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Estimation of the laser cutting operating cost by support vector regression methodology

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Abstract Laser cutting is a popular manufacturing process utilized to cut various types of materials economically. The operating cost is affected by laser power, cutting speed, assist gas pressure, nozzle diameter and focus point position as well as the workpiece material. In this article, the process factors investigated were: laser power, cutting speed, air pressure and focal point position. The aim of this work is to relate the operating cost to the process parameters mentioned above. CO_2 laser cutting of stainless steel of medical grade AISI316L has been investigated. The main goal was to analyze the operating cost through the laser power, cutting speed, air pressure, focal point position and material thickness. Since the laser operating cost is a complex, non-linear task, soft computing optimization algorithms can be used. Intelligent soft computing scheme support vector regression (SVR) was implemented. The performance of the proposed estimator was confirmed with the simulation results. The SVR results are then compared with artificial neural network and genetic programing. According to the results, a greater improvement in estimation accuracy can be achieved through the SVR compared to other soft computing methodologies. The new optimization methods benefit from the soft computing capabilities of global optimization and multiobjective optimization rather than choosing a starting point by trial and error and combining multiple criteria into a single criterion.

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1 Introduction

Laser cutting process has a wide range of applications in different manufacturing processes in industry due to its advantages of high cut quality and cost effective production rate [1–3]. The material to be cut is locally melted by the focused laser beam. The melt is then blown away with the aid of assist gas, which flows coaxially with the laser beam, forming a kerf. In metal cutting procedures, different types of assist gases are used such as oxygen and nitrogen. The selection of an appropriate gas type or a mixture of gases with a given mixing percentage is fundamental to minimize the cutting cost.

For certain well-defined applications, suppliers of laser cutting machines provide a comprehensive database for process parameters. However, in general, new customized cutting processes have to be individually optimized with respect to the targeted geometry and the material to be cut while taking into account the equipment to be used. Since laser cutting processes are often governed by a multitude of parameters, some of which interacting with each other, the optimization of a process is determined by a high degree of complexity. As a consequence, the optimization of an industrial laser process might be a time-consuming and cost-intensive task, particularly, in case simplified methods such as the one-factor at a time approach are applied. In addition, possible interactions of different factors might remain partly unconsidered if such intuitive approaches are chosen. Above all, optimal cutting parameter settings for achieving a desired goal are not guaranteed. Improper selection of cutting parameters causes high manufacturing costs, low product quality and high waste.

In article [4] was analyzed optimization of laser cutting of thin Al_2O_3 ceramic layers using a design of experiment approach, and it was demonstrated the potential of the approach to optimizing the laser material processes. In article [5], it was shown that process optimization was needed for beam shapes on cutting performance of silicon using a diode-pumped solid-state Q-switched UV laser. A two-stage sequential optimization procedure was presented in article [6] for nesting and cutting sequence for the objectives of maximizing material utilization and minimization of ideal (non-cut) travel distance of laser cut tool. Laser process parameters influence greatly the width of kerfs and quality of the cut edges. A numerical optimization was performed in article [7] to find out the optimal process setting at which both kerfs would lead to a ratio of about 1, and at which low cutting cost take place. In study [8], was reported an application of non-contact type (thermal energy based) pulsed CO_2 laser cutting process on Al6061/SiCp/Al_2O_3 composite where a substantial improvement in the surface finish was observed in the responses obtained with the optimal setting of parameters. Precision laser cutting involving various materials is important in high-volume manufacturing processes to minimize operational cost, error reduction and improve product quality. In study [9], was used gray relational analysis to determine a single optimized set of cutting parameters for three different thermoplastics, and the set of the optimized processing parameters was determined based on the highest relational grade and was found at low laser power (200 W), high cutting speed (0.4 m/min) and low compressed air pressure (2.5 bar). In work [10], was applied laser welding with filler wire to join a new-type Al–Mg alloy where welding parameters of laser power, welding speed and wire feed rate were carefully selected with the objective of producing a weld joint with the minimum weld bead width and the fusion zone area, and Taguchi approach was used as a statistical design of experimental technique for optimizing the selected welding parameters. Taguchi's approach has become one of the most powerful methods of statistical design of experiment techniques in recent years. It helps to improve productivities and reduce the time required for the experimental investigation, so that high-quality products can be produced quickly and at low cost. Numerous studies indicate that Taguchi's approach has been widely used in several investigations to control or optimize processes. The Taguchi and linear regression were used in analysis [11] to determine the impact of laser-engraving process, and the results obtained from the new experimental conditions were shown that the predicted models could explain the process. The Taguchi's experimental method with orthogonal array was employed in [12] to obtain optimal combinatorial laser parameters. An experimental investigation of laser-assisted machining of Inconel 718 using turning process was presented in [13], and the experiments were planned according to Taguchi orthogonal array of experimental design, and the optimal cutting conditions were determined using the Taguchi's signal-to-noise (*S*/*N*) ratio.

