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The quality systems of additive technologies for aerospace parts manufacturing

Los sistemas de calidad de las tecnologías aditivas para la fabricación de piezas aeroespaciales

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ABSTRACT

In this study, the quality system for Ti-6Al-4V alloy manufacturing by selective laser melting was analyzed by using the Grey relation analysis and additive manufacturing quality methodology. In proposed methodology, the multicriteria problem is solved by selecting an optimal alternative AM technological process parameters combinations to meet the required quality parameters (desired goals) of the aerospace parts according several criteria. Decision algorithm for planning additive manufacturing was developed for building alternatives matrix and the adaptation coefficient evaluating. As quality criteria in model were chosen accuracy, roughness, strength, cost, printing time. Based on the analysis of the values of the adaptation coefficients for SLM, DMD and EBM technologies, the first type of technology for the manufacture of aerospace product, selective laser melting, is accepted as optimal.

Keywords: Aerospace parts; Additive manufacturing; Quality parameters; Grey relation analysis; Adaptation coefficient.

RESUMEN

En este estudio se analizó el sistema de calidad para la fabricación de aleaciones Ti-6Al-4V mediante fusión selectiva por láser utilizando la metodología de análisis de relación de Gray y calidad de fabricación aditiva. En la metodología propuesta, el problema multicriterio se resuelve seleccionando una combinación alternativa óptima de parámetros de proceso tecnológico AM para cumplir con los parámetros de calidad requeridos (objetivos deseados) de las partes aeroespaciales de acuerdo con varios criterios. Se desarrolló un algoritmo de decisión para la planificación de la fabricación aditiva para la construcción de la matriz de alternativas y la evaluación del coeficiente de adaptación. Como criterios de calidad en el modelo se eligieron precisión, rugosidad, resistencia, costo, tiempo de impresión. En base al análisis de los valores de los coeficientes de adaptación para las tecnologías SLM, DMD y EBM, se acepta como óptimo el primer tipo de tecnología para la fabricación de producto aeroespacial, la fusión selectiva por láser.

Palabras claves: Partes aeroespaciales; Fabricación aditiva; parámetros de calidad; análisis de relaciones de Gray; Coeficiente de adaptación.

1. INTRODUCCIÓN

The technological core of the Industry 4.0 concept is additive technologies that allow, based on material layer-by-layer deposition on a substrate and its melting and solidification according 3D model, to obtain finished products of various shapes and geometries configurations, with internal channels and cavities, the manufacture by traditional method is difficult or impossible (Bank et al., 2022; da Silva Oliveira et al., 2022).

The conventional manufacturing is characterized by high cost and cycle time, steps of technological processes that are connection with huge number of tools and equipment. Additive manufacturing present a significant cycle time and cost reduction, tool-less fabrication, capability for novel designs no limited by manufacturing constraints.

Additive technologies are actively used in aviation and space industry, where complex geometry and high strength materials are main driver for engineering development (Alekseev et al., 2023; Dmitrienko et al., 2023). The availability of additive technologies makes it possible to establish the production of aviation parts from titanium alloy, Ti-6Al-4V, with reducing the cost and production time.

The main advantage of additive technologies in comparison with traditional, subtractive production methods are (Blakey-Milner et al., 2021): a significantly less time of the production cycle; the ability to make a “free” geometry form and configurations in design and technological preparation of production; lower costs for storage and transportation costs, equipment, tools; higher rate of material utilization; the possibility of obtaining products with gradient properties and chemical composition; minimization of the product mass; higher reliability of the design; and higher production flexibility, etc. However, additive technologies have the following disadvantages: the impossibility of achieving high accuracy; the need to improve the properties of the surface layer; insufficient quality of additive blanks that need the post-processing and heat treatments procedures; insufficient automation of design and preparation of production; lack of a data base of optimal technological parameters for additive manufacturing different materials; and insufficiently developed system of suppliers of materials, etc.

In this regard, the task of organizing additive production based on selective laser melting is to identify the area of their effective practical application in aviation, taking into account the limitations to provide improved functional properties of the product in a shorter production time and reduce consumed resources using numerical multi-parameter optimization tools.

In this context, the functional properties of an aviation product include the parameters of strength, rigidity, weight, geometric complexity, the presence of internal channels and cavities, and the range of assembly units.

Titanium alloy, Ti-6Al-4V, is an attractive, lightweight material for spacecraft structures, as it provides an excellent combination of high strength, low density, high modulus, low coefficient of thermal expansion, and higher operational temperature than aluminum alloys (Rawal et al., 2013). Additive manufacturing (AM) technology in case of selective laser melting (SLM) offers a unique approach to design and build complex shape aviation and space components without the need for tooling and with minimal machining at low scrap rates (Kulikov, Minakov, 2023).

