# Smart Buildings and the Smart Grid

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***Abstract*—So far the worlds of building automation and power networks have co-existed electrically attached but without data interaction, with different, and sometimes divergent, goals and requirements. The smartgrid community is coping nowadays with a new phase in the deployment of its vision: the integration of smart buildings, making use of their services and advantages to enable more complex functionalities at a global level. The main objective of this paper is to review latest results of the research community of industrial electronics, whose society within the IEEE, the IES, acts as the organizer of this conference. At the conference, latest advances and developments in design, modelling, simulating and implementing tools for, or systems of, sensor and/or actuator networks with advances towards user orientation, wireless connectivity, dependability, energy efficiency, context awareness and ubiquitous computing will be presented.**

## I. Introduction

Smart grids rose as an evolution of classical power networks to face new challenges that advances in diverse techniques and technologies have posed. Thus, the tight schema in which electricity flew from the generation points to the final customer through the transport and distribution networks has been altered with the emergence of distributed generation, dual consumer-generator roles, virtual power plants, micro-grids, moving demand and storage (e.g. the Electric Vehicle), and so on. Moreover, it is very likely that new problems and demands will appear.

The different historical circumstances have left a high number of smart-grid-related protocols, as noted by EPRI and NIST [1], [2], [3]. Luckily, these institutions and the IEC, have joined efforts in the design of a widely-accepted standard that satisfies all smart grid requirements. In this way, there are two *de facto* champions nowadays : CIM [4] and the IEC 61850 series and their harmonisation is being currently achieved [5], [6], [7].

Building automation presents a worse perspective in this sense with a tangle of incompatible Field-Area Network (FAN) protocols: different media and communication protocols which may even vary from country to country, each one presenting its own goals and capabilities. Although some initiatives dealing with FAN interoperability date in the late 90s [8], in the praxis many different FANs may co-exist in the same building each one devoted to the management of a separate technology such as HVAC (heating, ventilation, and air condition), alarm, fire control or lightning.

Everybody takes for granted that smart buildings are a pillar in the smart grid construction, a key stone, since their ability to self-control their consumption (and having the so-called Zero-Energy Building as the goal to reach), accurately predict it and engage in advanced demand-response programmes, between others, converts them in a crucial tool for grid operators. Still, in order to achieve the proper integration, we first must bridge the gap existing between the two worlds; in other words, to standardise the integration of smart-buildings into the smart grid.

Finally, this integration comprises both low level problems, such as how to manage sensor networks, and higher-level ones, such as how to harmonise both world's data models or how to use sensor networks for a value-added service such as consumption prognosis. In this paper we give account on the latest advances on these areas.

## II. Ultra-low power wireless sensor networks

The topic of wireless sensor networks is a keystone in smart buildings. In modern constructions and private homes, many devices like lighting, heating and cooling (with temperature sensors), elevators, windows, data displays, and even household appliances like dish washers and refrigerators have to be able to communicate in order to coordinate their functionality. All of these devices can be controlled in a centralized manner if the required environment data (e.g. room temperature, number of present persons in a room, open-state of windows, doors, and refrigerator doors, etc.) is available. This data can then be used to enhance security (mostly in terms of theft protection) and safety (e.g. by setting a foundation for ambient assisted living (AAL) applications).

Another very active area of research is automotive communication. Many systems are changed from cable-based to wireless in order to save cables and thereby weight and in the end fuel. Examples are many comfortability systems like distance sensors or safety related systems like tire pressure monitoring [9], [10]. This trend was extended recently when "Car2X" [11], [12] moved into focus of many research groups. This research is intended to help lowering the number of car accidents (and thereby the number of traffic deaths and injuries) worldwide. Car2X is an umbrella term for "Car2Environment" and "Car2Car"; the former meaning communication between cars and stationary objects, e.g. street signs, traffic lights, bridges, etc. Typical data to be communicated could be information about current traffic jams, dangerous bends, frozen-over bridges, routing changes, or traffic congestions. The latter [13], [14], [15] focuses on communication between cars themselves. Typical data to be communicated could be information about car crashes ahead, cars braking ahead (being

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the electronical equivalent of the brake lights the driver can see), burst tires, and many more.

The data needed for control is collected by numerous specialized sensors and transferred to the central unit (of a building or car) or distributed local central units.

Nowadays, mainly two channels are used for this, namely power-line-communication (PLC) [11], [12] and wireless communication. The former is easily applicable for devices which have to be connected by cable to the power grid, anyway. However, a large number of connected PLC devices lead to diverse problems from channel congestion to security issues [13]. More commonly, wireless communication is used. Wireless sensor networks (WSN) do not need physical cable infrastructure and can even connect ad hoc to devices currently in reach.

