An AI Based Framework for Energy Efficiency in Smart Homes

Kuldeep Sharma 1[1], Arun Malik*[2], Isha Batra[3]

Abstract: An Efficient AI (Artificial Intelligence) Based Framework for Energy Efficiency at Smart Home is designed for optimum utilization of the electricity with shifting of the load across the day with priority to benefit to consumer point of view in monetary terms and electricity point of view for demand control at peak loads. In this article, A deep analysis carried out for a smart home with respect to the instantaneous maximum load. The proposed framework prioritizes the smart appliances as per tasks and schedules in that order accordingly keeping load time of the day to save the tariff penalty for load overflow from the sanctioned load. IoT device embedded with the appliances controls the load with enhanced smart home framework. The HDFS setup in the framework caters the big data for fast and real-time control over the electricity demand. The framework automatically manages the electricity consumption patterns with Artificial Intelligence and Machine Learning Techniques. This approach not only saving the money of the consumers but also helps the electricity distribution companies to supply electricity with quality and demand technology. Various sampling techniques and machine learning algorithms and big data approximation frameworks are reviewed for analyzing the trends of the electricity consumption and optimizes the schedules of the home appliances accordingly. This framework is an automated self-contained controller with state-of-the-art technology.

Keywords: *Energy, Artificial Intelligence, IoT, Smart energy Home*

Number: 10.14704/nq.2022.20.7.NQ33351 **Neuro Quantology 2022; 20(7):2733-2743**

1. Introduction

1.1. ROPOSED ML based framework is a state of art in enhancement in all the aspects starting from ingestion of data to analysis to visualized dashboard in electricity consumption of the smart homes for energy efficiency. The proposed framework captures the interdependencies with knowledge based bult from diversified methods among the different big data value chain sequential stages. i.e., ingestions of the data from the metering data acquisition systems, data storage, big data analysis, and visualization taking the dependencies on the 3Vs into the account. In this framework, mahaut is used for analytical processing on the Hadoop distributed file system with mLib on Apache Spark along with the data and information. The decision tree resides in the knowledge based on relationship with layers of big data specific constraints of volume, velocity and variety with technology and infrastructure available. For setup of the framework, the critical decision depends on the strategy of the setup with a cluster or single node, a processing of data in sequential or parallel with Apache spark or Apache Strom, data ingestion with Apache Kafka or Apache Sqoop etc. a decision tree is a systematic way of representing them in a hierarchical way. For the broad implementation the commercialized, multi-node NoSQL storage setup like Apache Cassandra is recommended. In the prediction phase, as the data acquired is real - time, so tools like Apache Kafka or Apache flume are very effective to provide data-as-service for processing layers in the framework. The Data (Input Output) IOs are very high as the read/write operations are with high throughput to such huge data, quicker response time, and scalability are essential for the user's layer, at distribute storage, noSQL database is preferable. In Smart Home energy efficiency as user requirements are dedicated equal in all the scenarios along with all criteria, therefore commercialized multi-node HDFS (Hadoop Distributed File System) setup such as Cloudera, with an open-source single node HDFS setup would be preferred from the big data aspects in the data ingestion. And in the processing phase, advanced analytics are required for file-based batch processing. The huge sized files are processed on the HDFS environment. In these distributed processing, the tools like clustering tasks are R server supported by the Microsoft Azure for our enhanced framework. On this big-data extension for open-source statistical programming language R is widely used with various mathematical prediction algorithms of statistics library. Apache Kafka is listening to the microservices consisting of the data variety like structured, semi-structured and unstructured format for exchanging the data in the applications in the framework. Extraction, transformation, and loading are the main threads of the data ingestion process in the proposed framework.

The rest of this paper is organized in total six sections as follows. In section II, the related work on the electricity consumption, IoT, Artificial intelligence, big data analytics and machine in context with the smart home consumption are reviewed. In section III, the AI Based Framework for Energy Efficiency in Smart Homes is proposed with implementation and experiments. In Section IV, the architecture, algorithm is discussed, in section V, experimental setup is built, finally, the section VI concludes this paper.

2. Literature Review

In the current era, the emerging techniques in the electricity consumption facilitates the electricity consumption to control their peak demands in the electricity smart grid. The prior art of the approximation frameworks on the HDFS, techniques of the sampling, machine learning algorithms in the literature are studied. A comparative analysis of the sampling methods is tabulated in the below table.

Table 2 A summary of common sampling methods.

