SEBHA UNIVERSITY JOURNAL OF PURE & APPLIED SCIENCES VOL.24 NO. 3 2025
DOI: 10.51984/JOPAS.V24I3.4191

مجلة جامعة سبها للعلوم البحتة والتطبيقية
Sebha University Journal of Pure & Applied Sciences

Journal homepage: www.sebhau.edu.ly/journal/jopas

Genetic Algorithm (GA)-Based Single- and Multi-Objective Optimization for the Simulation and Evaluation of the Laser Cladding Process

Adnan Hamad[a*], Dingli Yu[b]

[a]Omar Al-Mukhtar University, Department of Electrical Engineering, Faculty of Engineering, El-Bayda, Libya
[b]Liverpool John Moores University, Engineering and Technology Department, Liverpool L3 3AF, UK

Keywords:
Genetic Algorithm (GA).
Hardness.
Laser Cladding Process.
Layer Thickness.
Radial Basis Function Neural - Network (RBFNN).

ABSTRACT

In the manufacturing field, it is essential to determine the optimum operating conditions of a process as well as the best values for the system input parameters. In other words, it is necessary to identify the best possible solutions for the system variables in order to minimise the operational cost and maximise product quality simultaneously. To address these challenges, a Radial Basis Function Neural Network (RBFNN) was employed to model the laser cladding process and predict the hardness and layer thickness of the deposited layers. The operational data set was collected from Talleres Mechanics Comas (TMC). Additionally, a Genetic Algorithm (GA) framework for single- and multi-objective optimisation of the laser cladding process is presented in this paper. The main objective of this technique is to identify optimal values for three input variables Travel Speed (TS), Powder Feed Rate (PFR), and Laser Power (LP) to assist in the optimal design of the laser cladding process. Simulation results demonstrated that very good optimisation solutions were obtained for all three process parameters (TS, PFR, and LP).

استخدام الخوارزمية الجينية المعتمدة على التحسين الفردي والمتعدد الأهداف لمحاكاة وتقييم عملية التغليف الليزري

عدنان حمد[a*] ودنقلي واي يو[b]

[a]جامعة عمر المختار، قسم الهندسة الكهربائية، كلية الهندسة، البيضاء، ليبيا.
[b]جامعة ليفربول جون موريس، قسم الهندسة والتكنولوجيا، ليفربول، المملكة المتحدة.

الكلمات المفتاحية:
الخوارزمية الجينية.
الشبكة العصبية لدالة الأساس الشعاعي.
عملية التكسية او التغليف الليزري.
سمك طبقة التغليف الليزري.
صلابة طبقة التغليف الليزري.

الملخص

في مجال التصنيع، من الضروري للغاية إيجاد ظروف التشغيل المثلى للعملية التشغيلية بالإضافة إلى أفضل قيم إدخال لمتغيرات النظام. بمعنى آخر، إيجاد أفضل الحلول الممكنة لمتغيرات النظام لتحقيق أدنى تكلفة لعملية التشغيل وأعلى جودة للمنتج في آنٍ واحد. ولمواجهة هذه التحديات، استُخدمت الشبكة العصبية لدالة الأساس الشعاعي (RBFNN) لنمذجة عملية التغليف الليزري وكذلك للتنبؤ بصلابة وسمك طبقة عملية التكسية او التغليف الليزري. تم الحصول على بيانات التشغيل المستخدمة في هذه الدراسة من شركة Talleres Mechanics Comas (TMC). كما تُقدم هذه الورقة خوارزمية جينية (GA) لإطار تحسين أحادي ومتعدد الأهداف لعملية التكسية او التغليف الليزري. الهدف الرئيسي من هذه التقنية هو إيجاد حلول مثالية لثلاثة متغيرات إدخال مختلفة، وهي سرعة إنجاز عملية التغليف الليزري (TS)، ومعدل تغذية المواد الأولية (PFR)، وقوة الليزر (LP)، والتي يمكن أن تساعد المستخدم على التصميم الأمثل للتغليف الليزري. أظهرت نتائج المحاكاة أنه تم الحصول على حلول تحسين ممتازة لضبط المتغيرات الثلاث (TS، PER، وLP) لضمان الحصول على أفضل منتج.

