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Journal of Materials Processing Technology 99 (2000) 207–218

Journal of Materials Processing Technology

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# Prediction of laser butt joint welding parameters using back propagation and learning vector quantization networks

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Received 2 December 1998

## Abstract

Laser welding parameters include not only the laser power, focused spot size, welding speed, focused position, etc., but also the welding gap and the alignment of the laser beam with the center of the welding gap, these latter two parameters being critical for a butt joint. These parameters are controllable in the actual operation of laser welding, but are interconnected and extremely non-linear, such problems limit the industrial applicability of the laser welding for butt joints. The neural network technique is a useful tool for predicting the operation parameters of a non-linear model. Back propagation (BP) and learning vector quantization (LVQ) networks are presented in this paper to predict the laser welding parameters for butt joints. The input parameters of the network include workpiece thickness and welding gap, whilst the output parameters include optimal focused position, acceptable welding parameters of laser power and welding speed, and welding quality, including weld width, undercut and distortion for the associated power and speed used. The results of this research show a comprehensive and usable prediction of the laser welding parameters for butt joints using BP and LVQ networks. As a result, the industrial applicability of laser welding for butt joints can be expanded widely. 

*Keywords:* Laser welding; Neural network; Welding automation

## 1. Introduction

Laser welding is one of the ‘keyhole’ welding processes because of its high power density. This is characterized by its parallel sided fusion zone, narrow weld width, and high penetration [1]. The welding performance is strongly determined by the laser welding parameters. For laser welding parameters, the energy input is controlled by the combination of the following parameters: focused spot size, focused position, keyhole shielding gas, laser power, and welding speed. Also, the repetition of welding performance depends on the material preparation, the joint fit-up and the laser beam-to-joint alignment [2], the latter two parameters being particularly important for a butt joint [3]: they usually limit the industrial applicability of laser welding for butt joints. The optimal focused position, laser power, and welding speed are three controllable welding parameters, which need to be determined for actual laser welding. Therefore, the prediction of these three parameters in terms of weld width, degree of penetration, distortion and undercut size are very important for laser butt joint welding.

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. Also, non-linearity and input–output mapping are the two most important benefits in the use of neural networks [4]. Hence neural networks have been adopted to model the input–output relationship of non-linear and interconnected systems [5]. The most common network used is back propagation (BP), which is essentially a stochastic approximation to non-linear regression [6]. Several researchers have adopted BP to model welding processes, in particular tungsten inert gas (TIG) welding [7–13]. A main contribution of these research studies was to establish a non-linear model of welding, and hence to predict welding parameters using a neural networked technique, because the welding process is a strongly non-linear and parameter interconnected process. However, the number of the input parameters

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0924-0136/00/$ – see front matter 
PII: S0924-0136(99)00424-0

is always larger than that of the output vector for all of these applications.

There are few published documents which discuss the modeling of laser welding using a neural network. Actually, laser welding is a more complicated and higher response process than that of TIG. The reason for the lack of application of a neural network on laser welding may be that laser welding is a relatively new and expensive process for research. Another main reason may be the limited applicability of laser welding for butt joints, because the determination of welding parameters, gap maintenance and alignment are difficult. One of the main criteria for neural network modeling is to establish learning data, and this is very costly for laser welding.

Two back propagation (BP) and one learning vector quantization (LVQ) neural network models were adopted in this study to predict laser welding parameters and the associated welding quality individually, because some of the parameters are strongly interconnected and must be determined by sequence. These three local networks were also integrated for the modeling of laser welding and the prediction of welding parameters and associated weld quality. LVQ is a supervised learning technique that uses class information to move the classification set slightly, so as to improve the quality of the classifier decision region [4]. The classification characteristics enable the definition of the set of weldable parameters, because in actual welding the weld parameters usually occur in a group, not singly.

In this research, the material thickness and gap size were the input of the integrated neural network model, and the output of the model included the optimal focused position, laser power, welding speed, weld width, undercut, and distortion. Hence the controllable parameters including the laser power, optimal focused position, and welding speed could be predicted. Also, the weld quality of the predicted laser welding parameters used can be estimated. The results show that the welding parameters and the associated weld quality can be predicted comprehensively using neural networks.

## 2. Laser welding

A focused laser beam is one of the highest power density sources available to industry today. At this high power density, all materials will evaporate if the energy can be absorbed. Thus, when welding in this way a hole is usually formed by evaporation. The ‘hole’ is then traversed through the material, with the molten walls sealing up behind it, the result being what is known as a ‘keyhole’ weld [1]. A cross-sectional view of laser welding is shown in Fig. 1. The aspect ratio (penetration depth/weld width) is much higher than that of general conduction welding processes. Also, several common dimensions, such as the weld width, undercut, drops, etc., used in laser welding are defined in Fig. 1, which shows a typical keyhole welding profile. A laser butt joint welding example is shown in Fig. 2. As shown in this figure, the welding gap must be less than half of the laser spot size on the workpiece surface.

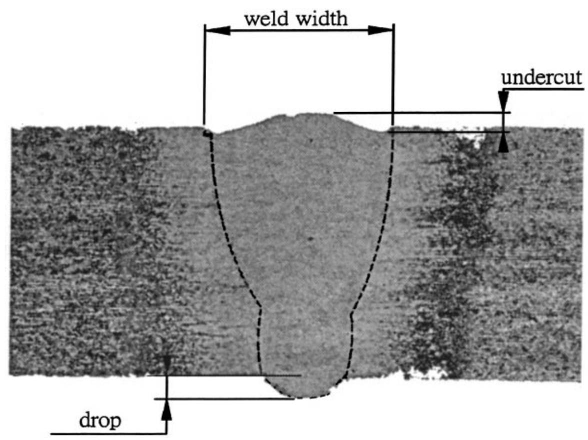



Fig. 1. Typical cross-sectional view of laser welding.

Laser welding relies on a finely focused beam to achieve high penetration and low distortion. The only exception would be if the seam to be welded was difficult to track or of a variable gap, in which case a wider beam would be easier and more reliable to use. However, in this case, once the beam is defocused the competition from plasma processes should be then considered [1]: this is the significant limitation of the applicability of laser welding for butt joints. The experimental arrangement of laser welding for butt joints is shown in Fig. 3. The focused laser beam must be aligned with the center of the welding gap, and the gap must be less than half of the beam diameter. A misalignment of the laser beam with the welding gap for a butt joint is shown in Fig. 4: one side of the material was completely melted, and the other side of material was partially melted. The penetration was not great enough because too little energy was absorbed on the misaligned side of the material, although a keyhole was still formed for this weld.

