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POWER QUALITY IMPROVEMENT BY MONITORING AND USING CONVERTOR IN HOUSEHOLD ELECTRICITY

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Abstract- *Enhancing strength efficiency by way of tracking household electrical consumption is of massive importance with the weather exchange issues of the prevailing time. Home owners are now and again ignorant of how older appliances, newly mounted appliances and modifications in occupant behavior affect the energy intake of their residence. As an example, putting in an extra green furnace will no longer necessarily reduce electricity payments if the occupants forestall turning down the thermostat at night.*

INTRODUCTION

The approach of extraction of the constituent elements of the overall load is known as Load Disaggregation.

It produces extra accurate statistics approximately the electric power consumption of end users without measuring the give up uses at once for long intervals of time; therefore, fewer sensors are wished, and much less records is collected.

Word that the disaggregated data offers for households to better understand their intake practices, determine fee-powerful measures to boom their strength performance, and eventually reduce their standard consumption.

NIALM

In this project, it is proposed to implement a non-intrusive appliance load monitoring system (NIALM). It could determine the working agenda of whole electrical masses in a goal gadget from measurements made at a centralized area. Similarly it can pick out the operation of electromechanical devices from other sorts of energy distribution net and distinguish masses even when many are working at one time. This system captures the alerts from the mixture consumption, extracts the capabilities from these indicators and classifies the extracted functions to be able to become aware of the switched on appliances. We will employ for feature extraction the estimation signal parameter via a rotational invariant technique method (ESPRIT), a well known parametric estimation technique. ESPRIT is primarily based on theorems that make the extension to higher spatial dimension and to sign containing more than one frequencies viable NIALM can screen the operation of the electrical distribution system itself, figuring out situations in which or extra otherwise healthy hundreds interfere with each deferent's operation through voltage waveform distortion or electricity best troubles. We can also have a look at a classification method.

LITERATURE REVIEW

Attique [1] In order to tackle today's energy and sustainability issues, there are two paths to be followed by the world community. Either they have to establish new generation plants with an expense of millions of dollars or to look deeper into the existing system to design and deploy techniques that can lead to a significant amount of energy saving. Today, researchers are extensively working towards energy efficiency and conservation via developing different techniques. In the said domain, energy monitoring is one of the key techniques which his an attractive and popular research topic in the field of sustainable energy. It is single-point sensing or commonly known as Non-Intrusive Load Monitoring (NILM) that is used to extract the appliance level energy consumption. For a NILM system, event detection plays a key role and is a pre-requisite for the later stages of the system. In this paper a simple and low complexity event detection algorithm is proposed. Digital simulation and sensitivity studies have been carried out using real world data to check the performance and sensitivity of the proposed algorithm. Furthermore, the results of the proposed algorithm are compared with the existing event detection algorithm for evaluation purposes

`Pedro Garcia (2018) [2] presents a nonintrusive load disaggregation scheme. The proposed methodology uses a kernel based nonlinear regression strategy to analyze a set of RLC loads with chaotic switching, considering the time series of the total power consumption. The employed approach, to the authors' knowledge, represents a novelty in the treatment of the problem. The attained results suggest that the exposed methodology can be useful in the design of efficient load disaggregation tactics.

Ahmed F. Ebrahim Osama Mohammed (2018) [3 represent a massive section of the grid infrastructure which could not be considered as a smart grid without smart households integrated into it. Short Term Load Forecasting (STLF) is the essential tool needed in the management and control techniques required for households to be smart. STLF at this level of the grid is very challenging due to the high percentage of uncertainty in the load demand, influenced by customer behavior, which is too stochastic to predict. In this paper, a new approach for STLF of household load demand is employed based on artificial neural network (ANN) and a pre-processing stage of Non-Intrusive Load Monitoring (NILM) techniques. The NILM techniques extract the individual load pattern from the available historical aggregated load demand. These new features increase the training data window for the ANN forecaster and achieve a significant enhancement for its prediction performance. By comparing the new approach with the state of the art techniques in household load forecasting, the proposed method outperforms feed-forward artificial neural network (FFANN) regarding RMSE. Two techniques of NILM were used to emphasize the correlation between the NILM disaggregation accuracy performance and the load forecasting enhancement performance.

THE PLATFORM

All the simulation, implementation and analysis work was done on Windows seven. Since the platform provided the premise for doing everything, so it becomes essential to debate some options and additionally somewhat on however it evolved and the way is actively operating behind the scenes.

Simulation Setup

About MATLAB

MATLAB may be a software program package deal that lets you do arithmetic and computation, examine facts, increase algorithms, do simulation and modeling, and turn out graphical displays and graphical user interfaces. Common makes use of encompass:

- Math and computation
- Algorithm development
- Data acquisition
- Modeling, simulation, and prototyping
- Data analysis, examination, and apparition
- Scientific and engineering graphics
- Application development, including graphical user interface building

REGRESSION LINE METHOD

- Regression evaluation is most customarily used for prediction. The goal in regression analysis is to create a mathematical version that can be used to are expecting the values of a established variable primarily based upon the values of an impartial variable. In different phrases, we use the version to expect the value of Y while we recognize the fee of X. (The dependent variable is the one to be predicted).
- Correlation analysis is regularly used with regression analysis because correlation evaluation is used to measure the energy of affiliation between the two variables X and Y.
- In regression evaluation concerning independent variable and established variable plots are drawn to analyze the information conduct.
- The plots permit us to visually look at the data prior to running a regression evaluation. Frequently this step permits us to see if the connection among the variables is increasing or lowering and offers best a hard idea of the relationship.
- The only relationship among variables is a instantly-line, linear and nonlinear dating. Of direction the statistics may well be curvilinear and in that case we would need to use a exclusive version to describe the connection.
- This segment of the bankruptcy deals with distinctive analysis and possible effects of the consequences of the Euclidean Norm based totally Fuzzy Inference device for STLF

for the proposed studies work. The fuzzy Inference gadget has been evolved the usage of the bushy logic toolbox to be had in MATLAB and relaxation of the implementation of the Euclidean Norm primarily based selection of similar Days has been carried out the usage of the MATLAB programming.

