I-BAT: A Data-intensive Solution based on the Internet of Things to Predict Energy Behaviours in Microgrids

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Microgrids present the challenge to reach a proper balance between local production and consumption, in order to reduce the usage of energy from external sources. This work presents a data-intensive solution to predict the energy behaviours. Thereby, control actions can be carried out such as decrease heating systems levels and switch off low-priority devices. For this purpose, this work has deployed an Advanced Metering Infrastructure (AMI) based on the Internet of Things (IoT) in the Techno-Pole testbed. This deployment provides the data from energy-related parameters such as load curves of the overall building through Non-Intrusive Load Monitoring (NILM), a wireless network of IoT-based smart meters to measure and control appliances, and finally the generated power curve by 2000 square meters of photovoltaic panels. The prediction model proposed is based on recognition of electrical signatures. These electrical signatures have been used to detect complex usage patterns. The modelled patterns has allowed to identify the work day of the week, and predict the load and generation curves for 15 minutes with an accuracy over the 90%. This short-term prediction is allowing us to carry out the proper actions in order to balance the microgrid status (i.e., get a proper balance between production and consumption).

Keywords: Internet of Things; Advanced Metering Infrastructure; Energy information management; Smart grid; Microgrid; Data intelligent analysis

Received 20 January 2014; revised 00 Month 2014

1. INTRODUCTION

The balance between produced and consumer power is gaining special attention during the last decade, when a wide range of experiments and net-zero buildings are being deployed.

This interest on optimize the energy usage, and focus on renewable energies, is coming as a consequence of the increase of costs of the fossil fuels, and the negative consequences for the nature of them.

These factors have driven research of solutions for sustainability in energy production, distribution, storage, and consumption.

In energy distribution, new "smart metering" solutions have been proposed, based on the idea that exploiting properly data on power generation, distribution and consumption, a substantial increase in efficiency is achievable [1].

This data exploitation requires the capabilities to provide bidirectional communication with the appliances, production plants, and the smart meters. For that reason, the Internet of Things plays a crucial role for the development of the energy distribution in microgrids.

Examples of the relevance of the communications have been discussed in the DINAR project. DINA project has explored technological aspects of the coordination within the low-voltage. For thus purpose, a communication infrastructure between different

The Bidirectional Energy Management Interface

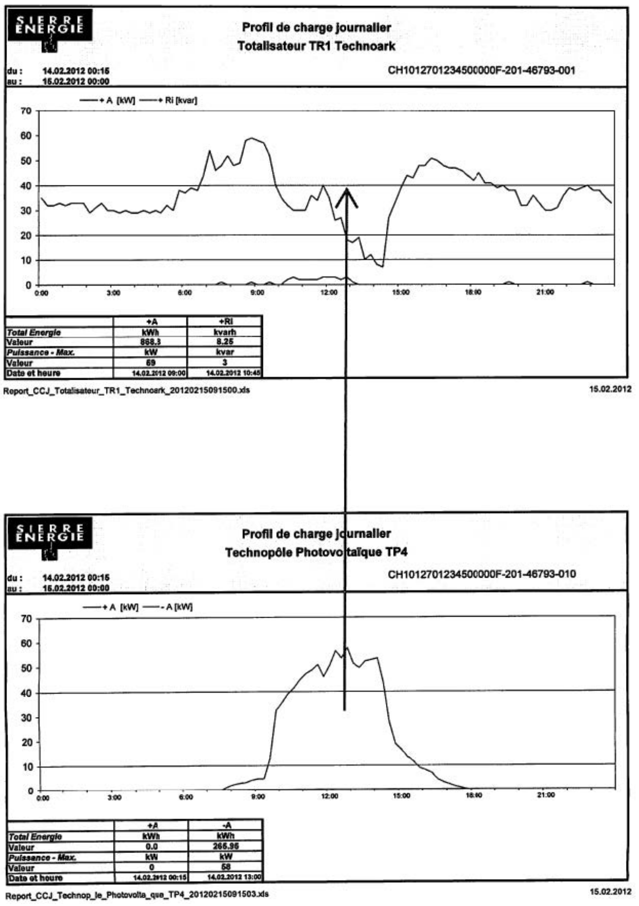


FIGURE 1. Example in our testbed (Techno-pole) of the necessity of load balancing of the microgrids.

(BEMI) has been developed as a communication interface to each other and the utility. Thus energy consumption and generation can be coordinated.

For these communications, the Internet of Things aims at facilitating the communications. In particular, smart metering is one of the initial and more extended use cases for the Internet of Things [2]. Several solution have been deployed with ZigBee [3], 6LoWPAN [4, 5], and ZigBee-IP [6]. In addition, Wireless Smart Utility Network (WI-SUN) is also extended with new IoT-related technologies such as IEEE 802.11g (subGhz) [7], and presenting a new generation of opportunities to monitor the energy consumption at different levels, i.e., overall consumption and also the independent consumption from specific devices.

An essential goal of the Internet of Things is to have ability to identify devices (using identification technology), and allow local computing and communication among different smart devices [8]. These essential goals are also keys for the future smart grid, and of particular importance for microgrids.

A microgrid is formed by the electric grid and connected devices, e.g. in a group of offices or apartments. Microgrids are on the low voltage level (usually 400V in Europe), in contrast to the high and middle voltage grids, used for power transmission and distribution [9]. The challenge for smart grids is that the topology of the grid will change dramatically due to the integration of microgrids. In current power distribution grids the energy is still transmitted from a few large power stations to a large number of consumers. The producers of energy are located at the highest level. The energy is distributed across different layers, depending on the voltage level used for transportation. There exist the extra-high, the high, the middle and the low voltage layers. The grid is hierarchically structured, and thus is the control of the grid.

