importantly, the precedence relationships between features are forced to follow a correct sequence. Therefore, the following two constraint sets are employed.

$$\sum_{h=1}^{|F|} V_{ih} = 1, \quad \forall i \in F \tag{15}$$

$$\sum_{h=1}^{H} V_{ih} \geq \sum_{h=1}^{H} V_{i'h} - A\left(1 - FP_{i,i'}\right), \quad \forall i, i' \in F, \ i \neq i' \quad \forall H \in [1 \ \ |F|] \tag{16}$$

Finally, the energy consumption coefficient of two adjacent features is determined using constraint sets 17 and 18.

$$W_h \geq \lambda_{i,i'} - A\left(2 - V_{ih} - V_{i',h+1}\right), \quad \forall i, i' \in F, \ i \neq i', \quad \forall h \in [1 \ \ |F|] \tag{17}$$

$$W_h \leq \lambda_{i,i'} + A\left(2 - V_{ih} - V_{i',h+1}\right), \quad \forall i, i' \in F, \ i \neq i', \quad \forall h \in [1 \ \ |F|] \tag{18}$$

The MILP model above for the process planning problem studied in this paper has not been investigated before; the proposed MILP model can be applied to solve process planning problems. Nevertheless, due to massive 0-1 variables in the model, a satisfactory solution usually cannot be captured using the commercial solvers in reasonable computational time. To overcome such drawbacks, many researchers turn for aid to meta-heuristics; this research, however, tries to develop a novel approach for the bi-objective process planning optimization problem using a dynamic programming-like heuristic algorithm.

IV. THE DP-LIKE HEURISTIC ALGORITHM

Dynamic programming is suitable for the cases where a series of interrelated decision making is required. After one decision is made, the current state is transformed into a new optimal state, and the global optimal solution is obtained after all the stages are completed. In the proposed MILP model, all the features can be obtained by performing operation selection, operation sequencing, and machine selection simultaneously; in the proposed DP-like heuristic, however, it is impossible to decide which operation can be selected and which one to be left as it is because the number of operations in operation sets of a feature is not determined (for example, according to Table 1 there is only one operation O_{13} in the first operation set of feature F_9 while the other operation set has two operations $O_{14}-O_{15}$); in other words, the number of stages in a DP model in such a case is not determined. Instead, the proposed DP-like heuristic is established based on features since the number of features is predetermined. Meanwhile, with the given ECCM, the best feature processing sequence can also be captured using the dynamic programming based approach such that a process plan (feature sequence) with lowest energy consumption can be obtained by minimizing the sum of elements in the corresponding ECCM (e.g. $\sum \lambda_{i,i'}$). In the following, the DP-like heuristic algorithm will be detailed.

A. SEARCH MECHANISM

The operation sequence can be determined one by one from the first operation (operation ID $=$ 1) to the last one in a conventional manner; in the proposed algorithm, however, the backward recursion search mechanism is adopted and thus the search process can be started from any one of the available features with the lowest priorities according to the given feature precedence relationships. Since the feature permutation in a process plan has an impact on the energy consumption during manufacturing, both the production time as well as the total energy consumption will be considered in a weighted sum manner to realize the multi-objective optimization. For the first objective, e.g. the total production time, it consists of two parts: the machining time and the part transmission time between machines. For the other objective, a more "green" feature processing sequence can be obtained by properly sequencing two features that have no precedence relationship (placing the feature i before feature i' if $\lambda_{i,i'} < \lambda_{i',i}$). If two features have no precedence relationship, as analyzed before [6], this may result in great differences in energy consumption. By referencing to the ECCM, the optimal or near optimal feature processing sequence for low carbon emission can be determined. Thus, based on the Yin *et al.*'s method and the normalization technique, the energy consumption coefficient of two features can be calculated. Eq.19 gives the corresponding ECCM of the example part in Table 1. According to Table 1, feature 4 is bound to be arranged before feature 7, and therefore, $\lambda_{4,7}$ in 19 equals 0; for features 5 and 9, however, they have no precedence relationship and clearly feature 5 should be processed directly before feature 9 if possible because $\lambda_{9,5} > \lambda_{5,9}$. After this, about 21% of the energy will be saved compared with the case where feature 9 is placed directly before feature 5.

