

Electric Load Monitoring of Residential Buildings using Goodness of Fit and Multi-Layer Perceptron Neural Networks

Aaron R. Rababaah
Math and Computer Science
University of Maryland Eastern Shore (UMES)
Princess Anne, USA
arrababaah@umes.edu

Eniye Tebekaemi
Math and Computer Science
University of Maryland Eastern Shore (UMES)
Princess Anne, USA
etebekaemi@umes.edu

Abstract—Nonintrusive appliance load Non-intrusive load monitoring is an emerging signal processing and analysis technology that aims to identify individual appliance in residential or commercial buildings or to diagnose shipboard electro-mechanical systems through continuous monitoring of the change of On and Off status of various loads . The goal of the NIALM system is to identify and track instances when appliance in a building is turned on and off. This is achieved by collecting electric power data measure live from the service entry point of a building; disaggregate it and extracting unique features of the signal that can be used to identify appliances in the building. The NIALM provides a relatively cheap and efficient way to monitor appliances without invading the home or disrupting the normal configuration of the household appliances. To better plan for our current and future energy needs, it is important for us to know how each of our electrical appliance is been utilized. This information would help facility managers to better manage and distribute power; appliance producer to design and produce more energy efficient appliances; and also home owners/building managers understand each appliance, utilization and energy consumption which would help in decision making.

Keywords - *Nonintrusive Electrical Load Mointoring, Godness of Fit, Multi-Layrer Perceptron Neural Networks.*

I. INTRODUCTION

Over the years Energy and power needs of residential building has grown tremendously, with the development of new household electrical products and appliances increasing by the day. This has revolutionized the way we live our lives, especially in the developed economies, where we are now more electrical energy dependent than ever. With current trends in world economies; depleting energy resources and the transition to cleaner energy sources, it becomes necessary to be more aware how energy is spent in residential/commercial buildings. In the United States, the US Energy Information administration reports that U.S. electricity use in 2009 was about 13 times greater than electricity use in 1950, residential and commercial sectors

are consume 75%, while Industrial sector consume 25% of total electricity use [3]. To better plan for our current and future energy needs, it is important for us to know how each of our electrical appliance is been utilized, through energy smart meters based on Non-Intrusive Load Monitoring or NILM techniques. This information would help facility managers to better manage and distribute power; appliance producer to design and produce more energy efficient appliances; and also home owners/building managers understand each appliance, utilization and energy consumption which would help in decision making. Nonintrusive appliance load Non-intrusive load monitoring is an emerging signal processing and analysis technology that aims to identify individual appliance in residential or commercial buildings or to diagnose shipboard electro-mechanical systems through continuous monitoring of the change of ON and OFF status of various loads [5]. The goal of the NIALM system is to identify and track instances when appliance in a building is turned on and off. This is achieved by collecting electric power data measure live from the service entry point of a building; disaggregate it and extract unique features of the signal that can be used to identify appliances in the building. Although one could argue that by placing sensors on each appliance one could monitor its usage and obtain more detailed and accurate load energy consumption information. This approach however would require the extensive use of hardware, and for simple appliances like table lamps the cost of the sensors might be more than the cost of the lamp. The NIALM provides a relatively cheap and efficient way to monitor appliances without invading the home or disrupting the normal configuration of the household appliances. NILM is basically a signal processing problem, and in this work we would explore extensively various signal process techniques, event detection algorithms and pattern recognition schemes. The goal would be to design a system that would more accurately monitor appliances real-time.

II. THEORY AND TECHNICAL APPROACH

Figure 1 depicts our proposed approach as the conceptual architecture of the NILM system. The main components of this architecture are: data acquisition, event detection, event classification, device identification, and reporting. These components are discussed as follows:

