Abstract—Microgrid is a cluster of distributed generation sources, storages and loads that cooperate so as to improve the reliability and quality of the local power supply and of the power system. In this paper we present a power flow optimization of a DC microgrid that consists of photovoltaic array, batteries stack and fuel cell stack with electrolyser, and is connected to the grid via bidirectional power converter. The optimization problem aims to minimize microgrid operating costs and is formulated using a linear program that takes into account the storages charge and discharge efficiency, and considers the residual state of the energy storage systems in the criterion function. Performance of the proposed approach is verified through year-scale simulations based on the actual meteorological, electricity price and consumption data. The analysis performed points out that especially for short prediction horizons it is very important to ensure proper penalization of the residual storages state in the criterion function in order to yield optimum revenue from microgrid operation.

I. INTRODUCTION

Microgrid concept is expected to enhance utilization of renewable energy sources [1] through distributed storage (e.g. electric vehicles) by enabling time-shift between production and consumption. More importantly, these distributed storage systems can also be used for electricity peak (price) shaving by buying and selling energy from/to the grid when it is most convenient for the end-user [2]. In this way microgrid becomes an active part of the power system, and enables decentralization of today’s still centralized power system, thus increasing its reliability and stability [3]. In this paper we consider a residential DC microgrid [4] that consists of a photovoltaic (PV) array, valve-regulated lead-acid (VRLA) batteries stack and fuel cells (FCs) stack with electrolyser, and is connected to the grid via bidirectional power converter.

A decision when to buy and sell energy to the utility grid and in which amount, i.e. when to charge and discharge storages, is a complex function of the predicted microgrid load, power production (mainly by renewables), and of the current storages state-of-charge (SoC). This function is also subject to various constraints like energy storages capacity, power converters power ratings, and even to utility grid’s possibly reduced availability. As it will be shown later, instead of using a Mixed Integer Linear Program (MILP) formulation [5]–[8] due to taking into account discharging and charging efficiencies of the energy storage systems, the described decision making process can be formulated as a Linear Program (LP) which significantly simplifies optimization and control, as well as interaction of the microgrid with the utility grid and the building energy management.

Because of the economic and environmental benefits that stem from the optimal microgrid power flow, considerable attention is directed to development of better optimization algorithms and suitable modelling frameworks [9]. In [10]–[13] several metaheuristic and heuristic algorithms are proposed to solve the power dispatch problem for microgrids, such as evolutionary and genetic algorithms. The advantage of these methods is in possibility to implement more complex models compared to those used in LP or MILP formulations, but with the consequence of not being able to guarantee the optimality of the found solution. In [5]–[8] MILP formulation (based on [14]) of the optimization problem is used to take into account predicted future electricity price, renewables power production and demand load. Justification of using MILP instead of LP formulation is in different charging and discharging efficiencies of storage systems, and in different price when selling and buying electrical energy. As it will be shown in this paper, despite piece-wise affine nature of the storages model, the optimization problem can still be formulated as an LP. We also pay special attention to penalization of residual storages state in objective function, since stored energy at the end of prediction horizon can also be transformed in economic gain [15]. This is particularly interesting for shorter prediction horizons when disturbance effects, such as power production, consumption and price profiles, are more prominent. Performance of the proposed approach is verified through year-scale simulations based on actual meteorological, electricity price and consumption data.

The length of the prediction horizon is also very important when power flow is optimized, since optimization is based on future predictions of electricity price, power production and consumption profiles. Since all these predictions are uncertain (to some extent), for longer prediction horizons, due to the presence of disturbances/uncertainties, there may be a significant mismatch between predicted system behaviour and the real system behaviour, thus leading to a suboptimality in the closed-loop controller performance. These problems are more prominent in smaller (i.e. residential) microgrids, where bad predictions have bigger impact on the microgrid behaviour. There is a significant effort in research community trying to address these issues in a stochastic control framework [16]–[20], mainly using scenario based simulations and two-stage stochastic programming. In this paper we consider a deterministic system variables description.
This paper is organized as follows. A DC microgrid model for power flow optimization is presented in Section II. In Section III the microgrid power flow optimization problem is defined by using an LP formulation. A receding horizon based closed-loop control scheme is formulated in Section IV. Year-scale simulations of the proposed approach based on the actual meteorological, electricity price and consumption data are presented in Section V.

