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Original research article

Achieving energy efficiency in industrial manufacturing

Thomas Schmitt [a,b,*], Sandra Mattsson [c], Erik Flores-García [d], Lars Hanson [e]

[a] Scania CV AB, Global Industrial Development, Södertälje, 151 38, Sweden
[b] Uppsala University, Department of Civil and Industrial Engineering, Division of Industrial Engineering & Management, Uppsala, 752 37, Sweden
[c] RISE Research Institutes of Sweden AB, Mölndal, 431 50, Sweden
[d] KTH Royal Institute of Technology, Department of Production Engineering, Stockholm, 100 44, Sweden
[e] University of Skövde, School of Engineering Science, Skövde, 541 28, Sweden

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ABSTRACT

This paper explores the use of digital technology stages and knowledge demand types for achieving energy efficiency. Digital technology stages are the steps toward developing an intelligent and networked factory: computerization, connectivity, visibility, transparency, predictive capacity, and adaptability. Knowledge demand types refer to the knowledge and skills needed to implement energy management through technical, process, and leadership knowledge. Empirical data were collected from a critical single case study at an industrial manufacturing company. The study made two significant contributions. Firstly, it identifies fourteen challenges and improvement potentials when working with energy monitoring, evaluation, and optimization, demonstrating the critical role of digital technology stages and knowledge demand types. Secondly, the study presents a conceptual framework indicating how companies could overcome pitfalls and enhance energy efficiency by combining digital technologies and knowledge demands. Future work will include technical implementations and its connection to knowledge management.

1. Introduction

Industry is under increased pressure to reach net zero. *Net zero* is a state where no more emissions of greenhouse gases are emitted to the atmosphere than are removed by carbon sinks such as forests. To achieve the net zero target, the Science Based Targets initiative, which has garnered support from various industrial companies, proclaims a reduction of carbon emissions for businesses of 90%–95% by 2050 [1]. One way to reach net zero is by working with *energy efficiency*, which is defined as the ratio of energy used to the output of a system [2]. Achieving energy efficiency is relevant to society because the industry is responsible for approximately 38% of global final energy consumption and 24% of total CO2 emissions [3]. Additionally, enhancing energy efficiency can generate cost savings for businesses exposed to increased uncertainty caused by higher and fluctuating energy prices.

Enhancing energy efficiency involves reducing power demand and processing time, or a combination of both, while keeping output or productivity constant [4]. This can be done by improving existing processes (reducing non-value-adding energy) or by replacing the current equipment and design with more energy-efficient alternatives (reducing value-adding energy but low efficiency) (see Fig. 1) [5,6].

Previous research states that digital technology can be used to improve energy efficiency [3,7–10]. *Digital technologies*, also known as Industry 4.0, are tools capable of generating, collecting, and analyzing data; they help achieve the intelligent connection and steering of machines and processes in industry [11,12]. Digital technologies are, among others, sensors, data flows, analytics, digital twins, machine learning, and extended reality [13]. The latest Intergovernmental Panel on Climate Change (IPCC) report states that digital technologies for energy management could lead to a 5%–10% reduction in energy demand and related greenhouse gas emissions [10] and have been used to reduce energy waste in processes [12,14,15].

However, although digital technologies have been used, new types of knowledge and skills are needed to adopt energy efficiency initiatives [16]. *Knowledge demands* refer to the knowledge and skills necessary for meeting the challenges of implementing digital technologies, e.g., data analytics and software development, as well as understanding energy flows [17,18]. These challenges are supported by Longo, Nicoletti, and Padovano [19], who argue that little attention has been paid to the capabilities and competencies of operators in conjunction with digital technologies within developing industrial systems. To address this, a framework consisting of three types of knowledge demand (technical, process, and leadership) was proposed, in order to enhance the understanding of the adoption of innovation in energy management in the industry [16,20]. Knowledge and skill

* Corresponding author at: Scania CV AB, Global Industrial Development, Södertälje, 151 38, Sweden.
E-mail address: thomas.schmitt@scania.com (T. Schmitt).

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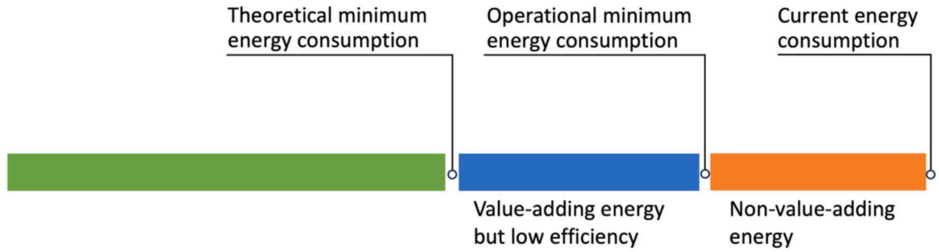

Fig. 1. Energy efficiency can be achieved by improving existing processes (reducing non-value-adding energy) and by replacing the current equipment and design with more energy-efficient alternatives (reducing value-adding energy but low efficiency).
Source: Adapted from [6].

are relevant in reaching the vision of Industry 5.0; the vision states that a human-centered application of Industry 4.0 should be adopted that supports sustainability targets such as reductions in energy [21]. Ways to support humans include establishing standardized methods and visualizations [22], using simple implementable solutions [23], and increasing the efficiency of communication to enhance personnel understanding of manufacturing strategies [24].

There is a research gap in understanding how digital technologies and knowledge demands interact and are used to achieve energy efficiency in practice. To address this, this study explores the application of digital technologies and knowledge demand types for achieving energy efficiency in a company that has effectively tackled energy waste. The study aims to (i) identify and describe challenges and improvement potentials in practical energy management and (ii) propose a conceptual framework that can be used to overcome pitfalls. To achieve the goals, this paper addresses the following research question: *How can energy efficiency be achieved through using digital technology stages and knowledge demand types?* The research aspires to offer guidance to practitioners and researchers engaged in the field of energy management in industrial manufacturing.

2. Literature background

2.1. Digital technologies for energy efficiency

Research on digitalization for energy efficiency focuses on developing ways to save power and apply methods to monitor, manage, and predict energy consumption [7]. According to Schuh et al. [25], digitalization in manufacturing has six development stages, computerization, connectivity, visibility, transparency, predictive capacity, and adaptability (see Fig. 2). *Computerization* and *connectivity* lay the groundwork to generate and collect (energy) data through the application of sensors and information management software. The *visibility* stage answers to "what happened?" or "what is happening?", e.g., as presented by Tan, Ng, and Low [26], through an energy monitoring application. In *transparency*, causal relationships are presented stating "why something is happening". Then, the *predictive capacity* stage answers to "what will happen?" based on historical data, for which simulation tools can be used [27]. *Adaptability* aims to answer "how can autonomous response be achieved?" by suggesting or steering adaptations to the process. For *adaptability*, potential applications are multi-objective optimization [28] and control modes [29]. The last four stages correspond to the Gartner analytics model, which defines descriptive, diagnostic, predictive, and prescriptive analytics stages [30].

Generally, the goal of utilizing digitalization in manufacturing is to allow for better and faster business decisions through generated data turned into knowledge through knowledge discovery. *Knowledge discovery* is the extraction of information from data [31]. To balance between multiple goals in an increasingly connected factory, data-driven methods can help discover knowledge to support decision makers [25,31]. As an example, Bandaru, Ng, and Deb [32] provide an overview of data-mining techniques applied to the extraction of knowledge from multi-objective optimization datasets. The techniques span from descriptive and visual statistics to advanced machine learning methods. In addition, Barrera-Diaz et al. [33] and Lidberg et al. [34] employ a combination of simulation-based optimization and process mining techniques for knowledge discovery. Their approach aims to identify the distinguishing attributes between Pareto-optimal and non-Pareto-optimal solutions. Consequently, the process of knowledge discovery unfolds from the visibility stage and progresses forward (see Fig. 2).

Applying digital technologies for energy management often faces obstacles during real-world implementations. Challenges highlighted include the importance of addressing full data pipeline development, from data acquisition over pre-processing to implementation [35]. Additionally, Tesch da Silva et al. [7] stress the significance of data granularity and real-time monitoring capabilities. Identified challenges for energy-efficient factories, as noted by Menghi et al. [36], encompass (i) simplifying data collection, (ii) establishing standardized methods for energy assessment, (iii) providing user-friendly decision-support tools, and (iv) adopting a holistic approach considering necessary trade-offs. Geng, Evans, and Kishita [23] argue that a significant potential lies in simpler, easily implementable solutions that do not require advanced technology or substantial investment but involve training of operators.