Method	Description	Reference
Simple random	Data items are selected with equal probability and the sample size is fixed.	[1-3]
Bernoulli	Data items are selected with equal probability, but the sample size is random.	[4-5]
Stratified	Data items are divided into strata and a sample is drawn from each stratum.	[6]
Reservoir	Data items are added to a reservoir of a fixed size.	[7]
Bootstrapping	Multiple samples are drawn with replacement and used for statistical estimation and diagnose	[8-9]

Table 3 Related frameworks for approximation on Hadoop clusters.

Fraemwork	Description	Reference
ApproxHadoop	Uses multi-stage sampling for approximate MapReduce job execution	[10]
EARL	Uses online uniform sampling from HDFS files with the bootstrap method	[11]
ApproxSpark	Uses multi-stage sampling or adaptive stratified reservoir sampling Supports both record-level and block-level sampling	[12]
BlinkML	Uses online uniform sampling without replacement If the dataset cannot fit into the memory, either uses Bernoulli sampling or offline samples	[13]
IncApprox	A stream data analytics system which depends on both approximate and incremental computing	[14]
Sapprox	Uses it to facilitate online sampling	[15]
RSP approach	Approach for approximate big data analysis Depends on a step-wise process to analyze data in batches of RSP blocks	[16]
ApproxIoT	Sampling-based approximation in IoT with an online hierarchical stratified reservoir sampling algori	[17]

The rapid technological trends and internet world have entirely reshaped the electricity consumption world by facilitating and entertaining the needs of everyone especially, smart home, smart grids, smart meters etc. The main progress and easiness in electricity consumption domain is brought with the support of emerging technologies like IoT driven small portable devices with actuators and sensors smart tools with gentle and wise data collection, exchange, and communication capabilities. Thus, AI-based intelligent methods are the key indicators to be adopted and encouraged in the domain of the smart home electricity efficiency.

Unbelievable trends and emerging proliferation in electricity assets like smart meters, smart grids, smart intelligence home energy efficiency, market have not only induced the concept of smart and pervasive platforms but also high consumers satisfaction i.e., QoE and better network performance i.e., QoS. Researchers in [1]–[5], proposed the DL driven edge computing platform for the IoT applications especially, industrial and healthcare. IoT and edge computing with association of Artificial Intelligence, Deep Learning and Machine Learning are contributing extraordinary. The main key aspects are on the resource management as well as on the monitoring priceless tasks to perform wisely. In the same way, for current scenario, emerging technologies like 5G, is important in smart resource allocation for bandwidth, transmission power with efficient power saving battery lifetime [6]–[8]. Various researchers in literature [9]–[11], elaborated the ML-driven technological trends, and relevant technologies, workflows, and shows a significant contribution in various domains like smart home energy efficiency, smart industry, electricity consumption, pervasive healthcare, smart grids and enterprise wide resources like ERP, MRP etc. NBIoT plays a vital role in the scheduled and resource management for short range networking. A detailed analysis for network characterizing tasks is carried out in works [12] and [13]. Researchers in the literature [15] and [16], proposed the techniques for the DL-based radio resource allocation with cellular networking in context of the power, bandwidth, and reliability. Researchers proposed the unmanned aerial vehicles platform [17] for QoS optimization for swarm-based edge cloud computing. The Edge computing allocation of the resources are optimized to reform the smart home energy efficiency, as the sensor embedded electrical assets are accelerating the actuations, sensibility, and processing [18]. High mobility and dynamic nature of wireless link in smart vehicles is necessary for safety and security aspect for transferring of the data in a secure channel and private tunnel to safeguard from the intruders from leakage of the sensitive information by alteration [19]. Smart 6G-driven industrial NIB can be achieved by integration and incorporation of IoT embedded traditional legacy transportation system. In the smart cities, the key ingredients for modern & future electricity consumption, medical, industrial, and academic domains [20]. In [21], 5G network embedded AI-driven with scheduling algorithms are proposed for effectively handle the QoS of the networks. Mobility of the vehicular networks through 5G trends and tools [22] are self-adaptive methods as proposed for efficient management and controlled optimization. The smart home electricity consumption and energy efficiency mainly dependent on emerging actuators and sensors embedded devices with effective network.

