Towards the Future Internet
G. Tselentis et al. (Eds.)
IOS Press, 2010

Real time energy management in smart cities by Future Internet

Mikhail SIMONOV[a,b,1], Marco MUSSETTA[b,c], Andrea PIRISI[b] , Francesco GRIMACCIA[b], Davide CAPUTO[b] and Riccardo E. ZICH[b]

[a] *ISMB, Via P.C. Boggio 61, 10138 Torino, Italy*
[b] *Politecnico di Milano, Dipartimento di Energia, Via La Masa 34, 20156 Milano, Italy*
[c] *Politecnico di Torino, DELEN, Corso Duca degli Abruzzi 24, 10129, Torino, Italy*
simonov@ismb.it, {mikhail.simonov , marco.mussetta, andrea.pirisi, francesco.grimaccia, davide.caputo, riccardo.zich}@polimi.it

Abstract. Human behavior, both individually and socially, is aimed at maximizing some objective functions, and this is directly reflected in energy dynamics. New issues are emerging now, such as the unpredictability of some renewable sources generation and the new technologies enabling real time energy optimized use in smart cities. Here the role of the Future Internet in the smart grids is addressed, in particular enlightening how the anticipatory knowledge of the future occurrences of the energy consumption dynamics may be effectively promptly exchanged between competing actors.

Keywords. Future Internet, cooperative environments, smart cities, smart grids, real time energy management

1. Introduction

Nowadays more than 50% of the overall population of the world lives in urban contexts, contexts that are involved in a “natural” evolution process towards “smart” cities. The growing of this percentage makes smart urban environments dense and complex spaces, in which the energy distribution component, known as smart power grid, day after day presents a growing need of a new distributed intelligence in order to effectively manage all the incoming issues. Furthermore, the reduction of the carbon footprint of the cities is a pressing issue, necessitating a sophisticated control and management of the energy use on both the supply and demand sides over all aspects of city life. Much of the current studies on smart cities focus on this aspect. Future Internet [1] in a smart urban environment appears to us as the most effective tool that can enable the infrastructure to manage, control, optimize, and improve these aspects at both the micro- and the macro- level. For example, the detection of some repetitive events happening locally in real life, might impact on more cooperating or competing entities, suggesting the accounting and propagation of such events because of the expected consequences maturing elsewhere. This work is exactly focused on how to model, measure, monitor, optimize and control complex interdependent event flows happening in power grids, representing a significant infrastructure characterizing smart

[1] Corresponding Author.

cities. The use of Future Internet (FI), providing the means for a multiplicity of services, enabling the management of many different aspects of urban life, will be proposed and discussed in detail.

Human beings, especially in smart cities, rely on external sources of energy in order to achieve their personal and social goals. They consume every day a combination of different kinds of energy for above-mentioned dynamic processes, taking the real-time electric energy from the smart power grids. Nowadays, the energy in power grids is monitored using smart metering devices, but the load forecasting and control systems are separate fieldbus/SCADA entities, considering the under-frequency and shapes, but ignoring at all the human behavior influence on them because of the complexity [2]. Becoming smart requires a proactive awareness and semantic knowledge about the processes happening in real life. Modern electric energy networks have a distributed grid structure [3] with static nodes. Smart grids were originally designed following the top down approach, but they have been gradually adapted to accept bi-directional energy flows coming from the distributed energy generation, such as photovoltaic (PV hereafter) one. Since the PV production is weather-dependant, because of the solar activity, the season and the clouds, it is intrinsically characterized by production drops. In particular the cloud migration is a continuous natural process, which replicates the drops manifesting in one point of the topology at other nodes after Δt time elapsed. The monitoring of the PV drop due to the clouds shows a great industrial interest. The local negative PV production dynamics anticipate the future energy production drops at other locations, permitting to set up in advance some control actions which enable the optimization and management of the blackout conditions, as shown in Fig. 1.

