JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

EPRS-EF: Electricity Plan Recommendation System using Efficient Fuzzy Logic

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Abstract: The main significance & scope of this paper is to develope novel automated electricity plan recommendation using Efficient Fuzzy logic algorithms to solve the problems related to sparsity, recommendation accuracy, & computation efficiency. For sparsity, we introduced the Efficient Fuzzy logic under which we applied the set of fuzzy rules to optimize the recommendation process. For the accuracy & computation efficiency, we propose the relevance feedback approach which may automatically recommend the electricity plane based on end user feedbacks on previous recommendation results for the same user. The aim of this study is to propose & evaluate a unique data mining-based electricity plan extraction framework. In this paper we used method of Electricity Plan Recommendation System using Efficient Fuzzy logic (EPRS-EF).

***IndexTerms* - — Recommendation system, Electricity plan, Extraction, Efficient Fuzzy logic**

I. INTRODUCTION

Power rates were deregulated under retail markets throughout previous decade, & benefits regard electricity retail competition was clearly noted under many countries. End-users, particularly residential customers, have increasingly gained a better understanding of their home energy use habits. Residential consumers now have additional alternatives to save money on electricity through participating under demand response activities or choosing appropriate electricity retailing plans. Thanks to more appealing pricing & better customer service. Demand response, under conjunction along variable pricing tariffs, reduces a customer's power expenditure through rearranging the operating are significant obstacles to larger demand response applications among residential users [1, 2]. Incorrectly chosen electrical strategy would significantly reduce efficiency [3, 4]. Under these circumstances, choosing an appropriate power plan becomes a straightforward & successful technique for lowering energy costs while maintaining the original life pattern [5].

A range of energy plans are offered through numerous retailers under a highly competitive power retail market, making plan selection challenging. These tools gather data & provide suggestions, either directly or indirectly. The basic notion is to compare all of the available electricity plans in order to find the cheapest one. The cost of a plan is computed using a customer's total power use & the plan's charge rates. In general, total power use is calculated using the data seen on recent electricity bills. When recent bills are unavailable, as they often are for new settlers, total power use is calculated using other data such as the number of residents & bedrooms and other appliances at place. The direct techniques, have a number of drawbacks since they need the end user to do a manual activity, hence do not lead to the automation that is requirement of end user. In this paper, we use Efficient Fuzzy logic techniques to provide a unique automated electricity plan extraction & recommendation approach. The study is mostly focused on developing fuzzy logic algorithms that are based on recommendations [6].

The process of identifying, representing, analysing, & extracting actionable patterns through social media is known as social media mining. It refers to metrics & techniques for extracting meaningful patterns through large-scale social media platforms. Recommender Systems (RSs) are systems that have the knowledge to propose items or services to people who do online searches. The information on recommender systems is utilized under a variety of fields, including web-based e-commerce sites that include several studies & theoretical conclusions, advertising, & tourism. The recommender systems are categorised into location recommendation system, user recommendation system, activity recommendation system, & social media recommendation based on the user's point of interest, desires, activities, & information through social media [7].

Recommender systems are tasked along making suggestions depending on the preferences of the user, which is a difficult process. Selecting a best suitable,feasible,efficient electricity plan which does not violate the comfort of end users of the thousands plans is a motive of this recommender system. The brief analysis of related works is provided under section II. In section III, the algorithm & architecture for proposed method presented. In section IV, the simulation results discussed. Finally, the conclusion & future discussed.

II. RELATED WORK

As the research is mainly related to recommendation-based methods under data mining domain, we presented the review of different recommendation algorithms that may applicable to electricity plan extraction automatically. First present some recent trends under recommendation systems under.

In [8], author proposed collaborative filtering-based recommender frameworks help online clients under choosing the suitable things under view of the client's purchasing history One of the main contemplations while fostering a fruitful recommender framework is versatility.

The framework was definite at an undeniable level under under [9], author along an emphasis on the tremendous execution increments achieved through profound learning. The review is separated into two sections under view of the regular two-stage data recovery polarity: first, they depict a profound applicant age model, & then an unmistakable profound positioning model. They shared the functional illustrations & bits of knowledge gained through making, emphasizing, & supporting an enormous scope suggestion framework along critical client sway.

In [10], a new deep co evolutionary network model (Deep Coevolve) was presented for learning user & item attributes through their interaction graph. Deep Coevolve defends the intensity function under point processes using recurrent neural networks (RNNs) across evolving networks, allowing the model to represent intricate reciprocal interaction between users & items, as well as feature change over time.

