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Estimation of Household Energy Consumption: A Survey

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Abstract— Now-a-days energy consumption has become one of the most studied topics, not just from a climate prospective, but also from technological view of point. The power consumed by millions of household, around the globe, comes majorly from non-renewable sources of energy, which are rapidly depleting. There is an urgent need generating to find ways to effectively consume energy for a sustainable environment. Many researchers have proposed model for Energy Consumption, especially Household sector, to gather different optimized patterns, thus to find solutions to various energy consumption problems. This paper considered various previous works done in the related field, from the year 2010 to 2019, to give a comprehensive study about models applied and dataset used, besides their optimization techniques and results.

Keywords— Energy Consumption; Household Energy Consumption; Optimization; Machine Learning Techniques; Survey.

I. INTRODUCTION

Energy is one of the primary required source of all life on the planet. The energy generated by non-renewable sources enable us to cook our food, drive our cars, power our systems and do tons of chores. It provides an environment for living organism to thrive and evolve. The recent trend of consumption of energy shows that it is being used beyond recovery. This has generated an urgent need to find conservative ways to prevent overconsumption, besides exploring renewable sources to generate power.

Energy Consumption, especially household, depends on various factors, which can be divided into Internal and External factors. Internal Factors incorporate features like income of the family, number of members, appliances used, and so on whereas external Factors include things like temperature, seasons, other weather conditions and so on. Regularly, the utilization is relying on financial and climatic states of an area feasible for the evaluating exercise.

The Machine learning and prediction models have drawn the attention of various researchers to work and find effective solutions towards energy consumption. In recent years, a large spike is seen on the usage of Machine Learning and Neural Network to solve the problem of household energy overconsumption. Researchers have included variety of datasets, ranging from a few hundred to thousands of houses, to test and present their results.

In this paper, we studied works done in the field, mostly ranging from the year 2010 to 2019, thus giving us detailed insights about various algorithms used and their efficiency, dataset used and their results. It enables readers to have a wide-ranging material on work done in Energy Consumption, especially Households.

In this paper, elaborative survey is done to study the efficiency of traditional algorithms, and the recent trends towards Neural Networks. Also the range of households, and its various factors, contributing towards the energy consumption can also be deliberated from this literature.

The various segments of the paper are as follows: Section II contains the objectives of the paper, Section III gives us a classification of papers based on the models applied, datasets used and optimization techniques applied. Section IV contains analysis of previous literature. Section V finally concludes the paper.

II. OBJECTIVE

The work is fixated on the finding of various works completed in the domain of household power utilization and enhancement. Therefore the key focuses of this paper are:

- To examine the previously proposed work in the pertinent field, from 2010 to 2019.
- To spread out various techniques used to prepare the data and clean it. Also various interconnections among the different attributes of the dataset.

- To study different models applied on the dataset to gauge and enhance the results for achieving higher accuracy and proficiency.
- To give a comprehensive study about the work done in the related field.

III. CLASSIFICATION

A. *Models Applied*

Researchers used different combination of algorithms to apply on their dataset to find desired results. The models can be sub classified into the following:

1. Applied Machine Learning Models: The paper[1] integrates arithmetic data similarity, along with machine learning techniques to carry out the synthesis of the population. Paper [2] used Machine Learning algorithms, specifically Boosted Decision Tree Regression for modeling and forecasting of energy consumption for smart meters. Paper [3] uses hierarchical clustering[4] and grade data analysis, K-Nearest Neighbors algorithm and other machine learning techniques. Regression techniques namely "K Nearest Neighbors", "Ridge", "Lasso", "Support Vector" and "Decision Trees" are used in.[5] Multivariate Multiple Regression Models are used in [6], whereas specifically Lasso regression is used by [7]while Support Vector Regression is considered in [8]. The cluster analysis in [9] is done by K means algorithm, while multiple algorithms like "K-Nearest Neighbors Regression", "Ordinary Least Squares Regression", "Decision Tree Regression" "Support Vector Regression", are applied on "Smart Meters" data in [10].Variations of "K-means algorithms" like "K- medoid" and "Fuzzy K-means" are used in [11] and [12].

