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Energy efficiency in digital infrastructures: a framework towards a sustainable cloud manufacturing

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Abstract

Cloud manufacturing integrates cloud computing technologies with traditional manufacturing processes, improving operational efficiency and flexibility. However, it also increases the demand for energy, especially in data centres, which exacerbates the environmental impact. To address this issue, this research work presents a framework suitable for identifying, characterising, and managing energy inefficiencies in digital infrastructures. The framework includes energy data collection, inefficiency characterisation, root cause analysis and implementation of a targeted solution. By focusing on key factors such as server utilisation, data management and resource allocation, the proposed methodology aims to contribute reducing energy consumption, operational costs and CO_2 emissions. The iterative approach proposed in the framework could enable continuous improvement and adaptation, promoting sustainable cloud manufacturing in digital infrastructure environments.

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Keywords: Cloud manufacturing; Energy efficiency; Sustainable digital infrastructure; Energy optimisation

1. Introduction

Cloud manufacturing represents a transformative integration of cloud computing technologies into manufacturing processes, stimulated by the exponential growth of the digital economy [1]. In particular, this integration has enhanced operational efficiency and flexibility within the industry [2]. However, the implementation of cloud manufacturing is energy-intensive due to the need to run high-performance computing tasks, extensive data storage and real-time processing. This contributes to an increased environmental impact due to the significant energy demand of cloud-based services, especially within data centers. The expansion of data centers, driven by increasing consumer requests for on-demand resources, requires a significant electrical load for various operational and peripheral devices [3]. Historical data shows a significant increase in global data centre power consumption, from 70,000 million kWh in 2000 to 330,000 million kWh in 2007, with projections estimating 2967 TWh by 2030 [4]. This growing energy demand poses a challenge to the cloud computing infrastructure due to the related CO_2 emissions. Accordingly, while the integration of cloud technologies in modern manufacturing heralds a new era of increased efficiency, flexibility and interconnectivity, this evolution also raises sustainability concerns [5]. In such a context, this research aims to help reconcile technological advances with sustainable practices in cloud-based digital infrastructures, such as cloud manufacturing or, more generally, on-demand service

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platforms [6]. The focus is on understanding the dynamics of energy use and developing strategies to mitigate excessive consumption. Methodologies for monitoring and measuring energy in cloud-based environments have been explored to detect inefficiencies and areas for improvement. Key factors influencing energy demand have been identified by analysing equipment use and cloud-service processing requirements. To explore viable optimisation strategies, an energy optimisation framework is proposed to identify inefficiencies, strategically allocate resources and implement conservation measures.

2. Framework

The framework in Fig. 1 summarises the structure of the proposed methodology to identify, characterise, and improve energy inefficiencies, which is the basis for promoting sustainable practices.

2.1. Data collection and preparation

The methodology starts with data collection, measuring energy demand through methods such as the dynamic energy meter (DEM), measurement-based approach (MBA), multi-port hardware energy meter system (MPEM), intelligent energy consumption model (IECM), workload-specific power measurement (WSPM), and online monitoring system (OMS). The DEM monitors server energy metrics via slave nodes and combines the data at a master node to analyse CPU, memory, and disk performance [7]. The MBA collects highly accurate operational data, adjusting CPU frequencies and using scripts for CPU, disk, and network power measurements. The MPEM gathers real-time voltage, current, active power, and power factor data using sensors and a Raspberry Pi for data processing [8]. The IECM employs power meters and machine learning algorithms to monitor and predict energy demand [7]. The WSPM method models power consumption based on workload types [7]. The OMS tracks energy demand in real-time across different departments [9].

Measured parameters include CPU utilisation, memory utilisation, disk I/O operations, network traffic, voltage, current, active power, and power factor. All these methods ensure comprehensive monitoring and optimisation of energy usage in cloud-based environments, such as cloud manufacturing [9]. Pre-processing, feature extraction, and labelling are then applied to the collected data to prepare it for further machine learning analysis.

