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Comparison Criteria and Efficiency of Thermomechanical Process Control Methods

Tatiana Lebedeva[a], Natalia Kepp[b], Andrey Yakovlev[c], Elmira Nazarova[d] and Mikhail Radkevich[e]

Peter the Great St.Petersburg Polytechnic University Polytechnicheskaya st., Saint-Petersburg, Russia

foxfree@mail.ru, maxima1971@gmail.com, yakovlev_aa@spbstu.ru, green.tea.with.mint@yandex.ru, radmich@mail.ru

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Abstract: The article presents a comparative study of process control methods for thermomechanical treatment of steels, emphasizing their relevance under the trends of digitalization and automation in metallurgical industries. Ten key performance criteria are identified and used to assess five major control method groups: technological, mathematical, machine learning-based, automated systems (ACS), and statistical. A comparative matrix highlights strengths, weaknesses, adaptability, interpretability, and cost factors. The results demonstrate that hybrid methods integrating automation, mathematical modeling, and machine learning offer superior performance, with intelligent neural network systems showing the greatest promise due to adaptability and high predictive accuracy.

1 INTRODUCTION

Thermomechanical processes play a pivotal role in determining the functional characteristics and longevity of steel products. Effective control over such processes is imperative for ensuring high-quality output and process efficiency. The complexity of these processes, involving intricate interactions among multiple parameters, necessitates advanced control strategies. This paper addresses the pressing need for evaluating the comparative effectiveness of available control methodologies in light of modern industrial demands for flexibility, automation, and predictive precision.

2 MATERIALS AND METHODS

The study utilizes a qualitative evaluation approach grounded in ten essential criteria: prediction accuracy, reproducibility, operational speed, adaptability, resource demand, implementation cost, interpretability, robustness, scalability, and integration capability. We classify the principal methods of thermomechanical process control into five distinct groups, the selection of which is grounded in empirical observations, industrial documentation, and peer-reviewed sources. Their comparative merits are presented in a structured analytical matrix.

3 RESULTS AND DISCUSSION

Thermomechanical treatment constitutes a fundamental element in both scientific inquiry and industrial application. The quality and endurance of the final product are determined largely by the precision with which such processes are governed. The system's inherent complexity lies in its parametric interdependence, wherein a deviation in one variable induces structural shifts across others.

[a] https://orcid.org/0000-0002-9429-6716
[b] https://orcid.org/0009-0001-7256-7810
[c] https://orcid.org/0000-0002-8744-0783
[d] https://orcid.org/0000-0001-8088-3939
[e] https://orcid.org/0000-0002-6178-3841

Effective control, therefore, presupposes a clear comprehension of these interrelations. This paper identifies the principal evaluative criteria—accuracy, temporal responsiveness, and adaptability under variable conditions—as decisive in assessing management strategies. The objective is to establish the most efficacious methodological approach for the optimisation of thermomechanical regimes under real-world conditions.

Selecting an appropriate method for managing thermomechanical processing significantly affects steel quality. Comparing these methods using objective criteria facilitates informed decision-making during technological design (Okrepilov, 2019), as methods markedly differ in capabilities, requirements, and effectiveness [Stojadinovic, 2020, Jafari, 2021). For an objective assessment and optimal method selection, it is advisable to compare them against several key performance criteria. Below are ten critical criteria commonly considered in comparative analyses of control methods for thermomechanical processing:

– Accuracy of Prediction/Control: This refers to a method's ability to minimize deviation from specified parameters or accurately predict output properties. For example, physical models and neural networks typically achieve high prediction accuracy, whereas simplified empirical rules tend to be less accurate.

- Reproducibility: This is the degree to which a method consistently produces identical results over multiple repetitions. Automated control systems tend to have high reproducibility of processing modes, while manual methods have greater variability.

- Speed of operation (responsiveness): The time required to make a decision or perform a calculation using a particular method. Real-time responsiveness is highly valued in production environments. For example, simple control algorithms work instantly, whereas detailed numerical calculations can take several hours.

- Flexibility and adaptability: The ability of a method to adapt effectively to changing conditions or different processes. Methods based on machine learning (ML), which can be retrained with new data, and generalized statistical approaches exhibit high adaptability. Conversely, rigid, pre-programmed algorithms are less adaptable without substantial reprogramming.

– Resource Requirements: This includes both computational resources (such as powerful computers and specialized software) and human resources (availability of specialized personnel) as well as the volume of data required. Neural networks, for example, necessitate large datasets and GPU-based training, numerical modeling requires licensed software and significant computing time, whereas statistical process control (SPC) methods require only standard statistical software packages.

– Implementation and Operational Costs: These encompass the total expenditures associated with utilizing a specific method, including investments in hardware (sensors, controllers), software, personnel training, and experimental validation. Conventional technological methods are generally the most economical, while deploying comprehensive automated control systems is considerably more expensive.