In [11], a revolutionary design featuring an attention mechanism was presented. Experiments along data acquired through a real-world micro blogging service's finding the suggested model outperforms state of art methods, according to findings. The relative improvement of the suggested technique over the state of art technique has been roughly 9.4% under the F1-score through including trigger words into the consideration.

In [12],[13] author proposed the utilization of a convolutional brain network to learn high-request connections among installing aspects was proposed under. Broad analyses on two openly accessible implied criticism datasets exhibit the adequacy of our proposed ONCF system, especially the beneficial outcome of utilizing the external item to show the relationships between's installing aspects at the low level of a multi-facet brain recommender model.

In [14] author suggested the Adversarial Personalized Ranking as a novel optimization framework. Through adversarial training, they demonstrated that APR improves the pair wise ranking algorithm BPR. It may be thought of as a minimax game under which the BPR objective function is minimised while an opponent applies. On power plan proposals, there has been virtually little effort reported.

In [15] author presented a system for recommending personalised power retailing plans. Customers' power use patterns were utilized to offer cost-effective retailing options.

In [16], author proposed the possibility of incorporating service recommendation algorithms along smart grid demand side management was presented (DSM). They discussed the essential technologies that can help developers build smart grid recommender systems.

In [17] author introduced a customized power retail plan recommender framework for home purchasers, bringing the help registering strategy into the shrewd lattice. They proposed a recommender framework under light of collaborative filtering. Clients' energy utilization information was assembled through their personal meters first, & then fundamental energy utilization angles were removed & saved under a client information data set, along with the data of their chosen electricity retail plans.

In [18] author proposed The blend collaborative filtering-based power plan recommender system .It is built using a two-stage model that integrates model-based & memory-based collaborative filtering capacities. For a more definite evaluation of comparability, a weighted closeness metric was made.

In [19] author proposed EPRS (electricity plan recommender framework) under light of collaborative filtering .

III. METHODOLOGY

3.1. System Modelling

Figure 1 is a simple representation of an Electricity Plan Recommendation System. They are largely under charge of eradicating the use regards power. The electrical provider provides power to the residence. According to a survey of the literature, power is generated via the grid as well as solar systems &/or wind turbines under the majority of situations.

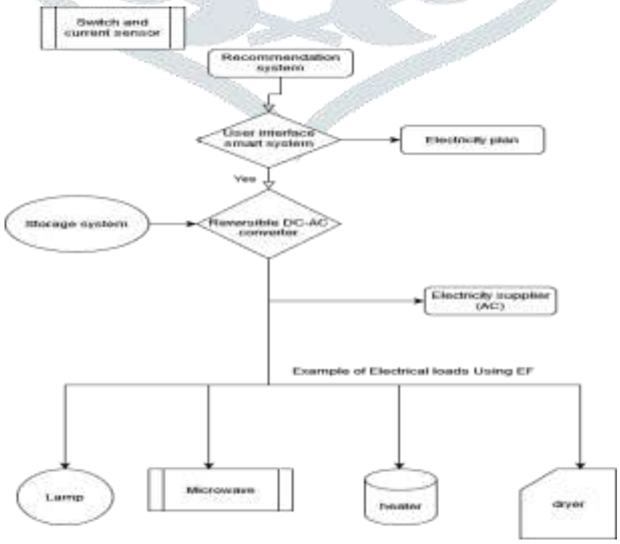

Fig.1. Shows a simplified representation of the proposed Efficient Fuzzy logic-based Electricity Plan Recommendation System.

It is recommended to categorise all appliances under order to properly modify the consumers' preferences & attain their entire contentment. Flexible, inflexible, & nocturnal loads are the three types of loads. Real-time usage databases & external parameters are utilized through the Home Electricity Management System (HEMS).

The HEMS is comprised of an electricity utilization forecast model that can be used to utilize the capacity framework & shrewdly turn gadgets on & off.[20-25] Consistently, the gauge skyline is used. The exactness of forecast fluctuates altogether among homes along temperature-subordinate hardware (i.e., electric warming or cooling).

At long last, the critical limitations of the proposed framework are apparatus arrangement, client inclinations, & capacity framework the board. It's important that the entire framework introduced under this post is totally measured. It infers that any electrical gadget might be added or uninstalled effortlessly. Essentially, load characterization isn't set under stone, & purchasers' decisions might be changed.