2.2. Knowledge demands for energy efficiency

New types of knowledge and skills are needed to adopt energy efficiency initiatives [16]. To solve this, a framework with three types of knowledge demands, technical, process, and leadership knowledge, was identified when applying digital technologies for energy management in manufacturing [16,20] (Fig. 3). *Technical knowledge* is defined as the practical know-how that is tacit, pragmatic, and context-dependent [16]. It is used for practical rationality, e.g., identifying the root cause of energy waste in a system. As an example, Máša et al. [37] state that (new) technical knowledge and experience of workers is important. *Process knowledge* is defined as theoretical know-how and is explicit, context-independent, and procedural, e.g., using a method for finding deviations in a process. Examples include Braglia et al. [38] and Svensson and Paramonova [39], who use lean and systems methods, respectively, to systematically classify, evaluate and eliminate energy wastes. These studies highlight the importance of increased technical knowledge among energy experts using these methods, coupled with a structured and systematic process. *Leadership knowledge* is used for reasoning and is both practical and theoretical. It is described as the know-why and is pragmatic and context-dependent. This knowledge type is focused on action and is used for, e.g., conducting workshops with a focus on identifying and reducing energy waste [16]. The knowledge demands have been used to describe what attributes of knowledge are used in energy management [16] and to provide an overview of energy efficiency strategies across different levels of the manufacturing systems.

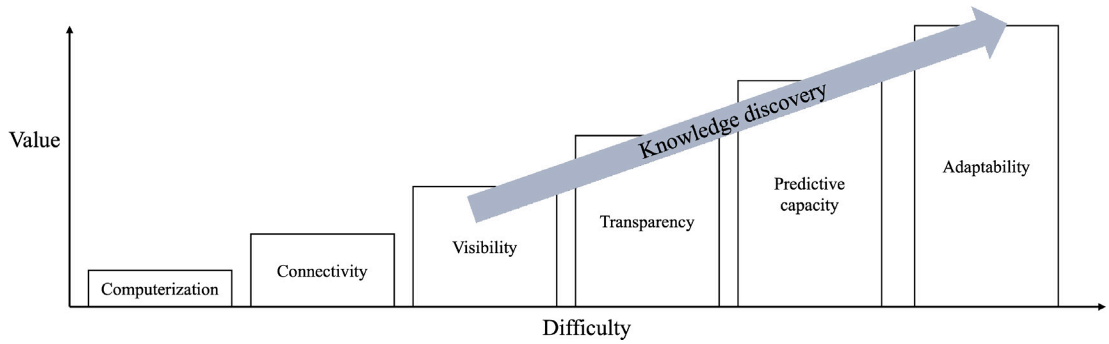

Fig. 2. Digital technology stages and Gartner analytics framework combined [25,30]. The first two steps generate processed information from collected data. From the visibility step onwards, data-driven methods such as process mining become important to discover actionable knowledge [32].

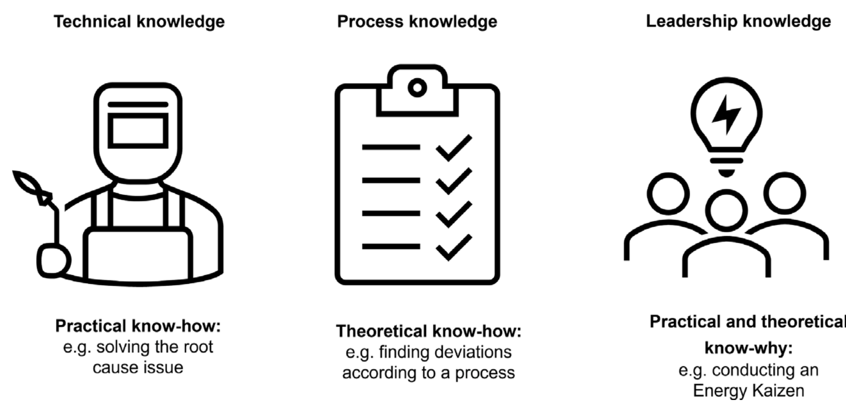

Fig. 3. The three knowledge demand types according to Andrei, Thollander, and Sannö [16].

2.3. Energy management in lean manufacturing systems

Lean production is often the context in which to use digital technologies and knowledge demands for energy management in industrial manufacturing, with the aim to increase energy efficiency. As shown in Fig. 1, energy efficiency can be achieved by improving existing processes as well as by replacing the current equipment and design with more energy-efficient alternatives [5,6]. Geng and Evans [6] call these two types of energy waste management-oriented (focused on improving the existing production setup) and technology-oriented (focused on changing to more energy-efficient technologies or product design). In lean terms, these two types of energy waste can be referred to as 'non-value-adding energy' and 'value-adding energy but low efficiency'. The authors emphasize the significant potential for addressing management-oriented waste by improving the production process without major changes or investments. This can be aided by, e.g., integrating digital technologies to visualize daily hidden energy waste.

In industrial manufacturing, energy management can be categorized into energy monitoring, energy evaluation, energy optimization, and energy benchmarking [8]. Other review studies use similar categories and highlight the use of digital technologies to support these steps and overall energy efficiency [20,36]. In this paper, energy benchmarking is included in the energy evaluation step.

2.3.1. Energy monitoring

Energy monitoring is an essential step to identify savings potential; it involves the continuous tracking and analysis of energy consumption patterns in real time [8]. It tells companies how much their processes consume. Energy monitoring requires the use of various tools to automatically collect, analyze, and visualize energy data, as suggested in sensor-based frameworks in several studies [40,41]. O'Driscoll and O'Donnell [42] provide an overview of power and energy metering equipment. Tan, Ng, and Low [26] split energy monitoring into machine, line, and factory level, and suggest a framework to collect both energy and production data coupled with analysis methods. Energy monitoring is often conducted at the plant or line level, making it difficult to identify and assess energy-saving measures. This is exemplified by Wen et al. [43], whose case study at a chinese die-casting plant highlights that, despite 30% of expenses being energy-related, there is still inadequate energy monitoring infrastructure.

2.3.2. Energy evaluation

This step involves developing an index system to identify and evaluate energy consumers in processes, as well as modeling and analyzing process and energy data to pinpoint inefficiencies and opportunities for improvement [8]. Energy evaluation helps define a company's future direction and identifies the energy-saving measures through which it plans to achieve its goals. As an example, Benedetti, Cesarotti, and Introna [44] proposed an energy performance control system allowing the comparison of energy indicators to a baseline, and Fysikopoulos et al. [45] developed energy efficiency indicators for comparing different processes to choose the most energy-efficient. Energy evaluation also involves using standardized methods based on lean manufacturing, such as energy audits utilizing energy billing information [36]. Braglia et al. [38] presents a lean method to classify, evaluate, and eliminate energy losses using a systematic approach. Wen et al. [43] focus on the integration of energy efficiency into production management to aid decision-making, proposing a method with three steps: energy losses modeling, lean energy analysis, and determining improvement strategies. In addition, Svensson and Paramonova [39] propose a four-step approach, including understanding the process, estimating the required energy use, quantifying the potential, and identifying improvement opportunities. A promising technique supporting a holistic analysis of the manufacturing system is simulation modeling, which includes energy flows and offers predictive capabilities [46], or data modeling [47,48].

For instance, Baysan et al. [49] employed energy value stream mapping as a simulation method to assess the impact of various lean tools, such as altering production layouts and enhancing machine performance, on energy efficiency.

2.3.3. Energy optimization

This step aims to correct the identified deviations in existing processes or implement new, more energy-efficient processes. This can be as trivial as switching out fluorescent lamps to LED lamps or improving building insulation. When improving energy efficiency in production processes, it is usually more complicated. For example, to explore optimal parameter settings and configurations for production processes, optimization algorithms can be employed, providing prescriptive capabilities, as demonstrated by, for example, Pimenov et al. [28] to align power consumption, carbon emissions, productivity, production costs, and waste generation in machining. As an example, Saez et al. [50] propose a simulation-based optimization framework that combines machine- and system-level models for production control for productivity, energy consumption, and other goals. Diaz et al. [29] design a control strategy for optimal activation of peripheral devices dependent on the current production program.

3. Materials and methods

The performed study has an exploratory research approach, investigating a phenomenon to gain a deeper understanding [51]. The phenomenon investigated is how digital technologies and knowledge demands are used to achieve energy efficiency at a single case. The selection of the company is justified by its implementation of energy management protocols, its application of lean procedures, and its commitment to the Science Based Targets initiative. To increase the validity of the findings, multiple sources are used [52]. The reliability is strengthened by having a structured and well described approach [53].