2.2. Intelligent classification of energy inefficiencies

The methodology for detecting energy inefficiencies then focuses on four main areas: (*i*) server utilisation, (*ii*) infrastructure, (*iii*) memory, and (*iv*) storage. In terms of (*i*) server utilisation, the methodology is first aimed at evaluating the server performance metrics to detect various states such as overload, underload, and idleness. Each state is analysed to understand its impact on energy requirements, using dynamic thresholds adjusted through methods such as Gradient Descent Regression based on historical data [10]. For (*ii*) infrastructure, the approach involves monitoring the energy used by all IT components, with an emphasis on the energy drawn by cooling systems, which play a critical role in managing the heat generated by the active equipment [11]. With regards to (*iii*) memory usage, the focus shifts to examining the energy efficiency of Dynamic Random Access Memory (DRAM), where inefficiencies are often due to the demand of high-speed operations. The analysis of (*iv*) storage focuses on the energy usage patterns of storage devices, integrated into the overall assessment of the energy demand of IT equipment [10].

2.3. Allocation of energy inefficiencies

Following the classification, the framework analyses the allocation of energy inefficiencies. This step involves identifying the specific software within the cloud infrastructure responsible for the inefficiencies, such as computer-aided design (CAD), customer relationship management (CRM), enterprise resource planning (ERP), database management systems (DBMS), quality management systems (QMS), manufacturing execution systems (MES), supervisory control and data acquisition (SCADA), and big data analytics (BDA) [12]. This analysis focuses on identifying inefficiencies in data processing and management. The identification can be carried out using a variety of methods, including performance monitoring tools, energy requirements tracking and detailed software audits [13].

Performance monitoring tools analyse system resource usage and identify bottlenecks, while energy tracking reveals excessive energy demand patterns. Detailed software audits examine the configuration and operation of each system to find inefficiencies in data handling and processing [13].

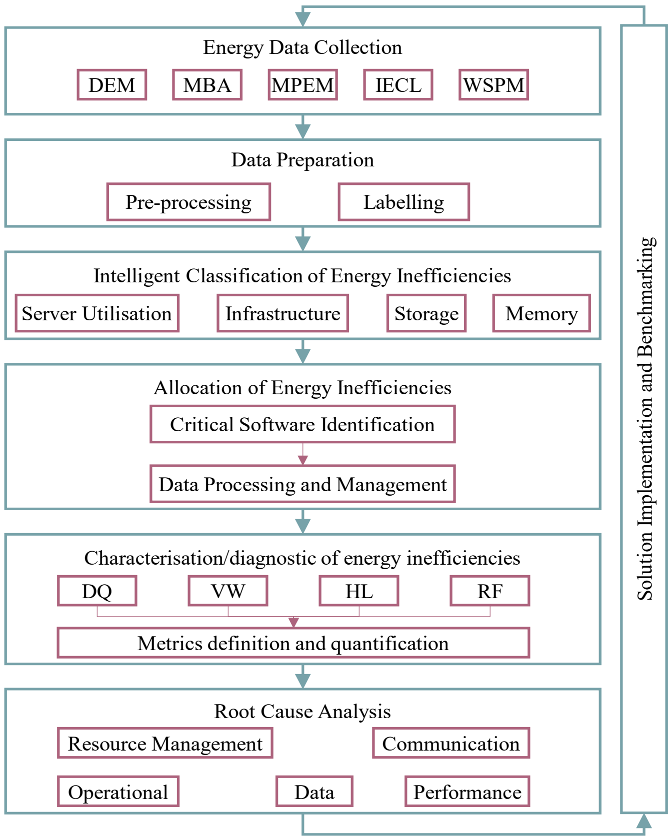

Fig. 1. Framework for monitoring and optimising energy efficiency.

2.4. Characterisation/diagnostic of energy inefficiencies

The next phase is to characterize the identified inefficiencies as a diagnostic tool for precise intervention strategies. Key factors to assess include data quality, workload variability, latency and request frequency.

Data quality assessments focus on identifying ‘dirty data’, redundant entries, and empty data that can lead to inefficient processing and increased energy consumption [14]. Workload variability examines fluctuations in demand, with high variability leading to inefficiencies due to over-provisioning [7]. Latency measures delays in data transfer and processing, indicating inefficiencies that increase energy requirements [15]. Request frequency analyses how often data requests are made, with high frequencies leading to constant system activity and higher energy consumption. Characterisation and diagnostics can use qualitative and quantitative methods. Advanced techniques, such as statistical analysis and machine learning, process large datasets to identify patterns and anomalies, while visualisation tools aid interpretation. Simulation tools model scenarios to predict the impact of various factors on energy demand [16].

