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Real-time battery state of charge estimation in smart grid application by Multi Agent System

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ABSTRACT

This paper presents a SOC estimation model in real-time applications such as smart grid. Authors list the existing SOC estimation methods and propose a SOC model to overcome the limitations of the precedent methods presented in the literature. Furthermore, this paper proposes a scalable, self-adaptive, and generic SOC model to meet the smart grid requirement. Multi-agent system approach is proposed to manage the smart grid and a co-simulation is proposed enabling the physical variables modeling while the discrete decision-making is given by developing agents under Jade framework. The results analyses have shown a SOC model which depends on the battery use conditions that can match with all batteries technologies and therefore can be suitable for smart grid applications.

Introduction

The battery is an electrochemical system; it stores the chemical energy and converts it into electrical energy. This conversion is reversible. The electricity storage is a strategic issue. The battery system follows the actual energetic transition. It is the key profile for the electric vehicle development [1–3] as well as the Renewable Energy Sources (RES) implementation [4–6]. A large expansion of intermittent renewable energies (solar and wind) will therefore require in the future an important deployment of storage facilities. Solar energy and wind energy are available intermittently and subject to large fluctuations. The electricity storage smoothes out these variations in output and reduces the use of fossil fuel. Furthermore, storing large quantities of electricity during off-peak hours helps to meet daily fluctuations and peak demands. This allows possible to store the electricity when it is not expensive to resell it when it is expensive. Therefore a smart control is strongly needed.

In the smart grid a battery safe use is ensured by avoiding the battery over-charge or over-discharge that can lead to prematurely battery lose. For this reason, the real-time battery state of charge (SOC) should be permanently updated. The SOC indication plays a significant role to compute the battery available energy and therefore to predict its autonomy. Because in real-time application, for instance, smart grid control, the battery behavior varies while operating according to non-controllable conditions as the RES intermittent generation which is not correlated with the demand changes and

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the distributed generation with different capacities and properties flowing within the grid. Thus a reliable SOC estimation which takes over the battery online variation especially, for real-time applications is quite complex and also a challenging issue [7].

The battery is a complex electrochemical system, the battery SOC cannot be directly measured by a sensor. Thus it should be estimated. The available SOC estimation methods have some limitations and cannot be generalized for unknown battery dynamics configurations, and therefore are not generic. Furthermore these methods do not take into account the variables battery internal characteristics and its uncontrollable use conditions in real-time applications. Sometimes the battery should be disconnected to compute parameters to give a SOC estimation [8] which is not possible during smart grid operation. Accordingly, providing a reliable SOC estimation for any battery technology regardless of its internal characteristics and its use conditions in real-time applications such as smart grid is strongly required.

The Multi-Agent System (MAS) is extensively suggested as a suitable approach to manage complex distributed systems such as smart grid architecture [9–14]. The distributed behaviors, and responsibilities of each agent in parallel, let the control of unforeseen events or faults reliable without implying the system exhaustively. The parallelism in agents' interaction was the subject of [15] where authors have proposed a framework which is MacsimJX to overcome the parallelism issue enabling distributed system modeling with Simulink, because S-functions of Simulink are unable to handle multiple threads of execution such as MAS architecture. They become unstable if several processes run concurrently inside Simulink [15] as shown in Fig. 1. In the previous paper JADE was chosen to be the framework to assist agent modeling for Simulink. It is the most used platform when developing agent, Jade provides a runtime environment for agents and a library of specified classes. However, it is not well appropriated for modeling physical systems, where variable parameters are continuously updated in an evolving environment, as the battery internal characteristics and SOC estimation model.

Indeed, the SOC model can be estimated through a physical or electrochemical model based on monitoring physical quantities which are continually updated and variable. Therefore a SOC estimation model taking into account the random change of external conditions of use in smart grid application managed by MAS is necessary.

In this paper, the SOC estimation of any battery technology according to its external use conditions operating in a smart grid managed by MAS is proposed. Furthermore, a tool enabling physical agent modeling is shown. This allows combining the simultaneous use of Simulink facilitating the proposed SOC estimation model graphically and Jade framework to develop agents. Section II overviews the existing SOC estimation models which can be limited when are applied in real-time. Section III describes the proposed estimation model while section IV introduces the battery agent behavior allowing a smart SOC estimation and demonstrates the co-simulation Matlab/Simulink and JADE enabling to model the SOC under Simulink and to control agents by Jade in smart grid application. Section V concludes the paper.

SOC estimation models

Many studies have brought more interest to give accurate SOC estimation methods. It was proposed methods based on the linear relations between the SOC and the variables parameters allowing the SOC estimation following look-up table. Electrochemical methods, that model the battery electrochemical phenomena as well as physical methods that depict the battery dynamics by an equivalent electric circuit. More details are given hereafter.

