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Consumer-Oriented Recommendation System For Demand Side Management

Master's thesis

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TALLINNA TEHNIKAÜLIKOOL
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Tarbijale Suunatud Soovituste Süsteem Nõudpoolseks Juhtimiseks

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Author's declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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Abstract

Effective demand-side management has become a necessity with the rising demand for energy across the globe. The incorporation of smart grid technologies and information technologies generates an abundant amount of data that can be used to extract useful information for utilities and consumers. Utilities send a personalized recommendation to a particular consumer based on their energy consumption behavior. One of the effective methods of demand-side management is using a recommendation system. Different methods of recommendations have been discussed in this thesis in detail.

The author has categorized energy consumers in three clusters using the K-means clustering method and discussed various clustering methods also. Categorized data of energy consumers are used to generate recommendations for energy consumers. The proposed recommendation system is based on a collaborative filtering method as preferences of other consumers have been taken into account for recommending energy-saving tips for a consumer. The recommendation results have been described and put into tables. In the future, advancements in emerging information technologies such as AI, Machine learning, IoT, etc., will make recommendation systems smarter.

This thesis is written in the English language and is 52 pages long, including 5 chapters, 14 figures and 5 tables.

Annotatsioon

Tarbijale Suunatud Soovituste Süsteem Nõudpoolseks Juhtimiseks

Tõhus nõudlusepoolne juhtimine on muutunud hädavajalikuks seoses kasvava energianõudlusega kogu maailmas. Nutikate võrgutehnoloogiate ja infotehnoloogiate kaasamine loob suurel hulgal andmeid, mida saab kasutada kommunaalteenuste ja tarbijate jaoks kasuliku teabe hankimiseks. Kommunaalettevõtted saadavad konkreetsele tarbijale isikupärastatud soovituse, mis põhineb tema energiatarbimise käitumisel. Üks tõhusamaid nõudlusepoolse juhtimise meetodeid on soovitussüsteemi kasutamine. Käesolevas lõputöös on üksikasjalikult käsitletud erinevaid soovituste andmise meetodeid.

Autor on K-keskmiste klasterdamismeetodit kasutades liigitanud energiatarbijad kolme klastrisse ning käsitlenud ka erinevaid klasterdamismeetodeid. Energiatarbijatele soovituste koostamiseks kasutatakse kategoriseeritud energiatarbijate andmeid. Kavandatav soovitussüsteem põhineb koostööl põhineval filtreerimismeetodil, kuna tarbijale energiasäästunõuannete soovitamisel on arvesse võetud ka teiste tarbijate eelistusi. Soovituste tulemused on kirjeldatud ja toodud tabelitesse. Tulevikus muudavad edusammud uutes infotehnoloogiates, nagu AI, masinõpe, asjade internet jne, soovitussüsteemid targemaks.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 52 leheküljel, 5 peatükki, 14 joonist, 5 tabelit.

List of abbreviations and terms

DSM	Demand side management
IoT	Internet of things
DR	Demand response
DCT	Digital comparison tools
EM	Energy management
PRS	Personalised recommendation system
NILM	Non-intrusive load monitoring
AMI	Advanced metering infrastructure
HR	Hybrid recommendation
NDCG	Normalized Discounted Cumulative Gain
AMR	Automatic meter reading
AMM	Automatic meter management
HEMS	Home energy management system
OPF	Optimal power flow
RSME	Root mean squared error

Table of contents

List of figures

List of tables

1 Introduction

The increasing problem of global warming coupled with expanding need for energy creates a need for demand-side management (DSM) solutions. Additionally, incorporating the latest technologies in the power sector, such as smart grid technologies, which support the production of a large amount of data, provides the consumer the opportunity to optimize their energy operation (management). This fast-growing need for energy has created a need for effective demand-side management.

Over the last few years, the global use of energy has risen exponentially. Specifically, the construction industry consumes more than 40% of all energy produced globally [4]. This substantial energy demand has led to an increase in energy prices. The figure below depicts electric prices for household consumers in the first half of 2021. Electricity rates for household consumers in the EU were highest in Germany, followed by Denmark, Belgium, and Ireland. Hungary, Bulgaria, and Malta were the countries with the lowest electricity prices in the EU in the first half of 2021. Electricity price in Hungary is one-third of electricity price in Germany.

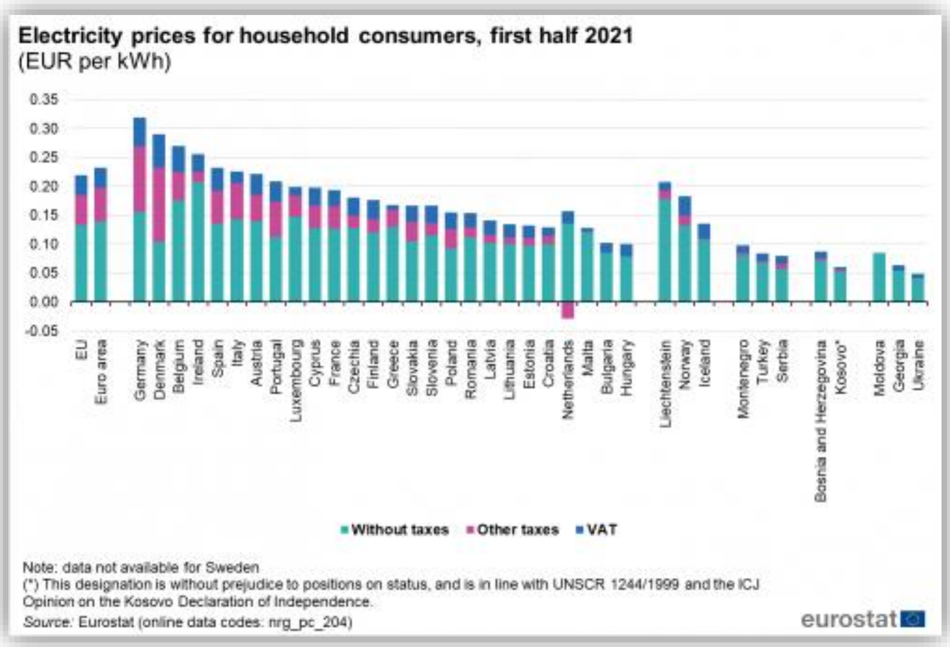

Figure 1. Electricity costs for household consumers in the EU.

Electricity is vital to modern society, and power outages and disruptions have a considerable detrimental influence on people's quality of life. The present energy management problems include reducing the power supply-demand gap and strengthening power supply reliability. Thus, there is a necessity for efficient management of the power supply and supply of high-quality and reliable electric energy to the customers [10].
To deal with the ever-growing demand for energy can only be controlled via proper implementation of demand response procedures applied on the load side. This demand response is a type of DSM. DSM techniques involve the implementation of the plan and observing such activities of electric utilities by which it is possible to encourage users to regulate their level and pattern of electricity usage [9]. The figure below depicts demand-side energy management from paper [23].

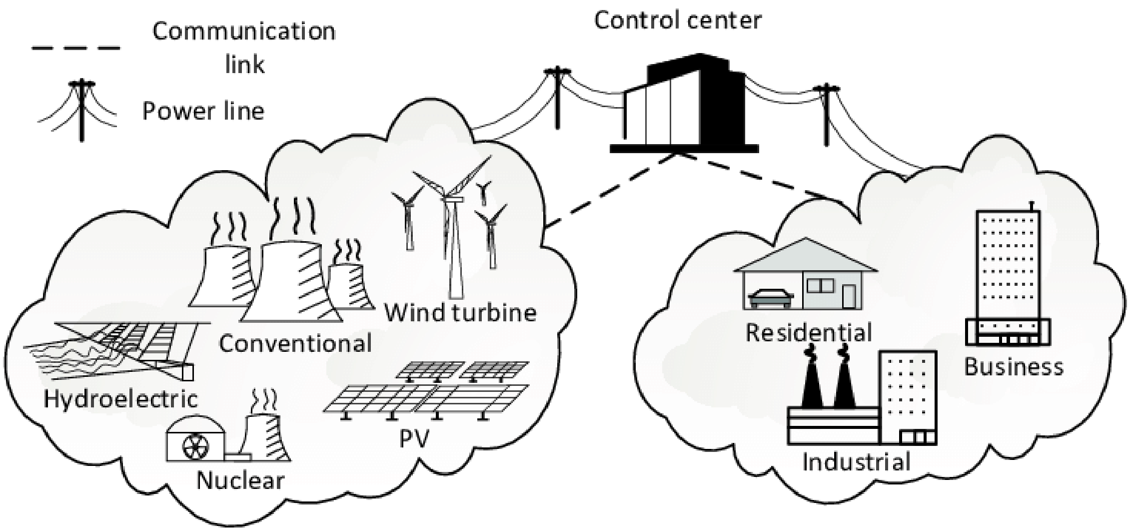

Figure 2. Demand-side energy management [23]

Each household has a different energy consumption pattern since consumption depends on numerous factors such as the number of appliances and the lifestyle of people living there. Utilities can get information about the different groups of energy consumers, and using this useful information, utilities recommend specific recommendations to a user. This helps both utilities and consumers to save energy and control energy demand fluctuation at peak hours of the day.