II. DC MICROGRID MODEL

The DC microgrid formed in Laboratory for Renewable Energy Systems\(^1\) (LARES) is shown in Fig. 1. It consists of a PV array, VRLA batteries stack and FCs stack with electrolyser, and is connected to the utility grid via bidirectional power converter. Note that FCs stack with electrolyser is also an energy storage system, since electrolyser produces hydrogen when there is excess power, while FCs use this stored hydrogen when there is power shortage. For simplicity, system of FCs with electrolyser will be considered as a single energy storage controllable unit. For a more detailed description of the DC microgrid formed in LARES see [4].

Considering a hierarchical design of microgrid controllers, the focus is here put on high-level optimization of power flows, whereas voltage stability and power quality are supposed to be controlled at lower microgrid control levels. The following balance equation is always satisfied:

\[
P^\text{PV} + P^\text{BAT} + P^\text{FC} + P^\text{Load} = P^\text{EL},
\]

where \(P^\text{PV}\) is power production by PV array, \(P^\text{BAT}\) and \(P^\text{FC}\) are batteries stack and FCs stack charging/discharging power, \(P^\text{Load}\) is demand load. By convention, power components \(P^\text{BAT}\), \(P^\text{FC}\), and \(P^\text{Load}\) are positive when supplying power to the DC link. Therefore, power components \(P^\text{BAT}\) and \(P^\text{FC}\) will be negative for charging, and power component \(P^\text{Load}\) will be negative for exporting energy to the utility grid. Load is assumed to be unidirectional, i.e. \(P^\text{EL}\) is always positive.

A. Energy storage systems

Energy storage systems (i.e. batteries and FCs) are modelled as a discrete-time first-order difference equations with a sampling time \(\Delta T = 1\) h:

\[
\begin{align*}
x_{k+1}^{\text{BAT}} &= x_k^{\text{BAT}} - \frac{\Delta T}{\eta_{\text{BAT}}} (P_{\text{ch},k} + P_{\text{dis},k}), \\
x_{k+1}^{\text{FC}} &= x_k^{\text{FC}} - \frac{\Delta T}{\eta_{\text{FC}}} (P_{\text{ch},k} + P_{\text{dis},k}),
\end{align*}
\]

where \(k\) denotes discrete time instant, state \(x_k\) is normalized state-of-charge (SoC), \(C\) is capacity, and \(\eta_{\text{BAT}}\) is charging or discharging efficiency that depends on the sign of \(P_{\text{ch}}\) for the corresponding energy storage system. In [9] a binary variable is introduced to decide which value of \(\eta\) to use at \(k\)th time instant. Here we use a different approach. Instead of introducing binary variable, one can split power components of energy storage system \(P_{\text{ch}}\) into charging and discharging components \(P_{\text{ch,k}}\) and \(P_{\text{dis,k}}\) as follows:

\[
\begin{align*}
x_{k+1}^{\text{BAT}} &= x_k^{\text{BAT}} - \frac{\Delta T}{\eta_{\text{BAT}}} (P_{\text{ch},k} + P_{\text{dis},k}), \\
x_{k+1}^{\text{FC}} &= x_k^{\text{FC}} - \frac{\Delta T}{\eta_{\text{FC}}} (P_{\text{ch},k} + P_{\text{dis},k}),
\end{align*}
\]

where \(P_{\text{ch}} \geq 0\) and \(P_{\text{dis}} \leq 0\) represent discharge and charge components, respectively. Note that situation where both \(P_{\text{ch},k}\) and \(P_{\text{dis},k}\) components of a single storage system are different than zero would correspond to a (practically) unacceptable scenario, since it would imply that it "pays out" to charge and discharge storage at the same time. In all realistic optimization problems (i.e. objective functions) this will never be true since this would imply more power dissipation at the DC link, and thus bigger operating costs. This hypothetical situation would only make sense when there is excess power that cannot be exported to the grid (e.g. PV array produces more power than the current load demand, and the power surplus cannot be exported to the grid due to the grid-tied bidirectional power converter power rating limitations). In such hypothetical situation, PV array should leave the maximum power point tracking (MPPT) mode and deliver only the necessary amount of power and not misuse storages to dissipate some power. To conclude, we avoid

\(^1\)url: www.lares.fer.hr
expensive MILP formulation of the optimization problem, and instead we use much simpler and more effective LP formulation while also gaining an insight into any possible misuse of the resources in the microgrid.