The main task of organizing additive manufacturing is to ensure the required quality and productivity in a given time, taking into account technological limitations and equipment capabilities.

The main technological limitations are:

– The limitation of the building volume of printing, determined by the specification of equipment, which is most taken into account when choosing a technology for printing large-sized products;

– The printing speed (scan speed), determined by the number of layers, therefore, the height of the product on the build platform, layer thickness, speed of application and alignment of powder layers, spraying and deposition of materials;

– The thickness of the construction layer, determined by the resolution of the z axis and the size of the alloyed particles, the injection nozzle.

In paper (Liu et al., 2021) directed energy deposition or direct metal deposition (DED, DMD) is observed as one of the additive manufacturing technologies, offers a high deposition rate, being suitable for fabricating large metallic components from titanium alloys. The development of high mechanical performance DED products is limited by time consuming searching for optimized processing parameters, such as laser power, scanning speed, spot size, and layer thickness. Therefore, a fast and cost-efficient way to discover new alloys and optimized processes for fabricating high-performance components is desired.
Several investigators (Wooten, Dennies, 2008; Al-Bermani et al., 2010) are conducting studies to assess the build rate, surface quality, overall deposition accuracy, level of impurities, post-processing treatment such as hot isostatic processing, heat treatment, extent of machining, and cost, compared electron beam melting (EBM) process with conventional subtractive processes. EBM method is implemented in Boeing Aerospace during Ti-6Al-4V parts production using Arcam machines.

In this paper, we developed the quality systems of additive technologies for aerospace parts manufacturing from Ti-6Al-4Al alloy metal powder based on Gray relation analysis and Isikawa diagram. The design of SLM technology is to create and develop a decision-making algorithm and evaluating its effectiveness. Decision-making is based on the results of studying the influence of technological parameters on the properties of manufactured parts by means of dispersion analysis, grey relational analysis, planning experiments (Yang et al., 2020). Thus, machine-learning technology is implemented based on mathematical models and parametric optimization to predict technological parameters that satisfy the mechanical properties of the aerospace product.

Development of mathematical models that take into account all the physical features of the additive process for microstructure, mechanical and electrochemical properties prediction. The mathematical models allow producing the materials with requirement mechanical behavior.

2. METHODOLOGY

The proposed methodology is shown in Figure 1: variation (dispersion) analysis and regression model allow estimating the value of each technological parameter: laser power, layer thickness, scanning step, and their combination. An algorithm for parametric optimization is forming the set of optimal SLM parameters determined by the relationship of the influence of technological parameters on the properties of the product.