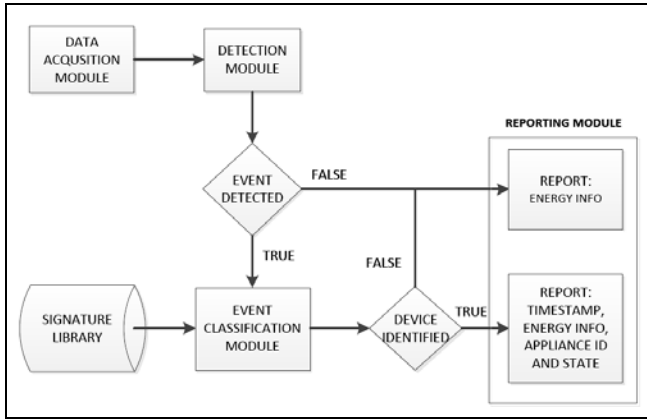


Figure 1: Conceptual Architecture of the Proposed Approach

Data Acquisition Module: The current and voltage measurements already obtained from a calibrated signal database. The signals are read and the average power information calculated. Both current and voltage measurements were sampled using 9 kHz sampling rate. The average power is computed over every Period T of the fundamental frequency 60 Hz. To obtain the size of the averaging window n we divide the sampling rate 9 kHz by the fundamental frequency 60 Hz, $n = 9000/60 = 150$ samples.

Signal Segmentation: This step involves cutting the signal into segments of fixed size, which is passed on for detection. The important point to consider here is the size of the segments. We choose the segment size as stated earlier (150 sample points). By empirical analysis, we found that this rate is sufficient to cover the maximum startup transient signal; under the assumption that only one event can occur at a time. The segment signal is then passed to the event window detector.

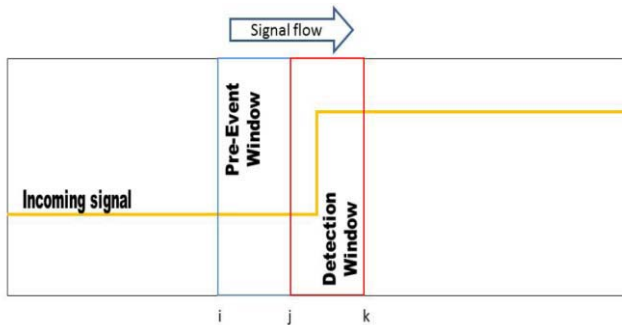


Figure 2: Event Detection Window Scanning

Event Detection: The event window detector (Figure 2) scans the signal window by window. It works with two consecutive windows, the current window of which detection is to be performed on (detection window), and the immediate past window use as reference (pre-event window). As discussed in chapter two we compare our new approach the GOF proposed in [4] and the popular GLR method, using the following performance metrics: Mean time between false alarms; Probability of false detection; Mean delay for detection; Probability of non-detection;

Accuracy of the change time and magnitude estimates. Our choice of the GOF detector is based on the above performance metrics, after implementing and testing both the GOF and the GLR algorithms. The results of these test and analysis is reported in the respected section below.

Generalized Log-likelihood Ratio: The GLR is by far the most talked about detector in NILM applications. [5] Introduced a statistical algorithm more reliable and powerful than a simple trigger based change of mean detector, developed by extending the generalized likelihood ratio. The GLR detection algorithm in [5] calculates a decision statistic from the natural log of a ratio of probability distributions before and after a potential change in mean:

$$S_j^k = \frac{\mu_1 - \mu_0}{\sigma^2} \sum_{n=j}^k \left(y_n - \frac{\mu_1 - \mu_0}{2} \right) \quad (1)$$

Where y_n is the sampled variable at position n, μ_0, μ_1 are the mean values for the pre-event window and the detection window respectively, $P_{\mu_0}(y_n), P_{\mu_1}(y_n)$ are the probability density function about the mean μ of the pre-event and detection window respectively and s_{kj} is the detection statistic, which can be simplified as:

$$S_j^k = \frac{\mu_1 - \mu_0}{\sigma^2} \sum_{n=j}^k \left(y_n - \frac{\mu_1 - \mu_0}{2} \right) \quad (2)$$

Where σ is the noise variance present in the incoming signal. The GLR compares the s_{kj} detection statistic with a previously determined threshold ξ and makes a decision. If $s_{kj} > \xi$ the GLR records the presence of an event otherwise there is no event. The GLR method describes the detection threshold, a dimensionless quantity, as a trained parameter. The magnitude of an appropriate detection threshold scales with signal noise, the minimum signal change of interest (which comes from a knowledge of rated equipment-power levels), and the abruptness of potential changes in the system. The threshold for the detection statistic can be initiated as an arbitrary small number, for example a magnitude of one, and then increased until all events of interest are identified with a minimum occurrence of false or missed alarms. The GLR detector requires that four parameters be trained for a given application: The length of the pre-event averaging window; The length of the detection window; The threshold for the detection statistic; and The standard deviation (or variance) of the power data. These training requirements of the GLR make it less robust for practical usage in homes and buildings, because it will always require an expert to tune the system on site during installation on the NILM. Furthermore any degradation of the incoming signal maybe due to faulty appliances will cause the GLR to perform poorly in that it has to be trained again.