1. Introduction

One of the most promising methods in the field of natural adaptive systems under the Evolutionary Algorithm (EA) paradigm is the Genetic Algorithm (GA), which has gained considerable attention due

*Corresponding author.
E-mail addresses: adnan.hamad@omu.edu.ly, (D. Yu) d.yu@ljmu.ac.uk
Article History : Received 22 June 25 - Received in revised form 02 October 25 - Accepted 22 October 25

to its adaptability and efficiency in complex system optimisation [1]. Furthermore, GA is one of the most effective and flexible techniques for system identification and has been applied extensively across numerous scientific domains [2,3]. GA provides robust sampling of the solution space and does not require gradient information from the model, which is an advantage over analytical modelling techniques [4]. Moreover, because GA uses objective function information directly and does not require additional auxiliary information, it can handle both single- and multi-objective optimisation problems [5].
Multi-objective optimisation is often applied to achieve either maximum reliability or quality, or to minimise production costs [6]. A decision maker can select an appropriate solution using the Pareto front, which is a curve or surface representing the best trade-off solutions between conflicting objectives [7]. Therefore, identifying the Pareto front, composed of Pareto-optimal solutions, is a primary goal of multi-objective optimisation. The objective functions in multi-objective optimisation typically conflict with one another.
Sourabh Katoch et al. [8] analysed recent developments in GA and reviewed the variants of GA that attracted the most attention in the research community. Their study detailed the widely used methods, their implementations, and discussed future prospects for genetic operators, fitness functions, and hybrid algorithms. Golap Chowdhury and Gour Roy [9] applied GA to predict rate parameters from experimental data during the solid-state reduction of iron ore in the presence of graphite. Their findings indicated that the reduction process involves three main stages: haematite to magnetite, magnetite to wustite, and wustite to iron. Mehmet Fatih Dilekoglu [10] introduced GA for optimising phenol adsorption on grapefruit and banana peels, using GA to solve the four-parameter Jeager-Erdoes equation without making assumptions. This equation provided the most accurate fit to experimental data among the considered models.
H. Abarghouee et al. [11] employed GA to calibrate three semi-empirical models describing the superposition effect of work hardening and dynamic recovery or recrystallisation on flow stress. The aim was to minimise the discrepancy between model predictions and experimental data. The results demonstrated that the models accurately estimated flow stress and agreed closely with experimental measurements.
As previously mentioned, system identification techniques can determine unknown model parameters by minimising the difference between experimental data and model outputs. Among the dependable and adaptable techniques widely used in scientific research, GA stands out. In this study, a Radial Basis Function Neural Network (RBFNN) is employed to model the laser cladding process and predict outputs such as layer thickness and hardness. GA is subsequently utilised to determine the optimal operational parameters Travel Speed (TS), Powder Feed Rate (PFR), and Laser Power (LP) while simultaneously minimising two conflicting objectives: hardness and layer thickness.

2. Methodology

This section presents single and multi-objective evolutionary algorithms to derive single or a set of optimal operation policies for laser cladding process case using experimental data from Talleres Mechanics Comas (TMC). The main goal in optimization is to find a single or set of feasible solutions which correspond to optimal values of one or more objectives. Command line in Matlab has been utilized in this research to run the optimization. Therefore, an objective function and its corresponding constraints must be defined. Also, appropriate settings such as population size/type, initial population/range, fitness scaling function, selection function, elite count, crossover fraction/function, mutation function, and stopping criteria can be chosen otherwise the default setting will be applied by Matlab. Moreover, GA has been used as an optimization tool that searches for the optimal solutions for the laser cladding process variables which are: Travel speed (TS), Powder Fed Rate (PFR) and Laser Power (LP) where the information obtained from the RBFNN was used to build the GA's chromosomes. The variables that need to be optimised are V_1 to V_r. The initial population (IP) for the GA can be defined by Equation 1.

$$IP = N_{vr} \times P_S \tag{1}$$

Where:
N_{vr}: The number of variables.
P_S: The size of the population
In order to apply the single or multi-objective optimization RBFNN model must be trained and tested first to predict Hardness and Layer Thickness. The calculated centers (c), sigma (σ) and weights (ω) values from the RBFNN model are used to define the structure of the chromosome. The GA evaluates the objective function by minimizing the error between the calculated neural network output and desired output. In TMC case, the GA optimization was applied for single-objective and multi-objective problems. The GA strategy applied for single and multi-objective problems is shown on Fig. 1. In the following sections, hardness and layer thickness modelling using RBFNN, strategy of single and multi-objective optimization is presented. Then the discussions of simulation results are discussed.

