Embedded Networked Monitoring and Control for Renewable Energy Storage Systems

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***Abstract*—Energy storage plays an important role in managing effectively the integration of distributed renewable energy generation within the electrical networks of the future. Pervasive monitoring and control of these systems makes growing use of information and communication technologies, which aim at secure and economic operation at various scales from microgrids to system-wide integration. Among these, low power wireless communication and computing embedded systems, in the main form of wireless sensor networks (WSN), have become a robust solution. Through hardware and software architectures, along with appropriate mechanisms e.g. for data collection and aggregation, wireless communication protocols and standards, they represent a valid solution in assuring continuous and reliable operation. The paper introduces a cyber-physical framework for renewable storage systems monitoring and control and discusses the application of wireless sensor networks to densely instrument such deployments. A hardware-in-the-loop type structure is designed which allows both testing various types of real storage systems, as well as more complex simulated models derived from large scale applications. We argue that the specific advantages brought forward by the advances in WSN technology can be put to efficient use for local distributed intelligence and control. Experimental data collected is analyzed in order to achieve an insight into the characteristics of the proposed solution.**

Keywords—renewable energy; energy storage systems; hardware in the loop; pervasive monitoring and control; industrial wireless sensor networks

I. INTRODUCTION

Clean and sustainable energy has become an overarching societal goal which transforms the way people and businesses perceive energy. A natural push towards environmentally safe energy resources has been accompanied by various initiatives that help accelerate this trend. In order to accommodate the inherent variability of renewable energy sources like solar or wind, efficient design and new control strategies have to be implemented in order to assure viable economic operation of the grid.

Microgrids [1] are a type of self-enclosed electrical grid architecture which include generation, low and medium voltage distribution and loads which should be at least partially controllable. These types of small scale electrical networks can be operated either in islanded mode, separated from the main grid, or in grid-connected mode. Offering specific advantages for system operators in flexibility and scalability as well as serving as test beds for validation of hierarchical control for generation, distribution and consumption they have been the subject of many research projects over the last years. Microgrids are seen as a vital building block of the future smart grid where modern electrical networks are enhanced by real-time communication and computing to increase service level and environmentally friendly operation. Among the disadvantages, one can list the lack of reserve power to accommodate demand peaks and the need to provision back-up generation. For example, a microgrid might lack the spinning reserve of conventional generators, which in traditional electrical networks allows the system to quickly respond to increased demand and variations in network parameters. Therefore, within microgrids, the role of storage [2] has become very important. Several technologies are currently in use with intensive research efforts underway aimed at reducing cost and increasing adoption among utilities. The most important energy storage system technologies include: conventional batteries, sodium-sulfur batteries (NaS), flywheel energy storage (FES), supercapacitors and superconducting magnetic energy storage. Among batteries, as form of electrochemical energy storage the main differentiator is chemical composition whether Lead-acid, Nickel-iron, Nickel-Cadmium (NiCd), Nickel-Metal Hydride (NiMh) and Lithium Ion. The choice of electrochemical storage technology takes into account several criteria like capacity, the number of rated discharge cycles, energy density in Wh/kg, resilience to poor charge-discharge conditions and overall costs.

The kind of distributed generation and consumption across future electrical networks offers a suitable application domain for deploying dense monitoring and control entities in the form of wireless sensor networks (WSN). This category of embedded networked devices enables distributed communication and computing and can lead to optimized decentralized control structures by exploiting mesh networks and local processing capabilities of the individual nodes. Industrial wireless sensor networks (IWSN) [3] have emerged as a ruggedized class of WSNs, suitable for demanding environments and applications. Implementations have already occurred at various scales in monitoring industrial processes. Specific requirements cover robustness of the communication protocols, determinism in the form of real-time or near real-time behaviour and standardization efforts to assure vendor interoperability.

The rest of the paper is structured as follows. Section 2 discusses the related work concerning similar developments of embedded networked systems for renewable energy monitoring while underlining the novel nature of our work. In Section 3 a system architecture is introduced that was designed in order to allow testing of monitoring and control for energy storage systems, including a model-based hardware-in-the-loop approach. Experimental set-up and results concerning the monitoring through and IWSN are illustrated in Section 4. Section 5 discusses the conclusions of the work as a solid basis for further developments.