- The load forecasting is performed for all the days of the take a look at forecasting month of August'. The values of $w1,2$, $w$three, the weight elements, are determined through least squares technique based totally on the regression version and it's far built the usage of 6 months historical information.

Results of 24 Hours from Last 1400 Hours

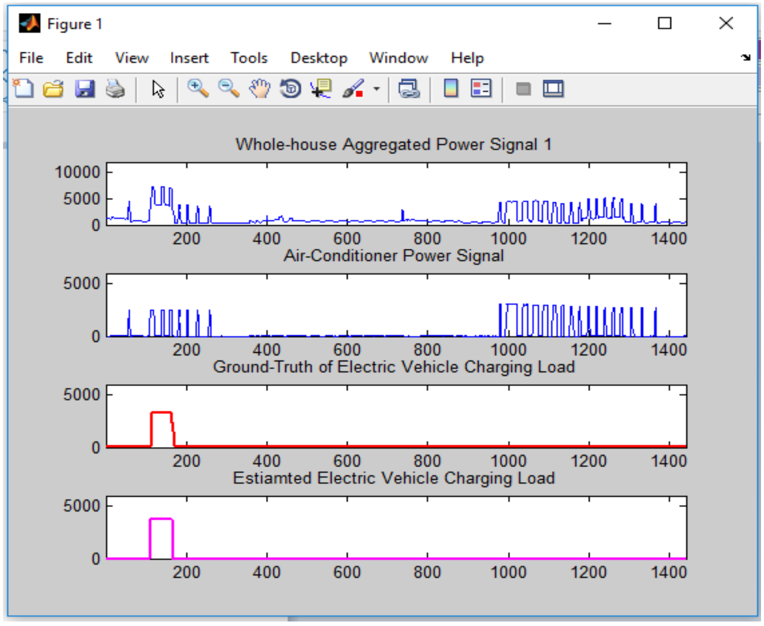

Figure 4.1 Power Used Against Total Hours

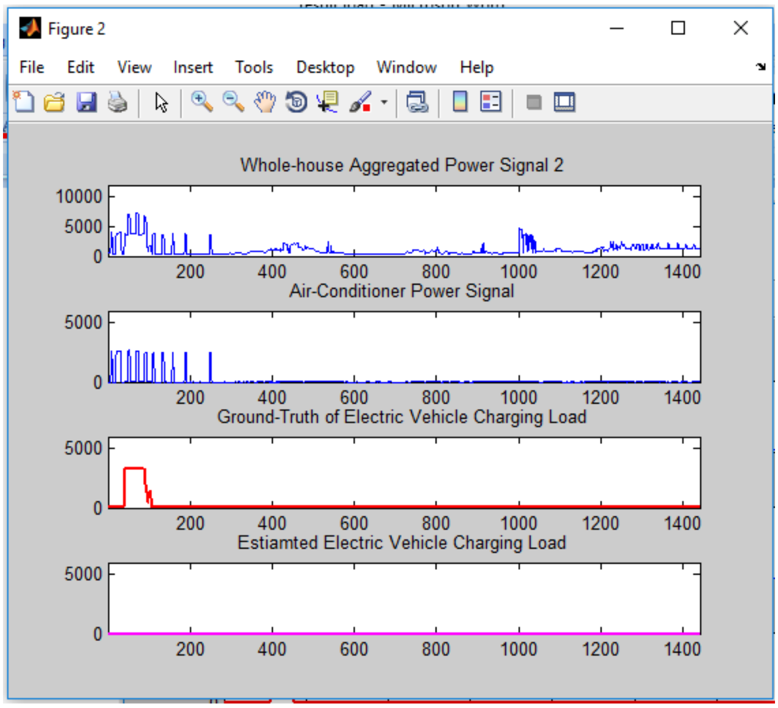

Figure 4.2 Power used Against Total Hours

Figure 4.3 Power Used Against Total Hours

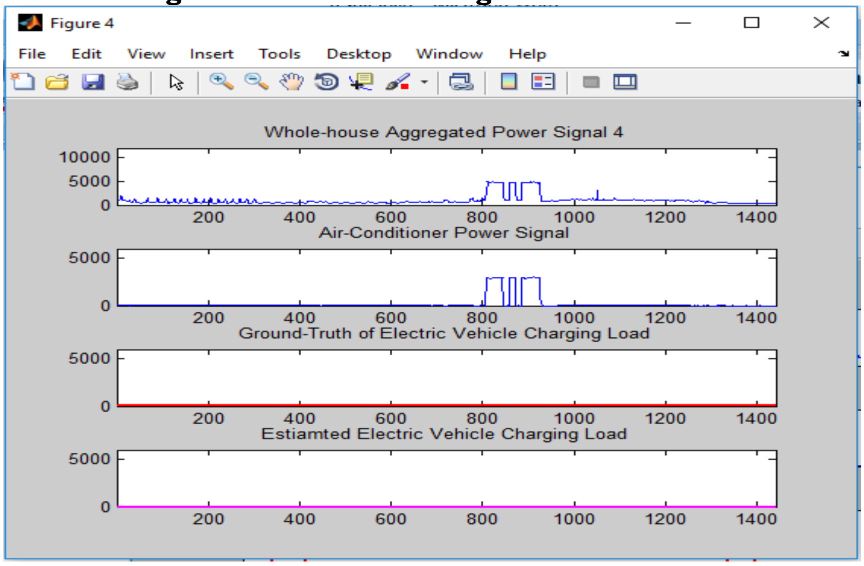

Figure 4.4 Power Used Against Total Hours

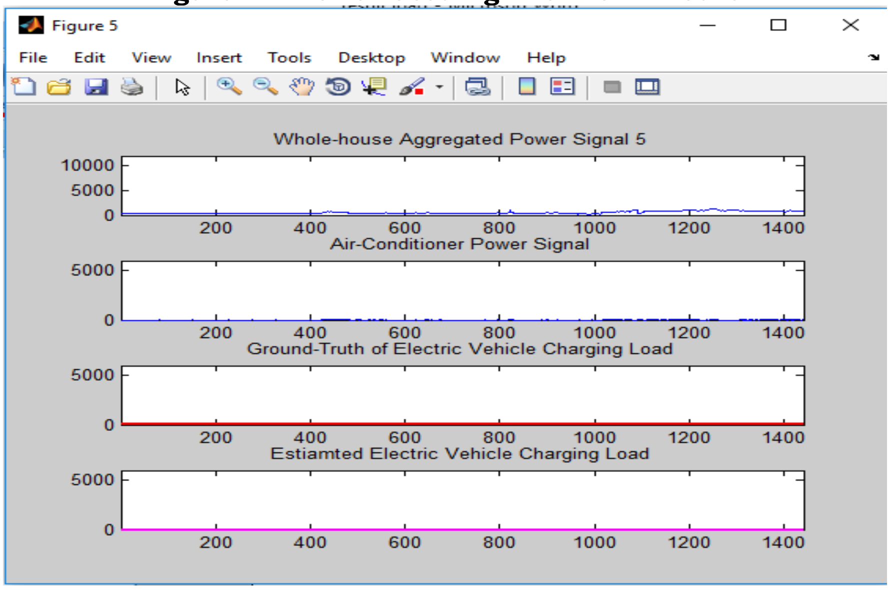

Figure 4.5 Power Used Against Total Hours

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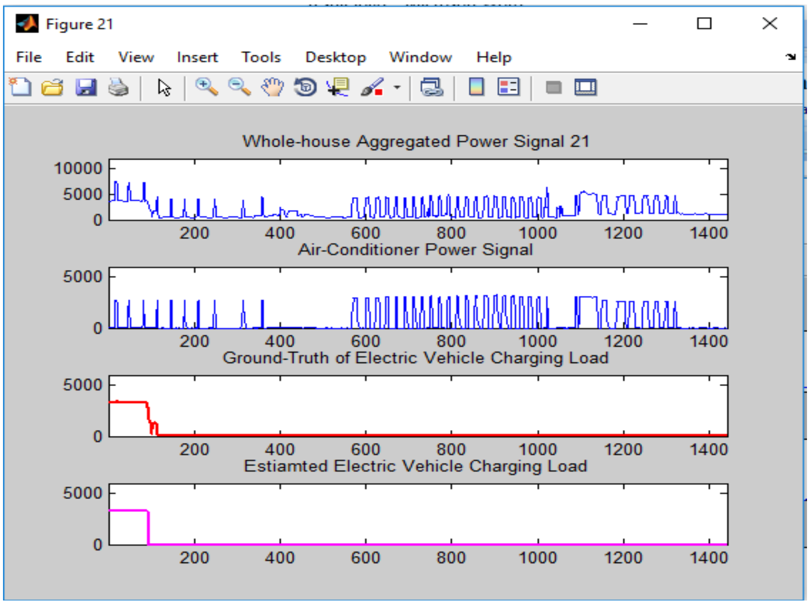

