J.A. Lopez-Leyva [1,*], M. Ponce-Camacho[1], A. Valle[2], A. Talamantes-Alvarez[1]

J. Electrical Systems 15-2 (2019): 169-180

Regular paper

JES Journal of Electrical Systems

High performance COTS-IoT prototype for dynamic power control in an electrical grid

A low-cost energy-monitoring prototype using a COTS-IoT de-vice for dynamic automatic control of an electrical grid is present-ed. In particular, the design, electrical characterization and real implementation considering the use of a portable universal test equipment (PTE-100-C) are showed. The proposed system was connected to a real electrical grid (emulated scenario) and a central server during 168 hours in order to establish a maximum dynamical threshold and generate control commands for the local electrical station based on the dynamical energy consumption profile according to some physical aspects and acceptable performance criteria mentioned in ANSI C12.20.

Keywords: Automatic control; Power system analysis computing; Prototypes; Microcontrollers; Internet of Things

Article history: Received 5 September 2018, Accepted 11 February 2019

1. Introduction

Unit Nowadays, better electrical measuring equipment is necessary in order to improve the real life technical and administrative decisions of domestic and industrial sectors [1-3]. These measuring systems use different sensor techniques according to the electrical signal monitored and, mainly, using the non-intrusive sensors [4]. Thus, important power quality parameters such as the power factor, harmonics, phase shifting, reactive power, current and voltage unbalance, rapid voltage changes - transients, voltage dips and short-term overvoltage, flicker among other can be monitored [5,6]. Furthermore, but no less important, Smart Grids/Home and Internet at Things (IoT) concepts require instruments for measuring, storage, processing and communication between systems in an electrical management context. For example, the electric power consumption validation in a local or remote way is necessary for many purposes such as energy-management algorithms, increasing the lifetime of different instruments and systems, providing smart protection, among others [7, 8]. In addition, better energy management strategies that involve different important concepts (e.g. monitoring, communications, hard-ware/software design, analysis, implementation and control) are necessary in order to optimize the energy consumption, according to the particular custom necessities, and also for the support to the renewable energy alternatives (e.g. micro inverter connected to individual solar panel in a solar panel array in order to remotely monitor the energy generation and consumption) [9,10].

Besides, there exist many high-power-industrial monitoring devices capable to operate in network environments (Local Area Network and Wide Area Network), however, the low-cost Commercial off-the-shelf (COTS) devices are crucial in order to increase the using/accessibility of the instrument in the Smart Grid-Home/IoT context, basically for low

[*] Corresponding author: J.A. Lopez-Leyva, CETYS University, Centre of Excellence in Innovation and Design, Baja California, Mexico. E-mail: josue.lopez@cetys.mx

[1] CETYS University, Centre of Excellence in Innovation and Design, Baja California, Mexico

and medium electrical power consumption. In this case, the high demand electricity sectors and principal management problems are highly related to the large number of users and the inexistent/inoperable centralized unit for monitoring and control [11,12]. In addition, ANSI C12.20 establishes the physical features and tolerable performance criteria for particular accuracy (0.2% and 0.5%) class electricity meters meeting the Blondel's theorem [13]. Although many high-power-industrial monitoring devices satisfy the standard mentioned, to the best of our knowledge, there are no systems that make use of COTS devices based on ANSI C12.20. On the other hand, there exist some trade-offs between the degree of automation and the number of devices/features in smart systems, in fact, these characteristics permit different smart systems (e.g. too complex, simplistic and clever) that can be grouped in: Integrated Wireless Technology (IWT), Home Energy Management System (HEMS), Smart Home Microcomputers (SHMC) and Home Automation (SHS/HA). [14]. In particular, many smart systems use an IoT Cloud provider offering IoT as a Service (IoTaaS) based on smart sensors [15,16]. In this work, the design, electrical characterization and overall performance of a prototype for measuring the electric power consumption and determining the energy-consumption profile in real-time and a remote way using COTS device, PTE-100-C and a central server is presented. In addition, the dynamical maximum energy capacity threshold is calculated and transmitted to the local electrical station in order to optimize the power management according to the particular electrical requirements. Therefore, the prototype proposed can use the energy consumption information for improving the overall energy efficiency of the system (i.e. energy-aware applied in Smart Home [17]) in order to avoid or reduce diverse problems presented in the distributed generation (e.g. short circuit currents, complexity of automation and protection systems, complexity of voltage regulation, due to a modification of power flows). The paper organization is a follow: Section 2 shows a conceptual and experimental scenario for testing the prototype, the design and electrical characterization of the prototype is presented in Section 3, the experimental results obtained in laboratory are showed in Section 4. Section 5 shows the experimental results for a remote user. Finally, Section 6 shows a conclusion and important analysis regarding the prototype