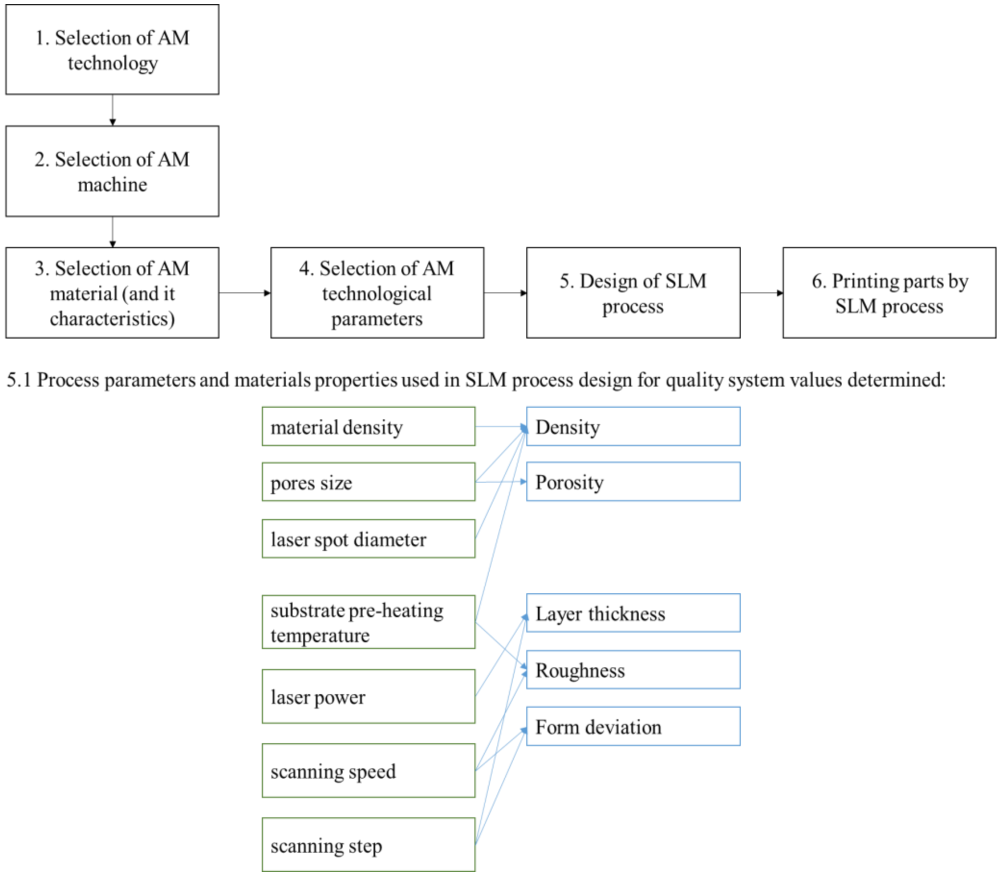

Figure 1. Methodology for the quality systems of additive technologies for aerospace parts manufacturing from Ti-6Al-4Al alloy metal powder

Unlike most conventional manufacturing processes, the repeatability of most metal AM processes cannot be taken for granted. Certain processes are particularly sensitive to material input and process variables which are hard to control. This is what reinforces the need for a robust quality strategy that addresses machines and materials. Processes which are able to directly measure and control the metal deposition (printing) process will have an advantage.

Key features of materials produced by additive manufacturing are:

– The fine microstructure, due to the very rapid solidification process

– A slight anisotropy in Z direction, which induces slightly lower mechanical properties due to the superposition of layers.

– Anisotropy can be avoided in X and Y directions by using an adapted laser strategy.

– A few small residual porosities, in particular below the surface. However, densities of 99.9% are commonly reached with additive manufacturing processes. To achieve full density, post processing by HIP can be done, like for parts made by investment casting.

Today research and development aimed at improving the AM process and enhances the performance properties of the aerospace parts produced. Next important step is the selection of the optimal technological parameters of AM types and subsequent processing as by experimentation and mathematical modeling techniques that will improve and accelerate the process of creating a product with the specified requirements, including the desired roughness of samples.

Grey relational analysis (GRA) is a decision-making approach which has been derived from Deng's grey system theory which uses the terms black and white to denote systems with incomplete data and systems with complete data. The partial information is used to represent the grade of association between two sequences, a grey relation is utilized to characterize the distance between two components. Gradient augmentation compensates for a lack of statistical regression when the experiment is ambiguous or the experimental procedure is incorrect (Singh, Bharti, 2022).

The main difficulty in solving problems of planning and quality optimizing additive manufacturing is the select and describe of suitable objective functions, since technological parameters and their relationships are extremely difficult to determine or express with exact mathematical models, especially for discrete variables. In addition, there are a large number of decision support methods for choosing a more optimal Pareto-Optimal-Front option. The application of different decision methods will lead to different decision results even for the same problem, which is likely to cause a different type of problem, stability or reliability, model adequacy.

In proposed methodology the multicriteria problem (Fig. 2) is solved by choosing the optimal SLM strategy, parts location on the building platform (substrate) and technological parameters by implementing the vector of alternative technological process parameters combinations and required quality parameters (desired goals). The formation of alternatives is carried out on the basis of the knowledge base, respectively, each alternative is considered as a unit of knowledge, and the attributes of the alternatives are considered as elements of the knowledge vector.

The required quality parameters (desired goals) of the aerospace part are:

– material;

– roughness, i.e. surface quality;

– strength;

– cost.

The criteria for selecting alternative technological process parameters combinations are:

– type of AM technology;

– materials;

– the size of the working area;

– accuracy (distance between layers);

– layer thickness (minimum layer thickness);

– scanning speed;

– cost.