II. Related Work

Solar plant monitoring and control through wireless sensor networks has been actively approached in the scientific literature. In [4] a ZigBee WSN was deployed to measure voltage, current, solar irradiance and temperature at the module level. Information is used to control a DC-DC converter for maximum power point tracking, along with suitable visualization software for the plant operator. A thorough similar application covering sensor node design and going up to the system level and database integration is described in [5]. Nodes are powered directly from the solar panel and store their energy in supercapacitors for night-time operation. In depth profiling of power supply and communication traces is carried out to optimize the system.

Applications of wireless sensor networks to wind plant monitoring are mainly of indirect nature, relating to condition monitoring of mechanical structures. In [6], structural monitoring for both electrical machines in the turbine tower and for the structure itself is carried out through a network of wireless sensors with integrated acceleration (vibration), displacement and force transducers. Comparison with traditional wired data acquisition equipment is also performed for validation. It is concluded that wireless sensor networks offer a viable alternative even in high frequency sampling for structural monitoring. In [7], a probabilistic method to assess such deployments of wireless sensor networks in a wind farm is described. The technique relies on Markov models to build fault tolerant systems in wind turbine monitoring.

Battery modeling for renewable energy systems has been surveyed in [8]. An economic comparative study of various technologies was performed focusing mainly on purchase and installation costs. Also models for realistic discharge and charge curve in grid operation are derived. The authors of [9] perform a comprehensive study of charge controller design for a renewable energy system composed of a solar panel and a lead acid battery. A first order dynamic model is experimentally computed through a step response method. A PI controller is designed in order to assure appropriate charging behaviour and avoiding overcharging. The three steps of battery charging are identified: high intensity charge, exponentially decreasing current and finally trickle current to keep the battery in a charged state. In this context, our main contribution relates to a general architecture for modeling and control of renewable energy storage systems, focused mainly on electrochemical storage within batteries, and discussion regarding embedded networked devices implementation for distributed monitoring and control. This is covered by experimental results for storage system identification over an industrial wireless sensor network.

III. Modeling and Control Framework

A. Lead Acid Battery Fundamentals

With over a century since their initial development, lead acid batteries have been proven as a robust technology for electrochemical energy storage. Their advantages include lower cost and well known manufacturing technology and validated behaviour. Among the disadvantages are: lower energy density, sensitivity to charging and discharging conditions, temperature effects and lower usable capacity as deep discharge cycles reduce the useful life of the battery. Main characteristics of lead acid batteries, which are to be considered in designing a renewable energy storage system are nominal capacity, rated number of charge/discharge cycles, and allowable depth of discharge which defines usable capacity. Large scale energy storage facilities dispose of battery banks to achieve a specified voltage and capacity. In this case the control system has to take into account individual battery parameters in order to optimally distribute the charge and discharge load. Battery dynamic capacity is strongly dependant on discharge current rate, as stated by Peukert's law:

$$C_p = I^k \cdot t \tag{1}$$

where Cp is the capacity in Ah at constant 1A discharge rate, I is the actual discharge current and t is the actual time to discharge the battery, in hours. The exponent k is a constant which depends on battery construction. In our case, for gel lead acid batteries, it ranges between 1.1 and 1.25. Figure 1 illustrates this dependency for the BSB Solar 12V 200AH battery [10] which we use as reference for the present study.

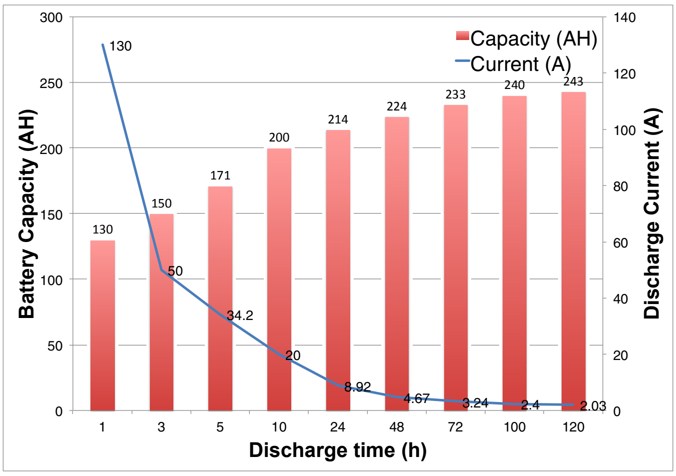

Fig. 1. BSB 12-200 Lead Acid Battery Capacity Depending on Discharge Current.

