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# FlexEnergy - A Prosumer-based Approach For The Automated Marketing Of Manufacturing Companies' Energy Flexibility

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## Abstract

The transition to renewable energy sources and the need to address climate change has significantly changed the energy landscape. However, the fluctuating nature of renewables and increased electricity price volatility pose challenges to power grids and companies. This study focuses on energy flexibility achieved through industrial demand-side management (DSM) as a solution. Information technology (IT) and standardization are vital for enabling energy flexibility by optimizing energy consumption and facilitating interoperability. Digital energy platforms allow energy-intensive industries to optimize energy usage, thus enabling industrial demand optimization and effective communication within the energy ecosystem. Standardization ensures efficient implementation of energy flexibility measures across diverse energy markets. This study proposes a process model to streamline the integration of energy flexibility measures into manufacturing processes. This model eliminates the labor-intensive manual implementation process, enabling seamless adoption of energy flexibility measures and participation in energy markets. Marketing energy flexibility is addressed through the prosumer-based process that leverages standardized communication facilitated by the energy flexibility data model (EFDM), optimizing the energy consumption of manufacturing companies. The contributions of this paper lie in the proposed process model for marketing energy flexibility, streamlining energy flexibility implementation through automated EFDM modeling. The findings provide insights for researchers and practitioners, guiding the adoption of energy flexibility measures and supporting a sustainable energy future.

## Keywords

Industrial Energy Flexibility; Energy Flexibility Measures; Energy Flexibility Data Model; Process Model

## 1. Introduction

Climate change concerns and global commitments to reduce greenhouse gas emissions have significantly changed the energy landscape [1–3]. Governments worldwide, including Germany, are phasing out fossil energy sources such as coal and oil while promoting renewable energy sources such as wind and sun [4, 5]. However, the intermittent nature of renewable energy sources poses considerable challenges to power grids and results in greater electricity price volatility [6–8]. One potential solution to the challenges at hand is the concept of energy flexibility (EF), which can be achieved through industrial DSM [9–12]. In this context, IT and standardization are crucial in enabling EF. By leveraging digital energy platforms, energy-intensive industries can use EF measures to optimize their energy consumption according to energy price forecasts or network operators' flexibility requirements while maintaining logistical and operational objectives [13–16]. Standardization facilitates interoperability between manufacturing and energy-related domains, enabling the efficient use and marketing of EF measures in various energy markets. Despite the advantages of IT and standardization, a major challenge remains in modeling and marketing EF measures in manufacturing.

Currently, manufacturing companies often do not know how to monetize EF of manufacturing processes. Also, the generic description of EF with the EFDM poses a significant hurdle for companies and often is manually implemented for each manufacturing process and EF, which is a time-consuming and labor-intensive task. To address these issues, our paper proposes a process model for the automated description and marketing of EF in manufacturing processes utilizing the EFDM to streamline the implementation of EF measures and enable seamless participation in different energy markets. The approach takes into account both proactive and reactive EF marketing. Proactive marketing aims to optimize energy consumption based on forecasts, while reactive marketing focuses on responding to real-time changes in energy markets [17–19]. While existing approaches and tools address aspects of EF in manufacturing processes, they do not provide a comprehensive framework for both describing and marketing EF measures in a seamless manner. This leaves manufacturing companies with fragmented solutions that lack end-to-end automation and standardization. Recognizing this gap, the research question of our work is defined as:

*How can an information technology process be modeled that enables manufacturing companies to automate the description and marketing of energy flexibility?*

Adopting a design science research (DSR) approach, an artifact in the form of a process model informed by literature and qualitative expert interviews is developed, thereby ensuring rigor. DSR, pivotal for developing solutions to real-world problems, supports our endeavor to offer a holistic and applicable model for automating the description and marketing of EF in manufacturing processes. This research directly responds to the need for the communication of EF, thus ensuring relevance. Therefore, our main contribution is a prosumer-based approach leveraging the EFDM for standardized communication with energy markets to monetize EF of manufacturing companies. The proposed process addresses the challenges associated with both proactive and reactive EF marketing and enables seamless participation in different energy markets. The remainder of this paper is structured as follows: The literature review highlights EF, the EFDM's foundations, and its application. The proposed process model details automated description and marketing of manufacturing companies' EF, emphasizing continuous information flow between companies and energy markets. A case study showcases the process models and resulting EFDM's practical application in an industrial setting. The findings, research implications, and future prospects in EF conclude the discussion.