2. Conceptual and Experimental Scenario

Fig. 1 shows the conceptual scenario used for testing the energy-monitoring prototype with COTS-IoT device for domestic applications in Smart Grid test-bed. Although a complete and ideal smart energy system involves different smart subsystems (such as power generation, transmission and distribution grids) [18,19]; in particular, the scenario proposed is only concerned to the distribution grid. The domestic users were labelled and each one has a monitoring prototype connected to the public electrical network and to the Internet in order to monitor the power consumption. Therefore, the prototype sends the energy consumption information to the central server (using TCP/IP, HTTP or Telnet) where the energy consumption pro-file for each user is calculated, although an IoT Cloud is being currently analysed for future applications. Next, the central server uses the energy consumption profile as an input signal to an electrical management algorithm in order to send control commands to the local electrical stations through classical communication channels (e.g. radio frequency links, optical links among others). Therefore, the objective of the control commands is to modify the electrical performance according to the electrical loads currently used by each user.

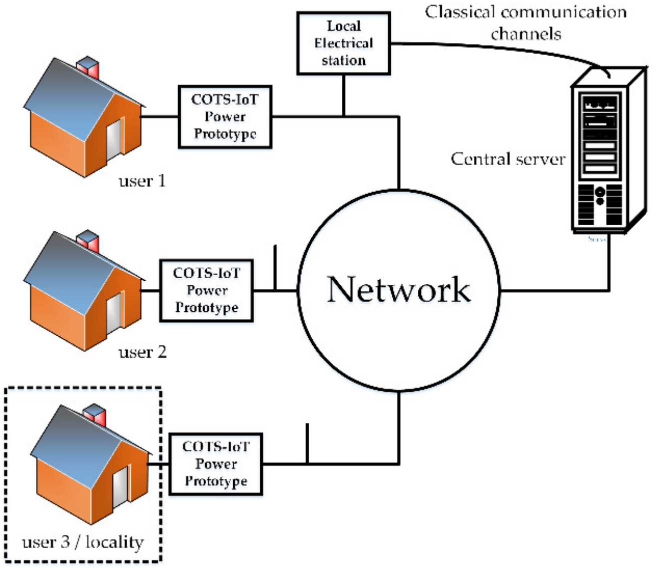

Fig. 1. Conceptual experimental set-up using COTS-IoT power prototypes connected to the network in order to monitor the energy consumption in a remote way of users and locations

In order to clarify, the users proposed in the Fig. 1 can mean a specific region with many particular users; thus, the control commands will be according to the complete electrical load. In particular, Fig. 1 involves the key elements in the smart grid: demand of user, control commands, total energy demand, among others. In addition, the central server has a very similar functional structure like a conventional SCADA (Supervisory Control and Data Acquisition) system [20, 21]. Fig. 1 does not consider special parameters on the network for Smart Grids application such as: reliability, scalability, efficiency, security and support to the deployment of renewable and distribution energy system [22,23].

3. Design and Electrical Characterization

In this section, the design and electrical characterization of the prototype proposed is presented. Fig. 2 shows the general electrical connection of the prototype proposed using two electrical loads: 1) a low power test-bed (upper side) designed and 2) a universal test equipment (lower side) (PTE-100-C), both experimental systems implemented in our laboratory. The electrical loads mentioned correspond to the different users that Fig. 1 shows. In particular, the low power test-bed uses four loads (40, 60, 75 and 100 Watts) that will be monitored. Each load is selected using a specific electro-mechanical switch (SW1-SW4) in order to fix different theoretical electrical power and perform the electrical characterization of the particular subsystems. Thus, a specific electrical cable (AWG 10) is used for monitoring the electromagnetic field (EM) generated by the electrical current consumed by the loads and a computer is used for recording and sending data in a private network. In other words, the prototype is connected to a telecommunication network in a remote location for sending the data according to the IoT concept as was mentioned previously. Next, diverse load power combinations (P_C) were used in the test-bed; from 40 to 275 W (i.e. different switch combinations were turn-on and turn-off in a manual way) for calculating the theoretical consumed electrical cur-rent (I_C) using a generic hook-clamp digital multimeter.