Applications	Results	Component being optimized	Proposed Techniques	Ref
6G, Deep Learning, Resource Allocation, QoE/QoS Optimization, IoT	QoE Estimation	Throughput, Delay	Intelliglent and Q Learning	[18-19]
6G, AI Health Care	QoS Optimization	Energy and Battery Related	Network routing	[20-21]
Smart Mobile System, NIB	Power-Aware Healthware	Charge Optimization	Battery LifeTime	[22-23]
Energy Efficiency, NIB	Delay and Packet Loss Optimization	Time Scheduling	Q-Learning	[24]
sustainable and Smart NIB	Rate Control	Power and Data Rate	Adaptive Resource	[25]

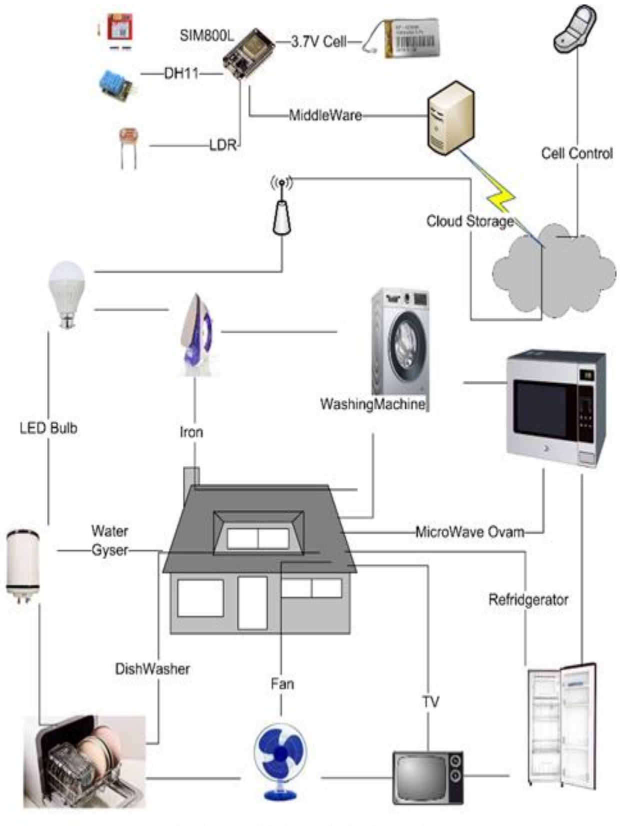
Smart transportation and Resource allotment, 6G	Improve quality of health	Heat Absorption and energy consumption	Allocation Energy Efficinet Health Monitoring System	[26-27]
Radio Resource in Mobile Networks	Smart Mobile Systems	RSSI and Battery LifeTime	Deep Leraning	[28-29]
smart Industrial NIB	Intelligent and preservtive system	High Reliability and low latency	Cloud and vehicular Network	[30-31]
Data transmission in 6G based vechicesl, IoT	Qoe and buffer healthware	to optimize the idle time, buffer size and bandwidth	ML Driven data scheduling and Q-Learning based bandwidht managemet	[32-35]
Cloud vehicluar network	5G Based Mobile System	Power Packet Ratio	emerging deep Learning	[36-38]
5G enabled mobile platform	AI Driven Mobile Edge	Link and Route Optimization	Self Adaptive edge	[39-41]
Big Data and Massive IoT	smart Optical Networks	Sensing and computaiton	Statistical Signal estimation	[41-45]
Energy Efficiency, Fast Mobile Network	Delay-Aware Mobile Platform	Delay Monitoring	ML Based Latency Management	[46-49]

IMPLEMENTATION AND EXPERIMENTS

The implementation of this framework is done in R with MapReduce and parallelization packages. In implementation, the framework algorithm is encapsulated with the data set of the model trainer. This generates the data set as per the electricity consumption parameters like KWH (Kilo Watt Hour), V (Voltage), f (Frequency), pf (Power Factor), TOD (Time of Day), KVAH etc. It generates training data subsets according to desired parameters like U(m,b,c), By this, the past historical consumption of the electricity is accumulated at one place and the big data analytics is applied to get the data processed very fast to get real-time analysis. In exploring the smart home electricity consumption data and applying the findings from learning, we encountered numerous ethics related issues and impacted our choices of implementation, and approaches of addressing the issues.

Criticality	Appliances	Power(W)	Star Rating
B	Television	150	5
C	Air Conditioner	600	4
B	Refrigerator	150	5
A	LED Light Bulb	15	4
A	Incandescent Light Bulb	60	3
C	Dishwasher	900	3
A	Fan	60	5
C	Microwave-ovum	900	3
B	Water Cooler	600	5
B	Water Pump Motor	900	3
C	Water Geyser	900	4
C	Iron Imerson Rod	900	3

In constructing this AI based framework, first we analyzed various data partition schemes such that, round-robin, hash, range and random data partitioning etc. In the round-robin being the sequential scan scheme on the entire dataset, with range queries, in both point is complicated for processing, and hence is a well-organized balanced data partition. Hash partitioning is also scanning the full data set in the sequential scan and not suited for the range queries in comparison with the point-based queries. It has the constraint in the non-partitioning attributes also as only one partition attribute must be



AI Based Framework for Energy Efficiency in Smart Homes

searched. Same way, the range partitioning is also scanning the entire data set, as all the processes are executing in on which may cause the execution skew. It is a well-organized balanced data partition and suited well for both point and range queries as it searches only a few or only one partition. Whereas in the case of random partitioning, records are randomly distributed and not following any order, with an approximately balanced data partition and requires additional compute for random values calculations.