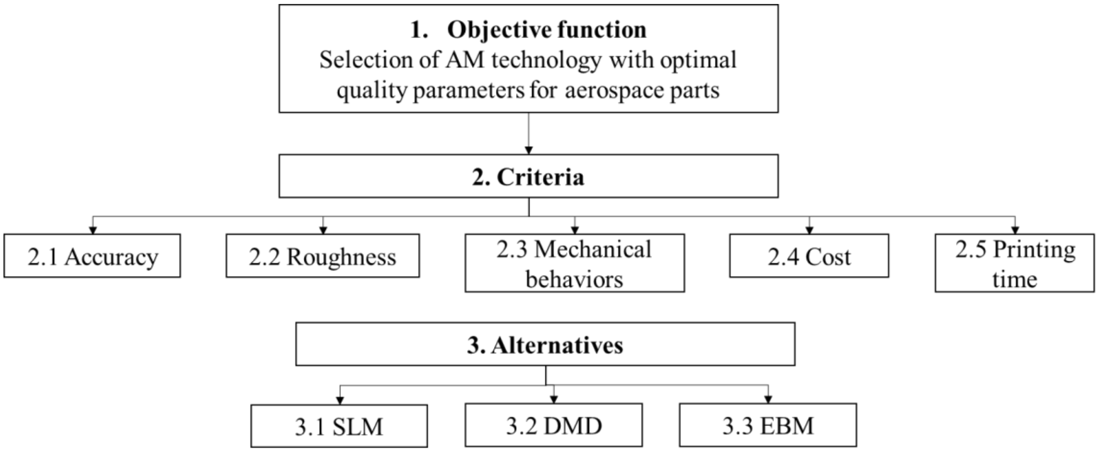

Figure 2. Multicriteria decision problem of additive manufacturing planning

The additive manufacturing process is represented as a vector of specified attributes to obtain the required product quality parameters (Russell et al., 2019; Global Aerospace Additive Manufacturing Market Research Report – Forecast 2016-2021, 2019):

1. Attributes: accuracy (A), roughness (R), tensile strength (S), material cost (C), printing speed (B).

2. Vector of technology type *V= (A, R, S, C, B).*

The reference process or objective function is represented as:

$$X_0 = \{x_0(1), x_0(2), \dots x_0(n)\}, \tag{1}$$

where $x_0(n)$ are the attributes of the *target vector.*

Variants of AM technological processes types (i = 1, 2, … m):

$$X_i = \{x_i(1), x_i(2), \dots x_i(m)\}, \tag{2}$$

where $x_i(m)$ are attributes of the *alternative vector.*

Based on GRA the task is to determine the deviations of the value of each attribute in vector of attributes in relation on the value of quality parameters in objective function (target vector) and to determine the *adaptation coefficient*.

D is the value of the deviation of the attribute of the alternative AM process A_a from the values of the attribute of the objective function A_g. The index of compliance of the alternative AM process with the required quality parameters - the adaptation coefficient, according to the formula:

$$K^d = \frac{1}{e^D} = \frac{1}{e^{|A^a - A^g/A^g|}}. \tag{3}$$

The value $A_a \neq A_g$, if the values of the parameters in the *alternative vector of the technological process A_a* coincide with the values of the parameters in the *target vector A_g*, then the *adaptation coefficient* is

$$K^d = \frac{1}{e^0} = 1. \tag{4}$$

Thus, we use a large number of attributes, and then the adaptation coefficient will take the form:

$$K^d = \frac{1}{e^{\sum \omega_i D_i}} = \frac{1}{e^{\sum \omega_i |A^a - A^g / A^g|}}, \tag{5}$$

where ω_i is the weight indicator of the attribute (degree of importance, priority).

Decision algorithm for planning additive manufacturing:

Step 1. Determining possible AM alternatives (additive manufacturing strategies) and establishing the required parameters - the objective function.

Step 2. Description of alternatives and the objective function in the form of matrices and data arrays.

Step 3. Building and processing of attribute matrices.

Step 4. Normalization of attribute matrices and target vector.

Step 5. Building a decision matrix.

Step 6. Formation of a weighted normalized decision matrix.

Step 7. Determination of the adaptation coefficient of each alternative.

Step 8. Ranking adaptations and choosing the best one.

In this case the quality systems of additive technologies for aerospace parts manufacturing is based on evaluating the adaptation coefficient of each AM technological alternatives:

So, for example, we have *m* strategies or types of additive manufacturing – vectors of alternatives: X_1, X_2, … X_m, consisting of attribute values ($x_i(1)$, $x_i(2)$… $x_i(n)$), from which it is necessary to select the best in *n* criteria (attributes): C_1, C_2, …C_n. If the criteria C_i , i = 1,2, … n, consists of n_i elements, then the *alternatives matrix* X_j, j = 1,2,…m, with respect to the criteria C_i can be represented:
$X_{ij} = \{x_{ij}(1), x_{ij}(2) \dots x_{ij}(n_i)\}$,

where $x_{ij}(k)$, k = 1, 2, … n_i, is the value of the attribute according to the selected criteria.

In addition, each attribute is assigned a weight depending on the purpose and requirements for the part: $\Omega = [\omega_1, \omega_2, \dots \omega_n]$.

