Appliance Level Energy Characterization of Residential Electricity Demand: Prospects, Challenges and Recommendations

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ABSTRACT The advent of information and communication technologies has paved the way for smart cities. Residential customers are the major consumers of electrical energy in such cities. Smart meters gather the energy consumption behavior of consumers at the aggregate/household level. Characterization of aggregate demand data has several advantages but significant benefits in terms of energy sustainability require Appliance Level Energy Characterization (ALEC). Various solutions for ALEC rely on sensors, smart plugs, smart appliances, smart meters, and/or energy disaggregation algorithms but smart meters with built-in energy disaggregation algorithms seem to be the most scalable option. This work is one of the pioneering contributions to present comprehensive applications and prospects of ALEC for smart residential communities. It also links these applications with 2050 decarbonization pathways and various United Nations (UN) sustainable development goals (SDGs). Prospective uses of ALEC in diverse fields such as power systems, health care, the social sciences, economics, surveillance, marketing, appliance manufacturing, technology development, etc. are highlighted. Moreover, the requirements and challenges hindering the large-scale deployment of the ALEC frameworks are outlined with some recommendations and open research directions. It is envisaged that ALEC of residential electricity can be exploited not only for achieving 2050 decarbonization targets but also for several 2030 SDGs. This work will provide a one-stop source of information on ALEC and will open the doors of cooperation among various stakeholders of smart cities to achieve long-term SDGs.

INDEX TERMS Demand side management, energy characterization, energy consumption behavior, energy disaggregation, non-intrusive load monitoring, smart cities, sustainable development.

I. INTRODUCTION

Being part and parcel of daily activities, the role of electrical energy is vital in achieving any decarbonization goals [1]. Most of its generation through conventional sources in the past had originated alarming threats to sustainable development due to the depletion of fossil fuels, their rising costs, and polluting nature. Conceivably, the power sector is the major contributor to anthropogenic global warming which accounted for 38% of total energy-related carbon dioxide emissions and 66% of carbon dioxide emission growth in

The associate editor coordinating the review of this manuscript and approving it for publication was Bong Jun David Choi.
climate system [5]. Biosphere issues have led the attention of relevant stakeholders to engage all partners through different pacts. Some significant pacts include Montreal Protocol 1987 [6], UN Framework Convention on Climate Change (UNFCCC) 1994, Kyoto Protocol 1997 [7], United Kingdom (UK) Climate Change Act 2008 [8], and Paris Agreement 2015 [9]. These pacts set targets for GHG emissions, renewable energy integration, Energy Efficiency (EE) & conservation and other measures for environmental protection and economic development. Paris Agreement sets a threshold for the average rise in global temperature well below 2°C above pre-industrial levels and advocates for efforts to cease this increase below 1.5°C [10], [11].

Economic issues, environmental threats and legal bindings have tracked the attention of researchers toward (i) energy conservation and EE (ii) renewable energy for deep decarbonization of electricity and gas supplies and (iii) switching of end energy usage to low-carbon energy supplies [12]. Adoption of energy-efficient measures reduces net costs and their non-adoption would result in higher demands of low-carbon power, hydrogen and carbon capture, and storage [11]. All pathways essentially rely on these three measures to achieve the deep carbonization goals of 2050 as shown in Figure 1. Meeting decarbonization targets would ultimately result in sustainable, affordable and secure energy as envisioned in Sustainable Development Goal (SDG) ‘SDG7’ set by the UN [13].

The residential sector is the major consumer of electrical energy. In the member countries of the Organization for Economic Cooperation and Development, this sector accounts for 30-40% of electrical energy consumed [14]. Transitioning toward the smart grid, some electrical utilities are gathering the aggregate demand of residential consumers through Advanced Metering Infrastructure (AMI). Characterization and analysis of the smart metering data after their storage and processing can originate various technical, economic, social and environmental benefits for diverse stakeholders [15], [16]. Various uses and implications of these data are reviewed in [17]–[20]. By revealing lifestyles [21], Energy Consumption Behaviors (ECBs) [22], [23] and socioeconomic status [24] of consumers, it can act as a valuable resource for energy sustainability through energy management [25] and efficient grid operations [26].

Despite various applications of smart metering, significant benefits in terms of energy-saving and efficiency have not been achieved as expected [27]. To achieve more gains,
a detailed time-coupled Appliance Level Energy Characterization (ALEC) of consumers is required [28]. ALEC can be used by multiple stakeholders to obtain diverse benefits by offering innovative services. ALEC, when integrated with optimal management strategies, can resolve energy crisis issues and can foster different techno-economic benefits [29], [30].

Carrie Armel, et al. [27] described the hardware and software modifications required to extract the appliance level ECB from the smart meters but a little discussion was included on the benefits of this information. A committee decision mechanism based on multiple steady-state and transient features was proposed by Liang, et al. [31] to extract the appliance level demand information from smart metering data. Few application areas of these data were also enlisted in this work.

Gupta, et al. [32] combined appliance level energy demand with other non-electrical parameters of the building to customize the settings of a Programmable Communicating Thermostat (PCT) in different seasons. Few benefits of ALEC for the utilities and customers were highlighted but uses for other stakeholders were not mentioned. Some business applications of ALEC through energy disaggregation were briefly presented in [33]. Applications of ALEC for realizing energy-efficient residential homes were highlighted in [34]. Najafi, et al. [35] provided a comprehensive discussion on various energy disaggregation methods for ALEC. Some use cases of disaggregated energy information were also discussed but this work neither stated the associated requirements nor fully covered the prospects of ALEC data.

None of the prior works presented a comprehensive discussion on the applications and prospects of ALEC especially in the context of 2050 Pathways and UN SDGs. The major contribution of this work is to fill this gap by presenting the broad applications and uses of ALEC in diverse fields involving various stakeholders. Uses of ALEC in achieving 2050 deep decarbonization goals and 2030 UN SDGs are presented. Some innovative services for smart residential communities are also envisioned using ALEC. According to the best of the authors’ knowledge, it is one of the pioneering works to map prospective applications and uses of ALEC with UN SDGs of 2030. Challenges and requirements for large-scale deployment of the ALEC framework are also highlighted. Additionally, some research directions associated with the large-scale deployment of the ALEC framework and its applications are outlined. The paper is organized as: various techniques for implementing the ALEC framework are described in Section II. Section III is devoted to various applications and prospects of ALEC in smart residential communities. Section IV maps ALEC with various decarbonization and SDGs and also discusses the requirements and challenges for deploying its large-scale framework. In Section V, some promising research directions related to ALEC are highlighted and Section VI concludes the paper.