During the actual operation of laser welding for butt joints, the welding gap must be maintained at a reasonable size to make sure that it is small enough for the laser beam not to pass straight through the welding gap. Hence the focused spot size and focused position are determined definitely by the welding gap size and the alignment position of laser beam. However, the focused spot size, focused position, laser power, welding speed, material thickness, and even the shielding gas, and gas shielding device, affect

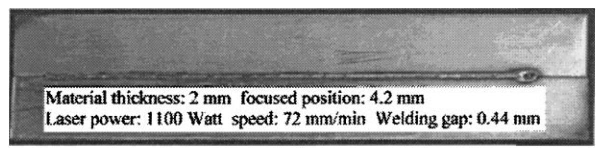



Fig. 2. One example of laser welding for butt joints.

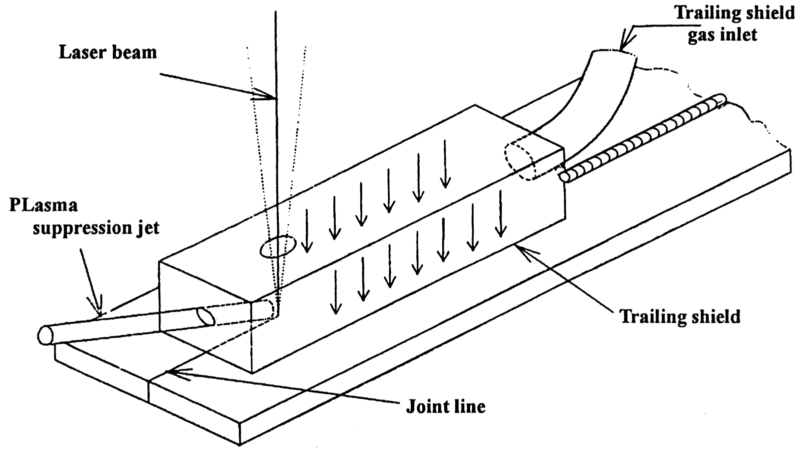



Fig. 3. Schematic arrangement of laser welding for butt joints.

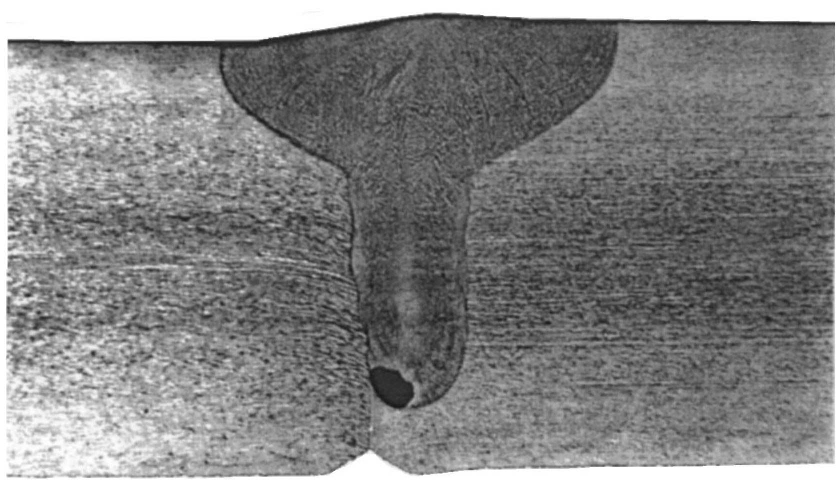


Fig. 4. Illustration of the misalignment of the laser beam for laser butt joint welding.

the formation of the keyhole. Several laser welding shapes, varying with speed, are shown in Fig. 5 [1], where it is seen that the welded shapes vary dramatically with changes in welding speed. If the laser power and focused position are considered together, the weld shape is even more unpredictable, the relationship of these parameters being strongly non-linear and interconnected. The expected high penetration, narrow weld width and low workpiece distortion result from the formation of the keyhole. In general, during laser welding, the selection of welding parameters depends not only on the highest welding speed and laser power, but also the lowest undercut and distortion must be considered. For example, in the aerospace industry, the undercut size must be less than one-tenth of the material thickness, but this may not be so critical for other industrial applications. Also, the undercut size is not usually accessed visually. These factors make the determination of laser welding parameters more complicated and difficult.


Fig. 5. Range of the variation of laser welding shapes with speed: (a) normal/good, (b) undercut, (c) humping (longitudinal section), and (d) drop out (after [1]).

## 3. Neural network

Neural networks, or artificial neural networks to be more precise, represent an emerging technology rooted in many disciplines. They are endowed with some unique attributes: universal approximation (input–output mapping), the ability to learn from and adapt to their environment, and the ability to invoke weak assumptions about the underlying physical phenomena responsible for the generation of the input data [4]. The operation of a neural network can be divided into two steps. The first step is called the learning phase, whilst the second step is called the retrieving phase. During the learning phase, the learning rule can be also divided into supervised learning and unsupervised learning. The supervised learning rule includes the error correction rule and delta algorithm, and the unsupervised learning rule includes the competitive learning rule and the Hebbian learning rule. The back propagation algorithm is also called the generalized delta rule, and is one of the supervised learning rules. The other algorithm used in this research is LVQ, which is one of the competitive learning rules.

## 4. Back propagation networks [4]

Typically, the network consists of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes, as shown in Fig. 6. The BP algorithm is based on the error correction learning rule, and it has been used successfully to solve some difficult and diverse problems. Basically, the BP process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an input vector is applied to the sensory nodes of the network, and its effect propagates through the network, layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass, the synaptic weights of the network are all fixed, whilst during the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with the error correction rule. The synaptic weights are adjusted so as to make the actual response of the network move closer to the desired response. The forward process, backward process and adjustment of weights are iterated until the error of the output is satisfied. Hence the mapping between the input vector and the output results can be established. BP is most often applied in the modeling of non-linear and interconnected parameter systems. However, although some systems can be modeled, it is difficult to achieve a reasonable result during iteration, and sometimes the systems diverge. Therefore, other algorithms are adapted for other specific applications.