$$\lambda = \begin{bmatrix} 0 & 0 & 0 & 1 & 1 & 0.62 & 0.8 & 1 & 0.99 & 0.66 & 0.89 \\ 0 & 0 & 0 & 0.59 & 0.83 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0.6 & 1 & 0.85 & 1 & 1 & 0.57 & 0.72 \\ 0.84 & 1 & 0.51 & 0 & 0 & 0 & 0 & 0.53 & 1 & 0.9 & 1 \\ 0.91 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0.79 & 0.99 & 0.76 \\ 1 & 0.85 & 0.57 & 0 & 0 & 0 & 0 & 0.79 & 1 & 0.9 & 1 \\ 1 & 0.98 & 1 & 0 & 0 & 0 & 0 & 0.88 & 1 & 1 & 0.91 \\ 0.61 & 0.74 & 0.67 & 1 & 0.8 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0.58 & 0.51 & 0.59 & 1 & 0.97 & 0.52 & 0 & 0 & 0 & 0 \\ 1 & 0.7 & 1 & 1 & 1 & 1 & 0.88 & 0 & 0 & 0 & 0 \\ 1 & 0.82 & 1 & 0.58 & 1 & 0.99 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{19}$$

In single objective optimization, the total cumulative production time can be deemed as the current objective value; in multi-objective optimization, the weighted sum manner is adopted to minimize the two objectives simultaneously. Suppose each feature can be deemed as a stage, the immediate total production time and the energy consumption from stage (the total objective value) k to stage $k-1$ can be formulated as $T(S_{j,k-1}, S_{i,k})$, where i and j are the indexes of states that represent the determined feature as well as the selected machine for that stage. In the backward search mechanism, the algorithm begins by determining the best feature with the corresponding machine(s) for operations in an operation set with the the lowest priority; that is, the total cumulative objective value of the last stage (for the last feature) satisfies $\widetilde{T}(S_N) = T(S_{j,N})$, where N is the total number of features or stages. For the stage except the last stage, e.g. stage $k-1$, the optimal policy can be obtained using a recursive procedure based on the cumulative total production time up to stage k:

$$\widetilde{T}\left(S_{k-1}\right) = \min_{1 \le i \le m} \left\{ \widetilde{T}\left(S_k\right) + T\left(S_{i,k-1}, S_{j,k}\right) \right\} \tag{20}$$

where $\widetilde{T}\left(S_{k-1}\right)$ denotes the cumulative total production time from stage N up to stage $k-1$ and m refers to the the number of available states in stage $k-1$. We assume that the two objectives are equally important in this multi-objective optimization, and the total objective value can thus be expressed as the sum of the two ratios: $\frac{\sum\left(t_{k,l}+MT_{l,l'}\right)}{UB_1} + \frac{\sum \lambda_{i,i'}}{UB_2}$; where UB_1 and UB_2 are the upper bounds of the two objectives, and they can be obtained by adding up the production time, transmission time between machines, and energy consumption coefficients in the extreme case, e.g. $UB_1 = \left(\sum t_{k,l\,\max} + \sum |S_i| MT_{l,l'\,\max}\right)$ and $UB_2 = |F| \lambda_{i,i'\,\max}$. If one aims to obtain the best result from the last stage to stage $k-1$, he will first obtain the best results from stage N to stage k; consequently, the best result of stage 1 is obtained at last. As we discussed before, the significant barriers stem from the operation sets because there may be more than one operations in an operation set and some features may have more than one operation sets. Worse still, one should decide a feasible precedence relationship between operations. For a certain stage, there may be more than one available features and each feature should be considered. Only one feature will be selected for a stage finally.

B. DETERMINE FEATURES FOR A STAGE

According to Table 1, since the "Feature precedence" column only gives some broad or loose restrictions, the feature to be assigned for a stage is not determined. For example, the precedence relationships given in Table 1 can be depicted with a directed graph shown in Fig. 2a) (a feature in the figure can also be called a 'node').

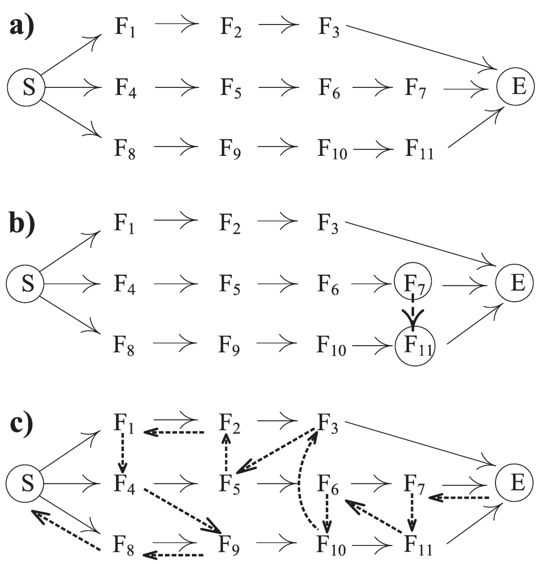

FIGURE 2. **Directed graphs of the example part in Table 1: a) The direct graph of the example part in Table 1. b) and c): Direct graphs used to illustrate DP-like heuristic algorithm.**

