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Deriving Digital Energy Platform Archetypes for Manufacturing – A Data-Driven Clustering Approach

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Abstract

External factors such as climate change and the current energy crisis due to global conflicts are leading to the increasing relevance of energy consumption and energy procurement in the manufacturing industry. In addition to the growing call for sustainability, companies are increasingly struggling with rising energy costs and the power grid's reliability, which endangers the competitiveness of companies and regions affected by high energy prices. Appropriate measures for energy-efficient and, not least, energy-flexible production are necessary. In addition to innovations and optimizations of plants and processes, digital energy platforms for the visualization, analysis, optimization, and control of energy flows are becoming essential. Over time, several digital energy platforms emerged on the market. The number and the different functionalities of the platforms make it challenging for classic manufacturing companies to keep track of and select the right digital energy platform. The characteristics and functionalities of digital energy platforms have already been identified and structured in literature. However, classifying existing platforms into archetypes makes it easier for companies to select the platforms providing the missing functionality. To tackle this issue, we conducted an explorative and data-driven cluster analysis based on 47 existing digital energy platforms to identify digital energy platform archetypes and derive implications for research and practice. The results show four different archetypes that primarily differ in terms of energy market integration functionalities: Research-Driven Energy Platforms, Energy Flexibility Platforms, SaaS-Aggregators / Virtual Power Plants, and (Manufacturing) IoT-Platforms. Decision makers in manufacturing companies will benefit from the archetypes in future analyses as decision support in procurement processes and modifications of digital energy platforms.

Keywords

Digital Energy Platform; Demand Side Management; Energy Flexibility; Clustering

1. Introduction

The negative consequences of climate change, global crises, and local energy shortages require targeted and effective measures to achieve the climate targets in the international climate agreements [1]. The German government has adopted the phase-out of coal and nuclear power generation as a critical measure [2]. To ensure a sufficient power supply, the share of electricity generation from renewable energy sources should already increase to 80% of electricity consumption by 2030 [3]. However, the output of renewable energy

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sources is highly dependent on external circumstances such as the sun and wind [4]. Therefore, an increase in storage capacities and synergy effects (e.g., in sector coupling) is necessary for transforming towards clean electricity generation. Demand side management (DSM) offers a competitive solution to meet the expected challenges by increasing energy flexibility (EF) on the demand side [5]. The industrial sector offers significant potential for savings. This sector accounts for 44 percent of electricity consumption in Germany [6]. At the same time, this sector offers considerable potential for balancing fluctuations in the power grid by adjusting power consumption to the available power [7]. Energy-intensive industrial companies typically can shut down, shift, or regulate their (production) processes and equipment to adjust their electricity demand [8]. Exploiting EF helps companies to benefit from reduced energy procurement costs by responding to volatile electricity prices or reducing their grid charges by avoiding peak loads while contributing to the stabilization of the power grid [9]. Despite these advantages, the exploitation of EF in manufacturing companies is low [10]. For companies that intend to exploit EF and need to select suitable platform solutions, it is often unclear which aspects and functions of a platform are relevant to them [11]. Evaluating available platforms is time-consuming, and tools and assistance such as a pre-classification of platforms and their characteristics do not exist. Besides platform selection obstacles, Leinauer et al. [12] identify technical obstacles such as high IT requirements, high effort, and complexity within IT systems, IT security and data security, lack of IT prerequisites in companies, lack of standardization of IT systems, and the lack of interoperability of IT systems that refrain companies from exploiting EF. Additionally, Honkapuro et al. [13] found the "lack of economic benefits, lack of motivation among the customers, [and] missing standards in data system interfaces" as major obstacles to exploiting available EF. DEPs tackle all said obstacles by providing economic benefits, simplifying exploitation, and proposing standards. As a first step to shedding light on the perceived black box and support companies, Duda et al. [11] developed a multi-layer taxonomy of digital energy platforms (DEPs) for DSM applications in the industry that includes a general and a more specific data-centric and transaction-centric perspective. While the taxonomy creates a solid foundation for understanding and analyzing DEPs in detail, structuring the market and landscape of existing platforms to simplify the selection process is still arduous. To identify, conceptualize, and define typical setups of platforms, deriving archetypes, such as done by Arnold et al. [14] for the case of IIoT platforms, has established a solid approach in literature. To address this vacuum of missing archetypes of DEPs, we formulate our guiding research question as follows:

Which archetypes of digital energy platforms exist in the manufacturing domain?