2. Proposed New Methodology: Many researches guided us through their own proposed new algorithm, or an enhanced version of general algorithms. Paper [13] describes Home Energy Management Systems algorithms which works on the data gathered from energy monitors. Paper [14] uses MGB .i.e. Model of Goal-directed Behavior and a non-linear algorithmic method with multi-objective and varied figures is developed in [15]. For domiciliary smart energy systems, an energy administration system based on queuing methods us presented by [16]. Using the power price rates of generating and consuming power, an optimized control methodology is recognized[17]. Paper [18] presents CONDUCTS (Consumption Duration Curve Time Series) which, along with unsupervised machine learning, gather patters from raw data. Being progressive and incremental, an optimized unsupervised mining mechanism is proposed in [19] whereas revised Support Vector Regression is presented in [20].

3. Applied Neural Networks: Some proposed works use neural networks to enhance the prediction model. Neural networks are models based on the working of human mind, with high efficiency and accuracy. A feed forward artificial neural network is used in [21], while paper[22] uses neural network prediction model. [23], [11] and [24] uses fuzzy neural network models along with traditional algorithms, namely liner regression, K means and other regression models. The load demand forecasting of residential buildings is done by artificial neural networks in [25], while a hybrid of genetic algorithm and adaptive fuzzy interpretation system based on network(GA-ANFIS) is presented in [26].

B. *Dataset*

Dataset is the key factor while developing any model of machine learning. The richer the dataset, the more efficiently the model will work.

1. Organizational dataset: The data used in [2] paper is obtained from the Europe's Public Data, DECC live data website on electricity and gas consumption. In[27], data is gathered from the major units of the "eBox" software design namely "Control Logical Unit " and the "Optimization Element". The dataset used in [3] integrates a couple of years gathered data from "Almanac of Minutely Power dataset (AMPDs)". In[22], aforementioned data of Seoul is used. The "ASHRAE" Residential Power data set have been used in [23].Hourly usage patterns are taken from the United States disposition of inhabited "Advanced Metering Infrastructure (AMI)"in[28].

   Dataset from North American electric utility has been used in [20]. Forecasting models are applied on the data sets collected from the "Contest on Energy Prediction Shootout" and from a library in

Zhejiang University of China [26]. Yearly usage information from year 2014 to 2016 is taken by Utility Company situated in Canada [29].In Paper [29], over 16000 housing data is studied and effectively classified.

2. Smart Meter Dataset: In paper[30]data from smart meters have been collected for efficient analysis of household characteristics. In [8], the customers' usage patterns are taken every fifteen minutes with the help of "Smart Meters. Smart meter data from the Danish, a city in Esbjerg in [9] have been collected. In [4] paper, the authors have applied their architecture on the information collected from the area of Western United States as a residential Demand Supply platform between year 2012 and 2014. Data collected from Smart Grids in residential sector have been used in [16] and [31]. Figures are collected from Smart Meters in [19] for clustering daily load curves. These meters are also capable of providing real time usage data of energy, as done in [32] and [33].

3. Collected dataset: In [6], for the dataset, the athors carried out their own survey for thousands of houses, gathering information on various factors and parameter, like power usage per month, family members and so on. In paper [21], data is gathered from the area of Otaniemi area of Espoo, Finland. Data of 24 (or 48) observations a day have been collected on hourly traded prices in paper [7]. Real household data of single-zone of low-energy house in Sydney has been used in [15]. Anonymised format is used to collect information, protecting personal data, in [12]. To see the motivation behind power saving, dataset from a metropolitan area of southern china is collected [14]. The statistics set is gained from an indigenous university in Malaysia on a day-to-day base for couple of hundreds of days in [24] for predicting consumption of electricity.

C. *Optimization Techniques*

Optimization of models becomes necessary with respect to getting better and accurate information from our raw data.

