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Original Article

Human-in-the-loop validation of a decision-support interface for blast furnace operation

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ABSTRACT

To achieve the efficient and stable operation of a blast furnace (BF) in the steel industry while retaining the critical skills of expert human operators, we developed a novel human-machine interface (HMI) grounded in ecological interface design (EID) principles. The BF is a complex, large-scale chemical reactor to produce hot metal where internal temperatures can reach up to 2000 °C. Due to the inherent difficulty of full process automation, the EID framework was adopted to support operators' situation awareness and keep human expertise central to decision-making. The developed ecological interface (EI) enhances manual control using a transient model, allowing operators to explore the best control action by showing the predicted future states of controlled variables resulting from their hypothetical control actions. Furthermore, the developed EI provides operators with explicit information on the mass and energy balances linking control means and ends, which is intended to support situation awareness. To facilitate comprehensive training, an operation simulator, capable of running at 300 times real-time speed, was integrated with the developed EI. Human-in-the-loop experiments with 16 subjects showed that the EI significantly reduced the number of control actions in both scenarios and reduced the HMT control error and the duration of ΔP upper-bound violations in the complex scenario, whereas no statistically significant reductions were observed in coke rate or carbon intensity.

1. Introduction

In the field of process control, process digitalization has been promoted to achieve more efficient and stable operations (Peterson et al., 2025; Pantelides et al., 2024). The construction of virtual process models drives automation that calculates optimal control actions. While advanced automation suggests a future of full automation, human involvement remains indispensable in safety-critical domains, such as nuclear power plants, to deal with real-world complexities that current algorithms and their human designers cannot fully anticipate (Bainbridge, 1983; Rasmussen, 1983; Parasuraman et al., 2000). Trained human operators remain the only agents capable of creative problem-solving required to handle unforeseen crises (Rasmussen, 1983). Therefore, the goal of automation technologies in such domains should be to better support human operators to accomplish those complex tasks on their own (Parasuraman et al., 2000). Effective design

must focus on enhancing human operators' situation awareness, ensuring they understand the system functioning states and possess the tools to act efficiently (Endsley, 1995).

To achieve such human-centered automation, an ecological interface design (EID) framework proves beneficial (Vicente et al., 1992; Vicente, 2002). While many conventional support systems merely output optimal control actions for the operators to implement, support systems based on EID aim to help operators enhance their situation awareness and derive control actions for achieving highly efficient and stable operation. EID is not limited to process control in nuclear power plants (Itoh et al., 1995; Burns et al., 2008), polymerization reactors (Lindscheid et al., 2019), and petrochemical plants (Jamieson et al., 2001; Jamieson, 2007); its application is actively expanding into fields where ensuring safety is crucial and achieving full automation is difficult, such as in the aviation industry (Van Paassen et al., 2018; Amelink et al., 2005; Borst et al., 2017). More recently, Mulder et al. (2026) highlighted an ecological

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approach to supporting operator situation awareness across different levels of automation in aviation.

The authors aim to build an EID-based control system targeting human-centered automation in blast furnaces in the steel industry. Blast furnaces are highly efficient iron ore smelting processes, producing over one billion tons of molten hot metal annually in the world. A blast furnace is a massive reactor, typically reaching 40 m in height with a furnace volume of 5000 m³, producing approximately 10,000 tons of hot metal per day. It is a high-temperature process where complex chemical reactions occur among coexisting gas, solid, and liquid phases. As illustrated in Fig. 1, iron ore and coke are charged into the furnace from the top. While descending toward the furnace bottom, these materials are heated by the hot blast air (approximately 1200 °C) and the pulverized coal (PC) blown through the tuyeres located around the lower section of the furnace. During this process, the iron oxides in the iron ore are reduced by the carbon contained in the coke and PC. The resulting hot metal, at approximately 1500 °C, is then discharged from the bottom.

Recent societal demands for CO₂ reduction have driven efforts to decrease carbon-based reducing agents, raising concerns about process instability due to inadequate energy sources. Achieving low-carbon and stable operation through automation remains a challenge. While automation of hot metal temperature (HMT) and gas permeability control has advanced in blast furnaces (Hashimoto et al., 2022a; Masuda et al., 2023; Mu et al., 2026), full automation remains out of reach due to complex phenomena that are difficult to model. Failure of automatic controls can lead to furnace cooling and hot gas blowouts, causing significant economic losses and safety issues. Therefore, a human-centered automation approach is desirable for the future.

Nevertheless, because blast furnace operation itself is highly challenging, human-centered automation must support operators rather than merely return control authority to them. The blast furnace is a complex process involving multiple manipulated variables and controlled variables, with interference between their process gains. Furthermore, due to the large and variable time constant, the causal relationship between the control actions and their outcomes is difficult to grasp with human operators' time perception. In the previous study, the authors developed the ecological interface (EI), including the mass-energy balance visualization and what-if analysis framework (Hashimoto et al., 2026). The contribution of the present study is to integrate this previously developed interface with a dynamic blast furnace simulator and to quantitatively evaluate its effectiveness

through human-in-the-loop experiments involving expert and novice participants.

The structure of this paper is as follows. Section 2 describes the blast furnace simulator combined with the EI and explains the simulator-based experiment involving subjects to verify the effectiveness of EI. Section 3 presents the experimental results, and Section 4 discusses possible operation improvements through EI. Finally, Section 5 presents the conclusions.

2. Methodology

This section briefly describes the ecological interface (EI) developed in the previous study and introduces a training simulator incorporating the EI. Subsequently, a human-in-the-loop experiment conducted to validate the effectiveness of the EI is presented.

2.1. EID

2.1.1. Mass and energy balance

Fig. 2 shows the means (manipulated variables) and ends (controlled variables) of blast furnace operation. In the blast furnace process, it is necessary to maintain a constant HMT at the furnace bottom. If the HMT is too low, the viscosity of the slag increases, making discharge from the furnace difficult and hindering the productivity. In contrast, if the HMT is too high, excess coke or PC is consumed, increasing CO₂ emissions. Furthermore, to maintain the production volume required by the subsequent steelmaking process, the production rate (Prod), defined by the iron charging rate from the furnace top, must be controlled to a target value. Recent blast furnace operations aim for a low coke rate to reduce operating costs, necessitating operation that prevents pressure loss (ΔP), which is defined as the pressure difference between the tuyere level at the lower part and the furnace top, from exceeding its upper bound. Furthermore, to reduce CO₂ emissions, it is necessary to minimize the carbon intensity (Ic) per ton of hot metal. To appropriately control these four controlled variables, the coke rate (CR), the PC flow rate (PCI), the blast air flow rate (BV), and the blast air moisture content (BM) are manipulated. Table 1 summarizes the direction of changes in the controlled variables when these manipulated variables are increased.

In the previous paper, the authors conducted the abstraction hierarchy analysis and constructed an EI which can visualize the mass and energy balances within the process, linking manipulated variables and controlled variables (Hashimoto et al., 2026). Two types of mass and energy balances are relevant for BF operations: per second and per ton of

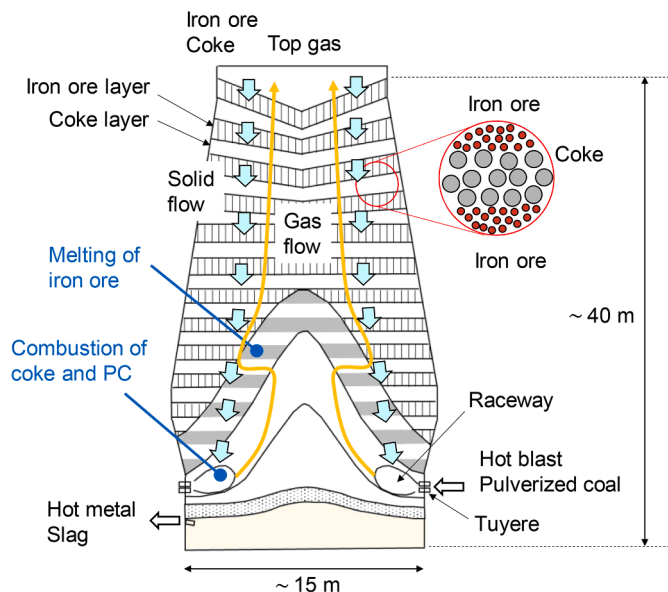


Fig. 1. Schematic of blast furnace process (Hashimoto et al., 2026).

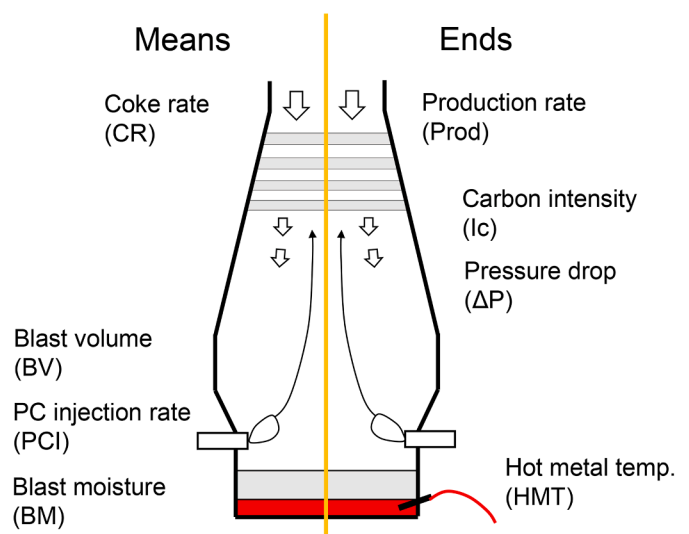


Fig. 2. Means and ends in BF operation. (Modified from Hashimoto et al., 2026).

Table 1

Means and ends relationship in BF operation.

Manipulated variables (means)	Controlled variables (ends)			
	HMT	Prod.	ΔP	I_c
BV	-	↑	↑	-
CR	↑	↓	↓	↑
PCI	↑	↓	-	↑
BM	↓	-	-	-

iron (Hashimoto et al., 2018), and a visualization method to express these in an integrated manner was created. On the one hand, the Prod is determined by the mass balance per second, and ΔP is significantly influenced by the mass balance per second since it is related to the gas velocity within the furnace. On the other hand, HMT and the carbon intensity are determined by the mass and energy balance per ton of iron. Therefore, simultaneous consideration of these two balances is essential to derive control actions that achieve all control objectives.