To adequately address our research question, we follow an explorative, data-driven clustering approach embedded in an adapted process of the well-established Cross Industry Standard Process for Data Mining (CRISP-DM). Moreover, we derive four archetypes of DEPs, illustrating which roles digital energy platforms can play. The remainder of this paper is structured as follows: Section 2 provides the theoretical background of DEPs before we detail the methodological approach in Section 3. Section 4 presents our cluster analysis and the derived archetypes. Section 5 gives implications for research and practice before it concludes with limitations and prospects for further research.

2. Literature

Digital platforms are emerging in almost all industries [15]. To enable the industry to use DSM and exploit their EF in their production processes, DEPs provide innovative services [16] and connect the industry with providers for control parameters (e.g., contemporary energy procurement costs [17]) or marketplaces (e.g., for trading EF) [18]. Zhong et al. [19] show that integrating DEPs into the existing production planning and controlling is key for the practical usage of DSM and exploiting the EF. A platform architecture has advantages since platforms can connect a company's heterogeneous components, planning systems, and machines [18]. In recent years, many DEPs have been developed (see Table 1). Yet, the DEPs provide different functionality and are based on various architectures and business models. Taxonomies can help to classify and compare DEPs.

Taxonomies aid in classifying entities into their dimensions. Depending on whether one can choose one or multiple characteristics of a dimension, the dimension is exclusive (E) or non-exclusive (NE). This allows decision-makers and researchers to distinguish between and compare different manifestations of the entities. Based on the taxonomy, real-world examples can be classified by creating groups of entities - archetypes. Decision-makers can use a taxonomy and respective archetypes to select the appropriate entity for their needs. There is an active research stream that develops taxonomies for platforms. Blaschke et al. [20] developed a taxonomy to categorize digital platforms according to four dimensions (infrastructure, core, ecosystem, and service dimensions). Blaschke et al. [20] used the method to build taxonomies proposed by Nickerson et al. [21]. In addition, they derived three archetypes of digital platforms. Moreover, there are taxonomies for platforms in multiple domains. Bouadjenek et al. [22] developed a taxonomy that classifies social information retrieval platforms. A taxonomy of mobility platforms was developed by Harri et al. [23]. Arnold et al. [14] developed a taxonomy and derived archetypes of industrial internet of things platforms. Also, in the domain of energy management, there are taxonomies. Khan et al. [24] developed a smart meter data taxonomy, Behrens et al. [25] proposed a taxonomy on constraints in DSM methods, and Karlin et al. [26] derived a taxonomy of energy feedback systems. However, the academic discourse lacks a more detailed look at DEPs. Duda et al. [11] propose a taxonomy to categorize DEPs but to better understand these platforms, the derivation of respective archetypes is critical. This paper builds on their taxonomy (see Figure 1) to derive archetypes.

	Dimensions	**Characteristics**				**Exclusivity**
General dimensions	Platform operator	Company	Consortium	Aggregator		E
	Access	Web-App	Native-App	Specific interface		NE
	Operational concept	On-Premise	Cloud	Hybrid		NE
	Access requirements	Free Access	Certain criteria to fulfill	Certain devices necessary		NE
	Platform structure	Fixed structure	Modular structure without external interfaces	Modular structure with external interfaces		E
Data-centric dimensions	Platform type	SaaS	PaaS			E
	Communication	One-to-Many	Many-to-Many			E
	Data flow	Unidirectional	Bidirectional			E
	Data processing	Transactional	Visual analysis	Data-driven analysis		NE
	Data source	Device	Cloud			NE
Transaction-centric dimensions	Main function	Electricity trading	Energy flexibility trading	Virtual power plant		E
	Trading venue	Stock Exchange	Markets for system services	OTC		NE
	Flexibility type	Market flexibility	System flexibility	Grid flexibility		NE
	Market design	Open	Closed			E
	Pricing	Free	Regulated	Free with regulating elements	No pricing	NE

Figure 1: The multi-layer taxonomy for DEPs of Duda et al. [11]

3. Methodological Approach

In this paper, we used the CRISP-DM process to address the paper's research question adequately. We follow a CRISP-DM-based data-driven clustering approach to derive the archetypes of DEPs based on selected real-world entities. CRISP-DM is a standardized process that aims to increase business understanding and gain insights by applying data mining methods [27]. Figure 2 displays our process. In the first step of "Business

Understanding”, we focus on understanding the field of DEPs (see Section 2), and setting the objective of deriving archetypes of DEPs. In the second step of “Data Understanding”, we review the data necessary for subsequently applying clustering techniques. Here, we build on data from Duda et al. [11], who developed a taxonomy for DEPs using real-world examples (cf. Figure 1). In doing so, we dispose of the data of 47 real-world DEPs with information about their nature in the 15 dimensions depicted in Duda et al.’s taxonomy [11]. Each platform considered in this work (cf. Table 1) was characterized/labeled in the taxonomy’s dimensions based on information available in project reports, data sheets, or interviews conducted in Duda et al.’s work [11] to the best of the authors’ knowledge.

