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Optimal process planning for a combined punch-and-laser cutting machine using ant colony optimization

G. G. WANG*† and S. Q. XIE‡

†Department of Mechanical and Manufacturing Engineering, University of Manitoba, Winnipeg, MB, Canada R3T 5V6
‡Department of Mechanical Engineering, University of Auckland, Private Bag 92019, Auckland, New Zealand

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A machine that performs both punching and laser-cutting operations is referred as combined punch-and-laser machine. Such a machine has been in the market for about two decades. Although process-planning tools have been used on such a combined machine, the optimization of process planning dedicated to combined machines, based on our literature search results, has never been directly studied. This work addresses the process-planning problem for the combined punch-and-laser machine by integrating knowledge, quantitative analysis, and numerical optimization approaches. The proposed methodology helps making decisions on following issues: (i) which type of operation should be applied to each feature, and (ii) what is the optimal operation sequence (tool path) to achieve the maximum manufacturing efficiency. The ant colony optimization (ACO) algorithms are employed in searching the optimal tool path. Sensitivities of control parameters of ACO are also analysed. Through applications, the proposed method can significantly improve the operation efficiency for the combined punch-and-laser machine. The method can also be easily automated and integrated with the nesting and G-code generation processes. Some issues and possible future research topics have also been discussed.

Keywords: Combination machine; Combined punch-and-laser machine; Sheet metal; Process planning; Optimization; Ant colony optimization

1. Introduction

Modern computer numeric controlled (CNC) turret punches represent highly versatile machine tools capable of producing sheet metal and plastic components quickly and accurately. However, the versatility of such turret punches is limited in that material can be removed from the work piece only by a punching type operation. When large areas of the work piece are to be removed, or when the work piece is to be subdivided into a number of separable work pieces, or when relatively long or large diameter parts are to be made, this can be accomplished only by a series of slightly overlapping punching type metal removal operations. Such overlapping material

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*Corresponding author. Email: gary_wang@umanitoba.ca

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removal operations can be effectively used to increase the versatility of a punch, however, those operations, at times, lead to undesired consequences, such as formation of burred edges, inability to produce highly accurate, smooth side edges, relative slowness of operation, etc. (Clark and Carbone 1980). Moreover, when the cut-out shape is not one of the common punch tool shapes, special tools have to be made and the costs of making such tools are normally high. As a result, many cutting or shearing type operations are performed by other machine tools in a subsequent operation that requires additional work piece handling. This multi-machinery requirement influences not only the manufacturing efficiency, but also the manufacturing quality and cost. The above stated reasons motivated the development of a so-called combined punch-and-laser cutting machine (Clark and Carbone 1980), or compound machine (Katayama 1989a, b, Xie *et al.* 2001), or combination punch press and laser cutting machine (Klingel and Doettling 1990, Ulrish 2000). In this work, this machine will be referred as combined punch-and-laser machine.

The combined punch-and-laser machine was first invented in 1980 (Clark and Carbone 1980), and then gradually matured by overcoming its vibration interference problem through a number of patents (Bredow 1982, Katayama 1989a, b, Klingel and Doettling 1990, Ulrish 2000). With variations on detailed machine structure as described in various patents, a combined punch-and-laser machine, in principle, integrates a punch tool with a laser beam cutter into one machine. The current version of the machine allows the separation of the punching system from the laser system, and a standard punch tool can be readily retrofitted with a laser system to therefore become a combined machine (Ulrish 2000).

The advantages of the combined punch-and-laser machine are manifold. Such a machine increases the ability of conventional punching equipment to provide large and/or irregularly shaped parts in the work piece. It represents a major advance in the art of machine tools to provide a single machine tool capable of high speed, high accuracy punching, cutting, and surface marking wherein all functions are controllable from a central automatic control and wherein work piece movement is accomplished by a single mechanism so as to eliminate the necessity of work piece handling between operations.

In the past 20 years, the industry embraced the combined punch-and-laser machine. Companies that supply such machines include, for example, Dalsin Industries, Inc. in Minnesota, LVD Corporation in North Carolina, GE Capital Manufacturing in Connecticut, all USA, TRUMPF Group, Germany, Amada America, Inc. in California, USA, and Finn-Power International, Inc. Figure 1 shows an example of such a machine by Amada America.

Given the capability of combined punch-and-laser machines, the process planning of the machine becomes more complex. However, no study has been found in literature directly on process planning for combined punch-and-laser machines. Neither was found the optimization of process planning dedicated to combined punch-and-laser machines. This is incommensurate with the development of the machine in industry. Two related studies are found on the process planning for a flexible manufacturing cell that includes a punch and a laser (Ghosh *et al.* 1993), and a simulation method to optimize the work sequence in a job shop (Endo *et al.* 1996). While, process planning as a topic in general has a long history with many fruitful results. A recent work with a good review is done by Li *et al.* (2004).

Figure 1. Amada Apelio combined punch-and-laser machine (Amada American, Inc. ©).

This work will focus on the process-planning problem for the combined punch-and-laser machine in order to improve the efficiency of the machine and fully automate the process from layout nesting to machining. This work will be the first on optimal process planning for combined punch-and-laser machines.

2. Process planning problem for a combined punch-and-laser machine

For the process planning of a combined punch-and-laser machine, one has to make two important decisions for each batch of work pieces, i.e.

- Which feature is to be punched or cut?
- What is the optimal sequence of operation to ensure the overall maximum machine efficiency?

Let us use the work piece shown in figure 2 as an example. On a sheet metal of 1000×1120 mm, two types of components are laid out. The first component has a square shape with round corners, a central hole, and four small holes. The second component is a combination of a semicircle and a rectangle, with a small hole. For the combined machine, there are four different operation features, i.e. 23 small holes of $\Phi50$, four large holes of $\Phi180$, four contours for the first component, and 7 contours for the second component. For automatic process planning, which feature is to be punched and which is to be cut? If the first question were answered, what would be the optimal operation sequence that yields the maximum machine efficiency?

This work will develop a quantitative method guided by heuristics to address the first question, and then apply the ACO algorithms to answer the second question. The methods are then tested with the problem shown in figure 2 and a more complex sheet metal work piece. Integration of the proposed methods with Computer-Aided Nesting (CAN) and G-Code generation tools will also be discussed.