Figure 4.6 Power Used Against Total Hours

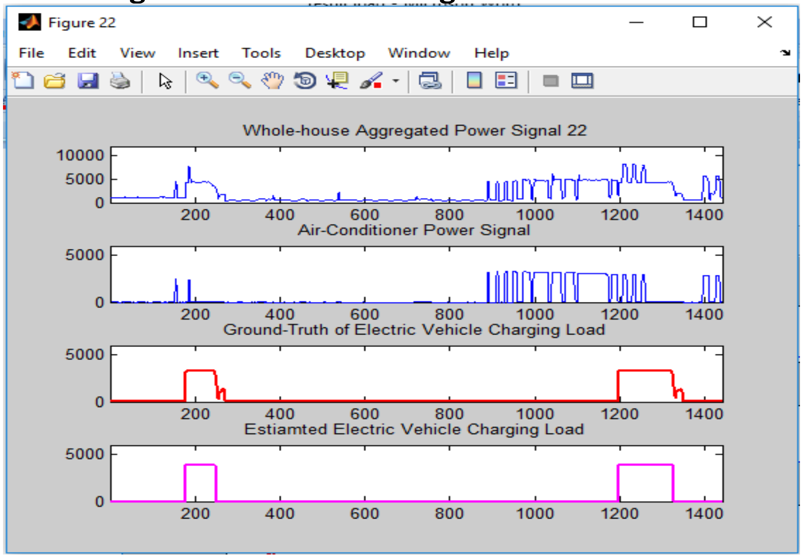

Figure 4.7 Power Used Against Total Hours

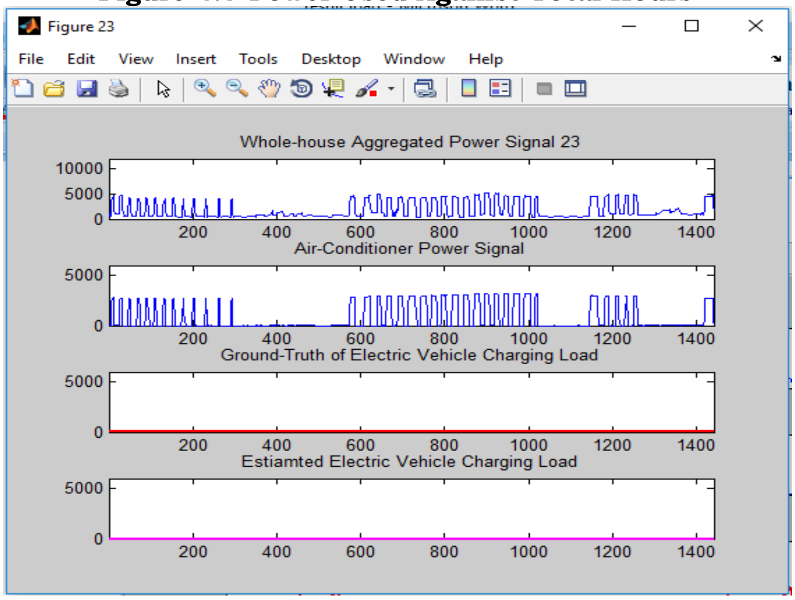

Figure 4.8 Power Used Against Total Hours

Load Calculation Results

Table 4.1 Load Analysis

1.	**Energy Accuracy:**	**95.0%**
2.	**Difference(kWh):**	**6.5**
3.	**MSE:**	**0.093059**
4.	**Percentage:**	**16.28%**
5.	**Truth:** **Estimated:**	**130.732 (kWh)** **124.245 (kWh)**

Efficiency Factors of Proposed Parameters
Conduction losses that depend on load:

- Resistance whilst the transistor or MOSFET switch is engaging in.
- Diode ahead voltage drop (typically 0.7 V or 0.Four V for Scotty diode)
- Inductor winding resistance
- Capacitor equal collection resistance

Switching losses:

- Voltage-Ampere overlap loss
- $Frequency_{switch}$*CV^2 loss
- Reverse latency loss
- Losses due driving MOSFET gate and controller consumption.
- Transistor leakage current losses, and controller standby consumption.

1. Inside the operation of buck power converters, the loss of IGBT is one of the major energy dissipation. For this reason, correct loss evaluation and loss dimension of IGBT will become to be an critical issue in designing higher strength density converters.
2. Conduction losses in addition to switching losses are included within the calculation the use of a simplified version, based on power semiconductor data sheet.

There are masses of papers on DC-DC strength converter loss research. But the temperature-associated accurate layout-orientated loss modeling isn't analyzed. And lots of recent researches are both too complicated or faulty. Considering that it is desired to use best datasheet records with minimum measurements.

Contributions
IGBT related thermal losses.
The Total Losses of IGBT include three Aspects:

1) The switching loss during the process of turn on and turn off;
2) The conduction loss during the state of conducting;
3) The turn-off loss during the turned off state. The turn-off loss can be ignored

This method will be independent of circuit models with decent accuracy and simulation speed. This proposed model (GUI) will divide the power losses of buck converter into four different parts, considering the relation of each component to temperature variation

Simulation and Results

By using placing every part together (GUI version), the temperature-associated electricity loss version for dollar converter may be built. The numerical simulation might be completed the usage of MATLAB in temperature ranging from 25°C to 125°C.