For a easy implementation of the proposed heuristic algorithm, two dummy nodes (features), e.g. S and E, have been added in Fig. 2a) as a symbol of the start and the completion of the manufacturing process respectively. Therefore, there are totally $N' = N + 2$ stages. Clearly, some features have no precedence relationships; for example, any one of three features: F_3, F_7 and F_{11} can be selected for the stage $N' - 1$ in a backward recursion procedure. In order to avoid any infeasibility, based on the characteristics of the directed graph, Algorithm 2 is provided to determine a set of feasible features for a certain stage. Given a predetermined feature $'node'$ in stage k, according to Algorithm 2, all the available features for stage $k - 1$ after *node* can be obtained in either of the following two cases:

- Except the feature *node* and feature i itself, if node i does not point to the nodes that have not been processed, then it can be selected as an alternative node for the stage $k - 1$. In Fig. 2b), if E is exactly the predetermined feature *node* in stage k, F_3, F_7 and F_{11} can be three alternative features for stage $k - 1$. However, if there is an arc coming from F_7 to F_{11} as shown in Fig. 2b), feature F_7 cannot been deemed as an alternative node in stage $k - 1$ any more according to this rule.
- For an unprocessed node i, if i has no precedence relationship with *node* and the nodes which i points to have all been processed in previous stages, then node i can be deemed as an alternative feature for stage $k - 1$. In Fig. 2b), suppose features E, F_7 and F_{11} have been processed and node F_7 is given as the selected feature *node* in stage k, in such a case node F_3 is one of the available feature to be considered in stage $k - 1$.

If a node i satisfies the condition in Algorithm 2, it may be selected in stage $k - 1$; then similar process is repeated for the $(k - 2)$th stage until the algorithm reaches the first stage, where only the dummy node S is considered.

Algorithm 2 Determine Alternative Features for Stage $k - 1$

Require: TF: the total number of features;
node: the given feature in stage k;
$Pre[i][j]$: =1, if node i points to node j; =0, otherwise;
$Ped[i]$: =1, if node i have been processed; =0, otherwise.

Ensure: FS: the set that contains alternative features for stage $k - 1$;

for $i \leftarrow 1$ *to* TF **do**
  $flag \leftarrow true$
  if $(Pre[i][node] == 1) and (Ped[i] == 0)$ **then**
    for $i' \leftarrow 1$ *to* TF **do**
      if $(i' \neq node) and (i' \neq i) and (Ped[i'] == 0) and (Pre[i][i'] \neq 0)$ **then**
        $flag \leftarrow false$; Exit the for-loop.
      end if
    end for
    if $flag == true$ **then**
      $FS \leftarrow i$
    end if
  end if
  $flag \leftarrow true$
  if $(Ped[i] == 0) and (Pre[i][node] == 0) and (Pre[node][i] == 0)$ **then**
    for $i' \leftarrow 1$ *to* TF **do**
      if $(i' \neq node) and (Pre[i][i'] == 1) and (Ped[i'] == 0)$ **then**
        $flag \leftarrow false$; Exit the for-loop.
      end if
    end for
    if $flag == true$ **then**
      $FS \leftarrow i$
    end if
  end if
end for

C. APPROXIMATION EVALUATION STRATEGY

In some cases, a feature may have more than one operation sets and an operation set may have more than one operations.

TABLE 3. Transmission time between machines.

Machine ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	5	7	9	10	11	7	6	14	13	12	10	5	6	9
2	5	0	3	4	5	7	2	7	6	4	7	12	10	7	8
3	7	3	0	6	5	4	3	7	2	4	3	5	6	8	9
4	9	4	6	0	4	4	6	7	4	10	12	13	14	15	16
5	10	5	5	4	0	10	12	7	8	9	10	12	11	10	8
6	11	7	4	4	10	0	4	4	5	5	6	7	6	7	8
7	7	2	3	6	12	4	0	5	6	6	6	7	7	7	8
8	6	7	7	7	7	4	5	0	4	2	3	4	2	4	3
9	14	6	2	4	8	5	6	4	0	5	7	4	7	6	8
10	13	4	4	10	9	5	6	2	5	0	8	10	12	14	7
11	12	7	3	12	10	6	6	3	7	8	0	7	10	14	10
12	10	12	5	13	12	7	7	4	4	10	7	0	10	12	10
13	5	10	6	14	11	6	7	2	7	12	10	10	0	8	8
14	6	7	8	15	10	7	7	4	6	14	14	12	8	0	9
15	9	8	9	16	8	8	8	3	8	7	10	10	8	9	0

On the other hand, the proposed heuristic algorithm works based on the features instead of operations; therefore, we shall develop an approximation method to evaluate the production time in an operation set of a feature. For the features that have only one operation set and only one operation in the operation set, its production time can be directly calculated. For the feature that has two or more operation sets, the production time of each operation set should be evaluated and recorded; further, if there are more than one operations in an operation set, each operation will be evaluated to obtain production time. Finally, the total production time of each operation set in a feature is compared and the operation set with minimum production time is selected as the production time of the feature. Then, the feature with minimum production time in all the available features will be selected for the stage.