Generalized mathematical model of the quality systems of additive technologies for aerospace parts manufacturing:

$$K_j^d = \frac{1}{e^{\sum_{i=1}^{n}[\omega \left|(x_{ij} - x_n^o)/x_n^o\right|]}} \to 1; j = \overline{1,m},\ i = \overline{1,n}. \tag{6}$$

$$X^o = \{x_1^o \dots x_n^o\}\,; \tag{7}$$

$$X_{ij} = \left\|x_{ij}\right\|_{m\times n}; \tag{8}$$

$$\omega_i = \{\omega_1 \dots \omega_n\}; \tag{9}$$

$$\sum_{i=1}^{n} \omega_i = 1; \tag{10}$$

$$x_{min\ j \leq}\ x_{ij} \leq x_n^o, \tag{11}$$

$$x_n^o \leq\ x_{ij} \leq x_{maxj}, \tag{12}$$

where K_j^d – the adaptation coefficient of j alternatives, $0 < K_j^d \leq 1$; j = 1…m - number of AM technology types; i = *1…n*, number of technology type attributes; ω_i – weight value of the i-th attribute; X^oarray of the reference type of additive manufacturing (vector of objective function); X_{ij} – matrix of alternative types of additive manufacturing (alternatives matrix).

To perform actions with arrays and matrices, we need to normalize them. There are several ways to normalize matrices. For the selected *k*-th element of the criteria C_i:

$$\text{Method 1: } \overline{x_{ji}}(k) = \frac{x_{ji}(k)}{M_{ik}}, \tag{13}$$

$$\text{where } M_{ik} - max\ \{x_{1i}(k),\ \ldots\ x_{mi}(k)\}. \tag{14}$$

$$\text{Method 2: } \overline{x_{ji}}(k) = \frac{x_{ji}(k)}{m_{ik}}, \tag{15}$$

$$\text{where } m_{ik} - min\ \{x_{1i}(k),\ \ldots\ x_{mi}(k)\}. \tag{16}$$

$$\text{Method 3: } \overline{x_{ji}}(k) = \frac{x_{ji}(k)-D_{ik}}{M_{ik}-m_{ik}}. \tag{17}$$

After normalizing the alternatives, matrix of different decisions (alternatives) are built:

$$\overline{X_{ji}} = \{\overline{x_{ji}}(1)\}, \ldots \overline{x_{ji}}(n_i)\}. \tag{18}$$

Then we compare them with each other and with the objective function. In this case, the array of the objective function is determined by the set of optimal attribute values among all matrices for each element of the criteria:

$$X_{0i} = \{(x_{0i}(1),\ x_{0i}(2)\ldots\ x_{0i}(n_i)), \tag{19}$$

$$\text{where } X_{0i}(k), k = 1,2..\ n, \text{ is the optimal (best) value among } \overline{x_{1i}}(k), \overline{x_{2i}}(k), \ldots \overline{x_{mi}}(k). \tag{20}$$

Taking into account the values of the weights of each criteria, a weighted matrix of decisions (alternatives) and the objective function is constructed:

$$\overline{\omega X_{ji}} = \{\omega_{ni}(1)\overline{x_{ji}}(1)\}, \ldots \omega_{ni}(n)\overline{x_{ji}}(n_i)\}, \tag{21}$$

$$\overline{\omega X_{0i}} = \{\omega_{ni}(1)x_{0i}(1)\}, \ldots \omega_{ni}(n)x_{0i}(n_i)\}, \tag{22}$$

where ω_{ni} – weight n_i Criteria.

The incidence matrix (estimation matrix) and – the adaptation coefficient will take the form:

$$
\begin{array}{c c}
 & \begin{array}{ccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_n} \end{array} \\
\boldsymbol{X} = \begin{array}{c} \boldsymbol{X_1} \\ \boldsymbol{X_2} \\ \boldsymbol{X_m} \end{array} & \begin{bmatrix} \boldsymbol{x_{11}} & \boldsymbol{x_{12}} & \boldsymbol{x_{1n}} \\ \boldsymbol{x_{21}} & \boldsymbol{x_{22}} & \boldsymbol{x_{2n}} \\ \boldsymbol{x_{m1}} & \boldsymbol{x_{m2}} & \boldsymbol{x_{mn}} \end{bmatrix},
\end{array} \tag{23}
$$

$$
\boldsymbol{K_j^d} = \frac{\boldsymbol{1}}{\boldsymbol{e}^{\sum_{i=1}^{n}[\omega_i \left|(x_{ij}-x_n^o)/x_n^o\right|]}} \, . \tag{24}
$$

The optimal technological type (alternative) among a finite set of alternatives is the one that has the less deviation and the greatest similarity to the objective function.

The adaptation coefficient allows to determine the degree of deviation of the values of the vector of alternatives from the target, taking into account the weighted values of the criteria for selecting alternatives, is within (0;1].

