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Artificial Neural Network-Based Energy Disaggregation for Industrial Machinery Using Non-Intrusive Load Monitoring

Burcu Aydin[1*], Emre Kaya[1]

Abstract

This article investigates the use of non-intrusive load monitoring methods within industrial settings to separate and analyze the power usage of production equipment. As efforts toward decarbonization and energy efficiency intensify, establishing clear visibility into manufacturing energy use is essential. By employing non-intrusive load monitoring, the evaluation and handling of power data can yield critical knowledge to guide choices regarding emission cuts and efficiency upgrades. Although non-intrusive load monitoring is well-documented in residential and commercial buildings, its implementation in manufacturing requires deeper investigation. This study bridges that knowledge gap by applying proven non-intrusive load monitoring approaches to industrial data. Utilizing artificial neural networks to disaggregate power data allows for the accurate measurement of industrial equipment's energy usage. Consequently, a universal, cross-energy framework for isolating the power draw of manufacturing machinery is formulated via a design science research methodology and then verified via a real-world case study featuring a compressed air demonstrator. Findings indicate that artificial neural networks are highly capable of disaggregating industrial power data, successfully detecting simple on-and-off phases, multi-tiered operations, and continuously shifting states. Future studies examining novel artificial intelligence tools for energy assessment should strongly consider non-intrusive load monitoring. It serves as a practical substitute for intrusive load monitoring, negating the need to equip each machine with individual power meters.

Keywords Non-intrusive load monitoring, Artificial neural networks, Energy transparency, Energy consumption evaluation, Industrial manufacturing

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Introduction

Driven by climate change, the manufacturing industry currently faces substantial hurdles regarding energy use and greenhouse gas emissions. Consequently, managing CO2 output has evolved into a central corporate priority. During the European Union's Fit for 55 initiative led by its climate policy commission, the current EU emissions trading framework faced tighter regulations. Under these rules, businesses demonstrating high energy efficiency and a minimal CO2 footprint will gain increased backing, while facilities with wasteful production methods will encounter tighter constraints [1].

Yet, managing CO2 output is just one of several hurdles for the industrial domain. The sector was responsible for 37 percent of worldwide power consumption in 2022 [2]. Achieving superior energy efficiency, minimizing power expenses, and cutting emissions are all vital to guarantee the long-term sustainability of the manufacturing sector [3]. To reach these goals, establishing clear energy visibility is the crucial first move. Such transparency allows businesses to track power usage across manufacturing stages, thereby highlighting wasteful practices or highly demanding procedures [4]. Without

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insight into the specific power demands of factory equipment, it is impossible to formulate impactful improvement strategies.

Non-intrusive load monitoring (NILM) is an analytical method used to break down aggregate power data, pinpointing the electricity draw of specific machinery or appliances without needing extra physical sensors. Compared with intrusive load monitoring (ILM), NILM offers a low-installation alternative for achieving energy visibility. Implementing NILM lays the groundwork for data-driven choices regarding efficiency upgrades and CO2 mitigation tactics [5]. Ultimately, this approach permits the extraction of individual machine power profiles using only the readings from a primary central meter, bypassing the need for dedicated sub-meters [6, 7].

Academic literature explores numerous load separation methodologies, commonly featuring pattern recognition systems or Hidden Markov models (HMM). However, separating power data via artificial neural networks (ANNs) shows immense promise and is rapidly gaining traction within the NILM academic sphere. Current research indicates that ANN-driven separation can successfully detect all load categories, even the continuous power signatures generated by industrial equipment; hence, this article concentrates on deploying ANNs for NILM [8].

Investigations into NILM have spanned multiple decades, primarily targeting power tracking within residential homes and commercial properties. Based on a review conducted by Tan *et al*. [9], out of 788 scholarly articles on power disaggregation published between 1990 and 2019, only five pertained to industrial production. While a handful of NILM frameworks exist for the industrial realm, they generally overlook core manufacturing equipment [10]. Gathering data within industrial environments presents greater difficulties, as manufacturing units are complex amalgamations of various parts (e.g., drives, pumps, or conveyor systems) [10]. Consequently, deploying NILM in manufacturing is inherently tougher given that the temporal signatures, load categories, and power tiers are significantly more intricate than those found in domestic buildings [11, 12]. Nevertheless, NILM holds substantial promise for industrial applications, particularly in environments lacking extensive sub-metering where installing new physical sensors is unfeasible.

Further study is needed to confirm if NILM methodologies can be effectively mapped onto industrial power datasets. Tailoring proven NILM frameworks for manufacturing datasets presents a clear path to achieving energy visibility on the factory floor. The primary aim of this work is to formulate a universally adaptable technique capable of isolating the power draw of manufacturing equipment via ANNs for NILM. To fulfill this goal, the study seeks to answer this primary research query:

How can the energy consumption of value-adding machinery in industrial manufacturing be disaggregated using ANNs for Non-intrusive Load Monitoring?

The approach to tackling this research question proceeds as follows. The methodology relies heavily on the scientific paradigm of design science research (DSR). Leveraging this DSR framework, the current study aims to resolve the research query and bridge an existing literature gap by designing an artifact—specifically, a procedural method—that facilitates the separation of machine energy profiles in an industrial environment. To achieve this, necessary specifications are extracted from existing academic literature and evaluated against the cutting-edge capabilities of industrial NILM. Armed with these insights, a novel procedure is engineered and subsequently verified using a versatile compressed air demonstrator.

This research enriches the current body of literature through multiple avenues. The key contribution aspects of our investigation include:

- A semi-structured literature review concerning power disaggregation within an industrial context.
- The establishment of specific requirements for implementing NILM on the factory floor.
- The creation of a transferable framework for executing NILM in manufacturing scenarios.

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· An exploration of NILM's viability across diverse energy carriers for load tracking (e.g., compressed air).

Research Design

Aligning with the framework established by Gregor and Hevner [13], the investigation detailed in this study is organized around the DSR paradigm within information systems (IS) [14]. This problem-solving method is anchored in both practical relevance and academic rigor, merging real-world corporate demands with theoretical insights to enrich IS scholarship [15]. Utilizing this DSR methodology, this paper aims to bridge a knowledge gap by developing an artifact—specifically, a procedural method—that facilitates the NILM tracking of machinery power usage in an industrial environment. The scarcity of current strategies involving artificial intelligence (AI) systems, particularly NILM applications, for assessing industrial power usage underscores the significance of this study. Academic rigor is maintained by integrating conceptual frameworks, establishing core requirements, and testing the outcome against these standards. Merging theory with practical execution leads to the creation of a meaningful artifact, illustrated in **Figure 1.**

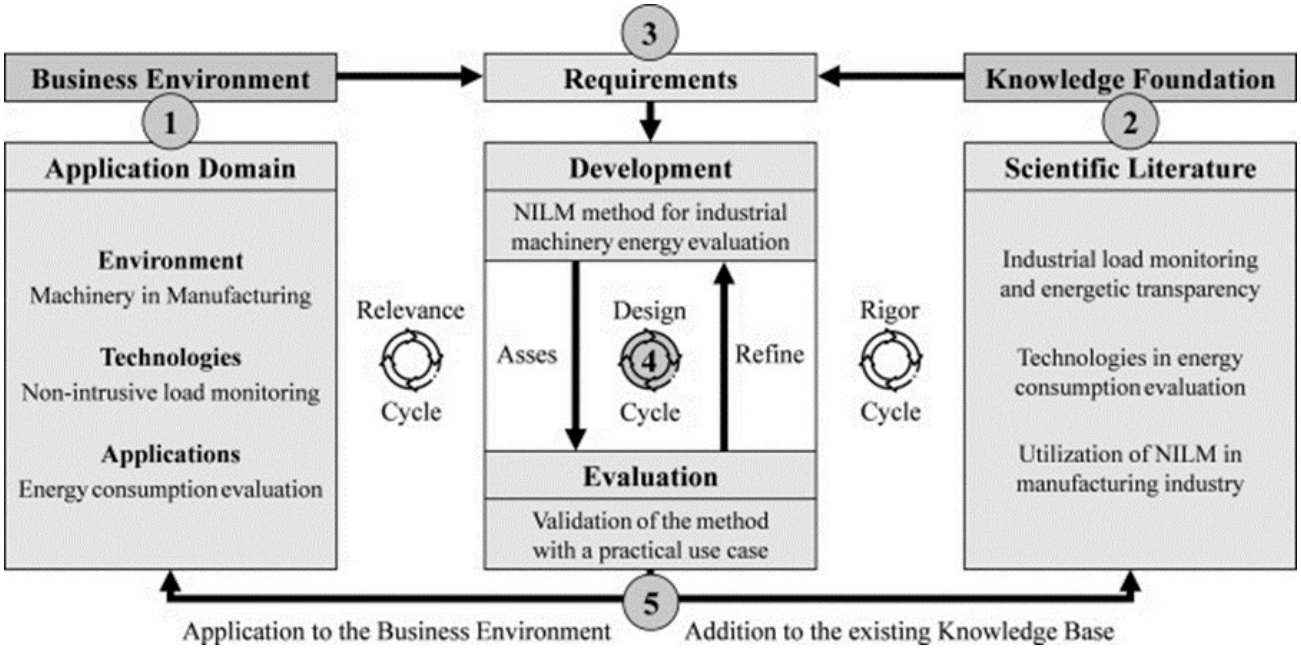


Figure 1. Research design of this study (grounded in design science research and adapted from [14]).

This study deploys the design science research methodology (DSRM) formulated by Peffers *et al*. [16], which encompasses six distinct stages: problem identification, objective definition, design and development, demonstration, evaluation, and communication. Nevertheless, this framework was adapted to align closely with our designated artifact.

