Performance Evaluation and Optimization of AlFeSi10Mg Alloy Processing Using Data Envelopment Analysis-Based Ranking (DEAR) Technique

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Abstract. In this work, the performance and efficacy of several experimental runs are evaluated using the DEAR (Data Envelopment Analysis-based Ranking) approach, with an emphasis on materials and process factors for an AlFeSi10Mg alloy system. Laser Energy Density (LED), Specific Energy Density (SED), and Volumetric Energy Density (VED) were the outputs of the analysis of the following input factors: Power (P), Speed (V), Hatching Distance (H), and Layer Thickness (T). These inputs and outputs were standardized to a single dimensionless scale in order to ensure comparability. The performance of each experiment was then efficiently rated using computing efficiency scores. This approach determines the ideal circumstances for achieving the desired material qualities by balancing the inputs and outputs using weighted calculations. Future high-performance material research studies can benefit from the DEAR methodology's quantitative and methodical approach to performance comparison, which identifies the most effective trials and provides a helpful.

Keywords: AlFeSi10Mg alloy, Additive manufacturing (AM), Selective laser melting (SLM), Process optimization, Data Envelopment Analysis-Based Ranking (DEAR),Multi-response optimization.

1 Introduction

Aluminum alloys especially the AlFeSi10Mg alloy is crucial in some modern industries of manufacturing because of its inherent physical characteristics, light weight nature and high endurance. These alloys are employed in aerospace, automotive and electronics industries because of their properties such as high strength-to-weight ratios, corrosion resistance and ease of manufacture. The necessity for improved processing conditions in AM and SLM is evident because of the increasing interest in obtaining the preferable microstructure and mechanical properties of the material. In AlFeSi10Mg alloys, optimal properties are significantly influenced by the control of

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process parameters such as power, scanning speed, hatching distance, and layer thickness. Loying elements, including silicon (Si) and magnesium (Mg), in AlFeSi10Mg play essential roles: silicon makes the metal softer and reduces crack formation, whereas magnesium contributes to the strength by having a solute solution strengthening effect. These alloys are sensitive to high-temperature processes, which may cause such microstructural flaws as porosity, residual stress, and anisotropy of the mechanical characteristics. It is necessary to use sophisticated approaches in the process of fabricating materials with uniform microstructures in order to solve these problems and achieve the necessary characteristics of materials. Previous research on manufacturing have applied techniques such as response surface methodology and regression analysis for the optimization of manufacturing parameters which often lack full characterization across multiple responses or linear assumptions that may not hold in various manufacturing systems. The DEAR technique stands as an effective multi-response optimization technique that offers a broad range of efficiency assessment in terms of input factors, including power, speed, hatching distance, and layer thickness, as well as diverse energy density responses like LED, SED, and VED. Thus, while single-response optimization methods consider a single-response optimization problem, DEAR compares and evaluates each experimental configuration with other configurations, and then ranks the experimental runs based on the efficiency scores assigned to specific weight inputs and outputs. This research seeks to apply R methodology for the assessment of the processing conditions of AlFeSi10Mg alloy using data collected from a number of experiments. Thus, this study aims to identify the most suitable process parameters of the alloy through the process of normalization of input and output data, evaluation of efficiency scores, and ranking of each experiment. This method provides information about the best set of parameters and presents a clear explanation of how the input parameters influence and affect the output parameters, thus playing a significant role in decision-making process in manufacturing environments. Selective laser melting (SLM) is a highly significant technique of AM in the manufacturing of metal parts due to its surface finish, density and accuracy [3, 7]. From the study presented in Fig 1, the machine learning application of LLDPE employs both linear and polynomial regression by making oven dwell time the basis for estimating primary attributes, leading to improvement of mechanical traits and optimisation of expense. An inverse technique is used to calculate oven time depending on the required attributes [11]. According to Trevisani et al. [16] SLM achieves this because it employs temperature gradients, high concentrated heat flux and rapid cooling thus having the ability to produce metal parts with ultrafine grain structures and a wide array of alloy components and improved tensile strength, hardness and density from the base material.