Architecture

As depicted in the above figure, the IoT based system composed of a Micro-Controller Unit (MCU) integrated with different sensors. The DHT11 sensor is used for humidity and temperature, Reed switch, Operated by applied magnetic field, which detects the door opening with a proximity sensor, Light Dependent Register, very sensitive to light where resistance changes as soon as light falls on the sensor which makes it to be used to measure outdoor light for using it in functionality of the streetlights for making them off and on as per need. This system is capturing the real-time data through the sensors to the middleware system built on the Linux open-source operating system with Apache web browser, PHP language, MYSQL as database. The IoT Device is connected to the various electricity appliances for making them on and off with the help of the relay switch embedded into the device. The curl APIs are built at this middleware server for various functions. All the instruments are connected to this middleware through this IoT device via WiFi connectivity. A 3.7V battery is connected to this module for power supply to the IoT Device. With the help of the home are network, wifi connectivity is available to this IoT Device. The SIM800L also embedded in the IoT device for the connectivity to the cloud also. The middleware is connected to the cloud over internet connectivity.

All the devices like TV, Refrigerators, LED Bulbs, FANs, Iron, Dishwasher, washing machines etc. are connected with middleware via IoT Device and Home are network or WiFi. The input from the sensors is provided by the IoT Device to the framework at Linux based System for managing and controlling the connected devices at the smart home. the data captured at the MySQL database is further sent to the cloud for analyzing with the trends and optimized data set is provided to the middleware for appropriate triggering of the events to the connected devices. For example, if the sensor detects the dim lights or darkness at the yard of the home, the triggering events will be initiated by the framework will be switch on the Lights. Same way, if the temperature is less than 18 degrees

Celsius, the command for switching off air-conditioner will be triggered. If there is no movement in the room for a specific time duration, the light will be switched off. By performing such situation-based triggering by the framework itself, the energy can be saved in numerous ways.

With the help of the middleware server, the various sensors communicate with and passes the indication to the IoT devices attached to the smart home appliances for controlling and managing in an efficient manner. Like If air conditioner is switched on then IoT attached with the windows will automatically close that. In case there is motion/movement inside the room, it will turn off light. With the brightness in yard will switch off the light of that area. In the real-time instantaneous tariffs, If electricity rates are low, it will send message for laundry and other heavy loads for the operations, if rate fluctuates to high, will command accordingly to the attached appliances in the smart home.