## **2. State of the Art**

EF is defined as the "ability of a manufacturing system to quickly and process-efficiently adapt to changes in the energy market" [17]. An energy-flexible factory allows for potential economic use of energetic flexibility [18]. The temporal deployment of EF is specified in the definition of the Federal Network Agency, which describes flexibility as "the change in feed-in or withdrawal in response to an external signal (price signal or activation), to provide a service in the energy system" [20]. In general, numerous types of energy (electricity, heat, natural gas) can be described by this term. In the energy transition context, the term mainly describes measures necessary to enable the power system to accommodate additional volatile renewable energy sources such as wind and solar power plants. Thus, the term "energy flexibility" represents an extension of the concept of "power grid flexibility", but is often also used synonymously [8]. The VDI guideline 5207 describes industrial EF measures such as adapting shift times, changing manufacturing sequences, interrupting orders but also technical EF measures on the shop floor level, such as storing energy inherently or changing the energy source of a manufacturing process [18]. The EFDM aims to model and describe EF from technical, organizational, and energetic aspects, therefore enabling standardized communication of EF data captured in manufacturing processes to market it to flexibility markets [21]. Consequently, the EFDM is the foundation for all services that automate and standardize the entire EF trading process from the machine to the energy market. Based on this, data models for specific use cases, such as optimization of manufacturing processes or flexibility marketing, can be derived, only containing part of the information of the central data model [22].

The EFDM represents EF using a flexibility range and specific measures. This description uses a minimal set of parameters to convey essential technical and energetic details, while minimizing data complexity and volume. Sensitive manufacturing data exchanges are avoided. The flexibility range describes the possibilities of an energy-flexible system to adjust its performance compared to the reference operation. This technical energy-flexible system is characterized with the classes "flexible load", "dependency", and "energy storage" [21]. In addition to the three classes for describing the "flexibility range" of a system, the EFDM also includes the class "energy flexibility measure", which describes a specific change in the system's performance within its flexibility range [23]. A flexible load models a technical system or the interaction of different technical systems that have the potential to bring about a change in performance. Whether the technical system is a producer or consumer of power is irrelevant. The ability to market EF measures in manufacturing provides potential economic benefits for companies [11]. By adjusting energy consumption in response to price signals or other external factors, companies can exploit fluctuations in energy prices and potentially reduce their overall energy costs [24]. The process of marketing EF measures typically involves participating in energy markets or demand response programs.

Companies can participate directly in wholesale energy markets, such as day-ahead or intraday, to sell their EF. Through demand response programs, they adjust energy consumption based on grid conditions, receiving financial incentives or reduced rates in return. Small manufacturers or those with limited flexibility resources may engage via an aggregator. Aggregators pool the flexibility resources of multiple companies and market them collectively, enabling smaller companies to access the benefits of participating in energy markets or demand response programs [23, 25]. By marketing their EF measures, companies can reduce energy costs and enhance energy system stability. As renewable energy integration rises, the role of EF in supporting energy transition will grow. This underscores the need for a systematic approach to identify and market EF measures adaptable across various industries. Especially the challenges associated with proactive and reactive EF marketing, enabling seamless participation in different energy markets, and fostering efficient use of energy resources must be overcome. Compared to the extensive literature on energy-oriented production planning and control, the novelty of the presented approach resides in the application of the EFDM to facilitate standardized communication and automate the description and marketing of EF in manufacturing processes. This application streamlines the marketing process and permits a broader range of EF marketing strategies, including proactive and reactive approaches. While various tools and software applications, such as the "Flexfinder" and the "EFDM GUI" developed in the SynErgie project, provide valuable solutions in the domain, our approach offers a comprehensive integration of the EFDM for standardized communication with energy markets and emphasizes the diverse applications of the data model. This distinction underscores the novelty and relevance of our work in the context of EF.