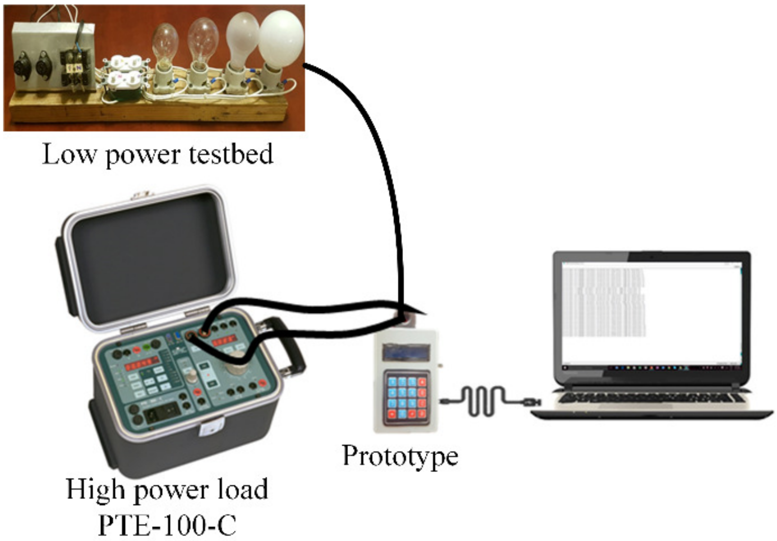

Fig. 2. Electrical connection between the low power test-bed, PTE-100-C, prototype and computer.

Fig. 3 shows the theoretical and experimental results, it meaning that the test-bed has a linear model in the particular cur-rent range (from 0 to 2 Amperes). In particular, the prototype uses a non-invasive current sensor and it was electrical characterized based on the same experimental conditions used for the results showed in the Fig. 3.

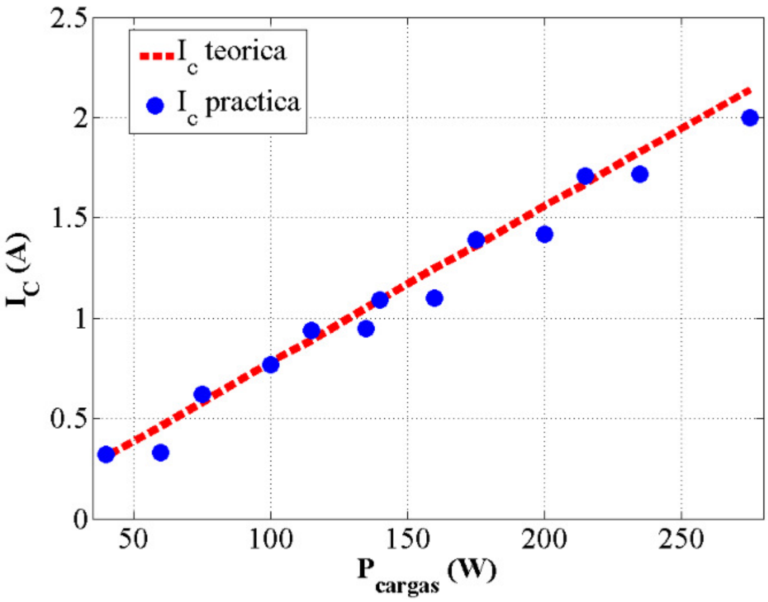

Fig. 3. Theoretical and experimental results for different power loads @ 127 Vrms. The consumed electrical current was measured and calculated in order to characterize the real electrical power consumption for different loads.

Hence, Fig. 4 shows the output sensor voltage (V_S) according to the electrical current consumed by the variable electrical loads (I_C). Roughly speaking, equation (1) shows the mathematical relation to determine the V_S value based on the dynamical performance of the IC measurements from 0 to 25 A. In particular, Fig. 5 shows the complete electrical performance of the overall sensing system.

$$V_s = 0.19I_c - 0.0014 \approx 0.19I_c \tag{1}$$

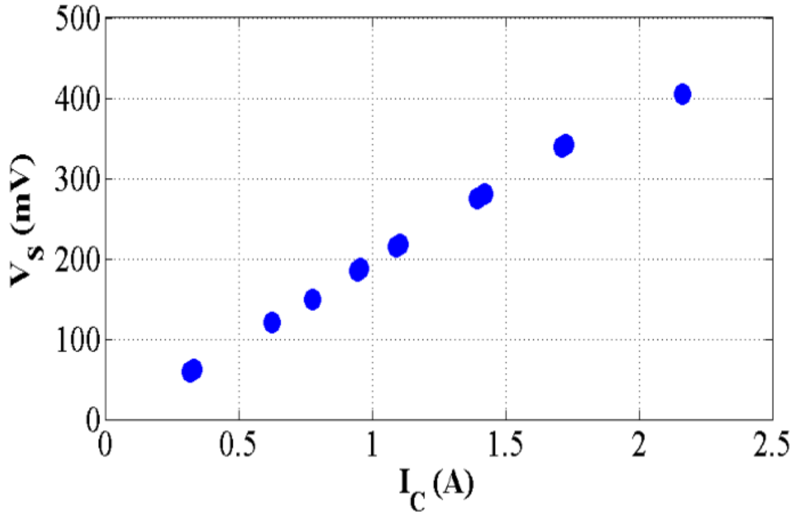

Fig. 4. Electrical characterization of the EM sensor.