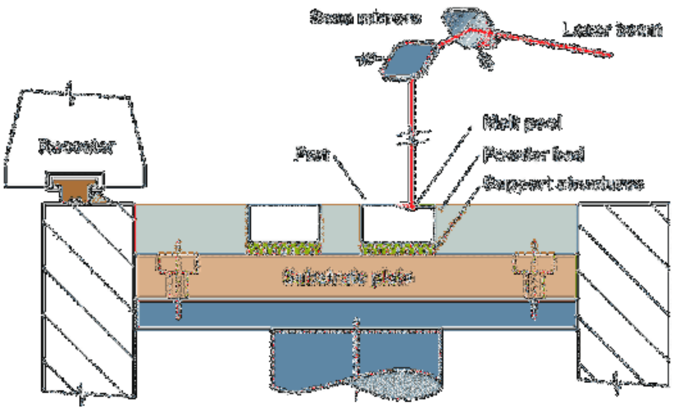

Fig. 1. AlFeSi10Mg alloy in SLM Process

2 Material used with Selective Laser Melting Technology

Aluminum blends, like AlFeSi10MG are crucial in industries such as aerospace and automotive for their lightness and toughness attributes; they are also favored for their durability and resistance to corrosion in applications too. These alloys are highly valued for their strength to weight ratio and ease of production. The rising need for manufacturing conditions in manufacturing (AM) especially, with selective laser melting (SLQ technologies underscores the importance of controlling process variables to achieve specific structural and mechanical qualities effectively. In alloys like AlFeSi10MG alloys changes during processing are crucial and affect the alloys characteristics based on factors, like power settings scanning speed hatching distance and layer thickness in use. Alloy components such as silicon (Si)and magnesium (Mg) play a role in determining these qualities ; Si aids in enhancing flowability and reducing fractures while Mg boosts the alloys strength through solution reinforcement. Exposure to temperatures, during processing can result in issues related to microstructure including pores tensions and uneven mechanical traits. Utilizing optimization techniques is key, to tackling these challenges by promoting microstructures and improving material effectiveness. The AlFeSi10Mag alloy that was investigated in this research is widely used in applications due, to its characteristics. In Table 1 of the study report provided the breakdown of the alloys composition and how each element. Silicon, Iron and magnesium. Affects its behavior during laser melting (SLN). SLM involves building components gradually using a laser and powdered material which results in the solidification of AlFeSi10Mag. These alloy elements play a role in developing microstructures, with properties. AlFeSi10Mag offers benefits in the laser melting (SLV) process, including a remarkable strength-to-weight ratio and the capacity to create complex structures and forms. Notwithstanding these benefits, problems like microstructure control and solidification cracking still exist. Research and ongoing optimization show that AlFeSi10Mg integration with SLM can promote advances in areas including engineering, aerospace, and automotive that need high-performance, lightweight, and precisely made components. Even though AlSi10Mg and AlFeSi10Mg have slightly different compositions, studies show that both alloys have a consistent density of 2.68 g/cm³.

Table 1. Chemical Composition of the AlFeSi10Mg

Element	**Wt%**	**At%**
Mg	0.45	1.08
Al	69.64	73.05
Si	9.9	14.49
Cr	0.79	0.14
Fe	0.55	10.28
Cu	0.05	0.96
Total	**81.62**	**100**

Response surface methodology (RSM) and regression analysis are commonly employed in traditional production parameter optimization techniques. These approaches might, however, be based on linear assumptions that would not be appropriate in complex manufacturing situations or lack comprehensive evaluation over a range of responses. As a thorough multi-response optimization tool, the Data Envelopment Analysis-Based Ranking (DEAR) technique offers an integrated assessment of efficiency by taking into account a variety of inputs (such as power, speed, hatching distance, and layer thickness) and outputs (such as energy density responses like LED, SED, and VED). This way, DEAR provides a better analysis of performance compared to single-response optimization technqiues due to the usage of efficiency scores based on weighted input and output characteristics to compare experimental runs. Based on the result of many times experimental data, this paper utilizes the DEAR approach to optimize the processing conditions of AlFeSi10Mg alloy. The research identifies the process parameters for the alloy production based on trial analysis, input and output standardization, and efficiency rating computation. In this way, manufacturers can make rational decisions indicating the most effective parameter values and describe the interconnections between input and output parameters.