Goodness of Fit (GOF): The goodness of fit addresses the above training requirements of the GLR and produces arguably better performance. As discussed in [4] the

goodness-of-fit test seeks to determine whether a set of data could reasonably have originated from some given probability distribution. The goodness-of-fit test seeks to determine whether a set of data could reasonably have originated from some given probability distribution. Assume that we have n independent and identically distributed (iid) random samples x_i ; $i = 1, 2, \dots, n$, drawn from a distribution $G(x)$, which is a priori unknown. We have a supposed distribution function $F(x)$. The problem can be formulated as the binary hypothesis testing problem.

$$(H) : G(x) \neq F(x) \quad (3)$$

$$(H) : G(x) = F(x)$$

GOF tests will allow deciding between the two hypotheses in 3. In event detection, we will explain the GOF problem differently: There exist two sets of iid samples. The reference set (i.e., the pre-event window data set) consists of n samples x_i ; $i = 1, 2, \dots, n$, with the distribution $G(x)$. The test set (i.e., the detection window data set) consists of n samples y_i , $i = 1, 2, \dots, n$ with distribution $F(y)$. Both $G(x)$ and $F(y)$ are unknown. The goal of GoF tests is to decide between the two hypotheses of 3. If the null hypothesis H_0 is rejected, we claim that an appliance event occurs. Among various goodness-of-fit tests, the χ^2 test has been widely used in statistics literature. In a standard application of the χ^2 test, the test procedure requires a random sample of size K from a population whose probability distribution is unknown. These K observations are arranged in a frequency histogram, having n bins or class intervals. Let p_i ($i = 1, 2, \dots, n$) denote the probability of an observation falling into the i -th bin, and y_i be the observed frequency in the i -th bin, the test statistic is

$$\chi^2 = \sum_{i=1}^n \frac{(y_i - Kp_i)^2}{Kp_i} \quad (4)$$

Where, the quantity Kp_i is the expected frequency in the i -th bin. If the observed frequency satisfies the supposed distribution, these observed values follow a multinomial distribution with p_i being probabilities, [20]. In power signal event detection, we consider the observation in the detection window $y_i \sim F(y)$ be the observed frequency in the i -th time instant within the detection window [21]. Because the quantity Kp_i is unknown, it will be estimated from the data samples $y_i \sim G(y)$ in the pre-event window. We can show that the maximum likelihood estimate of Kp_i based on the pre-event window data x_i ; $i = 1, 2, \dots, n$, is given by:

$$\widehat{Kp_i} = x_i \quad (5)$$

Substituting for (5) in (4), we obtain the χ^2 test for goodness-of-fit:

$$\ell_{GOF} = \sum_{i=1}^n \frac{(y_i - x_i)^2}{x_i} \quad (6)$$

$$\ell_{GOF} = \chi_{\alpha, n-1}^2 \quad (7)$$

We would reject the H_0 hypothesis that the distribution of the population is the hypothesized distribution if the calculated value of the test statistic [20] with $100(1 - \alpha)\%$ confidence interval and $n-1$ degrees of freedom. We should note that $\chi_{\alpha, n-1}^2$ is the decision threshold that depends on the window size n and the detection confidence level α . The aggregate power signal data e can be modeled as expressed in (8).

$$y_i = e_i + w_i, \quad | \quad i = 1, 2, 3, \dots, n \quad (8)$$

The w_i term is assumed to be Gaussian-distributed noise with mean μ_w and standard deviation σ_w . These two quantities are unknown and need to be estimated from (pre-event) training data of n samples. If we use the sample mean

$$\bar{w} = \frac{1}{n} \sum_{i=1}^n w_i \quad (9)$$

To estimate μ_w , we can be $100(1-\alpha)\%$ confident that the error $|\bar{w} - \mu_w|$ will not exceed a specified amount E when the minimum sample size is given by, [22]

$$n_0 = \left(\frac{z_{\frac{\alpha}{2}} \sigma_w}{E} \right)^2 \quad (10)$$

$\sigma/2$ is the upper percentage point of the standard normal distribution. The quantity E can be chosen by the user. For example, if we decide to discard appliance events that are less than 30 Watts, we could set $E = 30$. Furthermore, the maximum window size, n_1 , of the detection window should be limited by twice the maximum length of the transient of appliance signatures. Thus, we obtain $n_0 < n < n_1$. The importance of this analysis in GOF event detection is that they provide a guideline for choosing the window size, and then the decision threshold, based on no-event training data. Once the window size is chosen, repeated training or a data-dependent threshold becomes unnecessary. This is a significant advantage compared with the conventional generalized likelihood ratio test discussed above.

