Data-driven multi-objective optimization of laser welding parameters of 6061-T6 aluminum alloy

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Abstract. In this paper, a data-driven multi-objective optimization approach using optimal Latin hypercube sampling (OLHS), Kriging (KRG) metamodel and the non-dominated sorting genetic algorithm II (NSGA-II) is presented for the laser welding process parameters on 6061-T6 aluminum alloy. The experiments are designed by OLHS and carried out to obtain the data results. The complex relationship between the process parameters and the bead profile geometry is established by KRG using the data results. The accuracy of the established KRG metamodel is validated using experiments. Then, NSGA-II is used to explore the design space and search the Pareto optimal solutions of process parameters. Besides, the validation experiments were carried out to obtain ideal LW bead profile, which shows that the approach can bring dependable guidance for LW experiments.

1. Introduction

The weight saving and mechanical properties improvement attracts a significant attention in the advanced manufacturing for aerospace applications \cite{1, 2}. AA6061-T6 Aluminum alloy is widely applied in aerospace, automobile and railway industries to obtain high specific strength, since it has light weight, high strength, good formability and corrosion resistance \cite{3-5}.

As an important advanced manufacturing technology, laser welding (LW) is widely used in automobiles, aerospace and shipbuilding industries by the virtue of its small thermal deformation, accurate positioning and large molten pool aspect ratio \cite{6, 7}. Compared with other welding methods, LW has deeper penetration, higher processing speed and energy density \cite{8}. Studies indicate that LW process parameters (eg. welding speed, laser power and laser focal position) affect the bead profile and the welding quality significantly \cite{9}. However, the relationship between bead cross-section geometry and process parameters is complicated. Therefore, it is difficult to find the optimal process parameters for different processing condition.

To overcome the shortcomings, this paper presents a data-driven multi-objective optimization approach for the LW process parameters using optimal Latin hypercube sampling (OLHS), Kriging (KRG) metamodel and the non-dominated sorting genetic algorithm II (NSGA-II). The OLHS is used in the design of experiments (DOE). Then the experiments are conducted to obtain the data result of bead cross-section geometry, which is used as the training data to construct the KRG metamodel to describe the relationship between process parameters and bead profile. After that, the NSGA-II is employed to
find the Pareto fronts of process parameters. In this paper, the data-driven multi-objective optimization approach is used to find optimum process parameter of LW on 6061-T6 alloy.

2. Experimental details

2.1. Material and equipment

The experiments were carried out on 100 × 200 × 2.5 mm AA6061-T6 aluminum alloy plates. The surface of the workpiece was properly polished and cleaned with acetone to remove the surface oil and oxide layer before welding. Table 1 gives the chemical composition of the AA6061-T6 aluminum alloy.

| Elements | Si     | Fe | Cu   | Ti    | Zn    | Mn   | Mg   | Al        |
|----------|--------|----|------|-------|-------|------|------|-----------|
| Mass %   | 0.4~0.8| <0.7| 0.15~0.4| 0.15  | 0.25  | 0.15 | 0.8~1.2 | Balance  |

The LW equipment employed in our paper consists of an IPG YLR-4000 fiber laser system, an ABB IRB4400 robot, a gas nozzle, a jig and a workbench. Figure 1 shows the schematic of LW process. The flow rate is set as 1.0 m/h for the shielding gas of argon.

Figure 1. Schematic of LW process.

After the LW, the bead profile samples were prepared by wire electrical discharge machining, followed by the metallographic mosaic method and further sanded by molybdenum sandpaper. Then, the cross-section of welding bead were revealed using the etchant and observed by microscope.

2.2. Design of experiment

The bead profile of LW is mainly affected by three factors, namely, laser power (P), welding speed (S) and defocus distance (D). The weld width (WW) of the upper surface and the weld depth (WD) are taken as two features of the bead cross-section. Figure 2 illustrates the bead profile of LW.

Design of experiment (DOE) is applied to decrease the influence of errors from experiments on the results, which make the approximation model constructed by researchers be more accuracy. The OLHS is improved from LHS, in which the level combination of each factor is optimized instead of random [10]. The OLHS is used in this paper to effectively generate 21 set of sample points in the process parameters ranges, which is listed in Table 2.

| Parameters | Units | Lower bounds | Upper bounds |
|------------|-------|--------------|--------------|
| P          | kw    | 2.8          | 3.2          |
| V          | mm/s  | 50           | 70           |
| D          | mm    | -1           | 1            |
3. The proposed optimization methodology