Therefore, the prototype does not measure current signals higher than 25 A. Finally, the expected error of the voltage transformed (*εvt*) is ≈0.35% and error current transformed (*εct*) is ≈ 0.5% (both of which relate to the used sensor), therefore, the expected instrument transformer error (*εit*) is ≈ 0.6%. In addition, the measurement error of the meter (*εm*) is ≈ 0.2%. Hence, the total error of the system (*εit)* is ≈ 0.63%, it means that the performance of the prototype based on a COTS device is close to the ANSI C12.20 Class .5 requirements.

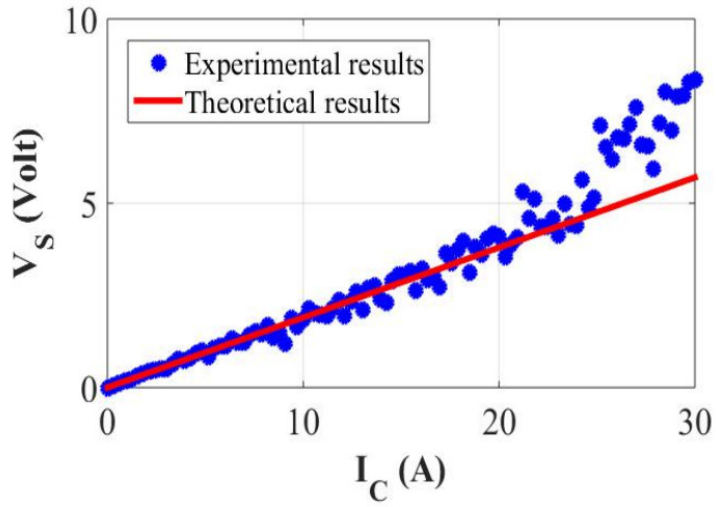

Fig. 5. Complete electrical performance of the EM sensor.

4. Experimental Results in Laboratory

Fig. 6 shows the variable instantaneous electrical power (Pc) using the test-bed with an analysis period of 120 minutes, and, 5 minutes between each measurement. In addition, the Pc modifies the electrical power consumption rate that is represented in KWh. The constant regions mean that there are no output results in the digital processor used in the IoT device for this particular time. Therefore, Fig. 6 shows the ANSI C12.20 tests: no load, starting load and load performance.

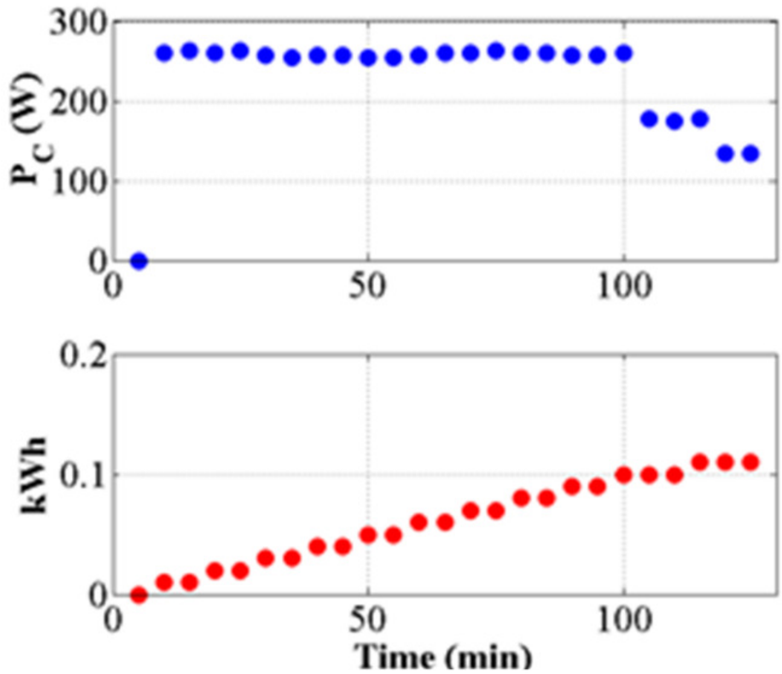

Fig. 6. Power consumed (blue trace) and accumulated power rate (red trace).

Next, the prototype proposed was connected to the PTE-100-C to increase the electrical power limit of the final load; this is due to the test-bed only consuming 2.03 A (with ≈127 Vrms), while the PTE-100-C can consume up to 250 A (with ≈250 Vrms, 2 KW limit, approximately). However, the output electrical signal was fixed to 10 A in the PTE-100-C for security reasons. Fig. 7 shows the experimental results of the consumed electrical current, accumulated power and KWh considering a total analysis time (1500 minutes) with particular measurements each 30 minutes. Based on the last, the consumed electrical current measurement was from 9.5 to 10.9 A due to the PTE-100-C presents a relatively high resolution for the output signal, although it does not affect in an important way the final performance of the *Pacum* and PCR.

