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Towards energy and material efficient laser cladding process: Modeling and optimization using a hybrid TS-GEP algorithm and the NSGA-II

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ABSTRACT

The soaring global additive manufacturing (AM) market implies considerable potentials of energy and material savings. However, very few researches have addressed the energy and material efficiency issue in AM process through processing parameters optimization. In this study, we developed a predictive model of specific energy consumption (SEC) and metallic powder usage rate in laser cladding process. Three approaches were adopted to perform the modeling, namely, basic gene expression programming (GEP), response surface methodology (RSM), and integrated Tabu search and GEP (TS-GEP). Comparison amongst these methods revealed that TS-GEP demonstrated the highest fitting performance in terms of the root mean square deviation (RMSD) and coefficient of determination (R^2). The experimental validation showed that TS-GEP enabled high robustness and precision of the modeling even though the accuracy of prediction was slightly lower than that of RSM in some cases. Analysis of variance was conducted to examine the contribution of the processing parameters. Results presented that the dominating factor was powder feed rate followed by laser power, Z-increment, and scanning speed irrespective of the interactive effects. With the predictive models, the Pareto front was determined by non-dominated sorting genetic algorithm II (NSGA-II) to provide the optimal set of processing parameters for the maximization of energy and metallic powder efficiency. This study would facilitate appropriate parameter selection of laser cladding process and assist the sustainable manufacturing in AM domain.

1. Introduction

Substantial amounts of resources and energy consumption in manufacturing industry drive manufacturers to seek innovative sustainable methods to mitigate these issues. According to the statistics of OECD countries reported by International Energy Agency (2017), amongst the largest energy end-use sectors (transport, manufacturing, residential, and services), the manufacturing activity accounts for 27% of gross final energy consumption in 2014. Manufacturing dominates the industrial energy use with the share of 90% and is responsible for 84% of energy-related greenhouse gases (GHG) (Duflou et al., 2012). Preliminary studies (CECIMO, 2009) regarding the machine tools demonstrated that over 99% of environmental loads stem from energy consumption. Energy and materials conservation in manufacturing industry will significantly contribute to the economic benefits and the environmental credits. Efficiency promotion is a pivotal and cost-effective strategy to guarantee the energy supply, to enhance business competitiveness, and to decline the environmental burden (International Energy Agency, 2016). Due to the increasing production demand and growing energy price, the enhancement of energy and material efficiency has been a relevant issue in sustainable manufacturing.

AM has been a leading technology widely applied in biomedical,

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Nomenclature

a (W)	laser power
b (mm/s)	scanning speed
c (g/min)	powder feed rate
d (mm)	Z-increment
E (kWh)	total energy consumption
f	fitness value
LH	length of head domain
LT	length of tail domain
Δm (g)	mass of deposited powder

Acronyms

AM	Additive Manufacturing
ANN	Artificial Neural Network
ANOVA	Analysis of Variation
CM	Conventional Manufacturing
EBM	Electron Beam Melting
EP	Evolutionary Programming
ET	Expression Tree
GA	Genetic Algorithm
GEP	Gene Expression Programming
GP	Genetic Programming
IS	Insertion Sequence
LENS	Laser Engineering Net Shaping
NSGA-II	Non-dominated Sorting Genetic Algorithm II
R^2	Coefficient of Determination
RIS	Root Insertion Sequence
RMSD	Root Mean Square Deviation
RNC	Random Numeric Constant
RSM	Response Surface Methodology
SEC	Specific Energy Consumption
SLS	Selective Laser Sintering
TS	Tabu Search

aerospace, and automotive industry etc., and is also the current fastest growing technology (Popovich and Sufiiarov, 2016). Even though some prior studies (Huang et al., 2016; Morrow et al., 2007; Serres et al., 2011) have claimed the superiority of AM such as reduction in energy consumption, environmental emissions, and materials use, the energy consumption rate of diverse AM technologies varies significantly (Huang et al., 2016). If the overall operation processes are considered, AM presumably consumes greater amounts of energy than conventional manufacturing (CM) process (Huang et al., 2013). Kellens et al. (2017) indicated that the energy intensity of current AM system can be 1 to 2 orders of magnitude greater than CM process. For the manufacturing of component with simple and normal shape, AM methods not necessarily have an edge over the CM in term of energy use (Peng et al., 2017). The work of Paris et al. (2016) also confirmed that electron beam melting (EBM) is environmentally superior option for the shape complicated parts and five axes milling process generates lower environmental impacts for parts with acceptable level complexity. Multiple cases studies conducted by Ingarao et al. (2018) revealed that AM was a sustainable solution only under the specific conditions: remarkable weight reduction, application in transportation, and high shape complexity. A comparison study of 8 a.m. and CM processes conducted by Weissman and Gupta (2011) indicated that energy consumption of AM is highly geometry-dependent and rests on the volume of products. Yoon et al. (2014) compared and summarized the specific energy consumption (SEC) of bulk-forming, subtractive, and additive manufacturing processes. The results revealed that the SEC of AM is projected to be 100-fold higher than traditional bulk-forming.

An overview conducted by Wong and Hernandez (2012) shows that, based on the deposited materials, AM could be roughly classified into the liquid-based, solid-based, and powder-based process. Take the powder as an example, the price of iron, cobalt, and nickel-based powder usually range from 20 to 40 USD/Lbs (CARPENTER, 2018). Particularly, the powders designed for biomedical, defense, and aerospace sectors are highly expensive. Although the metal powder is recycled in some cases, the unfused powder could have experienced chemical or physical degradation issues and irregular shaped agglomerates would also be created in the AM process. For example, the reusability of Inconel 718 would be restricted due to the deterioration of physical properties like flow-ability and morphology even though it is chemically stable. Titanium powders are highly susceptible to oxygen, which only allows a couple of recycling times. Contaminated, unfused, and deteriorated powders will cause material waste and economic lost. Performing the AM process with higher energy and material efficiency, therefore, would be expected to significantly lower the energy consumption and economic cost.

An accurate and reliable modeling the energy and resource consumption as a function of processing parameters is prerequisite for the reduction of energy and material (Kara and Li, 2011). Two common ways to determine the energy consumption in machining process are the machining theory (mainly the cutting force) (Armarego et al., 2000) and electricity monitor tool (Li and Kara, 2011; Liu et al., 2016; Xie et al., 2016).