3. Hardness and Layer Thickness Modelling using RBFNN

RBFNN model is presented to predict the outputs of hardness and layer thickness. Table (1) shows the input data sets and the output targets provided by TMC. This data set was used to train and test the RBFNN- self-learning-system (SLS) model. Moreover, cross-validation approach was applied to test and verify the performance of the model. Consequently, the data set was divided into two groups, the first group (70%) for training and the second group (30%) for testing. Figs. 2 to 5 shows the prediction performance for training and testing for hardness and layer thickness. It can be seen from the simulation results of training and testing the RBFNN model were very good; in general, a good prediction for hardness and layer thickness was achieved. Figs. 6 to 9 illustrates the behavior of the model using 3-D plots. The Mean Absolute Error (MAE) between the outputs and the targets is very small. The MAEs between the outputs are shown in Table (2).

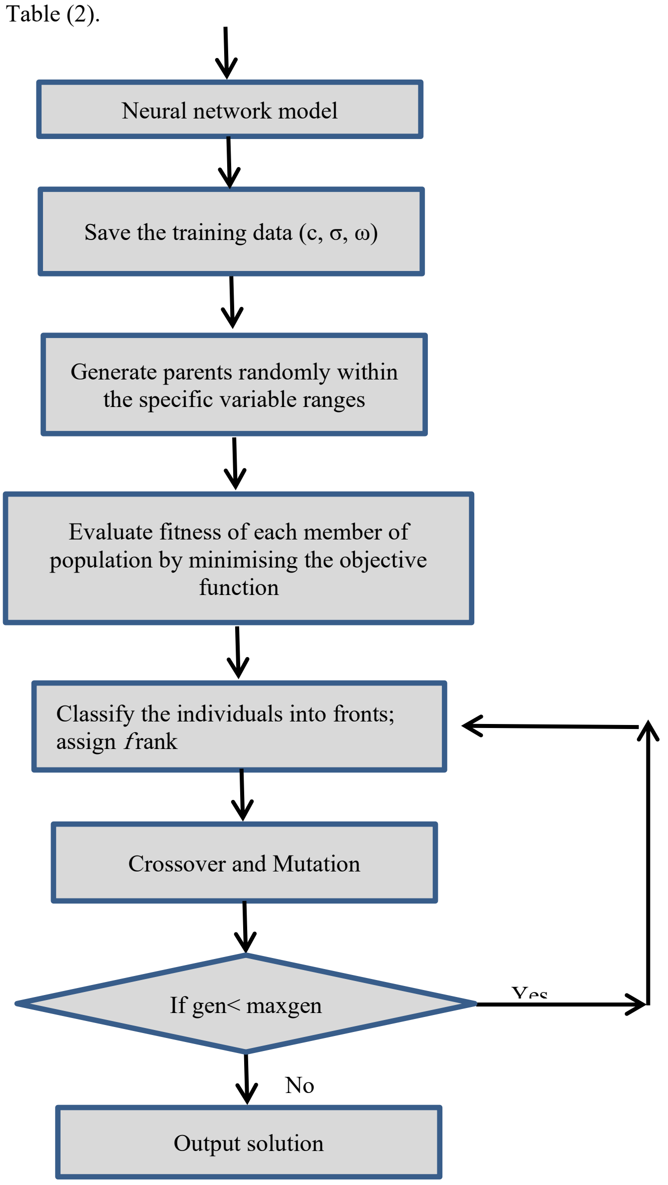

Fig. 1: Flowchart of the GA single and multi-objective optimization

Table 1: List of experiments provided by Talleres Mechanics Comas (TMC)

Radial Basis Function Neural Network (RBFFNN) inputs data (process condition)				Output Target	
Travel Speed (TS) (mm/min)		Powder Fed Rate (PFR) (g/min)	Laser Power (LP) (W)	Hardn-ess (mm)	Thicn-ess (mm)
1	1200	40	2400	52	1.7
2	1500	40	2400	50	1.3
3	1700	40	2400	53	1.2
4	1200	34	2400	52	1.7
5	1500	34	2400	53	1.3
6	1700	34	2400	52	1.1
7	1200	26	2400	52	1.6
8	1500	26	2400	53	1.3
9	1700	26	2400	52	1
10	1200	40	2700	54	2.1
11	1500	40	2700	53	1.7
12	1700	40	2700	56	1.4
13	1200	34	2700	51	1.8
14	1500	34	2700	55	1.6
15	1700	34	2700	51	1.5
16	1200	26	2700	52	1.5
17	1500	26	2700	49	1.2
18	1700	26	2700	55	1.2