Due to irreversible chemical phenomena occurring at low charge states which reduce battery capacity and lifetime, the battery state of charge (SOC), which quantifies the actual energy stored in the battery at a given time, has to be permanently monitored. The two main methods used involve either battery terminal voltage monitoring or measurement of discharge current from a full charge state, also known as ”Coulomb counting”. Inferring SOC from battery terminal voltage involves using look-up functions which correlate the measured voltage to specific discharge curves given by the manufacturer. The current measurement suffers from the ability to precisely estimate the current SOC and accumulation of errors during the integration of the discharge current. As both methods are usually imprecise to a certain degree, more advanced methods like the application of Kalman filtering to predict the SOC based on noisy measurement and uncertainties have been developed. According to the simplified equivalent model of the lead acid battery equivalent electric circuit presented in [11], the SOC and depth of charge (DOC) can be expressed as:

$$SOC = 1 - \frac{Q_e}{C(0,\theta)}; DOC = 1 - \frac{Q_e}{C(I_{avg},\theta)} \quad (2)$$

with Q_e being the battery charge in Ampere-second, C the battery capacity in Ampere-second, θ the electrolyte temperature in degrees Celsius and I_{avg} the mean discharge current in Ampere. Accounting for a non-uniform discharge current, the SOC variation can be written as [8]:

$$\Delta SOC_k = -\frac{I_i \Delta t}{3600 C_n}\left(\frac{I_i}{I_n}\right)^{n-1} \quad (3)$$

$$SOC_k = SOC_{k-1} + \Delta SOC_k \quad (4)$$

This relationship enables computing the charge state at the k-th instant, with C_n a known battery capacity, I_i a given discharge rate and I_n a known charge rate.

Also, more often use as a reference to characterize battery behaviour is the depth of discharge indicator (DOD). Periodic high DOD cycling of the battery results in faster aging while low DOD can extend battery lifetime, albeit with a lower effective capacity related to nominal capacity. DOD is computed directly as the opposite of the SOC:

$$DOC[\%] = 1 - SOC \quad (5)$$

As ambient temperature affects battery voltage, the monitoring system has to compensate for thermal variations in order to avoid dangerous overcharge and discharge conditions. A coefficient around -15mV/C has to be taken into account when computing overcharge voltage of the battery.

B. System Architecture and Extension to Networked Monitoring and Control

As a way to enable repeatable and efficient experimentation of modeling and control of storage systems in laboratory environments with direct impact on real applications we introduce an open and unified framework. It takes a cyber-physical approach to system design which includes the following components: the actual battery/battery bank, a controller to monitor the system and run the control algorithm for adaptive charge and discharge operation. The main goal is to achieve maximum stored energy usage while protecting from dangerous conditions like overcharge and high discharge. This is performed while accounting for ambient conditions and high currents. At the border between the simulated and real domains lay predefined interfaces which merge information coming from both sides which result in action upon the device under test. In our particular case, we achieve realistic charging and discharge conditions upon a real lead acid battery for renewable energy storage. The framework is illustrated in Figure 2.

