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A digital life-cycle management framework for sustainable smart manufacturing in energy intensive industries

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ABSTRACT

Energy intensive industries can be classified into those that process metal, glass, ceramics, paper, cement, and bulk chemicals. They are associated with significantly high proportions of carbon emissions, consume a lot of energy and raw materials, and cause energy wastage as a result of heat escaping from furnaces, reheating of products, and rejection of parts. In alignment with UN sustainable development goals of industry, innovation, infrastructure and responsible consumption and production, it is important to ensure that the energy consumption of EIIs are monitored and reduced such that their energy efficiency can be improved. Towards this aim, it is possible to employ the concepts of digitalisation and smart manufacturing to identify the critical areas of improvement and establish enablers that can help improve the energy efficiency. The aim of this research is to review the current state of digitalisation in energy-intensive industries and propose a framework to support the realisation of sustainable smart manufacturing in Energy Intensive Industries (EIIs). The key objectives of the work are (i) the investigation of process mining and simulation modelling to support sustainability, (ii) embedding intelligence in EIIs to improve energy and material efficiency and (iii) proposing a framework to enable the digital transformation of EIIs. The proposed five-layer framework employs data acquisition, process management, simulation & modelling, artificial intelligence, and data visualisation to identify and forecast energy consumption. A detailed description of the various phases of the framework and how they can be used to support sustainability and smart manufacturing is demonstrated using business process data obtained from a machining industry. In the demonstrated case study, the process management layer utilises Disco for process mining, the simulation layer utilises Matlab SimEvent for discrete-event simulation, the artificial intelligence layer utilises Matlab for energy prediction and the visualisation layer utilises grafana to dashboard the e-KPIs. The findings of the research indicate that the proposed digital life-cyle framework helps EIIs realise sustainable smart manufacturing through better understanding of the energy-intensive processes. The study also provided a better understanding of the integration of process mining and simulation & modelling within the context of EIIs.

1. Introduction

Energy Intensive Industries (EIIs) are important for the economic growth of a country since they produce raw materials such as paper, glass, steel and metal. They produce basic materials that are sold to other industries downstream in the supply chain and while they only account for approximately 1%–6% of the end-user product value, they are accountable for a large proportion, typically 60%–80%, of the industrial greenhouse gas emissions (Åhman et al., 2017). Technological improvements in EIIs, improving energy efficiency, and investing in cleaner production technologies can help achieve the goal of reducing CO_2 emissions to at least 80% by 2050 (Chowdhury et al., 2018; Liu and Wang, 2017). However, barriers such as lack of interest in energy efficiency, inertia, energy price distortion, complex decision making, improper evaluation criteria, lack of information and initial investment costs impede the transition. Nonetheless, there exist drivers to achieve sustainable EIIs, stemming from international competition, environmental management systems, long-term energy strategy, rising energy prices, and renewable energy incentives (Chowdhury et al., 2018).

Owing to the above-mentioned drivers, it is possible to address energy efficiency improvements at multiple levels by designing for environment, re-using wasted energy, upgrading legacy systems, analysing

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the product life-cycle from raw material extraction to end-of-life, improving material efficiency and implementing the best available technologies. Large-scale implementation of such methods can result in improving the energy efficiency by around 15%–30%. However, further improvement depends on the realisation of breakthrough technologies and fundamental changes to the core process (Åhman et al., 2017). Existing literature has highlighted key enabling technologies that can support this endeavour; this includes big data analytics, artificial intelligence, digital twin, Internet-of-Things, advanced robotics and cloud computing (Murri et al., 2019; Majeed et al., 2021).

A review of current knowledge presents the lack of a systematic framework to support digital transformation in EIIs partly due to the limited understanding of existing processes and their deviations. A few research articles on using big data analytics, AI, and digital twins to support EIIs have been published, however, they do not consider the benefits of integrating process mining and simulation. In addition to this, EIIs do not have proper infrastructure to realise the holistic digital transformation to support energy efficiency. In summary, the research gaps can be highlighted as:

1. the limited research on systematic approaches to support energy efficiency in EIIs;
2. the lack of existing knowledge on the integration of process mining and simulation;
3. the lack of necessary infrastructure and policies in EIIs to enable digital transformation towards sustainability;
4. the limited integration between digital models and AI for sustainability.

The insights from literature review enabled the authors to formulate the following research questions.

R1: How can the integration of digitalisation and AI support sustainability in EIIs?

R2: What strategies can be employed to improve the process understanding of EIIs?

This article aims to answer the questions by providing an overarching methodology that encompasses AI, data acquisition, data visualisation in addition to process management, and simulation & modelling in order to support the digital transformation in EIIs. The main contributions of this article can be summarised as below.

- A survey of the key enablers for improving energy efficiency, the current state of digitalisation in EIIs, the opportunities to improve energy efficiency, and the barriers to sustainable smart manufacturing (SSM).
- Proposing a framework to support the digital life cycle management of EIIs which is then demonstrated with the help of a case study.
- The integration of process mining and simulation to support sustainability.
- The introduction of process mining within the context of EII digital transformation.
- Embedding intelligence within EIIs to improve energy and material efficiency.

Section 2 of the article explains the state-of-the art in sustainable smart manufacturing and digitalisation of EIIs and identifies the key enabling technologies. This is followed by a detailed review of frameworks that are relevant for Sustainable EIIs. The summary of the literature review highlights research gaps and how the proposed framework is intended to fulfil them. Section 3 explains the methodology that comprises of five different layers: data acquisition, process management, simulation & modelling, AI, and data visualisation. Section 4 discusses the implementation of the framework in a test case and Section 5 explains potential applications for the methodology and reviews the challenges to digital transformation in EIIs. Section 6 concludes this article and scopes out the future work.

2. Sustainable smart manufacturing (SSM)

The term 'Sustainable Smart Manufacturing' is defined by Ren et al. (2019) as "*the paradigm that integrates data analytics with up-to-date information to support operations and decision making with the ultimate aim of achieving intelligent and sustainable production*". The goal of SSM encompasses responding to dynamic markets, optimising and enabling flexibility, improving economical and environmental aspects and improving intelligence in decision making for the whole life-cycle. Towards this aim, Abubakr et al. (2020) identify the opportunities for implementation of sustainable practices for SSM and the challenges faced by industries in the implementation of SSM. Dincer and Acar (2015) highlight three different routes to achieving sustainability, namely, the use of renewable sources that are environmentally friendly, optimisation of system resource utilisation, and recycling and waste recovery.

A work-centre digital twin for smart and sustainable manufacturing is presented by Park et al. (2020). In their research, a work centre for textile dyeing and finishing is chosen as the test case and a digital twin is employed for functionalities such as planning, scheduling, and diagnosis; the steps involved in the practical implementation of the digital twin are also discussed in detail. From the perspective of developing frameworks, Ren et al. (2019) have proposed a conceptual framework of big data analytics in Sustainable Smart Manufacturing. In their work, a comprehensive review of big data analytics and its role in SSM is explored. The author concludes the article by highlighting the key contributions in smart manufacturing. The framework comprises of Intelligent design, Intelligent production, Intelligent maintenance and service, and Intelligent recovery. Although the approach is detailed and covers various aspects, it does not consider some enablers such as simulation & modelling, and process management.

A data driven sustainable smart manufacturing framework is proposed by Mahiri et al. (2020) that comprises of following components: (i) smart design of product and production, (ii) smart production planning, (iii) smart production, (iv) smart equipment maintenance and service, (v) smart product recycling and (vi) re-manufacturing. The framework provides an overview of the key enablers at a high level of abstraction and does not delve deeper into the details of implementation. In a work proposed by Majeed et al. (2021), a framework combining big data analytics, additive manufacturing and sustainable smart manufacturing technologies is presented. Their framework, named Big Data-Driven Sustainable and Smart Additive Manufacturing (BD-SSAM), targets the additive manufacturing industry and comprises of the following phases: (*i*) perception and acquisition of big data, (*ii*) big data storage and pre-processing, (*iii*) data mining and decision making, and (*iv*) big data application services. The BD-SSAM framework is demonstrated with a test case where the optimisation of process parameters to improve product quality and reduce energy consumption is presented. In another related work, Mahiri et al. (2022) proposed a 5G enabled IIoT (Industrial Internet of Things) architecture for sustainable smart manufacturing comprising five different layers: business, application, support, edge computing, and perception. The focus of the architecture is on enabling IIoT in smart manufacturing. Following the brief review on frameworks and approaches to support Sustainable Smart Manufacturing, the next section explores the Key Enabling Technologies for SSM in EIIs.

