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ORIGINAL ARTICLE

Why slow down? Factors affecting speed loss in process manufacturing

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Abstract
Loss of production speed is an unavoidable reality for process manufacturers. Reduced production speeds are shown to consume 9–15% of available production capacity in various production contexts and create substantial costs for capital-intensive process industries. Amongst the least examined of the six big efficiency losses measured within total productive maintenance, speed loss presents significant opportunities for potential efficiency improvements in manufacturing companies. Based on the literature, this paper presents a framework of the factors related to speed loss, including three overall dimensions: technology factors, human factors and product factors. Next, a case study of two production lines to investigate this framework and quantify the scale of speed loss for the factors identified in the case study. For quantification, generalised least squares regression is performed to study the relationship between each factor and speed loss. The analysis of the production data reveals that technology and human factors have the strongest correlations with speed losses in this industry and account for the most speed loss. This research can directly support operational improvement initiatives in practice by identifying the factors with the strongest relationships to speed loss, aiding practitioners to select the most relevant means to improve speed and identify appropriate overall equipment effectiveness targets.

Keywords Speed loss · Total productive maintenance · Overall equipment effectiveness · Productivity · Process industry

1 Introduction

Speed loss is an expensive, technical reality for large-scale, complex production processes. Formally identified as a source of lost capacity by Nakajima [1] in the total productive maintenance (TPM) methodology, speed loss is any deviation from the designed production speed or throughput in a manufacturing context caused by rough running, equipment wear, tool wear and operator inefficiency, amongst other factors [2]. Running at reduced speed can silently reduce the capacity of production lines, impacting service levels in capacity-constrained situations and eroding efficiencies in situations of surplus capacity. Reduced production speeds are shown to consume 9–15% of available capacity in cases in the literature [3, 4]. Furthermore, reduced capacity from reduced production speeds is expected to be higher in the large, automated production and packaging systems characteristic of process manufacturing [3, 5]. For large-scale process manufacturing lines with millions of euros of annual revenue, increasing speed efficiency in production by only 1% can give firms competitive cost advantages over other players in the market [6].

Capacity losses due to reduced speed, though, are often overlooked by management and are not prioritised due to (1) a mindset which sees some speed loss as allowable and (2) to the difficulty of eliminating speed loss [7, 8]. When optimising maintenance tasks, factory management and maintenance departments tend to focus on the more pressing demands of large production stop times than the smaller,

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persistent losses from variations in run rate [3, 8]. Speed loss is also difficult to notice in production as familiarity with the process can hinder operators' ability to detect deviations in speed [8], and unambitious speed targets keep factories from achieving their maximum potential speed [3].

Many companies have not been able to calculate the precise magnitude of speed loss due to poor data registration [3, 4, 9]. Difficulties in data collection partly stem from the chronic nature of speed loss as a production disturbance. Unlike sporadic disturbances easily recognisable as large deviations from the normal state, chronic disturbances are usually small, numerous, hidden and complicated; have many concurrent causes; and are often regarded as normal [10].

Considering the chronic nature of speed loss and the difficulties addressing its causes, the operations management and TPM literature lacks solutions specifically addressing speed loss [8]. Furthermore, the TPM literature includes limited quantification of speed loss and even less work guiding the identification of factors and quantifying factors' relative effects, particularly for process industry manufacturers (e.g. producers of food, oil, gas, chemical, metals and commodity materials). Lastly, there is no discussion on the possibility of minimum expected speed losses for different operations based on the process technology, process variability and other factors unique to individual production settings. This information could aid operations managers in driving improvement initiatives, helping them discern potential speed improvements that could be realised through standardisation, capital expenditures and technological advancements.

This article contributes to the TPM and operations management literature with a framework of speed loss factors and a study examining actual speed loss for two production lines, a measure often unquantified in overall equipment effectiveness (OEE) studies due to the difficulty of data collection. Additionally, the study examines the mechanical underpinnings of speed loss on process manufacturing equipment, the factors that may impact this speed loss and the relative effects of each identified factor. To the best of the researchers' knowledge, this study presents the first comprehensive examination of possible factors leading to speed loss and the first application of regression analysis to quantify speed loss related to each factor in a case of two production lines.

The research question used to guide this investigation of speed loss is: *How do different factors affect speed loss on production lines?*

The study is structured as follows. First, a review of the literature discussing OEE, speed loss and factors related to speed loss is presented. On this basis, a framework of speed loss factors is constructed. Next, a case study of two production lines is presented and analysed through regression analysis. The factors identified in the case study are presented and used to build a generalised least squares (GLS) regression model, which is interpreted and discussed. Strong evidence is found of associations of speed loss with (1) technological factors and (2) human factors related to management decisions. Finally, conclusions are drawn, and avenues for future work are presented.

2 Literature review

2.1 Speed loss and overall equipment effectiveness

The use of speed loss as an operational performance measure has its roots in TPM, a methodology to maintain and improve equipment performance in manufacturing organisations developed by Nakajima [1]. The TPM methodology focuses on three main areas: maximisation of equipment effectiveness, operators' autonomous maintenance of equipment and the use of small group activities [5, 11]. OEE is defined as a measure of 'the ability to run equipment without failure, at the designed speed and with zero defects' [12] and is primarily used to prioritise efficiency improvements in manufacturing [7].

To maximise equipment effectiveness, Nakajima [1] defines six big losses in OEE that should be quantified and reduced. The six big losses are subdivided into three categories as follows:

Availability losses (A)

1. Equipment breakdown, causing reduced productivity or waste in defective products
2. Setup and adjustment losses

Performance losses (P)

3. Idling and minor stops due to interruptions or temporary malfunction
4. Speed loss from reduced run rates, measured as the difference between the equipment's designed speed and operating speed

Quality losses (Q)

5. Defects and rework
6. Start-up losses occurring in an early stage of production

OEE is calculated as shown in Eqs. 1–4 based on the method proposed by Nakajima [1]. Equation 2 for performance efficiency is written in an expanded form to reveal the two sub-calculations: (1) the ratio of production speeds; and (2) the calculation of small stops' impacts [11, 13]. The ratio of production speeds can be expressed as speed efficiency (Eq. 5), with its complement being speed loss (Eq. 6).