– Interpretability and Transparency: How easily the internal decision-making mechanisms of a method can be understood. Physical models and statistical charts are straightforward for engineers to interpret, while complex neural networks or decision-tree ensembles typically function as "black boxes," making their outputs challenging to explain. This criterion is crucial for building trust in the method and ensuring its widespread adoption.

– Robustness and Reliability: A method's ability to function correctly under atypical conditions, disturbances, or incomplete data. Robust physical models integrated within systems can predict behavior even in anomalous situations, whereas empirical or ML-based models may produce errors when confronted with scenarios beyond their training data range. Reliability includes fault tolerance - for example, sensor redundancy in automated systems significantly increases SPC reliability.

Scalability. A method’s applicability beyond the confines of experimental setups serves as a test of its practical merit. Approaches that rely on manual oversight or tacit expert judgement—though effective in controlled conditions—prove inadequate when transferred to industrial scales. Conversely, automated systems and algorithmic routines exhibit a structural advantage: they permit reproducibility and uniform deployment across extended production arrays without degradation of performance.

Integrability with Composite Systems. In contemporary manufacturing, the capacity to incorporate a control method within broader operational frameworks is essential. Practical superiority belongs to those systems which permit seamless coupling with programmable controllers, predictive modules, or supervisory architectures such as SCADA. Methods lacking in such interoperability are hindered in application, regardless of their standalone precision.

The selection of criteria may be expanded depending on the priorities of specific enterprises—

additional considerations may include ecological sustainability, safety compliance, or adherence to industry standards. However, the ten criteria listed above serve as the foundational benchmarks for technical evaluation of thermomechanical treatment control methods.

This study categorizes the methods into five distinct groups: technological, mathematical modeling, machine learning-based approaches, automated control systems, and statistical methods. Each group has unique strengths and limitations that are critical to consider during selection. The comparative analysis was conducted according to the aforementioned ten criteria, particularly highlighting accuracy, interpretability, cost, and resource demand (Montgomery, 2017, Bianchini, 2022, ISO 9001, 2015, Breyfogle, 2003, Visutech Systems, 2020, Lebedeva, 2020).

In order to provide a clear and concise comparative assessment, a summary table has been developed (see Table 1). In this table, different groups of methods are qualitatively assessed against each criterion. The ratings - 'high', 'medium' or 'low' - indicate the relative strength of each method for a given criterion (with higher ratings indicating superior performance). The final column succinctly summarises the main advantages and disadvantages of each method based on the evaluation criteria.

As shown in Table 1, process automation ensures the highest levels of reproducibility and accuracy in maintaining operating modes, significantly improving overall production efficiency. Analytical and numerical models provide deep insight into process mechanisms and offer high predictive accuracy, but require significant resources and specific application conditions.

Machine learning methods distinguish themselves through adaptability and their capacity to model complex dependencies—under favorable conditions, their predictive accuracy equals or even surpasses that of modeling methods. Nonetheless, ML methods require extensive and reliable datasets and are characterized by low interpretability, operating largely as "black boxes." Experience-based technological methods are simple and cost-effective but heavily reliant on human expertise, hence offering no guarantee of optimality. Statistical methods contribute effectively to maintaining process stability and continuous incremental improvements but do not independently provide active process control, typically being employed alongside other methodologies.

Below is a summary outlining the main advantages and disadvantages of each method group:

- Technological Methods:

Advantages: Simplicity of implementation, low costs, extensive practical experience base; easy and direct modification of processes.

Disadvantages: Limited accuracy and reproducibility (results depend significantly on personnel expertise), time-consuming trial-and-error optimization, inability to accurately predict outcomes beyond existing empirical knowledge.

- Mathematical Modeling:

Advantages: High accuracy and predictive capabilities, physically grounded decision-making, clarity of cause-effect relationships, suitability for optimization and "what-if" scenario analysis.

Disadvantages: Development is resource-intensive, requiring considerable time and specialized expertise; models may generate errors if essential data is unavailable; complexity of adapting models (each new material or process necessitates a new model); high computational costs, particularly for complex simulations.

Machine Learning Methods.

Merits. Capable of discerning latent dependencies within voluminous data arrays. They do not require explicit functional formulations, instead refining predictive precision through progressive assimilation of empirical data. Once trained, such models exhibit high-speed operation, rendering them viable for real-time control applications.

Limitations. Effective operation demands comprehensive and well-structured datasets. Their internal mechanics, particularly in deep architectures, remain largely opaque to the practitioner. Under extrapolative conditions—those not represented in the training corpus—prediction accuracy may degrade. Regular calibration and supervised retraining are necessary to preserve functional integrity.

Automation (Automated Control Systems – ACS).

Merits. Enforces technological discipline through strict parameter regulation, thereby minimizing stochastic deviations and excluding human error. Enhances consistency, operational throughput, and workplace safety. Proven to replicate successful regimes across facilities with minimal variance. For instance, automated quenching units demonstrate increased thermal precision, higher yield, and reduced manual intervention.