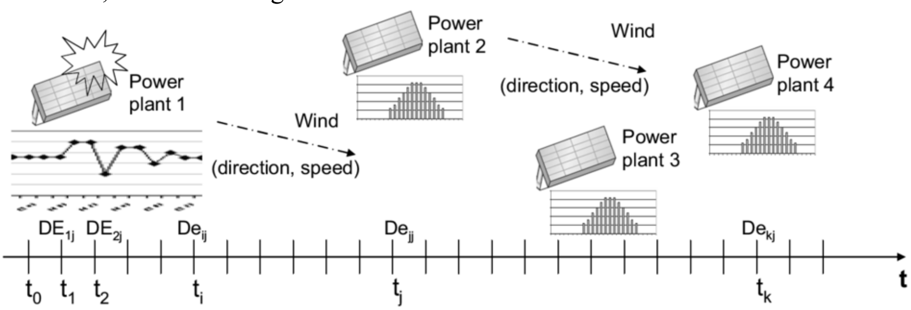


Figure 1 – Cooperating photovoltaic plants

Future Internet plays a new role: it interlinks completely independent fieldbus systems in one system-of-system topology, enabling new business scenarios impossible in the near past. The broadband communication supports the automated transactions at static nodes in real time, publish-subscribe assures the prompt actuation, while mobile and wireless loops extend the mobility. However the “intermittent” entities – not managed by current paradigms - go off-line frequently and stay in the gap between the Internet of Services (IoS hereafter) and Internet of Things (IoT hereafter). Future Internet can solve the extended cooperation business challenge, linking smart city entities in a way, permitting the optimization of the individual (profit) and collective (low carbon footprint) goals and generating concrete social benefits. Real time knowledge about causes of events becomes an IoT entity, capable to predict, rule and optimize the behavior of the whole network. It can be shared and made available, bringing the anticipatory knowledge about the relevant events which are going to happen at other sites. Hereunder we exploit this potential of Future Internet by one concrete photovoltaic distributed generation application class, showcasing how to network autonomous stakeholders in optimizing multi-agent cooperative system.

2. Anticipatory knowledge for extended cooperation

Currently the energy production is highly distributed with a significant contribute from small PV and wind plants which complement the energy needs of smart cities. Independent business actors run the above power stations injecting the produced energy into the grids. Their local fieldbus systems are not necessarily integrated in TCP-IP networks. Individually they try to maximize profits taking autonomously the energy trading commercial decisions. The decision making is based on the local information about the energy production dynamics, without any cooperation with the competing neighborhood. The renewable PV and wind energy is in some extent unpredictable because it depends on weather conditions which limit the maximum percentage of available renewable energy. The weather forecast can be provided to the individuals by different sources, including locally installed sensors and weather stations, but nowadays this information is not exchanged among the different energy production plants, which not necessarily have awareness about each other. The negative energy production dynamics satisfy the cause-effect relationship while the mobility of the clouds is a process that evolves and propagates continuously over the space. The lack of the anticipatory knowledge about the forthcoming production drops is a drawback of the independent distributed generation. Here we propose the knowledge sharing between PV power plants. The knowledge in advance of the expected production drop enables to set up a better load management strategy, offering an additional Δt time for the real time decision making. The transformation of the topology composed by autonomous PV generation entities in an inter-linked multi-agent cooperative topology able to process the anticipatory knowledge, eliminates the above-explained drawback and offers an improved energy efficiency. Let us observe a number of photovoltaic plants ubiquitously available in a smart city, which are interconnected – thanks to FI - and share the digitized energy events. The first plant that discovers negative energy production dynamics ("energy fall" event) now propagates this knowledge to neighborhood, advising about the cloud movement (Fig. 2).

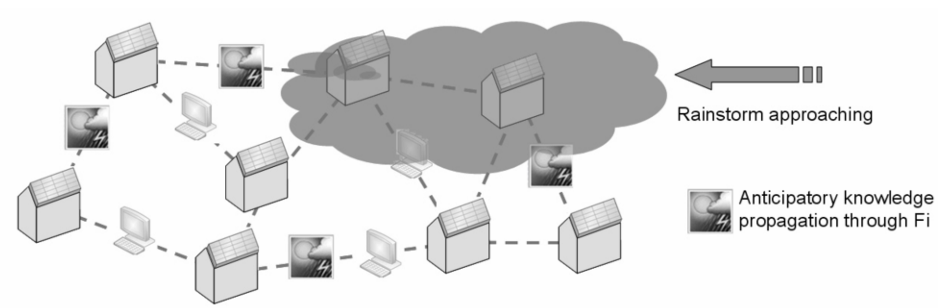


Figure 2 – An example of the use of anticipatory knowledge propagation over a FI infrastructure for forecasting PV production drops due to bad weather conditions in interconnected smart power grids.