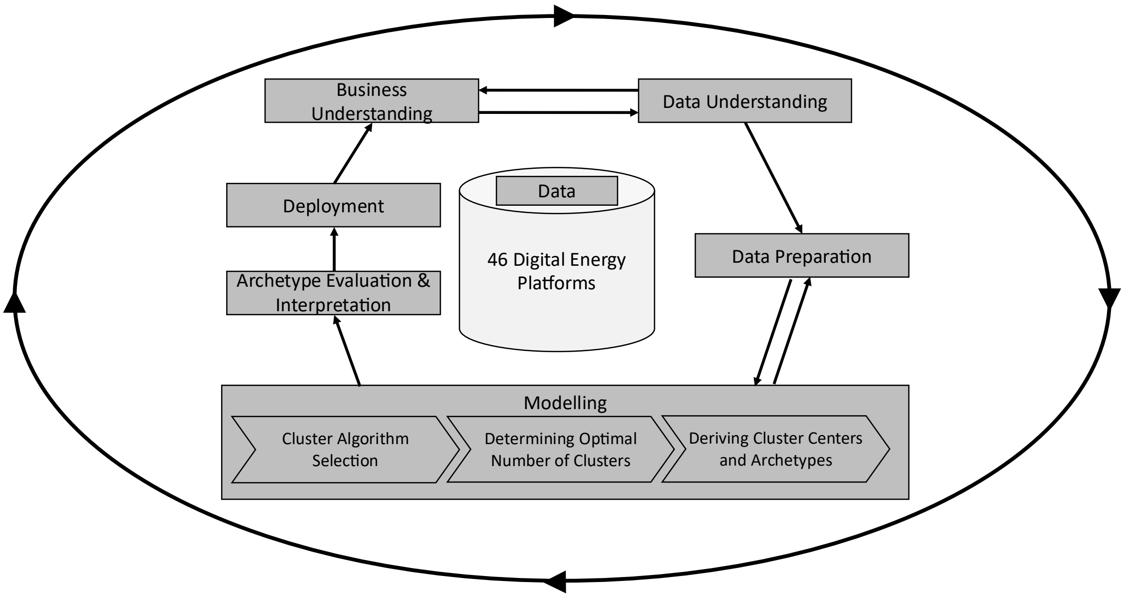

Figure 2: Adapted CRISP-DM process to derive DEP archetypes using a data-driven clustering approach (own illustration adapted from [27])

Table 1: DEPs considered in this work

Cordinet Project, Cornwall Local Energy Market, Electron Platform, ETPA, Flexible Power, FutureFlow, GoFlex, Nextra, Nodes Market, Piclo Flexibility Marketplace, wepower, AWS IoT Core, Bosch IoT Suite, CELOS, Cloud der Dinge, Connected Factories, Connected Factories 2, Enterprise IoT Platform, FIWARE, Google IoT Core, IBM Watson, ITAC.MES.Suite, LITMUS, OpenIoTFog, Productive 4.0, PTC Thingworx, Siemens Mindsphere, tapio, Virtual FortKnox, Bosch Energy Platform, DEXMA Platform, EMPURON EVE, EnCoMOS, ennex OS, ITC Power Commerce EnMS, KMUPlus - Energy Intelligence, opti.node, PHI-Factory, SIMATIC Energy Suite, Smart Energy Hub, ENIT, Balance Power, BayWa r.e. CLENS, Centrica Business Solutions, e2m, Entelios, Next-Kraftwerke, ENIT Systems