With the energy consumption experiments performed under varying processing conditions, common methods applied to the subsequent modeling and optimization in the manufacturing system include: artificial neural network (ANN) (Ahilan et al., 2013; Aprea et al., 2017), empirical equation (Li and Kara, 2011), response surface methodology (RSM) (Ahilan et al., 2013; Arriaza et al., 2017; Draganescu et al., 2003), and fuzzy logic approach (Ighravwe and Oke, 2017; Lau et al., 2008). Empirical equation and RSM could predict and optimize the energy consumption with specific amounts of experiments, which could be easily performed by data analysis software. The accuracy of results, however, is very limited. Although the ANN and fuzzy logic method can obtain more accurate results, the model is like a “black box” and difficult to interpret. To overcome these drawbacks, the gene expression programming (GEP) approach proposed by Ferreira (2006) could be adopted to model the energy and material consumption of a unit process. Data analytics enable uncovery of hidden information amongst process parameters (Ren et al., 2019). As a classical data mining algorithm, GEP could create an explicit and precise expression for functional relationship among multiple variables. More specifically, the GEP can be used to build a model that express the energy and material consumption as a function of processing parameters of conventional subtractive manufacturing or AM.

Material wastage and energy consumption in AM are two important concerns that need intensive attentions (Verma and Rai, 2013). In the present study, we developed a predictive model of the energy and metal powder utilization in laser cladding process and optimized the processing parameters for sustainable manufacturing. Similar to other evolutionary algorithms such as genetic algorithm (GA), genetic programming (GP), and evolutionary programming (EP), GEP also has some inherent problems such as premature convergence and limited local search capability, which make it easily get trapped in local optima. As a heuristic local search technique, the Tabu Search (TS) technique can be incorporated into the GEP. Since TS and GEP are superior in local search and global search, respectively, this hybrid TS-GEP algorithm would complementarily integrate the advantages of both algorithms to enhance the accuracy and efficiency of the solving process. With the designed physical experiments, response data (energy and material efficiency) were observed by varying processing parameters. The result comparison with conventional GEP and RSM was conducted to demonstrate the superiority of the TS-GEP in this study. Additionally, we performed the analysis of variation (ANOVA) test to examine the influence and contribution of concerned processing parameters in laser cladding process. Then, the model was optimized to determine the best set of parameters for the maximization of energy and material utilization by non-dominated sorting genetic algorithm II (NSGA-II). Overview of the research procedure is presented in Fig. 1. This study would provide a robust empirical basis for the AM practices to develop potential energy and material saving strategy.

2. Literature review

The unit process level of manufacturing is the basis of the entire system. Energy consumption and environmental burden of upper levels can be regarded as the synthesization of power use and emissions generated in multiple unit processes. There are no one-size-fits-all approaches to explain the energy and material consumption behaviors of manufacturing systems which could be directly affected by machining path, material types, processing parameters, machine tools etc. The common strategies of energy and resources conservation on unit process level include: selective actuation of non-continuously required device (shut down unrequired functions in specific operations) (Santos et al., 2011), appropriate process path or machine tool selection (Peng et al., 2019), reduction of idle processing time (Schmitt et al., 2011), energy or resource efficient scheduling and planning (Gong et al., 2016), and optimized processing parameters (Arriaza et al., 2017). The former two approaches are not necessarily feasible in specific manufacturing practice due to the fixed equipment or inadequate optional candidates. While the optimization of process parameter is practicable in most cases.

Previous studies of the energy efficiency evaluation on the unit process level are mainly focused on conventional subtractive machining. Li and Kara (2011) established an empirical model to predict the energy consumption of turning process and considered

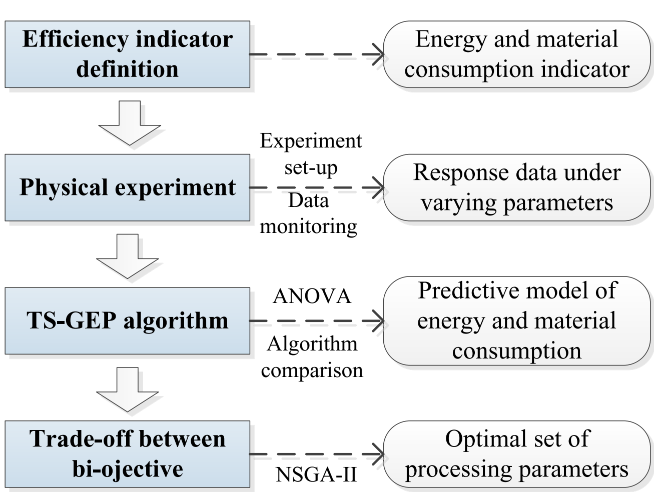

Fig. 1. Overview of research undertaken in this study.

both the tool tip and auxiliary functions. The empirical modeling was claimed to predict the energy use accurately. However, the independent variables in the formulas were material removal rate (MRR) instead of direct processing parameters of the machine tool. Xie et al. (2016) proposed a Stochastic Petri Nets-based energy consumption model and innovatively applied to a turning machine. The optimal parameters were estimated under varying cutting conditions. Nonetheless, this rough estimation is merely based on the concave curve rather than numerical computation. Mori et al. (2011) investigated the required power of unit material removal under different sets of cutting parameters. However, the authors failed to develop a mathematical model of energy consumption and the optimal processing condition was determined based on 9 experiments. Similar to the former study, the accuracy and reliability of optimal parameters remains to be improved. Briefly, the literature mentioned above are focused on the energy modeling of a conventional machine tool with one single objective, i.e., the optimization of energy consumption.

The sustainability of AM has been a great concern in the manufacturing community. Magnol et al. (2006) measured the electric energy consumption of three rapid prototyping systems and investigated the influences of critical parameters such as thickness of layers, geometry of part, manufacturing time, and manufacturing strategies. A set of parameters for energy reduction is selected based on the observations of 18 experiments. However, these selected processing parameters are not necessarily the best set. In the study of Bourhis et al. (2013), the detailed energy and material flows of AM system were traced within the system boundary. Nevertheless, their work merely focused on the assessment without any improvement of energy or materials. To make a robust evaluation, the experiment is insufficient considering the uncertain factors in manufacturing process. Verma and Rai (2013) took the selective laser sintering (SLS) as an illustrative example and developed a multi-step optimization approach enabling an energy efficient AM process. Their study was essentially a multi-objective optimization problem with the goal of minimizing processing energy, surface quality, and material waste. The accuracy of final results highly depended on the formulated model of the three objectives. Liu et al. (2016) investigated the energy-saving potential of laser engineering net shaping (LENS) and examined the effects of processing parameters. However, the optimization was roughly estimated by the trend graph and the accuracy of the so-called optimal parameters was actually near-optimal. Further, the electric power consumption was calculated by multiplying system current by the voltage, which led to imprecise estimation of energy consumption in each experiment.