To solve the previously identified problem, this thesis attempts to implement a DSM solution using recommendation provision enabled by categorization consumers' energy profiles. A set of data is collected from the demand side, need to be analyzed, and generate useful information to set up an efficient demand-side management system. The extracted information help in observing consumer energy utilization pattern and recommend energy-efficient recommendations.

1.1 Background

Exponential rise in consumption of energy along with the evolution of modern advancement, effective utilization of available energy resources has become a grave concern in today's era.

DSM encompasses everything done on the demand side of an energy system, from replacing aging incandescent light bulbs with compact fluorescent lights (CFLs) to establishing a complex dynamic load management system. Some primary objectives of demand-side management are peak clipping, valley filling, load shifting, etc as shown in figure 4.

In the past few years, recommender systems have considerably evolved along with the advancements in technologies such as the internet of things (IoT) and artificial intelligence (AI). Additionally, various forms of data, including social, local, and personal information, have been incorporated into these systems, enhancing the applicability and performance of recommendation systems. Researches are being done focusing on efficiency in the building sector, where recommendation systems play a vital role by encouraging energy-saving actions and lessening carbon emissions [4].

A recommendation is one way to send energy-saving recommendations to energy consumers based on some information collected by utilities from smart devices used on the utilities' side and consumer's side. Recommendation is made non-intrusively, and there are various methods of recommendations. Popular and widely used recommendation methods are content-based, collaborative filtering, and hybrid approaches.

1.2 Statement of the Problem

With the growing need for energy in the past few decades, utilities have observed instability in demand and supply of energy, particularly in peak hours in a day. Energy utilities cannot predict how climatic conditions will vary in the upcoming days because electrical load is dependent on various elements, some of which are nonlinear, such as weather conditions related to global warming. Once the weather is hot and the humidity level rises, the amount of power consumed rises due to the increased usage of air conditioners to maintain a comfortable temperature. Similarly, if the weather is colder and less humid, the demand for heating will rise. Sudden and high demand for energy at a certain time leads to peak demand. Utilities have to bear a huge cost of production and maintenance of power grids due to the fluctuation of energy demands in peak hours and off-peak hours. A recommendation system is one way to deal with this varying demand for energy and curb peak demand. There is a need for a system that can support utilities in finding groups of various consumers based on their consumption behavior and recommend them energy-saving recommendations.

There is a need for smart meter awareness campaigns, which is an important component of the home energy management system, along with making this component cost-effective. In an earlier proposed method require human intervention, and there is a lack of information about practical implementations. Analysis of energy consumption data and finding different clusters of energy consumers based on their consumption behavior by microgrid operator is not covered in past researches. This cluster of energy consumers assists microgrid utilities in sending more personalized recommendations to energy consumers.

In this thesis, considering above mentioned problems, different groups of energy consumers has been identified, and energy-saving recommendation is generated accordingly. Moreover, RSME is calculated for similarity scores generated by the recommendation system to check system accuracy.

1.3 Scope of the project

The proposed system will not only assist utilities to stabilize their demand and supply but also electricity consumer can reduce their bills. Different clusters of the consumer has been identified based on their consumption pattern in peak hours. On the basis of this categorization, a recommendation system based on a collaborative method will recommend energy-saving recommendations to these consumers. Additionally, Consumers will be motivated to alter their consumption behavior in peak hours of the day.

1.4 Aim and Objective of the project

The main goal of this project thesis is to find different clusters of consumers based on their electricity consumption throughout the day and develop a recommendation system. Energy consumers are grouped into 3 clusters i.e. high, medium, and low energy consumers. This data is used in a recommendation system that recommends certain energy-saving recommendations to a particular consumer.

In past research papers, different methods of demand-side management and recommendation methods have been discussed. In this research, the novelty is that energy consumers are grouped in a certain group based on their energy utilization behavior. This data is used in a recommendation system to generate a personalized energy-saving recommendation for energy consumers.

Objectives

- Analyze the daily consumption pattern of electric energy consumer
- Find three different groups of energy consumers based on their consumption behaviour
- Calculate load factor for energy consumed at different hours
- Apply k-means algorithm for generating 3 clusters of consumers and scoring
- Find correlation between the recommendations using cosine similarity
- Generate energy-saving recommendations for energy consumers
- Calculate RSME for the results
- Discuss the results

Overview of proposed method

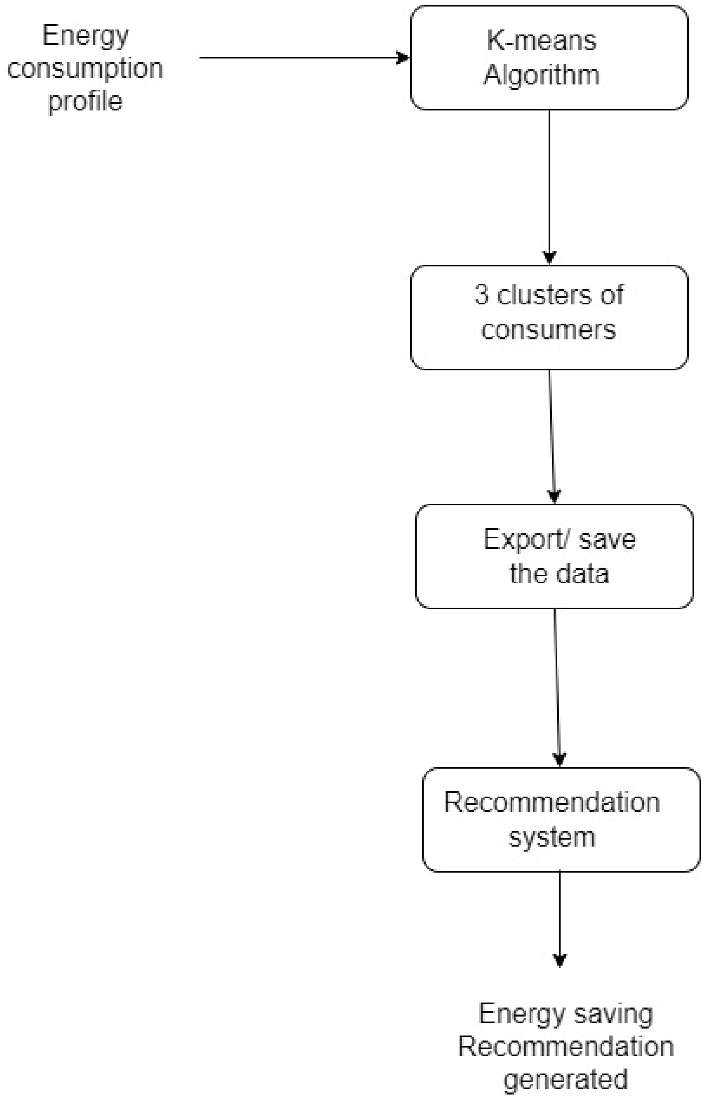

Figure 3. Overview of the proposed method

1.5 Motivation and Research questions

The need for Effective demand-side management and global warming are significant reasons to think in the direction of implementing a recommendation system that recommends energy-saving recommendations to the electric consumers. In addition, the evolution of information technologies and smart grid technologies provides an opportunity to improve prevalent technologies.

Employing this proposed project, we are seeking answers to the following research questions:

1. Find a suitable method to group electric consumers based on their consumption level.

   -which methods should be chosen for clustering?

2. Study various methods of clustering
   - What are the various methods for clustering?
3. Study recommendation techniques and chose a method
   - What are the different methods of recommendation, and which recommendation method is most suitable for this project
4. How can we assist consumers in non-intrusively altering their energy consumption behaviors without significantly impacting their lifestyles using the recommender system?

2 Literature review

In [1], the authors proposed three major ways to promote engagement of residential consumers with demand response (DR): (a) increase smart tariffs, smart meters, and storage awareness among consumers (b) Provide support for electric vehicles and automation technologies (c) use of smarter digital comparison tools (DCTs) for enhanced demand response. The interdependency between components within this DR technology cluster delivers efficiency but also poses a risk that one delayed component (e.g., smart metering) will stall policy and industry support for other components. This interconnection and complexity promise better efficiency, savings, and impact in terms of reducing emissions, but it also poses a barrier for policy and consumer engagement strategies, as well as a possibility of stalemate.