Methods based on linear relations with SOC

There is a linear and a direct relation between the battery open circuit voltage (OCV) and the battery SOC [16,17] as expressed in (1) [18]. As well as between the battery internal impedance and the electrolyte density that characterise the battery dynamic behavior. These relationships are expressed by look up table [19,20]. The OCV expressed in Volts is the measured terminal voltage for zero battery current [21], when no load is applied. Admittedly this method gives a precise SOC estimation, but an accurate measurement requires a long rest period [22] and however the use of this method is limited in real-time applications such as smart grid operations because the battery should be disconnected or offline to give the OCV or the impedance measurements. Moreover, this method is

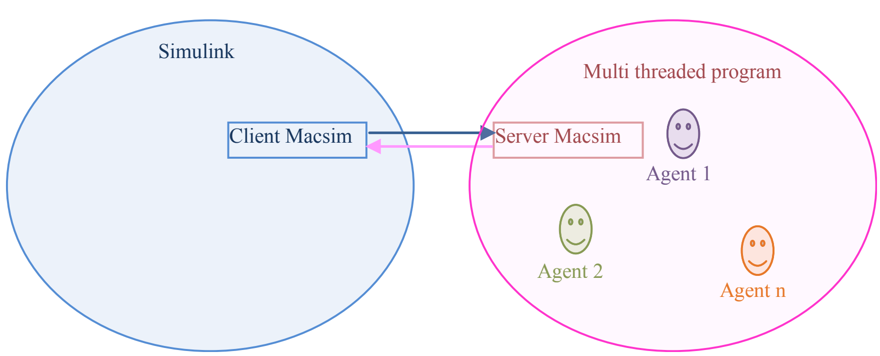

Fig. 1 – MacsimJX architecture.

not recursive; several tests are required to build one table, thus a lot of look up tables should be implemented and stored in real-time applications depending on the battery use conditions and the battery characteristics [23]. Also this method is not generic and depends on the battery technology.

$$s(t) = \frac{v_{oc}(t) - a_0}{a_1} \quad (1)$$

S(t)-State of charge (%)
a_0-The battery terminal voltage when s(t) = 0%
a_1-Depends on a_0, voc at s(t) = 100%

Electrochemical model

Several chemical reactions and phenomena occur in the battery. Giving an electrochemical model can describe the battery dynamic [24–26]. The SOC is influenced by all these reactions and cannot be directly measured. However, the electrochemical model estimates the OCV or the concentration of the active material in the anode, and then the SOC is estimated. This method requires a thorough parameters identification, which can be quite difficult in large battery packs and therefore in smart grid application.

Physical model

The battery dynamic can be modeled as an equivalent electric circuit [27–29]. Therefore the OCV and the variable parameters are estimated by a physical model (electric circuit) and the SOC is then computed following the linear relationships [30]. Otherwise estimating the battery voltage and following a closed loop control, the SOC is set thanks to battery voltage measurements in real-time [31,32] benefits from the strong linear link between the SOC and the variable parameters to give an updated SOC permanently and automatically thanks to the equivalent circuit battery model. These variables parameters are strongly dependent on the uncontrollable extern use conditions, and therefore an adequate model for these parameters cannot be generalized for unforeseen use cases [32].

In fact these methods come to improve the coulometry method (Ampere-hour counting - Ah-counting) [33,34]. It consists to sum the cumulated inputs and outputs battery currents. Admittedly, no modeling method is required but the current sensor cumulating errors can give a wrong SOC estimation and accordingly this method is not accurate.

In light of the above, all of SOC estimation methods present many drawbacks. These methods are not generic and scalable. Furthermore, the need of direct measurements of inherent battery physical quantities is quite complex in real-time circumstances. The electrochemical model of each batteries technology is very specific and depends on low-level parameters identification. In physical method context, although, the variable parameters can be measured and estimated in real-time through an equivalent electric circuit, the accuracy of this method remains contestable, in addition, an efficient sensor is very expensive. The calibration points can overcome the cumulated SOC estimation error issue but in specific battery charging states which are rarely available in real-time applications. To get around these difficulties, this paper proposes a generic SOC model providing the SOC estimation for any battery technology. It is updated online and depends strongly on the use conditions that change the battery dynamics. The proposed model is described in the following section.