Adhering to the DSRM, **Figure 1** outlines a tailored, holistic representation of our investigative setup.

· Phase 1: The initial stage focuses on articulating a concrete research issue stemming from the commercial landscape and operational field, while validating the worth of the intended artifact (1). As previously noted in the introduction, adopting NILM to secure energy visibility in production settings yields vital benefits for industrial firms. Thus, the objective of our study is to deliver a universally transferable technique for separating the energy profiles of factory equipment by utilizing ANNs within a NILM framework.

· Phase 2: The second stage entails pinpointing and examining the current state of academic research and industry practice to guide the construction of our artifact through pertinent literature (2). To support this effort and isolate key

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requirements, a semi-structured literature review was conducted. Drawing from the concepts of Gregor and Hevner [13], the current body of literature is leveraged to introduce an exaptation to IS scholarship, thereby reconfiguring the NILM technique—traditionally deployed for property energy tracking—for a novel context: the industrial setting. Although a few attempts have been made to introduce NILM to manufacturing, a standardized methodology for using NILM to assess equipment energy profiles remains absent.

· Phase 3: Accordingly, during the third phase, precise criteria for the artifact are mapped out to ensure both academic precision and practical utility (3). To achieve this, we execute a systematic appraisal of current practices and identify unresolved research gaps. From this assessment, we extract both the design constraints for our artifact and the metrics used to judge its performance.

· Phase 4: The design and development stage encompasses the generation and presentation of the artifact (4) [16]. Guided by DSR tenets, a system for utilizing NILM to analyze equipment power profiles in manufacturing plants is engineered. Following multiple cycles of drafting and polishing the artifact, a case study is executed to exhibit its functionality. The proposed method is put into practice to resolve the core issue of using NILM to monitor the electricity usage of multiple factory assets via a single power meter.

· Phase 5: By sharing our outcomes with scholars and targeted stakeholder groups, such as operational experts in manufacturing small and medium-sized enterprises (SMEs), this artifact aims to enrich the established body of knowledge, thereby accelerating the deployment of this technique within corporate operations (5).

Problem Context and Theoretical Background

Technologies in energy consumption measuring and modelling

Tracking the operational states and load profiles of equipment requires an appropriate monitoring framework [5]. Load tracking entails measuring power usage and device statuses to grasp individual behavior relative to the broader infrastructure. Two separate strategies are employed for monitoring loads: ILM and NILM [17].

ILM represents systems where every individual piece of equipment is paired with its own dedicated sensor for power tracking. The term “intrusive” implies that the sensor is positioned directly at or inside the monitored equipment. Because it captures measurements directly from each asset, this method delivers superior precision; however, it incurs steep financial expenses alongside intricate setup and upkeep procedures [5, 7].

On the other hand, NILM is an approach where the cumulative power demand of an electrical circuit feeding multiple standalone devices is captured by a single upstream meter, which is subsequently analyzed to isolate the power needs of each component [18, 19]. By bypassing complex hardware setups and minimizing expenditures, NILM serves as an optimal alternative for power observation when individual sub-meters are missing or cannot be integrated. The purpose of NILM is to break down the aggregate electrical load into device-specific power signatures. Electrical profiles display distinct operational footprints, frequently termed device or load signatures. By evaluating the aggregate load, a mathematical algorithm detects these distinct electrical blueprints to ascertain the energy usage of individual devices at any moment. Ultimately, NILM provides a power monitoring framework whose primary benefit lies in utilizing a single electrical meter per circuit instead of dedicating separate hardware to every unit [5, 18, 19].

A multitude of diverse methods have been deployed within NILM frameworks to identify operational equipment. This standard workflow can be summarized in three primary steps:

1. Data acquisition: Gathering data via appropriate hardware to capture raw power metrics.

2. Feature extraction: Computing diverse characteristics and behaviors from these raw wave signals.

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3. Disaggregation: Isolating and breaking down these features using an automated learning algorithm.

Within scholarly texts, the term *energy disaggregation* is frequently used interchangeably with NILM. During this phase, computational models serve to isolate the distinctive power footprint of each asset [20-22].

Algorithms driving NILM generally fall into two distinct categories: regression structures and event-driven classification setups. Classification setups are designed to spot fluctuations in load behavior and map out the initiation and conclusion of a specific event, which enables, for instance, the identification of a machine's active mode. Conversely, regression models break down the collective electrical signal directly into distinct device elements, tracking an asset's exact power draw at any given interval [21-23].

The academic landscape covers an array of load separation strategies. As classified by Gebbe [10], these approaches can be grouped into four distinct classes:

· Disaggregation driven by switching events

· Disaggregation treated as an optimization problem

· Disaggregation based on correlations

· Disaggregation utilizing neural networks

As asserted by Bernard [20], Jorde [23], and Martins *et al*. [24], utilizing ANNs for power separation stands out as an exceptionally encouraging strategy. Salem *et al*. [21] likewise emphasize the benefits of this approach regarding its capacity to adapt to unfamiliar machinery and its positive impact on lowering overall system complexity.

Within NILM research, three primary categories of ANNs have taken center stage: convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their specialized variants such as long short-term memory (LSTM) configurations and denoising autoencoders (dAEs). Frameworks based on CNNs represent the most dominant ANN methodology found across NILM literature. Spanning numerous variations, they constitute close to 50 percent of all ANN deployments [25]. Furthermore, these distinct methodologies are frequently merged. While alternative network architectures are under exploration, they have occupied a marginal position in NILM literature so far; for instance, generative adversarial networks (GANs) have seen only occasional application for solving NILM tasks [26].

Challenges of NILM in the industrial context

Isolating the energy metrics of standalone machinery demands highly precise power and production datasets [27]. This baseline information is gathered via appropriate logging hardware during the energy measurement phase. To deploy NILM applications successfully, digital monitoring hardware (smart meters) must be used to establish the foundational dataset [28]. Digital power measurement relies on a sampling technique where the monitored variable is logged at consistent intervals. The inverse of the duration separating consecutive logs represents the sampling rate, which is quantified in samples per second (S/s) or expressed as a frequency in Hertz (Hz).

The accuracy of the digital representation of an electrical wave hinges directly on this sampling frequency [28]. For instance, capturing the behavior of specific factory machine sub-assemblies during joining operations like welding demands logs within the millisecond to low-second bracket due to their rapidly fluctuating operational cycles. Pinpointing these quick shifts is only achievable when utilizing elevated sampling rates [29]. Additionally, recognizing concurrent occurrences—such as simultaneous power-on or power-off actions—poses a major hurdle, particularly for event-driven NILM frameworks. It is common for distinct manufacturing components to cycle on or off synchronously, a phenomenon that can only be successfully untangled by logging equipment operating at rapid sampling rates [20, 30].

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Manufacturing machinery is composed of multiple power-drawing sub-systems [20]. Based on research conducted by Gebbe *et al*. [29], the majority of components on a shop floor can be classified as:

- Variable-speed drive motors
- DC power units
- Pumps
- Compressors
- Heating elements
- General motors (excluding those driving fans, pumps, or compressors)

Furthermore, these units can be organized and defined by their working patterns (the equipment signature) using various load categories. Defining and sorting equipment according to their operational modes rests upon four foundational types [19, 31]:

1. Assets featuring just two functional modes (on/off)
2. Units with a restricted, finite set of distinct operational steps
3. Devices exhibiting a continuously shifting energy draw lacking pre-established routines
4. Steady-state hardware whose load remains unaltered across extended intervals [32]

As observed by Gebbe *et al*. [29], manufacturing facilities are dominated by binary on/off power paths and continuously fluctuating profiles as their primary classification templates. The cumulative electricity demand of a full machine equals the combined consumption of its internal parts. These operational workflows show extreme temporal dynamism, shifting based on both the machine's real-time state and the overarching factory schedule, which injects profound complexity into the collective load footprint [33].

In contrast to domestic appliances, factory machinery frequently relies on speed-regulated drive motors, which account for a massive share of the equipment's aggregate active power draw. This specific variant of drive maintains a stable active power profile when mechanical resistance is uniform. Conversely, any fluctuation in the mechanical workload triggers a continuously shifting active power demand devoid of a discernible pattern. Separating the energy share of these components presents a significant hurdle, as they cannot be mapped using rigid, pre-defined operational states [20, 29]. This difficulty in tracking fluid, continuously variable load behaviors deserves special attention; according to data from Gebbe *et al*. [34], variable-speed drive motors represent more than one-third of all electrical demand within industrial facilities.

The density of power-drawing assets in the industrial world typically vastly exceeds that of residential buildings. Furthermore, the volume of electricity required by individual elements varies widely. Managing consumers with such drastically disparate energy appetites hinders effective disaggregation, as the subtle load adjustments of smaller units might fall completely below the sensor's detection threshold [20, 30]. Moreover, electrical demands are shaped by external dynamics including manufacturing timelines, shift rosters, upkeep routines, equipment failures, or variations between workdays and weekends [33]. Although a portion of these variables can be foreseen and accounted for, the primary difficulty resides in successfully isolating and assessing the poorly tracked, intermittent incidents.

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The scarcity of open-source datasets remains a pronounced obstacle in the industrial landscape. While an assortment of open datasets exists for bench-testing NILM configurations, they are overwhelmingly focused on residential homes [12, 23]. At present, there is a severe shortage of public data repositories featuring the high sampling frequencies required to reflect industrial machinery throughout active manufacturing cycles properly [23]. Be that as it may, Martins *et al*. [24] launched an initiative to share an open industrial dataset tailored to a specific application scenario. Another notable open data pool sourced from a production facility is HIPE, which logs the electrical power usage of ten distinct machines spanning a three-month duration [25].