2.1. Key enablers for SSM in EIIs

Artificial Intelligence (AI), a branch of computer science, comprises of a set of tools and techniques that allow human behaviour to be transferred to a machine (Simmons and Chappell, 1988; Taulli and Oni, 2019). AI, when coupled with simulation models, has been found to support production optimisation, performance monitoring, scheduling, fault diagnosis and predictive maintenance through the approaches of descriptive, prescriptive, predictive, and diagnostic data analytics supported by surrogate modelling and predictive modelling (Örs et al., 2020).

Big Data Analytics is an important base technology of Industry 4.0 and is a core element of smart manufacturing (Frank et al., 2019). Big data essentially represents the significant amount of structured, semi-structured and unstructured data obtained through various data acquisition technologies and allows the exploration of hidden value and information about a system (Qi and Tao, 2018). Through analysis of the collected data, various applications such as health and condition monitoring, asset maintenance, and defect detection and prevention have become a reality. There are opportunities to improve the sustainability aspects of manufacturing systems that are associated with costs, environmental impact, waste management, energy consumption, etc., by leveraging AI technologies (Kishawy et al., 2018). However, there exist challenges associated with the cost of implementing sustainability measures, lack of knowledge, lack of guidance on AI-enabled SSM, and lack of metrics to measure sustainability (Tanco et al., 2021).

Energy simulation and modelling encompasses physics-based simulations, discrete-event simulations, virtual commissioning model, kinematic models, etc., that enable decision-making and production planning when connected to the physical entities in real-time. The term 'Digital Twin' (DT) was originally coined by NASA in the aerospace domain as *"integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin "* (Shafto et al., 2012). Over the years, DT technology has evolved and established itself as an imperative element in various domains for (*i*) collective impact assessment, (*ii*) AI-based ecosystem decision submodel, and (*iii*) independent interlinked ecosystem control submodel (Miehe et al., 2021). Through the use of digital twins, it is possible to represent a physical entity and its behaviour as a virtual model for various analyses throughout the lifecycle of the system (Qi and Tao, 2018).

In EIIs, the digital transformation starts with first measuring the energy consumption and other relevant data. Smart meters and soft sensors can capture and calculate energy consumption while protecting the sensor elements from harsh environmental conditions; various dashboards and platforms can then be used to display the real-time consumption (Meijer et al., 2018). On establishment of the energy monitoring system, digital models and data analytics can capture the behaviour of the system and enable the comparison of different scenarios and support autonomous decision-making.

The term 'Edge Computing' refers to computing performed in close proximity to the data source (Satyanarayanan, 2017; Shi et al., 2016). This opens up various possibilities such as edge analytics, higher responsiveness, and reduced concerns regarding privacy; the processing of data is done at the edge and raw data does not need to be shared to the cloud (Shi et al., 2016). Edge computing is beneficial for SSM due to the ability to process high volumes of data generated from smart sensors without the need to rely on external cloud services.

Within the context of business process management, process mining is a technique that can be used to discover business processes and support decision making with the use of event logs (van der Aalst et al., 2012). The state-of-the art research in process mining pertains to the development of process mining algorithms, particularly for the healthcare sector (Zerbino et al., 2021). This elicits the opportunity to adopt and apply process management and mining to discover and analyse process flows and process deviations in EIIs.

The key strategies to realise digital transformation rely on leveraging the above-mentioned key enabling technologies for fault diagnosis, condition monitoring, implementing planned maintenance, avoiding energy expensive restarts (Abubakr et al., 2020), better capture of energy data, planning or optimisation for energy efficiency, building novel soft sensors for extreme working conditions, and better management of the temperatures used for energy intensive processes. A thorough comprehensive review of enabling technologies for smart manufacturing is available in the study published by Ren et al. (2019).

2.2. Current state of digitalisation in EIIs

The Digital Intensity Index (DII) of metals sector is found to be lower than chemical manufacturers which could be attributed to the fact that the metals industry had a period of stability and focussed on continuous improvements. Interviews with 27 global metals and mining industries, revealed the lack of existing capabilities in EIIs to bring about such radical changes. This is due to the fact that current practices do not align with digital transformation and creates a stagnant system with lack of focus. Furthermore, the limited support from managerial personnel, inadequate training in digital tools, cynical attitude to AI, concerns regarding privacy and data breach, challenging operating environment, use of safety policies as an excuse to improve, and fear of unemployment create a challenging ecosystem with barriers to innovation (Gao et al., 2019). Moreover, the EIIs are not considered as an attractive workplace for people with digitalisation and IoT skills. Therefore, the recruitment of younger workforce who are familiar with such technologies and the training and bridging the gap between older and younger employees might act as catalysts to realise radical changes (Branca et al., 2020b; Murri et al., 2019; Branca et al., 2020a).

A review of the pulp and paper, steel, and chemical industries in Sweden highlighted that EIIs comprehend the importance of digitalisation; however, the digital maturity of EIIs is not high and digitalisation is not linked to energy efficiency measures. As previously highlighted, the level of digital maturity varies across the sectors and was the lowest for steel industries and strongest for the pulp and paper industries (Jasonarson, 2020). A report on the Swedish environment protection agency showed that 34% of greenhouse gas emissions are from the Iron and Steel sector. Pulp and paper industry have high energy consumption but their emission is low due to use of bio fuels and low carbon electricity.

Continuous improvements and small-scale changes can make a step change in the consumption of energy in EIIs. In alignment with this notion, steel-specific decarbonisation can be achieved by: (*i*) replacing coal with biochar, (*ii*) use of hydrogen or biogas as reducing agent, (*iii*) electrolytic steel production, and (*iv*) carbon capture and storage. In the case of mining, improvements achieved by renewable electricity generation, electrifying the mining equipment, innovations in process and technology, and replacing fossil energy with biomass can drive the progress in sustainability. In case of the cement industry, fuel switching, electrification, carbon capture and storage and clinker substitution are some of the approaches that can be employed. In the pulp and paper industry, fuel switching and electrification can help reduce energy emissions. The chemical industry is continuous and hence any problem in equipment could result in unexpected maintenance cost. Improving equipment reliability plays a key role in achieving better energy efficiency in such industries. Few other techniques include the use of LED lighting, reusing waste heat, better insulation, equipment redesign, etc., such that the energy efficiency can be increased. Although such improvements are beneficial, the emissions in iron and steel refineries is expected to be higher in 2045 due to a marked increase in production. On the other hand, pulp and paper and cement industries are expected to have lower CO_2 emissions by 2045 (Nurdiawati and Urban, 2021).

To ensure attainment of sustainability goals, it is evident that there is need for radical changes to policies and manufacturing paradigms in EIIs. This section highlights the extent of such advancements, particularly in steel working. Approximately 156 projects on coal and steel manufacturing research have been funded for the realisation of digitalisation and Industry 4.0 (Arens, 2019). It is envisioned that the research on digitally connected products and processes can allow for intelligent automation (Zsifkovits et al., 2020). In alignment with this notion, the following projects highlight the extent to which innovation and energy efficiency in steel production is currently realised. The 'NewTech4Steel' project focusses on advanced data analytics in steel processing (Avellino et al., 2022), the 'DROnes for autonomous MOnitoring of Steel PLANts' (DROMOSPLAN) project explores the use of Unmanned Aerial Vehicles (UAV) for steelworks (Piancaldini et al., 2019), the 'Robotic workstation in harsh environmental conditions to improve safety in the steel industry' (RoboHarsh) project identifies opportunities for human robot collaboration in the steel industry (Colla et al., 2021), the 'DEtection of Steel DEfects by Enhanced MONitoring and Automated procedure for self-inspection and maintenance' (DESDEMONA) project utilised robotics and automation for steel defect detection (Kazemi Majd et al., 2022), the 'Optimisation of the management of the process gases network within the integrated steelworks' (GASNET) project uses neural networks and predictive modelling to improve energy efficiency in steelworks (Dettori et al., 2019), the AdaptEAF project focusses the optimisation of energy efficiency of electric arc furnaces (European Commission and Directorate-General for Research and Innovation et al., 2019), and the Cyber-POS project employs concepts of cyber–physical production systems for the steel industry (Iannino et al., 2022). Research on embedding intelligence in steel manufacturing is done as part of the steel 4.0 paradigm (Hsu et al., 2018). Another interesting work done with respect to Internet of Things is the tracking of product from steelmaking to delivery, and the use of data analytics to prevent error and improve safety (Branca et al., 2020a). The shift from product-based to consumer-centric services using digital technologies to create a shared digital ecosystem can bring about some innovation in EIIs (Newman and McClimans, 2017). An interesting research pursued by the facility for intelligent fabrication in Australia is on the use of CAD designs, integration of smart sensors, and use of AR and VR for enhanced robotic handling in steel industries (Australian Steel Institute, 2020). In summary, the extent of research and project funded in this domain highlights the attention provided for sustainable steelworking. The majority of work conducted employ one or more key enabling technologies to ensure energy efficient steel production. The next section will highlight the key articles that are relevant to this research and identify the research gaps that need to be fulfilled.