Fig. 3 illustrates the mass and energy balance visualization developed in the previous paper. This figure includes the four controlled variables and four manipulated variables shown in Table 1. The upper half represents the mass balance, while the lower half represents the energy balance. The yellow-colored area indicates the mass balance per second in the raceway, and the pink-colored area indicates the coke carbon balance per second throughout the entire furnace. The green-colored area represents the energy balance per second throughout the entire furnace. In these three pairs, all left and right elements represent inputs and outputs, respectively, and they should balance in steady states. The left axis represents the flow rates of mass and energy per second, while the right axis represents the amount of mass and energy per unit of iron. This diagram is inspired by the concept of Duress (Vicente, 1999), where the energy in the Duress dual reservoir is

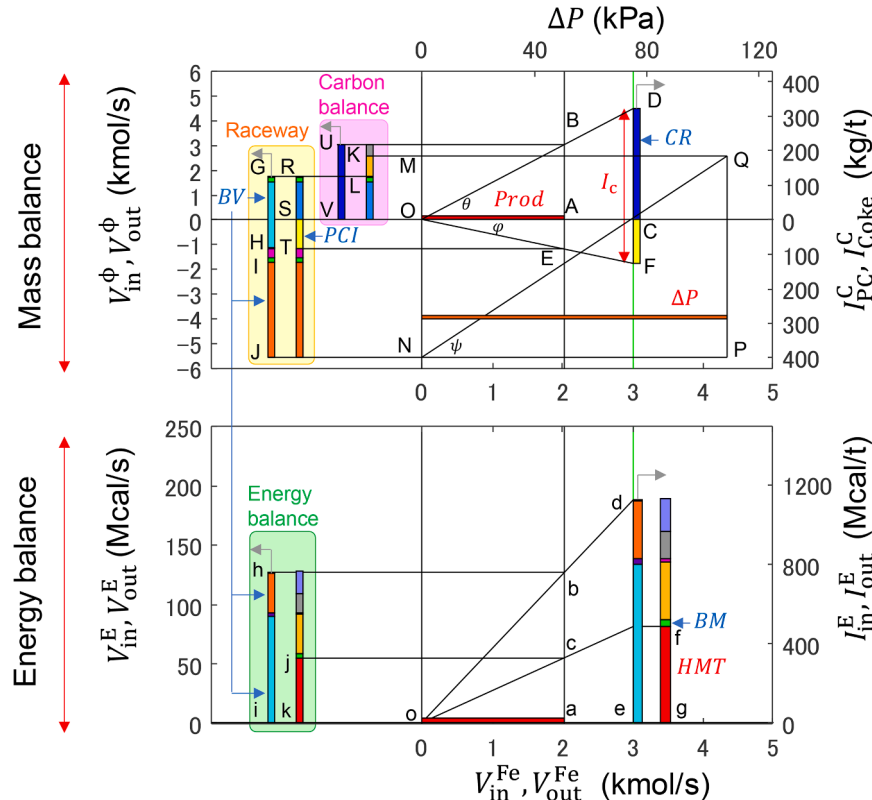
normalized by mass to derive the temperature, i.e., energy per unit mass. This normalization is achieved using the lengths of segments OA and oa, representing the iron production rate and the melting rate, respectively.

The manipulated variables affect the following elements of the mass and energy balance. Increasing BV proportionally increases the lengths of segments GH and IJ in the mass balance, representing the oxygen flow rate and nitrogen flow rate supplied to the raceway, respectively. It also proportionally increases the lengths of the blue and orange elements within the segment hi in the energy balance, representing the supply rates of the carbon combustion heat and the sensible heat of the blast in the raceway. Increasing PCI increases the length of segment ST. Increasing CR increases the length of segment CD, representing the carbon intensity deriving from the coke. Furthermore, increasing BM increases energy consumption, shown by the green element directly above the HMT element (segment fg in the energy balance).

The four control variables are represented by the following elements. The production rate is the length of segment OA, which is determined by the coke carbon input rate (segment UV) and the CR (segment CD). ΔP is expressed by the length of segment NP and is proportional to the total gas flow rate (segment MN). The carbon intensity (segment DF) consists of the coke-derived component (segment CD), which is directly determined by manipulating CR, and the PC-derived component (segment CF), which is calculated by normalizing PC flow rate (segment ST) with the production rate (segment OA). HMT is normalized by dividing the energy discharge rate from the hot metal and slag (line segment jk) by the iron melting rate (line segment oa).

2.1.2. What-if analysis

We developed a method of instantly calculating the responses of controlled variables when hypothetical control actions are performed, hereafter referred to as what-if analysis. This enables operators to quickly explore possible control actions based on the transient model

**Fig. 3.** Integration of mass and energy balance of BF process.

calculations in actual operation settings. Furthermore, simultaneously presenting changes in the mass and energy balances linking manipulated and controlled variables is intended to support operators' situation awareness.

Fig. 4 shows an example of a what-if analysis when the CR is decreased. The blue curves in Figs. 4(e)–(h) show the free response prediction based on the transient model, assuming no control actions are taken while maintaining the current manipulated variables. The magenta curves show the predicted what-if response if control actions were taken, calculated by the linear combination of the free response and the step responses which were calculated in advance. Figs. 4(e) and (g) show the target values of Prod and HMT as horizontal red lines, while Fig. 4(h) shows the upper limit for ΔP as a horizontal red line. Regarding the mass and energy balance shown in Figs. 4(i) and (j), the thick bars represent the current and future states, respectively. The future state corresponds to 30-hour-ahead state indicated by the red dashed lines in Figs. 4(a)–(h).

2.1.3. Training simulator for operators

We developed a blast furnace operation simulator incorporating the what-if analysis and mass and energy balance. Using a previously established transient 1D model, the simulator runs simulations at 300 times real time, enabling real-time calculations for both the current and future blast furnace state. The free response prediction, assuming no control action is taken, is calculated using the same 1D transient model as the simulator model with the same parameters, states, and disturbance information, and therefore no model mismatch exists between the simulator and the free-response prediction in the present experiment. The what-if predictions are calculated based on the linear combination of the free response and the precomputed step responses. Thus, the

what-if prediction may deviate from the nonlinear simulator response because of the linear approximation. However, the previous study showed that the what-if prediction agreed well with the nonlinear prediction of the original model, as long as the operating conditions remained close to the typical operating condition.

As shown in Fig. 5, the interface is structured into three main sections: manipulated variables in the left column, controlled variables in the right column, and the mass and energy balance in the center. The horizontal time axes in the left and right columns are centered on the present, showing trends over the past 20 h and predicting those for the next 20 h. Within the future time interval, the blue dashed curves indicate the free response, while the magenta dashed curves represent the what-if prediction.

The manipulated variables are listed from top to bottom in the left column: blast air flow rate (BV), enriched oxygen flow rate (BVO), coke rate (CR), PC flow rate (PCI), blast air moisture content (BM), and blast air temperature (BT). For the purposes of this study, BVO was automatically controlled in proportion to BV, because the oxygen enrichment rate does not vary significantly during standard blast furnace operation. Since BT is often fixed at its maximum value to reduce the carbon intensity, it was fixed at 1200 °C in this paper.

The controlled variables are shown in the right column, from top to bottom: carbon intensity, control error of the daily production, the absolute daily production, the production rate, HMT, and ΔP . The daily production, which is the integral of the production rate, resets to zero at the end of each day. A persistent negative control deviation in the production rate would cause the daily production to fall well below its target, resulting in significant economic losses. Consequently, a target range of ± 100 tons was set for the daily production volume to mitigate this risk.

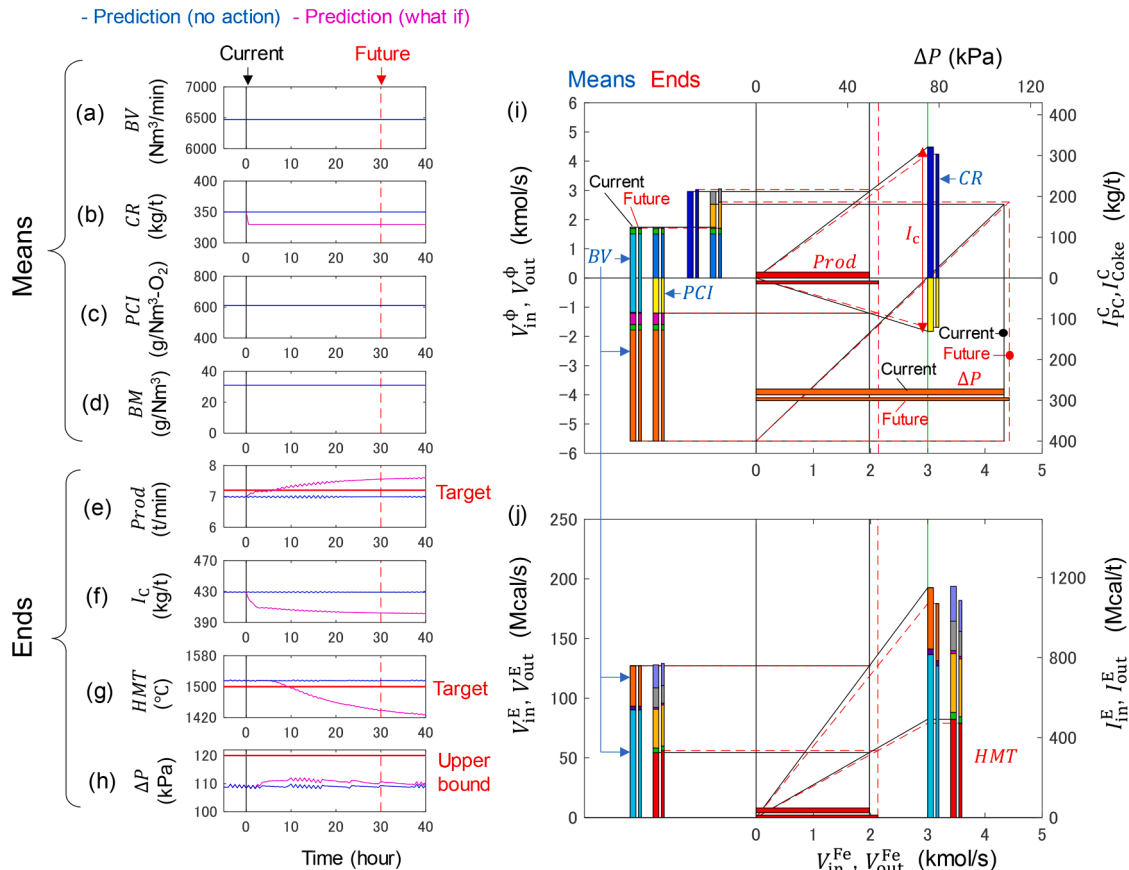


Fig. 4. An example of what-if analysis.