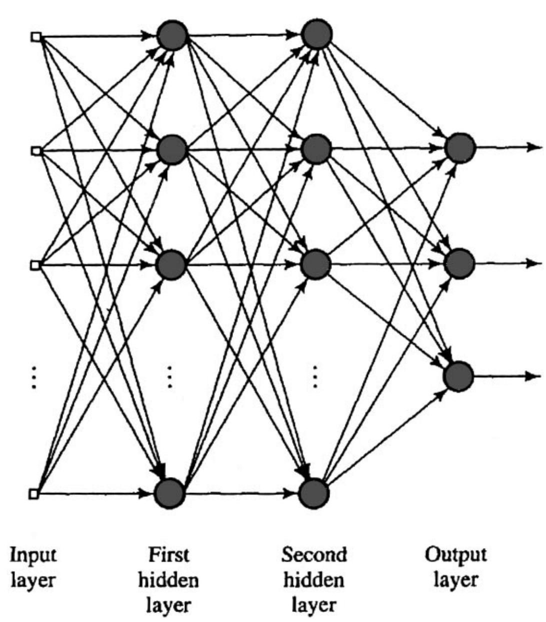



Fig. 6. Architectural graph of a BP with two hidden layers (after [4]).

## 5. Learning vector quantization networks

LVQ is one of the competitive learning networks. The output neurons of the competitive learning network compete among themselves to be activated or fired, with the result that only one output neuron, or one neuron per group, is on at one time. The output neurons that win the competition are called 'winner-takes-all' neurons. The general classification learning algorithm only learns when there is an error in the learning case. The LVQ algorithm always learns the training case no matter whether there is an error or correct learning. However, the weight is only adjusted at the winner neuron for LVQ.

LVQ is a very useful network in the application of classification because its output is logically '0' and '1' resulting from the 'winner-takes-all' as shown in Fig. 7. Fault diagnosis and classification of signals are two typical applications of an LVQ network. An LVQ network was employed in this research to classify whether the welding parameters were acceptable or not.

## 6. Modeling of laser butt joint welding using BP and LVQ

The parameter prediction of laser butt joint welding is concerned with controllable parameters such as the laser power, welding speed, and focused position. The welding

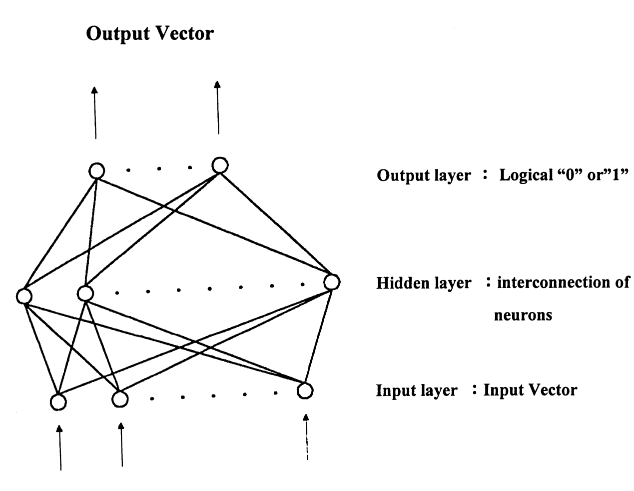



Fig. 7. An LVQ neural network structure.

gap and material thickness were already determined in the welding design of fit-up and material preparation. The welding quality can also be predicted based on the welded parameter employed. The welding quality usually is expressed in terms of weld width, undercut and distortion, etc. Hence the input vector of the prediction system is the welding gap and material thickness, and the output vector is the laser power, welding speed, optimal focused position, weld width, undercut, and distortion. The user is required to provide the prediction system with information on material thickness and welding gap size. The prediction system will provide information on the necessary welding parameters such as the laser power, welding speed, and optimal focused position, as well as information on the weld quality such as weld width, undercut, and distortion. The system is also expected to avoid mistakes in laser welding design, if the welding gap size is too large to be welded. The reason for the system to provide information on welding quality is that the users can select the optimal combination of welding parameters and welding quality according to their individual requirements. As described previously, the undercut size must be less than one-tenth of the material thickness for the aerospace industry and the distortion must be almost negligible, but the requirements may not be as high for other general industries.

A BP neural network was employed initially to model the laser butt joint welding for two input parameters (thickness and gap size) and six output parameters (power, speed, focused position, weld width, undercut size, and distortion). However, the minimum error was always larger than 40% no matter how many hidden layers and net numbers were employed in the BP neural network. If the input vector was only limited to successful welding parameters, the network was able to easily and quickly achieve a minimum error lower than 30%. Hence LVQ was adapted in this investigation to define the boundary of the weldable parameters, because of its classification characteristics. Three neural networks were integrated in this application to predict the welding parameters for butt joints, as shown in Fig. 8. During the actual laser welding, the optimal focused position was usually determined from laser surface melting instead of laser welding itself. In the first network, the LVQ algorithm was adapted to define the weldable laser power and welding speed from the thickness and optimal focused position. Then the maximum acceptable welding gap was predicted from the thickness, power, and speed using the first BP network. The other BP network predicted the welding quality from the thickness, gap size, power, and speed. These three networks and the optimal focused position determination are discussed in more detail below.

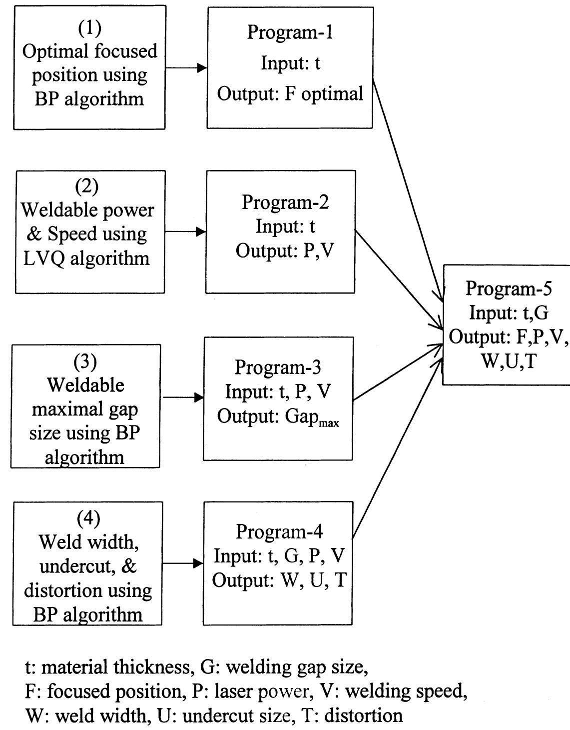



Fig. 8. Integration of three neural networks and the optimal focused position determination model to predict the welding parameters for butt joints.