The cooperating neighbors calculate their respective Δt_i times and estimate the events which are going to happen in a near future. The elaborated forecast, based on the anticipatory knowledge, can be used now to perform an anticipatory control, enhancing the efficiency of the cooperative load management strategies and optimizing the future energy injection/trading flows (Fig. 3).

In the liberalized energy markets, the price changes in real time and the users – energy consumers or renewable sources producers – should trade energy automatically, using advanced data management algorithms. This approach will give the possibility of choosing from different energy partners in real time, but it will require the exact information about the own - both current and expected - energy dynamics scheme. The precision and the accuracy of the estimation should be sufficient to cover time slots, corresponding to the expected commercial transactions, hourly or daily. This requires a real time data analysis plus the correlation of the available (historical) data with the real time conditions. In a PV distributed generation context, the wrongly estimated cloud variability might result in economic losses and energy imbalance, a factor to account before contracting any power selling. We propose a reference application class which comprises local weather sensors, the forecast, and (multi-agent) intelligent algorithms, contributing in the short-term trading decision. The knowledge of the exact position and displacement of the clouds is relevant to the neighbors, because it permits to forecast their sites' future load conditions; thanks to the FI, this knowledge can now be shared, enabling the collective optimization of the expected energy resources.

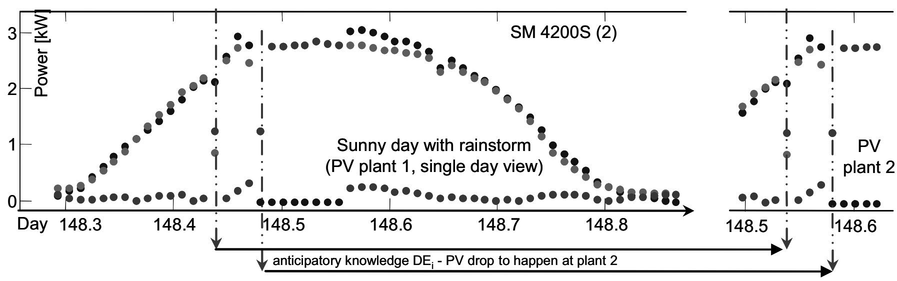


Figure 3 – Anticipatory knowledge about photovoltaic energy production dynamics

In addition, the above-said decisions – as a new entity - might be also shared for a-posteriori assessment, introducing further self-learning and self-correction capabilities in the distributed cognitive system. The complexity of this example highly increases; however it exemplifies **the use of the anticipatory knowledge** in smart power grids.

3. New challenges

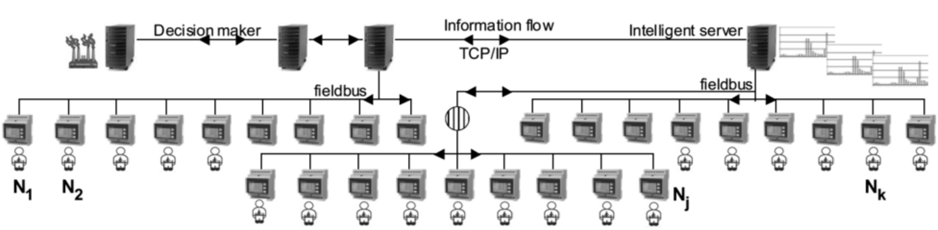
In a new forthcoming business scenario the local automated networks over fieldbus will be integrated as entities of the FI system-of-system, contributing in the creation of the new cognitive distributed smart power grid. In order to improve the predictability it is necessary to overcome the local unmanageability of the aggregated entities, proposing them some extended cooperation advantages. An issue is the integration of the billions of fieldbus subsystems (transformers LV/MV/HV separate physically PLC lines), and the WWW Legacy, challenging the adoption of intermediate servers and ubiquitous computing. Drawbacks of this approach are that the fieldbus protocols to integrate are different, in any case they bring some vulnerability, and the data flows are intense. The main research question now is how FI will help to ensure the real time proactive manageability of smart cities. Among the additional research questions we see: 1) how to calculate the expected timing/duration of the phenomena manifesting at a given node; 2) how to estimate precisely the entity of the expected transaction; 3) how to optimize the future flows and so on. The support comes from the semantic awareness about the dynamics of complex evolving systems.