Before discussing the proposed methodology, some assumptions are given first to confine us to an appropriate scope of study:

- Operation sequence (process) will be optimized to improve the machine efficiency of the combined punch-and-laser machine. The increase of machine

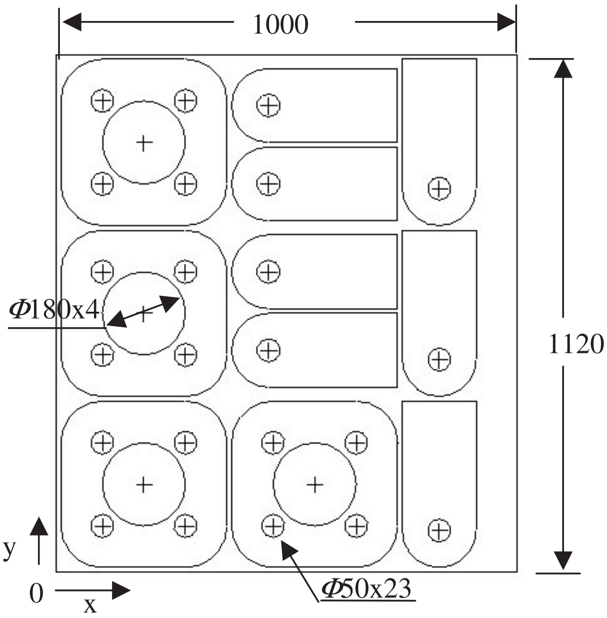

Figure 2. Batch of work pieces to be machined in the combined punch-and-laser machine (unit:mm).

efficiency is expected to translate into reduced machine cost, labour cost and increased throughput, etc.

- Given the fact that most combined machines have only one punch head and one laser cutter, this study will focus on this type of machine. Extension of the proposed method to machines with multiple heads should not be difficult.
- Combined punch-and-laser machine is assumed to be CNC so that the optimal operation sequence can be output to generate G-codes.

3. Proposed strategy

In today's sheet metal manufacturing industry, all of the components to be fabricated are first laid out on the sheet metal in a computer. This process is called Computer-Aided Nesting (CAN). For CAN, the input data is usually a standard DXF format file. CAN recognizes and stores all the geometric information of the components to be laid out. It then generates a scheme, usually optimal, to layout the components on the sheet metal to achieve a certain objective, which is usually the maximum material utilization ratio. Certain CAN tools can even automatically generate G-Codes for CNC devices such as punch press, cutters, etc. (Xie *et al.* 2004). In this step, the operation (including both punching and cutting) sequence has to be determined before outputting the G-Codes. For a combined punch-and-laser machine, the type of operation should be determined for each feature, as compared with conventional machines normally involving only one type of operation.

Each component may contain more than one operation feature. For example, the first component shown in figure 2 consists of the outer contour, the large centre hole and four small corner holes. In total, there are three different operation features in this component. Similarly, the second component in figure 2 consists of two different operation features, which are the outer contour and the circle. The two different components yet share an identical operation feature, i.e. the small holes of $\Phi 50$. Therefore for the sheet metal manufacturing, we concern about the operation features rather than components. For the example in figure 2, in total four different operation features exist.

Since CAN stores all the necessary geometric information of the components to be laid out, it is not difficult to find the geometric information of each operation features. The process-planning task therefore involves the operation and operation sequence on each operation feature. From the information stored in CAN process, operation features are first classified and coded according to its geometric shape and size. Holes of different sizes are treated as different features.

3.1 *Decision I: Punch or cut?*

The punch operation is usually limited by the available punch tools and the capacity of the punch press, though it can potentially reach a very high efficiency. The maximum feature size for punching should be within the limit of the machine such as the maximum power and force limit. The minimum hole diameter in punching should normally be larger than the sheet thickness. Also there should be an available punch tool for such a feature (Schey 2000, Kalpakjian and Schimid 2003). For the laser beam cutting, the allowable minimum size of a feature is, in general, 0.5 mm for CO_2 type of lasers; and 0.08 mm for Nd:YAG lasers (Schey 2000). The first task for process planners for a combined punch-and-laser machine is to check if there is any operation feature out of the capacity of both the punch and the laser cutter. If the answer is yes, other means rather than the combined punch-and-laser machine are to be used.

Assuming all the features can be fabricated by either punching, laser cutting or both, decisions on using punch or laser cutting can be made using the following procedure:

Step 0: Identify each operation feature from the existing geometric data, as discussed above.

Step 1: According to the limitation of punch-and-laser cutting operations, classify all of the operation features to punch (cannot be laser cut), laser cutting (cannot be punched), and an intermediate group. It is easy to understand that the difficulty comes from the features that fall into the intermediate group. The goal is eventually to determine whether either punch or laser cutting is to be used for each feature in this group. Such a decision on which operation is to be used for the intermediate group mainly concerns with the time of operation (which can be translated into costs).

Step 2: Decide an operation for each operation feature in the intermediate group.

As we know that the punch operation generally has a very high efficiency and it is inexpensive for high volume production as compared with the laser cutting. Based on this intuitive understanding, it is reasonable to deduct the following rules in support of Decision I.

- Rule I: The operation feature with the largest quantity is assigned for punching. This rule ensures that at least there is one feature to be punched fully to take advantage of the punch operation.
- Rule II: For the rest of the features in the intermediate group, unless the minimum time for (laser) cutting the feature including the tool exchange time is less than the minimum punch time if punch continues to be used, the feature is to be punched.

Assume T_c is the total laser cutting time if the laser is used, and T_p is the total punch time if the punch is used. Therefore,

$$T_c = t_c + t_t = \frac{L_c}{V_c} + \frac{L_t}{V_t} \tag{1}$$

where t_c is the actual laser cutting time, which equals the cutting length L_c divided by the laser cutting speed V_c; t_t is the travelling time between identical operation features, or the positioning time, which equals the total length of travelling L_t, and the positioning speed V_t. Similarly for the punch operation, we have

$$T_p = t_p + t_t = n * t_{\text{stroke}} + \frac{L_t}{V_t} \tag{2}$$

where n is the quantity of the operation feature and t_{stroke} is the time per punch stroke. Assuming t_x is the tool exchange time between the punch-and-laser cutter, Rule II can be written as:

- Rule II: If $\min(T_c) < \min(T_p) + t_x$, the feature is to be fabricated by laser cutting; otherwise, it is to be punched.