$$AE = \frac{Total\ time - Unplanned\ downtime}{Total\ time} \quad (1)$$

$$PE = \frac{Ideal\ cycle\ time}{Actual\ cycle\ time} \times \frac{Actual\ cycle\ time \times Output}{Operating\ time} \quad (2)$$

$$QE = \frac{Output - Quality\ defects}{Output} \quad (3)$$

$$OEE = AE \times PE \times QE \quad (4)$$

$$Speed\ efficiency = \frac{Ideal\ cycle\ time}{Actual\ cycle\ time} \quad (5)$$

$$Speed\ loss = 1 - \frac{Ideal\ cycle\ time}{Actual\ cycle\ time} \quad (6)$$

where

Total time	Operational time of equipment, excluding planned stops for holidays, maintenance and lack of orders
Unplanned downtime	Time when equipment is scheduled for production but is unable to produce
Ideal cycle time	Average theoretical processing rate of equipment for a given product mix
Actual cycle time	Weighted average processing rate for equipment with a given product mix
Output	Gross output of material produced by the equipment
Quality defects	Material rejected for not passing quality inspections

Nakajima [1] defines world-class performance in the OEE subcategories as availability efficiency (AE) of more than 90%, performance efficiency (PE) of more than 95% and quality efficiency (QE) of more than 99%, with the three measures multiplied to a world-class OEE of 84%. However, good OEE performance is argued to be industry-specific as OEE is influenced by external factors, such as material handling systems and inventory buffers [9, 13, 14]. For example, in a study of 23 companies, food and beverage companies are found to have a higher median OEE (74%) than other types of companies, while automated discrete production companies have the lowest OEE (59%) [9].

2.2 Previous speed loss studies

Whereas the magnitude of lost PE is known to be large, the magnitude of speed loss (and its complement, speed efficiency) is not directly calculated in many papers. Table 1 displays the PE of the case studies identified in the literature, with speed efficiency calculated in only two of the nine articles. PE varies from 54 to 100% across the nine studies while speed efficiency ranges from 85 to 91% in the two studies, which explicitly calculate it.

Table 1 Performance loss in OEE case studies detailing performance efficiency

Author	Company	Performance efficiency	Speed efficiency
Ahmad, Hossen and Ali [15]	Yarn producer, single process	80–89%	85–91%
Dal, Tugwell and Greatbanks [11]	Airbag producer, weaving department	85%	N/A
Hedman, Subramaniyan and Almström [9]	23 companies (7 food/beverage plants, 9 mechanical workshops, 4 discrete automated plants, 3 polymeric plants)	100% for 80% of companies	N/A
Jonsson and Lesshammar [7]	Construction vehicle producer, metal profiles manufacturer	85–94%	N/A
Ljungberg [3]	23 machinery systems	68%	91%
Morales Méndez and Rodriguez [16]	Auto-parts machining line	84%	N/A
Ohunakin and Leramo [17]	Beverage bottling facility	54–65%	N/A
Tsarouhas [2]	Pizza production line	80–97%	N/A
Tsarouhas [18]	Italian cheese production line	87%	N/A

N/A not available

2.3 Factors related to speed loss

Researchers and practitioners cite several reasons for reduced operating speed on manufacturing lines, including factors related to process technology, factory management, materials and quality, amongst other aspects (see Table 2). By design, the characteristics of process technology influence production speed. Mechanical and electrical issues, old age and high wear can cause machines to run below the ideal cycle time while operating [1, 2]. Unplanned maintenance stops are also known to affect speed loss as time is needed to bring production back to normal speed after unplanned stops [6]. While physical limitations are considered in determining the ideal cycle times for machines in the engineering stage, machinery may operate at less than ideal capacity due to further technological constraints (e.g. downstream bottlenecks) and environmental limitations placed on factories [19]. Depending on the technology, there might also be a natural level of variation in the speeds of machines which affects speed loss figures but which may be difficult to avoid [20].

Differences in crews, work standards, performance targets and the management of operators are also known sources of

Table 2 Publications discussing factors affecting the loss of production speed in manufacturing contexts

Speed loss factors	Publications discussing factors
Machine reliability and production stops	[2, 6, 17, 21]
Equipment age and wear	[1, 8]
Technological and environmental limitations	[11, 19, 22]
Natural process variation	[20]
Queue capacity for work in process	[23]
Operator training and inefficiency	[2, 8, 23, 24]
Improper maintenance	[1, 6, 8]
Measurement error	[11, 19, 25]
Ideal cycle time set too low	[1, 3, 7]
Production scheduling	[20, 22, 23, 26]
Capacity utilisation	[3, 21]
Material availability and quality	[8, 11, 19, 27]
Raw material mix	[27]
Quality (finished goods)	[1, 2, 28]
Product variety	[1, 21–23, 26]

variations in production speed [24] and are directly controllable by factory management. Beyond production, a lack of standard operating procedures for maintenance activities can contribute to technical issues, such as equipment malfunction, forcing operators to reduce production speed [1]. A further factor within management's discretion is the determination of ideal cycle times and speeds for equipment if no ideal cycle times are given in the equipment specifications. In industrial applications of OEE, speed loss is found to be negative in certain instances, implying that ideal speeds are often set too low for certain processes [3].

Production scheduling and sequencing, often under the influence of factory management, are shown to be significant factors affecting speed variations in production [20, 26]. When producing multiple product variants with different ideal speeds and sequence-dependent setup times, it is critical that products are sequenced to avoid large shifts in production speed and long stops for setup [20].

Speed on production lines may also be reduced to prevent products from being rejected in quality inspections [1]. Nurani and Akella [28] identify an inverted U-shaped relationship between production speed and profit accrual rate: at very high levels of speed, profits decrease due to higher quality-related expenses (e.g. scrap costs and opportunity costs of lost sales). Determining the maximum production speed that does not reduce product quality, therefore, is of interest when managing speed loss.

Other factors, such as capacity utilisation and product variety, are also shown to be related to the loss of production speed. The number of product variants sold by firms is shown to grow as firms globalise, expand markets and expand capacity [21, 22]. If not properly managed, product variety can decrease production speeds as low-volume products increase the number of changeovers and destabilise process settings [1, 21, 22, 26]. Similarly, the utilisation of machines can be related to the degree to which they operate at ideal speed because of the pressure operators may face from management or because of an increased occurrence of equipment breakdown. Capacity-constrained machines are commonly pressed to operate closer to the ideal production speed than machines with excess capacity, as in the case of an OEE study by Ljungberg [3].