Requirement Definition

Based on Lackes [35], requirements are defined directly after problem analysis. In this step, the precise needs of the proposed solution are established. The core topic has been thoroughly examined within existing literature, revealing specific research gaps. This section outlines the prerequisites for creating an approach that facilitates the NILM of industrial machine power usage. Following a review of pertinent academic papers to gain a broad view of current research, two distinct requirement categories—method (M) and implementation (I)—were extracted, outlined in **Table 1**, and detailed below.

Table 1. Prerequisites for the energy disaggregation of industrial equipment using NILM.

Classification group	ID	Evaluation requirement
Methodology	M1	Validation using sub-metering measurements
Methodology	M2	Availability of high-resolution smart meter data
Methodology	M3	Inclusion of value-generating equipment or processes
Methodology	M4	Capability to distinguish among multiple machines
Implementation	I1	Application of artificial neural networks for energy disaggregation
Implementation	I2	Support for continuous operating loads and overlapping consumption patterns
Implementation	I3	Manufacturing environment involving five machines
Implementation	I4	Presence of recurring cyclical behaviors within the dataset

Guaranteeing the verifiability of results using submeter data (M1) is essential for maintaining dependability. To fully grasp how well the disaggregation technique performs, validating the outcomes with submeter readings from isolated equipment is crucial. This strategy permits a direct comparison between the projected outputs and the genuine sensor recordings, safeguarding the precision of the conclusions. Concerning data collection, it is critical to obtain industrial equipment metrics from a main smart meter operating at a high-frequency sampling rate (M2). A primary smart meter records power usage, establishing the groundwork for disaggregation. This information must be logged at a high-frequency sampling rate (≥ 1 Hz) to identify fluctuations in machine loads properly. Beyond these standard criteria, the energy disaggregation assessment must concentrate on value-adding machines and processes (M3). This stipulation guarantees that the breakdown and evaluation are specifically aligned with the manufacturing tasks that directly enhance the end product's value. Identifying distinct machines (M4) is another critical component of this technique. The system should be capable of distinguishing various pieces of equipment along the assembly line by analyzing their distinct energy usage signatures.

Additionally, employing ANNs for energy disaggregation (I1) must be a central element of the deployed model. Contemporary studies show that only disaggregation techniques using ANNs can successfully recognize all load variations, thereby uncovering intricate data trends and enabling accurate forecasts of each device's power usage [8]. The system must also be capable of identifying continuously variable machines alongside overlapping events (I2). This

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functionality is crucial because industrial manufacturing often includes equipment with constantly fluctuating load profiles. The difficulty of handling concurrent events, particularly within active production lines, requires a resilient disaggregation approach to detect overlapping machine activities. The created solution must successfully separate the electricity usage of a manufacturing line containing a minimum of 5 separate machines (I3). This figure was deduced from a comprehensive review of modern research, indicating it is an appropriate baseline for such tasks. Finally, cyclical data patterns (I4) play a major role. Cyclical trends are fundamental because manufacturing equipment frequently runs in repetitive loops due to mass production demands. Identifying and utilizing these sequences can drastically improve the precision of power usage forecasts for individual machines, making it a critical system requirement.

To link our defined criteria with actual deployment, it is necessary to benchmark them against existing research. Utilizing a structured comparison matrix enables us to gauge how effectively current methods meet our specific needs. This matrix will pinpoint deficiencies and highlight avenues for innovation regarding our energy disaggregation solution. Consequently, a semi-structured literature search was performed across repositories like Google Scholar, Science Direct, Scopus, SpringerLink, Researchgate, and IEEE Xplore, looking for “Non-intrusive Load Monitoring”, “NILM”, “Industrial Energy Consumption”, “NILM in an Industrial Environment”, “ML for Industrial Energy Disaggregation”, “Energy Consumption”, “Industrial Machinery”, and “Energy Disaggregation”. This investigation encompassed both English and German search phrases and reviewed research progress up to and including October 2023. To guarantee the relevance of the papers featured in the comparison matrix, the articles were weighed against particular metrics such as publication date, citation count, and thematic relevance to the study’s core focus. Furthermore, a qualitative review of the research methodologies and conclusions was executed to ensure that only the most pertinent literature was incorporated **(Figure 2).**

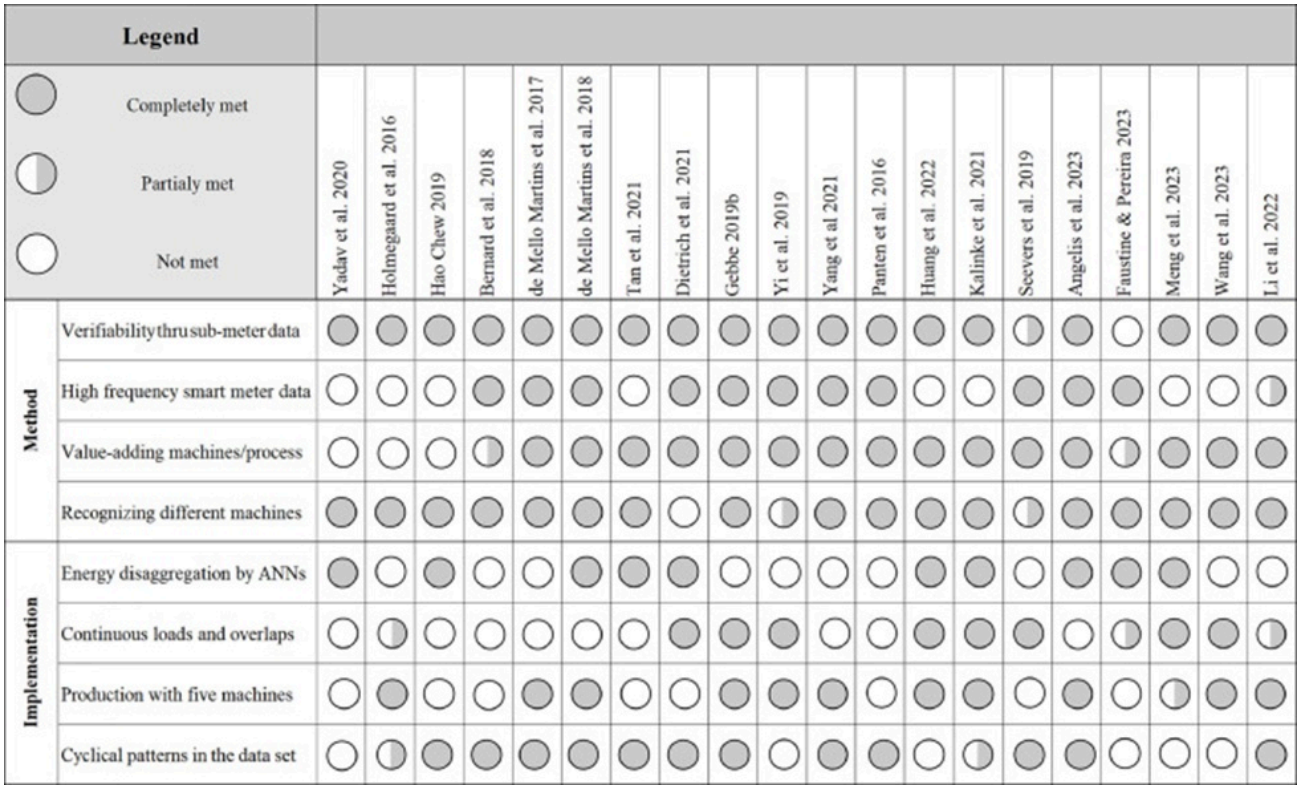


Figure 2. Comparison matrix of applicable academic literature [8, 9, 20, 24, 36-51].

The evaluation matrix categorizes the academic literature into two distinct requirement domains. The initial domain focuses on the method. Most articles investigate supervised learning and the associated verification of disaggregation using sub-meter readings. In most studies, capturing active power serves as the foundational data and proves adequate

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for the disaggregation process. Notably, numerous industrial data research initiatives utilized a high-frequency sampling rate. This is essential given the widespread application and significance of continuously variable equipment in industrial settings. Most research concentrates on value-adding procedures. Conversely, the power usage of integrated manufacturing lines featuring multiple machines is only rarely examined.

The implementation domain represents the second requirement category. The number of machines analyzed varies across studies. Cyclical power usage patterns were identified in the majority of the literature. These patterns can offer insights into the equipment's manufacturing process and are crucial for the effectiveness of the disaggregation. Very few papers tackle the breakdown of a combined total load caused by the simultaneous operation of machines or parts. Within this framework, some papers also explore energy disaggregation using ANNs, even though many studies ignore the application of ANNs entirely.

In summary, the following observation can be made: Up until now, no NILM studies have attempted to use ANNs to decode the power profiles of 5 or more manufacturing machines—including some with continuously fluctuating loads—operating within a connected manufacturing process. Our research addresses this gap by engineering and verifying a novel approach as a practical artifact, thereby bridging the identified research gap.

Method For Energy Disaggregation of Industrial Machinery Using NILM

The technique depicted in **Figure 3** comprises a 3-stage operational model designed to facilitate NILM of industrial machine energy usage. Initially, the production process is evaluated. During this stage, the foundational manufacturing process is scrutinized by gathering pertinent details and metrics. Here, the workflow is inspected to verify that it meets the prerequisites for energy disaggregation. The subsequent phase focuses on data acquisition and preparation. The information is formatted to ensure a suitable database is ready for the upcoming disaggregation phase. The final phase entails deploying an ANN to execute the energy disaggregation. Following this, the power consumption of the machinery can be calculated based on the completed disaggregation.