II. IMPLEMENTATION OF APPLIANCE LEVEL ENERGY CHARACTERIZATION FRAMEWORK

ALEC involves monitoring runtime electrical parameters of various household appliances. This monitoring helps understand various temporal and spatial characteristics of appliance level energy consumption such as appliances’ status, frequency of usage, energy intensity, power consumption, appliance usage patterns, energy patterns in a zone/room, etc. Different preferences regarding space and time granularity lead to multiple options for energy characterization as shown in Figure 2. ALEC can assist control of the individual appliances and support reductions in energy consumption costs through optimum appliance usage. The intensity of appliance usage can be quantified in units of energy (kWh, Wh), power (kW, W), money ($, £, €), carbon dioxide emissions (Gt, kg), etc. at various timescales [36]. Depending upon the nature and requirement, ALEC data can be represented in various formats e.g., charts, tables, figures, etc. Sometimes ECB of a particular room/zone in a household is desired instead of individual appliances.

A. LOAD MONITORING TECHNIQUES FOR ALEC

Monitoring runtime electrical parameters of various appliances for ALEC can be performed in two ways: (a) Intrusive Load Monitoring (ILM) and (b) Non-intrusive Load Monitoring (NILM).

1) INTRUSIVE LOAD MONITORING

ILM generally requires individual sensors for each target appliance which makes it more costly, difficult to install, complex to maintain, and thus limits its adoption [37]. Sometimes instead of ALEC, the consumption behavior of a specific zone or a room is required to be monitored through ILM [38]. Different interests lead to the installation of individual sensors, smart plugs or/and submeters in different ways as shown in Figure 3. Since an individual sensor is dedicated to track information of an individual appliance, single room or a small zone, the results of extracted behavior and ALEC are much accurate in ILM [39].

2) NON-INTRUSIVE LOAD MONITORING

The high cost and installation complexity of multiple sensors in ILM have diverted the attention of energy researchers toward NILM. NILM techniques employ statistical, Machine Learning (ML) and/or optimization methods to disaggregate the data collected from a single sensor into individual load demands. This sensor is usually the smart meter installed by the utility company. Occasionally, data collected through the submetering of a particular zone can be input to NILM algorithms and these algorithms will characterize the ECB of the appliances installed in the zone as illustrated in Figure 3.

Sometimes demand data of a circuit supplying high power appliances are disaggregated by the NILM algorithms for ALEC. The accuracy of earlier NILM algorithms for energy disaggregation was not up to the mark. But
nowadays, due to the advent of sensor, communication and artificial intelligence technologies, the accuracy of energy disaggregation through NILM techniques has been much improved. However, the ALEC with NILM is much challenging for appliances with overlapping features [40], appliances with low usage [41], small appliances or appliances with varying energy consumptions. But the characterization of major appliances with higher power ratings is easy using NILM algorithms.

Different types of NILM algorithms have been devised in literature such as optimization-based models, ML based models, and Hidden Markov models (HMMs) [42], [43].
Integer linear programming [44], Integer Non-Linear Programming (INLP) [45], mixed ILNP [46], quadratic programming [47], particle swarm optimization [48], [49], genetic algorithm [50], differential evolution [49], simulated annealing [49], the cuckoo search algorithm [49], firefly optimization [49], etc. are some optimization techniques used for solving NILM problem.

ML-based models take NILM as classification, regression or a hybrid problem [51], [52]. A detailed review of multilabel classification formulations used for NILM is presented in [53]. Some classification approaches applied to solve NILM include multilabel sparse classification [54], K Nearest Neighbors (KNN) [55], [56], decision tree classifiers [55], [56], Support Vector Machines (SVMs) [57], Random Forest (RF) [56], extreme gradient boosting [58], clustering [59], [60], etc. Authors of [61] solved NILM as a regression problem using KNN, SVM, Deep Neural Networks (DNNs), and RF.

The modern trend in NILM is to apply Deep Learning (DL). Some recent DNN models used for NILM include recurrent convolutional denoising autoencoder [62], Convolutional Neural Networks (CNN) [63], [64], adaptive weighted recurrent graphs [65], Long Short Term Memory (LSTM) networks [62], [66], [67], Generative Adversival Networks (GANs) [68], sequence to sequence learning [69], Sequence To Point (seq2pt) learning [70], deep pair supervising hash [71], attention-based DNN [51], etc. Authors of [72] have presented a comprehensive review of DL-based NILM approaches applied to low-frequency data.

Many researchers extended the concept of transfer learning to solve the NILM problem. Transferability refers to the ability of a generalized ML or DL model to detect appliances from the aggregate data of an unseen house, not available in the training set. Transfer learning abilities of seq2pt [70], GANs [73], CNN [74], [75], gate current unit [74], and a combination of LSTM and the probabilistic neural network [76] are applied to solve the NILM problem. In transfer learning, a general trend is to convert feature trajectories into greyscale or color images. A CNN model trained on a visual dataset was used for NILM by converting voltage and current trajectories into HSV (Hue, Saturation, Value) color model [75]. Trials indicate that DL exhibits better performance as compared to optimization and factorial HMMs, but they require large training data [69].

B. SOLUTIONS FOR ALEC

Various devices for ALEC and related energy management frameworks involve devices for measurement, communication, appliance recognition, optimal management, and control [77]. A brief description of the functions performed by these devices and their examples are depicted in Table 1. Employing these devices and load monitoring methods described in Section 2A, different solutions are possible for ALEC. These solutions vary in terms of sensing equipment, cost, deployment effort, and adoption rate as presented in Table 2. A straightforward way to characterize the ECB of an appliance is to install a smart plug on the appliance. All these plugs can be linked with the desktop computer, laptop,
or mobile phone through the Home Area Network (HAN). As one smart plug costs around £15-£55 and dozens of such plugs are required for a single home, therefore this excessive cost limits its adoption for all the appliances. Different smart plugs such as Samsung SmartThings, D-Link, Bosch, Hive Active, TP-Link HS110, Belkin WeMo, Eve Energy, Ikea, Amazon, etc. are available in the market.

Smart appliance option for characterizing ECB requires £75-£80 extra cost for the smartness as compared to the conventional version of the same appliance. Moreover, the smartness option is mostly available with white goods such as refrigerators, freezers, washing machines, tumble driers, dishwashers, and Air Conditioners (ACs), etc. Such goods are not sold out quickly and their complete turnover from

FIGURE 4. ALEC framework and its prospective applications and uses.
the market requires about 12 years making their adoption rate uncertain [27].

Some ALEC solutions are cloud-based. Such solutions collect aggregate demand data through home level energy monitor/gauges and send them to cloud services at regular periods ranging from one minute to one second. The cloud services disaggregate this whole house consumption into appliance level consumptions which can be accessible by the consumer through web services. But adoption of such solutions is low because they are costly and need users’ consent and interest.

Another solution for ALEC is to implement the NILM algorithm on the smart meter. In comparison to other solutions, ALEC through the smart meter is the most scalable and economical option [27]. It requires few hardware and firmware upgrades in smart meter design to perform energy disaggregation inside the smart meter. The modifications required in metering infrastructure for energy disaggregation are discussed in [27]. The data of ALEC can be sent to utilities, consumers, and any third party. This solution has a huge penetration potential as it does not require any extra hardware to be installed by the customer. It is mainly driven by the utility which will upgrade the existing smart meters or replace them with newer versions with built-in NILM capabilities.