Energy audits examine usage across components and processes, identifying inefficiencies in data handling, activity times, processing delays, and request frequencies. Key performance indicators and metrics, such as energy per transaction and power usage effectiveness provide a standardised way to measure and compare performance [7–9].

2.5. Root cause analysis

Following the characterisation and diagnostics of energy inefficiencies, the framework progresses to the root cause analysis phase. This step identifies the underlying sources of the diagnosed inefficiencies. The primary sources are categorised as (*i*) operational processes-related, (*ii*) performance-related, (*iii*) data-related, (*iv*) resource management-related, and (*v*) communication-related. *Operational processes-related* inefficiencies include sub-optimal server utilisation, inefficient cooling systems, and inadequate maintenance practices, all of which contribute to increased energy consumption [17]. *Performance-related* inefficiencies arise from system bottlenecks, latency issues, and fluctuations in workload demand that cause energy waste [7]. *Data-related* inefficiencies result from poor data management practices, including low data quality, redundancy, and inefficient data handling processes, that lead to excessive energy use in storage, retrieval, processing, and transfer. *Resource management-related* inefficiencies involve the misallocation and under-utilisation of resources, including over-provisioning and lack of dynamic resource allocation [18]. *Communication-related* inefficiencies are caused by inefficient data communication protocols and infrastructure, leading to bottlenecks, high latency, and increased energy consumption due to frequent and inefficient data transfers [15]. The root cause analysis uses methodologies such as fishbone diagrams, which visually map out potential causes of inefficiencies, and the Five Whys analysis, which delves into the underlying reasons for each inefficiency [19]. Pareto analysis is used to identify the most significant factors contributing to energy inefficiencies and prioritise them for intervention [20]. Process mapping provides detailed visualisations of operational workflows, highlighting inefficiencies and areas for improvement [21].

2.6. Solution implementation and benchmarking

The final step focuses on applying targeted interventions to address the identified sources of inefficiency, leveraging strategies across the hardware and network, data management and security, and software and application domains, as shown in Fig. 2. In the *Hardware and Network* domain, solutions such as server virtualisation and power management features can be implemented to optimise operational efficiency [22]. Dynamic resource scaling and network optimisation (e.g., DVFS) address performance-related inefficiencies by adjusting resources based on real-time demand and optimising network hardware performance [23]. For data-related inefficiencies, fog and edge computing and the use of SSDs can be employed to improve data processing efficiency and reduce latency.

Virtualisation and consolidation, along with load balancing and scaling, can be used to manage resources more effectively, ensuring optimal utilisation and reducing energy waste [24].

	Hardware and Network	**Data Management and Security**	**Software and Application**
Operational	Server Virtualisation Power Management Features	Data Governance Operational Data Optimisation	Monitoring and Predictive Maintenance Coding Practices
Performance	Dynamic Resource Scaling Network Optimisation (e.g., DVFS)	Data Access Methods Data Encryption	Application Performance Management Algorithms and Data Structures
Data	Fog and Edge Computing Use of SSDs	Data Deduplication and Compression Data Encryption at Rest and in Transit	Energy-Aware Software Design Data Processing Techniques
Resources	Virtualisation and Consolidation Load Balancing and Scaling	Data Lifecycle Management Backup and Recovery Efficiency	Dynamic Resource Allocation Containerisation and Microservices
Communication	Network Protocols Reduce Transmission Overhead	Data Transfer Protocols Network Access Control	Inter-Process Communication Network Usage Within Applications

Fig. 2. Solutions map

To improve communication efficiency, advanced network protocols and techniques to reduce transmission overhead are used, minimising energy requirements related to data transfer [15]. In the *Data Management and Security* domain, operational inefficiencies can be mitigated through data governance and operational data optimisation. Performance can be enhanced by implementing efficient data access methods and robust data encryption. For data inefficiencies, data deduplication and compression, as well as data encryption at rest and in transit, are utilised to ensure efficient data storage and security [25]. Resource-related solutions include data lifecycle management and improving backup and recovery efficiency. Communication inefficiencies are addressed by optimising data transfer protocols and strengthening network access control for secure and efficient data flow [18]. In the *Software and Application* domain, monitoring and predictive maintenance, together with improved coding practices, can enhance operational efficiency [26]. Application performance management and optimisation of algorithms and data structures could address performance-related inefficiencies. Sustainable software practices, e.g., energy-aware software design and efficient data processing techniques, can target data-related inefficiencies [27]. Resource management can be improved through dynamic resource allocation and the use of containerisation and microservices, enabling scalable and efficient application deployment [28]. Communication within applications can be optimised through better inter-process communication and efficient network usage, reducing the energy overhead associated with software operations [18].