2.4 Methods for quantifying the effects of speed loss factors

Improvement methodologies in the lean and TPM toolboxes are used to address speed loss in the literature [1, 8], but the methodologies are few and have limited explanatory and statistical power. First, Nakajima [1] proposes a four-step method to set progressively higher speed targets and reduce speed loss:

1. Achieve the standard speed for each product.
2. Increase the standard speed for each product.
3. Achieve the designed speed.
4. Surpass the designed speed.

This approach is designed to expose hidden problems, such as inadequate maintenance, inappropriate setup and tuning and improper testing in the equipment design phase [1]. However, the method offers little guidance on how to isolate and quantify the speed loss arising from specific factors.

Second, Benjamin et al. [8] take an explanatory approach applying the 5 Whys technique to assess speed loss at a metal barrel manufacturer. Benjamin et al. [8] apply Pareto analysis to speed loss issues and perform the 5 Whys approach with the most commonly occurring issues to identify and address the cause. While the approach does help achieve a reduction in speed loss equalling 32,000 USD at the case company [8], the approach gives only rudimentary consideration to speed loss from different factors, examining each factor in isolation instead of assessing the factors' collective, incremental impact on speed loss. Furthermore, the 5 Whys approach is not ideal for assessing process manufacturing systems, which have many interacting sources of speed variation and many parameters to consider when increasing speed.

3 A framework of speed loss factors

As argued in Section 1, the operations management and TPM literature lack solutions specifically addressing speed loss [8], which includes the absence of an overview of speed loss factors. To address this issue, this paper proposes a framework of speed loss factors at three abstraction levels, including three dimensions, ten categories and 20 factors. Specifically, 15 types of speed loss factors were identified in the literature (Table 2), of which, however, some were multifaceted. To increase concept clarity, these 15 speed loss types were divided into 20 distinctive factors, organised under ten categories, placed under three overall speed loss dimensions: (1) technology factors, (2) human factors and (3) product factors. This is shown in Table 3. In this context, it should be noted that management and operator factors are placed under a common dimension (human factors) since the line between such factors in some contexts is blurry. It should also be noted that the factors 'equipment wear', 'improper maintenance' and 'equipment age' are only indirect causes in the sense that they result in unreliable or obsolete machines, which are the direct causes of speed loss.

4 Methodology

A case study approach was employed to investigate the developed framework. The case study method is appropriate for studies with unclear boundaries between the phenomenon and the context [29]. This research is aimed at identifying factors related to speed loss in a process manufacturing firm and quantifying their relationship, so the case study approach is appropriate. In the following sections, the case company is introduced, and the analysis approach is detailed.

4.1 Research context

The case company selected for analysis is a building insulation production facility in Europe, hereafter referred to as InsCo. InsCo is selected as it utilises a high-volume, continuous-flow process representative of the process industry [30]. The factory consists of two production lines with similar layouts and product mixes. Both lines operate 24 h a day, 7

Table 3 Dimensions and categories of speed loss contributors

Dimension	Category	Factors identified in the literature
Technology	Technology reliability	Machine reliability
		Production stops
		Equipment wear
		Improper maintenance
	Technology limitations	Technological limitations
		Equipment age
		Queue capacity for work in process
	Environmental limitations	Environmental limitations
Human	Operator inefficiency	Operator training
		Operator inefficiency
	Measurement error	Measurement error
	Planning issues	Production scheduling
		Ideal cycle time set too low
		Capacity utilisation
Product	Material availability	Material availability
	Material quality	Material quality
		Natural process variation
		Raw material mix
	Product variety	Product variety
	Product quality	Quality (finished goods)

days a week, with a four-crew, rotating work schedule. The managers and personnel operating both lines are well acquainted with lean tools and recently implemented OEE to measure production losses on the two lines. The lines have not experienced any major changes in capacity utilisation, production technology or product mix in the past 5 years, making them favourable for analysis. Both lines are assessed in this study and are referred to as L1 and L2 throughout the paper.

The insulation production process (see Fig. 1) consists of a hot end where a combination of raw materials is melted and spun into fibres. The fibres are combined with recycled fibres from downstream waste, creating the primary material, which is compressed into a final form before being cured, cooled, cut and packed per product specifications. The continuous, circular nature of InsCo's production process is characteristic of process manufacturing [19].

Amongst the measures of speed or throughput on the production line, the primary material throughput (i.e. primary speed) is used to measure speed in this study. Primary speed is selected for analysis of speed loss as it is a directly controllable speed upstream in the process, and live data on primary speed are immediately relayed to operators through process control visuals. Downstream speed measures are not favourable for analysis as they are subject to many additional sources of variation, including manual data registration. Primary speed can be adjusted by melting and spinning more fibres or adding more recycled fibres to the material flow. Increasing the output of the spinning process must be done gradually, given the technological limitations and environmental constraints of the process. The recycled material content can be increased almost instantaneously if recycled fibres are present in the system.

Each production batch represents a single product variant, which is a unique combination of mechanical and thermal properties, dimensions and packaging materials. Changes between batches of different products can occur during production stops and run time with non-conforming products rejected from the line as waste. Primary speed thus encompasses the production of non-conforming material rejected downstream.

In the spring of 2016, InsCo implemented a speed standardisation programme. Lacking official ideal cycle times for product variants, factory management set maximum speed targets for the primary speed for each product based on performance in the previous year. The targets are incorporated into a visual control tool: a digital speedometer (see Fig. 2), indicating whether the operators are on target (green), slightly under target (yellow) or far under target (red). If the target primary speed is not achieved for a given production batch, the operators enter an explanation into a free text field in the manufacturing execution system (MES).

Examining the target primary speed compared to the actual primary speed reveals that L1 and L2 often exceed the speed targets set by management (see, e.g. Fig. 3), creating negative speed loss. The highest demonstrated sustainable primary speed for each product is used as the ideal speed to avoid negative speed loss in the quantitative study [19]. To determine the highest demonstrated, sustainable primary speed, the researchers assess batches within the technical capabilities of the processes demonstrated in the period analysed and sustainable for a batch of greater duration than 30 min. If no feasible primary speed is found for a product in the period analysed, the factory target primary speed is used.

