A Method of Managing Technological Heredity in the Additive Growing of Objects from Cold-Resistant Materials on a Machine with Technology for Electric Arc Welding

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Abstract. The article considers the issue of managing print parameters to minimize the impact of technological heredity on the layers of the formed object. An analysis of the stability of the 3D printing process was carried out using acoustic emission data. The fractal dimensions of the acoustic emission attractor for a stable and unstable 3D printing process have been obtained. A method for controlling process stability by tracking 3D printing modes and assessing their stability using an artificial neural network is proposed. The mechanical properties of printed samples were evaluated under normal conditions and at low temperatures in the Arctic and the far north.

1. Introduction
Today, the leadership of our country is particularly interested in the development of the northern regions. The tasks set in the framework of federal programs for the development of the Arctic and the Far North of the Russian Federation dictate urgent tasks to the scientific community. In particular, the development of technologies capable of producing products capable of withstanding the low temperatures that prevail in these regions.

A direction is actively developing for the study of cold-resistant materials, which can provide the specified strength characteristics of structures and withstand low temperatures [1, 2]. At the same time, the direction of technologies for the production of structures from these materials is becoming relevant, one of the promising areas here is additive growing, in other words, 3D printing of objects using digital models.

At present, the most widely used for 3D printing with metals are alloyed metal powders (SLM), laser powder surfacing (DMD) and electric arc welding (WAAM), the latter two being considered the most flexible ones that can be integrated into CNC machines [3–9]. At the same time, the processes are still quite uncontrollable and depend on many factors, including technological heredity, which the next layer perceives from the previous one. In this case, technological heredity is understood as how each subsequent forming layer, a single roller (or track) takes on macro and micro defects from the previous layer already laid.

2. Aim and objectives
The aim of the work is the development of technology for the additive growing of products from cold-resistant materials on CNC machines. As part of the goal, tasks were formulated, which
include: researching the manifestation of technological heredity and its influence on the quality of the formed object, the reflection of defects in printing modes, the search for ways to control heredity in 3D printing and assessing the mechanical properties of formed objects at low temperatures.

3. Equipment
To achieve the goals and objectives, an experimental bench was assembled, shown in Figure 1 [6], which is a hybrid complex consisting of a portal-type vertical milling machine upgraded in such a way that, in addition to the function of mechanical processing, it could carry out additive growing of workpieces by arc welding technology. This function was made possible thanks to the installation of a print head, which is installed in the machine spindle and the MIG 200 semiautomatic welding machine, whose control system was integrated into the machine control system. In order to fix the print modes and acoustic emission signals, the following were installed on the stand: SC145-600 sensor for measuring the arc current, SV025 sensor for measuring the arc voltage, GT200 acoustic emission sensor, which were connected to the PC via NI 6356 analog-to-digital converters and NI 9205 and NI cDAQ-9188 data acquisition bus. A pyrometer was also used to control temperature and prevent excessive metal overheating in the print zone.

![Figure 1](image)

**Figure 1.** An experimental bench for 3D surfacing on the basis of a CNC machine (1–3 coordinate machine with portal type CNC), 2 – a broadband acoustic emission sensor GT350, 3 – a PC with a wireless access system to the Microsoft Azure cloud service, 4 – power sensors current and voltage, 5 – ADC / DAC, 6 – CNC system, 7 – welding semiautomatic device, 8 – Microsoft Azure cloud service, 9 – shielding gas cylinders).