III. APPLICATIONS AND PROSPECTS OF ALEC

Large-scale deployment of the ALEC framework requires NILM algorithms to be implemented on smart meters. About 2-5% compromise of accuracy due to NILM might be there but it is not meaningful [33]. ALEC data of consumers can be stored at the central server maintained by the utility company via data link as shown in Figure 4. A smart and secure data sharing platform can be developed to provide secure access to this data for authenticated stakeholders only. ALEC data can be accessible to consumers through In-House Displays (IHDs), web services and HANs, and can be used by the consumers according to their preferences.

Data access to consumers is already available in California through Green Button Program where consumers can access their energy usage data after 24 hours [78]. Additionally, under this program, consumers can share their data with third parties to get energy management services. This sharing coincides with the recommendation of the report published by CCC which emphasizes the need for an infrastructure to enable consumers to share their data with third parties for novel services that support low-carbon options and practices [79]. ALEC data can also be shared with different stakeholders and third parties offering emerging/innovative services for smart cities and to achieve sustainable development and decarbonization goals targeted by 2050 [57].

Table 3 enlists UN SDGs of 2030 and the potential applicability of ALEC in their achievement. Most of the SDGs can be targeted through ALEC. Various stakeholders cooperating to exploit ALEC data for different applications are shown in Figure 5. Mutual engagement of diverse stakeholders is also desired by UN SDG 17 and 2050 Pathways Platform to achieve long-term and sustainable development.

A. FEEDBACKS, RECOMMENDATIONS AND CUSTOMIZED MARKETING

The ALEC framework not only delivers direct or indirect feedback to consumers about their appliance usage but also helps implement automated customized recommendation systems. A report published by UK’s CCC also advocates for the development of feedback systems to lead behavior change, policy and industry [79]. It is observed that feedback systems entice consumers to save energy [80]. About 5-20% of energy savings are estimated in the household due to
feedback programs [81]. Direct feedback systems, where consumers get real-time information about their consumption, are more effective in energy saving as compared to indirect type where consumers get information after the consumption.

Maximum savings through feedback systems are achieved when such systems are augmented with personalized recommendations as shown in Figure 6. One such attempt is made for the demand side by extracting the appliance level usage data through particle filtering algorithms [82]. Feedback systems for consumers can be made more effective by customization, detailed data representation, storage extension for historical data, higher feedback frequency, and making them interactive [36], [83]. Integration of behavior transformation mechanisms can also enhance their effectiveness [84].

The role of web portals, IHDs, and PCTs is also significant in this regard [85]. Similarly, educating people regarding economic and environmental concerns of energy usage, and building their trust in fine-grained ALEC through innovative services can also help implement effective feedback systems for energy conservation as given in Table 4. Specific consumers can be targeted for specific products/programs through effective marketing [82]. Electric utilities, environmental and energy conservation agencies and appliance manufacturers can effectively run their marketing campaigns by stating quantified terms of emissions and costs obtained through ALEC.

Effective advertisement and consumer success stories can also be produced using ALEC data. Data-assisted marketing can be effective in molding the behavior of consumers towards energy savings. Over 50% of the emission reductions just demand individuals to behave differently in their tasks [86].

B. ENERGY-EFFICIENT APPLIANCES AND LABELLING STANDARDS
ALEC informs consumers about less-efficient appliances in their premises. Energy-efficient appliances can partially tackle the inclining consumptions and emissions in both developed and underdeveloped countries as the number of appliances increases with the increase in income [129]. Japan through its Top Runner approach aimed to produce the world’s most efficient appliances and achieved efficiency improvements of 16.3%, 43% and 60.1% in ACs, refrigerators and Plasma/LCD televisions respectively [130]. In India, about 52 TWh-145 TWh originating 10-27% reduction in energy consumption and 42 Mt-116 Mt reduction in carbon dioxide emissions are projected in 2030 using
| Prospective applications | Ref. | Features | Algorithms | Remarks /Additional Results |
|--------------------------|------|----------|------------|-----------------------------|
| Feedbacks, recommendations, and customized marketing | [36] | Various types of feedback systems are developed while analyzing the understanding of consumers and their preferences about various feedback representations. | Consumer interface prototypes and interviews | Consumers prefer feedback systems giving cost information, appliance specific information, and a comparison with their historical data. |
| | [87] | The authors analyzed 12 prior studies on the effectiveness of appliance level energy information in feedback systems. An average reduction of about 4.5% is observed in these studies using appliance level energy information whereas energy information at the household level originates around 5% reductions. | Systematic review | Feedback can originate more savings if consumers are more energy conscious and this saving does not need fine-grained appliance level energy information. |
| | [88] | The energy consumption of Qatar is analyzed, and recommendations are made to guide consumers about EE and sustainability. | Mixed method approach using quantitative consumption data and qualitative data from surveys. | Instead of financial incentives, consumers' understanding regarding sustainability and environmental risks is effective for energy conservation and this understanding is highly dependent on effective energy monitoring. |
| | [82] | Consumer energy usage habits regarding different appliances are extracted using energy disaggregation. These habits are then used to recommend specific energy-efficient appliances to consumers. | Particle filtering based NILM | Cost-effective utilization plans can be recommended for consumers by comparing their energy profiles with similar households using a similar tariff scheme. |
| | [89] | An application-assisted socio-technical behavior modification model is developed to stimulate consumers for energy conservation. | Descriptive statistics | Interactive visualizations of energy consumption can help motivate consumers to save energy. |
| | [90] | With aims to stimulate individual behavior change for energy and water saving, the authors present the design of resource-saving programs and the methodologies to assess their effectiveness. | Analysis of various DSM projects | A vision for the future is presented with open issues that could lead to new research directions. |
| Energy-efficient appliances | [91] | Data from the national survey are utilized to assess the energy and emission savings by using the energy star versions of four residential appliances (ceiling fans, A/Cs, televisions and refrigerators). | Projection method for consumption estimation | A reduction of 40% in carbon dioxide emissions is possible with an effective financing policy and reduced cost of appliances. |
| Load identification | [92] | An edge analytics approach to identify home appliances is presented using the features extracted from smart meter data through wavelet transform. | Neural network | The proposed method is 99% accurate and reduces the data transmission cost through NILM implementation within the smart meter. |
| | [93] | Consumption of A/Cs was extracted from the total household energy profiles through an energy disaggregation algorithm. Effects of outdoor temperature on the average operating time, percentage of energy, and the number of cycles are also studied. | edge detection algorithm, K-means clustering | Increased granularity of smart meter data increases the accuracy of the energy disaggregation algorithm. |
| | [94] | ON status of the residential appliance combinations was identified using the uncorrelated spectral information of the low-frequency real power signal. Features for identification were extracted by decomposing the real power signal into its subspace components. | Karhunen Loeve expansion, likelihood estimation technique | The proposed method can identify the energy contribution of appliance combinations in actual households. |
| Customer segmentation | [95] | Households with plug-in Electric Vehicles (EVs) are identified based on energy envelopes of the consumption profiles. | Group of data mining algorithms | DR programs to modify the charging behavior of consumers can be designed to avoid grid congestion. |
| Load forecasting | [37] | Prior knowledge of the appliance usage is integrated with NILM to enhance its accuracy. Results of NILM and appliance usage knowledge are then used to forecast the total demand of a residential aggregation a few minutes ahead of the real-time. | Karhunen Loeve Transform, fuzzy expert system, priori biased NILM | The proposed NILM method and the knowledge of appliance usage can be effectively used in load control programs for DSM. |
| | [96] | This work performs short-term load forecasting for a residential home using the data of household power consumption and power consumption of a few selected appliances. The power consumption of the selected appliances is found using a DL-based NILM algorithm. | Feedforward neural network and DNNs | Load forecasting results using autoencoder-based NILM are found better as compared to other DNN architectures in this study. |
### TABLE 4. (Continued.) Summary of Research Works Related to the Prospective Applications of ALEC.