2.3. Review of frameworks related to sustainable EIIs

Zhang et al. (2018) address the need for a big data driven analytical framework for EIIs wherein they consider four components: (*i*) energy data perception and acquisition, (*ii*) energy big data storage and preprocessing, (*iii*) energy big data mining and energy intensive decision making, and (*iv*) application services of energy big data. Their approach is implemented in a ceramic industry test case and their framework provides a comprehensive overview of the current state of EIIs. The focus of their work is on Big Data Analytics and opportunities for integration with other enabling technologies such as data acquisition devices. However, there is scope to improve the work by considering other enabling technologies such as process management tools and virtual modelling.

A framework for sustainable intelligent manufacturing for EIIs is proposed by Ma et al. (2020). Their framework comprises of three different layers: the perception layer, management layer and application service layer. The primary focus of their work is the impact of data-driven energy consumption analysis on Circular Economy. A case study in ceramic industry is used as the proof of concept. While their approach is detailed and applicable in the manufacturing stage of an EII, it could be improved by considering further integration with other enablers. In another related article, an architecture of energy cyber–physical system and synergistic models of energy flow material flow and information flow is presented (Ma et al., 2019). Their work is demonstrated in a test case and the energy consumption modelling is discussed.

A framework for sustainable smart manufacturing by integrating concepts of big data and digital twin is proposed by Ma et al. (2022). In their work, the energy monitoring and management across the production lifecycle is analysed along with the creation of an energy digital twin. Nilsson et al. (2021) propose an industrial policy framework that explores the changes that need to be brought about in EIIs to achieve zero emission targets. Their work predominantly focusses on the unexplored area of bringing about green policy changes in EIIS and presents a brief discussion of socio-economic implications and international coherence. The concept of Industrial Symbiosis in EIIs by symbiotic coupling of iron and steel, thermal power and cement industries is proposed by Xue et al. (2023). The implementation in a test case highlights the benefits of the approach for energy and emission reduction.

2.4. Summary of literature review

A summary of the literature review is presented in Table 1. A brief review of relevant articles elicits the various facets of sustainable smart manufacturing; it can be seen that there is lot of attention towards implementation of Big Data Analytics, IoT and Artificial Intelligence in SSM. Although the concept of SSM continues to garner attention, it is evident that there is a lack of research highlighting the technical know-how and implementation of SSM frameworks in EIIs. Specifically, it can be seen that (*i*) there is limited practical research and implementation of the integration of multiple enabling technologies to support sustainable smart manufacturing in EIIs, (*ii*) the existing knowledge on smart manufacturing cannot be adapted seamlessly to EIIs due to limited knowledge and understanding of the processes and energy monitoring, and (*iii*) there is lack of research on the use of simulation & modelling and process management tools to support energy consumption analyses in EIIs despite their benefits for intelligent energy decision making.

Therefore, this research aims to:

- propose a framework to support the digitalisation of EIIs along with a detailed approach highlighting the information flow between the various steps;
- investigate the interplay between process mining and simulation modelling to support sustainability in EIIs and SSM.

3. Methodology

The proposed methodology can help realise two main strategies, directly improving energy efficiency by reducing the energy consumption and indirectly improving energy efficiency by reducing the material wastage (also referred to as improving the material efficiency). The key enablers such as data acquisition using IoT, simulation & modelling, artificial intelligence, and process management are integrated to create a comprehensive framework to support sustainable smart manufacturing in EIIs. As seen from literature on existing frameworks for EIIs, the link between process management, and simulation for sustainability is an area that is least explored. The authors present Fig. 1 as a synthesis of the organisational enablers and technological enablers for smart sustainable manufacturing at various stages of a manufacturing system lifecycle. Extending this further, in Fig. 2, the authors identify steps to monitor and improve energy efficiency at each stage of product lifecycle, starting from raw material extraction to end-of-life. From Fig. 1 and Fig. 2, the scope of this research pertains to the technological enablers of smart sustainable manufacturing and the steps to improve energy efficiency in the operation phase of the system and product lifecycle.

The proposed framework is constructed on five main layers that are indicated in Fig. 3; the data acquisition layer, process management layer, simulation & modelling layer, artificial intelligence layer, and data visualisation layer. Each layer is explained in detail in the following paragraphs and it is important to note that the various layers are not to be viewed as sequential steps.

Table 1
Summary of literature review.

Article	Big Data	CPS	IoT	AI	Process mgt	Simulation	Overview
(Zhang et al., 2018)	✓		✓	✓			Focus on big data analytics and energy data mining for EIIs
(Ma et al., 2019)		✓	✓	✓			Focus on energy CPS and energy management for EIIs
(Ma et al., 2020)		✓	✓	✓			Focus on data analytics & circular economy for EIIs
(Ma et al., 2022)	✓	✓	✓	✓			Focus on digital twins and big data for energy efficiency for EIIs
(Ren et al., 2019)	✓		✓	✓			Focus on Big Data and its application in Sustainable Smart Manufacturing
(Mahiri et al., 2020)	✓		✓	✓			Focus on improving intelligence in Sustainable Smart Manufacturing
(Majeed et al., 2021)	✓		✓	✓			Focus on big data analytics for sustainable and smart additive manufacturing
Proposed approach (2023)			✓	✓	✓	✓	**Focus on data acquisition, AI, process mining and simulation for EIIs**

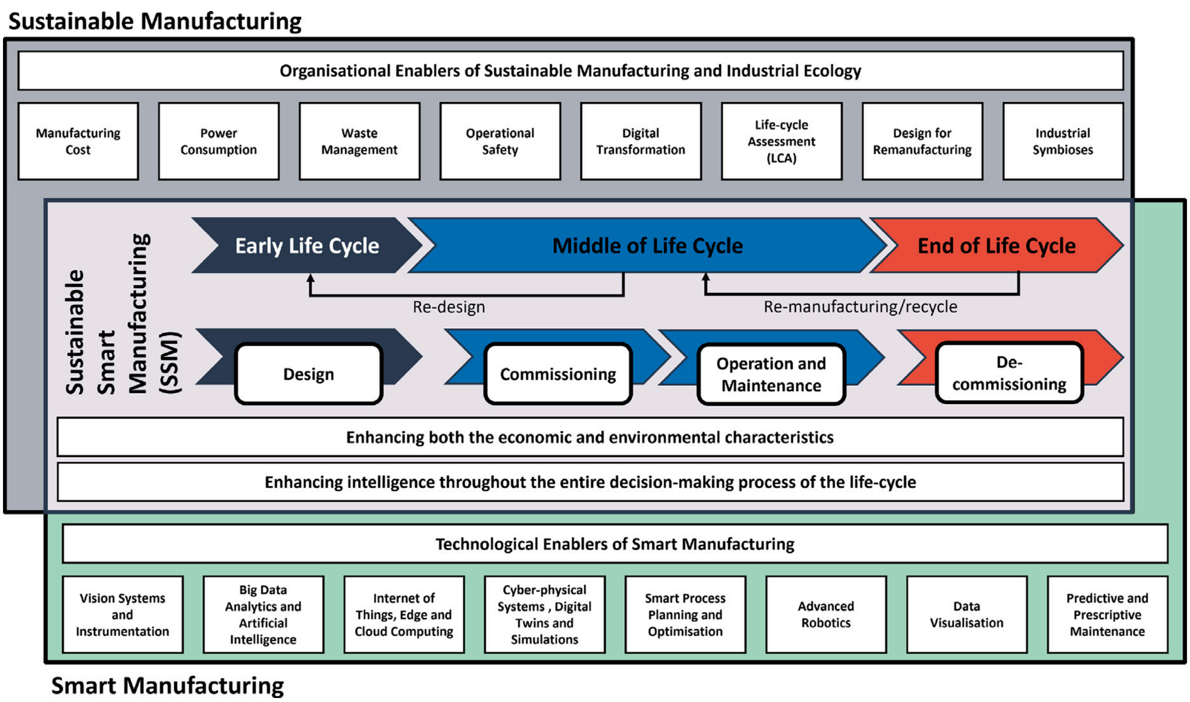


Fig. 1. Organisational and technological enablers for Sustainable Smart Manufacturing.
Source: Adapted from (Malek and Desai, 2019; Koho et al., 2011)