## 7. Determination of optimal focused position

In order to determine the optimal focused position for laser welding in as short a time as possible, laser surface melting is usually used instead of laser welding to find the optimal focused position. For laser surface melting, the experimental arrangement is similar to that of laser welding, except that the workpiece for melting is a simple one instead of the two pieces used in a welding operation. Also, the operation parameters of melting are similar to that of welding. According to operational experience, the optimal focused position for melting can be applied to laser welding, because their operational parameters are almost the same, if the welding gap is far less than half of the laser beam focused spot size and less than half of the material thickness.

Firstly, suitable laser surface melting speed and power were selected according to the user's experience. Secondly, the optimal position was adjusted from above the workpiece surface to beneath the workpiece surface. Finally, the bottom surface of the welded workpiece was examined visually to obtain the maximum penetration for the individual focused position, enabling the optimal focused position to be determined. Hence, the optimal focused position for an individual material thickness could be obtained and programmed for the further calculation of the optimal focused position.

## 8. Weldable parameter model

The objective of the prediction model is to predict the welding parameters from the input data. The controllable welding parameters are the laser power, the welding speed, and the optimal focused position, and the input data include the material thickness and the welding gap. As mentioned previously, acceptable welding parameters depend on the quality required. Hence optimal weldable parameters may not exist: they are determined by the associated user's requirements for weld quality. Therefore, the output of the prediction system consists of the weldable parameters and the associated weld quality of the welding parameters employed. This is useful for the user in selecting the appropriate parameters, because the determination for acceptable welding parameters depends on the degree of penetration of laser welding.

The penetration can be divided into three categories as successful penetration, over penetration, and no penetration. Over penetration means that the input heat is too high, and no penetration means the input heat is too low. In order to simplify the system, the dynamic effect of the welding gap on the determination of the welding parameters was neglected. Only the maximal weldable gap size was considered in this investigation and it is modeled in Section 9. In this weldable parameter model, the gap size was set at zero. Hence the learning data for the neural network model were laser power, welding speed and material thickness, and the output of this model was over penetration (input heat too high IhH), or successful penetration (S), or no penetration (input heat too low IhL).

A BP network was first employed to model the welding system for the prediction of the weldable parameters. The performance of the neural network was determined by the convergence of the network, the convergence criterion being determined by the average root-mean-square error (RMS error). However, the performance of the BP network system is always not satisfactory no matter how many nets and hidden layers are used. The reason for this unsatisfactory performance may be that the number of the input parameters is less than that of the output parameters. Hence, the LVQ network system was employed because its ability to classify. Using trial-and-error, it was found that the performance of the LVQ network with one hidden layer and 21 nets was the best model. Fig. 9 shows the LVQ neural network model with weldable parameters for laser butt joint welding. The learning data of the model include the material thickness $t$ (mm), laser power $P$(W), and welding speed $V$ (pps 0.01 mm s$^{-1}$), and the output vector is expressed as over penetration (IhH), no penetration (IhL), and successful penetration (S). Only one of the output vectors is equal to unity, and the remaining two equal to zero because only one of the condition exists.

The performance of the LVQ network for laser butt joint welding is expressed in terms of an RMS error and is shown in Fig. 10. The RMS error converged to 0.1 after 27 000 iterations, and no further reduction of the RMS error could be obtained even with additional iteration. The prediction result of the learning data and evaluated data is shown in Fig. 11, the evaluated data being for a prediction system with a material thickness of 0.6 mm. Fig. 11 shows that the prediction of successful penetration (S) and no penetration (input heat too low IhL) is very accurate. However, the prediction of over penetration (input heat too high IhH = 1) is not accurate enough. This inaccurate prediction may result from the shortage of learning data due to the restriction of high laser power used in this investigation.

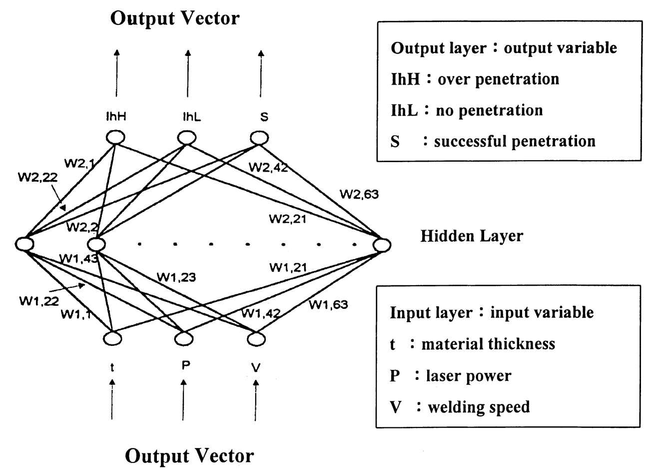



Fig. 9. Weldable parameters for the LVQ network model for laser butt joint welding.

## 9. Maximal welding gap size model

The purpose of this maximal welding gap size model is to predict the maximal acceptable welding gap size for the controllable welding parameters employed. Hence, the input vector of the model includes material thickness $t$ (mm), laser power $P$ (W), and welding speed $V$ (0.01 mm s$^{-1}$), whilst the output of the model is maximal welding gap size $Gap_{max}$ (mm). A BP network was employed to model the maximal welding gap size, as shown in Fig. 12. Using trial-and-error, the performance of the model with two hidden layers, six nets for the first layer and eight nets for the second layer, was judged to be the best. The RMS error converged to 0.05 after

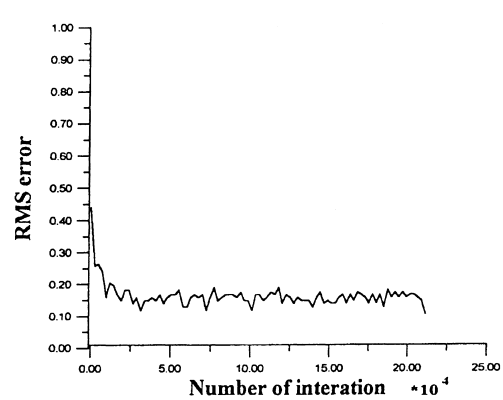



Fig. 10. Illustration of the performance of the LVQ network for the weldable parameter model.