### **3. Automated description and marketing of manufacturing companies' energy flexibility**

This chapter presents FlexEnergy, a process model implemented in the business process modeling notation (BPMN) that illustrates how manufacturing companies can automate the process of describing and marketing EF to achieve electricity cost savings [26, 27]. The approach is designed to help manufacturing companies benefit from increasingly volatile electricity prices by exploiting unused EF potential with proactive as well as reactive EF marketing. The fundamental prerequisite for minimizing electricity costs is to reduce electricity consumption in phases of high electricity prices. To adjust the electrical load accordingly, it is necessary to optimize the production plan and the underlying plant parameters concerning predicted electricity prices and thus be able to react dynamically to fluctuating prices of the volatile electricity market of the future [25]. Furthermore, adjusting the production schedule based on volatile electricity prices leaves room to identify additional EF potentials. These residual EFs can be characterized as an EFDM and sold on energy markets. To maximize the revenue generated in this way, it is necessary to examine in which energy markets or with which energy market products the highest revenue can be generated.

When making manufacturing processes more flexible, care must be taken to ensure that the EF measures implemented do not harm the overriding objectives of factory operations [28]. To combine the objectives of short processing times, high-quality products, and low costs with an energy-flexible mode of operation, production planning, and control must always be involved. Energy management forms the interface between manufacturing operations and strategic energy procurement and therefore plays an essential role in marketing EF. To benefit from the opportunities of marketing EF, an end-to-end IT connection of the energy-flexible manufacturing systems to the external energy markets is required. The market enables communication between flexibility buyers and sellers and forms the basis for reducing electricity costs and helping to stabilize the power grid. To optimize the power flows in the grid and avoid bottlenecks, flexibility purchasers such as grid operators can use the EF marketed on flexibility markets to stabilize the energy system.

### 3.1 Adjusting the production plan to fluctuating electricity prices

The first part of the process model FlexEnergy, describes utilizing energy flexibilities as a consumer to benefit from fluctuating electricity prices. Figure 1 presents the step-by-step sequence for production plan adjustment based on forecasted electricity prices.