In the final step, the framework implements solutions and quantifies their benefits. Implementation involves strategies across hardware, data management, and software using phased deployment, pilot testing, and continuous monitoring. Benefits are measured in terms of the impact on energy consumption, costs, and CO_2 emissions. Energy use is monitored through loggers and sensors, cost variations can be obtained from energy bills and maintenance costs, and CO_2 reductions using standard conversion factors. Effectiveness is assessed by comparing pre- and post-implementation data, validating interventions and promoting continuous improvement and adaptation through the Energy Data Collection loop.

3. Case study

The proposed framework, due to its general formalisation, can be applied with few specific adaptations to a variety of cloud-based digital infrastructures characterised by the prevailing challenges of digital resource allocation, such as on-demand services like cloud manufacturing, e-commerce, smart manufacturing networks. The similarities between e-commerce and cloud manufacturing environments have already been highlighted in the literature [29]; both sectors face significant demands in terms of resource and energy demands. Therefore, to demonstrate the applicability of the framework, the server usage in e-commerce was considered. The case study examines how resource allocation during different operating periods could optimise efficiency and consequently reduce the environmental impact. Key metrics such as CPU usage, RAM, and network errors, listed in Table 1, were recorded hourly over a month, creating a dataset of 450 instances, partially shown in Fig. 3. To identify energy inefficiencies, a logistic regression model was used to classify server states as (*i*) right-sized, (*ii*) over-utilised, and (*iii*) under-utilised. Three different scenarios were therefore investigated. In the *right-sized scenario*, the system maintained an optimal balance of resources to meet operational needs without excess or deficiency. Continuous monitoring and adjustment can ensure efficient resource use, reducing both environmental impact and costs. *Over-utilisation scenarios* were analysed in two contexts: (*ii-a*) continuous over-utilisation and (*ii-b*) peak over-utilisation. Continuous over-utilisation was associated with a sustained strain of resources, leading to performance bottlenecks and increased energy requirements. Solutions may include scaling up infrastructure and optimising existing resources. Peak over-utilisation can occur during limited periods of high-demand. Performance monitoring, capacity planning, and the use of cloud services can be identified among the proactive mitigation measures.

Table 1. Server metrics

Variables	Critical Behaviours	Optimal
Network Traffic	Spikes	High, stable
Network Error	High, increasing, spikes	Minimal
Latency	High, increasing, spikes	Minimal
CPU Utilisation	Extremes (high or low)	Moderate
RAM Utilisation	Extremes (high or low)	Moderate

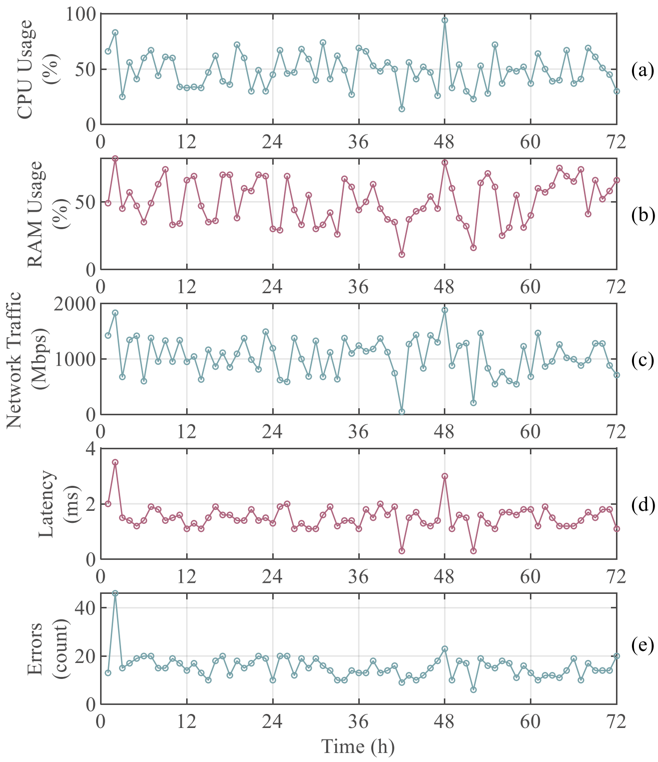

Fig. 3. Extract of time series plots for system metrics over 72 hours: (*a*) CPU usage, (*b*) RAM usage, (*c*) network traffic, (*d*) latency, and (*e*) error count.