The expression (3) can be written in a matrix form as:

\[ x_{k+1} = A x_k + B u_k, \]

where \( A \) is identity matrix \( I_{2 \times 2} \), \( B \in \mathbb{R}^{2 \times 4} \) is system input matrix, state vector is defined as \( x_k = [x_{PV}^k, x_{BAT}^k]^T \), and input vector is defined as \( u_k = [P_{ch,h,k}^k, P_{ch,k}, P_{dc,h,k}, P_{dc,k}]^T \).

### B. Photovoltaic array power production

Photovoltaic array power production is calculated based on measured solar irradiance and temperature data obtained by Croatian Meteorological and Hydrological Service (DHMZ). Meteorological data are used to calculate PV array power production via simple power production model [21]:

\[ P_{PV}^k = \theta_1 G_{PV}^k + \theta_2 T_{PV}^k + \theta_3 G_{PV}^k T_{PV}^k, \]

where \( G_{PV}^k \) and \( T_{PV}^k \) are incident solar irradiance and temperature, and \( \theta_1, \theta_2 \) and \( \theta_3 \) are the PV array model parameters.

### C. Load

For simplicity we assume load \( P_{IL} \) to be critical, i.e. demand levels must always be met. On the contrary, controllable loads can be reduced or shed during supply constraints or emergency situations, e.g. utility grid failure etc. Load data are measured for entire complex of buildings of University of Zagreb, Faculty of Electrical Engineering and Computing [22], and are scaled to meet the considered microgrid design.

### D. Utility grid

When operating in grid-connected mode, the microgrid can import/export energy from/to the utility grid through the grid-tied bidirectional power converter. Although electrical energy price can vary when buying or selling, for simplicity we assume here the same price for both cases. Electricity price, \( c_N \), for the utility grid power \( P_{Ut}^k \) at each instant \( k \) must satisfy:

\[ P_{Ut}^k (u_k) = -I^T u_k + P_{Ut}^0, \]

where \( I \in \mathbb{R}^4 \) is a column vector with all elements equal to 1.

The equivalent electricity contained in storages \( x_N \) is a function of control sequence \( u \) and initial storages state \( x_0 \):

\[ x_N = [x_{BAT}^N, x_{DC}^N]^T, \]

where \( x_{BAT}^N \) is the current state of the microgrid storages, \( x_{DC}^N \) is the residual storages state penalization on the optimization results vanishes out as the prediction horizon \( N \) gets longer.

## III. PROBLEM FORMULATION

The power flow optimization is formulated based on: (i) the current state of the microgrid storages \( x_0 \), (ii) the predicted local power production and consumption profiles in the microgrid, and (iii) the information obtained from the utility grid, i.e. predicted electrical energy price profile \( c_k \), where \( 0 \leq k \leq N - 1 \), and \( N \) is the length of the prediction horizon. As a result the power flow optimization gives the best values of discharging and charging power profiles for the microgrid storages \( P_{ch,h,k}, P_{ch,k}, P_{dc,h,k}, P_{dc,k} \), throughout prediction horizon, which achieve the best possible economical gain for the microgrid operation under presence of specified technical constraints. For the sake of simplicity, in this paper we neglect power predictions uncertainty [20], i.e. we consider a deterministic system variables description.

### A. Objective function

We consider the following economic criterion \( J \) of the microgrid operation where negative values mean revenue:

\[ J(u, x_0, c, d) = -c_N x_N + \sum_{k=0}^{N-1} c_k P_{Ut}^k \Delta T, \]

where \( N \) is the length of the prediction horizon, \( c_k \) is the electricity price, \( c_N \) is estimated electricity price under which the equivalent electricity contained in storages \( x_N \) could be sold to the utility grid or could replace the utility grid electricity after the \( \bar{N} \)th hour in the future, and vectors \( u, c, \) and \( d \) are control, electricity price, and disturbance sequences, respectively, defined as:

\[ u = [u_0^T, u_1^T, \ldots, u_{N-1}^T]^T, \]

\[ c = [c_0, c_1, \ldots, c_{N-1}]^T, \]

\[ d = [P_{Ut}^0, P_{Ut}^1, \ldots, P_{Ut}^{N-1}]^T, \]

where \( P_{Ut}^k = P_{Ut}^k - P_{Ut}^0 \) is disturbance at time instant \( k \). From (1) it follows that the utility grid power \( P_{Ut}^k \) at each instant \( k \) must satisfy:

\[ P_{Ut}^0 (u_k) = -I^T u_k + P_{Ut}^0, \]

where \( I \in \mathbb{R}^4 \) is a column vector with all elements equal to 1.