For that reason, the needs for the communication, prediction, and coordination are crucial for the success integration of the microgrids in the smart grid. The necessity of load balancing of the microgrids is demonstrated in the Figure 1, where can be found the de-synchronization between the generation and consumption in our installations. The objective is to reach a proper coordination between the local consumption and production in order to avoid external costs, i.e., consume from the grid.

This paper we investigate the abilities of microgrids to reduce energy costs using forecast information.

Inside a building we have constant demanding devices, which define our baseband, and also eventual or periodical devices, which present peak-loading events.

This work extracts the usage patterns for electricity out of load curves by using classifiers that extract the load curve of one device using single signature and the global signature. In addition, the Ecowizz smart meters, based on ZigBee, from the partner of the project Gerocco [3] are also used to collect information of the power consumption for specific devices.

Energy consumption and production forecasting is a challenging research topic. Even though it is possible to generate predictions on a very high level, e.g., in form of standard load profiles [10, 11], it is still very challenging to create forecasts at the level of microgrids or devices. This is due to the high non-linearity of load curves of devices. Typical stochastic forecasting methods like ARIMA assume a (quasi-) linear model in the time series for which a forecast should be generated.

The large number of consumers typically minimize these non-linear effects of each devices, so that forecasts for larger grids can be generated. Currently techniques to create forecasts in microgrids are based on neural networks, naive Bayes [12], or hybrid methods [11, 13, 14], because these methods can handle non-linearity better than stochastic models.

This work presents an approach to create forecasts for microgrids. This approach is based on extracting usage patterns for electricity out of load curves. The identification of the different patterns allows to create classifiers that can identify devices in the load curve.

To create such classifiers we need to measure the

[3] EcoWizz Smart Meter - http://www.ecowizz.net/

overall load of a microgrid. In addition, we are measuring the load curves by single devices (with ZigBee smart meters) in order to refine our classification scheme by collecting usage information of smart devices, which can be identified and can record their consumption.

For the purpose of measure the overall load of the microgrid, this work has been carried out with the collaboration of Sierre Energy, which has offered all the interaction with the meters that has been deployed in the Techno-Pole testbed. In addition, another partner and collaborator for this project has been the company Gerocco, specialized in Internet of Things-based smart meters (Ecowizz ZigBee smart meter).

This hybrid approach between overall load and specific appliances load will allow to provide a detailed classifier of the different appliances, that avoid the need to continue using a smart meters per appliance in the future deployments.

With this classification scheme of a specific grid we can create a symbolic model of the energy consumption. In this model the non-linearities do not exist anymore, and we can find usage patterns. An example of such a pattern is that the coffee machine is turned on between 7:30 and 8:00 each morning during working days, with a given distribution within the interval. Based on this symbolic forecast and the identified patterns we can re-translate our symbolic forecast into load profiles again.

This work is contextualized in the I-BAT Switzerland Project [4]. This project is a convergence of expertise in several areas of energy management. The objective of this work has been to build a modular and intelligent information system capable of regulating futures sub-networks of the power supply grid, i.e., micrograids. For this purpose, many static or dynamic energy parameters are taking into account in order to predict the consumption. The interest to predict the consumption is to be able to control in the future the energy consumption of buildings, and the most important to regulate the cooperative energy behaviour of microgrids.

In details, the data-intensive solution has as inputs the low frequency parameters (load curves from the photovoltaic plant provided by ELKO, and the grid consumption provided by Sierre Energy) and high frequency parameters (device measures from the Ecowizz smart meters).

The work presents, on the one hand, how the different devices are classified based on recognition electrical signatures defined by a clustering solution based on k-nearest neighbours (knn) algorithm, and on the other hand, how once the devices are identified, patterns can be learned among different days in order to classify the consumer behaviour per days and forecast load curves during the following minutes. The short-term prediction of the load curves provide to the system the

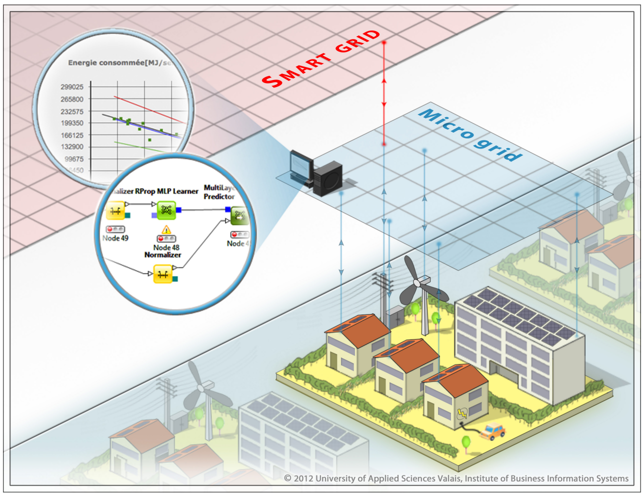


FIGURE 2. Microgrid integration in the Techno-pole.

information required to carry out a control of the smart appliance, and offer the feedback to the users, that ensure to reach a better balance between the production and the consumption.

Thereby, this 15 minutes forecast allows to minimize the amount of energy that needs to be consumed from utility companies, minimizing peak loads, which can be the base for pricing or minimizing the total cost of energy.

2. ARCHITECTURE

The Figure 2 presents an overview of the microgrid integration deployed in the Techno-Pole testbed inside of the Sierre Energy Smart Grid.

For the deployment of this testbed has been required the integration of multiple metering devices from different vendors. These metering devices offer the interface between the local microgrid and the grid of the utility, the microgrid and the photovoltaic plant, and finally the end-user appliances.

In details, the integrated meter devices are presented in the Figure 3. In addition, new generation and IoT-based smart meters to measure specific appliances, such as the ZigBee smart meters from Gerocco.