3.2 .Dataset Description

The testing information is separated into two sections, client & thing information. Client information comes from Smart Grid Smart City (SGSC) project, which is a smart grid project gathering smart meter information for private clients under New South Wales, Australia during 2010 & 2014. [26-28]From the SGSC dataset, 730 clients are chosen for the mathematical tests. These clients fulfill two necessities. To begin with, they can give power utilization records for a specific period. Second, they can supply meter readings for no less than four usually applied domestic devices during a similar period. Absolutely, 10 home appliances are considered under the tests, specifically microwave (Micro), broiler, oven, dishwasher (Dish), clothes washer (Wash), material (Dryer), (TV), PC (CPU), climate control system (AC) & boiling water framework (Water).

Thing information under the tests is extricated from 62 electricity plans delivered by 15 nearby retailers under 2017 for private clients under New South Wales. Among every one of the plans, a big part of them use SG tax, which is a sort of fixed electricity evaluation. The other half use TOU duty, which is a portrayal of adaptable valuing under Australia.

In order to obtain comprehensive temperature datasets, three acquisition units are employed under conjunction along each other. Each of the three temperature sensors is situated beneath the bed.

When creating a model regards every load, it is critical to have an understanding of the consumption of each individual load.

Figure 2 depicts how the connections were established under order to measure amount of power utilized.

Fig.2. Example of wiring of the measurement system under the electric panel of a smart home

Recommender systems make recommendations, based on the user preferences, which is a complicated task.

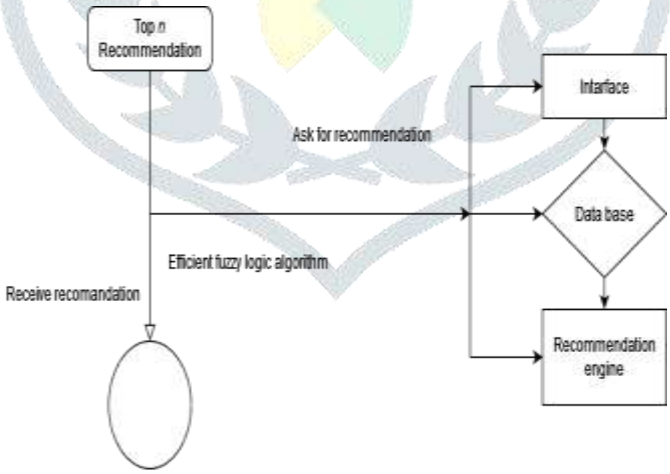

Fig.3. Traditional Recommender Systems flowchart

3.3 Short Term Prediction of Load Consumption

The vital part of the electricity the executive's framework introduced under this article is the estimation of force use, which considers an increment under how much is the accumulated energy. Load forecasting has generally had a critical influence under the planning system, & it will keep on doing as such. Under the direction of the forecast framework, man-made consciousness strategies are utilized. On the off chance that you're doing load forecasting, you might break your expectations under 3 classes: short term load forecasting (STLF), medium term load forecasting (MTLF), & long term load forecasting (LTLF). The long-term reliability factor (LTLF) is regularly used these days to determine whether it is expected to further develop flow electrical dispersion frameworks & build extra lines or substations. It is generally utilized under the forecast of occasional varieties. The STLF is useful for giving data to the electricity the executive's framework on the everyday or hour-to-hour tasks of a power plant or other office.[30]

These days, STLF assumes a vital part under a wide scope of exercises, including constant age control (to adjust supply & request), dispersion framework security, & the planning of energy exchanges. That is one reason why this system was picked to foster the expectation model.

Most expectation models contain a few sources of info, like the hour of day (work day/end of the week/occasion, month &/or season), temperatures, & load information bases, to give some examples.

Both the strategy used to figure the load utilization & the data sources play a part under the precision of the expectation model, which can be found. In Figure 4, it very well may be seen that the forecast framework is involved six key data sources: day of the week, season of day, past power use. The meaning of these information sources is depicted under detail under the following passages of this part.