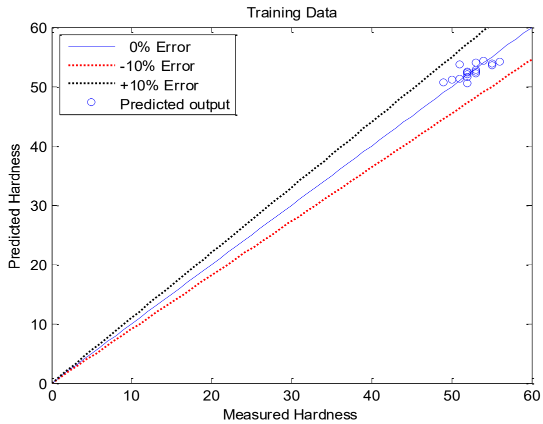

Fig. 2: Predicted hardness outputs for training

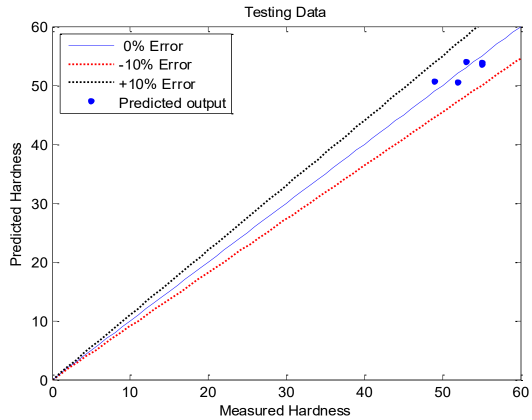

Fig. 3: Predicted hardness outputs for testing

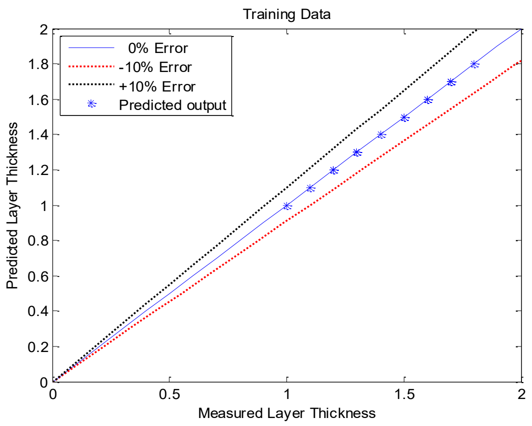

Fig. 4: Predicted layer thickness outputs for training

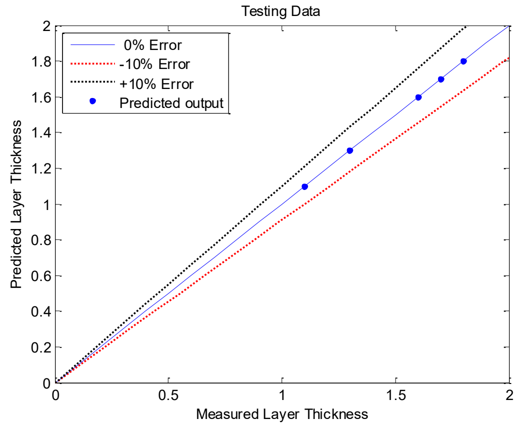

Fig. 5: Predicted layer thickness outputs for testing

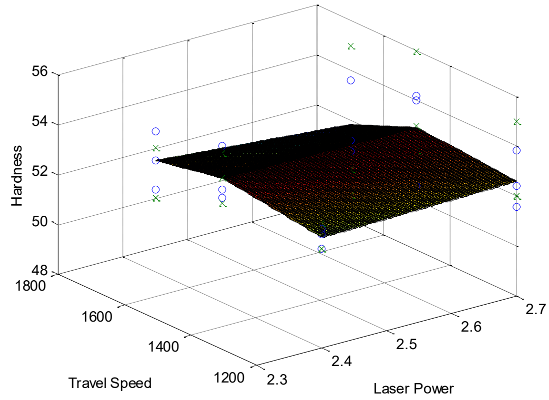

Fig. 6: The model behaviour using hardness, Travel Speed (TS) and Laser Power (LP)