For example, Fig. 2c) gives a feasible feature permutation for 13 stages (marked with dotted arrows) based on the backward recursion mechanism. Clearly, feature F_8 will be processed at first except the dummy node S. Assume that feature F_3 has been evaluated with the backward sequence $E \rightarrow F_7 \rightarrow F_{11} \rightarrow F_6 \rightarrow F_{10} \rightarrow F_3$ shown in Fig. 2c), three features are available for the next stage: F_2, F_5 and F_9; each of the three features has two operation sets according to Table 1. Provided that the machine of feature F_3 is M_5 with processing time 46, for feature F_2, operations in two operation sets $O_2 - O_3$ and $O_4 - O_5$ are checked one by one. In an operation set, the last operation should be evaluated first; in the case of F_2, operation $O_3(O_5)$ is evaluated before $O_2(O_4)$. With the transmission time between any two machines given in Table 3, the minimum production time of two operation sets of F_2 is 45 $(O_6(M_5) \rightarrow O_3(M_2) \rightarrow O_2(M_6))$ and 48 $(O_6(M_5) \rightarrow O_5(M_9) \rightarrow O_4(M_{10}))$ respectively. Therefore, the first operation set $(O_6(M_5) \rightarrow O_3(M_2) \rightarrow O_2(M_6))$ is deemed as the best operation set of feature F_2. Similarly, the best production time for features F_5 and F_9 can also be obtained respectively. After that, the feature with minimum production time is selected for the stage; then, the procedure discussed above is repeated till the dummy node S is encountered. For the two dummy nodes, we assume that the machining time as well as transmission time between machines in any case is 0.

V. EXPERIMENTS WITH DISCUSSIONS

The proposed algorithm is coded in C++ language and implemented on a computer with an Intel i7-7700 CPU (3.6GHz) and 16GB of memory. In order to verify the effectiveness of the proposed heuristic algorithm, some experiments are performed, and the resultant production time and the energy consumption of each instance is compared with that obtained by other approaches. This paper assumes that there are 15 machines with the transmission time given in Table 3. For a comprehensive evaluation of the proposed algorithm, both the single-objective and the multi-objective optimizations are performed successively.

A. CASE 1

The data of this instance is given in Table 1. Li *et al.* [21] have also solved this instance using a modified particle swarm optimization (PSO) algorithm; corresponding results are presented in Table 4. The total production time of this instance for single objective optimization is 360 using the proposed DP-like heuristic algorithm while the value is 377 using other meta-heuristics. Clearly, the proposed heuristic is much better than meta-heuristic algorithms. This shows the powerful search capability of the proposed DP-like heuristic algorithm in single objective optimization.

In multi-objective optimization, both the two criteria are considered. For a clear comparison, corresponding results are listed in Table 5 as follows. According to Table 5, the total production time has increased by 6.4 percent in the multi-objective optimization case. For the other criterion, surprisingly, promising results have been observed. It shows that the energy consumption in the multi-objective optimization case takes up only 21.2% of that in the single objective optimization case; in other words, the energy consumption in single objective optimization will be 4.72 ($= 7.46/1.58$) times more than the one where the environment related criterion, e.g. energy consumption, is considered. Computational results show that considering only total production time or other economy-related criteria in process planning optimization is not enough because this may induce great negative impacts on environment (more energy consumption means more carbon emission). It also shows that the proposed multi-objective

TABLE 4. Single objective optimization results of case 1.

Algorithm	Best	Mean	Average convergent generation
Simple SA[a]	377	378.1	90.6
Simple GA[a]	377	380.2	87.8
Modified PSO[a]	377	377	47.2
Best process plan of the modified PSO[a]	$O_7(M_3)-O_1(M_3)-O_8(M_5)-O_9(M_5)-O_{12}(M_5)$ $-O_4(M_5)-O_5(M_9)-O_{13}(M_9)-O_{16}(M_4)$ $-O_{10}(M_3)-O_{17}(M_{10})-O_{11}(M_{10})-O_6(M_8)$		
DP-like heuristic	**360**	-	-
Best process plan of the proposed heuristic algorithm	$O_{12}(M_5)-O_7(M_3)-O_1(M_3)-O_4(M_{10})-O_5(M_9)$ $-O_{13}(M_9)-O_9(M_{15})-O_{10}(M_{15})-O_{16}(M_{15})$ $-O_6(M_8)-O_{17}(M_{10})-O_{11}(M_{10})$		

[a]The data are taken from Li et al.'s work [21].

TABLE 5. Multi-objective and single objective optimization results of case 1.