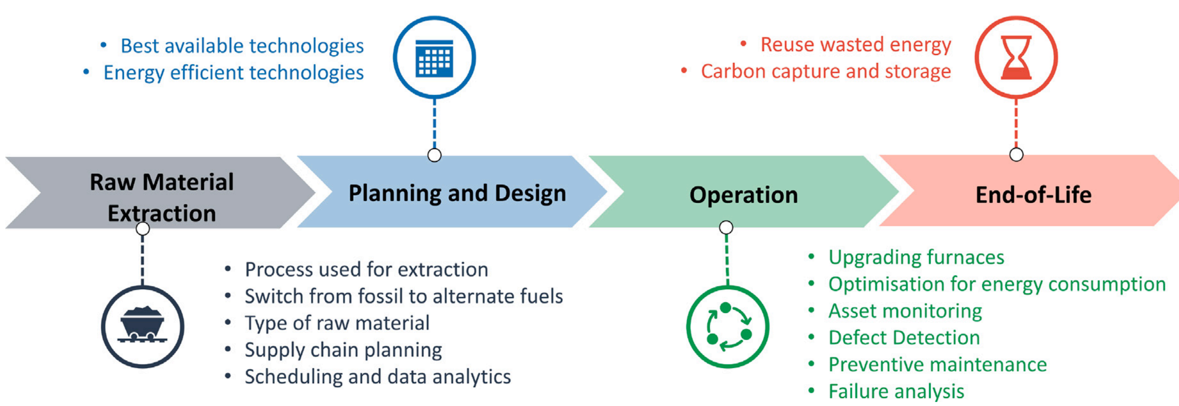


Fig. 2. Energy efficiency strategies at various stages of product lifecycle.

3.1. Data acquisition layer

The data acquisition layer comprises various components such as smart sensors, smart meters, IoT, RFID, thermocouples, energy monitoring devices, Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), databases, Excel/CSV, and data warehouses that capture both direct and indirect energy consumption and carbon emissions.

- Direct energy consumption — refers to recording of temperature, pressure, vibration, acoustics, water usage, gas usage, electricity usage, power usage, and fuel consumption that enable the calculation of machine-level or manufacturing system-level energy consumption. An example of direct energy consumption is the recording of temperature values using thermocouples.
- Indirect energy consumption — refers to the recording of number of parts rejected, reworked, machine utilisation statistics and process-related statistics that enable the calculation of wasted

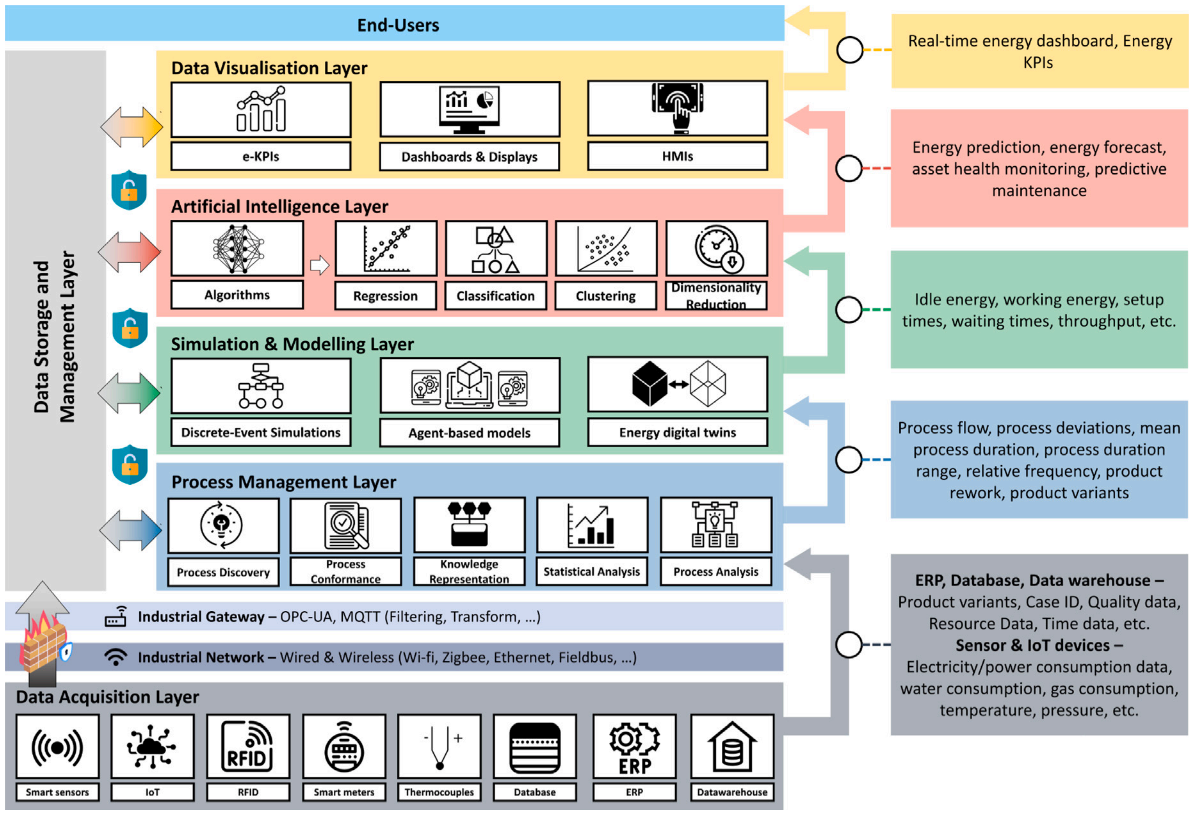


Fig. 3. Digital Life-cycle Management framework.

energy. An example of indirect energy consumption is the use of RFID tags to record products that are rejected or sent for rework.

The data acquisition is the first step in the methodology and the captured data is crucial for forecasting and monitoring the energy consumption. It is important to note that data might be available in different formats and needs to be pre-processed, cleaned, filtered and stored either locally or in the cloud. Therefore, this initial step is significantly time-consuming and becomes tedious as the volume and variety of data increases; strategies to convert unstructured and semi-structured data to structured data will alleviate the problems associated with big data.

3.2. Process management layer

This layer retrieves information from the data acquisition layer to actively manage and monitor the process. Considering the operation stage of the system lifecycle, existing process records play an important role in energy consumption forecasting and prediction. Process mining is a data-driven technique that can extract hidden evidence from event logs and records (Zerbino et al., 2021) that exist in the data acquisition layer. Since EIIs lack an understanding of existing processes, the authors believe that the process management layer and process mining can help overcome the issue. This layer comprises of various components for process discovery, process conformance checks, knowledge representation, and process analysis and can be realised using tools such as ProM, Disco, etc.