Under-utilisation scenarios were also examined in two contexts: (*iii-a*) continuous under-utilisation and (*iii-b*) peak under-utilisation.

Overall, under-utilisation results from inefficient resource allocation or fluctuating demand, leading to wasted resources. Strategies such as downsizing, server consolidation, and workload balancing can be implemented to address these inefficiencies [24]. Peak underutilisation can occur during specific periods of low demand, requiring auto-scaling policies and the rescheduling of resource-intensive tasks to optimise utilisation [23].

4. Results and discussion

The dataset (Fig. 3) was split evenly into training and testing sets, achieving high accuracy and reliable predictions with minimal false positives and negatives, as shown in Table 2. A root cause analysis was performed to understand and mitigate inefficiencies with reference to issues related to over- and under-utilisation, which have a significant impact on system performance and sustainability. Such mitigating solutions are reported in Table 3. Costs were calculated by evaluating operational expenses of different instance types, factoring in hourly rates and scaling adjustments. Energy demand was based on the data centre power usage efficiency and specific energy requirements, including both active and idle states. The $CO_{2\text{-eq}}$ calculations were derived using the Amazon Web Services (AWS) database, which accounts for the carbon intensity specific to the AWS region in Italy, considering its local energy mix, and insights from Teads Engineering on estimating carbon emissions for AWS EC2 instances [30, 31]. In the *Continuous over-utilisation* scenario (Fig. 4a), although there was an increase in costs, energy demand, and CO_2 emissions, scaling up the infrastructure effectively addressed performance issues and ensured system reliability. This mitigation measure highlights the importance of maintaining a robust infrastructure to cope with sustained high demand, ensuring operational continuity and user satisfaction. The *Peak over-utilisation* scenario (Fig. 4b) experienced significant spikes in costs, energy demand and CO_2 emissions during peak periods. Implementing auto-scaling policies to dynamically adjust resource capacity proved beneficial in managing these peaks efficiently.

This approach optimised costs and reduced waste at non-peak times, demonstrating the value of flexibility and responsiveness in resource management. The *Right-sized* scenario (Fig. 4c) maintained optimal costs, energy demand, and CO_2 emissions with balanced resource allocation. Continuous monitoring and proactive maintenance ensured efficient use of resources, demonstrating the benefits of strategic resource management.

Table 2. Confusion Matrix Results

	Predicted Over-utilisation	Predicted Rightsize	Predicted Under-utilisation
Actual Over-utilisation	98.72%	1.28%	0.00%
Actual Rightsize	0.00%	100.00%	0.00%
Actual Under-utilisation	0.00%	0.00%	100.00%

Table 3. Implemented solutions by scenario

Scenario	Mitigation Action
Peak Over-utilisation	Upgrade to higher-capacity instances and use auto-scaling during peaks to allocate resources dynamically
Continuous Over-utilisation	Upgrade to higher-capacity instances or increase baseline resources to consistently meet the demand
Peak Under-utilisation	Schedule automated shutdown of idle resources during off-peak hours
Continuous Under-utilisation	Consolidate underutilised workloads to fewer machines to optimise resource usage
Right-sized	Continuously monitor and right-size resources to align with actual usage patterns.