Items	Results
Best process plan of the proposed DP-like heuristic algorithm	$O_1(M_3)-O_2(M_6)-O_3(M_2)-O_6(M_5)-O_{12}(M_5)$ $-O_{13}(M_9)-O_{16}(M_4)-O_{17}(M_3)-O_7(M_{13})$ $-O_8(M_{13})-O_{10}(M_3)-O_{11}(M_{10})$
Best feature sequence	$F_1-F_2-F_3-F_8-F_9-F_{10}-F_{11}-F_4-F_5-F_6-F_7$
Best total production time	383
Best energy consumption (sum of energy consumption coefficients)	1.58
Best process plan in single objective optimization	$O_{12}(M_5)-O_7(M_3)-O_1(M_3)-O_4(M_{10})-O_5(M_9)$ $-O_{13}(M_9)-O_9(M_{15})-O_{10}(M_{15})-O_{16}(M_{15})$ $-O_6(M_8)-O_{17}(M_{10})-O_{11}(M_{10})$
Best feature sequence in single objective optimization	$F_8-F_4-F_1-F_2-F_9-F_5-F_6-F_{10}-F_3-F_{11}-F_7$
Best total production time in single objective optimization	360
Best energy consumption in single objective optimization	7.46

TABLE 6. The data of case 2.

Feature	Operations	Alternative machines	Processing time	Feature precedence
F_1	O_1	M_1, M_2, M_4, M_5	$10, 12, 13, 8$	BeforeF_6
F_2	O_2	M_1, M_2, M_4, M_5	$22, 21, 18, 25$	BeforeF_1
F_3	O_3	M_1, M_2, M_4, M_5	$15, 16, 18, 20$	
F_4	O_4	M_1, M_2	$8, 10$	BeforeF_5, F_6
F_5	O_5-O_6	M_1, M_2	$19, 21$	
		M_1, M_2, M_3, M_4, M_5	$8, 6, 7, 10, 12$	
F_6	$O_7-O_8-O_9$	M_1, M_2, M_3, M_5	$12, 14, 18, 11$	BeforeF_8
		M_1, M_2	20,23	
		M_1, M_2, M_3, M_4, M_5	8,6,7,9,5	
F_7	$O_{10}-O_{11}$	M_1, M_2	$18, 20$	
		M_1, M_2	21,24	
F_8	O_{12}	M_1, M_2	$31, 33$	
F_9	O_{13}	M_1, M_2, M_4, M_5	$30, 33, 28, 34$	BeforeF_1

DP-like heuristic algorithm can strike a balance between the economical criterion and the environment related criterion.

B. CASE 2

Case 2 is taken from [40]; the part is shown in Fig. 3a) and corresponding data is presented in Table 6. Table 7 gives the computational results of this instance in single objective optimization case. The total production time obtained by DP-like heuristic is 222, and the ones obtained by other approaches are also 222. It can be found that the machine M_1 was selected for each operation to reduce the total transmission time between machines in both process plans in Table 7. Although the total production time can be shortened by using machine M_1 frequently in this case, the negative effect is that the machine utilization rate (machine work load) of M_1 is considerable high and this will further intensify the wear and tear of machine tools.

The ECCM used in multi-objective optimization of Case 2 is presented in 21. Table 8 presents both of the multi-objective and single objective optimization results of this case. Computational results demonstrate that it is quite necessary to consider environment related criteria in process planning optimization because in this case about 35.1% ($=\frac{4.16-2.7}{4.16}$) of the total energy consumption can be saved

TABLE 7. Single objective optimization results of case 2.

Algorithm	Best	Mean	Average convergent generation
Simple SA[a]	222	222	70.3
Simple GA[a]	222	222	45.2
Modified PSO[a]	222	222	31.8
Best process plan of the modified PSO[a]	$O_{13}(M_1)-O_3(M_1)-O_2(M_1)-O_4(M_1)-O_1(M_1)$ $-O_5(M_1)-O_6(M_1)-O_7(M_1)-O_8(M_1)-O_9(M_1)$ $-O_{12}(M_1)-O_{10}(M_1)-O_{11}(M_1)$		
DP-like heuristic	222	-	-
Best process plan of the proposed heuristic algorithm	$O_{13}(M_1)-O_4(M_1)-O_2(M_1)-O_1(M_1)-O_7(M_1)$ $-O_8(M_1)-O_9(M_1)-O_{12}(M_1)-O_{10}(M_1)-$ $O_{11}(M_1)-O_5(M_1)-O_6(M_1)-O_3(M_1)$		

[a]The data are taken from Li et al.'s work [21].

TABLE 8. Multi-objective and single objective optimization results of case 2.