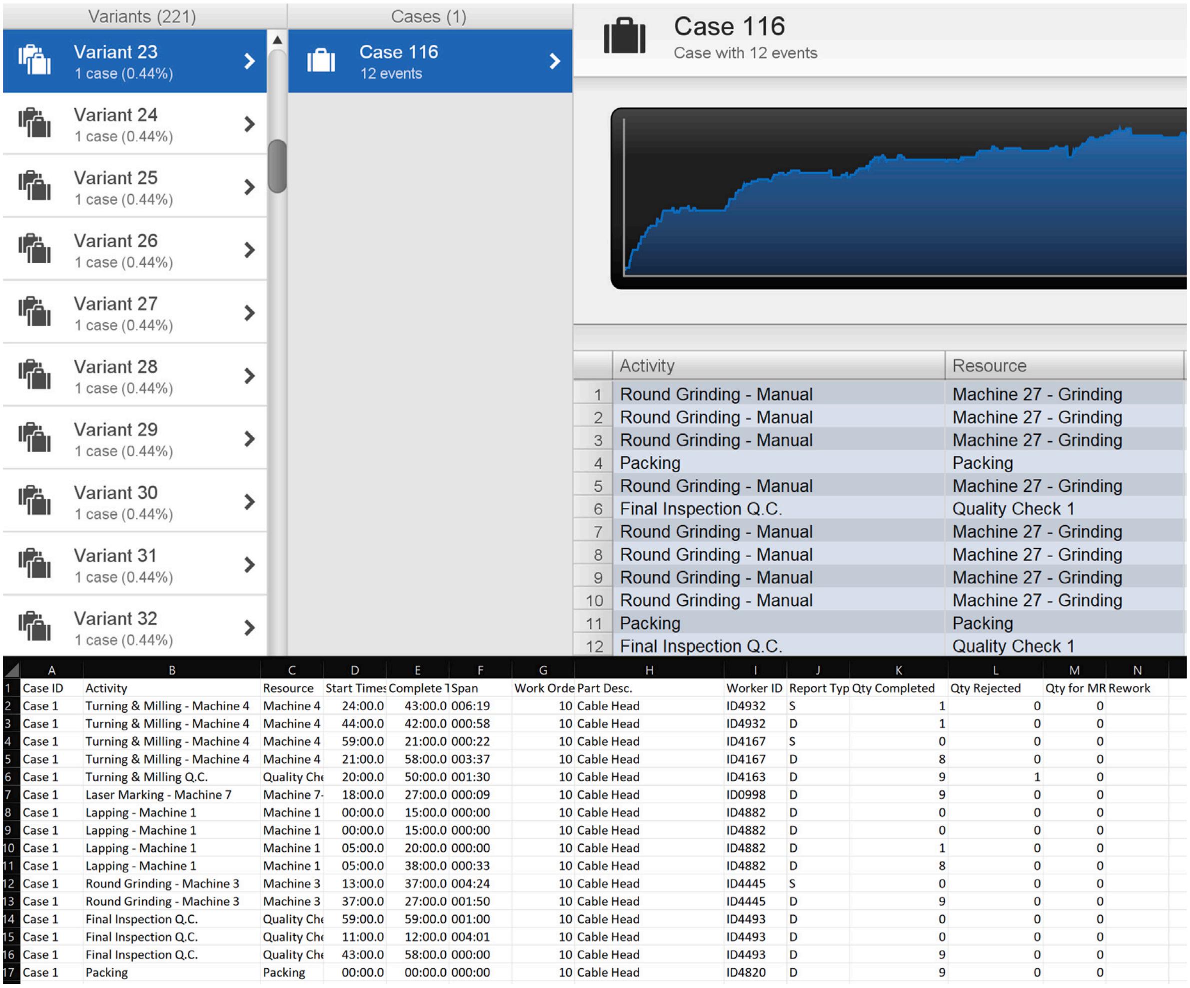
- Process discovery — the process-related information are discovered from event logs through process mining. For example, event logs obtained from database, transaction logs or workflow systems can be used to unearth and visualise the factual representation of the industrial process.
- Process conformance — the event log 'traces' can be re-run to check for conformance and process deviations.
- Knowledge representation — the existing process knowledge can be mapped to products and equipment using tools such as Protêge.
- Statistical analysis — process metrics such as the number of events, cases, case variants, events per case, case duration, case utilisation, mean activity duration, mean waiting times, etc., can be obtained using this component.

Through process discovery and analysis, the frequency of the processes, the variants catered to, and the process routes through the system can be obtained. This not only enables further understanding of the industrial process for policy generation and continuous improvements that are much needed in EIIs, but also helps analyse the process with metrics such as mean duration of processes, process variants and their frequencies, part rejection and rework, etc.

3.3. Simulation & modelling layer

The simulation & modelling layer comprises of components such as Discrete-Event Simulation (DES), kinematics model and digital twins that can be generated with the process logs and process metrics obtained from the process management layer. Energy flow simulation paradigms have benefits such as process improvements, efficiency analysis and can help calculate yearly cost savings, production output and energy consumption (Herrmann et al., 2011). Therefore, the authors believe it is a suitable choice for the framework.

- Discrete-Event Simulation — this component is used to model the stochastic behaviour of a system and analyse 'what-if' scenarios.
- Agent-based models — this component can be used to represent the behaviour of various resources, people, and products in a manufacturing system and their interaction with each other.
- Energy Digital Twin — represents the physics and behaviour of energy intensive equipment such as furnaces, heat treatment and annealing chambers.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Case ID	Activity	Resource	Start Times	Complete T	Span	Work Orde	Part Desc.	Worker ID	Report Typ	Qty Completed	Qty Rejected	Qty for MR	Rework
2	Case 1	Turning & Milling - Machine 4	Machine 4	24:00.0	43:00.0	006:19	10	Cable Head	ID4932	S	1	0	0	
3	Case 1	Turning & Milling - Machine 4	Machine 4	44:00.0	42:00.0	000:58	10	Cable Head	ID4932	D	1	0	0	
4	Case 1	Turning & Milling - Machine 4	Machine 4	59:00.0	21:00.0	000:22	10	Cable Head	ID4167	S	0	0	0	
5	Case 1	Turning & Milling - Machine 4	Machine 4	21:00.0	58:00.0	003:37	10	Cable Head	ID4167	D	8	0	0	
6	Case 1	Turning & Milling Q.C.	Quality Che	20:00.0	50:00.0	001:30	10	Cable Head	ID4163	D	9	1	0	
7	Case 1	Laser Marking - Machine 7	Machine 7-	18:00.0	27:00.0	000:09	10	Cable Head	ID0998	D	9	0	0	
8	Case 1	Lapping - Machine 1	Machine 1	00:00.0	15:00.0	000:00	10	Cable Head	ID4882	D	0	0	0	
9	Case 1	Lapping - Machine 1	Machine 1	00:00.0	15:00.0	000:00	10	Cable Head	ID4882	D	0	0	0	
10	Case 1	Lapping - Machine 1	Machine 1	05:00.0	20:00.0	000:00	10	Cable Head	ID4882	D	1	0	0	
11	Case 1	Lapping - Machine 1	Machine 1	05:00.0	38:00.0	000:33	10	Cable Head	ID4882	D	8	0	0	
12	Case 1	Round Grinding - Machine 3	Machine 3	13:00.0	37:00.0	004:24	10	Cable Head	ID4445	S	0	0	0	
13	Case 1	Round Grinding - Machine 3	Machine 3	37:00.0	27:00.0	001:50	10	Cable Head	ID4445	D	9	0	0	
14	Case 1	Final Inspection Q.C.	Quality Che	59:00.0	59:00.0	001:00	10	Cable Head	ID4493	D	0	0	0	
15	Case 1	Final Inspection Q.C.	Quality Che	11:00.0	12:00.0	004:01	10	Cable Head	ID4493	D	0	0	0	
16	Case 1	Final Inspection Q.C.	Quality Che	43:00.0	58:00.0	000:00	10	Cable Head	ID4493	D	9	0	0	
17	Case 1	Packing	Packing	00:00.0	00:00.0	000:00	10	Cable Head	ID4820	D	9	0	0	

Fig. 4. ERP data used for process discovery.

These models can support decision making, analyse 'what-if scenarios', virtual commissioning, reconfiguration analysis, and process planning. Majority of EIIs have limited understanding of their processes that makes it difficult to gather data such as rework rate, process flow, product variants, etc., for simulation & modelling.

3.4. Artificial intelligence layer

Machine learning techniques can be coupled with simulation models for explainable analytics, improving system performance, predictive visibility, and optimising performance (Biller and Biller, 2023). Specifically, the energy consumption, scrap rate and product rework data can be analysed to monitor assets, detect failures, and realise preventive maintenance measures. Therefore, the artificial intelligence layer is introduced in the proposed framework such that existing energy consumption data can be used to forecast the energy consumption for subsequent weeks. It can also be coupled with an online real-time simulation model to enable real-time energy predictions using data streaming platforms such as Apache Storm and Kafka.

3.5. Data visualisation layer

The data obtained from the AI layer such as the forecast of energy consumption and cost, and forecast of machine usage can be displayed in the form of graphs and plots using data visualisation software such as PowerBI, Tableau, and Grafana. This layer can also be coupled with the simulation & modelling layer to display real-time energy and usage statistics at varying levels of granularity. When displayed as dashboards and reports, it can help making informed decisions about the system. For purposes of communication between the different layers, OPC-UA servers can be established to ensure that the dashboards are regularly updated. Another point to note is that the dashboards from this layer can be displayed in desktops, hand-held devices, laptops or Human–Machine Interfaces (HMIs) to managers and engineers. Subsequently, any discrepancy in the system can then be visualised and necessary actions could be taken before it propagates to a serious problem.

The next section delves deeper into each of the layers and demonstrates one possible application of the methodology as proof of concept. Please note that there are multiple applications for the proposed framework, but only one is discussed in detail.