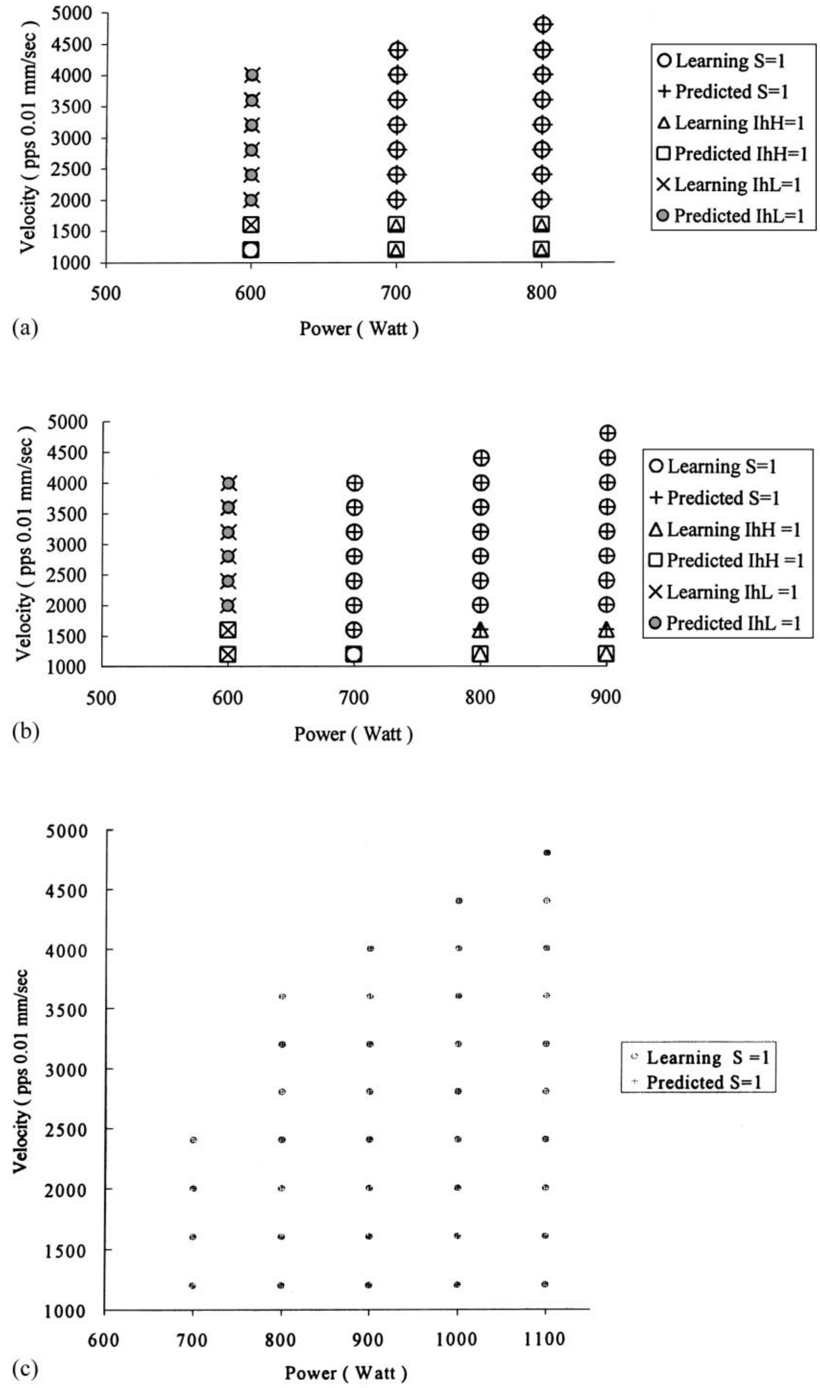



Fig. 11. Predicted result of learning data and evaluated data: (a) 0.5 mm learning sample, (b) 0.6 mm test sample, (c) 0.8 mm learning sample, (d) 1.5 mm learning sample, and (e) 2.0 mm learning sample.

40 000 iterations, as shown in Fig. 13. The network model was evaluated using a material thickness of 0.6 mm, the evaluation result being shown in Fig. 14. As shown in this figure, the lower is the welding speed, the more accurate is the prediction, the reason being that the effect of the welding gap size on a greater weld width is low. The weld width is usually greater and the tolerance of the laser beam alignment with the gap center is higher at a lower welding speed.

## 10. Weld quality prediction model

The weld quality was expressed as weld distortion ($T$), weld width ($W$), and undercut ($U$) in this investigation, and these data were set to be the output data of the weld quality prediction model. The input data of this model were the material thickness ($t$), the welding gap size (gap), and the acceptable welding parameters, laser power ($P$) and welding

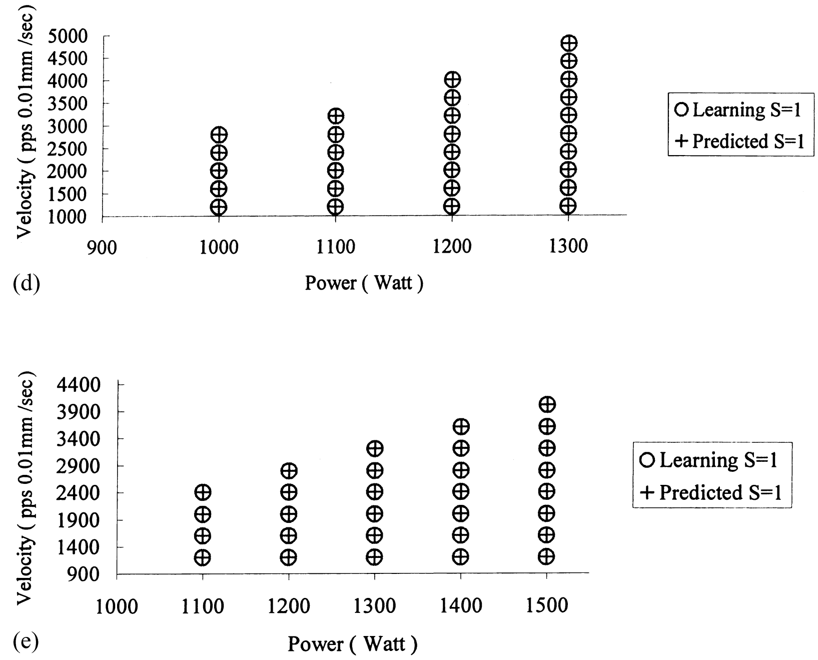



Fig. 11. (*Continued*).

