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A Recommendation System for Prosumers Based on Large Language Models

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Abstract: As modern technologies, particularly home assistant devices, become more integrated into our daily lives, they are also making their way into the domain of energy management within our homes. Homeowners, now acting as prosumers, have access to detailed information in 15-minute or even 5-minute intervals, including weather forecasts, outputs from Renewable Energy Sources (RES)-based systems, appliance schedules and the current energy balance, which details any deficits or surpluses along with their quantities and the predicted prices on the Local Energy Market (LEM). The goal for these prosumers is to reduce costs while ensuring their home's comfort levels are maintained. However, given the complexity and the rapid decision-making required in managing this information, the need for a supportive system is evident. This is particularly true given the routine nature of these decisions, highlighting the potential for a system that provides personalized recommendations to optimize energy consumption, whether that involves adjusting the load or engaging in transactions with the LEM. In this context, we propose a recommendation system powered by Large Language Models (LLM), Scikit-llm and Zero-Shot Classifiers, designed to evaluate specific scenarios and offer tailored advice for prosumers based on the available data at any given moment. Two scenarios for a prosumer of 5.9 kW are assessed using candidate labels, such as Decrease, Increase, Sell and Buy.

Keywords: LLM; recommendation system; prosumers; energy communities; RES integration

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1. Introduction

Recommendation systems for prosumers in the context of energy management involve sophisticated algorithms designed to analyze various data points, like energy production, consumption patterns, weather forecasts and market prices, to provide personalized advice. These systems aim to optimize energy use, reduce costs and even generate revenue by engaging in energy trading [1]. General types of recommendation systems and technologies that play a significant role for prosumers in the energy sector are usually associated with: (a) Smart Home Energy Management Systems (HEMS). These systems integrate with smart home devices and RES (like solar panels) to optimize energy consumption [2]. They may suggest the best times to use energy-intensive appliances based on the lowest energy prices or highest RES production, contributing to cost savings and increased energy efficiency [3,4]; (b) Demand Response (DR) programs. Utilities often run DR programs that incentivize prosumers to reduce or shift their energy consumption during peak intervals [5,6]. Recommendation systems may alert users to these opportunities, advising when to decrease usage or temporarily store energy in home batteries for later use or sale back to the grid; (c) Predictive analytics for RES production. For prosumers with RES, predictive analytics forecast production levels based on weather data and historical performance. These systems may recommend optimal times to store, use or sell energy, maximizing the financial and environmental benefits of RES installations [7]; (d) Peer-to-Peer (P2P) energy trading platforms. Emerging blockchain and digital platform technologies enable P2P energy trading, allowing prosumers to sell excess renewable energy directly to neighbors or other local consumers [8,9]. Recommendation systems may suggest the best times to buy or sell energy based on market trends and individual consumption patterns; (e)

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LLMs for personalized recommendations. LLMs and other Artificial Intelligence (AI) technologies may analyze vast datasets to provide tailored advice for energy management [10]. These systems consider the unique preferences and behaviors of each prosumer, offering personalized recommendations for optimizing energy usage and participation in LEMs.

There are several innovative technologies and platforms in the energy sector designed to support prosumers, such as (a) HEMS: Nest (Google Nest) well-known for its smart thermostats, which learn schedules and preferences to optimize heating and cooling for energy efficiency [11]; Tesla Energy offers solar panels, Solar Roof and Powerwall battery systems, integrating with a mobile app for energy monitoring and management [12]; (b) DR and energy optimization services: OhmConnect rewards users for saving energy during peak hours, integrating with smart home devices to automate energy savings; AutoGrid uses big data analytics and AI to offer DR, distributed energy resource management and energy storage optimization; (c) P2P energy trading platforms: LO3 Energy (Exergy) is a blockchain platform enabling LEM for P2P energy trading; Power Ledger utilizes blockchain technology to facilitate energy trading, allowing consumers to buy and sell renewable energy directly [13]; (d) Predictive analytics and AI for energy management: Bidgely utilizes AI and Machine Learning (ML) to disaggregate energy data from smart meters, providing personalized energy insights and recommendations [14]; Tibber is a digital electricity supplier that uses AI to optimize electricity consumption for its customers, offering dynamic pricing based on real-time market conditions; (e) Platforms integrating LLMs are a cutting-edge area of development and not yet sufficiently investigated. They have not been applied to prosumers' energy systems and thus we identified a research gap.

While specific platforms and solutions may vary, the integration of Internet of Things (IoT) devices, smart meters, blockchain platforms and advanced analytics forms the backbone of modern recommendation systems for energy prosumers. They have the potential to transform energy markets and consumer behavior in several impactful ways: (a) Empowerment and autonomy for consumers. By providing personalized insights and actionable recommendations, these systems empower consumers, turning passive users into active participants in the energy market [15]; (b) Enhanced energy efficiency. Through optimized scheduling and operation of appliances, heating, cooling and lighting based on real-time data and predictive analytics, these systems significantly reduce wasted energy [16]; (c) Support for RES integration. By efficiently managing the production and consumption of RES, these systems facilitate a smoother integration of RES into the grid; (d) For prosumers, the ability to sell excess energy creates new economic opportunities. P2P trading platforms democratize energy markets, potentially leading to more competitive prices and innovative services [17].

In this paper, we propose a recommendation system that integrates heterogenous datasets and provides advice to prosumers to improve the consumption profile and trade on LEM. The novelty of our approach consists in building datasets and several scenarios that are handled using LLM technology, namely OpenAI and Zero-Shot-GPT classifiers in order to extract meaningful recommendations at high frequency – 5 minutes. These recommendations allow prosumers to adjust consumption (load) or trade on LEMs, by obtaining suggestions driven by data.

The current research is structured in several sections. In the next section, a brief literature review in this field is provided offering a comparison of the research's main focus, outcomes, related fields, involved technologies and whether they include Large Language Models (LLM) or AI. Section 3 is focused on the proposed methodology to handle input datasets and obtain recommendations. In section 4, two scenarios are shown, and their results are presented, whereas in section 5, the insights of these analyses are summarized, and the main conclusions related to recommendation systems based on LLM are drawn.

2. Literature Review

Recent years have witnessed a significant transformation in traditional power systems, primarily due to the extensive integration of RES. This shift has notably included the emergence of residential consumers as prosumers, challenging the conventional operation of electricity markets. This evolution introduces both new challenges and opportunities, leading to the development of new

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Business Models (BM). A key focus is the shift towards a prosumer-centric model, which encourages greater participation of small consumers in power systems. [1] explored the role of recent BM in facilitating the growing influence of prosumers. It covered the definition of prosumers, their regulations, potential market designs in power systems and the technologies enabling the rise of prosumer-driven markets. Furthermore, this research reviewed current and emerging BM and discussed their future implications for modern power systems, along with recommendations to support BM. It concluded that while innovative BM are economically feasible, regulatory barriers may limit their global dissemination.