3. RESULTS

The study considers the case of *m* = 3 (types of AM technologies), *n* = 5 (quality parameters): the following attributes are accepted as Criteria for substantiating the types of additive manufacturing:

A - Accuracy, mm;

R - Roughness, µm;

S - Strength, MPa;

C - Cost, rub.;

B - Printing time, minutes.

$$
K_j^d = \frac{1}{e^{\sum_{i=1}^{5}[\omega_i \left|(x_{ij}-x_n^o)/x_n^o\right|]}} \to 1;\ j = \overline{1,3},\ i = \overline{1,5}. \tag{25}
$$

$$
X^o = \{A^o, R^o, S^o, C^o, B^o\} ; \tag{26}
$$

$$
X_{ij} = \begin{Vmatrix} A_1 R_1 S_1 C_1 B_1 \\ A_2 R_2 S_2 C_2 B_2 \\ A_3 R_3 S_3 C_3 B_3 \end{Vmatrix}; \tag{27}
$$

$$
\omega_i = \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5\}; \tag{28}
$$

$$
\textstyle\sum_{i=1}^{n} \omega_i = 1; \tag{26}
$$

$$
A_{min\, machine} \leq\ A_m\ \leq\ A^o \tag{29}
$$

$$
R_{min\, typy}\ \leq R_m \leq R^o \tag{30}
$$

$$
S^o \leq S_m \leq S_{max\, powder} \tag{31}
$$

$$
C_{min\, powder} \leq C_m \leq C^o \tag{32}
$$

$$B_{min\,machine/type} \leq B_m \leq B^o \tag{33}$$

Vectors of alternatives for selective laser fusion (SLM), direct laser fusion (LMD/DMD), electron beam metal (EBM) are defined:

$$X_{SLM} = (\text{A, R, S, C, B}) = (0.04, 10, 700, 0.7, 3), \tag{34}$$

$$X_{LMD} = (\text{A, R, S, C, B}) = (0.1, 100, 610, 0.5, 10), \tag{35}$$

$$X_{EBM} = (\text{A, R, S, C, B}) = (0.2, 200, 580, 0.3, 125). \tag{36}$$

Evaluation model:

$$X^o = \{0.04, 10, 700, 0.3, 125\}, \tag{37}$$

$$X_{ij} = \begin{Vmatrix} 0.04 & 10 & 700 & 0.7 & 3 \\ 0.1 & 100 & 610 & 0.5 & 10 \\ 0.2 & 200 & 580 & 0.3 & 125 \end{Vmatrix}, \tag{38}$$

$$\omega_i = \{0.4;\ 0.2;\ 0.1;\ 0.1; 0.2\}. \tag{39}$$

Normalization of the matrix of alternatives was carried out according to the method:

$$\overline{x_{ji}}(k) = \frac{x_{ji}(k)}{M_{i k}}, \text{ where } M_{ik} - max\ \{x_{1i}(k), \ldots x_{mi}(k)\}. \tag{40}$$

Normalized matrix $X_{ij} = \|x_{ij}\|_{m\times n}$- decision matrix:

$$\overline{X_{ij}} = \begin{bmatrix} 0.2 & 0.05 & 1.0 & 1.0 & 0.02 \\ 0.5 & 0.5 & 0.87 & 0.71 & 0.08 \\ 1.0 & 1.0 & 0.83 & 0.43 & 1.0 \end{bmatrix}. \tag{41}$$

Normalized array X^o:

$$\overline{X_o} = [0.2 \quad 0.05 \quad 1.0 \quad 0.43 \quad 1.0] \tag{42}$$

$$\text{К}^{d1} = \frac{1}{e^{\left|0.4(\frac{|0.2-0.2|}{0.2})+0.2(\frac{|0.05-0.05|}{0.05})+0.1(\frac{|1-1|}{1})+0.1(\frac{|1-0.43|}{0.43})+0.2(\frac{|0.02-1|}{1})\right|}} = 0{,}1. \tag{43}$$

$$\text{К}^{d2} = \frac{1}{e^{\left|0.4(\frac{|0.5-0.2|}{0.2})+0.2(\frac{|0.5-0.05|}{0.05})+0.1(\frac{|0.87-1|}{1})+0.1(\frac{|0.71-0.43|}{0.43})+0.2(\frac{|0.08-1|}{1})\right|}} = 0{,}001. \tag{44}$$

$$\text{К}^{d3} = \frac{1}{e^{\left|0.4(\frac{|1-0.2|}{0.2})+0.2(\frac{|1-0.05|}{0.05})+0.1(\frac{|0.83-1|}{1})+0.1(\frac{|0.43-0.43|}{0.43})+0.2(\frac{|1-1|}{1})\right|}} = 0{,}00001, \tag{45}$$

$$\text{К}^{d3} < \text{К}^{d2} < \text{К}^{d1} < 1. \tag{46}$$

Based on the analysis of the values of the adaptation coefficients, the first type of technology for the manufacture of aerospace product, selective laser melting, is accepted as optimal.