1. Applied Optimization: Paper [2] uses a boosted optimized decision tree, while metaheuristic techniques, namely local search combined with exhaustive enumeration stages, is used in [27]. BFGS (Broyden-Fletcher-Goldfarb-Shannon) algorithm is implemented by [3]. Adaptive version of K means method is incorporated in [28]. K-medoid clustering along with a series of profile classes are used to classify data without any proper information about it [12]. Fuzzy k-means has been used to optimize the results obtained from basic k-means technique in [11]. Fuzzy based approach is used in [34]. Multiple approaches are used in [33] to reduce the rebound peaks. "K means" method followed by optimization through Particle Swarm technique in [35] provided an effective and fair allocation of the supply of power, for it improved consumption and conservation. Paper [36] evaluated the raw data and identified diverse factors on which it depends. Optimized version of Support Vector Regression, along with locally weighted regression is proposed in [20].
2. Proposed Techniques: Paper [30] presents an optimized way to predict load profiles based on factors algorithms. GA-ANFIS, which corresponds to "a genetic hybrid model algorithm-adaptive network-based fuzzy inference system", is presented in [26]. Depending upon various conditions, an ideal regulatory policy is given in [17] for domestic vitality efficacy management. An efficient way of visualization, known as time tone, is presented in [42]. Paper [18] and [19]proposed efficient and optimized methodology for energy prediction and conservation, namely Conducts and unsupervised mining mechanism respectively. A quick review of the existing work in house hold energy consumption is depicted in Table 1.

Table 1. Existing work in household energy consumption

S.No	Title of Paper	Objective	Database Used	Algorithm Used	Remarks
1.	Estimating residential energy consumption in metropolitan areas: A micro simulation approach [1]	Estimate energy demand using datasets available in the US using a bottom-up approach.	Atlanta metropolitan area data along with Public Use Micro data Sample (PUMS) with American Community Survey (ACS) is used.	Statistical data matching techniques as a part of machine learning is applied on the data	The model is validated with the data available and gives us the desired results.
2.	Energy consumption forecasting for smart meters [2]	Feature engineering techniques for time series forecasting for smart meters is applied.	Europe's Public Data, DECC live data website on electricity and gas consumption	Machine Learning algorithms, specifically Boosted Decision Tree Regression .	Results are not discussed as the data is not open for public sharing.
3.	Load scheduling for household energy consumption optimization [27]	An optimal scheduling of the usage pattern of the various appliances from an end-user's view.	The core constituents of the eBox software design.	The algorithm is a heuristic structure combining local search with exhaustive enumeration phases	Schedules the different appliances in a household and gives a pattern to it.
4.	Energy demand model for residential sector: a first principles approach [37]	For building a high-resolution energy model using First principles approach	Synthetic Population, ATUS and RECS Data	Mapping the wattages of the appliances to the activities of a residential sector.	Two kinds of energies are concluded i.e. the active energy and the passive energy.
5.	Electricity forecasting on the individual household level enhanced based on activity patterns [3]	To address short-term electrical energy load predicting for 24 hours	Almanac of Minutely Power dataset (AMP ds) which consists of recorded data for 2 years (at one minute intervals)	Hierarchical clustering KNN, BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm, machine learning techniques	An inclination towards Machine learning techniques is displayed which is based on the activity pattern.
6.	Residential demand response targeting using machine learning with observational data [5]	To give an outline on short term load forecasting at a single handler level.	Data is collected from Residential Demand Response program in the US from2012 to 2014.	Lasso, Ridge,KNN Regression, SVR, Decision Tree Regression are used	Users with variably consuming patterns could not provide us with any suitable result.
7.	Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy [38]	To apply sensor-based estimation and information driven procedure to the multi-family household territory	Records from a multi-family household working in New York	Support Vector Regression (SVR)	Results demonstrate that sensor based models can be extended to multi-family housing and that the ideal checking granularity happens at the base level in hourly breaks
8.	Feature selection approach for reducing the power consumption for a greener environment [39]	It shows the structures which have obvious effect on the power use.	Various multivariate attributes are used.	Filter methods like Chi squared test, correlation methods.	The box plot graph specifies the significance of attributes of dataset which thus reduces the power consumption for greener environment.