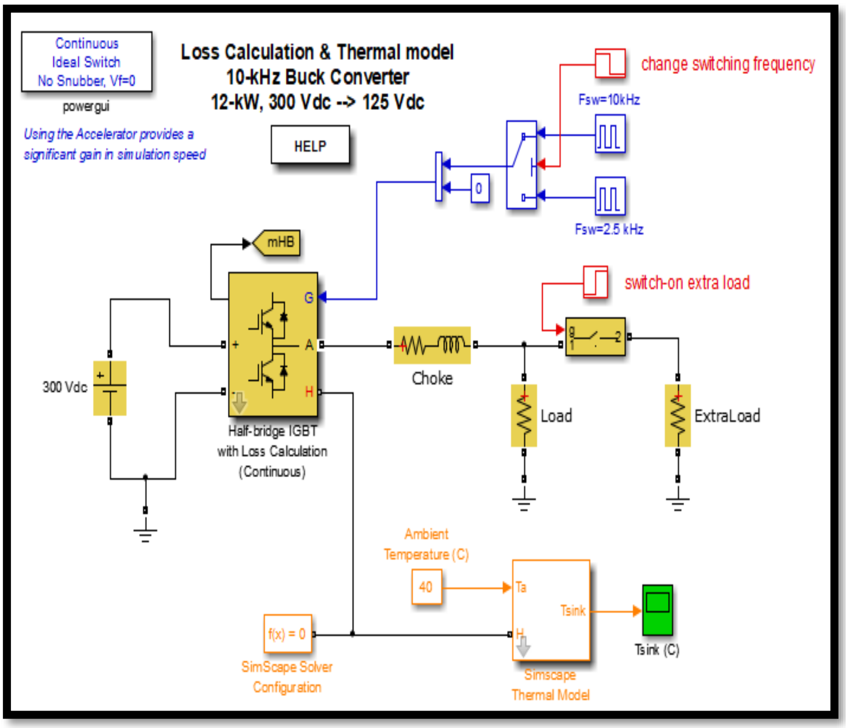

Figure 4.9 GUI Model for Simulation Loss Calculation

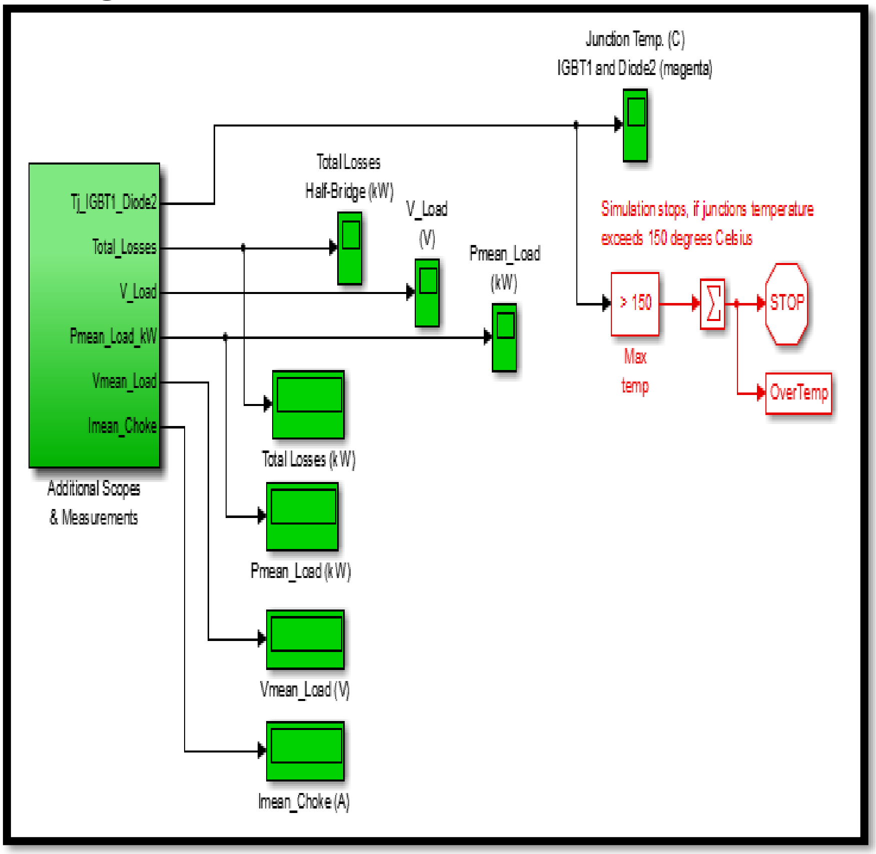

Figure 4.10 GUI Model for Simulation Junction Temperature

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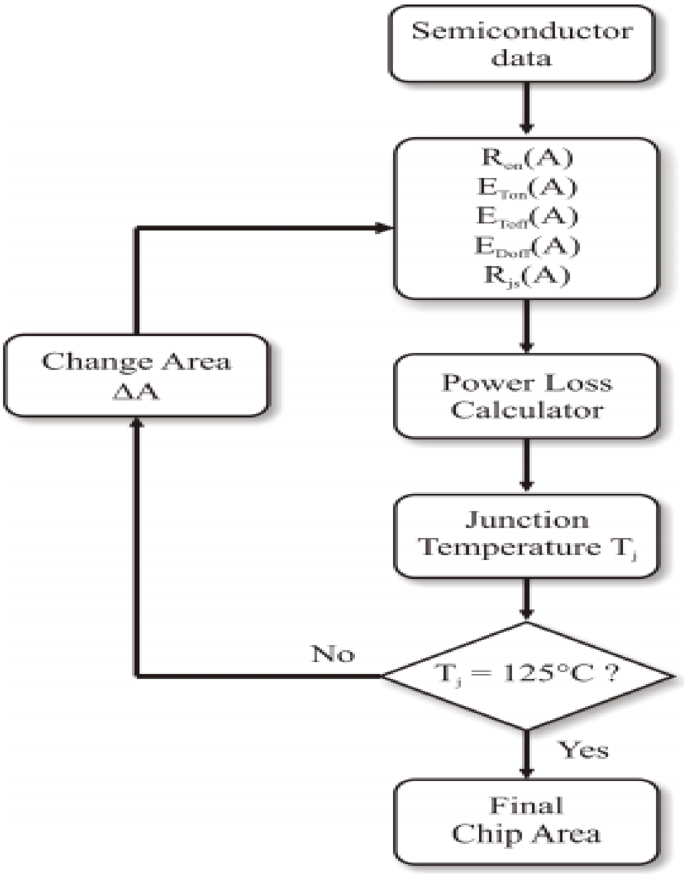
FLOWCHART