The qualitative data were collected through interviews (see Appendix A.1) that followed a semi-structured protocol (see Appendix A.2) to allow for adaptation of questions according to the knowledge and experience of the interviewees, and to give flexibility to their answers. The participants, denoted as P1–16, were chosen based on their engagement in energy efficiency projects and their spread across different production areas, captured through eleven semi-structured interviews (P1–13 and P16); there were also two workshop leaders (P14 and P15) (see the list of interviewees in Appendix A.1). The participants' roles included energy engineers (5), production and automation engineers (3), environmental sustainability experts (4), software developers (2), and managers (2). Empirical data were collected from December 2021 until July 2022. The participants worked at the case company in different areas such as the energy, media & support department, the axle paint shop, the final assembly, and the battery factory. The interview focused on the identification of energy waste and the evaluation and implementation of energy efficiency projects using digital and data-driven tools. The interviews had the following parts: (1) background and experience of the participants, (2) what the concept of energy waste means to them in their daily work, (3) what is measured in regard to energy waste (i), how energy waste is measured (ii), how it is reported (iii), how it is followed up and acted upon (iv), and (4) how digital technologies for reducing energy waste are used today, e.g., what technologies can be used for reducing energy waste in production (i), how data communication and visualization is or can be used (ii), how data analysis and artificial intelligence can be used (iii).

The interviews were transcribed using Amazon Transcribe and the transcriptions were double-checked by re-listening to the interviews. The analysis was performed systematically by identifying, reviewing, and defining themes and sub themes according to Braun and Clarke [54], searching for challenges and improvements as stated by the participants. The themes were then structured according to digital technology stages and knowledge demand types; then, if applicable, sub themes were constructed following a deductive approach.

Multiple sources were used to compare findings from the interviews, i.e., further information about how the company works with energy waste was collected from internal documents and one author attended a workshop focusing on energy efficiency in new factories (data triangulation) [52]. All authors participated in the analysis (researcher triangulation). Additionally, one author held multiple sessions with an energy expert (P14) at the case company to evaluate and refine the findings and framework. The framework was further validated through discussions with an environmental sustainability expert from a competing firm in the same sector. This was done to ensure the frameworks broader applicability (source triangulation). Finally, links to previous research supported the validity and reliability of the case study [52].

3.1. Context description

The company categorizes methods and activities on energy consumption into energy waste and energy efficiency. Energy waste refers to energy utilized during non-value-adding activities, e.g., sub-optimal parameter settings in machines, whereas energy efficiency refers to realizing (increased) value with reduced energy consumption, e.g., by using more energy-efficient equipment. The energy, media & support department developed an energy roadmap for its industrial operations in accordance with the Science Based Targets initiative. The goal of the organization is to reduce energy consumption by 25% in its industrial operations by the year 2025 as compared with the year 2015. Then, energy consumption reduction goals for the different production units were formulated, based on their potential for energy savings.

4. Results

Fourteen challenges and improvement potentials (CI) were identified. Seven were identified as being connected to digital technology stages (see Table 1) and seven on knowledge demand types (see Table 4). A description of the CIs is presented according to their digital technology stage or knowledge demand type.

4.1. Challenges and improvement potentials for achieving energy efficiency through digital technologies

Data-driven decision making for increased energy efficiency using digital technologies is of growing interest to the company. The company faces several challenges when working with it. As an example, the existing energy meter infrastructure is limited, which makes it hard to monitor energy accurately. Furthermore, the energy management system responsible for data collection and sharing incurs high installation and maintenance costs, while also lacking scalability and stability. In the company, energy consumption data are aggregated on a monthly basis and shared with specific production personnel via an Excel file which allows only the most significant deviations to be addressed. Currently, there is only one energy dashboard actively utilized on the shop floor to mitigate energy waste during non-production hours; this dashboard operates using legacy visualization software. The personnel generally possess broad knowledge and ideas for enhancing energy efficiency but lack simulation tools to assess its impact. In one instance, algorithms were developed and tested to automatically shut down affected machines following a failure, but implementation proved challenging. The adoption of AI for energy efficiency improvements has not yet been initiated.

To measure energy consumption and expand the currently sparse energy sensor infrastructure, the company attaches clamp-on or installs permanent sensors to measure old equipment (brownfield), and sets purchasing demands on new equipment (greenfield) (see 4.1.1 and 4.1.2 *Computerization*). A new energy management system is being

Table 1
Challenges and improvement potentials (CI) found on digital technologies, sorted according to the digital technology stages.

CI	Code	Digital technology stage
1	Measuring of brownfield machines	Computerization
2	Requirements for greenfield equipment	Computerization
3	Energy management system: Automated data flows through state-of-the-art OT/IT systems	Connectivity
4	Energy visualizations: Quickly identifying the problem	Visibility
5	Root cause analyses of energy losses: Quickly diagnosing the problem	Transparency
6	Simulation and data modeling to predict outcomes	Predictive capacity
7	Self-adaptive control system using AI models	Adaptability

Table 2
Relevant indicators for energy efficiency and life cycle cost calculations.

Indicator	Unit
Energy Consumption	
Electricity consumption during processing	kWh
Electricity consumption during standby	kWh
Energy consumption per part produced	kWh/pcs
Energy consumption per area	kWh/m^2
Water Usage	
Cooling water (14–21 °C)	kWh
Heating water	kWh
Air Usage	
Compressed air (5 Bar)	Nm^3/min
Air ventilation	m^3/hour

Table 3
Signal descriptions for machine & equipment connection (MEC) guidelines.

Signal Description	Unit
Electricity	
Instantaneous power (e.g., electrical engine)	kW
Consumed energy since last power off (e.g., electrical engine)	kWh
Compressed Air	
Total flow in circuit(s)	m^3/h
Instantaneous flow in circuit(s)	m^3/h
Air consumption	m^3
Production	
Total parts produced	pcs
Parts produced of current part number	pcs

developed to facilitate the collection and sharing of energy data to the shop floors (see 4.1.3 *Connectivity*). The system contains visualization software to generate reports and dashboards for the shop floors (see 4.1.4 *Visibility*). The data collected can serve for troubleshooting, to help understand energy consumption behavior and improving machine operation (see 4.1.5 *Transparency*). The acquired knowledge prompts corrective actions, assuming that the future state will be improved compared with the present. These assumptions can be validated using simulation or data models, providing predictive capabilities (see 4.1.6 *Predictive capacity*). Ultimately, the goal is to develop a self-adaptive control system capable of autonomously identifying, diagnosing, and resolving issues without direct human intervention (see 4.1.7 *Adaptability*).

4.1.1. Measuring of brownfield machines (Computerization)

Today, the energy meters in the factories are connected to transformers supplying electricity to a multitude of consumers. Sometimes, it is not known to production units what equipment these meters are connected to (P7). This makes it hard to monitor energy accurately. When necessary, brownfield machines are temporarily and manually measured using clamp-on meters (P2, P11). This allows comparisons between actual and reference energy consumption in equipment. A crucial first phase in projects involves determining the necessary level of detail. Larger equipment comprises several sub-processes, such as spindle motors and lubricant pumps, each of which can be individually measured (P11). Measurement accuracy is an important consideration when taking measurements; this can usually be mitigated through choosing the right measuring instrument, regular sensor calibration, and accounting for error margins during analysis and when aggregating separate measurements. These energy data can support targeted improvements in energy efficiency, where the greatest potentials lie. Relevant indicators are shown in Table 2. This manual approach is deemed unsustainable due to the time and resources it takes (P14). On the other hand, retrofitting existing equipment with energy meters is costly.

4.1.2. Requirements for greenfield equipment (Computerization)

Previously, no purchasing standards regarding energy efficiency existed as part of the procurement process for new equipment. The company has now begun integrating standard monitoring features into new equipment, including built-in electricity meters (P11) and energy-saving modes (P14). This prompts the company to define energy data requirements for continuous machine monitoring, including required tags, granularity, and data communication system (P13). An example of signal demands on energy and production-related measurements is shown in Table 3. Establishing these requirements from the start can ensure data availability (P9) and prevents the need to later adjust to different data collection practices (P13). In addition, the company started including a validation test of the energy consumption demands during line implementations (site acceptance test) (P12, P14). The remaining challenge is to design the process in a way that everyone follows it, and understand in what granularity the data are most useful (P14).