The equivalent electricity contained in storages \( x_N \) is a function of control sequence \( u \) and initial storages state \( x_0 \):

\[ x_N = [x_{BAT}^N, x_{DC}^N]^T, \]

Selection of \( c_N \) determines to which extent will the power optimization algorithm force storage systems to be full at the end of the prediction horizon. One strategy is to have \( c_N \) set to maximum value achieved on a prediction horizon. This implies that the energy contained in storages will be sold (i.e. used) only when maximum prices, at some instant in the future, take place, and will implicitly force the power flow optimization algorithm to keep the storages nearly full and ready for peak (prices) shaving in the future. As will be shown in simulation results section, influence of the residual storages state penalization on the optimization results vanishes out as the prediction horizon \( N \) gets longer.

### B. Constraints formulation

Minimization of the criterion (6) is subject to various constraints on microgrid variables over the future horizon. These constraints can be either physical or designer-introduced in order to protect the system and prolong its life.

Storages state \( x_k \) always must be inside capacity limits:

\[ x_{min} \leq x_k \leq x_{max}, \quad 0 \leq k \leq N, \]

where \( x_{min}, x_{max} \in \mathbb{R}^2 \).
Power components limits are defined by corresponding power converter power rating, and by physical constraints (e.g. $P_{\text{dc}} \geq 0$ and $P_{\text{ch}} \leq 0$):

\begin{align}
&u_{\text{min}} \leq u_k \leq u_{\text{max}}, \quad 0 \leq k \leq N - 1, \\
&P_{\text{min},k} \leq P_{k} \leq P_{\text{max},k}, \quad 0 \leq k \leq N - 1,
\end{align}

where $u_{\text{min}}, u_{\text{max}} \in \mathbb{R}^4$, and $P_{\text{min},k}, P_{\text{max},k} \in \mathbb{R}$. If information about the predicted utility grid availability is at disposal, one can include this information by modifying constraint (12) as:

\begin{align}
&P_{\text{min},k} \leq P_{k} \leq P_{\text{max},k}, \quad 0 \leq k \leq N - 1,
\end{align}

where $P_{\text{min},k}, P_{\text{max},k} \in \mathbb{R}$ is the information about predicted utility grid availability at time instant $k$ on the prediction horizon. In this paper we consider only constraint defined in (12), i.e. we do not consider any additional limitations on the utility grid.

C. LP formulation

Once objective function and constraints have been defined, one can write down the power flow optimization problem in an LP form as follows:

\begin{equation}
\begin{aligned}
\min \quad & \mathbf{1}^T \mathbf{u} + c, \\
\text{s.t.} \quad & \mathbf{E}_u \mathbf{u} \leq \mathbf{E}_x x_0 + \mathbf{E}_d \mathbf{d} + \mathbf{g},
\end{aligned}
\end{equation}

whereas constant $c$, vectors $\mathbf{f}$ and $\mathbf{g}$, and matrices $\mathbf{E}_u$, $\mathbf{E}_x$ and $\mathbf{E}_d$ are straightforwardly calculated from (6)–(12).

IV. MODEL PREDICTIVE CONTROL

In this section we formulate the Model Predictive Control (MPC) scheme [23] for closed-loop power management in the considered microgrid. Solution to the MPC problem yields a trajectory of states and inputs (i.e. control signals) that satisfy the dynamics and constraints of microgrid operations while optimizing some given criteria [9].

Let the real system dynamics be

\begin{equation}
x(t + 1) = \mathbf{A} x(t) + \mathbf{B} u(t),
\end{equation}

with electricity prices $c(t)$, and disturbances $d(t)$, $\forall t \in \mathbb{Z}$. At each time instant $t$, the MPC scheme computes the optimal control sequence $\mathbf{u}^*$ given an initial storages state $x_0 = x(t)$, electricity price $c = (c(t), c(t+1), \ldots, c(t+N-1))^T$ and disturbance sequence $\mathbf{d} = (d(t), d(t+1), \ldots, d(t+N-1))^T$:

\begin{equation}
\begin{aligned}
\mathbf{u}^* &= \arg \min_{\mathbf{u}} J(\mathbf{u}, x_0, c, \mathbf{d}), \\
&\text{s.t.} \quad (10), (11), (12),
\end{aligned}
\end{equation}