To verify the adaptation coefficient with the gray relational coefficient ε_{ji}, the calculation of last was performed:

$$\varepsilon_{ji} = \frac{min_m min_{ni}\,|\omega_{ni}x_{oi}(n_i)-\omega_{ni}\overline{x_{mi}}(n_i)|+0.5\;max_m max_{ni}\,|\omega_{ni}x_{oi}(n_i)-\omega_{ni}\overline{x_{mi}}(n_i)|}{|\omega_{ni}x_{oi}(k)-\omega_{ni}\overline{x_{ji}}(k)|+0.5\;max_m max_{ni}\,|\omega_{ni}x_{oi}(n_i)-\omega_{ni}\overline{x_{mi}}(n_i)|} \tag{47}$$

From the analysis of the distribution graphs of values (Fig.3), it can be seen that the values of the adaptation coefficients for various alternatives are within (0; 1], and the nature of the distribution is comparable to the distribution of the values of the gray relational coefficient. Due to the homogeneity of the behavior of the distribution graphs of the values of the gray relational coefficient and the coefficient adaptation in the calculation of determining the type of additive manufacturing, the adaptation coefficient is taken, since the time of its determination is much less than the time of calculation of the gray relational coefficient.

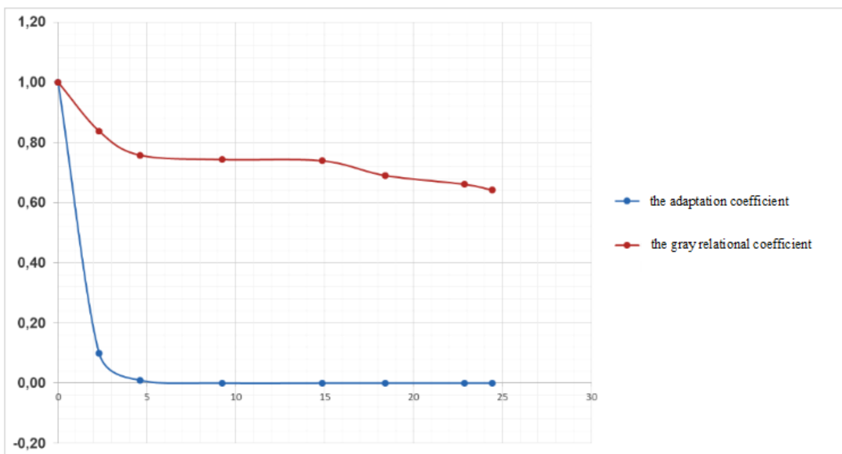

Figure 3. Graph of the distribution of gray relational coefficient and adaptation coefficient values

SLM as laser powder bed fusion AM type allows to produce fully dense aerospace components with high precision in a relatively short time, the manufacturing process is relatively expensive and is only applicable in industries with high-value components and where higher performance can result in cost reduction (Angrish, 2014). Aerospace industry applications are particularly well explored due to the reduced fuel costs achieved through mass reduction on aircraft and spacecraft. Additive manufacturing techniques have been shown to help reduce cost and lead times and also for reducing the mass of components aboard spacecraft and aircraft. Many popular publicized examples of AM applications in aerospace boast mass reductions, among many other benefits (Petrenko et al., 2023). While this is an attribute that holds much promise, lightweighting is currently still not the primary driver for AM in aerospace (Martirosyan et al., 2022). Lead time reduction is currently the main benefit, which can be significant for complex aerospace components often taking months or years of (traditional) fabrication time for complex systems).

4. CONCLUSIONES

Additive digital technologies refer to global science smart production and are included in the core of the fourth-technological revolution. It mean that this type of technologies must meet to advanced quality requirements of aerospace products.

This work considers the issues of operational planning of additive manufacturing. The adaptation coefficient makes it possible to determine the rational type of additive manufacturing at the pre-production stage, when the calculation by traditional methods (GRA) is very laborious. The coefficient used in the quality model characterizes the organizational and technical potential of additive manufacturing and contains the characteristics of the powder material, parts specifications, equipment and process parameters, and the values of the parameters of quality: accuracy, surface characteristics and strength of aerospace products.

The additive manufacturing processes (SLM, DMD, and EBM) were represented as vectors of specified attributes to obtain the required product quality parameters, were built a target vector and alternative vectors in order to determine the adaptation coefficient for each AM technology types.

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REFERENCIAS

Al-Bermani, S. S., Blackmore, M. L., Zhang, W., & Todd, I. (2010). The origin of microstructural diversity, texture, and mechanical properties in electron beam melted Ti-6Al-4V. Metallurgical and Materials Transactions A: Physical Metallurgy and Materials Science, 41(13), 3422–3434. https://doi.org/10.1007/s11661-010-0397-x

Alekseev, E., Ivashkin, M., Shelygov, A., Aleshkov, A., Vukovich, G., Shestemirov, A. (2023). Problems of the efficiency of ensuring environmental security: development of constitutional and legal norms. Lex Humana, 15(2), 473–486.