The application of Taguchi methodology is an attractive alternative to determination of optimal cutting parameters in laser cutting and is particularly popular when dealing with multiple-performance characteristics [14]. The Taguchi methodology focuses on determining the optimum operating conditions in order to minimize performance variability and deviation from the target value of interest. However, Taguchi methodology limits the search for the optimal parameters only on discrete parameter values used in the experiment matrix.

To overcome this shortcoming, an approach of integrating Taguchi methodology with soft computing methodology was proposed in this study. Soft computing offers advantages such as no required knowledge of internal system parameters, compact solution for multi-variable problems.

Support vector machines (SVMs) as one type of meta-heuristic soft computing technique have gained importance regarding issues related with the environment. There are two fundamental classes of support vector machines: support vector classification (SVC) and support vector regression (SVR). SVM is a learning framework utilizing a high-dimensional peculiarity space [15–18]. SVR is focused around a measurable learning hypothesis and structural risk minimization rule and has been effectively utilized for non-linear frameworks [19, 20]. The correctness of an SVM model is to a great extent reliant on determining the model parameters. Notwithstanding, organized strategies for selecting parameters are important. Hence, model parameter alignment ought to be made. SVR is used to determine the optimal parameters of the laser cutting process. Hence, this paper presents an application of combined SVR approach to determining the operating cost of laser cutting process. SVR is compared with artificial neural network (ANN) and genetic programming (GP).

2 Materials and methods

2.1 Experimental methodology

In this study, five process parameters are considered, namely: laser power, cutting speed, air pressure, focal point position and material thickness. Table 1 shows the process input parameters.

A CW 1.4 kW CO_2 Rofin laser with a linear polarized beam angled at 351 provided by Mechtronic Industries Ltd. A focusing lens with a focal length of 125 mm was used to perform the cut. In addition, the compressed air is cheaper

Table 1 Input and output parameters

		Min	Max
Input 1	Laser power (W)	120	750
Input 2	Cutting speed (mm/min)	2000	5000
Input 3	Air pressure (bar)	1	5
Input 4	Focal point position (mm)	−7.5	0
Input 5	Material thickness (mm)	3	9

than nitrogen. Furthermore, the compressed air system was used to remove smoke and fumes generated by the laser cutting operation. The nozzle used has a conical shape with nozzle diameter of 1.3 mm. The standoff distance was kept to 0.4 mm.

Laser cutting operating costs can be estimated as cutting per working hours or per unit length. The laser system used in this work utilized CO_2 using a static volume of laser gases. The total approximated operating cost per unit length of the cut was given by [7, 21] which was used in this investigation.

2.2 Support vector regression application

The fundamental working principle of SVMs is to perform the data mapping in some spaces through non-linear mapping and perform the linear algorithm in the feature space. If a way of computing the inner product in a feature space is available directly as a function to the original input points, it is possible to build a non-linear learning machine, which is known as a direct computation method of a kernel function, denoted by K.

The flexible nature of the SVM is attributed to the kernel functions that implicitly chart the data to a higher-dimensional feature space. A linear solution in the higher-dimensional feature space corresponds to a non-linear solution in the original, lower-dimensional input space. There are some available methods that employ non-linear kernels in their strategy for regression problems and that simultaneously apply SVMs. One kernel function is the radial-basis function. The main benefit of the radial-basis function is that it is computationally more efficient than the customary SVM method, since radial-basis function training needs only the solution of a set of linear equations instead of the lengthy and computationally demanding quadratic programming problem that is entailed in standard SVM. Compared with other probable kernel features, the radial-basis function is a more compressed, supported kernel, which makes it very suitable for restricting the computational training process and improving the generalization efficiency of the radial-basis function—an attribute of great value in model design. The non-linear radial-basis kernel function is defined as:

$$K(x, x_i) = \exp\left(-\frac{1}{\sigma^2}||x - x_i^2||\right). \tag{1}$$

where x and x_i are vectors in the input space, i.e., vectors of features computed from training or test samples.

