Systems & Control Transactions

**Original Research Article**
*Peer Reviewed Conference Proceeding*
ESCAPE 36 - European Symposium on Computer Aided Process Engineering
Sheffield, UK. 21-24 June 2026

PSE PRESS

# Data-Driven Multi-Objective Optimization of Energy, Environmental, and Economic Performances in Manufacturing with Physics-Consistent Deep Learning

**Hyeonrok Choi[ab], Jaewook Lee[a], Won Yang[a] and Seong-il Kim[ac]***

[a] Low-Carbon Emission Control R&D Department, Research Institute of Sustainable Development Technology, Korea Institute of Industrial Technology, Cheonan 31056, Republic of Korea
[b] School of Mechanical Engineering, Sungkyunkwan University, Suwon 16419, Republic of Korea
[c] Green Process and Energy System Engineering, University of Science and Technology, Cheonan, Chungnam, Republic of Korea
* Corresponding Author: ksungil85l@kitech.re.kr.

## ABSTRACT

Aluminium cold rolling is an energy-intensive process that has a substantial impact on $CO_2$ emissions and production cost, yet plant-level optimization remains challenging due to strong process nonlinearities and various operational constraints. This study develops a physics-consistent hybrid model that combines a Stone–Hitchcock–Ludwik analytical rolling-energy formulation with a residual deep neural network to predict the daily electricity consumption of three single-stand cold rolling mills. Using plant raw data, the hybrid model achieves lower prediction errors than conventional data driven model and yields line-specific physical parameters that agree well with the observed behaviour of each mill. On this basis, an NSGA-II-based tri-objective optimization is carried out to minimise daily energy use, $CO_2$ emissions, and specific production cost (SPC) by adjusting pass-wise reduction and tension schedules and line-wise production allocation. Case studies on a representative operating day and additional plant data show that the optimised operating strategy shifts production load from less efficient to more efficient lines and smooths pass-wise operating conditions, thereby consistently reducing daily energy consumption and unit cost while moderately decreasing $CO_2$ emissions without any hardware modifications. The proposed hybrid prediction–optimization framework thus provides a practical decision-support tool for integrated energy–environment–economic optimization in multi-line aluminium cold rolling operations.

**Keywords**: Aluminium cold rolling, Physics-consistent hybrid modelling, Rolling energy consumption, Multi-objective optimization, NSGA-II (Non-dominated Sorting Genetic Algorithm II)

## INTRODUCTION

Global efforts to mitigate climate change have tightened greenhouse gas (GHG) reduction requirements toward carbon neutrality by 2050 across the manufacturing sector [1]. The aluminium industry, responsible for about 2% of global industrial emissions (≈1.1 $GtCO_2$-eq/year), is a representative carbon- and energy-intensive sector in which process electricity use is a major driver of emissions [2, 3]. In power systems still dominated by fossil fuels, electricity consumption translates directly into GHG emissions, making renewable penetration and fuel switching key mitigation options. In the Republic of Korea, however, a high fossil share in the generation mix and strong industrial dependence on electricity [4] limit the pace of power-sector decarbonisation, so process-level energy efficiency improvement and operational optimization emerge as particularly effective short- to mid-term options.

Cold rolling of aluminium is a power-intensive process that determines final strip thickness (tens of micrometres), flatness, and mechanical properties, and therefore requires high-speed, high-tension operation with precise control [5]. In single-stand foil mills operated under multi-pass schedules, the combination of reduction, entry/exit tension, and rolling speed at each pass jointly determines rolling load, torque, and thus electrical power