3 DEAR Technology

A statistical tool referred to as data envelop analysis (DEA) is used to compare the efficiency of a large number decision making units (DMUs) that use several inputs to produce certain quantities of outputs. DEA is most useful in cases where other regular performance assessments like ratios are ineffective or where the KPIs cannot be measured by one output. The DEA framework enables one to find best practice and evaluate operating efficiency across multiple runs or over several units which makes assessing multiple aspect systems easier to perform. DEAR is an acronym that stands for Data Envelopment Analysis for Resources and its fundamental usage is to benchmark, evaluate performance and allocate resources for usage by the business. They are helpful across a number of sectors and can be used to recover valuable resources that many people do not think can be reused. By development benchmarks that can be used to compare the company with competitors or industry practices, DEAR assesses operational performance to identify process advantages, and disadvantages. It also makes a better judgment when it comes to process improvement and where to allocate more resources to reduce underachieving units. DEAR has several favourable attributes among which are non-parametric; it can handle many inputs/outputs; correctly rank high performers to encourage information sharing and adopt best practice. The following are limitations of DEAR analysis: Dependence on quality data: DEAR demands the use of high quality data Efficiency affected by outliers: DEAR is affected by outliers hence efficiency assessments can be distorted Weight assignment:While assigning weight, prejudice and subjective judgments may be used.

STEP1 : A. Efficiency

Technical efficiency is therefore a measure of how well a DMU is able to transform inputs into outputs. If a DMU lies on the production frontier or cannot produce more with less input, then it is termed as technically efficient. An inefficient DMU may be able to produce the same output with less power or produce more with the same input. Allocative efficient is defined as the efficient distribution of resources in consideration with the cost of the resources. This is the situation where a DMU uses its inputs in the optimum proportions that have been set by the productivity and cost of the inputs.

B. Inputs and Outputs :

Inputs are the resources that are utilized during the production process. The DEAR framework includes relevant quantitative measures for labor hours, energy use, operating expenses, and raw material utilization. The term "outputs" describes the observable outcomes of the production process, such as the quantity of goods produced, the caliber of the services rendered, the revenue generated, or other performance metrics pertinent to the DMUs under evaluation.

STEP 2: Calculation of Efficiency Score:

Efficiency scores, which show how well a DMU uses its inputs to produce outputs, are essentially calculated as part of DEAR. The following describes the formula used to determine the efficiency score:

$$\text{Efficiency Score} = \frac{Weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ Inputs}$$

A. Weighted Sum of Outputs:

The weighted sum of outputs consolidates performance metrics according to the designated weights for each output parameter. The calculation is performed as follows:

Weighted Sum of Outputs $=W_1$*R1LED + W_2*R2 SED + W_3*R3VED

Where :

- R1,R2 and R3 represent the various output measures(LED,SED and VED)
- W1 ,W2 and W3 are the weights assigned to each output,reflecting their relative importance.

B. Weighted Sum of Inputs:

Similarly , the weighted sum of inputs aggregates the input resources used by DMU:

Weighted Sum of Outputs $=W_4$*Power(P) + W_5*Speed(V) + W_6 Hatching distance(H) +W_7 Layer Thikness(T)

Where:

- Power , Speed, Hatching Distance and Layer thickness are the input measures.
- W_4,W_5,W_6 and W_7 are the weights assigned to each input parameters.

The following Fig.1 describes the flow chart of the proposed framework for coverless steganography to communicate confidential data from one end to another.