In this study, the following polynomial kernel function was used:

$$K(x, y) = \left(x^T y + c\right)^d \tag{2}$$

where x and y are vectors of features computed from training or test samples and c is a constant making a trade off for the influence of higher-order versus lower-order terms in the polynomial.

As a data-driven model, the ability of the SVR to make reasonable estimations is mostly dependent on input parameter selection. Adequate consideration of the factors controlling the system studied is therefore crucial to developing a reliable network.

2.2.1 Complexity of SVM

There are two intuitive lower bounds on the computational cost of any algorithm that solves the SVM problem for arbitrary kernel matrices K_{ij}.

Suppose that an oracle reveals which examples are not support vectors ($x_i = 0$), and which examples are bounded support vectors ($x_i = C$). The coefficients of the R remaining free support vectors are determined by a system of R linear equations representing the derivatives of the objective function. Their calculation amounts to solving such a system. This typically requires a number of operations proportional to $R3$.

Simply verifying that a vector is a solution of the SVM problem involves computing the gradient g of the dual and checking the optimality conditions. With n examples and S support vectors, this requires a number of operations proportional to nS.

Few support vectors reach the upper bound C when it gets large. The cost is then dominated by the $R^3 \sim S^3$. Otherwise, the term nS is usually larger. The final number of support vectors therefore is the critical component of the computational cost of solving the dual problem.

Since the asymptotic number of support vectors grows linearly with the number of examples, the computational cost of solving the SVM problem has both a quadratic and a cubic component. It grows at least like n^2 when C is small and n^3 when C gets large [22].

2.3 Model performance evaluation

To assess the success of the SVR models and other soft computing techniques, some statistical indicators were examined as follows:

1. root-mean-square error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}}, \tag{3}$$

2. coefficient of determination (R^2)

$$R^2 = \frac{\left[\sum_{i=1}^{n} \left(O_i - \overline{O_i}\right) \cdot \left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n} \left(O_i - \overline{O_i}\right) \cdot \sum_{i=1}^{n} \left(P_i - \overline{P_i}\right)} \tag{4}$$

where P_i and O_i are known as the experimental and forecast values, respectively, and n is the total number of test data.

3 Results and discussion

3.1 SVR results

Polynomial functions were applied as the kernel functions for SVR prediction in this study. The five parameters associated with the kernel are C, e, γ, d and t. SVM model accuracy is principally dependent on model parameter selection. To select user-defined parameters (i.e., C, e, γ, d and t), a large number of trials were carried out with different combinations for polynomial kernels. Table 2 provides the optimal values of user-defined parameters for this dataset with polynomial-basis kernel for SVR.

Figure 1 shows scatter plots of SVR forecasting of the operating cost according to the laser cutting parameters. This observation can be confirmed with very high value for coefficient of determination. The number of either overestimated or underestimated values produced is limited. Consequently, it is obvious that the forecasted values enjoy high-level precision. The better forecasting accuracy can be observed for SVR models than ANN and GP models.

3.2 Performance analysis and computational complexity

It is very hard to characterize correctly computational complexity. First, there are two complexities involved: at training time and at test time. For linear SVMs, at training time, the vector w and bias b by solving a quadratic problem must be estimated, and at test time, prediction is linear in the number of features and constant in the size of the training data. For kernel SVMs, at training time, the support vectors must be selected, and at test time, the complexity is linear on the number of the support vectors (which can be lower bounded by training set size) and linear on the number of features (since most kernels only compute a dot product, this will vary for graph kernels, string kernels, etc.).

To evaluate the performance of the methods, experiments were conducted to determine the relative significance of each independent parameter on the output. The root-mean-square error (RMSE), coefficient of determination (R^2) and computational complexity served to evaluate the differences between the expected and actual values for SVR and other soft computing techniques. Table 3 compares the single polynomial-basis SVR models with ANN, and GP. The results in Table 3 indicate that the polynomial-basis SVR model has the best capabilities of estimating the parameters.