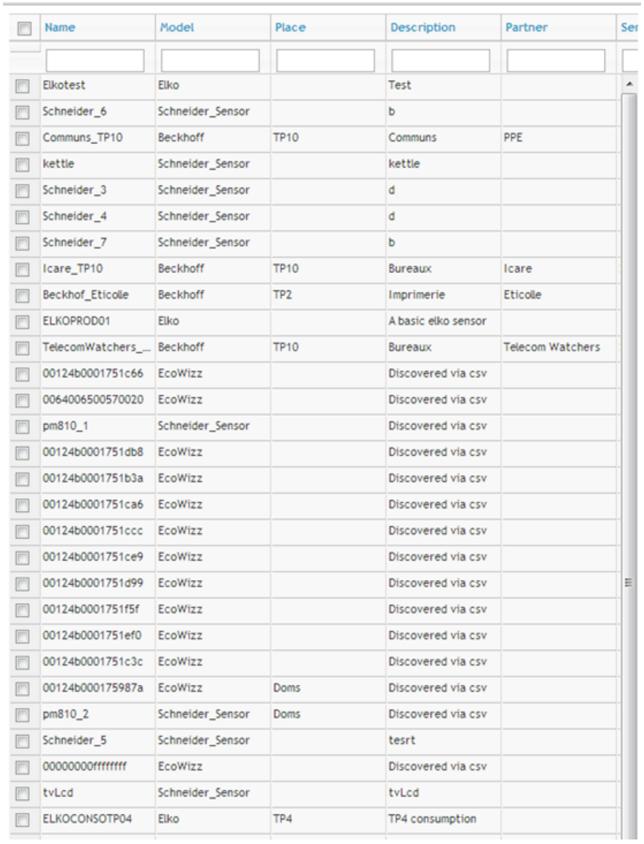
2.1. Information System

The Figure 4 presents the information architecture designed in I-BAT. Since, the solution proposed is data-intensive, one of the main basis of the proposal has been the gathering of the data at different levels.

One of the major goals of the Internet of Things is to provide common standards and semantic description of the data through RESTFul / WebServices interfaces, that facilities the development and deployment of these kind of solutions.

In this case, the ZigBee Ecowizz smart meter) have offered an easier and more flexible integration that

[4] I-BATs project - http://iig.hevs.ch/valais/i-bats.html



Name	Model	Place	Description	Partner	Ser
Elkotest	Elko		Test		
Schneider_6	Schneider_Sensor		b		
Communs_TP10	Beckhoff	TP10	Communs	PPE	
kettle	Schneider_Sensor		kettle		
Schneider_3	Schneider_Sensor		d		
Schneider_4	Schneider_Sensor		d		
Schneider_7	Schneider_Sensor		b		
Icare_TP10	Beckhoff	TP10	Bureaux	Icare	
Beckhof_Eticolle	Beckhoff	TP2	Imprimerie	Eticolle	
ELKOPROD01	Elko		A basic elko sensor		
TelecomWatchers_...	Beckhoff	TP10	Bureaux	Telecom Watchers	
00124b0001751c66	EcoWizz		Discovered via csv		
0064006500570020	EcoWizz		Discovered via csv		
pm810_1	Schneider_Sensor		Discovered via csv		
00124b0001751db8	EcoWizz		Discovered via csv		
00124b0001751b3a	EcoWizz		Discovered via csv		
00124b0001751ca6	EcoWizz		Discovered via csv		
00124b0001751ccc	EcoWizz		Discovered via csv		
00124b0001751ce9	EcoWizz		Discovered via csv		
00124b0001751d99	EcoWizz		Discovered via csv		
00124b0001751f5f	EcoWizz		Discovered via csv		
00124b0001751ef0	EcoWizz		Discovered via csv		
00124b0001751c3c	EcoWizz		Discovered via csv		
00124b000175987a	EcoWizz	Doms	Discovered via csv		
pm810_2	Schneider_Sensor	Doms	Discovered via csv		
Schneider_5	Schneider_Sensor		tesrt		
00000000ffffffff	EcoWizz		Discovered via csv		
tvLcd	Schneider_Sensor		tvLcd		
ELKOCONSOTP04	Elko	TP4	TP4 consumption		

FIGURE 3. List of smart meters integrated.

the rest of industrial smart meters, providing data formatted in ZigBee profiles, CSV, and JSON.

The developed information system, in addition to provide de functions for data collection, this also analyses and model the energy data. Specifically, this information system has been designed and developed to offer the capability of controlling the energy consumption of buildings to be able to understand how to predict the energy behaviour of a microgrid and regulate it.

Regarding to get access to their power consumption. of data from the different companies, the approval from the different companies located at the Techno-pole building have been required.

For the presented evaluations, the following companies have responded positively and participated in this testbed: Mikado, Eticolle SA, Schoechli printing, Computer T.I., Netplus.ch SA, Telecom Watchers, TechnoArk SA, Consultec, ICARE, HES-SO Valais-Wallis, and Canal9.

The system has been adapted to support different communication protocols. Since, multitude of sensors that vary by location, frequency, environment, data to be collected and the type of input and output of unit.

In addition, we found it necessary to involve all stakeholders in the energy chain, from producer to final consumers through the distributor.