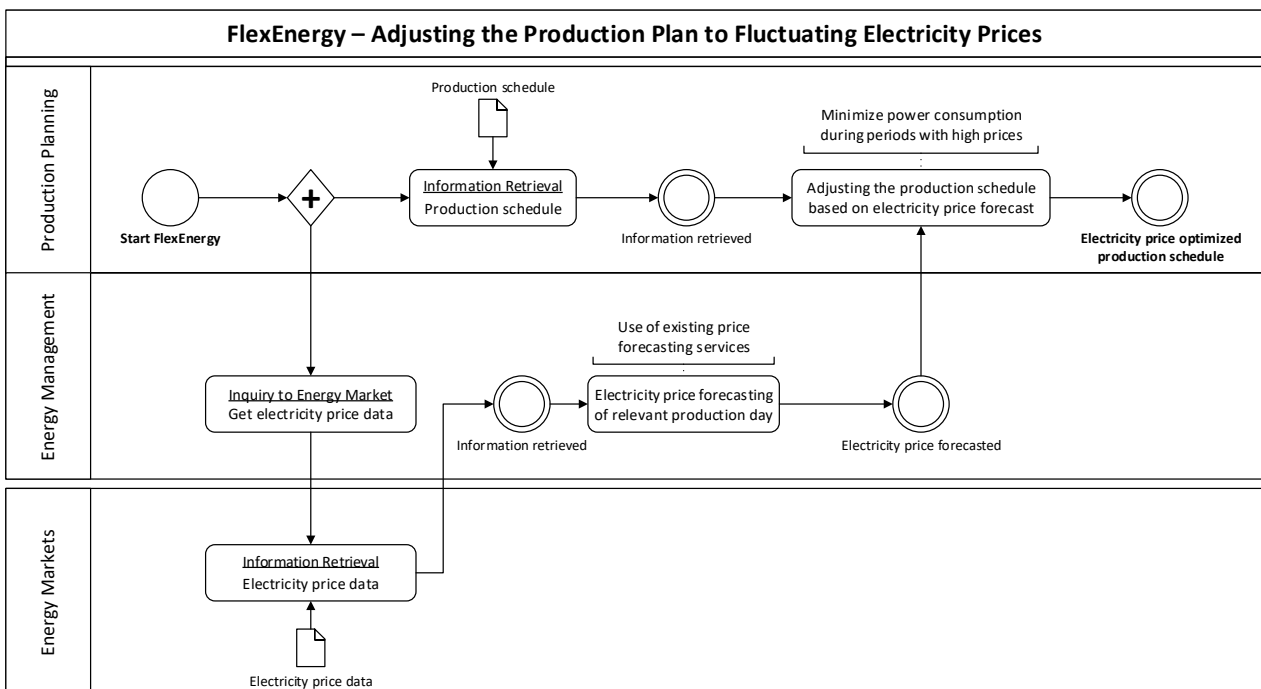


Figure 1: Process model for adjusting the production schedule to electricity price forecasts

The company’s production planning and control trigger the start of FlexEnergy. To be able to react to volatile markets and utilize fluctuating electricity prices to reduce electricity costs, market information must be obtained first. To this end, the company's energy management team acquires electricity price data from the relevant electricity market. In parallel, production planning and control must acquire the production schedule of those manufacturing systems capable of energy-flexible operation to enable optimization of the load profile. Based on the electricity price data, energy management can generate electricity price forecasts for the relevant electricity markets and trading days. The focus is getting forecasts of the electricity prices for the day-ahead and intraday electricity markets as early and as accurately as possible so that they can be considered in short-term production planning and adjustments to reduce electricity costs can be planned. By implementing existing solutions for electricity price forecasting, like those developed in the SynErgie project, companies can optimize the load profile of energy-flexible manufacturing systems based on the forecast and reduce electricity costs by minimizing electrical power consumption during periods of high electricity prices. By implementing the described adjustments, the company’s operations can be optimized regarding forecasted electricity prices, and electricity procurement costs can be reduced sustainably [29].

### 3.2 Automated description and marketing of energy flexibility of manufacturing companies

After implementing the first segment of the FlexEnergy process model, which provides an electricity price-optimized production schedule, the second section of FlexEnergy presents a systematic approach to identify, describe, and market additional EFs of manufacturing companies. Identifying additional EFs in the electricity price-optimized production plan is a sub-process detailed in the case study. The second part of the FlexEnergy process model is illustrated in Figure 2 and explained in detail.