One of the most important scientific questions is the energy consumption of wireless sensors, since many of them are implemented in the form of battery-powered embedded systems. Obviously, it is important to design cheap, small devices with a long battery life. This can be achieved by a clever chip design or by power management in the running system itself [16], [17], the use of smart compression schemes [18] for communications, or even network-topology-based optimizations [19]. In some approaches, the extension of battery life is achieved by means of energy harvesting. This means that energy is taken from the environment to partly or fully fuel the device in question. In buildings, e.g. ambient light can be harvested [20], [21]; in the automotive area, e.g. vibrations of the tire on the street can be exploited [22]. Other approaches try to compare different possible designs and choose the most energy-saving approach (design space exploration); this is mostly done by energy consumption estimation in simulations [23]. In some cases, only single chips are simulated and optimized, other approaches simulate and monitor the energy consumption of specific messages throughout the whole sensor network [24], [25].

Another field of research is the analysis of the data sent throughout the network. There are many available wireless protocols like ZigBee, OneNet, EnOcean, 6LoWPAN, etc., so the designer of a wireless sensor has to decide which protocol to use [26], [27]. In many cases, a specific routing is proposed to enable real-time operation [28], [29].

In order to be able to monitor the energy consumption of devices used in building automation environments, even software-in-the-loop approaches are interesting. Typically a complete experimental set-up of a building or apartment containing household devices like refrigerators, washing machines, air conditioners, etc. is expensive and bulky, therefore specific devices are replaced by real-time simulations [30], [31]. Another more recent approach is the simulation of complete buildings using simulators which were intended for systems on chip by setting the simulation period to seconds instead of picoseconds [23].

All these optimizations make sensor networks in buildings and automotive applications useful and help enhance safety and security.

## III. Integration Challenges

Related to the previous section, not only should the devices can communicate between them but they need to understand each other. In this sense there are tree main challenges that have to be tackled in order to achieve the integration of the diverse smart building scenario protocols into the real-time framework controlling the smart grid.

### A. Harmonisation of the data model

One of the most urgent requests in the smart grid is to finish with the existing protocol mess. For instance, in low-voltage meters, ANSI C.12 rules in the USA whereas COSEM (Companion Specification for Energy Metering) is the standard Europa-wide. Thus, it seems sound to unify and harmonise all standard protocols that might be used in the scenario we target at: IEC 61850 [32], DLMS/COSEM [33] and CIM [4]. The first technique proposes the construction of an unified UML model based on CIM, and extending it with concepts referent to 61850 [32]. The second approach has to do with the maintenance of independent semantic models and the definition of the relationships between them through OWL ontology assertions. Both means require the description of the IEC61850 data model, which is not offered by the standard itself.

In the first case, the main problem is that the harmonised ontology is so far too big be used on embedded devices. A solution for this problem has been described in [32], [34], [35] where the authors present a semantically distributed system, in which each device only has a piece of the ontology (the so called *profile* describing its piece of the world but, at the same tame, it has the mechanisms to *discover* the rest of the infrastructures.

As stated before, the second approach maintains an independent semantic data model defined in each standard. The integration of the semantic data models is managed by the explicit definition of equality OWL axioms between classes of IEC 61850 and CIM. Following this technique, there is a recent research [36] that has developed a tool for translating between configuration files written in CIM to Substation Configuration Description (SCD), and vice versa.

### B. Abstraction upon the network protocol

There are many different fieldbus area protocols, communication protocols and proprietary applications that have to be abstracted seamlessly. This enterprise is not new, since it was already tackled in the late 90s connecting diverse fieldbus protocols to an IP network through a three-layered gateway [37]. In that case, the bottom layer included a number of fieldbus protocols, the middle one the data model layer and the upper one provided the IP connection. By analogy, the right strategy seems to be mapping each of the protocols to the data model layer obtained above.

### C. Connection to the real-time middleware

DPWS offers a rigid get-set functionality (i.e. read or write a variable of a device) as in [38], converting the operations on that variable on a so-called *internal* service. In this way, external services are the aggregation of a number of several internal ones; in the SOA jargon, the arrangement in sequence

and organisation of them is called service *orchestration*. This third upper layer will wrap the other two, connecting to the DDS network as an OSGi real-time service. This strategy will allow to perform the aggregation and coordination of services both locally and remotely in a natural way.