Furthermore, the energy transition's momentum has necessitated utilities to adopt new strategies for managing local energy demand and supply, owing to the increasing prevalence of prosumers. Addressing this requires an enhanced understanding and management of local energy consumption and production patterns. Small municipal utilities face particular challenges due to their lack of access to advanced modelling and forecasting tools. In this context, [18] proposed a user-centered, visual analytics approach for developing a tool that facilitates interactive and explainable day-ahead forecasting and analysis in prosumer environments. This research included the use of behavioral analysis to examine the connection between consumption patterns and prosumer interaction with energy tools. By employing explainable Machine Learning (ML) methods like kNN and decision trees alongside interactive visualization, utility analysts could better understand consumption influencers and make more accurate demand forecasts under uncertain conditions.

Transactive Energy Management (TEM) introduced a pioneering P2P energy trading concept, aiming for enhanced sustainable energy use by involving local prosumers as key participants in the energy ecosystem [19]. Thus, addressing prosumer concerns is vital for adopting the P2P trading model, where regulatory and policy considerations play a significant role. This research simplified transactive energy to identify its core components and reviewed each to highlight their importance and efficiency. It further discussed enabling technologies for TEM systems and concluded with policy recommendations to accelerate adoption. Additionally, the incorporation of regulatory, security concerns and the use of Non-Fungible Tokens (NFTs) and techniques like ML and IoT were proposed to optimize the TEM process by addressing technological constraints.

The complexity of Multi-Agent Systems (MAS), along with developments in AI and LLMs, has exposed significant gaps in understanding agent behaviors and interactions in dynamic settings. However, traditional game theory's effectiveness is limited by its static and homogeneous assumptions. To address this, [20] introduced an Extended Coevolutionary Theory (ECT) that incorporates coevolutionary dynamics, adaptive learning and LLM-based strategic insights to analyze heterogeneous agent interactions in MAS. This framework transcended game theory by considering diverse interactions, risk preferences and learning abilities among agents. The researchers demonstrated the ECT effectiveness through a simulation that explored cooperation and defection patterns, indicating its potential to foster cooperative behaviors and system robustness. This research highlighted the role of LLMs in enhancing cooperation and strategic resilience in MAS, offering insights into strategic decision-making, adaptive learning and LLM-guided management in complex systems.

Android robots equipped with dialogue systems were further expected to offer advanced conversational capabilities, reliability and hospitality, mimicking human interactions [21]. However, dialogue systems based solely on LLM may produce irrelevant or contradictory responses. The researchers proposed a scenario-based system that breaks down tasks into sub-tasks like summarization and response generation, utilizing LLM more effectively to address these issues. This system, tested in a tourist-spot recommendation competition, showcased superior performance over rule-based systems, highlighting both the potential and challenges of integrating LLM in android dialogue systems, such as computational delays and coordination with robot movements.

ChatGPT and similar LLM-based conversational agents have revolutionized research with their human-like performance. However, their predominantly reactive nature limits their ability to fully understand users and the context, missing out on proactive engagement opportunities like initiating conversations or offering context-aware recommendations. In this context, researchers explored

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methods to endow conversational agents with proactive abilities, covering system design, recent LLM advancements and conversation management strategies [22]. Through interactive exercises, it aimed to enhance agents' proactive interaction capabilities, thereby improving user engagement and safety in conversational applications.

Another research investigated how individuals react to recommendation options from ChatGPT across five studies [23]. Unlike prior studies on choice overload, findings revealed a positive response to a large array of options, showing varied consumer perceptions towards AI-generated recommendations. Further studies highlighted the influence of the recommendation source on consumer reactions and reveal a preference for ChatGPT, especially with numerous options. These insights were important for the design of recommendation systems and understanding user preferences for AI-generated recommendations.

Agenda 2030's Sustainable Development Goals (SDGs) 9 and 11 underscored tourism's pivotal role in addressing global challenges, with ICT transformations propelling e-tourism's global evolution [24]. This research delved into contextual suggestion and recommendation systems within e-tourism, spotlighting approaches and their associated challenges through a systematic literature review of articles published between 2012 and 2020 across major repositories. The review followed a structured protocol, culminating in a taxonomy analysis that categorized the literature into review articles, models/frameworks and applications. The analysis critically evaluated the limitations of current methods, predominantly content-based and collaborative filtering, alongside preference-based ranking and language modeling. Evaluation metrics and test collections for these systems were discussed, highlighting their relevance in achieving SDGs by integrating real-time data and web-based services for sustainable urban planning and development in the tourism sector. These recommendation and guidance systems based on LLMs and AI have been more extensively investigated for medical field [25–27], robotics [28], hospitality and tourism management [29], policy [30], education [31,32], etc.

As for the decision-making models, integrating expert judgments expressed in natural language via sentiment analysis may enrich decision-making processes. The sentiment analysis in recommender systems with multi-person, multi-criteria decision making method leveraged written expert reviews and ratings to inform decisions, addressing the challenge of information overload through intelligent recommender systems [33]. These systems, traditionally based on single-grading algorithms, were enhanced by multi-criteria systems that evaluate various product aspects. This research introduced a model that combines deep learning with multi-criteria decision-making, showcasing its effectiveness in providing accurate recommendations with a sentiment analysis accuracy of 98%. The system's performance, evaluated through precision, recall and F1 scores, marked a significant improvement over previous models, demonstrating deep learning's potential in refining recommender systems' predictive capabilities and user satisfaction. In Table 1, we provide a summary of the information from the analyzed references.

Table 1. Comparative analysis of the investigated references.

Ref.	Objective	Brief Results	Field	Technologies	Includes LLM/AI
[1]	Discuss recent business models as enablers of increasing prosumers' role in power systems.	Comprehensive review of existing and innovative business models, discussion on future roles, and set of recommendations.	Power Systems	Enabling technologies for new prosumer-driven markets.	No
[18]	Develop a tool for day-ahead forecasting and analysis of energy demand in local prosumer environments using a visual analytics approach.	Suggestion of using explainable ML methods and interactive visualization for understanding consumption patterns.	Energy Management	Explainable machine learning (kNN, decision trees), interactive visualization.	Yes
[19]	Explain transactive energy and examine enabling technologies for P2P energy trading involving prosumers.	Discussion on key components of transactive energy systems and policy recommendations for adoption.	Energy Trading	Machine Learning, IoT, NFTs.	Yes