Analyses are performed using 3 months of data at InsCo from 1 November 2017 to 31 January 2018, a stable period of operations at the company when the use of the speed tool was well established in the organisation.

4.2 Data collection

Data on suspected causes of speed loss from the operators' perspective were extracted at the batch level from the manufacturing execution system (MES), translated from the local language into English using Google Translate software and coded by the researchers [31]. Translated meanings unclear to the researchers were verified with the factory manager. A preliminary set of speed loss causes was presented to the factory manager, whose feedback was incorporated to consolidate the factors. Three 1-h, semi-structured interviews with the factory manager were held to understand the production context, scope the analysis and report the results. These discussions focused on the format of the speed variance tool,

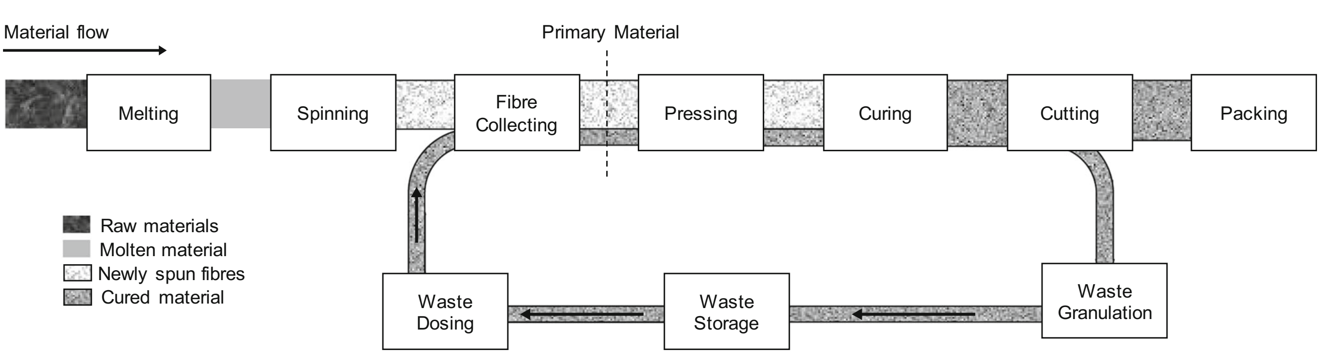

Fig. 1 Insulation production process

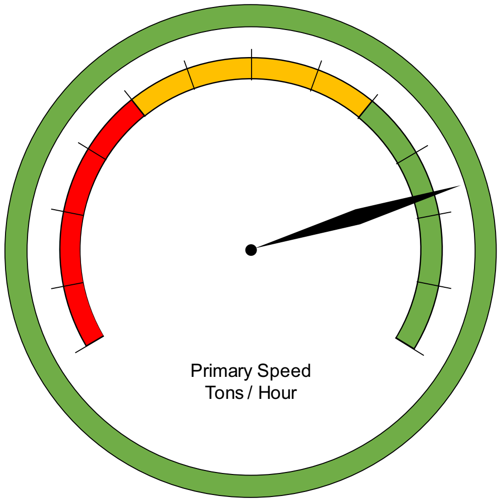

Fig. 2 Speedometer used to monitor primary speed-target status at InsCo (conceptual)

structure of the data, use of the tool and factors likely to affect speed loss at the factory.

Data for the speed loss factors from the thematic analysis were compiled from various sources at the case company to inform the quantitative study. Sensor data on the primary speed and recycled material speed were collected from the production data warehouse and pre-processed in the statistical software program R, using a local regression to create smooth curves and eliminate signal noise while fitting the predominant trends in the process variables. The data were cleaned of production stop times (primary speed of 0 ton per hour) to assess only equipment uptime. Outliers for the primary speed, classified using 1.5 times the interquartile range of the signal, were removed from the dataset. Sensor data from every 30 min of production time were analysed to capture the dynamic nature of production activities not visible at higher levels of aggregation [20].

Batch-level data containing the coded operator data, primary speed targets and downtime information were also extracted and mapped to the sensor data. The data included a total of 1231 production batches for 600 products from L1 and 626 batches of 300 products from L2. Additional data used in the analysis were the crew schedule and maintenance data from Excel spreadsheets at the factory.

4.3 Data analysis

First, a rigorous qualitative, thematic analysis of written operator input is performed to identify possible factors influencing speed reductions at the case company. This is followed by a regression analysis of production data to quantify the magnitude of the relationship of speed loss with each identified factor.

The maximum likelihood estimates of regression coefficients for the combined factors were calculated using GLS regression using the nlme package in R [32, 33]. Regression analysis is proven to be an appropriate method for analysing changes in throughput and costs in chemical and glass producers [20, 26]. General linear regression is specifically applicable to regressing on time-series data due to serial correlations and heteroskedasticity in error terms [34].

In the following discussion of the findings, statistically significant factors are evaluated from a mechanical perspective to determine if the correlations evaluated in the regression analysis are causal. Although a significant correlation coefficient in regression analysis cannot be taken as direct evidence of a causal relationship between the factors and speed loss [34], the combination of a significant correlation coefficient and a mechanical explanation of a relationship can paint a stronger picture of causality.