Rather than approaching them as separate consumer engagement challenges, they proposed promoting a better understanding of DR services, smart meters, storage and automation technologies, and renewable energy as equally supportive elements within a common 'technology cluster' that delivers household savings and system efficiency, and decarbonization. This could be accomplished by expanding the smart meter awareness campaign, but it would be more effective if it were accompanied by new policies that made connecting components of this technological cluster more cost-effective.

Urban regions nowadays consume about two-thirds of the world's energy and are major contributors to the carbon footprint. Households and public buildings account for more than 40% of total energy usage, making them the primary focus of relevant research. The multitude of sensors, which come in varied costs and modalities, is used in data fusion solutions for energy efficiency in households, offices, and commercial facilities. These are combined with Machine Learning (ML) techniques to gain meaningful information about appliance consumption data and to suggest or enforce energy-saving measures. Such measures have a great impact on end-user awareness towards saving energy and deliver concrete savings in the form of money. The authors of this paper proposed an online recommender system implemented into the EM3 system, a platform for Consumer Engagement Toward Energy-Saving Behaviour. The recommender system combines sensor data with user habits and feedback to deliver individualized energy efficiency recommendations at best possible time. The proposed system is based on a stacked-LSTM for combining sensor data, and accuracy is observed up to 97% in various scenarios [2].

The authors of this article[3] propose the Exploiting Micro Moments and Mobile Recommendation Systems (EM)3 recommendation engine, which supports household and office consumers with real-time personalized recommendations for avoiding excessive energy consumption and reducing the total household (or office) emission, presents the anatomy of the Consumer Engagement Towards Energy Saving behavior. A series of sensors monitors energy usage, room occupancy, and environmental variables inside and outside the living space, as well as a set of actuators that allow remote control of appliances, constitute the recommendation engine. This recommendation engine's unique feature is that it involves humans in energy efficiency by recommending measures at the right time, in real-time scenarios, with user acceptance and rejection alternatives.

This paper presents a comprehensive reference for energy-efficiency recommendation systems through (i) surveying existing recommender systems for energy saving in buildings; (ii) discussing their evolution; (iii) providing an original taxonomy of these systems based on specified criteria, including the nature of the recommender engine, its objective, computing platforms, evaluation metrics and incentive measures; and (iv) conducting an in-depth, critical analysis to identify their limitations and unsolved issues. Recommendation systems methodologies discussed are case-based, collaborative filtering, context-aware, Deep learning-based, and more. Some major limitations and challenges outlined in this paper are data sparseness, cold start problem and lack of benchmark datasets [4].

Smart grid was introduced in the early 21st century as a solution for the sustainable growth of human society, prompted by the energy crisis and the global warming problem. To address the problem of increasing energy consumption, current research and development programs and activities have concentrated on constructing almost zero-energy buildings in the past decade, which combine renewable and sustainable energy resources as well as energy management technologies. Behavioral modification is a challenging approach that allows end-users to revise their energy consumption patterns and eliminate wasted energy without investing surplus time or effort, but only by using recommender algorithms, artificial intelligence (AI) technologies, and already-owned smartphones. With the two-way communication infrastructure available in smart grids, interpreting and gaining information from the acquired grid big data to optimize grid operations is a current problem. In this paper, the authors present Service recommendation approaches that offer potential tools for extracting knowledge from grid data and recommending energy-conscious products, services, and suggestions to smart grid participants. This is one of the earliest papers to look into the possibility of incorporating service recommendation algorithms into smart grid demand-side management (DSM) [5].

This research [6] employs the service computing paradigm to the smart grid and proposes a demand-side personalized recommendation system (PRS). The proposed PRS uses service recommendation techniques to infer home users' possible interests and needs in energy-saving appliances and then suggests energy-saving equipment to them, potentially resulting in grid energy savings. To disaggregate the end users' domestic appliance usage profiles from the smart meter data, the suggested technique uses a non-intrusive appliance load monitoring (NILM) method based on generalized particle filtering.

Demand-side management (DSM) with dynamic pricing systems is one possible alternative. However, due to the herding effect of customers' load shifting behavior, instead of reducing peak loads, these strategies can cause peak-shifting. In this paper, the authors investigate ways for assigning (non-uniform) participation rates to consumers in order to solve this problem. To determine a near-optimal distribution setting for participation rates, a generic technique has been adopted. DSM designers can use this method to fine-tune the system for consumer convenience. This means less frequent consumption schedule changes in the price of system performance [7].

Demand Side Management (DSM) is a collection of methods aimed at improving the energy system's demand side. It includes anything from enhancing energy efficiency through the use of better materials to smart energy tariffs that offer incentives for specific consumption patterns to sophisticated real-time control of distributed energy supplies.

This paper [8] presents an overview and taxonomy for DSM, as well as an analysis of the many forms of DSM and a look at the most recent demonstration projects in this field. The figure below shows some main objectives of demand-side management

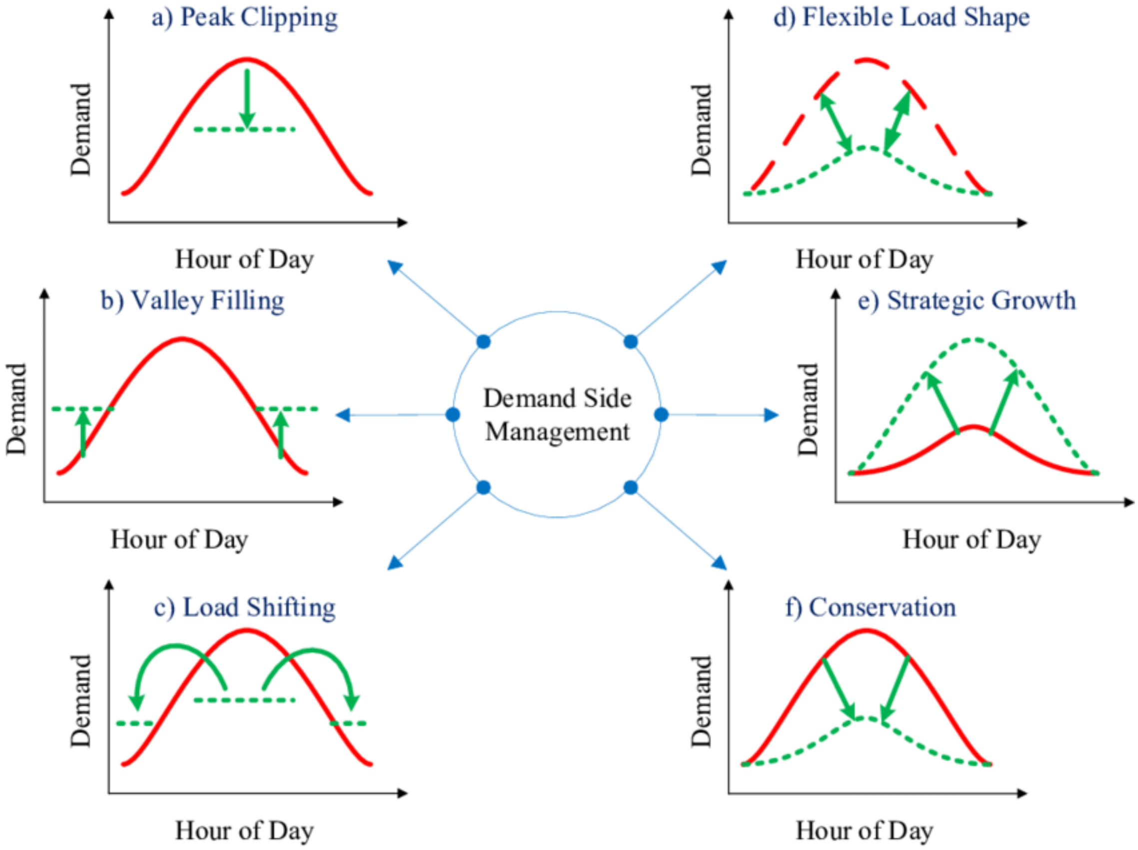

Figure 4. Objective of demand-side management [23]

In this paper [9], the authors list out the possible solution for power crises through effective DSM techniques for load management of the devices. The proposed technique considers residential houses under similar conditions but follows different DSM techniques and is supported by simulations and modeling of those houses. The included results and analysis depict the amount of energy saved. The load (control) technique is used to modify the priority circuit, which can control the peak load demand and results in overall less energy consumed in the sector.

Smart meters are an important part of smart grid infrastructure. Smart meters have complex hardware, software, calibration, and communication capabilities for measuring and calculating. Smart meters are designed to execute operations, store, and communicate data according to particular standards in order to ensure interoperability within a smart grid architecture. In this paper [10], the authors examine smart meters, many aspects of smart metering in this paper, and the existing state of smart grid technologies, smart meters, advanced metering infrastructure (AMI), and meter data, flow in the smart grid. This research also covers smart meter standards, meter data format and transmission, smart meter capabilities, and smart meter functionality that are now being used by utilities all over the world.

