Lecture Notes in Networks and Systems 1028

Michael E. Auer
Reinhard Langmann
Dominik May
Kim Roos *Editors*

Smart Technologies for a Sustainable Future

Proceedings of the 21st International Conference on Smart Technologies & Education. Volume 2

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Editors
Michael E. Auer
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Frankfurt/Main, Germany

Reinhard Langmann
Edunet World Association e.V.
Blomberg, Germany

Dominik May
University of Wuppertal
Wuppertal, Germany

Kim Roos
Programme Director MScEng
Arcada University of Applied Sciences
Helsinki, Finland

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Preface

It is a great privilege for us to present the proceedings of the 21st "International Conference on Smart Technologies & Education" (STE2024) to the authors and delegates of this event and to the wider, interested audience. The 2024 edition of STE was held under the general theme "Smart Technologies for a Sustainable Future", which was visible throughout the conference program.

The STE conference is the successor of the long-standing annual REV Conferences and the annual meeting of the International Association of Online Engineering (IAOE) together with the Edunet World Association (EWA) and the International Education Network (EduNet). Initiated in 2004, REV has been held in Villach (Austria), Brasov (Romania), Maribor (Slovenia), Porto (Portugal), Dusseldorf (Germany), Bridgeport (USA), Stockholm (Sweden), Brasov (Romania), Bilbao (Spain), Sydney (Australia), Porto (Portugal), Bangkok (Thailand), Madrid (Spain), New York (USA), Dusseldorf (Germany), Bengaluru (India), Georgia (USA), Hong Kong, Cairo (Egypt), and Thessaloniki (Greece).

This year, STE2024 has been organized in Helsinki, Finland as an onsite event supporting remote presentations, from March 6 until March 8, 2024. The co-organizers of STE2024 were the Arcada University of Applied Sciences, the International Association of Online Engineering (IAOE) together with the Global Online Laboratory Consortium (GOLC), the International Education Network (EduNet), and the EDUNET WORLD Association (EWA). STE2024 has been attracted 140 scientists and industrial leaders from more than 40 countries.

STE2024 is an annual event dedicated to the fundamentals, applications, and experiences in the field of Smart Technologies, Online, Remote, and Virtual Engineering, Virtual Instrumentation, and other related new technologies, including:

- Applications & Experiences
- Artificial Intelligence
- Augmented Reality
- Open Science Big Data
- Biomedical Engineering
- Cyber Physical System
- Cyber Security
- Collaborative Work in Virtual Environments
- Cross-Reality Applications
- Data Science
- Evaluation of Online Labs
- Human–Machine Interaction & Usability
- Internet of Things
- Industry 4.0
- M2M Concepts
- Mixed Reality

- Networking, Edge & Cloud Technology
- Online Engineering
- Process Visualization
- Remote Control & Measurements
- Remote & Crowd Sensing
- Smart Objects
- Smart World (City, Buildings, Home, etc.)
- Standards & Standardization Proposals
- Teleservice & Telediagnosis
- Telerobotic & Telepresence
- Teleworking Environment
- Virtual Instrumentation
- Virtual Reality
- Virtual & Remote Laboratories

The conference was opened by the Founding President of IAOE, Michael E. Auer, who underlined the importance to discuss guidelines and new concepts for engineering education in higher and vocational education institutions including emerging technologies in learning. In her greeting, the Rector of Arcada, Mona Forsskåhl pointed out the importance of the digitalization of education and more specifically the engineering education.

STE2024 offered an exciting technical program as well as networking opportunities concerning the fundamentals, applications, and experiences in the field of online engineering and related new technologies.

As part of the conference program, three pre-conference workshops have been organized:

1. Overcoming Traditional Boundaries of STEM Education and Enabling the Engineer of the Future
2. Logiccloud: The Next Generation Of Industrial Control
3. High-Performance Extreme Learning Machines

Furthermore, special sessions have been organized at REV2024, namely

1. Online Laboratories in Modern Engineering Education (OLMEE)
2. Human–Robot Interaction for Sustainable Development (HRI4SD)
3. Advances and Challenges in Applied Artificial Intelligence (ACAAI)

Four outstanding scientists and industry leaders accepted the invitation for keynote speeches:

1. Doris Sáez Hueichapan, University of Chile, Santiago, Chile, talked about “Energy & Water Management Systems for Agro-Development of Indigenous Rural Communities”
2. Dieter Uckelmann, HFT Stuttgart, Stuttgart, Germany, shared his valuable insights to “Why providing a comprehensive IoT education is impossible – but we should nevertheless strive to do so”
3. Roland Bent, Retired CTO Phoenix Contact GmbH & Co.KG, Germany, painted a vision for the future in his talk “The All Electric Society”

4. Hans-Jürgen Koch, Dipl.-Ing. for Communications Engineering, Executive Vice President of the Business Area Industry Management & Automation, Phoenix Contact GmbH, Germany, gave a fascinating introduction to “Innovative and collaborative automation platforms – The key for a sustainable world”

The conference was organized by the Faculty of Arcada University of Applied Sciences and Program Director Kim Roos served as the STE2024 chair. The President of IAOE, Prof. Dominik May has served as STE2024 general chair and Prof. Reinhard Langmann and Prof. Michael E. Auer served as Steering Committee Co-chairs.

Submissions of Full Papers, Short Papers, Work in Progress, Poster, Special Sessions, Workshops, Tutorials, Doctoral Consortium papers have been accepted.

All contributions were subject to a double-blind review. The review process was extremely competitive. We had to review about to 233 submissions. A team of over 100 program committee members and reviewers did this terrific job. Our special thanks goes to all of them.

Due to the time and conference schedule restrictions, we could finally accept only the best 76 submissions for presentation or demonstration.

The conference was supported by

- Phoenix Contact as Platinum Sponsor
- Air France and KLM as Diamond Sponsor
- As always Sebastian Schreiter did an excellent job to edit this book.

Kim Roos
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Human-Robot Interaction for Sustainable Development

Smart Technology and Education

A Machine Learning Framework for Improving Resources, Process, and Energy Efficiency Towards a Sustainable Steel Industry

Andrea Fernández Martínez[1](✉), Santiago Muiños-Landín[1], Angelo Gordini[2], Luca Ferrari[2], Matteo Chini[3], Loris Bianco[3], and Mircea Blaga[4]

[1] AIMEN Technology Centre, Pontevedra, Spain
andrea.fernandez@aimen.es
[2] OPTIT Srl, Bologna, Italy
[3] Ferriere Nord SpA, Osoppo, Italy
[4] Tenaris Silcotub S.A., Calarasi, Romania

Abstract. In response to geopolitical instability, supply chain issues, and environmental concerns, initiatives like the European Green Deal highlight the need for a green transition in the EU industry. The steel sector, as an Energy-Intensive Industry, is crucial in this shift. This work introduces a Machine Learning framework for sustainability in the Steel Industry, addressing Resource, Process, and Energy efficiency with three ML algorithms. The framework, integrated into a Decision Support System, assists plant operators in the transition to a more sustainable process.

Keywords: Machine Learning · Sustainability · Steel Industry · Energy Efficiency · Process Optimization

1 Introduction

The Steel Industry is considered an Energy-Intensive Industry (EII) due to the reliance of its industrial processes on the use of high amounts of energy to provide essential materials and products to other industries e.g., construction, automotive, and other energy industries [3]. Recent geopolitical instability, supply chain issues, and climate change emphasize the urgency of new policies. These are essential for long-term competitiveness and the transition to a greener economy of the EU Industry as defined in new initiatives such as the European Green Deal. On this subject, the green transitioning of EIIs plays a key role as they account for more than half of the total energy consumption of the EU Industry [4, 12].

In modern steel-making processes, there can be distinguished two main technologies, namely Basic Oxygen Furnace (BOF) and Electric Arc Furnace (EAF). EAF, using recycled scrap steel, has been shown as more energy-efficient, aiding the steel industry's decarbonization [13]. Nevertheless, there are still several challenges hindering the green transitioning of this sector as the lack of digitization and data exploitation of the large

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amounts of data that cover the steel value chain due to the sparsity of data sources and the complexity of its analysis [1]. In this context, Artificial Intelligence and Machine Learning are increasingly popular for their ability to analyze complex data patterns in applications like predictive maintenance, process optimization or even process oriented materials design [5], among others [6].