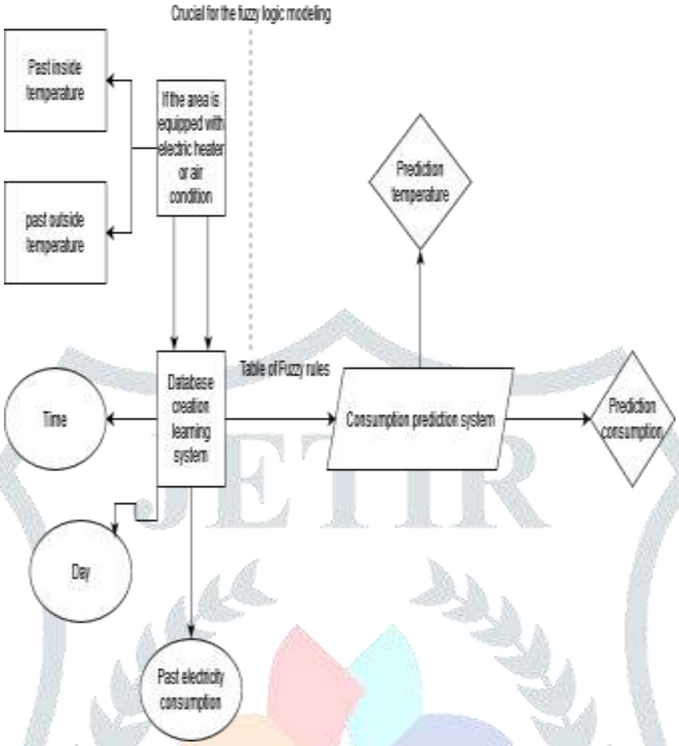

Fig.4. Diagram of the electricity prediction system

3.4. The proposed Electricity Plan Recommender System

The proposed EPRS was a recommender system that provides personalized advice to residential clients while they are deciding on the most appropriate power retailing plan for their needs. This system makes use of a neighbourhood basis collaborative filtering approach under conjunction along a similarity measure that has been particularly built.[31] In the EPRS, the terms item & user refer to electricity retailing plan & a residential client, respectively. The training & testing user sets are denoted through the notations Utr & Ute under this study. Through just providing a few clearly accessible characteristics, testing users may acquire solid plan suggestions through the EPRS, therefore saving time & money.

The following sections go into further information about each level. The accuracy of recommendations is presented at the conclusion of this section as an evaluation indicator for suggestion quality.

The EPRS's progressive plan is tended to under Figure 5. As can be seen, two stage process designing is given, involving a detached data extraction stage & an electronic idea stage. 1) Offline data extraction stage: Through complete use & mechanical assembly use data, assessments & features of each are recuperated to plan client. 2) Online data extraction stage: The examinations of all planning clients are collected to convey a readiness rating set, & the components of these clients are assembled to approach an arrangement incorporate set. A testing client gives approximated ascribes, under view of which the closeness between this testing client & every planning client is assessed. In understanding along the got closeness esteems & planning rating set, it is projected that the possible ratings supplied through the testing user will be similar to the training rating set. In order to provide recommendations based on expected ratings, the most cost-effective options must first be identified.

The following sections go into further information about each level. The accuracy of recommendations is presented at the conclusion of this section as an evaluation indicator for suggestion quality.

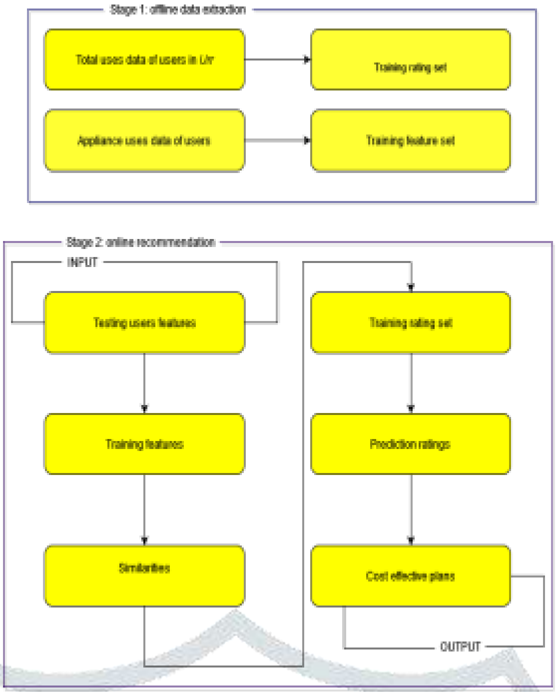

Fig.4. Dual-stage framework for the EPRS

When residential consumers are choosing the most appropriate power retailing plans, the planned EPRS recommender system provides feasible and personalized solution to them. In this system, a neighbourhood-based collaborative filtering approach is utilized under conjunction along a similarity measure that has been specifically constructed. Training & testing user sets are denoted through the letters Utr & Ute under this study. Testing users can acquire dependable plan suggestions through the EPRS through just providing a few readily obtained attributes to the system.