After reviewing the available data, we ensure high data quality and modify the data in the “Data Preparation” step for the following modeling step, checking for missing characteristics – if we cannot extract platform information, we set the respective value to zero, indicating missing information. The fourth step of “Modelling” consists of three sub-steps to correctly and replicable derive archetypes. First, we select cluster algorithms that can handle the hierarchically structured platform data. Considering several algorithms allows us to avoid algorithm-biased results on the number and composition of archetypes. We apply the commonly used clustering algorithms k-modes, k-means, k-means minibatch, spectral clustering, agglomerative clustering, and Birch. All steps of data preparation and modeling are implemented in Python using the algorithms available in the open-source “scikit-learn” [28] and “scipy” [29] library that provides tools for data analysis. Second, to determine the number of clusters k, i.e., the number of archetypes, we use the elbow method with a specific metric called distortion score for each algorithm [30]. The elbow method is typically used in cluster analysis and can be applied to different metrics. The distortion score measures and calculates the sum of square distances from each point to its assigned center [31]. We subsequently compare the results of k_{opt} for each algorithm and determine the optimal global number of clusters $\overline{K}_{opt}$ with Equation 1 where N is the number of clustering algorithms:

$$\overline{K}_{opt} = \left\lfloor \frac{\sum_{i=0}^{N} k_{opt}(i)}{N} \right\rfloor \tag{1}$$

$$Alg_{opt} = \underset{dist\_score}{argmin}\left(\sum_{i=0}^{N_{\overline{K}_{opt}}} dist\_score(i, \overline{K}_{opt}) \right) \tag{2}$$

Third, we derive the cluster centers, i.e., the characteristics of each archetype, by applying the clustering algorithm Alg_{Opt} exhibiting the lowest distortion score by comparing the clustering algorithms with K_{opt}, thus, the best separated and tightest clusters on the data (see Equation 2). The clusters represent DEPs with similar characteristics identified based on the taxonomy. Using typical characteristics based on recurring patterns, knowledge can be synthesized in a cumulative form of archetypes [32]. The results then serve as a basis for the step "Archetype Evaluation & Interpretation", where we graphically present the cluster analysis results transforming the information on cluster centers into interpretable archetypes with individual characteristics. Section 4 reports the clustering analysis results before Section 5 discusses the findings. The results' discussion and the publication within this piece of research present the last step, "Deployment" and contribute to the initial "Business Understanding" step. Further iterative analysis loops are possible, i.e., for future analysis of novel platform data.

4. **Results**

4.1 **Clustering Results**

The applied data-driven clustering approach led to the following results. For all algorithms except k-modes, the optimal number of clusters was 4, in line with Equation 1, which is why we continued with four archetypes for further analysis. The distortion scores of the different algorithms were at a relatively similar level, with the Birch algorithm having the lowest score of 169.003 and thus being used to determine the exact archetypes. Table 2 reports the detailed results.

Table 2: Optimal Number of Clusters and Distortion Scores for each Algorithm tested

Cluster Algorithm	Optimal Number of Clusters	Distortion Score
k-modes	5	159.569
k-means	4	172.833
k-means mini batch	4	178.765
spectral clustering	4	169.100
agglomerative clustering	4	169.940
Birch	4	169.003

For better visualization, we calculated the two principal components of the data and visualized it as depicted in Figure 3. Figure 3 reports the two principal components on the x and y-axis. Each of the four clusters is colored differently to distinguish the archetypes we present in subsection 4.2 in detail. The archetypes

"Energy Flexibility Platform" (blue) and "SaaS-Aggregators" (orange) differ quite strongly from the two remaining archetypes, "Research-based Platform" and "Manufacturing IoT Platform". Both last-named archetypes seem to be more similar to each other. Nevertheless, the two-dimensional depiction may not be capable of distinguishing between the multiple dimensions resulting from the input data. We further analyze the archetypes in the following.