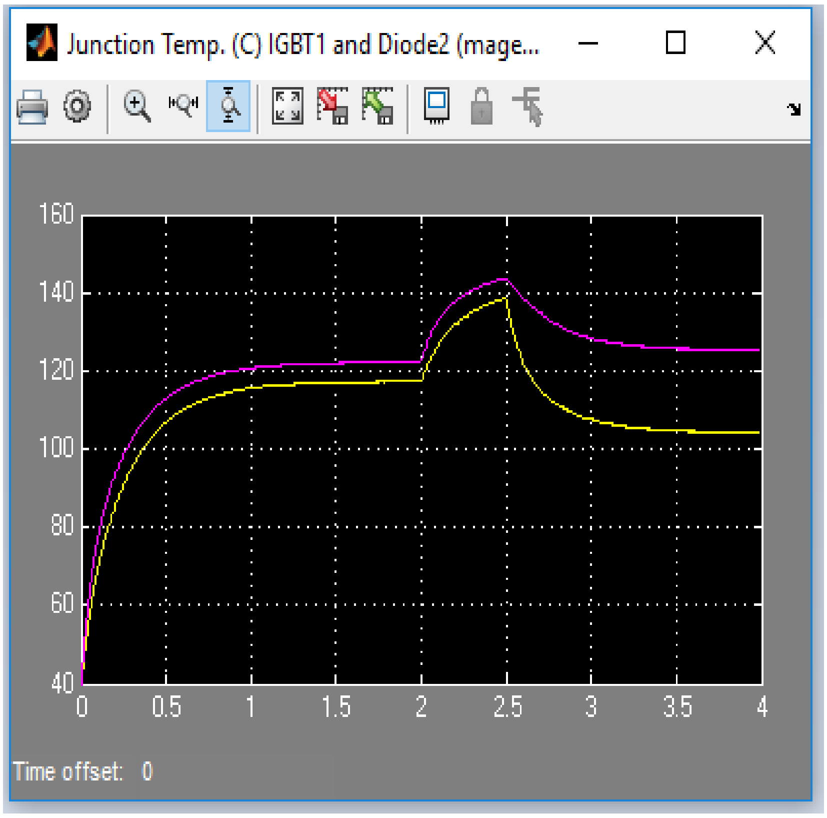


Figure 4.11 Loss Calculation Results

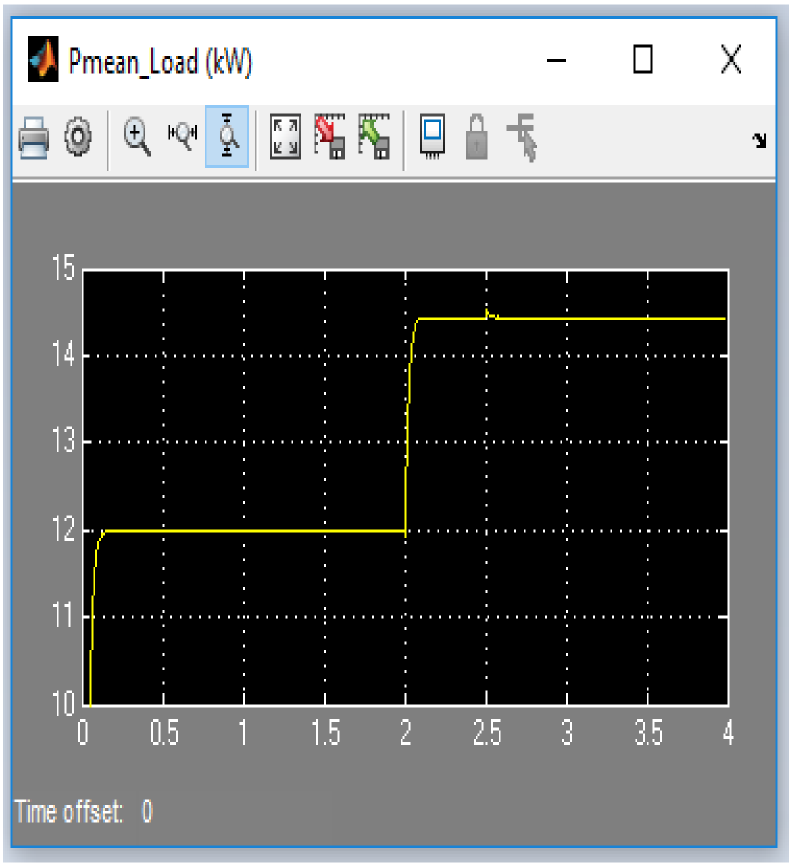


Figure 4.12 Loss Calculation Results

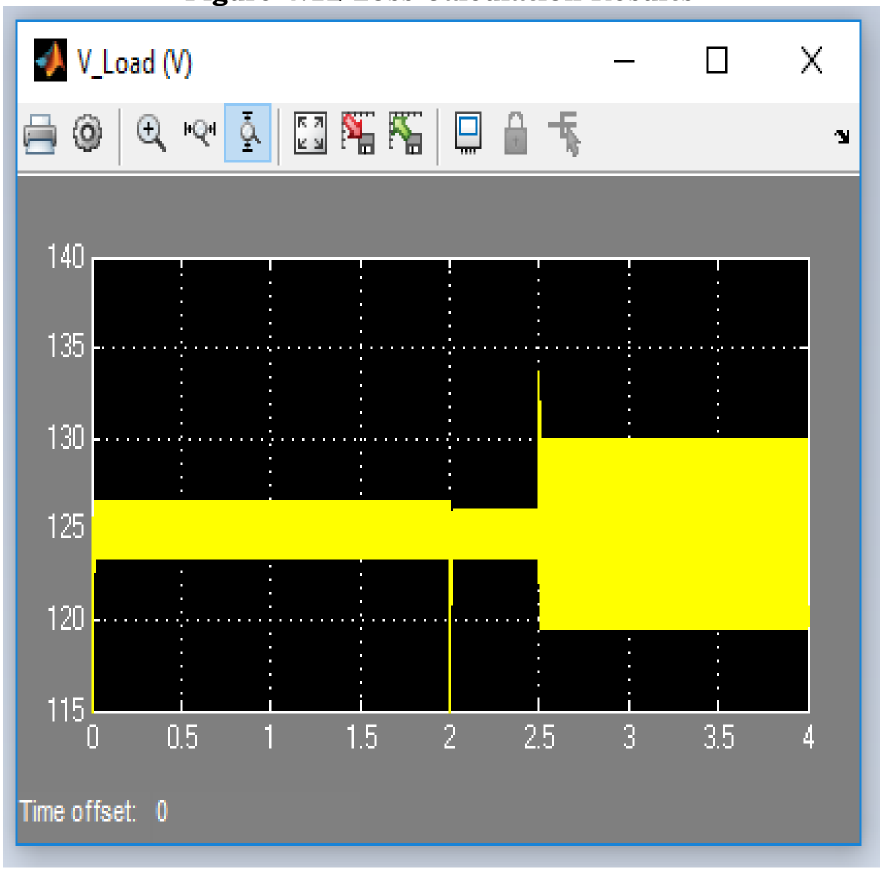


Figure 4.13 Loss Calculation Results

Result Discussion

Prototype Model of Controller

- We've advanced a prototype version of DC-DC dollar converter.
- The dollar converter is designed with mH; C= 100uF; and load 20 ohms.
- The responsibility cycle of the PWM signal with consistent load is 50%.
- We've got tested our prototype version with resistive load handiest. By changing the burden, present day varies which changes the voltage.
- For consistent voltage, the duty cycle of the PWM switching pulse will trade for that reason.
- We have examined the controller performance with the aid of lowering the burden; step by step the cutting-edge requirement will increase.
- A lower in the output voltage with an boom in current density is shown. So, for a consistent output voltage, the duty cycle will boom progressively
- Voltage sensing is accomplished through simple voltage dividing circuit so that you can be. This is subtracted from the usage of an op-amp subtractor circuit.
- This mistake sign is fed to the FPGA based totally controller that's synthesized in XC3S500E development board.
- It's miles given to ADC (analog-to-virtual conversion) module of XC3S500E board. LTC1407A-1 ADC converter IC has been used in this board which offers 1- bit digital output represented in 2's supplement binary fee.