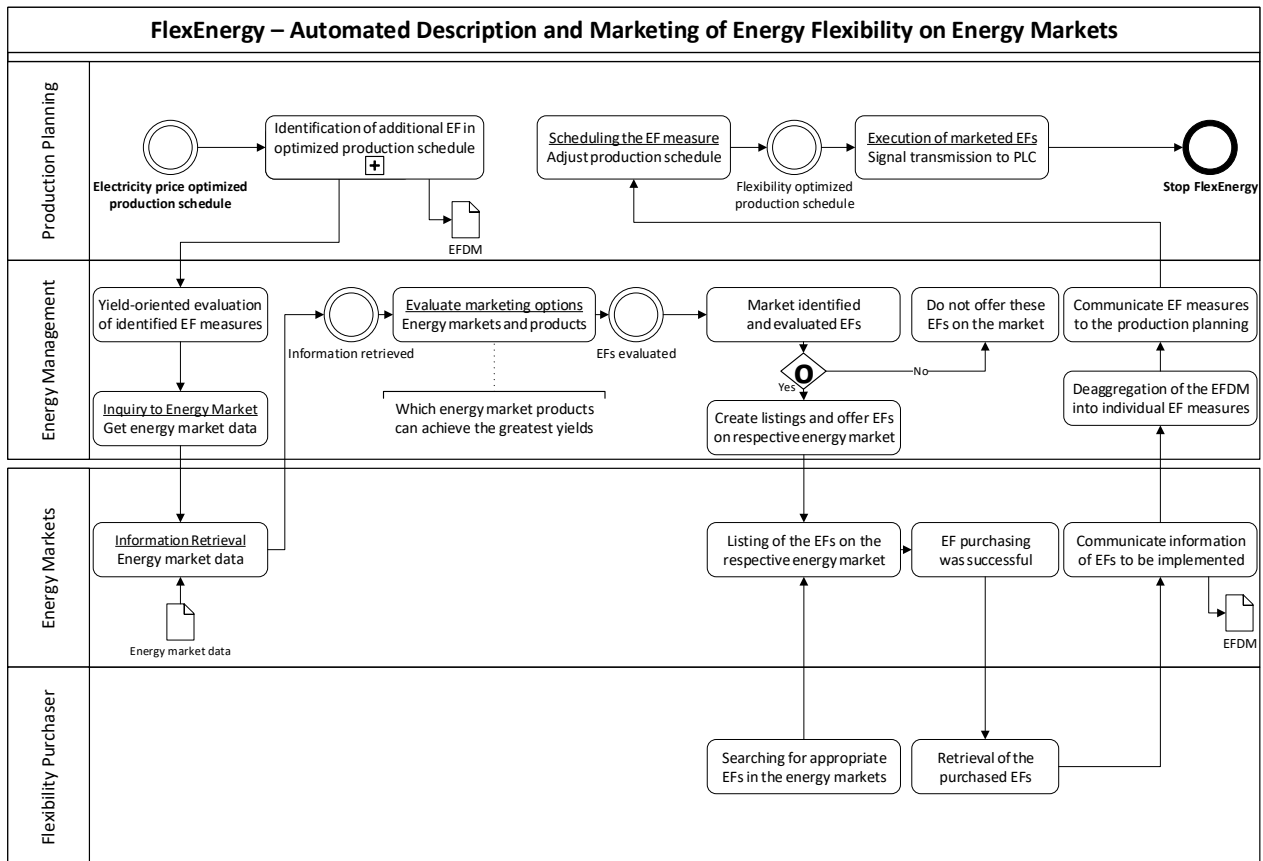


Figure 2: Process model for the automated description and marketing of energy flexibility on energy markets

For marketing manufacturing companies' EF, it is first necessary to identify additional EF measures in the electricity price-optimized production schedule and to describe them with appropriate figures. The additional EFs identified in this process are described with the help of an EFDM and form the basis for all downstream process steps. One of the central goals of FlexEnergy is to maximize revenue when marketing EF. Based on this objective, energy management performs a yield-oriented evaluation of the identified EF measures. It also acquires information on which markets and with which products the most significant revenue can be achieved with the identified EFs. The revenue-based assessment can be automated by utilizing services such as the flexibility deployment planning tool, developed as part of the SynErgie project, and thus help companies decide which EFs should be marketed on which energy market [25]. EFs advertised on markets that enable EF marketing can be viewed and purchased by interested flexibility buyers, such as grid operators. In the case of a successful purchase and call, the information about the EF measure to be provided is transmitted from the market to the company utilizing the EFDM. Subsequently, the EFDMs are disaggregated into EF measures and forwarded to the production planning and control, where the sold EF must be entered into the electricity price-optimized production plan to block the marketed periods for different operational measures. To ultimately provide the marketed EF, a control signal must be provided to the PLC of the respective energy-flexible manufacturing system, enabling an adjustment of the electrical load to provide the EF sold.

#### 4. Automated energy flexibility marketing of a magnesium die casting company

Based on the process model developed for the automated identification, description, and marketing of EF of manufacturing companies, a case study is presented, demonstrating and validating the applicability and benefits of FlexEnergy. The focus here is, in particular, on EFDM modeling. The use case originates from the SynErgie project and involves the energy-flexible operation of a magnesium die-casting process [30]. To contribute to science and practice, it is shown how EFs can be identified, described, and marketed utilizing the EFDM. The furnace, needed to melt the magnesium and keep it at a specific temperature, can be utilized as inherent energy storage to make energy consumption in manufacturing more flexible and, through the marketing of EF, help reduce the company's energy costs. The use of inherent energy storage is an EF measure that can be implemented on the shopfloor level and, according to VDI guideline 5207, is defined as the "use of tolerances of various state variables in processes as energy storage" [17]. Depending on the material, the furnace must be operated within a defined temperature range to ensure consistent product quality. Within this range, the furnace exhibits EF. The power consumption of the furnace can be adjusted by controlling the output of its electric heating elements, provided the process limits are maintained. Description of the furnace static EF space enables deriving concrete EF measures, thus facilitating EF marketing. The energy-flexible furnace is modeled using the EFDM JSON format to represent its operating possibilities.