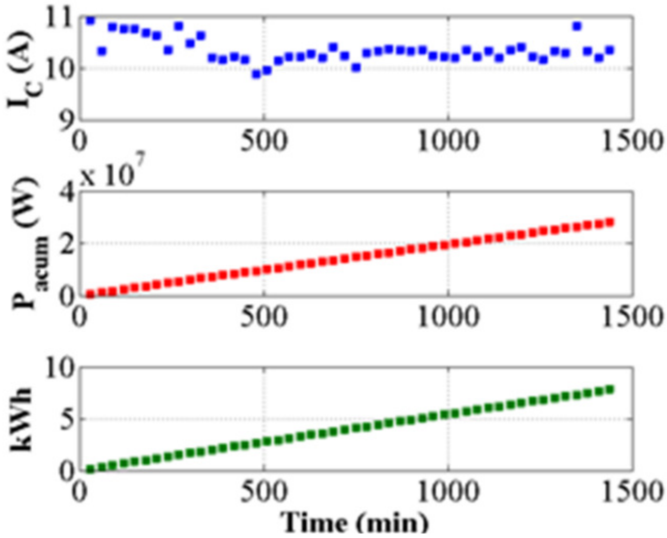

Fig. 7. Experimental results using the prototype proposed and the PTE-100-C

In particular, the measurements shown were performed considering controlled environmental and telecommunications conditions for the experimental setup shown in Fig. 2; in the next section, the testing scenario will be under real life conditions.

5. Experimental Results Monitoring Remote User in Real Emulated Locations

After the electrical characterization and energy consumption measurements were performed in laboratory, the prototype was tested in real conditions (i.e. two users with different energy consumption demands in different locations sending consumption information to the central server).

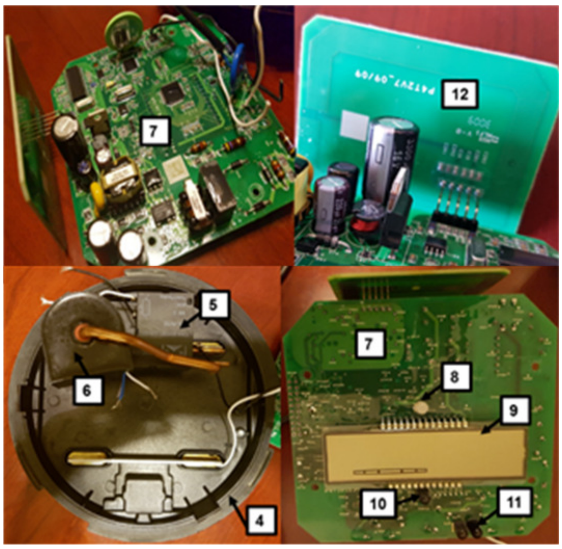

Fig. 8. General description of the Monophasic Power Meter (parts 1,2 and 3 are not shown due to institutional reasons), 1) principal protection cover, 2) secondary protection cover, 3) technical data label, 4) metallic base, 5) high power relay, 6) internal sensor, 7) principal printed circuit board, 8) light indicators, 9) (liquid crystal display, 10) display calibration port, 11) Monitoring port, 12) Radio-frequency identification adapter.

Fig. 8 shows the Monophasic Power Meter (MPM) used in which the COTS-IoT prototype was adapted and tested. In particular, the prototype is adapted to the internal sensor (part 6 of the Fig. 8) of the MPM for monitoring the power in parallel way (i.e. the MPM also monitors but it cannot interconnect with other digital systems in a Smart Grid scenario). Once that the prototype sends the information regarding the power consumption to the server, an algorithm will determine the energy consumption profile. Firstly, the minimum power demand fixed $P_{i,min}(t)$ for each user (i) was 50 KWh, therefore, the instantaneous power demand $P_i(t)$ is always above the limited mentioned, according to the equation (2).

$$P_i(t) \geq P_{i,\min}(t) \forall i \in N, t \quad (2)$$

, where $t \in [1,2, \cdots]$ represents the analysis time cycles, e.g. 1 hour in our case, and $N \in [1,2, \cdots]$ represents the users in the electrical network that are being monitored, N=2. Therefore, the central server has to guarantee the minimum power demand and the optimum instantaneous power. Fig. 9 shows the power consumption detected and sent by the prototype to the central server. In the server side, two users were monitored in a continuous way during 168 hours (1 week), essentially, the measurements were performed each hour. The maximum energy consumption detected in the user 1 (blue trace) was ≈240 KWh and also is the maximum power demand $P_{i,max}(t)$, while the minimum consumption was ≈70KWh. Besides, the user 2 shows ~280 KWh and ≈140 KWh as maximum and minimum consumption, respectively. In addition, some measurements of the user 2 are zero power consumption due to a fail in Internet connection in specific hours (≈30-≈40 and ≈100-≈110); the zero power consumption measurements mentioned are not take into account (deleted) in the algorithm process.

