SET OF ECONOMIC MODEL PREDICTIVE CONTROLS WITH DIFFERENT COMPLEXITY FOR SMART HYBRID PV-BATTERY MICROGRID

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The paper describes a set of economic model predictive controls with different complexity for smart hybrid PV-battery microgrid. The work of such controllers is shown and it is presented that the most optimal result does not necessarily give the most complex or fastest predictive control.

Key words: function complexity, economic model predictive controls, smart grids, battery, converters

INTRODUCTION

Nowadays, different Battery Energy Storage Systems (BESS) are of profound interest due to the need to balance energy in the grid and maximize the utilization of Renewable Energy Sources (RES) [1]. However, Li-Ion batteries are consumable materials, and special inverters and converters are necessary to connect them to RES, load, and grid. Predicative algorithms are usually used for such tasks. Algorithm model can be described by different complexity. A complex algorithm model should provide more accurate results, but at the same time, it takes more time to calculate it. This work defines several algorithms and tests it on a virtual smart grid. Additionally, the work shows that it is necessary to find a compromise between the complexity and speed of the algorithms.

METHODOLOGY

In this paper, we consider a system consisting of RES, BESS (hybrid high voltage inverter, converters and battery), load and connection to the main grid.

Economic Model Predictive Control (EMPC) can be used for a system that includes BESS [2], [3]. The basic idea behind this combination is to minimize total electrification expenses by transferring energy from one time to another. It can be used for load pick shaving in a system with renewable energy or a system with a non-flat price program.

In general, EMPC equations for system with BESS is represented by (1-4).

$$\min\{\textstyle\sum_{i=1}^{H} MOF_i\} \tag{1}$$

$$MC \tag{2}$$

$$SOC_i = SOC_0 + \frac{1}{Q^A}\cdot\sum_{k=1}^{i}\Delta t_k\cdot\left(I_k^C - \frac{I_k^D}{\eta^{CE}}\right),\ \forall i \tag{3}$$

$$\begin{gathered} 0 \le SOC_i \le 1,\ \forall i \\ I_i^{bat} = I_i^D - I_i^C,\ I_i^C \ge 0,\ I_i^D \ge 0,\ \forall i \\ (I_i^C > 0) \wedge (I_i^D > 0) = 0,\ \forall i \end{gathered} \tag{4}$$

MOF_i is Main Objective Function (or cost function) for every horizon step i. H is horizon length in steps. MC is a set of Main Constraints. It includes power equality constraints with linking renewable energy sources, loads, main grid, inverter, converters and buttery. Additionally, there is safety limitations of parameters. Q^A is a battery capacity in Ah. Δt_i is time of related horizon step. I_i^C and I_i^D are charging and discharging currents, respectively. η^{CE} is Coulomb efficiency of discharging.

Since the battery loses its capacity with the style of use, additional cost function can be added to (1):

$$\min\{\textstyle\sum_{i=1}^{H} MOF_i + BUC_i\} \tag{5}$$

where

Table 1: Component complexity table

TYPE	EQUATIONS	ORDER
<u>Battery voltage</u>		
Constant	$V_i^{bat} = V_i^{bat,mean}$	0
Linear	$V_i^{bat} = k \cdot SOC_i + b$	1
<u>Converter dead zones</u>		
No	$P_i^{out} = P_i^{in}$	0-1
Yes	$P_i^{out} = \begin{cases} \eta \cdot P_i^{in}, & P_i^{in} > \alpha \\ \frac{P_i^{in}}{\eta}, & P_i^{in} < -\frac{\alpha}{\eta} \\ 0, & otherwise \end{cases}$	0-1 + bin. vars
<u>Battery aging</u>		
No	$\left.\frac{dSOH}{dt}\right\|_i = 0$	0
1-st order	$\left.\frac{dSOH}{dt}\right\|_i = f_i(I_i^C, I_i^D, SOC_i, SOH)$	1
2-nd order	$\left.\frac{dSOH}{dt}\right\|_i = f_i(I_i^C, I_i^D, SOC_i, SOH)$	2