In this paper [11], the authors present a modified recommender system that is established based on the combination of matrix factorization and deep neural network that work on users' implicit feedbacks and auxiliary information of both users and items. In order to increase the accurateness of the predictions, a hybrid recommender system combines the content and collaborative method. Furthermore, it collects additional trends discovered via the usage of users and film demographic data, thus improving HR and NDCG.

In this paper [12], the authors suggested Demand-side Management system for demand response applications can control and manage the functioning of numerous appliances in an anticipatory and efficient manner to keep overall power consumption within a predetermined power limit. As a result, loads are prioritized and controlled accordingly. The graphical user interface (GUI) view will be employed in the proposed system to monitor and control appliance status, power consumption and calculate the instantaneous cost. Hardware results demonstrate the proposed DSM algorithm's effectiveness.

In this paper [13], the authors proposed particle swarm optimization methods for both operation modes for the production scheduling of distributed energy resources. In this study, profit maximization for utilities and increased usage of renewable power in microgrid operation are discussed, along with the effects of demand response. Micro grid energy management was concentrated on cost-effective generation scheduling with load shedding for demand-side management. The Energy Management System (EMS) also takes steps to guarantee that microgrids run smoothly and efficiently. The Unit Commitment (UC) and Optimal Power Flow (OPF) models were used to develop the two centralized EMS systems for microgrids. While the operational restrictions associated with distributed energy resources have been taken into consideration by a Unit

Commitment (UC) based energy management system (EMS), the network flows are taken into account by OPF-based EMS.
Furthermore, the two independent notions of demand-side management functions, demand shifting, and peak shaving, which are responsible for demand-side, had major impacts on the entire system under extreme operating conditions.
The purpose of the demand shifting function is to transfer demand from peak to off-peak time intervals in order to lower end-user energy prices and alleviate operational stress.
The most costly generation units were operated to fulfill system demand during peak demand hours, resulting in a high-priced energy. As a result, peak shaving can help to reduce energy consumption during peak hours.

Generation diversification, optimal utilization of expensive assets, demand response, energy conservation, and minimization of the sector's overall carbon emissions are all issues that the utility industry is attempting to address around the world. Such crucial challenges can evidently not be handled within the limits of the current power grid.
The existing power grid is a one-way system. It produces only one-third of the fuel's energy into electricity, with no waste heat recovered. Almost 8% of its production is wasted in transmission lines, while 20% of its electricity production is only available to satisfy peak demand. Furthermore, the existing energy infrastructure suffers from domino-effect failures because to the hierarchical topology of its components.
The next-generation energy grid also referred to as the "smart grid" or "intelligent grid," is projected to overcome the existing grid's primary inadequacies.
In other words, the smart grid must give utility firms complete insight and control over their assets and services.
The smart grid must be self-healing and perseverance in the face of system failures. Last but not least, the smart grid must enable its users to develop and implement new ways of interacting with one another and transacting energy throughout the system. [23].

Smart meters play a diverse role in the Smart Grid, with sophisticated capabilities to satisfy the expectations and objectives of consumers. Smart meters can record and communicate extensive real-time electrical consumption, enable remote real-time monitoring and management of power consumptions, and provide consumers with real-time pricing and assessed usage data, which is technical data to be communicated to utility providers. In this regard, utility companies utilize demand-side management (DSM) programs to regulate energy consumption in residential appliances by interfacing the digital meter with a variety of DSM technical qualities, and a home energy management system is also used for the same purpose. Future smart grids is likely be more closely integrated with cyberinfrastructure for sensing, control, scheduling, dispatch, billing, and cyber threats can be prevented using smart meters, and power demand orders placed online.

The home energy management system (HEMS) is a connected system that helps govern the power supply to homes in order to save energy. Advanced metering infrastructure (AMI), which uses smart meters to provide automatic meter reading (AMR) and automated meter management (AMM), facilitates communication between the smart grid and home network services. A smart meter is a crucial component of the AMI that aids in the operation of the AMR by assisting in the monitoring of consumer electronics utilization. The data is sent from the smart meter to the utility companies, who use it to make decisions about electricity generation and distribution, as well as billing. [24].

3 Methodology

Methods used for implementation of the thesis project are the K-means clustering algorithm and collaborative filtering method for recommendation. K-means algorithm is applied to the consumption profile of energy consumers. Additionally, various clustering methods and recommendation methods have been discussed in detail.

3.1 Clustering methods

In machine learning, cluster analysis or clustering is a technique used for unlabelled grouping datasets. In other words, clustering is a method of categorizing data points into distinct groups consisting of similar data points. The objects with possible similarities are kept in a group with few or no similarities to another one.

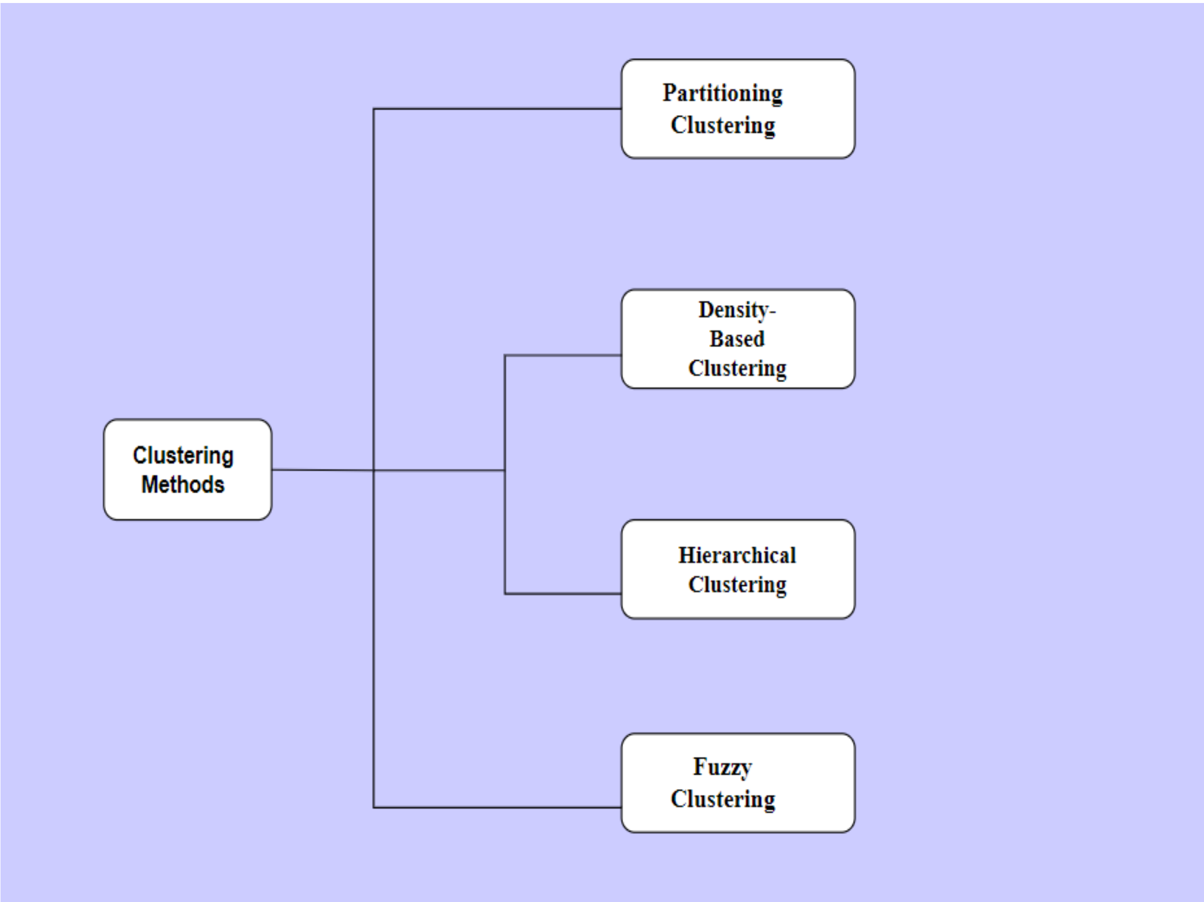

Figure 5. Clustering methods.

3.1.1 Partitioning Clustering

It is a type of clustering that distributes the data into non-hierarchical groups. It is also recognised as the centroid-based technique. The most common example of partitioning clustering is the K-Means Clustering algorithm.

The dataset is partitioned into a collection of k groups in this method, with K indicating the number of pre-defined groups. The group center is located so that the gap between data points in one cluster and the centroid of another cluster is as small as possible. [19].