As the punch speed, position speed, and tool exchange time of a single machine normally does not vary with the operation, the criterion can be further simplified:

$$\begin{aligned}\min(T_c) = \frac{L_c}{\max(V_c)} + \frac{\min(L_t)}{V_t} < \min(T_p) + t_x = n * \min(t_{\text{stroke}}) + \frac{\min(L_t)}{V_t} + t_x \\ \frac{L_c}{\max(V_c)} < n * \min(t_{\text{stroke}}) + t_x \end{aligned} \tag{3}$$

where $\max(V_c)$ is the maximum allowable laser cutting speed for a certain operation feature, which might vary with the material, sheet thickness, environment, etc. So is it for $\min(t_{\text{stroke}})$. It is also noted that as the punch speed can reach very high in modern machines, t_{stroke} is thus very small. For example, the Trumatic 6000L–1300 combined punch-and-laser machine made by Trumpf, Inc. has a maximum punch rate as 900 strokes/min (Trumpf 2004), which translates to 15 strokes/s. For a small quantity of features, i.e. n is small, the term $n * t_{\text{stroke}}$ becomes negligible.

Applying Rule II, one can make decisions on all the other features in the intermediate group. Eventually all of the operation features can be classified to either the punch or the cut group.

3.2 *Decision II: What is the optimal operation sequence?*

Now that the operation is decided for each feature, the next question is what is the best operation sequence that gives the maximum manufacturing efficiency.

To address the question, following issues are to be considered:

- What is the optimal sequence to fabricate features from the two groups? Is it more efficient to perform the punch operations all at once than a mixed punch-and-laser operation, or vice versa?
- For different features in one operation group, what is the reasonable sequence of operation? In other words, what is the manufacturing order for different features with the same operation?
- Based on the answers to the first two questions, what is the best sequence of manufacturing? In other words, what is the shortest travelling path to fabricate all the features?

As the tool exchange is still a time consuming process, intuitively it is more advantageous to perform one type of operation all at once. There exists a possibility that by optimizing the tool travelling path the time saved in the travelling may counteract the increase of tool shuffling. In this work, we assume that the tool exchange time is more of a concern and stipulate that all of the punch operations will be performed first, followed by the laser cutting operations. For the second question, we need to distinguish the punch group from the cut group. For features in the punch group, one can easily find that inner features are to be manufactured first. For example, if a ring is to be manufactured, the central hole is to be punched first and then the outer circle from the sheet metal. For the cut group, similar rules apply. If there is no inner feature in the group and since we assume there is only one laser cutter and there is no need to change tools, all of the features in the cut group can then be treated as only one feature. Their machining sequence will be determined by the optimal tool path. In this work, the ACO algorithms are employed and tailored to search for the optimal travelling path among copies of each feature and the optimal transition between different types of features. Details of the optimization will be described in the following section.

In summary, figure 3 illustrates the proposed process planning process for the combined punch-and-laser machine.

4. Ant colony optimization algorithms

The development of Ant Colony Optimization (ACO) algorithms was inspired by the observation that a colony of ants has great potential to carry out a coordinated activity. Their main medium of communication is through the building up of the path through an artificial chemical substance called ‘pheromone’. When ants leave nests to search for food, they lay a trail of pheromone on their path. The number of ants that has travelled on the same path determines the strength of the pheromone trail. The ant that travels the shortest path reinforces the path with more amount of pheromone. After a certain period of time, the ants, as a group, find the shortest travelling path. ACO algorithms were first developed by Dorigo *et al*. (1996). Then ACO algorithms have been modified and applied to solve many problems such as the quadratic assignment problem, travelling salesman problem (TSP), vehicle routing problem, connection-oriented network routing, graph colouring, sequencing, scheduling, optical network problem, etc. Interested readers can find most of the relevant references on ACO algorithms through the website developed by Dorigo (2003). The ACO algorithms are chosen in this work based on the following reasons: (1) they

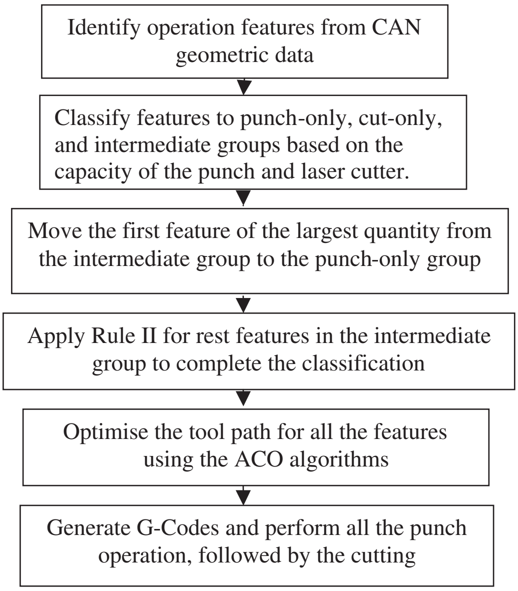

Figure 3. Flow chart of the process planning procedure for the combined punch-and-laser machine.

have been successfully applied to the Travelling Salesman Problem (TSP), which shares many similarities between the tool path problem for the combined machine; (2) by applying the ACO algorithms to solve production problems we can gain better understanding of this emerging technique; and (3) we may test the efficacy of the algorithms and provide guidelines on the use of this technique in process planning. Choosing ACO, however, does not exclude the possible application of other meta-heuristics such as genetic algorithms (Gen and Cheng 1997), simulated annealing (Kirkpatrick *et al.* 1983), particle swarm optimization (Eberhart and Kennedy 1995), tabu search (Glover and Laguna 1996), etc. to this problem.

This work gives a brief overview of the essence of the ACO algorithms by using the travelling salesman (TSP) problem (Dorigo *et al.* 1996).

Given L cities, the TSP is the problem of finding a minimal length closed tour that visits each city once. Let $b_i(t)$ $(i = 1, \ldots, L)$ be the number of ants in city i at time t and let

$$m = \sum_{i=1}^{L} b_i(t) \tag{4}$$

be the total number of ants. Each ant has the following characteristics:

- When going from city i to city j, it lays a substance, called *trail*, on edge (i, j).
- It chooses a city to go to with a probability $p_{ij}(t)$ that is a function of the city distance and of the amount of trail present on the connecting edge.
- Movement to already visited cities in one tour is prohibited.