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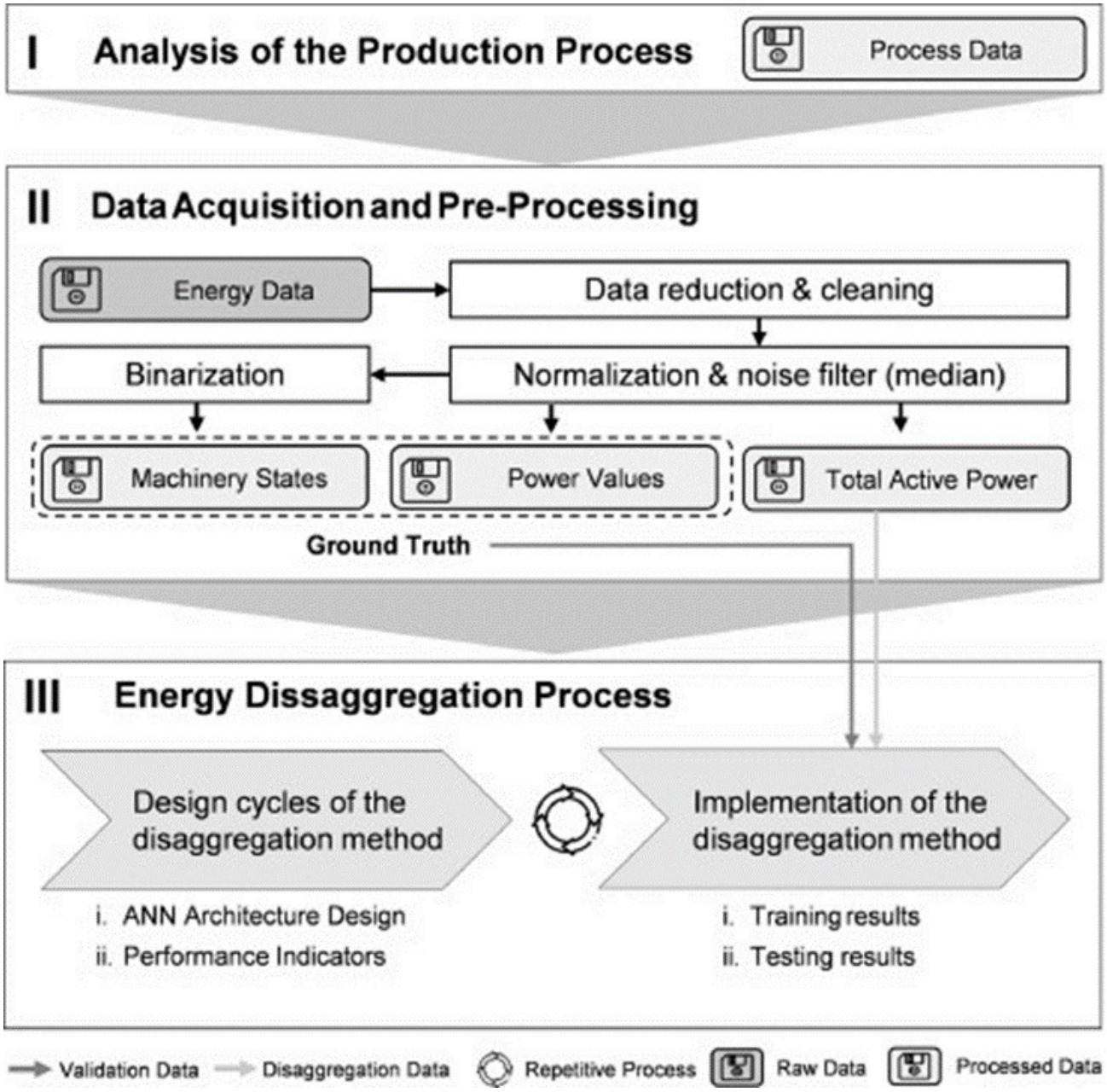


Figure 3. 3-stage framework for the energy disaggregation of industrial equipment using artificial neural networks for non-intrusive load monitoring.

The 3 stages of the framework—analyzing manufacturing processes, gathering and processing data, and performing energy disaggregation—are thoroughly detailed below. Additionally, specialized checklists are provided to aid in the real-world execution of this 3-step procedure.

Analysis of the production process

The initial stage requires a deep evaluation of the specific industrial manufacturing process, acting as the groundwork for the ensuing data collection, processing, and examination. To support this process analysis, a questionnaire-style checklist was created, outlined and clarified below. This checklist aims to guide readers, industry professionals, and leadership in deploying the technique **(Table 2).**

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Table 2. Checklist for the evaluation of the manufacturing process.

Category	Evaluation criterion	Assessment questions	Implications for disaggregation
I. Production process evaluation			
Process factors	**Production configuration**	• Which production model is implemented? • How are production activities scheduled and coordinated?	Standardized and synchronized production workflows support easier disaggregation.
	Machine inventory	• How many machines are involved and what categories do they belong to? • Which machines directly contribute to value creation?	A small number of machines with limited equipment diversity simplifies disaggregation.
	Automation degree	• What proportion of the production process is automated? • Are any operations dependent on manual intervention?	Extensive automation and the absence of manual tasks improve disaggregation performance.
	Product characteristics	• What types of products are being manufactured? • How many product variants are produced?	Discrete production environments with low product diversity are more suitable for disaggregation.
Energy factors	**Available energy sources**	• What energy source(s) supply the production process? • Are backup or supplementary energy sources available?	Utilizing a single energy source reduces complexity in data processing and disaggregation.
	Energy consumption behavior	• Do machines exhibit similar or different energy consumption profiles? • Are consumption patterns cyclic or anti-cyclic?	Comparable machine loads and cyclic energy usage patterns facilitate effective disaggregation.
	Metering architecture	• Is the energy monitoring infrastructure digitally enabled? • Can the metering system be expanded with additional devices?	A scalable and fully digital metering framework provides the most favorable conditions for disaggregation.
	Meter availability and granularity	• What level of measurement detail is available from existing meters? • Are sub-meters installed for individual measurements?	The presence of both higher-level and subordinate meters supports supervised and unsupervised disaggregation approaches.

When assessing the type of production, grasping its fundamental nature is vital. Questions center on the exact manufacturing style and how the workflow is scheduled and structured. In this regard, synchronized and repetitive workflows, like assembly lines or workshop manufacturing, are best suited for applying this method. Regarding machinery, an equipment inventory is crucial for comprehending the current production setting and for establishing the requirements for the tracking strategy and needed data feeds. Based on our methodological prerequisites, the objective is to pinpoint the value-adding equipment within this list. Consequently, production settings characterized by a low quantity and narrow variety of value-adding machines make the disaggregation process much easier. When deploying this

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technique, the degree of automation is a major factor. Highly automated settings with few manual tasks are well suited for this approach. Product variety is investigated by questioning product details. By recognizing the items being made and evaluating the range of product categories, the goal is to estimate the intricacy of the production environment. The discrete production of individual goods and settings with minimal product fluctuation streamlines the energy disaggregation workflow.

Shifting focus to the energy sector, an analysis of the existing energy sources is paramount. Settings defined by a limited variety of energy sources offer simplicity and align with the core principles of this method. Historically, NILM has been utilized to disaggregate electrical data. Nevertheless, as demonstrated in Chapter 6, the NILM concept can be adapted for alternative energy resources, like compressed air. Analyzing consumption patterns requires pinpointing areas of high energy use and determining if the power draw exhibits cyclical or anti-cyclical rhythms. The most favorable conditions involve clear cyclical patterns. The measurement concept acts as the foundation of this methodology. Investigations center on the availability of main energy meters and supplementary sub-meters. Facilities equipped with a thorough and digital tracking infrastructure are highly compatible with this method. Lastly, meter availability is crucial. This evaluation includes reviewing the level of detail of the existing energy meters—which serve as the baseline for industrial energy disaggregation—and ensuring that corresponding sub-meters are present to validate the accuracy of the disaggregation.

Data acquisition and preprocessing

The second stage consists of acquiring and preprocessing data, which are essential steps that heavily impact the model's effectiveness in various industrial settings. As shown in **Figure 3**, the data preprocessing workflow is modeled after the work of Jafari [52] and García *et al*. [53], tailored to fit the unique requirements of our study. This phase involves selecting, cleansing, and building the final dataset, as well as combining information from various sources and formatting the data.

A primary activity is data integration, where information from disparate sources is merged to enrich the dataset. This is achievable by linking data via unique identifiers or by appending new records that share an identical structure. Data reduction is another critical component, designed to shrink the dataset's volume by eliminating extraneous features, isolating the most pertinent ones, or decreasing the volume of numerical entries using methods such as aggregation or discretization. Furthermore, data cleaning is vital to ensure data precision; it involves eliminating anomalies, addressing missing information, fixing inaccuracies, removing duplicates, and standardizing formats. This procedure frequently incorporates a median noise filter to smooth the time series information by minimizing the impact of outlier points.

Furthermore, data transformation methods are utilized to change data formats, adjust attribute scales, normalize numbers, or switch units. Normalization plays a highly critical role when preparing time series data for evaluation, requiring the realignment of measurements from varying scales onto a unified standard scale. Binarization serves as an additional preprocessing measure, converting numerical figures into binary counterparts. This is especially beneficial regarding machine statuses, where the operational condition of the equipment (for instance, 0 indicating off/idle, and 1 indicating on/active) is logged. Transforming these statuses into a binary structure streamlines the input for machine learning algorithms, as the ANN deployed in the third stage of our approach acts as the ground truth for these models.

Finally, data enrichment focuses on generating novel, valuable features derived from domain expertise. Here, 'Power Values' represent the real power consumption readings from the equipment, which are fundamental for comprehending energy consumption trends. We utilize these figures to compute features like 'Total Active Power', representing the cumulative power usage over a specific timeframe and functioning as an additional ground truth for energy disaggregation operations [52, 53].