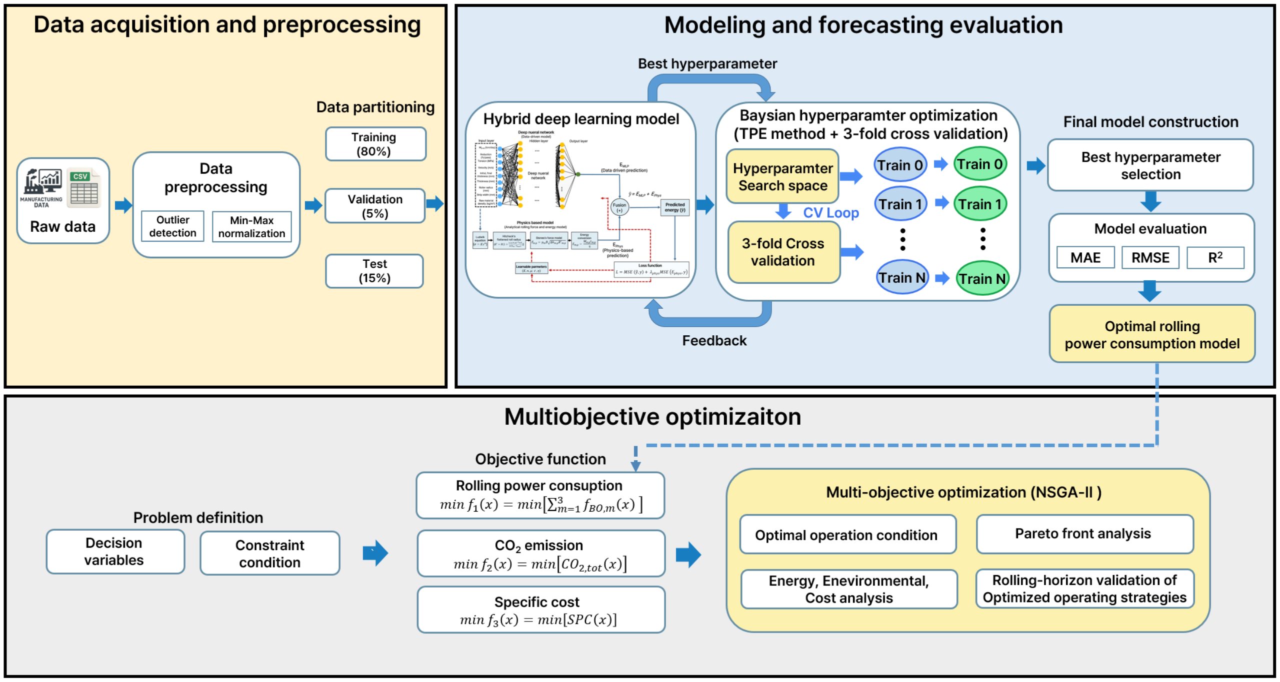



**Figure 1.** Overall framework of data-driven rolling power prediction and multi-objective optimization for aluminum rolling.

demand, under equipment constraints such as motor rating, drivetrain and inverter capacity, and available power supply. Designing pass schedules and allocating production among parallel lines is therefore a constrained decision problem, in which energy performance must be optimised concurrently with process stability and product requirements. Predictive models that reliably quantify the impact of process variables and production allocation on power demand and daily energy use are a key enabler for such optimization.

Modelling approaches for rolling load and power have evolved from analytical formulations and finite element method (FEM) simulations to artificial intelligence (AI)-based methods. Analytical models are computationally efficient and interpretable, but they require calibration for friction, work hardening, and drive efficiency, and their simplifying assumptions can limit accuracy and general applicability. FEM can represent roll–strip contact and deformation in detail, but it is too computationally expensive for repeated evaluation in plant-wide optimization. Data-driven AI models, including artificial neural networks (ANNs), have been applied to rolling load, power, and process monitoring tasks [6–9]; however, their black-box nature can limit interpretability and reduce reliability under extrapolative conditions. To address these limitations, hybrid modelling approaches that embed data-driven correction layers within physics-based structures have been proposed to balance computational efficiency, physical consistency, and predictive accuracy. In particular, previous studies have reported FEM–ANN hybrid models, genetic algorithm–backpropagation neural network (GA–BP) models, and stacking ensemble models combining extreme random tree (ET), AdaBoost regression tree (AdaBoost-RT), linear regression (LR), and backpropagation neural network (BPN) base learners with an LR meta-learner for load and flatness prediction [10–13].

As predictive models have improved, multi-objective optimization studies that embed such models into decision-making frameworks have become more common. In rolling applications, differential evolution (DE)- and Non-dominated Sorting Genetic Algorithm II (NSGA-II)-based methods have been used to derive Pareto-optimal solutions considering energy reduction, strip quality, slip prevention, and motor load balancing, while more recent studies have explored reinforcement learning-based pass schedule design and energy-oriented scheduling under time-of-use (TOU) tariffs and peak-demand constraints [14–16]. However, process-condition scheduling, such as pass-wise load and tension control, and TOU-based operating-time scheduling have mostly been treated separately. Consequently, integrated frameworks that link a physics-informed daily energy model with plant-level energy, environmental, and economic indicators for single-stand, multi-pass, high-speed, high-tension aluminium cold rolling mills remain very limited. To address this gap, this study develops an integrated framework that combines actual plant operating data, including pass-wise reduction, tension, speed, and thickness, with manufacturing execution system (MES)-based production data, including daily throughput and line-wise allocation, to predict mill-wise daily electricity consumption and to use these predictions in NSGA-II-based tri-objective optimization of energy consumption, carbon dioxide ($CO_2$) emissions, and specific production cost (SPC) across operating conditions and inter-line production allocation. The overall workflow is summarised in Figure 1.