We anticipate a possible architecture and define some tools for enabling an open electricity market managed in real time through IoT and IoS components, bridging between fieldbus components and IP network and allowing new roles for stakeholders. In our vision smart metering devices perform the real time energy digitization and the relevant events filtering, broadcasting them for the further elaboration done by intelligent servers with cognitive capabilities. The energy consumption dynamics are correlated with the formalized knowledge in Ontology about the firm relationships impacting on the energy dynamics. For example the Fuzzy rule “IF cloud THEN photovoltaic drop” permits to trigger the anticipatory knowledge and proactive reaction in a distributed context. The collective decision making in an inter-linked smart grid becomes a self-managed entity, offering a higher efficiency and safety. The capability to support real time transactions with digitized energy between *prosumers* on the open liberalized energy markets appears pre-competitive today, but it changes the way of operating power grids, because B2B automated operations by service delivery platform become new e-services and replace Legacy.

The FI will bring the openness to different business models already existing on the market and will support in particular new models, ensuring new roles for digital energy brokers, such as energy advisors, user needs consultants and other advanced functions. Service platform, being enriched by knowledge technologies, contribute in semantic understanding of the events; this enables self-configurability and adaptation to the changing requirements of the evolving markets, nowadays still in their definition phase. Moreover, the FI services create borderless B2B marketplace of the global energy services, enabling to operate from different geo-political realities, eliminating the national diversities and making other technical aspects transparent for the final users.

4. Future Internet for smartness

Modern smart cities, and smart power grids as integral part of them, can be seen as a common distributed information space, where people interoperate using the artifacts with communication capabilities. This topology from the ICT viewpoint has a structure shown on Fig. 4, where arrows show the information and knowledge exchange.



Since smart city with an embedded power grid is a distributed environment, it can be assumed as a system-of-system topology in which a continuous information and knowledge flows exist.

The main backbones of this topology are served by TCP-IP connectivity, where the power line supports the data communication over the local topologies such as households and industries, by linking the fieldbus of the devices belonging to the same voltage segments. This solution requires an additional technical solution to overcome the limitation imposed by the physical peculiarity of the voltage transformers, by physically separating High Voltage (HV), Medium Voltage (MV), and the Low Voltage (LV) segments that should be considered as linked layers, integrated in the global Web. The collection of the automated metering devices [4] belonging to a given power grid becomes the set of the static nodes – IoT entities – and it defines the topology of the distributed environment.

Take into account that the Web of communicating electric devices it is not only an abstract distributed environment, but it is an important candidate for e-business in a liberalized electricity market, that it is made possible by information about the real asset (energy), such as digital information representing the real energy in the virtual Internet of Things world [5]. Since the storage-less smart power grids have static nodes, a suitable commercial policy aims to make the energy trend of the nodes as much predictable as possible. In this sense, the cooperation between multi-agent PV systems and electric vehicle will play a crucial role electric in future smart cities, since electric vehicles can be used as local storage units [6] for PV energy production. For those reasons, a predictable oncoming scenario is expected to rely on dynamic FI nodes, which aspects are discussed in [7].

The experience about the management of users energy demand will trigger the decision-making tools that operate in smart power grids, and it will also make available the possibility to realize the best clustering of the virtual communities [8].

5. Distributed and cooperating photovoltaic grid

Energy management by means of FI requires high computational capability in order to realize a real-time optimization of energy production, distribution, storage and consumption in smart cities, villages and also rural areas [9, 10]. In fact, it is possible to conceive an energy hub as a micro-grid where electrical loads and small generation systems (such as renewable energies in the range of 25-100kW) are integrated into a Low Voltage (LV) distribution network with micro-storing systems (composed e.g.. by the integration of electric vehicle into the grid infrastructure). By this point of view, an energy hub appears as a micro-marketplace since it should be composed by generation units, storing devices and a small number of consumers and it can operate interconnected to the main distribution grid or in autonomous way in case of external fault. By integrating FI into the architecture of energy hubs, it is possible to have instant access to load forecasting, demand side management, economic scheduling of micro-generators and to trade energy and information with local providers [11].