9.	Estimation of temperature correlation with household electricity demand for forecasting application [40]	A hybrid of nonparametric model with time series analysis is presented.	Several relations between housing energy demand and temperature.	Autoregressive (AR) models, Short Term Load Forecasting.	The hybrid model greatly reduces the load profile estimation.
10.	Household energy consumption prediction by feature selection of lifestyle data [6]	Proposes a figure model for the yearly power utilization of basic houses.	A feedback survey for 7842 homes is conducted. [6]	Multivariate multiple regression.	Predicting the regression coefficients simultaneously and accurately
11.	Evaluating Feature Selection Methods for Short-Term Load Forecasting [41]	Learning the utilization of attribute selection techniques for estimation of domestic energy consumption .	A subdivision of pertinent attributes are chosen from the dataset [41]	Filter, wrapper and embedded algorithms.	The techniques improved the forecasting accuracy of the model.
12.	Machine learning based integrated feature selection approach for improved electricity demand forecasting in decentralized energy systems [21]	It puts forward a machine learning based cohesive attribute selection approach.	Records from energy frameworks arranged in the Otaniemi part of Espoo in Finland is utilized.	A feed forward artificial neural network (FFANN) model.	The total energy cost is lowered considerably by applying demand response concept
13.	Home energy monitors: impact over the medium-term [13]	It discovers the level to which people achieve their initial electrical energy savings over a period.	Data from energy monitors.	Various Home Energy Management System (HEMS) algorithms.	The aim is to benefit the gas or electricity provider.
14.	Effective Prediction Of Electricity Consumption Based On Efficient Analysis Of Household Characteristics [30]	To enable utilities to benefit from the knowledge related to consumer segments	Data from Smart Meters	Load profile based upon factors algorithms	It helps in making an intelligent system to detect fluctuations
15.	Predicting residential electricity consumption using neural networks: A case study [22]	Electrical energy demand estimation plays a vital role in short-range load division and long-standing development	Based on the aforementioned data of Seoul	Neural network prediction model	It confirms the effect of a number of factors i.e. over-all population, elderly residents and so on .
16.	Forecasting Electricity Spot Prices using Lasso: On Capturing the Autoregressive Intraday Structure [7]	Lasso regression model is applied to estimate day-ahead electricity spot prices.	24 (or 48) observations a day containing prices, both hourly and half hourly.	Lasso model is applied besides Linear Regression Methods.	The results displayed the effectiveness in the prediction by the Lasso Regression Model.
17.	Predicting future hourly residential electrical consumption: A machine learning case study [23]	The assessment of various algorithms applied with the target of deciding the most ideal strategy for expectation is done.	The Houses energy data is taken from ASHRAE.	Linear Regression, Neural Network with feed forward properties, Support Vector Regression"	The outcomes indicated that the neural network outperformed the other two techniques on the dataset.