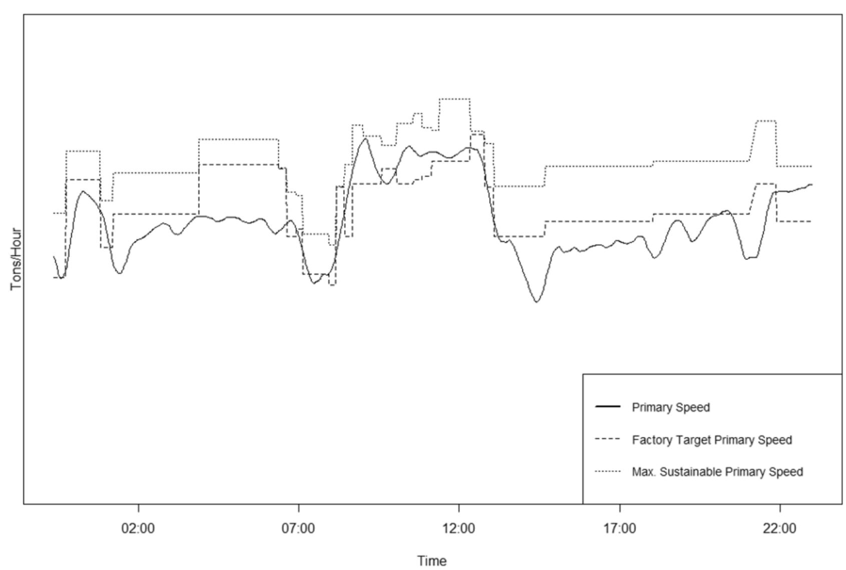

Fig. 3 Primary speed for one day of production on L1 showing periodic overachievement of factory speed targets and underachievement of maximum sustainable primary speed targets for 1 day of production (y-axis labels removed to maintain confidentiality)

Table 4 Overall equipment effectiveness for two lines, L1 and L2, at InsCo, November 2017–January 2018

OEE measure	L1	L2
Availability efficiency (%)	96	96
Performance efficiency (%)	90	91
Quality efficiency (%)	86	90
OEE (%)	74	79

5 Findings

5.1 Current speed loss at InsCo

Before addressing the factors affecting speed loss, first, the efficiency of the two production lines is calculated. The OEE for L1 and L2 for the period studied are assessed using the method described by Nakajima [1], and the results are summarised in Table 4. The data registration practices at the firm allow recording all production stops, small and large, as unplanned downtime, moving the effect of small stops from the PE measure to the AE measure. Consequently, PE in this study measures speed loss in isolation.

Table 4 shows that QE is the lowest of the OEE sub-measures at InsCo. The second lowest sub-measure is PE in the form of lost speed efficiency, equating to 9–10% of lost capacity at InsCo. AE for both lines is higher than 90% and reaches the world-class standard within the TPM literature [1].

5.2 Identifying factors related to speed loss

Nine main groups of speed loss factors were identified through a thematic review of operator input to the MES through the speed tool at InsCo. These can be distributed across the three dimensions of the proposed framework (Table 3). In the following, the relationships to the factors of the framework are stated in parentheses after the identified speed loss factors from the case. The main technology factors include

1) Furnace limits (technology limitations and environmental limitations)
2) By-product drain (technological limitations)
3) Technical issues (technology reliability)
4) Production stop (technology reliability)

The main human factors include

5) Planning (planning issues)
6) Start-up of the production line (operator inefficiency)

The main product factors include

7) Quality issues (product quality)
8) Raw materials issues (material availability and quality)
9) No recycling (material availability and quality)

Figure 4 shows the frequency distribution of the cited causes of speed loss on the two lines over the 3-month period. The analysis is restricted to runs when InsCo's speed loss target is not achieved. More than one speed loss cause may be cited for a single batch. The most frequently cited causes of speed loss are furnace limitations (e.g. approaching a furnace's maximum capacity and approaching environmental limits on emissions) and draining of by-products created during melting from the furnace. Also cited are reduced speeds due to production planning (e.g. short run duration and large shifts between product speeds), production stops, raw material

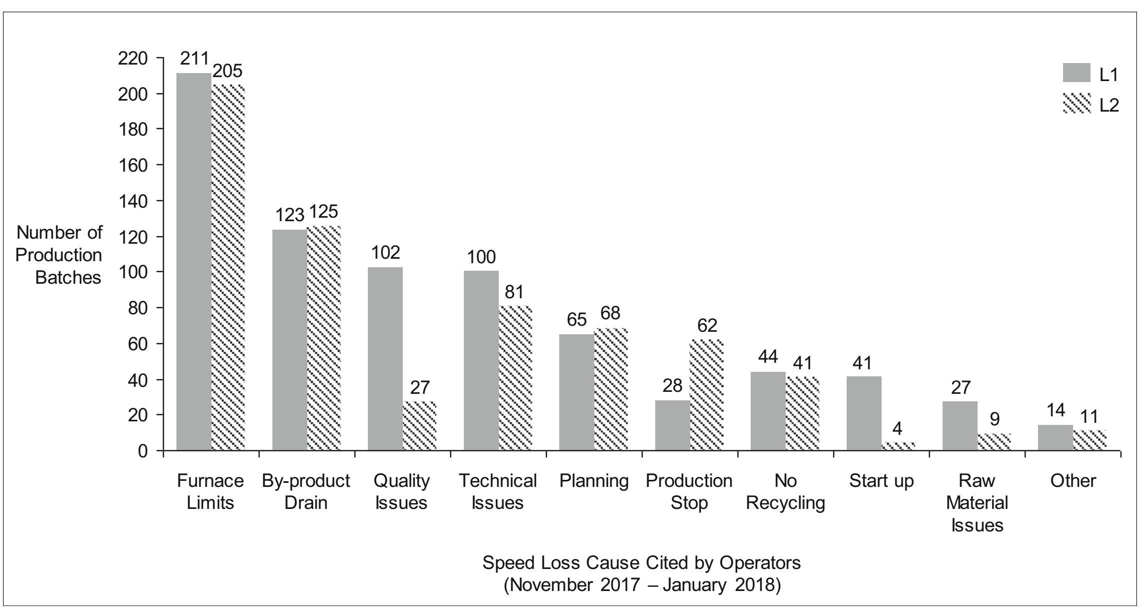

Fig. 4 Distribution of operator-suspected causes of speed loss

issues, lack of recycling material, start-up of the line, technical issues with equipment and quality issues experienced at the end of the line.

Interview data from factory management and process experts enabled the identification of additional possible causes of speed loss, including crew differences, product variety, factory learning curve, recycled content and natural process variation. These variables and those in Fig. 4 are aggregated, and the impact on speed loss is assessed in the following section.