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[20]	Propose an Extended Coevolutionary Theory for modeling strategic interactions in Multi-Agent Systems (MASs) with AI and LLMs.	Development of a simulation environment and visualization of cooperation and defection patterns in MASs.	Multi-Agent Systems	AI, Large Language Models.	Yes
[21]	Develop a hospitable dialogue system for android robots using LLMs in a fine-grained manner.	Achieved high placement in Dialogue Robot Competition 2022, identified challenges with LLMs in android systems.	Robotics, Dialogue Systems	Large Language Models.	Yes
[22]	Review methods for equipping conversational agents with proactive interaction abilities.	Discussion on enhancing conversational agents' proactiveness, including LLM-based advancements.	Conversational Agents	LLMs, Reinforcement Learning with Human Feedback (RLHF).	Yes
[23]	Examine consumer responses to recommendation options generated by ChatGPT.	Found preferences for AI-generated recommendations and distinct consumer reactions to choice overload.	Consumer Behavior	AI-powered language model (ChatGPT).	Yes
[24]	Survey literature on contextual suggestion and recommendation systems in e-tourism.	Identified gaps and critical analysis of current approaches, discussion on implications for SDGs.	E-Tourism	Contextual suggestion systems, recommendation systems.	No
[33]	Present SAR-MCMD method for incorporating expert judgments into recommender systems through sentiment analysis.	Suggested system demonstrated high accuracy and performance metrics in case studies.	Recommender Systems	Deep learning, sentiment analysis.	Yes

This table encapsulates each research's main focus, outcomes, related fields, involved technologies and whether they include Large Language Models (LLM) or AI.

3. Methodology

The input data may consist of the following variables at 15-minute or even 5-minute resolution: weather forecast, RES system output, schedule of the appliances, status: deficit/surplus, quantity of deficit/surplus, predicted prices on Local Energy Market (LEM).

The prosumer may inquire his home assistant and obtain the updated information related to the weather forecast and RES system forecast in a speech format. This is actually a text format conveyed into speech by a home assistant. The entire input at a given moment becomes input for a classification problem that provides a recommendation out of a list of recommendations. Even if the input is not labeled, the indication is given to the prosumer considering a candidate list of recommendations. The potential recommendation output could be to adjust local consumption - increase or decrease, to trade on LEM - sell or buy.

The prosumer's objective function is to minimize the electricity cost, that is the product between consumption level (quantity) and price. The price could be the price from the LEM or the Time-of-Use price from the grid. Several constraints can be formulated. The indoors constraints when sensing the presence of humans could be related to the temperature = 21-23°C during winter season; 23-24°C during summer season.

To formulate the given scenario as a mathematical optimization problem, we will define the input parameters, decision variables, the objective function and the constraints of the problem.

Input parameters:

W_t - Weather forecast at time *t* in text format;

RES_t - Output of RES system at time *t*.

S_t - Schedule of the appliances at time *t*.

D_t - Energy status at time *t* (deficit or surplus).

Q_{D_t} - Quantity of deficit or surplus at time *t*.

P_{LEM_t} - Predicted price on LEM at time *t*.

The input parameters may contain performance metrics such as Self-Sustainability Index (SSI) for prosumers that represents an index for measuring the effectiveness with which individuals or households produce and use their energy, particularly from renewable sources such as photovoltaics

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(PV). The SSI indicates the proportion of a prosumer's energy consumption that is met by their own renewable energy production. The SSI can be described as the percentage of the energy consumption that is both generated and used by the prosumer, showing how much of their energy needs are met independently. SSI thresholds (SST) are depicted in eq. (2).

$$SSI(\%) = \frac{Self\,generated\ energy\ consumed}{Energy\ consumed} \times 100 \tag{1}$$

$$SST_{\Delta d}^{t} = \begin{cases} low, if\ SSI_{\Delta d}^{t} < 0.25 \\ emerging, if\ SSI_{\Delta d}^{t} \geq 0.25\ and\ SSI_{\Delta d}^{t}\ < 0.5 \\ moderate, if\ SSI_{\Delta d}^{t} \geq 0.5\ and\ SSI_{\Delta d}^{t} < 0.75 \\ high, if\ SSI_{\Delta d}^{t} \geq 0.75 \end{cases} \tag{2}$$

The self-sufficiency thresholds for the Self-Sustainability Index (SSI) provide a structured approach to assess the sustainability levels of prosumers based on their energy generation systems. These thresholds classify prosumer sustainability into four distinct categories: (1) Low Sustainability (SSI < 25%) encompasses prosumers who generate a minor portion of their energy needs; (2) Emerging Sustainability (25% ≤ SSI < 50%) describes prosumers who are somewhat sustainable but still rely significantly on external energy sources; (3) Moderate Sustainability (50% ≤ SSI < 75%) applies to prosumers who cover a substantial portion of their energy needs through self-generation; (4) High Sustainability (SSI ≥ 75%) is attributed to prosumers who meet most of their energy requirements from renewable sources.

The Self-Consumption Index (SCI) serves as a measure for prosumers to gauge the proportion of the energy they generate that is directly consumed versus the amount fed back into the grid or left unused. This metric is particularly significant for those with renewable energy setups like PV systems. The SCI calculation is straightforward and involves determining the ratio of self-consumed energy against the total generated.

$$SCI(\%) = \frac{Self\,consumed\ energy}{Generated\ energy} \times 100 \tag{3}$$

$$SCT_{\Delta d}^{t} = \begin{cases} minimal, if\ SCI_{\Delta d}^{t} < 0.25 \\ lower, if\ SCI_{\Delta d}^{t} \geq 0.25\ and\ SCI_{\Delta d}^{t}\ < 0.5 \\ moderate, if\ SCI_{\Delta d}^{t} \geq 0.5\ and\ SCI_{\Delta d}^{t} < 0.75 \\ high, if\ SCI_{\Delta d}^{t} \geq 0.75 \end{cases} \tag{4}$$

Similar to SST, various threshold values of SCI (as in eq. (4) – SCT) have been established to classify the self-consumption levels: (1) High Self-Consumption (SCI ≥ 75%) indicates that a significant majority of the energy produced is used directly by the prosumer, reflecting a high efficiency in power utilization; (2) Moderate Self-Consumption (50% ≤ SCI < 75%) suggests that while a good portion of energy is utilized directly, there is still potential to enhance efficiency; (3) Lower Self-Consumption (25% ≤ SCI < 50%) reflects that a substantial amount of generated energy is not being directly consumed, highlighting potential inefficiencies; (4) Minimal Self-Consumption (SCI < 25%) shows that most of the generated energy is not being used by the prosumer, suggesting a significant misalignment between generation and consumption patterns. These structured recommendations provide a blueprint for prosumers at different levels of self-consumption to optimize their energy systems and enhance sustainability.