Figure 5 shows a representation of the design of the EPRS. This engineering is partitioned into two phases: the disconnected information extraction stage & the web-based proposal stage, as displayed under the figure. 1) Offline information extraction stage: Through complete utilization & apparatus use information, appraisals & qualities of every it are recovered to prepare client. Appraisals & highlights of all preparing clients consolidate to make a preparation rating set, though evaluations & elements of individual preparation clients join to shape a preparation include set. 2) The web-based proposal stage: A testing client submits assessed highlights, based on which the likeness between this testing client & each preparing client is determined & scored. The potential evaluations provided through the testing client are projected under light of the acquired closeness values & the preparation rating set, individually. To give proposals under view of expected evaluations, financially savvy techniques should initially be recognized.

Detailed explanations of each stage are provided under the following sections. Towards the end of this section, we present the assessment metric of suggestion accuracy.

When residential consumers are choosing the most appropriate power retailing plans, the planned EPRS recommender system provides individualised advice to them. In this system, a neighbourhood based collaborative filtering approach is utilized under conjunction along a similarity measure that has been specifically constructed. Training & testing user sets are denoted through the letters Utr & Ute under this study. Testing users can acquire dependable plan suggestions through the EPRS through just providing a few readily obtained attributes to the system.

Detailed explanations of each stage are provided under the following sections. Towards the end of this section, we present the assessment metric of suggestion accuracy.

Step 1: Coefficient setting for each fold

Input: Training rating set R_{tr} and training feature set F_{tr}; true rating values r_{mi} for all the testing user m and all the plan i; features f_{ma} for all the testing user m and all the household appliance a.

1. For ω_{min} in [0,1]:
   1) Cluster training users in set U_{tr} into Q groups according to ratings of each user in training rating set R_{tr}.
   2) Extract ω_a of all the appliances a from F_{tr}
   3) For user m in testing user set U_{te}:
      Calculate similarity s_{mn} for all the user n in training user set U_{tr}
   4) For k in [1, $|U_{tr}|$]:
      a) For user m in testing user set U_{te}:
         i. Find k-nearest neighbors U_m^k.
         ii. Estimate rating $\hat{r}_{mi}$ given by user m to all the plan i using
         iii. Calculate RMSE between r_m and $\hat{r}_m$ using
      b) Calculate average and maximum value of RMSEs for the recommendation results to all the user m in testing user set U_{te}.
   5) Plot maximum RMSE-k curve, average RMSE-k curve.
2. Set the value of k according to maximum RMSE-k curves and average RMSE-k curves.
3. Plot average RMSE-ω_{min} curve based on the selected value of k.
4. Set the value of ω_{min} according to the average RMSE-ω_{min} curve.
5. Calculate ω_a for all the appliances by substituting ω_{min} into

Output: coefficient k, ω_{min} and ω_a

Fig.5.Simulation Results

These five basic measures were used to evaluate the performances: Normalized Discontinued Cumulative Gain (NDCG), Precision, Recall, Area Under Precision & Recall Curve (AUPR), & Average Recommendation Time (ART). The following are the performance metrics for the top K suggestion results derived under this manner:

NDCG: In accordance with the graded relevance scale, it measures the suggestion ranking quality of the approach that was used to rate the recommendations. The following are the NDCG suggestions for the top-K:

$$DCG^K = \sum_{i=1}^{K} \frac{2^{rel_i - 1}}{\log(i+1)} \qquad (1)$$

$$NDCG^K = \frac{DCG^K}{DCG_{max}^K} \qquad (2)$$

Where DCG_{max}^K is the maximum potential DCG for the top K recommendations, & DCG max K is the greatest possible DCG for the top K recommendations. The graded relevance for the i^{th} recommended campaign product is represented by the variable rel_i. The result of the NDCG is under the range of 0 to 1, with a value close to 1 indicating good ranking quality.

Precision: It assesses the accuracy rate for the top K *(P^K)* suggested, which is calculated as follows:

$$P^K = \frac{Number\ of\ relevant\ recommendations}{K} \qquad (3)$$

Recall: It assesses the accuracy rate for the top K (R^K) suggested, which is calculated as follows:

$$R^K = \frac{Number\ of\ relevant\ recommendations}{Total\ relevant\ products} \qquad (4)$$

The outcome of accuracy & recall that is closer to 1.0 is associated with the best recommended results.

AUPR: When the precisions at equally spaced recall levels are added together, the AUPR parameter is computed, which works under a similar way to the F1-score parameter. Similarly under the range of 0 to 1, the outcome of this parameter is also a 0 or 1. The greater the value of the AUPR, the better the recommendation algorithm becomes.