It is important to add that the company Consultec,

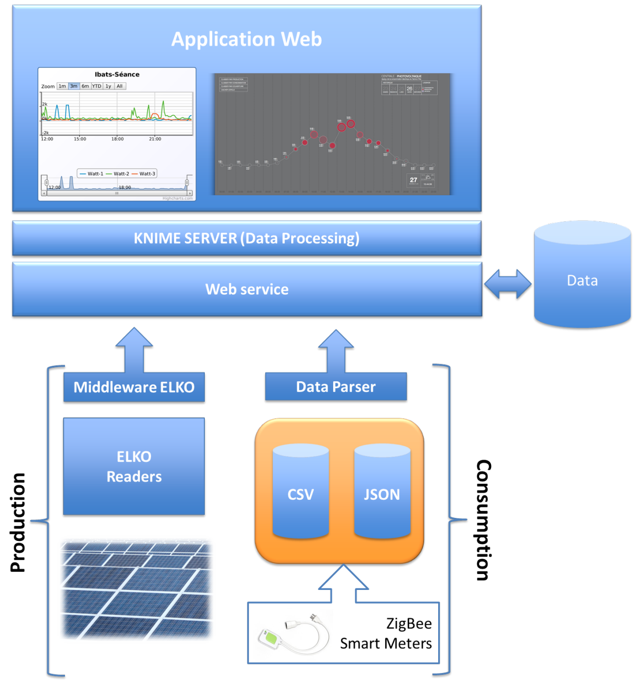


FIGURE 4. I-BAT architecture.

FIGURE 5. Transformer deployed in the Techno-pole.

the administrator of the EPP Techno-Ple, supports this approach and we will provide information on consumption related to heating and lighting.

Specifically, for the data gathering from the information system has been carried out on three levels:

1. **Level 1:** Data Recovery at the transformer (see Figure 5 and photovoltaic panels (see Figure 6).
   - Data: active and reactive power on the three phases of a transformer active power level panels
   - Sampling frequency: second.
2. **Level 2:** Data Recovery at the Techno-Pole offices (see Figure 7, and retrieving data from the largest consumers within the Techno-Pole (TP)

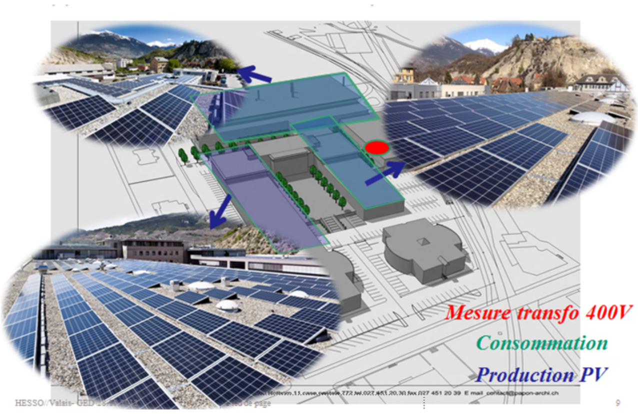


FIGURE 6. Production deployment based on solar panels (photovoltaic).

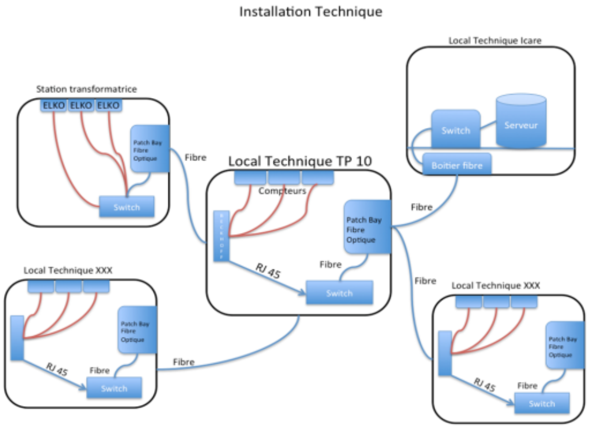


FIGURE 7. Installation deployed to retrieve the data from each company electric meter in Techno-pole.

FIGURE 8. Deployment to retrieve the data from each company electric meter in Techno-pole.

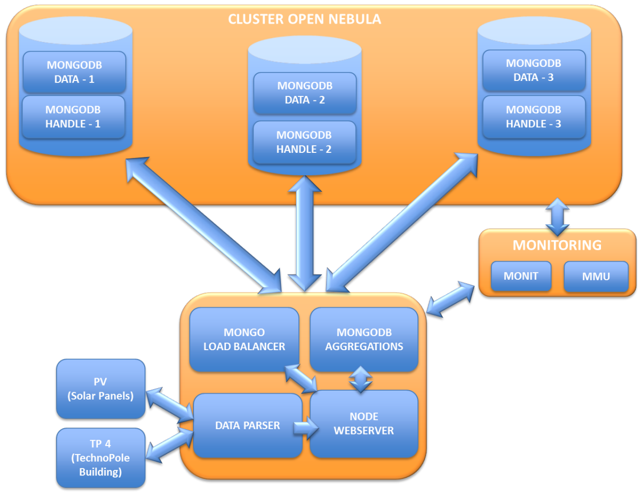


FIGURE 9. I-BAT information system architecture based on No-SQL distributed databases built on MongoDB.

(see Figure 8).

- Data: Active power
- Sampling frequency: second

3. **Level 3:** Retrieving data within companies.
   - Data: active power, reactive power, number of people, outside temperature, inside temperature
   - Sampling frequency: second

An interface and an API have been developed to visualize and access to all the data connected to the information system.

Finally, this information system contains the elements necessary for the storage of data NO-SQL, since the data is formatted in JSON. The Figure 9 presents the data storage infrastructure deployed.

2.2. Techno-pole

The Figure 10 presents the areas monitored. The area TP10 is monitored at their different power energy phases, and in the area TP4 is also monitored the different phases. In addition, the brown rooms from TP4 are also monitored specific appliances with the Ecowizz Smart meter.