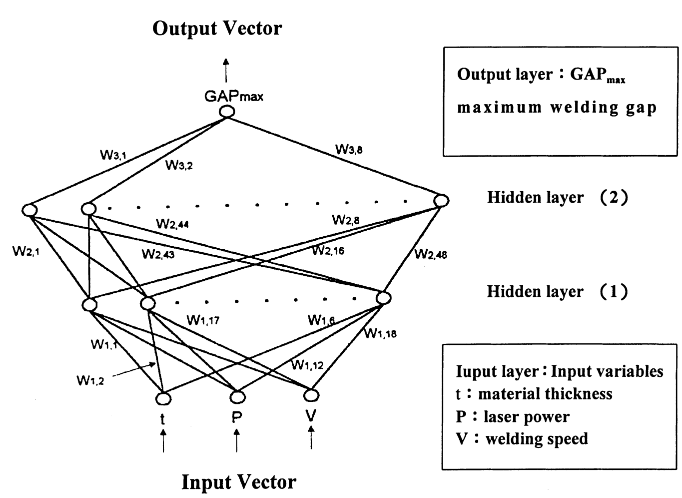



Fig. 12. Construction of the maximal welding gap size network model.

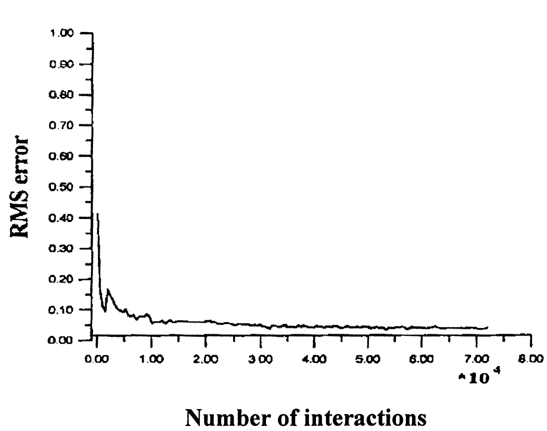



Fig. 13. RMS error of the maximal welding gap size model.

speed ($V$). The network construction diagram of the weld quality prediction model is shown in Fig. 15. There are two hidden layers, eight nets in first layer and six nets in second layer. Fig. 16 illustrates the RMS error of the weld quality model: the error converged to 2% after 50 000 iterations.

The welding distortion and the evaluated distortion of the network model is illustrated in Fig. 17. According to the comparison between Fig. 17a and b, the error between actual experimental data and the model prediction is very small. The thicker is the material the lower is the distortion, because thicker material has a greater stress endurance. Also, the higher is the welding speed the lower is the distortion, because less heat is absorbed at a higher welding speed.

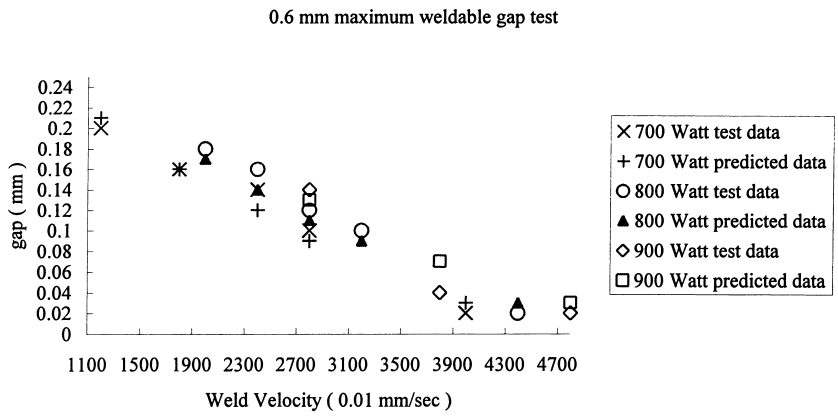



Fig. 14. Evaluation diagram of the maximal welding gap size model.

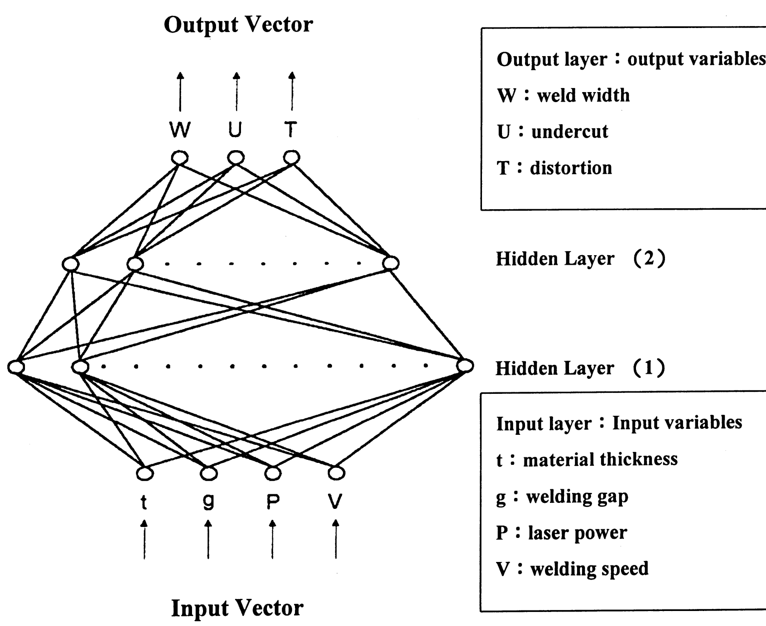



Fig. 15. Network construction diagram of the weld quality prediction model.