Energy disaggregation process

During the creation of an energy disaggregation structure, several variables must be evaluated as they heavily dictate the resulting framework. The chosen parameters are outlined below. To guarantee understanding and clarity, comprehensive explanations of the terminology are supplied in the text after the table. The choice of criteria stems from the research

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conducted by Kaselimi *et al*. [54] and Huber *et al*. [55]. This supplementary checklist aims to aid phase III, which encompasses the methodology's energy disaggregation workflow. Moreover, it is crucial to stress that the application of an ANN is a core premise of the energy disaggregation workflow in this paper, corresponding directly with our primary research question **(Table 3).**

Table 3. Checklist for energy disaggregation (derived from [54]; * outside the scope of this paper).

Section	Criterion	Key question	Representation/Recommended choice
III. Energy disaggregation framework			
Disaggregation methodology	Problem formulation	Is the goal to determine machine operating states or to estimate the power demand of equipment?	Machine state identification: classification; power consumption estimation: regression
	Modeling strategy	Should the focus be on achieving maximum accuracy or maintaining efficiency across varying machine conditions?	Accuracy-oriented: single-target approach; efficiency-oriented: multi-target approach
	Learning paradigm	Does the application rely on annotated datasets, or must it operate without labeled examples on unfamiliar scenarios?	With labeled data: supervised learning; without labeled data: unsupervised* learning
	Neural network design	Is it more important to evaluate energy behavior over extended time horizons or to capture short-term fluctuations?	Long-term analysis: recurrent-based architectures; immediate change detection: convolutional architectures
	Temporal sequence modeling	Should the analysis emphasize prolonged consumption patterns or identify specific energy-use events?	Long-term trends: sequence-to-sequence (Seq2Seq); event detection: sequence-to-point (Seq2Point)
	Input data structure	Does the model use only basic power measurements or multiple energy-related variables?	Single power variable: uni-dimensional input; multiple parameters: N-dimensional input

Concerning the energy disaggregation procedure, the initial phase involves defining the problem. Within NILM studies, classification and regression are utilized for event recognition and performance evaluation. Regression focuses on calculating the power usage of individual devices, whereas classification assesses a device's operational status. This classification enables binary state recognition (on/off) and serves as the foundation for verifying equipment conditions. Conversely, regression offers a straightforward approximation of energy usage. It is also viable to merge both models, permitting a more thorough analysis of appliance status and consumption, which yields precise outcomes and boosts disaggregation efficacy.

Within the NILM modeling framework, the term "multi-target" describes a model designed to detect and disaggregate the power usage of several appliances concurrently. The goal is to ascertain the distinct contributions of numerous devices to the total energy load. This multi-target method provides benefits such as lower computational demands, shorter training durations, and fewer model setups. Alternatively, a "single-target" model detects and disaggregates just 1 appliance per

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iteration. While this technique demands substantial computational power and massive volumes of training data for every single device, it delivers heightened precision. As outlined, each method carries unique pros and cons, and both are utilized and investigated within NILM studies, even though single-target models currently receive more attention.

In the field of NILM, model architectures fall into unsupervised and supervised categories. Supervised NILM frameworks require a training phase and perform exceptionally well on the specific equipment they were trained on. Yet, their effectiveness might falter when introduced to unfamiliar machines or different contextual situations. Conversely, unsupervised NILM frameworks operate without labeled data and can adjust to diverse datasets. While their effectiveness might not match the optimal levels of supervised techniques, they present the distinct benefit of transfer learning when applied to novel machinery.

Recent improvements in the accessibility of load data have spurred the use of ANNs for load disaggregation. Concerning ANN configurations, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are 2 prevalent architectures within this field. RNNs can handle temporal data thanks to their recurrent connections. Nevertheless, they face difficulties in acquiring long-range dependencies. LSTM models overcome this hurdle by employing gate-controlled memory cells. While highly effective, LSTM frameworks tend to elevate the model's overall complexity. On the other hand, 1D CNNs excel at handling time series data and stand as the most frequently implemented models in NILM studies. When contrasted with RNNs, they generally demand lower computational resources [54].

Sequence-to-point (seq2point) and sequence-to-sequence (seq2seq) represent 2 popular sequence modeling approaches deployed for load disaggregation operations. Each relies on neural networks to determine the energy usage of singular appliances derived from an aggregated power data sequence. Within the seq2seq method, a sliding window sweeps over the combined power signal to produce disaggregated, device-specific power readings for a sequence matching the input's dimensions. Conversely, the seq2point method solely forecasts the central element within the sequence window. The window size is critical and can be customized based on the specific appliance category and its operational runtime. Seq2seq models face convergence challenges when dealing with lengthy input and output sequences, whereas the seq2point strategy eases the forecasting challenge but demands greater computational power during inference.

In terms of input dimensionality, energy disaggregation typically uses unidimensional time series information. Consequently, the algorithm trains on a one-dimensional input feed (such as overall active power tracked over time) to rebuild the distinct time series for a specific machine. Another method involves shifting the NILM challenge out of a one-dimensional realm and into a multi-dimensional arena featuring numerous input signals [54].

After detailing the 3-stage framework for the non-intrusive load monitoring of industrial machinery energy usage, validating the approach is necessary. Chapter 6 explores the validation procedure using a case study, ensuring that the previously detailed method is tested and its overall efficacy is evaluated.

Validation

Case study: compressed air demonstrator

The adaptable compressed air demonstrator utilized in this case study features 16 separately adjustable compressed air actuators. Powered by compressed air, these actuators execute vertical lifting and lowering motions, simulating the physical movements of machinery components during a production workflow. Modifying actuator resistance allows for control of the load response, resulting in distinct load signatures for each actuator. This capability facilitates the creation of varied load profiles. These individualized profiles replicate the true energy signatures found in real-world machinery. Information is captured using a digital tracking system linked to compressed air flow sensors, logging the metrics at a 10 Hz sampling rate. The demonstrator's combined data is collected via a sensor located at the primary machine connection

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junction. Furthermore, an additional flow sensor is attached upstream from every actuator to record data for that specific component independently.

Further technical details regarding the setup are outlined below. The compressed air demonstrator incorporates 16 Ethernet-based flow sensors. The vertical lifting and lowering actions are executed by 4/6/8 mm double-acting actuators alongside 6 mm single-acting actuators. The primary server responsible for logging and archiving this information is equipped with a Core Intel Xeon E-2288G Processor, a 16-gigabyte Nvidia Quadro RTX5000 graphics card, 28 gigabytes of RAM, and an 8-terabyte hard drive.

A tool known as a pattern generator is utilized to configure the activation intervals for specific actuators. These actuators receive individual commands and perform predetermined maneuvers. For this case study, 2 distinct load profiles were generated utilizing an identical set of 5 actuators. The combined energy draw of these 5 actuators constitutes the demonstrator's aggregate energy usage. As illustrated in **Figure 4**, these 5 actuators are designated as A1–A5. The pattern generator was configured to run a 30 s test cycle, followed by a 15 s pause before the initiation of the subsequent cycle. Consequently, the total timeframe for the simulated manufacturing workflow is 45 s. A single test cycle is partitioned into 10 distinct time blocks, each lasting 3 seconds. The designated actuator begins its motion at the start of each time block, dictating the test itinerary. The specific chronological order of these actuator maneuvers is visualized in the subsequent Gantt charts.

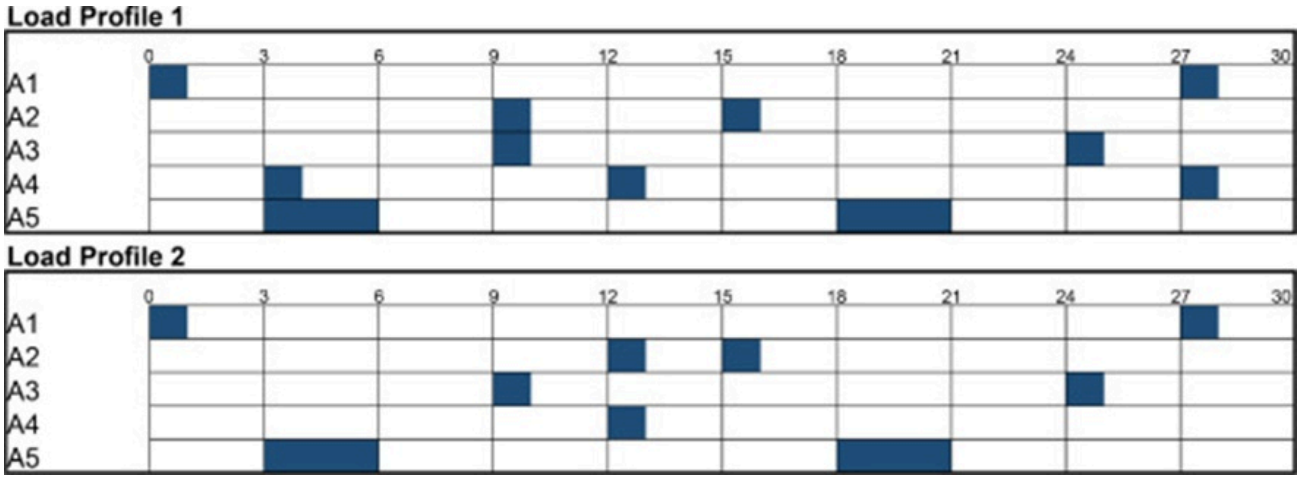


Figure 4. 2 distinct load profiles were generated utilizing a compressed air demonstrator to serve as the foundational database for this case study.