5.3 Quantifying the relationships between the factors and speed loss

A GLS regression model is constructed using the aggregated set of variables to reveal the potential causal relationships between the main factors of speed loss at InsCo. The two production lines are assessed individually as it is hypothesised that the significance of different factors varies across the two lines. Equation 7 shows the dependent variable measured as the percentage speed loss based on the defined target speed for each product. Speed loss is expressed in percentage form to normalise the differing primary speed targets for the various products (Table 5).

$$SPLOSS_t = (Target_t - Actual_t)/Target_t \times 100 \tag{7}$$

A parsimonious array of 15 variables is assessed based on the qualitative speed loss causes cited by the operators and the feedback from management given in the interviews. Exploratory, univariate analysis reveals that all 15 variables are suitable for modelling with a linear relationship to percentage speed loss. During interviews, operators and factory management did not suspect any interaction effects amongst the process variables. To test their view empirically, nine interaction effects were tested based on the researchers' understanding of the system variables and how they could affect one another (e.g. *FURN* × *TECH* representing how the furnace limitations may affect other mechanical breakdowns, *QUAL* × *PRSTOP* representing how the presence of a production stop may affect product quality, etc.).

The final model tested using GLS regression is shown in Eq. 8. Crew four is selected randomly as the base crew to which the other crews are compared in the model, so the crew four variable is excluded from Eq. 8.

$$\begin{aligned} SPLOSS_t = {} & \beta_0 + \beta_1 RUNTIME_t + \beta_2 NEXTSP_t + \beta_3 PREVSP + \beta_4 FURN_t \\ & + \beta_5 TECH_t + \beta_6 PRSTOP_t + \beta_7 QUAL_t + \beta_8 BYPROD_t + \beta_9 MATER_t \\ & + \beta_{10} LEARN_t + \beta_{11} RECYC_t + \beta_{12} RAWMAT_t + \beta_{13} CREW1_t + \beta_{14} CREW2_t \\ & + \beta_{15} CREW3_t + \beta_{16}(RUNTIME \times NEXTSP)_t + \beta_{17}(RUNTIME \times PREVSP)_t \\ & + \beta_{18}(TECH \times FURN)_t + \beta_{19}(TECH \times PRSTOP)_t + \beta_{20}(TECH \times QUAL)_t \\ & + \beta_{21}(QUAL \times FURN)_t + \beta_{22}(QUAL \times PRSTOP)_t + \beta_{23}(QUAL \times BYPROD)_t \\ & + \beta_{24}(BYPROD \times RAWMAT)_t + \varepsilon_t \end{aligned} \tag{8}$$

The GLS regression results are shown in Table 6 for L1 and L2. For both models, the intercept is positive and significant (not shown because of confidentiality agreement). The variables with statistically significant correlations with speed loss include learning curve, select crew variables, batch run time, percentage change in target speed between consecutive batches, limitations of the melting furnace and draining of

Table 5 Independent variable definitions

Variables	Description
RUNTIME	Hours of uptime for the current batch, mean centred to 0
PREVSP	Percentage change in the target speed of the current batch and the target speed of the previous batch, mean centred to 0
NEXTSP	Percentage change in the target speed of the current batch and the target speed of the following batch, mean centred to 0
FURN	1 if the current batch has a furnace limitation cited by the operators; 0 otherwise
TECH	1 if the current batch has a technical issue cited by the operators; 0 otherwise
PRSTOP	1 if the current batch has a production stop per the MES data; 0 otherwise
QUAL	1 if the current batch has a quality issue cited by the operators; 0 otherwise
RECYC	Recycling fibres in tons per hour from smoothened sensor data, mean centred to 0 and scaled using standard deviation.
RAWMAT	Tons of raw material per hour added to the melting process from smoothened sensor data, mean centred to 0 and scaled using standard deviations
BYPROD	1 if a by-product is drained from the furnace during run time; 0 otherwise
MATER	1 if the current batch has a material issue cited by the operators; 0 otherwise
LEARN	A continuous variable measuring the number of days since 1 November 2017, the beginning of the analysis period
CREW1	1 if the current batch is produced by the crew 1; 0 otherwise
CREW2	1 if the current batch is produced by the crew 2; 0 otherwise
CREW3	1 if the current batch is produced by the crew 3; 0 otherwise

Table 6 Maximum likelihood estimates for the relationships between the process variables and the percentage speed loss on the two lines, L1 and L2, using GLS regression

	L1				L2			
Factor	Estimate	Std. error	*T* value	*p* value	Estimate	Std. error	*T* value	*p* value
(Intercept) [a]	–	0.206	38.181	< 0.001***	–	0.248	30.150	< 0.001***
Main effects								
RUNTIME	0.044	0.019	2.307	0.021*	− 0.267	0.033	− 8.142	< 0.001***
NEXTSP	− 0.177	0.015	− 11.696	< 0.001***	− 0.251	0.020	− 12.268	< 0.001***
PREVSP	0.159	0.017	9.595	< 0.001***	0.203	0.022	9.082	< 0.001***
FURN	3.269	0.229	14.289	< 0.001***	1.898	0.219	8.663	< 0.001***
TECH	0.127	0.254	0.501	0.616	0.784	0.408	1.922	0.055.
PRSTOP	− 0.716	0.463	− 1.544	0.123	− 0.378	0.234	− 1.617	0.106
QUAL	0.630	0.282	2.234	0.026*	1.652	0.615	2.686	0.007**
RECYC	− 2.400	0.089	− 27.023	< 0.001***	− 1.704	0.104	− 16.341	< 0.001***
RAWMAT	− 0.704	0.083	− 8.443	< 0.001***	− 1.333	0.132	− 10.124	< 0.001***
BYPROD	3.643	0.462	7.890	< 0.001***	1.447	0.225	6.421	< 0.001***
MATER	0.271	0.431	0.629	0.529	− 0.182	0.539	− 0.338	0.735
LEARN	− 0.028	0.003	− 9.158	< 0.001***	− 0.020	0.003	− 6.089	< 0.001***
CREW1	0.471	0.235	2.001	0.046*	0.339	0.259	1.305	0.192
CREW2	1.006	0.235	4.278	< 0.001***	0.730	0.265	2.756	0.006**
CREW3	1.578	0.239	6.588	< 0.001***	0.532	0.255	2.084	0.037*
Interaction effects								
RUNTIME × *NEXTSP*	0.005	0.005	1.055	0.292	− 0.011	0.005	− 2.359	0.018*
RUNTIME × *PREVSP*	0.002	0.003	0.487	0.626	0.029	0.004	8.075	< 0.001***
TECH × *FURN*	− 3.089	0.624	− 4.951	< 0.001***	− 0.839	0.482	− 1.741	0.082.
TECH × *PRSTOP*	3.001	1.192	2.518	0.012*	0.195	0.497	0.394	0.694
TECH × *QUAL*	1.918	0.704	2.724	0.007**	0.553	1.016	0.544	0.587
QUAL × *FURN*	− 2.830	0.666	− 4.251	< 0.001***	2.460	0.640	3.843	< 0.001***
QUAL × *PRSTOP*	1.122	2.242	0.501	0.617	− 0.598	0.624	− 0.959	0.338
QUAL × *BYPROD*	− 0.032	1.206	− 0.027	0.979	− 3.544	0.638	− 5.551	< 0.001***
BYPROD × *RAWMAT*	2.009	0.595	3.374	0.001***	0.205	0.182	1.126	0.260
Pseudo R squared 0.675 Residual standard error 4.324, degrees of freedom 2965					Pseudo R squared 0.525 Residual standard error 4.900, degrees of freedom 3020			