4.1.3. Energy management system: Automated data flows through state-of-the-art OT/IT systems (Connectivity)

The primary challenges of the current energy management system include high installation and maintenance costs, scalability issues, and stability concerns (P2). These challenges mostly stem from heterogeneous sensor technology (P5) (operational technology, OT), unstable sensor–gateway connections (P5), and isolated databases (information technology, IT) making data collection a time-consuming process (P1, P12). Therefore, the company is implementing a new energy measurement system, using new OT/IT infrastructure and storing data both in a time-series database and in the corporate data warehouse (P1) (see Fig. 4). This allows for real-time data visualization as well as historic analysis alongside production data.

Given the absence of a one-size-fits-all solution, a combination of technologies was needed that would enable a cost-effective and scalable way to measure, store, and stream data (P12). Considering the company's existing sensor infrastructure, the ability to connect existing wired technology (e.g., M-Bus/Mod-Bus meters) to wireless adapters (akin to using a single-board computer with hardware attached on top (HAT)), is considered one of the greatest potentials today (P10). Therefore, the focus is on testing different wireless communication protocols (e.g., LoRa, Wi-Fi, 5G). The company has found that LoRa is ideal for less frequent, wide-range communication, while others, such as 5G, are better suited for instantaneous streaming of highly granular data over shorter ranges (P10). Currently, the company is evaluating a new technology, mioty, and comparing its performance to that of LoRa (P2).

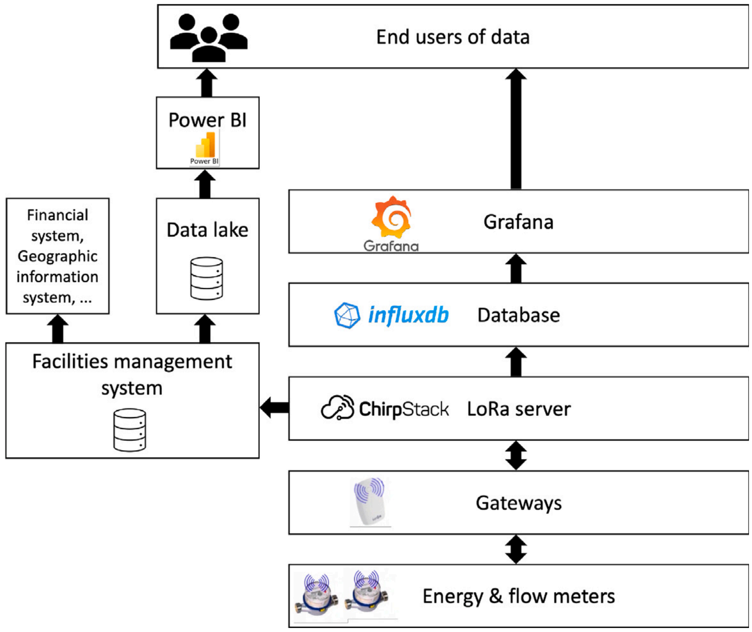

Fig. 4. The existing energy management system is being expanded with modular OT/IT components, utilizing LoRa communication. Data ingestion into InfluxDB occurs instantaneously, enabling closer-to-real-time data visualization. Conversely, data ingestion into the company's data lake is conducted once daily and used to merge with production data for historical analysis.

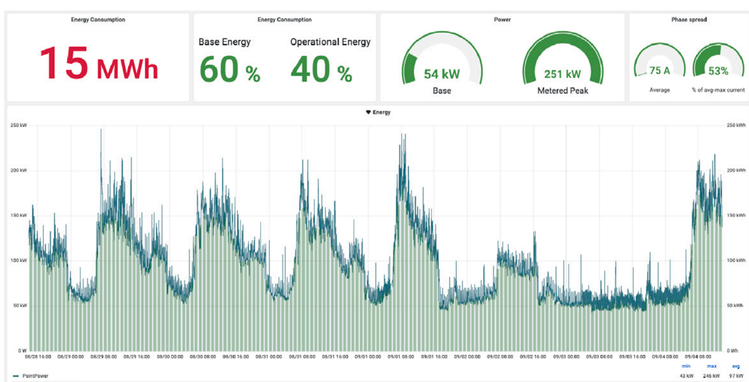

Fig. 5. Energy dashboards for service workshops at the case company.

4.1.4. *Energy visualizations: Quickly identifying the problem (Visibility)*

One challenge of energy visualizations is to quickly identify deviations. Today, the feedback delay of sharing energy consumption data to the shop floor is between one day to one month (P9). For most production units, the follow-up consists of comparing the monthly consumption value with the one during the same month last year, to see large-scale deviations. With the new energy management system, the company's goal is to make the collected energy data accessible to personnel in near real time through visualization software such as Power BI and Grafana (P1). The first energy dashboard employed in the company displayed energy waste from production equipment running during non-production hours. A current project collects data from a single production line and merges production metrics with energy consumption (P1, P2). Another project measures energy consumption in service workshops (Fig. 5).

When measuring energy per line or facility, a potential next step involves identifying the biggest consumers on a site, creating a top-ten consumer list for targeted initiatives (P16). This can be done by either taking individual machine measurements using sensors or using algorithms to decompose the high-level signals to identify consumers and their run times (P1, P16). The consumers are often organized by Pareto principle (an example is shown in Fig. 6).

4.1.5. *Root cause analyses of energy losses: Quickly diagnosing the problem (Transparency)*

The company's way of working with energy consumption deviations is reactive and manual. If personnel detect large deviations in the monthly spread sheet, and if time allows, manual investigations are started. This includes looking into why equipment was running outside of production hours, such as a vault not closing and preventing the machine from shutting down. Alternatively, a more serious machine malfunction would require deeper investigation into the behavior of machines (P2, P3, P9, P12). A challenge is therefore to do quick root cause analysis based on data. As an example, some participants mentioned the goal of finding critical faults in real time (P10, P12, P14). For this, data and analytic tools are necessary to help generate new knowledge about the processes and understand certain events, e.g., what leads to high or low energy consumption or costs for a given day or month by connecting the energy consumption profile to process parameters, the production schedule, and the billing (P10). A better

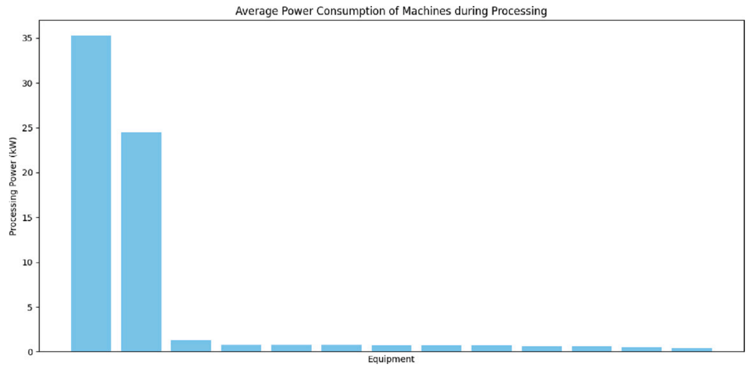

Fig. 6. List of energy consumers in a transmission assembly line at the case company, with the top two consumers accounting for over 83% of the total energy consumed.

Table 4
Challenges and improvement potentials (CI) found on knowledge demands, sorted according to the knowledge demand types.

CI	Code	Knowledge demand type
8	Develop cross-disciplinary competences in digitalization and automation	Technical knowledge
9	Apply the right strategy to reduce energy waste	Technical knowledge
10	Establish normal situation: Define and compare energy indicators	Technical knowledge
11	Establish effective (lean) methods to identify energy waste and educate personnel	Process knowledge
12	Apply easy-to-use and stable digital technologies to support processes	Process knowledge
13	Communicate the energy strategy clearly	Leadership knowledge
14	Define clear ownership and resources	Leadership knowledge

understanding of machine behavior can also help to develop control logic that automatically issues maintenance orders (P14).

4.1.6. Simulation and data modeling to predict outcomes (Predictive capacity)

Several ideas were mentioned to use simulation for estimating effects of projects, for instance, to predict the effect of a more even flow of products on productivity and energy consumption (P3), the effect of production layout changes on energy consumption (P6), or predictions on energy consumption and product output of future lines by knowing the type of equipment and tact (P8). This allows to test assumptions computationally and prevents the need for design of experiments. A simulation model of a production line can provide theoretical consumption calculations under optimal conditions (P12). This helps to establish an accurate 'normal situation' scenario, which can be compared with the actual energy consumption, so that energy waste can be quantified.