The energy models described above are within the scope of energy consumption profile quantification and optimal parameters estimation in the case of AM or CM. Majority of the works involving parameter optimizations adopted the statistical analysis approaches based on the design of experiment. Even though this method is interpretable, the accuracy of results is limited. While the GEP is appropriate for the modeling of a complicated system with the merit of explicit and precise mathematical expressions. Specifically, the GEP has been successfully applied to the predictive model of cutting force in face-milling operation (Yang et al., 2012), annual electricity consumption in southeast Asia (Aghay et al., 2017), and national CO_2 emission (Hong et al., 2018) with high precision. Very few efforts have been performed to build a predictive energy and material consumption model of AM. Furthermore, the literature review shows that very few researches addressing the bi-objective, i.e., the balance of energy and material consumption issue can be found. To further improve the accuracy of energy and material estimation and prediction, a TS-GEP algorithm is utilized in the present study. Based on the mathematic expressions created by this algorithm, we made a trade-off between the energy and material consumption by pointing out the Pareto front using NSGA-II.

3. Experimental set-up

The laser cladding process utilizes laser energy focused into a narrow region to melt metallic powder to be deposited on substrate. This process can be controlled through the motive manipulation of substrate, deposition head, or their combination. This study aimed to improve the energy and powder efficiency in the laser cladding process by optimizing the processing parameters. Four primary parameters of laser cladding include scanning speed, Z-increment, powder feed rate, and laser power. They have direct influences on experimental responses such as processing time, power of equipment, and melting capability. The values of energy and powder efficiency-related indicators could be determined under the variation of parameters as listed in Table 1. This equipment is capable of operating under a wide range of parameters. For example, the maximum laser power can reach 4000 W and the recommended range is 500–2500 W. However, the commonly used laser power in manufacturing practice is around 800–1600 W. Similarly, the selected levels of other factors are the ranges in practice. We conducted 19 experiments as inputs for the algorithm and additional five experiments for the model validation. Details on the efficiency indicators and physical experiment are described in the following two sections. Table A1 of Appendix A listed details of the experimental data.

3.1. Indicator definitions

Considering the volume of deposited materials is difficult to measure and AM is utilized for various components, other indicators such as energy consumption per unit volume or per component are inappropriate in AM cases. As one of the most commonly used energy efficiency indicators, the SEC (unit: J/kg) of AM, i.e., energy consumption for adding unit mass, is widely applied to facilitate the quantification and comparison of the energy intensity amongst various AM technologies (Kara and Li, 2011; Yoon et al., 2014). The SEC of AM was calculated by Eq. (1) as a dependent variable.

$$SEC = \frac{total\ energy\ consumption}{deposited\ material} = \frac{E}{\Delta m} = \frac{\int P\,dt}{m_{\mathrm{terminal}} - m_{\mathrm{initial}}} \tag{1}$$

where the $m_{initial}$ and $m_{terminal}$ are the mass of part before and after the cladding process, Δm refers to the mass of powder deposited on the part.

In the cladding process, merely part of metal powders is melted in the molten pool due to various complicated factors such as the chemical and physical property of powder, laser beam, and powder distribution. For a specific AM equipment, the powder usage is closely related to the processing parameters. For example, the greater powder feed rate, high scanning speed, and low laser power will presumably decline the possibility of powder fusion. As expected, high laser power will ensure the thoroughly melting of powder. While higher powder feed rate and scanning speed might refrain the powder from absorbing enough heat, which leads to insufficient melting. Here, we define the material (metallic powder) efficiency λ as expressed in Eq. (2) with the underlying assumption that the powder-based metallic feedstock system is stable during the operation time.

$$\lambda = \frac{\Delta m}{M_p} \times 100\% = \frac{m_{\mathrm{terminal}} - m_{initial}}{r_p \cdot t_p} \times 100\% \tag{2}$$

where r_p and t_p are the powder feed rate and feeding time, respective. M_p is the total mass of supplied powder during the processing period.

3.2. Physical experiment

Laser cladding equipment investigated (model: RS-LCD-4000-D-R) in this study is comprised of six primary subsystems: control cabinet, mechanical arm, compressor, water-cooling machine, powder feeder, and laser device. Basic information on the equipment is presented in Table 2. Materials consumed in this experiment include water, powder, and inert gas (Ar). The flow of inert gas transporting powders is constant during each experiment. In most AM practices, the inert gas is released in the atmosphere directly, while the water is usually recycled in the cooling system. Therefore, only the metallic powder has potentials to be conserved. Both the substrate and powder materials in this study are 316L stainless steel.

An accurate and reliable energy measurement is critical for the modeling. Many previous studies (Gao et al., 2017; Peng et al., 2019; Shi et al., 2015) associated with energy measurement are simply based on the product of rated power and relevant processing time, i.e., the electric power consumption was inaccurately estimation by multiplying system current by the nominal voltage. In the present study, we developed an energy metering system using a power analyzer (model: PA2000mini) in conjunction with a MATLAB platform. This power analyzer enables continuously record of current, voltage, and power with a 0.1-s sample interval. MATLAB software can be used to convert the recorded data regarding power

Table 2
Basic information of the laser cladding equipment.

Items	Values
Range of laser power (capability)	0–4000 W
Range of laser power (recommended range)	500–2500 W
Rated power of powder feeder	0.09 kW
Rated power of control cabinet	7.8 kW
Rated power of water-cooling machine	6 kW
Rated power of mechanical arm	3.2 kW
Rated power of compressor	0.52 kW
Flow rate of inert gas	10 L/min
Pressure for powder feeding	<1 MPa
Maximum working range	2033 mm
Diameter of laser	2 mm

Table 1
Factor layout for the laser cladding process.

Factor layout	Scanning speed (mm/s)	Z-increment (mm)	Laser power (W)	Powder feed rate (g/min)
High level	3	0.2	800	10
Central point	6	0.3	1200	25
Low level	9	0.4	1600	40

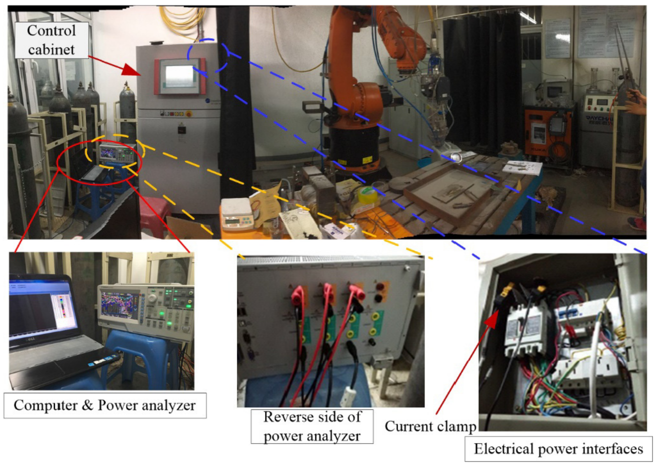

Fig. 2. Photography of experimental set-up for monitoring energy consumption.

variation with one single experiment into the data of energy consumption through integral computation. The physical experiment set-up is displayed in Fig. 2. The electrical power interface is installed on the wall behind the control cabinet. Three current clamps are located at the power bus and another side connects the power analyzer for measuring the current for the entire laser cladding system. Similarly, the voltage monitoring is performed by bringing the power analyzer in the circuitry. In this way, the measured energy consumption reflected the electric power of overall equipment rather than the subsystems. A software specifically for this power analyzer installed in computer enables the real-time long-range control and data collection. The configuration is shown in Fig. 2.