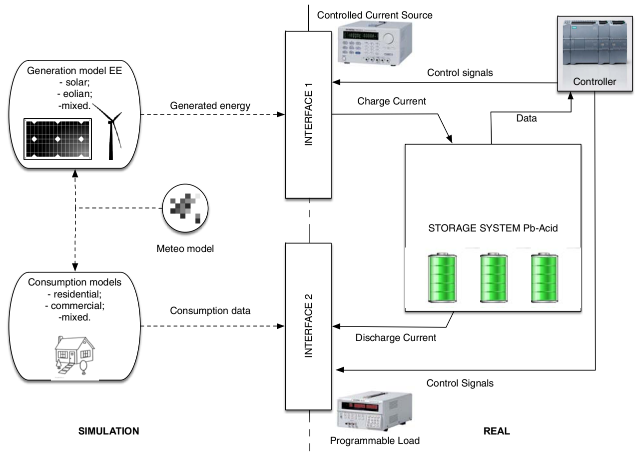

Fig. 2. Storage System Modeling and Testing Framework: Actual Battery

The architecture relies on three models to supply information from the virtual world to the physical domain. The power generation model delivers the available energy from renewable energy sources, either solar, wind, or a combination of both. This is parameterized according to a user specified configuration. The consumption model aims at a realistic representation of residential, commercial and mixed loads, at a microgrid level. It accounts for base and peak loads as well as for uncertainties and controllable demand. Both generation and consumption models can be easily replaced by real data provided by a system operator or experimental installations. An important role is played by what is denoted as the meteorological model. This provides the real weather conditions which influence both generation in the case of renewable energy sources and consumption e.g. HVAC and electricity use. The meteorological data, including temperature, humidity, solar irradiance, wind speed, wind direction, etc. is extracted from a variety of sources. These can be open source web databases, commercial local databases and packages like METEONORM [12], or modules of renewable energy planning tools. The interfaces between simulation and real devices receive inputs in the form of dynamic energy generation and demand data and control signals from the automation equipment, which can be implemented for example on a programmable logic controller (PLC). The difference between generation and demand is computed. A controlled current source generates the necessary current to supply the storage system, or in the case of higher demand, a programmable load discharges the battery. The system architecture is designed with flexibility and scalability in mind as the components can be easily replaced and the overall structure extended to accommodate multiple storage equipment of various types.

Hardware-in-the-loop represents a technique to model, simulate and test control systems in real-time conditions. It is mainly used for development of control devices and algorithms in the automotive and energy/power electronics domain. The main advantages of this method lay in the fact that some systems are to complex or dangerous to operate in the early stages of control algorithm development. Therefore the control equipment is connected to a virtual representation of the plant through real signals fed into and read from data acquisition devices. In relation to our development, we present an alternative based on this concept in Figure 3. It replaces the actual storage system with a dynamic simulated model based on a known representation which runs on a PC. The PC is equipped with suitable DAQ boards to relay the measured data and control systems to/from the storage system model and suitable software packages like Simulink of VeriStand are available for adequate implementation. Finally, we argue that in the above described structure for battery modeling and testing, the main controller functions can, in some cases, be better served by a distributed network of embedded sensor nodes. This approach brings several advantages: data aggregation, in-network computation of feedback control laws and increased fault tolerance. The main idea is illustrated in Figure 4. End nodes (E) are assigned to individual energy storage devices, monitoring their SOC. Data is transmitted towards a main gateway (GW) by means of wireless communication and through a self-organizing and self-healing mesh network. The router node (R) has a similar structure as the end nodes but includes the additional functionality of relaying the messages of the neighbour nodes towards their destination. Measurements travel upstream from end-nodes to the gateway and commands are transmitted downstream from the gateway to the end-nodes with actuation capability. The gateway is the point of integration with the industrial control network and plant IT systems.

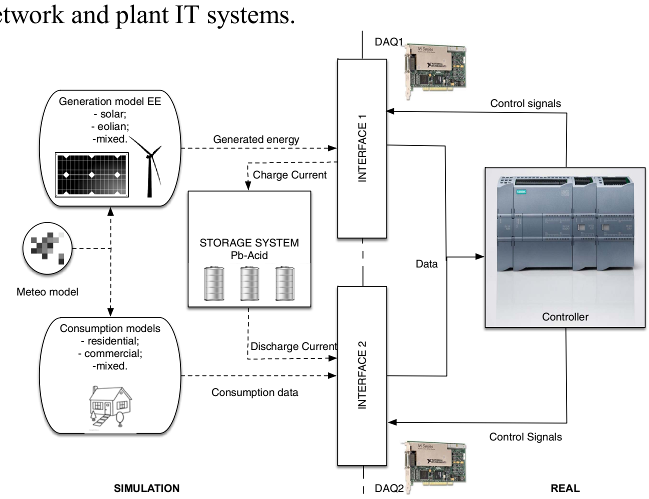

Fig. 3. Storage System Modeling and Testing Framework: Model-based

Data aggregation is illustrated by collecting voltage measurement at the router nodes, compensating them with ambient temperature and merging the information into a single package, thereby reducing communication needs. This leverages on- board computing resources of the nodes which can be as well applied to partially computing the control strategy for simple tasks, achieving a decentralized control system. Fault tolerance is implemented so that in the case of a single node failure, the rest of the network can quickly take over the functions of the lost node. As sensor node operation is optimized for low duty- cycle and low energy operation, they can either run on batteries for several months or be powered by the actual storage system, with minimal impact.