Items	Results
Best process plan of the proposed DP-like heuristic algorithm	$O_4(M_1)-O_5(M_1)-O_6(M_1)-O_{10}(M_1)-O_{11}(M_1)$ $-O_{13}(M_1)-O_3(M_1)-O_2(M_1)-O_1(M_1)$ $-O_7(M_1)-O_8(M_1)-O_9(M_1)-O_{12}(M_1)$
Best feature sequence	$F_4-F_5-F_7-F_9-F_3-F_2-F_1-F_6-F_8$
Best total production time	222
Best energy consumption (sum of energy consumption coefficients)	2.7
Best process plan in single objective optimization	$O_{13}(M_1)-O_4(M_1)-O_2(M_1)-O_1(M_1)-O_7(M_1)$ $-O_8(M_1)-O_9(M_1)-O_{12}(M_1)-O_{10}(M_1)-$ $O_{11}(M_1)-O_5(M_1)-O_6(M_1)-O_3(M_1)$
Best feature sequence in single objective optimization	$F_9-F_4-F_2-F_1-F_6-F_8-F_7-F_5-F_3$
Best total production time in single objective optimization	222
Best energy consumption in single objective optimization	4.16

TABLE 9. The data of case 3.

Feature	Operations	Alternative machines	Processing time	Feature precedence
F_1	O_1	M_1, M_2, M_4, M_5	$20, 18, 22, 25$	Before F_2,F_3,F_4, F_5,F_6 and F_7
F_2	O_2	M_1, M_2, M_4, M_5	$30, 31, 25, 34$	
F_3	O_3	M_1, M_2	$28, 24$	
F_4	O_4	M_1, M_2, M_4, M_5	$45, 50, 48, 39$	
F_5	O_5-O_6	M_1, M_2, M_3, M_4, M_5	$10, 6, 7, 13, 16$	
		M_1, M_2, M_3, M_4, M_5	$34, 39, 40, 45, 36$	
F_6	O_7-O_8	M_1, M_2, M_3, M_4, M_5	$20, 22, 28, 25, 19$	
		M_1, M_2, M_3, M_4, M_5	27,29,24,26,30	
F_7	O_9	M_1, M_2, M_4, M_5	$12, 14, 15, 10$	

with the identical total production time.

$$\lambda = \begin{bmatrix} 0 & 0 & 0.94 & 1 & 0.62 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0.83 & 0 & 0.8 \\ 1 & 0.5 & 0 & 1 & 1 & 1 & 0.68 & 0.99 & 1 \\ 0.65 & 0.63 & 0.81 & 0 & 0 & 0 & 0.67 & 0 & 0.6 \\ 1 & 0.5 & 0.53 & 0 & 0 & 0.55 & 0.57 & 0.74 & 0.86 \\ 0 & 1 & 0.92 & 0 & 1 & 0 & 0.61 & 0 & 1 \\ 0.57 & 1 & 1 & 1 & 1 & 1 & 0 & 0.7 & 1 \\ 0.75 & 0.69 & 1 & 0.91 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0.63 & 1 & 1 & 0 & 0.96 & 0 & 0 \end{bmatrix} \tag{21}$$

C. CASE 3

The data of this case is taken from [41] and the part is shown in Fig. 3b). Corresponding data is presented in Table 9 and it can be seen that this part contains 7 features. Computational results as well as comparisons are presented in Table 10. Again, the total production time values obtained by the proposed algorithm and meta-heuristics are the same. However, Table 10 reveals that meta-heuristic algorithms cannot always ensure relative good results because the mean value of the results obtained by 'Simple SA' is larger than the best one 212.

The corresponding ECCM in multi-objective optimization of this case is given in 22. Table 11 gives the comparison between the results of single objective optimization and that of the multi-objective optimization. As presented in Table 11, if we concentrate on total production time only, the corresponding value is 212 and it is slightly better than the one obtained in multi-objective optimization; To put this in perspective, however, the result in multi-objective optimization

TABLE 10. Single objective optimization results of case 3.

Algorithm	Best	Mean	Average convergent generation
Simple SA[a]	212	212.2	60.7
Simple GA[a]	212	212	51.3
Modified PSO[a]	212	212	42.5
Best process plan of the modified PSO[a]	$O_1(M_2)-O_3(M_2)-O_5(M_2)-O_6(M_5)-O_4(M_5)$ $-O_9(M_5)-O_7(M_5)-O_8(M_4)-O_2(M_4)$		
DP-like heuristic	212	-	-
Best process plan of the proposed heuristic algorithm	$O_1(M_2)-O_3(M_2)-O_5(M_2)-O_6(M_5)-O_9(M_5)$ $-O_4(M_5)-O_7(M_5)-O_8(M_4)-O_2(M_4)$		

[a]The data are taken from Li et al.'s work [21].

TABLE 11. Multi-objective and single objective optimization results of case 3.