Feature Extraction and Event Classification: The event classification is the matching of the events detected to the appliance responsible for it. In other to accomplish this it is important to obtain unique characteristics (features) of the appliance signal that can be easily used to identify the appliance. Electric load signature is the electrical behavior of an individual appliance/piece of equipment when it is in operation [7]. Similar to any human signature, each electrical device contains unique features in its consumption behavior. The measured electric power signal contains the net behavior of more than one appliance operating simultaneously and their collective behavior measured at a central location. Electrical appliances in their ON state consist of transient state and steady state. The transient state as discussed earlier is a result of load excitation (turn ON/OFF of appliance) and last for a very short period of time. Both transient and steady state possess useful features which we intend to extract. We assume that for any given window W that only one appliance is turn ON or OFF. If

this is true then only one appliance can be on transient state at a particular time. The transients of each individual appliance is unique due to the circuitry composition of the appliance, thus the electric transients hold a unique waveform characteristic of the appliance. It is then possible to use this transient information to detect turn ON events by just observing the corresponding curve when the appliance is switched on. For OFF events, no such curve is observed, so we use the steady state information to properly classify the appliance.

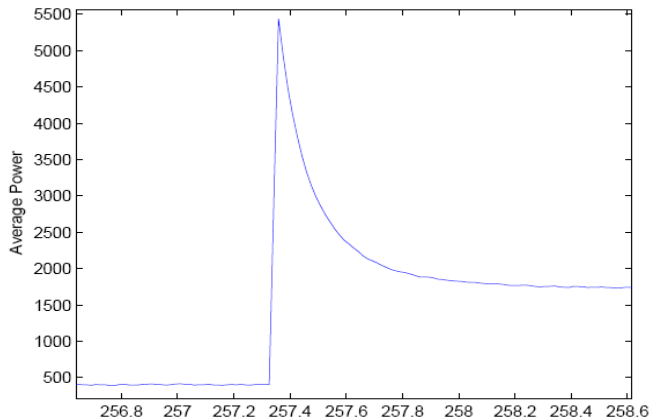


Figure 3: Sample of ON State of an Appliance

For this study, we used a power level difference to detect the OFF state. A sample of the ON/OFF signal behavior is given in Figure 3&4.

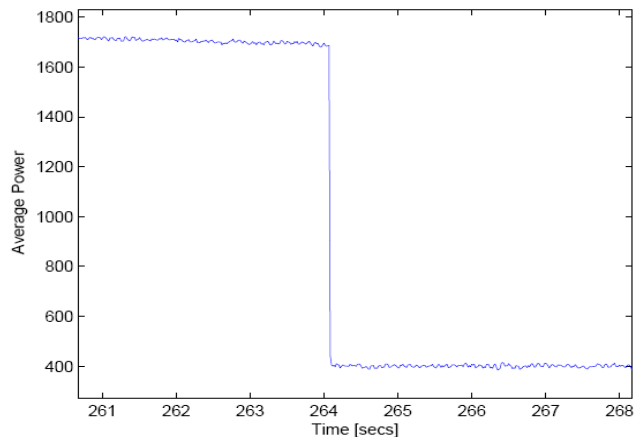


Figure 4: Sample of OFF State of an Appliance

We created a database of 29 appliance states signatures shown in table 1 Generated from 29 appliance power signals as the training examples. Using the neural networks model described and provided in [23], we trained a network for classification of events in the test dataset.