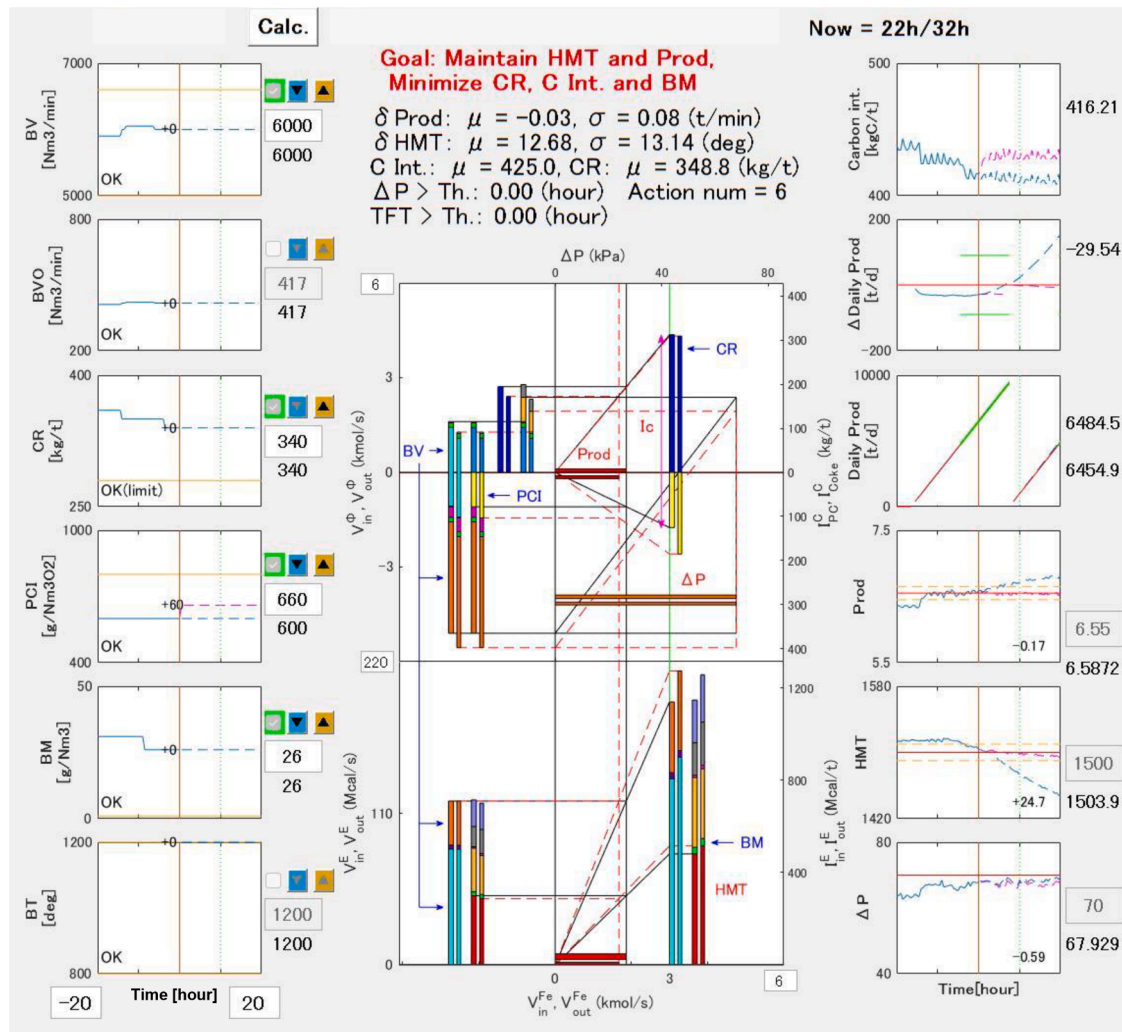


Fig. 5. Blast furnace simulator combined with ecological interface.

Users interact with the simulator using the triangular buttons to the right of each manipulated variable. The moment the users change the manipulated variables, the what-if prediction lines for the controlled variables and the mass and energy balances are updated simultaneously. The example shown in Fig. 5 illustrates a scenario where the CR was reduced twice within the past 20 h, resulting in a substantial drop in the free response of HMT (blue dashed curve). To address this, a control action to increase the PCI by 60 g/Nm³ is being explored. According to the what-if prediction, this control action is projected to successfully bring HMT to its target value (magenta dashed curve).

2.2. Human-in-the-loop experiment

2.2.1. Independent variables

To evaluate the effectiveness of the developed EI, we designed an experiment with two conditions, i.e., EI and NoEI, as shown in Table 2.

Table 2
Independent variables of experiment.

	EI	NoEI
Prediction (free response)	Shown	Shown
Prediction (what-if)	Shown	Not shown
Bar graph	Shown	Not shown

In the EI condition, the simulator interface displayed the what-if prediction and the bar graph; in the baseline NoEI condition, it did not. The free-response prediction, calculated under the assumption of no future control actions, was visible in both conditions. This is because showing the free response is a common feature in conventional blast furnace control systems (Hashimoto et al., 2019a, 2019b; Masuda et al., 2023), and thus it can serve as a baseline.

2.2.2. Dependent measures

To measure the effectiveness of the developed EI, we evaluated subjects' operation performance using the six metrics shown in Table 3. To account for the initial familiarization period, the first six simulated hours (80 s of real time) were excluded from the evaluation. The

Table 3
Dependent measures in the experiment.

Variable	Definition
HMT control error (σ_{HMT})	Root mean square (RMS) of control error of HMT
Prod control error (σ_{Prod})	Root mean square (RMS) of control error of Prod
Mean coke rate (μ_{CR})	Mean value of coke rate
Mean carbon intensity (μ_{IC})	Mean value of carbon intensity
Violation duration of ΔP ($\tau_{\Delta P}$)	Duration of period when ΔP exceeded its upper bound
Number of actions (N_{act})	Number of control actions during each scenario

performance was subsequently analyzed from six hours until the end of the scenario, with total durations ranging from 12 to 54 h depending on the scenario.

2.2.3. Procedure

Sixteen subjects were recruited. They were divided into two groups: an expert group ($n = 8$), consisting of employees from a steel manufacturing company familiar with blast furnace operations, and a novice group ($n = 8$), consisting of university staff with no prior knowledge of a blast furnace. As shown in Fig. 6, all subjects underwent a pre-explanation (30 min), a training period (40 min), and an evaluation period (40 min). During the training period, scenario complexity was gradually increased to familiarize subjects with the blast furnace operation.

Table 4 lists the manipulated and controlled variables for each scenario. Scenarios 1 through 3 gradually increased the number of manipulated and controlled variables. Specifically, in Scenario 1, BV and PCI were manipulated to maintain HMT and Prod at their target values. In Scenario 2, CR was introduced as an additional manipulated variable, aiming at reducing CR for lower operating costs. Because coke represents a major component of hot metal production cost, operating-cost minimization in this study was approximated by minimizing CR. Since decreasing CR increases ΔP , CR reduction was performed within the upper limit constraint of ΔP . In Scenario 3, BM was further introduced as a manipulated variable to minimize carbon intensity. Users were instructed to minimize BM while maintaining stable operation, thereby reducing excess consumption of coke and PC. Scenario 4 increased operation difficulty by raising the target Prod in the middle of the scenario. Scenarios 3 and 4 lasted for 54 simulated hours (evaluated over 48 h), taking approximately 11 min of real time. Hereafter, Scenarios 3 and 4 are referred to as the simple scenario and the complex scenario, respectively.

During the evaluation period, we evaluated two scenarios, Scenarios 3 and 4, each under the two conditions (EI and NoEI) defined in Table 2. To minimize the impact of the order effect on operation performance, we conducted the evaluation using a pseudo-random sequence of scenarios, as detailed in Table 5. Consecutive runs of the same scenario tend to result in improved performance in the latter due to adaptation, making it difficult to accurately estimate the effect of EI. Therefore, Scenarios 3 and 4 were arranged not to appear consecutively. The test was conducted by assigning these eight scenario combinations to the eight subjects in the novice and expert groups.

Table 4

Scenario design.

Scenario number		1	2	3 (simple)	4 (complex)
Manipulated variables (means)	BV	X	X	X	X
	CR		X	X	X
	PCI	X	X	X	X
	BM			X	X
Controlled variables (ends)	HMT	X	X	X	X
	Prod.	X	X	X	X
	ΔP		X	X	X
Cost function	Carbon intensity			X	X
	Operating cost (CR)		X	X	X
Target prod. increase					X
Duration of simulation scenario		12 h	28 h	54 h	54 h

Table 5

Arrangement of scenarios in measurement session.

Participant No.	Scenario No., Availability of EI			
1	#3, EI	#4, EI	#3, NoEI	#4, NoEI
2	#4, NoEI	#3, EI	#4, EI	#3, NoEI
3	#3, NoEI	#4, NoEI	#3, EI	#4, EI
4	#4, EI	#3, NoEI	#4, NoEI	#3, EI
5	#4, EI	#3, EI	#4, NoEI	#3, NoEI
6	#3, NoEI	#4, EI	#3, EI	#4, NoEI
7	#4, NoEI	#3, NoEI	#4, EI	#3, EI
8	#3, EI	#4, NoEI	#3, NoEI	#4, EI

2.2.4. Hypotheses

The primary objective of this study is to investigate the impact of EI on operation performance. Therefore, the following hypotheses were formulated.

H1: The use of EI enables more precise control, as measured by reductions in the RMS control errors of Prod and HMT.

H2: The use of EI enables more efficient operation, as measured through the decrease in the average carbon intensity and coke rate.

H3: The use of EI leads to more stable operation, as measured through a decrease in the duration of ΔP upper-bound violations.

H4: The use of EI reduces the control activity of operators, as measured through the decrease in the number of control actions.

H5: The effects of EI described through H1 to H4 are larger for novices than for experts.

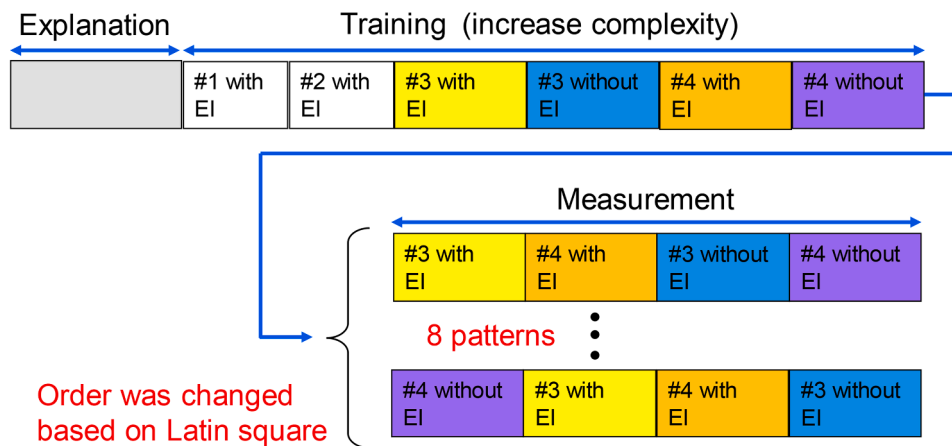


Fig. 6. Timeline of experiment.
Number sign (#) denotes scenario number.

2.2.5. Data treatment

To evaluate the effects of the ecological interface (EI), expertise level, and their interaction on operation performance, the dependent measures presented in Section 2.2.2, except for the ΔP violation duration, were analyzed using linear mixed-effects models (LMMs). The ΔP violation duration was excluded from the LMM-based analysis because it showed a strongly zero-inflated and bounded distribution. Separate models were fitted for the simple and complex scenarios. For each dependent measure, EI availability (EI or NoEI), participant expertise level (expert or novice), and their interaction were treated as fixed effects, while participant identity was treated as a random effect to account for repeated measurements within subjects. Thus, the following model structure was applied.

$$Y = \beta_0 + \beta_1 EI + \beta_2 Expertise + \beta_3 (EI \times Expertise) + b + \epsilon \quad (1)$$

where Y is the dependent measure, EI is the EI condition (EI or NoEI), $Expertise$ is the participant expertise level (novice or expert), β_0 is the intercept, $\beta_1 - \beta_3$ are the fixed-effect coefficients, b is the subject-specific random effect, and ϵ is the residual error.