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##### EFDM 1: Static modeling of the energy flexibility space of the magnesium-melting furnace

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```
1: {
2:   "flexibility": {
3:     "id": "b7c4d95d-4d3b-4f48-9dcf-3bde75e7c67e",
4:     "origin": "f8c54c80-34a6-4d4f-8da8-62755a44d7e3",
5:     "flexibleLoads": [{
6:       "flexibleLoadId": "d62a3c5b-8c16-40e6-a9e9-0195c1655b68",
7:       "marketingDeadline": "2023-05-03T12:00:00+00:00",
8:       "measurementLocation": "Shopfloor - Magnesium Melting Furnace 001",
9:       "deactivationGradient": {"unit": "kW/s", "value": -4.0},
10:      "activationGradient": {"unit": "kW/s", "value": 4.0},
11:      "regenerationDuration": {"unit": "s", "value": 0.0},
12:      "reactionDuration": {"unit": "s", "value": 10.0},
13:      "modulationGradients": [{
14:        "min": {"unit": "kW/s", "value": -4.0},
15:        "max": {"unit": "kW/s", "value": 4.0}}],
16:      "validity": [{
17:        "from": "2023-05-04T05:00:00+00:00",
18:        "until": "2023-05-04T08:00:00+00:00",
19:        "temporalType": "TOTAL"}],
20:      "powerStates": [{
21:        "power": {
22:          "min": {"unit": "kW", "value": 0.0},
23:          "max": {"unit": "kW", "value": 0.0}}, {
24:        "power": {
25:          "min": {"unit": "kW", "value": 40.0},
26:          "max": {"unit": "kW", "value": 40.0}}, {
27:        "power": {
28:          "min": {"unit": "kW", "value": 80.0},
29:          "max": {"unit": "kW", "value": 80.0}}, {
30:        "power": {
31:          "min": {"unit": "kW", "value": 120.0},
32:          "max": {"unit": "kW", "value": 120.0}}}
33:    ]},
34:   "storages": [{
35:     "storageId": "a2c7ca70-f0f4-435c-9f94-ee2228e3c1fc",
36:     "usabelCapacity": {
37:       "min": {"unit": "kWh", "value": 0.0},
38:       "max": {"unit": "kWh", "value": 7.8}},
39:     "suppliers": [{
40:       "flexibleLoadId": "d62a3c5b-8c16-40e6-a9e9-0195c1655b68",
41:       "conversionEfficiency": 1.0}],
42:     "energyLoss": {"unit": "%/s", "value": "E_Loss%"},
43:     "drain": [{
44:       "time": "2023-05-04T05:00:00+00:00",
45:       "power": {"unit": "kW", "value": 10.0}}, {
46:       "time": "2023-05-04T08:00:00+00:00",
47:       "power": {"unit": "kW", "value": 10.0}},
48:     "initialEnergyContent": {
49:       "time": "2023-05-04T05:00:00+00:00",
50:       "value": {
51:         "min": {"unit": "kWh", "value": 0.0},
52:         "max": {"unit": "kWh", "value": 7.8}},
53:     "targetEnergyContent": {
54:       "time": "2023-05-04T08:00:00+00:00",
55:       "value": {
56:         "min": {"unit": "kWh", "value": 0.0},
57:         "max": {"unit": "kWh", "value": 7.8}}
58:     }
59:   ]}
```

Static modeling of the EF of the furnace is the basis for electricity price-optimized operation and identification of marketable EFs. In addition to mathematical and evolutionary optimization, another possibility for energy-flexible optimization of the furnace is implementing a (deep) reinforcement learning (RL) agent that controls the operation based on a simulation model. RL works through a series of actions that can trigger a reward or a punishment. In this process, an agent interacts with its environment, aiming to find appropriate actions to maximize rewards without the actions being predetermined by a teacher. The characteristic of RL is learning by trial and error and often delayed rewards for the agent's actions [31, 32]. Within the framework of this case study, a simulation model was developed that allows the calculation of the temperature inside the furnace as a function of power and time and serves as the basis for energy-flexible operation optimization. Furthermore, an AI-based control system was implemented utilizing deep RL to enable energy-flexible operation. Using a reward function, the agent learns a strategy to adjust the furnace's load profile based on electricity price forecasts. [31]. According to EFDM 1, the agent can only select from four power states: 0, 40, 80, or 120 kW as actions (cf. lines 20-32). The reward function is based on two constraints: adhering to the temperature limits of 640 °C and 660 °C modeled as the usable capacity (cf. lines 36-38) and reducing electricity costs by adjusting the furnace's load profile. In a simplified description, the choice of a particular action is influenced by the current temperature or energy content in the furnace and the boundary conditions determined by the reward.

The optimization output of the agent is automatically transferred into an EFDM format, which describes the furnace's electricity price-optimized load profile as a flexibility measure. An exemplary flexibility measure in the form of an EFDM can be found in the appendix of this paper. To market additional EFs in the electricity price-optimized production schedule (cf. Figure 2), additional EF measures must be identified and modeled as an EFDM. The EF measures to be marketed are identified utilizing a rule-based approach. This method, implemented utilizing a Python script, automatically detects suitable EF measures based on two conditions and translates them into an EFDM. Specifically, the case study focuses on identifying load increase measures by detecting phases where the electric heating element's power is 0 kW, and the furnace's temperature is below 641 °C, subsequently transforming these findings into the EFDM. An exemplary EFDM based on the agents' optimized load profile and the resulting EF measure attached in the appendix (cf. EFDM 3) is shown below.

---

**EFDM 2: Additional energy flexibility in the melting furnaces optimized production schedule**

---