4. Experimental studies
In the process of experimental work, 09G2S steel was printed, which is widely used in the northern regions of the country. From the selected material, 3D printing of walls with a thickness of one roller was carried out, the length of the walls was 250–300 mm, height 150–180 mm, depending on the samples obtained in the future, as well as 3D printing of the “body” part was performed, the workpiece and the final part are presented in the figure 2. Printing of each of the samples was carried out on a different combination of modes, for this, the values of the welding current strength, voltage and printing speed were changed.
To fix technological heredity during the formation of one of the samples, a situation was simulated in which a single roller was printed on a previously formed part of the wall with a temperature of more than 500 °C. Due to excess heat in the surfacing zone, the stability of the system was violated, which led to excessive melting of the previous layer and leakage of metal from the weld pool, resulting in a violation of the geometry of the layer with the formation of a depression, as shown in Figure 3. Following the layer the next roller was laid under similar conditions, which led to an increase in the defect in geometry and the growth of the depression along the length and height. After this, the conditions were changed and the next roller was printed at a lower wall temperature, of the order of 300 °C, while the spreading of the weld pool in the place of the formed underestimation ceased, and when printing subsequent layers, the technological defect was leveled into a flat layer. Thus, due to timely local changes in technological parameters during additive growth by electric arc welding, minimization or complete elimination of the influence of technological heredity on the geometry of the formed object is possible. It should also be separately noted that the obtained sample showed mechanical properties identical to those obtained at stable conditions, which indicates that technological heredity can be minimized at the same level of microstructure and mechanical properties.
bandpass and Wavelet filters. After that, acoustic emission attractors, shown in Figure 5, were reconstructed and their fractal dimensions were calculated. From previous studies it is known that the smaller the fractal dimension, the more stable the process is [9], in this case the results also confirm this, for the stable mode the attractor dimension was $D_f = 3.1$, and for the unstable mode the fractal dimension increased to $D_f = 3.8$.

![Graphs of the regime of electric arc growing: a) without a defect, b) with a defect.](image)

*Figure 4.* Graphs of the regime of electric arc growing: a) without a defect, b) with a defect.

![3D printing system attractors: a) attractor of a stable arc b) attractor in case of loss of stability.](image)

*Figure 5.* 3D printing system attractors: a) attractor of a stable arc b) attractor in case of loss of stability.

The experiment demonstrates the need to develop adaptive systems for controlling the process of 3D printing of objects, which would allow, depending on changing conditions, to automatically adjust the modes, maintain stability and eliminate technological heredity.
During the additive cultivation of the object, a large amount of statistical data is generated that can be used to diagnose 3D printing processes with cold-resistant materials. For the purpose of their application, the apparatus of artificial neural networks [6, 7] was taken and the structure of ANN is formed. Figure 6. The created ANN is aimed at classifying the state of the additive growth process to further maintain process stability. The data source for the ANN was data from current, voltage, and acoustic emission sensors whose waveforms are shown in Figure 7. A data vector characterizing a time series representing pulses with a time shift is fed to the input of the developed neural network. The described approach made it possible to assess the stability of the system taking into account the history of dynamic events, as well as to identify scenarios of loss of stability and to classify defects. At the output of the neural network, there are 2 neurons that show the class of the defect during its manifestation and the degree of process stability. In this case, three states are assigned to the stability of the system: stable, unstable, and a transition state from stable to unstable. Neural network training took place on the Microsoft Azure cloud service. In the formation of training samples of neural network models, [10–16] methods of data mining were used.

Figure 6. Artificial neural network for the classification of the dynamic state of 3D printing processes.

Figure 7. Oscillograms of current, voltage and acoustic emission signal during 3D printing by electric arc welding on a CNC machine.
This approach was chosen to search for patterns and trends in large volumes of data that continuously flow throughout the 3D printing process. As a rule, such regularities are difficult, and sometimes impossible to detect in the usual statistical analysis, since the relationship between the data can be quite complicated. In particular, the following Data Mining technologies were applied: neural network clustering and classification of data (self-organizing maps of Kohonen and k-nearest neighbors), exploratory data analysis, to study the statistical properties of available samples (distribution of variables, outliers, the need for transformation, etc.) and identifying the nature of the relationship between response and predictors, estimating model parameters and diagnosing them using numerical resampling methods (cross-validation (CV), bootstrap), analysis of the contribution of individual predictors and optimal selection combinations of them, ranking of several alternative models and fine-tuning their most important parameters. After training, the neural network for classifying status and defects (Figure 6) was downloaded from a cloud service to a PC. Important here is the response time of the neural network in order to maintain the stability of the system, since the processes that occur during additive growth proceed quickly and continuously change. Especially for this, the neural network was hardware implemented, based on the Neuro Mem NM 500 neuro processor, made using 110 nm technology, and combining 576 neurons. There is no central processor in this neuroprocessor, so an additional control processor will be needed to supply the neurons with process data. Communication is carried out on a parallel bi-directional 26-bit bus. NM500 is a chain of neurons that are connected to a common parallel bus and are connected to each other. The developed neural network on the NM500 is capable of working in two main modes: training and recognition.