For each experiment, the "zigzag" processing path was adopted to build a simple wall with the length of 80 mm and width of 2 mm as shown in Fig. 3. The whole equipment would stop each time after cladding three layers. The energy consumption would be determined by the metering system described above, and the mass of deposited powder and gross feeding powder were based on the electronic balance and powder feed rate. Then, Eqs. (1) and (2) were utilized to determine the SEC and powder efficiency.

4. Algorithm description

4.1. Gene expression programming

With the inherited merits of GP and GA, the GEP algorithm has been particularly applied to data mining and data classification. One main difference distinguishes the GEP from GA and GP is how they encode individuals. With the functional genotype-phenotype system as shown in Fig. 4, GEP could be encoded in simple linear strings of chromosomes (i.e., the genotype, a feature of GA) and expressed in the form of the parse tree (expression tree) with different shapes and sizes (i.e., the phenotype, a feature of GP). More specifically, due to the plasticity and simplicity of GEP, it could encode by symbolic chromosomes of fixed length for a complex system, then grow and adapt in training environment, and also decode the parse tree into an algebraic expression. The linear chromosome with fixed length is easily manipulated without the compromising of functional complexity. Similar to the GA, genetical operators in GEP work at the chromosome level rather than the expression tree (Aghay et al., 2017). A chromosome in GEP usually have one or multiple genes with identical size and structurally organized in head and tail domain (Aghay et al., 2017). Elements, i.e., mathematical symbols, in genes are derived from predefined function set and terminal set. The function set contains common arithmetic operators like {+, -, *,/, ^2, sqrt, ln}, whereas the terminal set contains the variables of specific model and random numeric constants (RNC). When initializing the chromosome, the elements of head domain in genes can be selected from both function set and terminal set, and the tail domain merely elements from terminal set, which guarantees the gene a valid sub-expression tree (sub-ET). In the example of gene 2 in Fig. 4, its algebraic expression is $\cos(b)\times(c\text{-}a)/(d+2.1)$, and the head domain is all derived from function set, whereas tail domain is from the variables of a model (i.e., a, c, d in this case) and RNC (i.e., 1 and 1.2). This unequivocal expression is named open reading frames (ORF) and also typically called Karva-expression (K-expression) (Ferreira, 2006). Linking functions such as "+", "-", "/", and "*" etc. are utilized to connect multiple genes. In this figure, "+" is adopted to connect sub-ET1 and sub-ET2. The length of head and tail domain should satisfy the relationship reflected in Eq. (3):

$$LT = LH \times (n-1) + 1 \tag{3}$$

where LT and LH are the length of tail domain and head domain, respectively. Suppose the number of arguments that the i-th element f_i in function set takes is nf_i, then $n = \max\{nf_i \mid \text{for all } i \text{ in function set}\}$.

The K-expression can be mapped into the ET according to specific rules (Ferreira, 2006): (1) the start of K-expression corresponding to the root node of ET (top of the parse tree) forms the first line of ET; (2) the total amounts of nodes in the second line of ET is determined by the number of required arguments of the nodes (functions have one or multiple following arguments and

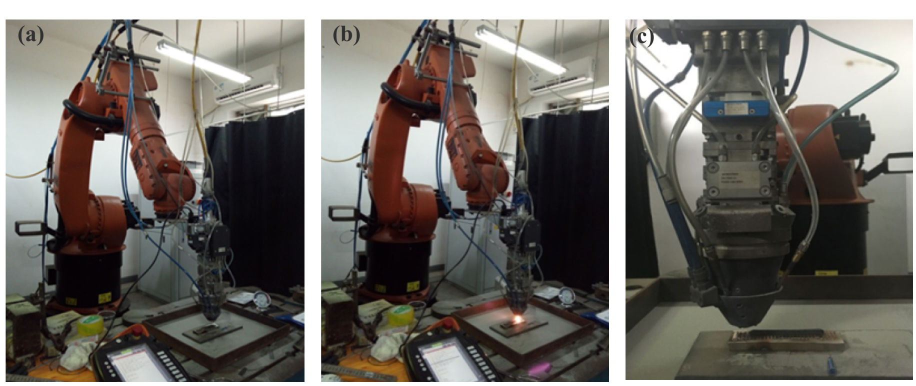

Fig. 3. The laser cladding process: (a) pre-processing; (b) under processing; (c) processing completed.

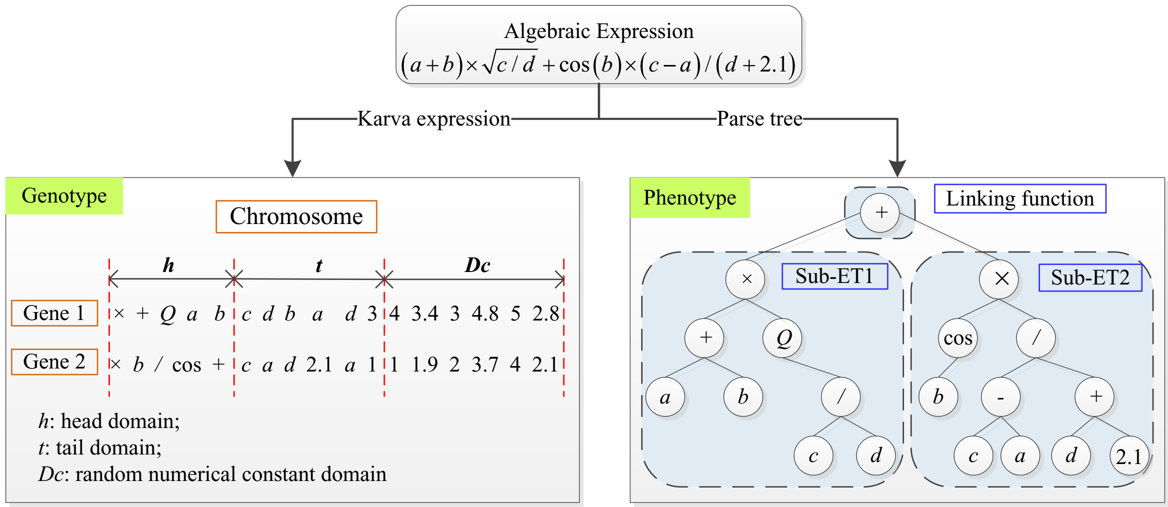

Fig. 4. The genotype-phenotype system of GEP with an illustrative example.