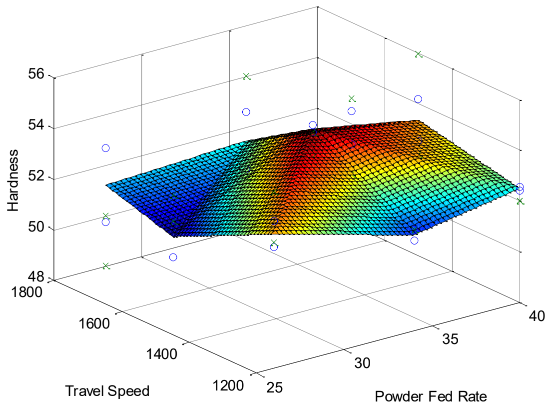

Fig. 7: The model behaviour using hardness, Travel Speed (TS) and Powder Fed Rate (PFR)

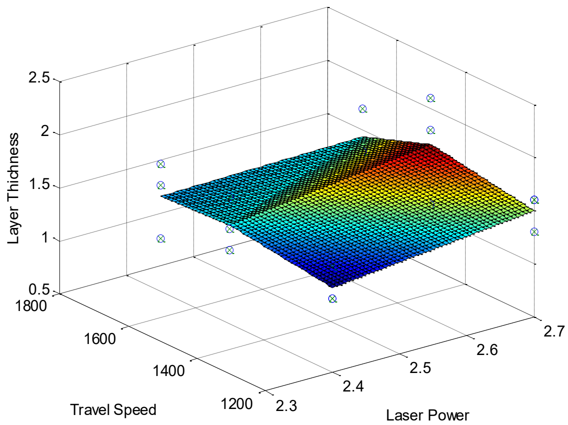

Fig. 8: The model behaviour using layer thickness, Travel Speed (TS) and Laser Power (LP)

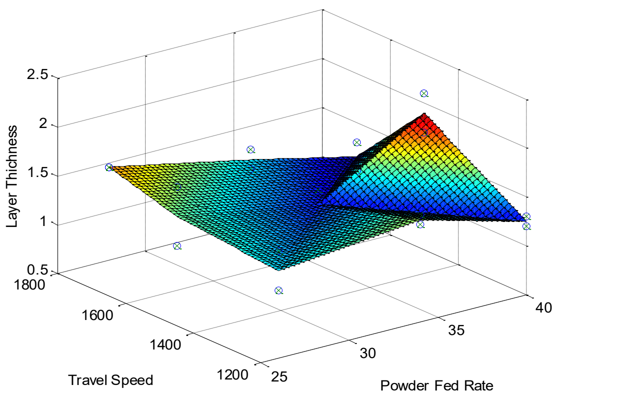

Fig. 9: The model behaviour using layer thickness, Travel Speed (TS) and Powder Fed Rate (PFR)

Table 2: The performance of the SLS model of hardness and layer thickness

	Mean Absolute Error (MAE) of training	Mean Absolute Error (MAE) of testing
Hardness	2.1538	2.2329
Layer Thickness	0.0029	0.0019

4. Strategy Of Single-Objective Optimization

The data used for the single optimization is obtained from the training data during the RBFNN evaluation. This data is centre (c), sigma (σ) and weight (ω). For the RBFNN, three inputs were used to predict one output (hardness or layer thickness). Using c, σ and ω, the structure of the GA chromosome can be defined. The RBFNN is used as a fitness function in order to find the optimal solutions or the optimal data for the setting process. Consequently, in this case the variables to be optimised are three variables which are (TS, PFR and LP). Additionally, based on Equation 2 the GA minimises the error between the desired property and the calculated property by the RBFNN which are hardness and layer thickness. GA gives the possible optimal solutions for the TS, PFR and LP. Thus, the number of variables (N_{vr}) is defined as $N_{vr}=3$, the population size (P_S) is 50 and the initial population can be defined by Equation 1 as mentioned above. The GA generates the possible solution of TS, PFR and LP and minimises the error between the calculated output and the desired output and then the final optimal solutions can be defined. The optimization routine stops once the termination criterion is achieved. Figs. 10 and 11 show the fitness values against generation to optimise hardness using deferent ranges of cladding travel speed.