The testing phase was divided into 4 distinct segments. Initially, the single actuators associated with the first load profile were tested. To achieve this, each actuator was run independently for 5 minutes. This step aims to streamline the disaggregation process within the NILM framework, given that the isolated actions are pre-integrated into the training phase individually. Following this, the complete sequence involving all 5 active actuators was executed continuously for 2 hours. This exact protocol was then repeated for the second load profile. The updated actuator configuration was similarly tested individually in 5-minute bursts. After that, the full sequence ran again for 2 hours. This methodology allowed for the recording of several hundred test iterations. Within the resulting dataset, this rigid sequencing was disassembled, and the 2 separate load profiles were intertwined.

Data acquisition and processing

In the present case study, the compressed air demonstrator's information is captured using 16 integrated flow sensors. These devices log various metrics related to compressed air, which are subsequently stored as time series data. The collected raw data is formatted as a .csv file. This raw dataset contains 460 distinct features gathered at a rapid 10 Hz

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sampling rate. These features encompass a broad spectrum of system sensor parameters. Critical metrics include mass flow rate, flow velocity, pressure, volume, temperature, and volumetric flow rate, all tracked across several sensor groups. The information was gathered during a 5-hour experiment. Throughout this timeframe, only 5 of the 16 independently manageable actuators were engaged. During the preprocessing phase, we confirmed the absence of corrupted or missing data points, guaranteeing a consistent and complete dataset. Additionally, the dataset was purged of undesirable time windows within the time series so that they were excluded from the training data.

Initially, feature reduction involved removing data from non-operating actuators. Non-numeric or purely descriptive columns were also dropped to concentrate on essential measurements. This left the features for only the 5 active actuators: Actuator_1-1, Actuator_1-3, Actuator_3-1, Actuator_3-3, and Actuator_4-1. We used a correlation matrix to identify and eliminate highly correlated features, further refining the dataset. This correlation matrix enables the quantification of linear relationships between feature pairs. We applied the Pearson correlation coefficient to build this matrix for our analysis. Features exhibiting a correlation coefficient above 0.9 or below -0.9 were deemed highly correlated and targeted for exclusion to prevent multicollinearity. This threshold aligns with standard feature selection practices to ensure that each remaining feature provides the model with unique insights. After eliminating highly correlated variables, we kept pressure, temperature, and mass flow rate (MFR).

For this research, the MFR acts as the input feature for the ANN. After dropping the pressure and temperature features, the resulting dataset contains 7 features: the MFRs of the aforementioned actuators and the overall MFR, along with their corresponding timestamps. Choosing to keep the MFR relies on previous data preprocessing stages and specific domain knowledge. In pneumatic setups, the MFR directly relates to the compressed air's energy content, making it comparable to electrical power in standard NILM use cases. This metric reveals the mass moving through a specific zone over a given timeframe.

To smooth the information and mitigate outliers, a median noise filter was applied. This technique replaces perceived noise or outlier values with the median of a specific data sequence. Because the metrics were gathered in a single day, our dataset lacks seasonal patterns or long-term trends. For subsequent data processing, we extracted additional parameters for every individual actuator. These included the maximum MFR, mean MFR, standard deviation of the MFR, and the on/off threshold limits, which were then stored in a dictionary. The data normalization follows the method of Huber *et al*. [55], where the mean MFR is subtracted from the MFR, and the result is divided by the MFR's standard deviation. We also pinpointed the specific on/off statuses of the actuators by binarizing the data based on the defined threshold limits. During binarization, any value exceeding the threshold becomes a 1, while values below the threshold become a 0. The actuators' operating statuses and independent performance metrics serve as ground-truth data. These procedures convert the data into binary states and normalized targets, which are saved as NumPy arrays, properly formatting them as input for the ANN's subsequent disaggregation analysis.

The subsequent illustration displays a brief segment of the normalized and aggregated MFR, featuring the actuators responsible for creating the 2 load profiles. The ground truth status data (Off: 0/On: 1) for the distinct actuators illustrates which component is causing which fluctuation and highlights instances of actuator overlap. The variation between the 2 graphics stems from the differing timing of the actuator maneuvers **(Figure 5).**

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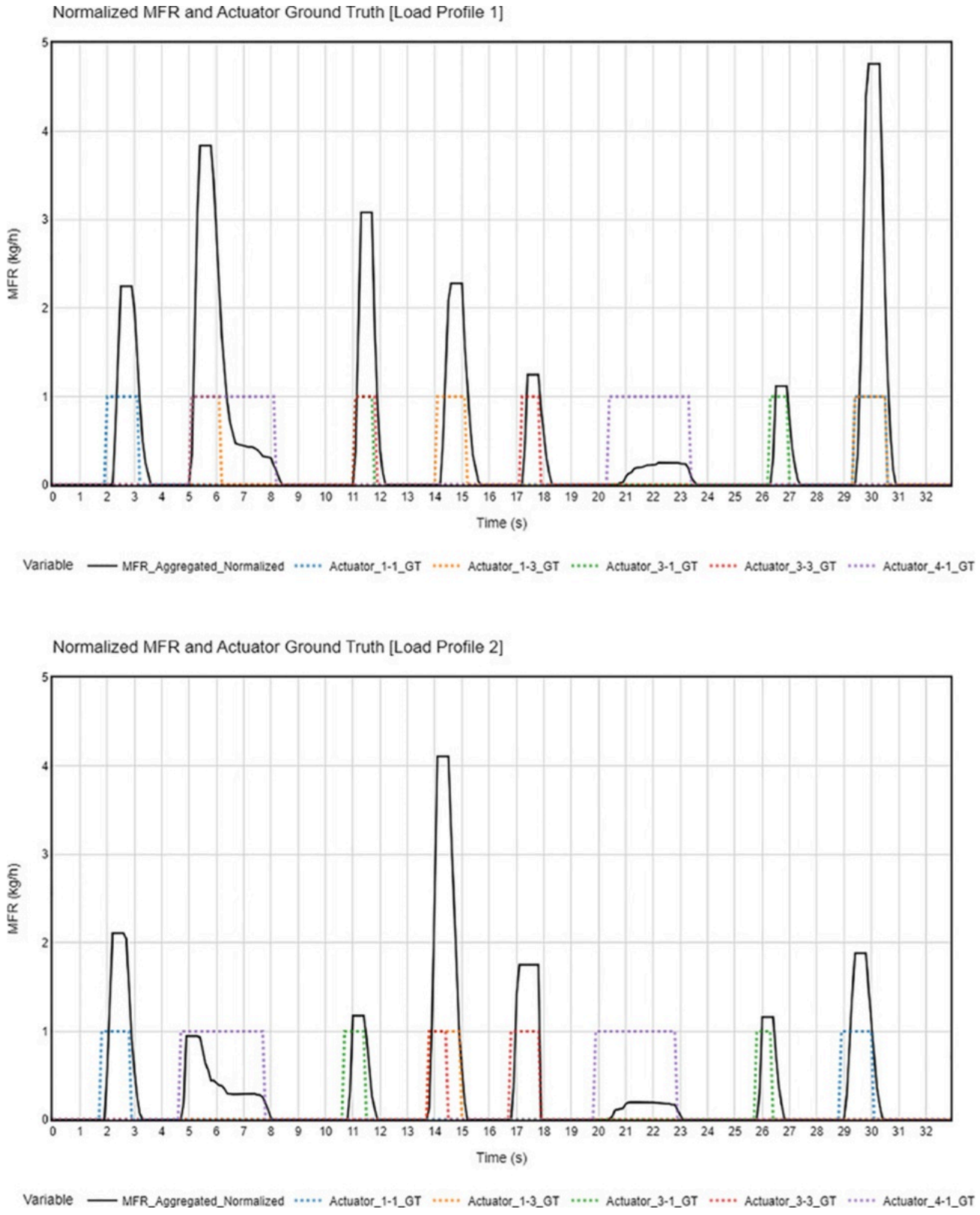


Figure 5. Aggregated and normalized mass flow rate alongside actuator ground truth (Off: 0|On: 1) for load profile 1 (top) and load profile 2 (bottom).

Implementation of the energy disaggregation

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Multiple factors require consideration when building an energy disaggregation framework, as they profoundly impact the final implementation. The table below outlines the criteria integrated into our disaggregation model. Adhering to the modeling methodology of Faustine *et al*. [56], we tailored the suggested UNet-NILM model to suit our needs. The UNet-NILM structure is a one-dimensional CNN engineered for multi-task learning, explicitly targeting power estimation and appliance state detection in NILM frameworks. It uses a series of downsampling blocks to reduce the input power signal's dimensionality and capture high-level features, followed by upsampling blocks that rebuild the signal to preserve temporal resolution. For state detection, the architecture uses multi-label learning, applying softmax activation to manage multiple states per device, alongside multi-target quantile regression to calculate energy usage while accounting for uncertainty **(Table 4).**

Table 4. Disaggregation approach of this case study.

Category	Aspect	Revised description
Disaggregation methodology	Problem formulation	Estimation of appliance energy consumption through regression and identification of appliance operating conditions through classification.
	Modeling strategy	Adoption of a multi-output (multi-target) framework to reduce training complexity and minimize the number of required model setups.
	Network framework	Supervised machine learning model trained using labeled data obtained from the demonstrator.
	ANN design	Implementation of a 1D Convolutional Neural Network (1D-CNN) to effectively capture short-term variations in energy consumption.
	Sequential learning	Monitoring energy-use patterns through a Sequence-to-Sequence (Seq2Seq) modeling approach.
	Input dimension	Single-dimensional input configuration based exclusively on one signal, namely the Mass Flow Rate (MFR).