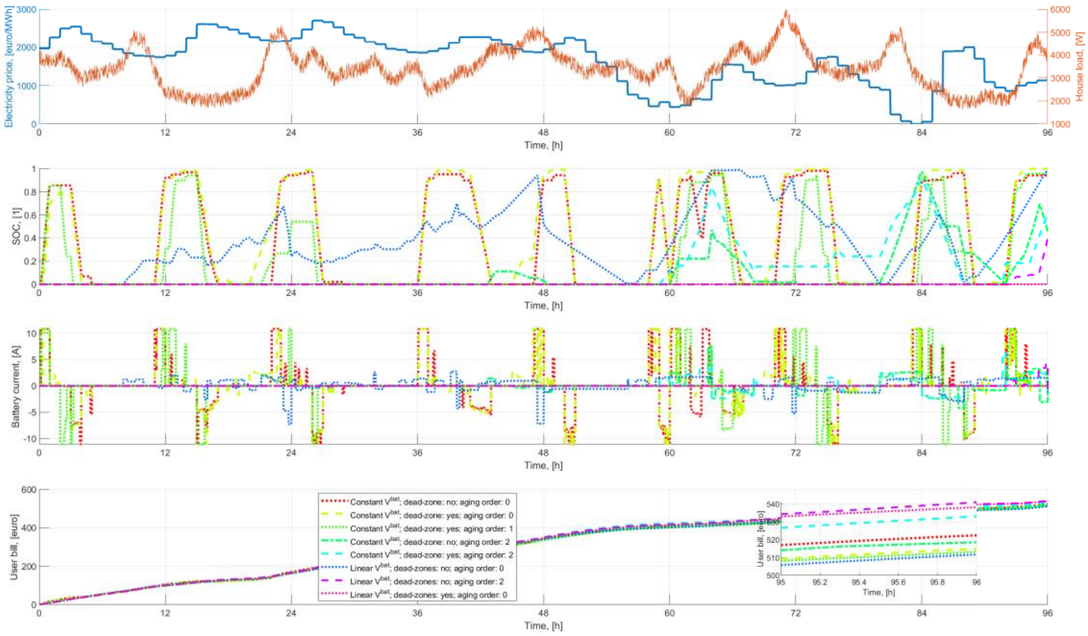

Figure 1: Example of different controller behavior. Horizon length is 24 hours.

$$BUC_i = \frac{Price^B \cdot \Delta t_i}{1 - EOL} \cdot \frac{dSOH}{dt}_i \qquad (6)$$

BUC_i is Battery Usage Cost for every horizon step i, which depicts the part of full battery price $Price^B$ that should be depreciated. BUC_i depends on battery aging rate (6). In its turn rate depends on main EMPC variables [4].

It can be possible to highlight 3 components which can have different representation. They are listed in Table 1. Each of these component type can be described through different complexity, which is presented by function order, binary component and additional number of variables. Using different complexity types, it is possible to specify set of EMPC problems. The easiest problem has mixed integer linear programming complexity. The heaviest problem has mixed integer quadratic constrained quadratic programming complexity. It is logical that easy problems, compared with heavy problems, can provide more frequent responses with less accurate control.

RESULTS AND DISCUSSION

The virtual smart grid model is the model of the considered system. Figure 1 shows the day-ahead electricity price, load, SOC, battery current, and final cost for different controllers. It is seen that the most complex controller, which includes linear battery voltage, converter dead-zones, and 2nd-order aging function, cannot reach minimal cost for four operation days. It is because solving such a controller takes a significant amount of time.

CONCLUSION

The paper describes a set of economic model predictive controls with different complexity for smart hybrid PV-battery microgrid. It has been shown that the most complex or fastest controllers do not give the best result on the horizon and it is necessary to find a compromise complexity when choosing a control.

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