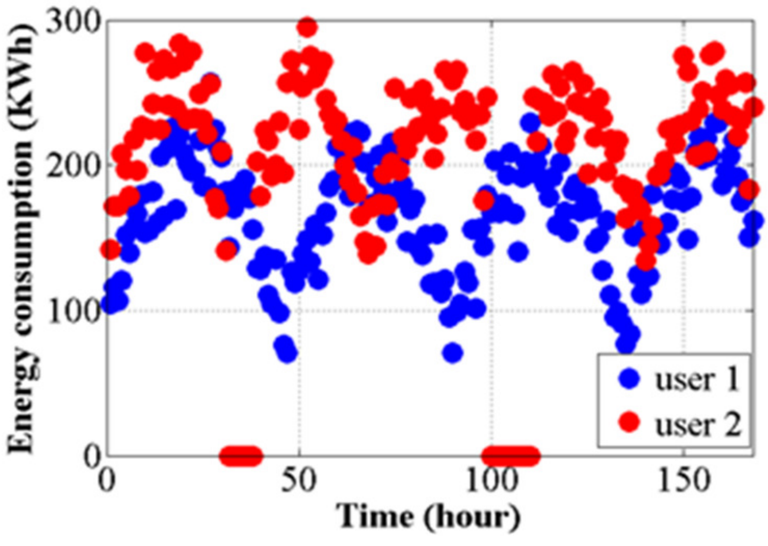

Fig. 9. Energy consumption of two users monitored in a remote way where the Voltage Interruptions Test of ANSI C12.20 is showed.

In general, the total power demand $P_{net}(T)$ of the electrical network is calculated using the equation (3).

$$P_{net}(T) = \sum_{i=1}^{N} \sum_{t=1}^{T} P_i(t) \tag{3}$$

Thus, the $P_{net}(T)$ value allows measuring the real power demand and performs management activities with the higher power demand electrical stations in order to optimize the demand based on the minimum and maximum value of the equation (3). However, the particular consumption profile of each user is needed due to that the scheme proposed uses local electrical stations. In particular, M and m represents random variables needed in order to perform a statistical and stochastic analysis in-depth. Hence, the equations (4) and (5) calculate the maximum and minimum values, respectively, considering the results shown in Fig. 9.

$$\overline{M} = \max P_i(t) \tag{4}$$

$$\overline{m} = \min P_i(t) \tag{5}$$

In addition, the Moment-Generating Function (MGF) is used to calculate the first three moments of both variables. Although the statistical and stochastic parameters calculated are very useful, the first version of the energy consumption profile presents some rapid power changes, therefore, a convolutional digital filter was implemented for equations (4) and (5) using the equations (6) and (7), respectively, where S is the number of samples of the maximum and minimum variables used by the filter and its dynamic parameter according to the rapid power changes behavior mentioned. Then, the central server uses the final energy consumption profile (i.e. filtered profile) of different users based on the method used for the equations (3) - (7) in order to establish a dynamical maximum energy capacity threshold (black trace) for each local electrical station using an online algorithm. In order to clarify:

$$\overline{M}_f(i) = \frac{1}{S} \sum_{j=0}^{S-1} \overline{M}[i+j] \tag{6}$$

$$\overline{m}_f(i) = \frac{1}{S} \sum_{j=0}^{S-1} \overline{m}[i+j] \tag{7}$$

Thus, Fig. 10 shows a particular measurements trace in a specific date, but many measurements in different dates were performed in order to generate the profile mentioned. This maximum threshold information is returned to the local electrical station via classical communication channel (radio frequency links) to modify the power output limit to optimize the power management. Naturally, the threshold information is highly depending on many natural and random factors such as occupancy, weather, routine, activity, time, type of consumers, among others [24, 25].