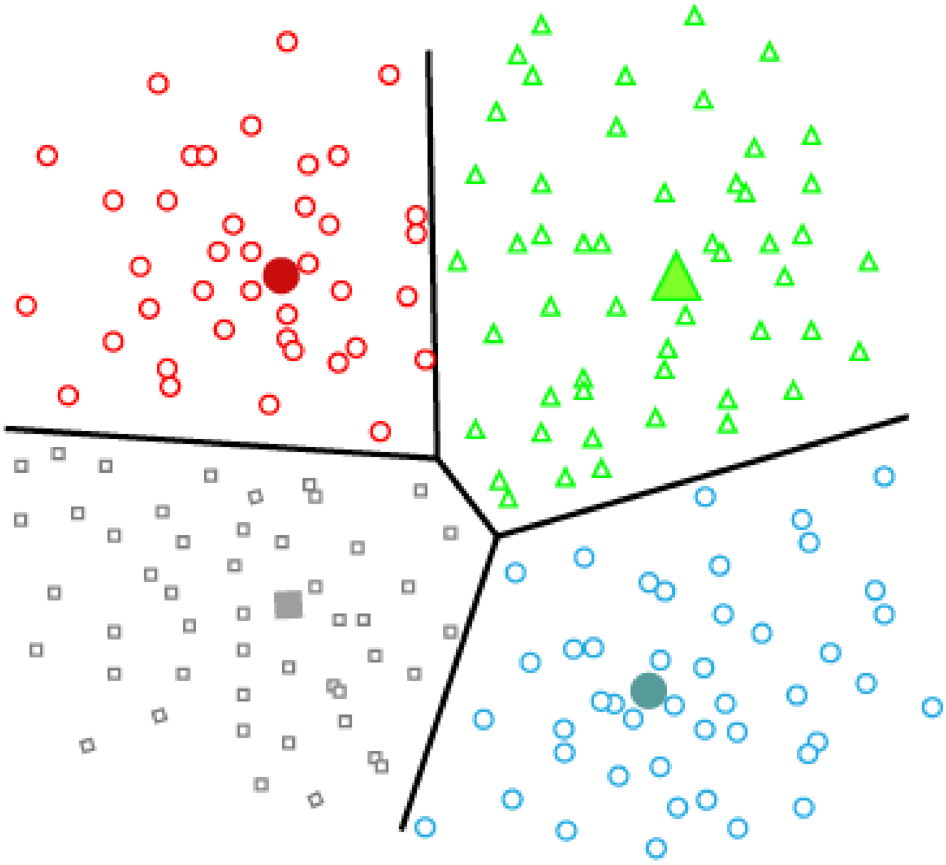

Figure 6. Partitioning clustering [35].

3.1.2 Density-Based Clustering

The density-based clustering method merges dense areas into clusters, resulting in arbitrarily shaped distributions as long as the dense region can be connected. This method accomplishes this by finding several clusters in the dataset and connecting high-density areas into clusters. In data space, sparser zones separate dense areas from each other. If the dataset includes varied densities and large dimensions, these algorithms may have issues grouping the data points [19]. If two dense regions a and b fulfill the following formula, they are combined:

$$Nab(Na+Nh)/2 \geq \alpha merge$$

The total number of edges that link border items within the dense regions a and b are Na and Nb, respectively. The number of edges connecting border items from dense region a to dense region b is denoted as Nab. [26]

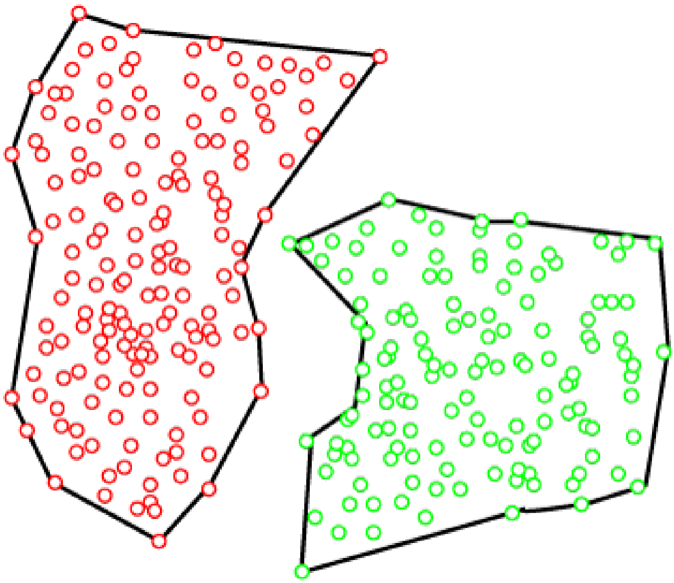

Figure 7. Density-based clustering [34].

3.1.3 Hierarchical Clustering

Since there is no need to pre-specify the number of clusters to be produced, hierarchical clustering can be considered as an alternative to partitioned clustering.

The dataset is separated into clusters in this technique, which results in a tree-like structure known as a dendrogram. By clipping the tree at the proper level, you can select the observations or any number of clusters. A common example of this method is the Hierarchical Agglomerative algorithm [19].

Agglomerative clustering begins with N clusters, each of which contains only one object. After that, a series of merge procedures are performed, resulting in all objects being assigned to the same group. Divisive clustering works in the opposite direction..[28]

The following approach summarizes the generic agglomerative clustering.

1. Begin by creating N singleton clusters. Calculate the N clusters' proximity matrix.

2. Search the minimal distance

$$D(C_i,C_j)=\min_{1\leq m,l\leq N, m\neq l} D(C_m,C_l)$$

where D (∗,∗) is the distance function discussed before in the proximity matrix, and combine cluster Ci and Cj to form a new cluster.

3. Calculate the distances between the new cluster and the other clusters to update the proximity matrix.

4. Repeat steps 2)–3) until all of the elements are grouped together.

Classic HC algorithms are widely criticized for their lack of robustness, making them prone to noise and outliers. Once an object has been allocated to a cluster, it will not be evaluated again, implying that HC algorithms will not be able to correct any earlier misclassifications [28].

3.1.4 Fuzzy Clustering

A data object can belong to more than one group or cluster in fuzzy clustering, which is a sort of soft technique. Each dataset has a set of membership coefficients that are based on the degree of cluster membership. This sort of clustering is represented by the Fuzzy C-means method, which is also known as the Fuzzy k-means algorithm [19].

There are two parameters, μ ijand c i, and one hyperparameter, m, in the Fuzzy c-means (FCM) clustering algorithm. The membership value, μ_ij, is the probability that the jth data point belongs to the ith cluster, and it is bound by the fact that the total of μ_ij over C cluster centers equals 1 for every data point j. The fuzzifier, m, determines how fuzzy the cluster radius should be.

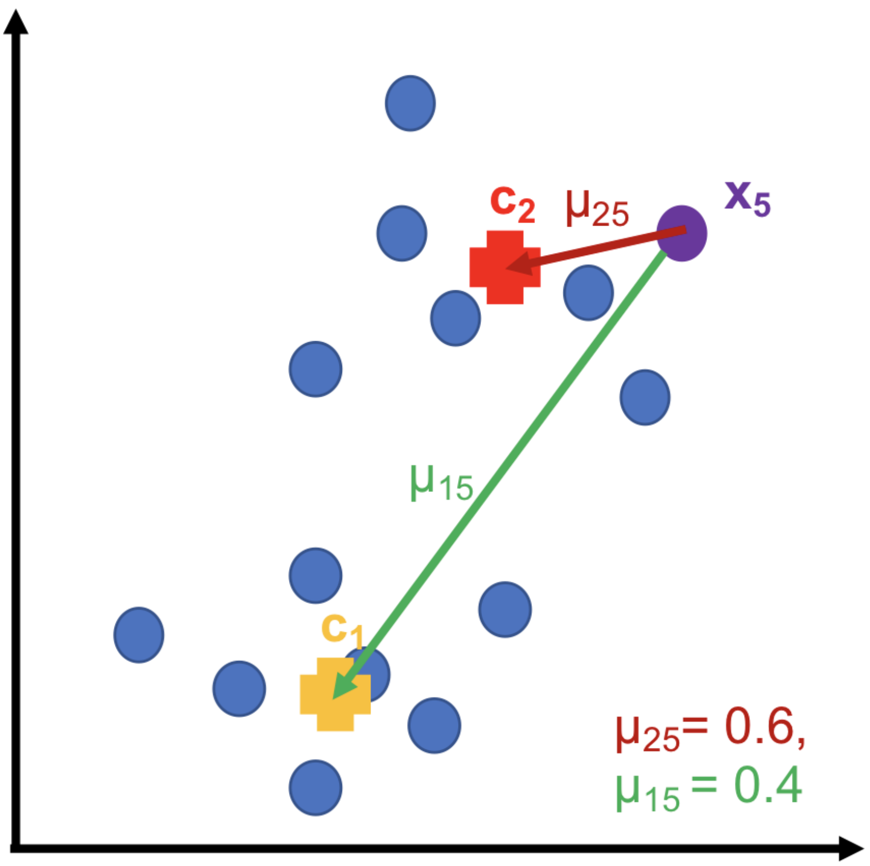

Figure 8. Fuzzy clustering.