Proposed SOC estimation model

The proposed SOC model depends on the goal and the context of the battery use. In the smart grid application, the battery should be able to meet the intermittent RES production and the random load changes. According to the SOC, it provides the energy needed or consume the energy excess. If the amount of energy to consume or to provide is applied to the battery as a set point this implies an energy transfer is imposed from or to the battery. In the smart grid application when RES are integrated the voltage control is the main consideration. Thanks to the bus voltage control the amount of energy transferred to the battery is already known and the battery behavior is predicted. That means, according to the energy flowing within the bus (extern battery use conditions) the battery (Independently to its technology) will undergo a charge (or a discharge) by consuming (or by providing) the amount of energy needed to be rejected from (or supplied to) the bus in order that the bus voltage remains constant. Therefore if the battery inputs and outputs currents are accurately computed in real-time to meet the DC bus voltage regulation, the SOC model can be accurately estimated as expressed in (2) according to papers mentioned above, where the SOC is expressed in (%). It is the ratio between the actual capacity and maximal capacity that the battery is able to deliver. The actual capacity does not require to be modeled; it can be computed by integrating the battery current, and however it is recursive. Thus the SOC_0 can be estimated offline using look-up table [31].

$$soc(t) = \frac{\int i_{battery}}{Q_{max}} + soc_0 \quad (2)$$

This equation depends on the instantaneous battery currents calculations. The control of these currents responsible for battery charging and discharging that vary the battery dynamics is clarified by proposing a DC bus voltage control in a PV-battery system depicted in Fig. 2.

A custom role for power electronics is the development of RES by meeting their distributed production constraints. Two DC-DC converters are used to tie the PV-battery system to the DC bus for power conditioning. The boost converter is connected to PV system and a buck-boost converter is linked to the battery. The average model of each converter is expressed in (3)–(4) following Kirchoff's voltage law as shown in Fig. 3 [35]. In order to boost the PV output voltage to the DC bus voltage, the Maximum Power Point Tracking (MPPT) approach is used, that let the PV operates at the voltage corresponding to the maximum power extracted [36–38]. A voltage control and a current control are necessary to control the DC bus voltage [39–42]. The voltage controller consists on a PI

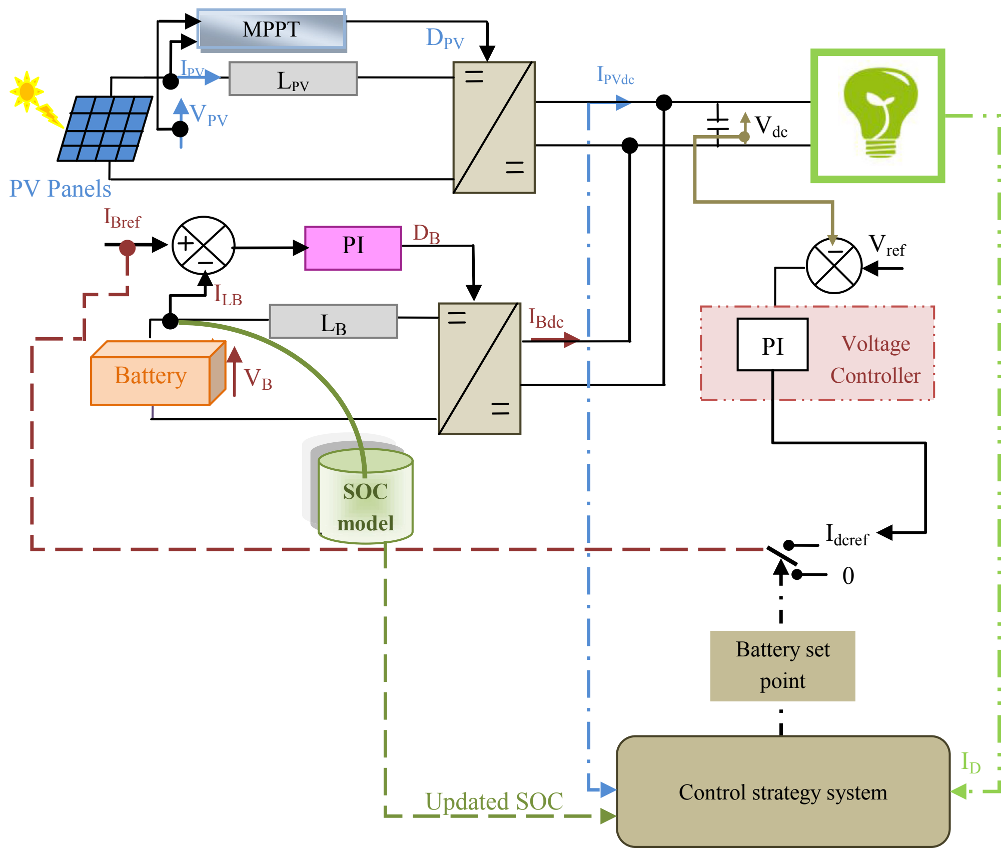

Fig. 2 – PV-Battery system control principle.