| Demand flexibility | [97] The electrical demand of a complex district is scheduled to provide flexibility potential for DR. | Central and distributed optimization techniques | Balance responsible parties and grid operators can reduce the mismatch between supply and demand. |
|--------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------|---------------------------------------------------------------------------------|
|                    | [98] The flexibility of electric vehicles’ charging demand is assessed non-intrusively from smart meter data. | Independent component analysis | The results of the study can be helpful for grid operators for energy conservation and grid stability enhancement. |
|                    | [99] Charging patterns of EVs are extracted from residential demand to quantify their flexibility potential for DR. | NILM, statistical probability model, clustering | The results of the study can assist grid operators in developing incentive programs to change the charging behavior of consumers. |
|                    | [100] An aggregated model for residential air conditioning demand is developed by incorporating the effects of indoor and outdoor temperatures to quantify DR potential. | Equivalent thermal model and probability distributions | The proposed model can be used to design DR strategies for residential ACs. |
| Load modeling      | [101] A simple and novel method for empirical load modeling is developed using the common usage profiles of a few common appliances which is more accurate than on-off modeling of appliances. | Model-based data analysis | Some applications of this modeling related to the synthesis of building energy usage profile and identification of rapid power varying loads and specific load models in demand profile are highlighted. |
|                    | [102] A NILM based approach is developed to model the demand of home appliances using smart meter data at the household level. REDD dataset is used for simulation purposes. | Explicit-duration HMM, forward-backward algorithm, estimation algorithm | The proposed method can be used for demand modeling of specific appliances using the whole-house demand data. |
| Energy auditing    | [103] A prototype NILM setup by modifying an existing algorithm is developed using a data acquisition system. The effectiveness of NILM was shown in residential audits. | Event detection algorithm | The F1-score for detecting state transition is 100% for most of the cases. |
|                    | [104] A small size 39 mm x 49 mm NILM device “minion” is developed for energy auditing. | DNN | Accuracy is 98.24% up to 64 devices and it would decrease for more devices. |
|                    | [105] AI-assisted NILM is developed on a laptop using a Data Acquisition (DAQ) system and related accessories to identify appliances in a real household. | Hybrid of K-means clustering and artificial neural networks | The rate of load classification is 72.57%. |
|                    | [106] A novel self-organized and non-intrusive model to identify major appliances is developed for DSM in smart homes. | Unsupervised automatic clustering-integrated neural networks | Averaged-generalized classification rate is 95.73%. |
|                    | [107] Arduino-based DAQ system is integrated with MATLAB’s K-means toolbox to develop an energy disaggregation algorithm. | K-means | Quantitative results of accuracy are not disclosed. |
| Energy management and conservation | [78] It is an experimental study in California to evaluate the impact of ALEC on energy conservation using a disaggregation-based energy management solution. | Non-intrusive pattern recognition method | Maximum, average, and minimum reductions of 24%, 14%, and 3.5% in energy consumption are observed respectively. About 80% of the audience desired the provision of this solution to all customers. |
|                    | [108] A NILM algorithm is trained using data of multiple substations to identify energy conservation options by the energy suppliers and consumers. | Software-based NILM algorithm | The use of non-electrical sensors is envisioned to improve the performance of the NILM algorithm. |
|                    | [109] An intelligent management system to control energy-intensive household appliances (AC, water heater, cloth dryer, electric vehicle) is developed to limit customer’s demand below a threshold level while considering comfort. | HEMS algorithm | The limit of DR potential from residential customers can be assessed. |
|                    | [110] A DSM management approach to shed unnecessary loads is devised after their identification in generation deficit periods. | HMM | The recognition system can be a part of a load controller for islanded microgrids. |
|                    | [111] A BEMS is introduced to control the operation of AC, electric vehicle, water heater, and battery based on the behavioral data of consumers and price data. | Model predictive control | The proposed BEMS can be used in residential buildings for cost savings under various pricing schemes. |
|                    | [112] A novel model is used to assess the impact of DR on the system’s stability and its optimal operation. Varying demand side participation and willingness of consumers’ participation in DR are also considered. | Hybrid algorithm | Customers’ willingness should be essentially considered by utilities for effective DR programs. |
|                    | [113] Shedding of consumer appliances in a load control program is verified using the energy usage data of individual appliances. | Event detection based distributed NILM | Guaranteed shedding of loads is possible through this technique. |
|                    | [114] The principle of decentralized active DR control to modify the consumption patterns of fridges and freezers is presented for peak reduction. | Stochastic control algorithm | The proposed control can enhance the reliability of the power system. |
| No. | Reference | Description of Research Work | Methodology | Summary |
|-----|-----------|------------------------------|-------------|---------|
| 115 | [115]     | A Bayesian network-based HEMS solution is proposed that characterized user behavior from its preferences and prioritized the usage of household appliances under consumption limitations. | Bayesian network | The proposed framework can control household appliances automatically as per the consumer’s preference under restricted and non-restricted energy usage environments. |
| 116 | [116]     | A personalized HEMS is devised to schedule the appliances at the minimum cost while incorporating consumers’ preferences, varying environmental parameters and prices. | Event detection based NILM | It can act as a practical HEMS in the smart grid environment. |
| 117 | [117]     | Activation of major loads for DSM is identified in the presence of photovoltaic (PV) generation. | Mixed integer quadratic programming | Despite the error in PV estimation, the water heaters and heat pumps are correctly identified. |
| 118 | [118]     | A NILM based customized cloud computing application with low bandwidth requirement is developed to identify electromechanical loads responsible for energy wastage. | Time-series database, Probability distributions | The proposed method can be helpful in preventive maintenance and energy conservation through the early detection of faults. |
| 119 | [119]     | A NILM based computing approach is proposed to identify faulty and vulnerable appliances using the leakage current feature. | Event detection method | The proposed application can enhance electrical safety in residential houses. |
| 120 | [120]     | An anomaly detection framework is developed for the identification of faulty appliances (ACs and refrigerators) using the appliance usage data gathered through NILM. | Rule-based anomaly detection algorithm with modified NILM | For better detection, some post-processing techniques are needed to reduce the effect of noise in NILM output. |
| 121 | [121]     | A framework is proposed to infer the activities of consumers using the appliance level information of energy usage obtained through NILM. The usage of appliances is mapped with daily activities to build an ontology. | Decision tree technique | The proposed method can help understand the routines of daily activities and their energy footprints. |
| 122 | [122]     | Activities of elderly people are assessed based on the disaggregation of smart meter data to develop a smart health application. Basic belief functions for appliances are developed based on the probability of their usage using Dempster-Shafer theory (DST). | DST, existing NILM algorithm | The proposed solution is more effective in detecting abnormal activities and generates fewer false alarms due to long inactive periods. |
| 123 | [123]     | Whole-house demand collected by the smart meter is disaggregated using deep feedforward neural network to monitor the living activities of residential consumers. Rules are defined to classify activities with the usage of specific appliances. | Rule-based edge detection method, deep feedforward neural network | The proposed method can be applied for consumer behavior analysis, remote monitoring, and smart health applications. |
| 124 | [124]     | Abnormalities in energy usage of appliances are used to detect abnormal activities of the consumer. Detection of abnormal activities can lead to the development of smart health applications. | Clustering, frequent pattern mining technique | The proposed technique can be used to send alarm signals to caretakers or health providers in case of abnormal energy usage. |
| 125 | [125]     | Event detection and event classification models are developed to realize NILM for assessing activities of daily living. A novel feature based on the trajectories of active, reactive, and distortion powers is used. | Event detection based NILM, principal component analysis | The novel feature based on trajectories used in this paper is proved suitable as it does not overlap among various types of appliances. |
| 126 | [126]     | This paper highlights the contribution of the UK’s SERL which is initiated to collect smart meter data and make these data available to energy researchers, policymakers, and other stakeholders for novel services. | Position paper | Highlighted applications of smart meter data apply to appliance level energy data as well. |
| 127 | [127]     | Demands of different household appliances in twelve EU member countries are characterized through data surveys to unveil saving potential using different appliance models. Policy recommendations regarding market transformation and behavioral modification are also presented. | Energy monitoring campaign, market surveys, consumer interviews | About 48% of savings are estimated in the EU’s residential sector by integrating the improved behavior with existing appliance technologies. |
| 128 | [128]     | Using the dataset of U.S. residential energy consumption and assuming different types of households, this work identifies the number of appliances consuming a specific percentage of energy consumption considering ownership and usage rates of appliances. | Survey data, statistical data analysis | The work advocates for the careful analysis and inclusiveness of residential consumption datasets for the identification of energy-intensive appliances, accurate energy modeling, and better policies. The results of the study can be supportive in the development of energy disaggregation algorithms. |
energy-efficient upgrades of four appliances [91]. Details of these appliances are presented in Table 4. In the modern era, where data act as a tool to shift behaviors regarding technology adoption [79], ALEC enables consumers to make knowledgeable decisions. It provides quantified savings from energy-efficient appliances and thus justifies their adoption [108].