We're looking at the fifth data point, X 5, in the example plot above, and we know there are only two clusters, and the current cluster centers are c 1 and c 2. The chance that the 5th data point belongs to the 2nd cluster is 25, while the likelihood that the 5th data point belongs to the 1st cluster is 15. The 5th data point is more closer to c 2 than c 1, indicating that μ 25 (0.6) is greater than μ 15 (0.4). They also satisfy the condition that for each data point, the sum of is 1, where μ 15 + μ 25 = 1

The objective function

$$J = \sum_{i=1}^{C} \sum_{j=1}^{N} \mu_{ij}^{m} \|x_j - c_i\|^2$$

The objective function can be viewed of as a weighted sum of the distances between data points (X j) and cluster centers (C i). In the equation above, the "distance" term is the L2 norm, and in the example (the 5th data point) above, it is the precise length of the arrows. [27]

3.1.5 Clustering using K-means algorithm

K means clustering is categorized into unsupervised learning in machine learning.

The data is separated into numerous groups, each with data points that share similar features. The distance between data points is used to determine these clusters. Distance can be calculated using one of four methods: Euclidean, Manhattan, Correlation, or Eisen. For distance measurement, the Euclidean approach is used, which means the distance between two locations (x1,y1) and (x2,y2) will be

$$\sqrt{(x2-x1)^2 + (y2-y1)^2}$$

3.2 Recommendation techniques

A recommendation system's purpose is to present consumers with helpful suggestions for things they might be interested in. In this section, recommendation approaches discussed are content-based, collaborative filtering, knowledge-based and hybrid approach.

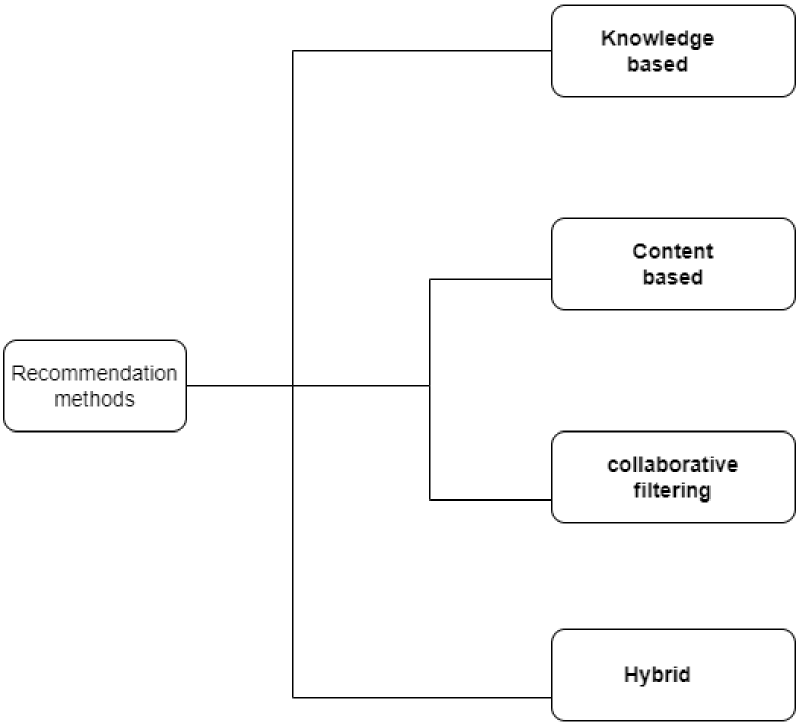

Figure 9. Recommendation methods.

3.2.1 Knowledge-based

A Knowledge-Based Recommendation System (KBRS) differentiates itself from other types of recommendation systems by employing a different method to generate a recommendation. On the basis of domain knowledge, a KBRS generates suggestions. A user will receive a suggestion based on his profile, and the activities of other users will either not be considered at all or will play a minor role in determining the recommendation. The KBRS's primary constraint is the creation of the knowledge base, which is typically a difficult undertaking requiring extensive subject knowledge and competence in the representation of knowledge [21].

3.2.2 Content-based Filtering

Content-based filtering (CBF) makes recommendations based on user preferences for product features. The content-based filtering technique makes recommendations based on user profiles and features collected from the content of items the user has already evaluated. Other users' profiles aren't needed for content-based filtering because they have no effect on recommendations. Furthermore, if the user profile changes, the CBF approach may still update its recommendations in a short time. The main inadequacy of this strategy is that it necessitates a thorough understanding and description of the characteristics of the items in the profile [16].

Content-based filtering can suggest a new item, but in order to incorporate the best match, additional information about the user's preferences is required.

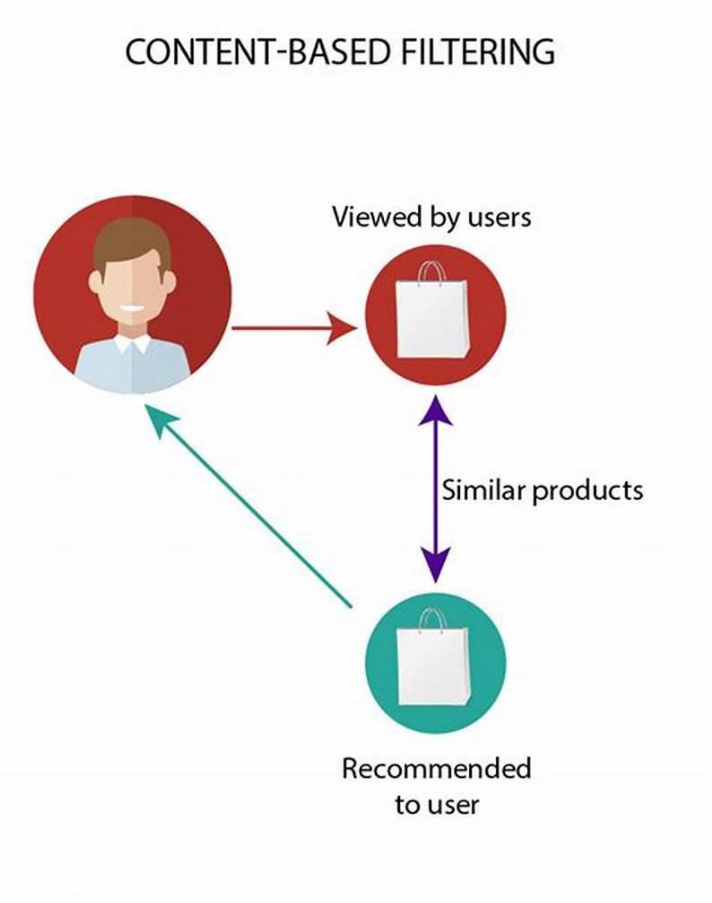

Figure 10. Content based filtering [29].

3.2.3 Collaborative filtering

Collaborative filtering (CF) is a commonly used technique in developing recommendation systems deployed in many industries. Users' feedback mainly impacts collaborative filtering in the form of rating. It is used to make collaborative filtering a method that personalized prediction by collecting different users' preferences. This technique was first used by David Goldberg in 1992 [22] to introduce an email filtering system.

User-to-user recommendations are modelled using collaborative filtering. It forecasts users' preferences as a weighted linear mixture of other users' choices. In order to produce reliable predictions, collaborative filtering requires a big dataset of active users who have previously rated a product.

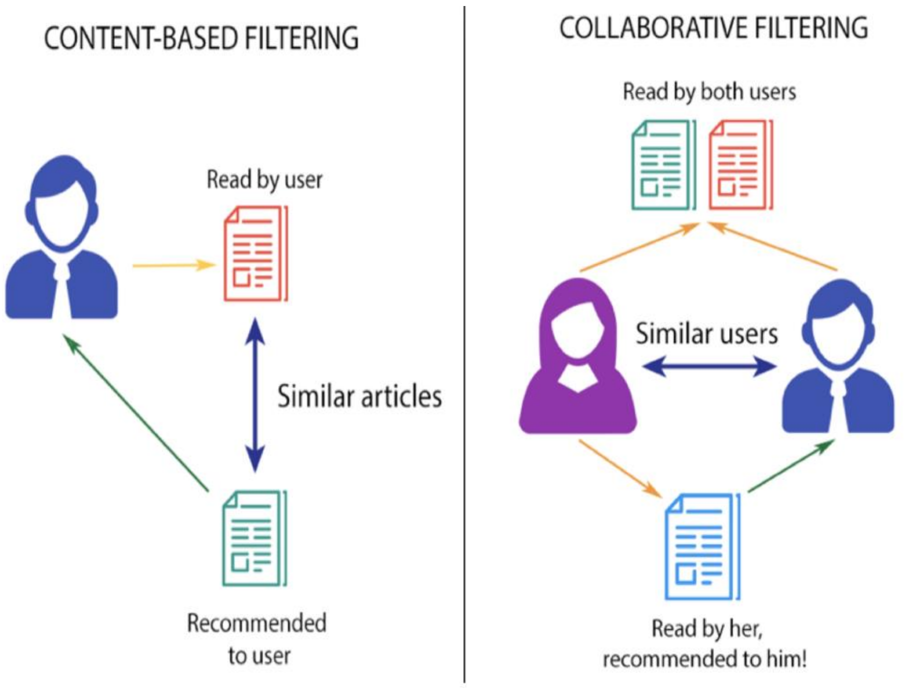

Figure 11. Content-based and collaborative filtering comparison [30].