regulator able to compute the amount of current required to remove the excess or the need of energy through the DC bus called I_{dcref}. Whereas the battery converter is current controlled, thanks to PI regulator the amount of current needed is injected to the DC bus. The DC bus control and therefore the battery inputs and outputs currents control is depicted in Fig. 2. It is shown that the battery current converter I_{LB} which follows the battery set point I_{Bref} is assigned to the SOC model, therefore the SOC is computed and updated in real-time according to the DC bus control where the I_{dcref} is permanently calculated in real-time.

$$L_{PV}\frac{di_{PV}}{dt} = \upsilon_{PV} - (1 - D_{PV})\upsilon_{dc} \tag{3}$$

$$L_{B}\frac{di_{B}}{dt} = \upsilon_{B} - (1 - D_{B})\upsilon_{dc} \tag{4}$$

The battery set point is communicated to the battery through the control strategy system, which the SOC indication is strongly required to determine I_{Bref} in order to disconnect the battery when it is over-charged or discharged in order to increase the battery life-cycle. Therefore the SOC model in the smart grid application should be able to estimate the SOC regardless the battery intern characteristics and the extern conditions, especially when the battery is full charged or discharged to avoid the battery damage. The battery should be disconnected when it reaches its maximum or minimum charging limits (the battery do not receive the set point in this case) even if the system operation is maintained, that means the remaining capacity should also be known to indicate the battery autonomy. Likewise, the SOC model should depend on the battery use context (for example starting the battery at a predefined SOC level to meet a control system requirement). A scalable SOC model allows the smart grid reorganization in the future by meeting the unpredictable load growth. Furthermore, SOC model in smart grids application ought to be based on distributed communication capabilities to reduce the volume of exchanged information. To overcome these requirements an intelligent, self-adaptive, and dynamic SOC model is needed. This is the battery agent responsibilities which are described in Fig. 4 and detailed in the next section.

Toward an agent-based smart SOC model estimation

In the scenario studied, which it is focused on the PV-Battery system in the smart grid. The battery is the only dynamic system where various phenomena can happen namely the charge and discharge and therefore many physical parameters change such as voltage, current, density, temperature, resistivity … etc as shown in Fig. 5 [43–45]. Furthermore, the proposed SOC model is based on recursive function as well as the converters' control. A numerical implementation of this dynamic model as well as these recursive functions and physical parameters requires a temporal discretization which is quite complex. Therefore a user-friendly method allowing dynamic system modeling such as PV-Battery and SOC in