terminals have an arity of zero) in the previous line; (3) from the left to the right, elements from K-expression are successively placed in the nodes in the second line; and (4) repeat these steps until all nodes in the last line contain only terminals, i.e., the "leaves" of the parse tree are either RNC or variables. It should be noted that elements in K-expression could be redundant in most cases. Only part of elements is mapped into the ET, i.e., the length of gene could be greater than the number of nodes in the sub-ET. For example, gene 1 shown in Fig. 4 has the length of 11. But the valid size of its corresponding sub-ET is 8, which implies that only the former 8 elements in K-expression are used to construct the algebraic expression.

4.2. The integration of Tabu Search

Algorithms hybridization is a common strategy to improve the accuracy of solutions and integrate the advantages of both algorithms. The TS was incorporated into the GEP for a more accurate solution. The detailed procedure of TS-GEP is presented in Fig. 5. The generic GEP initialization has four major steps: evaluation, selection, and reproduction.

With the pre-determined quantity of populations, the initial chromosomes were generated by randomly assigning the elements of terminal and functional set to the genes. The chromosomes were mapped into ET, in which the linking function is fixed as "+" in the present study. Then, ETs were translated into solutions of the problem, i.e., the algebraic expressions. Fitness value in GEP measures the feasibility of a solution to the problem and its design affects the effectiveness of solving a problem. As the objective of this study is to find an algebraic solution with minimal error that performs best for all sets of experimental data. The root mean square deviation (RMSD) was adopted for fitness measurement, as presented in Eq. (5):

$$RMSD_i = \sqrt{\sum_{j=1}^{N}(T_j - C_{ij})/N} \tag{4}$$

where N is the number of fitness cases or the size of population. If the $RMSD_i$ is directly used as the fitness value, there will be a scaling problem that $RMSD$ values vary significantly amongst the chromosomes of one generation. To deal with this problem, the rank-based fitness assignment demonstrated with high robustness (Wang and Cao, 2002) was adopted for fitness computation as shown in Eq. (6):

$$Fit(Pos) = 2 - SP + \frac{2(SP-1)(Pos-1)}{N-1}, \qquad SP\in[1.0, 2.0] \tag{5}$$

where Pos denotes the individual position in the descending $RMSD$ ranking, SP is the selection pressure and ranges from 1 to 2. This parameter was fixed at 2 in this study, and thus the fitness value of individual in populations range from 0 to 2. The selection process selected 80% of individuals from the initial population based on the roulette wheel selection approach. To preserve the best chromosome, this elite was selected into the next generation without experiencing the later reproduction process.

The reproduction process can genetically manipulate and modify chromosomes by multiple genetic operators with predefined probabilities. GEP has much more genetic operators than GA and GP. This study concerned the operators such as mutation, transposition of insertion sequence (IS) and root insertion sequence (RIS), gene transposition, and combination. Mutation is an effective operator to increase the diversity of population. In the GEP, mutation randomly occurs at any location of a chromosome without affecting its structure. Alleles in the head domain are modified into other terminals or functions and these in the tail domain are changed into other terminals. To facilitate the evolutionary process and significantly modify the chromosomes, IS transposition randomly selects the manipulated chromosomes, genes, starting point of transposition, and transposition length. The selected gene sequence can be randomly inserted into any position of the head domain except for the first position. Redundant alleles in the original head domain would be removed. The RIS transposition manipulates a randomly chosen chromosome and gene. In this operation, a sequence starting with a function is inserted into the root of this gene. Similarly, the redundant alleles in the head domain are directly deleted. Gene transposition randomly moves a gene to the root of the chromosome. The basic combination operators in GEP include one-point, two-point, and gene combination. In the two-point combination operator, two randomly selected points divide the chromosome into three parts, and the substring counterparts are exchanged between two parental chromosomes. After the reproduction process, all these chromosomes should be reinserted into the last generation (i.e., randomly substitute 80%

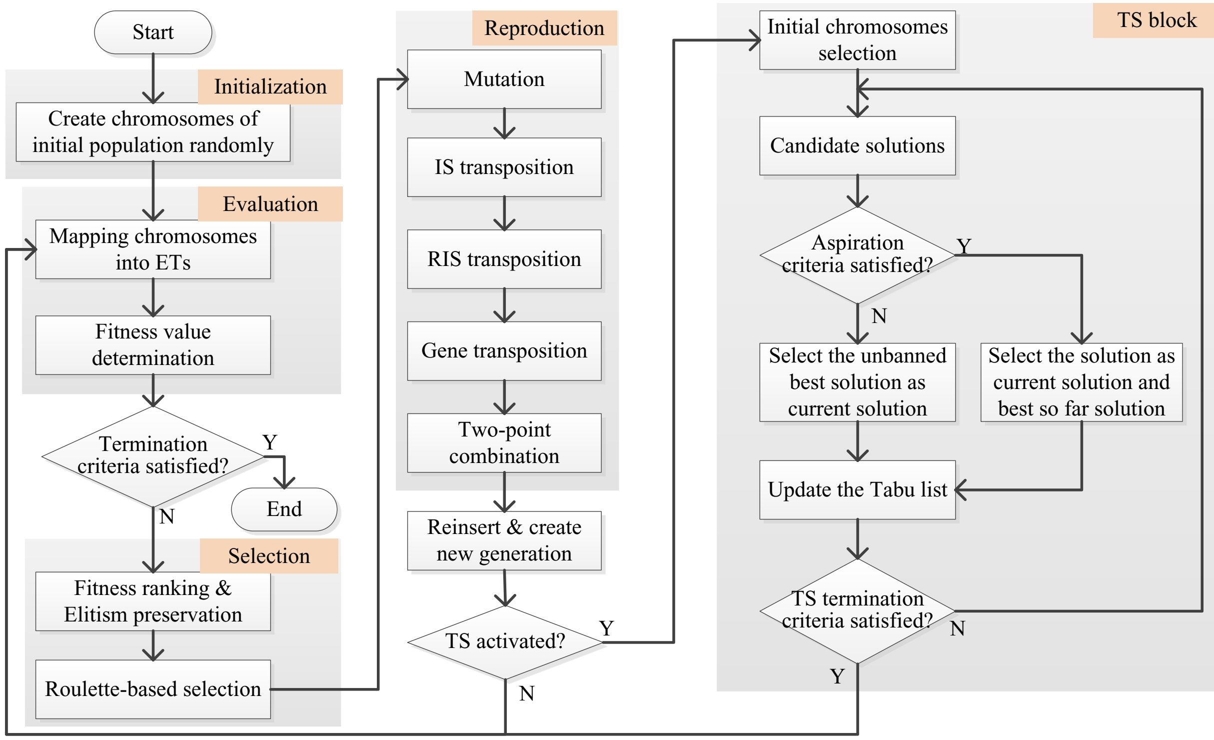

Fig. 5. Flow chart of the TS-GEP algorithm.