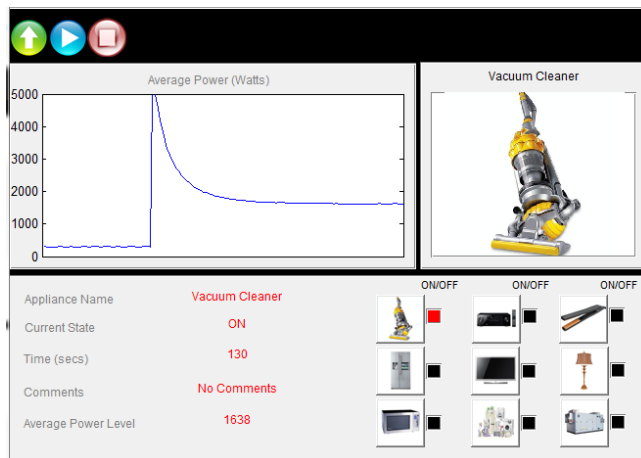


Figure 5: Example of the developed NILM Interface

Figure 5 shows snapshot of the developed interface depicting the vacuum being identified as has been turned on. Figures 6 and 7, illustrates performance comparisons between GLR and the proposed GOF methods in terms of detection probability and CPU execution time, respectively.

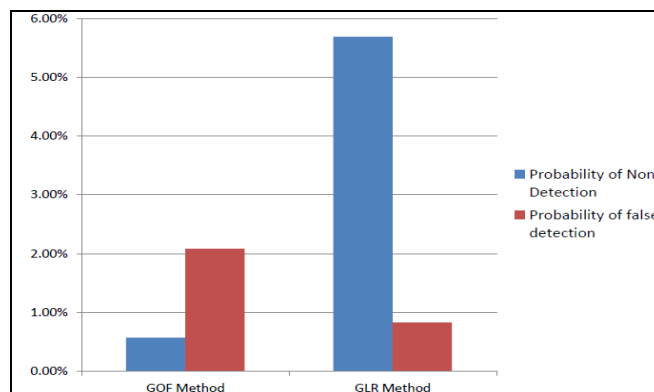


Figure 6: Comparison of Detection Probability between GLR and GOF

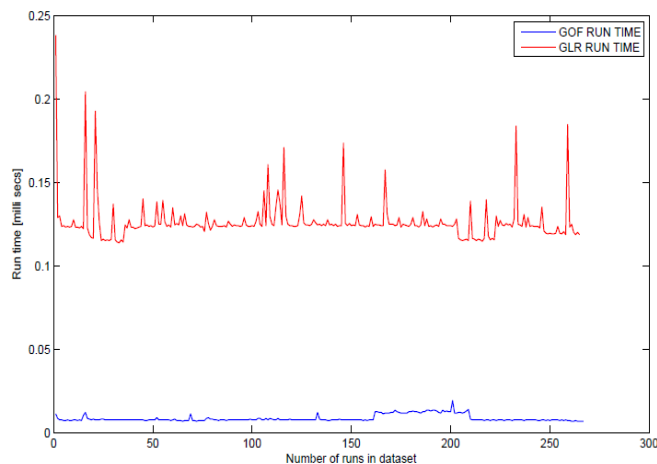


Figure 7: Run Time for GOF and GLR

III. CONCLUSIONS AND FUTURE WORK

NILM is a very interesting area which can be implemented anywhere electrical energy is used. We introduced a very simple, scalable, robust and cost effective framework for which NILM systems can be built. This is a preliminary work and the results are a proof of our concept. We focused on events where only one appliance is responsible for that event. In some cases there might be more than one event occurring at the same time. Finally, our proposed GOF approach demonstrated superior performance in both metrics of probability of detection as well as time efficiency.

The detection and classification of multiple events occurring at the same time, like power extensions that have more than one device connected to it, is a challenge in NILM systems. We hope to continue to explore techniques to properly detect and classify such events. We also believe that appliances have footprints in their steady states which can be used for appliance tracking simply by looking at the steady data. Since different classes of appliances consist of components unique to their class, by studying these appliance classes and their component composition one could obtain a unique steady state waveform for each class of appliance.