Typically, an ANN's weights are fine-tuned through the optimization of a loss function. For this study, quantile regression serves as the loss function to optimize the ANN's weights. To properly assess the UNet-NILM model's capabilities, we applied 2 standard classification and regression metrics: the F1 score and the mean absolute error (MAE). MAE evaluates predictive precision by calculating the average absolute deviation between actual and predicted values, which is fundamental for assessing regression performance. The F1 score, which balances recall and precision, is well suited for classification tasks—particularly when handling imbalanced data—to ensure accurate appliance state recognition. Together, these metrics offer a well-rounded evaluation of the model's classification and regression capabilities. We used a train-test split, designating 25% of the information from both load profiles for evaluation. This standard machine learning procedure ensures the model is tested against unfamiliar data, yielding an objective assessment of its generalization capacity and helping prevent overfitting. The next table outlines the ANN's composition and provides overarching details regarding the model's architecture **(Table 5).**

Table 5. Adapted supervised machine learning report card by Kühl *et al*. [57] documenting algorithm-specific information for replicability.

Category	Aspect	Revised description
Information	Problem Statement	Detection of appliance power signals and operating states for five independently controllable compressed-air actuators.
	Sampling Strategy	No data sampling technique was applied.

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	Data Quality	High-quality dataset achieved through comprehensive preprocessing procedures.
	Data Preprocessing Techniques	Refer to Section "**Data acquisition and processing**" for the applied preprocessing methods.
Training	Activation Function	Utilization of the Softmax activation function.
	Optimization Algorithm	Model parameters optimized using the Adam optimizer.
	Learning Rate Scheduler	Employment of the ReduceLROnPlateau learning-rate scheduling strategy.
	Dataset Partitioning	Data divided using a 75–25 training-to-testing ratio.
	Training Objective	Training loss computed as the combination of Negative Log-Likelihood (NLL) Loss and Mean Squared Error (MSE) Loss.
Artificial neural network (ANN)	Loss Function	Adoption of the Quantile Loss function.
	Training Evaluation Metrics	MAE is used to assess regression performance, while F1-Score is used to evaluate classification performance.
	Network Architecture	Adapted version of the UNet NILM architecture.
	Software Packages	• PyTorch (torch.nn) utilized for neural network implementation.• PyTorch-Lightning employed for model training and evaluation.• PyTorch (torch.optim) used for optimization procedures.
	Additional Details	• Parametric ReLU (PReLU) applied as the activation mechanism.• Xavier Uniform initialization adopted for network weights.• Linear MLP layers employed to generate both regression and classification outputs.

Initially, we present how well the algorithms predict the actuators' MFR. Comparing the actual MFR against the predicted MFR highlights the regression model's disaggregation capabilities. **Figure 6** illustrates the forecast utilizing a segment from both load profiles. The actual aggregated MFR serves as a baseline, depicted by a dashed line. The colored lines represent the individual actuators' predicted MFRs. It is evident that overlapping concurrent actuator actions closely approximate the actual aggregated MFR.

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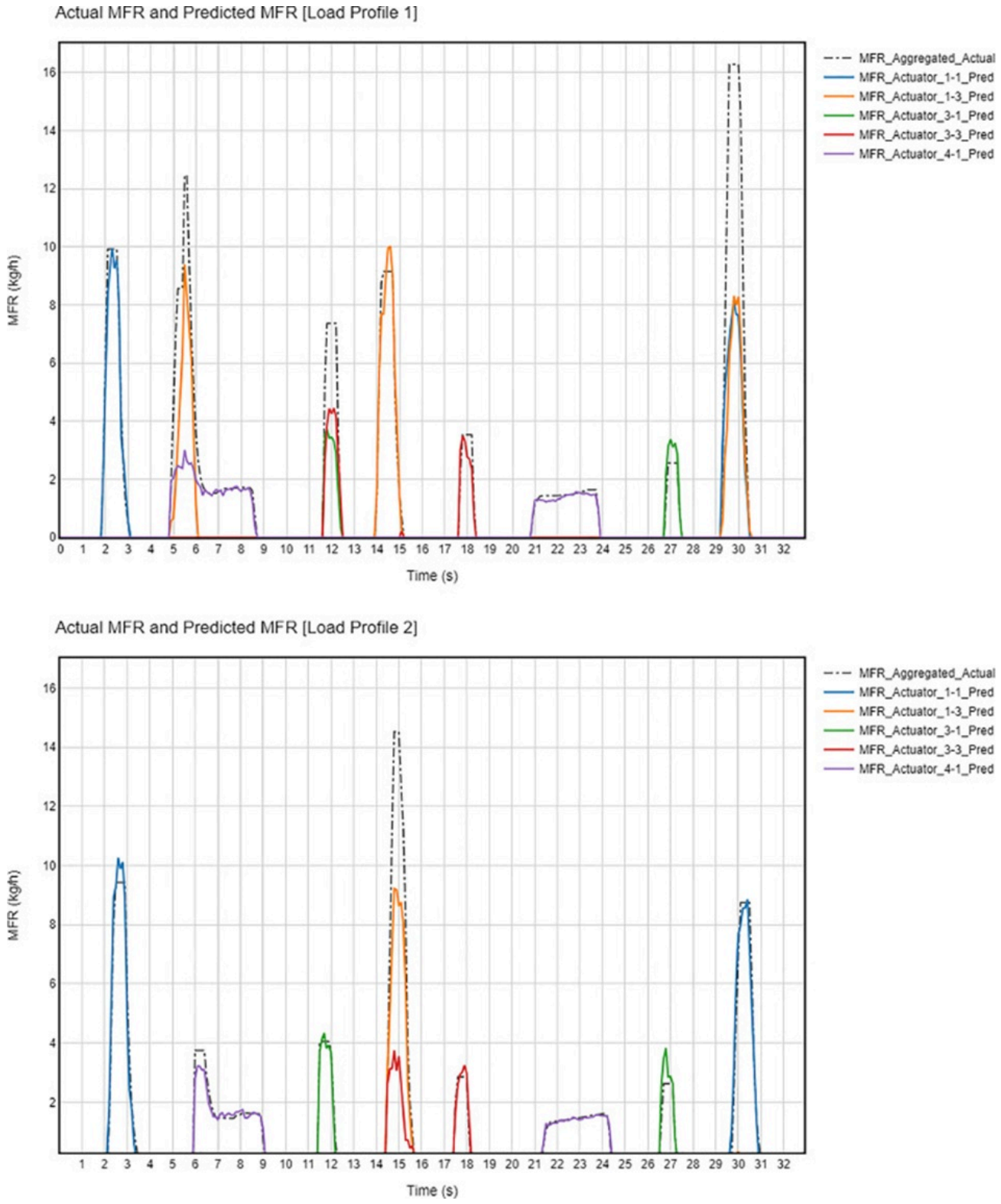
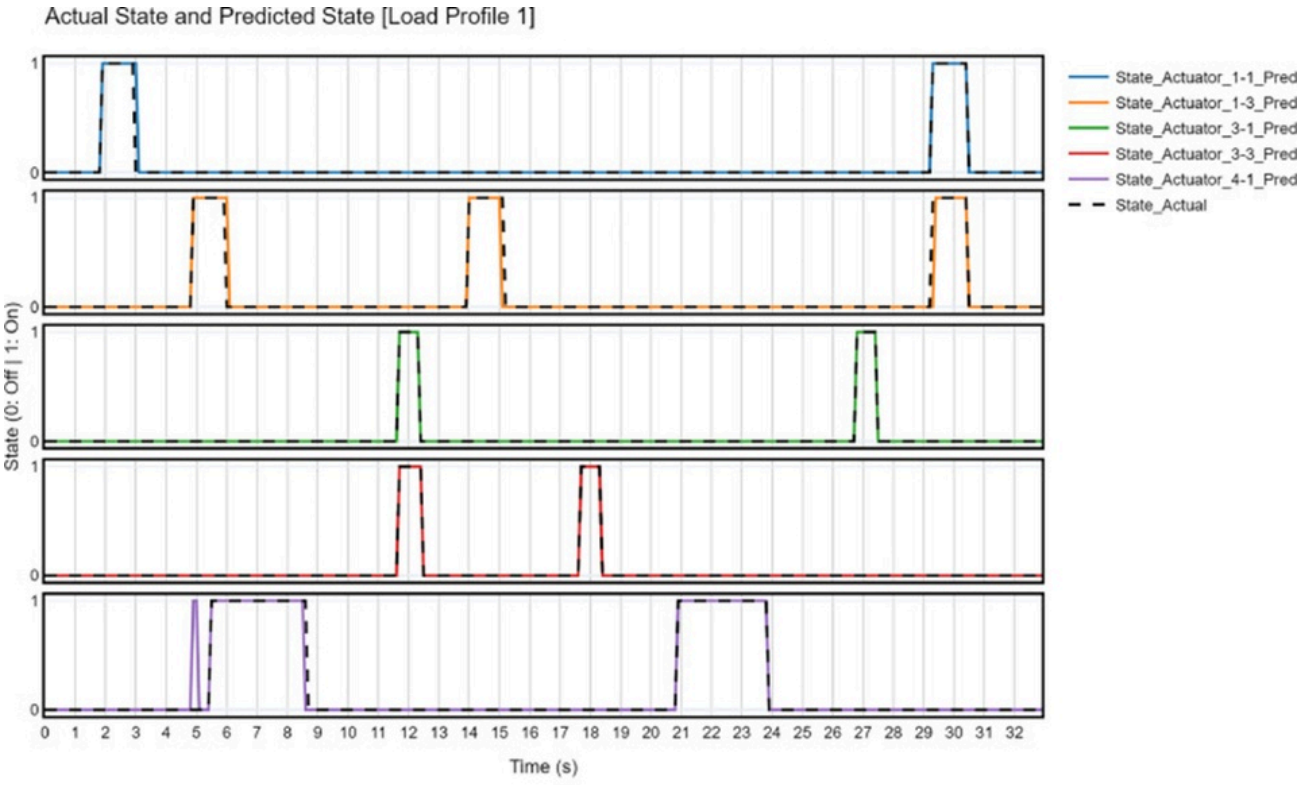