individuals) to form a new generation. To obtain an explicit and accurate algebraic formula, a certain number of iterations are required to generate better populations. In the present study, the termination criterion of GEP is based on the maximum number of generations. The relevant parameters associated with the GEP block is listed in Table 3. Processing parameters of laser cladding process such as laser power, scanning speed, powder feed rate, Z-increment are presented by *a*, *b*, *c*, *d*, respectively.

TS algorithm will be activated when the best *RMSD* value remains unimproved for consecutive certain amounts of generations. At this point, the population has relatively lower diversity and tends to get stuck at a local optimum. Individuals with high fitness value will be selected as the initial chromosomes for TS. The neighborhood solutions of an individual are created by the mutation operator. Even though different operators will generate distinct neighborhood solutions with varying quality, there are no consensus on the best operators in TS community. In the tabu list, tabu objects are based on the *RMSD* value of the chromosome. More specifically, the study selected the best chromosome in each iteration and took its *RMSD* value as tabu object. The aspiration criterion is that if the banned solution is better the best so far solution then this banned solution will be the current solution as well as the best so far solution. The TS termination criterion rested on the numbers of maximum iteration and the unimproved iterations. Details on the TS block in this study can be reflected by the pseudocode (Table 4) below.

The parameters with regard to the TS is summarized in Table 5. Output of the TS was the best so far solution which would be inserted into the original population to substitute the input solution. TS block would improve the *RMSD* value of the population.

4.3. Response surface methodology

As a relevant multivariate statistic technique in analytical optimization, RSM is commonly applied to examine the relationship among variables under a set of experimental data. This method is based on the fit of a polynomial equation to the data (Almeida et al., 2008). The first-order and second-order models in RSM are presented in Eqs. (6) and (7).

$$y = \beta_0 + \sum\nolimits_{i=1}^{k} \beta_i x_i + \varepsilon \tag{6}$$

$$y = \beta_0 + \sum\nolimits_{i=1}^{k} \beta_i x_i + \sum\nolimits_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{7}$$

Table 3
Relevant parameters in GEP.

Settings	Values/Symbols	Settings	Values/Symbols
Function set	{+, -,/, × , Q, ln, sin, cos, exp, ^2}	Maximum generation	100
Terminal set	{a, b, c, d, M}	Population size	100
Length of tail domain	9	Length of head domain	8
Generation gap	80%	Mutation rate	0.01
IS transposition rate	0.1	RIS transposition rate	0.1
Recombination rate	0.3	Gene transposition rate	0.1
Dc range	[-10, 10]	Number of genes	6

Note: Q is the square root, exp is the exponential, ln is the natural logarithm, ^2 is the second power.

Table 4
Pseudocode of TS block performed in this study.

```
Input: selected chromosomes in the unimproved population, TS parameters
Output: best so far chromosome
for each chromosome_i ∈ selected chromosomes in the unimproved population do
//Initial set-up//
    tabu_list ← []
    current_solution ← chromosome_i
    best_so_far_solution ← chromosome_i
    tabu_list.push RMSD (chromosome_i)
//Loop//
    while (not    <maximum iteration & <unimproved iteration of TS) do
       candidate_set ← generate_neighborhood (current_solution)
       sort candidate_set with respect to the RMSD values
       for C_i ∈ candidate_set do
          if RMSD (C_i) < RMSD (best_so_far_solution) then
               best_so_far_solution ← C_i ; current_solution ← C_i ; update the tabu_list;
               break loop
          else if RMSD (C_i) ∉ tabu_list then
               current_solution ← C_i ; update the tabu_list;
               break loop; end
         end
       end
     end
     return best_so_far_solution
end
```

Table 5
Relevant parameters for TS.

Settings	Values
Unimproved generations of GEP	10
Number of selected chromosomes	6
Tabu length	4
Number of neighborhood candidates	30
Unimproved iteration of TS	12
Maximum iteration	90

where x_i represents the variables, β_0 is a constant term, β_i is coefficient of the linear variable, β_{ii} is coefficient of the quadratic variable, β_{ij} is the coefficient of interaction variable, and ε denotes the residual term. These coefficients could be determined by the method least square and regression analysis (Arriaza et al., 2017).

The data source of RSM is usually generated by central composite design, three-level factorial design, Doehlert design, and Box-Behnken design. In this study, we fitted the second-order model with observed data points to obtain the mathematical expressions of energy and powder efficiency, which was performed on the Minitab platform. Since the experiment design in this study is not orthogonal, uncoded units were used in Minitab to conduct the RSM analysis. Additional validation experiments were adopted to compare the RSM results and evolution results of the TS-GEP algorithm.

5. Computational results

5.1. Comparison of algebraic expressions

In this study, we compared the algebraic expressions generated by RSM, basic GEP, and TS-GEP. The algebraic expressions of SEC and powder efficiency in laser cladding process obtained by these methods are presented in Table 6. Variables *a*, *b*, *c*, and *d* represent laser power, scanning speed, powder feed rate, Z-increment, respectively. The RSM initially obtained a full efficiency model that included all possible terms shown in Eq. (10). However, to simplify and improve the precision of predictions, the model reduction technique was adopted to eliminate the insignificant terms. Criterion for terms reduction rested on the statistical significance. This study chose significance level with 0.05 and found the model without insignificant term (P-value > 0.05). The exclusion of these statistically insignificant terms would increase the precision of the predictive model (Minitab support, 2018).