Significance codes: (.) $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

[a] Intercept estimates excluded for confidentiality

by-products from the furnace. Quality issues with finished goods are significant only in the L1 model, while technical issues are significant in the L2 model.

The researchers expected higher *RUNTIME* to be associated with decreased speed loss. However, the results in Table 6 show that this is true only for L2. For L1, on the other hand, longer run times are related to increased speed loss. One potential underlying cause is that the average run times on L1 are half of L2. Thus, it could appear that higher run time is associated with decreased speed loss if the run time is over a certain level (e.g. runs over two hours in duration are related with decreased speed loss). In this context, it should be noted that for both models, the run time coefficient is not large and explains only 1–2% of the change in speed loss based on typical run times at InsCo.

As seen in Table 6, both variables measuring the percentage change in speed targets for subsequent batches are significant (i.e. *NEXTSP and PREVSP*). During operation, operators are known to anticipate higher speed later in the schedule and pre-emptively increase speed to prepare for the coming fast product. Evidence for this behaviour can be seen in the negative coefficient for *NEXTSP*, which reveals that if the next product to be produced on L1 or L2 has a higher primary speed target than the current product being processed, speed loss for the current product decreases. When assessing the effect of the previous product, the positive coefficient for

PREVSP shows that if the previous product has a lower primary speed target than the current product being processed, speed loss for the current product increases (i.e. the line runs slower). In other words, it is preferable to schedule a product with high-speed loss either after a faster product or before a faster product to avoid lost speed.

The variables *RUNTIME, NEXTSP and PREVSP* are largely determined by the production planning department. Although planners optimise the batch size and production sequence using experience-based heuristics, the production plan is still subject to last-minute schedule changes, which can cause large changes in speed.

The quality of the finished product at the end of the line (*QUAL*) is also a statistically significant factor related to increased speed loss on both lines as seen in Table 6. Quality issues are cited by the operators as a cause for decreased speed performance in 14% of all run time on L1 and 11% of all run time on L2. In the case of poor product quality, operators controlling primary speed receive feedback from the testing and inspection department on how the products' physical and aesthetics specifications are not met. In some cases, corrective action is taken to reduce line speed. The results in Table 6 show that the occurrence of a quality issue is estimated to increase speed loss by 0.6% for L1 and 1.7% for L2.

Technical issues on the line (e.g. machine breakdown and reduced capacity) are moderately related to a 1% increase in speed loss only in the L2 model. The reason for the lack of significance of *TECH* on L1 is interesting as there are no noticeable differences in run time affected by technical issues on L1 and L2. Further context was provided from the factory manager who explained in an interview that L2 suffered from higher severity mechanical failures in the period studied than L1, being a possible explanation for the significance of *TECH* on L2 and not L1.

The variables with the most negative impact on speed loss (positive coefficients) are by-product drain (*BYPROD*) and furnace limitations (*FURN*). Draining by-product from the furnace is an obligatory task which operators perform periodically to fulfil product specifications and factory safety procedures. Table 6 shows that when the by-product is drained from the furnaces, the speed is reduced by 3.6% on L1 and 1.5% on L2. Since by-product is drained from the furnace during approximately 4% of all run time on both L1 and L2 in the period analysed, this factor accounts for only a minor fraction of the total speed loss for the two lines. When the furnace limitations are reached, the lines experience a roughly 2–3% speed loss based on the model coefficients for *FURN*. This loss is sizeable considering that operators cite furnace limits for 25% and 47% of the run time on L1 and L2, respectively. Multiplying the coefficients by the frequency of occurrence of *FURN* in the data, the variable *FURN* alone is related to an average 0.8% speed loss for the entire three-month period analysed.

Raw materials (*RAWMAT*) and recycling (*RECYC*) have negative, statistically significant coefficients in both models in Table 6, indicating that additional flow of material from upstream allows operators to achieve speed targets better. A lack of recycling material has dramatic effects on the speed loss on the production lines and is cited as a cause of speed loss in 5% of batches on L1.

The variables for crews 1–3 indicate statistically significant differences from the performance of the control crew (crew 4) on both lines, except for crew 1 on L2 which was not significantly different from crew 4. The positive coefficients for all crew variables in both models suggest that crew 4 performs with the lowest speed loss on both lines.

An additional variable with a negative, significant regression coefficient in both models is the learning curve variable. The results show that for each additional day of experience operators on L1 and L2 have, the percentage speed loss on the line decreases by nearly one-fortieth of a percentage point or one percentage point in 40 days. The factory manager stated that his team focused on speed loss activities on both lines in the period examined, corroborating the identified trend in improved speed loss.

Variables with no significant relationship with percentage speed loss are production stops and raw material issues (i.e., *PRSTOP and MATER*). These variables were expected to relate to increased speed loss as they interrupt the process flow, but this is not supported by the regression results.

The interaction effects tested reveal additional behaviour of the production system that is largely unobservable to the crews operating the machines. On L1, *TECH* × *PRSTOP* and *TECH* × *QUAL* both have positive significant coefficients. This indicates that when technical issues with machines occur at the same time as either a production stop or quality issue, speed loss is increased even more then when a technical issue is experienced in isolation. Variables with negative and significant coefficients on L1 include *TECH* × *FURN and QUAL* × *FURN*. Based on these results, it appears that quality and technical issues limit the strong increase in speed loss caused by furnace limitations. The final significant interaction effect on L1 is that of *BYPROD* × *RAWMAT*, with the negative coefficient accurately modelling the system dynamics in that raw material flow is reduced directly when by-product is drained from the furnace. L1 shows no significant interaction effects amongst the planning and scheduling variables.