The hypotheses H1–H5 were treated as confirmatory. For H1, H2, and H4, the marginal EI effect, defined as the EI effect averaged equally across the expert and novice groups, was used to evaluate the effect of EI. For H3, the difference in ΔP violation duration between the EI and NoEI conditions in the complex scenario was evaluated using a Wilcoxon signed-rank test. No statistical test was applicable to the ΔP violation duration in the simple scenario because all values were zero. For H5, the $EI \times Expertise$ interaction was evaluated for the dependent measures analyzed using LMMs. The ΔP violation duration was not included in

H5. The expertise effect at NoEI was treated as exploratory.

To control for multiple testing, the Holm procedure was applied separately within each confirmatory hypothesis family. The H1 family comprised the Prod and HMT control errors in both scenarios ($m = 4$), H2 comprised the coke rate and carbon intensity in both scenarios ($m = 4$), H3 comprised the ΔP violation duration in the complex scenario ($m = 1$), H4 comprised the number of control actions in both scenarios ($m = 2$), and H5 comprised the $EI \times Expertise$ interaction tests for the dependent measures analyzed using LMMs ($m = 10$). Statistical significance for the confirmatory tests was assessed at Holm-adjusted $p < 0.05$. For the LMM analyses, raw and Holm-adjusted p -values, model-based effect estimates, and their 95% confidence intervals are reported. For the Wilcoxon signed-rank test, the median, interquartile range (IQR), test statistic, and raw and Holm-adjusted p -values are reported.

3. Results

This section presents the results of the human-in-the-loop experiment described in Section 2.2, which was conducted to validate the effectiveness of the developed EI.

3.1. Typical operation results (simple scenario)

Fig. 7 shows examples of operating results for the simple scenario. These two examples were selected to illustrate contrasting operation patterns in terms of coke rate and carbon intensity. The blue curves represent an example of highly efficient operation characterized by low values for both the coke rate and the carbon intensity. The red curves

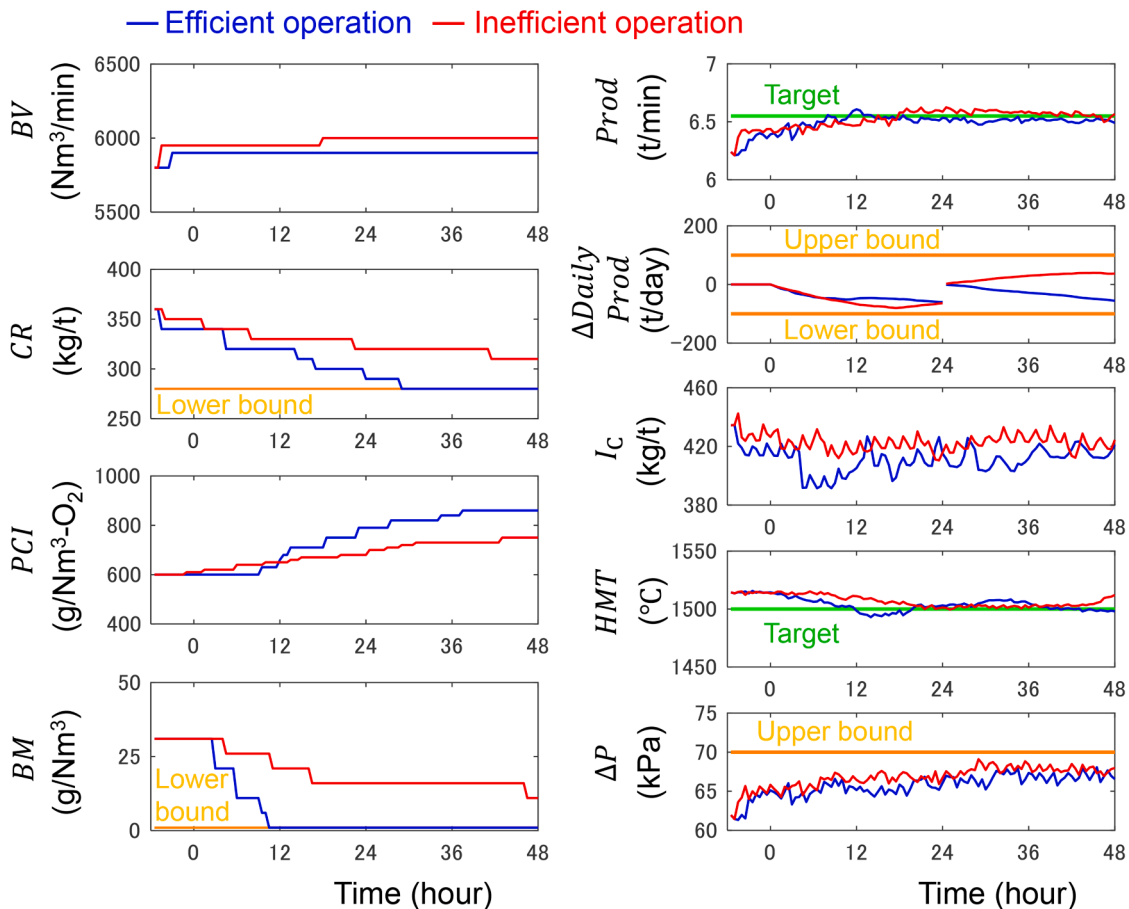


Fig. 7. Example of operation (simple scenario).

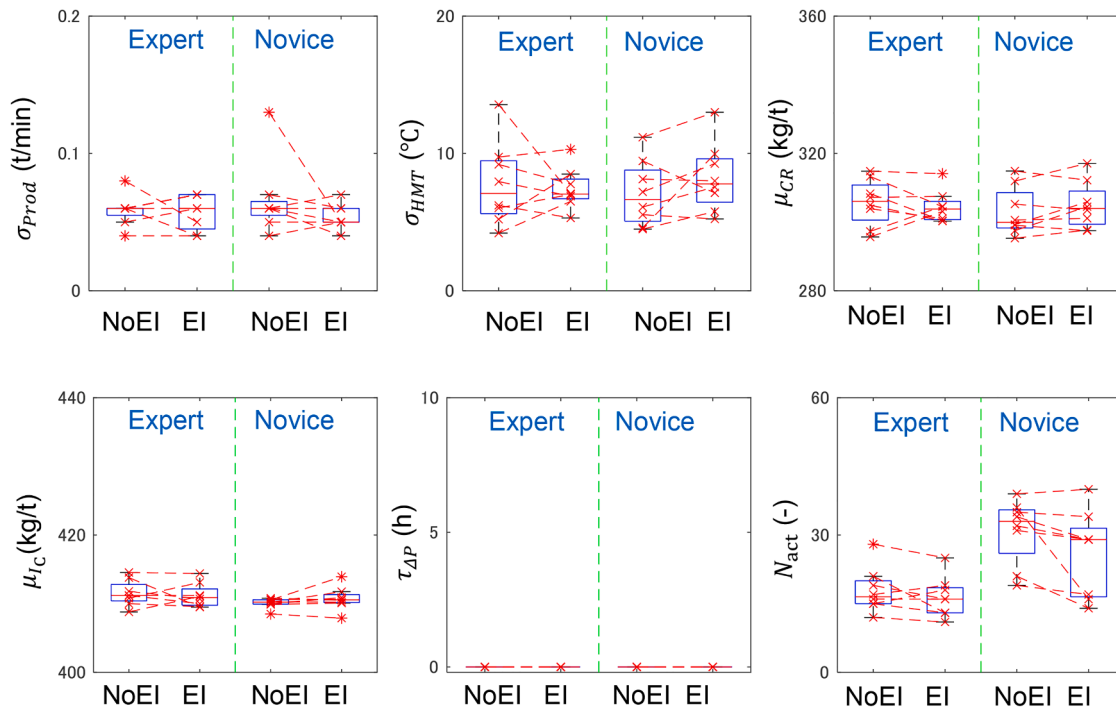


Fig. 8. Differences in dependent measures between EI and NoEI conditions (simple scenario).

represent an example of inefficient operation with higher coke rate and carbon intensity.

In both operations, the initial values started from a point where HMT=1515 °C, which is higher than the target, and Prod=6.3 t/min, which is lower than the target. The CR is decreased to reduce the production costs, which subsequently causes HMT to drop. Thus, the BM is reduced and the PCI is increased to maintain the constant HMT. Furthermore, BV is adjusted to maintain Prod near the target value, and the daily Prod remains within the target range. Although ΔP tends to increase as CR is reduced, it has been maintained below the upper limit.

Compared to the inefficient operation (red curves), the efficient operation (blue curves) achieves lower production costs by rapidly reducing the CR. Furthermore, in the efficient operation, the consumption of excess energy is reduced by quickly lowering the BM compared to the inefficient operation. This enables the operators to decrease CR and

PCI, thereby lowering the carbon intensity.

3.2. Effects of EI and expertise on operation performance (simple scenario)

Fig. 8 shows the differences in the dependent measures between the EI and NoEI conditions for the expert and novice groups. In both groups, the use of EI was associated with a reduction in the number of control actions, while no clear differences were observed for the other performance metrics.

To quantify the effects of EI, expertise, and their interaction, linear mixed-effects models (LMMs) were applied to each dependent measure other than the ΔP violation duration. The results are summarized in Table 6. A significant marginal effect of EI was observed only for the number of control actions (Estimate = -3.188 , 95% CI $[-5.699$,

Table 6
Results of LMM analysis (simple scenario).