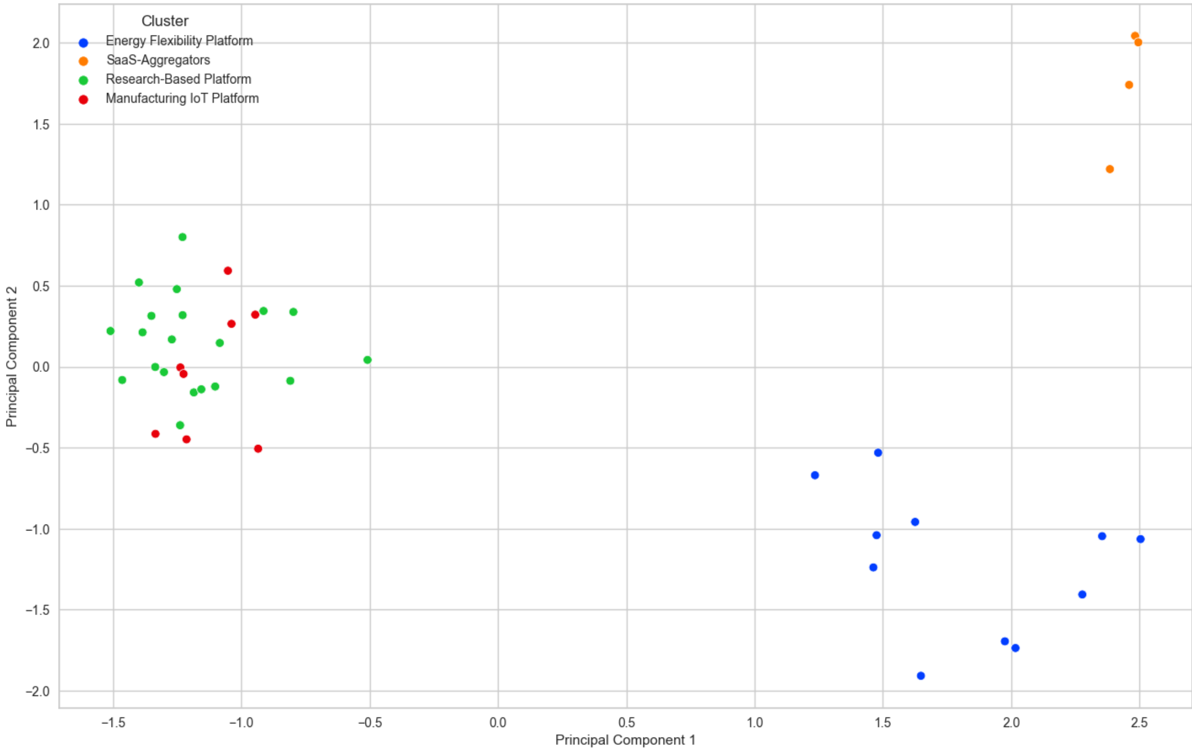

Figure 3: Simplified graphical representation of the derived archetypes after principal component analysis

4.2 Digital Energy Platform Archetypes

This section presents and analyses the DEP archetypes in detail. Table 3 provides an overview of each archetype with its central attributes and characteristics, exemplary platforms, and the number of platforms associated with the specific archetype. We observe a relatively high share of research-driven energy platforms followed by energy flexibility and manufacturing IoT platforms. The smallest share holds for the SaaS-Aggregators/Virtual Power Plant archetype.

Research-driven Energy Platforms are developed by research institutes, universities, and companies. These are sometimes organized in larger research projects financed by several ministries (e.g., the German Ministry of Education and Research) or the European Union. Nevertheless, the platforms in this cluster are not only platform concepts or prototypes but also fully functional platforms with international customers in the manufacturing field. The energy platforms offered are primarily open and web-based. Furthermore, the platforms use statistical tools and methods to analyze and especially visualize the energy consumption of manufacturing plants.

Energy Flexibility Platforms implement a new concept and connect energy suppliers and commercial energy consumers – e.g., typically found as local energy markets. The platform's objective is to enable the flexibilization of power consumption to allow a flexibility marketing for specific use cases such as electricity grid congestion management. The development of these platforms is mostly research-driven. Compared to the research-driven energy platforms, we could not identify any development toward the commercialization of the flexibility platforms. Thus, research projects and consortiums mainly dominate this cluster instead of company-only solutions or products.

SaaS-Aggregators / Virtual Power Plants are company-based, well-established aggregators that offer SaaS products for their customers in energy-intensive industries. The provided software offered participation in virtual power plans to optimize energy procurement for energy-intensive industries. Most of the platforms in this cluster have highly restricted access possibilities. Therefore, companies that want to participate in virtual power plants must fulfill the criteria. The platforms are also used for trading flexibilities on the spot markets (e.g., Intraday). Furthermore, the platforms offer to trade the given flexibilities from manufacturing companies in the energy markets.

(Manufacturing) IoT-Platforms offer the broadest functionality of all platforms and, thus, focus least on the energy domain. The platforms are mainly responsible for acquiring, aggregating, visualizing, and analyzing data streams out of the manufacturing processes, as well as controlling these processes. The platforms are offered by well-established companies and are cloud-based platforms. They also give free and unrestricted access to the resources and services they offer in their ecosystems. Platforms in this cluster are typically generic platforms without a focus on energy management. However, some of the platforms in this cluster also develop native applications, e.g., for industrial PCs, to simplify the platform's integration with the machines and components.