## IV. Short Term Load Forecasting

One of the holy grails of the smart grid is achieve the so-called Demand Side Response (i. e., be able to influence the consumption pattern of a client seamlessly). The two previous challenges are necessary conditions to this end but when the aim is to improve the overall consumption (namely, optimise in one or other sense) it is not enough since in this case, a control strategy is needed [39], [40]. It is common knowledge [41] that the use of a good forecast improves the optimisation made for any control strategy.

Short-term load forecasting (STLF) is the tool to cope with this problem. Traditionally, STLF refers to the prediction of the load of a large region composed of several hundred of buildings and industrial consumers. In this situation, it has been measured that the the cost of the deviation from the forecast can represent millions of Euros of losses to the Transmission and System Operator [42]. Therefore, it does not surprise the huge interest in improving the forecast accuracy (see [43] for example) or the huge number of research works in this sense (see [44], [45], [46] and [47]). On the other hand, building short-term load forecasting (bSTLF) is a novel field of interest in the research community but it has presented an hectic activity these last years [48], [49], [50], [51], [52], [53] given the new possibilities of the smart grid.

Historically, the solutions proposed have been grouped into two main branches, depending on the strategy chosen. First, statistical methods are designed to estimate a regression function that matches the points recorded in the historical load data. There exist a number of very effective ways to approach regular curves but, since load forecasting usually lacks of regularity, statistical methods alone normally present poorer results than their counterparts [42], [54]. Still, the most notable results have been achieved with dynamic linear or non-linear ARMAX models [55], and non-parametric regression [56] with ARIMA [57].

Second, Artificial Intelligence has devised plenty of techniques, methods, and models that address risk and uncertainty (the main aspects behind prediction). Support Vector Machines (SVM) and Neural Networks (NN) [58], [59] are the most popular, principally due to their accuracy. Yet, despite being effective, they are usually not efficient and, additionally, they also present other drawbacks such as difficult parametrization, non-obvious selection of variables and over-fitting. Furthermore, in the praxis they normally require much historical data to *discover* the patterns inherent on it [54], [60].

Moreover, the most widely-used method, NN, further presents more shortcomings such as a very time-consuming learning process, the risk of local minima [61], the lack of an exact rule for setting the number of hidden neurons to avoid over-fitting or under-fitting [62], the inability to generate explanations for their results, and, finally, their poor scalability [63]. Lately, the research in this area has evolved to improve SVM-based models' performance through clustering [64], or to combine regression with evolutionary algorithms for parameters settings [65].

As it can be seen, the trend is not to lay on a certain model but to address a number of them together in order for instance to take advance of their synergies or complementaries. Indeed, some methods may be successful under certain conditions whereas fail in others. In the same vein, each one has been devised with a certain goal in mind and, therefore, they offer different sort of information and precision degrees. Choosing the model whose error is minimal as the optimum may result in losing some important feedback. Model combination faces exactly this problem: it is a well-established methodology that improves the accuracy of a forecast [66] and has already been already applied to other disciplines with success (see [67] for a comprehensive survey).

Now, prediction methods are not the only thing that can be combined to achieve a better forecast. Adjacent buildings usually share a number of common features such as the weather, social class, or work schedule. Moreover, they would be influenced by the same special circumstances, say sportive events, festivities, and so on. [68] analyses several forecast aggregation techniques of the compounding loads of a primary substation. While it is not immediate that the same techniques can be used to buildings it could represent an important improvement.

Following this vision, there have been research initiatives in which different models where applied to take advantage from common features, such as for instance, using information of adjoining sensors in a tide measurement system [69] (applying gaussian processes). There, the commonalities among the sensors are evident, which is not the case. Two contiguous primary substation may supply energy to highly different neighbourhoods, resulting in completely contrary demand profiles (think of contiguous commercial and residential areas). Hence, this demanding issue is not clear and, to our knowledge, is still open since nobody has coped with it before.

## V. Conclusions

The research around building automation, smart grids, sensor networks, and their integration is well established within the Industrial Electronics Society of IEEE. This conference, being the flagship event of the society, annually brings together researchers from all over the planet, which fosters exchange and communication, topics that cannot be overestimated in interdisciplinary research, which arises when previously mature stand-alone fields grow together.

We have focused here on giving an outlook on the advances on three aspects, namely ultra-low power wireless sensor networks, the strategies to cope with the integration of smart buildings into the smart grid and an added-value application that brings together both worlds, short-term load forecasting and its branch, building short-term load forecasting.

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