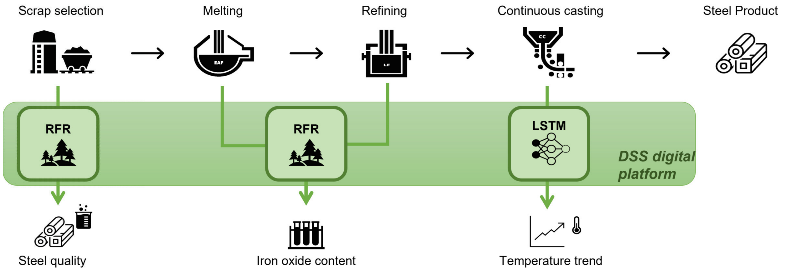

Fig. 1. Conceptual representation of the ML framework proposed. In the upper layer, schematic diagram of the phases of steel-making; in the middle layer, the ML algorithms as part of the DSS digital platform; in the lower layer, the targeted outputs of each algorithm.

This work proposes a Machine Learning (ML) framework for smart sustainability in the Steel sector, addressing resource use, melting efficiency, and energy needs during cooling. Key contributions of the ML framework include: First, a Random Forest Regressor (RFR) [2] to support the decision-making process of scraps and input materials for the steel mixture considering the final chemical composition of the steel product. Second, a RFR to forecast the composition of iron oxide in the steel slag during the melting process, which is essential for the iron content and oxygen present in the steel. Third, a Long Short-Term Memory (LSTM)-based Recurrent Neural Network (RNN) [10] to predict temperature rises in the cooling system as an indicator of the energy required.

2 Methodology

2.1 The Sustainability Challenge in the Steel Industry

The EAF-based steel-making process operates in a batch basis, referred as heats, that comprises six main operations: i) furnace charging, ii) melting, iii) refining, iv) de-slagging, v) tapping, and vi) furnace turnaround. The process starts with the selection and load of scraps in a charge bucket, followed by the introduction of the selected charge inside the furnace. After charging, the electric arc initiates the melting process, creating a molten steel pool. Oxygen injection accelerates scrap meltdown and forms steel slag. Refining operations use carbon and oxygen injection to achieve desired steel chemistry and enhance process efficiency through slag foaming. De-slagging empties the furnace of slag, followed by tapping for transferring molten steel to a ladle for molding and cooling in continuous casting (see Fig. 1).

Optimization of the Use of Resources for the Steel Mixture. EAF-based steel-making uses recycled scrap steel as its primary feedstock—material from rejected or end-of-life products. This circular approach reduces environmental impact by avoiding the use of additional resources and minimizing overall waste [3, 4]. Nevertheless, other secondary feedstock e.g., HBI, might also be incorporated as sources of clean iron to enhance the properties of the scrap charge due to the variability and frequent lack of knowledge of the properties of recycled scrap steel. To optimize melting and reduce alloy additions, our study proposes an RFR decision support model. It evaluates input material combinations for the steel composition, covering 16 materials, including diverse scrap steel types, and focusing on 7 key chemical elements, namely, Cr, Ni, Mo, Cu, Sn, V, and Pb.

Process Efficiency Through the Steel Slag Composition. Slag foaming is an essential part of the steel-making process in which foam generation is induced to generate total or partial liquid solutions i.e., slags, comprised of oxides and fluorides at the upper surface of the metal bath [7]. Foamy slag offers process benefits like increased energy efficiency by capturing heat from the arc, while also preventing metal oxidation and nitrogen incorporation. Nevertheless, there are still many limiting factors e.g., FeO content of the slag, that impede the proper control of slag foaming in industrial scenarios [7, 8]. Our study proposes an RFR, considering injections and various materials, to estimate iron oxide percentage in steel slag, crucial for slag iron content and CO gas generation in foaming.

Energy Efficiency in the Cooling Phase. Cooling systems are crucial for maintaining optimal conditions in the EAF and other components, preventing structural damage from prolonged overheating [11], and ensuring proper melting conditions. The conditions in the cooling system are directly affected by the melting process and the relationships between materials and the energy-matter within the EAF [9]. When injected materials don't properly penetrate the steel slag during melting, they can lead to temperature increases in the settling chamber and cooling system. This results in higher energy consumption. The ML framework addresses this using an LSTM Neural Network to predict temperature trends in the cooling system within 80-s time windows. It considers injections (carbon and lime), temperatures in the cooled shell and settling chamber, and the flowrate of fresh inlet water into the Water-Air Cooled (WAC) system.