# METHODOLOGY

## Overview of the target process

The case study considers an industrial aluminium sheet cold rolling plant with a nominal capacity of approximately 500 ton/day. The plant consists of three single-stand cold rolling mills (RM4, RM5, and RM6). In each line, intermediate sheet stock supplied from upstream processes is reduced to the target thickness over multiple passes. The layout of the three mills, coil transfer routes, and pass directions are illustrated in Figure 2.

## Problem definition

The plant energy management system (EMS) and process databases provide operating and production data, including alloy grade, strip geometry, pass schedule, key operating variables such as reduction, tension, and speed, and line-wise daily electricity consumption. Among the frequently used production routes, this study focuses on AA8075-series sheets operated under a six-pass cold rolling schedule.

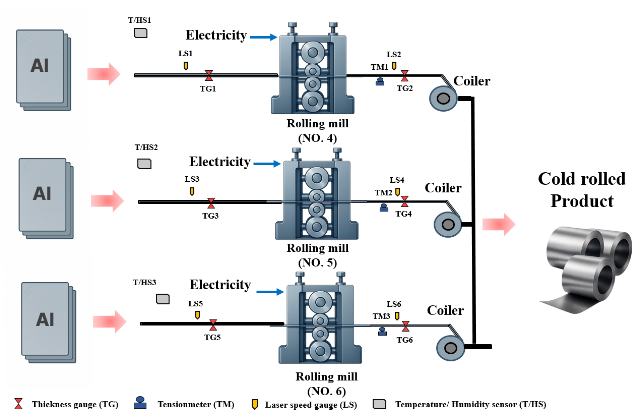



**Figure 2.** Schematic of three parallel aluminum rolling mills (No. 4–6) and product material flow.

The statistical characteristics of the full raw dataset are summarised in Supplementary Material S1. The process variables exhibit typical multi-pass cold rolling behaviour: the reduction ratio is highest in the initial passes and decreases with pass number; tension starts at an intermediate level in pass 1, increases up to pass 5, and slightly decreases in pass 6; and roll speed increases gradually with pass number. The exit thickness for all three lines is tightly distributed around the target value, indicating stable thickness control.

**Table 1:** Detailed values of the model parameters

| Parameter | Description | Unit | Value |
|---|---|---|---|
| $\rho$ | Density of strip (A8075) | kg/m$^3$ | 2710 |
| $N_m$ | Number of rolling mills | - | 3 |
| $N_p$ | Number of passes | - | 6 |
| $h_0$ | Initial thickness of foil | mm | 0.3 |
| $h_{aim}$ | Target thickness of foil of final production | mm | 0.03 |
| $R$ | Work roll radius | m | 0.375 |
| $B$ | Width of strip | mm | 1690 |
| $\psi$ | Force arm coefficient | - | 0.45 |
| $\eta_m$ | Mechanical efficiency | - | 0.85-0.995 |
| $\mu$ | Friction coefficient | - | 0.05-0.08 |
| $K$ | Strength coefficient | MPa | 110-200 |
| $n$ | Strain hardening exponent | - | 0.2-0.25 |

A representative operating condition is defined such that the total daily throughput of the three mills is 219.3 ton/day, with the incoming strip thickness $h_0=0.3$ *mm* and target final thickness $h_{aim}=0.03$ *mm* over six passes. The material, geometric, and operating parameters used in the analytical cold rolling model for this base case are summarised in Table 1, including strip density $\rho$, number of passes $N_p$, number of mills $N_m$, initial and target thickness $h_0$, $h_{aim}$, roll radius $R_w$, strip width $B$, arm coefficient $\psi$, mechanical efficiency $\eta_m$, friction coefficient $\mu$, strength coefficient $K$, and strain-hardening exponent $n$. These parameters, summarised in Table 1, constitute the nominal parameter set and are applied to both the analytical cold rolling model and the hybrid energy prediction model, except where indicated otherwise.

## Data preprocessing

Process raw data can contain noise, input errors, and missing values, which may deteriorate the stability and reproducibility of model training. To address this, pass-wise reduction, tension, speed, thickness, daily throughput, and electricity consumption are preprocessed by removing physically unrealistic outliers and imputing missing values with the variable-wise median, followed by min–max normalisation of all input variables.

Normalisation is defined as

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}, \quad (1)$$

$X'$ is the normalised value, $X$ is the original value, and $X_{\max}, X_{\min}$ are the maximum and minimum of each variable. The preprocessed data are split into 80% for training, 5% for validation, and 15% for testing.