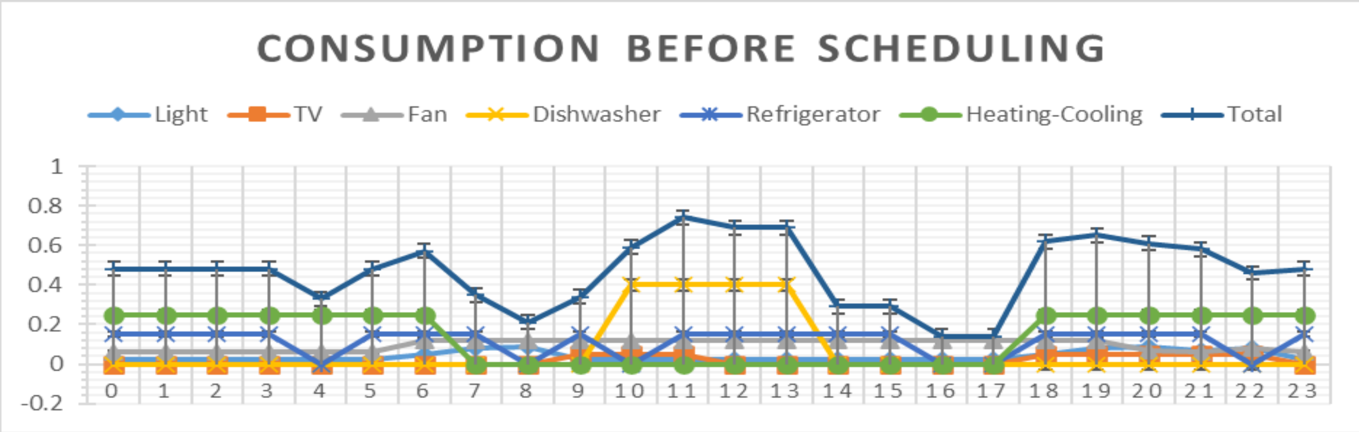
Experimental Setup

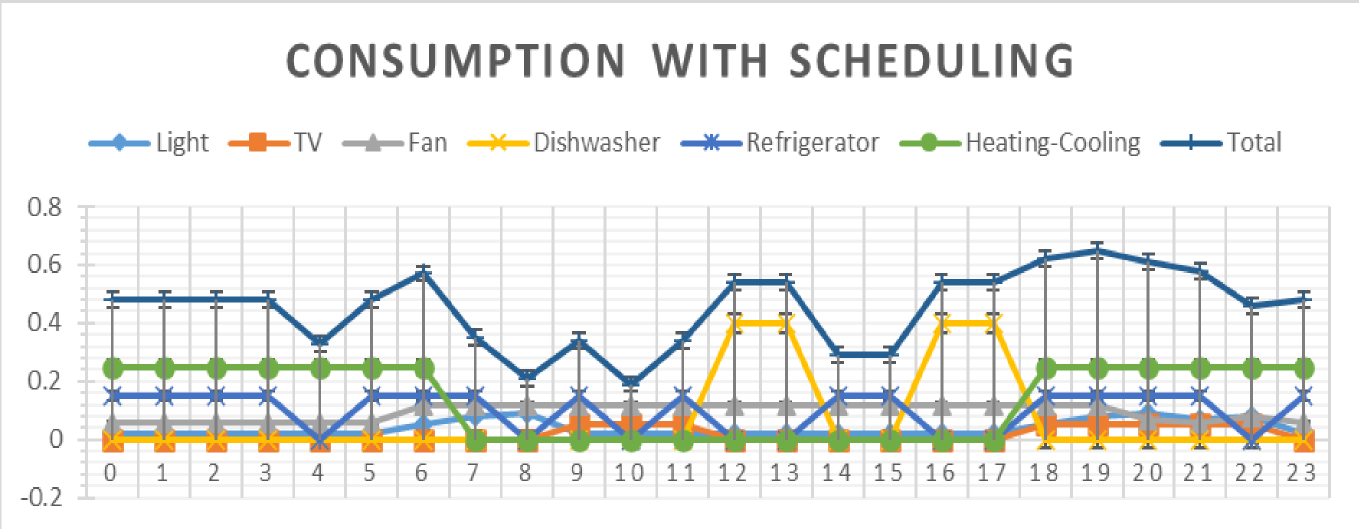
For carrying out the experiment, the framework is setup in the two distinguishing layers i.e., a processing layer and a visualization layer. In the processing layer, the database-based processing is done in the RDBMS (Relational Database Management System) with help of processing tool like SQL (Structured Query Language) for operational processing whereas file-based processing is done in the batch mode or real-time mode as per the situation for advanced analytical operations. Hadoop mahout is taken for the operational part whereas the mLib and TensorFlow are taken on Apache Spark for the real-time big data analytics and gives analytics services as data as services (DaaS). Spark cluster and Kafka Clusters are used for capturing the unstructured data generated at the various sources of the information like twitter, google, Facebook or any social media platforms with real-time streaming.

The data transformation in the big data, has the major concern of the veracity and the value of the unstructured data. This unstructured data push to the transformation leads to the loss of the veracity and the value characteristics of the big data. The enterprise resource planning, manufacture resource planning, customer relationship management are running and generating the structured data sets. Whereas the social media values, complaints, concerned, grievances, accumulation of the data from the various make and model of the actuators, sensors, smart metering devices etc. are the unstructured data with different patterns as well like text, images, XMLS etc.

Proposed methodology for STLF in the Big Data context

Srage 1: Data gathering Preprocessing Storing.





In this stage, the data from smart devices likes smart meters are collected and accumulated at metering data acquisition system at real-time in the non-uniform structure of data format like JSON, XML, CSV, RawFormat etc. the weather/climate variables are collected from the online real-time weather data from web API for stations in the JSON, CSV, XML or RawFormat. And other relevant related data from web survey of the social media websites.

The data is extracted, cleaned, validated, and filtered from the above raw data acquisition servers and transformed in the meaningful information and then the data is loaded in the framework in the Hadoop distribute file system in the NoSQL database. This data is processed on the distributed nodes on the HDFS.