$$OB_H = (H_D - H_C)^2 \tag{2}$$

Where:
OB_H: Objective function of hardness
H_D: The Desired target of hardness
H_C : The calculated hardness by RBFNN

5. Discussion of the Simulation Results for the Single Objective Function Problem

The GA for a single-objective optimization was applied to minimise the error between the target of hardness and the calculated hardness output that obtained from the RBFNN model. From Figs.10 and 11, it can be seen that very good results of optimization have been gained. The GA was able to minimise the fitness function successfully in very short time and therefore was able to suggest the optimum solutions for the three variables. The obtained optimal solutions of the three-process setting and the best function values for the fitness function are shown in Table (3). These results were found using different travel cladding speed range.

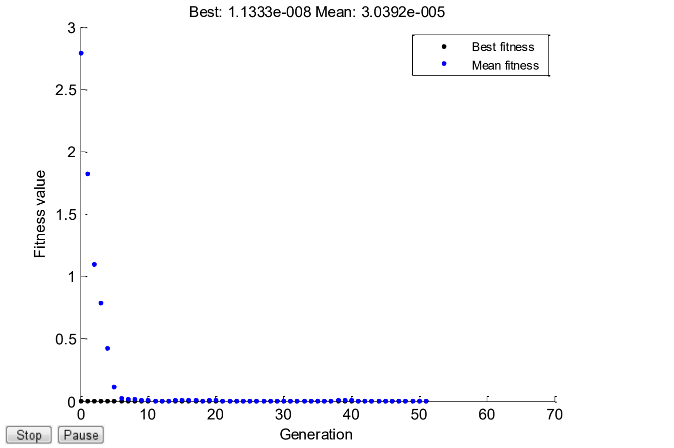

Fig. 10: Fitness vs. generation to optimise hardness using cladding travel speed range (1200-1700) W

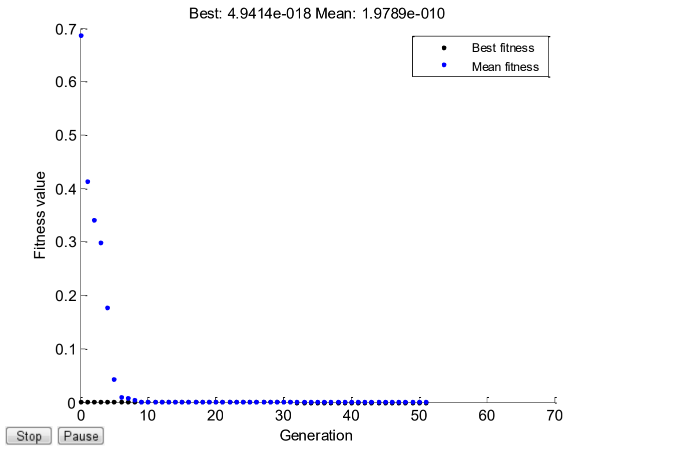

Fig. 11: Fitness vs. generation to optimise hardness using maximum cladding travel speed range (1600-1700) W

Table 3: Single-objective function results

Hardnes-s (Target)	Boundaries Constraint		Best function value found	Recommended solutions for 3 processes setting (suggested optimal values)		
	Travel Seed (TS)	Laser Power (LP)		Trave-l Seed (TS)	Powder Fed Rate (PFR)	Laser Powe-r (LP)
54	1600-1700	2.5-2.8	4.941e-18	1600	35	2.7
54	1200-1700	2.5-2.8	1.133e-08	1700	35	2.8

6. Strategy Of Multi-Objective Optimization

Evolutionary multi-objective optimization has become a popular and useful field of research and application over the past decade. A multi-objective optimization problem involves a number of objective functions which are to be either minimized or maximized subject to a number of constraints and variable bounds [12]. One of the main goals in multi objective optimization is to find a set of well distributed solutions along the Pareto front which is consists of Pareto optimum solutions. [2]. In many multi-objective optimization problems, the objective functions are usually in conflict with each other. In this study, multi-objective optimization using GA was used to minimise two objectives in order to find the optimal solution for the three-setting process. Both objectives are to minimise the error between the desired property and the calculated property of hardness and layer thickness respectively. Accordingly, the multi-objective optimization was used to design the optimal hardness values and at the same time reduce the layer thickness and then find the solutions of the three different variables [TS, PFR and LP]. The Equations 3 and 4 were used to minimise two objectives and estimates the optimal design of the process, where the target of hardness need to be optimised together with the layer thickness. For the multi-objective optimization, generation = 200, population size (P_S) =50 , number of variables (N_{vr}) to optimise=3 variables (TS, PFR and LP) and the initial population can be defined by Equation 1. By using the obtained knowledge from the RBFNN model (c, σ and ω), the calculated hardness and layer thickness can be defined. Then GA evaluates the fitness function by minimising Equations 3 and 4 and determines the Pareto optimum solutions. Table (4) shows multi-objective function results and Table (5) illustrated the optimum solutions for the three variables and the achieved results when these optimum solutions used as an input data for the RBFNN model.