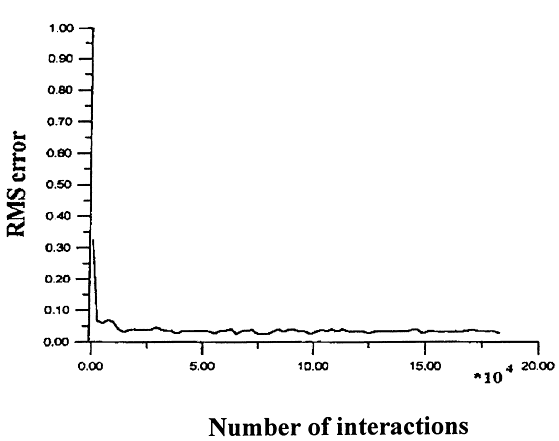
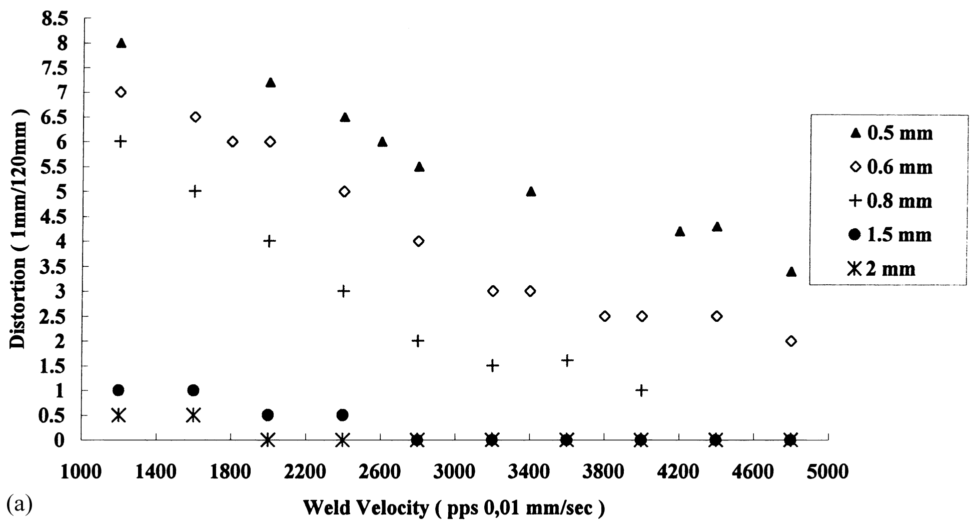
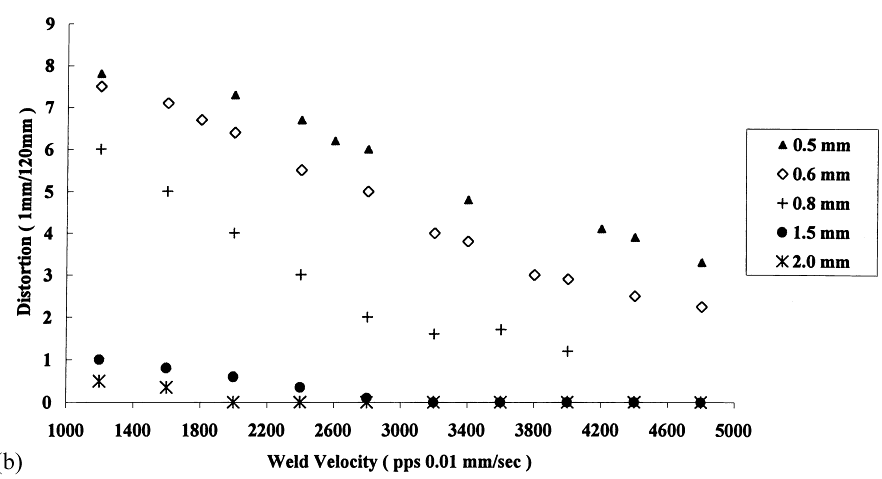



Fig. 16. RMS error of the weld quality prediction neural network model.

The relationship of weld width and welding speed is shown in Fig. 18 for a material thickness of 0.6 mm, from which it is seen that the predicted data of the weld quality model is very close to the experimental data. The higher is the welding speed the wider is the width of the weld, because less energy is absorbed at a higher welding speed. Also, the error between the predicted data and the experimental data is very small. One of the relationships between undercut size and gap size for several welding speeds is shown in Fig. 19. As shown in this figure, the larger is the gap size the smaller is the undercut size, because the workpiece is short of material to be welded for the larger welding gap size. The predicted results are very close to the results of the experiments.




(a)




(b)

Fig. 17. Illustration of: (a) the welding distortion for the welding experiment, and (b) the network model.

## 11. Integration of neural networks and determination of optimal focused position

The previous three neural network models and the determination of optimal focused position prediction program were integrated, as shown in Fig. 8. The programming flowchart of the integrated models is shown in Fig. 20. Firstly, data of the material thickness and welding gap size were entered into the program by the user, because they were determined during material preparation and joint fit-up

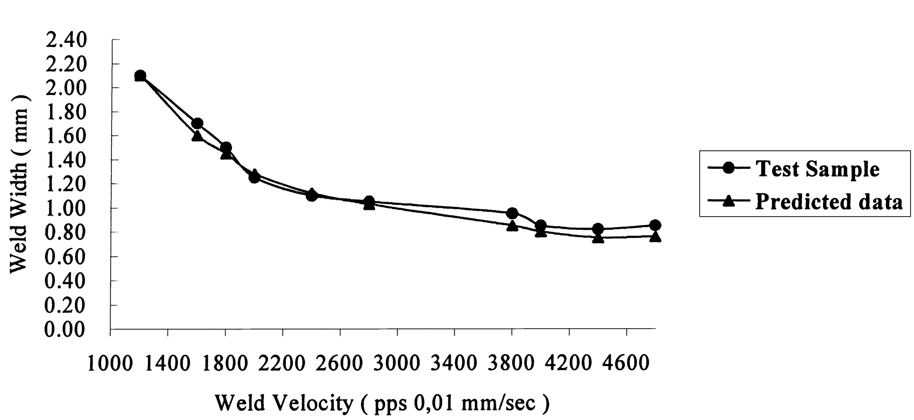



Fig. 18. Relationship of weld width and welding speed for 0.6 mm material.