```

1: {
2:     "flexibility": {
3:         "id": "f47ac10b-58cc-4372-a567-0e02b2c3d479",
4:         "origin": "f8c54c80-34a6-4d4f-8da8-62755a44d7e3",
5:         "flexibleLoads": [{
6:             "flexibleLoadId": "d62a3c5b-8c16-40e6-a9e9-0195c1655b68",
7:             "marketingDeadline": "2023-05-03T12:00:00+00:00",
8:             "measurementLocation": "Shopfloor - Magnesium Melting Furnace 001",
9:             "deactivationGradient": {"unit": "kW/s", "value": -4.0},
10:            "activationGradient": {"unit": "kW/s", "value": 4.0},
11:            "regenerationDuration": {"unit": "s", "value": 0.0},
12:            "reactionDuration": {"unit": "s", "value": 10.0},
13:            "price": {"unit": "EUR", "value": 50.0},
14:            "usageNumber": [{
15:                "min": 0,
16:                "max": 1}],
17:            "modulationGradients": [{
18:                "min": {"unit": "kW/s", "value": -4.0},
19:                "max": {"unit": "kW/s", "value": 4.0}],
20:            "validity": [{
21:                "from": "2023-05-04T07:00:00+00:00",
22:                "until": "2023-05-04T07:05:00+00:00",
23:                "temporalType": "TOTAL"}],
24:            "powerStates": [{
25:                "power": {
26:                    "min": {"unit": "kW", "value": 40.0},
27:                    "max": {"unit": "kW", "value": 40.0}},
28:                "holdingDuration": {
29:                    "min": {"unit": "s", "value": 60.0},
30:                    "max": {"unit": "s", "value": 300.0}},},
31:                "power": {
32:                    "min": {"unit": "kW", "value": 80.0},
33:                    "max": {"unit": "kW", "value": 80.0}},
34:                "holdingDuration": {
35:                    "min": {"unit": "s", "value": 60.0},
36:                    "max": {"unit": "s", "value": 300.0}}
37:            ]}
38:    ]}

```

---

The furnace's additional EF can now be introduced to energy markets, ideally targeting a specific market for its offering. If a flexibility buyer acquires the EF, the corresponding measure is relayed to the company for execution, increasing the furnace's load. Additional revenue opportunities arise from marketing the existing EFs as control energy via a flexibility marketer, minimizing peak loads and thus reducing costs through lower grid fees, and from atypical grid usage models and thus reduced grid fees. The economic benefits from EF also lead to environmental benefits from increased energy purchases and usage from renewable sources. Through the intelligent usage of inherent energy storages and intelligent control of manufacturing processes, companies can save energy costs and, at the same time, contribute to the stabilization of the power grid.

## **5. Conclusion and implications**

In the course of the energy transition and the associated volatile supply of electricity, the use of flexible loads as a balancing mechanism to stabilize the power grid is being increasingly intensified. Due to the high energy consumption, the demand-side EF of the industrial sector is becoming more important. By making electricity consumption more flexible, manufacturing companies can create an instrument that, on the one hand, helps to ensure grid stability and, on the other, makes it possible to save electricity costs. The basis for benefiting from the monetary advantages of demand flexibility and, at the same time, contributing to the energy transition is the implementation of EF measures in manufacturing. Given this context, a process model was developed that enables manufacturing companies to automate EF identification, description, and marketing. This paper specifically focuses on the comprehensive modeling of EF using the EFDM and the associated marketing of EF in energy markets. The case study has demonstrated the practical use of the process model FlexEnergy, utilizing a concrete EF measure, the use of inherent energy storages, and thereby presented how companies' identification, description, and marketing of EF can be implemented in practice to achieve more cost-efficient and sustainable factory operations.

Naturally, our study is subject to limitations and prospects for further research. Within the validation scope, it was shown that the complete characterization of the melting furnace makes it possible to identify numerous EF measures in the available flexibility range and market them. Numerous EF configurations can be described as EFDM and offered in energy markets by varying the power states and their holding periods. To satisfy market needs and achieve the highest yield, it will be important in the future that the scheduling and marketing of EFs are made in close consultation with the market or the flexibility purchaser. For suppliers and purchasers to benefit maximally from the existing flexibilities, an IT architecture that enables end-to-end communication between the two sides must be created, enabling further automation of the individual steps described in the process model and simplifying the EF identification, description, and marketing. Only in this way can the marketing of EF of manufacturing companies become a valid option in the future, in order to save energy costs on the one hand and stabilize the power system on the other.



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## Appendix

As stated in chapter four, an excerpt of an exemplary flexibility measure in the form of an EFDM can be found hereafter. The measure is a concrete output of the deep RL agent, which is automatically transferred to an EFDM and illustrates an electricity price-optimized load profile of the melting furnace.

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### EFDM 3: Electricity price optimized production schedule of the magnesium-melting furnace

---