3. RECOGNITION OF ELECTRICAL SIGNATURES

Electrical signatures recognition techniques proposed to monitor appliance consumption, non-intrusive ones (called also NILM [15]) are of particular interest, since they do not require specialized, costly hardware and installation and maintenance of a sensor network. Moreover, they adapt over time in changes in households (such as changes in appliance number and type) without requiring new installations or reconfiguration of existing hardware and software. The extensive deployment of smart meters which is planned in many countries for the near future will enable a large scale deployment of NILM techniques [16]. Such deployment will make available measurements of the

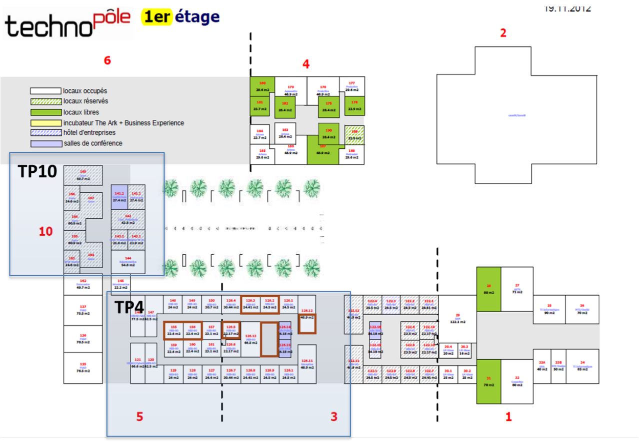


FIGURE 10. Techno-pole floorplan, where TP4 and TP10 areas are being used as part of the testbed.

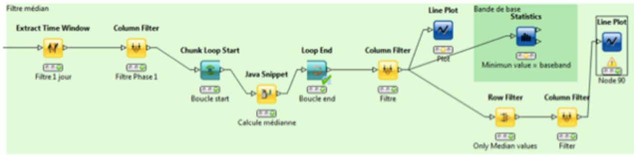


FIGURE 11. Filter median developed for KNIME.

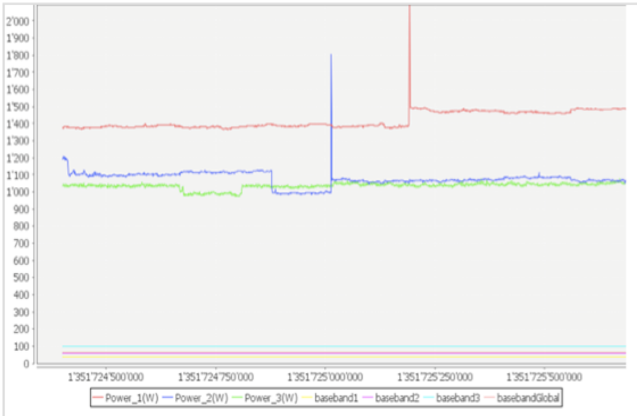


FIGURE 12. Filter median results to detect the baseband. x-axis: time in seconds, y-axis: power in Watts.

total active and reactive power consumed, typically sampled at low frequencies, allowing non-intrusive load monitoring without the use of additional hardware.

NILM methods have been first proposed in [17], and they are typically structured in three phases: feature extraction, events detection, and events classification. They make use of a database of electric signatures of appliances, and they are based on the measure of the total active power consumed, sampled at frequency of one Hertz. Later methods [18, 19] try to decrease the duration of the training period. Indeed, the main drawbacks of these techniques reside either in the need of a learning phase requiring intrusive measurements, and/or on the fact that they cannot detect appliances whose power consumption patterns vary drastically over time (e.g., washing machines, whose power consumption varies substantially during a washing cycle). Indeed, a fine granularity and a good accuracy in load disaggregation are crucial in order to enable useful feedback to users, to set up appropriate measures for changing consumption patterns, and to enable detection of anomalies and appliance malfunctioning. Many of the techniques proposed in order to overcome these drawbacks imply a substantially higher sampling frequency, and therefore more expensive hardware [21, 22].

The described NILMs techniques have demonstrated the capability to identify different appliances based on the total power consumption (measure three-phase voltage, current, active and reactive power).

The following subsections describe the process carried out to recognize the electrical signatures from the different appliances.

3.1. Baseband detection

We started by detecting the baseband. Baseband is defined by the continuous power consumption on a phase. This represents the devices such as routers, cameras and other appliances that are continuously switched on.

It has been calculated obtaining the minimum on each phase after median filter. The median filter has been implemented with the KNIME platform.

KNIME platform (the Konstanz Information Miner) is an open source data analytics, reporting, visualization and integration platform. KNIME integrates various components for machine learning and data mining through its modular data pipelining concept. One of the major advantages of KNIME is its abstraction through a graphical user interface that allows assembly of nodes for data pre-processing, for modelling and data analysis and visualization. Thereby, KNIME offers a very powerful and intuitive environment based on workflows instead of classic scripts or low level programming languages.

The integration of KNIME is opening the integration of other several technologies and tools from artificial intelligence and data mining research areas in order to make more powerful the capabilities from the deployment, make easier the access and use of the infrastructure, homogenize the access to the services/resources/devices.

The Figure 11 presents the implementation over KNIME of the filter median. A partial result for a specific time window result is presented in the Figure 12, where the baseband is equal to 270W. This is calculated dynamically in order to adapt to different seasons, evolve to the presence of new offices, people, and appliances.

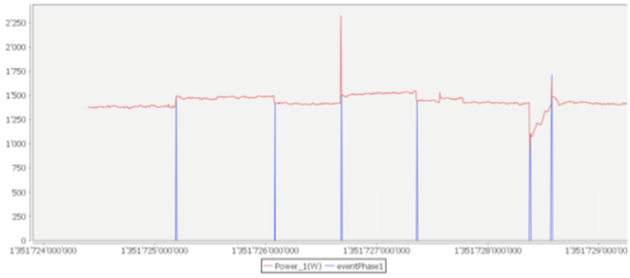


FIGURE 13. Event detection. x-axis: Time (s), y-axis: Power (W).