Stage 2: Clustering And Dimensionality Reduction.

In the clustering, the load profiles are determined and in the dimensionality reduction the most important attribute of STLF is chosen.

Stage 3: STLF with ANN

For the Short term load forecast (STLF), the processes are simultaneously executing the ML algorithms, e.g for last one day. Then it selects the Best performing Algorithm in terms of Root Mean Square Error and forecast the electricity consumption with Best Performing Algorithm for next 24 hours.

Root mean square errors. by grouping the consumers into relevant clusters considering the consumption pattern similarities, the performance of STLF is improved, RMSE decreasing from 5.72 to 1.93. The results are compared in terms of RMSE, correlation coefficient R, average, minimum and maximum of absolute error.

: timestamp, meter id, active power (electricity consumption), reactive and apparent power. As mentioned before, weather conditions have a major influence on the electricity consumption, therefore weather data should be included as input. Accurate weather data and forecast may be obtained from weather sites as web APIs or from the weather stations located in the proximity of the consumption place (apartments, houses).
then, the consumers with similar consumption behavior are grouped into load profiles using the k-means algorithm. K-means is an unsupervised machine learning algorithm that builds clusters by grouping instances (consumers) around k centroids by computing the distance or the similarity between these instances. The distance between two instances is determined with one of the following classical methods: Euclidean, Manhattan or Mahalanobis. Initially, a centroid value for each cluster (μk) is randomly chosen, then the following steps are performed iteratively:

To analyze their impact, we compared three feature selection algorithms: univariate selection, Recursive Feature Elimination (RFE) and Lasso Regularization (LassoR). For univariate selection

Acknowledgements

This research was supported/partially supported by [Name of manuscript.

Author contributions

Name1 Surname1: Conceptualization, Methodology, Software, Field study **Name2 Surname2:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Name3 Surname3:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

CONCLUSION

In this paper, we have provided an ML based framework for identification of the suitable deployment and implementation ways wisely from the different prior arts of diverse big data solutions. The framework will be further applied to a group of smart houses for electricity consumption domain. The partitioning of data based on the sampling can provide tremendous benefits with improvement in manageability, scalability, and performance in the algorithms of computing clusters of big data analytics. Review of detailed analysis of the big data partitioning and sampling techniques is also carried out.
For increasing the scalability, new sampling-based partition model plays a vital role in computing clusters with classification portioning schemes as approximation of the results directly depends on the quality of selected samples.
. In addition to the framework, key indicators in the electricity consumption with sampling-based approximation in the analytics were briefly reviewed. Critical technical challenges in the electricity consumption of the smart home highlighted in support of the big data analytical approximation on computing clusters.

References

1. T. E. Oliphant, Scipy: Open source scientific tools for python, Computing in Science and Engineering, vol. 9, no. 3, pp. 10–20, 2007.
2. M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, The weka data mining software: An update, ACM SIGKDD Explorations Newsletter, vol. 11, no. 1, pp. 10–18, 2009.
3. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer,R. Weiss, V. Dubourg, et al., Scikit-learn: Machine learning in python, The Journal of Machine Learning Research, vol. 12, no. 10, pp. 2825–2830, 2011.