ALEC through NILM not only provides EE in the residential sector but also provides comfort and economic benefits [34]. Energy Efficiency Standards and Labelling (EESL) programs had been initiated in many parts of the world and showed significant reductions in energy consumption as shown in Table 5. Sectoral reductions from 10-20% are achievable by implementing large-scale EESL programs in the European Union (EU), the US and China [131]. ALEC data can also be used for rating the environmental and energy performance of the buildings. Demographic data of buildings or households can be linked with energy usage data and a smart solution for issuing the energy performance certificates can also be developed.

C. UTILITY AND GRID OPERATIONS

Accurate load monitoring and forecasting are key to effective operational planning of grid systems and optimal dispatch of system resources. In earlier days, large utility companies used to rely on sample load monitoring data collected from an aggregation residential consumers by installing sensors installed on some of the major appliances such as ACs, space heaters, refrigerators and water heaters [132]. Sample sizes were ranging from dozens to hundreds. Estimations from such sampling were not much accurate. But ALEC data assist utilities in more accurate load monitoring and forecasting [37] and hence help achieve better resource efficiency in consumption and production targeted in SDG 8. Moreover, utilities can get information about flexible and non-flexible residential demand from this data to design effective Demand Response (DR) programs for Demand Side Management (DSM). DR programs can target specific appliances [133]. Consumer segments with specific appliances can also be identified using ALEC data [95] and novel pricing and control schemes can be designed for targeted appliances [100]. Evaluation of load control programs can also be assessed by ALEC [113]. The role of such programs has become more significant in maintaining supply-demand balance to achieve reliable and secure grid operations [134]. About 30-50% of the balance services are intended by the system operator from DR in the UK [135]. Some works related to load forecasting, load modeling, customer segmentation and load identification are presented in Table 4.

D. FLEXIBILITY FOR RENEWABLE ENERGY INTEGRATION

Rapid electrification through high proportions of variable generation (e.g. wind) mostly for transport and heating
demands extended flexibility of the electricity system to keep supply-demand balance [86], [136]. The UK’s independent CCC has recommended deep reductions in GHS emissions from the power supply sector through the 2020s and has urged for its essential decarbonization by 2030-2040 [137]. Penetrations of 30 GW and 75 GW of offshore wind energy in the UK are foreseen by 2030 and 2050 respectively [11]. The role of the demand side can also be significant in enhancing the flexibility of the power system besides backup capacity, storage, and interconnection [134], [138]. But accurate load models to compute flexibility potential in various sectors still lack [139]. ALEC facilities integration of Renewable Energy Resources (RERs) in the power sector by providing flexibility from various appliances. This flexibility is exploited through DR programs and support in attaining UN’s SDG 1, SDG 7, SDG 11, SDG 12, and SDG 13. ALEC framework allows more accurate appliance models and enables balance responsible parties to determine usage time for individual appliances and assess the flexibility potential of individual appliances [140]. Some works related to demand flexibility assessment and load modeling are highlighted in Table 4. This assessment can be used to evaluate the impact of DR programs and their economic feasibility [136]. By 2050, it is estimated that exploiting flexibility from smart residential appliances and passenger vehicles together can reduce the peak demand by 9% cultivating cost savings of around £30.9 billion in the UK [141].

E. Energy Auditing and Fault Diagnosis
ALEC provides itemized charges and disaggregated energy data for various appliances during a particular period. These appliance level data support effective energy auditing [103], [142] and help find ways to minimize the energy cost from individual appliances [132]. Effects of implemented measures can also be quantified through this data [143]. About 30% savings in energy consumption [104] and 80% savings in auditing time [107] are reported due to NILM based energy auditing.