Grid Dependence Index (GDI) is a metric designed to quantify how much a prosumer relies on the grid to meet their energy needs. This index is calculated using a specific formula that contrasts the amount of energy consumed from the grid with the total energy consumption of the prosumer. The purpose of the GDI is to highlight how dependent a prosumer is on the power grid.

$$GDI(\%) = \frac{Energy\ purchased\ from\ the\ grid}{Energy\ consumed} \times 100 \tag{5}$$

$$ESI = Energy\ cost\ from\ the\ Grid - Self\ generated\ energy\ cost \qquad (6)$$

The Economic Savings Index (ESI) quantifies the cost savings realized by a prosumer from using their own generated energy versus the alternative of purchasing the equivalent amount of energy from the grid. It effectively measures the economic impact of self-sufficiency in energy production.

Decision variables:

C_t - Consumption adjustment at time t (Increase or Decrease).
T_{LEM_t} - Trading action on LEM at time t (Sell or Buy).

Objective Function:

To minimize the total cost over the considered time horizon T, the objective function can be expressed as:

$$\text{Minimize} \sum_{t=1}^{T} Q_{C_t} \times P_{LEM_t} \qquad (7)$$

where:
Q_{C_t} is the adjusted quantity of consumption or trading (selling/buying) at time t.

Constraints:

1. Energy balance constraint ensures that energy consumption and production are balanced after any adjustments and trading actions.

$$Q_{RES_t} + Q_{T_{LEM_t}} + Q_{C_t} = Q_{D_t} \forall t \qquad (8)$$

where Q_{RES_t} is the energy produced from RES, $Q_{T_{LEM_t}}$ is the quantity traded on the LEM (positive for buying, negative for selling).

2. Indoor temperature constraints maintain indoor temperature within specified ranges according to the season, when human presence is detected.

- Winter: $21^oC \leq T_{indoor} \leq 23^oC$
- Summer: $23^oC \leq T_{indoor} \leq 24^oC$

These constraints imply the adjustment of energy consumption for heating/cooling as part of C_t.
Notes:

- T is the set of discrete 15-minute intervals considered.
- The decision variables C_t and T_{LEM_t} must be chosen such that they satisfy all constraints for each time interval t.

Multiple datasets are usually inserted into the model. The weather forecast is usually a text or a json format data that can be added to the rest of the variables to create a list of string elements that forms the input of a classification problem. To process the text data, ChatGPT showcases an impressive feature: the ability to categorize text without undergoing specific training by leveraging descriptive labels for effective classification. ZeroShotGPTClassifier is a component of *skllm*, designed to streamline the creation of text classification models. It does not require text pre-processing pipelines.

This tool parallels the simplicity and functionality of classifiers found in the scikit-learn library. Essentially, the ZeroShotGPTClassifier taps into ChatGPT's inherent skill to interpret and classify text using labels, offering a straightforward approach to text classification devoid of the usual training hurdles.

The two datasets for the classification problem can be defined as:

$$X = [\text{"}text_1\text{"}, \text{"}text_2\text{"}, \dots \text{"}text_n\text{"}]$$
$$y = [\text{"}label_1\text{"}, \text{"}label_2\text{"}, \dots \text{"}label_n\text{"}] \qquad (9)$$

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The text input may include weather forecast and RES system output, whereas the label can be to adjust consumption and trade on the LEM.

The X and y are split into train and test, and an OpenAI model is applied to train the classifier. The prediction is performed on test data and the results are paired with their input for analysis.

The interesting part lies in the fact that there is no need for prelabeled data to train the model but a set of possible labels to begin with. Thus, the labels list is passed only for prediction. This method unveils opportunities for training models in scenarios where access to pre-labeled datasets might not be available.

The proposed methodology flow is presented in Figure 1.

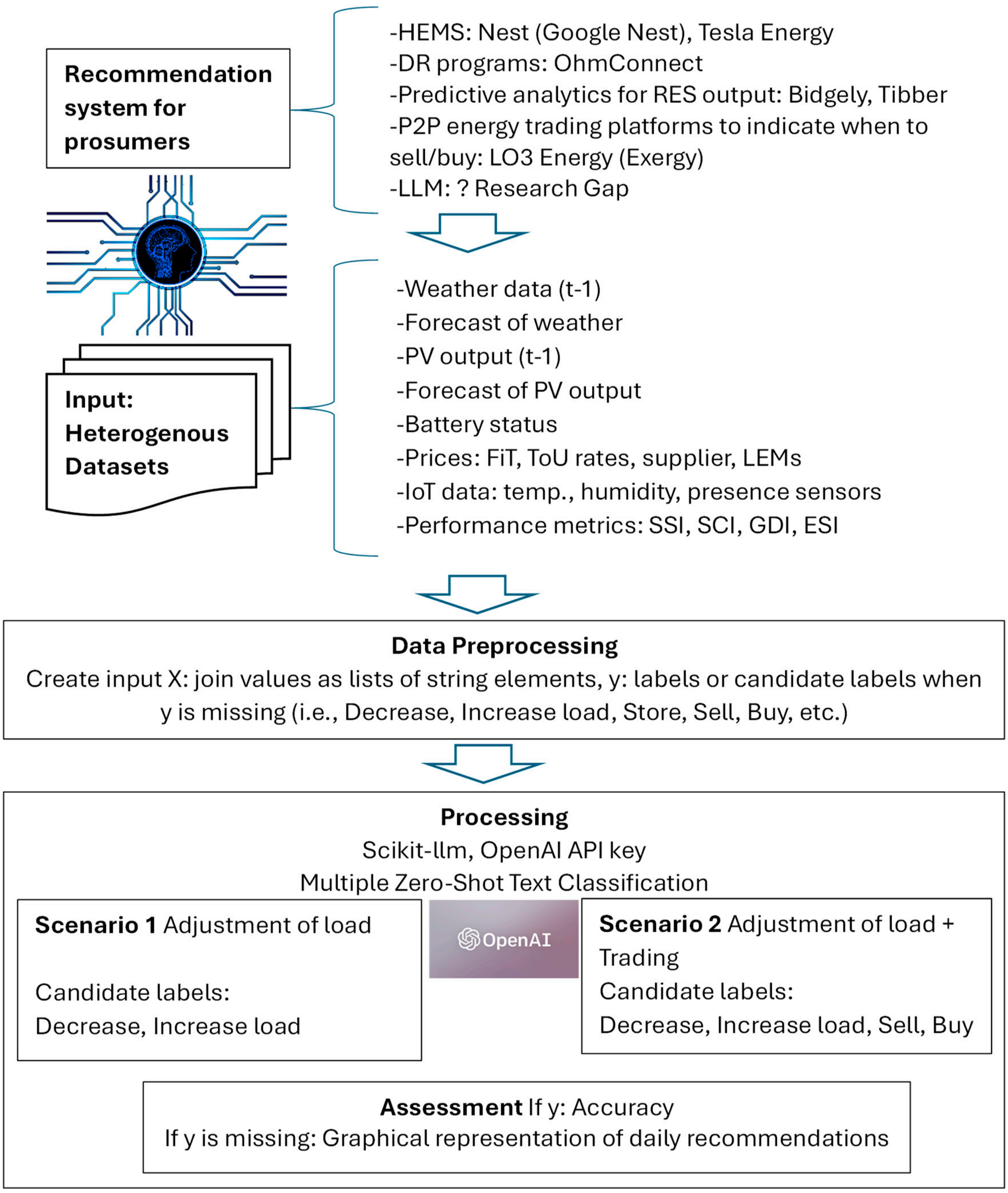

Figure 1. Methodology processing flow.