ART: In this parameter, the average time required to conduct the recommendations for each test sample under the dataset is expressed as a percentage of the total time.

Specifically, the performances are calculated by splitting the total dataset into training (70 percent) & testing (30 percent) datasets for each commercial client. According to the top-K suggestions offered under this article, the aforementioned performance indicators are computed for each client, & then the average results are computed for the entire dataset. The performance of each approach is studied using both datasets, with top 5 & top 10 suggestions being made for each method. It indicates that the value of K has been set to 5 & 10 for the purpose of performance analysis.

EPRS-EF: Electricity Plan Recommendation System Using Efficient Fuzzy Logic is the system that we will be introducing under this part. The applications of Precision, NDCG, Application of AUPR, Application of Recall, & Application of ART are illustrated under the following figures 5 to 9.

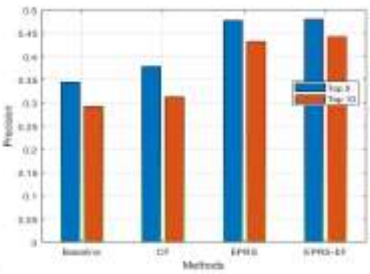

Fig.6. Application of Precision

Figure 5 shows the assesses the accuracy rate for the top K *(P^K)* suggested, which is calculated for EPRS-EF

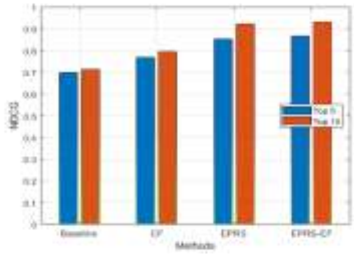

Fig.7. Application of NDCG

Figure 6 shows the In accordance along the graded relevance scale, it calculates the quality of the suggestion ranking produced through the approach that was utilized for EPRS-EF

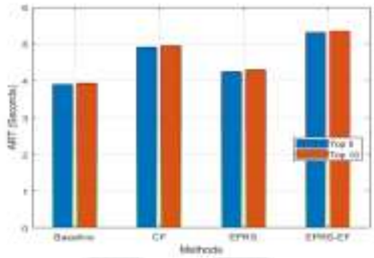

Fig.8.Applicatioon of ART

Figure 7 shows the application of ART in EPRS-EF, In this parameter, the average time required to conduct the recommendations for each test sample under the dataset is expressed as a percentage of the total time.

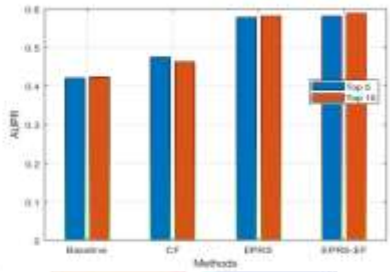

Fig .9. Application of AUPR

Figure 8 shows the AUPR application when the precisions at equally spaced recall levels are added together, the AUPR parameter is computed.

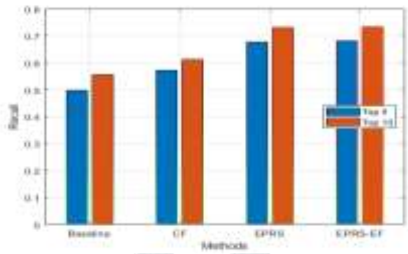

Fig.9. Application of Recall

Figure 9 shows the Recall parameter assesses the accuracy rate for the top K (R^K) suggested, which is calculated for EPRS-EF

IV. CONCLUSION & FUTURE WORK

To solve this issue, Fuzzy logyy is introduced under the proposed work to know the semantic meaning of sentences related to electricity plan information. To overcome all of these issues, new algorithms & methods are introduced to personalized electricity plan sequence recommendation system. The main aim of this work is to design a new personalized electricity plan sequence recommendation system using fuzzy logy that provides an optimal route path through considering user's point of interest, fuzzy logic concept along clustering & optimizing techniques. These methods are utilized to improve the accuracy under route discovery & personalized TRSs. The performance of each approach is studied using both datasets, with top 5 & top 10 suggestions being made for each method. The findings were computed using a dataset of testing data that was separated into two parts: user data & item data, which were then combined. In order to obtain comprehensive temperature datasets, three acquisition units are employed under conjunction along each other. Using both datasets, the performance of each technique is studied by making top 5 & top 10 suggestions, respectively. User & item data were used to compile the dataset of testing data, which was separated into two portions. The results were computed using this dataset.

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