2.2 Decision Support System Digital Platform

A Decision Support System (DSS) is an information system used to assist teams and organizations in complex decision-making processes that usually rely on a large number of parameters and constrains. The ML algorithms in this work are part of a DSS digital platform, facilitating information exchange via REST API. The platform comprises container images for ML models, a DSS, and a "model orchestrator" module. These container images encapsulate all dependencies, ensuring seamless interoperability and scalability. The platform is deployed on a private cloud-based server, with HTTPS protection and access control policies for secure data exchange.

3 Experimental Results

3.1 RFR for the Optimization of the Use of Resources

The dataset for the decision-support model to evaluate the combination of materials ad scraps comprised 207 samples from 11 different steel types e.g., Fe45 and Fe50. Nevertheless, the contribution of materials to the final steel quality is not considered to be steel-type-dependant.

After performing a 5-cross-validated grid-search analysis to fine-tune the hyper-parameters of the RFR, a 500-estimator-based RFR with unlimited depth of Trees and using the mean-squared-error as criterion to assess the quality of splits was trained over the 80% of the dataset (165 samples) and tested in the remaining 20% (42 independent samples) previously re-scaled within a range [0, 1] using the min-max normalization method.

The RFR predicts the percentage of the 7 targeted chemical components (Cr, Ni, Mo, Cu, Sn, V, and Pb) taking as input 16 different materials and scraps commonly used in the steel case of study. Table 1 lists the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root MSE (RMSE) obtained in the test dataset for each chemical component targeted, respectively. The results obtained confirmed that the RFR algorithm successfully achieved mapping the inputs materials with the targeted chemical components, with a maximum MAE of 0.021 for Chromium (Cr).

Table 1. Estimated MAE, MSE, and RMSE for the percentage prediction of the seven chemical components of study, respectively

	Cr%	Ni%	Mo%	Cu%	Sn%	V%	Pb%
MAE	0.021	0.014	0.008	0.035	0.005	0.000	0.001
MSE	0.001	0.000	0.000	0.002	0.000	0.000	0.000
RMSE	0.030	0.018	0.012	0.044	0.008	0.000	0.001

Figure 2 depicts the predicted targets (orange) by the RFR against the ground truth test samples (green) for the elements Mo and Pb to better visualize the error range independently. These results support our hypothesis that the RFR properly predicts the targeted chemical components with high accuracy, although there can be seen appreciable errors for the cited elements in samples close to their range limits (Mo $>$ 0.06%, Pb $<$ 0.001%). Overall, the RFR model is considered to be reliable for modelling the final expected quality of the steel based on the input materials and scraps used in the steel-making process.

3.2 RFR for Estimating the Content of Iron Oxide in the Steel Slag for Process Efficiency

For the fitting of the RFR to predict the content of iron oxide in the steel slag, an analog 5-crossed-validated hyper-parameter fine-tuning procedure was conducted considering

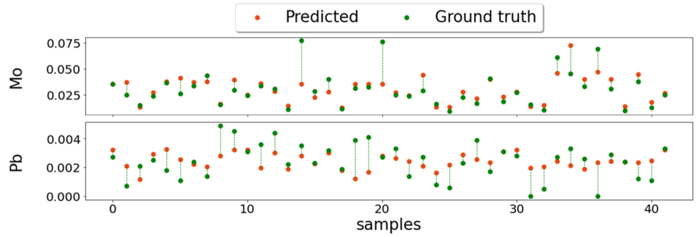

Fig. 2. Scatter plot of the predicted values (orange) vs. ground truth (green) for the seven chemical components of study

a dataset containing 4239 heat processes from November 2020 to September 2021, after performing a filtering procedure of a complete dataset containing 4714 heats to avoid introducing noise to the model due to unusual process behaviours e.g., heats during transition times in the process.

As in the previous case, 80% of the data (3391 samples) was used for training and fine-tuning, whereas the 20% of the remaining data (848 samples) was used as an independent test set to assess the model performance. The dataset was initially re-scaled in a range [0, 1] using the min-max normalization method. From the grid-search procedure, an RFR composed of 500 estimators and with the MSE as criterion for the quality of splits was found to yield the best results predicting the percentage of iron oxide in the steel slag.