	Coefficient	Estimate	95% CI	F (df1,df2)	p	Holm-adjusted p
σ_{Prod}	Marginal EI effect	-0.0069	[-0.0181, 0.0043]	1.58 (1,28)	0.21	0.656
	Expertise effect at NoEI	-0.0075	[-0.0235, 0.0085]	0.92 (1,28)	0.34	-
	EI $\times$ Expertise interaction	+0.0113	[-0.0111, 0.0336]	1.06 (1,28)	0.31	1.00
σ_{HMT}	Marginal EI effect	+0.405	[-0.860, 1.670]	0.43 (1,28)	0.52	1.00
	Expertise effect at NoEI	+0.679	[-1.63, 2.99]	0.36 (1,28)	0.55	-
	EI $\times$ Expertise interaction	-1.4975	[-4.03, 1.03]	1.46 (1,28)	0.23	1.00
μ_{CR}	Marginal EI effect	+0.35	[-2.125, 2.825]	0.08 (1,28)	0.77	1.00
	Expertise effect at NoEI	+2.69	[-3.456, 8.836]	0.80 (1,28)	0.38	-
	EI $\times$ Expertise interaction	-3.185	[-8.134, 1.765]	1.73 (1,28)	0.19	1.00
μ_{IC}	Marginal EI effect	+0.159	[-0.679, 0.999]	0.15 (1,28)	0.70	1.00
	Expertise effect at NoEI	+1.425	[-0.085, 2.935]	3.73 (1,28)	0.065	-
	EI $\times$ Expertise interaction	-0.973	[-2.652, 0.705]	1.41 (1,28)	0.24	1.00
N_{act}	Marginal EI effect	-3.188	[-5.699, -0.676]	6.758 (1,28)	0.014	0.0147
	Expertise effect at NoEI	-13.000	[-19.47, -6.533]	16.95 (1,28)	0.000306	-
	EI $\times$ Expertise interaction	+3.375	[-1.648, 8.398]	1.894 (1,28)	0.1796	1.00

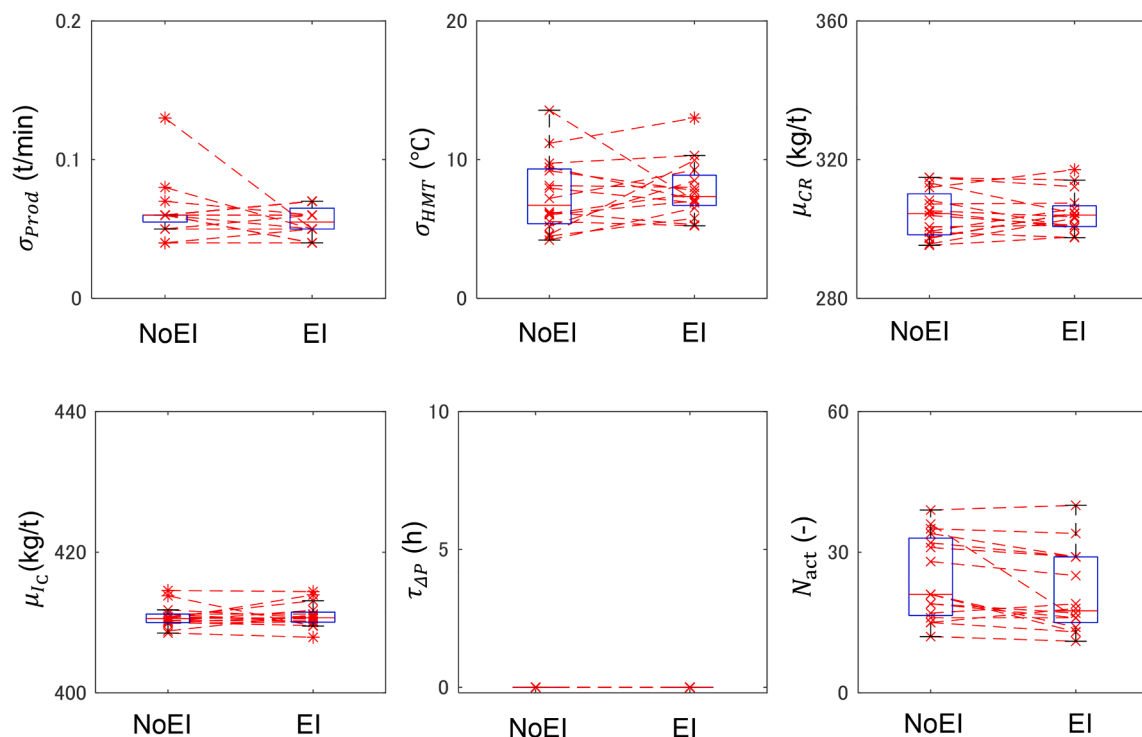


Fig. 9. Difference in dependent measures between EI and NoEI conditions. (simple scenario, all subjects).

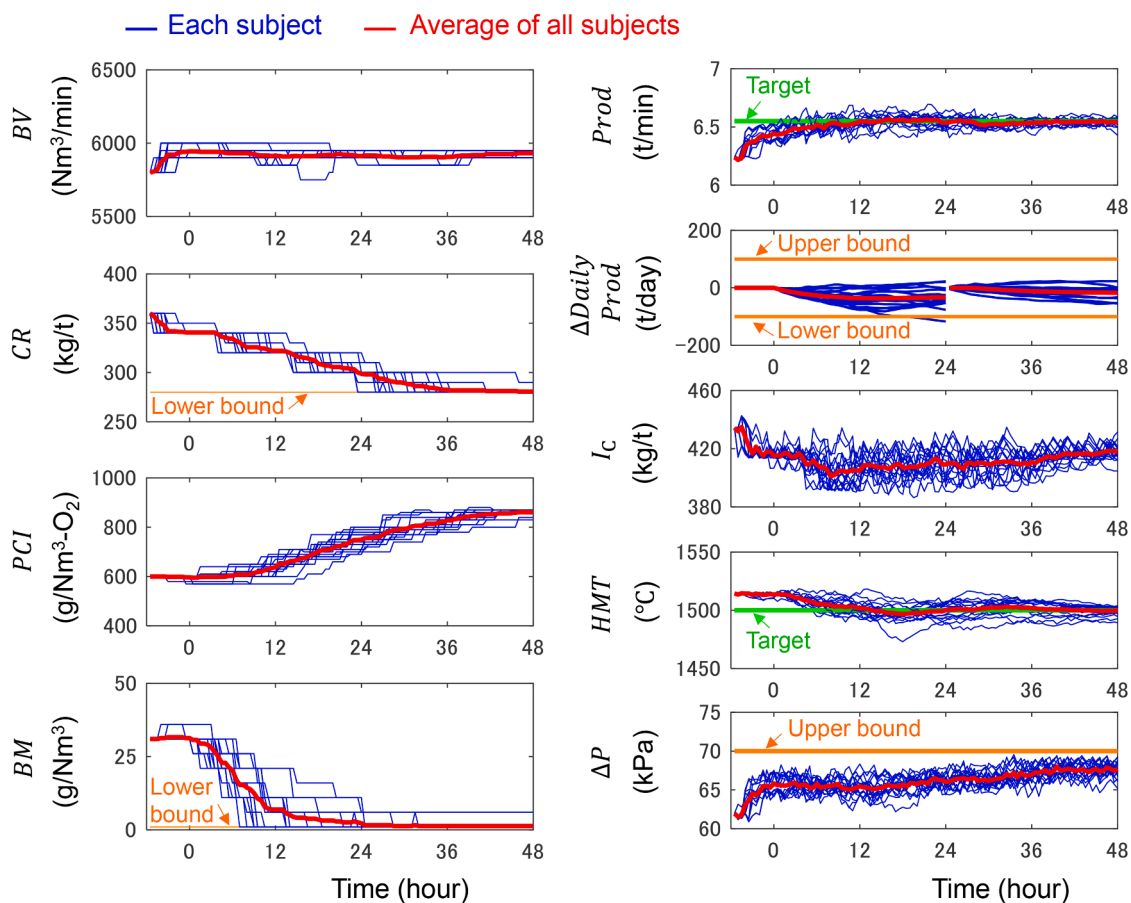


Fig. 10. Trends of manipulated and controlled variables in simple scenario. (EI condition, data for all subjects).

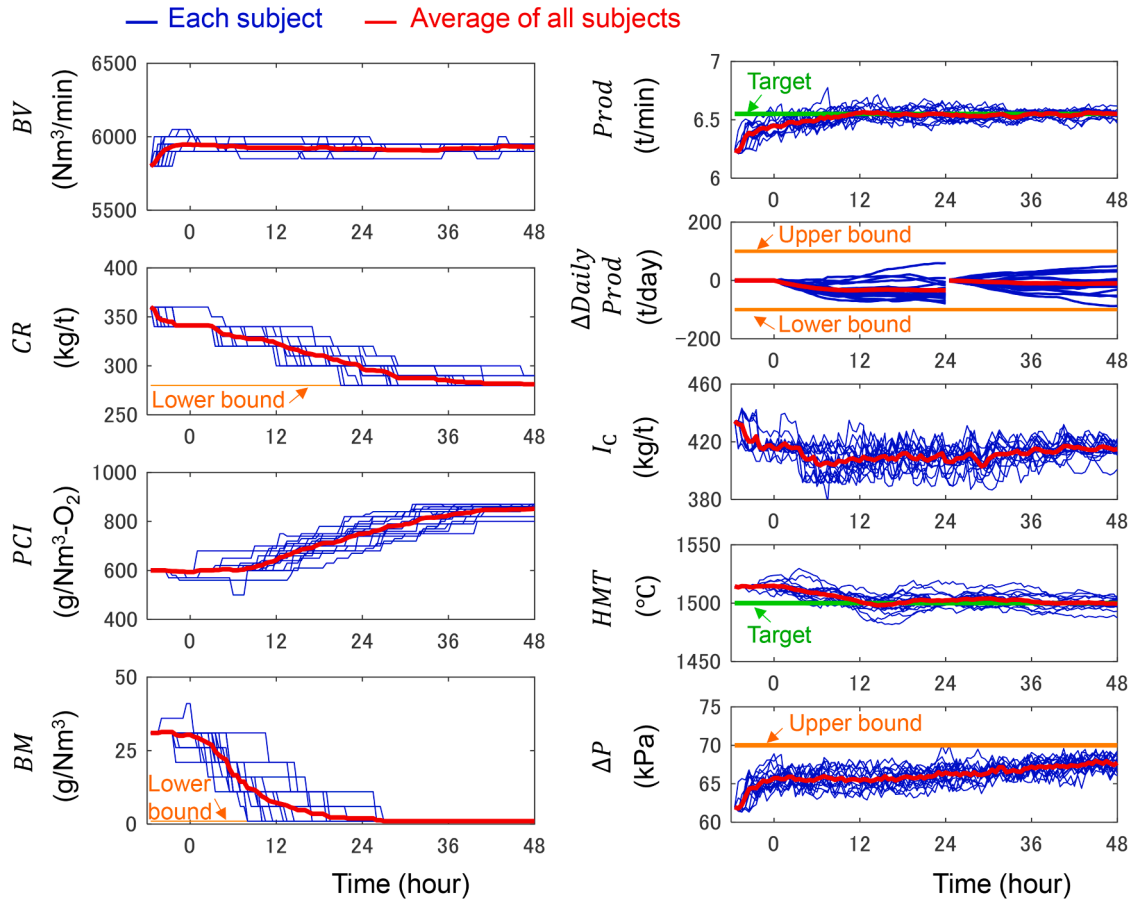


Fig. 11. Trends of manipulated and controlled variables in simple scenario. (NoEI condition, data for all subjects).

$-0.676]$, $F(1, 28) = 6.758$, Holm-adjusted $p = 0.0147$), indicating that EI reduced control activity in the simple scenario. No statistical test was performed for the ΔP violation duration because all participants had zero violations in both the EI and NoEI conditions. No statistically significant EI $\times$ Expertise interaction was observed among the measures evaluated for H5, indicating that no expertise-dependent EI effect was identified in the simple scenario. Finally, an exploratory expertise effect at NoEI was observed for the number of control actions (Estimate = -13.0 , 95% CI $[-19.47, -6.53]$, $F(1, 28) = 16.95$, $p < 0.001$), indicating that experts performed fewer control actions than novices in the NoEI condition.