The key of the ant algorithms is to define the scheme of updating the trail, and design the $p_{ij}(t)$ function. Different choices about when and how to update the trails, as well as the $p_{ij}(t)$ function, causes different instantiation of the ACO algorithms. This work introduces the Ant-quantity and Ant-cycle algorithms developed by Dorigo *et al.* (1996).

Let $\tau_{ij}(t)$ be the intensity of trail on edge (i, j) at time t. At each iteration of the algorithm, trail intensity becomes

$$\tau_{ij}(t+1) = \rho * \tau_{ij}(t) + \Delta\tau_{ij}(t,t+1) \tag{5}$$

where ρ is a value in (0, 1) and $(1-\rho)$ is the evaporation rate of trail, and

$$\Delta\tau_{ij}(t,t+1) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t,t+1) \tag{6}$$

where $\Delta\tau_{ij}^{k}(t, t+1)$ is the quantity per unit of length of trail substance (pheromone in real ants) laid on edge (i, j) by the k-th ant between time t and $t+1$.

For the Ant-quantity algorithm,

$$\Delta\tau_{ij}^{k}(t, t+1) = \begin{cases} \dfrac{Q}{d_{ij}} & \text{if } k\text{-th ant goes from } i \text{ to } j \text{ between } t \text{ and } t+1 \\ 0 & \text{Otherwise} \end{cases} \tag{7}$$

where d_{ij} is the distance from city i to city j; Q is a user defined constant. If d_{ij} is replaced with L_k, which is the tour length of the k-th ant, then the Ant-quantity algorithm becomes the Ant-cycle algorithm. The Ant-cycle algorithm takes the entire tour length as a feedback to update the trait, while the Ant-quantity takes the local distance as the feedback. It was found in general more efficient than the Ant-quantity algorithm for the closed-loop TSP (Dorigo *et al.* 1996).

The transition probability $p_{ij}(t)$ function from city i to city j for the k-th ant is defined as:

$$p_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{j \in \text{allowed}} [\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} & \text{if } j \in \text{allowed} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where η_{ij} is called *visibility* and it equals the inverse of the distance d_{ij} from town i to town j; α and β are parameters that allow users to contrast the relative importance of trail versus visibility. Following the recommendation in Dorigo *et al.* (1996), this work chooses $\alpha = 1, \beta = 2, \rho = 0.5,$ and $Q = 100$.

For the standard TSP, normally the number of ants, m, is set to be L, the number of cities. The problem is initialized so that there is one and only one ant at each city.

5. Application of ACO algorithms in operation sequence planning

For the proposed operation sequence planning for the combined punch-and-laser machine, there are two slightly different types of optimization problems. As the operations are performed in a sequence and the material flow on a workstation has a certain direction, the optimization problem is not a standard closed-loop TSO problem. For batches on a combined punch-and-laser machine, the starting point of each batch should usually be given. Assuming there are two consecutive batches of work, the machine has to start from the starting point of the first batch, and then moves to the starting point of the second batch once the first is finished.

Between the two starting points, the tool can either return to the starting point (origin) after completing each feature, or continue from its current location for the next feature. Specifically, two types of optimization problems exist corresponding to two situations.

- For the first feature, the tool should start from a fixed location and end at a point that yields the shortest travelling path for copies of the first feature. For the second and following features, it starts from the current tool location and ends at a point that yields the shortest travelling path for copies of each feature.
- For the last feature, the tool should start from the current location and end at the starting point of the next work batch.

This work applies the algorithms described in Dorigo *et al.* (1996) with minor modifications corresponding to the above mentioned two types of problems:

- For both types of problems, the TSP is changed from a closed loop to an open loop problem. Both Ant-quantity and Ant-cycle algorithms were employed. They both have similar performance. It is found that the Ant-quantity algorithm often gives better solutions than the Ant-cycle algorithm, while the latter converges more quickly to the neighbourhood of the global optimum. This phenomenon is due to the presence of a strong constraint, i.e. the path has to start from a given point. Secondly, the Ant-quantity algorithm does not include the entire tour length as the feedback; it thus has more chances to generate random information to reach the global optimum. On the other hand, since the Ant-cycle algorithm uses the entire tour length as a ‘global’ feedback, it guides the search quickly to be near the global optimum but the feedback may be too strong to prevent more random steps to reach the final solution.
- For the first type of problem, all the ants are initialized to be at one location, i.e. the starting point of a particular path. Hence, all identified optimal paths have to start from the given location.
- For the second type of problem, besides that all the ants are initialized to be at one location, the path distance includes the distance between the final feature to the starting point of the next batch. The overall distance is then used as the tour length for the Ant-cycle algorithm.

The next section will present detailed information on how the proposed method was applied to solve the problem illustrated in figure 2 and a more complex problem. The solutions are compared with those generated by conventional experience-based process planning.

5.1 *Example 1*

As discussed above, the problem described in figure 2 entails four different operation features. Applying the rule ‘The operation feature with the largest quantity is assigned for punching’, one can easily decide the small holes are to be punched as shown in figure 4. For the two types of contours shown in figure 5, we assume that there is no such big punch tool available and they have to be cut.

For the large holes in figure 6, we need to call equation (3) to calculate the time for each alternative. Let us assume that the maximum laser cutting speed is

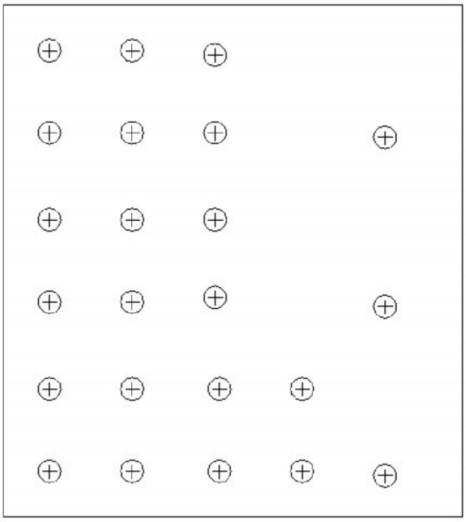

Figure 4. Punch-for-sure feature.