18.	Demand Forecasting in Smart Grids[8]	To carry out STLF of totals of intensity meters	The meters to be conveyed at client areas and their observed values are examined after each 15 Min.	Support vector regression.	The last execution of average of SVR expectations on the framework wide information arrives at an efficiency of around MAPE with 3%.
19.	Household Energy Consumption Segmentation Using Hourly Data[28]	An electricity division procedure of a house deploying an encoding framework with a pre-prepared burden shape lexicon.	US organization of private progressed metering foundation gave hourly electricity utilization information.	Adaptive K-mean algorithm, Hierarchical clustering.	The kind of k-means algorithm applied in this calculation does not ensure an ideal separation between clusters.
20.	Electricity consumption clustering using smart meter data[9]	Clustering household power utilization utilizing smart meter information.	Information of smart meters taken from Esbjerg-the Danish city.	K-Means clustering method.	K-Means excludes correlation, and basically overlooks the characteristic data.
21.	A Bayesian Perspective on Residential Demand Response Using Smart Meter Data[10]	To find the decreased amount of hours of Demand Response, considering not the homogeneity of power clients.	Information related to smart meter of responses of residents of the United States mainly west portion.	Regression methods like Standard Least Squares Regression, Hidden Markov Model, Support Vector Regression, and Regression with decision trees.	OLS is related to a dormant variable that creates the least one-sided estimator for DR decreased.
22.	Structured Literature Review of Electricity Consumption Classification Using Smart Meter Data[11]	To make an efficient writing review of power utilization order utilizing smart meter information.	An information quality score consisting of 13 distinct properties is utilized as the fundamental information.	K-medoid, K-means grouping and Fuzzy logic for k-means after which the transforms of Leader and Fourier have been used.	An organized and straightforward bit by bit rules for guaranteeing consistency, target assessment and choice of papers is given.
23.	A Clustering Approach to Domestic Electricity Load Profile Characterization Using Smart Metering Data[12]	To develop progression of classes of profile intelligence of home power deploy to group information with no appropriate data about the information.	The information given is in anonymized position so as to 188 secure work force and secret data identifying with the 189 clients.	Clustering techniques: Self Organizing Maps (SOM), k-medoid and k-means comes under unsupervised models.	It got conceivable to group information and the way with which they deploy power depending on their individual attributes, and without earlier information on family unit electrical energy utilization.
24.	The effect of self-determined motivation on household energy consumption behavior in a metropolitan area in Southern China [14]	To look at the significance of self-decided inspiration on good ecological practices that advance environmental change alleviation in Southern China.	Dataset from a metropolitan area of southern china.	A coordinated model of Goal-coordinated Behavior (MGB) is utilized as the calculated structure.	Incorporation of self-decided inspirations to MGB increased the model's predictive power.
25.	Forecasting Residential Energy Consumption: Single Household Perspective[29]	To analyze power utilization at a house unit level utilizing smart meter information to household's private electricity administrations and addition bits of knowledge into arranging request reaction programs.	The power utilization informational index from 2014 till 2016 is gotten from a Canadian service organization.	With day by day and hourly information, Support Vector Regression (SVR) is deployed for displaying results.	Predicting utilization of electrical energy for singular family units is achievable, however the precision is exceptionally trustworthy on behavior of household inconstancy.

26.	Predicting Electricity Consumption: A Comparative Analysis of the Accuracy of Various Computational Techniques[24]	To investigate the dynamic connection between mugginess, temperature and value; and its impact on power utilization of electric machines.	Dataset is acquired from a nearby college of Malaysia every day for 273 days, from 1 January till 30 September 2013.	Adaption of kalman filter, models of regression and ANN.	It recognized the kalman algorithm calculation as the best evaluating technique in forecasting for future power utilization.
27.	Predicting the Energy Consumption of Residential Buildings for Regional Electricity Supply-Side and Demand-Side Management[35]	To take care of the issue of unevenness order, bearing a superior comprehension of the quarterly power utilization for structures of homes.	Month to month power utilization appraisals are definitely grouped dependent on open information in a whole locale, which incorporates more than 16000 households.	K-means with the nature inspired technique of particle swarm optimization.	Given an essential initiative reference for the recognizing task of the power supply, which is significant in improving the general power grid quality.
28.	Socio-Economic Factors Affecting Individual Household Energy Consumption: A Systematic Review[36]	To create successful energy approaches for finding the financial components of household sector influencing family energy utilization.	ERIC, Search Premier of Academic, Science Direct.	Synthesis of data after inclusion and extraction, then identification of factors on the basis of the used literature.	Factors like urbanization level, dwelling size, economic condition, time at home are recognized.
29.	Optimal Smart Home Energy Management Considering Energy Saving and a Comfortable lifestyle[15]	To consider an ideal utilization of vitality in a smart home with balance between pleasant way of life and energy sparing.	Sydney's real unit-zone, low-energy household.	Multiple objective mixed integer nonlinear programming model (NLPM) is created and used.	Results showed complete utilization of energy cost and thermal well-being level are dependent on eachother.
30.	Smart meter based short-term load forecasting for residential customers [32]	To examine the impact of automatic meter readings.	Real-time data of the customers.	Shaping filter is calculated using spectral analysis, Kalman filtering is used for load prediction.	Accomplishing the ideal prediction accuracy while keeping away from a computational load requires confining the amount of data used.
31.	Nonlinear predictive energy management of residential buildings with photovoltaic& batteries [25]	To study residential building's nonlinear predictive energy management strategy.	Real meter load data from various residential sector.	Load demand forecasting using artificial neural networks is used.	The proposed control scheme achieves 96%to98% of the optimum performance.
32.	Forecasting building energy consumption using neural networks and hybrid neuro-fuzzy system: A comparative study [26]	To present an alternative approach to the predefined Artificial Neural Networks (ANNs) for estimating energy.	The exhibition of this given methodology is contrasted with the ANN utilizing two diverse data's, which are picked up from the Energy Prediction Shootout I challenge with a library working in University of Zhejiang in China.	Calculation of hybrid genetic on the basis of fuzzy derivation framework - versatile system is utilized in the work.	Results tells that the type of hybrid method used has very preferable execution over the typical ANN as far as forecasting is considered precisely.
33.	Electric Load Forecasting Based on Locally Weighted Support Vector Regression[20]	To give an optimization method to take care of the energy prediction issues	The two of the datasets used included: former data is day by day top electricity prediction contest (European Network of Excellence on Intelligent Technologies for Smart Adaptive Systems (EUNITE) contest), whereas the latter is taken from a North American electrical company.	In this research, a better and improved version of Support Vector Regression (SVR) along with the Locally Weighted Regression (LWR) is given, Distance with assigned weights calculation is dependent on the distance of Mahalanobis and is likewise consolidated.	The outcomes related to quant based on box plots , distinctive estimating errors, and U test of Mann–Whitney , displays the betterness of the model given , LWR, SVR over local and many more different models