Angrish, A. (2014). A critical analysis of additive manufacturing technologies for aerospace applications. In IEEE Aerospace Conference Proceedings. IEEE Computer Society. https://doi.org/10.1109/AERO.2014.6836456

Bank, S., Sekerin, V., Gurtskoy, L., Bryzgalov, D., Zadornov, K. (2022). Impact of digitalization on transformations in the management of production and social processes. Revista Gestão & Tecnologia, 22(4), 304-316. https://doi.org/10.20397/2177-6652/2022.v22i4.2394

Blakey-Milner, B., Gradl, P., Snedden, G., Brooks, M., Pitot, J., Lopez, E., Leary, M., Berto, F., du Plessis, A. (2021). Metal additive manufacturing in aerospace: A review. Materials and Design, 209. https://doi.org/10.1016/j.matdes.2021.110008

da Silva Oliveira, L., Vieira Vasconcelos, A.P., Silva, S.V., Pereira dos Santos, R. (2022). A systems-of-information identification method based on business process models analysis. Revista Gestão & Tecnologia, 22(4), 90-115. https://doi.org/10.20397/2177-6652/2022.v22i4.2309

Dmitrienko, A., Lipovenko, M., Gostilovich, A., Kolosov, A., Ming, L. (2023). Development strategies of high-tech companies in China: Huawei and Tencent. Nexo Revista Científica, 36(02), 176–187. https://doi.org/10.5377/nexo.v36i02.16058

Global Aerospace Additive Manufacturing Market Research Report – Forecast 2016-2021. (2019). Market Research Future. Retrieved from: https://www.marketresearchfuture.com/reports/aerospace-additive-manufacturing-market-1551.

Kulikov, I., Minakov, I. (2023). Impact of technical and technological modernization and special measures in addressing food security. Nexo Revista Científica, 36(02), 155–164. https://doi.org/10.5377/nexo.v36i02.16055

Liu, Z., He, B., Lyu, T., & Zou, Y. (2021, June 1). A Review on Additive Manufacturing of Titanium Alloys for Aerospace Applications: Directed Energy Deposition and Beyond Ti-6Al-4V. JOM, 73, 1804-1818. https://doi.org/10.1007/s11837-021-04670-6

Martirosyan, A. V., Ilyushin, Y. V., Afanaseva, O. V. (2022). Development of a Distributed Mathematical Model and Control System for Reducing Pollution Risk in Mineral Water Aquifer Systems. Water, 14(2). https://doi.org/10.3390/w14020151

Petrenko, V., Tebueva, F., Antonov, V., Ryabtsev, S., Sakolchik, A., & Satybaldina, D. (2023). Evaluation of the iterative method of task distribution in a swarm of unmanned aerial vehicles in a clustered field of targets. Journal of King Saud University - Computer and Information Sciences, 35(3), 283–291. https://doi.org/10.1016/j.jksuci.2023.02.022

Rawal, S., Brantley, J., & Karabudak, N. (2013). Additive manufacturing of Ti-6Al-4V alloy components for spacecraft applications. In RAST 2013 - Proceedings of 6th International Conference on Recent Advances in Space Technologies (pp. 5–11). https://doi.org/10.1109/RAST.2013.6581260

Russell, R., Wells, D., Waller, J., Poorganji, B., Ott, E., Nakagawa, T., Sandoval, H., Shamsaei, N., and Seifi, M. (2019). Qualification and certification of metal additive manufactured hardware for aerospace applications. In Additive Manufacturing for the Aerospace Industry (pp. 33–66). Elsevier Inc. https://doi.org/10.1016/B978-0-12-814062-8.00003-0

Singh, M., Bharti, P. S. (2022). Grey relational analysis based optimization of process parameters for efficient performance of fused deposition modelling based 3D printer. Journal of Engineering Research (Kuwait), 10. https://doi.org/10.36909/jer.ICMET.17159

Wooten, J. R., & Dennies, D. P. (2008). Microstructural evaluation of electron beam melted Ti-6Al-4V. In Microscopy and Microanalysis (Vol. 14, pp. 616–617). https://doi.org/10.1017/S1431927608082792

Yang, B., Lai, Y., Yue, X., Wang, D., & Zhao, Y. (2020). Parametric Optimization of Laser Additive Manufacturing of Inconel 625 Using Taguchi Method and Grey Relational Analysis. Scanning, 2020. https://doi.org/10.1155/2020/9176509.

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