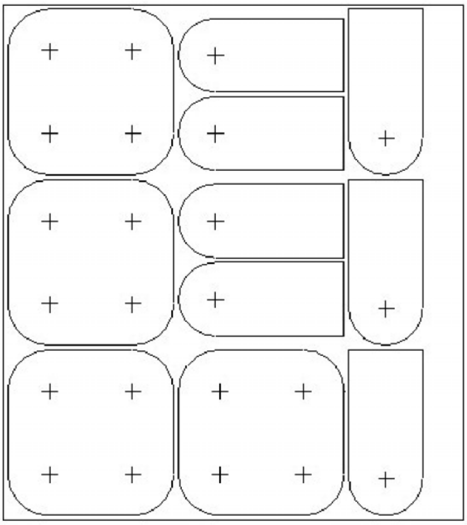

Figure 5. Contour features of Example 1.

10 m/min, the tool exchange time is 3s, and the maximum punch stroke is 900/min. Applying equation (3),

$$\frac{L_c}{\max(V_c)} = \frac{180 * 3.14159 * 4 * 60}{10 * 10^3} = 13.6s$$

$$n * \min(t_{\text{stroke}}) + t_x = 4 * 1 * 60/900 + 3 = 3.3s$$

$$\therefore \frac{L_c}{\max(V_c)} > n * \min(t_{\text{stroke}}) + t$$

Thus, the four large holes are to be punched.

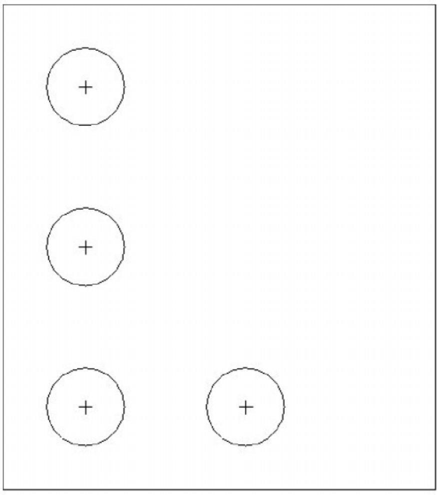

Figure 6. Large holes, punch or cut?

5.1.1 Tool path optimization. The coordinate system is set up as shown in figure 2. The starting point (100, 100) is the centre of the small circle at the left bottom corner of the sheet.

Small holes. To apply the ACO algorithm searching for the optimal path, each hole-centre is considered as a city in a typical TSP set-up. The task is to find the minimum distance to travel through all the cities starting from a given city. The optimal path is found by running the ant algorithm and plotted as the solid line in figure 7. The dotted line indicates an intuitive path that a reasonable engineer would generate. For clarity, the dotted line is drawn away from the circle centres; it in fact should goes through the circle centres. From figure 7, it is clear that both paths end at (1100, 100).

Large holes. The following feature to be machined is the large hole, which is also a punch operation (recall the rule to finish all the punching first, followed by laser cutting). Please note that the starting point is the end of the last path, i.e. the circle centre at the upper right corner shown in figure 7. It is at (830, 830). The optimal and intuitive paths are drawn in figure 8. The intuitive path was generated on the assumption that the tool has to return to the origin from its current location before operating on the second feature.

Contours. Since there is no other inner feature, the contours shown in figure 5 are cut together. The laser is assumed to start from the left bottom corner of each feature, traverse along the contour, and return to the left bottom corner. For the path comparison purpose, the actual traverse length along lead-in line, lead-out line, and the perimeter of each feature is identical regardless of what the operation process is. Therefore, only the bottom left corner is used to represent each feature in figure 5.

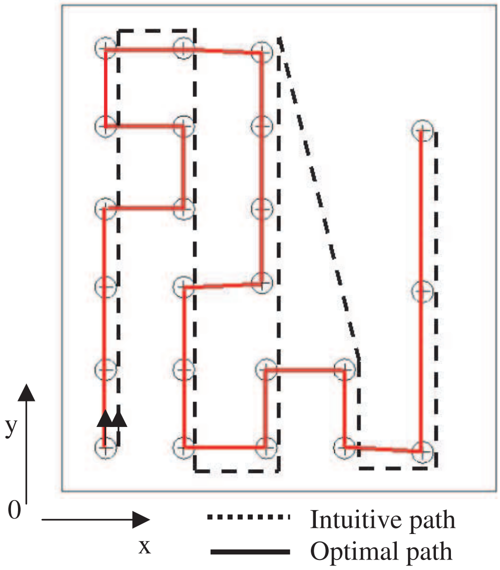

Figure 7. Comparison of the optimal and intuitive paths for small holes in Example 1.

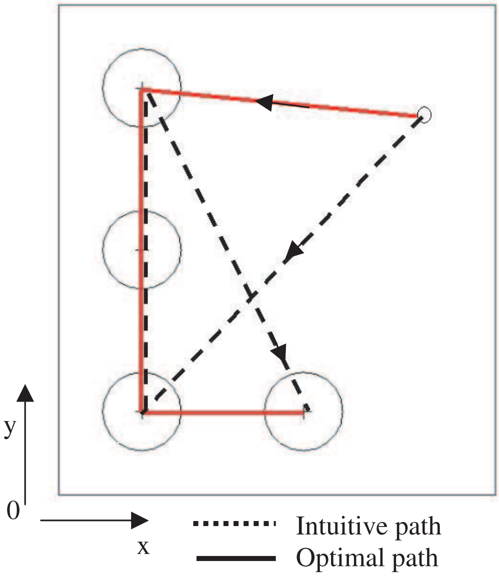

Figure 8. Comparison of the optimal and intuitive paths for large holes in Example 1.

Starting from the end of the last path (190, 560), the path is expected to end at the starting point of the next batch of work, which is assumed to be (1100, 100) for Example 1. The optimal and the intuitive paths are plotted in figure 9.

Table 1 summarizes the details of the optimal as compared with intuitive process planning results. The total reduced travelling distance in a 1000 × 1120 mm sheet from 11 942 to 10 046 is 1896 mm.

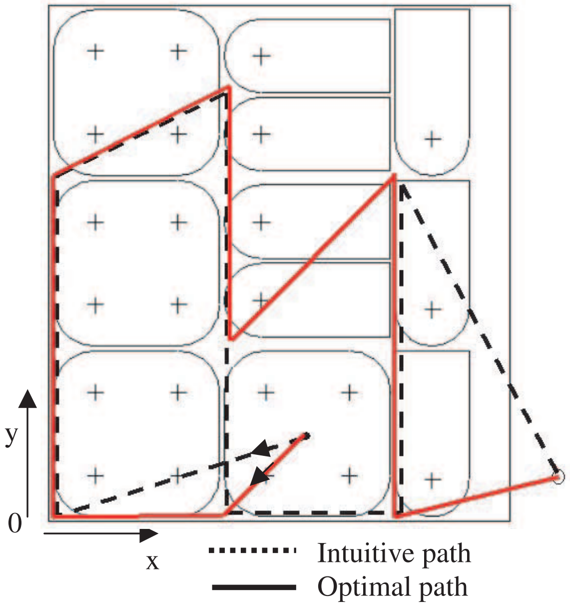

Figure 9. Comparison of the optimal and intuitive paths for the contour features of Example 1.