In the multi-objective function, the hardness target was 54 mm and layer thickness was 1.5 mm, the constraints and bound used were (1200-1700) mm/min, (26-40) gr/min and (2.5-2.8) Kw for TS, PFR and LP respectively. Fig. 12 shows the Pareto front for the two objectives, hardness and layer thickness.

$$OB_{HM} = (H_{DM} - H_{CM})^2 \quad (3)$$

$$OB_{LM} = (L_{DM} - L_{CM})^2 \quad (4)$$

Where:

OB_{HM}: Objective function of hardness for multi optimization

OB_{LM}: Objective function of layer thickness for multi optimization

H_{DM}: The Desired target of hardness

H_{CM} : The calculated hardness by RBFNN

L_{DM} : The desired target of layer thickness

L_{CM} : The calculated layer thickness by RBFNN

Table 4: Multi-objective function results

Desired target for hardness (H) layer thickness (L)		Boundaries Constraint		The values of the objective function in the suggested optimal values for process variables	
Hard-ness (H)	Layer thickness (L)	Travel speed (TS)	Leser power (LP)	Hardness (H)	layer thickness (L)
54	1.5	1600-1700	2.5-2.8	1.53e-06	4.54e-21
				1.01e-08	2.47e-13
				3.95e-12	6.10e-06
				5.68e-12	1.47e-07
				9.90e-08	3.58e-17
				1.34e-07	2.98e-19
				4.11e-08	2.36e-16
				1.28e-08	7.23e-15
				7.25e-12	2.74e-10
				7.26e-20	6.10e-06
				1.53e-06	4.44e-23
				9.90e-08	3.58e-17
				4.44e-12	1.55e-07
				5.68e-12	1.47e-07
				4.11e-08	2.36e-16
				1.53e-06	4.44e-23

Table 5: The suggested optimal values for the three variables

Achieved outputs		Recommended solutions for 3 processes setting		
Hard-ness (H)	Layer thick-ness (L)	Travel speed (TS) Range (1200-1700)	Power fed rate (PFR) Range (26-40)	Laser power (LP) Range (2.4-2.7)
52	1.3	1600	38.81	2.56
52	1.3	1600	38.81	2.56
52	1.6	1700	38.85	2.56
52	1.3	1600	38.81	2.56
52	1.5	1600	38.81	2.56
52	1.6	1600	38.81	2.56
52	1.6	1600	38.81	2.56
52	1.6	1600	38.81	2.56
52	1.3	1600	38.81	2.56
52	1.5	1700	38.85	2.56
53	1.3	1600	38.81	2.56
53	1.3	1600	38.81	2.56
52	1.7	1600	38.82	2.56
52	1.3	1600	38.81	2.56
52	1.3	1600	38.81	2.56
52	1.5	1600	38.81	2.56