where $J$ is economic criterion defined in (6) which is linear function in $\mathbf{u}$. According to the receding horizon philosophy, only the first control vector $u_0^*$ from the optimal control sequence $\mathbf{u}^*$ is applied, i.e. $u(t) = u_0^*$. The optimization problem (16) is repeated again at the next time instant $t + 1$, with the new initial storages state, electricity price and disturbance sequences. By this approach, the new optimal control plan can potentially compensate for any disturbance that has meanwhile acted on the system. To solve optimization problem formulated in (16) we used IBM ILOG CPLEX 12.6. For easier control problem implementation, one could also consider using YALMIP [24].

V. SIMULATION RESULTS

In this section we verify performance of the proposed approach on year-scale simulations based on the actual meteorological, electricity price and consumption data for year 2013. Numerical data of all parameters defined in Section II and Section III are given in Appendix. We consider closed-loop control scheme simulations with receding horizon philosophy as discussed in Section IV, for different lengths of the prediction horizon $N$, and for different final price value $c_N$, whereas final price value is calculated as a share of maximum price value over the prediction horizon:

\begin{equation}
c_N = \frac{p_{\text{max}}}{100} c_k, \quad t \leq k \leq t + N - 1,
\end{equation}

where $t$ is time instant as discussed in Section IV, and $p_{\text{max}}$ is parameter that goes from 0% to 120%. For $p_{\text{max}} = 0\%$ there is no penalization of the residual storages state, and for $p_{\text{max}} = 120\%$ the power flow optimization algorithm will try to keep the storages nearly full and ready for peak (prices) shaving in the future.

Revenue (i.e. economic gain) at the end of one-year period can be calculated as:

\begin{equation}
\text{rev} = \sum_{t=0}^{8759} c(t) \{ d(t) - P_{G}(t) \},
\end{equation}

where $c(t)$ and $d(t)$ are electricity price and disturbance, and $P_{G}(t)$ is the utility grid power at time instant $t$. In other words, revenue at time instant $t$ is defined as a difference between power demand and actually imported power from the utility grid, multiplied by the electricity price.

Fig. 3 shows revenue at the end of considered one-year period for different lengths of the prediction horizon $N$ and for different final price values $c_N$, i.e. different shares $p_{\text{max}}$ of maximum price value over the prediction horizon from which final price value is formed, as discussed above. As it can be seen from Fig. 3, longer prediction horizons lead to higher revenue, while shorter prediction horizons are more sensitive to penalization of the residual storages state.

Numerical indicators of revenues are shown in Table I.

As it can be seen from Table I, for the prediction horizon $N = 3$ there is a significant improvement in the revenue when using residual storages state penalization, i.e. revenue improvement is 11.41\% (or 5.45\% in absolute value) in comparison between the best case and the case where no penalization of residual storages state is used ($p_{\text{max}} = 0\%$). However, this improvement vanishes as the prediction horizon gets longer, e.g. for prediction horizon $N = 24$ this improvement is only 0.06\% (or 0.05\% in absolute value).

<table>
<thead>
<tr>
<th>Prediction horizon</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>18</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best case</td>
<td>53.2</td>
<td>78.4</td>
<td>80.8</td>
<td>83.5</td>
<td>83.9</td>
<td>84.2</td>
</tr>
<tr>
<td>No penalization</td>
<td>47.7</td>
<td>77.2</td>
<td>81.8</td>
<td>83.5</td>
<td>83.8</td>
<td>84.1</td>
</tr>
<tr>
<td>Improvement (%)</td>
<td>11.41</td>
<td>1.51</td>
<td>0.05</td>
<td>0.02</td>
<td>0.07</td>
<td>0.06</td>
</tr>
<tr>
<td>Mean penalization</td>
<td>51.2</td>
<td>77.8</td>
<td>81.9</td>
<td>83.5</td>
<td>83.8</td>
<td>84.1</td>
</tr>
</tbody>
</table>
Fig. 2. Responses in closed-loop control simulation over 48 h period where $N = 24$ h and $p_{pct} = 90\%$: (i) price profile, (ii) utility grid, PV array and load power profiles, (iii) batteries and FCs power profiles, and (iv) batteries and FCs normalized state-of-charge profiles.