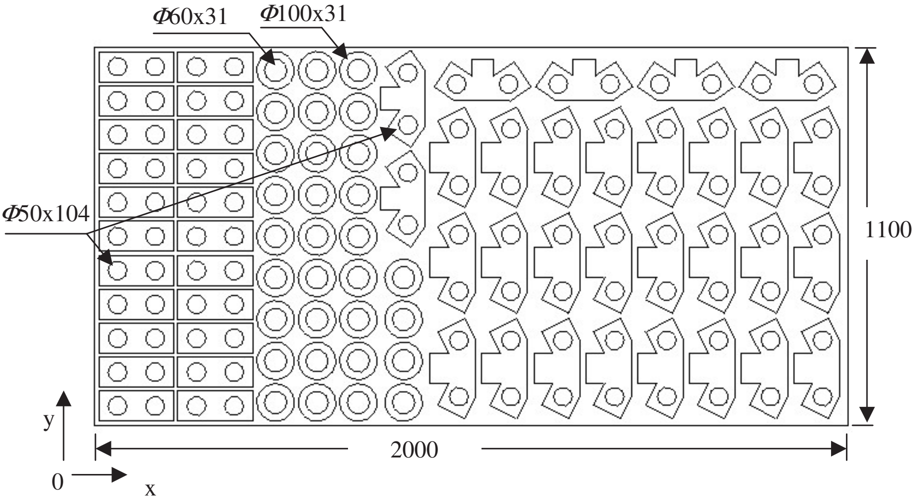

Figure 10. Work batch in Example 2.

5.2 *Example 2*

Example 2 shows a more complicated batch of work pieces (see figure 10). It includes four different types of components, i.e. the rectangular block with holes, ring, small head clip, and large head clip. On the operation feature level, there are 104 small holes of a diameter *Φ*50, 31 holes of *Φ*60, 31 *Φ*100 contouring, and numerous contours of the rectangular block and clips.

Table 1. Summary of process optimization results for Example 1.

	Ø50 Hole punching			Ø180 Hole punching			Laser cutting			
	Start point (x, y)	End point (x, y)	Path length (mm)	Start point (x, y)	End point (x, y)	Path length (mm)	Start point (x, y)	End point (x, y)	Path length (mm)	Total length (mm)
Optimal path	100, 100	830, 830	4371	830, 830	190, 560	1758	190, 560	1100, 100	3917	10 046
Intuitive path	100, 100	830, 830	4975	830, 830	190, 560	2472	190, 560	1100, 100	4495	11 942

Following the rules and the procedure described before, the small holes are to be punched, and contours of the blocks and clips are to be laser cut. For the $\Phi 60$ and $\Phi 100$ features, the calculation based on the same given parameters as in Example 1 is as follows:

$\Phi 60$ holes:

$$\frac{L_c}{\max(V_c)} = \frac{60 * 3.14159 * 31 * 60}{10 * 10^3} = 35.06\, s$$

$$n * \min(t_{\text{stroke}}) + t_x = 31 * 1 * 60/900 + 3 = 5.07\, s$$

$$\therefore \frac{L_c}{\max(V_c)} > n * \min(t_{\text{stroke}}) + t \Rightarrow \text{punching}$$

$\Phi 100$ contouring:

$$\frac{L_c}{\max(V_c)} = \frac{100 * 3.14159 * 31 * 60}{10 * 10^3} = 58.44\, s$$

$$n * \min(t_{\text{stroke}}) + t_x = 31 * 1 * 60/900 + 3 = 5.07\, s$$

$$\therefore \frac{L_c}{\max(V_c)} > n * \min(t_{\text{stroke}}) + t \Rightarrow \text{punching}$$

For all features in the punch group, the inner features are punched first. For example for the ring component, the $\Phi 60$ holes have to be punched out first before the $\Phi 100$ contour of the rings can be punched out as the final component.

Following the same legend as in Example 1, figures 11 and 12 depict the obtained paths by optimization as compared with the ones generated from experience. Since the $\Phi 100$ contour are concentric with the $\Phi 60$ holes, it is easy to understand that the path optimization result should be identical to that for the $\Phi 60$ holes.

The detailed data for each path optimization are recorded in table 2. Table 2 lists two possible intuitive paths. One is the path with the assumption that the tool will return to the starting point between machining different features, which are plotted in figures 11–13. This is called 'Intuitive path with return'. The other intuitive path removes the assumption so that the tool can start from the current tool location without returning to the starting point between machining different features. This is simply referred to as 'Intuitive path' in table 2.

As one can see from table 2, with an 1100 × 2000 mm sheet, the optimal process saves 2653 mm (which is obtained by $31\,298 - 28\,645 = 2653$) as compared with the

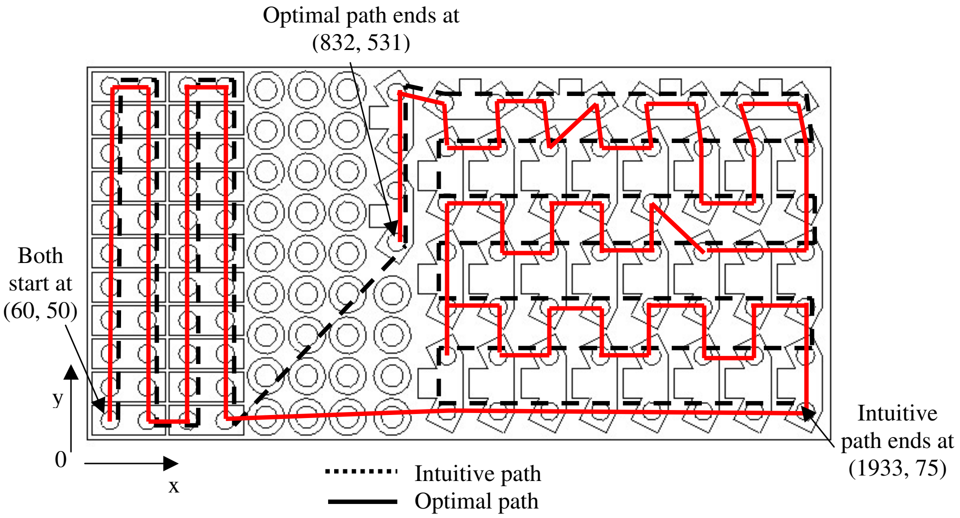

Figure 11. Comparison of the optimal and intuitive paths for $\Phi 50$ holes in Example 2.