## Model development

The model architecture used to predict the daily electricity consumption of the cold rolling mills is illustrated in Figure 3. Normalised process inputs x (Production, pass-wise reduction, speed, tension, exit thickness, etc.) are fed in parallel to a data-driven deep neural network $f_{DL}(x, \theta)$ and to an analytical rolling-energy model $E_{phys}(x, \phi)$ based on the Stone–Hitchcock–Ludwik formulation. The network is a fully connected deep neural network (DNN) with rectified linear unit (ReLU) activation and a linear output layer for regression, trained using mean squared error (MSE) and the Adam optimiser with early stopping. The analytical module computes per-pass rolling force, torque, power, and energy for each mill and aggregates them to daily energy using mill-specific physical parameters $\phi = (K, n, \mu, \eta)$.

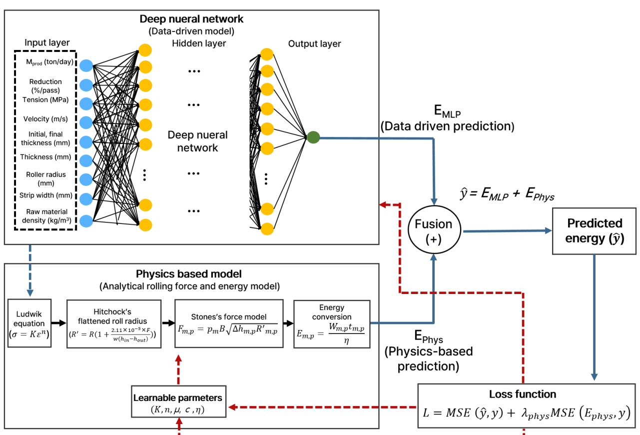



**Figure 3.** Physics-consistent hybrid model for rolling-energy prediction

The detailed equations and formulation of the analytical rolling-energy model are summarised in Supplementary Material S2. The hybrid predictor is formulated in residual form and trained with the composite loss.

$$\hat{y}(x; \theta, \phi) = f_{DL}(x, \theta) + E_{phys}(x, \phi) \quad (2)$$

$$L = MSE\,(\hat{y}, y) + \lambda_{phys} MSE\,(E_{phys}, y) \quad (3)$$

where $\lambda_{phys} > 0$ controls the weight on physics consistency. The physical parameters $\phi$ are treated as learnable and updated jointly with $\theta$, so that the DNN mainly captures residual patterns while the analytical model provides the physical baseline and global energy scale.

## Bayesian optimization

Bayesian hyperparameter optimization was employed to enhance the predictive performance of the physics-consistent hybrid model. A Tree-structured Parzen Estimator (TPE)–based algorithm, implemented via the Optuna library, was used to efficiently explore a mixed continuous–discrete search space, tuning key hyperparameters such as the number of hidden units, learning rate, weight decay, physics-loss weight ($\lambda_{phys}$), and batch size. Each trial was evaluated using the hybrid loss $L(\theta, \phi)$ on the validation set, and the hyperparameter configuration yielding the minimum validation loss over all trials was selected.

## Model evaluation

The dataset was randomly shuffled and split into 80% for training, 5% for validation (Bayesian hyperparameter optimization), and 15% for testing. Test-set performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination ($R^2$), defined for $N$ test samples as

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i| \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_i)^2}, \bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i \quad (6)$$

# MULTI-OBJECTIVE OPTIMIZATION

## Objective function

The multi-objective optimization problem is solved using the NSGA-II evolutionary algorithm. The previously developed physics-informed hybrid surrogate model is used as the evaluator: for each candidate operating condition (pass-wise reduction, tension, and production allocation), it predicts the daily electrical energy use of each mill. NSGA-II then searches for a set of Pareto-optimal solutions that simultaneously minimise energy consumption, $CO_2$ emissions, and economic cost.

$$\min f_1(x) = \min \sum_{m=1}^{3} f_{BO,m}(x) \quad (7)$$

$$\min f_2(x) = \min \alpha_{elec.} E_{total,day}(x) + \alpha_{raw} M_{raw,day}(x) + \alpha_{lub} M_{lub}(x) + \alpha_{add} M_{add}(x)\ [ton/day] \quad (8)$$

$$\min f_3(x) = \frac{C_{elec.}(x) + C_{ETS}(x) + C_{raw}(x) + C_{O\&M}}{M_{prod,day}(x)} \quad (9)$$

The objective functions in this study are defined at the plant level as follows: (i) total daily electricity consumption, evaluated as the sum of the hybrid-model-predicted daily electricity use of the three mills; (ii) total daily

$CO_2$ emissions arising from electricity consumption as well as raw material, lubricant, and additive use; and (iii) the specific production cost (SPC), defined as the ratio of total daily operating cost to daily production. The coefficients required for evaluating the $CO_2$ and SPC objective functions are compiled and derived in Supplementary Tables S3 and S4, respectively.