4. C. T. Fan, Development of sampling plans by using sequential (item by item) selection techniques and digital computers, Publications of the American Statistical Association, vol. 57, no. 298, pp. 387–402, 1962.
5. P. J. Haas, Data-stream sampling: Basic techniques and results, in Data Stream Management, Data- Centric Systems and Applications Book Series. Berlin, Heidelberg, Germany: Springer, 2016, pp. 13–44.
6. M. Al-Kateb and B. S. Lee, Stratified reservoir sampling over heterogeneous data streams, in Proceedings of the 22nd International Conference on Scientific and Statistical Database Management (SSDBM'10), Heidelberg, Germany, 2010, pp. 621–639.
7. J. S. Vitter, Random sampling with a reservoir, ACM Transactions on Mathematical Software, vol. 11, no. 1, pp. 37–57, 1985.
8. B. Efron and R. J. Tibshirani, An Introduction to the Bootstrap. New York, NY, USA: Chapman & Hall, 1993
9. A. Kleiner, A. Talwalkar, P. Sarkar, and M. I. Jordan, The big data Bootstrap, in Proceedings of the 29th International Coference on International Conference on Machine Learning (ICML'12), Edinburgh, UK, 2012, pp. 1787–1794
10. S. Agarwal, B. Mozafari, A. Panda, H. Milner,S. Madden, and I. Stoica, BlinkDB: Queries with bounded errors and bounded response times on very large data, in Proceedings of the 8th ACM European Conference on Computer Systems (EuroSys'13), Prague, Czech Republic, 2013, pp. 29–42.
11. D. R. Krishnan, D. L. Quoc, P. Bhatotia, C. Fetzer, and R. Rodrigues, IncApprox: A data analytics system for incremental approximate computing, in Proceedings of the 25th International Conference on World Wide Web (WWW'16), Montral, Canada, 2016, pp. 1133–1144.
12. N. Laptev, K. Zeng, and C. Zaniolo, Early accurate results for advanced analytics on MapReduce, Proceedings of the VLDB Endowment, vol. 5, no. 10, pp. 1028–1039, 2012.
13. G. Hu, D. Zhang, S. Rigo, and T. D. Nguyen, Approximation with error bounds in spark, arXiv preprint arXiv: 1812.01823, 2018.
14. Y. Park, J. Qing, X. Shen, and B. Mozafari, BlinkML: Approximate machine learning with probabilistic guarantees, in Proc. of the 45th International Conference on Very Large Data Bases, Los Angeles, CA, USA, 2018, pp. 1–18.
15. X. Zhang, J. Wang, and J. Yin, Sapprox: Enabling efficient and accurate approximations on sub-datasets with distribution-aware online sampling, Proceedings of the VLDB Endowment, vol. 10, no. 3, pp. 109–120, 2016.
16. S. Salloum, J. Z. Huang, Y. He, X. Zhang, T. Z. Emara, C. Wei, and H. He, A random sample partition data model for big data analysis, arXiv preprint arXiv: 1712.04146, 2017
17. Z. Wen, D. L. Quoc, P. Bhatotia, R. Chen, and M. Lee, ApproxIoT: Approximate analytics for edge computing, in Proc. of 2018 IEEE 38th International Conference on Distributed Computing Systems (ICDCS), Vienna, Austria, 2018, pp. 411–421.
18. D. Wang and Z. Wang, "Second-order continuous-time algorithm for optimal resource allocation in power systems," IEEE Trans. Ind. Informat.,vol. 15, no. 2, pp. 626–637, Feb. 2019.
19. H. Cap and S. Wu, "Dynamic embedding & qos-driven adjustment for cloud networks," IEEE Trans. Ind. Informat., vol. 16, no. 2, pp. 1406–1416, Feb. 2020.
20. L. Zhao, J.Wang, and J. Liu, "Optimal edge resource allocation in iot-based smart cities," IEEE Netw., vol. 33, no. 2, pp. 30–35, Mar./Apr. 2019.
21. A. H. Sodhro and S. Pirbhulal, "Artificial intelligence driven mechanism for edge computing based industrial applications," IEEE Trans. Ind. Informat., vol. 15, no. 7, 2019, pp. 4235–4243, Jul. 2019.
22. H. A. Khattak and H. Farman, "Toward integrating vehicular clouds with iot for smart city services," IEEE Netw., vol. 33, no. 2, pp. 65–71,Mar./Apr. 2019.
23. Yu Fu and S. Wang, "Artificial intelligence to manage network traffic of 5G wireless networks," IEEE Netw., vol. 32, no. 6, pp. 58–64, Nov./Dec. 2018.