A different set of significant interaction effects are at play on L2 when compared to L1. First, Table 6 shows significant interaction amongst the planning variables on L2, with the coefficient for *RUNTIME* × *NEXTSP* being negative and the coefficient for *RUNTIME* × *PREVSP* being positive. Since the signs for these interaction coefficients correspond with the coefficient signs of the *NEXTSP* and *PREVSP* main effect, it can be concluded that longer run times amplify the speed loss effects of changes in speed for consecutive production runs. L2 also shows a positive and significant coefficient for *QUAL* × *FURN*, indicating that quality issues and furnace limitations occurring simultaneously result in higher speed loss. This is opposite to the relationship identified on L1. The reason for the change in coefficient direction on L2 compared to L1 is unknown to the researchers, but could be due to differences in operation or product mix. Lastly, the same interaction from L1 of by-product drain and raw material flow on speed loss is also seen on L2.

To sum up, the main findings from the GLS regression include

1) Variables with statistically significant correlations with speed loss include learning curve, select crew variables, batch run time, percentage change in target speed between consecutive batches, limitations of the melting furnace, draining of by-products from the furnace and quality issues, while technical issues were only slightly significant on one line.
2) Higher run time was only associated with decreased speed loss on the line which was scheduled with longer production batches.
3) Scheduling a product with a high-speed loss after a faster product or before a faster product reduces speed loss.
4) The variable with the largest and most negative impact on speed loss was furnace limitations, accounting for roughly 1% available production capacity in the 3-month period.
5) A lack of recycled input material has dramatic effects on the speed loss on the production line and is cited as a cause of speed loss in 5% of batches on one production line.
6) The variables for production stops and raw material issues (i.e. material availability and quality) had no significant effect on speed loss.
7) There are complex interaction effects at work in the system which differ across the two lines examined.

6 Discussion and conclusions

Based on TPM literature, the paper developed a framework of ten categories including 20 factors contributing to speed loss in manufacturing lines, grouped under three overall speed loss dimensions: (1) technology factors, (2) human factors and (3) product factors. With a basis in the constructed framework, a case study of speed loss on two process manufacturing lines was carried out. These studies revealed nine significant factors related to speed loss and multiple interaction effects across these factors. The nine factors identified are mainly related to the process design and technology installed at the factory, factors which operators have little influence over in daily operations. Instead, engineering resources are needed to better understand and mitigate furnace limitations, by-product draining and raw material and recycling dosing, which are related to speed loss.

The results of the analysis highlight specific, previously unseen sources of variation in production speed at InsCo, helping factory management to identify logical means to address these sources. Addressing furnace limitations is a key step to enable both production lines to run closer to their ideal speeds, and the study results can be used to inform the business case for the redesign of the furnace or capital investment for new technology.

Also found to be significant in this study are human factors, such as production scheduling, learning curve, unambitious target setting, crew differences and machine breakdowns from improper maintenance [2, 3, 22, 23]. This finding indicates that sizeable improvements in speed loss can be made by applying lean and TPM approaches, such as the speed loss method applied by Nakajima [1] and the 5 Whys analysis used by Benjamin et al. [8]. Actions to further optimise production planning and to implement best practice across crews should also be taken.

Production stops and material issues are not directly related to the percentage speed loss for either production line studied. This finding suggests that while these operational interruptions may catch operators' attention in the data as they affect speed loss, they are relatively minor compared to the natural fluctuations inherent in the process technology and human resources. Here, the benefit of applying more advanced statistical techniques to the analysis of speed loss in process manufacturing settings can be seen.

No evidence is found in the analysis to support the impact of measurement error and product variety. However, the impact of product variety on speed loss is seen indirectly through run time and order sequencing, as discussed in the literature [26]. Regarding measurement errors, these may have occurred in the data sample to a smaller extent but were not detected by the researchers.

This study is potentially limited by its determination of speed targets, which might have been skewed by outliers. The researchers took action to clean out obvious outliers to avoid this problem. Additionally, it is possible that critical variables are omitted from the regression model unbeknownst to the researchers. Another study limitation is possible measurement errors in the sensors, which may have contributed to variability in the dependent and independent variables. Lastly, while the coefficient for the learning curve variable implies that operators reduce their speed loss with time, the linear relationship is limited to interpolation within the analysed data set and should not be extrapolated. Extrapolation would assume that the speed loss can be minimised indefinitely as operators gain more experience, which is not feasible.

This study contributes with a framework of factors leading to speed loss and a parallel case study quantifying the impacts of the identified factors on speed loss on two insulation production lines. The results validate most speed loss factors described in the literature from a process manufacturing perspective and highlight the importance of technology and management-related factors in reducing speed loss. Speed loss was found to cause a 9–10% loss of production capacity on the two lines studied, falling within the previously described range of 9–15% in other TPM studies [3, 15]. Similar results are expected to be found in other capital-intensive, continuous-flow manufacturers (e.g. producers of foam mattresses, frozen baked goods and steel beams) due to the high rigidity and integration of the equipment. Due to the broad nature of the speed loss factors identified, the framework in Table 3 seems to be applicable to other manufacturing systems in its current state, but further research is needed to confirm this.

Finally, the paper demonstrated that the GLS regression approach utilised in this study is useful for practitioners to (1) identify factors related to speed loss; (2) set appropriate OEE and speed loss targets for unique production contexts and (3) prepare business cases for capital investment to overcome technology-related speed loss factors. This study adds to the work demonstrating regression analysis as an effective technique for discerning the effects of variables in process industry settings [20, 26]. Additionally, this study is the first to specifically investigate the causes of speed loss to the best of the researchers' knowledge. Due to the use of regression for the analysis of other process industry research problems, it is likely that the analysis approach used in this paper could be readily applied in another process industry setting. It is unclear whether the same approach could be effectively used in other production systems. Future research is needed to further explore the usefulness of the proposed framework and possibly extend it.

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