REFERENCES

- [1] Y. Jin, E. Tebekaemi, M. Berges and L. Soibelman, "A time-frequency approach for event detection in on-intrusive load monitoring," Proceedings of the SPIE Defense, Security and Sensing, Orlando, FL, April 25-29, 2011
- [2] Xingze He, Man-On Pun, C. C. Jay Kuo and Ye Zhao, "A Change-Point Detection Approach to Power Quality Monitoring in Smart Grids," Mitsubishi Electric Research Laboratories, Inc., 201 Broadway, Cambridge, Massachusetts, 2010
- [3] www.eia.doe.gov/energyexplained
- [4] Y. Jin, E. Tebekaemi, M. Berges and L. Soibelman, "Robust adaptive event detection for nonintrusive load monitoring," Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (ICASSP 2011), Prague, Czech Republic, May 22-27, 2011, pp. 4340-4343, IEEE.
- [5] Shaw, S.R., Leeb, S.B., Norford, L.K., Cox, R.W., "Nonintrusive Load Monitoring and Diagnostics in Power Systems" Instrumentation and Measurement, IEEE Transactions July 2008
- [6] Practical definitions for powers in systems with non-sinusoidal waveforms and unbalanced loads: A decision (IEEE working group on non-sinusoidal situations)," IEEE Transactions on Power Delivery, vol. 11, no. 1, pp. 79-87, January 1996.
- [7] Liang J, Ng S, Kendall G, Cheng J., "Load Signature Study - Part 1: Basic Concept". Power Delivery, IEEE Transactions 2010, Pages 25(2):551-560.
- [8] Liang J, Ng S, Kendall G, Cheng J., "Load Signature Study - Part 2: Disaggregation Framework, Simulation and Application". Power Delivery, IEEE Transactions 2010, Pages 25(2):551-560.
- [9] Mabrouka El Guedri , Guy D'Urso , Christian Lajaunie , Gilles Fleury, "time-frequency characterization for electric load monitoring". 17th European Signal Processing Conference (EUSIPCO 2009).
- [10] W K Lee, G S K Fung, H Y Lam, F H Y Chan and Mark Lucente. "Exploration on Load Signatures". international Conference on Electrical Engineering (ICEE) 2004, Japan
- [11] Hsueh-Hsien Chang, Hong-Tzer Yang and Ching-Lung Lin. "load identification in neural networks for nonintrusive monitoring of industrial electrical loads". International Conference on Electrical Engineering (ICEE) 2004, Japan.
- [12] Samuel Rivera-Gomez, David Culler and Jorge Ortiz. "Load-Disaggregation for Increased Coverage in a Building Energy Auditing Network"
- [13] Shwetak N. Patel, Thomas Robertson, Julie A. Kientz, Matthew S. Reynolds, and Gregory D. Abowd. "At the Flick of a Switch: Detecting and Classifying Unique Electrical Events on the Residential Power Line". UbiComp 2007: Ubiquitous Computing, 9th International Conference, UbiComp 2007
- [14] T. Yebra and V. Fuster, "Energy Quality in Voltage, Current and Power Signals" Instituto de Tecnologia Elctrica Parque tecnologico de Valencia 46022 Valencia (Spain).
- [15] Sen M Kuo, Bob H Lee and Wenshun Tian Real-Time Digital Signal Processing Implementations and Applications - Second Edition, John Wiley and Sons Ltd, 2006.
- [16] Francisco Jurado and Manuel Valverde, "Applications of signal processing tools in a power systems course". Department of Electrical Engineering, University of Jan, Linares (Jan)
- [17] Michele Basseville and Igor V. Nikiforov "Detection of Abrupt Changes: Theory and Application". published by Prentice-Hall, Inc.
- [18] The N. Vaswani, "The modified cusum algorithm for slow and drastic change detection in general hmms with unknown change parameters," in ICASSP'05, vol. 4. IEEE, 2005, pp. 701-704.
- [19] Dong Luo, Leslie K. Norford, Steven R. Shaw and Steven B. Leeb. "The Monitoring HVAC Equipment Electrical Loads from a Centralized Location. Methods and Field Test Results". ASHRAE Transactions 2002 Volume 108, Part 1
- [20] W. G. Cochran, The 2 test of goodness of fit, Annals of Math. Stat., vol. 23, pp. 315-415, 1952.
- [21] H. Chernoff and E. L. Lehmann, The use of maximum likelihood estimates in 2 tests for goodness of fit, Annals of Math. Stat., vol. 25, no. 3, pp. 579-586, 1954.
- [22] R. V. Hogg and A. Craig, Introduction to Mathematical Statistics. Upper Saddle River, NJ: Prentice Hall, 1994.
- [23] Aaron A. Rababaah, "A Novel Energy-Logic Model for Multi-Modality Multi-Agent Data and Information Fusion", Ph.D. Dissertation, College of Engineering, Technology and Computer Science, Tennessee State University, June-2009.