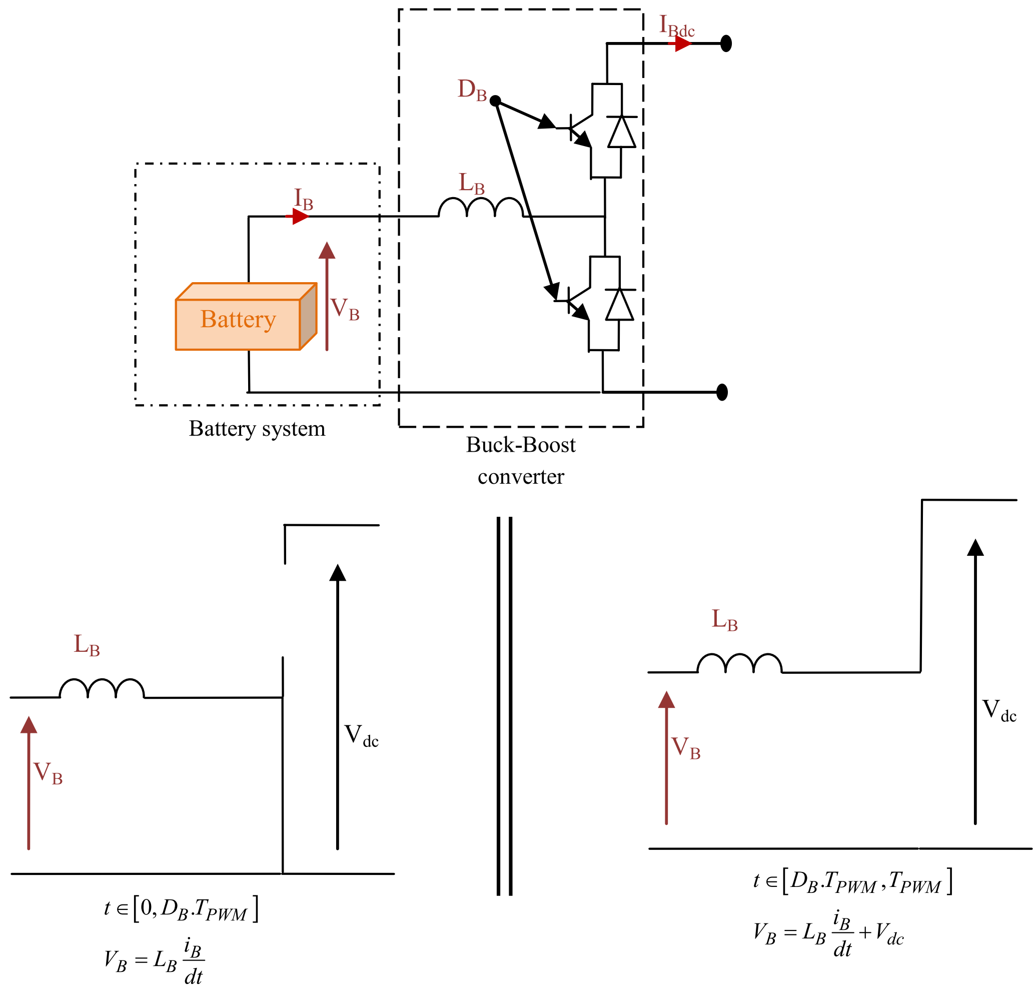

Fig. 3 – DC-DC battery converter average model.

smart grid application managed by MAS is presented in this paper. MAS provides a theoretical framework for the real-time operating systems, such as smart grid, in which the interactions between the smart grid components plays a significant role. Battery agent has its own behavior, which simplifies the analysis of complicated situations and the task of the designer rather than having to cope with the whole system and problem. As explaining earlier a co-simulation framework is proposed to enable the simultaneous use of Simulink allowing the PV-Battery system and therefore the

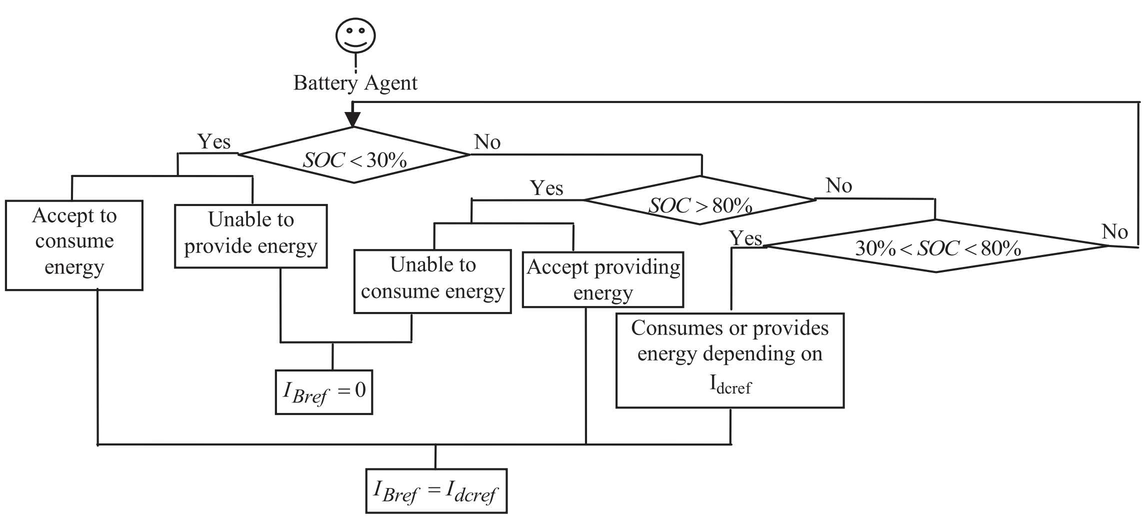

Fig. 4 – Battery agent behavior.

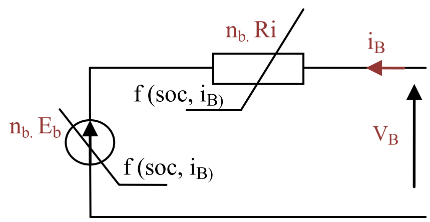

Fig. 5 – Battery model.

SOC modeling and control, and JADE framework enabling agents' development, in order to take full advantages from combining the both Softwares.

On the Jade side each agent has to register its services in the yellow pages provided by Jade [46], which can provide throughout the agent life, for being easily found by other agents.