FI network is a framework where energy is produced, distributed, stored and used by systems that are deeply connected each other. New high-voltage and low-losses underground lines can be designed with 'smart' feature nodes that will provide consumers with sophisticated information and easy-to-use tools in order to increase the efficiency of the network with a sensible reduction of costs. In such a smart system, customers will be equipped with smart measuring instruments that report their **real-time power consumption** to the authority that will be able to optimize the energy production in order to reduce the number and the size of energy demand peaks. The distributed information management techniques contribute in the above domain since the nodes of the power grid are ubiquitously distributed and integrated by FI. Further details on this topic can be found in [12].

Load forecasting has always been crucial for the effectiveness of the electrical system. Power load forecasting is a area of interest for many companies that rely upon traditional prediction methods [13]. However, since the relationship between power demand and load parameters is nonlinear, it is difficult to model the behavior of the net by using traditional prediction methods.

Since the complexity of this scenario requires the capability to predict the dynamics of the system and to offer an optimal management it has been proposed the application of an Artificial Neural Network (ANN) integrated to an optimization algorithm in order to create a predictive model of the physical system and to provide an efficient control of resources and information [8]. To implement this approach, evolutionary optimization procedures adaptively and dynamically analyzing consumer profiles have been defined. Through FI smart cities provide a complex amount of data with a relevant number of profiles, which can be effectively managed in real-time by evolutionary neuro-fuzzy tools.

In recent years, renewable energy sources have increased the complexity of this scenario: solar power is getting more and more important as an alternative and renewable energy source, especially for small autonomous electrical power systems, villages and also rural areas. PV plants can also be connected to the traditional grid for energy distribution, but variations in solar power can cause, in general, voltage and frequency fluctuations.

Advanced forecasting through evolutionary computation techniques provide utilities with reliable production predictions and the opportunity to plan for additional power supply and to make proactive actions. This aspect can have an impact on the economic balance of the systems especially in an integrated smart grid solution perspective. These tools provide the ability to use stored energy or electric vehicle load to firms and renewable productions, increasing their intrinsic value. On the other hand, in this way the system-plant management is capable to plan appropriate preventive maintenance strategies in order to minimize energy losses due to unproductive suspensions. It can be estimated savings up to 0.5 M$/MW per year adopting these predictive algorithms in the renewable energy sector and at least the 10% of these are due to an optimized operating efficiency [14, 15].

It is possible to increase the solar power penetration if suitable measures are taken concerning solar radiation forecasting. This procedure may also affect the energy efficiency of the conventional power stations, since it affects the operating point of power units. Solar power forecast is therefore important for the efficiency of load management in the system and it can rely on the use of ANNs, as suggested in literature [16].

Artificial Neural Networks (ANNs) are particularly appealing because of their ability to model an unspecified nonlinear relationship between load and weather variables. In fact, the complex nature of many engineering problems may involve Soft Computing techniques in order to solve optimization tasks. In particular an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Among many ANN implementations, the multilayered perceptron (MLP) is a well-known universal approximate and has been extensively used in engineering. It consists of an input layer, one or more hidden layer, and an output layer. In a MLP, the function *f(x)* is defined as a recursive composition of other functions $g_i(x)$, thus leading to the network structure depicted in Fig. 5, where the dependencies between variables are represented by the connections among neurons. The input composition in each neuron is made by a nonlinear weighted sum,

$$f(x) = k\left(\sum_i w_i g_i(x)\right) \tag{1}$$

where *k(x)* is a nonlinear activation function which models the activity of biological neurons in the brain. This function is modeled in several ways; the most common is the hyperbolic tangent, which ranges from -1 to 1:

$$k(x) = \tanh(x) \tag{2}$$

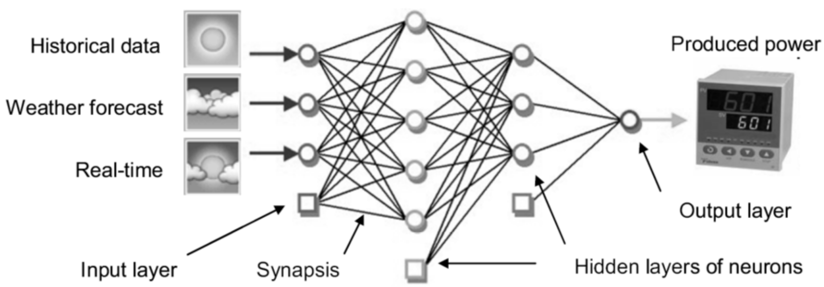


Figure 5 – Simplified view of the implemented feed-forward ANN with details on input, output, and hidden layers.