Memory-Based Collaborative Filtering Techniques

Memory-based CF algorithms generate a prediction by using the complete or a sample of the user-item database. Every user is a associated with a group of people who share similar interests. A prediction of a new user's (or active user's) preferences on new products can be made by identifying his or her "neighbors.".A prediction of a new user's (or active user's) preferences on new items can be made by identifying the so-called neighbors of the new user (or active user).

The following steps are used in the neighborhood-based CF algorithm, which is a typical memory-based CF algorithm:

- find the weight or similarity
- $w_{i,j}$, which represents distance, correlation, or weight, between two users or two items, i and j
- provide a prediction for the active user based on the weighted average of all the user or item reviews on a specific item or user

In memory-based collaborative filtering algorithms, computing similarity among objects or users is a crucial step. There are numerous approaches for calculating user or item similarity or weight [32].

Correlation-Based Similarity

In this situation, the Pearson correlation or other correlation-based similarities are used to calculate the similarity Wu,v between two users u and v, or wi,j between two items I and j.

The Pearson correlation coefficient quantifies the degree to which two variables are linearly related to one another. The Pearson correlation between users u and v in the user-based algorithm is

$$w_{u,v} = \frac{\sum_{i\in I}(r_{u,i}-\bar{r}_u)(r_{v,i}-\bar{r}_v)}{\sqrt{\sum_{i\in I}(r_{u,i}-\bar{r}_u)^2}\sqrt{\sum_{i\in I}(r_{v,i}-\bar{r}_v)^2}},$$

where the i ∈ I summations are over the items that both the users u and v have rated and ru is the average rating of the co-rated items of the uth user.

Cosine similarity

The cosine similarity formula is used in recommendation systems, question and answer systems, and plagiarism checks to check for text similarity. The fundamental idea behind cosine similarity is to compare the distance between two vector angles. A wide-angle indicates that the text vectors are dissimilar, whereas a small angle indicates that they are similar. The mathematical formula for cosine similarity is shown below [31]

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

By using the cosine_similarity() method from sklearn library we can compute the cosine similarity between each element in a data frame:

```
from sklearn.metrics.pairwise import cosine_similarity
similarity = cosine_similarity(df)
print(similarity)
```

Model-Based Collaborative Filtering Techniques

To overcome the drawbacks of memory-based CF algorithms, model-based CF algorithms such as Bayesian models, clustering models, and dependency networks have been researched.

Simple Bayesian CF Algorithm

To make predictions for CF problems, the simple Bayesian CF algorithm employs a nave Bayes (NB) technique. Considering that the features are independent of the class,

the likelihood of a particular class given all of the features may be calculated, and the class with the highest probability will be categorized as the predicted class.
The probability computation and classification production are computed over observed data for incomplete data [32].

3.2.4 Hybrid

Hybrid filtering mixes many recommendation algorithms in order to improve system optimization and avoid some of the restrictions and issues that come with particular recommendation systems. In a combined model, using numerous recommendation approaches can mask the flaws of each individual technique [16].

3.3 Evaluation metrics

Statistical and decision support accuracy metrics are two types of metrics for analyzing the accuracy of recommendation filtering systems. Each metric's applicability is determined by the dataset's characteristics as well as the tasks that the recommender system will perform.

- The difference between the expected and actual ratings supplied by a user to each recommended item is measured by rating accuracy. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) is the most basic and widely used errors, and they are defined as follows:

$$MAE = \frac{1}{|\hat{R}|} \sum_{\hat{r}_{ui} \in \hat{R}} |r_{ui} - \hat{r}_{ui}|$$

$$RMSE = \sqrt{\frac{1}{|\hat{R}|} \sum_{\hat{r}_{ui} \in \hat{R}} (r_{ui} - \hat{r}_{ui})^2}$$

where r_{ui} is the actual rating of user u for item i and $\hat{r}_{ui}$ is the predicted rating [32].

3.4 Tools and technologies

Python: Python will be used as a programming language for writing codes. Python can be used to handle big data and perform complex mathematics. It also provides syntax similar to the English language. Python libraries such as Numpy, pandas, sklearn, and matplotlib provide in-built functions for data cleaning, data analysis, and data visualization.

Jupyter notebook: The Jupyter Notebook is an open-source web application that allows us to create and share documents that contain live code, equations, visualizations, and narrative text. Uses include data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more [33].

4 Analysis ,result and discussions

The experimentation was carried out using synthetically generated simulation data that was used to simulate a microgrid scenario. The data obtained was used to represent consumption profiles of consumers from various households and devices on the microgrid with individual consumer_id and was further divided into four intervals, namely: interval1, interval2, interval3 and interval4

Implementation of the recommendation system starts with grouping these energy consumers into three different groups based on their daily consumption patterns.

Table 1 below indicates energy consumed by consumers in *Kwh* at different hours of a day.

24 hours is divided into 4-time slots as interval1, interval2, interval3, and interval4.

Table 1. Consumption of energy at different hours of a day

consumer_id	interval1 (6:00-12:00)	interval2 (12:00-18:00)	interval3 (18:00-00:00)	interval4 (00:00-6:00)
1	12	10	17	8
2	17	14	15	5
3	13	12	18	7
4	15	13	15	5
5	12	10	17	6
6	17	14	15	5
7	13	12	17	8
8	15	11	15	7
9	13	13	16	6
10	12	10	18	9
11	17	14	15	5
12	13	12	17	9
13	15	11	16	7
14	14	13	15	8
15	12	10	19	8
16	17	14	15	5
17	13	12	15	9
18	15	14	17	8
19	14	11	16	9
20	12	13	17	7

Based on this consumption data, we categorize consumers into three groups based on their consumption patterns. Using k-means algorithm, we have divided consumers into three different groups

```
km = KMeans(n_clusters=3)
y_predicted =
km.fit_predict(df[['interval1','interval2','interval3','interval4']])
y_predicted
```

The following table shows grouped consumers into three different clusters after application k-means algorithm. Energy consumers are divided into three different groups as high, medium, and low energy consumers. This high, medium, and low consumers are represented by the numbers 2, 1, and 0, respectively

Table 2. Energy consumers grouped in 3 clusters.

consumer_id	interval1	interval2	interval3	interval4	cluster
1	12	10	17	8	0
2	17	14	15	5	1
3	13	12	18	7	2
4	15	13	15	5	1
5	12	10	17	6	0
6	17	14	15	5	1
7	13	12	17	8	2
8	15	11	15	7	2
9	13	13	16	6	2
10	12	10	18	9	0
11	17	14	15	5	1
12	13	12	17	9	2
13	15	11	16	7	2
14	14	13	15	8	2
15	12	10	19	8	0
16	17	14	15	5	1
17	13	12	15	9	2
18	15	14	17	8	2
19	14	11	16	9	2
20	12	13	17	7	2

4.1 Load Factor calculation

Load factor is calculated using the formula below, which indicates how efficiently energy has been utilized in a certain period of time. A higher value of load factor indicates the better the utilization of energy in that particular time period.

$$Load\ factor = \frac{Average\ load}{Peak\ demand\ in\ a\ particular\ time\ period}$$

Load factor has been calculated for four time period interval1, interval2, interva3, and interval4. The value for interval1, interval2, interva3 and interval4 are found to be o.82, 0.86, 0.85 and 0.78, respectively. The maximum value of load factor is 0.86 for interval2 i.e. energy has been consumed efficiently in this time period, and the minimum value of load factor is 0.78 for interval4 i.e., energy is not utilized efficiently in this time period. The below chart indicates the value of the load factor in different intervals.