This paper focuses on the interaction between the PV-battery system in a smart grid. Two agents are considered such as the battery agent and the DC bus controller agent. The battery agent can provide two services namely 'supplying' or 'consuming'. It communicates with the DC bus controller agent through messages sent and received. The purpose of received messages concerns the actual energy available through the DC bus. As all the agents registered as 'consuming' service, the battery receives from the DC bus controller agent the proposal to consume the extra energy through the DC bus when the DC bus controller agent reveals that the PV production exceeds the load demand by processing the incoming signals received from a specific input port from Simulink describing the PV production and the load consumption. The battery receives also as all the agents registered as 'supplying' service, the proposal from the DC bus controller to provide extra energy needed when it receives the PV production and the load demand signals from Simulink and decide that it is needed to supply energy because the PV generation does not meet the load demand. Fig. 6 depicts the sequence diagram showing the negotiation/communication between agents within the system.

After processing the content of received messages, the content of the sent messages regards the battery agent decision-making according to the SOC correlation with the amount of energy should be injected or removed in order to control the DC bus. It accepts the proposal when the SOC allows the battery charge or discharge and refuses otherwise. Then the battery agent sends messages to a specific IP address and port to exchange information with Simulink. It sends in a specific output port the battery agent decision-making that will be implemented in the battery control block in Simulink in order to attribute the battery set point I_{Bref} to the battery model as shown in Fig. 7 and following the battery converter current control process, the required energy is injected in or removed from the DC bus and therefore the SOC is updated. In the other hand the battery agent receives from a specific input port the SOC updated and extracts it in order to process it with the incoming proposals received from the DC bus controller agent.

Results & discussion

The current circulating in the DC bus reveals of different possible scenarios; The PV generation exceeds the load demand, or the PV production does not meet the demand. Therefore the average current returned is the suitable to take into account. It represents the result of the different possible scenarios that can occur. The positive average current expresses that there is an excess of energy in the DC bus, while the negative one indicates that there is a lack of energy that should be removed. This resulting current variable is depicted in Fig. 8.

Fig. 8 shows also the battery current converter evolution I_{LB}; this current follows the battery set point I_{Bref} during the

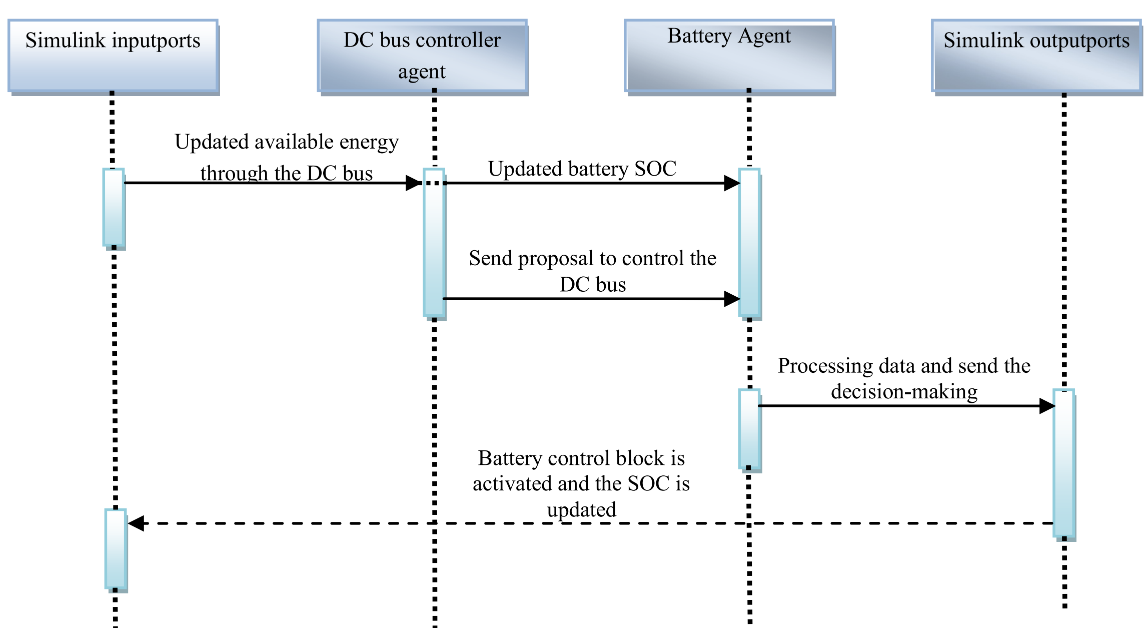

Fig. 6 – PV-Battery system sequence diagram.