3.2. Event detection

The methodologies applied for this process are, on the one hand, median filter of size 5, i.e., a minimum difference of 5W,

An event happens each time that an appliance is switched on or off.

This remove the high frequency derived signals and also the differences under 5W, in order to avoid noise and false positives.

The Figure 13 presents an example of the result from the event detection filter.

3.3. Event classification

Analysis of the active power and reactive power ($\frac{\Delta P}{\Delta Q}$) allows a good classification of large consumers.

We refer to the work of Georges Hart, which consists on detecting jumps of active and reactive power with regards to a predefined threshold. We also study the event recognition with regards to the frequency of data collection. We initially adjust the threshold of active and reactive power to 50W and 15VAR, and subsequently to 15W and 5VAR to study the impact of transitional effects on electrical signals. To train and test different algorithms, the data is normalized according to the min-max method. To allow either a study of consumed energy, or a study of available power, the data is then denormalized.

The Figure 14 presents the power-based signature space based on the Techno-pole measurements. This has been built a clustering applying a Knn algorithm. It can be seen a very similar signature space to de described in [20] from an experiment in a household in USA, with the main differences that the main number of appliances for buildings appear in the reactive-power since they are for motors, and pumps.

The electrical signals present interferences that we must identify on the global diagrams as well as on individual connected appliances diagrams. We use a median filter on each entry signal to remove high frequencies. Furthermore, the tolerance thresholds for event detection can also filter part of the noise. For the training data set, we have added confidence intervals that are the mean of the extremes of the appliances

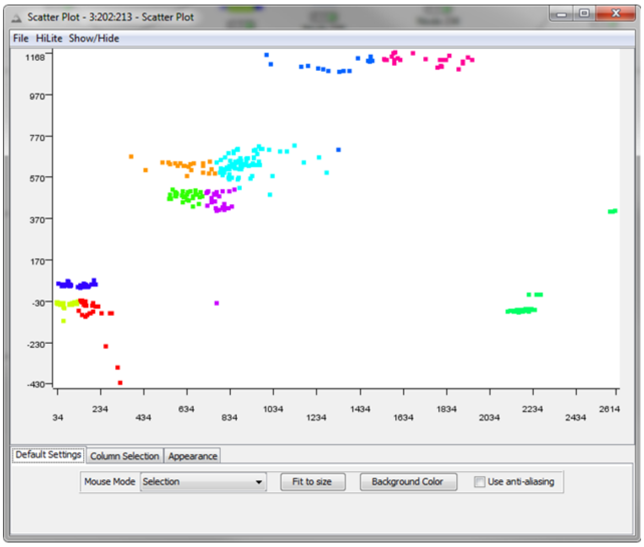


FIGURE 14. Power-based signature space detected in the Techno-pole. x-axis: Real power (W), y-axis: Reactive Power (VAR).

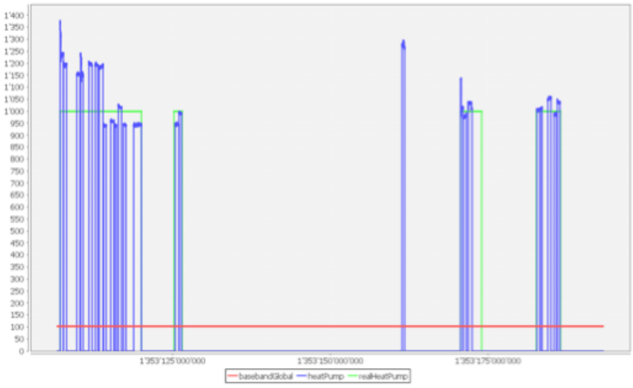


FIGURE 15. Heat pumps event pattern.

connected to our information system. This removes the possibility of outliers on the training set: the data taken within this confidence interval represent the representative events panel of each appliance that we wish to detect. They are:

- (Heat) Pump: event on {200 Watt; 1400 Watt} ; event off {-1400 Watt; -200 Watt}.

  The algorithm for detecting the heat pump is based on the following characteristics observed on different heat pumps, a three-phase device (comparing 3 phases) whose duty cycle is at least 5 minutes (morphological opening) and whose active power measured by each phase is greater than 500W (500W threshold) (see Figure Figure 15).
- (Cold) Freezer: event on {50 W; 250Watt}; event off {-200 W; -50Watt}.

  The operation of refrigerators or freezers is

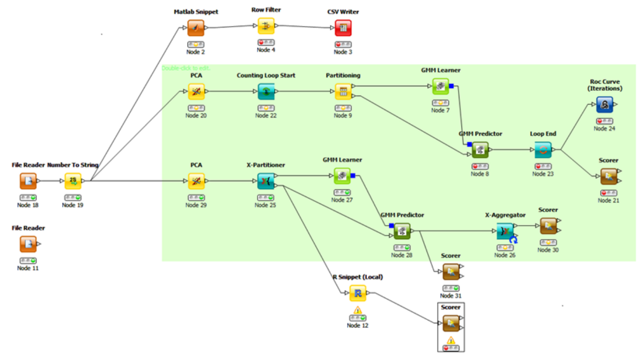


FIGURE 16. Freezer detection model based on a Gaussian Mixture Model.

virtually cyclic. Their consumption can be characterized by an ON period and an operating power and time. Using these three parameters estimated and modelled by a Gaussian Mixture Model (GMM), we look in the list of events those which can most probably belong to the cycle of the refrigerator or freezer. The Figure 16 presents the model developed in KNIME.

- (Appliances) Event on {1000 Watt; 3000 Watt}; event off {-3000Watt; -1000 Watt}.