**Table 2:** Prediction accuracy of energy consumption by different machine learning models

| Sheet | Model | MAE | RMSE | $R^2$ |
|---|---|---|---|---|
| Rolling Mill 4 | SVR | 0.357 | 0.653 | 0.964 |
| | RFR | 0.349 | 0.660 | 0.964 |
| | XGB | 0.314 | 0.637 | 0.966 |
| | DNN | 0.434 | 0.684 | 0.961 |
| | Hybrid DNN | 0.202 | 0.400 | 0.987 |
| Rolling Mill 5 | SVR | 0.284 | 0.366 | 0.983 |
| | RFR | 0.307 | 0.406 | 0.980 |
| | XGB | 0.285 | 0.376 | 0.982 |
| | DNN | 0.302 | 0.402 | 0.980 |
| | Hybrid DNN | 0.258 | 0.357 | 0.988 |
| Rolling Mill 6 | SVR | 0.153 | 0.274 | 0.963 |
| | RFR | 0.178 | 0.294 | 0.957 |
| | XGB | 0.154 | 0.254 | 0.968 |
| | DNN | 0.136 | 0.216 | 0.967 |
| | Hybrid DNN | 0.115 | 0.169 | 0.986 |

## Decision variables and industrial constraints

The decision vector comprises (i) daily production allocated to each mill, $M_{m,\,day}$(m=1, 2, 3) (ii) pass-wise reduction ratios $R_i$ (i=1, ..., 6), and (iii) pass-wise tensions $T_i$ (i=1, ..., 6), and can be written for each mill as

$$x = [\, M_{i,day},\ R_1, R_2R_3R_4R_5R_6, T_1, T_2, T_3, T_4, T_5, T_6] \tag{10}$$

Search bounds are chosen to reflect the feasible operating window of the actual equipment: lower and upper limits for $M_{m,\,day}$ $R_i$, and $T_i$ are set to the minimum–maximum values observed in plant data, thereby preventing unrealistic operating combinations. In addition, the total daily production is constrained to remain close to the reference target to avoid trivial improvements obtained by artificially changing throughput.

# RESULTS AND DISCUSSION

## Performance comparison of hybrid model

Table 2 compares the daily energy prediction performance of support vector regression (SVR), random forest regression(RFR), extreme gradient boosting (XGB), pure DNN, and the proposed Bayesian optimization (BO)-hybrid DNN for the three foil rolling lines (RM4–RM6) using identical inputs. The BO-hybrid DNN yields the lowest MAE/RMSE and highest $R^2$ across all lines, indicating that incorporating physical load–torque–power–energy relations improves both accuracy and robustness at the daily energy scale.

Figure 4 shows the BO-hybrid DNN predictions of

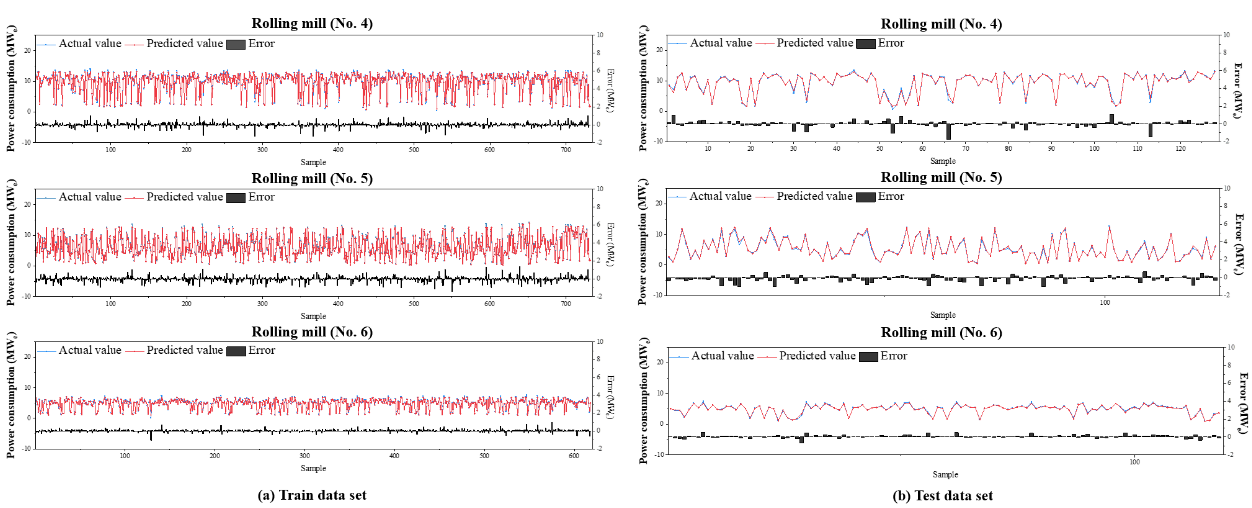
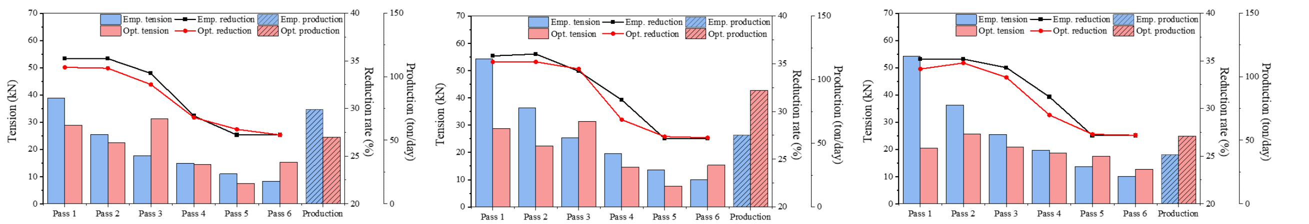