Items	Results
Best process plan of the proposed DP-like heuristic algorithm	$O_1(M_2)-O_5(M_2)-O_6(M_5)-O_9(M_5)-O_2(M_4)$ $-O_4(M_5)-O_7(M_5)-O_8(M_3)-O_3(M_2)$
Best feature sequence	$F_1-F_5-F_7-F_2-F_4-F_6-F_3$
Best total production time	222
Best energy consumption (sum of energy consumption coefficients)	3.83
Best process plan in single objective optimization	$O_1(M_2)-O_3(M_2)-O_5(M_2)-O_6(M_5)-O_9(M_5)$ $-O_4(M_5)-O_7(M_5)-O_8(M_4)-O_2(M_4)$
Best feature sequence in single objective optimization	$F_1-F_3-F_5-F_7-F_4-F_6-F_2$
Best total production time in single objective optimization	212
Best energy consumption in single objective optimization	4.2

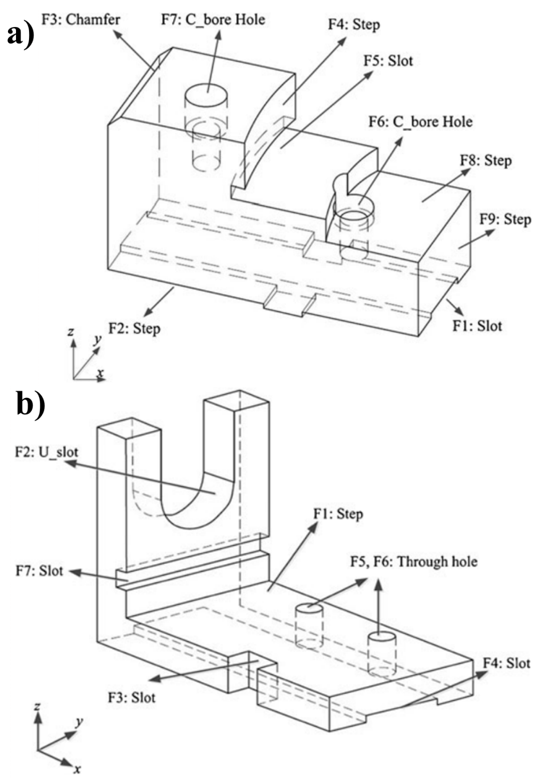

FIGURE 3. Two parts used in case 2 and 3: a) The example part used in Case 2. b) The example part used in Case 3.

looks more promising because the energy consumption in multi-objective optimization is better than the one in single objective optimization by 9.7 percentage points $(=\frac{4.2-3.83}{4.2})$ and the value of the total production time criterion in multi-objective optimization is worse than that of single objective optimization by 4.5% only $(=\frac{222-212}{222})$.

$$\lambda = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.81 & 0.81 & 0.98 & 0.92 & 0.9 \\ 0 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0.6 & 0 & 0.87 & 0.68 & 0.86 \\ 0 & 1 & 0.74 & 1 & 0 & 1 & 0.52 \\ 0 & 1 & 0.82 & 1 & 0.96 & 0 & 0.82 \\ 0 & 1 & 0.79 & 1 & 1 & 1 & 0 \end{bmatrix} \quad (22)$$

The genetic algorithm (GA) is a well-known and wide applied meta-heuristic algorithm. Besides the process planning problems, it has been applied to many difficult optimization problems with satisfactory results obtained because it is a powerful approach to address NP-hard problems. As a representative meta-heuristic algorithm, we adopt GA for experimental comparisons in this research. We solve the the same process planning instances using the well-known GA, and the weighted sum manner is adopted in multi-objective optimization in GA. The genetic algorithm is coded using C++ language and performed on the same computer. In GA, the size of population is set to 200 with the crossover probability 0.7 and the algorithm is terminated after 100 iterations. For each case, it is executed for 10 independent times. We compare the results obtained by the proposed heuristic algorithm with the ones obtained by the genetic algorithm as presented in Table 12.

For the first case, the average total production time is 384.2, and it is worse than the result obtained by the proposed DP-like heuristic algorithm. Although the best total

TABLE 12. Results comparison between algorithms.