The results indicated that TS-GEP has higher accuracy of estimating the energy and powder efficiency in terms of the RMSD and coefficient of determination (R^2). Conventional nonlinear regression method and RSM are favorable for fitting the lower-order functions, while the GEP method is more preferential in mining high-order functions. As identified from Table 6, the algebraic expression of powder efficiency obtained by RSM has relatively simple form and higher accuracy. Whereas the algebraic expression of SEC contains more interaction terms, i.e., the relationship among processing parameters and SEC are nonlinearly complicated compared with powder efficiency, the fitting precision ($R^2 = 0.85$, $RMSD = 0.365$) is comparatively lower. Additionally, for the SEC modeling, results of RSM is slightly superior to that of the basic GEP. For the powder efficiency modeling, the performance of basic GEP is still notably worse than RSM, which demonstrates the advantage of conventional regression method at fitting low-order function. Incorporating the TS technique into GEP improves the search capability of basic GEP and develops more accurate modeling of SEC and powder efficiency. Fig. 6 presents the actual data and the predictive data of SEC (unit: $\times 10^8$ J/kg) and powder efficiency (unit: %) determined by the TS-GEP method. As evident from this figure, we can see a close match between the actual and predictive curves.

Table 6
Energy and powder efficiency models found by RSM, basic GEP, and TS-GEP.

Methods	Efficiency	R^2	RMSD	Algebraic expressions
RSM	SEC	0.85	0.365	y = 11.76 - 0.01336 *a +0.0156 *b - 0.01379 *c - 4.92 *d + 0.000005 *a*a - 0.00654 *b*c + 0.519 *b*d
	Powder	0.93	3.170	y = 36.15 + 0.01376 *a - 2.029 *b - 1.222 *c + 29.28 *d + 0.0848 *b*c
Basic GEP	SEC	0.84	0.381	y = sin(d/sin(a))*log(abs(3.2498))+cos(d)+cos(sin(log(abs(3.2498/d))))+ cos(sqrt(abs(b))*5.9282)/sqrt(abs(c))+d + tan(exp(c))
	Powder	0.85	4.811	y = sin(0.16728)+(((4.8237-d)+sqrt(abs(a))-c)+8.1713+((sin(tan(-7.6367))+sin(c)*b)-d)+8.1738 + tan(cos((sqrt(abs((d-a)))+ exp(9.7753))))
TS-GEP	SEC	0.91	0.292	y = cos(sin(log(abs(c/b))))+cos(a)*d + cos(sin(log(abs(a))))+ sin(a)/(d + b)+ cos(c*c) + cos(cos(sin(cos(sin(c)))))
	Powder	0.96	2.567	y = tan(c)+log(abs(-2.7945))+tan((b-(b-c))*exp(b*b))+((-7.1978 + b)-(c/b-log(abs(b))))+sqrt(abs((cos(a)+a)))+ tan(sqrt(abs(b*c*d*c)))

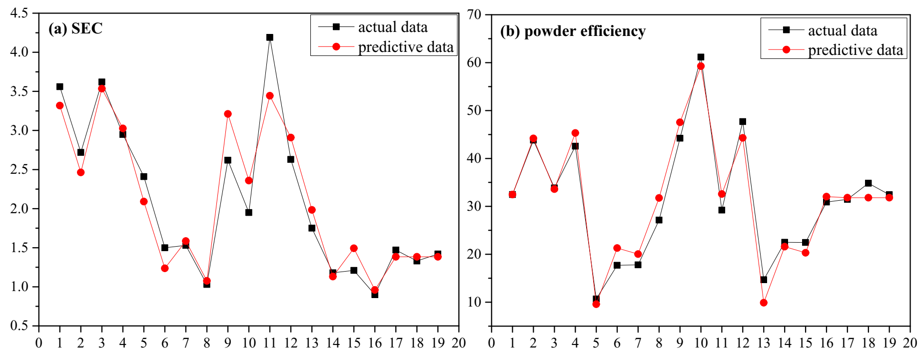

Fig. 6. Fitting results using TS-GEP: (a) SEC and (b) powder efficiency.

5.2. Model validation and contribution analysis

To validate the SEC and powder efficiency model shown in Table 6, an additional five experiments were conducted under varying processing parameters. Hereby, we compared the predictive errors of the SEC and powder efficiency models found by TS-GEP and RSM, and results were provided in Table 7. Even though the relative errors of powder efficiency obtained by TS-GEP are slightly higher than that of RSM, the prediction models are more robust, and the relative errors are confined to 16%. Particularly, the prediction of SEC has shown significantly higher precision. It should be noted that the experimental errors would presumably exert a high impact on the comparison results, in particular, the SEC indicator.

The SEC and powder efficiency are affected by the parameters of laser cladding in both straightforward and interactive ways. Contributions of processing parameters on SEC and powder efficiency are identified using ANOVA as illustrated in Table 8. Results suggest that the powder feed rate is the predominant factor contributing 59.3% and 63.6% for the SEC and powder efficiency, respectively, followed by laser power and Z-increment. As we can see from this table, the P-values of scanning speed is conspicuously greater than 0.05 and this parameter has the least impact on both objectives. However, it has interactive effects with other parameters. For example, in the modeling of SEC, scanning speed will exert moderate impacts in conjunction with powder feed rate and Z-increment.

5.3. Trade-off between specific energy consumption and powder efficiency

The SEC and powder efficiency are two conflict goals, and a trade-off is required in the manufacturing process. In order to obtain the optimal set of processing parameters, we performed a bi-objective optimization for energy and material conservation using NSGA-II algorithm proposed by (Deb et al., 2002). Since its inception, it has been one of the prevalent multi-objective meta-heuristic approaches. Since the objectives are the minimization of SEC and maximization of powder efficiency, a set of optimal solutions, also known as Pareto front, should be identified rather than one single optimal solution. The Pareto front refers to the optimal conditions that no further improvement of any objective can be found without compromising other objectives. It is essentially a set of nondominated solutions. The upper bound and lower bound of the four processing parameters are identical with the high level and low level in Table 1. Each solution in Pareto front (Fig. 7) weights objectives differently (Liao et al., 2018). For this laser cladding process, Fig. 7 provides a series of optimal combinations. For example, under the powder efficiency of 73%, the lowest SEC would be 37.1×10^8 J/kg. This nondominated solution implies that the laser power of 1387 W, scanning speed of 3 mm/s, powder feed rate of 24.5 g/min, and Z-increment of 0.4 mm would achieve an

Table 7
Model validation results for the comparison of TS-GEP and RSM.

Experiment number	Experiment data		Predictive data (RSM)		Predictive data (TS-GEP)		Relative error (RSM)		Relative error (TS-GEP)	
	SEC	powder	SEC	powder	SEC	powder	SEC	powder	SEC	powder
1	3.38	42.71	2.60	36.46	3.57	48.97	23.01%	14.63%	5.66%	14.65%
2	1.88	31.72	2.03	29.79	1.96	29.39	7.72%	6.08%	4.28%	7.36%
3	1.81	30.76	3.09	37.42	1.88	31.11	70.78%	21.65%	3.79%	1.13%
4	2.76	46.08	4.38	49.61	3.16	49.79	58.67%	7.65%	14.48%	8.05%
5	1.96	28.81	2.72	29.84	1.66	26.81	38.91%	3.56%	15.52%	6.94%

Table 8
Analysis of variance for SEC and powder efficiency.