**Figure 4.** Actual and predictive value calculated by BO-Hybrid model.




(a) Rolling mill (No. 4) (b) Rolling mill (No. 5) (c) Rolling mill (No. 6)

**Figure 5.** Optimization results of tension, reduction, and daily production for rolling mills No. 4–6 (empirical vs. optimized).

daily energy consumption for each line, with training results on the left and test results on the right. In each subplot, red markers denote measured values, black markers denote model predictions, and blue bars indicate the absolute error per sample. For all three lines, the predicted curves closely follow the measured trends, with most absolute errors remaining within a narrow range and only limited deviations at a few peak-load or non-standard operating points.

**Table 3:** Inferred physical parameters of the rolling process for the three mills

| Parameter | Unit | Description | RM4 | RM5 | RM6 |
|---|---|---|---|---|---|
| $K_{MPa}$ | MPa | Strength coefficient | 180 | 178 | 181 |
| $n$ | - | Strain-hardening exponent | 0.24 | 0.25 | 0.24 |
| $\mu$ | | Friction coefficient | 0.05 | 0.05 | 0.03 |
| $\eta$ | % | Mechanical efficiency | 90.8 | 93.1 | 92.2 |

***RM : Rolling mill**

In addition to predicting energy, the BO-hybrid DNN simultaneously back-estimates the physical parameters ($K$, $n$, $\mu$, $\eta$) for each mill, as summarised in Table 3. The inferred values fall within similar ranges but exhibit mill-specific variations, indicating that the model not only improves daily energy prediction but also yields interpretable, line-dependent physical parameters rather than purely statistical correlations.

## Multi-objective optimization results

### Case study of a representative operating day

Energy consumption and $CO_2$ emissions are strongly positively correlated, because $CO_2$ is computed directly from the predicted daily electricity use via a fixed grid emission factor; thus, reducing energy immediately reduces $CO_2$. In contrast, energy (or $CO_2$) and SPC exhibit an overall inverse relationship, since SPC is defined as total daily operating cost per unit throughput and includes fixed capital/ operations and maintenance (O&M) components as well as energy-dependent costs.

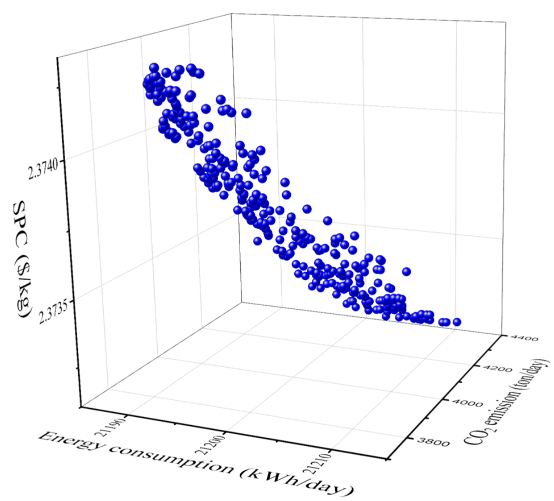



**Figure 6.** Pareto solution set in objective space for (a) 3D of energy consumption, $CO_2$ emission, and SPC

Along the Pareto front, some operating conditions slightly increase energy use but allow higher daily production and more favourable load sharing among mills, thereby diluting fixed costs per ton and yielding lower SPC despite higher energy and $CO_2$.