Limitations. Requires considerable initial investment—both in physical apparatus and in the technical preparation of personnel. Sustained operation depends upon the availability of qualified staff for diagnostics and adjustment. Without the

incorporation of adaptive logic—such as predictive models or learning systems—predefined routines may falter under nonstandard conditions.

- Statistical Methods:

Advantages: Enhance long-term stability and enable early detection of issues before defects occur (e.g., Statistical Process Control (SPC) identifies process deviations beyond acceptable limits);

Table 1: Comparative analysis of control methods of thermomechanical treatment of steel by key criteria.

Criterion	Technological methods	Mathematical modeling	Machine learning (ML)	Automation (ACS)	Statistical methods
Accuracy	Medium (limited by experience)	High (with accurate models)	High (if data available)	High (precise mode adherence)	Low[1] (indirect control)
Reproducibility	Low/Medium (operator dependent)	High (consistent results)	High (model repeatable)	Very High (identical cycles)	Medium (stability monitoring)
Operational Speed	High (real-time, no computations)	Low (requires computation)	High (rapid after training)	High (real-time)	Medium (real-time SPC, not DOE)
Adaptability	Medium (recipe-bound)	Low (fixed models)	High (retrainable)	Medium (reprogramming needed)	High (generalizable)
Resource Demand	Low (minimal resources)	High (specialists, software)	High (data, computing power)	Medium/High (equipment, software)	Low (basic statistics)
Implementation Cost	Low (standard equipment)	High (costly model development)	Medium (data, experts)	High (capital-intensive ACS)	Low (economical)
Interpretability	High (clear causal relationships)	High (equation-based clarity)	Low (black-box neural networks)	High (transparent logic)	High (easy to understand)
Robustness	Medium (limited by unforeseen issues)	Medium (input sensitivity)	Medium (errors beyond training set)	High (redundancies, safeguards)	High (detects deviations)
Scalability	Low (hard to replicate expertise)	Medium (new model each time)	High (universal algorithms)	High (easily replicable systems)	High (universally applicable)
Integration Capability	High (foundation for other methods)	High (model software integration)	High (ML integration in systems)	High (includes modeling, ML, stats)	High (complements other methods)
Main Advantages	Simplicity, low cost, experiential base	Accuracy, theoretical grounding	Accuracy, adaptability, insights	High stability, efficiency, safety	Quality stability, early issues detection
Main Disadvantages	Low accuracy, labor-intensive	Resource-intensive, complexity	Data-intensive, interpretability issues	High initial cost, expert required	Indirect control, reactive approach

Note: Statistical methods (SPC, MSA) do not themselves control parameters, but only monitor and guide improvements, so their "accuracy" is not understood in the sense of directly maintaining parameters, but in the sense of being able to accurately signal problems.

systematically guide experimental design (Design of Experiments, DOE) and measurement assessment (Measurement System Analysis, MSA) for quality improvement; inexpensive and universally applicable across diverse production settings.

Disadvantages: Do not directly control processes—merely indicate where intervention is required; necessitate sufficiently large observational datasets; effectiveness depends heavily on disciplined execution (regular construction of control charts and analysis performance).

4 CONCLUSIONS

A comparative analysis of control methods based on the proposed criteria significantly facilitates the selection of the most appropriate approach for specific industrial tasks. The most effective solutions are hybrid strategies that combine modeling, automation, and machine learning techniques (Lebedeva, 2015).

The dominant vector of development in materials science and industrial engineering lies in the increasing reliance on intelligent, self-adaptive systems. Within this framework, methods employing neural network programming demonstrate a number of technical advantages that position them above conventional approaches.

Foremost among these is their capacity for precise, nonlinear approximation. Neural structures—particularly those of deep-layered architecture—exhibit an exceptional ability to map complex dependencies between process variables and resultant mechanical properties of steel. In many cases, the fidelity of such models surpasses that of empirical formulae traditionally employed in the metallurgical domain.

Equally significant is the system's capacity for adaptation. Neural models are amenable to progressive refinement via incremental data integration. With each new series of production or alloy variation, the model need not be rebuilt; instead, it is recalibrated to conform to the revised regime. This trait is of particular utility under conditions of continuous process evolution, where the timely updating of predictive logic ensures sustained accuracy without operational interruption.

Reduced experimentation costs: The researchers note that the introduction of machine learning significantly reduces the number of physical experiments required to determine optimal processing parameters. In effect, the neural model takes on the role of a virtual expert, predicting results without the need for direct empirical testing, thus saving company resources.

However, neural network algorithms are not a universal solution. Their successful application requires a lot of upfront work, including the collection of large amounts of high-quality data, careful design of the network architecture, and thorough validation of the model's reliability. However, given the rapid progress in machine learning and the increasing availability of industrial data driven by the Industry 4.0 paradigm and big data technologies, it is expected that neural network methods will gradually be integrated into thermomechanical process control.

These methods are particularly promising when combined with physical models in physics-based AI, which combines the interpretability of mechanistic modelling with the flexibility and accuracy of data-driven learning.

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