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4. Results

For simulations, a prosumer with a PV system (of 5.9 kW) output located in rural area is used, as well as weather forecast and the PV system output forecast. Data readings from inverter were recorded at 5-minute intervals, whereas weather and PV system forecast are obtained at 1-hour intervals. The reading date was used to merge the datasets and the missing data due to the different resolutions were filled in using *bfill* for weather forecast and *interpolate* methods for PV system forecast. The following attributes (as in Table 2) are considered to classify the output of the recommendation system using Multilabel Zero-Shot Text Classification.

Table 2. Attributes description of input data.

No.	Attribute	Description
1	READING_DATE	Date and Hour
2	OPEN_WEATHER	Weather forecast
3	POWER_FORECAST	PV system output forecast
4	POWER_LOAD	Consumption power
5	POWER_GEN	Generated power
6	POWER_BAT	Power extracted from Battery
7	POWER_GRID	Power extracted from Grid
8	SD_CAPACITY	Battery capacity State of Charge
9	LOAD_PERCENT	Percentage of the load from rated power of the PV system
10	VPV	Voltage of the PV system
11	IPV	Current of the PV system

ChatGPT demonstrates a notable ability: it can categorize text without dedicated training, using merely descriptive labels to efficiently perform this task. Introducing the ZeroShotGPTClassifier from Scikit-LLM, this tool allows users to easily create a text classification model comparable to other classifiers in the scikit-learn library. Essentially, the ZeroShotGPTClassifier leverages ChatGPT's distinctive capability to comprehend and classify text based on labels, streamlining the text classification process and eliminating the need for conventional training. The most important library is scikit-llm that has to be imported, but depending on the environment, other libraries can be required (such as cython, watermark, skllm.config).

The compelling part is that there is no need for prelabeled data to train the model. Only a list of potential candidate labels is required. This method allows for the training of models even in scenarios where one lacks access to pre-existing labeled datasets.

The key difference between zero-shot and multilabel zero-shot classification is simply the instantiation of the MultiLabelZeroShotGPTClassifier class. For multilabel zero-shot classification, one defines the maximum number of labels to assign to each sample, such as specifying max_labels=3. This parameter gives the ability to control the number of labels the model can assign to a text sample during the classification process.

For simulation, a free instance of Google Collaboratory was used. In the first scenario, when the candidate labels are candidate_labels = ["Increase", "Decrease"], the following output of 5-minute recommendations from 3rd to 6th of August 2023 with the two potential labels are obtained (as in Figure 2). The input data is extracted from a larger dataset from 1st of August until 15th of August 2023, and consists of 4,301 rows and 11 columns. The graphical representation is significant as y test is missing, therefore accuracy cannot be calculated.

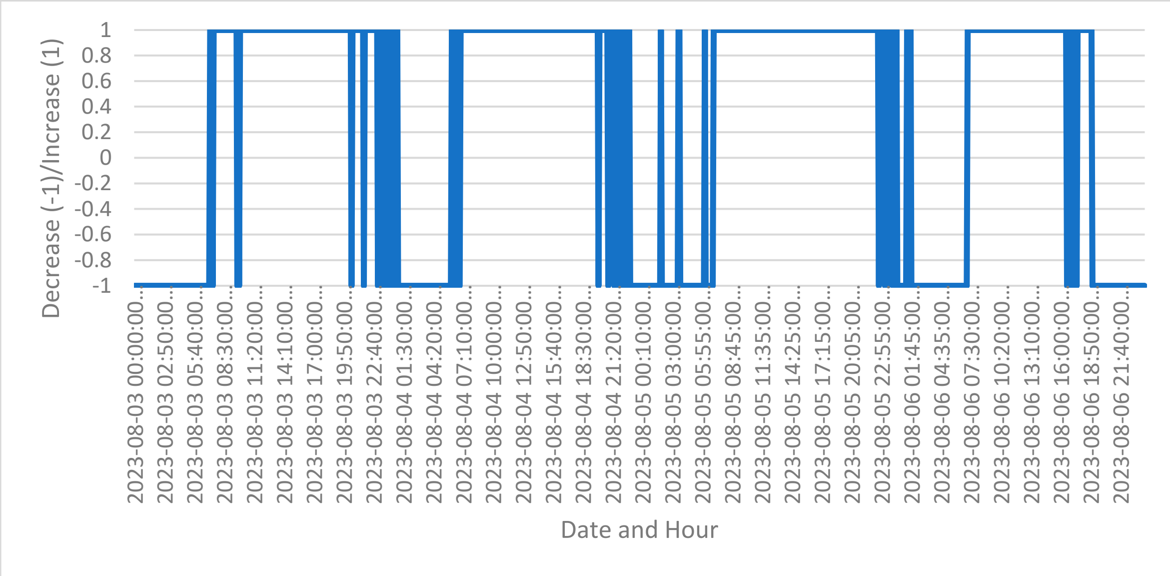

Figure 2. Output of 5-minute recommendations from 3rd to 6th of August 2023 using 2 potential labels.

This visualization shows the distribution and frequency of the recommendations "Increase" and "Decrease" load across the specified timeframe. Each row represents a different 5-minute interval with a recommendation derived from the ZeroShotGPTClassifier. The effectiveness of the ZeroShotGPTClassifier in this scenario largely depends on the capability of the underlying model (e.g., ChatGPT) to interpret the context accurately.

The input data format is structured in a way that is compatible with the classifier, typically requiring preprocessing to extract relevant textual information from each time interval. Each input data was joined into a list of string elements. This first scenario effectively showcases how advanced natural language processing tools can be leveraged for dynamic and context-sensitive decision-making processes in a highly granular manner.

Figure 2 shows 5-minute interval recommendations from August 3rd to August 6th, 2023, with the potential labels "Increase" (1) and "Decrease" (-1). An interpretation of the chart is provided: Y-axis represents recommendations as binary outcomes. The value 1 indicates a recommendation to "Increase" load and -1 indicates a recommendation to "Decrease" load, whereas X-axis shows dates and times, marked at 5-minute intervals over four days, from August 3rd to August 6th, 2023. It shows alternating periods where the recommendation switches between "Increase" and "Decrease" load. This suggests a dynamic situation where conditions or factors evaluated at these intervals are frequently changing. Some hours (like night and day hours) show a consistent recommendation (either to increase or decrease), which suggest more stable or predictable conditions during these periods. Other periods, notably around midday across the days, show more frequent switches between "Increase" and "Decrease" load. This reflects more volatile or variable weather conditions needing quick responses. Each day might have slightly different patterns, which are influenced by different external factors not shown on the chart but affecting the recommendations. This chart provides a clear, quick reference for actions recommended at regular intervals, reflecting an automated, data-driven decision process. In Table 2, sample data for the first scenario is provided.