The next step was the integration of the neural processor NM 500 into the data acquisition and processing system. For this, the Neuro Shield debug board was used. This board made it possible to ensure the interaction of the neuroprocessor with the integrated FPGA via a 28-pin data bus. In addition, the selected board has protocols for exchanging data according to I2C and SPI standards, which allows it to interact with external devices (IIoT) [20]. As part of the ongoing work, the Raspberry Pi platform was used as an IIoT device. Using this approach to the diagnosis of the dynamic state of 3D printing processes, it was possible to implement high-precision classification of multidimensional time series of a sensor system in real time.

The next stage was the testing of the developed system. Which was carried out on the basis of the choice of optimal modes and control of the surfacing process in the manufacture of experimental samples. To select the optimal modes, the obtained ANN was used (Figure 6). At the same time, this ANN worked in deconvolution mode using the back propagation method of error. The essence of the method is to select the necessary state of the output neurons, fix the weight coefficients of the intermediate layers and automatically adjust the weights of the input layer. As part of the study, the output values of the neurons were selected as “stable” and “0”, which corresponds to the absence of defects. Then the initialization of the neurons of the input layer occurred, until the learning error became minimal. At the end of the balance adjustment, time series of current, voltage, and acoustic emission were obtained based on the given stability conditions. After, the obtained time series were passed through an existing database on a cloud service using the correlation function. By the maximum of the correlation function, the closest in composition time series in the database and the corresponding modes were determined. Thus, optimal surfacing modes were selected that correspond to the most stable process.

Then experimental blanks were obtained during additive growth of which the modes obtained by ANN were applied and allowing to maintain a stable process. After this, the blanks without being removed from the table were machined on the machine on which 3D printing was performed.

5. Analysis of experimental studies
The next step was the evaluation of the microstructure of the samples and their comparison with the blanks obtained from sheet metal. The analyzed structures are presented in Figure 8. Based on the obtained images, one can observe the differences between the 09G2S structures obtained by different methods. A distinctive feature of the structure obtained by electric arc growing is its fine
grain size, this is due to the fact that the metal of the previous layers undergoes cyclic heat treatment when applying the next layer. At the same time, we note that a hundred fine-grained structure is more preferable from the point of view of cold resistance. It is also seen from the pictures that the material has discontinuities at the grain boundaries, which can lead to a change in the mechanical properties of the material not for the better.

![Figure 8. Microstructures of steel 09G2S: a) obtained by rolling and past annealing, b) obtained by electric arc welding](image)

Next, an assessment was made of the mechanical properties of printed blanks from 09G2S, followed by cutting to standard samples according to GOST 1497-84. In particular, a tensile test under normal conditions. The test results are presented in table 1.

**Table 1. Testing the quality of recognition of a viscous component using ANN.**

| Mechanical indicators, MPa | δ, % | σ₀.₂ | σₚ |
|-------------------------------|------|------|-----|
| Samples cut along the direction of surfacing | 27   | 361  | 506 |
| Samples cut across the weld direction | 22   | 352  | 502 |
| Samples obtained by machining from sheet metal | 23   | 325  | 490 |

The bottom line in the table shows the values for samples obtained from sheet metal. In this case, comparing the results, we can see that the mechanical properties according to all three criteria are higher for the images obtained by the method of electric arc growing. It can also be seen that the samples obtained by electric arc growing have anisotropy of properties depending on the direction of tension, so the relative elongation of the samples obtained along the deposition direction is 18% higher than that of the samples obtained across the layers, and differences in yield strength are also observed.

Next, shock bending tests were carried out in the temperature range from –80° C to + 20° C, the results are shown in Figure 9. The tests were also carried out in comparison with sheet metal samples. From the results obtained, it can be seen that the nature of the change in toughness values is the same for samples obtained from rolled products and 3D printing. In this case, the impact strength values themselves for samples from rolled metal sheets after annealing are 15 ... 20% higher than for samples obtained by electric arc growing in the entire temperature range.

**6. Conclusion**

Thus, we can conclude that the process of additive growth by electric arc welding can be applied to the production of workpieces, including for parts operating at low temperatures. At the same time, the 3D printing process requires constant monitoring and maintaining stability in order to eliminate technological heredity, for which systems incorporating artificial neural networks can be applied.
Figure 9. The results of tests for impact bending of steel samples 09G2S: 1 - from sheet metal with subsequent annealing; 2 - cut along the direction of cladding; 3 - cut across the direction of cladding.

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