4. Case study

To demonstrate the framework, a test case in an industry that does machining operations on metal parts such as drills, bearing, ball nuts, springs, etc., is presented. The dataset (Levy, 2014) used in this research is sourced from Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES). As a proof of concept, only one possible application of the framework is discussed starting with process discovery using 'Disco process mining software'. As machining operations are energy-intensive (Shang et al., 2019; Moradnazhad and Unver, 2017), the authors believe that the following demonstration can provide guidance on the practical implementation of the digital lifecycle management framework in EIIs.

Table 2
Process-level data obtained by process mining.

Resource	Frequency	Relative frequency	Median duration	Mean duration	Duration range
Quality Check 1	1193	26.26%	1 h 15 min	1 h 44 min	10 h 47 min
Machine 1 - Lapping	369	8.12%	1 h 15 min	1 h 46 min	22 h 41 min
Packing	277	6.1%	1 h	1 h	–
Machine 2 - Grinding	273	6.01%	3 h 3 min	3 h 55 min	15 h 50 min
Machine 3 - Grinding	275	6.05%	2 h 53 min	3 h 48 min	16 h 49 min
Machine 4 - Turning and Milling	271	5.97%	5 h 30 min	5 h 34 min	22 h 7 min
Machine 5 - Turning and Milling	264	5.81%	5 h 22 min	5 h 20 min	22 h 22 min
Machine 6 - Turning and Milling	261	5.75%	4 h 28 min	5 h 4 min	22 h 24 min
Machine 7 - Laser Marking	252	5.55%	52 min 30 s	57 min 45 s	4 h 9 min
Machine 8 - Turning and Milling	219	4.82%	2 h 45 min	3 h 38 min	14 h 36 min
Machine 9 - Turning and Milling	198	4.36%	4 h 1 min	4 h 40 min	23 h 49 min
Machine 10 - Grinding	178	3.92%	5 h 29 min	5 h 38 min	22 h 59 min

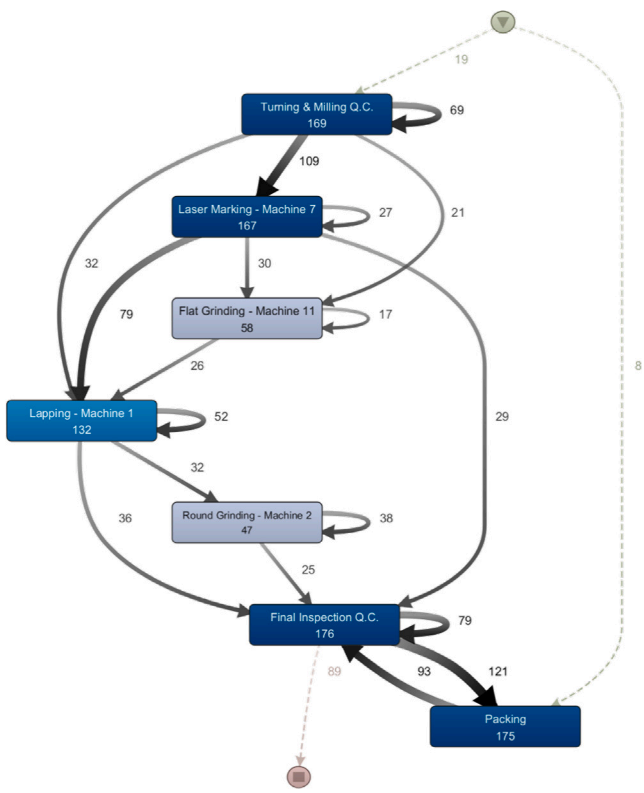


Fig. 5. Process discovery using event logs in Disco.

4.1. Process discovery

The data provided in Fig. 4 is the event log that was used for process mining. Each row in the event log represents a 'trace' that is a set of activities. By importing this data into the process mining software (Disco), the 'as-is' process is discovered. The process flow in Fig. 5 provides a high-level view of the actual activities that take place in the industry. It can be seen that the most frequent processes are shown in dark blue and accordingly the turning & milling and final inspection (quality check) processes are the most frequent. The arrows connecting the processes have different thickness depending on the frequency of the flow between two processes. Moreover, by zooming into each variant category, as seen from Fig. 4, the mean process duration, range of process duration, frequency of the process, and process routes can be obtained as shown in Table 2. From the above data, the ten most frequent process flows are identified and provided in Table 3. The product variants flow through different process routes spanning across 12 machines: five turning and milling machines, two round grinding machines, one flat grinding, one lapping, one deburring, one laser marking, and one wirecut machine. Apart from the operations carried out in these machines, two other less energy-intensive operations of quality check and packing also form part of the process flow. It can be seen that the products undergo different machining operations depending on their route. For example, from Table 3, variant 8 has three processes: round grinding, quality check and packing and variant 1 has seven processes: turning & milling, quality check, laser marking, round grinding, lapping, quality check, and packing. Therefore, variants 1 and 8 will follow different process routes through the system as a result of which they will have different process metrics. Each variant category has different 'cases' or 'instances' of products that follow the same process flow but have different timestamps, energy consumption and machining duration. Corresponding to the number of cases in each variant, the percentage of variant categories in the system is according to the values provided in the last row of Table 3.

4.2. Discrete-event simulation model

The idea behind the DES model is to use the process data that was discovered in the process management layer to further understand the system. With the help of the model, the KPIs such as machine-level energy consumption and machine-level utilisation are calculated using SimEvent parametric DES model in Simulink (Matlab version R2022). An overview of the simulation model is provided in Fig. 6. An inter-arrival time that varies between the range of 0 to 3 h was set in the entity generator block; the variant-specific service time for each machining process was set within the service blocks, as triangular probability distributions. The service time values were obtained from the process duration and mean duration statistics from the Fig. 4. The order in which product variants arrive for each run of simulation varies and the frequency of each variant is modelled according to Table 2 and Table 3. When products enter quality checks, there is a 5% chance that they might be sent for rework. All queues follow First In First Out (FIFO) rule and have a maximum capacity of 50. The simulation is run for a period of one week (168 h); the weekly demand for each product variant changes according to Table 4.

4.2.1. Assumptions for simulation

The main assumptions for the simulation are as follows:

- The machining operations and transportation are performed using appropriate equipment but operated manually.
- The final quality check, turning and milling quality check and round grinding quality check are considered as variations of the quality check process. Therefore, the same process block in DES is used to model them.
- The simulation runs over a period of three shifts per day. But the labour allocation per shift is not modelled; it is assumed that equipment/machines play a primary role in energy consumption.
- The warmup time for simulation is 10 h (based on trial runs) and the system reaches steady state after this period; as this did not significantly affect the statistics, the warm-up time is ignored in the output statistics calculations.

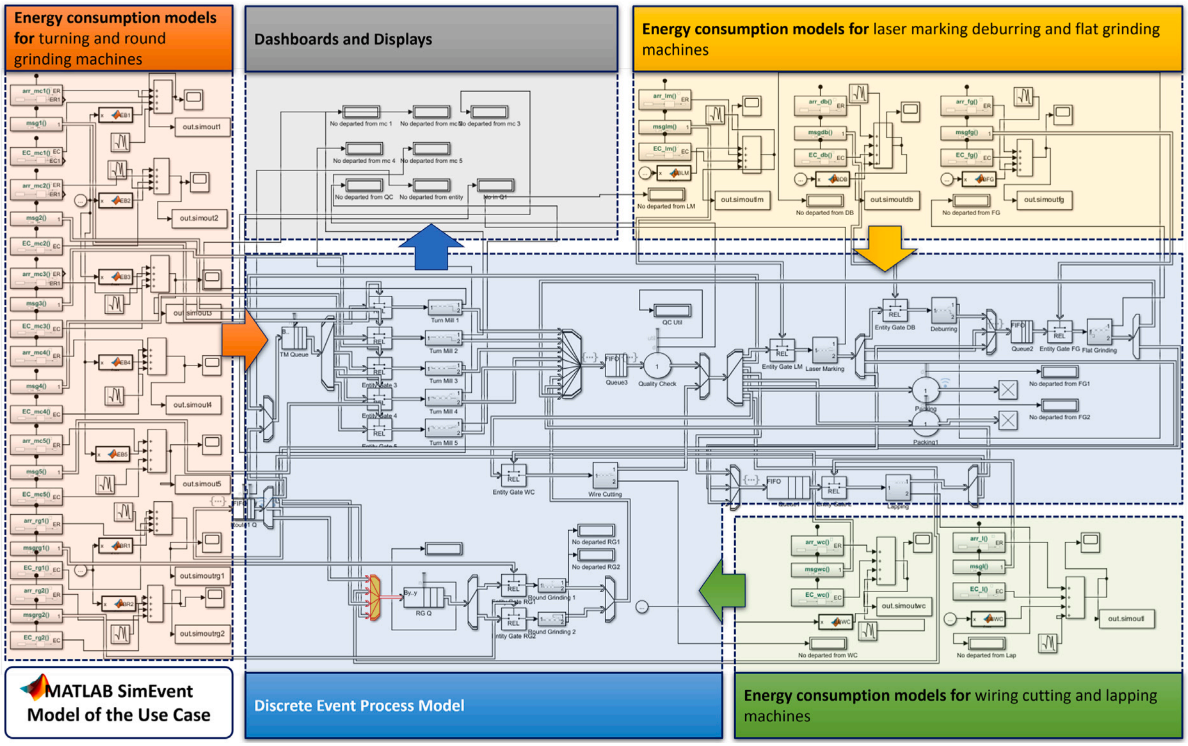


Fig. 6. SimEvent model of the test case (detailed image available in Link).