Table 2. Sample data for the first scenario.

Input	Predicted_Labels
2023-08-01 00:05:00 {"dt": "2023-07-31 23:00:00", "pop": 0.29, "uvi": 0, "temp": 22.69, "clouds": 92, "weather": [{"id": 804, "icon": "04n", "main": "Clouds", "description": "overcast clouds"}], "humidity": 77, "pressure": 1011, "wind_deg": 71, "dew_point":	['Decrease', '']

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	18.45, "wind_gust": 1.78, "feels_like": 23.03, "visibility": 10000, "wind_speed": 1.78}		3.5 108 0 109 0.0 87 2 0.0 0.0
2023-08-01 00:10:00	{"dt": "2023-07-31 23:00:00", "pop": 0.29, "uvi": 0, "temp": 22.69, "clouds": 92, "weather": [{"id": 804, "icon": "04n", "main": "Clouds", "description": "overcast clouds"}], "humidity": 77, "pressure": 1011, "wind_deg": 71, "dew_point": 18.45, "wind_gust": 1.78, "feels_like": 23.03, "visibility": 10000, "wind_speed": 1.78}	['Decrease', '']	3.4444444444444446 102 0 109 0.0 86 2 0.0 0.0
2023-08-01 00:15:00	{"dt": "2023-07-31 23:00:00", "pop": 0.29, "uvi": 0, "temp": 22.69, "clouds": 92, "weather": [{"id": 804, "icon": "04n", "main": "Clouds", "description": "overcast clouds"}], "humidity": 77, "pressure": 1011, "wind_deg": 71, "dew_point": 18.45, "wind_gust": 1.78, "feels_like": 23.03, "visibility": 10000, "wind_speed": 1.78}	['Decrease', '']	3.388888888888889 118 0 109 0.0 86 2 0.0 0.0
2023-08-01 00:20:00	{"dt": "2023-07-31 23:00:00", "pop": 0.29, "uvi": 0, "temp": 22.69, "clouds": 92, "weather": [{"id": 804, "icon": "04n", "main": "Clouds", "description": "overcast clouds"}], "humidity": 77, "pressure": 1011, "wind_deg": 71, "dew_point": 18.45, "wind_gust": 1.78, "feels_like": 23.03, "visibility": 10000, "wind_speed": 1.78}	['Decrease', '']	3.3333333333333333 111 0 109 0.0 86 2 0.0 0.0
2023-08-01 12:05:00	{"dt": "2023-08-01 12:00:00", "pop": 0, "uvi": 6.45, "temp": 29.53, "clouds": 1, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 42, "pressure": 1010, "wind_deg": 249, "dew_point": 15.27, "wind_gust": 0.61, "feels_like": 29.37, "visibility": 10000, "wind_speed": 0.8}	['Increase', '']	4299.0 98 125 -19 0.0 98 2 321.5 2.5
2023-08-01 12:10:00	{"dt": "2023-08-01 12:00:00", "pop": 0, "uvi": 6.45, "temp": 29.53, "clouds": 1, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 42, "pressure": 1010, "wind_deg": 249, "dew_point": 15.27, "wind_gust": 0.61, "feels_like": 29.37, "visibility": 10000, "wind_speed": 0.8}	['Increase', '']	4292.0 107 117 -19 0.0 98 2 320.4 2.3
2023-08-01 12:15:00	{"dt": "2023-08-01 12:00:00", "pop": 0, "uvi": 6.45, "temp": 29.53, "clouds": 1, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 42, "pressure": 1010, "wind_deg": 249, "dew_point": 15.27, "wind_gust": 0.61, "feels_like": 29.37, "visibility": 10000, "wind_speed": 0.8}	['Increase', '']	4285.0 98 118 -19 0.0 98 2 320.7 2.3
2023-08-01 12:20:00	{"dt": "2023-08-01 12:00:00", "pop": 0, "uvi": 6.45, "temp": 29.53, "clouds": 1, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 42, "pressure": 1010, "wind_deg": 249, "dew_point": 15.27, "wind_gust": 0.61, "feels_like": 29.37, "visibility": 10000, "wind_speed": 0.8}	['Increase', '']	4278.0 110 123 -19 0.0 97 2 319.1 2.4

For the second scenario, we added the prices for selling and buying energy from local market or supplier (as in Table 3). Price_buy_from_grid is a Time-of-Use tariff that is designed to encourage load at the off-peak hours. The candidate labels are candidate_labels = ["Increase", "Decrease", "Sell", "Buy"].

Table 3. Additional attributes for the second scenario-sample data.

Additional Attributes	Price_sell_to_grid	Price_buy_from_grid	Price_sell_to_LEM	Price_buy_from_LEM
EuroCents	9	14	11	12.5

The results of the simulation for the second scenario, that took place for the same interval, are presented in Figure 3.

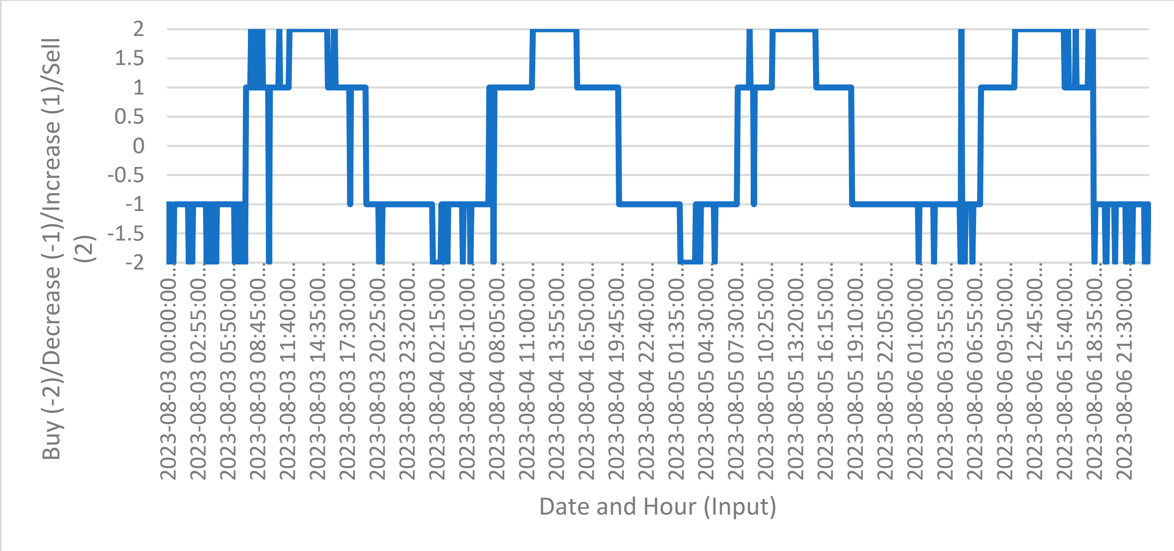

Figure 3. Output of 5-minute recommendations from 3rd to 6th of August 2023 using 4 potential labels.