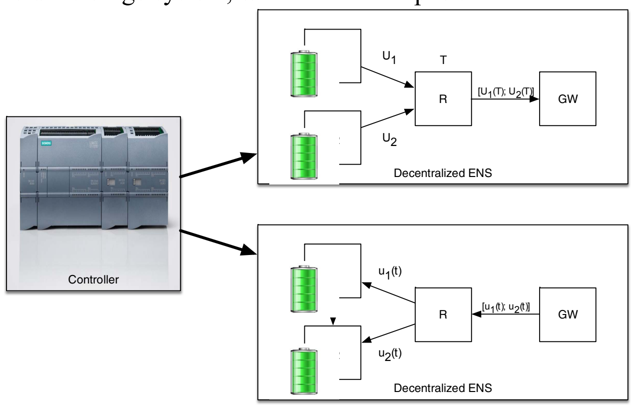

Fig. 4. Decentralized Controller implemented over Embedded Networked Systems: Upstream and Downstream Information Flow

IV. EMBEDDED NETWORKED MONITORING

The generic structure of an IWSN node is shown in Figure 5. The main components are common to the general structure of a wireless sensor node [13] and include: embedded microcontroller, low-power radio interface and on-board flash memory storage. These are accompanied by embedded sensors and limited power supply in the form of batteries or they can be externally powered and include some form of energy harvesting method. Specific elements which are more common in the IWSN case include interfacing for common industrial signal loops like 0-10V or 4-20mA as well as 0-24V digital inputs and outputs. These differentiating elements at the node hardware level are represented in red. Some industrial wireless sensor networks can also include on-board connectivity to fieldbuses like RS485, provided the embedded system overall has enough resources to store and run the protocol stack. Also, depending on the application and the role assigned to the node inside the network, the nodes can be mains powered e.g. the router node in the above-mentioned scenario, or use energy harvesting devices from miniature solar panels, temperature gradients, vibrations, etc. for fully autonomous operation. A non-trivial matter is also physical protection of the industrial node from water, mechanical and electrical shocks and strong electromagnetic fields which can be certified according to norms for industrial supplies.

A laboratory application was devised in order to showcase the concepts presented in the previous section. The experimental set-up (Figure 6) includes the following equipment:

- BSB 12V-200AH Solar Lead Acid battery;
- Industrial wireless sensor network composed of: NI WSN-3202 Analog Input Node as end device, NI WSN-3212 Thermocouple Input Node as router and NI WSN-9791 real time Ethernet gateway;
- Laboratory current source AxioMet AX-3003D-3 6A/30V and multimeter UNI-T UT803;
- PC running LabVIEW virtual instrumentation environment.

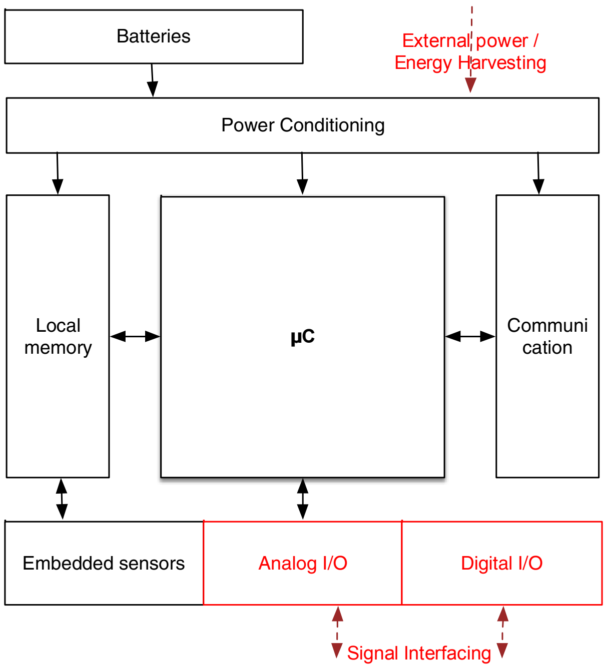

Fig. 5. IWSN Node Schematic

The analog input node periodically measures the battery voltage and transmits it via the router node to the gateway, which is connected to the local Ethernet network. The router node also measures ambient temperature with a J-type thermocouple. A dedicated software application has been developed to collect the data and log it to a file for subsequent processing. Nodes are battery powered and they also report their own battery voltage and link quality and the user can visualize the data in real time through an intuitive graphical user interface.