- The quality inspection and packing processes are manual process and are assumed to consume negligible amount of energy.

4.2.2. Simulink - energy consumption model

It is important to conceptualise an energy consumption model within Simulink in order to calculate the machine-level energy consumption. The machine tool power profile was adopted from existing literature (Zhao et al., 2017; Li and Kara, 2011) and considered for the energy consumption modelling. Accordingly, three different energy values for machine-level energy consumption, namely, E_{base}, $E_{cutting}$ and E_{ready} are considered. At the start of the simulation, the E_{base} value is updated; this value is the idle energy consumed by the machines. When a product variant enters the service block (machine), there is a setup phase, represented by the E_{ready} value, where the spindles and fixtures are readied. Following this, the cutting/machining operation begins and runs for a certain duration, represented by the $E_{cutting}$ value.

$$E_{machine} = E_{base} + E_{cutting} + E_{ready} \tag{1}$$

The E_{base}, $E_{cutting}$ and E_{ready} are defined as variables and the energy consumption of a machine is calculated as per Eq. (1). Each machine corresponds to three 'simulink function' blocks, one for each energy value. The 'E_{ready} simulink block' is triggered when product enters a machine. Following this, the 'E_{ready}' value is updated according to the time taken for setup. When material removal/cutting begins, the '$E_{cutting}$ simulink block' is triggered and the value is updated according to the time taken. The primary aim of the simulation model is to calculate the machine level energy consumption subject to stochasticity which was achieved using random number generators.

To test the working of the simulation model, desk checking, peer testing, submodel testing, model interface testing, visualisation and sensitivity analysis (Balci, 1998) were done with the help of data inspector and signal logging; the model was subject to several iterations before recording the output data in Matlab workspace.

4.3. Forecasting the energy consumption

Twenty datasets were obtained from the simulation model, one for each week of simulation run; each dataset comprises of timestamp in the first column, energy consumed by machine 1 in the second column, energy consumed by machine 2 in the third column and so on. It should be noted that the timestamps at which the energy values are recorded is not equally spaced and this is because the time interval between events in DES vary. The timestamp data is converted to timeseries using the 'retime' function in Matlab to obtain the daily and weekly energy consumption. The dataset is split into training set that corresponds to 90% of the data; the remaining is considered as the test set and the lag is '1'. During the training, the weights and bias values are updated using an LSTM neural network with the following parameters: adam solver, L2 regularisation of 0.0001, max epochs of 1000, and minimum batch size of 128. The results of the energy consumption forecast is provided in Fig. 7. Although there is scope to improve the architecture of the neural network, in view of delivering the proof of concept, further details will not be discussed in this article.

4.4. Visualising the results

The results obtained from both simulation and neural networks are displayed using grafana as it has good visualisation features such as charts and plots. The dashboarding data is sourced from multiple sources at different time intervals and needs to be constantly updated to show the real-time information. For this purpose, OPC-UA (Unified Architecture) which is a protocol for machine-to-machine communication is used. Kepware is a server that is built upon OPC-UA architecture and can enable the real-time data transfer between software for interoperability. In this study, Matlab and InfluxDB are established as clients to the Kepserver for real-time data transfer. Following this, grafana is integrated with influx DB to create real-time dashboards. A sample dashboard built for this proof of concept is shown in Fig. 8. Further details of the real-time communication using Kepserver and energy KPIs for manufacturing systems can be found in a previous work by the

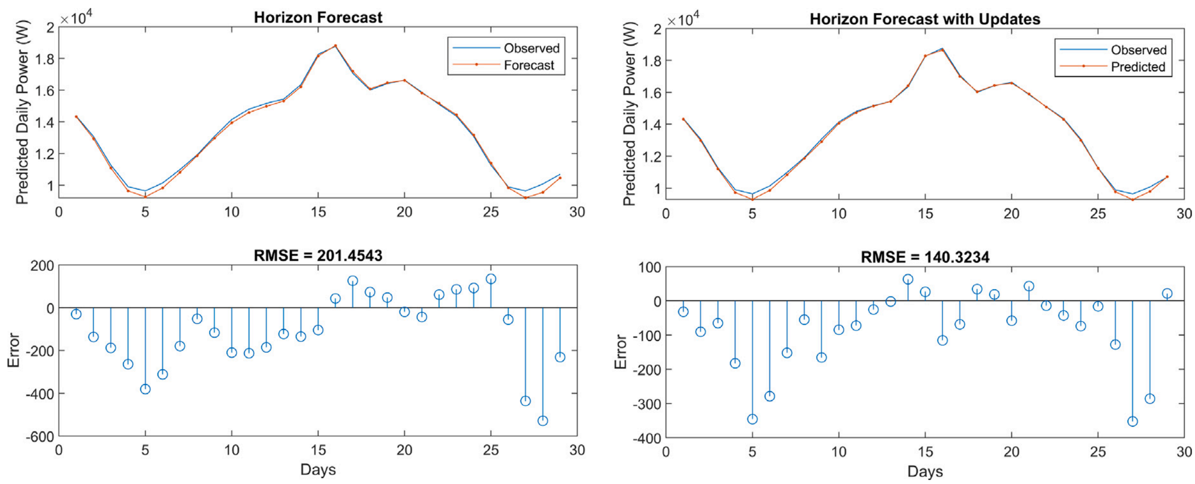


Fig. 7. Performance measurement of the LSTM architecture.

Fig. 8. Grafana dashboard.

authors (Chinnathai et al., 2021; Assad et al., 2019). From Fig. 8, it can be noted that machines 6 and 12 have the lowest utilisation and hence the least efficient.

5. Discussion

In this paper, a digital lifecycle management framework for EIIs is used to demonstrate how process discovery, discrete-event simulation and data analytics can be used to forecast the energy consumption of a machining industry. It should, however, be noted that the applicability of the framework is not restricted to the above-mentioned case study. The framework was developed to cater to the need of delivering radical improvements in EII energy efficiency. However, the applicability of the framework is not restricted to EIIs. The potential of integrating process mining and simulation for energy efficiency in a diverse range of manufacturing systems is an area of interest for future research. Considering the concept of Digital Twin, the proposed digital lifecycle management framework considers the integration of various software to create a digital representation of EIIs. They can be enriched with physics, electronics and data to be considered as a digital twin of the production system or its components. In this research, the operational phase of the EII was considered during demonstration of the methodology. It is to be noted that, in EIIs, concepts such as reconfiguration and production system changes do not happen as frequently as other manufacturing systems such as automobile assembly and semiconductor industries. However, the proposed framework is equally beneficial in the system design phase for planning and validation of systems. EIIs can also benefit from technologies such as block-chain enabled digital twins that can help in decarbonising the whole supply chain in addition to providing traceability, compliance, authenticity, quality and safety (Yaqoob et al., 2020). Moreover, the proposed framework helps achieve Industry 5.0 targets of adaptability, autonomous decision making while adhering to sustainability constraints and goals; this is with the help of AI and advanced forecasting to adapt to external circumstances through adaptive scheduling, job allocations, transparent and autonomous decision-making.

Table 3
Case study - Process details.