3.3. Overall trends in operation performance (simple scenario)

Fig. 9 presents the aggregated dependent measures across all participants to illustrate the overall trends between the EI and NoEI conditions. The statistical inferences are based on the LMM analysis summarized in Table 6. Consistent with the LMM results, the most noticeable difference was observed in the number of control actions, whereas no clear differences were observed in the other performance metrics. No ΔP violations occurred in either condition.

Figs. 10 and 11 show the trajectories of the manipulated and

controlled variables in the EI and NoEI conditions, respectively. The thin blue curves show the data for each of the 16 subjects, while the thick red curves show the average data across all subjects. Focusing on the CR and PCI data, the trajectories in the EI condition are more tightly clustered compared to those in the NoEI condition. This observation is consistent with a tendency toward reduced between-subject variability when using EI.

3.4. Typical operation results (complex scenario)

Fig. 12 shows the examples of stable and unstable operations in the complex scenario, indicated by the blue and the red curves, respectively. The two cases were selected to illustrate contrasting responses to the production-target increase, with one case maintaining ΔP below its upper bound and the other experiencing ΔP upper-bound violation. In this scenario, the target production rate was increased at 24 h. In the stable operation (blue curves), the subject increased BV around 22 h before the target Prod increased, without excessively lowering the CR to avoid exceeding the ΔP upper bound. This maneuver allowed immediate settlement in the new steady state, with no further control actions required after 30 h. In contrast, the unstable operation (red curves) shows that forcing an excessive decrease in CR caused ΔP to approach its

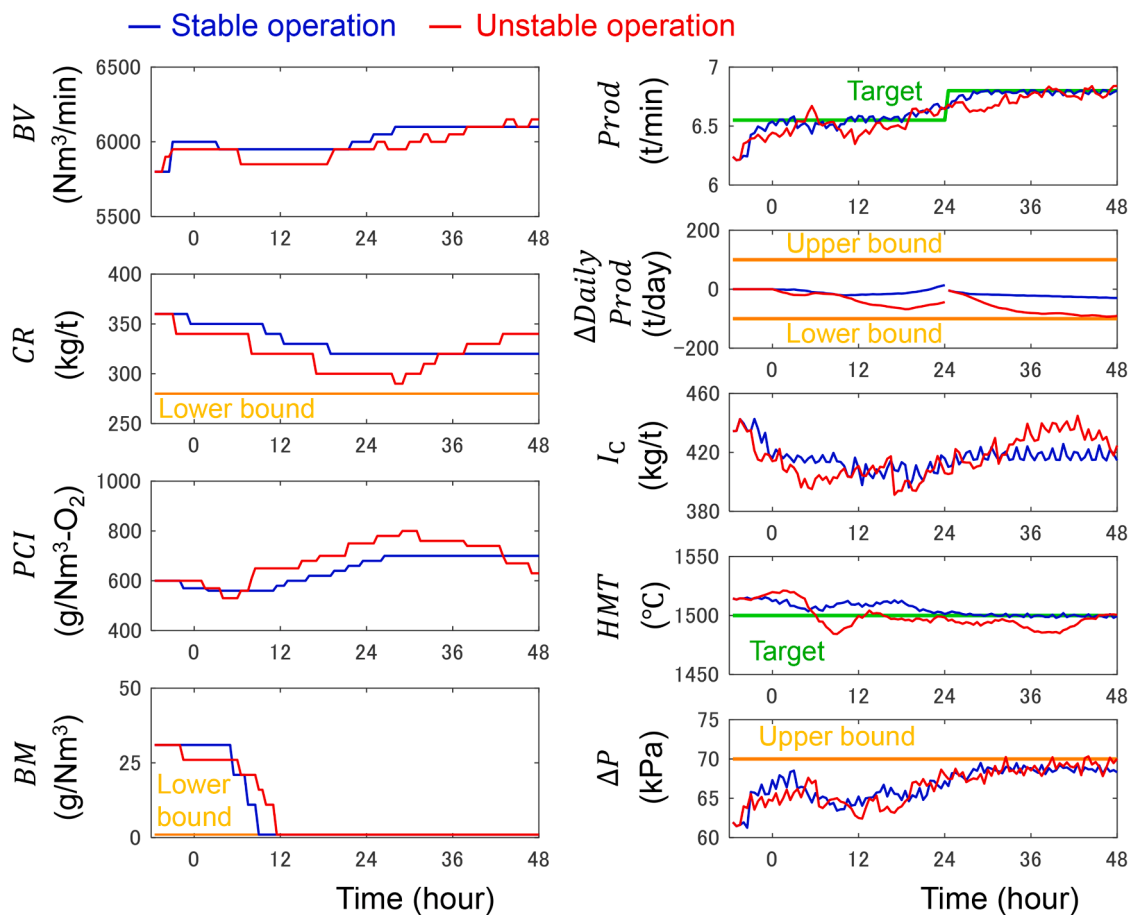


Fig. 12. Example of operation (complex scenario).

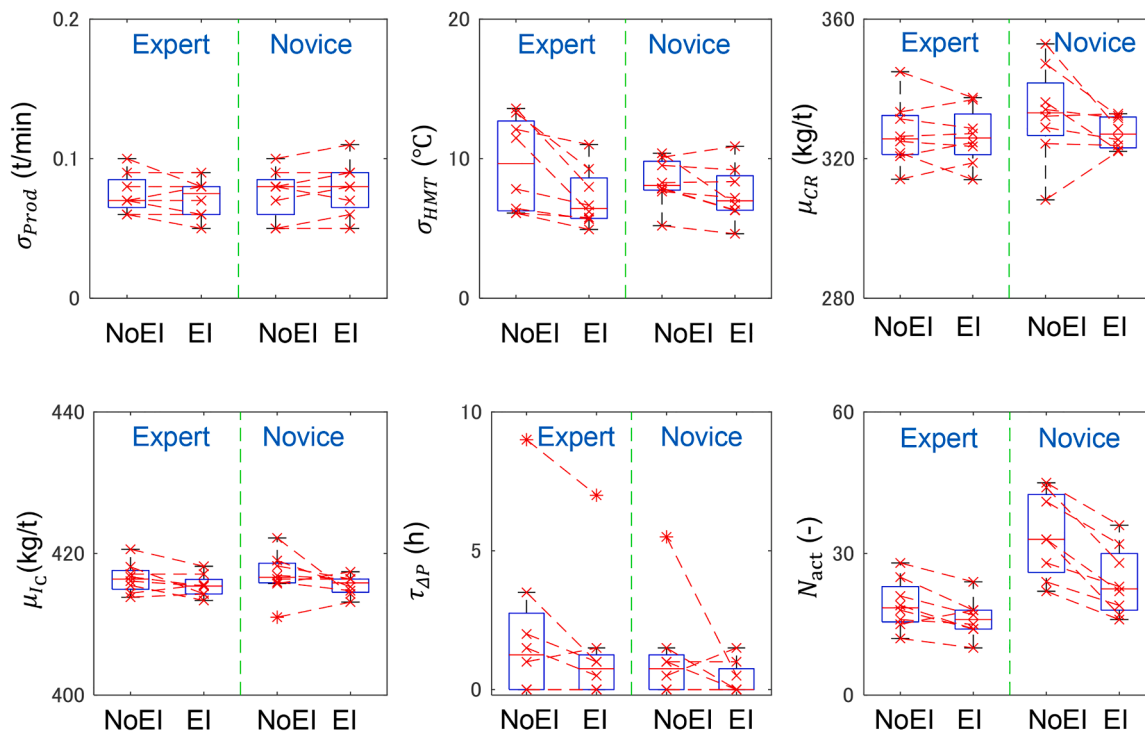


Fig. 13. Differences in dependent measures between. EI and NoEI conditions (complex scenario).

Table 7

Results of LMM analysis (complex scenario).

	Coefficient	Estimate	95% CI	$F(df1, df2)$	p	Holm-adjusted p
σ_{Prod}	Marginal EI effect	0.000	[-0.0040, 0.0040]	0.00 (1,28)	1.00	1.00
	Expertise effect at NoEI	0.000	[-0.0155, 0.0155]	0.00 (1,28)	1.00	-
	EI $\times$ Expertise interaction	-0.0075	[-0.0155, 0.0005]	3.692 (1,28)	0.065	0.649
σ_{HMT}	Marginal EI effect	-1.667	[-2.532, -0.801]	15.54 (1,28)	0.00049	0.00196
	Expertise effect at NoEI	+1.258	[-0.986, 3.504]	1.319 (1,28)	0.261	-
	EI $\times$ Expertise interaction	-1.526	[-3.258, 0.206]	3.258 (1,28)	0.082	0.737
μ_{CR}	Marginal EI effect	-3.201	[-7.509, 1.108]	2.315 (1,28)	0.139	0.418
	Expertise effect at NoEI	-5.816	[-14.945, 3.312]	1.703 (1,28)	0.203	-
	EI $\times$ Expertise interaction	+4.831	[-3.786, 13.449]	1.319 (1,28)	0.261	1.00
μ_{IC}	Marginal EI effect	-1.253	[-2.479, -0.0264]	4.378 (1,28)	0.0455	0.182
	Expertise effect at NoEI	-0.388	[-2.494, 1.716]	0.143 (1,28)	0.708	-
	EI $\times$ Expertise interaction	+0.331	[-2.122, 2.785]	0.077 (1,28)	0.784	1.000
N_{act}	Marginal EI effect	-6.312	[-8.141, -4.484]	50.03 (1,28)	1.07×10^{-7}	2.15×10^{-7}
	Expertise effect at NoEI	-14.50	[-20.853, -8.147]	21.86 (1,28)	6.74×10^{-5}	-
	EI $\times$ Expertise interaction	+6.625	[2.969, 10.281]	13.78 (1,28)	9.04×10^{-4}	0.00995

upper bound around 32 h. Despite a significant negative control deviation from the target Prod, increasing the BV to compensate for the control deviation became difficult due to the high ΔP situation. Although the CR was increased after 30 h to decrease ΔP , this control action had a limited immediate effect due to the time required for the material to travel within the furnace. Consequently, ΔP exceeded the upper bound for three hours, leading to an increase in the number of control actions such as adjusting the BV and PCI. Hence, to achieve stable operation, it is crucial to determine the required BV for the target production rate beforehand and then quickly derive the optimal CR that keeps the ΔP below the upper bound.

3.5. Effects of EI and expertise on operation performance (complex scenario)

EI and NoEI conditions in the complex scenario, with the results stratified for the expert and novice groups. In both groups, the use of EI was associated with a reduction in the number of control actions. Compared with the expert group, the novice group tended to perform a larger number of control actions and exhibited a larger reduction in control actions when using EI. No clear intergroup differences were observed for the other performance metrics.

To quantify the effects of EI, expertise, and their interaction, linear mixed-effects models (LMMs) were applied to each dependent measure other than the ΔP violation duration. The results are summarized in Table 7. Significant marginal effects of EI were observed for the HMT control error (Estimate = -1.667, 95% CI [-2.532, -0.801], $F(1, 28) = 15.54$, Holm-adjusted $p = 0.00196$) and the number of control actions (Estimate = -6.312, 95% CI [-8.141, -4.484], $F(1, 28) = 50.03$, Holm-adjusted $p = 2.15 \times 10^{-7}$), indicating that EI reduced the HMT control error and control activity in the complex scenario.