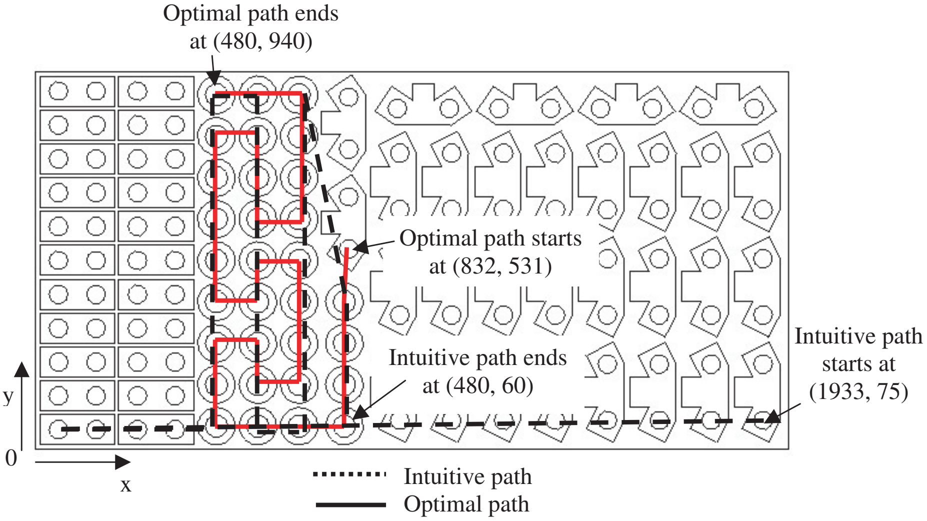

Figure 12. Comparison of the optimal and intuitive paths for $\Phi 60$ holes in Example 2.

Intuitive path; and it saves 4684 mm (obtained by 33 329 – 28 645) as compared with the Intuitive path with returns.

6. Sensitivity studies

Since the ACO algorithms are relatively new, to understand better its performance and the influences of the control parameters, α, β, ρ and Q, a parameter sensitivity study based on the theory of Design of Experiments (DOE) was carried out.

Table 2. Summary of process optimization results for Example 2.

	Ø 50 Punching			Ø 60 Punching			Ø 100 Punching			Laser cutting			
	Start point (x, y)	End point (x, y)	Path length (mm)	Start point (x, y)	End point (x, y)	Path length (mm)	Start point (x, y)	End point (x, y)	Path length (mm)	Start point (x, y)	End point (x, y)	Path length (mm)	Total length (mm)
Optimal path	60, 50	832, 531	12 535	832, 531	480, 940	3452	480, 940	480, 390	3310	480, 390	2060, 50	9348	28 645
Intuitive path	60, 50	1933, 75	12 688	1933, 75	480, 60	5206	480, 60	480, 60	4093	480, 60	2060, 50	9311	31 298
Intuitive path with return	60, 50	1933, 75	12 688	60, 50	480, 60	6046	60, 50	480, 60	4933	60, 50	2060, 50	9662	33 329

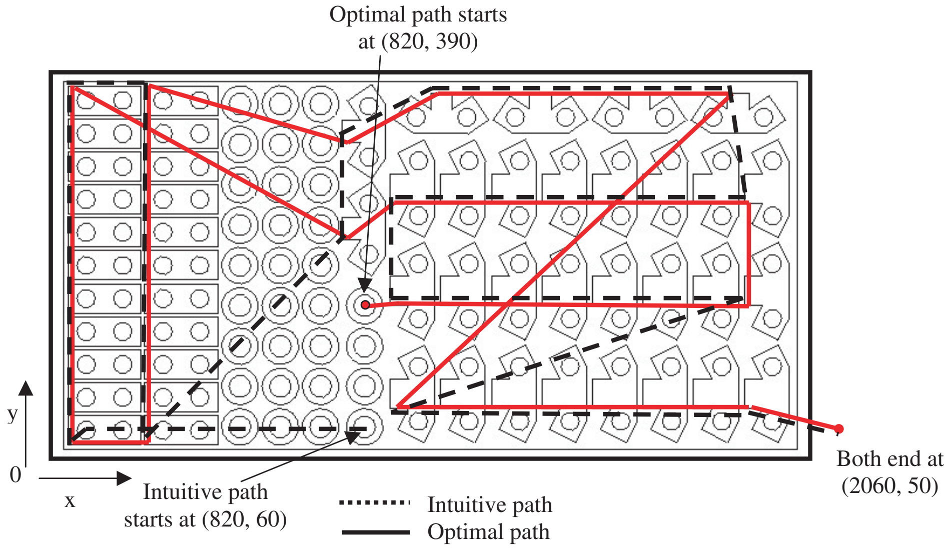

Figure 13. Comparison of the optimal and intuitive paths for the cutting features in Example 2.

For the four parameters, we set three levels for each parameter, i.e. α:{0 1 2}, β:{0 2 4}, ρ:{0.1 0.5 1}, and Q:{1 100 10 000}. A standard Box–Behnken design for four factors and three levels of each gives 27 designs, or 27 combinations of parameters. The first 25 are picked since the last two rows are the duplicate of the 25th row. The path-planning problem for the small holes in Example 1 is selected as the test case (figure 7). The 25 Box–Behnken design set up is listed in table 3 in the first four columns for four factors $X1, \ldots, X4$ where '−1' indicates the first level, '0' the second level and '1' the third level. The corresponding parameter values for α, β, ρ and Q, are listed in the next four columns. For each combination of parameters, five independent runs are carried out due to the algorithm involves random sampling processes. The best result from the five runs is then recorded in the last column of table 3 for the sensitivity study.