Data-driven methods were also stated as a potential. For instance, the downtime of certain equipment can be predicted. It was seen that failures in one machine propagated into other machines. Using historical data on failure duration and ramp-up times, the expected downtime can be predicted and the affected machines be put into energy-saving modes (P11). Energy data modeling can also be used for predictive maintenance. By employing sensors in critical machines, a reference scenario under ideal conditions can be established. Then, trends in the energy consumption behaviour can be detected that give an indication about the health of the machine (P3, P10, P11, P14).

4.1.7. Self-adaptive control system using AI models (Adaptability)

Despite the absence of examples applying AI for energy consumption reduction, several participants recognized the potential of integrating industrial automation software with AI for this goal (P1, P10, P11, P12). One participant mentioned that their plan moving forward is to eliminate logical programming entirely; instead *"everything is controlled by AI"* (P11). For this, the industrial automation system needs to be coupled with algorithms that dynamically optimize parameters and self-regulate during the running process. This demands knowledge in, e.g., cyber security and AI models (P2, P11, P12).

4.2. Challenges and improvement potentials for achieving energy efficiency through knowledge demands

The company faces challenges of performing changes on the shop floor, as solutions often do not follow a standard or guideline but instead demand specific technical knowledge of the machines and the control system. Even seemingly easy fixes such as switching off and on machines require good understanding of the underlying control system. The knowledge exists or can be acquired, but this often incurs costs and calls for resources that are not budgeted for today. Therefore, there are challenges seen in developing methods that are easy to use and to understand. Where (new) processes and methods exist, a challenge is the communication of the new standards across the whole organization.

The growing application of digital tools in the company will demand both more automation and digitalization skills (see 4.2.1). Here, it can be seen that different production units require different energy efficiency strategies (see 4.2.2). With the help of the energy management system, normal situations can be defined and compared against (see 4.2.3). User-friendly digital tools can then help aid the production teams to reduce energy waste (see 4.2.5). However, concentrated efforts through methods and processes to find and reduce further energy waste are implemented (see 4.2.4). A clear vision of the energy-efficient production system needs to be communicated (see 4.2.6), and the production units need to have the means to progress towards it (see 4.2.7).

4.2.1. Develop cross-disciplinary competences in digitalization and automation (Technical knowledge)

To help achieve increasing levels of digital technology in production, more digitalization and automation competence will be needed, additional to the operational engineering knowledge. Such competences are, among others, software development, data analytics, and energy and automation engineering. Some projects require competences from several teams, which work in silos today (P9). The need for the right competences is emphasized by one participant stating that if no processes are there then it is a problem to include the right people (P10). The same participant stated that *"you need to make IT understand production and production understand IT"* (P10). Another participant mentioned that all digital technologies already exist in the line, but nobody knows how to use them (P11). Additionally, the increasing

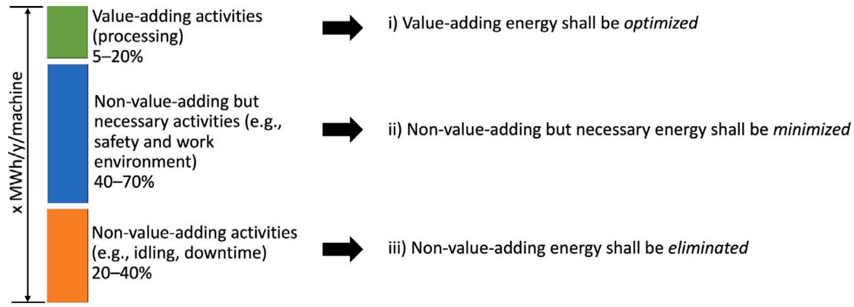

Fig. 7. The average range of energy consumption ratios between value-adding, non-value-adding but necessary, and non-value-adding activities in production machines, along with corresponding strategies.

relevance of control systems demands technical understanding of the support systems (P3, P12). As an example, a participant stated his understanding of why shutting down production equipment through the SCADA system may occasionally fail and lead to idle losses: *"So the entire system was just stuck waiting for the temperature to drop to a certain point, which it never would, since the valve regulating the hot water wouldn't close"* (P3).

4.2.2. Apply the right strategy to reduce energy waste (Technical knowledge)

Energy efficiency strategies, as well as the required competences, differ depending on the production context. First, the energy experts look for areas with high savings potential; for instance, the focus on brownfield machines is particularly significant in the most energy-intensive processes, namely foundry, hardening, and painting (P9, P12). Then, the energy consumption of the equipment is mapped and strategies defined that change either the process or the equipment. In some areas, such as final assembly and the paint shop, technical building services such as lighting, heating, and ventilation are the most significant consumers (P6). In other processes, such as machining, technical building services still account for the largest share of energy consumption. However, production equipment consumes a relatively larger share of the total energy compared to other processes.

Examples of strategies for existing processes (focused on non-value-adding energy) include lowering air temperatures in a paint shop by two degrees, leading to cost savings of one million SEK (P12). Another example is controlling the equipment in the process to help even out the consumption over time and prevent surcharges due to overcapacity, representing millions of SEK every year (P10, P16). A participant estimated that by only reducing peaks in service workshops, between 30 and 40 percent reduction of the electricity bill could be achieved every month (P10). Challenges, however, arose due to the complex setup of existing production equipment, rendering even simple tasks, such as turning off lights, difficult for personnel (P6). Additionally, participants mentioned several successful projects that replaced pieces of old equipment with more energy-efficient ones (focused on value-adding energy but low efficiency). This involved, for example, converting to LED lamps in one production facility, replacing compressed air with electric tools, and installing frequency inverters in fans, pumps, etc.

The company's energy experts estimate that generally only 5%–20% of the energy consumed is used for *value-adding activities* (P14, see Fig. 7). The remaining 80%–95% of energy consumed is utilized for non-value-adding activities, of which around 40%–70% is allocated to *non-value-adding but necessary activities* such as safety and work environment installations such as lights. 20%–40% of the energy consumed is considered *non-value-adding and unnecessary* and therefore pure waste (P12). Consequently, the three categories can be approached with the following strategies, (i) value-adding energy shall be *optimized*, (ii) non-value-adding but necessary energy shall be *minimized*, and (iii) non-value-adding and unnecessary energy shall be *eliminated*.

One participant provided an example in machining, where the company employs two different process technologies: wet machining and minimum quantity lubrication (MQL) machining. Both processes show a similar ratio of energy distribution between value-adding and non-value-adding activities. However, the total energy consumption of the two processes differs substantially (see Fig. 8). These insights lead to different strategies. For one, MQL machining should be set as the purchasing standard (65 MWh/y/machine vs. 90 MWh/y/machine), and personnel need to be trained to operate the equipment optimally and discover additional ways to reduce energy consumption. On the other hand, in terms of reducing non-value-adding activities, the focus should be placed on the wet machining process, as energy consumption can be reduced more in absolute numbers.

4.2.3. Establish normal situation: Define and compare energy indicators (Technical knowledge)

Key energy metrics play a crucial role in evaluating the energy efficiency of a site or equipment. Energy targets need to align with production goals and schedule (P10). The central energy group has established the company-wide metric 'energy used per produced unit' (P1). This metric is particularly meaningful for production areas characterized by more demand-driven energy consumption, such as machining. However, its relevance diminishes in production areas such as assembly, where the predominant energy usage is attributed to heating and lighting (P6). A starting point can be to assess the ratio of base load to operative energy consumption across various production areas (P16). In processes characterized by high base loads, the focus can be placed on technical building services, whereas processes with high variable energy consumption require attention to the running production processes. Other areas such as service workshops might best be measured and compared by energy used per square meter (P10).

Next, it is essential to define a 'normal situation' against which the current energy consumption can be compared (P2, P14). This can be done by utilizing the energy specifications of the machine or by benchmarking, i.e., measuring and comparing against similar production equipment or areas (P12, P14).