Preventive maintenance and health monitoring of appliances is another application of ALEC. Faulty and vulnerable appliances typically draw unusual power patterns. The operation of faulty devices may be cyclic which causes more energy wastage. Faults in cyclic devices can be diagnosed through ALEC [118]. Sometimes low power consumption and continuous ON status of a switching device can disclose its replacement time [132]. The leakage current feature was used by a cloud-based NILM solution to monitor the health status of residential appliances [119]. The health status of household appliances is of utmost importance for human safety. NILM based solutions have also been applied for fault identification in motors and shipboards [33]. Anomaly detection schemes, novel maintenance and service mechanisms for the appliances can be developed through ALEC [34], [120]. Some works using NILM based ALEC for residential energy auditing, anomaly detection, and fault diagnosis are summarized in Table 4.

F. ENERGY MANAGEMENT AND CONSERVATION
Energy management and conservation in residential buildings, households, and microgrids can be driven by ALEC [144], [145]. Buildings in the EU release 35-40% of the regional carbon dioxide emissions by utilizing 40-42% of the total energy consumption [146]. According to one estimate, unaware activities generally put an extra 33% burden on energy requirements of buildings and 27-30% of the energy savings are achievable through automated energy management in European buildings [146]. Previously such intelligent systems were not feasible on a large scale, but the advent of information and communication technology has made them viable [147].

Today’s smart buildings are adaptive, responsive, capable of incorporating modern monitoring and control schemes as shown in Figure 7 and have the ability to learn residents’ behaviors/preferences [148]. Moreover, AMI has enabled the residents to take an effective part in DSM programs [149]. Due to bidirectional communication, consumers receive DR signals from the utility through smart meters, and they can intelligently control their appliances for cost benefits [77]. ALEC data coupled with intelligent control capabilities assist in developing Building Energy Management Systems (BEMSs) and Home Energy Management Systems (HEMSs). Such systems ensure the operation of appliances in times when electrical energy usage is economical and eco-friendly [150]. Therefore, effective energy conservation, efficient DR participation and optimal appliance scheduling schemes can be driven through ALEC [151], [152]. Such schemes assist in achieving SDG 7, SDG 11, SDG 12, SDG 13 and SDG 17.

Some of the research studies related to energy management and conservation realizable from ALEC are briefly described in Table 4. An experimental study in California evaluated the performance of energy management solutions and demonstrated that energy savings are high for solutions providing disaggregated energy information at the appliance level [78].
Similarly, the adoption rate of consumers is also high for such solutions. The authors of [50] proposed a genetic algorithm-based NILM approach for DSM in residential buildings. A mathematical formulation for load scheduler is presented in their work. A fuzzy compromised HEMS is presented in [153].

The information of ALEC can be shared among cooperating prosumers. This information when integrated with forecasted values of distributed generation enables peer-to-peer trading of energy among different prosumers where one consumer can supply its surplus energy directly to other consumers [154]. Prosumers having detailed information about their ECBs can better participate in transactive energy markets.

G. EQUIPMENT MANUFACTURING AND TECHNOLOGY DEVELOPMENT

ALEC provides significant potential benefits for manufacturers of equipment and appliances, and technology developers. It indicates energy-intensive appliances and appliances with energy-saving potential. Such appliances can be furnished with remote control add-ons by the manufactures for conservation benefits. Moreover, appliance manufacturers can readily analyze the energy footprints of their various designs and go for design improvements [155]. This will especially help achieve goals specified in SDG 8 and SDG 9 related to economic growth and innovation.

The technology sector can integrate ALEC into its products to enhance their functionality for users’ comfort. Software developers can design better software platforms for building information modeling and simulation based on ALEC data. Many companies are offering NILM based technologies to individual consumers for ALEC. These companies access data according to their proprietary formats due to the unavailability of standardized formats [34]. A comprehensive review of energy monitors especially for NILM applications is presented in [156]. These products assist in energy analytics and energy management. Some leading companies are listed in Table 6.

The adoption of a large-scale ALEC framework provides numerous opportunities and business options for communication companies, smart meter manufacturers, web developers, data scientists, and cybersecurity providers. Novel innovative services using ALEC can open a wide range of business options for entrepreneurs.

H. SOCIAL SCIENCES AND ECONOMICS

ALEC being associated with the daily activities of consumers can be exploited to judge the lifestyle of the consumer [157]–[159]. Combining consumers’ activities with information available on social media platforms reveals a complete picture of their norms and lifestyles [160]. Using ALEC, social components of energy and its concerning demographic and economic factors can be understood by social scientists which support effective policy design [24], [121].

Energy consumption and economic growth are correlated [161]. The results of ALEC can be used to assess the economic condition of the consumers. More energy consumption and availability of luxurious appliance models in a household indicate the better economic condition of the residents and vice versa.

| Sr. No. | Company Name | Sr. No. | Company Name | Sr. No. | Company Name |
|---------|--------------|---------|--------------|---------|--------------|
| 1       | Bidgely      | 15      | Green Running | 29      | InfoMets     |
| 2       | Neuro        | 16      | Ipsum Energy  | 30      | Ecotagious   |
| 3       | Watty        | 17      | Home Energy Analytics | 31      | Onzo        |
| 4       | Chai Energy  | 18      | Smapppee     | 32      | Encore (EnerTalk) |
| 5       | Mirubeed     | 19      | Grid4C       | 33      | EnerTics     |
| 6       | HDOSN        | 20      | Qualisteo     | 34      | Fludin       |
| 7       | Motor        | 21      | HOME Pulse   | 35      | Inteli       |
| 8       | Verdigris Technologies | 22 | Smart Impulse | 36 | AlertMe |
| 9       | Powersavvy   | 23      | Opower       | 37      | Navetas      |
| 10      | Sense        | 24      | Qinergy      | 38      | Ecoisme      |
| 11      | Watt-IS      | 25      | Exibe (aka ELIQ) | 39      | You Know Watt |
| 12      | EEne         | 26      | Powerly      | 40      | smartH Energy |
| 13      | PlotWatt     | 27      | Voltaware    | 41      | LoadIQ       |
| 14      | CLEMAP       | 28      | Net2Grid     |         |              |

I. SMART SECURITY, SURVEILLANCE AND HEALTH CARE

Inclining life expectancy in developed nations necessitates novel solutions and services to aid the independent living of aged people [162]. According to UN estimates, around 21.6% of the people would be 60 years or older by 2050 [163]. The linkage of appliance usage data with consumer activity makes it suitable for remote monitoring and surveillance applications [164], [165]. Wellness monitoring of the elder or disabled people in smart homes could be done by their custodians through ALEC integrated with data of other sensors [166], [167]. The UN SDG 3 deals with the good health and well-being of the people.

The modern IoT systems have transformed conventional health care systems into data-linked remote health care systems [169]. As the wellbeing of an individual can be judged by its usual energy consumption patterns, therefore ALEC data can serve for smart health applications by finding the abnormalities after its proper mining [124]. Summary of some works using ALEC data for activity monitoring, surveillance and smart health applications is given in Table 4. These data can be linked with other sensors to realize smart health care solutions [170]. Such solutions can be developed by involving third parties where the health care provider or caretaker of the patient is automatically informed when some abnormality is detected [171], [172].