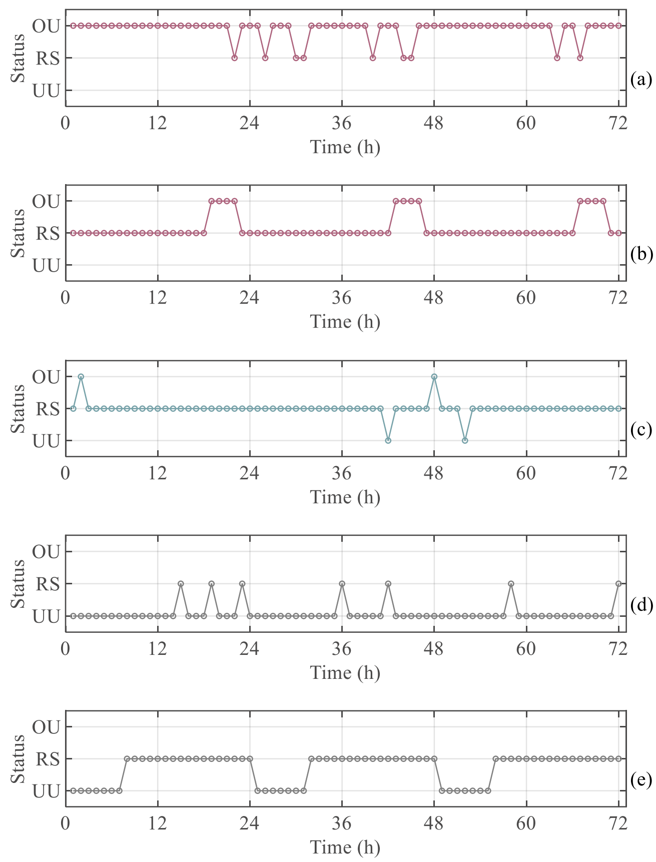

Fig. 4. Examples of server status: (*a*) continuously over-utilised, (*b*) peak over-utilised, (*c*) right-sized, (*d*) continuously under-utilised, (*e*) peak under-utilised (OU = over-utilised, RS = right-sized, UU = under-utilised).

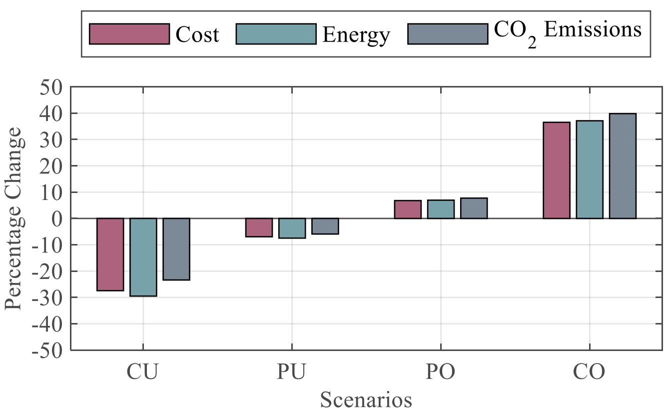

Fig. 5. Results by scenario (CU = continuously under-utilised, PU = peak under-utilised, PO = peak over-utilised, CO = continuously over-utilised).

For *Continuous under-utilisation* (Fig. 4d), reducing instance sizes to match actual demand resulted in reductions in costs, energy demand, and CO_2 emissions. Right-sizing proved to be an effective strategy for optimising resource usage and minimising waste. This scenario demonstrates the significant environmental and financial benefits of accurate and proactive resource management. In the *Peak under-utilisation* scenario (Fig. 4e), scaling down or decommissioning idle resources during off-peak hours resulted in moderate reductions in the three considered metrics.

This approach highlights the importance of targeting specific low-demand periods to improve the efficiency of resource allocation and reduce environmental impact. The bar chart in Fig. 5 shows the percentage change in costs, energy demand, and CO_2 emissions for the four scenarios, using the right-sized scenario as a benchmark. The values for the right-sized scenario were 1.07 $kgCO_{2\text{-eq}}$ for CO_2 emissions, 2.06 kWh for energy demand, and 19.09 € for costs.

5. Conclusions

A general framework for optimising energy use efficiency in cloud-based digital infrastructures (and, among others, in cloud manufacturing) has been proposed in this research. On-demand services require extensive use of digital resources, and both over- and under-utilisation scenarios have been addressed. The characterisation of inefficiencies and the root cause analysis can provide the basis for mitigation actions such as auto-scaling, right-sizing, and resource consolidation, thereby promoting optimisation of energy demand, operational costs, and CO_2 emissions.

The case study demonstrated the framework principles and practical applicability, albeit limited to a specific context. By continuously monitoring and adjusting resource allocation based on demand patterns, the methodology could help improve the sustainability of digital infrastructures. Further work should focus on applying the framework to other industrial environments, to validate its effectiveness and robustness in different cloud manufacturing scenarios.

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