4.2.4. Establish effective (lean) methods to identify energy waste and educate personnel (Process knowledge)

It is important to educate personnel on how to identify and reduce energy waste (P9, P12, P13, P6). One participant said, "*It's difficult to act and react on [energy waste]. Because it's not so visible*" (P12). The central energy group has implemented and leads several methods that are inspired from the company's long-standing lean methodology. Energy kaizen, green accelerator, rolling 12, the Investment Process for Production Equipment (PEIP), and benchmarking are examples. Effectively, the company seeks to teach personnel 'energy eyes' (P12), which, similar to the way the personnel identify productivity waste today, are able to identify energy waste. During an *energy kaizen*, a specific production process is investigated during a multi-day process bringing together personnel with different competences to assess and prioritize energy-saving activities. Its goal is to find waste in the production process, e.g., identify lower temperature demands in spray

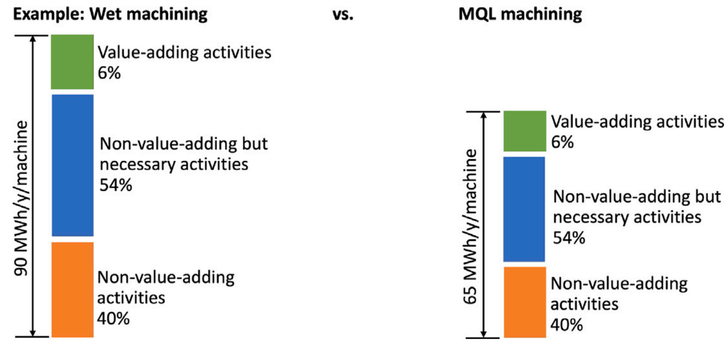

Fig. 8. Total energy consumption and average ratio of energy consumption during value-adding to non-value-adding activities in two machining process technologies. The example showcases that different strategies need to be applied. The purchasing standard should be set on MQL machining; when reducing non-value-adding activities, the focus should be on wet machining.

booths, as well as to develop competences and knowledge on how the employees can contribute to the goal without compromising the quality of another part of the process (P9, P12). The activities are ranked based on their potential for cost and energy consumption reduction and split into short- and long-term activities. Another example, the *green accelerator* method, maps all resource flows of unit processes, including energy and waste. The company uses *Rolling 12* for energy reporting, looking at figures of energy consumption of the past month compared with that month in the previous year, with the end month constantly rolling forward. This is used to troubleshoot large deviations. *PEIP* sets energy requirements during the procurement of new production equipment. *Night patrolling* involves the inspection of the production process during non-production hours, to identify equipment that is running unnecessarily. *Benchmarking* involves the comparison of energy consumption behavior among similar machines and processes.

4.2.5. Apply easy-to-use and stable digital technologies to support processes (Process knowledge)

Digital technologies could assist in establishing routines for energy efficiency. Measuring and visualizing energy consumption management is a significant potential for the company. In this context, two participants mention the need for 'plug and play' solutions (P5, P12). One participant stated that "*there is not a lack of different technologies, but it must be ... easy and stable so that the operator can manage it*" (P12).

For instance, dashboards played a role in cultivating a mindset, establishing routines, and measuring results (P6, P9, P12). One participant noted that they began implementing energy dashboards in 2017, but within a year, many were removed due to lack of use (P12). Only one in the paint shop and one in the office space of the energy experts remain (P12). The use of dashboard visualizations in the paint shop led to the creation of a checklist and a standard for shutting off machines (P9). The dashboards had the same visual coding as other lean tools (P9). Production personnel started monitoring energy consumption deviations, which helped them understand whether they shut off the equipment correctly and, if not, investigate why (P12). However, multiple participants pointed out that despite using the dashboard daily and its substantial contribution to reducing energy waste, there are challenges associated with the interface and the presented information, which makes troubleshooting deviations time-consuming for individuals such as P3 and P4. The dashboard requires continuously developing and adapting to the user's needs (P10). The paint shop working with the dashboards has been able to substantially reduce its energy waste and has started looking at more process-related issues to improve further.

4.2.6. Communicate energy strategy clearly (Leadership knowledge)

One problem was the translation of the high-level energy roadmap into performing the work on the shop floor level. The energy targets are communicated top-down, and every production unit is responsible for its energy consumption and for achieving the target (P12). This requires a company-wide strategy with clear responsibilities regarding which unit does what in regard to the environmental work, as well as a major organizational change to get the employees involved (P6). Top management support makes it easier to communicate the importance of this topic with the production units, which is a potential in simplifying this challenge (P12). One participant mentioned the progress during the last few years when it comes to the strategy of environmental work, which included them creating the energy roadmap and the waste material roadmap so that the units would know what the important issues are (P9). Environmental coordinators in each production unit try to meet these targets by implementing activities. The central energy group assists the units with its competence and creates so called 'score cards', documents stating the different energy savings activities per production unit and their estimated effect in kWh. This helped to spread best practices from all these activities across departments (P12).

A vision that has been formulated and communicated by the central energy group is the development of an energy-efficient production system, or 'demand-driven system design' (P12, P14). In such a system, the end user is supplied with only the amount of energy that is needed at that moment. This keeps the relative energy consumption per produced unit steady, regardless of the fluctuating demand. Today, fluctuations in production volume, which over a five-year cycle can lead to a reduction from four shifts to one shift, do not show an equivalent reduction in energy consumption (P12). But this can be achieved by advancing on the energy-efficiency maturity ladder that the company defined (Fig. 9). Different maturity levels are reached, depending on the production area and type of equipment investigated, as well as where the system boundary is drawn (P14). Some processes and machines are already at a higher level. However, if the system boundary is set on factory level, the company is still on the lowest level, where it always supplies energy to the factories (P14).

4.2.7. Define clear ownership and resources (Leadership knowledge)

In production environments, there is a prevalent use of legacy equipment that often operates inefficiently, leading to unnecessary energy consumption. Although there are many ideas, many projects were not executed due to the effort and costs of testing product and process quality (P9). Tests need to ensure a working process without ruining the product (P1, P3, P9, P12).

Often, the production units do not have the budget or personnel for energy improvements and instead end up negotiating internally on who takes the costs and responsibility (P6, P7). Similarly, during the monthly follow-up of energy consumption data, it is not clear who should act on deviations to fix the equipment in production (P12). As an example, an environmental project did not progress due to lack of competence, people, and time. Additionally, the production units do not know what to do with their data (P10). Another participant experienced a halt in the project due to information security (P11).

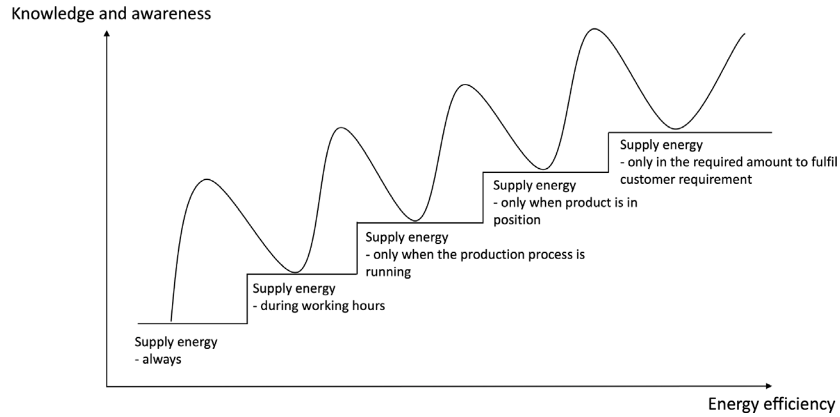

Fig. 9. The company's 'energy-efficiency maturity ladder' defines four steps toward an energy-efficient production system. The first step is attained by shutting down equipment outside of working hours. The second step involves shutting down equipment during, e.g., production or maintenance breaks. The third step encompasses switching machines into energy-saving modes while awaiting products. The final step means meeting the criteria for energy efficiency, where only the necessary amount of energy is supplied to meet customer requirements.

Therefore, reaching the targets requires to empower and motivate departments by having a clear set of responsibilities and goals as well as the resources to carry out initiatives. This is important, as "*it's crucial to get the feeling of 'this is my problem. I have the solution and the ability to make it better*" (P8). Relating energy consumption reduction potential to cost savings can help to rationalize investments (P3, P6).

5. Discussion

Using digital technologies and knowledge demands systematically, the authors believe that it is possible to properly overcome pitfalls connected with the energy management steps (energy monitoring, evaluation, and optimization) and that energy waste can be targeted more effectively. The investigated company takes energy efficiency seriously and has achieved success in reducing energy waste. However, it has not yet adopted higher levels of digital technology solutions, a trend also observed in other industrial companies [37]. Higher stages of digital technology were tested, but the associated implementation challenges were not overcome [16]. Although human-centered digital technologies are considered enablers for reducing energy waste [20,55], many companies still face challenges in their implementation and application [19]. Importantly, the results of the study suggest that companies progressively encounter CIs for enhancing energy efficiency, i.e., new challenges arise at already reached stages. The CIs and how they relate to previous research are presented in Table 5.