Fig. 13 shows the differences in the dependent measures between the

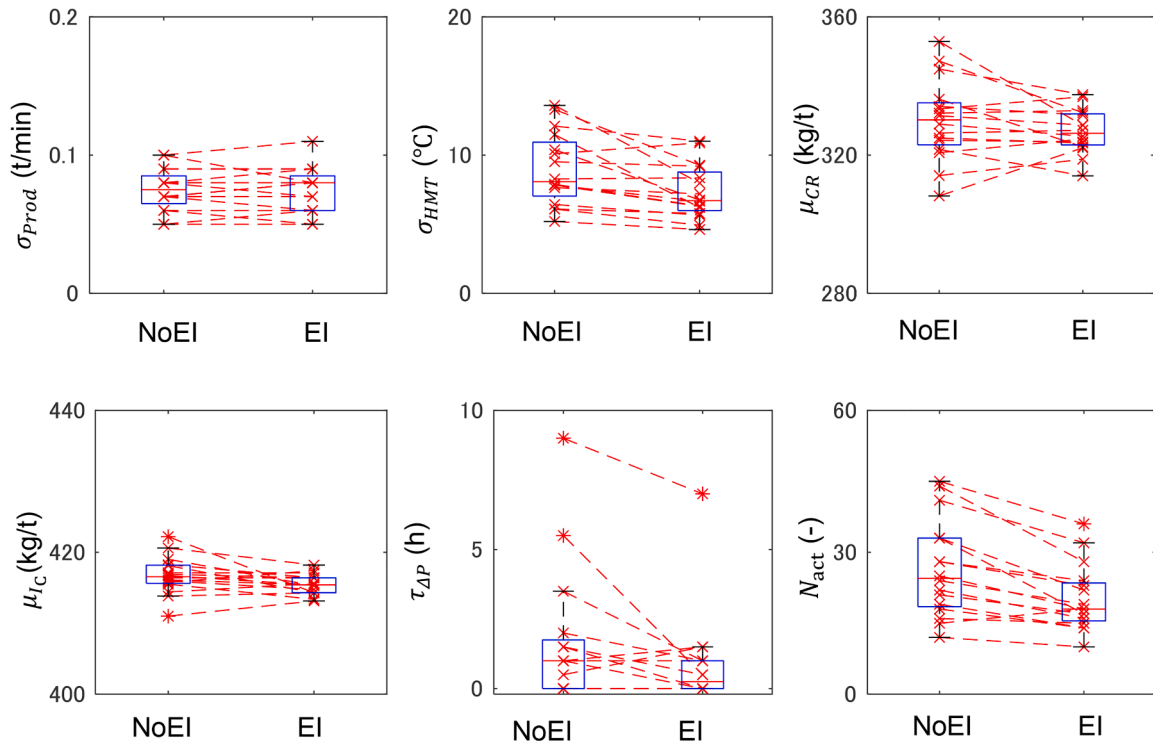


Fig. 14. Differences in dependent measures between. EI and NoEI conditions (complex scenario, all subjects).

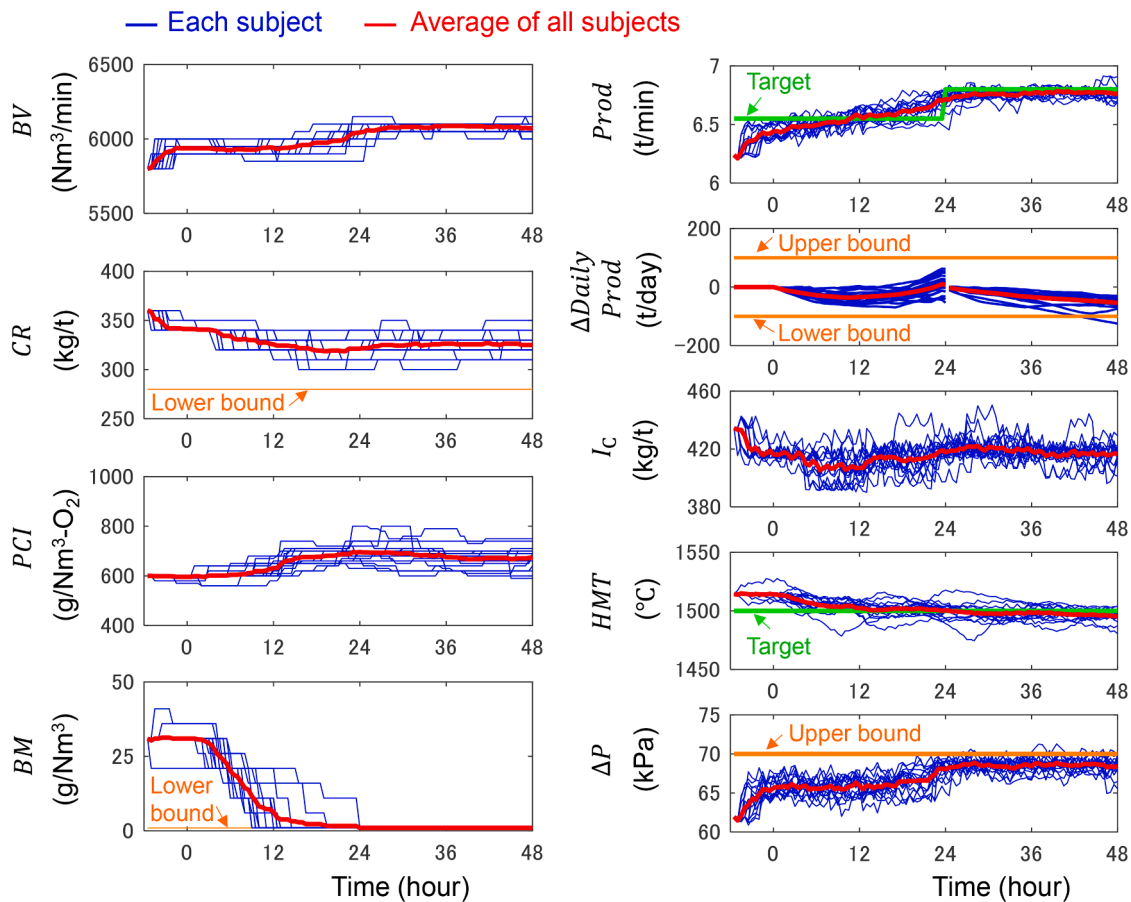


Fig. 15. Trends of manipulated and controlled variables in complex scenario (EI condition, data for all subjects).

For $\tau_{\Delta P}$, because the distribution was strongly zero-inflated and bounded, the confirmatory test for H3 was performed using a Wilcoxon signed-rank test. The duration of ΔP upper-bound violations was significantly lower in the EI condition (median = 0.25 h, IQR = 1.00 h) than in the NoEI condition (median = 1.00 h, IQR = 1.75 h; $W = 40.5$, $p = 0.039$). Since H3 contained only one applicable comparison, the Holm-adjusted p -value was also 0.039.

Among the measures evaluated for H5, a significant EI $\times$ Expertise interaction was observed only for the number of control actions in the complex scenario (Estimate = 6.63, 95% CI [2.97, 10.28], $F(1, 28) = 13.78$, Holm-adjusted $p = 0.00995$), indicating that the reduction in control activity due to EI was larger for novices than for experts. Finally, an exploratory expertise effect at NoEI was observed for the number of control actions (Estimate = -14.5, 95% CI [-20.85, -8.15], $F(1, 28) = 21.86$, $p < 0.001$), indicating that experts performed fewer control actions than novices in the NoEI condition.

3.6. Overall trends in operation performance (complex scenario)

Fig. 14 presents the aggregated dependent measures across all participants to illustrate the overall trends between the EI and NoEI conditions in the complex scenario. The statistical inferences are based on the confirmatory analyses reported in Section 3.5 and Table 7. Consistent with these results, the most noticeable difference was observed in the number of control actions. Significant reductions were also observed in the HMT control error and the duration of ΔP upper-bound violations.

Reductions in the coke rate and carbon intensity were observed numerically, but these differences were not statistically significant after Holm correction.

Figs. 15 and 16 show the transitions of manipulated variables and controlled variables in the EI and NoEI conditions, respectively. Focusing on CR and BV manipulations, variability among the subjects decreased on the second day using the EI. This is likely because, as discussed in Section 3.4, when the target Prod was increased, the subjects successfully derived the required BV to achieve the target Prod while simultaneously identifying an appropriate CR to avoid exceeding the ΔP upper bound. From 24 h to 36 h, instances of mistakenly decreasing the CR were frequently observed in the NoEI condition. This control action increases the number of times the ΔP upper bound is exceeded, resulting in unstable operation characterized by frequent BV decreases to avoid the ΔP upper bound and BV increases to achieve the daily Prod. In addition to CR manipulation, the presence of the EI enabled an earlier reduction in BM, which contributed to the overall reduction in carbon intensity.

Prioritizing operation cost reduction to lower CR typically increases ΔP , raising the risk of violating its upper bound. In other words, a trade-off must be found between economic efficiency and the furnace process stability. Fig. 17 shows a scatter plot of the two metrics. A negative correlation is evident, illustrating the trade-off. Furthermore, the data with EI shows a shift toward higher stability compared to the data without EI, suggesting the effectiveness of the developed decision support system.

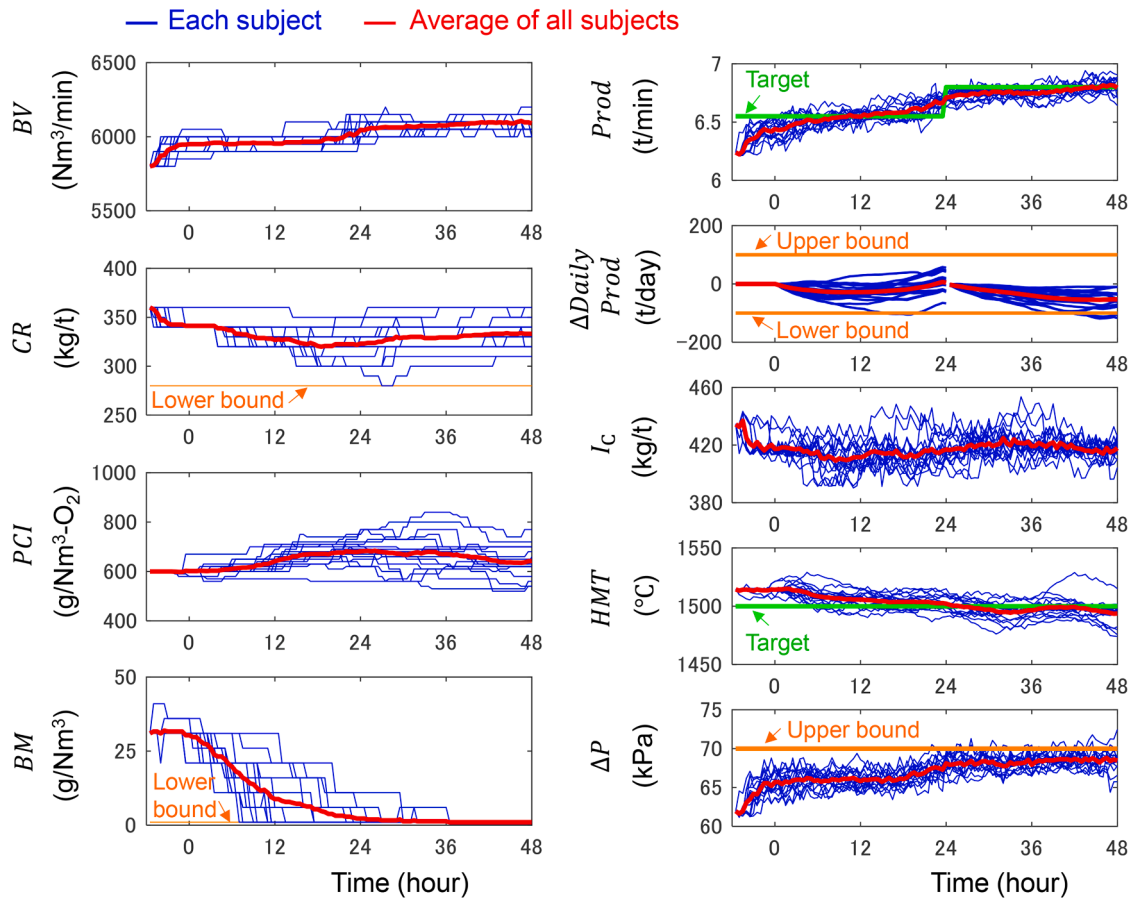


Fig. 16. Trends of manipulated and controlled variables in complex scenario (NoEI condition, data for all subjects).