4. ENERGY BEHAVIOURS PREDICTION

The information system provides the concept of dynamism thanks to the power consumed at time t. By correlating this information with the parameters collected and adding the right algorithms, we can predict the power at time (t + 15) minutes. From these data, the control system will then take over and act on the microgrid to regulate its consumption or use the smart grid to apply energy. To control multiple tracks are being considered as a pure offset.

Once all the system and data was integrated. In addition to the classification of different appliances, it has been analysed the overall power consumption curve.

The prediction (or forecasting) of the power consumption can be established by the ARIMA method (linear time series), when exist a large number of consumers, but for microgrids such as in our testbed, it is commonly used neural networks or hybrid methods.

The initial objective to understand and predict the energy behaviours. For this purpose, we have carried out a prediction of the week day.

The recognition capabilities and different between weekday and weekend day presents an affordable approach. However, the recognition becomes more complex between the different days of the week, some seeming to have larger patterns.

In details, two different evaluations have been carried out to classify the day based on the energy patterns. On the one hand, an analysis limited to 2 months of data, and on the other hand 5 months of data.

The first prediction model have presented a result of:

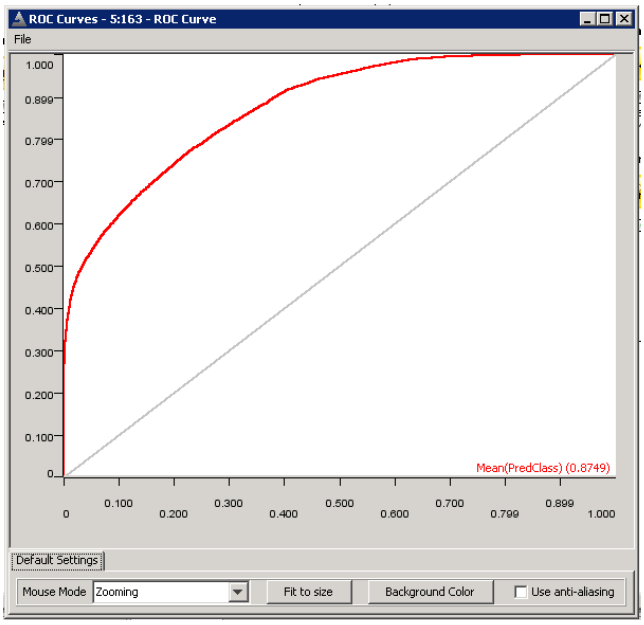


FIGURE 17. ROC Curve for the prediction of the week day.

- Prediction week / weekend: A mean accuracy of 90%.
- Prediction day of the week: A mean accuracy of 55%.

This analysis has been focused on the data from the TP4/TP10 area offices. The sampling frequency is equal to 1 s, and the total analysis time has been of 2 months (1 month of training and 1 months of test).

These results were low, for that reason, it was extended the test to 5 months, in order to offer a more extended training set.

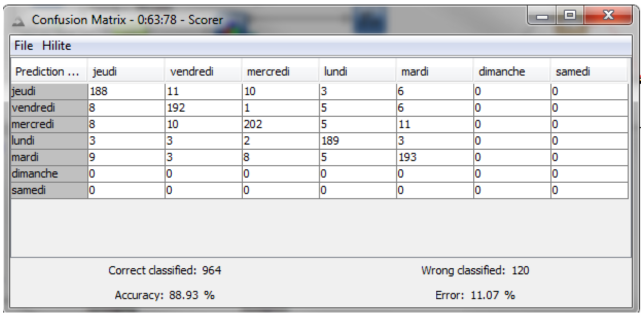
The results reached by the data-intensive predictive model of electricity for offices are:

- Prediction week / weekend: A mean accuracy of the 98%.
- Prediction day of the week: A mean accuracy of the 65%.

This analysis has been focused on the data from the TP4/TP10 area offices. The sampling frequency is equal to 1s, and the total analysis time has been of 5 months (3 months of training and two months of test).

The Figure 17 presents the Receiver Operating Characteristic curve (or ROC curve). This plot presents the the true positive rate against the false positive rate for the different possible cutpoints of the diagnostic test for the prediction of the week days, during one of the weeks, which has presented a 87.49% accuracy. In addition, the Figure 18 presents the confusion matrix for one of the tests, which has offered a 88.93% accuracy.

Finally, it has been evaluated the prediction of the power consumption in short-term. The goal of this work was to reach a suitable prediction for 15 minutes (t+15),


Confusion Matrix - 0:63:78 - Scorer

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Prediction ...	jeudi	vendredi	mercredi	lundi	mardi	dimanche	samedi
jeudi	188	11	10	3	6	0	0
vendredi	8	192	1	5	6	0	0
mercredi	8	10	202	5	11	0	0
lundi	3	3	2	189	3	0	0
mardi	9	3	8	5	193	0	0
dimanche	0	0	0	0	0	0	0
samedi	0	0	0	0	0	0	0

Correct classified: 964 Wrong classified: 120

Accuracy: 88.93 % Error: 11.07 %

FIGURE 18. Confussion matrix.

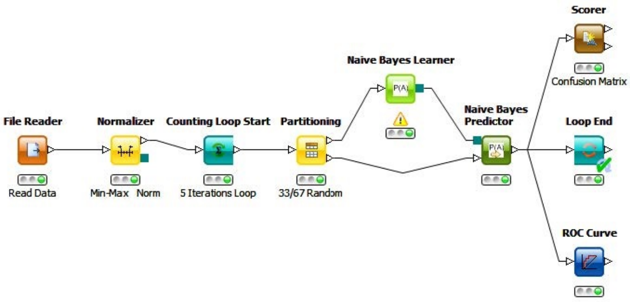

FIGURE 19. Predictor developed over KNIME based on Naive Bayes classifier.