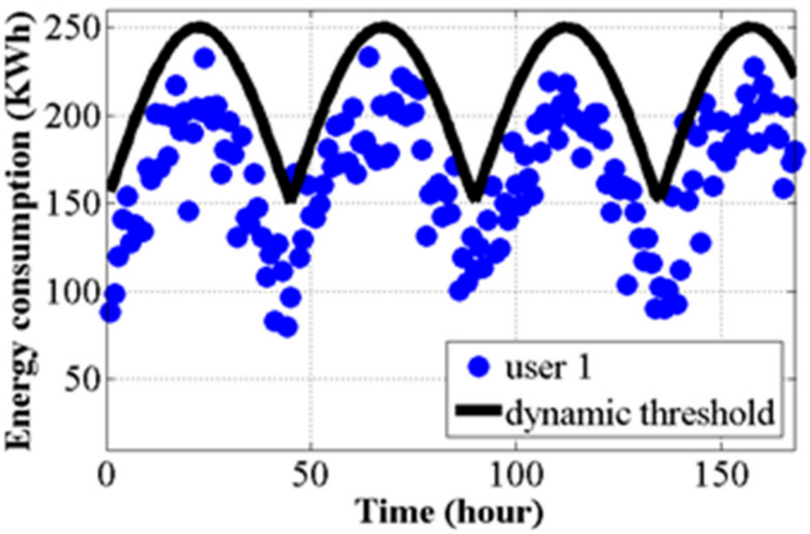

Fig. 10. Dynamical control information of the maximum threshold for the energy capacity of the local electrical station assigned to the user 1.

Particularly, the server calculates the skewness (third order moment) of the information received of the prototype. The skewness is an important parameter for the power consumption profile, because it determines the asymmetry of the random variables (M and m) about its mean (equation (4) and (5)), i.e. it is possible to determine the general consumption profile in a very accurate way for future applications considering different external parameters.

6. Conclusion

An energy-monitoring prototype using COTS-IoT device for measuring the power consumption in a laboratory and real public electrical network considering some ANSI C12.20 class .5 tests (i.e. tests such as effect internal heating, variation of frequency and external influence are not performed) is presented. The scheme and prototype proposed uses power flows in one-way and information flows in two ways (i.e. the electrical power is not redirected in different paths while the information flows have different paths according the process step). The experimental results showed that the prototype proposed has an adequate electrical performance regarding the measurements of the electromagnetic field generated by the electrical current and an adequate digital processing in a real electrical network. In general, the accuracy power measurement is 0.63%, which means that for higher power applications is needed an accuracy reduction in order to maintain a real power consumption user profile. Although Fig. 6 shows a 250 W consumption, due to the not continuous measurements (i.e. each 5 minutes a measurement was performed), the kWh at 1 hour is not 0.25 kWh. In fact, measurement periods of 5 minutes and 1 hours are preliminary conditions because an ideal dynamic power control requires a reduced period as possible (e.g. 1 minute) In particular, a central server calculates the electrical consumption profile of each user/remote location based on relevant information using the Moment-Generating Function. Thus, control commands are sent by the central server to the local electrical stations in order to modify in a dynamical way the maximum power available for particular hours (i.e. dynamic threshold control). Despite the power consumption preferences of each user were assumed independent, apparently, the consumption profiles are similar and a formal analysis of the users is needed. The non-intrusive sensor established an important limit regarding the maximum current that can be sensed (25 A); so that an improvement in the sensor is needed in order to using the prototype in a high power regime (e.g. 250 A as maximum level according to the PTE-100-C). The proposed scheme allows the development of new products, services, and markets in the Smart Grid / Home context and although there are exist power meter equipment that satisfy the ANSI C12.20 class .5, these systems do not use COTS devices and require an ideal power factor (i.e. ≈1). Finally, our group is working to improve the performance of the system based on IEEE Standard 1459-2010.

Acknowledgment

A special thanks to the CETYS University, Comision Federal de Electricidad (CFE), Instituto Tecnológico Superior de Cajeme (ITESCA) and Universidad de Sonora (USON) for the technical, administrative support and feedback