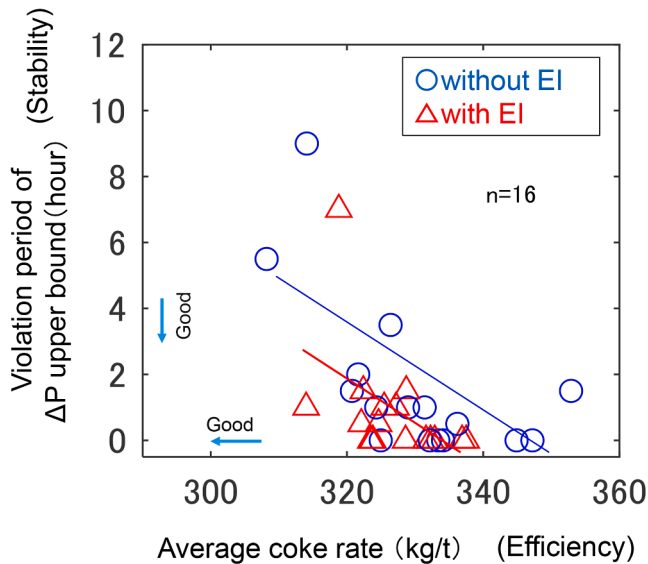


Fig. 17. Trade-off between efficiency and stability (all subjects).

4. Discussion

4.1. Interpretation of hypotheses H1-H5

The extent of possible operation improvement achieved through EI was investigated in this study. This section examines the hypotheses H1 through H5 presented in Section 2.2.4 and discusses the reasons behind

the results obtained.

Regarding H1, a significant reduction in HMT control error was observed only in the complex scenario. No significant reduction was found for Prod control error or for either control error in the simple scenario. Therefore, H1 was partially supported by the present results. Operationally, the 1.67 °C reduction in HMT RMS control error represents a meaningful improvement in HMT regulation and is comparable in magnitude to reductions reported in previous blast furnace control studies (Hashimoto et al., 2019c; Masuda et al., 2023). This result indicates a potential benefit of EI for thermal control in the complex scenario examined here. One possible explanation is that HMT is more strongly influenced by the thermal inertia of the blast furnace than Prod. The effects of control actions on HMT appear only after a considerable delay, making thermal control inherently more difficult. Consequently, the additional predictive information provided by the EI may be more beneficial for anticipating future thermal responses than for controlling production rate. Furthermore, the complex scenario required more demanding control maneuvers than the simple scenario, including changes in the direction of CR manipulation following the production-target increase. The predictive information provided by the EI may have assisted operators in managing these control maneuvers in this scenario.

Regarding H2, no statistically significant reductions in the coke rate or carbon intensity were identified after Holm correction. Therefore, H2 was not formally supported by the present results. However, both variables showed numerical reductions in the complex scenario, suggesting a potential improvement in operating efficiency when EI was available. One possible explanation is that the what-if prediction enabled operators to evaluate the future impact of control actions before implementation. This may have facilitated operating strategies that

simultaneously considered production targets, thermal control, and permeability constraints. In addition, the trajectories shown in Figs. 15 and 16 descriptively suggest a tendency toward reduced variability in coke-rate manipulation among subjects when EI was available. Although the reductions in coke rate and carbon intensity were not statistically significant after Holm correction, these descriptive trends suggest a potential benefit of EI for operating efficiency in the complex scenario.

Regarding H3, the duration of ΔP upper-bound violations was significantly reduced by the use of EI in the complex scenario, as indicated by the Wilcoxon signed-rank test. Therefore, H3 was supported in the complex scenario. In the simple scenario, H3 could not be statistically evaluated because no ΔP violations occurred in either condition. Operationally, reducing the duration of excessive ΔP is important because sustained high pressure drop can disturb burden descent and increase the risk of serious operational disturbances, such as hot gas blowouts. Thus, reducing ΔP violations can contribute to maintaining a more stable furnace condition. As discussed in Section 3.4, stable operation requires operators to determine the required BV for the target production rate while simultaneously identifying an appropriate CR that prevents ΔP from exceeding its upper bound. In the complex scenario, the additional predictive information provided by the EI may have assisted operators in this procedure. In addition, the shift toward higher stability observed in Fig. 17 is consistent with this interpretation. These results suggest a potential benefit of EI for maintaining stable operation in the complex scenario examined here.

Regarding H4, the number of control actions decreased significantly in both the simple and complex scenarios when the EI was available. Therefore, H4 was supported, confirming that the use of the EI reduces operators' control activity. One possible explanation is that operators could evaluate the consequences of potential control actions through the what-if prediction before implementing them. However, because the what-if prediction and the mass and energy balance visualization were introduced simultaneously, the present experiment cannot distinguish their individual contributions. In addition, the reduction in implemented control actions should not necessarily be interpreted as an equivalent reduction in cognitive workload. With the EI, operators could perform part of their trial-and-error exploration through the what-if prediction without affecting the simulated process, whereas without the EI such exploration had to be carried out through actual control actions.

Regarding H5, a significant EI $\times$ Expertise interaction was observed only for the number of control actions in the complex scenario. Thus, H5 was supported only for control activity in this scenario. The novice group tended to achieve the control targets through frequent small control actions. The EI enabled these operators to evaluate the consequences of control actions before implementation and to perform fewer, larger adjustments. Consistent with this interpretation, the reduction in control activity was significantly greater for novices than for experts.

Although several statistically significant effects were identified, the relatively small sample size ($n = 16$, comprising eight experts and eight novices) may have limited the statistical power and precision of the present study. Several variables showed favorable trends without reaching statistical significance. This sample-size constraint was primarily due to the limited availability of experienced blast furnace experts.

In summary, the results suggest that the developed EI can improve specific aspects of blast furnace operation. The most consistent effect was a reduction in control activity, which was observed in both the simple and complex scenarios. In the complex scenario, significant reductions were also observed in the HMT control error and the duration of ΔP upper-bound violations. Furthermore, the reduction in control activity was significantly greater for novice operators than for experts in the complex scenario. In contrast, no statistically significant improvements were identified for coke rate or carbon intensity after Holm correction. Overall, considering the limited number of subjects, the present results suggest that the developed EI is a promising decision-

support tool for supporting operator control, particularly in the complex scenario examined in this study.

4.2. Limitations and future work

The limitations of the developed EI and the issues to be overcome in future work are as follows. Firstly, a primary limitation of the present experiment is that the what-if prediction and the ecological visualization of the mass and energy balances were manipulated together. This was because the small sample size limited the number of experimental conditions that could be included. Therefore, the present experiment evaluates the effectiveness of the integrated interface as a whole and cannot determine the individual contribution of either component. In particular, because predictive preview is not unique to EID, part of the observed improvement may be attributable to the what-if prediction itself rather than to the ecological visualization. Future work will investigate these effects independently.

Secondly, although the EI was designed to support operators' situation awareness by explicitly presenting the relationships between manipulated and controlled variables, together with their predicted future states, situation awareness itself was not directly measured in the present experiment. Therefore, the observed improvements in operation performance should not be interpreted as direct evidence of improved situation awareness. Future work should directly evaluate whether the EI improves situation awareness using established situation-awareness measures.

Thirdly, the linear approximation used in the what-if analysis with the step responses may not be accurate when multiple manipulated variables are changed in larger operation amounts simultaneously. Explicitly accounting for this nonlinearity is a topic for future work.

Fourthly, the transient model lacks the capability to simulate abnormal operating conditions (Hashimoto et al., 2022b). It assumes that the materials descend smoothly inside the furnace, which is not the case under high-pressure drops that hinder the smooth burden descent. The authors aim to overcome these issues and evaluate the effectiveness of the developed EI in actual blast furnaces, including abnormal conditions.

Lastly, another limitation is the accelerated time scale used in the experiment. Although the same acceleration was applied to both the EI and NoEI conditions, compressing 54 h of operation into approximately 11 min may affect participants' time perception, monitoring behavior, and decision-making, thereby limiting the ecological validity of the experiment. Therefore, the present results should be interpreted as demonstrating the effectiveness of the EI under accelerated simulator conditions, and further validation under real-time or actual operating conditions is needed.

5. Conclusions

An ecological interface (EI) for blast furnaces in the steel industry was developed to achieve efficient and stable operation while maintaining human operators' skills. The developed EI consists of what-if prediction and the ecological visualization of mass and energy balances. An operational training simulator incorporating the developed EI was built to simulate dynamic blast furnace operation. An experiment was conducted with 16 subjects (8 experts and 8 novices) to verify the effectiveness of the EI across two accelerated-time scenarios representing 54 h of simulated blast furnace operation, with different operation complexity levels.

Results show that the most consistent effect of the EI was a reduction in operators' control activity, as measured by the number of control actions. This effect was observed in both scenarios and was significantly greater for novice operators than for experts in the complex scenario. In the complex scenario, significant reductions were also observed in the HMT control error and the duration of ΔP upper-bound violations. In contrast, no statistically significant improvements were identified for

the coke rate or carbon intensity after Holm correction. Overall, the results suggest that the developed EI is a promising decision-support tool that can facilitate more effective operator control while keeping human operators in the loop.

CRedit authorship contribution statement

Yoshinari Hashimoto: Writing – original draft, Visualization, Validation, Methodology, Conceptualization. **Ryosuke Masuda:** Methodology. **Satoki Yasuhara:** Methodology. **Max Mulder:** Writing – original draft, Supervision. **Marinus M. (René) van Paassen:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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