Cases	Total production time criterion		Best energy consumption criterion	
	The proposed algorithm	GA(Best, Worst, Mean)	The proposed algorithm	GA(Best, Worst, Mean)
Case 1	383	(381, 389, 384.2)	1.58	(1.58, 1.58, 1.58)
Case 2	222	(222, 247, 233.7)	2.7	(2.7, 2.86, 2.77)
Case 3	222	(224, 236, 230.0)	3.83	(3.76, 3.83, 3.8)

production time in GA is 381, as the inherent shortcoming of meta-heuristics stated above, the GA cannot always capture promising solutions and the solution quality cannot be ensured in each computation: in the worst case, the total production time is 389. The average total production time using GA is 384.2 and it is still larger than the one of DP-like heuristic algorithm(383). For the other criterion, the two algorithms get a tie. Thus, the proposed algorithm outperforms GA in general. For the second case, according to Table 12, the superiority of the DP-like heuristic algorithm can be observed again: the proposed algorithm outperforms GA in both of the two criteria: the results obtained by DP-like heuristic algorithm are equal to the best ones obtained by GA. Because GA cannot ensure the best solution each time, for the mean values of the two criteria, the value of DP-like heuristic algorithm is better than that of GA. In Case 3, the two algorithms show different advantages and strengths. For the total production time criterion, the DP-like heuristic algorithm outperforms GA with maximum improvement rate 5.93% $\left(= \frac{|222-236|}{236}\right)$ while GA is slighter better than the proposed algorithm in energy consumption optimization; nevertheless, the improvement rate of GA on the energy consumption criterion is rather limited in this case (the improvement rate of GA is $1.86\% = \frac{|3.76-3.83|}{3.76}$). Clearly, the total production time criterion receives more improvements in this case; therefore, provided that the two criteria are equally important, a decision maker may squint towards the results of the proposed DP-like heuristic approach. Besides, due to the congenitally deficient of the meta-heuristic algorithms, a satisfactory solution is not ensured in each computation in meta-heuristic based optimizations; in some computations one may obtain an indifferent solution. Thus, with a comprehensive comparison of the two algorithms, it can be seen that the proposed DP-like heuristic algorithm generally performs better than GA and this reflects the superiority of the DP-like heuristic algorithm.

VI. CONCLUSIONS

Carbon emission reduction in manufacturing has received tremendous research attentions in recent years. This paper gives an optimization modeling and solving method for both total production time and energy consumption reduction in process planning. Based on the existing energy consumption evaluation method, the energy consumption coefficients in an ECCM are established to describe the variety degree of energy consumption in sequencing two features which have no precedence relationship. We first established a novel MILP model for a kind of process planning problem, where the operation flexibility, the sequence flexibility and the machining flexibility are expressed in a table, using a position based modeling technique. Before this, there is no suitable MILP model developed for such process planning problems and hence such problems cannot be solved using the branch and bound method in commercial solvers. In the proposed model, the total energy consumption of a process plan is mapped into the sum of elements in the ECCM for all the neighbouring features. Due to the complexity in solving the problem, we then developed a dynamic programming like heuristic algorithm to address the problem. In the proposed heuristic algorithm, each feature of a part is deemed as a stage and the optimization is optimized stage by stage in a recursive manner with some approximate treatments in total production time evaluation. In order to test the algorithm, three typical instances, which have been reported and tested by other meta-heuristics, are used in the experiments to demonstrate the effectiveness of the proposed heuristic algorithm. Both the single objective and the multi-objective optimizations are performed. In single objective optimization, promising results have been observed: the results obtained by the proposed algorithm are as good as or better than the ones obtained by the meta-heuristic algorithms. This reflects the effectiveness and the powerful search capability of the proposed algorithm in conventional single objective process planning optimization. In multi-objective optimization, both the two criteria, e.g. the total production time and the energy consumption, have been optimized. Results in multi-objective optimization and the ones obtained in single objective optimization have been compared. It shows that taking environment related criteria into consideration is quite necessary in process planning since such multi-objective optimization can strike a balance between the two criteria. In other words, the optimality or near optimality of environment related criteria cannot be ensured in single objective optimization where only the economy related criteria, e.g. total production time, is considered. To illustrate the superiority of the proposed algorithm, the well-known genetic algorithm has also been adopted to optimize the three instances and corresponding results have been compared: it shows that the resultant solutions of DP-like heuristic algorithm are better than that of GA in general.

Since the example parts in three instances are taken from real manufacturing environment and more importantly, the corresponding ECCM of a part can be established by existing energy consumption evaluation method, the proposed algorithm can be used in real-life optimization problems. Therefore, the proposed method are very practical in both total production time and energy consumption (carbon emission) reduction in real-life process planning optimization; it provides a novel perspective and a general optimization framework for carbon emission reduction in process planning stage.

According to experimental results, some machines are selected frequently by the algorithm in order to reduce the transmission time between machines; however, this does not match the actual situation in shop floor because the unbalanced machine workload will intensify the wear and tear of machine tools. Therefore, a new objective related to balance machine workload can be considered in process planning stage in future research. Besides, through drawing lessons from vehicular route planning [42], [43], more effective and efficient methods can be developed in optimal feature sequencing, and this can be considered in further research. More in-depth and effective features will also be considered as further research directions; for example, less raw material usage, green production processes, and material reversibility in production can be considered and optimized in process planning optimizations.

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