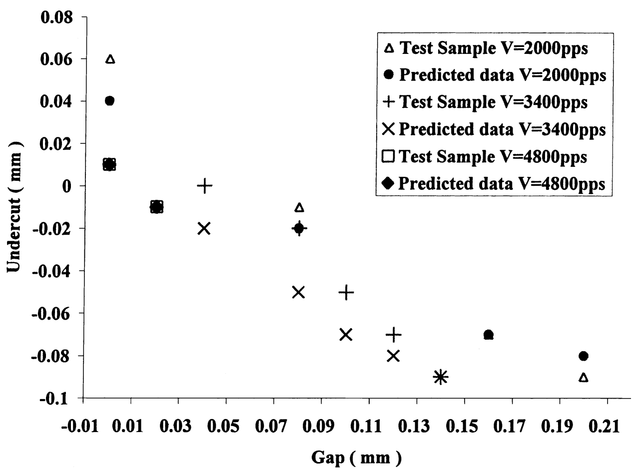



Fig. 19. Relationship of undercut size and gap size for several welding speeds, for 0.6 mm and 700 W.

design. Then program-1 calculates the optimal focused position according to the material thickness and the welding gap size. Then the acceptable welding parameters of laser power and welding speed are calculated in program-2

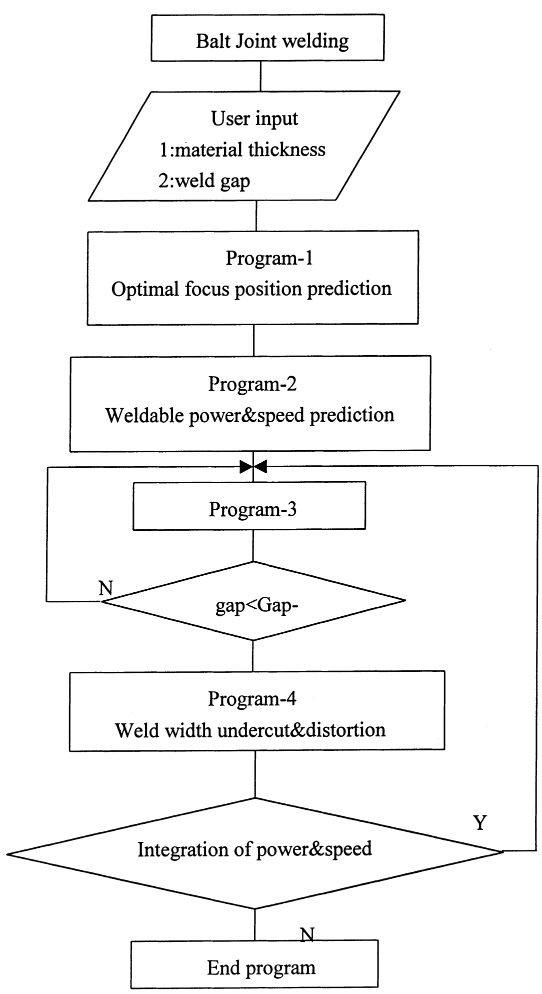



Fig. 20. Programming flow-chart of the integrated model.

Table 1
One of the prediction results for the welding parameters

*Please input thickness of material → 2.0 mm
*Please input the seam gap → 2.0 mm
*When material thickness is 2.0 mm
* seam gap is 0.24 mm
*The optimal focus position is under focus of 4.20 mm
*The parameter and result, can weld*

| No. | *P* (W) | *V* (pps) | *W* (mm) | *U* (mm) | *T* (mm) |
|---|---|---|---|---|---|
| 1 | 1100 | 1200 | 2.50 | −0.18 | 0.5 |
| 2 | 1100 | 1600 | 2.17 | −0.24 | 0.3 |
| 3 | 1200 | 1200 | 2.50 | −0.18 | 0.5 |
| 4 | 1200 | 1600 | 2.17 | −0.24 | 0.3 |
| 5 | 1300 | 1200 | 2.50 | −0.18 | 0.5 |
| 6 | 1300 | 1600 | 2.16 | −0.24 | 0.3 |
| 7 | 1300 | 2000 | 1.83 | −0.32 | 0.2 |
| 8 | 1400 | 1200 | 2.49 | −0.18 | 0.5 |
| 9 | 1400 | 1600 | 2.16 | −0.24 | 0.3 |
| 10 | 1400 | 2000 | 1.82 | −0.32 | 0.2 |
| 11 | 1500 | 1200 | 2.49 | −0.18 | 0.5 |
| 12 | 1500 | 1600 | 2.15 | −0.24 | 0.3 |
| 13 | 1500 | 2000 | 1.82 | −0.32 | 0.2 |

according to the material thickness and the degree of penetration. The maximal welding gap size is predicted in program-3 from the information on acceptable welding parameters and learning data. Also, the gap size entered by the user is compared with the predicted result. If the user's gap size is less than the predicted maximal gap size, another group of acceptable welding parameters is processed to obtain another maximal welding gap size until the user's gap size is larger than the predicted maximal welding gap size. These acceptable welding parameters, laser power, welding speed, material thickness and gap size, are processed in program-4 to calculate the associated welding quality in terms of weld width, welding distortion, and undercut size. One of the programming results for predicting the laser welding parameters for butt joints is shown in Table 1. The acceptable welding parameters are listed with the associated welding quality according to material thickness and seam gap size. Another prediction example of the larger welding gap size model is tabulated in Table 2, where the material thickness is 0.8 mm, and the welding gap size is 0.32 mm. The result of the prediction model is that the gap is too large to be welded. Hence, not only can acceptable welding parameters be predicted from this model, but also unsuitable welding design can be avoided. Therefore, industrial applicability can be expanded because the effect of welding gap size on the welding parameters can be established.

Table 2
Warning of the welding design

*Please input thickness of material → 0.8 mm
*Please input the seam gap → 0.32 mm
*When material thickness is 0.8 mm
* seam gap is 0.32 mm
*The gap is too big, cannot weld*

## 12. Conclusions

The following conclusions can be drawn from this study:

1. One program (optimal focused position determination), one LVQ network model (acceptable welding parameter), one BP network (maximal welding gap size), and another BP network (welding quality) can be integrated successfully to make a prediction model of laser welding parameters for butt joints.
2. The prediction results of the model are very close to the experimental results.
3. Not only can the prediction results be very useful in selecting suitable welding parameters, they can also help in avoiding inappropriate welding design.
4. Limitations in the industrial application of laser welding for butt joints can be reduced, because the difficulties in parameter determination due to welding gap size and their interconnection with each other can be established.

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