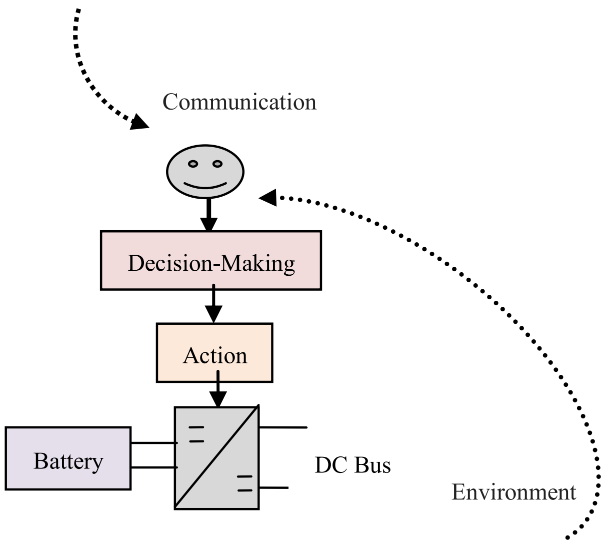

Fig. 7 – Battery converter control by battery agent.

simulation time. It represents the amount of current that should be applied to the battery in order to meet the DC bus control when the SOC allow it. I_{LB} is assigned to the SOC model and it is shown that the SOC evolution is correlated with the I_{LB}. When it is positive the SOC increases that signifies that the battery is charging. However, when it is negative it is shown that the SOC decreases and the battery is discharging. Therefore the accurate amount of current extracted from or provided to the battery is transferred to the SOC model to get the accurate SOC estimation.

As described in I_{Bdc} evolution which is the output battery converter current, when the SOC is out of its maximum or minimum limits fixed in this paper at 80% and 30% respectively, the battery takes over the DC bus current control, thus I_{Bdc} injected in the DC bus balances the resulting current.

In the other side, the battery agent following the decision-making undergoes two scenarios that can be separately treaty. The first one describes the battery agent behavior when the battery SOC is correlated with the resulting current, that means the battery agent accepts the proposal, by the result, the agent decision-making is equal to '1' as shown in Fig. 8. Then I_{dcref} is assigned to I_{Bref}, I_{LB} follows I_{Bref} to inject