Table 2: Input and Output Factors

4	A: power	B: Speed	C: Hatching Distance T	D-H Layer thickness	R1 LED	R2 SED	R3 VED
	watt	mm/sec	mm	mm	j/mm	j/mm^2	j/mm^3
1	325	1100	0.25	0.03	0.295	14.777	39.39
2	295	1300	0.125	0.06	0.226	3.8	30.05
3	317	1000	0.25	0.04	0.317	7.93	32.01
4	370	900	0.173	0.04	0.411	10.28	79.05
5	370	1300	0.25	0.02	0.284	14.23	57.22
6	370	955	0.15	0.02	0.387	19.37	129.45
7	370	1270	0.15	0.05	0.291	5.83	31
8	314	900	0.199	0.06	0.348	5.81	30.89
9	295	1100	0.125	0.03	0.268	8.94	71.55

10	310	1270	0.25	0.05	0.244	4.88	16.7
11	325	1250	0.25	0.04	0.26	6.5	25.745
12	325	1300	0.15	0.03	0.25	8.33	56.05
13	370	1235	0.1	0.04	0.3	7.49	74.68
14	370	1300	0.25	0.02	0.284	14.2	56.02
15	370	1270	0.15	0.03	0.291	7.3	49.61

STEP 3: Efficiency Score calculations with Ranking:

Assuming equal weights (W1=W2=W3=W4=W5=W6=W7 =1),the efficiency score for Run1 can be calculated as follows:

Weighted Sum of outputs :

=0.295+14.777+39.39 = 54.462

Weighted Sum of Inputs :

= 325+1100+0.25+0.03 = 1425.28

Efficiency Score for Run 1 :

Efficiency Score = $\frac{54.462}{1425.28}$

= 0.0382

Repeating this calculation for all runs allows to generate a comprehensive set of efficiency scores.

Table 3 : Efficiency Score with Rank

RUN	Efficiency Score	Rank
1	0.594	4
2	0.054648	15
3	0.43998	9
4	0.991	3
5	0.44759	7
6	**1.951**	**1**
7	0.2022	12
8	0.4779	6
9	**1.138**	**2**
10	0.0579	14
11	0.157	13
12	0.388072	10
13	0.4925	5
14	0.4434	8
15	0.346057	11

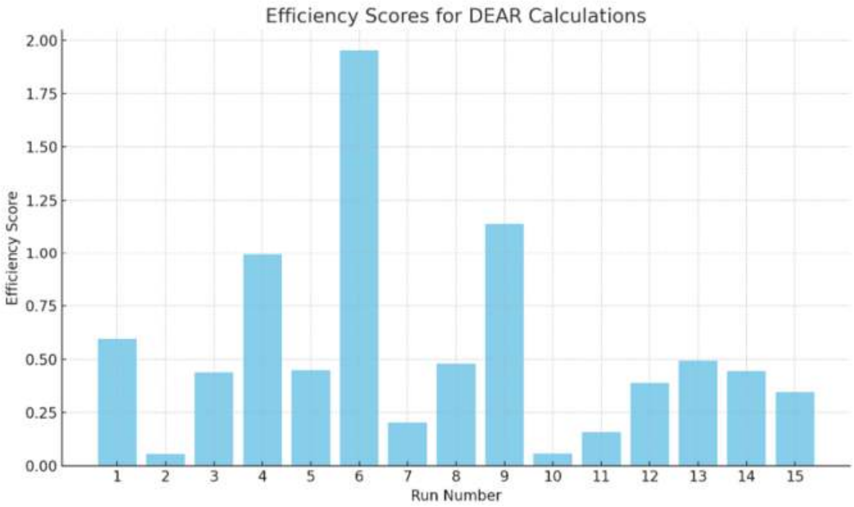

Fig. 2. Run Number Vs Efficiency Score

Experiment Run 6 ,9 an 4 are achieved the highest efficiency score, signifying superior performance relative to input-output balance compared to all other experiments. In contrast, Run 2 exhibits the lowest score, indicating it is the least efficient.

4 Conclusion

The DEAR method's application to the AlFeSi10Mg alloy process experiments effectively demonstrates its worth in multi-response optimization by enabling a comprehensive evaluation of each experimental setup's performance. The most efficient experimental run is Run 6, which is closely followed by Runs 9 and 4 due to its superior output-to-input balance. The approach is a versatile tool for selecting experiment setups and increasing material characteristics due to its adjustable weighting factors and adaptability to input and output parameters. This ranking approach offers useful information by enhancing material properties for industrial applications and helping researchers adjust process parameters in alloy synthesis. Future study that fine-tunes the weighing system according to experimental priorities or material behavior could further increase the DEAR method's adaptability to different alloy systems and other production processes.

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