34.	Queuing-based energy consumption management for heterogeneous residential demands in smart grid[16]	To manage the utilization of electricity for people residing in houses/clients in a framework of smart grids, besides formulating an optimizing problem.	Data collected from Smart Grids in residential sector.	A scheme for demand energy based on the model of queuing, the administration is exhibited in the work for the framework of smart grid related to different residents.	In the paper by permitting delay in the tolerant request hop and delay in the sensitive requests line, the electricity price and activity delay of clients is minimized by the central scheduler thus optimizing problem.
35.	Household energy efficiency management and optimization with energy storage[17]	To present an optimal control strategy for efficiently managing household energy	The data is composed from electricity utilization of household with proficiency along with multi-types factors.	An ideal control model is ingrained considering feed-in tax of supply of electricity, time-of-utilization cost, along with the life misfortune price of battery stock of energy.	Taking into consideration the hour of-utilization cost, a perfect control methodology for the administration of the energy utilization of a house is given for limiting clients' power cost.
36.	Estimation of appliance electricity consumption by monitoring currents on residential distribution boards [31]	The paper focuses on the residential electricity consumption taking into consideration the usage of appliances.	Data is gathered from residential distribution board and smart grids.	Grasp of structure of energy consumption and management of energy, XBee method.	To extract the structure of the household power request, this paper proposes the method to distribute board currents effectively.
37.	Temporal visualization of energy consumption loads using time-tone[42]	To exhibit representation related to time-tone, by helping clients by showing the varieties in electricity utilization from various classes of house unit gadgets over all energy utilization related to time along with load.	Information from the past times showed over a limited time frame. It takes, a m × n matrix as an input where there are (M) records of the energy consumption data.	The paper uses time tone visualization, having larger range of tonal variations of a single hue	The work showed that tone of time is bound to be better than the territory graphs in situations when there are immense varieties in energy utilization stacks as the time passed.
38.	Discovering electricity consumption over time for residential consumers through cluster analysis [18]	To give a noteworthy shape-based data in spite of the temporary dimensions for finding pattern in the data of energy.	The dataset contains information about residential electricity consumption behaviors over time.	The given procedure, namely Conducts (Consumption Duration Curve Time Series) extracts information stream preparing together with K means which is a non-supervised machine learning technique.	It could effectively cluster data and visualize it via Centroids based representation, boxplots distribution or Scatter plots.
39.	Feature construction and calibration for clustering daily load curves from smart-meter data[19]	To find configurations for appliance-appliance and appliance-time connotations to provide understanding into users consumption patterns.	Figures are collected from Smart Meters.	The paper proposes an unsupervised mining mechanism, which is incremental and progressive.	The work exhibits that the conduct of consumer's electricity utilization influences the machine while displaying the individual inclinations of ease.
40.	Automated Residential Demand Response: Algorithmic Implications of Pricing Models [33]	To address problems related to potential rebound peak for the algorithm of DR (Demand Response).	Real time residential meter data systems provided by utility company.	Many methods to decrease the highest point of rebound, and according to that proposing the algorithms for DR (Demand Response) for each individual home.	Effectiveness of the various approaches for the Demand Response (DR) is verified by numerical results obtained.