Figure 3 shows recommendations over a range of values from August 3rd to August 6th, 2023, labeled on the y-axis as Buy (-2)/ Decrease (-1)/Increase (1)/Sell (2). An interpretation is provided: Y-axis extends beyond binary outcomes to include values of 2, 1, -1 and -2. The values 1 and -1 still correspond to "Increase" and "Decrease" load recommendations, while 2 and -2 correspond to stronger recommendations like "Buy" and "Sell" respectively, whereas X-axis displays dates and times across the specified range, marked at 5-minute intervals. Positive values (2 and 1) indicate varying degrees of bullish recommendations. A value of 2 (Sell) suggests a strong action, while a value of 1 (Increase) suggests a moderate action. Negative values (-1 and -2) indicate varying degrees of bearish recommendations. A value of -1 (Decrease) suggests a moderate action, while a value of -2 (Buy) suggests a strong action. The chart shows significant fluctuations between the values, suggesting rapidly changing conditions or responses to new data. There are periods where the recommendations stay constant for a series of intervals, indicating stable conditions or sustained decisions based on the underlying data. Some intervals show sharp transitions from strong to moderate recommendations or vice versa, which indicate volatile conditions or moments of significant change in metric or data the model is assessing. Sample data for the second scenario is provided in Table 4.

Table 4. Sample data for the second scenario.

Input	Predicted_ Labels
2023-08-03 00:05:00 {"dt": "2023-08-03 00:00:00", "pop": 0, "uvi": 0, "temp": 22.85, "clouds": 59, "weather": [{"id": 803, "icon": "04n", "main": "Clouds", "description": "broken clouds"}], "humidity": 74, "pressure": 1009, "wind_deg": 46, "dew_point": 17.97, "wind_gust": 3.43, "feels_like": 23.12, "visibility": 10000, "wind_speed": 2.42} 14.166666666666666 76 0 69 0.0 86 2 0.0 0.0 0.09 0.14 0.11 0.125	['Buy', '', '']
2023-08-03 00:10:00 {"dt": "2023-08-03 00:00:00", "pop": 0, "uvi": 0, "temp": 22.85, "clouds": 59, "weather": [{"id": 803, "icon": "04n", "main": "Clouds", "description": "broken clouds"}], "humidity": 74, "pressure": 1009, "wind_deg": 46, "dew_point": 17.97, "wind_gust": 3.43, "feels_like": 23.12, "visibility": 10000, "wind_speed": 2.42} 13.333333333333334 78 0 74 0.0 86 2 0.0 0.0 0.09 0.14 0.11 0.125	['Buy', '', '']
2023-08-03 00:15:00 {"dt": "2023-08-03 00:00:00", "pop": 0, "uvi": 0, "temp": 22.85, "clouds": 59, "weather": [{"id": 803, "icon": "04n", "main": "Clouds", "description":	['Decrease', '', '']

"broken clouds"}], "humidity": 74, "pressure": 1009, "wind_deg": 46, "dew_point": 17.97, "wind_gust": 3.43, "feels_like": 23.12, "visibility": 10000, "wind_speed": 2.42} 12.5 75 0 74 0.0 85 2 0.0 0.0 0.09 0.14 0.11 0.125	
2023-08-03 00:20:00 {"dt": "2023-08-03 00:00:00", "pop": 0, "uvi": 0, "temp": 22.85, "clouds": 59, "weather": [{"id": 803, "icon": "04n", "main": "Clouds", "description": "broken clouds"}], "humidity": 74, "pressure": 1009, "wind_deg": 46, "dew_point": 17.97, "wind_gust": 3.43, "feels_like": 23.12, "visibility": 10000, "wind_speed": 2.42} 11.666666666666666 71 0 74 0.0 85 1 0.0 0.0 0.09 0.14 0.11 0.125	['Decrease', '', '']
2023-08-03 12:05:00 {"dt": "2023-08-03 12:00:00", "pop": 0, "uvi": 7.53, "temp": 33.42, "clouds": 0, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 35, "pressure": 1010, "wind_deg": 239, "dew_point": 15.87, "wind_gust": 3.01, "feels_like": 33.4, "visibility": 10000, "wind_speed": 2.04} 4138.25 96 132 -19 0.0 98 2 317.9 2.6 0.09 0.14 0.11 0.125	['Sell', '', '']
2023-08-03 12:10:00 {"dt": "2023-08-03 12:00:00", "pop": 0, "uvi": 7.53, "temp": 33.42, "clouds": 0, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 35, "pressure": 1010, "wind_deg": 239, "dew_point": 15.87, "wind_gust": 3.01, "feels_like": 33.4, "visibility": 10000, "wind_speed": 2.04} 4148.5 105 104 -19 0.0 98 2 317.7 2.0 0.09 0.14 0.11 0.125	['Sell', '', '']
2023-08-03 12:15:00 {"dt": "2023-08-03 12:00:00", "pop": 0, "uvi": 7.53, "temp": 33.42, "clouds": 0, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 35, "pressure": 1010, "wind_deg": 239, "dew_point": 15.87, "wind_gust": 3.01, "feels_like": 33.4, "visibility": 10000, "wind_speed": 2.04} 4158.75 89 117 -19 0.0 98 2 317.0 2.3 0.09 0.14 0.11 0.125	['Sell', '', '']
2023-08-03 12:20:00 {"dt": "2023-08-03 12:00:00", "pop": 0, "uvi": 7.53, "temp": 33.42, "clouds": 0, "weather": [{"id": 800, "icon": "01d", "main": "Clear", "description": "clear sky"}], "humidity": 35, "pressure": 1010, "wind_deg": 239, "dew_point": 15.87, "wind_gust": 3.01, "feels_like": 33.4, "visibility": 10000, "wind_speed": 2.04} 4169.0 101 126 -19 0.0 97 2 316.9 2.5 0.09 0.14 0.11 0.125	['Sell', '', '']