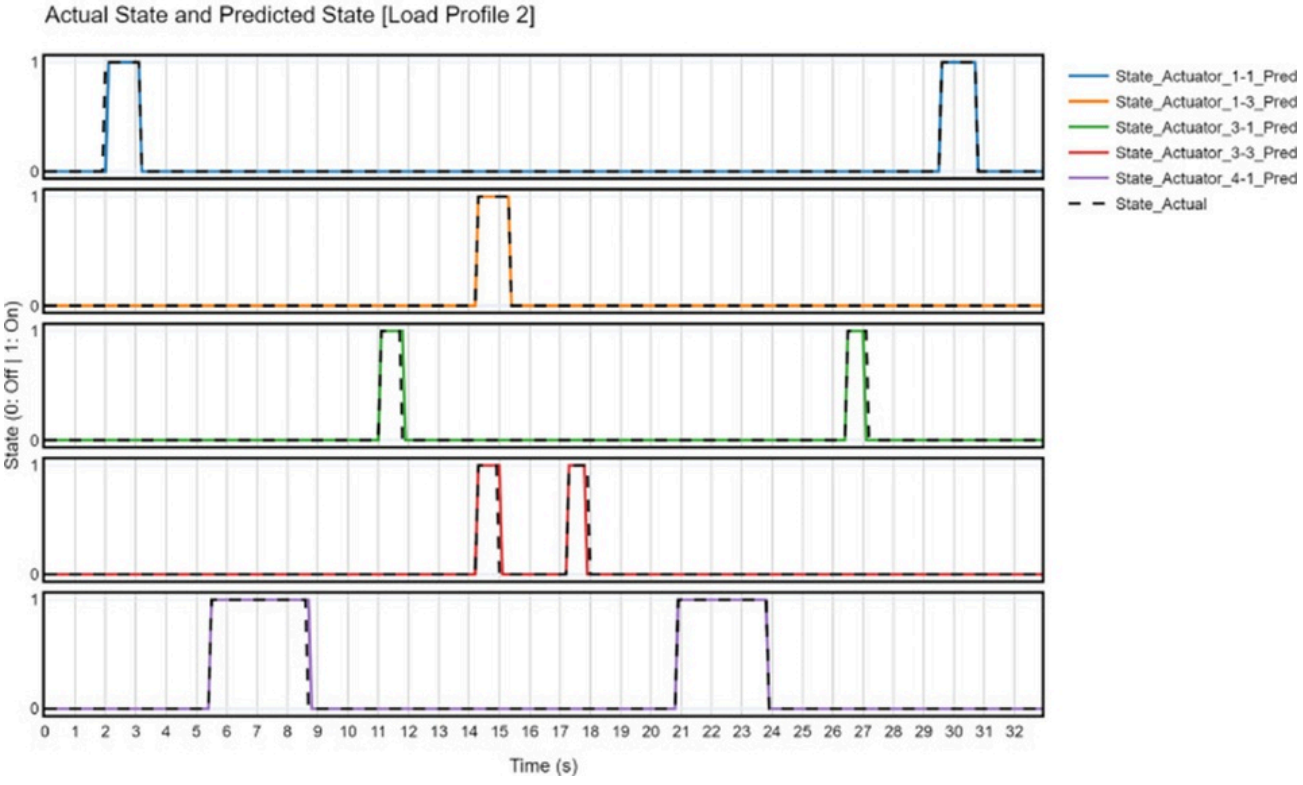
Figure 6. Aggregated actual MFR and predicted MFR of the individual actuators.

To assess the algorithms' ability to forecast actuator states, comparing predicted states against actual states evaluates the classification model's disaggregation effectiveness. **Figure 7** presents the forecasted state of individual actuators via colored lines, with the true state shown as a dashed line. To maintain comparability, the same segments of the 2 load

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profiles from **Figure 6** are used here. The model was trained to represent the ON state as a 1 and the OFF state as a 0. The predicted state classifications heavily align with the true states, indicating a highly successful disaggregation. Still, within the displayed segment of load profile 1, a discrepancy is visible in the results for actuator 4-1, where the model predicted an action that did not actually occur.





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Figure 7. Actual state and predicted state of the individual actuators (0: Off | 1: On).

The model's MFR and actuator state forecasts are verified using ground truth state and MFR data. **Table 6** outlines the resulting F1-Scores and MAE stemming from the energy disaggregation workflow.

Table 6. Results of the energy disaggregation process.

Component	Mean absolute error (MAE)	F1-score
Actuator_1-1	0.136	0.930
Actuator_1-3	0.155	0.959
Actuator_3-1	0.051	0.962
Actuator_3-3	0.082	0.945
Actuator_4-1	0.047	0.983
Overall Average	0.094	0.956

The energy disaggregation outcomes exhibit remarkable predictive precision, as shown by an average MAE of 0.094, indicating negligible variance between the real and forecasted values. When looking at the MAE, actuators 1-1 and 1-3 perform marginally worse than the rest. This likely occurs because these 2 actuators share a highly comparable load profile. Their peak loads hit nearly identical marks, presenting a significant hurdle for the algorithm. Furthermore, the impressive average F1 score of 0.956 underscores the model's capacity to precisely identify machine states, successfully balancing recall and precision across every actuator. It is also important to note that device on/off statuses follow a consistent cyclical pattern for each product. This uniform rhythm aids in event recognition, ultimately facilitating exceptional disaggregation performance.

Conclusion

Motivated by rising energy expenses and the imperative to lower CO2 emissions, manufacturing enterprises are prioritizing operational energy and CO2 reductions. Creating energy transparency is crucial to realizing this goal, a process that can be drastically improved by leveraging NILM techniques. While NILM has been heavily explored in domestic settings, its viability in industrial spheres demands further study, especially given its massive potential to boost energy transparency.

By employing DSR, this study created an innovative artifact: an industrial manufacturing technique meant to disaggregate machine power usage using NILM. The research evaluated the current landscape of industrial NILM applications via a semi-structured literature review, covering the theoretical underpinnings of NILM for energy tracking. The findings highlighted that standard NILM methods, though successful in residential environments, struggle with the complex load traits of industrial equipment, thus requiring a specialized approach. This document presented an ANN-driven NILM strategy to break down industrial energy usage. The framework features a 3-stage operational model aimed at enabling the NILM of industrial machine power consumption. The technique was verified using a compressed air demonstrator equipped with 16 independently adjustable compressed air actuators. This demonstrator allowed for the capture of 2 distinct datasets containing separate machine load signatures. Following rigorous data preprocessing, the UNet-NILM architecture was deployed to forecast actuator state and signal. The energy disaggregation findings show excellent predictive precision, validated by an average MAE of 0.094. Additionally, the algorithm demonstrates strong capabilities in pinpointing appliance statuses, reflected by a high average F1 score of 0.956. Ultimately, we determine that the presented approach is highly viable for the energy disaggregation of industrial equipment utilizing ANNs for NILM.

Discussion and outlook

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The effective implementation and verification of this framework represent a crucial step forward in applying NILM for industrial energy disaggregation. It proves the methodology's ability to accurately forecast machinery's operational states and energy usage, thereby adding considerable value to the fundamental knowledge base regarding industrial energy transparency. This study offers businesses a non-intrusive and economical alternative to conventional ILM approaches and supports broader research and deployment of NILM across the industrial landscape.

Even with the technique's success, certain limitations must be acknowledged. Real machinery was not utilized; instead, this study relied on data produced by a compressed air demonstrator, resulting in optimal testing conditions. Ultimately, to confirm its true capabilities, the model and method must undergo testing using data extracted from diverse production machines operating in an authentic manufacturing environment. Handling continuously variable loads presented another simplified aspect. While the dataset included a continuous load curve, it adhered strictly to a uniform pattern. The algorithm's response to appliances with continuously fluctuating, pattern-less loads remains unexamined.

Unsurprisingly, our research opens doors for future investigations. Stricter rules from OEMs and legislators fuel the growing demand for product-level energy transparency. Existing techniques for evaluating product-specific power usage are either overly vague or demand intensive measurement setups (ILM). There is an obvious demand for a system capable of automatically and non-intrusively separating machine energy usage, linking it to distinct products, and archiving this data within corporate IT infrastructures.

Additionally, future studies should explore the use of unsupervised learning models in this domain. These models could significantly optimize the workflow by learning from unlabeled inputs, thereby eliminating the tedious—and sometimes technically infeasible—task of logging ground-truth data. Engineering such models would greatly improve the practicality of deploying NILM systems for live energy disaggregation, providing a viable avenue for tracking and optimizing power use in industrial spaces.

Furthermore, generating accessible industrial datasets is vital for pushing NILM research toward commercial use in the industrial sector. Data scarcity represents a major roadblock for industrial NILM research. Robust industrial datasets would enable the benchmarking of algorithm performance, ultimately spurring the creation of superior NILM techniques. Establishing an industrial NILM benchmarking hub—similar to NILMTK created by Batra *et al*. [58] for the residential sector—and supplying open-source datasets alongside promising disaggregation algorithms would also be highly advantageous.

To conclude, the trajectory of NILM in industrial environments looks exceptionally bright. It offers profound avenues for research and innovation that could yield massive breakthroughs in sustainability, energy efficiency, and operational transparency.

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Conflict of interest

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Ethics statement

None

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