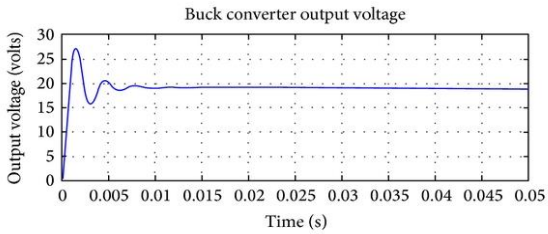


Figure 4.16 Output Voltage of Buck Converter

- It has a precision of 14 bits. Most sampling rate which can be performed is about 1.5 MHz.
- Using PI modules, the error is minimized and PWM output is generated with its reference and output is taken from I/O pin F8 of XC3S500E board (layout and evaluation completed on lab experiment.)

CONCLUSION

NIALM permit us to switching from aggregate to disaggregate consumption. By means of the usage of ESPRIT as a characteristic extraction method, we attain a database of signature of nine unique hundreds. We acquire an almost perfect reconstructed present day for the standard load and linear masses, and a great reconstructed modern-day for the nonlinear loads.

Then, the k-NN approach allows us to discover a moderate sample of information and assigning a label for it.

Future Scope

Inside the destiny, it is advocated to complement the database of signatures by using a biggest number of appliances that covers the most evolved technologies. Then using different category approach like aid Vector system allows acquiring a extra accurate classification. In the end the task could be writing a C code that performs the same algorithm of the MATLAB code that we write; here we can talk about a actual hardware implementation without the absence of a microcontroller having a excessive sampling frequency.

REFERENCES

1. Attique Ur Rehman, Tek Tjing Lie, Brice Valles and Shafiqur R. Low Complexity Event Detection Algorithm for NonIntrusive Load Monitoring Systems2018-19 IEEE Transactions on Instrumentation and Measurement
2. Pedro Garcia ; Xavier Dominguez; David Chiza; Jose Restrepo Non Intrusive Load Monitoring in Chaotic

Switched Networks 2018 IEEE Third Ecuador Technical Chapters Meeting (ETCM).
3. Ahmed F. Ebrahim; Osama Mohammed Household Load Forecasting Based on a Pre-Processing Non-Intrusive Load Monitoring Techniques2018 IEEE Green Technologies Conference (Green Tech)
4. Vijay Rathore; Sachin Kumar Jain Non Intrusive Load Monitoring and Load Disaggregation using Transient Data Analysis 2018 Conference on Information and Communication Technology (CICT)
5. Victor Andrean; Xin-Hong Zhao; Dawit Fekadu Teshome; Tai-Di Huang; Kuo-Lung Lian A Hybrid Method of Cascade-Filtering and Committee Decision Mechanism for Non-Intrusive Load Monitoring IEEE Access Year: 2018 | Volume: 6.
6. Yun Yang; Yajie Jiang; Siew-Chong Tan; Shu-Yuen Ron Hui A Frequency-Sweep Based Load Monitoring Method for Weakly-Coupled Series-Series Compensated Wireless Power Transfer Systems 2018 IEEE PELS Workshop on Emerging Technologies: Wireless Power Transfer (Wow).
7. Hero Rafael C. Arante; Alyanna B. Lopez; Michael Andre Jose P. Santos; Edwin Sybingco; Elmer P. Dadios; Aurenilo Macadaeg Bus Load Monitoring System With Image Analytics Using MyRIO 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM).
8. Peter A. Lindahl; Daisy H. Green; Gregory Bredariol; Andre Aboulian; John S. Donnal; Steven B. Leeb Shipboard Fault Detection Through Nonintrusive Load Monitoring: A Case Study IEEE Sensors Journal Year: 2018 | Volume: 18, Issue: 21.
9. Shuai Zhang; Zhicheng Zhu; Bo Yin; Xianqing Huang Event Detection Methods for Nonintrusive Load Monitoring in Smart Metering: Using the Improved CUSUM Algorithm2018 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC).
10. Srikanth Madala; Adam Herink; Matt Robinette; Tim Ramaekers; Roy Palk; Dan Brewer Improvements in Rural Load Management by Electric Cooperatives through an Effective SCADA System, and Distribution Connected Generation 2018 IEEE Rural Electric Power Conference (REPC).
11. Jouni Peppanen; Jason A. Taylor Enhanced Load Modeling with Expanded System Monitoring 2018 Clemson University Power Systems Conference (PSC).