Table 3: Overview of the Determined Archetypes

Archetype	Central Attributes and Characteristics	Platform Examples	Number of Platforms in sample
Research-driven Energy Platforms	Web-App, Research-driven Company, Open, Data-driven	Virtual Fort Knox, ENIT Systems, Smart Energy Hub	22
Energy Flexibility Platforms	Research, Many-to-Many-Platforms, Energy Flexibility Trading, OTC	WePower, GoFlex, Nextra, ETPA	11
SaaS-Aggregators / Virtual Power Plants	Aggregator, Interfaces, Cloud, Closed Access, Transactional, Trading,	NextKraftwerke, BalancePower, Entelios, e2m	6
(Manufacturing) IoT-Platforms	Company, Cloud, Free-Access, One-to-Many, Native-App	Siemens Mindsphere, Bosch IoT Suite, ITAC.MES.Suite	8

5. Implications and Conclusion

This paper addressed the lack for archetypes characterizing DEPs that make it easier for companies to select the platforms providing the missing functionality. Following an explorative data-driven clustering approach building on the well-established CRISP-DM process, we identified four DEP archetypes: Research-driven Energy Platforms, Energy Flexibility Platforms, SaaS-Aggregators / Virtual Power Plants, and (Manufacturing) IoT-Platforms. Our results and findings have several implications for practice and research. First, the archetypes structure DEPs in their functionality and services provided, which may serve as a first market overview. Market gaps can be identified, highlighting technological needs or opportunities for novel platforms, e.g., platforms that combine functionalities of two or more archetypes or business models beneficial for providers. Second, and in line with the first implication, the archetypes may represent a decision support system for the early stages of digital platform selection. Comparing a company's existing IT infrastructure with the identified archetypes can lead to a particular archetype that fills current gaps in automation or additional services. Third, with the goal of (entirely) automated energy flexibility marketing from the shop floor to the energy/flexibility markets, the archetypes clearly show that typical production and IoT issues should be thought of in line with energy supply and demand. Compared with Figure 3, we see that no overarching archetype covers the full range of functionalities provided for each archetype. Transferring this finding to practice, companies may consider several platforms in their enterprise architecture for automated flexibility marketing. This leads to implication number four: interfaces and standardized communication are crucial for the automation of flexibility marketing, which is in line with findings from Schott et al. [33]. Thus, selecting and implementing platforms requires expertise in requirements engineering and defining interfaces between different platforms. Alternatively, developing a "holistic" platform that covers every functionality needed from the shop floor to energy/flexibility markets would be a costly approach, as proposed by Bauer et al. [7]. Fifth, the archetypes "Research-Driven Energy Platforms" and "IoT Platforms" are comparatively most comparable (cf. Figure 3). It appears that the majority originate or were developed in the production domain and less in the energy domain. The focus of "Research-driven Energy Platforms" is on optimizing energy consumption (efficiency instead of flexibility), emphasizing data management and less on the marketing of flexibility and its economic potential. It may make sense to establish research consortia with additional specialists from the energy sector to further develop these platforms in flexibility marketing. In contrast, the "SaaS Aggregators / Virtual Power Plants" archetype differs significantly from the "Research-Driven Energy Platforms" and "IoT Platforms" archetypes. This indicates historically grown structures and proprietary solutions in a highly regulated energy sector [34], which aggregators have tapped in recent years [35]. The need for end-to-end communication and interfaces can also be derived here, which should be considered in practical implementation.

As with any research endeavor, our work has some limitations but spurs future research. First, our study is limited in data about existing DEPs focusing on Germany. Broadening the scope might distort the results and strengthen the validity of the derived archetypes. We leave this and the research's transferability to other countries for future studies. Second, the derived archetypes represent the status quo regarding existing DEPs. Ongoing development, market, and customer requirements (e.g., changing regulations) may lead to changes in archetypes. Thus, we recommend applying our methodological approach cyclically to obtain insights into trends from a market and functionality perspective. Third, there is room for improvement regarding our methodological approach next to limitations in data. There are several other clustering algorithms and metrics to derive the optimal number of clusters and evaluate the clusters' composition [36].In summary, despite these limitations, we contribute relevant archetypes of DEPs for production companies and researchers.

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