```
1: {
2:     "flexibleLoadMeasure": {
3:         "flexibleLoadId": "d62a3c5b-8c16-40e6-a9e9-0195c1655b68",
4:         "reactionDuration": {"unit": "s", "value": 10.0},
5:         "modulationGradients": [{
6:             "min": {"unit": "kW/s", "value": -4.0},
7:             "max": {"unit": "kW/s", "value": 4.0}],
8:         "startTime": "2023-05-04T07:00:00+00:00",
9:         "powerStates": [{
10:            "power": {"unit": "kW", "value": 0.0},
11:            "holdingDuration": {"unit": "s", "value": 300}}, {
12:            "power": {"unit": "kW", "value": 80.0},
13:            "holdingDuration": {"unit": "s", "value": 300}}, {
14:            "power": {"unit": "kW", "value": 0.0},
15:            "holdingDuration": {"unit": "s", "value": 300}}, {
16:            "power": {"unit": "kW", "value": 0.0},
17:            "holdingDuration": {"unit": "s", "value": 300}}, {
18:            "power": {"unit": "kW", "value": 0.0},
19:            "holdingDuration": {"unit": "s", "value": 300}}, {
20:            "power": {"unit": "kW", "value": 120.0},
21:            "holdingDuration": {"unit": "s", "value": 300}}, {
22:            "power": {"unit": "kW", "value": 0.0},
23:            "holdingDuration": {"unit": "s", "value": 300}}, {
24:            "power": {"unit": "kW", "value": 0.0},
25:            "holdingDuration": {"unit": "s", "value": 300}}, {
26:            "power": {"unit": "kW", "value": 0.0},
27:            "holdingDuration": {"unit": "s", "value": 300}}, {
28:            "power": {"unit": "kW", "value": 80.0},
29:            "holdingDuration": {"unit": "s", "value": 300}}, {
30:            "power": {"unit": "kW", "value": 0.0},
31:            "holdingDuration": {"unit": "s", "value": 300}}, {
32:            "power": {"unit": "kW", "value": 40.0},
33:            "holdingDuration": {"unit": "s", "value": 300}}, {
34:            [...]
35:        }
36:    }
```

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