Based on the results expressed in Table 2, it can be confirmed that the RFR successfully estimates the percentage of iron oxide in the steel slag with a MAE of 2.979. To better visualize the prediction error with respect to the dataset, Fig. 3 displays the predicted targets (orange) against the ground truth samples (green).

Table 2. Estimated MAE, MSE, and RMSE for the percentage of iron oxide in the steel slag

Element	MAE	MSE	RMSE
FeO%	2.979	14.654	3.828

Although the predicted values properly follow the trends of the test set as shown in Fig. 3, there can be noticed a "conservative" behaviour in the model performance when predicting extreme cases lying at the upper and lower limits of the dataset, forecasting those values towards the center of the distribution. Nevertheless, the errors obtained can be considered acceptable in the range of study [20, 48), confirming that the RFR algorithm successfully estimates the content of iron oxide in the steel slag following a complete data-driven approach.

3.3 LSTM-Based RNN for Energy Efficiency in the Cooling System

The dataset used for the development of the LSTM-based RNN comprised 50077 samples. Following best practices, the set was divided into training (72%, 36055 samples),

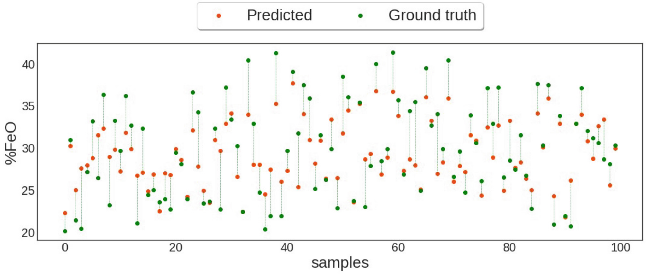

Fig. 3. Scatter plot of the predicted values (orange) vs. ground truth (green) for the percentage of iron oxide in the steel slag

validation (18%, 9014 samples), and test sets (10%, 5008 samples), respectively. The validation set was used during training to fine-tune the parameters of the network, whereas the test set was used during the final assessment of the network as an independent set.

After a fine-tuning analysis, the architecture of the final network consisted of 1-hidden layer with 8 neurons (LSTM cells), using MAE as the loss function and Adam as optimizer of the network. Due to the temporal nature of the problem, the features used as input data (see Sect. 2.1.3) were sampled in batches of 4 considering a time window of 60 s in time i.e., sampling frequency of 20 s between samples considering the last minute of data.

Figure 4 displays the evolution of 6 random samples over the fixed 80-s time-window of study from the test set (green) against the corresponding predicted trends by the LSTM (orange), manifesting the capability of the network to predict the evolution of temperatures in the cooling system in different temperature ranges (specified in the y-axis) and following different temperature patterns. Indeed, the network seems to appropriately predict the trends within a + 80-s time-window in 5 out of the 6 cases shown, that is, in all cases with the exception of the middle figure in the second row, in which the predicted trend differs from the real temperature evolution over time. Nevertheless, these results suggest that the network can successfully predict the temperature trends in the cooling system with high accuracy, especially considering the first +40-s time-window.

In order to delve in the model performance over time, the prediction error was assessed for the different time steps considered i.e., +20 s, +40 s, +60 s, and + 80 s. Table 3 expresses the MAE, MSE, and RMSE on the test set considering each time step separately i.e., errors were computed in a column-wise fashion based on the predictions of the 5008 test samples. It can be observed that the MAE increases from 0.372 in the +20 s-related predicted values to 2.174 in the +80 s prediction case, confirming our previous hypothesis that the predictive accuracy of the network decreases over time.

For visualization purposes, Fig. 5 displays the first 1000 samples of the test set (green) against their corresponding predicted values (orange) for the time windows of + 20s and + 80s, separately. The right rectangles in the sub-figures zoom in on a temperature peak, showcasing the evolving prediction errors over time. Despite the increase, these results suggest promising implications for using deep learning models in forecasting to counteract potential process issues before they occur.