24. R. Talat and M. S. Obaidat, "A decentralised approach to privacy preserving trajectory mining," Future Gener. Comput. Appl., vol. 102, no. 2020, pp. 382–392, 2020
25. O. W Samuel and G. Li, "Intelligent emg pattern recognition control method for upper-limb multifunctional prostheses: Advances, current challenges, and future prospects," IEEE Access, vol. 7, pp. 10150–10165,2019.
26. A. H. Sodhro and M. Guizani, "AI-enabled reliable channel modelling architecture for fog computing vehicular networks," IEEE Wireless Commun. Mag., vol. 27, no. 2, pp. 14–21, Apr. 2020.
27. Y. Liu, C. Yang, L. Jiang, S. Xie, and Y. Zhang, "Intelligent edge computing for iot-based energy management in smart cities," IEEE Netw., vol. 33, no. 2, pp. 111–117, Mar./Apr. 2019.
28. K-C. Chen, "Ultra-low latency mobile networking," IEEE Netw., vol. 3, no. 2, pp. 181–187, Mar./Apr. 2019.
29. W. Zhang, Z. Zhang, S. Zeadally, H. Chao, and V. C. M. Leung, "MASM: A multiple-algorithm service model for energy-delay optimization in edge artificial intelligence," IEEE Trans. Ind. In format., vol. 15, no. 7, pp. 4216–4224, Jul. 2019.
30. C. Nykvist and M. Larsson, "A lightweight portable intrusion detection communication system for auditing applications," Int. J. Commun. Syst., vol. 33, no. 7, pp. 1–15, 2020.
31. MLRepository, UCI: [Online]. Available: https://archive.ics.uci.edu/ml/ datasets/SECOM. Accessed: May 5, 2020.
32. A. H. Sodhro, Y. Li, and M. A. Shah, "Energy-efficient adaptive transmission power control in wban," IET Commun., vol. 10, no. 1, pp. 81–90, 2016.
33. Y. Zhou and Z M. Fadlullah, "Deep learning based radio resource assignment technique 5G ultra dense networks," IEEE Netw., vol. 32, no. 6, pp. 28–34, Nov./Dec. 2018.
34. L. Zhu and F. R. Yu, "Big data analytics in intelligent transportation systems: a survey," IEEE Trans. Intell. Transp. Syst., vol. 20, no. 1, pp. 383–398, Jan. 2019.
35. X. Liu and X. Zhang, "Noma-based resource allocation for cluster-based cognitive industrial internet of things," IEEE Trans. Ind. Informat., vol. 16, no. 8, pp. 5377–5388, Aug. 2020.
36. A. H. Sodhro and M. S. Obaidat, "A novel energy optimization approach for artificial intelligence-enabled massive iot," in Proc. IEEE Int. Symp. Perform. Eval. Comput. Telecom. Syst., 2019, vol. 22/24, pp. 1–6.
37. S. Pirbhulal and N. Pombo, "Towards machine learning enabled security framework for iot-based healthcare," in Proc. 13th IEEE Int. Conf. Sens. Technol., Sydney, Australia, 2019, pp. 1–6.
38. Y. Geng and O. W. Samuel, "A robust sparse representation pattern recognition approach for myoelectric control," IEEE Access, vol. 6, pp. 38326–38335, 2018.
39. A. Aijaz, "Enhanced wireless interface for com. in factory automation networks," IEEE Trans. Ind. Informat., vol. 14, no. 12, pp. 5346–5358,Dec. 2018.
40. M. G. Asogbon and O. W Samuel, "Towards resolving the co-existing impacts of multiple dynamic factors on the performance of emg-pattern recognition based prostheses," Comput. Methods Programs Biomed., vol. 184, 2020, Art. no. 105278.
41. M. Muzammal and R. Talat, "A multi-sensor data fusion enabled ensemble approach for medical data from body sensor networks," Inf. Fusion, vol. 53, pp. 155–164, 2020.
42. A. H. Sodhro and S. Pirbhulal, "Chapter#16: Energy-efficiency in wireless body sensor networks," Networks of the Future Architectures, Technologies, and Implementations, Computer and Information Science Series. Boca Raton, FL, USA: CRC Press, 2017.
43. Z. Zhou and Y. Guo, "Access control and resource allocation for m2m communications in industrial automation," IEEE Trans. Ind. Informat., vol. 15, no. 3, pp. 1350–1360, May 2019.
44. Y. Cao and F. Jia, "Efficient traceability systems of steel products using blockchain-based industrial internet of things," IEEE Trans. Ind. Informat.,vol. 16, no. 9, pp. 6004–6012, Sept. 2020.
45. Z. Lv, H. A. N. Yang, A. K. Singh, G. Manogaran, and H. Lv, "Trustworthiness in industrial IoT

systems based on artificial intelligence," IEEE Trans. Ind. Informat., pp. 1–9, 2020.

46. T. Zhang, A. H. Sodhro, and Z. Luo, "A joint deep learning and internet of medical things driven framework for elderly patients," IEEE Access, vol. 8, pp. 75822–75832, 2020.
47. J.Wang and C. Jiang, "Distributed q-learning aided heterogeneous network association for energy-efficient iiot," IEEE Trans. Ind. Informat., vol. 16, no. 4, pp. 2756–2764, Apr. 2020.
48. T. Hussain et al., "Intelligent embedded vision for summarization of multiview videos in iiot," IEEE Trans. Ind. Informat., vol. 16, no. 4, pp. 2592–2602, Apr. 2020.
49. A. Y. Awan, "Joint network admission control, mode assignment, pow-er allocation in energy harvesting aided d2d communication," IEEE Trans. Ind. Informat., vol. 16, no. 3, pp. 1914–1923, Mar. 2020.