Figure 7 compares the three objective values—daily energy consumption, daily $CO_2$ emissions, and SPC—between the empirical operating condition and the optimized condition, shown in normalized form with absolute values annotated on each bar. Daily energy consumption decreases from 25.91 to 21.19 MWh/day (≈18.22%), and SPC from 2.51 to 2.502 USD/kg (≈0.32%), indicating a simultaneous reduction in unit production cost, including electricity and emissions trading system (ETS)-related charges. $CO_2$ emissions change only marginally, from 4158.5 to 4156.4 kg/day (≈0.05%), as a substantial fraction of total emissions arises from non-electricity contributions such as materials and process auxiliaries. Overall, these results summarise that appropriate adjustment of line-wise production allocation and pass-wise operating conditions can improve energy, environmental, and economic performance simultaneously even under unchanged equipment and system configurations.

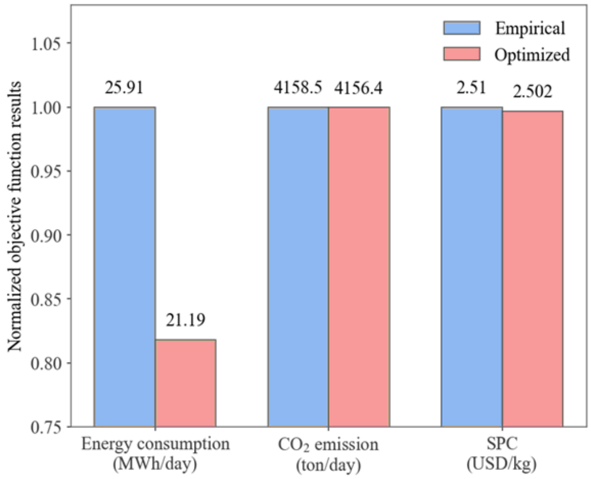



**Figure 7.** Relative comparison of normalized objective functions (Energy, $CO_2$, SPC)

## Case study with additional operating data

In this section, the proposed hybrid prediction–optimization framework is validated on 40 additional operating days that were not used for training, under the actual plant constraints of each day (target throughput, mill capacities, speed/tension limits, etc.). For each day, NSGA-II is applied with pass-wise reduction, tension, speed, and line-wise production allocation as decision variables. As shown in Figure 8(a), although the total daily production varies between approximately 288 and 489 ton/day, the optimised solutions consistently redistribute load away from Mill 4 and toward the more energy-efficient Mills 5 and 6. Consequently, Figure 8(b) indicates that empirical daily electricity use, which ranges from 20.9 to 33.1 MWh, is reduced and flattened to about 20.3–21.9 MWh under the optimised operation, corresponding to an average energy reduction of roughly 21.12%. Figures 8(c) and (d) show that, despite relatively small percentage reductions in $CO_2$ (0.01–0.068%, but on 2.56 ton/day in absolute terms) and SPC also decreased, with the relative reduction ranging from 0.21 to 0.283% and averaging approximately 0.24%. Despite the dominance of raw material cost in the total cost structure, the optimization consistently improves energy, environmental, and economic performance across all 40 days while satisfying the production constraints.

## CONCLUSION

This study developed a physics-consistent hybrid energy surrogate for daily electricity prediction in aluminium cold rolling by coupling a Stone–Hitchcock–Ludwik analytical rolling-energy model with a residual deep neural network. The hybrid model improved predictive capability while preserving physically interpretable mill-specific parameters consistent with actual plant behaviour. On this basis, an NSGA-II-based tri-objective optimization framework was formulated to minimise energy consumption, $CO_2$ emissions, and SPC through the adjustment of pass-wise operating conditions and line-wise production allocation. The results showed that the proposed framework can systematically improve plant operation by shifting production toward more energy-efficient mills and by smoothing pass-wise schedules under practical process constraints. Furthermore, out-of-sample validation confirmed that the framework remains effective under varying operating conditions. These findings demonstrate that the proposed approach offers a practical and scalable tool for integrated energy–environment–economic optimization of industrial aluminium cold rolling plants without additional hardware modification.

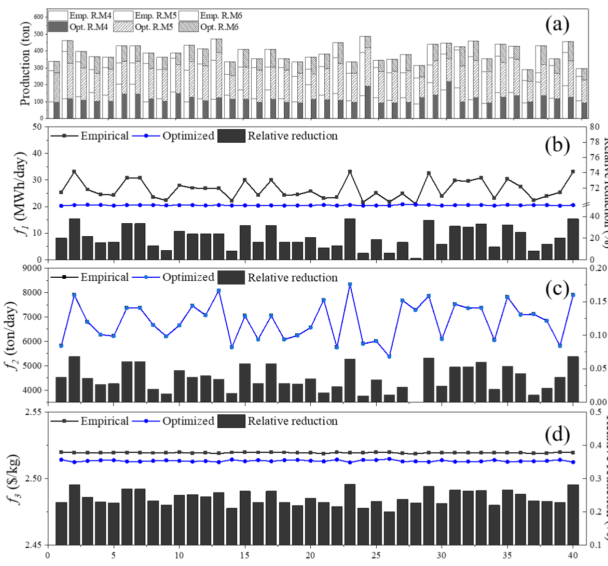



**Figure 8:** Effect of the optimized rolling schedules on (a) line-wise production, (b) daily energy consumption, (c) daily $CO_2$ emissions, and (d) daily SPC
DIGITAL supplementary material

## SUPPLEMENTARY MATERIALS

Digital supplementary material is included in the Supplementary Material file which is downloadable at https://PSEcommunity.org/LAPSE:2026.0041.