12. Shirantha Welikala; Chinthaka Dinesh; Mervyn Parakrama B. Ekanayake; Roshan Indika Godaliyadda; Janaka Ekanayake Incorporating Appliance Usage Patterns for Non-Intrusive Load Monitoring and Load Forecasting IEEE Transactions on Smart Grid Year: 2019 | Volume: 10, Issue: 1 | Journal Article |.
13. Junhyuck Seo; Hui Ma; Tapan K. Saha Analysis of Vibration Signal for Power Transformer On-Load Tap Changer (OLTC) Condition Monitoring2018 IEEE Power & Energy Society General Meeting (PESGM)
14. ZHU Jian-hong; MENG Bang-bang; Gu Ju-ping; HUANG Qiong ; Chen Ze-yu Intelligent Management Design on Air Conditioning Nonlinear Group Load2018 IEEE International Conference on Advanced Manufacturing (ICAM).
15. Kong W., Dong Z., Xu Y., Hill D. An Enhanced Bootstrap Filtering Method for Non- Intrusive Load Monitoring; Proceedings of the 2016 IEEE Power and Energy Society General Meeting (PESGM); Boston, MA, USA, 2016. 17–21 July; pp. 1–5.
16. Ducange P., Marcelloni F., Antonelli M. A novel approach based on finite-state machines with fuzzy transitions for nonintrusive home appliance monitoring. IEEE Trans. Ind. Informatics. 2014;10:1185–1197. doi: 10.1109/TII.2014.2304781.
17. Sultanem F. Using appliance signatures for monitoring residential loads at meter panel level. IEEE Trans. Power Deliv. 1991; 6:1380–1385. doi: 10.1109/61.97667. [CrossRef].
18. Kolter Z., Jaakkola T., Kolter J.Z. Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation; Proceedings of the Fifteenth International Conference on Artificial Intelligence and Statistics (AISTATS), PMLR 22:1472-1482; La Palma, Canary Islands. 21–23 April 2012; pp. 1472–1482. [Google Scholar].
19. Makonin S., Popowich F., Bajic I.V., Gill B., Bartram L. Exploiting HMM Sparsity to Perform Online Real-Time Nonintrusive Load Monitoring. IEEE Trans. Smart Grid. 2016; 7: 2575–2585. doi: 10.1109/TSG.2015.2494592.
20. Bonfigli R., Felicetti A., Principi E., Fagiani M., Squartini S., Piazza F. Denoising autoencoders for Non-Intrusive Load Monitoring: Improvements and comparative evaluation. Energy Build. 2018; 158:1461–1474. doi: 10.1016/j.enbuild.2017.11.054.
21. Kong W., Dong Z.Y., Hill D.J., Luo F., Xu Y. Improving Nonintrusive Load Monitoring Efficiency via a Hybrid Programing Method. IEEE Trans. Ind. Informatics. 2016;12: 2148–2157. doi: 10.1109/TII.2016.2590359.
22. Aiad M., Lee P.H. Unsupervised approach for load disaggregation with devices interactions. Energy Build. 2016; 116:96–103. doi: 10.1016/j.enbuild.2015.12.043.
23. Shao H., Tech V., Marwah M. A Temporal Motif Mining Approach to Unsupervised Energy Disaggregation; Proceedings of the 1st International Workshop on Non-Intrusive Load Monitoring; Pittsburgh, PA, USA. 7 May 2012; pp. 1–2.
24. He K., Stankovic L., Liao J., Stankovic V. Non-Intrusive Load Disaggregation using Graph Signal Processing. IEEE Trans. Smart Grid. 2016; 9:1739–1747. doi: 10.1109/TSG.2016.2598872.
25. Wójcik A., Winiecki W. The method of identification operating states of multi-state electrical devices with complex modes of operation. Przegląd Elektrotech. 2016; 92:87–90. doi: 10.15199/48.2016.11.22.
26. Reinhardt A., Burkhardt D., Zaheer M., Steinmetz R. Electric appliance classification based on distributed high resolution current sensing; Proceedings of the 37th Annual IEEE Conference on Local Computer Networks-Workshops; Clearwater, FL, USA. 22–25 October 2012; pp. 999–1005.
27. Yoshimoto K., Nakano Y., Amano Y., Kermanshahi B. Non-Intrusive Appliances Load Monitoring System Using Neural Networks. Inf. Electron. Technol. 2000; 2:183–194.
28. Agyeman K.A., Han S., Han S. Real-time recognition non-intrusive electrical appliance monitoring algorithm for a residential building energy management system. Energies. 2015;8:9029–9048. doi: 10.3390/en8099029.
29. Srinivasan D., Ng W.S., Liew A.C. Neural-network-based signature recognition for harmonic source identification. IEEE Trans. Power Deliv. 2006; 21:398–405. doi: 10.1109/TPWRD.2005.852370.