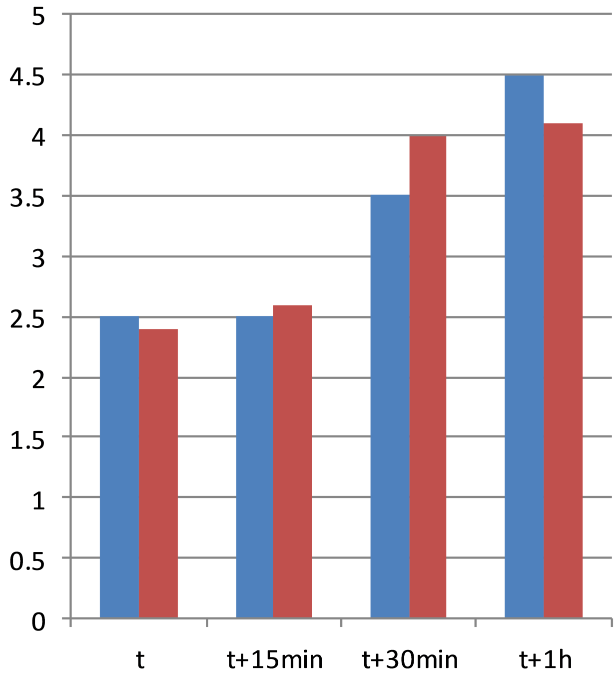

FIGURE 20. Prediction of the power consumption for short term. X-axis: relative time, y-axis (Kwh), red bars: predicted consumption, and blue bars:real consumption.

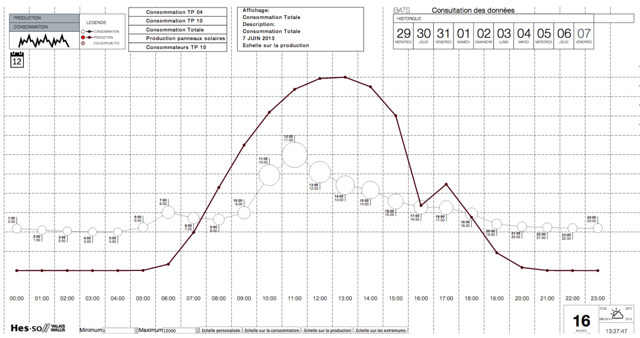

FIGURE 21. Visualization of the feedback data provided in the different screens distributed in the common areas of the bulding.

in order to be able to control some of the devices, in order to balance the microgrid status (i.e., get a proper balance between production and consumption).

For this purpose, a Naive Bayes classifier has been developed on the KNIME platform (see Figure 19). This algorithm has a input the low frequency parameters (load curves), high frequency parameters (EcoWizz smart meters measures), and optionally can be added external factors such as weather forecast.

The outputs are the forecast load curves (consumption), production curve, and optionally, it could also in the future give the instructions for the controllable smart devices that needs to be switched on or off during the coming 15 minutes, in order to balance the load and production curves.

The results presented in the Figure 20 shows an accurate prediction of both the load curve for the estimations for the next 15 minutes with an accurate over the 90

5. CONCLUSIONS AND FUTURE WORK

Microgrids can apply techniques like forecasting, planning and coordination to minimize their energy costs. Some fundamental forms of smart microgrids consumption management are techniques currently investigated in the context of the Internet of Things. Devices become smart by adding local computing and communication abilities to them.

The presented work has described the developed and deployed testbed. The development of this complex system with a full-scale testing has required the coordination and support from multiple institutions. For this, we have the opportunity, thanks to the contribution of Sierre Energy and officials of Techno-Pole in Sierre, to collect data of buildings as well as the network of 2000 square meters of solar photovoltaic panels producing electricity.

We have proposed a hybrid non-intrusive approach which use the real/reactive power to identify the class, a priori information and the Training/Testing Generalization. We have more than 85 percent of recognition on the studied devices.

In addition, intrusive IoT-based devices such as the ZigBee smart meters has been integrated in order to create a prediction model that allow to carry out the proper actions with a time window of 15 minutes, in order to reach a proper load and production balance.

Another consequence of this project has been the development of a website for viewing collected data on the site energy test Techno-Pole (see Figure 21). This information is presented in multiple screen deployed in the common areas of the building, in order to evaluate in long term the impact on users behaviours.

The ongoing work is focused on the Internet of Things scope, in order to integrate legacy and non-IP devices [23, 24, 25]. The Internet of Things will bring several opportunities in the future to build unified frameworks where all non-IP devices can discuss inside an holistic IPv6 network. Thereby, all the devices are interoperable through WebServices, i.e., offering a Service oriented information system, where the Legacy Devices are presented as Legacy Device as a Service (LDaaS).

Finally, future work will be focused on the integration with smart cities infrastructure and electric vehicles [26].

ACKNOWLEDGEMENTS

This research was undertaken as part of the I-BAT project and has been funded by The Ark Energy (Project No. 712-07). We would like to thank all the contributions from the partners involved our colleagues from HES-SO (Pierre Roduit, Milene Fauquex, Pascal Pitteloud, Pierre Roduit, Rene Vuilleumier, and Simon Martin), Icare Institute (Pierre Kenzelman), Alro Communication SA (Frdric Revaz), Geroco SA (Eric Nussbaum), Sierre Energie (Laurent Antille, Jean-Marc Salamin, and Christophe Darioly), Centre Suisse d'Electronique et Microtechnique - CSEM (Andreas Hutter, and Philippe Renevey), and Centre de Recherches Energtiques et Municipales - CREM (Thierry Bernhard, and Gaetan Cherix). Finally, we would like to thank the STREP European Projects "Universal Integration of the Internet of Things through an IPv6-based Service Oriented Architecture enabling heterogeneous components interoperability (IoT6)" from the FP7 with the grant agreement no: 288445.

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