Objectives	Factors	Degrees of freedom (DF)	Sum of squares (SS)	F-Value	P-value	Contribution (%)
SEC	*a*	1	2.2726	39.47	0	13.31%
	b	1	0.0086	0.15	0.707	0.05%
	c	1	10.1283	175.89	0	59.33%
	d	1	0.522	9.07	0.012	3.06%
	*a***a*	1	1.7308	30.06	0	10.14%
	*b***c*	1	1.3865	24.08	0	8.12%
	*b***d*	1	0.3875	6.73	0.025	2.27%
	Error	11	0.6334			3.71%
Powder efficiency	*a*	1	484.99	33.01	0	16.85%
	b	1	1.19	0.08	0.78	0.04%
	c	1	1830.34	124.59	0	63.61%
	d	1	137.18	9.34	0.009	4.77%
	*b***c*	1	232.94	15.86	0.002	8.09%
	Error	13	190.98			6.64%

Note: *a*: laser power; *b*: scanning speed; *c*: powder feed rate; *d*: Z-increment.

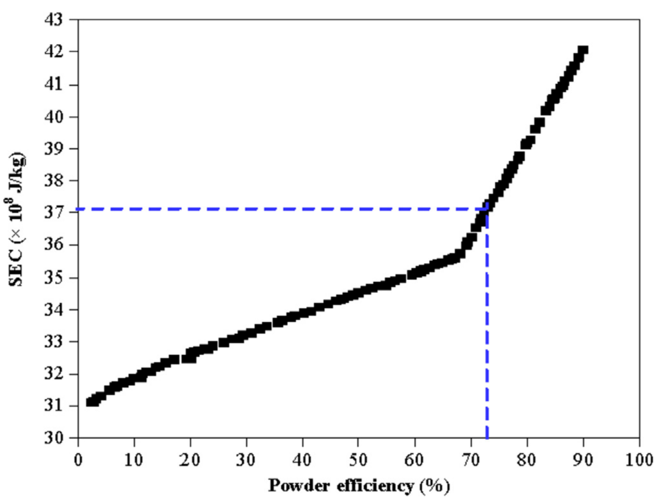

Fig. 7. Pareto front found by NSGA-II for the laser cladding process.

optimal energy and powder efficiency. The Pareto front affords an optimal solution space and enables a flexible and convenient parameter selection in processing practice. The parameter selection from the Pareto front is closely related to the relative importance of indicators. In some cases, the physical and chemical properties of metallic powder are not high demanding. To this end, powders can be simply recycled, and higher weighing factor should be assigned to the energy efficiency.

6. Conclusions and discussions

With the legislative pressure, growing energy and material price, and soaring AM market, a successful AM system requires a careful consideration of energy and material efficiency. The present study utilized the laser cladding system as an AM example and developed a TS-GEP algorithm for the predictive modeling of energy and powder efficiency. In these models, SEC and effective powder consumption rate were defined as efficiency indicators. An energy monitoring platform was built to more accurately investigate the energy consumption under varying processing parameters. With the data of physical experiments, a comparison of models developed by basic GEP, RSM, and TS-GEP was conducted to demonstrate the superiority of TS-GEP. The integration of TS and GEP inherited the merits of high local and global searching capability and showed improved fitting performance in terms of R^2 and RMSD. Validation experiments revealed that RSM demonstrated slightly higher accuracy in some cases. However, results of TS-GEP were robust and also displayed high precision. The ANOVA technique was adopted to examine the contributions of each parameter. Analysis showed that the dominating factor was powder feed rate followed by laser power, Z-increment, and scanning speed. Even though the direct effects of scanning speed were weak on energy and powder efficiency, the interactive effects with other parameters were non-negligible. Considering that SEC and powder efficiency were conflicted indicators, we applied the NSGA-II algorithm to this trade-off issue. The Pareto front of the laser cladding process, a set of nondominated solutions, was found for energy and metallic powder conservation simultaneously.

This study provided a set of optimal parametric combinations from the perspective of energy and material use, which would benefit and assist the technicians in shop-floor to select appropriate processing parameters under varying working conditions. In addition, as the research object was merely laser cladding, this modeling approach can be extended to other AM processes such as selective laser melting (SLM), SLS, and EBM. The soaring AM market with optimized manufacturing process implies a tremendous potential for energy and material savings. These savings also suggest huge amounts of reduction on economic cost and environmental burden, which highly complies with the concept of sustainable manufacturing.

Irrespective of mechanical properties such as surface roughness, bonding strength, and porosity is an important limitation of this study. However, inclusive consideration of factors in the cladding process, apart from material and energy, would increase the complexity significantly. To improve the adaptability in manufacturing practice, incorporating additional technical indicators in the optimization would be desirable. Although the TS-GEP presented good fitting performance, large amounts of parameters in this algorithm have great impacts on the operational efficiency and accuracy. Thus, following-up works could consider exploring optimum parameters to enhance the performance of algorithm. Subsequently, with the consideration of comprehensive processing objectives and development of a more efficient algorithm, a software tool can be developed to facilitate the selection of processing parameters in the future work.

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Appendix A

Table A1
Experimental data of the laser cladding process

Test no.	Laser power (W)	Scanning speed (mm/s)	Powder feed rate (g/min)	Z-increment (mm)	SEC (10^8 J/kg)	Powder usage rate (%)
1	800	3	10	0.2	3.56	32.47
2	1600	3	10	0.2	2.72	43.82
3	800	9	10	0.2	3.62	33.85
4	1600	9	10	0.2	2.95	42.56
5	800	3	40	0.2	2.41	10.67
6	1600	3	40	0.2	1.5	17.71
7	800	9	40	0.2	1.53	17.79
8	1600	9	40	0.2	1.03	27.14
9	800	3	10	0.4	2.62	44.22
10	1600	3	10	0.4	1.95	61.16
11	800	9	10	0.4	4.19	29.23
12	1600	9	10	0.4	2.63	47.69
13	800	3	40	0.4	1.75	14.7
14	1600	3	40	0.4	1.18	22.5
15	800	9	40	0.4	1.21	22.46
16	1600	9	40	0.4	0.9	30.9
17	1200	6	25	0.3	1.47	31.46
18	1200	6	25	0.3	1.33	34.83
19	1200	6	25	0.3	1.42	32.44

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