References

[1] N. Ichikawa, N., Electrical Fatality Rates in Japan, 2002-2011: New Preventive Measures for Fatal Electrical Accidents, Industry Applications Magazine, vol. 22, pp. 21-26, 2016.
[2] I. Kokshenev, R.O. Parreiras, P.Y. Ekel, G.B. Alves and S.V.Menicucci, A Web-based Decision Support Center for Electrical Energy Companies, Transactions on Fuzzy Systems, vol. 23, 2015.
[3] D. Niyato and P. Wang, Cooperative transmission for meter data collection in smart grid, Communications Magazine, vol. 50, pp. 90-97, 2012.
[4] G.C. Koutitas and L. Tassiulas, Low Cost Disaggregation of Smart Meter Sensor Data, Sensors Journal, vol. 16, pp. 1665 – 1673, 2016.
[5] M. Sumner, A. Abusorrah, D. Thomas and P. Zanchetta, Real Time Parameter Estimation for Power Quality Control and Intelligent Protection of Grid-Connected Power Electronic Converters, Transactions on Smart Grid, vol. 5, pp. 1602 – 1607, 2014.
[6] R. Iuzzolino and W.G. Krten-Ihlenfeld, High-Accuracy Methods and Measurement Procedures for Power Quality Parameters Using the Digital Synchronous Sampling Technique, Transactions on Instrumentation and Measurement, vol. 56, pp. 426 – 430, 2007.
[7] M. Shin and I. Joe, Energy management algorithm for solar-powered energy harvesting wireless sensor node for Internet of Things, IET Communications, vol. 10, pp. 1508 – 1521, 2016.
[8] M. Kuzlu, Score-based intelligent home energy management (HEM) algorithm for demand response applications and impact of HEM operation on customer comfort, IET Generation, Transmission & Distribution, vol. 9, pp. 627 – 635, 2015.
[9] J. Miao, N. Zhang, C. Kang, J. Wang, Y. Wang and Q. Xia, Steady-state Power Flow Model of Energy Router Embedded AC Network and Its Application in Optimizing Power System Operation, Transactions on Smart Grid, vol. 99, 2017.
[10] R. Yao, F. Xu, T. Mekkawy and J. Xu, Optimised power allocation to maximise secure rate in energy harvesting relay network, Electronics Letters, vol. 52, pp. 1879 – 1881, 2016.
[11] M.C. Lorek, F. Chraim, K.S.J. Pister and S. Lanzisera, COTS-Based Stick-On Electricity Meters for Building Submetering. Sensors, vol. 14, pp. 3482 – 3489, 2014.
[12] P. García, P. Arboleya, B. Mohamed and A.A.Vega, Implementation of a Hybrid Distributed/Centralized Real-Time Monitoring System for a DC/AC Microgrid with Energy Storage Capabilities, Transactions on Industrial Informatics, vol. 12, pp. 1900 – 1909, 2016.
[13] A. I. Lance, A high accuracy standard for electricity meters, Schneider Electric, white paper, 2011.
[14] G. Lobaccaro, S. Carlucci and E. Löfström, A Review of Systems and Technologies for Smart Homes and Smart Grids, Energies, vol. 9, pp.1-33, 2016
[15] S. S. Reddy-Depuru, L. Wang, V. Devabhaktuni and N. Gudi, Smart meters for power grid -Challenges, issues, advantages and status, In Proc. Power Systems Conference and Exposition, 2011.
[16] M. Barcelo, A. Correa, J. Llorca, A.M. Tulino, J. Lopez-Vicario and A. Morell, IoT-Cloud Service Optimization in Next Generation Smart Environments, Journal on Selected Areas in Communications, vol. 34, pp. 4077 – 4090, 2016.
[17] M. Giacobbe, A. Celesti, M. Fazio, M. Villari and A. Puliafito, A sustainable energy-aware resource management strategy for IoT Cloud federation, In Proc. International Symposium on Systems Engineering, 2015.

[18] G. Xu, W. Yu, D. Griffith, N. Golmie and P. Moulema, Toward Integrating Distributed Energy Resources and Storage Devices in Smart Grid, Internet of Things Journal, vol. 4, pp. 192 – 204, 2017.
[19] K. Utkarsh, A. Trivedi, D. Srinivasan and T. Reindl, A Consensus-Based Distributed Computational Intelligence Technique for Real-Time Optimal Control in Smart Distribution Grids, Transactions on Emerging Topics in Computational Intelligence, vol. 1, 2017, pp. 51 – 60, 2017.
[20] Y. Yang, K. McLaughlin, S. Sezer, T. Littler, E.G. Im, B. Pranggono and H. F. Wang, Multiattribute SCADA-Specific Intrusion Detection System for Power Networks, Transactions on Power Delivery, vol. 29, pp. 1092 – 1102, 2014.
[21] K.C. Budka, J.G. Deshpande, T.L. Doumi, M. Madden and T. Mew, Communication network architecture and design principles for smart grids, Bell Labs Technical Journal, vol. 15, pp. 205 – 227, 2010.
[22] C. Gentile, D. Griffith and M. Souryal, Wireless network deployment in the smart grid: Design and evaluation issues, Network, vol. 26, 2012.
[23] D.B. Nguyen, J. M.A. Scherpen and F. Bliek, Distributed Optimal Control of Smart Electricity Grids with Congestion Management, Transactions on Automation Science and Engineering, vol. 14, pp. 494 – 504, 2017.
[24] A. Malik and J. Ravishankar, A review of demand response techniques in smart grids, in Proc. Electrical Power and Energy Conference, 2016.
[25] Z. Li and Q. Liang, Performance Analysis of Multiuser Selection Scheme in Dynamic Home Area Networks for Smart Grid Communications, Transactions on Smart Grid, vol. 4, pp. 13-20, 2013.