The recommendations depicted in Figure 3 are based on several sets of input data attributes that influence the decision-making process for actions such as “Buy”, “Sell”, “Increase” and “Decrease”. These attributes potentially impact the recommendations: (1) READING_DATE (Date and Hour) serves as the temporal marker for each data point, aligning recommendations with specific times and showing patterns over daily cycles; (2) OPEN_WEATHER (Weather forecast) directly impacts PV system output predictions and can influence decisions about power management based on anticipated solar generation capacity; (3) POWER_FORECAST (PV system output forecast) is a critical input for planning whether to store energy, sell surplus or manage deficits, impacting “Increase” and “Sell” decisions; (4) POWER_LOAD (Consumption Power) determines how much power is needed at any given time, influencing “Decrease” or “Increase” in load management; (5) POWER_GEN (Generated Power) is the actual power generation data influences real-time decisions on whether there is a surplus to sell or a need to draw from other sources; (6) POWER_BAT (Power extracted from Battery) indicates decisions on whether to draw power from the battery or to charge it depend on other power availability and demands; (7) POWER_GRID (Power extracted from Grid) indicates the usage of grid power indicates whether to buy additional power or manage with generated or stored power; (8) SD_CAPACITY (Battery capacity State of Charge) affects decisions on battery charging or discharging strategies; (9) LOAD_PERCENT (Percentage of the load from rated power of the PV system) indicates how heavily the system is loaded compared to its capacity, influencing load management strategies; (10) VPV (Voltage of the PV system) and (11) IPV (Current of the PV system) inform about the operational status and efficiency of the PV system, affecting decisions related to system load and generation management. Additional attributes, such as (12) Price_sell_to_grid also known as Feed-in-Tariff, (13) Price_buy_from_grid usually tariff rates that

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takes into account the consumption moment, (14) Price_sell_to_LEM and (15) Price_buy_from_LEM are economic factors and play a critical role, as the decision to buy or sell power (either to/from the grid or a LEM) is influenced by these prices.

The cost-effectiveness of each action (buying or selling) dictates whether it is more advantageous to generate, store or purchase power. Each recommendation, whether it is "Decrease" or "Increase" in load, or "Sell" and "Buy" in terms of energy transactions, is derived from analyzing these diverse data inputs. The complexity and variability of these attributes underpins the advanced analytics required to optimize energy management in real-time.

5. Conclusions

This paper outlines the deployment of modern technologies such as home assistant devices and recommendation systems in energy management, specifically tailored for homeowners who also act as prosumers. These systems utilize detailed data collected at short intervals, including weather forecasts, energy production and consumption patterns to provide real-time energy management solutions. The goal is to optimize energy consumption, reduce costs and maintain comfort by dynamically adjusting energy usage or participating in energy trading through LEMs.

The proposed methodology outlines a recommendation system for prosumers. The system uses a variety of data inputs and processes to optimize both energy usage and trading decisions. Alternative systems are diverse, including Home Energy Management Systems like Nest or Tesla Energy, Demand Response programs such as OhmConnect and predictive analytics for renewable energy sources output from platforms like Bigdely and Tibber. It may also include data from P2P energy trading platforms, weather and PV output forecasts, battery status and pricing information including feed-in tariffs, time-of-use rates and LEM prices. Additional inputs may include Internet of Things data such as temperature, humidity and sensor data along with performance metrics like the Self-Sustainability Index, Self-Consumption Index, Grid Dependence Index, Economic Savings Index.

In the data preprocessing stage, several inputs are prepared and combined into a usable format. For instance, values are joined as lists of strings, or labels are processed for candidate actions when labels are missing. The processing stage involves using tools like Scikit-llm and the OpenAI API for natural language or other data processing tasks. It also includes multiple zero-shot text classification to determine actions. The proposed recommendation system supports multiple operational scenarios. The first scenario involves adjusting the load dynamically, increasing or decreasing energy load based on real-time data and forecasts. The second scenario adds the capability to make real-time decisions about energy trading, such as selling excess energy or buying additional energy as needed. The final step in the system involves assessing the accuracy of the outputs: y predicted is compared with y test. If key data (y) is missing, the system provides a graphical representation of daily recommendations.

For simulations, a prosumer with a 5.9 kW PV system located in a rural area utilizes a sophisticated recommendation system to optimize energy management based on various data inputs and machine learning and LLM techniques. The system processes data from multiple sources including inverter readings, weather forecasts and PV output forecasts to inform real-time decision-making. The data collected includes inverter readings at 5-minute intervals and forecasts at 1-hour intervals. Due to the varying resolutions, data merging is conducted based on reading dates, with missing data points filled using backward fill for weather forecasts and interpolation for PV system forecasts. Attributes such as date, weather forecast, power forecasts, consumption, generated power, battery status, grid dependency and more are considered to classify the output of the system using Multilabel Zero-Shot Text Classification. This classification approach leverages the ZeroShotGPTClassifier from Scikit-llm, allowing the system to categorize data without pre-existing labeled datasets. The classifier uses descriptive candidate labels to understand and assign categories, making it particularly useful in dynamic and data-rich environments.

The data spanning from August 1st to 15th, 2023, with 4,301 data points was processed to predict actions such as "Increase" or "Decrease" energy load. A graphical representation of these recommendations over several days illustrates the decision-making process of the system. Recommendations are made every five minutes, reflecting the rapid analysis and response capabilities of the system. Further expanding the simulation to include energy trading, additional labels such as "Buy" and "Sell" are introduced, taking into account the prices for energy transactions. This allows the system not only to manage energy efficiently but also to engage in energy trading based on real-time market conditions. The effectiveness of the ZeroShotGPTClassifier and the entire system is depicted through detailed graphs showing recommendations over time. These visualizations demonstrate how the system adapts to changing conditions, recommending different actions based on a complex set of input attributes. These attributes include operational data from the PV system, the state of battery charge and economic factors such as local energy prices.

This research highlights the integration of Large Language Models (LLM) and other algorithms in developing novel recommendation systems without using complex pipelines for data pre-processing. These systems analyze various data points to offer personalized advice, aiming to efficiently manage energy production and consumption, engage in profitable energy trading and utilize incentives such as Demand Response programs. Predictive analytics for renewable energy production and peer-to-peer energy trading platforms also play crucial roles in enhancing the financial and environmental efficiency of energy systems.

Furthermore, the use of artificial intelligence, including LLMs, to analyze and process vast datasets without the need for pre-labeled data represents a significant advancement in recommendation systems. This approach allows for the development of flexible, adaptive systems that can handle complex, dynamic data sets in real-time, providing tailored recommendations to prosumers. These novel systems support the integration of renewable energy sources and potentially transform energy markets through innovative services.

Author Contributions: Simona-Vasilica Oprea: Conceptualization, Validation, Formal analysis, Investigation, Writing – Original Draft, Writing – Review and Editing, Visualization, Project administration. Adela Bâra: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review and Editing, Visualization, Supervision.

Ethical approval. Not applicable.

Informed consent. Not applicable.

Data availability statement. The data will be made available upon reasonable request.

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