Fig. 2 shows (i) electricity price profile, (ii) power exchange with the utility grid, power production by PV panels and consumption profiles, (iii) optimal control sequence, i.e. storages charging/discharging profiles, and (iv) system state responses in closed-loop control simulation over 48 h period within considered one-year period, where $N = 24$ and $p_{pct} = 90\%$, and by using model predictive control scheme with receding horizon philosophy with sampling time of 1 h.

Note that power exchange with the utility grid is not the decision variable, but is determined by the microgrid balance equation (1). It can be seen that control algorithm uses FCs as little as possible compared to batteries stack, since overall efficiency of the FCs is below 30\%, and the overall efficiency of the batteries is over 80\%. As for buying and selling electrical energy from/to the utility grid, it can be seen that microgrid is importing energy from the utility grid mainly during lower electricity prices, while exporting energy to the utility grid during higher electricity prices. Note that there are no scenarios in whole considered one-year period for which both storages components, charging and discharging, were different than zero at the same time instant, which confirms validity of LP formulation, as discussed in Section II.

Fig. 3. Revenue at the end of the one-year period (year 2013) for different lengths of the prediction horizon $N$ and final price values $c_N$ (on x-axis: share $p_{pct}$ of the maximum power over prediction horizon; on y-axis: total revenue at the end of the one-year period $c_{rev}$ in €). Revenues for the scenario where $c_{N}$ is determined as mean value of price profile along prediction horizon are indicated with arrows.
VI. CONCLUSION

In this paper we proposed a linear program formulation for the power flow optimization in a residential DC microgrid. We showed that despite piece-wise affine nature of the storages model, the optimization problem can be formulated as a linear program, instead of a widely used mixed integer linear program formulation. We also paid special attention to the penalization of residual storages state in objective function. The closed-loop control algorithm is defined using the model predictive control scheme with receding horizon philosophy. Performance of the proposed approach is verified through year-scale simulations based on the actual meteorological, electricity price and consumption data. It is shown that the penalization of the residual storages state has significant impact on the economic revenue for the shorter prediction horizons, whereas this impact is decreasing as prediction horizon gets longer.

APPENDIX

In this section we give numerical values of all parameters specified in Section II and Section III. Note that when referring to the FCs, we actually refer to a system of fuel cells stack and electrolyser with hydrogen tanks, i.e. we refer to FCs as an energy storage system as discussed in Section II.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_{BAT}</td>
<td>10.0 battery capacity [kWh]</td>
</tr>
<tr>
<td>P_{ch}</td>
<td>0.9 battery discharge efficiency</td>
</tr>
<tr>
<td>P_{max}</td>
<td>1.0 battery maximum state-of-charge</td>
</tr>
<tr>
<td>P_{min}</td>
<td>0.1 battery minimum state-of-charge</td>
</tr>
<tr>
<td>P_{max}</td>
<td>3.0 battery maximum discharge power [kW]</td>
</tr>
<tr>
<td>P_{min}</td>
<td>–3.0 battery maximum charge power [kW]</td>
</tr>
<tr>
<td>P_{FC}</td>
<td>2.5 FCs capacity [kWh]</td>
</tr>
<tr>
<td>P_{DCH}</td>
<td>0.4 FCs discharge efficiency</td>
</tr>
<tr>
<td>P_{max}</td>
<td>0.7 FCs charge efficiency</td>
</tr>
<tr>
<td>P_{max}</td>
<td>1.0 FCs maximum state-of-charge</td>
</tr>
<tr>
<td>P_{min}</td>
<td>0.0 FCs minimum state-of-charge</td>
</tr>
<tr>
<td>P_{max}</td>
<td>0.5 FCs maximum discharge power [kW]</td>
</tr>
<tr>
<td>P_{min}</td>
<td>–1.2 FCs maximum charge power [kW]</td>
</tr>
<tr>
<td>P_{max}</td>
<td>3.0 utility grid maximum power [kW]</td>
</tr>
<tr>
<td>P_{min}</td>
<td>–3.0 utility grid minimum power [kW]</td>
</tr>
<tr>
<td>\theta_1</td>
<td>1.65 PV array irradiance parameter [m²/W]</td>
</tr>
<tr>
<td>\theta_2</td>
<td>–0.23 PV array temperature parameter [W/°C]</td>
</tr>
<tr>
<td>\theta_3</td>
<td>–0.01 PV array irradi-temp. parameter [m²/°C]</td>
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</table>

REFERENCES