The CIs can be categorized in line with the approach taken by Cai et al. [8] and Batouta, Aouhassi, and Mansouri [20] and occur across the three energy management steps: energy monitoring, energy evaluation, and energy optimization. *Energy monitoring* aims to achieve continuous tracking of energy consumption data in both brownfield and greenfield machines [8]. Most of the work in this category involves integrating and retrofitting OT/IT tools, i.e., sensors, databases, and visualization software. In addition, technical specifications for greenfield equipment are important and reduce the effort required for retrofitting technology in the company. For this, new competences are required to install stable and easy-to-use technologies. The *energy evaluation* step includes making the data visual. After making data visual, they need to be made useful. This is done by defining a normal situation in production, to be able to identify deviations and set realistic goals and a clear strategy. Then, modeling and analyzing the process is used to diagnose the deviations, generating improvement ideas [8,36]. This process is supported by a standardized approach, typically built on lean methods [39]. From *visibility* to *transparency* and onwards, digital technologies aid employees in knowledge discovery about energy consumption deviations and improvements to support decision makers [25,31]. In the *energy optimization* step, many strategies within the company effectively reduce energy consumption and costs without applying digital technologies. For each production unit, identifying the appropriate energy efficiency strategy is crucial [56]. Subsequently, production units need resources to implement the strategies. Looking ahead, a vision of the company is to optimize parameters and correct processes autonomously through the control system, coupled with real-time calculations by an AI [28]. In one unit, an algorithmic solution was developed and tested to shut down stop-affected machines.

5.1. Visualizing the findings in a conceptual framework

To organize the empirical findings in a way that allows other companies to address the identified challenges and improvements, a conceptual framework is presented in Fig. 10. The framework consists of (i) the digital technology stages, (ii) the identified CIs, (iii) three energy management steps, and (iv) the knowledge demand types. Each digital technology stage serves as a building block, establishing preconditions to succeed in the subsequent stage. This means that the quality of one step depends on the quality of the previous step. For instance, a precise diagnosis of deviations can only be made with high-quality data input. The knowledge demand type approach highlights and clarifies the need for different roles within the system (as was also suggested by Andrei, Thollander, and Sannö [16]). It strengthens organizational aspects that enable the reduction of energy waste, such as the relevance of standards, rules, top-down energy roadmaps, and the need to understand manufacturing processes amid the increasing complexity of OT/IT systems. Throughout the energy management steps, knowledge is gained and translated across knowledge demand types. For example, once *technical knowledge* of a process is gained and its applicability is proven elsewhere, a standard or routine can often be defined, leading to the acquisition of *process knowledge*. Therefore, some CIs were coded as technical and others as process knowledge, reflecting the company's maturity level concerning each CI. *Leadership knowledge* build upon technical and process knowledge; this is where strategic decisions regarding energy management are made and where long-term competence strategies are established.

5.2. Reflections

By integrating digital technology and knowledge requirements for energy management in lean manufacturing systems, the company can increase its understanding and the achievement of energy efficiency in industrial manufacturing. Although the interplay between these two concepts needs further investigation, their connection becomes evident when considering the impact of each individually or in combination. Even in the absence of digital technologies, energy efficiency can be

Table 5
Challenges and improvement potentials (CI) and their connection to literature.

CI	Connection to previous research
1: Measuring of brownfield machines	Consistent with prior studies emphasizing the importance of energy monitoring in production machines [8,42], the company employs manual metering alongside upgraded legacy energy metering equipment to provide the necessary measurement detail to identify savings potential.
2: Requirements for greenfield equipment	The company established standards to install sensors in new machines to enable data sourcing through the existing MES, as suggested in literature on enabling an advanced energy management system [57].
3: Energy management system	Establishing robust data pipelines is essential for accurate energetic evaluation and modeling of processes [35]. Similar to the company, prior studies have demonstrated modular energy management system utilizing various OT/IT tools, such as Raspberry Pis and Grafana [41].
4: Energy visualizations	According to Modig and Åhlmström [22], visual planning provides transparency which is essential for supporting processes and detecting deviations. Benedetti et al. [44] propose energy performance indicators and visualizations, such as cumulative sum charts, to identify deviations over time. A similar, less advanced approach was seen in the company.
5: Root cause analyses	Different authors suggest various approaches to diagnose and prioritize energy losses, e.g., through value stream mapping [43] and a step-wise lean method [38]. Implementing a real-time system enables real-time fault diagnosis [57], as seen in the company's ambition in greenfield environments.
6: Simulation and data modeling	Simulation modeling is effective for predicting the impact of lean improvement strategies on energy losses [27,49]. Coupling this with optimization can help prescribe activities [50]. Recently, data modeling to assess the effects of production parameters on energy consumption, emissions, and costs has gained interest [47]. The case company expressed the need for similar predictive capacities.
7: Self-adaptive control system	Few examples exist in literature of autonomous control systems. Diaz et al. [29] developed an autonomous control model for selectively activating devices based on the production program. The case company tested switching off downstream machines during upstream stoppages exceeding a certain duration, but implementation was hindered by IT security concerns.
8: Digitalization and automation competences	New types of knowledge, skills, and processes are needed to provide (digital) support for identifying, diagnosing, and eliminating energy waste in production [16]. The company adapts new technologies to new business needs such as energy efficiency; hence, different types of competences are needed [21].
9: Apply the right strategy	Duflou et al. [56] define strategies for improving energy efficiency in manufacturing. The case company applies a range of strategies, predominantly simpler implementations including the selective activation of machines.
10: Establish normal situation	Establishing a baseline is essential for identifying deviations, a key step in energy evaluation [43,44]. The company follows this approach to monitor and target processes.
11: Establish effective (lean) methods	The company employs lean-adapted methods like energy kaizens to monitor and target energy waste, aligning with literature that applies different lean techniques [39,43,49]. A result of these analyses is enhanced personnel knowledge, an outcome observed in our case study.
12: Stable digital technologies	Stable and easy-to-use solutions hold significant potential [23]. This is also supported by lean methodology [22]. In the company, a legacy energy management system is retrofitted to be able to scale simple dashboards that help personnel to, e.g., troubleshoot equipment that failed to shut off.
13: Communication of energy strategy	Effective communication is critical, as a lack thereof often hinders personnel's understanding of manufacturing strategies [24]. The findings underscore the need for clear communication of the energy strategy down to every production unit.
14: Ownership and resources	Production needs clear project ownership and sufficient resources to implement the right energy strategies [56].

improved through the knowledge and actions of employees. Behavioral approaches, such as not running production machinery outside of production hours, can be employed. Basic insights, like identifying the primary consumer or 'energy hotspot' in a production line, can be gained without relying on data. However, uncovering energy waste beyond obvious inefficiencies becomes time-consuming and resembles a guessing game. Conversely, lacking knowledge about energy efficiency may lead to the optimization of production processes solely based on lean methodology, which emphasizes productivity and operational efficiency. This focus can potentially result in adverse effects on energy or resource efficiency [23,58–60]. Instead, when digital technologies and knowledge demands for energy efficiency are combined, they can complement each other. The outcome is a well-informed workforce capable of detecting both energy waste and productivity waste with equal proficiency. For example, energy visualizations and data modeling can aid in discovering new knowledge about the energy consumption behavior of processes and its correlation with process parameters. This, in turn, supports personnel in identifying and addressing energy waste while balancing other goals, such as increased productivity. It also enables the implementation of more technical measures. One important aspect is understanding what constitutes value-adding versus non-value-adding energy, which was seen as challenging.

From a digital technology perspective, the stages are not seen as a linear process. Instead, the implementation of digital technologies can be seen as a progression where additional requirements emerge across the stages over time. Although there is progress in the company at the initial stages of digital technology—for example, in implementing an energy management system—it does not mean that everything is resolved. Given the company's large size, expanding the training of 'energy eyes' (employees skilled in energy awareness) and disseminating knowledge about using digital technologies are necessary. Consequently, the empirical confidence in the digital technology CIs at the lower stages is higher, as the company has been working on them for many years. Similarly, there is more research on implementations of the lower stages, while the higher stages appear in fewer publications.