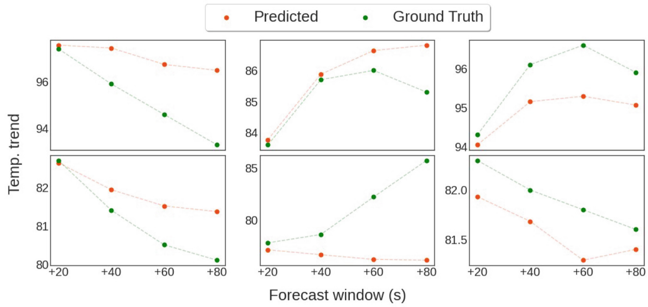

Fig. 4. Scatter plot of temperature trends in +80-s forecast-windows for predicted values (orange) vs. ground truth (green).

Table 3. Estimated MAE, MSE, and RMSE for the estimation of the temperature (T) for each time step considered.

	T+20 s	T+40 s	T+60 s	T+80 s
MAE	0.372	0.926	1.597	2.174
MSE	0.344	2.299	6.653	11.736
RMSE	0.587	1.516	2.579	3.426

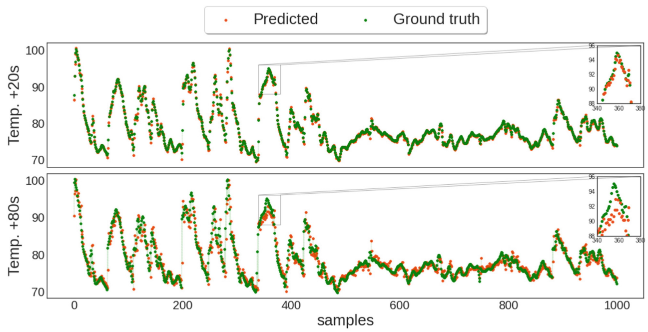

Fig. 5. Scatter plot of the predicted values (orange) by the LSTM network vs. ground truth values (green) in each specific time step considered.

4 Conclusion

The proposed ML framework for steel sustainability includes two RFRs and one LSTM-based RNN, addressing resource use, process, and energy efficiency. It integrates data across manufacturing stages, aiding operators in daily decisions and process control. As part of a DSS digital platform, it facilitates seamless interaction between ML algorithms and operators, supporting intelligent sustainability strategies.

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Overall Writing Effectiveness: Exploring Students' Use of LLMs, Pushing the Limits of Automated Text Generation

Simon Wilbers[1(✉)], Johanna Gröpler[2], Bastian Prell[1], and Jörg Reiff-Stephan[1]

[1] Technical University of Applied Sciences Wildau, Hochschulring 1, 15745 Wildau, Germany
simon.wilbers@th-wildau.de
[2] Freie Universität Berlin, Garystraße 39, 14195 Berlin, Germany

Abstract. The advent of generative artificial intelligence for text generation, epitomized by the introduction of ChatGPT in November 2022, represents a significant shift in the academic writing paradigm. This pre-study examines how students make use of Large Language Models (LLMs) for their academic writing processes, transitioning from solitary writing to true human-machine collaboration. Participants were recruited from a workshop on LLMs and were subsequently interviewed qualitatively after two weeks of unsupervised usage. These interviews were designed using the new Overall Writing Effectiveness (OWE) framework and focused on LLMs' role in academic writing. The qualitative content of these interviews was analysed following Mayring's methodology. Findings indicate that LLMs did not substantially accelerate the writing process but enhanced the quality of the texts and redefined writing as a collaborative effort. This study not only explores the limits of automation in academic writing but also highlights how generative AI is pushing the boundaries of what is considered genuine human capabilities. This analysis opens the discussion of how to incorporate such technologies into future education curriculums.

Keywords: Academic Writing · LLMs · Text Automation · Student Experiences · AI and Academia

1 Introduction

The convergence of AI and academia has prompted an unprecedented revolution in how students approach academic writing. Particularly after November 2022, a shift from traditional methods to automated text generation tools has gained momentum [1, 2]. As we address these new literacy practices, it is critical to understand the challenges and benefits of LLMs, such as the well-discussed ChatGPT. Especially user-friendly, commercially available, or even free-of-charge online services seem to have gained popularity among students and teachers in higher education. First quantitative studies found that generative AI-tools are widely used among students, mainly for private purposes [3]. The main reasons cited are time savings and idea generation [4, 5]. However, there are also