In this paper, the NSGA-II based on OLHS-KRG is presented to optimize the LW process parameters. The experiments are designed by OLHS and carried out to obtain the data results. The complex relationship between the process parameters and the bead profile geometry is established by KRG using the data results. Then, NSGA-II is used to explore the design space and search the Pareto optimal solutions of process parameters. The specific steps of the optimization methodology are listed as follows:

- **Step1:** Identify the optimization problem of LW process parameters, including objective function, the process parameters and corresponding design space.
- **Step2:** Design the experiments by OLHS, carry out the LW experiments for the data results.
- **Step3:** Construct KRG metamodel to investigate the connection between process parameter and bead profile geometry.
- **Step4:** Check whether the established KRG metamodel is accurate. If yes, then conduct step 5, otherwise, go back to adjust DOE.
- **Step5:** Based on the predicted value of the established KRG metamodel, NSGA-II is used to search the optical process parameters with the larger WD and the smaller WW.
- **Step6:** Experimental verifications are carried out.

4. Results and discussions

4.1. KRG metamodel construction

The experiments with 21 set of process parameters generated by OLHS were conducted. As shown in Figure 3, the bead profile (WW and WD) can be observed and measured by microscope based on the post-processing of the cross-section of each weldment.

![Figure 3. Post-processing to obtain experimental results.](image)

KRG model was initially employed to help geologists estimating mineral deposits though taking a few samples instead of excavating all plots of land. The approximate function at the unknown point \( \mathbf{x} \) can be calculated by Eq. (1). More information can be found in [11].

\[
\hat{f}(\mathbf{x}) = \hat{\mu} + \mathbf{r}^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{1}\hat{\mu}) \tag{1}
\]

where \( \mathbf{y} \) is a vector containing the \( m \) sample point of the responses. \( \hat{\mu} \) is an function of \( \mathbf{R} \).

The data results of bead profile are used to construct the KRG metamodel, which can be describe the relationship between process parameter and welding bead profile. Figure 4 demonstrates the established KRG metamodels of WW and WD.
Additional 4 sets of process parameters are stochastically chosen to validate the accuracy of KRG metamodel using actual LW experiments. The predictive values (PV) and the experimental values (EV) are shown in Figure 5 which indicates a good fit. Table 3 lists the process parameter and relative error of prediction from KRG. The average relative error between predictive and experimental values of WW and WD are 4.59% and 6.98%, respectively. Hence, the established KRG metamodels are effective and can be applied to predict welding bead profile and search Pareto-optimal solutions for the multi-objective optimization.
5.

**Figure 5.** Comparison of predictive and experimental values.

| No. | P  | S  | D  | Relative error (%) |
|-----|----|----|----|--------------------|
| 1   | 3.0| 60 | -1 | 3.64               |
| 2   | 3.1| 55 | 1  | 5.01               |
| 3   | 2.8| 70 | 0  | 6.09               |
| 4   | 3.2| 65 | 0  | 3.61               |

*Average error:* 4.59

4.2. **Optimization and verification**

Based on the KRG metamodel, NSGA-II is used to obtain the Pareto fronts of the LW process parameters. The larger WD and the smaller WW are set as the objectives. During the optimization process, predictive values by established KRG metamodels are taken as the fitness values of WW and WD. Figure 6 illustrates the calculated Pareto fronts for the multi-objective. Different points represent different optimal solutions. In general, Figure 6 indicates that the optimal solutions are non-inferior to each other since the trade-offs relationship between WW and WD.

**Table 4.** Results of the verifications.

| No. | P  | S  | D  | WW (µm) | WD (µm) |
|-----|----|----|----|---------|---------|
| 1   | 3.2| 51 | 0  | 2263    | 2298    |
| 2   | 2.8| 69 | -1 | 2047    | 1594    |

In order to validate the effectiveness of the optima, the 2 solutions in the Pareto fronts are chosen and carried out. The bead profiles of the 2 verification experiments of LW are measured, Table 4 lists the process parameters and corresponding experimental results. Table 4 shows that the maximum relative error (RE) of WW is 8.99%, while that is 4.67% for WD. It can be concluded that the presented data-driven multi-objective optimization method is reliable, which can facilitate finding the optimal process parameters.
5. Conclusion
In this paper, a data-driven multi-objective optimization approach using OLHS-KRG and NSGA-II is presented to find optimal process parameters of LW on the 6061-T6 aluminum alloy workpiece. The experiments are designed by OLHS and carried out to obtain the data results. The complex relationship between the process parameters and the bead profile geometry is established by KRG using the data results. NSGA-II is used to explore the design space and search the Pareto optimal solutions of process parameters. The proposed method can find the ideal LW bead profile which could achieve the quality improvement effectively. Besides, the validation experiments were carried out, which shows that the presented approach can bring dependable guidance for LW experiments.

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