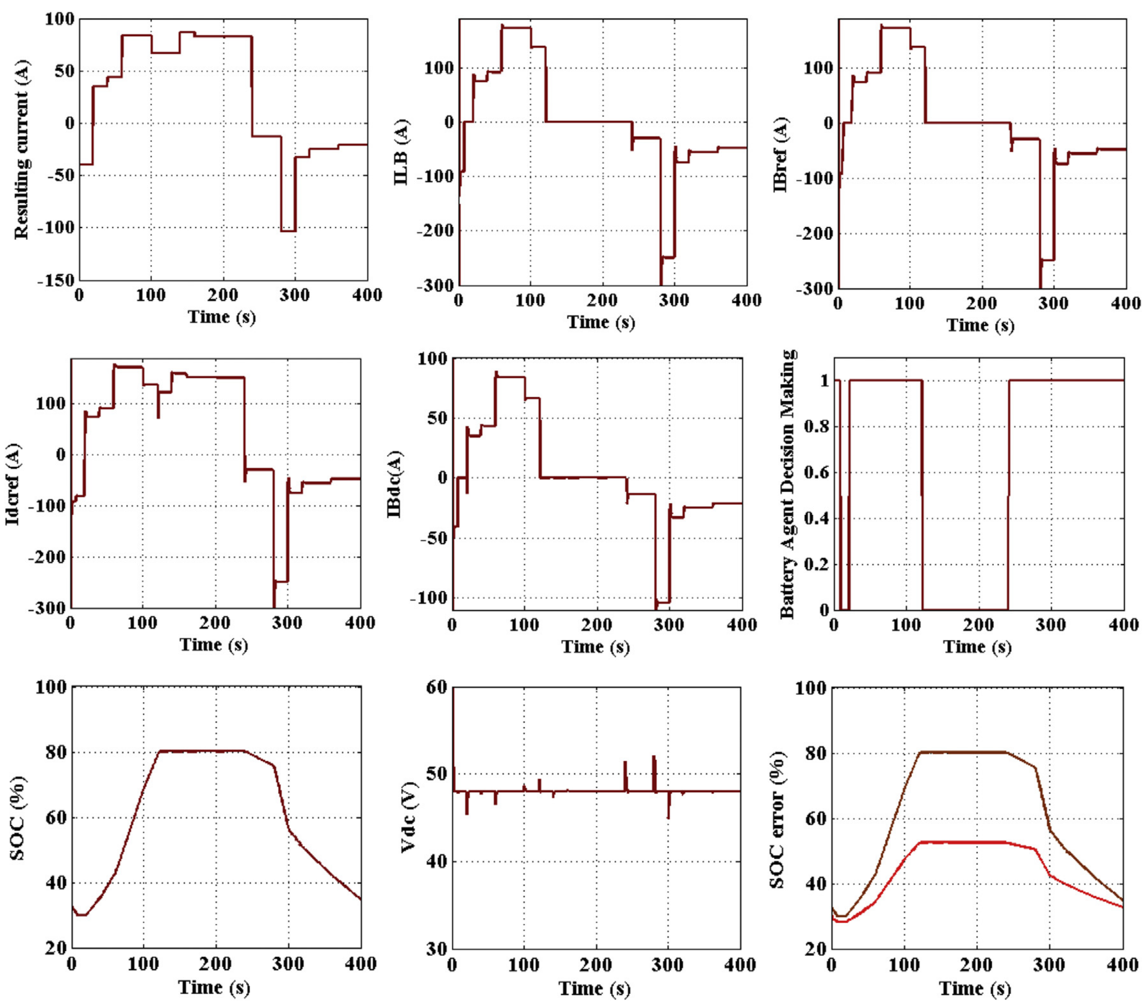

Fig. 8 – PV-Battery system control reaction in smart grid.

the required $I_B$dc and updates the SOC. However, when the agent decision-making is equal to ‘0’, the SOC does not allow the charge or discharge of the battery. Thus the battery set point I_{Bref} is equal to 0 that means there is no current applied to the battery because it is unable to take over the DC bus control. Consequently, it is shown that the SOC is kept constant.

When the SOC is at 80%, the battery can only provide current in order to be discharged. In this case if the resulting current is negative, the battery delivers the required current, the SOC decreases and the decision-making moves from ‘0’ to ‘1’ as shown at 240 s. On the other side, when the SOC equal to 30% only the positive resulting current that can be affected to the battery model thanks to I_{dcref}, I_{Bref} and I_{LB}, to allow its charge, then the SOC increases and the decision-making again moves from ‘0’ to ‘1’ as indicated in Fig. 8 at 20 s.

The resulting current varies during the simulation, the battery inputs and outputs currents, the SOC and the agent decision-making follow this variation as shown. It can happen that the agent decision-making occurs suddenly when the environment has not undergo any changes as indicated at the seconds 8 and 107. It means that the battery SOC reaches its limits and no changes have occurred in the resulting current. That shows the strengths of the architecture proposed in order to design a self-adaptive SOC model.

Fig. 8 expresses also the DC bus voltage evolution during simulation. It is shown that it exactly follows the DC bus voltage reference, therefore the energy flow balance within the DC bus is ensured and the battery inputs and outputs currents are accurately transferred to (or from) the battery to give a precise SOC estimation in real time.

The last graph in Fig. 8 shows the difference between the SOC evolutions when performing the integral of two different battery currents that can show the difference between the proposed SOC model approach compared with the existing ones. The brown curve expresses the SOC evolution while integrating I_{LB} which is the proposed method and it is similar to the SOC evolution presented earlier. I_{LB} is the accurate amount of battery current provided or consumed by the battery. Contrarily to the red one that depicts the SOC evolution while integrating I_{Bdc} that expresses the battery current injected or removed in or from the DC bus. This is due to the duty cycle.

Conclusion

In this paper a SOC estimation model for real-time applications such as smart grid is given. Different existing SOC estimation methods were listed and a SOC model was proposed to overcome the existing methods limitations. In the smart grid the SOC indication plays a significant role to safely operating the battery which follows the extern use conditions as shown in the PV-battery system studied in this paper. It was shown that the SOC model is permanently updated in the real-time and therefore can be suitable for smart grid applications. MAS technique was proposed to manage the PV-battery system. It was explained the complexity of this technique to control physical variable parameters such as SOC model. A co-simulation framework is proposed to enable the simultaneous use of Simulink allowing the PV-Battery system and therefore the SOC modeling and control, and JADE framework enabling agents' development, in order to take full advantages from combining the both Softwares. It was shown the ability of the proposed approach to attribute the decision-making to agents and performing all the calculation required by Simulink to take full advantage of the representation of PV-battery system real model.

The results analyses have shown a SOC model which depends on the battery use context which can be suitable in smart grid applications. Moreover, this paper has proposed a battery agent which its behavior is related to the SOC estimation. The battery agent decision-making depends strongly on reliable, self-adaptive, generic, and scalable SOC. Then it is shown that the decision-making is attributed to agents and all the calculation required are performed by Simulink to take full advantage of the representation of real models of physical and dynamics components.

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