30. Bouhouras A.S., Milioudis A.N., Labridis D.P. Development of distinct load signatures for higher efficiency of NILM algorithms. Electr. Power Syst. Res. 2014; 117:163–171. doi: 10.1016/j.epsr.2014.08.015.
31. Wichakool W., Avestruz A.T., Cox R.W., Leeb S.B. Modeling and estimating current harmonics of variable electronic loads. IEEE Trans. Power Electron. 2009; 24:2803–2811. doi: 10.1109/TPEL.2009.2029231.
32. Lam H.Y., Fung G.S.K., Lee W.K. A novel method to construct taxonomy electrical appliances based on load signatures. IEEE Trans. Consum. Electron. 2007; 53:653–660. doi: 10.1109/TCE.2007.381742. [CrossRef] [Google Scholar]
33. De Baets L., Ruyssinck J., Develder C., Dhaene T., Deschrijver D. Appliance classification using VI trajectories and convolutional neural networks. Energy Build. 2018;158:32–36. doi: 10.1016/j.enbuild.2017.09.087.
34. Duarte C., Delmar P., Barner K., Goossen K. A signal acquisition system for non-intrusive load monitoring of residential electrical loads based on switching transient voltages; Proceedings of the 2015 Clemson University Power Systems Conference (PSC); Clemson, SC, USA. 10–13 March 2015.
35. Meziane M.N., Ravier P., Lamarque G., Abed-meraim K., Le Bunetel J., Raingeaud Y., Blois D. Modeling and Estimation of Transient Current Signals; Proceedings of the 23rd European Signal Processing Conference; Nice, France. 31 August–4 September 2015; pp. 1960–1964.
36. Zeifman M., Akers C., Roth K. Nonintrusive monitoring of miscellaneous and electronic loads; Proceedings of the 2015 IEEE International Conference on Consumer Electronics (ICCE); Las Vegas, NV, USA. 9–12 January 2015; pp. 305–308.
37. Duarte C., Delmar P., Goossen K.W., Barner K., Gomez-Luna E. Non-intrusive load monitoring based on switching voltage transients and wavelet transforms; Proceedings of the 2012 Future of Instrumentation International Workshop; Gatlinburg, TN, USA. 8–9 October 2012; pp. 101–104.
38. Gupta S., Reynolds M.S., Patel S.N. ElectriSense: single-point sensing using EMI for electrical event detection and classification in the home; Proceedings of the 12th ACM international conference on Ubiquitous computing; Copenhagen, Denmark. 26–29 September 2010; pp. 139–148.
39. Chen K.Y., Gupta S., Larson E.C., Patel S. DOSE: Detecting user-driven operating states of electronic devices from a single sensing point; Proceedings of the 2015 IEEE International Conference on Pervasive Computing and Communications (PerCom).