Table 2 User-defined parameters

Polynomial-basis function				
C	t	e	γ	d
100	0.1	0.4	0.03	2

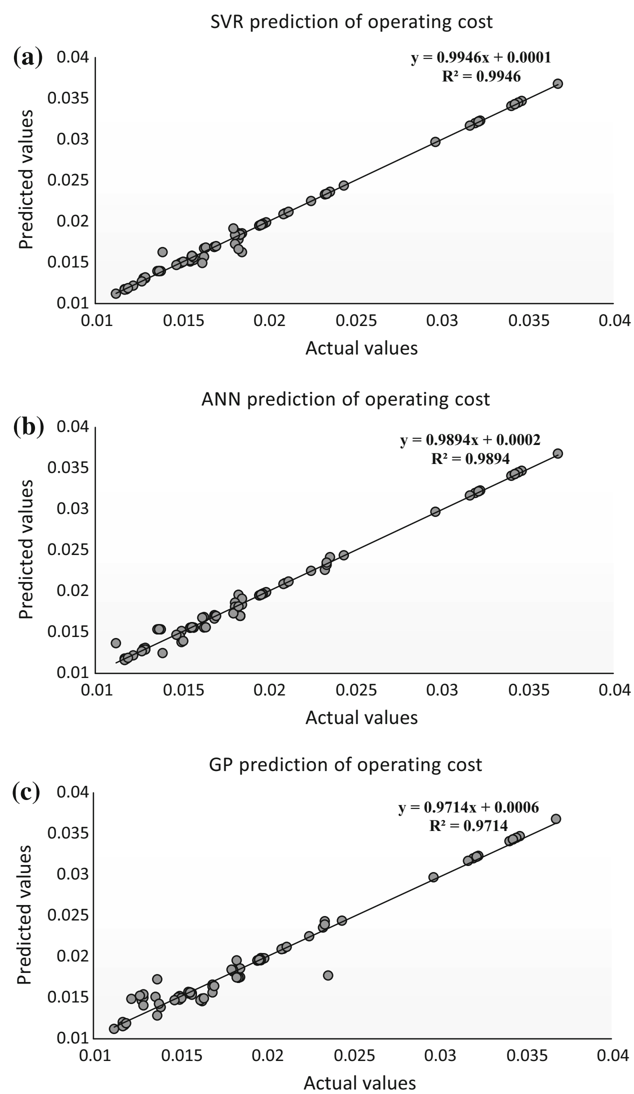

Fig. 1 Forecasting of operating cost

Table 3 Performance indices of various approaches for the estimation of the parameters

	SVR	ANN	GP
R^2	0.9946	0.9894	0.9714
RMSE	4.7192e−04	6.6084e−04	0.0011

4 Conclusion

To achieve the minimal operating cost of the laser cutting process, it is of prime importance to determine optimal laser cutting parameters. This paper presented the application of SVR approach for optimization of the CO_2 laser cutting process in order to minimize operating cost. In this article, the process factors investigated were: laser power, cutting speed, air pressure and focal point position. The aim of this work is to relate the operating cost to the process parameters mentioned above. CO_2 laser cutting of stainless steel of medical grade AISI316L has been investigated. The goal was to determine the optimal laser cutting parameter values in order to ensure the optimal operating condition for minimization of operating cost. Finally, the optimal laser cutting conditions have been found at which the minimum cost can be achieved.

The performance of the SVR approaches compared to the results from ANN and GP showed interesting improvements in the prediction system. SVR predictions with the polynomial kernel function are superior to other methodologies in terms of root-mean-square error and coefficient of error. Moreover, SVR takes less computation time than ANN and GP. The complexity of training a SVM is particular, time complexity and depends on both the number of free support vectors and the number of training samples. In this article, SVR computation time was 25 s for the given data. On the other hand, SVR approach is a data-driven model. It means the ability of the SVR to make reasonable optimization is mostly dependent on input parameter selection. This is the main limitation of the method. Also, the five parameters associated with two kernels, C, e, γ, d and t are user-defined parameters, and SVR model accuracy is principally dependent on the model parameter selection. These parameters are selected by a large number of trials and errors. It is the second limitation of the SVR model.

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