## AUTHOR IDENTIFIERS

Author ORCIDs:
Choi HR: 0009-0006-6282-4736

## REFERENCES


1. International Energy Agency (IEA), Net Zero by 2050, IEA, Paris, 2021. Available at: https://www.iea.org/reports/net-zero-by-2050 (accessed 01.12.2026).
2. International Aluminium Institute (IAI), Greenhouse gas emissions: Aluminium sector, 2024. Available at: https://international-aluminium.org/statistics/greenhouse-gas-emissions-aluminium-sector/ (accessed 01.12.2026).
3. Kvande H, Saevarsdottir G, Welch BJ. Direct and indirect CO2 equivalent emissions from primary aluminium production. The Minerals, Metals & Materials Series :998-1003 (2022). https://doi.org/10.1007/978-3-030-92529-1_130
4. U.S. Energy Information Administration (EIA), South Korea, Country Analysis Brief, EIA, Washington, DC, 2023 (accessed 05.12.2025).
5. D. Meech, P. Lawlor, Aluminium rolling: improving production and quality with minimum energy consumption, Mater. Technol. 24 (2009) 144–145.
6. Yang L, Zhiying G, Xiaomin Z, Qingdong Z. Industrial data-driven intelligent forecast for chatter of cold rolling of thin strip with LSTM recurrent neural network. Journal of Mechanical Engineering 56:121 (2020). https://doi.org/10.3901/jme.2020.11.121
7. Chen Z, Liu Y, Valera-Medina A, Robinson F, Packianather M. Multi-faceted modelling for strip breakage in cold rolling using machine learning. International Journal of Production Research 59:6347-6360 (2020). https://doi.org/10.1080/00207543.2020.1812753
8. Chen D, Zhang R, Li Z, Li Y, Yuan G. Temperature distribution prediction in control cooling process with recurrent neural network for variable-velocity hot rolling strips. Int J Adv Manuf Technol 120:7533-7546 (2022). https://doi.org/10.1007/s00170-022-09065-8
9. Lakshmanan K, Borghini E, Beckmann A, Pleydell-Pearce C, Giannetti C. Data modelling and remaining useful life estimation of rolls in a steel making cold rolling process. Proced Comp Sci 2022;207:1057–66. https://doi.org/10.1016/j procs.2022.09.16
10. Lv C, Wang GD, Liu XH, et al. High-precision prediction of rolling load of finishing stands with neural networks. Iron Steel 1998;03:33–5. https://doi.org/10.3321/j issn:0449-749X.1998.03.009.
11. He YY, Yan X, Li LX, et al. Prediction model of rolling force of CSP line based on BP neural network. MaterMechEng 2014;38(010):79–82. CNKI:SUN:GXGC.0.2014-10- 020.
12. Zhang SH, Deng L, Che LZ. An integrated model of rolling force for extra-thick plate by combining theoretical model and neural network model. Journal of Manufacturing Processes 75:100-109 (2022). https://doi.org/10.1016/j.jmapro.2021.12.063
13. Cui CG. Intelligent prediction model based on neural network algorithm and mechanism model for rolling force in tandem cold rolling. Comput Modernization 2019;000(008):74–78, 91. https://doi.org/10.3969/j.issn.1006-2475.2019.08.014
14. Jia S, Li W, Liu X, Du B. Multi-objective load distribution optimization for hot strip mills. J Iron Steel Res Int 2013;20:27–61. https://doi.org/10.1016/S1006-706X (13)60052-7.
15. Hu ZY, Yang JM, Zhao ZW, Sun H, Che HJ. Multi-objective optimization of rolling schedules on aluminum hot tandem rolling. Int J Adv Manuf Technol 85:85-97 (2015). https://doi.org/10.1007/s00170-015-7909-1
16. L. Chen, L.L. Cao, Y.M. Wen, H. Chen, S.L. Jiang, A knowledge-based NSGA-II algorithm for multi-objective hot rolling production scheduling under flexible time-of-use electricity pricing, J. Manuf. Syst. 69 (20)