Fig. 6. Laboratory Set-up

According to the procedure described in [9], we perform data collection and identification on the battery through the network of embedded sensor nodes. Starting from an estimated SOC of 76% at 12.9V, derived from initial voltage measurements and specifications provided by the datasheet we apply the following sequence of step current inputs of amplitude 1A and duration of around 300 seconds: 0A → 1A, 1A → 2A, 2A→3A, 3A→2A, 2A→1A and 1A→0A. Figure 7 illustrates the dynamic step response of the system and ambient temperature monitoring by the router node is listed in Figure 8. As can be seen from the graphic, room temperature during the experiments was close to the 25 °C value which is used as reference by manufacturers when listing system technical characteristics. It is known that lower temperatures lead to decreased battery capacity and voltage, while prolonged operation at higher temperatures reduces the overall battery life.

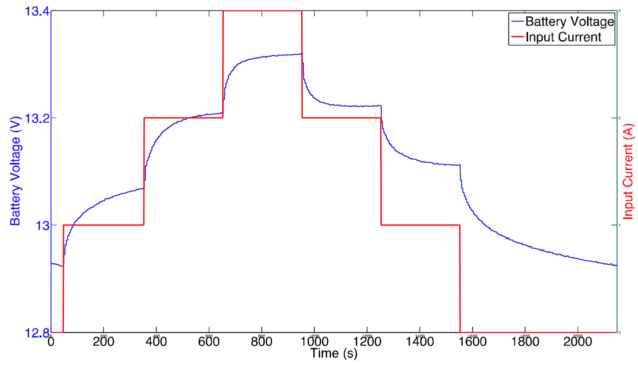

Fig. 7. Experimental Results: Step System Response

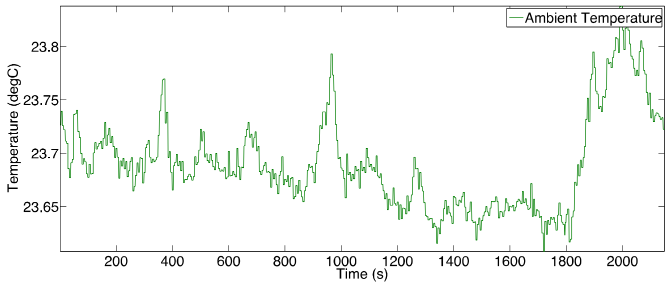

Fig. 8. Experimental Results: Ambient Temperature

The step response corresponds to a first order system:

$$T\frac{dy}{dt}+y(t)=Kx(t) \tag{6}$$

with the system output represented by:

$$y(t)=y_{\infty}+(y_0-y_{\infty})e^{-\frac{t}{T}}=y_0+(y_{\infty}-y_0)\left[1-e^{-(t/T)}\right] \tag{7}$$

are derived, and upon identification of the system gain K and time constant T, suitable control strategies can be designed and implemented [14].

V. Conclusion

The paper discussed the role of energy storage within renewable energy systems. A system framework was proposed for effective design of monitoring and control strategies along with suitable implementation and initial promising experimental results. We argue that this approach can lead to an increase in reliability and with direct impact on the design of future networks. The time to develop control strategies is lowered by applying hardware-in-the-loop methods while the application of industrial sensor networks brings decentralized monitoring and control across the components of the renewable energy system.

Future work will be directed at establishing an open test-bed for experimentation of control strategies for renewable energy storage systems through embedded networked controllers. It is envisioned that the developer will be able to choose between a predefined library of models, or create its own and select the equipment which he wants to include in the configuration. Long term studies are also required to validate the storage system behaviour under stress.

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