Security agencies can also utilize ALEC data to monitor the activities of suspected people. Electricity thefts and abnormal activities can also be detected through smart metering [173].
TABLE 7. Policy and Research Benefits of ALEC.

| Sr. No. | Stakeholders                     | Policy and Research Benefits                                                                 |
|---------|----------------------------------|---------------------------------------------------------------------------------------------|
| 1       | Energy researchers               | • Availability of data for energy analytics and research                                   |
|         |                                  | • Design of novel DSM and control schemes                                                    |
|         |                                  | • Novel methods for building information modeling and simulation                           |
| 2       | Data scientists                  | • Novel techniques to handle big data of customers at utility-scale                          |
|         |                                  | • Information retrieval from big data                                                       |
| 3       | Cybersecurity scientists         | • Novel cybersecurity techniques to ensure the privacy of customers                          |
|         |                                  | • Secure energy sharing platforms                                                          |
| 4       | Regulators                       | • New regulations and novel pricing schemes for load control programs using ALEC data      |
|         |                                  | • Develop standards for smart metering                                                      |
|         |                                  | • Regulations related to cybersecurity                                                    |
| 5       | Energy conservation agencies    | • Design energy labeling programs                                                           |
|         |                                  | • Design energy conservation programs                                                      |
| 6       | Environmental agencies          | • Design of CO₂ reduction campaigns based on careful usage of energy-intensive appliances  |
|         |                                  | • Design of energy-efficient usage campaigns based on ALEC                                 |
| 7       | Appliance manufacturers          | • Add-on decisions for specific appliances                                                  |
|         |                                  | • Decisions about design improvement and assessment of improved designs                    |
| 8       | Social scientists                | • Consumer behavior information associated with appliance usage                             |
|         |                                  | • Devising behavior modification programs                                                   |
| 9       | Economists                       | • Linking economic conditions with energy usage                                             |
|         |                                  | • Better economic policies for decarbonization                                             |
| 10      | Governments and policymakers    | • Data-driven policymaking                                                                  |
|         |                                  | • Devise better plans to achieve decarbonization and SDGs of 2050                          |

J. POLICY, RESEARCH AND BEHAVIORAL MODIFICATIONS

Human, being an important dimension of energy, asserts the understanding of social components of energy alongside other factors during policy design [174]. As the intensity of GHG emissions depends on population size, lifestyle, energy usage patterns, economic and industrial activities, and technologies adopted by the people, therefore any policy interventions and energy conservation programs cannot be introduced and succeeded without their engagement and behavioral changes [137]. Lavish funding is being released for EE programs, but results are not fruitful as anticipated. Over 50% of the emission cuts, to meet the net-zero target, demand individuals to behave differently while accomplishing their tasks [86]. Significant low-cost energy reductions possible in residential and commercial sectors are not achieved yet due to behavioral barriers [27]. ALEC results guide the governments and policymakers in devising wise decarbonization policies through behavioral modification. With improved behaviors and existing technology implementations, 48% of savings in residential electricity consumption are anticipated in the EU [127].

Energy analytics has become a multidisciplinary research area due to the intersection of different fields [175]. ALEC results can be used by scientists and researchers in various fields such as power systems, environmental sciences, data sciences, social sciences, economics, marketing, cybersecurity, appliance manufacturing, etc., and hence open the doors of cooperation as intended in SDG 17 advocating partnerships for goals. UK Research and Innovation had initiated the development of the Smart Energy Research Lab (SERL) to exploit the valuable data of smart meters [176]. In this project, high-resolution data with socio-demographic information will be collected from the volunteers and will be made available to authenticated researchers. The ultimate goal is to develop a secure, green, and economical energy system for future generations [126]. ALEC data integrated with socio-demographic, environmental, and economic information can support this agenda. Some policy and research benefits associated with ALEC for different stakeholders are highlighted in Table 7.

IV. REQUIREMENTS, CHALLENGES AND RECOMMENDATIONS

ALEC data are supportive in achieving 2050 decarbonization and 2030 UN SDGs. Table 8 attempts to map various prospective uses of ALEC with various decarbonization and UN SDGs. The ambiguous associations are described in the last row of Table 8 while the obvious linkages are left unmarked.

Small scale deployment of ALEC framework at a building or household level is straightforward as it engages few participants. Some programs such as US Green Button allow consumers to access their electricity, natural gas, and water consumption data for energy management and renewable integration decisions [177]. This accessed data can be shared with third parties for getting innovative services. Such services are easily realized due to the involvement of the consumer and a service provider. But the large-scale deployment of the ALEC framework at a utility-scale is a complex mechanism. It is hindered due to the involvement of diverse stakeholders, various regulatory requirements and diversified challenges. Some of these challenges and requirements are described here with recommendations.
TABLE 8. Mapping ALEC Prospective Applications with Decarbonization and SDGs.

| Prospective Applications                                           | Associated goals                                                                 |
|--------------------------------------------------------------------|-----------------------------------------------------------------------------------|
| Feedbacks, recommendations and customized marketing                | Decarbonization, SDG 4* (Quality education), SDG 12 (Responsible consumption and production), SDG 17* (Partnerships for the goals) |
| Flexibility for integrating RERs                                   | Decarbonization, SDG 1* (End poverty in all its forms), SDG 7 (Affordable and clean energy), SDG 11 (Sustainable cities and communities), SDG 12 (Responsible consumption and production), SDG 13 (Climate action) |
| Utility and grid operations                                        | Decarbonization, SDG 1* (End poverty in all its forms), SDG 7 (Affordable and clean energy), SDG 11 (Sustainable cities and communities), SDG 12 (Responsible consumption and production) |
| Energy-efficient appliances and labeling standards                 | Decarbonization, SDG 7 (Affordable and clean energy), SDG 9 (Industry, innovation and infrastructure), SDG 11 (Sustainable cities and communities), SDG 12 (Responsible consumption and production), SDG 17* (Partnerships for the goals) |
| Energy auditing                                                    | Decarbonization, SDG 4* (Quality education), SDG 11(Sustainable cities and communities), SDG 12 (Responsible consumption and production), SDG 13 (Climate action), SDG 17* (Partnerships for the goals) |
| Equipment manufacturing & technology development                  | Decarbonization, SDG 8 (Decent work and economic growth), SDG 9 (Industry, innovation and infrastructure), SDG 17* (Partnerships for the goals) |
| Energy management and conservation                                 | Decarbonization, SDG 7 (Affordable and clean energy), SDG 11 (Sustainable cities and communities), SDG 12 (Responsible consumption and production), SDG 13 (Climate action), SDG 17* (Partnerships for the goals) |
| Fault diagnosis and anomaly detection                             | SDG 12 * (Responsible consumption and production) |
| Surveillance and activity monitoring                               | SDG 3 (Good health and well-being), SDG 4* (Quality education), SDG 17* (Partnerships for the goals) |
| Smart health applications                                          | SDG 3 (Good health and well-being), SDG 17* (Partnerships for the goals) |
| Policy and research benefits                                       | Decarbonization, SDG 7 (Affordable and clean energy), SDG 13 (Climate action), SDG 17* (Partnerships for the goals) |

* Due to ability to provide knowledge for sustainable development and sustainable lifestyles.
* Different entities such as energy providers, consumers, marketing managers, energy conservation agencies, energy auditors, appliance manufacturers, security agencies, health care providers, policy makers, environmental protection agencies, energy researchers, etc. share ALEC data and cooperate with each other.
* Due to capability of combatting energy poverty.
* Faulty devices generally consume excessive energy.