S.No	Variant 1	Variant 2	Variant 3	Variant 4	Variant 5	Variant 6	Variant 7	Variant 8	Variant 9	Variant 10
Process 1	Turning & Milling	Turning & Milling	Turning & Milling	Turning & Milling	Turning & Milling	Turning & Milling	Turning & Milling	Round grinding	Turning & Milling	Turning & Milling
Process 2	Quality check	Quality check	Quality check	Quality check	Quality check	Quality check	Quality check	Quality check	Quality check	Quality check
Process 3	Laser marking	Laser marking	Laser marking	Laser marking	Laser marking	Laser marking	Packing	Packing	Flat grinding	Laser marking
Process 4	Lapping	Flat grinding	Flat grinding	Flat grinding	Deburring	Lapping			Lapping	Round grinding
Process 5	Round grinding	Quality check	Lapping	Quality check	Flat grinding	Quality check			Quality check	Quality check
Process 6	Quality check	Packing	Round grinding	Packing	Lapping	Packing			Wire cut	Packing
Process 7	Packing		Quality check		Round grinding				Packing	
Process 8			Packing		Quality check					
Process 9					Packing					
Percentage	**41%**	**4%**	**11.7%**	**7.9%**	**4%**	**15.6%**	**5.8%**	**2%**	**4%**	**4%**

Table 4
Case study - Variant details.

S.No	Variant 1	Variant 2	Variant 3	Variant 4	Variant 6	Variant 7	Variant 8	Variant 9	Variant 10
Week 1	1	0	1	1	1	1	3	0	1
Week 2	4	0	0	1	1	1	3	1	0
Week 3	2	0	1	1	1	1	3	2	0
Week 4	2	0	1	1	1	1	3	0	1
Week 5	3	0	0	1	1	1	3	1	1
Week 6	2	0	1	1	1	1	3	1	1
Week 7	2	0	1	1	1	1	3	2	1
Week 8	3	0	2	0	2	1	3	2	1
Week 9	1	0	0	1	1	1	3	2	2
Week 10	3	0	2	1	2	1	3	1	1
Week 11	3	0	0	1	1	1	2	1	1
Week 12	4	0	0	1	1	1	3	1	1
Week 13	1	0	1	1	2	1	3	1	2
Week 14	2	0	1	1	2	1	3	1	1
Week 15	3	1	1	1	2	1	3	1	0
Week 16	3	0	1	1	2	0	3	1	1
Week 17	3	0	1	0	2	1	3	1	1
Week 18	2	1	2	1	2	1	3	1	1
Week 19	3	1	1	1	3	1	3	2	0
Week 20	3	1	1	1	3	1	3	2	0

5.1. Implication for practitioners

- The research can be employed for condition monitoring using sensors, data acquisition systems, predictive and diagnostic techniques to formulate energy-efficient maintenance plans.
- Process data integrated with simulation models and machine learning can be used for anomaly detection and asset health monitoring. As a result, manufacturers can simulate maintenance strategies before implementation.
- EIIs can employ the framework to improve the process design and reduce wasted energy and materials. As an example, simulation-based optimisation can be employed to identify the best operating conditions and process parameters for various energy-intensive processes while maximising profit and minimising the energy consumption.
- Engineers can automatically generate energy DES models with embedded intelligence from ontologies, knowledge representation, and AI.

5.2. Implication for researchers

- The recent environmental policies and initiatives have put EIIs on the spotlight. As a result, EIIs are seeking to innovate and radically transform their processes with the support from academia and researchers. The focus has been on the integration of big data analytics and data acquisition systems. However, the proposed framework will aid researchers to explore other key enablers such as process mining and simulation & modelling to achieve a holistic digital transformation of EIIs.
- The experiment performed in this research study serves as a proof of concept for improving energy and material efficiency of EIIs.
- The digital life-cycle management framework considers the horizontal and vertical integration of the various components for real-time decision support. It paves way for researchers to explore the concepts of interoperability, data storage, and industrial network for ensuring organisation-wide sustainability in EIIs.

5.3. Key findings

A comprehensive evaluation of the proposed framework helped identify the below findings.

1. A review of past studies indicates the focus of existing research on IoT devices, and big data analytics. There is a lack of technical know-how regarding the seamless transition of EIIs from legacy systems to sustainable digital factories.
2. The proposed framework primarily relies on existing data from the data acquisition layer and any issues with data quality are propagated throughout the framework.
3. The accuracy of the models developed in the simulation and AI layers significantly depends on the quantity and quality of the data.
4. During implementation of the framework, there exist interoperability issues due to the use legacy systems in EIIs.
5. The framework can be applied in the operational phase of a system and all five layers of the framework play an important role in discovery and monitoring of the data.

5.4. Challenges and outlook

This section discusses the challenges and outlook for digital transformation from the perspective of organisational enablers. The first and foremost issue is that the investments in digital technologies are expensive. This is compounded by the lack of proper digital infrastructure as a result of outdated legacy systems, inexperienced personnel, lack of accurate data, and challenges in data collection. Long term strategies and radical changes are not easy to implement since they need to be considered at the organisational level. Existing industries lack knowledge on where and how the principles of Industry 4.0 can be applied. In order to build intelligent digital models it is important to have a good knowledge of the complex processes in a system. However, lack of proper documentation, and use of paper-based systems add to existing challenges (Jasonarson, 2020). The age gap between current workers and prospective employees is huge. The experienced workers who have a better idea of the factory are resistance to training (Murri et al., 2019). According to Newman and McClimans (2017), the key to achieving best effective use of digital technologies is successful vertical integration, horizontal integration, as well as considering the lifecycle assessment of the production. In order to bring about such a transformation, it is necessary to have a multi-disciplinary project team with skill set that allows digital modelling, embedding intelligence, and performing analysis.

5.4.1. Research question 1: How can the integration of digitalisation and AI support sustainability in EIIs?

Past studies show that increased collaboration among researchers, industries and academia plays an important role in digital transformation of EIIs. The digital models that will be created should be holistic to capture the different stages of the lifecycle along with integration of lifecycle assessment tools. To answer this research question, the digital life-cycle management framework considers five different layers that enable the integration of digitalisation and AI for asset monitoring, measuring utilisation, zero-defect manufacturing, traceability, adaptive online control and effective process plans to reduce wastes. However, it should be noted that this necessitates proper training to personnel along with improvements in safety, and working conditions. Additionally, it is worth considering cloud-based Platform as a Service (PaaS) and federated learning for specific stages of the digital transformation.

5.4.2. Research question 2: What strategies can be employed to improve the process understanding of EIIs?

The benefits of process mining for EIIs is established as part of this study. Event logs and traces obtained from industries help with process discovery and improves process understanding. Having established that the monitoring and understanding of processes in an EII can bring about a positive transformation, the proposed digital life-cycle framework enhances existing methodologies that are based on big data analytics, digital twin, and IoT with the addition of process management and simulation & modelling. This research study demonstrated the steps involved in the process discovery of a mining operation and identified data that can be readily used for the development of an energy DES model. The research can benefit from further understanding of the data model schema and interoperability between process mining and simulation.

6. Conclusion and future works

In this research, the authors have reviewed the current state of digitalisation in energy-intensive industries and proposed a framework to support the realisation of sustainable smart manufacturing in Energy Intensive Industries (EIIs). The investigation of process mining and simulation modelling to support sustainability has enabled the development of a five-layer framework consisting of (i) data acquisition, (ii) process management, (iii) simulation & modelling, (iv) artificial intelligence, and (v) data visualisation, to embed intelligence in EIIs such that energy and material efficiency can be improved. The framework is demonstrated with a machining industry test case and the various phases of the framework support different facets of sustainable smart manufacturing to bring about a holistic digital transformation. It should be noted that the primary research contribution is the application of process mining and simulation & modelling to understand the 'as-is' process; the process data was used to discover process deviations, represent knowledge, and analyse processes to support the creation of a parametric discrete-event simulation model. The output of the simulation model was used to forecast the energy consumption; the energy consumption is then displayed using dashboards to identify areas for improvement. The authors would like to point out that to the best of their knowledge there is no existing research that explores the process understanding of EIIs through the use of process mining integrated with simulation & modelling. The study also indicated the importance of the veracity of data and the accuracy of the modelling process. Moreover, the barriers associated with interoperability and hardware/software compatibility were also discovered. As part of the future work, the limitations associated with as data quality issues, interoperability and compatibility with legacy systems, can be addressed by: (i) considering and integrating data quality checks and data governance policies at the gateway of each of the five layers, (ii) identifying historical datasets that are relevant to the current processes and evaluating their suitability to train the models used in the AI layer, (iii) identifying open source software and APIs that can help overcome issues with real-time data transfer and compatibility issues. Additionally, there are plans to extend this research work with the inclusion of detailed knowledge representation, ontologies and mapping in the process management layer, consideration of cloud-computing and edge computing, and self-adapting automation & manufacturing systems.

CRediT authorship contribution statement

Malarvizhi Kaniappan Chinnathai: Conceptualization, Methodology, Software, Writing – original draft. **Bugra Alkan:** Methodology, Validation, Data curation, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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