An analysis of variance (ANOVA) was conducted based on the data in table 3. Table 4 lists the ANOVA results. The first column shows the source of the variability; the second shows the sum of squares (SS) due to each source; the third shows the degrees of freedom (d.f.) associated with each source; the fourth shows the mean squares (MS), which is the ratio SS/d.f.; the fifth shows the F statistics, which is the ratio of the mean squares; and the sixth shows the p values for the F statistics. As we know (Hogg and Ledolter 1987), if the p value is near zero, it casts doubts on the associated null hypothesis. In other words, if the p value is statistically significantly small (<0.05 or 0.01), the associated factor has a non-trivial effect on the result. From table 4, one can see that the parameters α and β are significant factors. From the sensitivity perspective, α and β are sensitive parameters. It is likely because they control the relative importance of trail versus visibility, which relates to the essence of ACO. The parameters ρ and Q are found to be less sensitive.

Table 3. Design of experiments for parameter sensitivity study.

$X1$	$X2$	$X3$	$X4$	α	β	ρ	Q	Minimum (mm)
−1	−1	0	0	0	0	0.5	100	8073
−1	1	0	0	0	4	0.5	100	5218
1	−1	0	0	2	0	0.5	100	4548
1	1	0	0	**2**	**4**	0.5	100	4371
0	0	−1	−1	1	2	0.1	1	4406
0	0	−1	1	**1**	2	0.1	10 000	4371
0	0	1	−1	1	2	1	1	5873
0	0	1	1	1	2	1	10 000	4561
−1	0	0	−1	0	2	0.5	1	6332
−1	0	0	1	0	2	0.5	10 000	5993
1	0	0	−1	2	2	0.5	1	4504
1	0	0	1	2	2	0.5	10 000	4419
0	−1	−1	0	1	0	0.1	100	4882
0	−1	1	0	1	0	1	100	6375
0	1	−1	0	1	4	0.1	100	4406
0	1	1	0	1	4	1	100	4406
−1	0	−1	0	0	2	0.1	100	5840
−1	0	1	0	0	2	1	100	6279
1	0	−1	0	2	2	0.1	100	4409
1	0	1	0	2	2	1	100	4371
0	−1	0	−1	1	0	0.5	1	5058
0	−1	0	1	1	0	0.5	10 000	5279
0	1	0	−1	1	4	0.5	1	4406
0	1	0	1	1	4	0.5	10 000	4406
0	0	0	0	1	2	0.5	100	4371

Table 4. ANOVA results for parameter sensitivity study.

Source	Sum of squares	d.f.	Mean square	F	Prob. > F
α	11 850 465.5	2	5 925 232.8	23.77	0
β	4 486 795	2	2 243 397.5	9	0.0024
ρ	1 188 444.2	2	594 222.1	2.38	0.1242
Q	263 244.6	2	131 622.3	0.53	0.5997
Error	3 988 970.6	16	249 310.7		
Total	21 830 971	24			

7. Discussions

This work provides an optimal process planning strategy for the combined punch-and-laser machine. It helps make decisions on (1) which type of operation should be applied to each feature, and (2) what is the operation sequence to achieve the maximum manufacturing efficiency. The proposed method integrates knowledge, quantitative analysis and numerical optimization to achieve the goal. From applications as demonstrated in Examples 1 and 2, the proposed method should lead to high manufacturing efficiency. The ACO algorithms are effectively applied and yield significant savings than intuitively designed operation paths. They handle a large number of variables (104 small holes in Example 2) with accurate optimization results. Through the sensitivity study guided by the theory of DoE, it is found for the ACO algorithms the parameters α and β are sensitive parameters, while ρ and Q are less sensitive.

Moreover, the proposed strategy can be integrated with the CAN tool and the NC G-Code generation program. The proposed strategy can be implemented as computer programs to automate the decision making process. All the input information needed by the strategy includes only the geometry and machining parameters such as cutting speed, positioning speed, stroke speed, tool change time, and physical and accuracy limitations. Geometric information can be retrieved from the CAN tool and machining information can be entered once and stored. Upon finishing, the determined operation sequence can then be used to generate G-Code to drive the combined punch-and-laser machine. The proposed strategy complements the current CAN to G-Code path (Xie *et al.* 2004), which focuses mainly on the material utilization ratio. As a result, the maximum machining efficiency can be possibly achieved. Besides the punch-and-laser machine, the proposed strategy should be able to be applied to other types of combination machines with slight modification.

It is well known that the common objective of nesting is to achieve the maximum material utilization ratio (Xie *et al.* 2004). It is observed in the study that the sheet metal layout generated under this objective may lead to less efficient operation process, because such layouts tend to fit all the spaces available without considering the complexity of the final layout. From the operation efficiency perspective, it is better to move all the identical features close to each other to reduce the tool traverse time. For example in Example 2, it would improve the operation efficiency if all the rings were laid out to the right of the clips. By doing so, all the small holes as well as all the cut contours, are close to each other and thus the entire tool travelling path should be shortened. A study on considering the operation efficiency in the optimal nesting process may be a worthwhile attempt.

Another observed issue relates to the size of a work batch. It is found that if the total number of an identical feature is too large, the ant algorithm may take too long to converge. In optimizing the path for 104 small holes in Example 2, the optimization process takes more than 10 min to converge on a Pentium 2.6 GHz desktop computer. Though one can run the proposed process planning programs including the optimization beforehand, it might be more attractive if the batch size is appropriate so that the operator can run the process planning on-line. In addition, if the batch size is too big, sometimes the tool has to travel back and forth in a large sheet, especially when the sheet layout does not consider the operation efficiency at all. On the other hand, if the batch size is too small, the overhead costs on moving to starting points, path recording, programming, etc., may increase. A study on designing the appropriate batch size is thus needed.

8. Conclusions

This work proposes a systematic approach for optimal process planning of combined punch-and-laser machines by integrating knowledge, quantitative analysis and numerical optimization. The ant colony optimization (ACO) algorithms are successfully tailored and applied for the problem. Based on our literature search results, it seems that this work is the first endeavour in addressing the optimal process planning for combined machines. The applications and comparisons demonstrate the effectiveness and potential efficiency improvement by using the proposed methodology. The test results in section 5 show that the proposed methodology has shortened tool travelling paths while comparing with the intuitive method and hence leads to improved machining efficiency. Moreover, the proposed method can be easily integrated with CAN and NC G-Code generation programs to achieve full automation. Sensitivity studies on the ant algorithm parameters should provide guidance to other applications. Future research topics are discussed as well.

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