A. POLICY
A policy for the provision and exploitation of ALEC data for EE, energy management, and conservation to be made like US’s Green Button program which allows data provision to consumers about the usage of their major utilities. Government, regulators, and utilities have to work together in policymaking to achieve SDGs.

B. STANDARDS & REGULATORY REQUIREMENTS
Regulations for ALEC and its exploitation need to be developed by the regulators. Currently, no common standard is in place for ALEC and its representation. Independent providers of NILM solutions are using their proprietary formats and frameworks for ALEC. So, there is a need to develop standard formats for data extraction, representation, exchange, and security. Such formats should be interoperable to realize their usage for novel services from third parties.

C. ADVANCED SENSOR TECHNOLOGY
NILM is the economically viable option for ALEC, but its accuracy is dependent on the sampling rate of whole-house demand measured by the sensors. Sensors capable of measuring at high sampling rates are to be developed at an economical cost and should be used in smart meters for realizing the ALEC framework at a large scale.

D. METERING INFRASTRUCTURE MODIFICATIONS
Smart metering infrastructure requires major modifications for implementing the ALEC framework. Existing smart meter designs require upgrades in hardware and firmware. As these modifications require money and time investments by the utility, therefore, the passive role of the utility’s management can hinder these modifications. Smart meters with embedded NILM functionality should be adopted.

E. GENERALIZED & ACCURATE NILM ALGORITHMS
The accuracy of the ALEC framework depends upon the accuracy of the NILM algorithm implemented for appliance level energy disaggregation. No generalized NILM algorithm is available that can identify all the appliances with 100% accuracy. Appliances exhibiting multiple states (may be due to operational settings), continuously varying demands, or low consumption powers are difficult to detect through
NILM algorithms. As these algorithms are usually developed using the prior data, therefore updates will be required to detect novel appliances and devices. Moreover, the nature of loads and types of loads are diverse across regions; and designs of individual appliances vary with manufacturers and appliance sizes, therefore the development of accurate and robust NILM algorithms for different regions involving local appliance manufacturers is a challenging task.

**F. COMMUNICATION INFRASTRUCTURE**

Current communication infrastructures used for smart metering provide limited bandwidth as limited data of whole-house demand are to be sent after regular intervals of 15-30 minutes. As the ALEC framework is supposed to send appliance level data at a higher frequency, therefore large bandwidth of communication system is required to realize the ALEC framework. The installation of emerging 5G and 6G communication networks will be supportive in this regard.

**G. STORAGE AND COMPUTATIONAL ISSUES OF BIG DATA**

Large-scale deployment of ALEC at utility-scale involves various stakeholders and all the utility consumers. Big data will be generated in such deployments from smart metering. Large spaces for storage and ultrafast computing machines for processing will be required at the central data point to extract knowledge from these data.

**H. PRIVACY/CYBER SECURITY**

Since ALEC data could leak consumer privacy by revealing the habits, therefore it should be shared with authenticated parties only. Firm cybersecurity and encryption mechanisms should be in place to avoid stealing these precious data. A smart and secure data-sharing platform needs to be developed to share ALEC data among authenticated stakeholders only.

**I. BUILDING STAKEHOLDERS’ TRUST & INTEREST**

Achieving all decarbonization and sustainable development benefits through ALEC requires the interest of the consumer in EE and conservation programs. ALEC data act as a tool for behavior modification. Building stakeholders’ trust in the behavior extraction technology for environmental and economic benefits is also a big challenge for large-scale adoption of the ALEC framework.

**V. OPEN RESEARCH DIRECTIONS**

To realize an effective, viable and applicable framework for the accurate ALEC of residential electricity demand, there is a need for research work in diverse fields like sensors development, communication, cybersecurity, NILM algorithms, web development, DSM, software development, consumer behavior modeling, building information modeling and simulation, etc. Some promising research directions related to the ALEC framework, its applications and its data security are given below.

- Standardization of data formats for the representation of ALEC data.
- Novel real-time robust energy disaggregation algorithms to identify appliances in residential homes without prior information.
- Development of high-quality regional datasets for appliance level energy research.
- Understanding energy usage habits and correlation of energy usage with various environmental and socio-demographic factors.
- Development of simulators for energy modeling of appliances considering global information system data.
- Novel data security & privacy schemes to secure ALEC data.
- Understanding the effects of supplier and tariff variations on electricity cost and appliance specific energy consumption.
- Building information modeling using ALEC data.
- Smart framework for energy performance certification of buildings considering their characteristics and demographic factors.
- Novel tariff schemes and DSM programs for reliable grid operations.
- Novel services and business models based on ALEC data.
- Novel behavior modification frameworks based on ALEC feedbacks.

**VI. CONCLUSION**

The role of residential electricity is vital in achieving decarbonization and other SDGs. Currently, data of residential electricity demand are collected by utilities at the household level through smart meters. However, the consumption data of residential consumers can be more valuable if characterized at the appliance level. ALEC data reveal the ECBs and lifestyles of consumers. These data can be more effective in energy conservation, energy management, EE and renewable energy integrations; and thus, help achieve the sustainable, secure and affordable energy goals of pathways 2050 and UN SDGs 2030. In this paper, we have presented different solutions for realizing ALEC ranging from individual household level to utility level. Upgrading smart meters looks like the most scalable option for such characterization at the utility level. Different benefits of ALEC for consumers, utilities, grid operators, policymakers, marketing managers, health care providers, researchers, security agencies, appliance manufacturers, technology developers, social scientists, economists, environmental and energy conservation agencies, etc. are highlighted.

The requirements and associated challenges with this characterization are also outlined. Besides policy and regulatory requirements, large-scale deployment of the ALEC framework demands upgrades in hardware and software components of smart meters and related data and communication infrastructure of the utility. A smart data-sharing platform is required for secure data transfer among authenticated users.
for prospective applications and smart innovative services. The discussion presented in this paper would be helpful for multidisciplinary researchers and would open the doors of mutual cooperation among stakeholders of smart cities to achieve the 2030 UN SDGs and 2050 decarbonization goals.

ACKNOWLEDGMENT

The authors would like to thank the Postgraduate Office, Department of Electrical Engineering, University of Engineering and Technology Taxila, for providing the facilities to accomplish this work.

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