IV. Analysis

Many researches have been carried out related to estimating and optimizing energy utilization of houses. Most common techniques used in the pre-processing of the dataset, models applied on the data and its optimization techniques are shown in Fig 1.

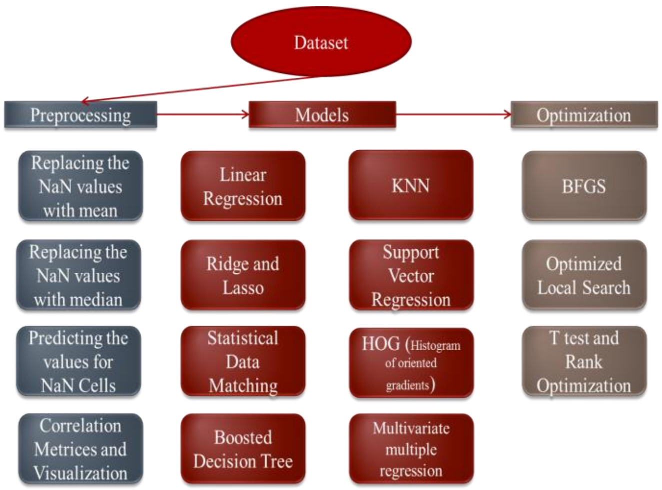

Fig 1: Representation of Common Techniques used

A. *Models Applied*

It is seen that many papers used regression models for predicting and load forecasting. Support Vector Regression and K means algorithm gave optimum results when predicting energy consumption. Researchers also worked upon modifying and further optimizing these techniques with combining it with other regression models or fuzzy networks. It shows the scope of further work which can be done in increasing the efficiency of the well-known methodologies in the field of energy conservation. The survey also indicates that Artificial Intelligence algorithms and Deep Learning Models are also making an operative entry into the field of energy consumptions. Neural Networks is one of the new and innovative fields of technology, and many researchers have tried to incorporate it into generating better models. Many new methodologies are also proposed by scholars, which are either developed from scratch, or are an advanced version of already known methods. The results showed that they are comparable to the already known models, which proves their effectiveness.

B. *Dataset*

Various works are done both on already gathered dataset and also dataset prepared from scratch. There are many variations of parameters given in various datasets. Dataset could be easily gathered from various organization comprising factors like appliances used, members in the house, temperature and so on. Many works carried out their own questionnaire to gather around reality data, thus getting much precise information according to their problem statement.

It is also seen that unfurnished data is collected from "Smart Meters", which give more real time data. This kind of data is being highly used by many models to learn upon, as they are much more real and accurate. Thus "Smart Meters" are much widely used, making it an optimal way to record energy usage of residential area.

The survey also showed various factors on which household power usage is dependent upon. Apart from external factors like topology, season, daily weather conditions like temperature and all, it also shows high correlation with internal factors like the income of the household, appliances used, number of members living and so on.

It is seen that many researchers proved their model effectiveness through their results and findings. Nevertheless there is a lack of concrete steps or guide on how to learn from the output gained, and what exactly to perceive from the patters founds. There is very less information provided on how to minimize energy usage post the results. Many works overcame this fault and proposed number of steps regarding the same, thus optimizing the power consumption.

V. Conclusion

This paper gives insight about various works done in the domain of household energy consumption, by carrying out the review of almost all the previous proposed work. After the detailed walk through, an analysis is also provided highlighting the key features from pertinent work. In the presented area, traditional algorithms like Support Vector Machine, K means, Regression Techniques etc. have proved their efficiency on variety of datasets. Researchers can use these algorithms as a base for further hybrid and complex models, incorporating Neural Networks too. The paper also opens roads for readers to get a comprehensive look on the work done in power usage to further optimize the models, and thus provide efficient household energy consumption prediction model.

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