One of the most critical phase in managing an ANN is the training one, when the best weights of the neural connections have to be defined. There are three major learning paradigms, each corresponding to a particular abstract learning task: supervised learning, unsupervised learning and reinforcement learning.

Supervised learning is commonly used for tasks like pattern recognition, classification, regression and approximation. The supervised learning paradigm can be also applied to speech recognition. Its implementation includes a function that provides continuous feedback on the quality of solutions obtained thus far.

In supervised learning, we are given a number N of set of example pairs (x_i, y_i), where $x_i \in X$, $y_i \in Y$, and the aim is to find a function $f : X \rightarrow Y$ that matches the examples. In other words, ANN wish to infer the mapping implied by the data; the cost function is related to the mismatch between the proposed mapping and the data and for this reason it must contains prior knowledge about the problem domain. The parameters of the network have to be optimized in order to reach a good and accurate output. Therefore the learning process should result in finding the weights configuration associated to the minimum output error, namely the optimized weights configuration. A commonly used cost is the mean-squared error which tries to minimize the average squared error between the network's output, *f(x)*, and the target value y over all the example pairs.

The MLP can be trained by several strategies, such as gradient descent based strategies, like the Error Back-Propagation algorithm (EBP) or evolutionary methods, like GA or PSO [17]. For network training, a data set of geometrical configurations of the patch is generated and the corresponding phase delays are estimated.

Trained ANN is tested on a Validation Set (VS) in order to validate its ability to properly reconstruct the correct data model. When the training is performed, the *rms* errors of both the training and validation processes decrease with increasing iterations.

As shown in fig. 5, weather prediction is a key input when the ANN is used for forecasting. But, in case of rapid changes in solar radiation or temperature at the analyzed day, the produced power changes greatly with respect to the forecast value. In traditional prediction methods the ANN uses a pattern of comparable data to learn the trend of the days with very like weather. However, learning all similar days' data is quite complex, and it does not help if weather conditions change suddenly. Therefore, it is necessary to integrate the neural network structure with real time information coming from local meteorological stations and, in particular, from surrounding regions and cities, where the weather change has already occurred. FI infrastructures among smart cities could provide the integration of all these data by real-time connecting all the sources of useful information for the load and energy production forecasting.

The results reported in fig. 6 show a more accurate forecasting obtained by using traditional weather forecasts. The integration of real-time information helps to estimate and correct the uncertainty in the weather forecast.

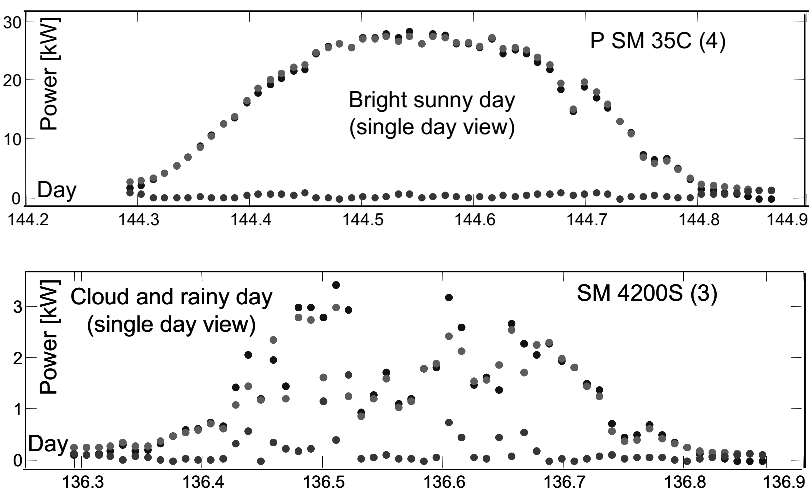


Figure 6 – Real time information integrating PV plants in smart cities

6. Conclusions

Future Internet deeply changes smart cities enabling new distributed business transactions on e-markets: it transforms former competitors in entities cooperating in the optimization of the collective social functions. The role of the anticipatory knowledge and its business contribute by considering a network of distributed photovoltaic generators that make possible an inter-operable system in smart power grid have been addressed. A Use Case on how one Internet of Things digital entity can enable an extended collaboration and knowledge management in smart grids has been presented. The Use Case about photovoltaic plants has been selected as representative of the concrete business potential, justifying the research effort required. In particular the authors suggest some models of the solar radiation based on artificial intelligence, such as ANNs, in order to improve the efficiency of short-range forecasting. Moreover, this predictive model has been enhanced by the integration with the real-time information coming from the surroundings, in the framework of the future IoT. Better predictability and observability improve the ratio between renewable and non-renewable energy. Future work will be related to the development of new algorithms to support FI dynamic entities and experimentations.