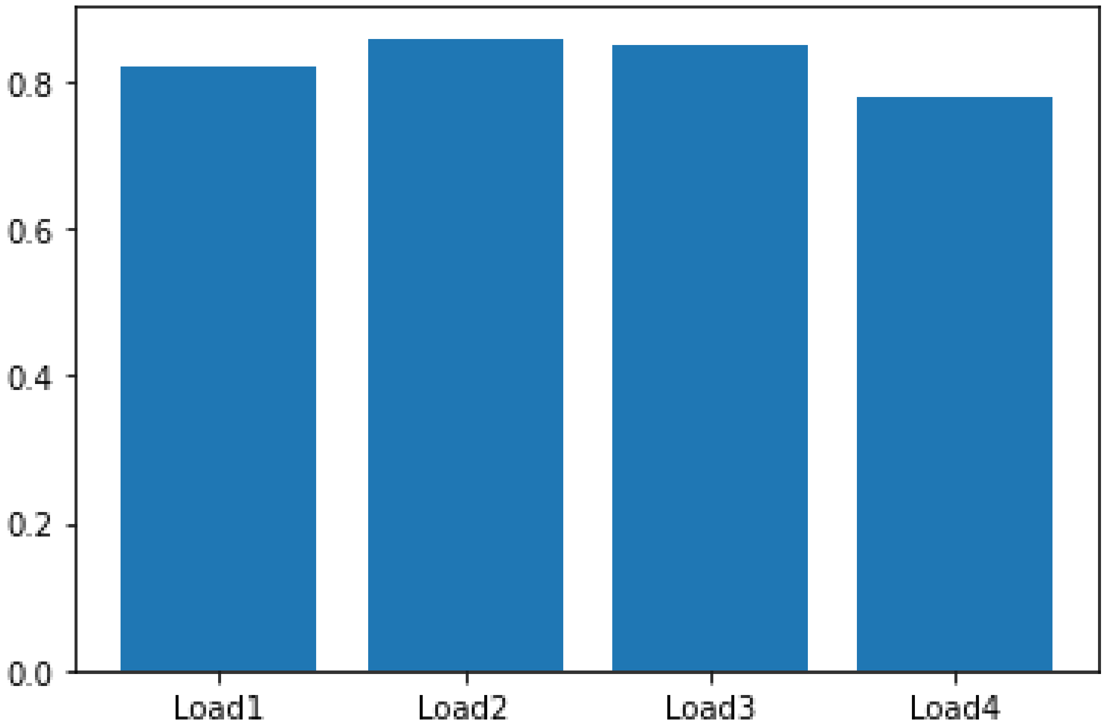

Figure 12. Load factor before applying recommendations.

Now, energy-saving recommendations are sent to consumers based on their consumption patterns. A set of recommendations is formulated by the utilities that operate a micro-grid energy system.

Table 3. Recommendations list and their description.

recommendation	**Description**
recommend1	Install heat pump
recommend2	Turn off lights in the kitchen at night
recommend3	Install energy-efficient LED bulbs
recommend4	Use washing machine in the evening
recommend5	Install programmable thermostat

Recommendation system implementation: The proposed recommendation system is based on a collaborative filtering method. Each consumer is given a list of recommendations, and they give a rating to each recommendation based on their suitability. The collaborative filtering method takes into account the rating of other users for generating recommendations.

The table below depicts consumers and ratings given by a consumer to various recommendations on a scale of 1 to 5.

Table 4. Rating is given by consumers to different recommendations.

consumer_id	recommend1	recommend2	recommend3	recommend4	recommend5
1	1	3	3	5	3
2	3	4	3	5	5
3	2	4	5	5	4
4	4	5	2	4	3
5	3	4	5	3	3

In the next step correlation between recommendations is calculated using *cosine similarity* and correlation matrix is depicted in figure 1 below.

```
corrMatrix =
pd.DataFrame(cosine_similarity(rating),index=rating.columns,columns=ra
ting.columns)
corrMatrix
```

	recommend1	recommend2	recommend3	recommend4	recommend5
recommend1	1.000000	0.959185	0.977590	0.886557	0.899500
recommend2	0.959185	1.000000	0.964773	0.951994	0.926198
recommend3	0.977590	0.964773	1.000000	0.902194	0.967672
recommend4	0.886557	0.951994	0.902194	1.000000	0.913139
recommend5	0.899500	0.926198	0.967672	0.913139	1.000000

Figure 13. Correlation between recommendations.

4.2 Recommendation results

After finding cosine similarity between recommendations, the recommended method is applied, and results are listed in table 5 below. In the below table, a consumer has given rating to a recommendation, and a relevant recommendation is suggested with a similarity score. RSME is calculated in the next step to finding the errors in the similarity scores.

Table 5. Recommendation results

Recommendation	Rating given by a consumer	Similarity score	Suggested recommendation	Similarity score
Recommend1	4	4.000000	Recommend3	3.910360
Recommend4	5	5.000000	Recommend2	4.759970
Recommend2	4	4.000000	Recommend3	3.859091
Recommend2	5	5.000000	Recommend3	4.823863
Recommend1	3	3.000000	Recommend3	2.932770
Recommend4	5	5.000000	Recommend2	4.759970
Recommend4	4	4.000000	Recommend2	3.807976
Recommend5	4	4.000000	Recommend3	3.870687
Recommend3	3	3.000000	Recommend1	2.932770

4.3 RSME calculation for similarity scores

Root mean square error (RSME) is calculated for the similarity score generated from the above table. The lower value of RSME indicates the model is working up to the

expectations and generating values with less errors.

```
from sklearn.metrics import mean_squared_error

from math import sqrt

mse=mean_squared_error(value_actual,value_pred)

rmse = sqrt(mse)

rmse
```

RSME value calculated is 0.17,that is showing recommendation system is generating results effectively.

4.4 Load factor

Expected load factor after implementation of recommendation system, where energy is consumed efficiently throughout the day. In earlier case before generating recommendations load factor in figure indicated energy is not consumed efficiently in interval4.

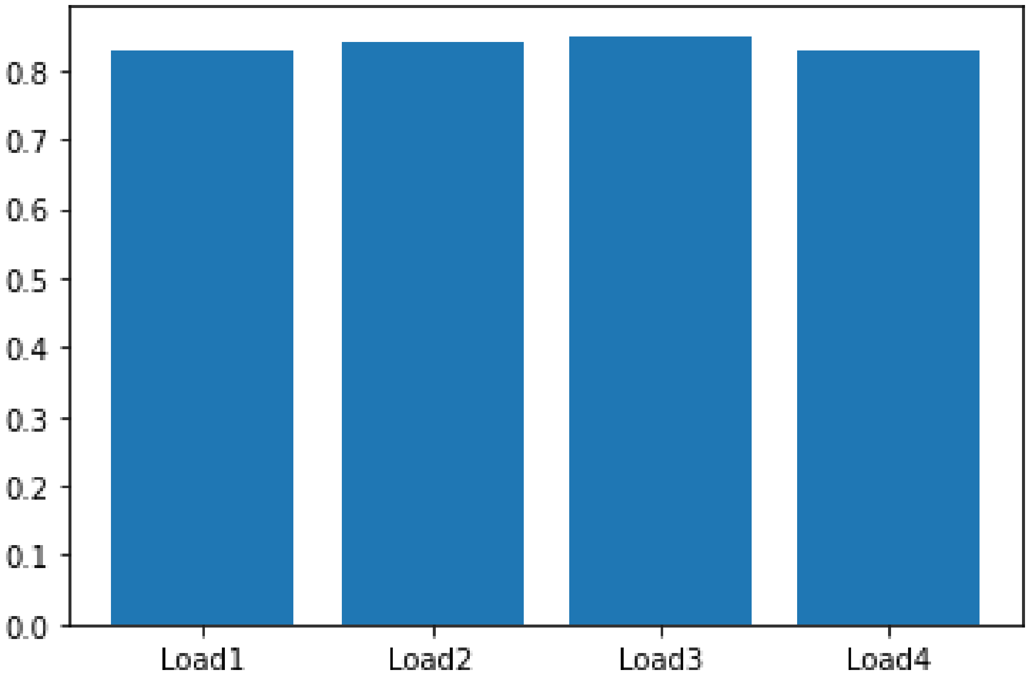

Figure 14. Expected Load factor after applying recommendations.

5 Conclusion

This research aimed to find to a solution for demand-side management and develop a recommendation system for electric energy consumers. K-means is chosen as the clustering method for grouping these consumers in 3 groups based on their energy consumption pattern. Various methods of recommendation has been highlighted in detail and a collaborative filtering method is used for developing an effective recommendation system.

The proposed recommendation system is generating energy-saving recommendations as expected. Evaluation metrics, RSME is calculated for similarity scores for evaluation of the recommendation system. RSME value is found out to be 0.17, which shows the recommendation system generating recommendations with high accuracy. The results have been discussed and well presented in the tables.

The objective of demand-side management is to control the high demand of energy at peak hours and load factor indicates how efficiently energy has been utilized. A comparison of load factor has been shown before and after applying recommendations. All objectives of this thesis project have been successfully accomplished. The proposed system is mainly focused on microgrid utilities and in order to make the best use of it by utilities, energy consumers should be encouraged to give input to the recommendation system.

Future work includes these systems can be upgraded further with the evolution of emerging technologies such as AI, IoT ,etc,.

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