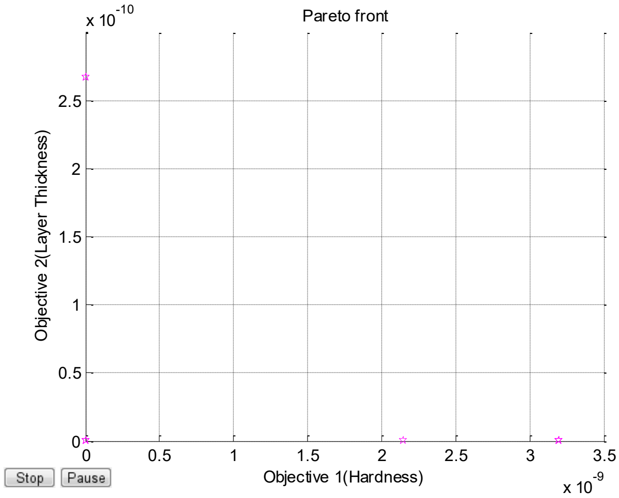

Fig.12: Pareto front for hardness and layer thickness

7. Discussion of the Simulation Results for the Multi-Objective Function Problem

The GA for multi-objective optimization was applied to derive operating policies for the laser cladding system under multiple objectives. In the multi-objective model, a set of optimal solutions for TS, PFR & LP were obtained by minimising the error between the target and calculated outputs of hardness and layer thickness as mentioned in Equations 3 and 4. Tables 4 and 5 show the results obtained from the GA multi-objective optimization in details. Fig. 12 shows the Pareto front for all cases. It can be observed that the GA multi-objective optimization was able minimise the error for both equations easily and therefore recommend the optimum solutions for the three variables of the operation.

8. Conclusion

The RBFNN self-learning system (SLS) model was selected in this study to model the laser cladding operation due to its capability to handle highly non-linear systems. The model utilised the data set provided by TMC to predict the hardness and layer thickness of the process. Simulation results for model training and testing demonstrated good performance and excellent agreement between the outputs of the laser cladding system and the RBFNN, as illustrated in Figs. 2–5.

Additionally, a Genetic Algorithm (GA) was applied in this research for both single- and multi-objective optimisation. The GA was used to minimise the error between the desired and calculated outputs for hardness and layer thickness, and to determine the optimal settings for Travel Speed (TS), Powder Feed Rate (PFR), and Laser Power (LP). The results confirm the robustness of the proposed methodology, and optimal operational settings for the three parameters were successfully obtained.

9. References

[1] D. E. Goldberg, Genetic Algorithm in Search, Optimization and Machine Learning, Reading, MA: Addison-Wesley, 1989

[2] Cingara, A., McQueen, H.J., (1992), New Formula for Calculating Flow Curves From High Temperature Constitutive Data for 300 Austenitic Steels., Journal of Materials Processing Technology., Volume 36, Issue 1, Pages 31-42.

[3] Fernández, A. I., Uranga, P., López, B., Rodriguez-Ibabe, J.M., (2003) Dynamic Recrystallization Behavior Covering a Wide Austenite Grain Size Range In Nb and Nb–Ti Micro-Alloyed Steels., Materials Science and Engineering., Volume 361, Issues 1–2, Pages 367-376.

[4] Wang, M. H., Li, Y. F., Wang, H. W., Zhou, J., Chiba, A., (2013), Quantitative Analysis of Work Hardening and Dynamic Softening Behavior of Low Carbon Alloy Steel Based on the Flow Stress., Materials and design, volume 45, page 384-392.

[5] Zang, X., Wu, C., (2015)., Energy Cost Minimization of

Compressor Station by Modified Genetic Algorithm., Engineering letters, volume 23, issue (4), page 258-268.

[6] K. Deb, Multi-Objective Optimization Using Evolutionary. John Wiley & Sons, Inc., 2001

[7] Reedy, M. J., Kumar, D. N., (2006), Optimal Reservoir Operation Using Multi-Objective Evolutionary Algorithm., Water Resource Management, Volume 20, page: 861-878

[8] Katoch, S., Chauhan, S. S., Kumar, V., (2021), A review on Genetic Algorithm: Past, Present, and Future. Multimedia Tools and Applications, Volume 80, pages 8091–8126.

[9] Chowdhury, G. M., Roy, G. G., (2009), Application of Genetic Algorithm (GA) to estimate the rate parameters for solid state reduction of iron ore in presence of graphite, Computational Materials Science, Volume 45, Issue 1, Pages 176-180

[10] Dilekoglu, M. F., (2016), Use of Genetic Algorithm Optimization Technique in the Adsorption of Phenol on Banana and Grapefruit Peels, Journal of the chemical society of Pakistan Volume 38, No. 06, 201 38(06)

[11] Abarghouee, H., Arabi, H., Seyedein, S. H., Mirzakhani, B. (2021), Modelling of hot flow behaviour of API-X70 microalloyed steel by genetic algorithm and comparison with experiments, International Journal of Pressure Vessels and Piping, Volume 189, 104261 https://doi.org/10.1016/j.ijpvp.2020.104261

[12] Deb, K., (2012), Advances in evolutionary multi-objective optimization. computational intelligence, Vol. II - Evolutionary Multi-Objective Optimization.