References

[1] G. Tselentis, J. Domingue, A. Galis, A. Gavras, D. Hausheer, S. Krco, V. Lotz, T. Zahariadis, *Towards the Future Internet – A European Research Perspective*, IOS Press, Amsterdam, 2009.

[2] J. Frunt, W.L. Kling, J.M.A. Myrzik, F.A. Nobel, D.A.M. Klaar, "Effects of Further Integration of Distributed Generation on the Electricity Market", *Proceedings from UPEC '06: The 41st Intl. Univ. Power Engineering Conf.* **1** (2006), pp. 1–5.

[3] Jiyuan Fan, S. Borlase, The evolution of distribution", *IEEE Power and Energy Magazine*, **7**(2) (2009), pp. 63–68.

[4] T. Singh, P.K. Vara, "Smart Metering the Clouds", *18th IEEE Int. Workshops on Enabling Technologies: Infrastructures for Collaborative Enterprises* (2009) , pp. 66–71.

[5] L.H. Tsoukalas, R. Gao, "From smart grids to an energy internet: Assumptions, architectures and requirements", *Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies* (2008), pp. 94–98.

[6] A. Brooks, "Integration of electric drive vehicles with the power grid-a new application for vehicle batteries", *The 17th Annual Battery Conference on Applications and Advances* (2002), p.239.

[7] J.A. Pecas-Lopes, P.M. Rocha-Almeida, F.J. Soares, "Using vehicle-to-grid to maximize the integration of intermittent renewable energy resources in islanded electric grids", *International Conference on Clean Electrical Power* (2009), pp. 290–295.

[8] M. Simonov, M. Mussetta, R.E. Zich, "Digital Energy: Clustering Micro Grids for Social Networking", *International Journal of Virtual Communities and Social Networking* **1**(3) (2009), pp. 75–93.

[9] R.B. Chedid, S.H. Karaki, C.El-Chamali, "Adaptive fuzzy control for wind-diesel weak power systems" *IEEE Trans. Energy Conversion* **15** (2000), pp. 71–78.

[10] A.N. Celik, "A simplified model for estimating the monthly performance of autonomous wind energy systems with battery storage", *Renewable Energy* **28** (2003), pp. 561–572.

[11] J.A. Pecas Lopes, "Advanced Microgrids as a Component for Active Management of Distribution Networks", *Proc. Int. Conf. on Power Engineering, Energy and Electrical Drives, PowerEng '09* (2009), pp. 7–8.

[12] A. Soro, E. Vargiu, G. Armano, and G. Paddeu (eds.), Information Retrieval and Mining in Distributed Environments, Springer, 2010 (in press).

[13] T. Senjyu, H. Takara, K. Uezato, "Two-hour-ahead load forecasting using neural network," *Proceedings International Conference on Power System Technology*, **2** (2000), pp. 1119–1124.

[14] Nazarko, J. El-Saadawi, M.S. Dehghan, B. Kiani, A. Kazemi, A. Parizad, "Optimal Sizing of a Hybrid Wind/PV Plant Considering Reliability Indices", *World Academy of Science, Engineering and Technology*, **56** (2009), pp.527–535.

[15] R. Karki, R. Billinton, "Reliability/cost implications of PV and wind energy utilization in small isolated power systems", *IEEE Trans. on Energy Conversion*, **16**(4) (2001), pp. 368–373.

[16] W. Taylor, and R. Buizza, "Neural network load forecasting with weather ensemble predictions," *IEEE Transactions on Power Systems*, **17**(3) (2002), pp. 626–632.

[17] E. Grimaldi, F. Grimaccia, M. Mussetta, R. Zich. "PSO as an effective learning algorithm for neural network applications", *Proc. of the 3rd International Conference on Computational Electromagnetics and Its Applications,* (2004), pp. 557–560.