5.3. Limitations and future research

A limitation of the study is its explorative nature, as it draws findings from a single company. This was strengthened through triangulation. In addition, after forming the framework, one author presented it to participants working at the company, who suggested changes to the framework so that it better aligned with their ways of working. The same author presented it to an expert from a competing company

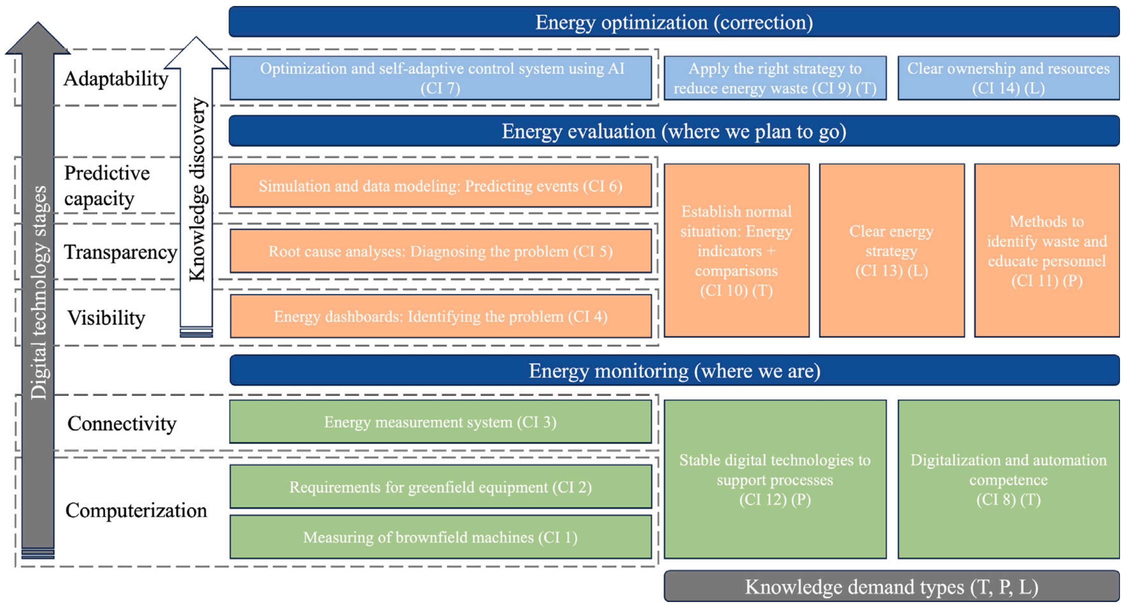

Fig. 10. Conceptual framework of achieving energy efficiency using digital technologies and knowledge demands in a lean manufacturing context. The CIs are clustered into the three energy management categories energy monitoring, energy evaluation, and energy optimization. The abbreviations associated with the knowledge demand type CIs refer to technical (T), process (P), and leadership (L) knowledge. Knowledge discovery occurs through data-driven methods.

in the same sector, who said that they used a similar approach to energy management, thereby enhancing both the validity and industrial applicability of the findings.

To further improve the generalizability of results, future research will explore technical implementations and its connection to knowledge management. A simulation study was performed to study how decision-support for energy efficiency and productivity in production processes can be achieved. Simulation fits, according to digital technology stages, with energy evaluation, which as stated in the framework, should make data visual and useful. In the study, knowledge demands were supported since the process of extracting information from the system can be standardized [32]. Preliminary results show that with the help of simulation- and data-modeling significantly higher energy efficiency can be achieved, and actionable knowledge can be extracted (knowledge discovery in the framework). This supports the CI placements in the framework.

6. Conclusion

This paper investigated the role of digital technologies and knowledge demand types in energy management practices. The study made two significant contributions. Firstly, it identified fourteen challenges and improvement potentials for achieving energy efficiency, demonstrating the critical importance of digital technology stages and knowledge demand types. Secondly, the study presented a conceptual framework to address these challenges, demonstrating how companies can integrate digital technologies and knowledge demand types to overcome pitfalls and achieve energy efficiency. Digital technologies and knowledge demand types are crucial for addressing diverse challenges across energy monitoring, evaluation, and optimization steps. By systematically integrating these elements, companies can bridge the gap between energy efficiency goals and practical implementation. Furthermore, the complementary interplay between digital tools and organizational knowledge build workforce skills, enabling a balanced approach to energy savings and productivity gains—an essential step toward sustainable manufacturing.

CRediT authorship contribution statement

Thomas Schmitt: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Visualization, Writing – original draft preparation. **Sandra Mattsson:** Methodology, Validation, Formal analysis, Investigation, Writing – original draft preparation, Investigation. **Erik Flores-García:** Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Investigation. **Lars Hanson:** Methodology, Investigation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Thomas Schmitt reports financial support was provided by Scania CV AB and a relationship with Scania CV AB that includes current employment. Lars Hanson reports financial support was provided by Scania CV AB and a relationship with Scania CV AB that included employment during the execution of the research. The other authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Interview appendix

A.1. Table of interviewees

See Table 6.

Table 6
Profile of interviewees.

	Department	Function
P1	Energy, media & support	Energy & development engineer
P2	Energy, media & support	Energy engineer
P3	Axle paint shop	Production engineer
P4	Axle paint shop	Technician
P5	Energy, media & support	Energy engineer
P6	Final assembly	Sustainability coordinator
P7	Final assembly	Environmental coordinator
P8	Battery factory	Safety, health, & environment coordinator
P9	Transmission assembly	Environmental & sustainability coordinator
P10	Smart factory	Software developer & IoT expert
P11	Smart maintenance	Maintenance & automation engineer
P12	Energy, media & support	Department manager
P13	Supervisory control and data acquisition (SCADA)	Production information system application specialist & business architect
P14	Energy, media & support	Energy & development engineer
P15	Energy, media & support	Energy & development engineer
P16	Purchasing	Partner manager

A.2. Interview protocol: Strategies for energy efficiency, capabilities for digital technologies, and knowledge demands

General questions

Topic: Background and current position
What is your current position and how long have you held it?
What did you do before your current position?
What does your current working day look like?

Topic: Energy waste
Can you define waste to us?
How important is reducing waste at Scania?
What key performance indicators (KPIs) are most important for Scania?
Why is reducing waste important?
What kind of KPIs are you (your department) concerned with?
What kind of waste do you see in your work?

Specific questions

Topic: How do you start projects?
How do you know there is waste that needs to be measured?
How do you start a project in general?
How do you know what to do (e.g., checklist, experience, work procedure, meetings)?

Topic: What do you measure in regard to energy waste?
What KPIs are you concerned with in regard to waste?
What type of waste would you like to measure that is not measured today?
Is there a type of waste that you think will become relevant in the near future?
How much waste is affected by external factors?
What are the parameters beyond the process that can affect the consumption?

Topic: How do you measure energy waste?
How do you measure waste?
How did you learn to do this?
How long did it take for you to learn?
What is good and not so good with the current way of measuring waste?
Does it happen that you do something, but this does not measure waste well?
What happens if there is waste?
Are you concerned with measures to reduce waste?
If yes: How do you reduce waste today? How do you prepare/plan for reducing waste in the future?
How do you report waste?
How often do you report?
What happens after you report waste?
If you have been to a meeting where waste was discussed, tell us about your experience.
What is the goal of the department for reducing waste?
How does the department discuss waste reduction?
What happens if the department does not achieve its goal for reducing waste?
How does the department measure waste?

Topic: How do you act if there is energy waste? What happens if there is waste?
Are you concerned with measures to reduce waste?
If yes: How do you reduce waste today? How do you prepare/plan for reducing waste in the future?
How do you report waste?
How often do you report?
What happens after you report waste?

Topic: Data communication and visualization
What tools do you use for data visualization and building reports?
How do you visualize the data on KPIs?
How do you report the data on KPIs? To whom?
How are the thresholds set? How are they updated over time?

Topic: Energy dashboards and users
Do you have users of the data visualization? Who are they?
Do you work with personas? If so: describe the personas to us.
Tell us about a typical user of the data visualization.
Describe two different users of the data visualization to us.
In what cases do you visualize to the user?
Why do you visualize it to the user?
What challenges do you have when visualizing and/or reporting these KPIs?

Topic: Tell us about a project you were involved in
Can you tell us about an energy project from its start to finish?

Topic: Digital technologies
What digital technologies could be used for reducing energy in production?
How could they be used?
Where do you think they have the largest potential for energy savings?
How do you think artificial intelligence or data analysis can be applied to energy savings?
Are there projects applying artificial intelligence to energy savings today?
Do you have good examples from other industries in regard to measuring and reporting waste?
Is there something that we have not asked that you think is relevant, that you would like to add?

Data availability

The authors do not have permission to share data.

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