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concerns among respondents about whether they are allowed to use such tools in an academic context [4, 6]. This pre-study seeks to contribute towards an understanding of how students use LLMs for their educational writing tasks. One main focal point is addressed by the self-perceived effects on the availability, performance, and quality of both the text generated and the process of generating text [7]. We anticipated an increase in all three indicators when it comes to human-machine collaboration. To measure the impact of LLMs on the student's writing process, the concept of Overall Equipment Effectiveness (OEE) [8] has been adapted and slightly modified. The contribution is structured as follows: the journey begins with an examination of the academic writing process, identifying common challenges and the potential for technology to mitigate these frictional losses. We then introduce a novel concept, Overall Writing Effectiveness (OWE), adapting the principles of OEE from manufacturing to the context of academic writing. This approach provides a fresh perspective on assessing writing efficiency in an era of technological integration. The paper also discusses the balance between speed and quality in writing, particularly concerning the limits of automation. We delve into how AI tools may influence a writer's maximum speed and explore the potential boundaries of this technology. Our findings are grounded in a detailed data collection process, capturing diverse perspectives from participants. The results offer insightful reflections on students' perceptions of LLMs and their impact on the writing process. Finally, the paper concludes with a synthesis of these findings, contemplating the implications of LLMs in academic writing and suggesting directions for future research. This exploration aims not only to inform, but also to engage readers in a critical discussion on the evolving intersection of technology and academia.

2 The Academic Writing Process and the Overall Equipment Effectiveness Model

2.1 Potential Difficulties in the Academic Writing Process

The academic writing process consists of several steps, each of which can present challenges for the writer. Table 1 shows a simplified concept of the writing process with examples of writing difficulties that may occur [9]:

Writing is inherently a highly individualized process, where the steps involved can either be undertaken in sequence or concurrently. The writer's excessive reliance on technology is already a norm, covering everything from searching digital sources to checking spelling and even employing voice commands to type, all of which are increasingly supported by technological devices. The presence and accessibility of these tools can significantly influence the overall writing process. In this context, identifying strategies to overcome the various challenges in writing with increasingly automated tools becomes crucial.

2.2 From Overall Equipment Effectiveness to Overall Writing Effectiveness

One approach is the application of the Overall Equipment Effectiveness [8], which facilitates the measurement of challenges by quantifying availability, performance, and

Table 1. Simplified concept of the academic writing process and potential writing difficulties.

Step in the writing process	Potential writing difficulty (examples)
Finding a topic and formulating a research question	Difficulty in defining a clear, manageable scope that is neither overly broad nor excessively narrow, often leading to ambiguity in the research direction
Finding sources	Challenges in sourcing relevant material, either encountering an overwhelming abundance of information or a scarcity of adequate research on the topic
Writing	Common issues include writer's block, where ideas don't flow, or anxiety about articulating thoughts coherently and persuasively
Revising	Difficulty in critically evaluating and restructuring the draft to enhance coherence, clarity, and argument strength
Submitting	Potential last-minute concerns about the quality or completeness of the work, or technical issues in meeting submission requirements

quality. This quantifying and separating into separate categories is particularly insightful for assessing where and how AI integration, especially through the use of LLMs, can be most beneficial in enhancing the writing process.

- **Availability:** How do AI tools affect the frequency and duration of both planned and unplanned stops in the writing process? Planned stops could be a lunch break, an unplanned stop would be a technical problem interrupting the writer.
- **Performance:** Insufficient writing tools, or incompetence in using them compromising the speed of the writing process, accounting for slow cycles and small stops.
- **Quality:** The extent to which (AI) tools contribute to or mitigate defects in academic writing, including the need for rework.

An OEE [8] score of 100% would indicate optimal writing conditions: uninterrupted writing time, at maximum speed, and without the need for revisions of the written text; unlike availability and quality, which are straightforward to measure and calculate:

$$100\%\ \text{Availability} = \frac{Operating\ (Writing)\ Time}{Loading\ (Planned\ writing)\ Time}$$

where $[LoadingTime] = [\text{Operating (Writing) Time}]$

$$100\,\%\ \text{Quality} = \big[\text{Number of parts Texts produced}\big] - [\text{Revisions/rework}]$$
$$-\big[\text{scrap}\big]\ \text{where}\ [\text{Revisions/rework}] = 0 \wedge \big[\text{scrap}\big] = 0$$